



REMOTE SENSING BIG DATA ANALYTICS FOR DETAILED GEOLOGICAL MAPPING IN EXPOSED ZONES OF DRY VALLEYS, SOUTH VICTORIA LAND, ANTARCTICA

ARTICLES FOR FACULTY MEMBERS

A continent-wide detailed geological map dataset of Antarctica / Cox, S. C., Smith Lyttle, B., Elkind, S., Smith Siddoway, C., Morin, P., Capponi, G., Abu-Alam, T., Ballinger, M., Bamber, L., Kitchener, B., Lelli, L., Mawson, J., Millikin, A., Dal Seno, N., Whitburn, L., White, T., Burton-Johnson, A., Crispini, L., Elliot, D., ... Wilson, G.

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OPEN

DATA DESCRIPTOR

A continent-wide detailed geological map dataset of Antarctica

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A dataset to describe exposed bedrock and surficial geology of Antarctica has been constructed by the GeoMAP Action Group of the Scientific Committee on Antarctic Research (SCAR) and GNS Science. Our group captured existing geological map data into a geographic information system (GIS), refined its spatial reliability, harmonised classification, and improved representation of glacial sequences and geomorphology, thereby creating a comprehensive and coherent representation of Antarctic geology. A total of 99,080 polygons were unified for depicting geology at 1:250,000 scale, but locally there are some areas with higher spatial resolution. Geological unit definition is based on a mixed chronostratigraphic- and lithostratigraphic-based classification. Description of rock and moraine polygons employs the international Geoscience Markup Language (GeoSciML) data protocols to provide attribute-rich and queryable information, including bibliographic links to 589 source maps and scientific literature. GeoMAP is the first detailed geological map dataset covering all of Antarctica. It depicts 'known geology' of rock exposures rather than 'interpreted' sub-ice features and is suitable for continent-wide perspectives and cross-discipline interrogation.

Background & Summary

Antarctica contains minimal geologic exposure compared to the overall area of ice, but there are over 52,000 km² of rock and unconsolidated cover deposits that contain a rich geological, geomorphological and glaciological history of the continent. Numerous, hard-copy, regional-scale geological maps were developed last century^{1–3}. Many have been scanned, some have been georeferenced, but few are more than raster digital information with an adjacent legend. For the most part they are geologically reliable for defining bedrock geology ('deep time') and construction of the continent. But the maps have poor spatial reliability in the context of modern science

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located by global positioning system (GPS) and other satellite sensors, and existing maps rarely contain much representation of glacial geology and cover sequences that hold information on the waxing and waning of Antarctica's ice sheets.

A strong imperative for a comprehensive digital dataset of Antarctica's geosphere comes from the need to understand its influence on global climate and potential contributions to sea level rise, as well as the effects of climate change on the frozen continent itself^{4,5}. This drives interest in a geospatial resource that can pinpoint the locations of glacial deposits, indicate their mode of formation, age, and likely source. Although there are some relatively small areas represented by detailed local maps^{6–8} there are no modern attribute-rich geographic information system (GIS) datasets to provide holistic information commensurate with the scale of the ice sheets/ice shelves. Spatial variations in geological characteristics, such as density, colour, heat-production or sub-ice structure, are also now deemed to be important as they influence ice sheet dynamics and the response of the continent to ice-removal^{9–12}. Geological data also provide contextual information for biological and ecological analysis, studies of albedo and meltwater production, soil conservation and managing human impact^{13–16}. Meanwhile, large quantities of satellite data are being rapidly acquired at sub-metre scale over most of the Antarctic continent, offering the opportunity to locate outcrops and derive high-resolution compositional information where data can be referenced to ground-based observations^{17–19}.

Following publication of the 1:250,000 Geological Map of New Zealand^{20,21} and release of a map sheet and GIS for southern Victoria Land²², GNS Science launched an ambitious project to build a similar high-quality digital geological dataset covering the entire Antarctic continent. International participation and support were sought through formation of a Geological Mapping Update of Antarctica (GeoMAP) Action Group at the 2014 Scientific Committee on Antarctic Research (SCAR) Open Science Conference in Auckland (<https://www.scar.org/science/former-groups/geomap/>). The aim was to capture existing geological map data, update its spatial reliability, improve representation of glacial sequences and geomorphology, then enable data delivery via web-feature services. Our broader intent is to provide a dataset describing the exposed geosphere that can be used for cross-discipline science, as well as continent-wide geological perspectives^{2,3,23}.

The GeoMAP Action Group attracted principal collaborators from United States of America, Norway, Italy, United Kingdom, Australia, Russia and New Zealand, but included contributions from at least 14 nations. Many others provided advice, data and support (see Acknowledgements). Much manual work was completed in the GNS Science office in Dunedin by 11 student volunteers, who visited New Zealand on internships or worked remotely by videoconferencing in return for GIS-training and professional development. Students presented the results of their local mapping in conference abstracts, talks and posters as the dataset progressively evolved and improved. An initial beta-test version of GeoMAP (v.2019-07) was released at the 2019 XIII International Symposium of Antarctic Earth Sciences meeting in Korea. Following a period for review and further improvements by GNS Science, the first formal version has been released and is documented here.

The new GeoMAP v.2022-08 dataset of Antarctic geology (Fig. 1) is now freely available from the World Data Center PANGAEA (<https://doi.org/10.1594/PANGAEA.951482>)²⁴. It describes and presents the 'known geology' of rock and bare sediment exposures in a unified framework. As well as providing a fundamental dataset for local- to continental-scale interrogations of bedrock and glacial geology together with glaciology and other physical sciences, the nature and composition of rock substrate as defined by GeoMAP also provides a contextual base for biological and ecological research.

Methods

Goals and context. The GeoMAP Action Group set itself a challenge to collaboratively build a modern geological dataset to classify and describe the bedrock and surficial deposits representing Antarctica's geology. The concept was to capture existing geological observations and map data, update its spatial reliability, develop data in a GIS format and enable data delivery via web-feature services. Providing links to all original publications through a spatial bibliography was deemed paramount in creating a fair and functional product. The goal was to provide a dataset describing the exposed geosphere which would enable cross-discipline science or, for continent-wide perspectives, that captured existing geological knowledge in a manner that can be easily improved by subsequent generations. A secondary goal was to improve representation of glacial sequences and geomorphology because of their potential to contain records of ice fluctuations relevant to climate change.

Rapid development of a continent-wide dataset was achieved by adapting a tried and tested GIS methodology from mapping New Zealand (QMAP 1993–2014)^{20,25} but adopting a distinct 'downscaling' work-stream from continental- to regional- to local-scale. This differs from the more-traditional and common approach of dividing a region of interest into a series of mapsheet areas that are completed sequentially at the same scale. Construction of GeoMAP started from a continent-scale, low density, attribute-poor dataset that was augmented and improved through multiple iterations. The work-flow followed a seven stage process adapted from the digital geological map of New Zealand: (1) adjusting rock and moraine polygons; (2) scanning and registering old maps to build a spatial bibliography; (3) coding polygons with attributes according to legacy map classification and source information; (4) assigning continent-wide classification and building a consistent legend (the hardest part); (5) reviewing depiction of glacial geology and cover sequences; (6) translating into the Geoscience Markup Language (GeoSciML) data standard²⁶ published by the International Union of Geological Sciences (IUGS) Commission for Geoscience Information (<https://cgi-iugs.org/project/geosciml/>); and (7) constructing a seamless continent-wide dataset, with associated reviewing, checking and quality control.

A key feature was the deliberate strategy to capture 'known geology' of rock and bare sediment exposures rather than 'interpreted' sub-ice features. In practice this meant classifying and describing around 52,000 km² of the continent, now distinguished by 99,080 distinct polygons. These have been unified for use at approximately 1:250,000 scale, although locally there are some areas with higher spatial precision. Feature classification and description of rock and moraine polygons utilised a mixed chronostratigraphic- and lithostratigraphic-based

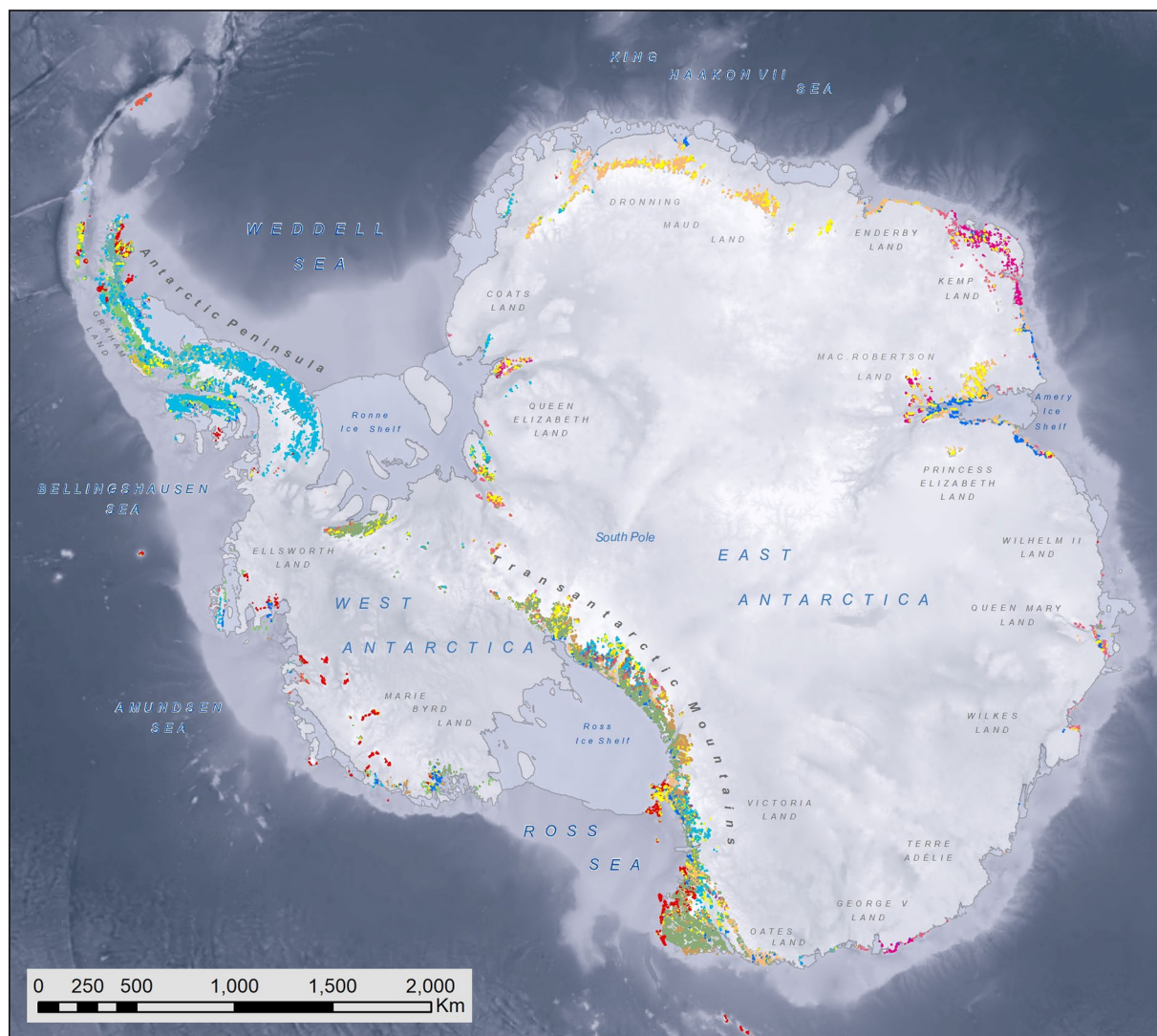


Fig. 1 A geological map of Antarctica generated using the GeoMAP dataset, here draped over subglacial topography from MEaSUREs BedMachine Antarctica^{11,55}. A rich attribute table enables data to be displayed or queried in a wide variety of ways. Here the map renders 99,080 polygons with colours reflecting rock or deposit age using MAPSYMBOL according to the legend in Fig. 2, many of which are too small to be seen at a continent scale. Other data captured in GeoMAP, but not displayed on this map, includes a source bibliography and fault data.

classification, which employs the international GeoSciML 4.1 XML-based data protocols²⁶ to provide attribute-rich and queryable data, including bibliographic links to the source maps and literature where original field observations were published. Although there are varying degrees of interpretation within any map at a local-scale, from a continental-perspective GeoMAP is more of an ‘observational dataset’ or discontinuous ‘fact map’, rather than a more-continuous ‘interpretational dataset’.

Input data. Areas depicting rock were initially derived from the SCAR Antarctic Digital Database (ADD) v5.0 shapefile Rock_outcrop_high_res_polygon.shp²⁷. Although there are known problems locally with the georeferencing, overestimation and generalisation²⁸, this dataset of 68,381 polygons provided a pragmatic balance between a continent-wide dataset with enough precision and accuracy to enable regional-scale work, yet it is not so large as to be unworkable on a standard desk-top computer. Rock outcrop and lake polygons were examined against aerial photographs, the Landsat Image Mosaic of Antarctica (LIMA) imagery²⁹ and against outputs from high-resolution satellite products and automated algorithms^{18,28,30}. Those polygons that were particularly poorly georeferenced (with >250 m error), or misshaped, were manually adjusted to concur with LIMA, which has 15 m panchromatic pixels geolocated to ± 54 m one-sigma accuracy²⁹. Mapping of unconsolidated Neogene cover deposits involved checking a combination of previous work and the ADD shapefile Antarctic_moraines_high_res_polygon.shp²⁷, then making new interpretations from aerial photographs, satellite imagery, light detection and ranging (LiDAR) elevation data and the Reference Elevation Model of Antarctica (REMA)^{29–31}.

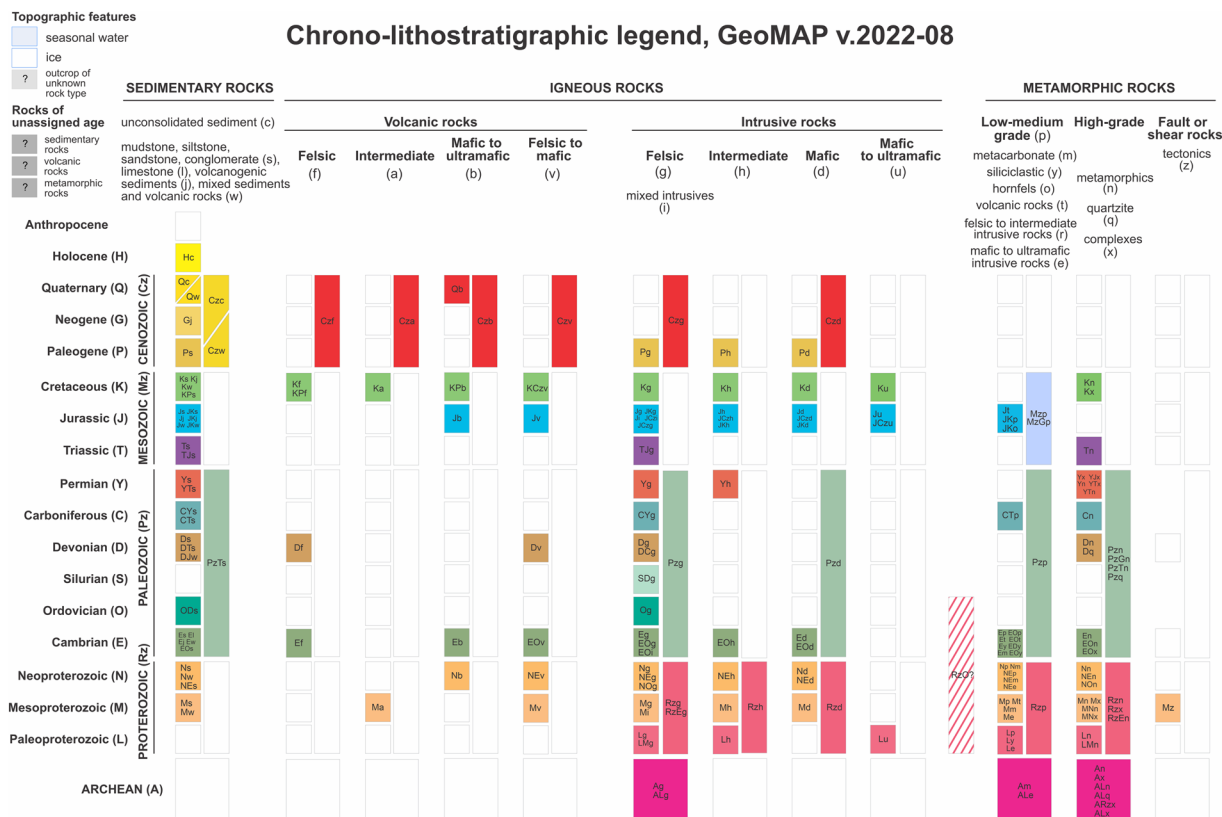


Fig. 2 The chronostratigraphic and lithostratigraphic convention adopted within the GeoMAP ATA geological_units layer by the attribute MAPSYMBOL to unify all the different geological studies across the continent. Coloured boxes on this chrono-lithostratigraphic legend show symbols present in the dataset, as used in Fig. 1, whereas clear boxes are not present (or have yet to be assigned). Note that geological units which span multiple time periods have symbols showing the oldest and youngest time periods. e.g. Cambrian to Ordovician sedimentary rocks = EO; Paleoproterozoic to Mesoproterozoic high-grade metamorphic rocks = LMn.

Geological observations were compiled from 589 sources, which include a wide variety of published maps^{1–3} and papers^{6,8,17}, unpublished maps, university theses and other compiled and already available digital data^{22,32}. Relocated and reshaped ‘rock’ and ‘moraine’ polygons were further cut and/or reshaped to represent variations and features of geology depicted in the source maps. Some areas have detailed mapping at scales of less than 1:50,000 whereas others are mapped more regionally at 1:250,000. Of the 589 maps scanned and georeferenced, 49% are local-scale (<1:250,000), 44% regional-scale (1:250,000 to 1:1,000,000), and 7% continental-scale (>1:1,000,000). In some places, older regional-scale maps³ remain the best legacy information available. Wherever possible the geological classification used the best, highest resolution maps available. The final classification of geological unit polygons cites 234 source maps. Of the original 68,381 ADD polygons, only 7920 remain in the derived GeoMAP dataset with the same position and geometry. The positional accuracy of final polygon boundaries is strongly dependent on the quality and scale of the original legacy maps, but for the most part it is around ± 250 m.

Although no new fieldwork was completed specifically for GeoMAP purposes, access to sub-metre scale satellite imagery and trimetrogon aerial (TMA) photographs was obtained through Google Earth (<https://www.google.com/earth/>) or the U.S. Polar Geospatial Center (PGC) (<https://www.pgc.umn.edu/data/aerial/>). These enabled some new observations and interpretations to be made at high-resolution, or for reasonable inferences to be transferred from one nearby outcrop to another. Regardless, a surprising number of places in Antarctica have had no geological observations and lack high-resolution imagery, resulting in local gaps and uncertainties in geological mapping. The question symbol ‘?’ was used for 4207 polygons in the dataset to indicate places where the exact nature of rock outcrops or their age is still unknown and future work is recommended.

Data Records

GeoMAP data are available for download directly from PANGAEA²⁴, or can be accessed through webmaps and webservices delivered by GNS Science³³. GeoMAP uses GIS methods to store, manipulate, and present bibliographic and geological information. There are four main feature classes (Table 1) in the archived ArcGIS geodatabase and QGIS GeoPackage. The database also contains a geological legend (feature dataset) that portrays a time-space diagram. A general overview of these data is provided here, but more-complete information,

ATA_GeoMAP_Feature Class	No. & Type	Description	Attribute Fields
sources	589 polygons	Spatial bibliography of key legacy geological maps that were consulted during GeoMAP construction. Provides link to sources used in geological_unit classification.	17 different fields describing the source's author(s), title, publication, year, institution, scale of map, type of publication, and lead national Antarctic program.
geological_units	99,080 polygons GeoSciML-Lite	Geological unit data for Antarctica. A synthesis of existing regional mapping of geology in a single dataset at continental scale. Polygons cover exposures of both bedrock and unconsolidated cover deposits (such as glacial tills), but also include areas of ice from re-frozen meltwater.	42 fields describing the unit type, name, age, lithology, stratigraphy, and supporting background information, where known. Each is linked to legacy maps through a sources attribute. Can be used to generate a variety of categorical classifications.
faults	1,784 lines GeoSciML-Lite	Fault data for Antarctica. A synthesis of existing published and unpublished mapping in a single dataset at a regional scale.	32 fields describing the locational accuracy, exposure, activity, type of fault, and sense of movement and displacement, where known. Also fields describing scale of data capture and bibliographic source.
quality	43,201 polygons	Areas covering 1° longitude and 15 minute latitude intervals, categorized by a subjective rank of quality for GeoMAP geological unit and fault data within the area. Also provides binary indication of whether there are geological units within the polygon.	5 fields including a numerical rank of quality from 1 (low) to 5 (high), with other contextual comments such as progress of data capture, work outstanding.
legend_geological_units	451 polygons Chronologic grids and annotation are also provided with the feature dataset	A geological legend portrayed as a time-space diagram illustrating the representative age and types of rock at the approximate longitude where exposures of that geology occur. Constructed using EPSG:4978 (WGS 84) these data are also suitable for projection in EPSG:3031 (WGS 84/Antarctic Polar Stereographic).	11 fields to match the ATA_GeoMAP_geological_unit feature class. Includes mapsymbol, sourcecode group name, simplecode lithology, stratigraphy, and tectonic province.

Table 1. Summary of the main GIS feature classes in the GeoMAP v.2022-08 dataset.

including tables of all attributes and attribute field content, is provided in metadata records³³ and some online documentation (<https://geomap.readthedocs.io/en/latest>).

Source map bibliography. The ATA_GeoMAP_sources_poly feature class is a spatial bibliography of polygons representing the geological maps consulted or directly used in construction of GeoMAP. Each polygon defines the spatial cover of maps and has attributes describing the source's authors, title, publication, year, program and scale of publication. The data structure complies with the GeoSciML 4.1 standard and uses the relevant Common Gateway Interface (CGI) controlled vocabularies²⁶. A unique identifier SOURCE is also used to link geological polygons in ATA_GeoMAP_geological_units to the bibliographic reference used for their definition.

Geological mapping units. Delineating geological units is a fundamental part of the geological mapping process. Geological maps are typically based on lithostratigraphy, biostratigraphy, age, and rock types, or combinations of these. A combined chronostratigraphic and lithostratigraphic approach was adopted for GeoMAP, in which the description of areas is based on dominant age and/or rock type. To be depicted the geological unit must have sufficient thickness and/or scale, which is typically greater than 10–20 metres thick or 200 m across for GeoMAP. Any units thinner or narrower than this are likely to have been omitted, unless particular emphasis on the unit is warranted through a need to highlight features of some special scientific significance²².

Geological polygons have been stored in the feature class ATA_GeoMAP_geological_units, the principal output from the project. These vector data comply with the GeoSciML Lite standard for GeologicalUnitView, and fields required by that standard were populated using the CGI vocabulary (v2016.01)²⁶. Polygons each have 42 populated fields holding attributes regarding stratigraphic nomenclature and hierarchy, age, lithology, and primary data source, etc. Perhaps the most important attribute fields are SOURCECODE and MAPSYMBOL.

SOURCECODE is the classification initially assigned by a legacy map author (source) pulled directly from the SOURCE publication, following whichever convention was used by the author(s) in their original publication. SOURCECODE values commonly follow conventional geological labels (1–2 characters indicating age followed by 1–2 characters indicating lithology) or they can be a number or character-number combination like a sample identifier. Question marks (?) have been placed in the symbol to indicate where there is uncertainty in the original author's identification, or that an area has yet to be mapped beyond reconnaissance level, and geology inferred. SOURCECODE provides a bibliographic link that enables initial hard-copy maps to be retrieved or reproduced locally in a digital format. The 993 distinct values in SOURCECODE, however, are not a useful way to classify the entire continent.

By way of contrast, the MAPSYMBOL code provides GeoMAP's main classification of the geological identity of the polygon, with values restricted by a formatting convention defined by the GeoMAP chrono-lithostratigraphic legend (Fig. 2). GeoMAP has adopted a convention that is very similar to the 1:1 million geological map of Australia³⁴. CAPITAL letters are used to represent age (Chronostratigraphic subdivision, also used for the AGECODE field) and small letters representing lithology (rock-type as a lithostratigraphic classification, also provided in a LITHCODE field). The MAPSYMBOL unifies the original SOURCECODE and classifies polygons consistently across the entire GeoMAP dataset into 186 different units (Fig. 2). A cartographic layer file symbolised according to this chrono-lithostratigraphic subdivision is provided for a spatially projected legend layer in the GeoMAP data download package.

The attribute field NAME provides either a textual name of the rock unit, or simplified type of rock. Where possible the formally defined and published stratigraphic name is assigned to the polygon, for example, as per the lexicon

LITHCODE	SIMPLE LITHOLOGY DESCRIPTION
	Seasonal ice and water
c	Unconsolidated sediment
j,l,s,w	Sedimentary rock
a,b,f,v	Volcanic igneous rock
d,g,I,u,h	Intrusive igneous rock
e,m,o,t,y,p	Low-medium grade metamorphic rock
n,q,x,z	High-grade metamorphic rock
?	Unknown or unclassified rock

Table 2. Basic grouping of the geological unit polygons can be achieved using the lithostratigraphic LITHCODE attribute (lower case letter of the MAPSYMBOL). A cartographic layer file of ‘Simple Lithology’ is provided in the data download package.

in the geologic map of southern Victoria Land²². However, many units have been named informally or only classified by lithology. For the most part, NAME has generally been derived from the SOURCE publication and follows whichever convention was established in the legacy work by the original authors. There are 789 unique NAME values.

A POLYCTYPE attribute with restricted fields of ‘rock’, ‘moraine’, and ‘ice’ is the simplest possible classification of the geological unit polygons. There are occurrences of water, or ice that have re-frozen from meltwater, throughout Antarctica. Seasonal accumulations of supraglacial water, small ponds, and lakes are commonly re-frozen into clear dark ice that can be distinguished from blue ablation ice in remotely-sensed imagery and digital surface models by their darker/clear colour and/or a flat surface. Many are defined in the ADD lakes dataset²⁷, but lots of new occurrences are added in GeoMAP, since quantification of surface meltwater is likely to be a feature of importance for understanding Antarctica’s future^{5,15}. There are 3383 ‘seasonal water’ polygons in the dataset within the POLYCTYPE = ice. For GeoMAP they were manually mapped, using either the ADD_lakes_high_res_polygon.shp or satellite-based observations, predominantly from LIMA. Other projects are now working towards automated machine learning approaches^{15,35,36} to ensure that future changes and variations in seasonal water are tracked.

A more basic geological classification can also be achieved using the LITHCODE attribute field derived from the lowercase letter of MAPSYMBOL (Table 2). A GIS layer file ‘Simple Lithology’ provided in the GeoMAP data download package classifies the geological unit feature into 8 classes. Alternatively, there is an attribute field SIMPLECODE to provide a generalised chronological and lithological subdivision into 21 classes (Table 3). These are expected to provide a more-useful definition of the variation in age, rock strength, and chemistry without going to the full 186 unit chronostratigraphic and lithostratigraphic classification provided by MAPSYMBOL.

Faults. The feature class ATA_GeoMAP_faults contains a series of lines that mark places where faults or shear zones have been observed to cross-cut geological units, forming boundaries between adjacent polygons, or interpreted as concealed sub-ice discontinuities based on otherwise unexplained changes in geology. Antarctica appears relatively unique in that there seem to be very few outcrops with fault or fault-rock exposures compared with ice-free continents, though examples do occur^{37,38}. Perhaps this is because fractured-rock is more easily eroded than unfractured-rock, the crushed rock in fault-zones tends to coincide with gullies and topographic low-points, and these preferentially fill with, and become obscured by, wind-blown snow and ice. Most legacy maps depict some form of faults beneath snowfields and glaciers, many of which are interpreted from changes in geology or geophysical characteristics. There are few studies, however, with accompanying documentation that rationalises the basis for interpreting such structures, fault-type, sense of motion, or scale of displacement. Many may simply reflect a geological paradigm applied at the time or were used to rationalise lack of information for understanding local geological relationships and structure.

The compiled faults feature class contains 1784 lines (arcs) each with 32 attribute fields to describe the locational accuracy, exposure, activity, type of fault, orientation, and the sense of movement, where this is known. It complies with the GeoSciML Lite standard for ShearDisplacementStructureView with fields required by that standard populated using the CGI vocabulary (v2016.01)²⁶. As it contains many interpreted structures, and some that may be speculative and debatable features, all lines within the ATA_GeoMAP_faults feature class are linked to the original bibliographic reference where they were first defined using the unique SOURCE identifier in the ATA_GeoMAP_sources_poly spatial bibliography. The faults feature class includes some uncertain ‘tectonic province boundaries’, concealed beneath the ice, that have been inferred at a continental-scale²³.

Chrono-spatial legend. An innovative feature of GeoMAP v.2022-08 is a geological legend portrayed as a time-space diagram (Fig. 3). The GIS feature dataset ATA_GeoMAP_legend was created to show geological map units by age in the approximate longitude at which exposures occur around Antarctica. Each polygon in the chrono-spatial legend has attributes derived from ATA_GeoMAP_geological_units enabling it to be coloured by MAPSYMBOL or SIMPLECODE. Alternatively, they can be queried and selected by any of the eleven attribute fields. Legend polygons also record the code used on the original published source map or dataset using the SOURCECODE attribute.

As the name implies, the chrono-spatial legend is a time-space graph showing the spatial location of objects as a function of time. Similar to most conventional geological legends, it shows time running up the diagram

SIMPLECODE	SIMPLECLASS	SIMPLEDESCRIPTION
10	OTHER	Seasonal water and ice
11		Unknown or unclassified rock
20	QUATERNARY-NEOGENE	Unconsolidated colluvium, talus, alluvium, and undifferentiated till
21		Youngest glacial gravel, till, and supraglacial material (Holocene)
22		Unconsolidated coastal ice shelf till, beach, or lake deposits
23		Older glacial gravel and till (Miocene-Quaternary)
30	CENOZOIC	Sedimentary rock with interbedded volcanic or volcanoclastic rock
31		Volcanic rock - basalt to rhyolite lava flows and pyroclastic material
32		Intrusive rock - granite, granodiorite, gabbro, or syenite (Eocene-Oligocene)
40	MESOZOIC-CENOZOIC	Sedimentary and volcanic rocks, pyroclastic material (Jurassic to Paleogene)
41		Volcanic rock (Jurassic-Paleogene)
42		Ferrar Igneous Province and related volcanic and sedimentary rock (Jurassic)
43		Silicic volcanic and continental sedimentary rock (Jurassic)
44		Unmetamorphosed granitoid, gabbro, and other intrusive rock
45		Metamorphosed gneiss and migmatite (Triassic, Cretaceous)
50	PALEOZOIC-MESOZOIC	Beacon Supergroup and other sandstone-rich sedimentary rock (Devonian-Triassic)
60	PROTEROZOIC-PALEOZOIC	Intrusive rock - granitoid, diorite, gabbro, and orthogneiss
61		Folded low-grade metasedimentary and metavolcanic rock
62		Low to medium-grade metamorphic rock - schist, marble, metavolcanic, metasandstone
63		High-grade metamorphic rock - orthogneiss, paragneiss, schist, and amphibolite
70	ARCHEAN	Metamorphic and intrusive rock - schist, gneiss, granulite, migmatite, and anatectite

Table 3. A simple classification of the geological unit polygons using the SIMPLECODE numerical attribute that distinguishes SIMPLECLASS and SIMPLEDESCRIPTION. A rendered layer file ‘Simple Geology’ is provided in the data download package.

equivalent to a Y-axis, so the bottom is the past, or older times, and the top is the present, or more recent times. Lines of longitude form an X-axis and provide the geographic context to anchor features in the legend data layer. The chrono-spatial legend was constructed using EPSG:4978 (WGS 84) coordinate system but is suitable for projection in other coordinate systems. Popular GIS software packages, such as ArcGIS and QGIS allow a user to project geospatial layers “on the fly”. Once the geological legend is loaded in a map project, by changing the coordinate system in the map properties, it is possible to see the spatial context of different rock ages from a different perspective. A user might switch between EPSG:4978 (WGS 84) or EPSG:3031 (WGS 84/Antarctic Polar Stereographic) or EPSG:3832 (WGS 84/PDC Mercator) coordinate systems to gain an appreciation of the geological age variation around the continent.

Technical Validation

With positional accuracy of final polygons predominantly ± 250 m, GeoMAP v.2022-08 reliably represents geology at 1:250,000 scale. However as well as the precision and accuracy of the polygons there are spatial variations in both the internal quality of interpretative information available for compilation of the dataset, as well as the degree of attention an area may have received by the GeoMAP team. One of the hardest tasks was, and still is, building consistency and capturing the local nuances of different interpretations available. There will undoubtedly be debate as to how well this has been achieved, but there has always been full expectation that GeoMAP should be a ‘live’ dataset that continues to evolve and improve over time.

As GeoMAP was being constructed from continental- to regional- and to local-scales, it evolved in both the positional accuracy and level of detail of geology represented. The feature class ATA_GeoMAP_quality was generated across 1 degree longitude and 15 minute latitude intervals to provide a subjective rating of ‘quality’ and used to track GeoMAP progress. It subjectively rates availability of geological mapping, availability of other legacy information, the attention various areas have received by the GeoMAP team and regions where there is data yet to be captured (Fig. 4; Table 4). It is inevitable that some degree of geological complexity and variety of scientific approach and interpretations will have also inadvertently been included in the ranking, although this was not the primary intent of this feature class. As well as tracking progress for project management as the dataset evolved, the final published v.2022-08 quality feature class can be used to indicate confidence for future cross-discipline work and an impetus for GeoMAP improvements. A number of areas for improvement are also listed in the Usage Notes below.

Usage Notes

GeoMAP is licensed under a Creative Commons Attribution 4.0 International License and available for download through a data repository²⁴. Acknowledgement of the source of data from both GNS Science and the SCAR GeoMAP Action Group is requested. It may be appropriate to cite both the data repository and this manuscript separately, depending on whether the data themselves are being used.

Chrono-spatial legend, GeoMAP v.2022-08

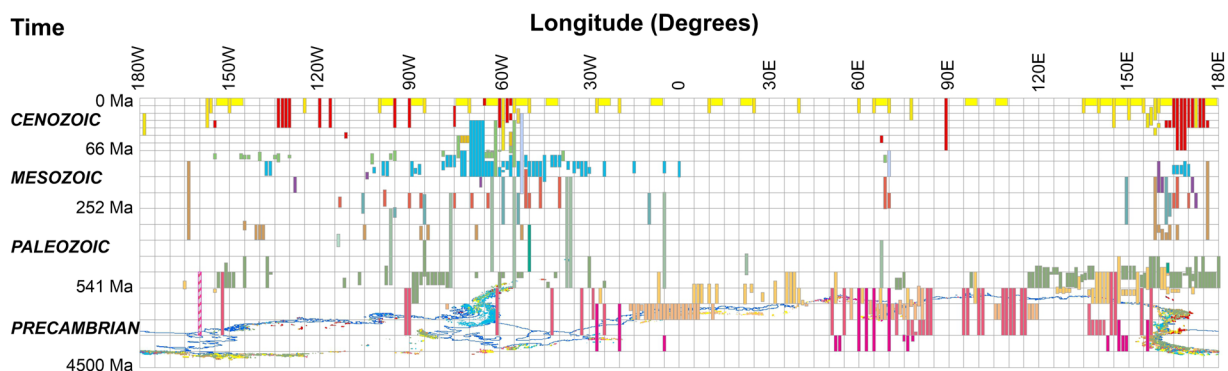
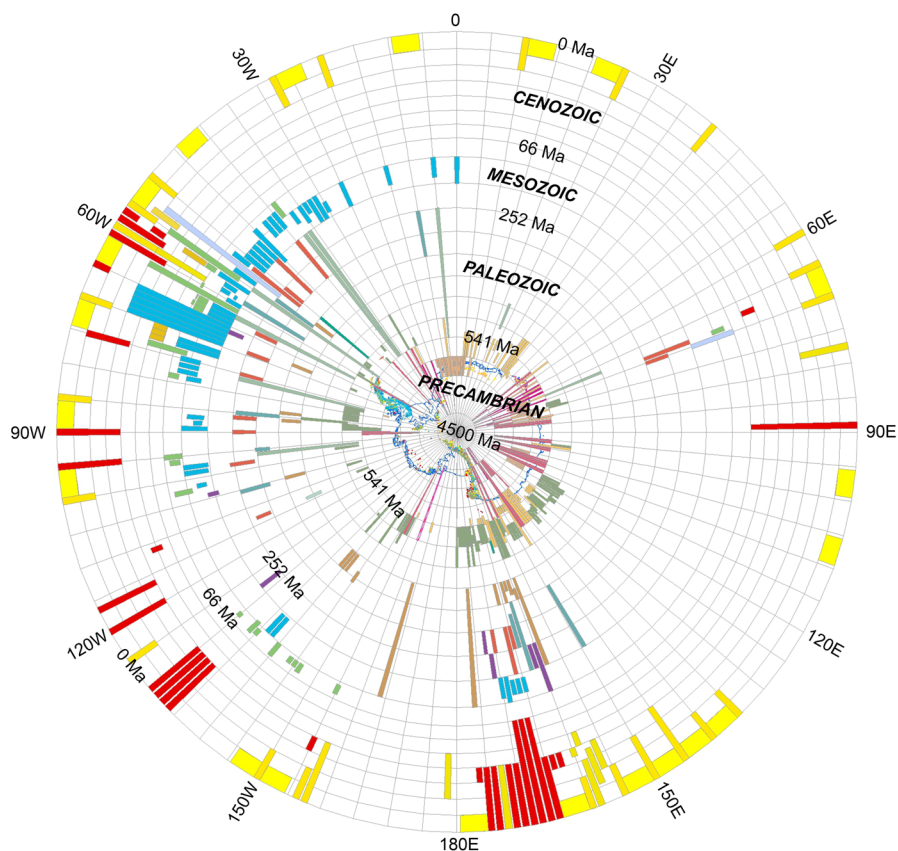
a EPSG:4978 (WGS 84) projection**b** EPSG:3031 (WGS 84/Antarctic Polar Stereographic) projection

Fig. 3 A unique chrono-spatial legend is provided as a feature dataset in GeoMAP v.2022-08 that can be displayed with different projections shown here with ‘thumbnails’. **(a)** The geological units on a time versus longitude graph using the EPSG:4978 (WGS 84) coordinate system. **(b)** The exact same data using EPSG:3031 (WGS 84/Antarctic Polar Stereographic) projection. Both follow the chrono-lithostratigraphic colour scheme used in Fig. 2 to colour the ATA_GeoMAP_geological_units dataset. This feature class has eleven geological fields that can be explored with the same attribute queries as used to select and find geological map unit polygons. Although it is impossible to show the detail of these diagrams in a journal-sized figure, they serve to indicate functionality provided by these data in a GIS program.

A goal of the GeoMAP Action Group has been to capture a digital dataset to first enable ‘cross-discipline science’, with a secondary intent to support ‘geological science’. But as the dataset evolved, there has been a natural tendency to add in and improve the geological information it contains, and shift focus towards the

GeoMAP v.2022-08

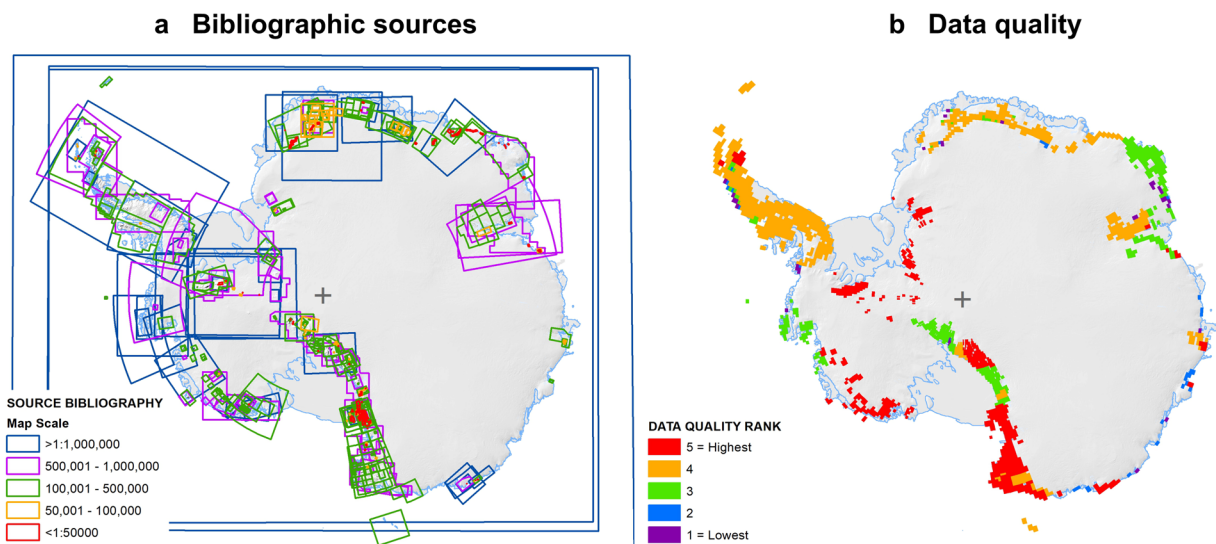


Fig. 4 Bibliographic source and data quality for GeoMAP v.2022-08. **(a)** The distribution of bibliographic source maps used in the compilation of GeoMAP, with map area outlines coloured by scale. **(b)** The subjective ranking of the relative quality of the geological data, where different colours represent a subjective ranking on a scale of 1 to 5 where there are rock outcrops. For a detailed description of the quality ranking see Table 4.

QUALITY	DESCRIPTION
5 (Highest)	Bedrock geology has been captured from mapping at 1:250,000 or more detailed; cover sequences and occurrence of seasonal water have been reviewed and classified from ground studies, or aerial or satellite imagery; fault data have been captured; rock outcrop polygon areas have been checked against LIMA or other satellite imagery (accurate to ± 100 m); links to a source bibliography are complete.
4	Bedrock geology captured from mapping at regional scale (mostly <1:250,000); cover sequences and occurrence of seasonal water have been reviewed and classified from aerial or satellite imagery, but there may not be local studies to constrain age; most faults have been captured; rock outcrop polygon areas have been checked against LIMA or other satellite imagery (accurate to ± 200 m); links to a source bibliography are complete.
3	Bedrock geology has been captured from mapping at regional scale (mostly >1:250,000); review of cover sequences and seasonal water is quite limited and could be rationalised; some fault data have been captured; there has been some checking of rock outcrop polygon areas against satellite imagery (accurate to ± 500 m); further bibliographic links to geological studies could potentially be added.
2	Bedrock geology may be well-constrained, or alternatively interpreted from large scale mapping (e.g. >1:1,000,000); there has been very limited review of cover sequences and seasonal water; fault data are unlikely to have been captured; rock outcrop polygon areas could be improved by checking against satellite imagery (only accurate to ± 1000 m); links to bibliographic source information are missing, or the bibliography is incomplete.
1 (Lowest)	Quality rank refers to the early stages of work where little or no information had been attributed to rock outcrop polygons; and polygons have not been checked for their locational position and/or shape. In some places there is no information to assign (where outcrops may not have been visited or had geology inferred) in which case polygons have been attributed as 'unknown'. There are still quite a few places in Antarctica where an entire $1^\circ \times 15$ minute grid polygon appears to be unknown.
0	There are no outcrops of rock or surficial deposits in the grid polygon.

Table 4. Outline of ATA_GeoMAP_quality ranking used to indicate variation in data veracity across a grid at 1 degree of longitude and 15 minute latitude, and to highlight regions that would benefit from further work or investigation.

more-specialised geological end user. Although it was not originally conceived as a specialist reference dataset for geologists undertaking detailed research, it clearly provides context for local research. GeoMAP may well become a useful first port of call for introductory overviews and bibliographic links to original work, acting like a spatial 'Wikipedia' of Antarctic geology. During construction of GeoMAP v.2022-08 there were several areas specifically identified where the dataset can be improved in future versions, particularly for geology. Some are listed in detail below, while other suggestions for localised improvement are recorded in the COMMENTS attribute field in the ATA_GeoMAP_quality feature class.

Cross-discipline application. The definition of rock and substrate composition has potential to inform ecological, environmental, biological, heat flow, and meltwater modelling, as well as many other cross-discipline studies. Of the 'Priorities for Antarctic Research' identified by the Antarctic Roadmap Challenges Project³⁹ we have identified at least 22 of the 80 questions that can be informed by GeoMAP data, including: Ice sheet & sea level: Q27, 29, 32–34; Dynamic Earth: Q35–42; Life on the precipice: Q46, 48, 49, 54, 55, 68; Human presence:

Q74, 75, 79). Future improvements in both the detail (scale) of mapping and bedrock, cover, and ice margin interpretation will help GeoMAP become more specifically useful for a wider range of scientists.

Classification can improve categorical reduction of chronostratigraphic and lithostratigraphic variability, and greatly simplify the use of geological data in cross-discipline interrogation. The most basic geological classification can be achieved using LITHCODE (Table 2) and the simple geology attribute fields (SIMPCODE, SIMPCCLASS, SIMPDESC) group geological units into 21 age and rock type classes (Table 3). Alternatively, the ATA_GeoMAP_geological_units attribute TECTPROV provides a different break-down of polygons into more-interpretative tectonic provinces^{23,40}. It is just one of many possible interpretations of cratonic blocks and tectonic belts^{41–47}, which tend to be strongly reliant on available geochronology, geophysics, and correlation to neighboring continents. The functionality of GeoMAP and other digital geological data might well be improved if a high-level stratigraphic/structural classification scheme were able to be collectively agreed upon for Antarctic Geology, similar to that developed for New Zealand⁴⁸.

Geological context and high-level classification. There are many ways by which Antarctica can be subdivided into high-level geological units. Areas of outcropping geology are commonly classified into ‘crustal blocks’, ‘tectonic provinces’, ‘cratons’ or ‘orogenic belts’. These define parts of the continent based on age and orogenic history and group the rock’s unique modification by accretionary and collisional additions, or rift-driven subtractions. By combining field geology with geochronology, geochemistry, geophysics and knowledge of geological history of neighbouring continents, such subdivision can be projected beneath ice-covered areas. Major tectonic boundaries can also be constrained by geophysical interpretation and the relative location of different rock outcrops. However, classification of outcrop geology then becomes strongly dependent on this interpretative process and the availability and scale of geophysical data to do so. As a consequence, a plethora of continental-scale subdivisions^{23,40–47} have evolved as rapidly as the available science.

A deliberate feature of GeoMAP has been to focus on the capture of ‘known geology’ of rock and bare sediment exposures, rather than interpreted sub-ice features, in part because it is scientifically conservative and enables the observational dataset to become a longer-lived product. GeoMAP v.2022-08 does, however, provide the attribute field TECTPROV which contains one version^{23,40} of a high-level subdivision. There are clearly a number of other possible high-level subdivisions or more-detailed groupings. The Dronning Maud Land sector of East Antarctica, for example, has been subdivided into at least five other distinct units (Grunehogna Craton, Natal Belt, Maud Belt, Tonian Oceanic Arc Super Terrane and Lutzow Holm Complex)^{32,41,44,46}. What could be really informative would be to capture different interpretations for a future GeoMAP, with the spatial resolution afforded in the GIS, using new attribute fields (e.g. TECTPROV.v1, TECTPROV.v2 etc.) in the ATA_GeoMAP_geological_units and ATA_GeoMAP_faults feature classes. Together with the latest geochronological and geophysical data, it may help scientific debate on the continent’s history and construction.

Local geological detail. There are places where local detail might be easily improved with some basic geological mapping. Throughout northern and southern Victoria Land the flat-lying sequences of Beacon Supergroup have been subdivided from the Ferrar Dolerite sills that intrude them. Individual units within the Beacon Supergroup have also been distinguished in much of the dataset. However there remain some large areas in the central Transantarctic Mountains where the Beacon and Ferrar rocks are yet to be distinguished, despite being clearly visible in high-resolution satellite imagery or aerial photographs. It would be desirable to subdivide these in future iterations of GeoMAP as their distinction reflects important local variations in rock colour, albedo, substrate chemistry, rock competence and fracture density.

There has also been some local-scale geological mapping yet to be captured by GeoMAP v.2022-08. The Japanese National Institute of Polar Research, for example, have produced a series of 39 beautiful, detailed, hard-copy map sheets at between $\leq 1:25,000$ to $1:250,000$ scale from Japanese Antarctic Research Expeditions (JARE) to Dronning Maud Land. Some of their map units have been grouped and/or simplified for subsequent digital data³² and GeoMAP v.2022-08. Numerous small-scale geological maps at $\leq 1:50,000$ scale have also been published locally within the South Shetland Islands^{49–54}. However, these maps are discontinuous and recent works appear to contain some marked interpretational differences. The next version of GeoMAP may need a concerted effort and a collaborative approach to rationalise detailed geological observations into a simplified syntheses of these regions.

Perhaps most importantly, the design and data structure of GeoMAP easily enables local maps, or new mapping, to be captured to future versions and linked back to the original work through the bibliographic ATA_GeoMAP_sources feature class (Fig. 4a). It is hoped sufficient time can be invested for the spatial resolution of GeoMAP to be improved in future versions. There are also a number of areas where we have yet to find any legacy data or observations of geology at all, which are distinguished in the geological_units layer with a ‘?’ symbol and ‘unknown’ attribute. These are clearly places to target searches through unpublished archives, acquisition of satellite data, and/or future expeditions.

Glacial processes and deposits. With strong polarity between onshore and offshore geological records of the Neogene in Antarctica, there is potential to greatly improve our understanding of the source of glacial deposits, cover sequences and past behaviour of ice. Although continuous records of climate exist offshore and have been a focus for two or three decades, they are expensive to collect and are spatially limited (total Antarctic drilling to date $\sim 5 \text{ m}^2$ in plan view). By way of contrast, onshore records are discontinuous but commonly visible and accessible, with 10 orders of magnitude greater spatial extent (outcrops $= 5 \times 10^{10} \text{ m}^2$) than drilling. A logical next step for mapping of these glacial deposits will be to use GeoMAP to help classify high-resolution imagery and multispectral datasets^{17–19}, then generate compositional maps at metre-scale resolution from which source areas can be inferred.

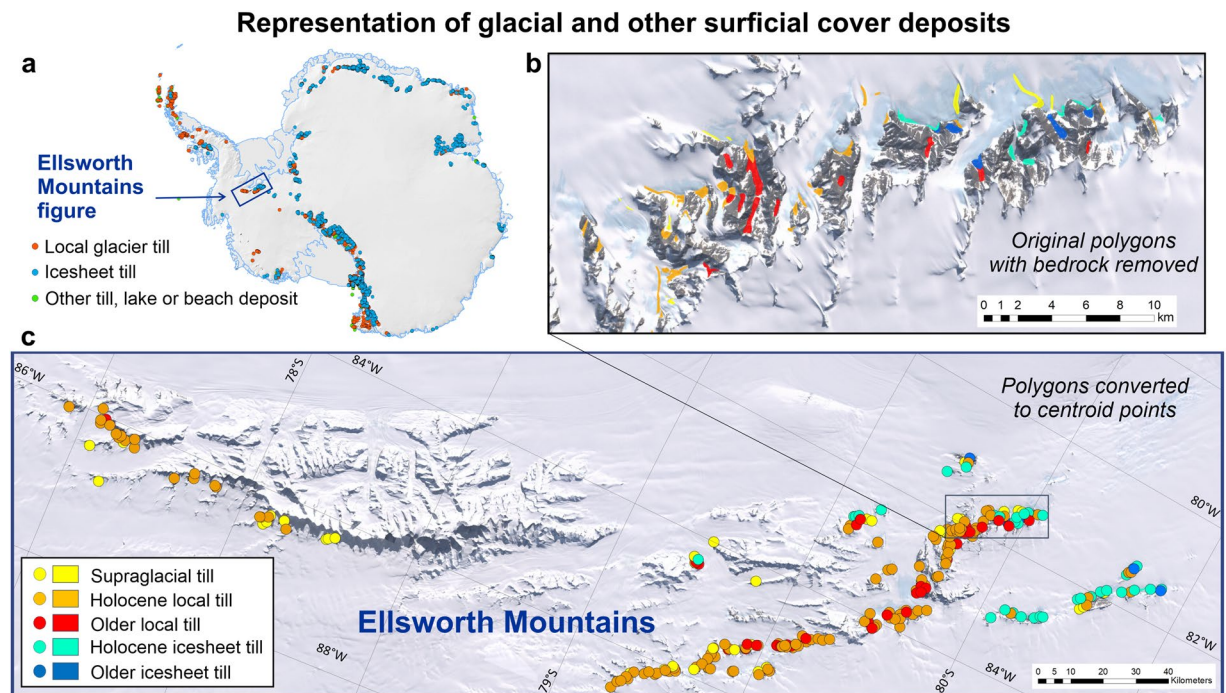


Fig. 5 Extract of GeoMAP data from the 350 km-long Ellsworth Mountains. **(a)** Location diagram and overview of the distribution of cover deposits as centroid points. **(b)** An enlarged frame for part of the Heritage Range to exemplify the degree of detail of glacial deposit polygons recorded as tills in the ATA geological units layer. The polygons are depicted over the LIMA satellite imagery²⁹, with bedrock geological polygons removed. **(c)** A wider regional-scale map in which geological unit polygons have been converted to centroid points, then displayed on the basis of geological NAME using the same colours as polygons in **(b)**. It exemplifies one way in which data can be rendered to provide new perspectives of climatic processes on the glaciers.

A specific focus of GeoMAP was to capture information on glacial sequences, which appear to be under-utilised in contemporary science related to climate change. To date, the mapping of glacial deposits and landforms has been mostly localised, and continent-wide geospatial data for glacial-geologic and meltwater features are lacking. Regional-scale maps have limited depiction of post-Miocene surficial geology and geomorphology, and have highly variable spatial reliability, but the joint use of maps and satellite imagery can provide a wealth of information for data mining. The second edition geological map of southern Victoria Land²² that was subsumed in GeoMAP, for example, recognises c. 70 units pinpointing the locations of deposits and indicating their mode of formation, age, and likely source, compared with two units (till and scree) mapped in the first edition¹.

To exemplify an application of regional data, maps of the Ellsworth Mountains have been generated with coloured polygons and dots depicting glacial till localities (Fig. 5). The higher-resolution inset map (Fig. 5b) has red and orange polygons showing location of tills from local glaciers, whereas blue and green dots represent tills left behind by the waxing and waning of ice-sheets during larger climatic events. Polygon centroids were used to generate simplified dot points (Fig. 5c). The Ellsworth Mountains have an impressive gradient in the distribution of these glacial deposits and landforms, with a complete absence in the higher central part of the range – where there is greater snowfall and katabatic winds are less extreme. In the search for ecological domains or places for life at the extremes, or hot-spots that will be first affected by climate change, GeoMAP has potential to elucidate regional-scale gradients and might be a useful first port of call.

Detailed investigations in southern Victoria Land⁸ enabled the regional geological maps to evolve from having just two cover sequence units¹ to >70 units related to either the East Antarctic Ice Sheet, West Antarctic Ice Sheet, or a local alpine glacier source. Where possible, GeoMAP v.2022-08 has also classified or interpreted glacial deposits elsewhere, depending on whether they pertain to either local glaciers, or more major trunk glaciers and ice sheets. The intent was to distinguish features that might potentially relate to local fluctuations in precipitation from those related to major climatic events. Similarly, some interpretations have been made of the relative age of cover sequence units, based on elevation and position relative to the waxing and waning of nearby glaciers and ice. This classification work should be considered preliminary. It is hoped it will enable hypotheses to be developed and tested, or underpin work on the source of deposits^{18,19} and exposure dating. The age and source of glacial deposits is an area where focussed work can be expected to change and improve future versions of the GeoMAP dataset.

Structural measurements. There are an infinite number of directions for true north from the South Pole, or 360 if measured in one-degree increments. Elsewhere in Antarctica, the direction of true north at a site is

dependent on the longitude at that site. This can present a problem for the collection of dip and strike observations, or dip and dip-direction, that are the foundation of structural geology. Over 7500 structural observations of features such as bedding, foliation, faults, joints etc were collected from legacy data for GeoMAP. These features form discontinuities in the rock and tend to have an influence on the geomorphology of peaks, ridges and valleys forming the landscape or present in sub-ice topography. It was initially hoped to be able to display the azimuth, or dip direction relative to true north. However, we subsequently discovered there are major difficulties in rotating data relative to true north at a continental scale using the EPSG:3031 (WGS 84/Antarctic Polar Stereographic) projection. Different rotations applied in capturing the structural data in ArcGIS also meant that many azimuths have been found to be locally incorrect. These structural data need dedicated checking and editing before they will be of sufficient quality to be supplied routinely with GeoMAP, but are available (with caveats) on request to the corresponding author.

Code availability

GeoMAP v.2022-08 has been generated for ArcGIS (10.8.1) and QGIS (3.4) as geodatabase and geopackage material, using a GCS WGS 1984 geographic coordinate reference and WGS 1984 Antarctic Polar Stereographic projection. Data were developed manually, then stored in a GIS database developed, web-delivered and maintained by GNS Science in New Zealand. Software ArcGIS® has been used to create the GIS database²⁴, but data can be exported in a variety of formats and compatible with most other GIS software. ArcGIS data are available from the PANGAEA data archive²⁴, an ArcGIS REST service (https://gis.gns.cri.nz/server/rest/services/SCAR_GeoMAP/ATA_SCAR_GeoMAP_Geology/MapServer), or viewed through a webmap (https://data.gns.cri.nz/ata_geomap/index.html). A series of QGIS and Google Earth KMZ files, exported from the ArcGIS geodatabase layers, are also available from the archive²⁴. The original data have been segmented into ten regions to keep KMZ files at a reasonable (<25 Mb) and useable size. GeoMAP documentation (<https://geomap.readthedocs.io/en/latest/>) has been generated using code deposited on GitHub (<https://github.com/selkind/GeoMap>).

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Author contributions

Simon C. Cox: Led data compilation, undertook extensive mapping, writing of manuscript, designed and managed project, SCAR action group co-chair. Belinda Smith Lyttle: Led data capture, data management, harmonization and quality control, design and creation of chrono-spatial legend, manuscript preparation. Samuel Elkind: Compiled data for Marie Byrd Land and Queen Elizabeth Land, wrote Python scripts to compile user documentation. Christine Smith Siddoway: Provided source data, quality control, and manuscript writing. Paul Morin: SCAR action group co-chair, provided terrain models and other source data. Giovanni Capponi: Provided source data and quality control, northern Victoria Land. Tamer Abu-Alam: Compiled Dronning Maud Land bedrock geology. Matilda Ballinger: Data compilation from Wilkes Land to Princess Elizabeth Land. Lauren Bamber: Compiled data for Queen Elizabeth Land. Brett Kitchener: Data compilation Princess Elizabeth Land. Luigi Lelli: Data compilation Antarctic Peninsula and northern Victoria Land. Jasmine Mawson: Data compilation Transantarctic Mountains and northern Victoria Land. Alexie Millikin: Data compilation central Marie Byrd Land and Ellsworth Mountains. Nicola Dal Seno: Data compilation Antarctic Peninsula and northern Victoria Land. Louis Whitburn: Data compilation Antarctic Peninsula and northern Victoria Land. Tristan White: Data compilation central and eastern Marie Byrd Land. Alex Burton-Johnson: Outcrop polygons. Provided source data and quality control, Antarctic Peninsula. Laura Crispini: Provided source data, interpretation and quality control, northern Victoria Land. David Elliot: Provided legacy maps, fieldsheets and revised mapping, central Transantarctic Mountains. Synnøve Elvevold: Provided source data, quality control Dronning Maud Land. John Goodge: Provided source data, help with classification and quality control, central Transantarctic Mountains. Jacqueline Halpin: Provided source datasets and information, Princess Elizabeth Land. Eugene Mikhalsky: Provided mapping from Mac Robertson Land to Princess Elizabeth Land. Adam P. Martin: Mapping of Cenozoic igneous rocks, data review, preparation of manuscript. Fraser Morgan: Contributed to database design and optimization for end-users. Phil Scadden: Built webmaps and feature services, data and metadata delivery. John Smellie: Provided local source data and synthesis of Antarctic Peninsula. Gary Wilson: Project design, politics and governance.

Competing interests

The authors declare they have no competing interests or conflicts of interest.

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ARTICLES FOR FACULTY MEMBERS

REMOTE SENSING BIG DATA ANALYTICS FOR DETAILED GEOLOGICAL MAPPING IN EXPOSED ZONES OF DRY VALLEYS, SOUTH VICTORIA LAND, ANTARCTICA

Advancing planetary sustainability through lithological mapping: Aster remote sensing in Antarctica's dry valleys / Riaz, K., Beiranvand Pour, A., M. Muslim, A., Khurram, S., & Habashi, J.

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(PCA), and the Optimal Index Factor (OIF) were employed to enhance the spectral characteristics of the lithologies. These approaches facilitated the identification of key lithological units, including sandstone, granite, gneisses, and basaltic flows, and the production of an accurate lithological map. By integrating remote sensing with sustainable scientific practices, this research article has the potential to advance planetary sustainability by making critical geological discoveries without regard to extreme environments.

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Introduction

The Dry Valleys of South Victoria Land in Antarctica are among the most extreme deserts on Earth, characterised by a cold, arid, and harsh climate often compared to conditions on Mars. Minimal atmospheric moisture and challenging logistic conditions make this region difficult to explore. From a geological perspective, it represents one of the most ancient and complex landscapes, offering valuable insights into Earth's history (Marchant *et al.*, 1993a; Denton *et al.*, 1993; Summerfield *et al.*, 1999; Schafer *et al.*, 1999). The Dry Valleys are part of the Transantarctic Mountains, a natural boundary extending across Antarctica from the Ross Sea to the Weddell Sea. This mountain chain shields the more ancient region of East Antarctica from the much younger folded mountains of West Antarctica. The current topography of the region is attributed to tertiary block faulting, with portions of West Antarctica subsiding below sea level, while sections of East Antarctica have been lifted by more than 4,000 m.

While contemporary geological studies uses a combination of geological, geophysical, and geochemical methods to infer geological events, direct observation through drilling remains essential. However, drilling in Antarctica poses significant challenges due to the ice, snow, and

permafrost, which is exacerbated by the lack of roads and infrastructure. These severe climate conditions complicate operational and logistical matters, resulting in cost overruns, prolonged delays, and a host of unique challenges (Talalay, 2016). Advanced remote sensing technologies provide an effective solution by enabling detailed geological investigations of such inaccessible regions and require only minimal physical intervention. Remote sensing not only facilitates geological research but also aligns with global efforts to reduce the environmental impact of human activity in fragile ecosystems (Nemmour-Zekiri & Oulebsir, 2020).

Remote sensing, particularly multispectral sensors have proven to be exceptionally effective at identifying and mapping geological features by analysing the spectral responses across visible, shortwave, and the thermal infrared regions of the electromagnetic spectrum (Feng *et al.*, 2020). High-resolution multispectral datasets such as those provided by the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) remote sensing platform, offer precise spatial information regarding the location and morphology of surface features while capturing essential spectroscopic data (Shao *et al.*, 2019). ASTER's enhanced spectral

capabilities in the Shortwave Infrared (SWIR) range, compared to the sensors on Landsat-7, make it a powerful tool for understanding geological processes in extreme and/or remote regions (Tommaso & Rubinstein, 2007).

Although no prior remote sensing studies have specifically focused on lithological mapping in the Dry Valleys, ASTER data has proven highly effective for mineral exploration and mapping in other regions. Over the past two decades, ASTER's ability and reliability with regard to geological applications has been amply demonstrated (Islam *et al.*, 2024). This study uses ASTER datasets to produce accurate lithological maps and analyse the spectral signatures of various rock formations in the Dry Valleys. These findings not only provide a foundation for understanding the geology of this unique region but also contribute to broader planetary sustainability efforts by demonstrating how advanced technologies can support research in extreme environments.

The harsh environmental conditions of South Victoria Land in Antarctica pose distinct challenges for geological assessments. This research uses ASTER remote sensing technology and integrates image processing methods like Band Ratio (BR), Principal Component Analysis (PCA), and the Optimal Index Factor (OIF) to effectively identify different rock types. The main goal of the research is to determine the feasibility of Multispectral Imaging Remote Sensing (MSI-RS) in extreme conditions for environmentally responsible geological surveys. This method acts as a terrestrial comparison for planetary science, especially with regard to Martian terrain, providing valuable knowledge for upcoming extra-terrestrial exploration.

Geology of the Study Area

The Dry Valleys form part of the Transantarctic Mountains, a prominent natural boundary spanning Antarctica from the Ross Sea to the Weddell Sea (Figure 1). This mountain range divides Antarctica into the far older region of East Antarctica and the younger folded mountains of West Antarctica. The region's current topography is shaped by tertiary block faulting, resulting in portions of West Antarctica subsiding below sea level, while areas of East Antarctica have been lifted to elevations exceeding 4,000 m.

The geology of the Dry Valleys includes a basement complex of Lower Palaeozoic igneous and metamorphic rocks, which are overlain by Devonian to Triassic sedimentary rocks of the Beacon Supergroup. These formations are intruded by Jurassic Ferrar dolerites and Cenozoic basaltic flows (Barrett *et al.*, 1992; Marchant *et al.*, 1993a). Higher elevations feature Sirius Group diamicts, which have played a central role in debates about the formation and timing of the Dry Valleys and the behaviour of the East Antarctic Ice Sheet (EAIS) (Webb *et al.*, 1984).

Granitoid plutons of varying compositions intrude the older metasediments of the Koettlitz Group. The lithological units include sandstones, siltstones, granites, granodiorites, gneisses, Jurassic diabase sills, basalt flows, and recent basaltic rocks (Figure 1). These units are crucial to understand the region's geological history.

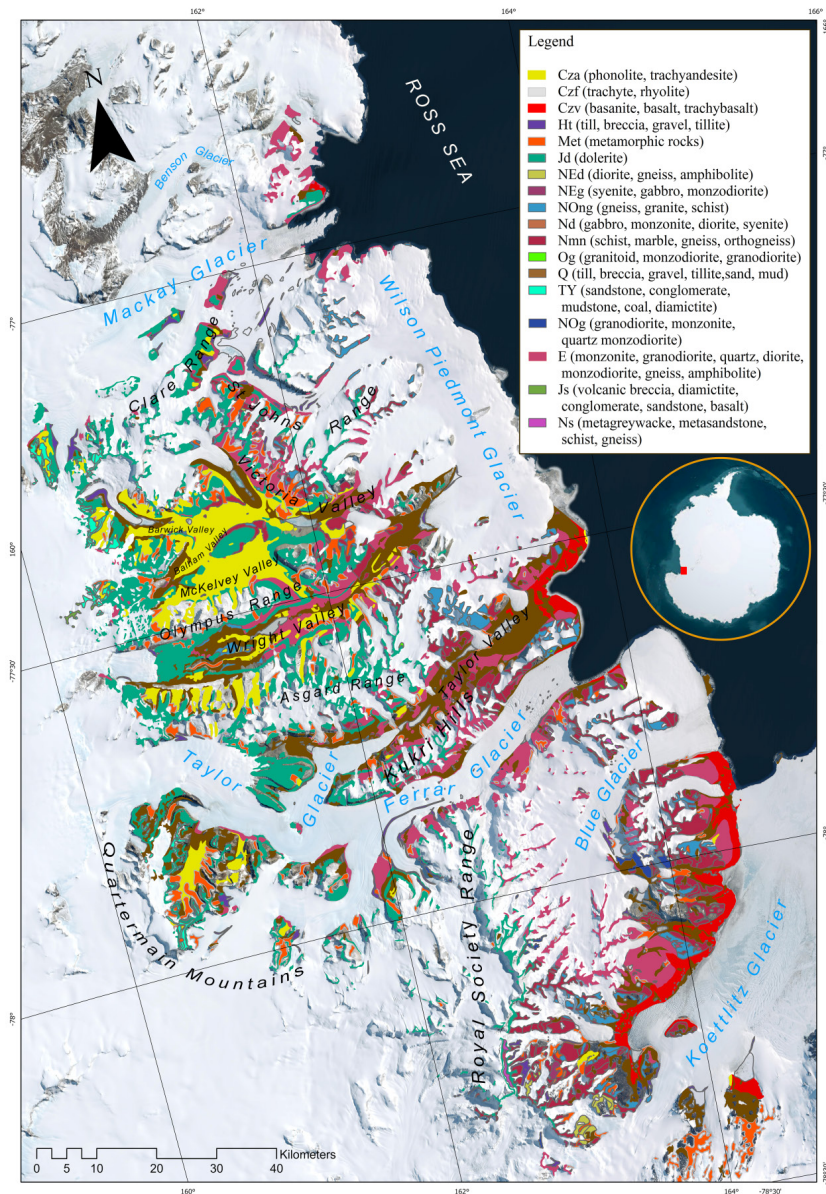


Figure 1: Geographical location and geology map of study area

Source: Authors

Materials and Methods

This research utilised a single ASTER Level 1T scene covering the southern part of the Dry Valleys. The ASTER is a highly regarded multispectral remote sensing instrument known for its exceptional spatial, spectral,

and radiometric resolution. It consists of three subsystems that cover the Visible and Near-infrared (VNIR) (0.52 to 0.86 μm ; 15 m resolution), SWIR (1.6 to 2.43 μm ; 30 m resolution), and Thermal Infrared (TIR) (8.125

to 11.65 μm ; 90 m resolution) regions of the electromagnetic spectrum (Figure 2). With a swath width of 60 km and scene coverage of $60 \times 60 \text{ km}^2$, ASTER is particularly suited for

regional geological mapping, using its spectral characteristics to support mineral exploration and lithological mapping (Abrams *et al.*, 2019).

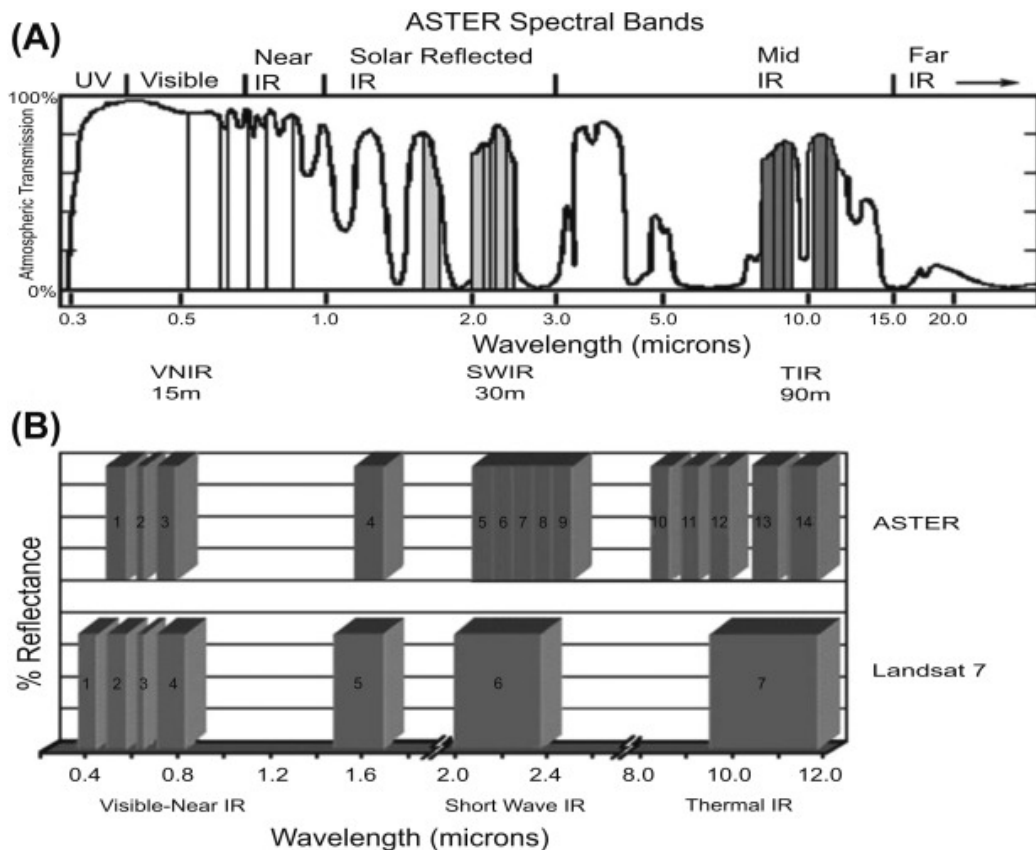


Figure 2: (a) ASTER spectral response channels superimposed over the spectral response of the Earth's atmosphere and (b) comparison of ASTER spectral response channels with those of Landsat 7. Notably, the increased spectral resolution of the SWIR and TIR bands, compared to Landsat TM, gives ASTER greater flexibility in responding to active volcanic features. A low gain state command for the SWIR channels enhances ASTER's dynamic range relative to TM (Wright *et al.*, 1999)

Advanced image processing techniques such as Band Ratio (BR), Principal Component Analysis (PCA), Optimum Index Factor (OIF), and Spectral Information Divergence (SID) classification, further enhance the capabilities of ASTER. BR highlights specific mineralogical features by combining spectral bands, while PCA, applied to multispectral

bands can significantly improve image quality by maximising spectral contrast. OIF optimises band combinations for maximum contrast and SID classification quantitatively assesses spectral similarity by measuring divergence in spectral signatures, making it particularly effective for distinguishing between materials with subtle spectral differences (Chang, 1999).

These methodologies, when combined with ASTER's high-resolution spectral data, make it a powerful tool for understanding the surface composition of the Earth, especially in arid and geologically complex regions.

Band Ratio (BR)

The Band Ratio (BR) is one of the most effective and commonly employed image processing techniques, which enhances the distinctions in colour composition of surface materials to detect irregularities while reducing the effect of lighting variations on the entire image (Sabins *et al.*, 1999). The band ratio is a quantitative method used to enhance the differences in spectra between several bands. This image processing technique exploits the changes in reflectivity within the spectral signature, involving the division of the Digital Number (DN) from one band by the DN values from another band in a scene consisting of multiple spectral bands (Githeny *et al.*, 2019).

Principal Component Analysis (PCA)

The Principal Component Analysis (PCA) is a mathematical method used for dimensionality reduction, particularly effective in addressing correlated information common in remote sensing data. It falls under a category of multidimensional descriptive techniques referred to as factorial methods (El Atillah *et al.*, 2019). Furthermore, it is used to collect data on characteristics in order to improve the targeted information within the image. This process involves converting a group of interconnected variables into multiple independent and uncorrelated linear variables by identifying the key axes in the original data that account for the greatest variation. These linear variables carry significant information relating to the spectral characteristics expected from specific bands within the VNIR and SWIR zones. This transformation is achieved through an orthogonal transformation known as Principal

Components (PCs) (Singh & Harrison *et al.*, 1985; Crosta *et al.*, 2003; Gupta *et al.*, 2013).

However, while PCA is notably effective at reducing the dimensionality of satellite data by compressing multispectral data sets into principal component bands, it also separates noise components by mitigating irradiance effects, removing data redundancy and calculating a new coordinate system. Additionally, it primarily preserves the vital information contained within the images. The application of PCA in image data involves three principal steps: (1) Assessing variance from the data matrix, (2) deriving eigen-values and eigen-vectors from the variance matrix, and (3) linearly transforming the image data using the coefficients of the eigenvectors (Khaleghi *et al.*, 2020). PCA is commonly used for lithological mapping by leveraging spectral bands from remote sensing devices, as this approach can consistently distinguish 90% geological features and mineral exploration outcomes effectively 90% of the time, as evidenced by numerous studies (Crosta *et al.*, 2003; Pour *et al.*, 2011; Sheikhrasimi *et al.*, 2019; Zoheir *et al.*, 2019). As a result, the derived components may provide more reliable interpretations compared to the original images (Tangestani *et al.*, 2008; Pour *et al.*, 2017a; Pour, 2018).

Optimum Index Factor (OIF)

The Optimum Index Factor (OIF) is used to select the best colour composites for analysing satellite images. OIF is a statistical method first introduced by Chavez *et al.* (1982) and later refined to identify the most suitable bands. This method involves a statistical evaluation of all possible combinations of three bands to create a Red, Green and Blue (RGB) image (Equation 1). OIF values are computed to find the most advantageous band combinations (Cengiz *et al.*, 2006) and to rank the three bands according to the amount of information each combination

provides (Beaudemin & Fung, 2001). The potential for RGB visualisation is determined by the overall variance and the correlation between the various bands (Jensen, 1996).

$$OIF = \frac{Std_i + Std_j + Std_k}{|Corr_{i,j}| + |Corr_{j,k}| + |Corr_{i,k}|} \quad (1)$$

Where Std_i is the standard deviation of band i , Std_j is the standard deviation of band j , Std_k is the standard deviation of band k , $Corr_{i,j}$ is the correlation coefficient between bands i and j , $Corr_{j,k}$ is the correlation coefficient between bands j and k , $Corr_{i,k}$ is the correlation coefficient between bands i and k . Such that:

$$\text{Standard Deviation (Std): } \sigma_x = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2} \quad (2)$$

where N is the number of points and $\bar{x}$ is the mean.

$$\text{Correlation Coefficient: } Corr_{xy} = \frac{Cov(x,y)}{\sigma_x \sigma_y} \quad (3)$$

where σ_x and σ_y represent the standard deviation of x and y , respectively.

Spectral Information Divergence (SID) Classification

The Spectral Information Divergence (SID) is a probabilistic approach for spectral classification that pairs pixels with reference spectra using a divergence metric (Kumar et al., 2020). This method assesses the disparity between probability distributions by employing spectral information from two-pixel vectors, with values calculated from zero to a predefined threshold for its probability.

Results and Discussion

Band Ratios Composite Image

Image enhancement techniques aim to increase the informational value of an image. Band ratios, a type of spectral enhancement technique, express the ratio of digital numbers across two or more distinct bands. A key challenge is selecting the best combinations of ratios that capture the full range of information within the scene. The OIF was used to address this. The OIF evaluates all potential combinations based on the total variance of each band and their level of correlation. High OIF values indicate bands rich in information. This research paper applied the OIF method to determine the optimal R-G-B ratio combination that contains the most spectral information for distinguishing various rocks. This study calculated the normalised reflectance values for all 72 potential ASTER band ratios, comprising four VNIR and five SWIR bands. A standard deviation was used to assess the variance in each band ratio image, while correlation was analysed through a correlation matrix for each image.

The statistical analysis of the various bands revealed that the ASTER band combination ratios of 3/1, 3/2, and 6/1 had the highest OIF values (Table 1), effectively differentiating granitoids and sandstone within the research area (Figure 3).

Table 1: OIF values for band ratios

OIF Values for Band Ratios				
1.	3/1	3/2	6/1	139.32
2.	3/1	3/2	6/4	137.44

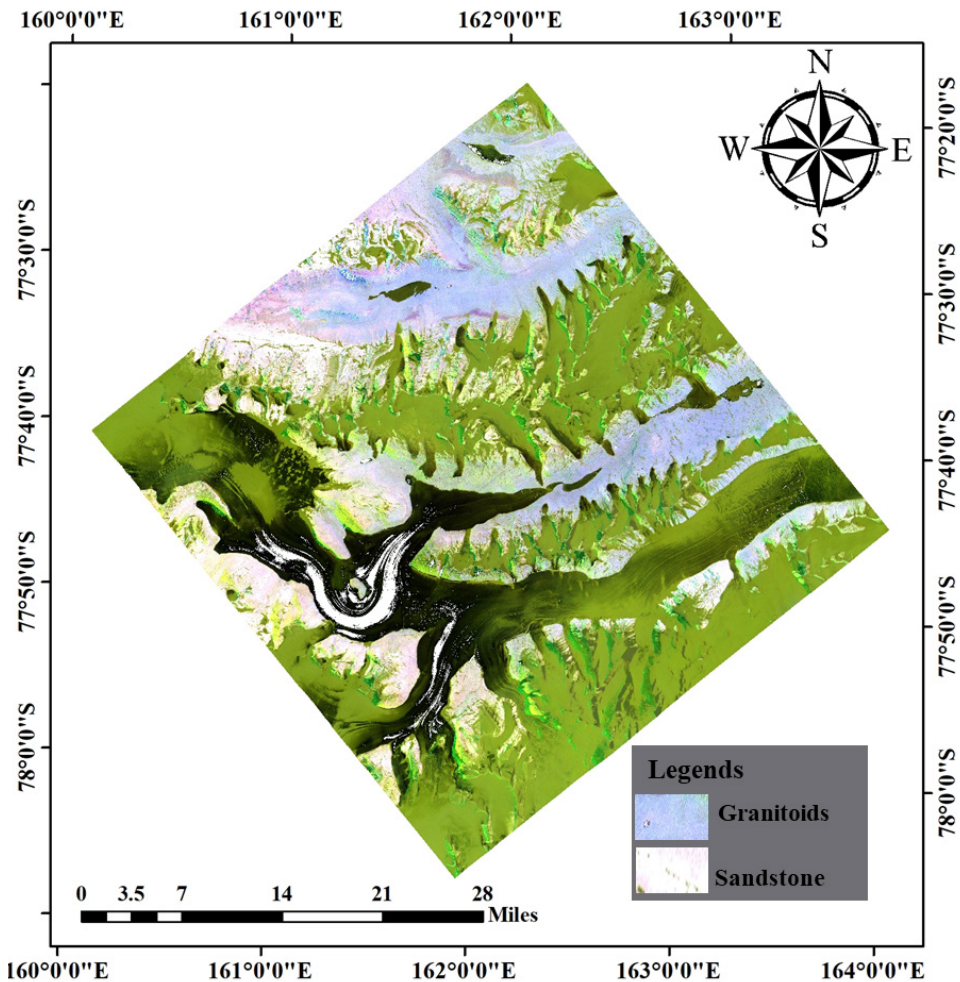


Figure 3: ASTER image map derived from the band ratio combination of 3/1, 3/2, and 6/1 as an RGB colour composite for a selected subset scene covering the southern part of the Dry Valleys

Source: Authors

The OIF method was used to identify the most efficient band combination for further analysis. The OIF technique helped select the best bands based on their contributions to the total spectral variance and classification performance. In this case, PCA 1, PCA 2, and PCA 6 were selected based on the OIF assessment (Table 2), which indicated that these

components had high OIF values and were well-suited for distinguishing lithological units using spectral data (Figure 4).

Table 2: OIF values for PCA				
OIF Values for PCA				
1.	PCA 1	PCA 2	PCA 6	19804.35
2.	PCA 2	PCA 3	PCA 7	15791.40

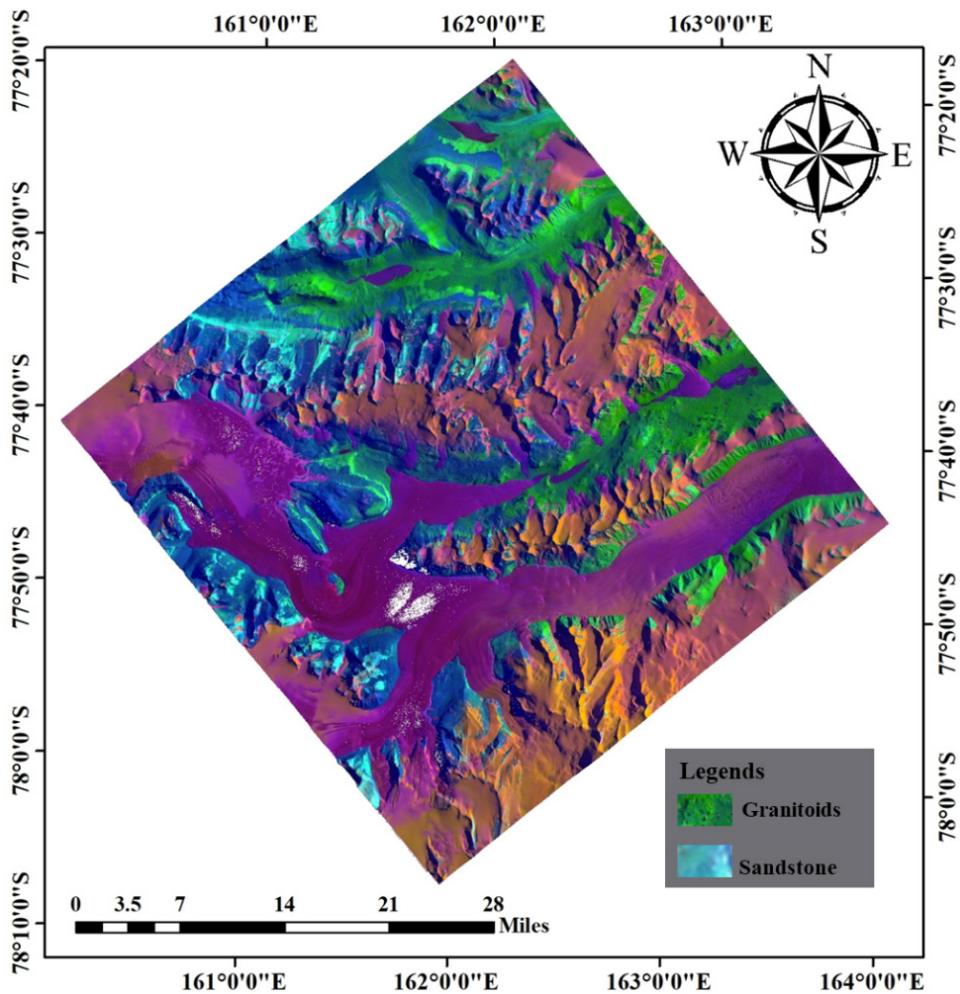


Figure 4: ASTER image map derived from the PCA 1, PCA 2, and PCA 6 components as an RGB colour composite for a selected spatial scene covering the southern part of the Dry Valleys

Source: Authors

A SID classification is a remote sensing method used to assess how distinct different classes (such as lithological units) are based on their spectral signatures. It employs the concept of divergence to measure the variance between spectral classes, which can enhance the effectiveness of classification algorithms by identifying which classes are more or less distinguishable in the spectral domain. SID measures the difference between two spectral signatures using the Kullback-

Leibler divergence, which quantifies how one probability distribution diverges from a second, expected probability distribution.

In this study, the reference spectra of granitoids and sandstone endmember minerals for applying SID were selected from spectra resampled to the response functions of ASTER's nine bands, which covered the VNIR and SWIR bands. Granitoid rocks are well discriminated using SID in the ASTER image of the study area (Figure 5).

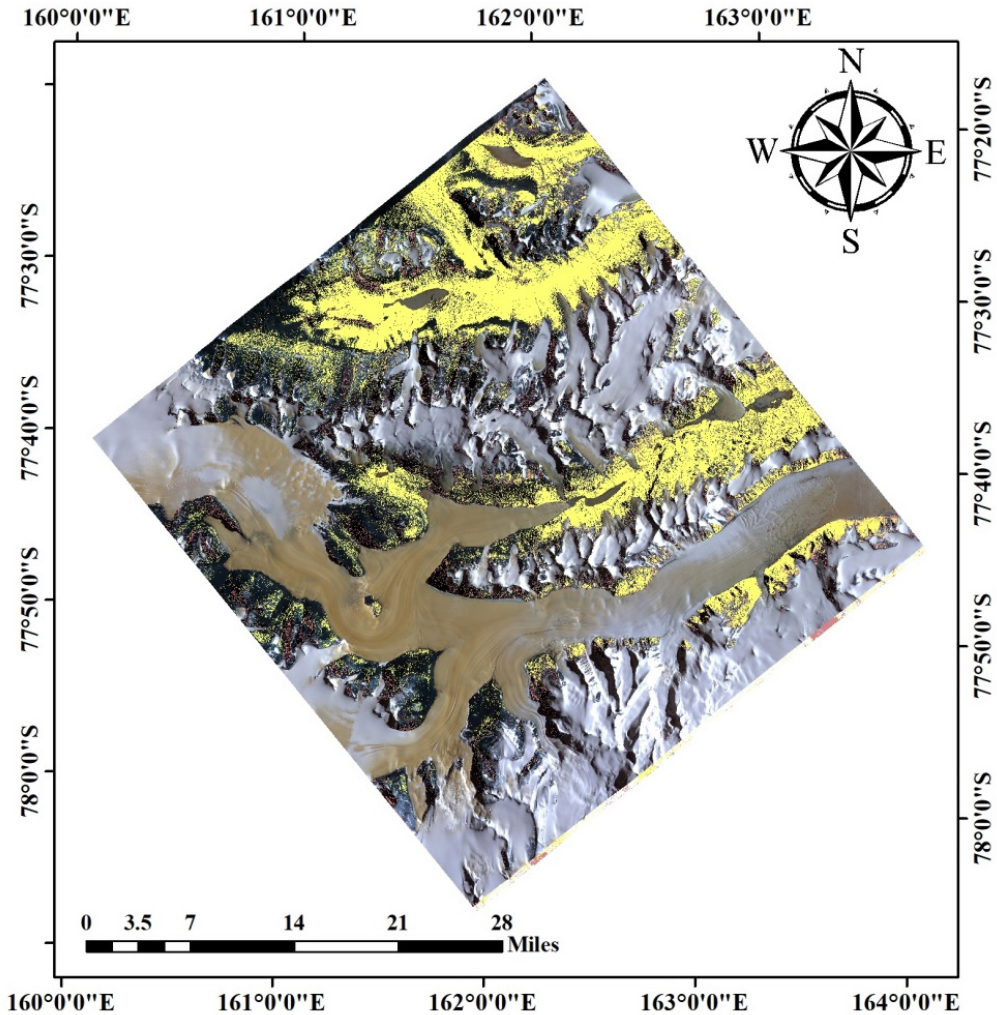


Figure 5: SID classification of the ASTER image (yellow representing granitoids and blue representing sandstone) for a selected spatial scene covering the southern part of the Dry Valleys

Source: Authors

The combination of methods like Band Ratio (BR) analysis, Principal Component Analysis (PCA), and Optimal Index Factor (OIF) optimisation increases the efficiency and precision of rock type identification, ensuring that the resulting maps meet both scientific and industrial standards for mineral exploration.

From an ecological perspective, such method significantly decreases the necessity for

extensive on-site field research, which typically requires considerable logistical support, including transportation and infrastructure. By reducing direct human intervention in delicate ecosystems, this technique limits ecological disruptions and helps preserve the unspoiled nature of locations like Antarctica. Additionally, this approach aligns with global sustainability objectives by decreasing the carbon footprint

associated with traditional field surveys such as those arising from vehicle use, fuel consumption, and heavy machinery deployment.

Conclusions

This research effectively showcases the value of ASTER remote sensing and image processing methods such as Band Ratio (BR), Principal Component Analysis (PCA), Optimal Index Factor (OIF), and the use of Spectral Information Divergence (SID) effectively demonstrated its potential to distinguish between granitoids and sandstone lithological units using ASTER imagery. The SID method, based on Kullback-Leibler divergence, highlighted the distinctiveness of these lithological categories by evaluating their spectral signatures, thereby improving classification accuracy. The integration with the OIF technique strengthened the analysis by identifying the most effective band combinations for lithological differentiation. Specifically, the PCA components (PCA 1, PCA 2, and PCA 6) exhibited high OIF values, indicating their importance for spectral analysis.

Additionally, the evaluation of band ratios based on OIF identified the most informative combinations such as 3/1, 3/2, and 6/1, which were successful in differentiating between granitoids and sandstone. This study underscores the critical role of advanced spectral enhancement techniques and statistical methods like SID and OIF in improving lithological classification through remote sensing, providing valuable insights for future geological studies and remote sensing applications. Using satellite data, this study successfully addresses the challenges posed by inaccessibility, severe weather conditions, and logistical limitations, facilitating detailed mapping of rock types including sandstone, granite, and basaltic flows. The approach emphasises the capability of remote sensing as a powerful instrument for geological investigations in isolated areas, where traditional field studies are not viable.

The results not only improve our comprehension of the tectonic and mineralogical framework of South Victoria Land but also open opportunities to apply such techniques to other remote and less-explored regions worldwide. Subsequent studies could enhance these methods by incorporating hyperspectral data and advanced machine learning techniques to better lithological classification and adaptability to various geological environments. Additionally, this method offers a dependable model for examining planetary surfaces, like Mars, where remote sensing would be the primary means of exploration.

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Conflict of Interest Statement

The authors declare that they have no conflict of interest.

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ARTICLES FOR FACULTY MEMBERS

REMOTE SENSING BIG DATA ANALYTICS FOR DETAILED GEOLOGICAL MAPPING IN EXPOSED ZONES OF DRY VALLEYS, SOUTH VICTORIA LAND, ANTARCTICA

A hierarchical network densification approach for reconstruction of historical ice velocity fields in East Antarctica / Feng, T., Li, Y., Wang, K., Qiao, G., Cheng, Y., Yuan, X., Luo, S., & Li, R.

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Article

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A hierarchical network densification approach for reconstruction of historical ice velocity fields in East Antarctica

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Abstract

Accurate ice flow velocity data are essential for studying the mass balance of the Antarctic ice sheet. However, there is a lack of ice velocity maps of 1960s–80s in basin-wide regions or the entire ice sheet. In this study, an enhanced hierarchical network densification approach is developed for basin-wide Antarctic velocity mapping using historical ARGON and Landsat images. The produced multiple historical velocity maps from 1963 to 1989 in the region of the Fimbul and Jelbart ice shelves, East Antarctica, achieved an accuracy better than 29 m a^{-1} . They revealed that the ice flow velocity had no significant changes over the period. Combining the surface mass balance estimate with the ice discharge estimated from our historical velocity maps and recently published velocity maps, we estimated a positive mass balance of $8.6 \pm 3.9 \text{ Gt a}^{-1}$ in the study area from 1963 and 2015. Our results indicate that the region's positive mass balance, as estimated in recently published studies, has been maintained since the 1960s. It is also in concordance with the low level of mass balance from 1992 to 2017 in East Antarctica. This suggests that the study area has been stable since the 1960s.

1. Introduction

The net mass loss of the Antarctic ice sheet is estimated as ice mass discharged across grounding line, from which the surface mass balance (SMB) on the continent is subtracted. It is considered as the Antarctic ice sheet contribution to global sea-level rise (Rignot and others, 2011a; Shepherd and others, 2012; IMBIE, 2018). The majority of this excess discharge enters oceans through ice-shelf basal melting and iceberg calving (Hogg and others, 2017; Bell and Seroussi, 2020). Ice flow velocity maps provide the rate at which ice is transported between different parts of the ice sheet, including mass transportation from the interior regions toward the ocean (Rignot and others, 2011a; Gardner and others, 2018b). Accurate flow velocity maps are essential for studying the ice flow dynamics and mass balance of the Antarctic ice sheet (Rignot, 2006; Liu and others, 2012; Li and others, 2017; Gardner and others, 2018b).

There are many ice velocity products that are generated using remote-sensing data for individual glaciers, ice shelves and the entire Antarctic ice sheet. Synthetic aperture radar (SAR) and optical images are the main remote-sensing data for observing ice flow. However, in the context of this study, there are no SAR-based velocity maps in the 1960s–80s, mainly because the SAR satellite images were acquired only after the mid-1990s. Since then, a long record of SAR satellite images of European Remote Sensing satellite (ERS)-1/2, Radarsat-1/2, Envisat's Advanced Synthetic Aperture Radar, Advanced Land Observing Satellite-1's Phased Array type L-band Synthetic Aperture Radar and Sentinel-1 have been applied to map Antarctic ice flow velocities by using the interferometric SAR (InSAR) and offset tracking techniques (Rignot, 2006; Rignot and others, 2011a; Mouginot and others, 2012, 2017a; Dirscherl and others, 2020). Despite its high precision, interferometric measurement of glacier velocities may be impossible if the imaged ice surface change exceeds half of the radar instrument wavelength, destroying the phase coherence between the two images. For example, this may occur in fast-flowing glaciers or regions with significant vertical deformation (Michel and Rignot, 1999). In these cases, the offset tracking technique that tracks speckles in the sequential SAR images is usually adopted as an alternative method (Joughin, 2002; Rignot, 2002; Scheiber and others, 2015).

A number of optical imaging satellite missions, including the Landsat series and the Moderate Resolution Imaging Spectroradiometer (MODIS), acquired remote-sensing data for ice velocity mapping in Antarctica. Ice surface features are extracted from optical images obtained at different times by feature tracking based on different matching algorithms (Heid and Käab, 2012; Fahnestock and others, 2016), and the ice velocity can then be estimated through the tracked feature positions. Although the geometric precision of feature tracking in optical images is lower than that in SAR images, optical images have the advantage of significantly better coverage around the world in both space and time. An additional characteristic is their spectral signatures that can help identify unique features in Antarctica, such as blue ice (Hui and others, 2014). Since the launch of Landsat-8 in 2013, its improved capability in both spatial resolution and spectral sensing has provided enhanced surface feature

extraction in Antarctica, resulting in higher quality ice velocity products (Mouginot and others, 2017a; Shen and others, 2018; Gardner and others, 2018b).

Although many efforts were made to collect geodetic-quality measurements of ice velocity from in situ observations in the 1960s to later GPS-based dynamic monitoring (King, 1994; Frezzotti and others, 1998; Bassis and others, 2005; King and others, 2007), as mentioned above, large-scale velocity mapping in Antarctica has been predominantly accomplished by satellite remote-sensing technology. However, compared to the recently acquired satellite data, early satellite observations have generally lower quality. For example, the Landsat images used in this study are from the Landsat program in the 1970s and 1980s, which are valuable but generally have lower image quality (e.g. stripes and low geolocation accuracy). They were only radiometrically calibrated and georeferenced through a systematic geometric correction using the spacecraft ephemeris data (USGS EROS, 2019). The data are supplied without georeferencing using ground control points (GCPs) and without terrain relief removal by orthorectification using digital terrain models. The geolocation error of these image data in Antarctica can be as large as 10 km, in addition to lower resolution, severe noises and stripe patterns in the images (Pan and Chang, 1992; Tsai and Chen, 2008; Cheng and others, 2019). Consequently, the widely used ice velocity products at the regional or continental scales have been generated using data collected since the 1990s. On the other hand, a long record of the historical ice velocity is of great importance for both understanding the long-term evolution trend of the Antarctic ice sheet and predicting future global sea-level change (Payne and others, 2004; Rignot and others, 2011b; Shepherd and others, 2012; IMBIE, 2018; Rignot and others, 2019).

From 1962 to 1963, KH-5 ARGON US reconnaissance satellites imaged the Antarctic ice sheet using photographic films during three missions (9034A, 9058A and 9059A) (Ruffner, 1995; Wang and others, 2016). The films showed significant deformation due to long-term storage before they were declassified and scanned in the 1990s (Galiatsatos, 2009). Analytical photogrammetric models have been developed to handle film deformation, scanning errors, large-format lens distortion and block bundle adjustment (BA) issues for topographic mapping of the Arctic and Antarctic ice sheets (Zhou and others, 2002; Kim, 2004; Ye and others, 2017). There are very limited numbers of ARGON stereo pairs in Antarctica for rigorous photogrammetric mapping of ice velocity from the 1960s (Li and others, 2017). The data selection for ice velocity mapping during the 1960s–80s in large glacier regions is thus focused on the combinations of ARGON (1960s)–Landsat (1970s–80s) and Landsat (1970s–80s)–Landsat (1970s–80s).

In addition to the difficulties in data processing and the defects inherent in the two datasets mentioned above, ice features for velocity estimation may not be tracked due to different appearances in the two datasets as well as physical changes in the ice surface over a period of 10–20 years. Furthermore, the traditional feature tracking methods suffer from difficulties in the trade-off between the search range and matching reliability, when applied to cases with a strong spatial variation in ice flow velocity (Liu and others, 2012; Li and others, 2017). If the search range is too large, the subsequent matching computation would be very intensive and may generate unreliable matching results. In contrast, if the search range is too small, the correct conjugate (corresponding) points could be missed, resulting in the failure of the matching. The hierarchical network-based image matching method was developed to address this problem by using a multi-layer image structure to control the search range by a coarse-to-fine scale and precise conjugate feature prediction to increase matching reliability and

computational efficiency (Li and others, 2011; Liu and others, 2012). Efforts in using manually selected points in the initialization of the densification process were demonstrated to increase reliability (Li and others, 2011; Wang and others, 2016). The method was further developed for simultaneous reconstruction of ice velocity fields and ice surface topography in Antarctica from stereo ARGON images of 1963 (Li and others, 2017).

Overall, due to the unavailability of high-quality remote-sensing data and difficulties in feature tracking methods, there is a lack of systematic ice velocity mapping from the 1960s–80s in basin-wide regions or all of Antarctica, although Li and others (2017) produced an ice velocity map for 1963 of the Rayner Glacier using four photogrammetrically processed ARGON stereo images and Wang and others (2016) generated a partial ice velocity map for 1963–79 of the Larsen B Ice Shelf using ARGON (orthorectified) and Landsat Multispectral Scanner (MSS) images.

The objective of this paper is to improve the methodology for systematic ice velocity mapping of Antarctica using the ARGON and Landsat images from the 1960s–80s. Our new historical velocity mapping framework uses an enhanced hierarchical network densification method to meet additional challenges, including heterogeneous image qualities of ARGON and early Landsat images, extremely diverse range of ice flow dynamics and disappearance of ice surface features after a long time-span of over 10 years. The method has been applied to a study area covering the Jutulstraumen Glacier, Fimbul Ice Shelf, Schytt Glacier, and Jelbart Ice Shelf. The produced historical ice velocity maps are compared with recent ice velocity products to characterize the ice dynamics. Finally, the maps are utilized to estimate the mass changes in the area during the early years, which provides important information for the long-term mass-balance study of Antarctica.

2. Study area and data

The Fimbul and Jelbart ice shelves are the two largest ice shelves along the northeastern Weddell Sea in Queen Maud Land (QML), East Antarctica (Fig. 1). The area of the two ice shelves is 63 347 km², and is representative of medium-sized and mid-latitude ice shelves in Antarctica (Griggs and Bamber, 2011). The Fimbul Ice Shelf is fed by the fast-flowing Jutulstraumen Glacier, which is responsible for ~10% of ice discharge from the QML sector of the Antarctic ice sheet (Langley and others, 2014). The Jelbart Ice Shelf is fed by the Schytt Glacier, which is narrower than the Jutulstraumen Glacier (Goel and others, 2017).

The ice velocity in recent years (1997–2017) in the study area can be described by three ice velocity products. The earliest is the ice velocity map derived by tracking features between the Antarctic Mapping Mission (AMM-1) mosaic of September–October 1997 and the Modified Antarctic Mapping Mission (MAMM) mosaic of the fall of 2000 (Jezek, 2002). The second product is the surface velocity map generated by applying the InSAR technique using multisource SAR satellite data obtained between 2007 and 2009 (Rignot and others, 2011a; Mouginot and others, 2017b). The latest product consists of several annual maps in the 2013–17 period constructed from Landsat-8 images (Fahnestock and others, 2016; Shen and others, 2018; Scambos and others, 2019). An ice flow center line runs from the glacier main trunk to shelf front and describes the pass of ice mass from the glacier feeding the ice shelf. Based on the InSAR ice velocity map from 2007–08 (Mouginot and others, 2017b), the ice flow velocity along the ice flow center line of the Jutulstraumen Glacier and Fimbul Ice Shelf is ~710 m a⁻¹ at the grounding line and ~750 m a⁻¹ at the shelf front. Similarly, the ice flow velocity of the Schytt Glacier and Jelbart Ice Shelf is ~370 m a⁻¹ at the grounding line and ~610 m a⁻¹ at the shelf front. In this

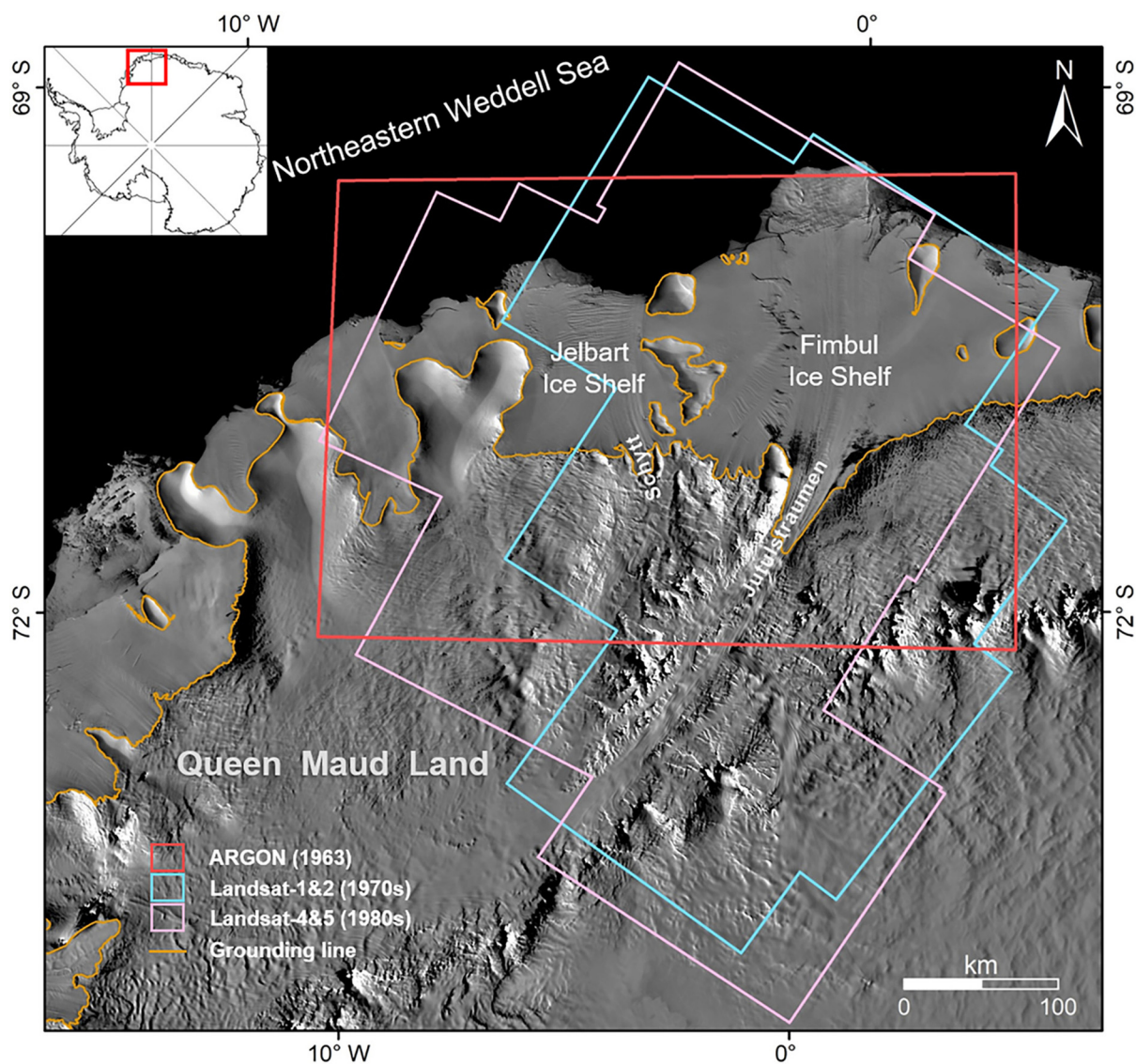


Fig. 1. Study area of the Fimbul and Jelbart ice shelves in QML with footprints of the satellite images, MOA mosaic 2004 as the background (Haran and others, 2005) and grounding line from Gardner and others (2018a).

paper we use the terms of velocity and speed interchangeably for simplicity and consistency.

The available satellite images from the 1963–89 covering the Fimbul and Jelbart ice shelves were selected to reconstruct the early ice velocity history in the study area. The selection considerations included low coverage of clouds, overlapping of two or more images in the mapping period and the existence of stable landmarks serving as controls for orthorectification. Subsequently, 77 images or products covering three decades were chosen (Table 1 and Table 6), namely, (1) ARGON images from 1963 presented as

Table 1. Summary of the historical remote-sensing images and products used in this paper

Satellite	Sensor/product	Period	Resolution m	Number of images
KH-5 9059A	ARGON mosaic	1963	100	1
Landsat-1	MSS	1972–74	60	21
Landsat-2	MSS	1975	60	6
Landsat-4	MSS/TM	1987–89	60/30	14
Landsat-5	MSS/TM	1984–87	60/30	35
Total images				77

See Table 6 for detailed image information.

an orthorectified mosaic product (Kim, 2004), (2) Landsat-1 and -2 images from the 1970s and (3) Landsat-4 and -5 images from the 1980s. The Landsat images are of the processing level L1GS which were radiometrically calibrated and required further geometric rectification before they could be used for ice velocity mapping. The data were downloaded from the USGS Landsat distribution site (<https://earthexplorer.usgs.gov/>). The near-infrared band of Landsat images is used for velocity computation (band 7 of the MSS sensor and band 4 of the TM sensor). For the geometric control of these selected satellite images, the Landsat image mosaic of Antarctica (LIMA), a higher resolution (15 m) digital mosaic produced from nearly 1100 Landsat-7 ETM+ images collected between 1999 and 2003 (Bindenschadler and others, 2008), was used as the horizontal reference; and the earliest Antarctic DEM product Radarsat Antarctic Mapping Project (RAMP) Digital Elevation Model (DEM) Version 2 (RAMPv2) served as the elevation reference (Liu and others, 2015). RAMPv2 synthesized elevation data originating from ERS-1 altimetry observations and survey data from the 1940s to 1990s, which is close to 1963–89, the time span of the historical images for velocity mapping in this study. Therefore, this justifies the selection of RAMPv2 for the use as vertical control data over the recently available Antarctic DEM, reference elevation model of Antarctica (REMA)

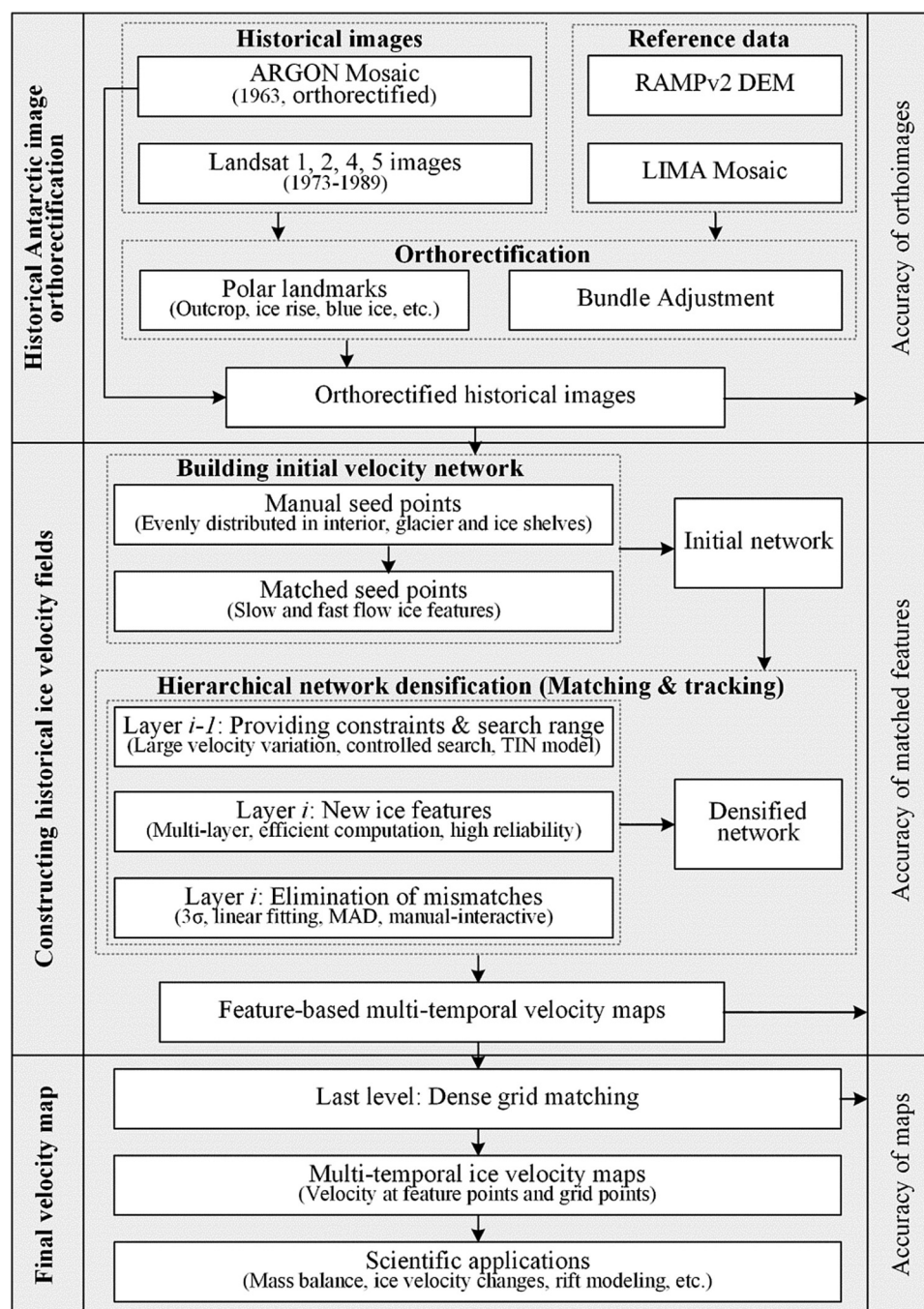


Fig. 2. Framework for systematic ice velocity mapping of Antarctica using historical images, with three modules (historical Antarctic image orthorectification, constructing historical velocity fields and final velocity map) and detailed processing steps and methods. Accuracies of the components evaluated in the first two modules are used to estimate the accuracy of final maps in the last module using Eqn (1).

of 2009–17 (Howat and others, 2019), despite of its higher resolution and accuracy.

3. Method

The proposed framework for the systematic ice velocity mapping of Antarctica using historical images consists of three modules, historical Antarctic image orthorectification, historical velocity field construction and final velocity map generation (Fig. 2). Challenges stemming from both historical image processing and the unique Antarctic environment are addressed by developing new techniques. The Landsat images of 1972–89 are orthorectified using GCPs measured on the RAMPv2 DEM and LIMA image mosaic to provide, along with ARGON Mosaic of 1963, orthorectified historical images for velocity mapping. The key module is

hierarchical network densification through a multi-layer recursive matching and tracking approach to build velocity vectors of the ice velocity field. This method overcomes difficulties faced by a single-layer matching technique in cases of significant spatial variations of displacements in a stereo image pair (e.g. cliff areas in terrain mapping or fast flowing glaciers in velocity mapping). The methodology was successfully applied in terrain surface reconstruction in urban areas (Rothermel and others, 2012) and planetary landing site topographic mapping (Li and others, 2011). It was implemented to estimate Antarctic ice flow velocities (Liu and others, 2012; Li and others, 2017) and further extended here for systematic reconstruction of basin-wide ice flow velocity fields. A set of manually selected seed points on the initial layer supplies the structural velocity information ranging from the slow ice flow in the inland interior to the rapid motion at the ice-

shelf front. Guided by the seed points and increasingly densified feature points in a triangulated irregular network (TIN) model, the recursive feature matching and tracking are carried out layer-by-layer where an adaptive search range is determined according to the velocity information in the existing TIN model. This ensures the reliability of the matched ice surface features through high-quality candidates and increased computational effectiveness by using reduced search ranges. The matched feature points are further filtered to eliminate outliers and then used to control the dense grid matching process to produce the final multi-temporal velocity maps, which can be used for various Antarctic applications.

3.1 Historical Antarctic image orthorectification

The first module of the framework (Fig. 2) is used to prepare the ARGON mosaic from 1963 and Landsat-1, -2, -4 and -5 images from the 1970s and the 1980s in the form of orthorectified images. The individual processing steps include image preprocessing, selection of GCPs, BA and orthorectification (McGlone, 2004). The datasets for the three maps are reprojected as orthorectified images of different decades in a single vertical and horizontal reference frame (WGS 84 and Antarctic Polar Stereographic projection EPSG 3031). Through these processing steps, the geometric imaging geometry differences, film distortion, cartographic projection differences and geolocation errors can be eliminated or significantly reduced (McGlone, 2004). More specifically, the ARGON mosaic of Antarctica (MOA) used in this study is already an orthorectified mosaic. The original ARGON images are processed using a rigorous photogrammetric model, BA, to estimate the interior and exterior orientation parameters of the images (Kim, 2004; Sohn and others, 2004). The BA process requires a set of GCPs for linking to the reference frame and a set of tie points for connecting the images. The estimated interior and exterior orientation parameters and a DEM are then used to produce the orthorectified ARGON image (Schenk, 1999; McGlone, 2004; Li and others, 2011). To orthorectify Landsat-1, -2, -4 and -5 images, we select a set of GCPs that appear in both the Landsat images of an image pair and the reference data that includes the LIMA image mosaic and RAMPv2 DEM. There are very few GCPs surveyed in Antarctica by GPS due to the remote and hostile environment. To address this problem, unique landmarks on the Antarctic ice sheet, which are stationary or whose motion is negligible, including outcrops, blue ice features, ice rises and others, should be used for georeferencing.

Rock outcrops are considered the most stable landmarks for GCPs, although they may be partially or completely covered by seasonal accumulations. Their initial locations can be identified with the help of the Antarctic Digital Database (Burton-Johnson and others, 2016; ADD, 2021), which provides the distribution of rock areas in Antarctica. The precise positions of the GCPs are determined in three steps. Assume that an outcrop protrudes from the ice surface, the first step is to identify the outcrop top through a shading examination. For example, given the solar altitude angles (α_{al}) and azimuth angles (α_{az}) of the two historical images, the same outcrop top can be distinguished from rock shadows, which may appear differently in the images (Figs 3a, b). Mistakes are often introduced by choosing shadow corners in two images, which may appear similar, but are cast from different features. In the second step, considering the detailed topographic information provided by its high-resolution gridpoints, the REMA DEM is used to generate two synthetic shaded relief maps using the same solar illumination geometry as at the respective image acquisition times (Figs 3c, d). The identified outcrop top in the first step can be checked against these shaded relief maps or those produced with different (artificial) illumination

geometry to ensure the same outcrop is matched in two images. In the third step, a set of 3-D views of the outcrop can be built by draping the historical images and shaded relief maps on the REMA DEM for the final verification (Figs 3e, f). This complex procedure is currently performed manually and requires automation in the future.

Blue ice areas in Antarctica may not be covered by snow due to wind and topography, and the ice appears blue, relatively smooth, and flat. In areas where the surface is covered by ice, and no outcrops are available, blue ice landmarks are often used as GCPs. Blue ice is formed when ice bubbles are squeezed out of ice over time, and the ice density increases, strengthening the ice surface and improving the surface hardness (Bintanja, 1999; Cui and others, 2019). The blue ice features with relatively low velocities that may move at $<1 \text{ m a}^{-1}$ occupy $\sim 37\%$ of the blue ice areas in Antarctica (Hui and others, 2014). We use a dataset of blue ice features with location information in Antarctica provided by Hui and others (2014). Given the initial location of a blue ice GCP candidate from the dataset (Fig. 4a), we examine the velocity within a relatively long period to confirm the locational stability. We require the velocity of the candidate area to be $<10 \text{ m a}^{-1}$ (or within map uncertainties) in two different velocity maps (Fig. 4c). The time separation of the two maps is more than 8 years, e.g. the MAMM velocity map from 1997/2000 (Jezek, 2002) and InSAR velocity map from 2007–08 (Mouginot and others, 2017b). To further avoid or reduce the influence of seasonal snow cover and outline changes of the blue ice area, we make measurements at higher and distinct locations within the blue ice area with the help of illumination and shadow interpretation in images or 3-D scene analysis using a DEM, if available (similar to Fig. 3).

In addition, ice rises are common, locally grounded features in ice shelves. They often have a dome-shaped surface that is 100–200 m higher than the surrounding ice shelf. GCPs can be selected from ice rise landmarks that usually remain stable long-term and are not overrun by the ice sheet, at least during the last glacial cycle (Matsuoka and others, 2015). However, the surface of an ice rise is usually covered with snow and ice and may be subject to seasonal snow changes. First, because stable landmarks are generally less available in ice-shelf regions, outcrops on ice rises should also be selected as GCPs (Fig. 4b). Second, peaks formed by sharp ice ridge intersections at high locations are relatively stable and should be selected as GCPs because they are less affected by snow accumulation (Fig. 4b). Lower areas with ice flow or migration of shear margins are not considered. One or more high-precision velocity maps, such as the InSAR velocity map of 2007–08 (Mouginot and others, 2017b), may be used to check the decadal-scale stability of the selected GCPs (Fig. 4d). Therefore, stationary features on ice rises can be used as GCPs, as suggested by Wang and others (2016).

In general, the principle is to select enough GCPs that are evenly distributed in the image to be orthorectified. In areas where the three types of landmarks are not available, other distinct image features with very slow motion ($<10 \text{ m a}^{-1}$) may also be selected as GCPs (Li and others, 2017).

With the selected GCPs measured on the historical image for image coordinates, the LIMA image mosaic for horizontal control and the RAMPv2 for vertical control, an orthorectification model that is described by Toutin (2004) and implemented in the PCI Geomatics system (Geomatics, 2005) is used to produce an orthorectified historical image for subsequent ice velocity mapping.

3.2 Construction of historical ice velocity fields

After the orthorectification process, both the orthorectified ARGON mosaic and Landsat images are free of distortion caused

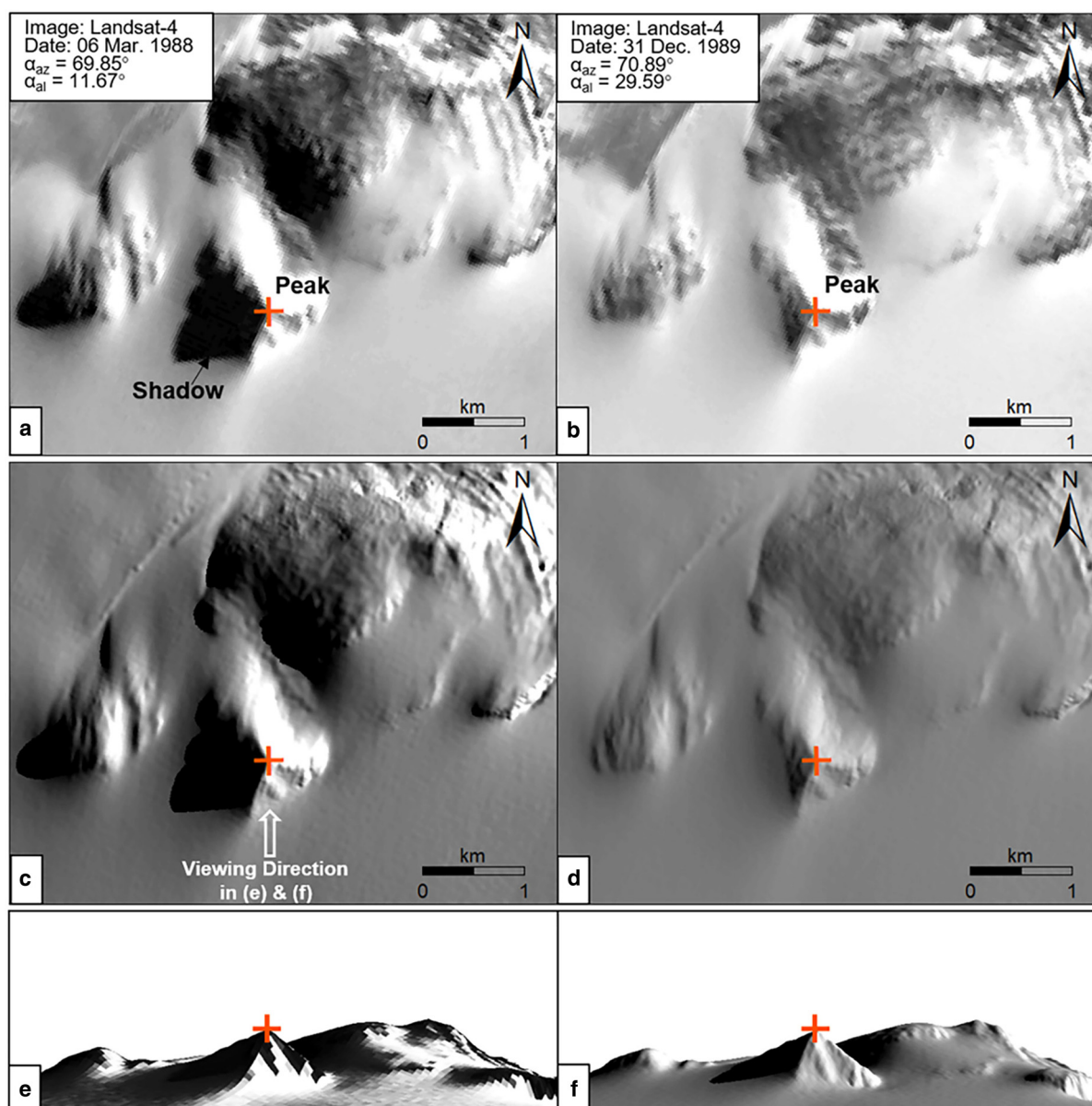


Fig. 3. Example of verification of an outcrop top as GCP: (a) and (b) are two Landsat-4 images from which the outcrop top is selected by distinguishing different shadows caused by varying solar altitude and azimuth angles; (c) and (d) are two shaded relief maps from the REMA DEM using the same solar illumination geometry at the image acquisition time; (e) and (f) are two 3-D views of Landsat-4 in (a) and the shaded relief map in (c) (the elevation is exaggerated by two times), respectively.

by terrain relief (Li, 1998). Tracing the same ice surface features on the two images produces a motion displacement map that describes the motion vectors of the ice velocity field. Therefore, the second module of the framework (Fig. 2) focuses on the construction of basin-scale historical ice velocity fields through a dynamically densifying motion vector network approach that is modified from our in-house hierarchical image matching system that was successfully applied for surface feature tracking in challenging polar environments (Li and others, 2017). One of the main advantages of this hierarchical image matching strategy is its capability in estimating adaptive search ranges for accommodating large velocity variations while maintaining a high level of reliability by obtaining high-quality matched points and avoiding mismatches; the computational efficiency is achieved by its reduced search range on each scale level and the coarse-to-fine multi-scale matching strategy.

Initialization: To estimate the velocity of an ice surface feature, the identified feature in the earlier image (reference image) must

be uniquely tracked in the later image (search image). The first difficulty for an automatic tracking process in an Antarctic scene is attributed to the lack of distinct textures, which most general tracking techniques rely on. In the second difficulty, velocity in a scene, thus, displacements between features in two images may vary dramatically or discontinuously. For example, the velocity of a fast-flowing glacier may increase from a very low velocity ($<10 \text{ m a}^{-1}$) in the inland interior to a high velocity (more than 800 m a^{-1}) at the ice-shelf front; furthermore, the velocity outside the shear margin of the fast-flowing main trunk may be relatively low. This makes it extremely difficult to determine the search range in the feature matching process. The third difficulty is that persistent surface features may not have been preserved over the long-time intervals of the historical images because of the Antarctic dynamic surface processes, such as snow accumulation and blowing snow. In this study, the hierarchical feature tracking approach builds a pyramid of multilevel velocity fields, where the aggregated large surface structures are matched on the top

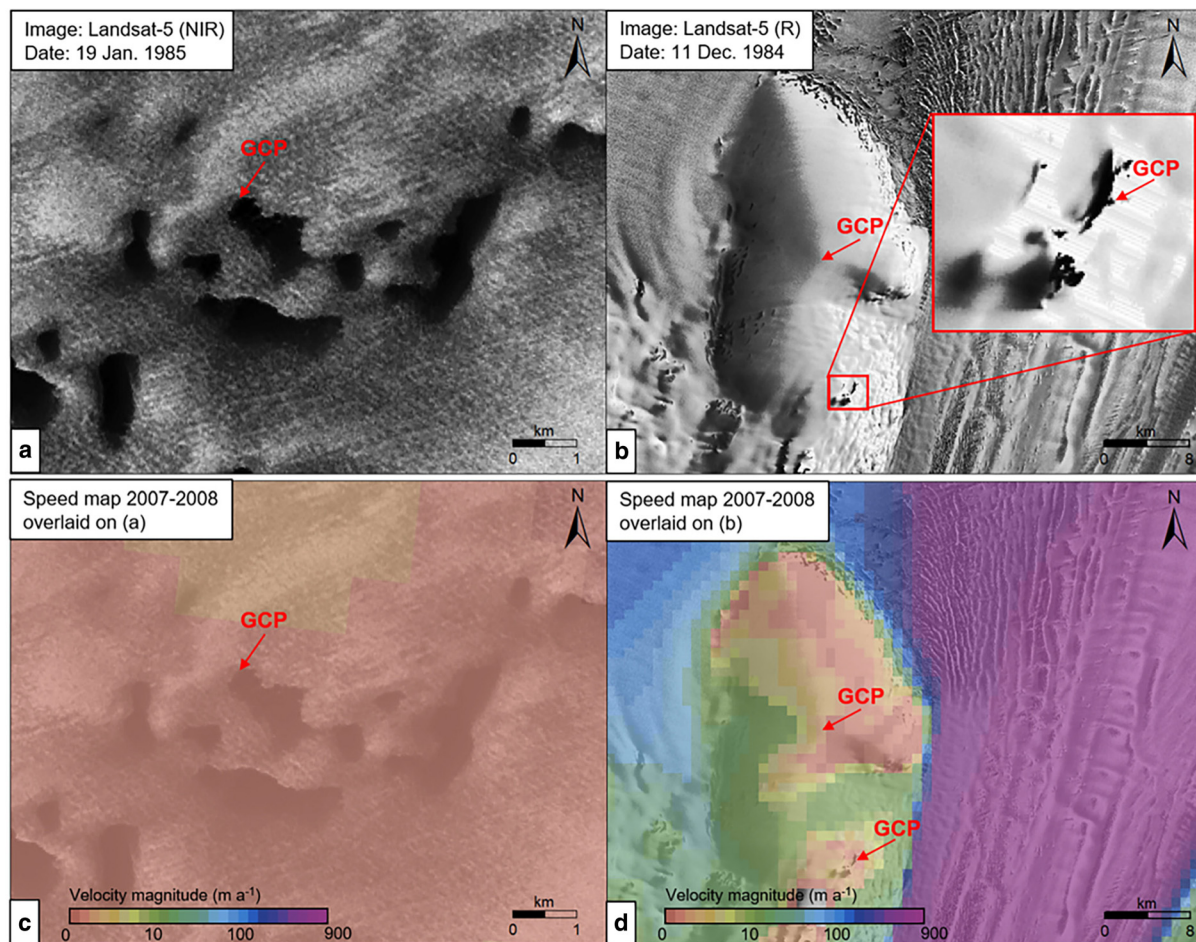


Fig. 4. Examples of landmarks used as GCPs: (a) blue ice shown in a near infrared band image of Landsat-5; (b) outcrop (in inset) and peak formed by an ice ridge intersection on ice rise in a red band image of Landsat-5; (c) and (d) InSAR velocity map of 2007–08 (Mouginot and others, 2017b) overlaid on (a) and (b), respectively.

level and used to control the subsequent lower level, leading to more expanded persistent features in a recursive manner. In the present experimental results, automated image matching techniques, both areal and feature-based matching, tend to find slow motion or stable ice features on the top level. Therefore, we start with a set of seed points that are manually selected and matched in two images (Wang and others, 2016; Li and others, 2017), which may include surface features in slow-flowing areas, such as those used as GCPs, for example, outcrops, blue ice and ice rises. Additional seed points are selected on high-velocity features such as surface undulations and fractures on glaciers and ice shelves (Fig. 5a). Such manually selected seed points are highly effective for handling images with a time interval of more than 3 years. Another example of features used for seed points is rifts that appear frequently near ice-shelf fronts. They may have evolved (widening and lengthening) from upstream fractures, showing different longitudinal velocities on the two sides of the rifts (Hulbe and others, 2010; Walker and others, 2013). The transverse rifts may meet flowlines at an angle; and tips of promontories formed by rift walls can be identified with the help of 3-D visualization, if possible, and used as seed points (Fig. 5b).

The distribution of different types of seed points in the area covering the Fimbul and Jelbart ice shelves is shown in Figure 6. A total of 1087 seed points are selected manually to provide structural information of the velocity field on the top level. The initial TIN model uses large-scale (a few kilometers to tens of kilometers) ice surface structure features (outcrops, blue ice, ice rise and others) and slow velocity surface features (<10 m

a^{-1}) to form a network that is used to constrain the stationary and slow-flowing part of the velocity field. Furthermore, at a smaller scale (hundreds of meters to a few kilometers) ice surface features in fast-flowing regions, such as main trunks of glaciers and ice shelves, are used to guide the densification process of the fast-flowing part of the velocity field.

Hierarchical network densification: Given an image with a dimension of M_1 pixels $\times$ M_2 pixels, an N -layer network has a dimension structure of $M_1/2^{N-i} \times M_2/2^{N-i}$ at the i -th layer ($i = 1, 2, \dots, N$), with the first layer of the coarsest image and the N -th layer of the original image (Fig. 7). In this study, we implement a network of a four-layer image pyramid which is generated through a top-down (from N -th to 1st layers) procedure. Images at each layer are generated using a Gaussian filter that simultaneously subsamples and smooths the images from the previous layer (Li and others, 2011).

The hierarchical ice velocity network is densified recursively by two processes, namely matching ice surface feature points from the reference image to the search image and tracking the matched features from the current layer to next layer (Fig. 7). Initially, a set of seed points (red crosses) is selected and matched manually on the top layer (layer 1) to construct the initial structural information of the velocity field. At each layer (layer i), the tracked feature points from the previous layer (layer $i - 1$) are used to form triangles of a TIN model on this layer. New feature points are then detected in both images using a Shi–Tomasi corner detector (Shi and Tomasi, 1994; Tulpan and others, 2014). For each feature point on the reference image its adaptive search range is adjusted

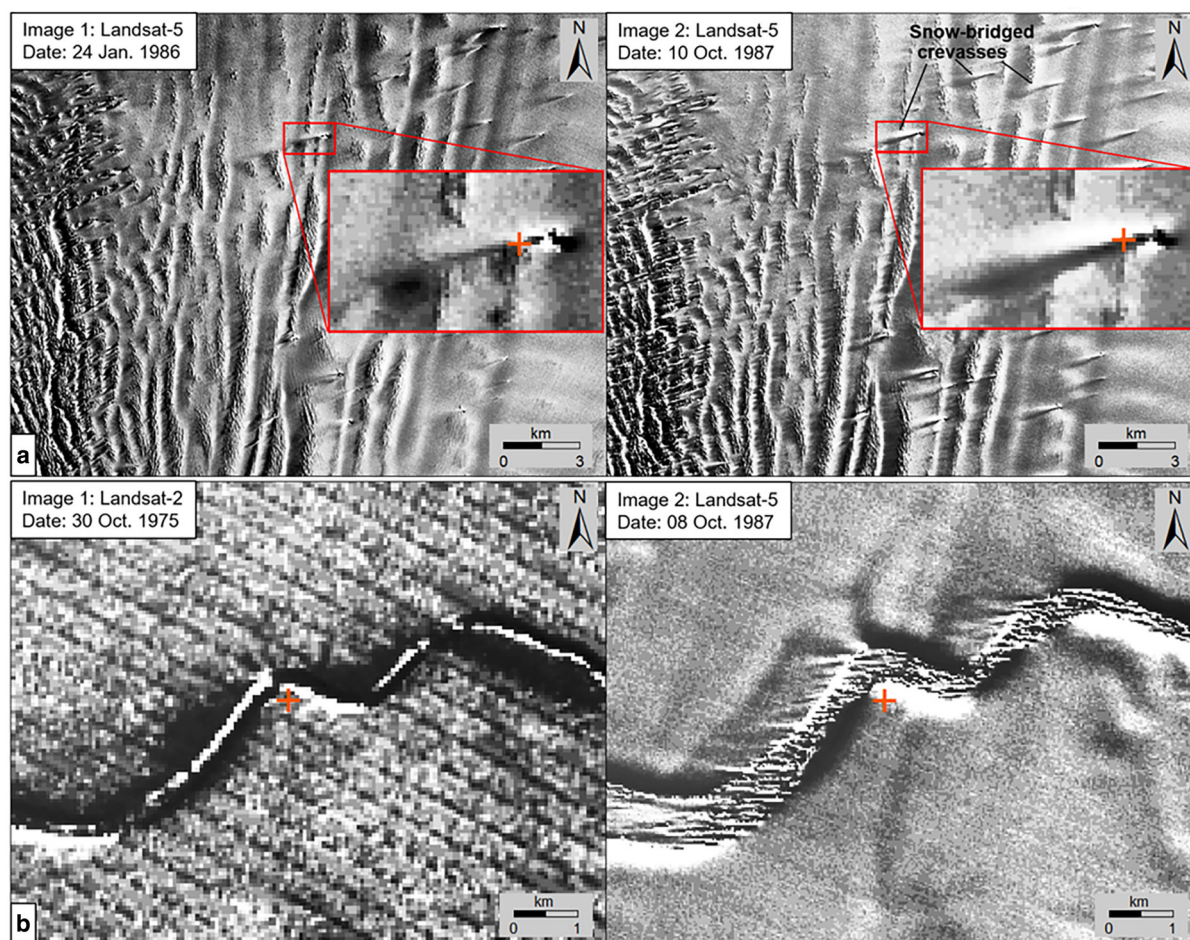


Fig. 5. Selection and matching of seed points from large structural features on an image pair: (a) intersections of crevasses (snow-bridged) and ice flow features on a glacier; (b) tips of promontories formed by rift walls on an ice shelf.

by the velocity information inherited in the TIN model (Li and others, 2017). Its corresponding feature point on the search image is found from a set of candidate feature points in the search range by using the area-based matching technique. After feature matching and outlier elimination are performed at all feature points, the matched feature points are passed on to the next layer (layer $i + 1$), where they are verified by an area-based feature tracking method. The tracking process includes an area-based matching between the feature point on layer i and its transformed point on layer $i + 1$. Then the tracked feature point is rematched on layer $i + 1$ between the reference and search images using detailed image information of a higher resolution. The remaining feature points after this tracking process are used to densify the TIN model. On the last layer (layer N), under the control of the TIN model, a dense grid mapping is performed at a grid spacing of 10 pixels through a subpixel matching process using normalized correlation coefficients (NCCs; Liu and others, 2012).

There are two additional techniques for eliminating mismatches and feature points of erroneous velocities at each level. The first uses a multi-thresholding technique of correlation coefficients to avoid mismatches caused by areas of different ice flow patterns. Among other factors, the correlation coefficients of the corresponding feature points are closely related to the quality of the image pairs involved. Generally, a mapped area in historical images may appear as a large, low-contrast and low-textured background with slow ice flow, where one or more fast-flowing glaciers may emerge (Fig. 8a), resulting in a bimodal histogram of the correlation coefficients (Fig. 8b). Experiments with manual measurements show that correct matches of slow ice flow features

exist within the first peak area of the relatively low correlation coefficients, while features with higher velocity are more distinct and thus have higher correlation coefficients and are less affected by the low-image quality (Heid and Käb, 2012; Li and others, 2017). Therefore, we separate the two groups of automatically matched feature points using the threshold between the bimodal distributions at each level and then determine the selected feature points within each group using a different threshold. This two-level thresholding process not only ensures that reliable feature points of both slow and fast flows are matched, but also that mismatches caused by a single threshold are avoided.

The second technique used for eliminating erroneous ice velocity vectors that are produced from the remaining mismatches is based on the knowledge that the ice velocity of a glacier must follow glaciological processes and generally does not abruptly change its magnitude and direction within a close neighborhood. Initially, we use a threshold based on the estimated error of the ice velocity map (e.g. 1–2 times) to remove ice flow vectors in the motionless or slowly moving areas to avoid the chaotic appearance. Then a velocity vector in a faster flowing area is considered abnormal and eliminated if its magnitude difference with the local mean is more than three times the std dev. In addition, the consistency of the flow direction of the velocity vectors is strongly correlated with the ice velocity. The velocity vectors in a small neighborhood may change their directions significantly only in low-velocity areas or even show a chaotic pattern because of the matching errors. Therefore, we perform a rule-based process to eliminate velocity vectors with erroneous directions. First, we pre-screen each velocity direction α against an existing ice velocity

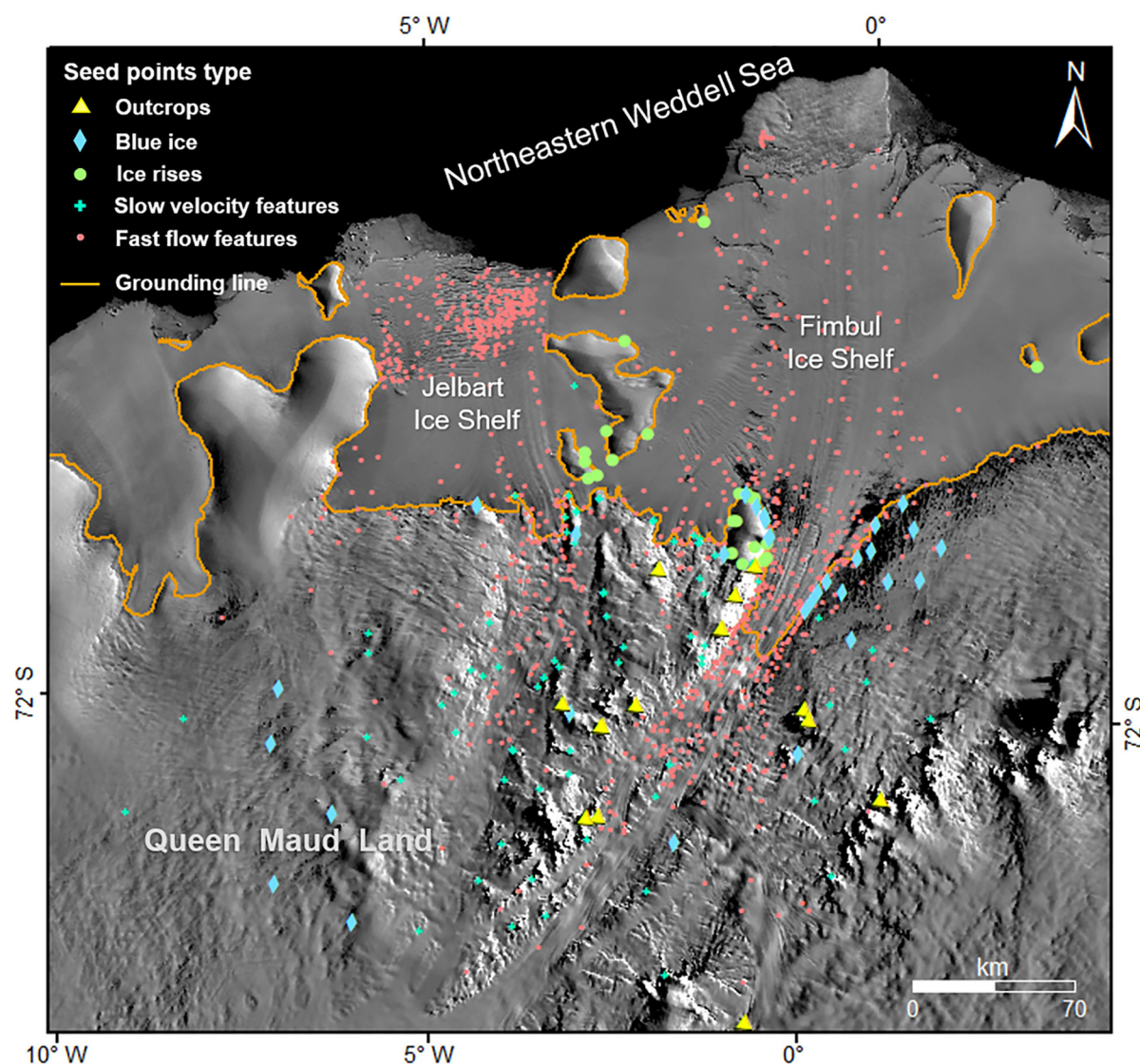


Fig. 6. Distribution of different types of seed points selected in the area covering the Fimbul and Jelbart ice shelves and the corresponding drainage basin. The grounding line is from Gardner and others (2018a). The background image is MOA mosaic 2004 (Haran and others, 2005).

map, for example, the InSAR velocity map by Mouginot and others (2017b). If the difference $d\alpha$ is greater than a threshold δ ($d\alpha \geq \delta$), the velocity vector is considered erroneous and should be eliminated; δ is set sufficiently large to prescreen blunders by using a set of descending values (δ_i for velocity range_{*i*}): 90° for 10–20 m a⁻¹, 70° for 20–50 m a⁻¹, 60° for 50–100 m a⁻¹, 52° for 100–200 m a⁻¹, 46° for 200–400 m a⁻¹ and 40° for ≥ 400 m a⁻¹, which are estimated through a number of experiments with manual measurements. Then, the remaining velocity vectors are checked for internal consistency. For each feature with ice velocity in the range of 10–20 m a⁻¹, we check its consistency with a mean and std dev. (1σ) calculated within a neighborhood (5 km is used in this paper) based on the trial result of several areas. For a feature with a velocity ≥ 20 m a⁻¹, the maximum angular difference within the neighborhood must be $<30^\circ$. Otherwise, the feature is checked against the median absolute deviation estimated within the neighborhood (Liu and others, 2012) and is accepted with a quantile of 90%. For those that have fewer than three feature points within the neighborhood, a manual check is performed (MPAIISSVP, 2019).

Overall, the hierarchical ice velocity network densification process is initiated with a set of reliable manual seed points to present the structural features at the first level. The subsequent recursive

network densification process is characterized by two main steps: (1) improved reliability and efficiency by producing high-quality matches and avoiding mismatches through inherited constraints and search ranges using tracked feature points from the previous level, and (2) elimination or reduction of remaining erroneous velocity vectors using a rigorous rule-based procedure.

3.3 Final ice velocity maps and accuracy assessment

The final ice velocity maps defined in a grid are generated using the relatively sparsely distributed feature points achieved through hierarchical network densification as a control; velocities at the densely distributed gridpoints are then estimated by displacements calculated using the dense grid matching technique (Fig. 2). The algorithms of NCC matching, geometric constraints and search range adaptation are implemented in a similar manner in both dense grid matching and hierarchical network densification. The grid spacing is generally selected as 1.5–3 times the lowest ground resolution of all images involved (Li, 1998). The grid spacing can also be estimated from the ratio of the mapping area to the number of matched feature points. However, the matched feature points spread more sparsely in some locations, and there may be unmatched blank areas due to the poor quality

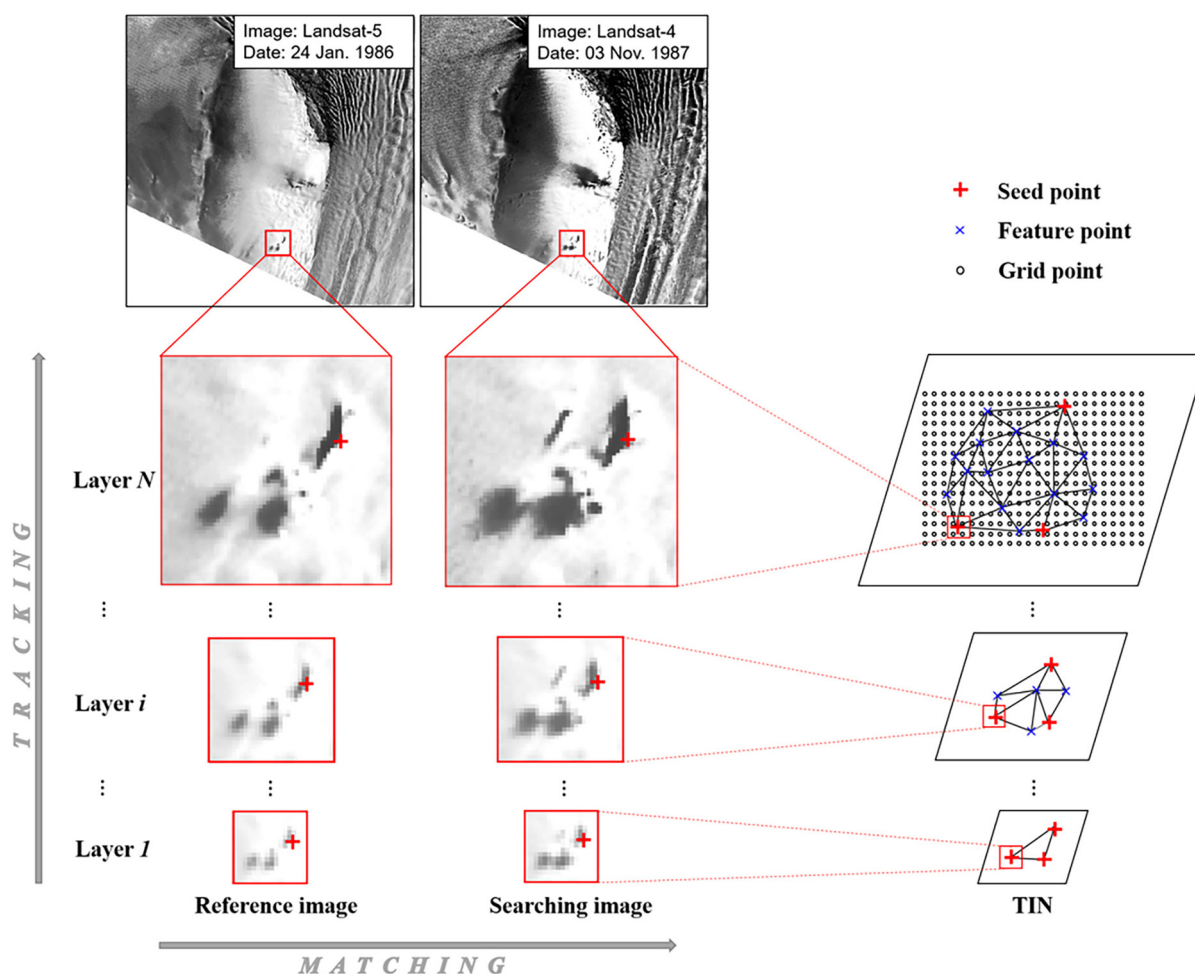


Fig. 7. Schematic diagram of the hierarchical network densification approach. The method is applied to the entire image pair. An enlarged area is used to explain the hierarchical matching and tracking process.

of the historical images and long-term glaciological processes. For applications that require high-accuracy velocities, large areas (e.g. $>12 \text{ km}^2$) without mapped velocity points are masked out. In this product, the ice velocity is split into its components in the x and y directions at each gridpoint, from which the magnitude and direction are calculated and/or stored in the dataset.

Figure 9 illustrates the effectiveness of the proposed method. Figure 9b presents the velocity map of the main trunk of the Jutulstraumen Glacier produced through the hierarchical network densification procedure using the seed points in Figure 6. In comparison, Figure 9c illustrates the result of a single layer area-based matching technique without seed points. The high velocity variation of the area makes it impossible to use a fixed search window size that would work with both the very slow-moving ice surface ($<10 \text{ m a}^{-1}$) and high-velocity ice flow ($>800 \text{ m a}^{-1}$) at the ice-shelf front. Without the guidance of the seed points in the TIN network (Fig. 9a), a larger search window caused many mismatched feature points that failed to map the very low-velocity areas ($<10 \text{ m a}^{-1}$), in addition to the increased computational cost (Fig. 9c). Similarly, mismatches along the high velocity main trunk are also obvious. Velocity maps with such large errors would influence the scientific conclusions.

In this study, we use σ_{ref} and σ_{src} to denote the geolocation uncertainties of the reference and search orthoimages. Because the final velocity maps contain both matched feature and grid-points at the last layer of the densified network, an identification accuracy σ_{idn} for localizing a feature in the reference orthoimage is used for feature points ($\sigma_{\text{idn}} = 0$ for gridpoints). Here, it is set to

0.5 pixels for Landsat images and, 2 pixels for ARGON images. The accuracy is further influenced by the matching accuracy σ_{mtc} . Assuming that the time span between two images is Δt and the errors involved are independent, the ice flow velocity error σ_{vlc} can be estimated as

$$\sigma_{\text{vlc}} = \frac{1}{\Delta t} \sqrt{\sigma_{\text{ref}}^2 + \sigma_{\text{src}}^2 + \sigma_{\text{idn}}^2 + \sigma_{\text{mtc}}^2}. \quad (1)$$

In principle, the orthorectification errors of σ_{ref} and σ_{src} consist of the error of the Landsat images and the errors introduced from LIMA and dominantly from RAMPv2 through the rectification process. In practice, we evaluate the orthorectification accuracy by comparing the horizontal locations of a set of checkpoints which are measured manually in the LIMA image mosaic and the orthoimages produced in the PCI Geomatica system (Toutin, 2004; Geomatics PCI, 2005). Displacements calculated on stable terrain, such as outcrops in the ADD database (Burton-Johnson and others, 2016; ADD, 2021), represent errors. We select up to ten checkpoints that are evenly distributed in slow-flowing areas (outcrops or points with velocity $\leq 10 \text{ m a}^{-1}$). The displacements between the locations of the checkpoints in the LIMA image and the orthoimages represent residual errors after the orthorectification process. The RMSE from the displacements is used to estimate the orthorectification uncertainties σ_{ref} and σ_{src} . Similarly, the image matching error σ_{mtc} can be estimated using the differences between the automatically matched and manually matched locations of a set of checkpoints. We divide the map into

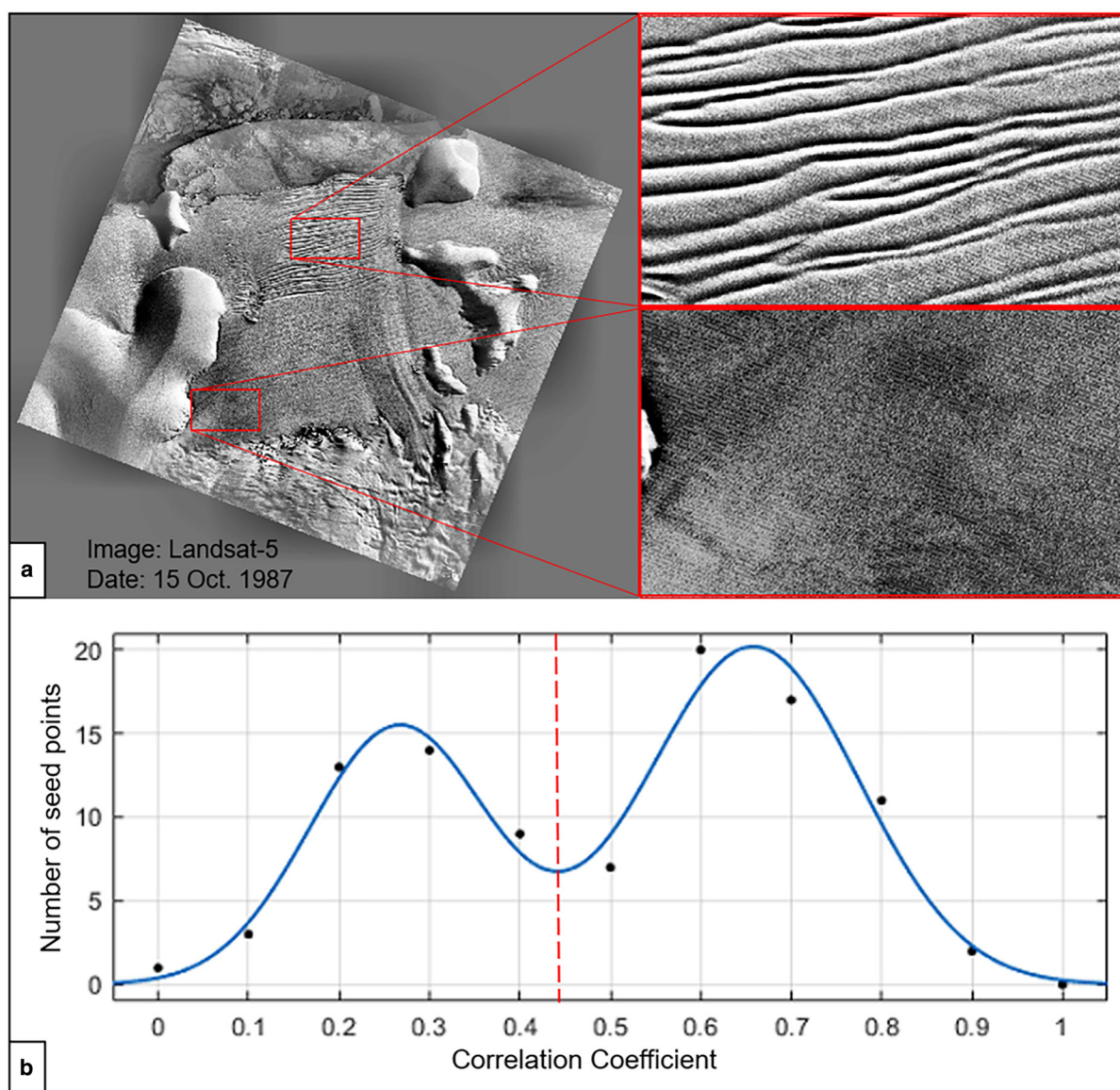


Fig. 8. Thresholding technique for eliminating mismatches: (a) historical scene with a large low contrast and low textured background and a fast-flowing glacier with corresponding enlarged areas; (b) bimodal histogram of correlation coefficients.

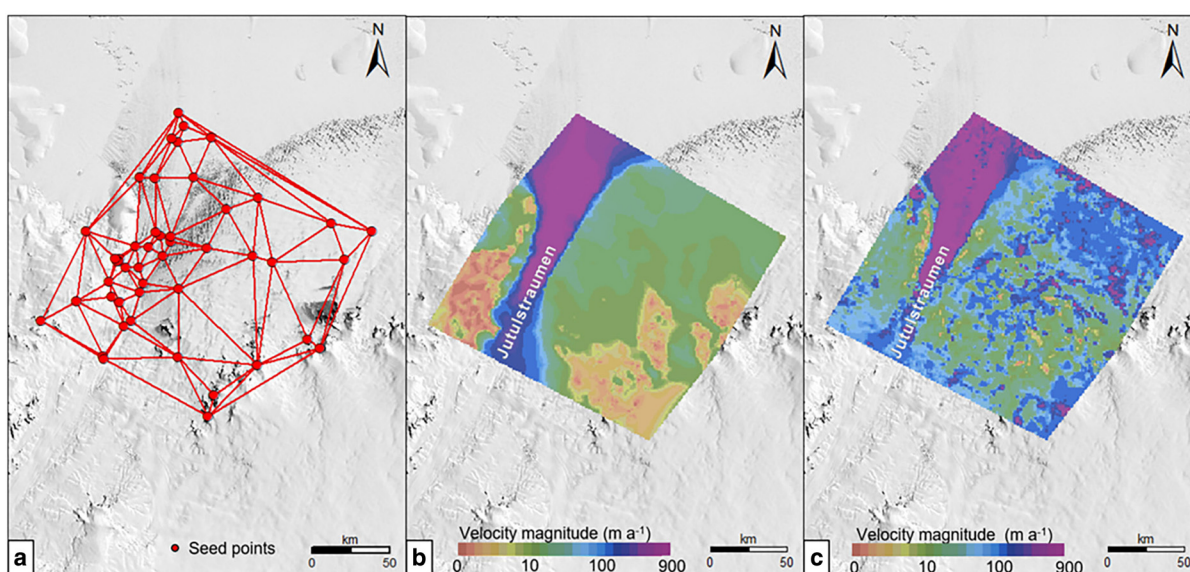


Fig. 9. Impact of the proposed method on historical ice velocity mapping in the main trunk of the Jutulstraumen Glacier: (a) initial network generated based on the seed points, (b) improved velocity map produced using the hierarchical network densification approach supported by the seed points and (c) undesirable result of single layer matching without seed points.

a checking grid and select one or more checkpoints (matched points) in each gridcell to ensure a uniform distribution (Li and others, 2011). The grid spacing depends on the coverage of image pairs, ranging from 25 to 50 km in this study. The ice velocity characteristics in East Antarctica are considered in the selection of these points at three levels, including high ice velocity ($\geq 450 \text{ m a}^{-1}$), medium ice velocity ($100\text{--}450 \text{ m a}^{-1}$) and low ice velocity ($\leq 100 \text{ m a}^{-1}$). The accuracies of orthorectification, identification and image matching are used in Eqn (1) to give an overall accuracy of velocity mapping.

4. Results and discussion

4.1 Reconstructed ice velocity fields and their accuracy

In the study area, 77 historical images (Fig. 1) are used to reconstruct the multi-period historical ice velocity field between 1963 and 1987, including ice velocity fields for 1963–75, 1973–87 and 1985–87. The selection of the time spans is constrained by the available images given the spatial coverage. All the ice velocity fields are then combined into an ice velocity map for 1963–87 by calculating the weighted average of the ice velocity. Taking one of the image pairs involved as an example to demonstrate the feature matching and tracking procedure, 52 seed points (row 1 and first layer in Table 2) are manually measured at the first layer of a four-layer network, which has an image resolution that is four times reduced from the original image. These seed points reconstruct the most general velocity structure of the scene. Then, 2139 detected feature points are matched initially (row 2 and first layer in Table 2), among which 1278 feature points are eliminated according to the threshold of correlation coefficients and the magnitude and direction of velocity vectors within a close neighborhood (row 3 and first layer in Table 2). Therefore, 861 newly matched feature points are confirmed. With the manually measured feature points, a total of 913 matched feature points are present on the first layer (row 5 and first layer in Table 2). In the second layer the resolution is increased to two times the original image. The matched feature points from the first layer are tracked and rematched. The remaining 786 feature points are used to construct the matching constraint (row 1 and second layer in Table 2). The remainder of the process is similar to that of the first layer. In the third layer the original image resolution of 60 m is reached and a total of 20 800 feature points is matched and confirmed (row 5 and third layer in Table 2). The final layer (fourth layer) has the same image resolution as the third layer, the original image resolution of 60 m. A grid with a spacing of 500 m is defined. In total, 22 114 gridpoints (row 4 and fourth layer in Table 2) are matched and confirmed under the constraint of the 20 800 matched feature points (row 1 and fourth layer in Table 2). Consequently, 42 914 matched feature and gridpoints (row 5 and fourth layer in Table 2) are used to calculate the displacements and the ice velocity field in the area. From the first layer to the fourth layer, the rate of eliminated feature points is reduced from 60 to 24% (row 3 in Table 2), which indicates

that the automatic matching confirmation rate (reliability) is gradually improved.

The detailed information for feature matching and tracking statistics for all image pairs and accuracy is listed in Table 7. To reconstruct the ice velocity fields of all three periods, 1087 seed points were selected manually to build the initial network at the top level. After the hierarchical feature matching process at all levels, 90 033 matched and confirmed feature points were obtained and applied as constraints to control the dense matching process. Finally, a total of 202 301 velocity vectors were reconstructed for the three mapping periods.

The ice flow velocity at each matched location was calculated according to the displacement between the two corresponding points and the time interval. The ice velocity maps of the Fimbul and Jelbart ice shelves during 1963–75, 1973–87 and 1985–87 in the form of color-coded velocity magnitudes of the matched feature points are presented in Figure 10. No interpolation was performed. For mass-balance estimation purposes, the velocity values of the three maps cover the Jutulstraumen Glacier and the Fimbul Ice Shelf and are used to compute the ice discharge of the three periods from the Jutulstraumen Glacier drainage sub-basin. However, there are velocity data gaps in the Jelbart Ice Shelf and near the grounding line of the Schytt Glacier drainage sub-basin. We used a regional velocity map (Cheng and others, 2019) to fill these gaps, which was produced using 76 Landsat images of 1972–89. Specifically, the velocity values of this map, with a temporal coverage of 1972–87 in this sub-basin, are combined with those produced in this study to produce a velocity field of 1963–87 in the Schytt Glacier drainage sub-basin, using a natural neighbor interpolation implemented in the ArcGIS system (Childs, 2004). The matched features in this study and the velocity points of the regional map are used to construct a Voronoi network. The velocities at the network nodes within a neighborhood are weighted to calculate the averaged velocities at gridpoints of the new velocity field. Both the neighborhood and weights are defined based on proximities of the gridpoints to the Voronoi network cells. This method has an advantage of handling clustered scatter points (Gold and others, 2006). The resulted velocity field (grid spacing 500 m) of the Schytt Glacier drainage sub-basin has a temporal coverage of 1963–87 and is used for mass-balance estimation. For visualization purposes, the same interpolation method is used to combine this regional velocity map (Cheng and others, 2019) with all matched features in this study to produce a velocity map of the extended region of 1963–89 with a grid spacing of 500 m (Fig. 11).

An accuracy assessment of the ice velocity is performed inside the footprint of each individual image pair. Taking an image pair (reference image no. 4 and search image no. 14 in Table 7) that covers the front of the Fimbul Ice Shelf as an example, the ice velocity was derived from two Landsat MSS images, with a time interval of 12 years. We used manually measured checkpoints to estimate the orthorectification errors, which are 42.8 and 44.0 m, respectively. The feature identification error for the

Table 2. Intermediate and final results of the hierarchical matching procedure for velocity mapping

(Row no.) Features\Matching step	First layer (res. 240 m, feature)	Second layer (res. 120 m, feature)	Third layer (res. 60 m, feature)	Fourth layer (res. 60 m, grid)
(1) Rematched from layer $i - 1$	52 (seeds)	786	2649	20 800 (features)
(2) Init. matched at layer i	2139	8515	29 099	29 141
(3) Eliminated from (2)	1278 (60%)	4587 (54%)	10 948 (38%)	7027 (24%)
(4) Confirmed at layer i : (2) – (3)	861	3928	18 151	22 114
(5) Total matched at layer i : (1) + (4)	913	4714	20 800	42 914

Reference image: no. 4 in Table 6, search image: no. 14 in Table 6, 60 m ground resolution.

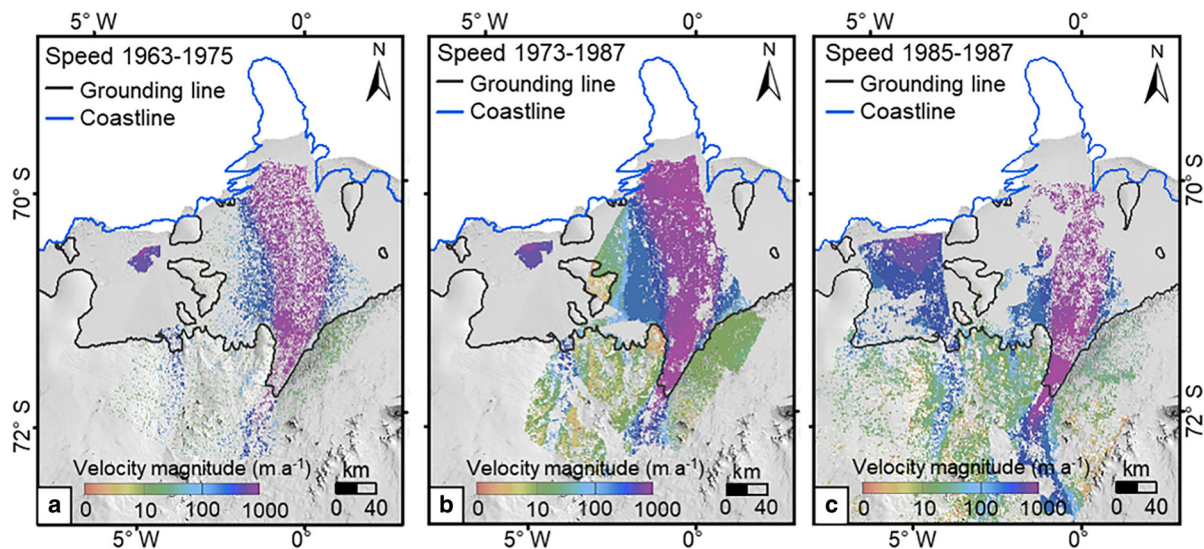


Fig. 10. Ice velocity (magnitude) maps of the region around the Fimbul and Jelbart ice shelves in 1963–75 (a), 1973–87 (b) and 1985–87 (c). The coastline (blue line), including the ice tongue, is extracted from the ARGON mosaic of 1963 (Kim, 2004). The grounding line (black line) is from Gardner and others (2018a). The background image is LIMA image mosaic (Bindschadler and others, 2008).

Landsat image is 30 m (0.5 pixels). We assessed the matching errors of feature points and gridpoints in separate velocity ranges using manually measured checkpoints, as described in Section 3.3 and Table 8. The average matching error within this image pair is 45.1 m. The ice velocity accuracy of this image pair is calculated according to Eqn (1) as 6.8 m a^{-1} . Finally, the ice velocity values of the individual maps (Fig. 10) and the integrated map (Fig. 11) are estimated by averaging the velocities from the individual image pairs (Table 7) involved in each map. Furthermore, the uncertainties (σ_{ref} , σ_{src} , σ_{idn} and σ_{mtc}) of each map (Table 3) are estimated by applying the error propagation law to the corresponding uncertainties of the involved individual image pairs (Table 7). Equation (1) is then used to estimate the velocity uncertainties (σ_{vle}) of the produced maps in Table 3. Partly because of the long-time intervals between the image pairs, all maps achieved an accuracy better than 29 m a^{-1} , which is appropriate for analyzing ice flow dynamics and mass changes in the area.

4.2 Ice velocity changes

We built historical ice velocity maps for three periods before 1987, and compared them with the InSAR ice velocity map for 2007–08 (Mouginot and others, 2017b). Accordingly, four sets of ice-shelf front boundaries with approximate time tags of the velocity maps are extracted from the Antarctic coastline products or satellite images, including the ARGON mosaic of 1963 (Kim, 2004), the MODIS-based MOA 2009 (Haran and others, 2014), and Landsat images from 1975 and 1987. The analysis of the ice velocity changes is primarily facilitated by the velocity comparison along two profiles, namely profile AA' from along the main trunk of the Jutulstraumen Glacier to the front of the Fimbul Ice Shelf and profile BB' from along the main trunk of the Schytt Glacier to the front of the Jelbart Ice Shelf (Fig. 12).

Along profile AA', the velocity of the Jutulstraumen Glacier and Fimbul Ice Shelf has an average of $685 \pm 22 \text{ m a}^{-1}$ (Fig. 12a). Because of the rapid elevation decrease of $\sim 700 \text{ m}$ from the inland interior to the grounding line, the ice flows at an initial velocity of $353 \pm 26 \text{ m a}^{-1}$ downstream for $\sim 60 \text{ km}$ along the main trunk of the Jutulstraumen Glacier (Fig. 11), and the velocity reaches $725 \pm 18 \text{ m a}^{-1}$ at the grounding line. Beyond this point, the glacier feeds the ice shelf at a lower velocity of $680 \pm 23 \text{ m a}^{-1}$ in the middle of the shelf. It then increases to

$744 \pm 7 \text{ m a}^{-1}$ at the ice-shelf front. The confidence intervals of the velocities along AA' from the four velocity maps from 1963 to 2008 overlap each other, indicating no significant velocity changes over the 45 years. In contrast, the ice flow velocity along profile BB' is generally $310 \pm 24 \text{ m a}^{-1}$ slower than that along profile AA' (Fig. 12b). The maximum velocity is at the Jelbart Ice Shelf front at $698 \pm 26 \text{ m a}^{-1}$. Similarly, the ice velocity of the Schytt Glacier and Jelbart Ice Shelf for 1963–87 does not differ from that for 2007–08, with confidence.

4.3 Mass-balance changes

The mass changes of the ice sheet can be estimated based on the difference between the SMB and the ice discharge from the ice sheet to the ocean. Therefore, the produced historical ice velocity maps provide a unique opportunity to estimate the flux from 1963 to 1987 and investigate the mass balance in the study area using additional later velocity maps. The SMB of a drainage basin is the sum of mass changes occurred during a period through all surface processes within the basin boundary, i.e. the total precipitation of snowfall and rain minus the total sublimation of surface snow, drifting-snow erosion and meltwater runoff (Van Wessem and others, 2014). The polar version of the RACMO regional atmospheric climate model (RACMO 2.3p2) provides annual SMB data in Antarctica at a resolution of 27 km (Van Wessem and others, 2018). The SMB value in a basin was calculated by summing the SMB estimate values from RACMO 2.3p2 at all cells within the basin boundary. Since the SMB model result does not cover the period prior to 1979, we use the averaged SMB of 1979–89 for these map periods that include time before 1979, e.g. 1963–75, 1973–87 and 1963–87. The SMB of other periods was derived directly from the RACMO2.3p2 results. The drainage basin boundaries (Fig. 11) used in this study are from Zwally and others (2012). To calculate changes of the mass fed into the Fimbul and Jelbart ice shelves separately, the boundary between the Jutulstraumen and Schytt sub-basins was derived based on a combination of two datasets, i.e. glacier outlines of global land ice measurements from space (GLIMS) database (GLIMS and NSIDC, 2005) and ridgelines in the area extracted from the REMA DEM by using the ArcGIS toolbox (Esri Inc., 2020).

On the other hand, ice discharge is the ice flux across the grounding line. We adopt the flux computation procedure

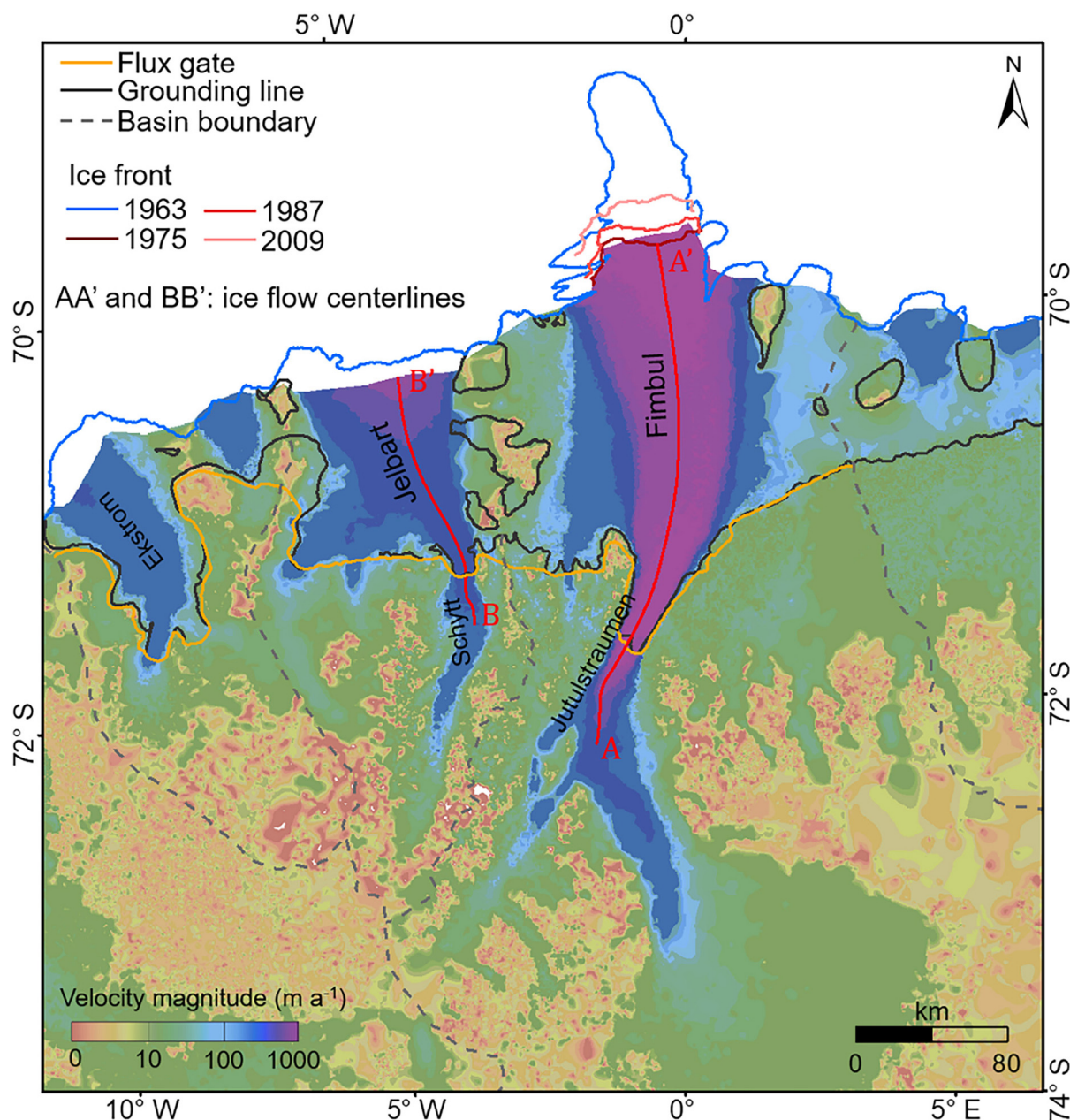


Fig. 11. Ice velocity (magnitude) map of the region around the Fimbul and Jelbart ice shelves from 1963 to 1989. The drainage basin boundaries are from Zwally and others (2012), and the boundary between the Jutulstraumen and Schytt sub-basins is derived based on data from GLIMS (GLIMS and NSIDC, 2005) and REMA (Howat and others, 2019). Four sets of shelf fronts of the Fimbul Ice Shelf are extracted from the ARGON mosaic of 1963 (Kim, 2004), MOA mosaic of 2009 (Haran and others, 2014) and Landsat images of 1975 and 1987. The shelf front of the Jelbart Ice Shelf in 1963 is extracted from the ARGON mosaic of 1963 (Kim, 2004). The grounding line is from Gardner and others (2018a). Ice flow center lines AA' and BB' are locations of the velocity profiles in Figure 12.

introduced by Gardner and others (2018b). The data used include the ice thickness data of Bedmap-2 (Fretwell and others, 2013) and the flux gate (FG) from Gardner and others (2018a). We used the FG from Gardner and others (2018a) in this study (yellow line in Fig. 11), which are generally defined at locations upstream from the grounding line where ice thickness observations are available. We used an FG width of ~280 m. Assuming that there are no vertical gradients in the ice velocity, the ice flux can be estimated by summing the product of the ice velocity, ice thickness and FG width at each flux node (Gardner and others, 2018a). Using the historical ice velocity maps obtained in this study and the existing ice velocity maps, including the RAMP ice velocity map for 1997 and 2000 (Jezek, 2002), the InSAR ice velocity map for 2007–08 (Rignot and others, 2011a), and the Landsat 8 ice velocity map for 2014–15 (Scambos and others, 2016), we calculate the ice fluxes through

the FGs in the Fimbul and Jelbart regions. The change in flux in the area between the FG and the grounding line is estimated using the SMB in this area (Gardner and others, 2018b). Ice discharge is the flux that crosses the grounding line and is estimated from the ice flux at FG with a correction for the mass change between the FG and grounding line. Consequently, the mass balance, net mass gain (or loss), is estimated by subtracting the ice discharge from the SMB (Table 4).

In the Jutulstraumen sub-basin both ice discharge and mass balance maintained a relatively stable level during the study period of 1963–87 (Table 4), resulting in an average mass gain at $6.2 \pm 3.6 \text{ Gt a}^{-1}$ during the 24 year period, while the neighboring smaller Schytt sub-basin showed a balanced mass change. Although the three time periods from 1963 to 1987 in Table 4 have 2 year overlaps between them, the mass-balance values are estimated as annual rates (Gt a^{-1}). Therefore, for simplicity of

Table 3. Accuracy assessment of the ice velocity maps produced in this study

Map	Images	$\sigma_{\text{ref}}/\sigma_{\text{src}}$ m	Δt years	σ_{idn} m	σ_{mtc} m	σ_{vlc} m a^{-1}
1963–75 (Fig. 10a)	ARGON Mosaic	119.5	10.7	200.0	62.6	23.2
1973–87 (Fig. 10b)	Landsat-1, -2	56.5	13.2	30.0	47.2	6.0
	Landsat-4, -5	40.6				
1985–87 (Fig. 10c)	Landsat-4, -5	37.9	2.1	25.0	31.6	28.7
	Landsat-4, -5	32.2				
1963–87 (central part of Fig. 11)	ARGON mosaic, Landsat images (averaged from Figs 10a–c)	31.3	24.0	–	–	221.6

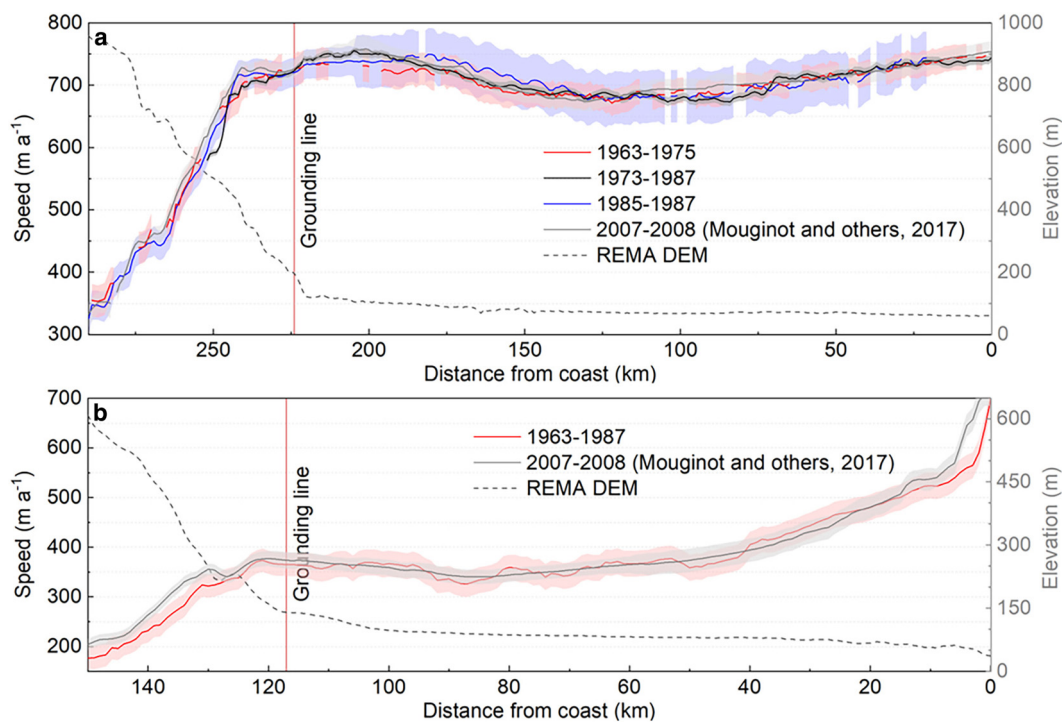


Fig. 12. Ice velocity (magnitude) of four periods from 1963 to 2008 along profile AA' (a) and that of two periods from 1963 to 2008 along profile BB' (b). The color bands represent the 1 – σ uncertainties of the corresponding velocities. The profile locations are illustrated in Figure 11. The grounding line is from Gardner and others (2018a). The velocity uncertainties along the profiles are represented by shadings of the same colors as their velocities.

computation, we used the average of the three mass-balance values for the overall mass balance from 1963–87; similarly, assuming the independency between the annual rates, we estimated the uncertainty of the overall mass balance from 1963–87 by applying the error propagation law to the corresponding mass-balance uncertainties of the three periods. This positive mass-balance trend continued in both sub-basins over the subsequent period from 1997 to 2015, as demonstrated by the mass-balance results (Table 4) estimated in this study using the three velocity datasets (Jezek, 2002; Rignot and others, 2011a; Scambos and others, 2016). The combined results show a long-term positive mass balance of $8.6 \pm 3.9 \text{ Gt a}^{-1}$ over 52 years from 1963 to 2015, with $7.3 \pm 3.4 \text{ Gt a}^{-1}$ from Jutulstraumen and $1.3 \pm 2.0 \text{ Gt a}^{-1}$ from Schytt.

4.4 Discussion

The errors of image orthorectification, feature identification and feature matching, which may be all influenced by the poor quality of the historical images, are the main error sources for ice velocity mapping. However, once two feature points are matched and the motion vector is determined, the accuracy of the estimated

velocity improves as the time interval increases. Therefore, we choose images with a longer time span, for example, more than 10 years, to estimate the velocity of the slower motion ice flows in the inland areas and ice rises and those with a relatively short time span, for example, <5 years, to map the fast-flowing glacier and ice-shelf areas. This short time span allows the ice surface features to be tracked before some of them may change due to glaciological processes. According to the velocity comparison results along both the profile of the Jutulstraumen Glacier and Fimbul Ice Shelf and the profile of the Schytt Glacier and Jelbart Ice Shelf (Fig. 12), there were no significant ice velocity changes between 1963 and 2008. In 1967, a major calving separated the ice tongue from the Fimbul Ice Shelf (Wilson, 1977), which caused an area loss of $\sim 5000 \text{ km}^2$ (Humbert and Steinhage, 2011) and a front retreat of $\sim 100 \text{ km}$. Since then, the ice tongue had grown back over $\sim 25 \text{ km}$ by 2009 (Fig. 11). The time span of the velocity map of 1963–75 covers this ice tongue collapse event in 1967, but the images used are 4 years prior to and 8 years after the event. Thus, the effect of the event on ice flow dynamics is not observed because the resulted signals of velocity changes may be smoothed out by the average velocity of the 12 year time span.

Table 4. Mass balance of the Jutulstraumen and Schytt sub-basins which the Fimbul and Jelbart ice shelves drain ice from (Fig. 11)

Sub-basin	Period of velocity map	Ice flux (FG) Gt a ⁻¹	Ice discharge Gt a ⁻¹	SMB Gt a ⁻¹	Mass balance Gt a ⁻¹
Jutulstraumen (Fimbul)	1963–75	14.4 ± 3.3	14.5 ± 3.3	20.2 ± 1.7	5.7 ± 3.7
	1973–87	13.0 ± 2.0	13.1 ± 2.1	20.2 ± 1.7	7.1 ± 2.7
	1985–87	15.0 ± 3.8	15.1 ± 3.8	20.8 ± 1.7	5.7 ± 4.2
	1997/2000 (Jezek)	15.2 ± 2.9	15.4 ± 2.9	22.5 ± 1.7	7.1 ± 3.4
	2007–08 (Rignot)	16.5 ± 3.0	16.7 ± 3.0	27.4 ± 1.7	10.7 ± 3.4
	2014–15 (Scambos)	16.2 ± 2.6	16.4 ± 2.6	23.7 ± 1.7	7.3 ± 3.1
Schytt (Jelbart)	1963–87	8.0 ± 2.7	8.4 ± 2.7	8.4 ± 0.4	0.0 ± 2.7
	1997/2000 (Jezek)	7.8 ± 1.7	8.3 ± 1.7	10.1 ± 0.4	1.8 ± 1.7
	2007–08 (Rignot)	8.5 ± 1.8	9.4 ± 1.8	11.4 ± 0.4	2.0 ± 1.8
	2014–15 (Scambos)	8.6 ± 1.6	9.1 ± 1.6	10.4 ± 0.4	1.3 ± 1.6

Velocity maps of 1963–87 are from this study and those of 1997–2015 are from Jezek (2002); Rignot and others (2011a); Scambos and others (2016).

Table 5. Mass balance of the combined basins of the Jutulstraumen and Schytt glaciers which feed the Fimbul and Jelbart ice shelves, respectively

Basin	Period	Ice discharge Gt a ⁻¹	SMB Gt a ⁻¹	Net mass change Gt a ⁻¹
Jutulstraumen (Fimbul) and Schytt (Jelbart)	1963–87	22.6 ± 4.1	28.8 ± 1.7	6.2 ± 4.5
	1997/2000 Jezek (2002)	23.7 ± 3.4	32.6 ± 1.7	8.9 ± 3.8
	2008/2015 Gardner (2018b)	27.8 ± 6.4	32.3 ± 7.0	4.5 ± 9.0
	1979–2017 Rignot and others (2019)	–	–	–0.2

To compare our mass-balance results to other published studies, e.g. Gardner and others (2018a, 2018b) and Rignot and others (2019), we combined the mass balance of the two sub-basins in Table 4 and averaged them over the period of 1963–87 (Table 5). The result of 1997/2000 (Jezek) is also a combined rate from Table 4. The row of 2008/2015 Gardner (2018b) is derived from the result of basin 5 in Gardner and others (2018b) using an areal ratio between our study area and the basin. Finally, the row of 1979–2017 Rignot and others (2019) is calculated based on the glacier-scale mass-balance data provided in Rignot and others (2019). As shown in Table 5, based on the first three studies from 1963 to 2015 the ice discharge in the study area maintained a consistent level at an average rate of $\sim 24.7 \text{ Gt a}^{-1}$. However, it was compensated by SMB over the years at an average rate of $\sim 31.2 \text{ Gt a}^{-1}$, resulting in a positive average mass balance of $6.5 \pm 6.2 \text{ Gt a}^{-1}$ for 52 years (1963–2015). Although the areal weighted mass-balance estimate from Gardner and others (2018b) is used here, this result is in line with our mass-balance estimate of $8.6 \pm 3.9 \text{ Gt a}^{-1}$ (1963–2015) for the region. On the other hand, Rignot and others (2019) presented an approximately balanced mass change in the area during the long period from 1979 to 2017. It should be noted that the velocity field in this study area for 10 years from 1979 to 1989 is not fully mapped in Rignot and others (2019), but only with very sparsely distributed velocity measurements on the glaciers (Supplementary information of Rignot and others, 2019). The ice discharge was estimated based on these measurements and the later period discharge through a scaling method (Rignot and others, 2019). This study area is one of the major positive mass contributors in Antarctica. Our results revealed a past state of 24 year positive mass balance (1963–87) in the Fimbul and Jelbart regions, which is extended to a 54 year long record of positive mass balance (1963–2017) in the region, when combined with the results of recent studies. This concurs with the low positive mass balance of $5 \pm 46 \text{ Gt a}^{-1}$, a reconciled estimate from 1992 to 2017 for the entire East Antarctic ice sheet (IMBIE, 2018). Compared to the dramatically retreating and thinning ice shelves in western Antarctica and the collapsed shelves along the Antarctic Peninsula (Rack and Rott, 2004; Rignot and others, 2011b; Hogg and Gudmundsson, 2017), the Fimbul and Jelbart ice shelves have been stable since the 1960s.

5. Conclusions

This study establishes a framework for the reconstruction of historical ice velocity fields with an implementation in the Fimbul and Jelbart ice shelves area in East Antarctica from 1963 to 1987. The developed methods are essential for investigating the ice sheet response to global climate change in earlier years. A hierarchical network densification approach is developed to meet the challenges of (1) the low quality of historical images from the ARGON and Landsat MSS and TM missions, (2) difficult image orthorectification with limited geometric control data and (3) velocity mapping with altered or untrackable ice features due to glaciological surface processes over long periods. The resulting historical ice velocity maps achieved an overall accuracy better than 29 m a^{-1} and revealed the ice flow dynamics for 1963–87 in the study area of the Fimbul and Jelbart ice shelves. Combined with existing velocity products, these historical ice velocity maps fill the time gap before 1990 and build a long record of ice velocity maps from 1963 to 2015. This extended historical velocity record reveals that the ice flow velocities of both the Jutulstraumen Glacier and Fimbul Ice Shelf region and the Schytt Glacier and Jelbart Ice Shelf region are relatively stable. The effect of the ice tongue collapse from the Fimbul Ice Shelf in 1967 on the ice velocity pattern is not reflected in the derived maps of average ice velocity due to long time spans. The estimated mass balance of the combined basins of the Jutulstraumen and Schytt glaciers which feed the Fimbul and Jelbart ice shelves, respectively, shows a change rate of $8.6 \pm 3.9 \text{ Gt a}^{-1}$ over the 1963–2015 period. Our results indicate that the region's positive mass balance, as estimated in recently published studies, has been maintained since the 1960s. The relatively stable trend in the study area appears to concord with the very low level of positive mass balance of the entire East Antarctic ice sheet. The methodology developed here can be extended to map the historical ice velocity fields of other ice sheets and glaciers.

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Appendix A

Table 6. Detailed information for the historical remote-sensing images used in Figure 10 (Nos. 1–14) and the inland interior region in Figure 11 (Nos. 15–77)

Image no.	Image ID	Acquisition date	Sensor	Resolution m
1	ARGON image mosaic of the Antarctic coast	29-Oct-63	ARGON	100
2	LM11861101973306AAA05	2-Nov-73	MSS	60
3	LM11841111973322FAK03	18-Nov-73	MSS	60
4	LM21841101975303AAA04	30-Oct-75	MSS	60
5	LT51751111985019XXX05	19-Jan-85	TM	30
6	LM51751101985051AAA03	20-Feb-85	MSS	60
7	LM51731101986024AAA03	24-Jan-86	MSS	60
8	LM51771101986052AAA04	21-Feb-86	MSS	60
9	LT51731111986072XXX04	13-Mar-86	TM	30
10	LM51751091987281AAA03	8-Oct-87	MSS	60
11	LT51751111987281XXX01	8-Oct-87	TM	30
12	LT51731111987283XXX01	10-Oct-87	TM	30
13	LM51761101987288AAA03	15-Oct-87	MSS	60
14	LM41731101987307AAA03	3-Nov-87	MSS	60
15	LM11731181972334AAA05	29-Nov-72	MSS	60
16	LM11731131972334AAA05	29-Nov-72	MSS	60
17	LM11731121972334AAA05	29-Nov-72	MSS	60
18	LM11771121972338AAA04	3-Dec-72	MSS	60
19	LM11781131972358AAA04	24-Dec-72	MSS	60
20	LM11751131973043AAA05	12-Feb-73	MSS	60
21	LM11751121973043AAA05	12-Feb-73	MSS	60
22	LM11811131973049FAK03	18-Feb-73	MSS	60
23	LM11811111973049FAK03	18-Feb-73	MSS	60
24	LM11801141973066AAA05	7-Mar-73	MSS	60
25	LM11831111973069AAA05	10-Mar-73	MSS	60
26	LM11861131973306AAA05	2-Nov-73	MSS	60
27	LM11861121973306AAA05	2-Nov-73	MSS	60
28	LM11771131973315FAK03	11-Nov-73	MSS	60
29	LM11791121973317FAK03	13-Nov-73	MSS	60
30	LM11281071973320AAA02	16-Nov-73	MSS	60
31	LM11831111973356FAK02	22-Dec-73	MSS	60
32	LM11741131974055AAA05	24-Feb-74	MSS	60
33	LM11741121974055AAA05	24-Feb-74	MSS	60
34	LM21811111975300AAA05	27-Oct-75	MSS	60
35	LM21821111975301AAA04	28-Oct-75	MSS	60
36	LM21901101975327AAA05	23-Nov-75	MSS	60
37	LM21901111975327AAA05	23-Nov-75	MSS	60
38	LM21771111975332FAK07	28-Nov-75	MSS	60
39	LT51741131984346XXX03	11-Dec-84	TM	30
40	LT51741121984346XXX03	11-Dec-84	TM	30
41	LM51741091984346AAA03	11-Dec-84	MSS	60
42	LM51741101984346AAA03	12-Dec-84	MSS	30
43	LT51781111984358XXX03	23-Dec-84	TM	30
44	LM51711101985007AAA03	7-Jan-85	MSS	60
45	LT51791111985015XXX02	15-Jan-85	TM	30
46	LT51751121985019XXX04	19-Jan-85	TM	30
47	LM51711121985055AAA03	24-Feb-85	MSS	60
48	LM51711131985055AAA03	24-Feb-85	MSS	30
49	LT51691111985057AAA08	26-Feb-85	TM	30
50	LM51691111985057AAA03	26-Feb-85	MSS	60
51	LT51731131986024AAA03	24-Jan-86	TM	30
52	LM51731091986024AAA03	24-Jan-86	MSS	60
53	LM51691121986028AAA03	28-Jan-86	MSS	60
54	LT51831141986030XXX04	30-Jan-86	TM	30
55	LT51691121986060XXX03	1-Mar-86	TM	30
56	LM51691111986060AAA03	1-Mar-86	MSS	60
57	LM51691131986060AAA03	1-Mar-86	MSS	30
58	LT51731121986072XXX05	13-Mar-86	TM	30
59	LM51691121986076AAA03	17-Mar-86	MSS	30
60	LM51771111987279AAA03	6-Oct-87	MSS	60
61	LT51801101987284XXX01	11-Oct-87	TM	30
62	LT51781111987286XXX01	13-Oct-87	TM	30
63	LT51781101987286XXX01	13-Oct-87	TM	30
64	LT51761121987288XXX01	15-Oct-87	TM	30
65	LT41791111987301XXX04	28-Oct-87	TM	30
66	LT41791101987301XXX04	28-Oct-87	TM	30
67	LT41771121987303XXX01	30-Oct-87	TM	30

(Continued)

Table 6. (Continued.)

Image no.	Image ID	Acquisition date	Sensor	Resolution m
68	LT41771101987303XXX05	30-Oct-87	TM	30
69	LT41771111988050XXX04	19-Feb-88	TM	30
70	LT41671111989014XXX01	14-Jan-89	TM	30
71	LT41691111989316XXX03	12-Nov-89	TM	30
72	LT41281071989317XXX01	13-Nov-89	TM	30
73	LT41811101989320XXX01	16-Nov-89	TM	30
74	LT41771101989324XXX03	20-Nov-89	TM	30
75	LT41721121989337XXX01	3-Dec-89	TM	30
76	LT41711121989362XXX03	28-Dec-89	TM	30
77	LT41701121989339XXX01	28-Dec-89	TM	30

Table 7. Statistical information of seed points used, matched feature and gridpoints, time span, estimated error sources and velocity accuracy for all image pairs that were used for production of the maps from 1963 to 1987

Reference image no.	Search image no.	Numbers of matched points			Δt years	σ_{ref} m	σ_{src} m	σ_{idn} m	σ_{mtc} m	σ_{vlc} m a^{-1}
		Seed points	Feature points	Gridpoints						
9 (TM)	12 (TM)	101	20 699	36 972	1.6	19.2	18.4	15.0	22.0	23.5
8 (MSS)	13 (MSS)	32	523	1871	1.6	41.3	34.5	30.0	38.1	44.0
7 (MSS)	14 (MSS)	74	6623	8007	1.8	36.1	44.0	30.0	38.0	42.1
6 (MSS)	13 (MSS)	108	5538	11 339	2.6	41.4	34.5	30.0	31.9	26.2
5 (TM)	11 (TM)	52	5648	6840	2.7	9.6	15.9	15.0	24.6	12.6
1 (ARGON)	2 (MSS)	55	313	586	10.0	100.0	37.6	200.0	57.5	23.4
1 (ARGON)	3 (MSS)	265	2888	1281	10.1	138.8	65.2	200.0	67.4	25.9
4 (MSS)	10 (MSS)	18	3033	3058	11.9	42.8	42.0	30.0	47.0	6.9
1 (ARGON)	4 (MSS)	56	4931	4828	12.0	116.6	62.6	200.0	62.4	20.6
4 (MSS)	14 (MSS)	52	20 800	22 114	12.0	42.8	44.0	30.0	45.1	6.8
3 (MSS)	12 (TM)	148	13 544	6617	13.9	39.6	18.4	30.0	49.9	5.2
2 (MSS)	13 (MSS)	66	1141	1860	14.0	37.6	34.5	30.0	41.6	5.2
3 (MSS)	14 (MSS)	60	4352	6098	14.0	39.6	44.0	30.0	51.9	6.0

σ_{ref} and σ_{src} are uncertainties of reference and search images, respectively. σ_{idn} is the feature identification uncertainty. σ_{mtc} is the matching uncertainty. σ_{vlc} is the ice flow velocity uncertainty.

Table 8. Matching accuracy estimated using checkpoints with different ice flow velocities for an image pair

Velocity of checkpoints	Number of checkpoints	RMSE	
		m	pixel
$V \geq 450 \text{ m a}^{-1}$	17	43.0	0.7
$100 \text{ m a}^{-1} < V < 450 \text{ m a}^{-1}$	16	42.4	0.7
$V \leq 100 \text{ m a}^{-1}$	16	49.6	0.8
Matching accuracy of the image pair (m)		45.1	

Reference image no. 4, search image no. 14 in [Table 7](#).



ARTICLES FOR FACULTY MEMBERS

REMOTE SENSING BIG DATA ANALYTICS FOR DETAILED GEOLOGICAL MAPPING IN EXPOSED ZONES OF DRY VALLEYS, SOUTH VICTORIA LAND, ANTARCTICA

A high-resolution record of surface melt on Antarctic ice shelves using multi-source remote sensing data and deep learning / de Roda Husman, S., Lhermitte, S., Bolibar, J., Izeboud, M., Hu, Z., Shukla, S., van der Meer, M., Long, D., & Wouters, B.

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A high-resolution record of surface melt on Antarctic ice shelves using multi-source remote sensing data and deep learning

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Surface melt

ABSTRACT

While the influence of surface melt on Antarctic ice shelf stability can be large, the duration and affected area of melt events are often small. Therefore, melt events are difficult to capture with remote sensing, as satellite sensors always face the trade-off between spatial and temporal resolution. To overcome this limitation, we developed UMelt: a surface melt record for all Antarctic ice shelves with a high spatial (500 m) and high temporal (12 h) resolution for the period 2016–2021. Our approach is based on a deep learning model, specifically a U-Net, which was developed in Google Earth Engine. The U-Net combines microwave remote sensing observations from three sources: Sentinel-1, Special Sensor Microwave Imager/Sounder (SSMIS), and Advanced Scatterometer (ASCAT). The U-Net was trained on the Shackleton Ice Shelf for melt seasons 2017–2021, using the fine-scale melt patterns of Sentinel-1 as reference data and SSMIS, ASCAT, a digital elevation model, and multi-year Sentinel-1 melt fraction as predictors. The trained U-Net performed well on the Shackleton Ice Shelf for test melt season 2016–2017 (accuracy: 91.3%; F1-score: 86.9%), and the Larsen C Ice Shelf, which was not considered during training (accuracy: 91.0%; F1-score: 89.3%). Using the trained U-Net model, we have successfully developed the UMelt record. UMelt allows Antarctic-wide surface melt to be detected at a small scale while preserving a high temporal resolution, which could lead to new insights into the response of ice shelves to a changing atmospheric forcing.

1. Introduction

Antarctica's ice shelves, the floating extensions of the grounded ice sheet, are crucial in regulating sea level rise (Dupont and Alley, 2005). However, these ice shelves are increasingly vulnerable to disintegration due to a mix of factors, including atmospheric-driven surface melt (van den Broeke, 2005; Lenaerts et al., 2017), ocean-driven basal melt (Pritchard et al., 2012), and loss of structural integrity from ocean forcing (Wilmes et al., 2017; Massom et al., 2018) and surface velocity differences (Lhermitte et al., 2020). While surface melt has played a marginal role in the past (Rignot et al., 2019), it is becoming more important to the Antarctic Ice Sheet's fate as temperatures continue

to rise (Gilbert and Kittel, 2021; Trusel et al., 2015; van Wessem et al., 2023). Therefore, it is essential to closely monitor surface melt on Antarctic ice shelves to better comprehend and anticipate climate change impacts.

Satellite remote sensing enables long-term and frequent mapping of the extent and dynamics of surface meltwater over the Antarctic ice shelves. Microwave remote sensing is particularly suited for this purpose because microwave signals are very sensitive to liquid water, and observations can be acquired even during cloudy conditions or at night (de Roda Husman et al., 2022). Microwave remote sensing

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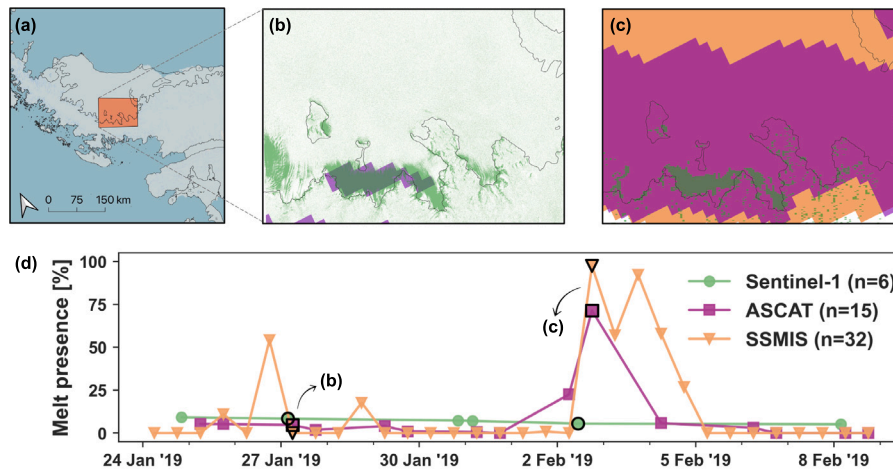


Fig. 1. Illustration of the temporal-spatial resolution trade-off for surface melt detection. A small part of the Larsen C Ice Shelf is selected as the area of interest, shown in (a). Spatial plots of detected surface melt by Sentinel-1 (green), ASCAT (purple), and SSMIS (orange) are presented for 27 January 2019 in (b) and 2 February 2019 in (c). Panel (d) displays a time series illustrating the percentage of pixels within the study region where melt was detected. Melt is determined using threshold-based melt detection algorithms, developed by Ashcraft and Long (2006) for Sentinel-1 and ASCAT, and by Zwally and Fiegles (1994) for SSMIS.

techniques can be separated into two classes: active microwave sensors, which measure backscatter intensity, i.e., the normalized radar cross-section (σ^0), and passive microwave sensors, which observe the brightness temperature (T_b) (Ulaby and Long, 2014). When melting starts, the emissivity and absorptivity of snow and ice increase significantly because of the abrupt increase of the dielectric constant, leading to a sudden decrease in backscatter intensity and an increase in brightness temperature (Ashcraft and Long, 2006; Liu et al., 2006).

Many recent studies have developed methods to detect surface meltwater over the Antarctic ice shelves using active or passive microwave satellite data (e.g., Trusel et al., 2012; Mousavi et al., 2022; Johnson et al., 2020). Even though these methods have shown widespread surface melt over the Antarctic ice shelves, detecting melt using data from a single satellite has limitations (see Fig. 1). Microwave sensors such as Special Sensor Microwave Imager/Sounder (SSMIS) and Advanced Scatterometer (ASCAT) cover the entire Antarctic Ice Sheet at a high, twice-daily temporal resolution. Nevertheless, their coarse, kilometer-scale spatial resolutions are insufficient to observe small-scale melt features, such as complex surface melt patterns induced by topography at the grounding line (Lenaerts et al., 2018). Data from synthetic aperture radar (SAR) sensors, such as aboard Sentinel-1, can be obtained with a much finer, meter-scale spatial resolution but often miss melt events that occur only during short periods of time due to the low revisit time of the satellite (i.e., a few times per week).

Deep learning techniques provide a promising solution to tackle the trade-off between temporal and spatial resolution in satellite imagery. U-Nets (Ronneberger et al., 2015), in particular, have gained widespread recognition in various fields, including cryospheric research (e.g., Radhakrishnan et al., 2021; Mohajerani et al., 2019; Niu et al., 2023; van der Meer et al., 2023; Baumhoer et al., 2019). The aforementioned studies have showcased the ability of U-Nets to identify and capture spatial patterns, positioning them as a promising tool for effectively capturing the complex spatial melt patterns observed on Antarctica. Additionally, by processing data at frequent time intervals, U-Nets enable valuable insights into the duration, frequency, and evolution of melt events.

In this study, we present a U-Net to combine data from multiple microwave satellites into a high-resolution surface melt record, referred to as UMelt. In this way, we overcome specific sensor limitations, related to the trade-off between spatial and temporal resolution, which allows us to establish a record of surface melt over the Antarctic ice shelves at a high spatial (500 m) and high temporal (12 h) resolution for the period 2016–2021. The record is based on a combination of three microwave satellites with varying spatiotemporal resolutions,

namely Sentinel-1, ASCAT, and SSMIS. Combining these data, the U-Net learned to recognize the fine-scale Sentinel-1 melt patterns, enabling the production of detailed melt maps from the coarse spatial resolution ASCAT and SSMIS observations, a digital elevation model (DEM), and multi-year Sentinel-1 melt fractions. In Section 2, the satellite and auxiliary data sets are introduced, and the training and validation of the U-Net are discussed. In Section 3, the performance of the model over training and testing ice shelves is presented, along with its application to all Antarctic ice shelves. The strengths and limitations of the developed U-Net are discussed in Section 4. The conclusion demonstrates how the high-resolution melt record can enhance our understanding of the impact of surface melt on Antarctic ice shelf stability in Section 5.

2. Materials and methods

2.1. Study area

We developed a U-Net to create UMelt, a high-resolution surface melt record for all Antarctic ice shelves. Like most deep learning algorithms, U-Nets require both training and testing data to effectively learn and make accurate predictions (Ronneberger et al., 2015). During the training phase, a U-Net is fed with a large data set consisting of input features (see Section 2.4.2) and their corresponding reference data (see Section 2.4.1), see Fig. 3. By exposing the U-Net to diverse training data, it becomes more capable of recognizing and generalizing spatial patterns in the data, allowing it to make informed predictions. After training, the U-Net's performance is evaluated using a separate set of testing data that it has never encountered before. This helps assess its ability to accurately segment unseen images.

Our U-Net model was trained on the Shackleton Ice Shelf, and subsequently tested on both the Shackleton and Larsen C ice shelves. The Shackleton Ice Shelf, a large ice shelf fronting the coast of East Antarctica, was selected as a training region based on three main factors. First, the Shackleton Ice Shelf has the most 'matching overpasses' (Fig. 2a), where Sentinel-1, ASCAT, and SSMIS overpasses were acquired with less than two hours difference. These 'matching overpasses' ensure comparable melt patterns between Sentinel-1, ASCAT, and SSMIS (see Section 2.5 for an elaborate description). Secondly, Saunderson et al. (2022) identified nine different melt patterns on the Shackleton Ice Shelf, which exhibited significant variability in the timing and spread of surface melt. This large variability in melt patterns on the Shackleton Ice Shelf provides a diverse and representative training data set for the U-Net model. Finally, the Shackleton Ice Shelf experiences substantial surface melting, averaging between 100–200 mm w.e. per year (Trusel

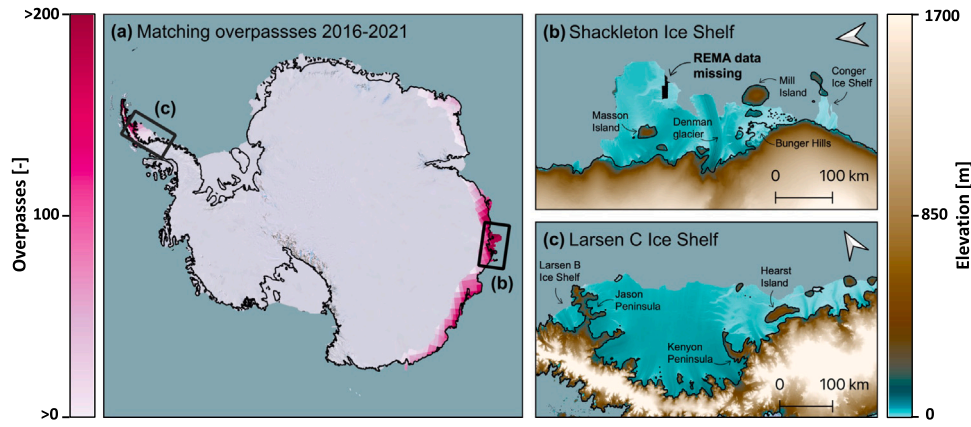


Fig. 2. The number of ‘matching overpasses’ in (a), indicating instances where the time difference between Sentinel-1, ASCAT, and SSMIS overpasses is less than two hours. The elevations of the training and testing regions, namely the Shackleton and Larsen C ice shelves, are depicted in panels (b) and (c). The Shackleton Ice Shelf has a small data gap, as indicated by the label “REMA data missing”. Other labels on the map indicate various place names on the ice shelves.

et al., 2013). Among Antarctic ice shelves, it ranks as one of the most susceptible to surface melting, except for those located on the Antarctic Peninsula (Gilbert and Kittel, 2021; Trusel et al., 2013). Consequently, the peak melting months (December to February) closely mirror the melt patterns and corresponding remote sensing signals seen on the ice shelves with relatively high surface melt. Conversely, the months marking the beginning and end of the melting season (i.e., November and March) align with ice shelves that experience less frequent surface melting.

We tested the U-Net on the Larsen C Ice Shelf, which yielded valuable insights into the performance of the trained U-Net for three primary reasons. First, the geographic location of the two ice shelves on opposite sides of the Antarctic Ice Sheet meant that different melt patterns were expected, allowing for a robust assessment of the U-Net’s transferability (i.e., the ability to apply knowledge gained from the training region to other regions without significant loss in performance). Secondly, the topography of the two ice shelves is markedly different. Large parts of the Shackleton Ice Shelf are surrounded by the ocean and buttressed by several ice rises, while the Larsen C Ice Shelf is mostly confined by land ice and has a more homogeneous elevation over its center but a notably steep grounding line (Fig. 2b and 2c). Finally, a more practical consideration was that, with around 50 ‘matching overpasses’ over the Larsen C Ice Shelf, a sufficiently large testing data set was available to evaluate the U-Net’s performance.

After training and testing, the U-Net model was applied on all Antarctic ice shelves between 2016 and 2021 to generate an Antarctic-wide high-resolution surface melt record: UMelt. Because there are (almost) no ‘matching overpasses’ for most of the Antarctic ice shelves (Fig. 2a), the accuracy of our UMelt record was only determined for the Shackleton and Larsen C ice shelves.

2.2. Melt masks

2.2.1. UMelt mask

Our UMelt record is available on a large part of the Antarctic Ice Sheet, but we have excluded some areas. The considered area of interest, referred to as the “UMelt mask”, is provided in Supplementary Figure 1a. First, extensive parts of the interior of the Antarctic Ice Sheet where high accumulation rates result in a low backscatter intensity (around -15 dB) were omitted, following the approach of Zheng and Zhou (2020). Under such conditions, surface melt detection algorithms may classify pixels erroneously as surface melting, whereas no surface melt has been observed on the interior of the ice sheet (e.g., Van Wessem et al., 2018). Moreover, pixels with an elevation over 1700 m were ignored, as surface melt is unlikely to occur there (Banwell et al., 2021; de Roda Husman et al., 2022). Finally, areas with no

Sentinel-1 overpasses were removed (refer to Figure 2 in de Roda Husman et al. (2022)), because we were unable to generate the multi-year Sentinel-1 melt fraction input feature. After implementing these exclusions, the study area was reduced to 1.8 million km², which accounts for 12.7% of the total area of the Antarctic Ice Sheet.

2.2.2. U-Net development mask

To test and train the U-Net model, we excluded additional regions beyond those covered by the UMelt mask (described in Section 2.2.1). Specifically, we omitted damaged regions, which are known to confuse melt detection algorithms on the reference product, Sentinel-1 (Zhou et al., 2019; Dirscherl et al., 2021). Damaged regions, i.e., regions containing fractures, rifts, or crevasses on the ice surface, lead to distortions in SAR images. These distortions result in high backscatter intensities for slopes facing towards the sensor (known as radar foreshortening) and low backscatter intensities for slopes facing away from the sensor (known as radar shadows). These radar shadows can be mistakenly identified as surface melt. Therefore, we created a “damage mask” using the damage detection method developed by Izeboud and Lhermitte (2023). This method detects the presence of a fracture feature within a group of pixels based on a line detection algorithm. Noise is removed using a sensor- and processing-resolution specific threshold, for which we used $\tau = 0.1$ (damage detection applied to Sentinel-1 EW images, processed on 100 m resolution with 10×10 pixel groups). Furthermore, a buffer with a radius of 5 km was applied to mask neighboring pixels.

In comparison to the UMelt mask (Section 2.2.1), removing the damage pixels for the Shackleton Ice Shelf resulted in an 8% reduction, transforming the UMelt mask from 52×10^3 km² to a UMelt development mask of approximately 48×10^3 km². Similarly, for the Larsen C Ice Shelf, about 9% of pixels were removed from the UMelt mask to derive the UMelt development mask, decreasing from 84×10^3 km² to 77×10^3 km².

2.3. U-Net architecture

We used an “Attention U-Net” architecture for our image segmentation task, which is an extension of the traditional U-Net (Ronneberger et al., 2015) that incorporates attention gates to selectively highlight relevant features (Oktay et al., 2018; Trebing et al., 2021). Our network consisted of two main parts: the contracting path for encoding and the expansive path for decoding (see Fig. 3).

In the contracting path, the input features were progressively downsampled by convolutional layers and max-pooling operations, allowing the network to extract high-level features (Girshick et al., 2014). These high-level features capture information about the rough outlines of surface melt events, disregarding small-scale melt details. These features

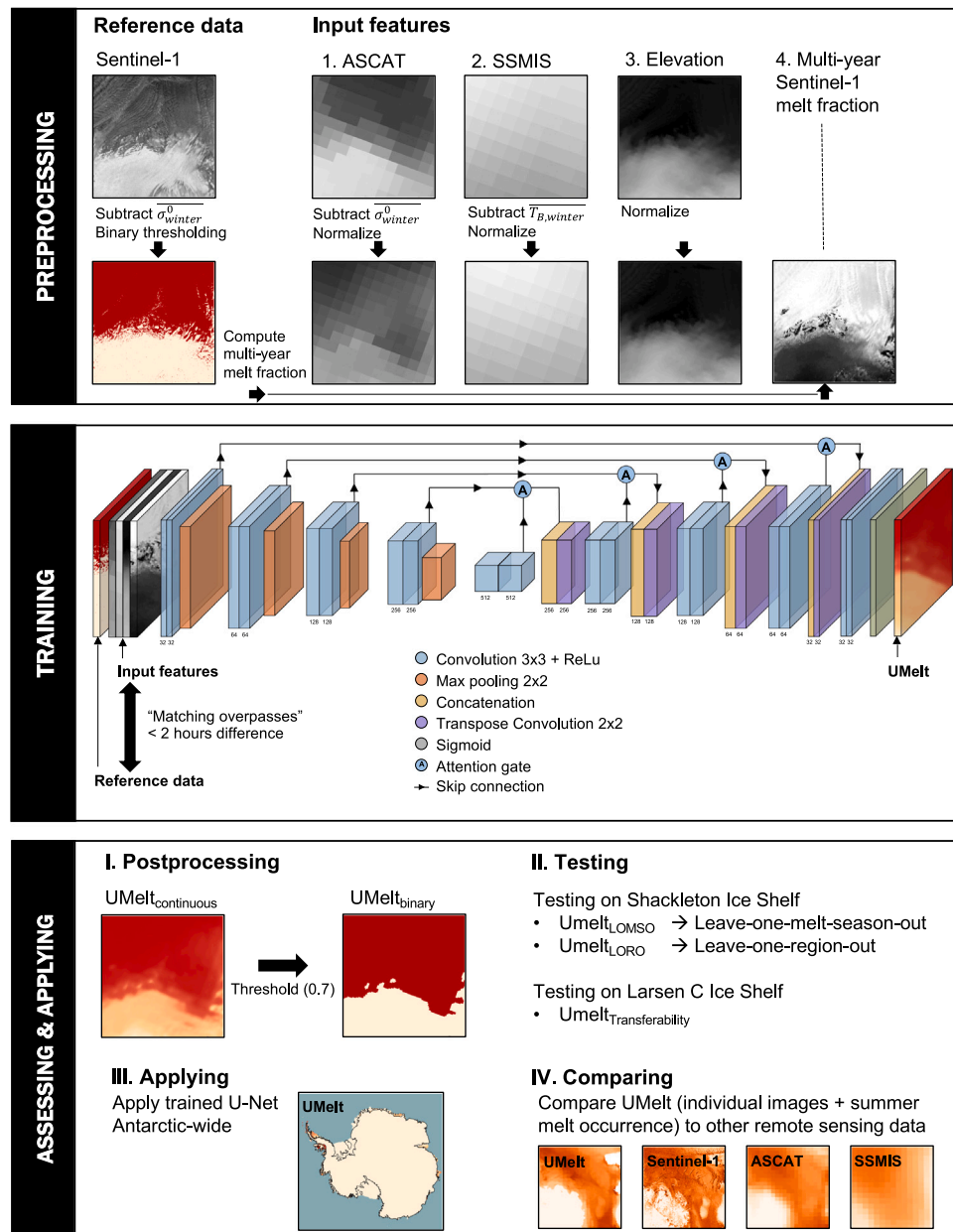


Fig. 3. Conceptual overview of the method employed in this study, which is divided into three key steps: preprocessing, training, and assessing & applying. The details of this method are discussed in Sections 2.4–2.7.

are analogous to the large-scale melt patterns observed by [Saunderson et al. \(2022\)](#), who studied surface melt using satellite data with a 25 km spatial resolution on the Shackleton Ice Shelf. In the expansive path, the features coming from the encoder are upsampled by transposed convolutions. Furthermore, they are concatenated with features from the contracting path through skip connections, which connect corresponding encoder and decoder layers. This preserves low-level features, such as the spatial arrangements of melt pixels on a small scale. The attention gates were added to these skip connections to allow the network to selectively focus on important features while filtering out irrelevant information ([Oktay et al., 2018](#)).

We conducted hyperparameter tuning on the validation data set (See Section 2.5) to optimize the performance of our Attention U-Net model. We did a grid search over all possible combinations of hyperparameters ([Bengio, 2012](#)), which included the learning rate (0.05, 0.01, 0.005, 0.001, 0.0005, 0.0001), batch size (16, 32, 64, 128), the number of filters for the first layer, which was doubled in each subsequent layer (16, 32, 64, 128), and the dropout rate (constant rate of 0.5 applied

to the different convolution layers). For each combination of hyperparameters, we trained the model on the training data set and evaluated its performance (i.e., segmentation accuracy) on the validation data set to identify the optimal configuration. The optimal hyperparameters maximized the segmentation accuracy (learning rate: 0.001; batch size: 32; number of channels: 32; dropout rate of 0.5: applied to the fourth and fifth convolution layers). In cases where the difference in validation accuracy was less than 1% for different hyperparameters, we selected the most computationally efficient ones.

We employed commonly used and standard algorithms for activation, loss, and optimization, which are (almost) similar to those employed in previous works such as [Dahle et al. \(2022\)](#), [Mastrofini et al. \(2023\)](#), and [Zhao et al. \(2022\)](#). Specifically, the Rectified Linear Unit (ReLU) activation function was utilized for the hidden layers, effectively eliminating negative values within the neural network and allowing only positive values to propagate. Additionally, the sigmoid activation function, commonly employed in binary classification tasks, was employed in the final layer to compress the output within the range

of 0 to 1, representing the probability. To address the class imbalance issue in the training data, where non-melt pixels outnumbered melt pixels by a factor of four, we incorporated class weighting based on the melt and non-melt pixels ratio into the binary cross-entropy loss function. This ensured that missing a surface melt event incurred a higher penalty compared to missing a non-melt event. The Adam optimization algorithm was used, which allowed efficient training and parameter optimization.

The model was trained for a maximum of 30 epochs, with each epoch taking approximately 10 min. Early stopping was implemented to stop training when the validation loss did not improve for three consecutive epochs. The default early stopping settings were used, considering any improvement, regardless of magnitude, as progress. As a result, the U-Net model used for generating the UMelt record was trained for 10 epochs. However, for other models used to evaluate spatial and temporal performance, the number of epochs varied between 5 and 12.

To perform the training, we utilized Google Colab, a cloud-based platform that offers GPU access for deep learning tasks. TensorFlow, the deep learning framework used to code our model, is integrated into Google Colab, simplifying the process of building and training the model.

2.4. Preprocessing

2.4.1. Reference data

Sentinel-1 observations were used to create the reference data (sometimes referred to as target or ground truth data) for the U-Net. We used Sentinel-1 Level-1 Ground Range Detected (GRD) scenes in the linear scale that were preprocessed in the Google Earth Engine (Gorelick et al., 2017). This preprocessing included orthorectification, radiometric calibration, thermal noise removal, and border noise removal. It is worth noting that border noise removal was applied to scenes from January 2018 onwards in the preprocessed images available in the Google Earth Engine. This occasionally leads to noisy pixels at the edges of scenes prior to January 2018.

We selected all available horizontally polarized GRD scenes over the Antarctic Ice Sheet for melt seasons 2016–2021, allowing a combination of Interferometric (IW) and Extra Wide (EW) overpasses. The scenes were resampled to a 500 m resolution using bilinear interpolation and reprojected to WGS 84 Antarctic Polar Stereographic projection (EPSG:3031). The utilization of a 500 m spatial resolution enabled the detection of surface melt features at a small scale, while concurrently ensuring the data could be processed efficiently.

Then, we derived the binary melt presence (i.e., melt/non-melt) for the Sentinel-1 observations using the widely used melt detection algorithm proposed by Ashcraft and Long (2006). Melt presence was assumed when the backscatter intensity was smaller than the annual winter mean minus a certain threshold by using the following equation:

$$m(t) = \begin{cases} 1, & \sigma^0(t) < \sigma_{winter}^0 + \Delta\sigma^0 \\ 0, & \sigma^0(t) \geq \sigma_{winter}^0 + \Delta\sigma^0 \end{cases} \quad (1)$$

where σ_{winter}^0 is the average backscatter intensity of the previous winter months, and $\Delta\sigma^0$ is the threshold which was set to -3 dB (similar to Ashcraft and Long, 2006). To address the substantial disparities in backscatter intensity across different orbits, we implemented Eq. (1) on a per Sentinel-1 orbit basis. This approach accounts for the variations in backscatter intensities stemming from differences in incidence angles.

2.4.2. Input features

The U-Net input received four input features: ASCAT, SSMIS, elevation, and the multi-year Sentinel-1 melt fraction (see Fig. 3), offering diverse information related to surface melt patterns and characteristics. ASCAT, similar to Sentinel-1, is an active microwave satellite. However, it exhibits lower spatial resolution (kilometer-scale instead of meters) and a higher revisit time (twice a day instead of a few times per

week) when compared to Sentinel-1. Consequently, we expect that ASCAT will provide valuable information on the dynamic changes in melt patterns over time, although it may primarily capture coarse-scale patterns. Similar to ASCAT, SSMIS also provides information on liquid water presence on a coarse spatial scale but with a high temporal resolution. However, it is important to consider that SSMIS measures the brightness temperature instead of the backscatter intensity. This distinction means that SSMIS is influenced by various parameters beyond just liquid water content, which can result in significant differences in large-scale patterns compared to Sentinel-1 and ASCAT (Mote and Anderson, 1995; Hofer and Mätzler, 1980). Nevertheless, SSMIS is highly sensitive to detecting even small amounts of liquid water, enabling valuable insights into less intense melt events (Picard et al., 2022). The role of elevation data is also crucial in this study, given its high spatial resolution and well-established inverse correlation with melt patterns (Trusel et al., 2013). In addition to the aforementioned input features, multi-year melt fractions from Sentinel-1 are also utilized to provide insights into spatial details. Although these details may not be critical for capturing day-to-day variations, which are significant in Antarctica, they offer valuable information about the most common fine-scale melt patterns. The subsequent paragraphs will sequentially elaborate on the details of the four input features.

For the ASCAT input feature, we utilized vertically polarized observations with a 4.45 km resolution, consistent with prior studies (e.g., Trusel et al., 2012; Bevan et al., 2018; de Roda Husman et al., 2022), obtained from the Brigham Young University Microwave Earth Remote Sensing Laboratory (www.scp.byu.edu). ASCAT captures observations of the Antarctic Ice Sheet every other day at 6 AM (morning) and 6 PM (evening). We calculated averages to address days without observations by combining the morning before and after a missing morning observation (and similarly for missing afternoon observations). This process allowed the creation of a twice-daily ASCAT time series. Then, instead of generating binary melt presence from ASCAT observations by applying a threshold (i.e., $\Delta\sigma^0$ in Eq. (1)), we only subtracted σ_{winter}^0 from the ASCAT observations. Continuous data carry more information than binary data, allowing the U-Net to learn the most appropriate threshold depending on the situation rather than relying on a specific threshold value. Finally, we normalized these values between the low (5th percentile) and high (95th percentile) values of ASCAT minus the winter mean over the Shackleton Ice Shelf for the melt seasons from 2016–2021, without capping values below zero or larger than one.

We utilized horizontally polarized 19 GHz SSMIS observations from the NASA MEaSUREs project (Brodzik et al., 2016) as the second input feature, with a spatial resolution of 6.25 km (similar to, e.g., Wang et al., 2022b; Wei et al., 2022). Observations from the F17 sensor were selected, which consistently passed over at approximately 6 AM and 6 PM during our study period. We applied a similar approach as for ASCAT and created continuous and normalized melt observations by subtracting the average brightness temperature of the previous winter months and scaling the values between the 5th and 95th percentiles.

As for the third input, we utilized the Reference Elevation Model of Antarctica (REMA) mosaic to inform the model on the elevation of the Antarctic Ice Sheet (Howat et al., 2019). The REMA mosaic has a high resolution of two or eight meters, depending on the location. For this study, the resampled version with a resolution of 200 m was used, which was sufficient for our purposes. While the REMA mosaic provides extensive coverage of the continent, there are some gaps in coverage, including a small area of the Shackleton Ice Shelf (as shown in Fig. 2b). We disregarded the data gaps, predominantly located along the edges of ice shelves with minimal surface melt.

The fourth input feature consisted of the multi-year melt fractions of Sentinel-1 data, derived from the reference data discussed in Section 2.4.1. The multi-year Sentinel-1 melt fractions were computed by summing the monthly melt pixels obtained using Eq. (1) and then dividing the sum by the total number of observations in that specific month. We are aware that using Sentinel-1 as reference and input

data may raise concerns about information leakage. To address this, we ensured the exclusion of the month of interest from the calculation, aiming to eliminate any potential correlation between the input features and reference data. For instance, when calculating the multi-year melt fraction for November 2016, the melt fraction was derived from the November months of 2017 until 2021. To validate that the U-Net model was not simply replicating the monthly melt fractions of Sentinel-1, we conducted an assessment of the importance of each feature, as described in Section 2.7.

Finally, the four input features were resampled to match the scale and projection of the preprocessed Sentinel-1 scenes, which were in the WGS 84 Antarctic Polar Stereographic projection with a resolution of 500 m.

2.4.3. Comparison UMelt to Sentinel-1, ASCAT, and SSMIS

To facilitate a comparison between the UMelt record and surface melt observations from Sentinel-1, ASCAT, and SSMIS, binary melt products were also derived from ASCAT and SSMIS observations. The approach used for Sentinel-1 was explained in Section 2.4.1, while continuous values were utilized as input for ASCAT and SSMIS (as described in Section 2.4.2). A further step was required to compare these data with the UMelt record: converting the continuous ASCAT and SSMIS data to binary melt estimates using thresholding algorithms. We applied the same melt detection algorithm used for Sentinel-1 (Eq. (1)) to ASCAT to achieve this. For SSMIS, a melt detection algorithm suggested by [Torinesi et al. \(2003\)](#) was implemented, which has been used in several previous studies (e.g., [Wille et al., 2019](#); [Banwell et al., 2021](#); [Johnson et al., 2020](#)). The algorithm defines surface melt based on the observed brightness temperature surpassing an empirical threshold, typically between 30 K and 40 K. This dynamic threshold is determined using the mean and variability of the brightness temperatures recorded during the preceding winter.

In addition to comparing UMelt with single observations from Sentinel-1, ASCAT, and SSMIS, we calculated the “summer melt occurrence” following the methodology of [de Roda Husman et al. \(2022\)](#). The summer melt occurrence, computed for each melt season spanning November through March, represents the ratio of the number of melt observations to the total number of observations per pixel. The metric is expressed as a percentage and was computed using binary products obtained from UMelt, Sentinel-1, ASCAT, and SSMIS.

2.5. Training, validation, and testing data

The training, validation, and testing data were selected according to the criterion that the temporal difference in Sentinel-1, ASCAT, and SSMIS overpass times was less than two hours. This criterion was important as surface melt can occur for a very short duration, and larger differences in overpass time may lead to disparities in the detected surface melt among the satellite observations. The ‘matching overpasses’ of Sentinel-1, ASCAT, and SSMIS were then combined with the elevation and Sentinel-1 multi-year melt fraction data sets, creating a 5-band (i.e., channels) image comprising reference labels (i.e., Sentinel-1 binary melt) and four input features (i.e., ASCAT, SSMIS, elevation, and multi-year Sentinel-1 melt fraction).

We employed stratified sampling to achieve a balanced data set for effective learning and recognition of melt patterns by the U-Net model. This process involved randomly selecting points on the Shackleton Ice Shelf, all within the U-Net development mask (Supplementary Figure 1b). For each ‘matching overpass’, a total of 10 points were selected, comprising an equal number of melt pixels (5) and non-melt pixels (5), determined by the Sentinel-1 labels. It is worth noting that only non-melt pixels were selected if a Sentinel-1 scene did not contain any melt pixels. Subsequently, we generated patches of input features and labels by selecting neighboring pixels around the sampled points. As the stratified sampling points were randomly distributed, patches could overlap. Each patch was sized at 64×64 pixels, equivalent to

32×32 km, ensuring they captured sufficient detail to represent the melt patterns accurately and guaranteeing an appropriate distribution of melt locations. Finally, all patches from one ‘matching overpass’ were assigned to either the training data set (80%), the validation data set (10%), or the testing data set (10%). Each set’s approximate number of pixels was 15 million for training, 2 million for validation, and 2 million for testing.

2.6. Post-processing

After training the U-Net, the model was applied to create the UMelt record. We stacked the input features (i.e., ASCAT, SSMIS, elevation, and multi-year Sentinel-1 melt fraction) and tiled the data into patches of 64×64 pixels (similar to in Section 2.5), using an 8-pixel overlap on all sides. In overlap regions, prediction results were calculated as the mean of the prediction probabilities.

Next, we converted the prediction probabilities into a binary product using a threshold of 0.7. We determined that this specific threshold value yielded the best performance on the validation set (see Supplementary Figure 3). Pixels with probability values exceeding the 0.7 threshold were identified as melt pixels, whereas those below the threshold were labeled as non-melt.

2.7. Accuracy assessment

To assess the performance of our U-Net model, we utilized the test data set, which was not used during the training and validation phases. Several performance metrics, including precision, recall, F1-score, and accuracy, were calculated. Precision measures the fraction of true positive predictions among the total predicted positive instances, while recall measures the fraction of true positive predictions among the total actual positive instances. The F1-score is the harmonic mean of precision and recall, providing a single value that combines both measures. Accuracy measures the overall proportion of correct predictions over all instances.

Cross-validation is essential for training the U-Net model as it enables reliable performance evaluation, prevents overfitting, and improves our understanding of its effectiveness ([Roberts et al., 2017](#); [Bolibar et al., 2020](#)). Specifically, to assess the temporal performance of the U-Net, we performed a ‘leave-one-melt-season-out’ (LOMSO) analysis. We evaluated the model’s performance when applied to the melt season that was excluded from training. In Section 3, we discuss the accuracies over a very wet season (2019–2020), a very dry season (2020–2021), and an average melt season (2016–2017). High accuracies over unseen melt seasons hint at a good performance of the U-Net over other ice shelves with more or less extreme melt intensities than at the Shackleton Ice Shelf.

In order to evaluate the model’s spatial performance, we partitioned the Shackleton Ice Shelf into four distinct parts with similar areas (see Supplementary Figure 1d). Then, we implemented a ‘leave-one-region-out’ (LORO) approach to assess the model’s accuracy when applied to an unseen region. The melt patterns are very diverse over the ice shelf. Therefore, a high accuracy over an unseen region means the model is probably well-capable over other Antarctic ice shelves.

We assessed the transferability of the U-Net by applying the model to the Larsen C Ice Shelf for melt season 2016–2017. We applied the trained model for which melt season 2016–2017 was excluded, so that we could assess the performance for both an unseen spatial and temporal domain. Please be aware that our model’s transferability was exclusively evaluated over the Larsen C Ice Shelf. This is due to a lack of ‘matching overpasses’ on other ice shelves (see Fig. 2a). Consequently, accuracy computations for ice shelves other than Shackleton and Larsen C were hindered.

In the final stage of the accuracy assessment, the significance of the four input features was evaluated by training four separate models, with each model excluding one feature at a time. The training was

conducted over melt seasons 2017–2021, and the performance was assessed on the unseen melt season 2016–2017. By comparing the accuracies and spatial patterns of these models, we could determine the importance of each input feature. If a model exhibited notably lower performance compared to the model utilizing all four features, it indicated the excluded input feature's significance.

3. Results

We evaluated the performance of the U-Net model using varying spatial and temporal domains of the training, validation, and testing data sets. We present the results over the Shackleton Ice Shelf, Larsen C Ice Shelf, and Antarctic-wide in Sections 3.1, 3.2, and 3.3, respectively. Supplementary Table 1 contains the accuracy assessment results for all experiments.

3.1. Surface melt over Shackleton Ice Shelf

3.1.1. Temporal performance

We first evaluated the performance of the U-Net model on the Shackleton Ice Shelf in terms of temporal performance. Specifically, we examined the model's ability to predict melt events during unseen seasons, which we refer to as UMelt_{LOMSO}. Fig. 4 shows that UMelt_{LOMSO} performed well on three distinct days at the beginning, middle, and end of the 2016–2017 melt season, despite not being trained on data from the 2016–2017 season (see Supplementary Video 1 for melt observations for all days with 'matching overpasses'). The model accurately identifies the complex melt patterns over the Shackleton Ice Shelf, resulting in an F1-score of 86.9% and an accuracy of 91.3% when compared to Sentinel-1. Notably, ASCAT and SSMIS (Fig. 4, column 4 and 5, respectively) detect mostly larger melt patterns, with the exception of the western part of the Shackleton Ice Shelf. Here, SSMIS tends to underestimate melt due to the presence of a frequently-occurring polynya that results in lower brightness temperatures, as noted by Nihashi and Ohshima (2015). However, both sensors often miss the detailed melt patterns captured by the reference product Sentinel-1. Our UMelt product is well able to detect these small-scale patterns, especially along the grounding line and on Masson Island (location indicated in Fig. 2).

The accuracy of UMelt, ASCAT, and SSMIS melt observations compared to the reference product Sentinel-1 is displayed in Fig. 4d. UMelt achieved an average accuracy of 91.3% for the 2016–2017 melt season, which is higher than the average accuracies of ASCAT and SSMIS, with 90.0% and 82.3%, respectively.

UMelt is particularly effective in detecting small-scale patterns, such as those found on the grounding line and on Masson and Mill islands (Fig. 5). In contrast, ASCAT and SSMIS incorrectly detect melt at Masson Island (Fig. 5f), where the elevation is over 1000 m and Sentinel-1 does not indicate any surface melt. In addition, Sentinel-1 shows a wide range of melt patterns over the grounding line (Fig. 5e and i), which UMelt_{LOMSO} accurately simulates. The detected melt on the Bunger Hills (Fig. 5h) demonstrates the most notable difference, with Sentinel-1 revealing complex melt patterns, while ASCAT and UMelt show minimal detection of melt. In contrast, SSMIS detects melt throughout the entire Bunger Hills region but lacks the expected level of detail considering the diverse terrain and varying elevations.

Additionally, our findings indicate that UMelt outperformed ASCAT and SSMIS for the 2019–2020 and 2020–2021 melt seasons (Supplementary Figure 2). In the 2019–2020 melt season, UMelt obtained an average accuracy of 90.9%, while in the 2020–2021 melt season, it achieved a higher accuracy of 95.7%. However, it is important to note that the F1-score for the 2020–2021 melt season was significantly lower (33.5%) than that of the 2016–2017 (86.9%) and 2019–2020 (82.7%) melt seasons. The 2020–2021 melt season experienced minimal melting, which is clearly reflected in the cumulative yearly melt maps by Picard (2022) (more details on the melt maps in Picard and Fily, 2006). Out of the small amount of melt that did occur, only 55.3% of the identified melt pixels were accurately classified.

3.1.2. Spatial performance

The model also showed a solid performance when regions of the ice shelf were not included during training, as shown in Fig. 6. In particular, we found that for the two regions located at the center of the ice shelf (Region 1 and Region 3), the accuracies of UMelt trained on all regions and UMelt_{LORO} were comparable, with an average difference in accuracies of 0.3% and 0.4%, respectively. However, Region 3 resulted in the lowest accuracy of the four regions, both for UMelt (i.e., 87.6%) and UMelt_{LORO} (i.e., 87.2%), whereas all the other regions resulted in accuracies exceeding 90%.

In the case of Regions 2 and 4, which are situated at the grounding line, we observed similar discrepancies in accuracy between UMelt and UMelt_{LORO} as for Regions 1 and 3, ranging from 0.2–0.4%. However, when examining specific pixels along the grounding line, UMelt_{LORO} exhibited over- or underestimation of surface melt occurrence by -25% to +25% compared to UMelt. In general, UMelt predicts a melt presence further inland, whereas the melt presence predicted by UMelt_{LORO} for Regions 2 and 4 ends closer to the grounding line. However, it comes as no surprise that the most significant discrepancy is evident along the grounding line. This region showcases exceptionally intricate melt patterns that ASCAT and SSMIS struggle to resolve adequately because of their limited spatial resolution. Despite this, the comparable performance of UMelt and UMelt_{LORO} is promising for the application of UMelt on an Antarctic-wide scale, showcasing that the U-Net demonstrates favorable performance even on untrained regions.

3.1.3. Feature importance

Convolutional neural networks are black-box algorithms, and their lack of transparency regarding feature importance remains a challenge (Olden and Jackson, 2002). However, we can get an estimate of the importance of features by iteratively removing them during the training of the model and evaluating its performance (Zhang et al., 2018).

Fig. 7 demonstrates the importance of the four input features used for the development of UMelt: ASCAT, SSMIS, elevation, and multi-year Sentinel-1 melt fraction. The results show that ASCAT is the most important feature, as evidenced by the drop in accuracy from 91.3% to 80.2% when ASCAT is removed from the training phase (Supplementary Table 1). The exclusion of ASCAT reduces surface melt across the entire study area, emphasizing its significance as an input feature. This is not surprising as both ASCAT and the reference data Sentinel-1 are C-band active microwave sensors, and therefore result in melt patterns that are comparable on a larger scale (although smaller details may differ due to spatial resolution differences).

In contrast, SSMIS, elevation, and multi-year Sentinel-1 melt fraction are less important, and their exclusion results in comparable disagreement with Sentinel-1 as the model trained on all input features (Supplementary Table 1). However, including these features results in the identification of detailed melt patterns similar to those in Sentinel-1. Additionally, multi-year Sentinel-1 melt fraction is important for melt detection on the eastern part of the Shackleton Ice Shelf (Fig. 7e), where small surface lakes are present annually (Arthur et al., 2020), but are not detected by ASCAT and SSMIS due to their low spatial resolution.

3.2. Surface melt over Larsen C Ice Shelf

In order to ensure that the U-Net model is applicable on an Antarctic-wide scale, we assessed its performance on the Larsen C Ice Shelf during the 2016–2017 melt season. We applied the UMelt_{LOMSO}, which was trained on the Shackleton Ice Shelf for the melt seasons between 2017–2021. This provides a fully out-of-sample performance estimate of our model since the trained model has neither seen the spatial region nor the temporal period of the target data set.

The general melt patterns from UMelt on Larsen C overlap well with the Sentinel-1 patterns, showing most melt in the western part of the

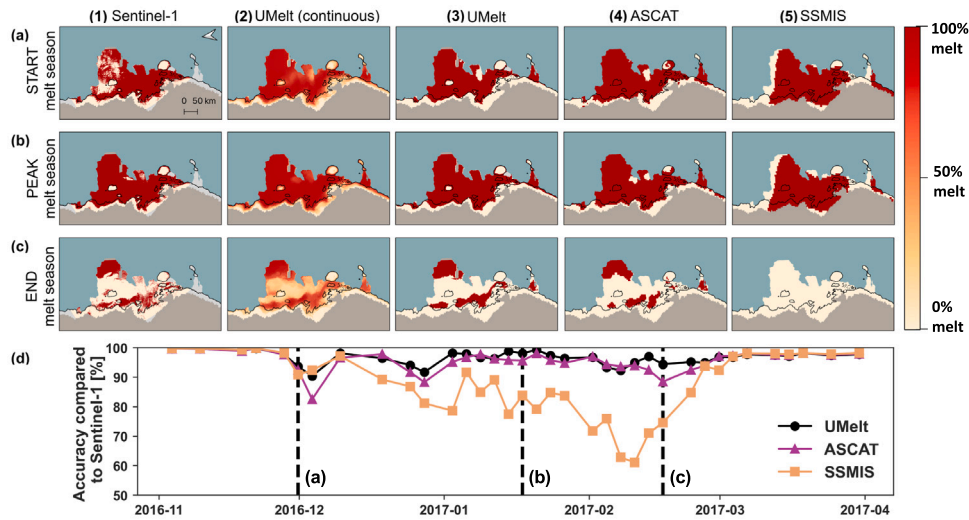


Fig. 4. The maps in (a), (b), and (c) present a comparison of reference data Sentinel-1 (first column) and our UMelt_{LOM_{SO}} product, visualized in both continuous format without threshold (third column) and binary format with a 0.7 threshold (second column), ASCAT (fourth column), and SSMIS (fifth column), at the beginning (30 November 2016, 6 PM), peak (17 January 2017, 6 PM), and end (16 February 2017, 6 PM) of the melt season of 2016–2017. The time series in (d) present the melt accuracy of UMelt (black), ASCAT (orange), and SSMIS (pink) compared to Sentinel-1 for melt season 2016–2017 on the Shackleton Ice Shelf.

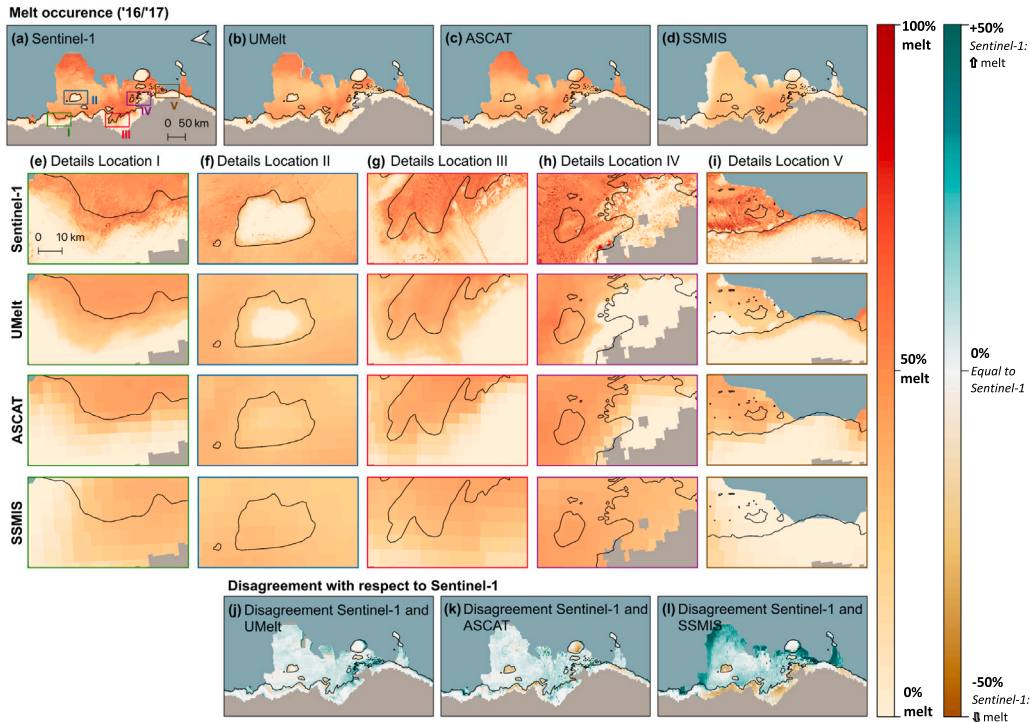


Fig. 5. The summer melt occurrence on Shackleton Ice Shelf for testing melt season 2016–2017 for Sentinel-1 (a), UMelt (b), ASCAT (c), and SSMIS (d). Details of five locations are shown in (e)–(i). The disagreements between Sentinel-1 and UMelt, Sentinel-1 and ASCAT, and Sentinel-1 and SSMIS are shown in (j)–(l).

ice shelf. However, in Figs. 8d and 8g, UMelt tends to overestimate surface melt landward of the grounding line where the elevation rapidly increases. There are two plausible explanations for this overestimation. First, the multi-year Sentinel-1 melt fraction, which is one of the input features, was derived from melt seasons spanning 2017 to 2021. During this period, surface melt was present landward of the grounding line. Hence, certain sections of the grounding line experienced an overestimation of surface melt during the 2016–2017 melt season, due to the comparatively wetter melt seasons observed between 2017 and 2021 (Bevan et al., 2020). Secondly, the Shackleton Ice Shelf, on which UMelt was trained, experiences surface melt at elevations up to around 300 m. The regions along Larsen C's grounding line where UMelt

overestimated the surface melt are situated at elevations of 100–300 m, within the range where the UMelt model was trained to detect melting. Nevertheless, UMelt demonstrated a strong overall performance during the 2016–2017 melt season with an average F1-score of 89.3% with many UMelt patterns that matched with Sentinel-1. This is a better performance compared to Sentinel-1 than ASCAT and SSMIS, which have F1-scores of 85.9% and 80.0%, respectively.

3.3. Antarctic-wide surface melt

The U-Net was trained on the Shackleton Ice Shelf using data from all five melt seasons (i.e., 2016–2021) and subsequently applied to the

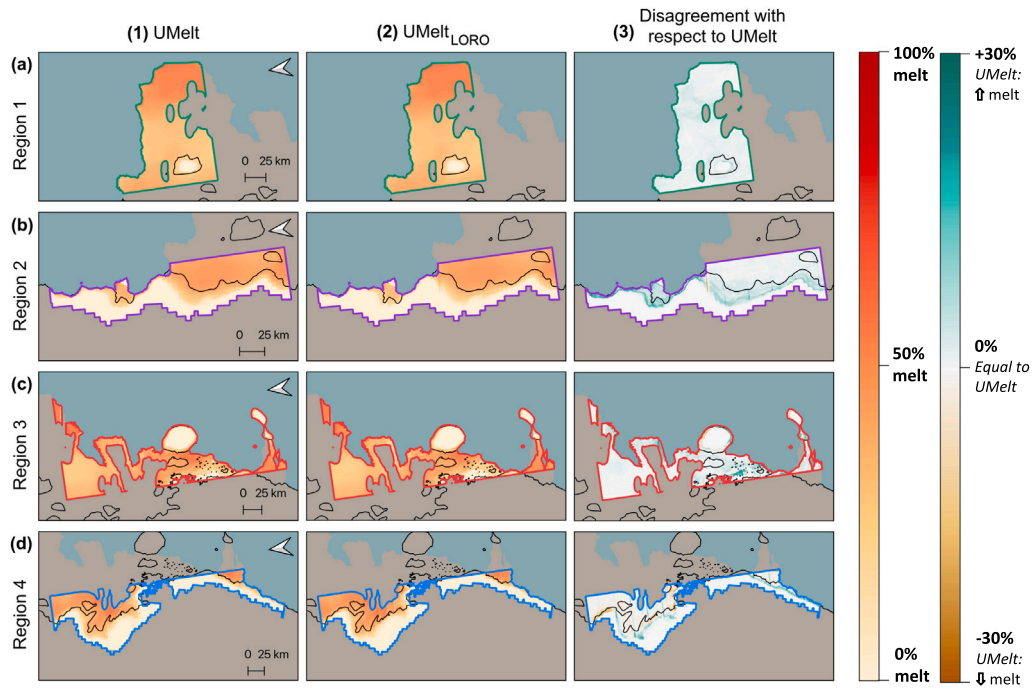


Fig. 6. Summer melt occurrence of UMelt (1) and UMelt_{LORO} (2) for melt season 2016–2017 on the Shackleton Ice Shelf for the four leave-one-region-out (LORO) regions (a–d). UMelt (1) was trained on the entire ice shelf using data from melt seasons 2017–2021. UMelt_{LORO} (2) was trained on the same period, but one region was excluded at a time. Then, the trained model was tested on the excluded region to evaluate the spatial transferability of the model. The disagreement between UMelt and UMelt_{LORO} is shown in (3).

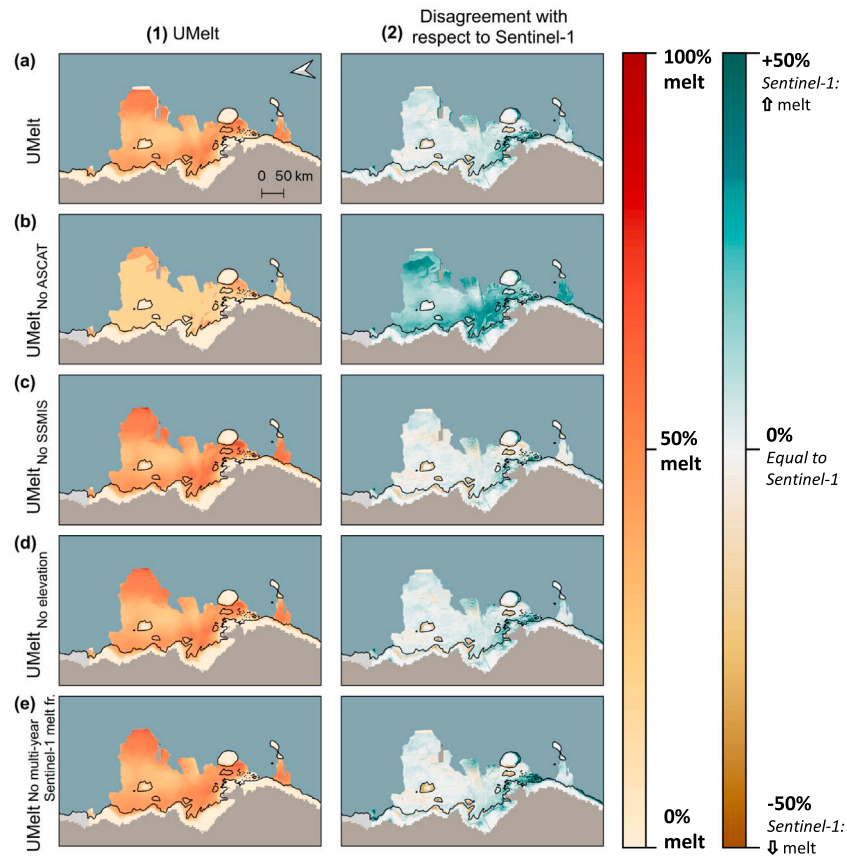


Fig. 7. Surface melt occurrence and performance compared to Sentinel-1 over the Shackleton Ice Shelf for the melt season 2016–2017 for different input features. Column 1 (a–e) displays the UMelt summer melt occurrence trained on different input features, where UMelt trained on all input features is presented in (a), and panels (b)–(e) correspond to UMelt with one of the input features excluded (ASCAT, SSMIS, elevation, and multi-year Sentinel-1 melt fraction, respectively). Column 2 (a)–(e) demonstrates the comparison of UMelt and Sentinel-1 performance, where the disagreements between Sentinel-1 and UMelt models trained with different input features are presented.

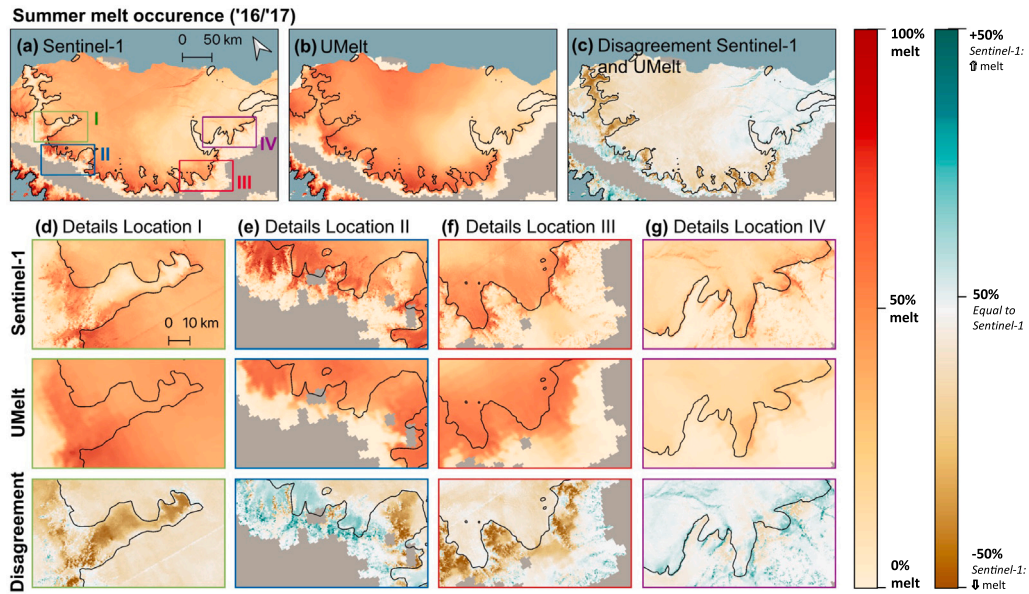


Fig. 8. The summer melt occurrence on Larsen C Ice Shelf for testing melt season 2016–2017 for Sentinel-1 (a), UMelt (b), and the disagreements between Sentinel-1 and UMelt (c). Details of four locations are shown in (d–g).

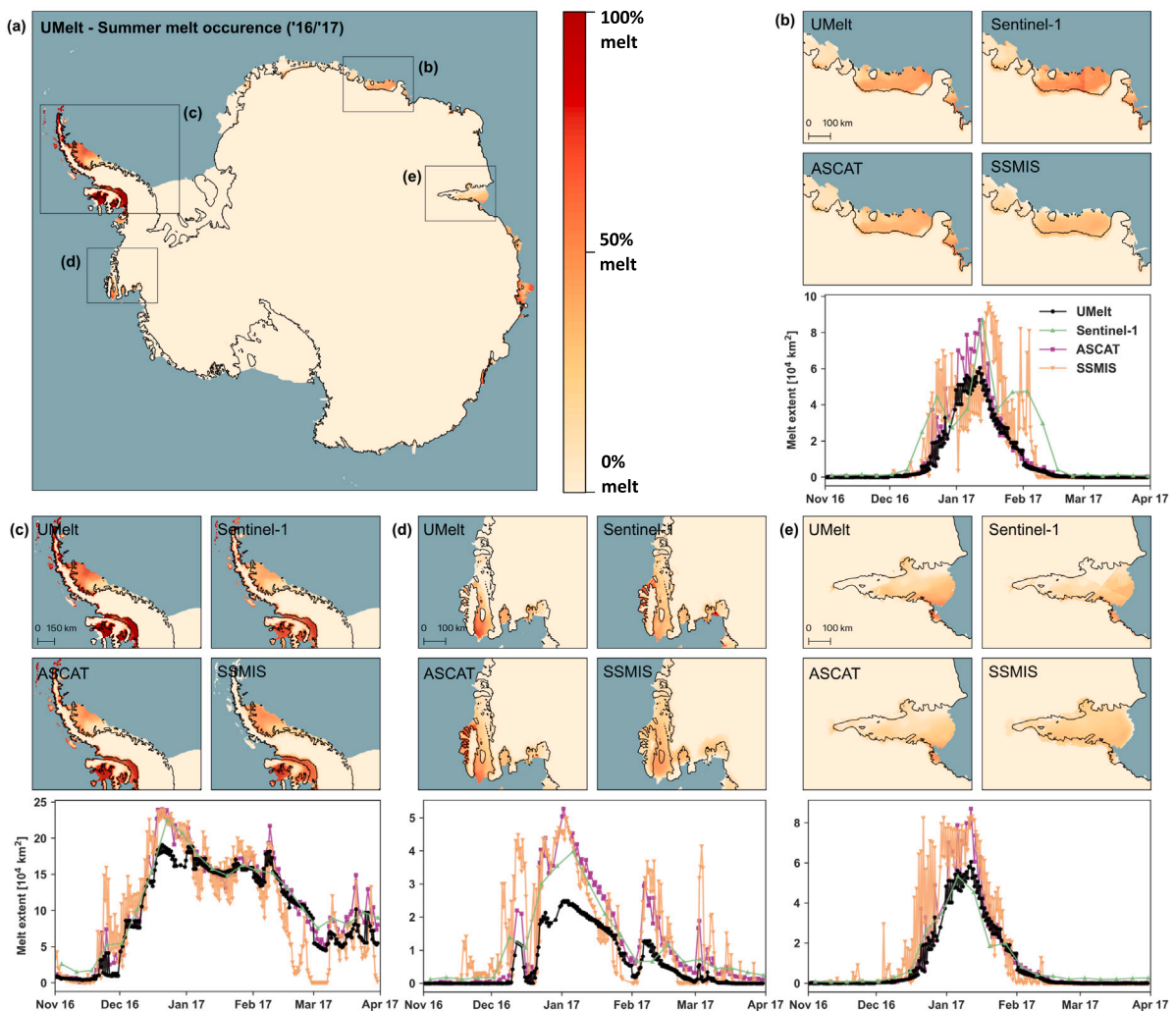


Fig. 9. The UMelt record, showing Antarctic-wide summer melt occurrence for melt season 2016–2017 (a), with details of Dronning Maud Land (b), the Antarctic Peninsula (c), Mary Byrd Land (d), and Amery Ice Shelf (e). The time series show a comparison in melt extent for the four regions between UMelt (black), Sentinel-1 (green), ASCAT (purple), and SSMIS (orange). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

entire Antarctic region, with the exception of the masked areas (see Section 2.2 and Supplementary Figure 1a), resulting in an observation area of 1.8 million km². The UMelt product for melt season 2016–2017 is presented in Fig. 9, while the summer melt occurrence derived from the melt observations of seasons 2017–2021 are shown in Supplementary Figure 4.

In the aggregated summer melt occurrence maps (Fig. 9), it becomes more difficult to identify the small-scale melt features captured by UMelt that were visible in earlier figures (Figs. 4, 5, and 6). However, almost all large-scale spatial melt patterns are consistent across UMelt, Sentinel-1, ASCAT, and SSMIS. Notably, the presence of melt in blue ice regions in the southeastern part of the Roi Baudouin Ice Shelf (Fig. 9b) and the western part of the Amery Ice Shelf (Fig. 9e) are only captured by the passive microwave satellite SSMIS. This discrepancy in detecting melt over blue ice areas is a recognized limitation of active microwave sensors (Zheng and Zhou, 2020; Zhou et al., 2019; de Roda Husman et al., 2022), including UMelt, which utilizes Sentinel-1 as the reference data. In the case of the Amery Ice Shelf (Fig. 9e), the Sentinel-1 summer melt occurrence map shows a clear boundary between areas with and without melt along the northern part of the grounding line. This distinction arises from the absence of Sentinel-1 observations in the northernmost region of the ice shelf during the 2016–2017 melt season. In the northern part of the Abbot Ice Shelf in Mary Byrd Land (Fig. 9d), UMelt successfully captures small-scale melt details that ASCAT and SSMIS are unable to capture. However, it is worth noting that UMelt tends to underestimate surface melt when compared to Sentinel-1, ASCAT, and SSMIS. Unfortunately, there are no ‘matching overpasses’ over Mary Byrd Land, including Abbot Ice Shelf, which prevents further evaluation of UMelt to Sentinel-1 in this region.

The time series plots in Fig. 9b–e illustrate the melt extent over the four regions throughout the 2016–2017 melt season. To account for the limited coverage of Sentinel-1, we created weekly aggregates representing the maximum melt extent. The time series analysis of Dronning Maud Land (Fig. 9b), Antarctic Peninsula (Fig. 9c), and Amery Region (Fig. 9e) reveals a close resemblance in total melt extent throughout the melt season among UMelt, Sentinel-1, ASCAT, and SSMIS. However, as we approach the conclusion of the melt season in Dronning Maud Land (Fig. 9b) and throughout the entire melt season in Mary Byrd Land (Fig. 9d), the time series indicate that UMelt tends to underestimate the extent of melt compared to the other sensors, especially compared to Sentinel-1 and SSMIS. It is crucial to take into account the restricted number of Sentinel-1 observations over Dronning Maud Land and Mary Byrd Land de Roda Husman et al. (2022). This means that the weekly averages are based on a limited data set, which may impact their reliability. The discrepancies with SSMIS could be attributed to the substantial difference in penetration depth between SSMIS and ASCAT/Sentinel-1 (Ulaby et al., 1986).

Fig. 9 demonstrates that UMelt serves as a viable alternative to existing satellite observations. In the context of high spatial resolution images of surface melt, Sentinel-1 observations have been commonly used (e.g., Liang et al., 2021). However, UMelt offers a significant advantage in terms of high temporal resolution. UMelt presents a notable advantage over Sentinel-1 by offering complete coverage without missing locations due to limited overpasses, a limitation observed in certain areas of the Amery Ice Shelf. Additionally, UMelt’s twice-daily observation frequency eliminates the gaps in time that exist in Sentinel-1’s time series.

Traditionally, sensors like ASCAT or SSMIS have been relied upon for high temporal resolution images (e.g., Bevan et al., 2018; Liu et al., 2006). However, their drawback lies in their low spatial resolution. In contrast, UMelt not only provides high temporal resolution but also captures spatial details that ASCAT and SSMIS fail to capture. Notably, UMelt reveals intricate features along the grounding lines of Larsen C and George VI ice shelves (Fig. 9c), as well as the western part of the grounding line on the Amery Ice Shelf (Fig. 9e). Therefore, UMelt proves to be a valuable tool in obtaining both detailed temporal and spatial information in melt observations, surpassing the limitations of Sentinel-1, ASCAT, and SSMIS.

4. Discussion

4.1. Opportunities of UMelt

The UMelt record demonstrates great potential as a new data product for surface melt monitoring, offering a viable alternative to existing remote sensing data sets such as Sentinel-1, ASCAT, and SSMIS. UMelt offers a significant advantage over ASCAT and SSMIS by effectively overcoming the limitations related to coarse spatial resolution while maintaining a high temporal resolution. By providing surface melt information at a higher spatial resolution of 500 m, UMelt allows for more precise and accurate detection of melt events. Additionally, UMelt captures short-lived melt events that may be missed by Sentinel-1 due to its low revisit time. This enhanced capability makes UMelt a valuable tool for studying and monitoring surface melt dynamics.

The UMelt record has the potential to provide valuable insights into specific melt dynamics that may be challenging to capture using Sentinel-1, ASCAT, or SSMIS. One notable application is the improved understanding of diurnal melt cycles, which provide valuable insights into the drivers and impacts of melt processes (Van Den Broeke et al., 2006). While ASCAT and SSMIS also provide temporal information, their coarse spatial resolution limits the ability to establish precise connections between surface melt patterns and local drivers. In contrast, UMelt enables us to examine highly localized melt triggers and track the evolving melt patterns throughout the day.

Another compelling research direction that utilizes the UMelt record involves monitoring surface melt on highly heterogeneous terrains, such as the Larsen C Ice Shelf. The Larsen C Ice Shelf is the largest remaining ice shelf on the Antarctic Peninsula and is vulnerable to potential collapse in a warming climate (Wang et al., 2022a). Notably, past disintegrations of Larsen A and Larsen B were preceded by elevated air temperatures and intense surface melt, underscoring the importance of understanding melt dynamics for assessing ice shelf stability (Banwell et al., 2013; Scambos et al., 2000, 2003). However, the spatial resolutions of ASCAT and SSMIS might be inadequate for accurately mapping surface melt along the grounding line of the Larsen C Ice Shelf. Depending solely on infrequent Sentinel-1 images that pass over the region a few times a week may restrict our comprehensive understanding of the intricate melt dynamics (see Fig. 1). Therefore, the UMelt record offers a promising addition to the currently existing remote sensing data for studying surface melt on highly heterogeneous ice shelves such as Larsen C.

4.2. Limitations of UMelt

Despite its promising capabilities, the UMelt product has inherent limitations due to the complex nature of its deep learning approach. The intricate workings of the model make it challenging to precisely identify the factors that contribute to the estimation of surface melt. While we have conducted assessments of the temporal performance (Fig. 5 and Supplementary Figure 2), spatial performance (Fig. 6), feature importance (Fig. 7), and transferability (Fig. 8) of the model, a complete understanding of its inner workings remains elusive. This is particularly evident in cases like Mary Byrd Land, where underestimation of surface melt is observed in melt season 2016–2017 (Fig. 9d). This highlights the need for further research and investigation to unravel the underlying mechanisms and improve the accuracy and performance of the UMelt product and/or the machine learning methods to develop such products.

Another limitation of deep learning networks is their tendency to mimic the patterns and characteristics they have been trained on. While UMelt incorporates inputs such as ASCAT and SSMIS, which provide real-time information about liquid water presence, it also considers elevation and multi-year Sentinel-1 melt fraction as input features. Given the current availability of Sentinel-1 data, the multi-year Sentinel-1 melt fraction input feature encompasses observations from both

Sentinel-1 A and -B, covering the period from 2016 (when Sentinel-1B was launched) to 2021 (when Sentinel-1B ceased operation). The model applies downscaling patterns based on past observations where ASCAT, SSMIS, elevation, and multi-year Sentinel-1 melt fraction collectively resulted in specific melt patterns. This means that when faced with unprecedented and dissimilar events that significantly deviate from its training data, the model may generate inaccurate results. This aligns with the insights presented in the study by Picard et al. (2007), which demonstrates that in regions with frequent melting, the number of melting days exhibits an almost continuous distribution, varying from year to year. Conversely, in areas where melting is infrequent, the distribution adopts an exponential pattern. In these cases, only a few years encounter a high number of melting days.

Finally, we utilized a basic Attention U-Net framework, which is renowned for its effectiveness in capturing spatial patterns in data (Oktay et al., 2018). A prospective advancement could involve integrating temporal information into the deep learning model, offering significant value for tasks that require the consideration of both spatial and temporal contexts to achieve accurate predictions. This holds true for surface melt prediction, as certain melt trends and patterns exhibit temporal dependencies throughout a melt season (Saunders et al., 2022). A common approach for incorporating temporal information into U-Nets is through the utilization of 3D convolutional operations (Çiçek et al., 2016). While the 2D convolutions employed in our study operate on spatial dimensions (i.e., width and height), 3D convolutions additionally incorporate the temporal dimension (i.e., time or sequence). By leveraging these 3D convolutions, U-Nets can effectively capture spatiotemporal patterns, enabling the analysis and processing of data with combined spatial and temporal variations.

4.3. Implications of selected training region

The Shackleton Ice Shelf was selected as the training region, as it provided us with sufficient training data. While training a U-Net model on each individual ice shelf would be preferable, there are insufficient (or no) 'matching overpasses' available on most ice shelves to accomplish this (Fig. 2). Another advantage is that the Shackleton Ice Shelf exhibits a wide range of fine-scale melt patterns, especially along the grounding line and ice rises. The U-Net captured and represented these patterns well, and the results can be extrapolated to other ice shelves, as shown in Figs. 8 and 9.

One of the encountered limitations of selecting the Shackleton Ice Shelf as the training region is the presence of surface melt at relatively high elevations (up to 300 m), due to strong katabatic winds. This aligns with earlier research that identified that low-elevation regions near the grounding line in East Antarctica are frequently exposed to persistent katabatic winds (Arthur et al., 2020; Lenaerts et al., 2017; Stokes et al., 2019). As a consequence, UMelt could potentially overestimate surface melt in regions with less pronounced or absent katabatic winds. A study by Laffin et al. (2023) demonstrates that along the grounding line of the Shackleton Ice Shelf, roughly 50% of the melt is linked to downslope winds. Conversely, for the Larsen C Ice Shelf and the Abbot Ice Shelf, this proportion drops to less than 20%. A potential solution to address this issue is adjusting the current binary melt threshold, which is consistently set to 0.7, by implementing a region-specific threshold. Since the model is able to capture fine-scale melt patterns accurately, this approach may be effective.

4.4. Implications of selected reference data

UMelt was developed using Sentinel-1 as the reference data. We filled the observational gaps of Sentinel-1 and created a simulated Antarctic-wide product with a much higher temporal resolution (12 h) than the original Sentinel-1 data (1–7 days). However, while Sentinel-1 is a reliable source for melt detection, it has limitations.

First, Sentinel-1 fails to accurately detect the presence of liquid water in icy regions without snow cover (Zheng and Zhou, 2020; Zhou et al., 2019; de Roda Husman et al., 2022), such as on the southeast part of Shackleton or southeast part of Roi Baudouin ice shelves. Over these regions, Sentinel-1 is unable to differentiate between a dry and melting ice surface, as for both cases the backscatter intensity is very low (de Roda Husman et al., 2022). Consequently, in our UMelt product, we also encounter limitations in detecting melt over these regions, as demonstrated in Fig. 9b and 9e of our study. Using Sentinel-1 as the reference data has a further limitation regarding damaged ice. Damaged ice has heterogeneous surface orientations and thus different local incidence angles than the surrounding ice, leading to potential over- or underestimation of surface melt. We addressed this issue by excluding damaged areas from the U-Net development mask. A potential path for future improvement could be to use a different reference product for blue ice regions (e.g., using the blue ice maps of Hu et al., 2022; Jawak et al., 2023) and damaged areas (e.g., using the damage map of Izeboud and Lhermitte, 2023). Multispectral imagers, such as Landsat, MODIS, or Sentinel-2, may be suitable for this purpose. If such a merged, optimized reference product were available, the U-Net could be retrained to improve its performance.

Using Sentinel-1 as reference data presents another limitation, as it, like all microwave sensors, detects the presence of liquid water rather than directly observing the underlying energy conversion process of surface melt. It is important to highlight that both ASCAT and Sentinel-1 have a significant penetration depth, theoretically reaching up to 10 m (Ulaby et al., 1986). These large penetration depths enable them to potentially detect more residual water in the snowpack compared to SSMIS, which is limited to a theoretical penetration depth of 2.5 m (Ulaby et al., 1986). This could potentially explain the surface melt overestimation for ASCAT and Sentinel-1 (along with UMelt) compared to SSMIS over the Wilkins Ice Shelf, particularly at the end of the melt season (Fig. 9c). This is especially plausible given the known tendency of the Wilkins Ice Shelf to retain meltwater in the subsurface (Montgomery et al., 2020). A potential avenue for improving the UMelt record could involve assigning greater weight to SSMIS for locations with higher levels of retained melt. One possible approach to identifying these locations could involve examining the ASCAT and SSMIS time series and assessing the disparity between morning and afternoon observations. In areas with no active surface melt and only retained meltwater, it is more likely that the difference between morning and afternoon observations would be minimal towards the end of a melt season.

4.5. Downscaling other surface melt products

The findings of this study demonstrate the value of deep learning as a tool for monitoring surface melt with a high spatial and temporal resolution, offering insights into both historical and current ice shelf conditions. Additionally, other surface melt products, such as regional climate model data, can be utilized for downscaling surface melt.

Regional climate models typically operate at a resolution of tens of kilometers (e.g., Van Wessem et al., 2018; Agosta et al., 2019), which often fails to capture small-scale surface melt events occurring in Antarctica (Barrand et al., 2013). By incorporating deep learning models, it becomes possible to explore the relationship between large-scale melt patterns derived from regional climate models and fine-scale variations found in additional data sets, such as elevation data or multi-year Sentinel-1 melt fractions employed in this study. Hence, deep learning provides the capability to downscale coarse surface melt data derived from regional climate models.

The application of a U-Net proves to be a promising method for this purpose. By downscaling regional climate model data using deep learning techniques, we can gain a more comprehensive understanding of high-resolution surface melt. This not only encompasses the analysis of historical surface melt patterns but also enables the exploration of future projections.

5. Conclusion

This study presents a novel workflow to create a record of high-resolution surface melt on the Antarctic ice shelves, UMelt. The core of our approach is a modified U-Net that learns the patterns from high temporal (i.e., ASCAT and SSMIS) and high spatial (i.e., elevation and multi-year Sentinel-1 melt fraction) data. The trained model mimics the detailed Sentinel-1 melt observations but on a much higher temporal resolution, resulting in melt maps with a high spatial (500 m) and temporal (12 h) resolution.

We demonstrated the spatial and temporal transferability of the U-Net on the Shackleton Ice Shelf, achieving accuracies ranging from 87.2% to 95.5% for spatial transferability and 90.9% to 95.7% for temporal transferability. The U-Net also performed well in terms of spatiotemporal transferability, with good performance over the Larsen C Ice Shelf (91.0%). This spatiotemporal transferability allows for the assessment of surface melt on the entire Antarctic continent. The U-Net can provide maps of surface melt with a high resolution for all previous years with available input data, meaning we could study surface melt in high detail from 2006 (when ASCAT was launched) until present day. However, for both past and future scenarios, it is important to acknowledge that the model may necessitate re-training, especially when confronted with surface melt patterns that significantly differ from the training data used for the U-Net model.

High-resolution observations are crucial to monitor surface melt on the Antarctic ice shelves because of the short duration and fine melt patterns. Therefore, the high-resolution surface melt record on the Antarctic ice shelves UMelt provides a valuable product to be used in further studies, uncovering melt dynamics and potential consequent ice shelf instability that remains hidden in low-resolution satellite imagery.

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CRediT authorship contribution statement

Sophie de Roda Husman: Conceptualization, Methodology, Visualization, Writing – original draft, Data curation. **Stef Lhermitte:** Conceptualization, Supervision, Writing – review & editing, Methodology. **Jordi Bolibar:** Methodology, Writing – review & editing. **Maike Izeboud:** Resources, Writing – review & editing. **Zhongyang Hu:** Methodology, Writing – review & editing. **Shashwat Shukla:** Methodology, Writing – review & editing. **Marijn van der Meer:** Methodology, Writing – review & editing. **David Long:** Resources, Writing – review & editing. **Bert Wouters:** Conceptualization, Methodology, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The scripts used to develop UMelt are available on GitHub at <https://github.com/SdeRodaHusman/UMelt>. The UMelt record, with a spatial resolution of 500 m and morning (6 AM) and afternoon (6 PM) observations for melt seasons 2016–2021, is accessible in two ways. First, as GeoTIFF files via 4TU.ResearchData (<https://doi.org/10.4121/8a8934ef-9407-406f-8bfb-573eb182ec54.v1>). Secondly, UMelt can be accessed as assets via Google Earth Engine. Users can access UMelt for specific melt seasons using the following link format: https://code.earthengine.google.com/?asset=projects/phd-detectionsurfacemelt/assets/UMelt_Antarctica/MeltSeasonXXXX/UMelt_AllData_MeltSeasonXXXX, where 'XXXX' should be replaced with the corresponding melt season. For example, replacing 'XXXX' with '1617' will provide the UMelt data for the 2016–2017 melt season. Similarly, replacing 'XXXX' with '1718', '1819', '1920', or '2021' will provide the UMelt data for the respective melt seasons. Users have the option to import UMelt into their Google Earth Engine environment using an example script provided on GitHub.

In addition to the UMelt record, melt occurrence data for a single melt season, as depicted in Fig. 9 and Supplementary Figure 2, are also available. These data can be downloaded from 4TU.ResearchData (<https://doi.org/10.4121/8a8934ef-9407-406f-8bfb-573eb182ec54.v1>) or accessed through Google Earth Engine (https://code.earthengine.google.com/?asset=projects/phd-detectionsurfacemelt/assets/UMelt_Antarctica/MeltSeasonXXXX/UMelt_MeltFraction_MeltSeasonXXXX).

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.rse.2023.113950>.

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ARTICLES FOR FACULTY MEMBERS

REMOTE SENSING BIG DATA ANALYTICS FOR DETAILED GEOLOGICAL MAPPING IN EXPOSED ZONES OF DRY VALLEYS, SOUTH VICTORIA LAND, ANTARCTICA

Dataset compilation by GRASS GIS for thematic mapping of Antarctica: Topographic surface, ice thickness, subglacial bed elevation and sediment thickness / Lemenkova, P.

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Dataset compilation by GRASS GIS for thematic mapping of Antarctica: Topographic surface, ice thickness, subglacial bed elevation and sediment thickness

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Abstract

This paper presents the GRASS GIS-based thematic mapping of Antarctica using scripting approach and associated datasets on topography and geophysics. The state-of-the-art in cartographic development points at two important aspects. The first one comprises shell scripting promoted repeatability of the GIS technique, increased automatization in cartographic workflow, and compatibility of GRASS with Python, PROJ and GDAL libraries which enables advanced geospatial data processing: converting formats, re-projecting and spatial analysis. The second aspect is that data visualization greatly influences geologic research through improving the interpretation between the Antarctic glaciation and surface. This includes the machine learning algorithms of image classification enabling to distinguish between glacier and non-glacier surfaces through automatically partitioning data and analysis of various types of surfaces. Presented detailed maps of Antarctic include visualized datasets from the ETOPO1, GlobSed, EGM96 and Bedmap2 projects. The grids include bed and surface elevation, ETOPO1-based bathymetry and topography, bed, ice and sediment thickness, grounded bed uncertainty, subglacial bed elevation, geoid undulations, ice mask grounded and shelves. Data show the distribution of the present-day glacier, geophysical fields and topographic landforms for analysis of processes and correlations between the geophysical and geological phenomena. Advances in scripting cartography are significant contributions to the geological and glaciological research. Processing high-resolution datasets of Southern Ocean retrieved by remote sensing methods present new steps in automatization of the digital mapping, as presented in this research, and promotes comprehensive monitoring of geological, permafrost and glacial processes in Antarctica. All maps have been plotted using GRASS GIS version 7.8. with technical details of scripts described and interpreted.

Key words: Antarctic, GRASS GIS, script, cartography, mapping, topography, ETOPO1, ice shelf thickness, sedimentation, geoid, geophysics

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Introduction

The aim of this paper is to present thematic mapping of Antarctica using shell scripting by GRASS GIS and open high-resolution datasets. Data visualization is a key issue in Polar studies which largely include geologic and glacial research. Effective mapping is a key tool in Earth sciences as it enables correct interpretation of the findings, helps to better understand the correlation between the geological processes, and points at hydrological and environmental issues. The concepts of cartography and thematic GIS applications are ever-evolving with recent advances in automatization of data visualization which implies scripting techniques.

The onset of the automatization in cartography took place as early as in the 1970s with rapid development of computerization (*e.g.* Babcock 1978, Williams 1987, Hernandez 1994) and is being continuously updated along with contemporary advances in GIS and RS and progress in computational techniques (Kloser et al. 2001, Takeda et al. 2002, Schenke and Lemenkova 2008, Tedesco 2009, Lemenkov and Lemenkova 2021a, Klaučo et al. 2013b, 2014, 2017; Ladroit et al. 2020, Johnson et al. 2020). It was followed by further methodological development of geoinformatics which resulted in a combination of spatial analysis with statistical libraries of the programming languages (Greene et al. 2017, Lemenkova 2020d, Brus 2019).

An increasing expectation of scripting cartography is that new, machine learning methods contribute to the development of geospatial visualization through automated geographical data analysis of big complex vector and raster datasets. Such automatization delivers faster and more accurate cartographic results compared to the hand-made traditional mapping. As a result, scripting cartographic approaches add to the geological science new datasets which

in turn provide new background for data interpretation. Often, the geological research is based on using traditional GIS with graphical user interface (GUI) which often involves a complex process of preparing maps and layouts. The advantages of scripting methods in cartography consists in repeatability of the code which fastens and smoothens data analysis, and contributes to the dissemination of the new findings through new maps. This paper demonstrates the importance of using and applying scripting based cartographic methods in topographic and geophysical visualization with a case study of Antarctic.

Many studies on Polar and marine systems undertake exploit surveys during the expeditions and collect datasets by the multibeam echo-sounders for seafloor mapping, data sampling, sorting, processing and post-processing (Aquilina et al. 2013, Gauger et al. 2007, Gohl et al. 2006a, b; Kuhn et al. 2006, Bell et al. 2016, Gales et al. 2014). Others are often supported by the statistical analysis and visualization of the datasets (Lemenkova 2019a, b; 2021a; Klaučo et al. 2013a), or present tectonic reconstructions based on geochemical analysis (Leat et al. 2009). However, it should be pointed out that mapping better presents graphical summaries of geospatial data distribution that enable to highlight correlations between the geological and glacial datasets. The practice, though, is that some works that do include maps are often based on previously made maps. Others include at least mapping based on the traditional GIS (Suetova et al. 2005, Lemenkova 2011, Lemenkova et al. 2012).

Using shell scripts and advanced methods of data processing (*e.g.* converting formats by GDAL library, re-projecting by PROJ) has revolutionized the contemporary cartography. However, in contrast with the common mapping practice, using scripting in GIS is less known.

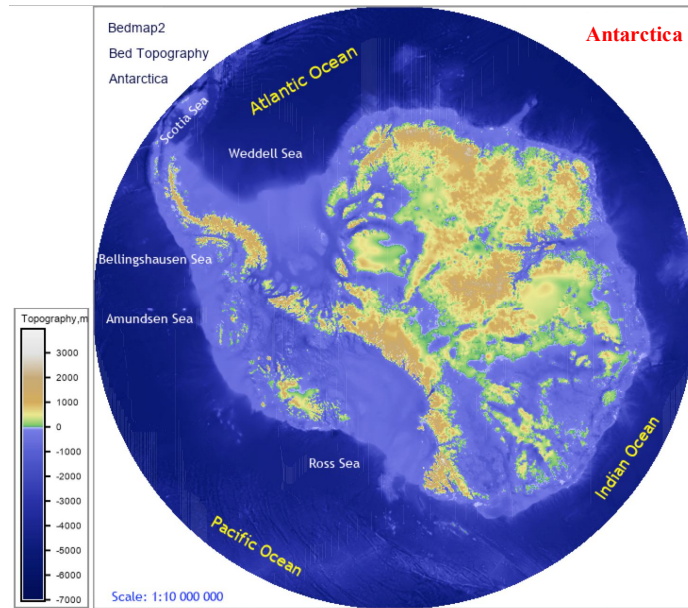


Fig. 1. Bed topography and bathymetry, Antarctica. GRASS GIS.

At the same time, the advantages of using shell scripts, such as GMT or GRASS GIS, machine learning algorithms, and open datasets in geologic studies are evident and presented in a variety of papers (*e.g.* Becker 2005, Bohoyo et al. 2019, Lemenkova 2020a, b, c; Bivand 2019, Jordan et al. 2013, Wessel et al. 2019). It becomes especially actual nowadays due to the general trend of the distance-based research which requires open datasets and free software. This paper aims to fill the gap by demonstrating the use of scripting approach of GRASS GIS for plotting thematic series of maps of Antarctica using open datasets. Besides general map of the study area (Fig. 1), these include bed topography (Fig. 2), surface elevations (Fig. 3), geoid model (Fig. 4), ice mask grounded and shelves (Fig. 5), sediment thickness (Fig. 6), ETOPO1 topography (Fig. 7), and grounded bed uncertainty (Fig. 8).

A motivation for developing these maps are the advantages presented by the

GRASS GIS that enables to process updated recent data on Antarctica using a scripting approach with respect to having a scripting methodology of drawing these maps that exhibits variations in the ice sheet according to the modern data: increase, decrease and homogeneous distribution of the ice in various regions of Antarctica and surrounding shelf areas. Second, compatible visualization of the geophysical, geological, topographic and glaciological data becomes possible due to versatility and flexibility of the GRASS GIS syntax in general, as well as open source availability of the updated datasets on Antarctic geophysical settings.

There has been a significant amount of Antarctic research into glacial dynamics (Cook and Vaughan 2010), trends in tectonic processes (Eagles et al. 2009), seafloor geomorphology (Camerlenghi et al. 2001), ice shelf thickness (Griggs and Bamber 2011) and seabed bathymetry (Hodgson et al. 2019). However, cartography-focused studies into Antarctic map-

ping are limited (Bamber et al. 2009). A systematic approach to search in the topographic and geologic datasets is the first step in Antarctic research. In this regards, the Bedmap2 by British Antarctic Survey [1] is one of the most comprehensive open geospatial resources specifically for Antarctica. It presents a set of open grids in-

cluding geological, geophysical and topographic data. Other useful datasets include ETOPO1, EGM-96, EGM-2008, GEBCO, GlobSed, SRTM, GLOBE. The British Antarctic Survey includes a variety of data on such categories as Hydrosphere, Land Surface, Oceans, Paleoclimate, Solid Earth and more.

Background: Study area

The study area is focused on Antarctica, which geology remains mostly unknown due to the ice sheet covering it by the layer with thickness reaching up to 3.5 km (Fretwell et al. 2013). The outcrops of bedrock are only occasional which makes the study of the continent complicated and requires remote sensing and digital methods of data processing. Antarctica is schematically composed of three major geologic-tectonic structures: 1) East Antarctica; 2) Transantarctic Mountain belt; 3) West Antarctica (Jordan et al. 2017).

The continental configuration of Antarctica was largely shaped during the Gondwana breakup, which significantly affected its hydrology, climate settings, cryosphere, and geology (Riley et al. 2020). The disintegration of Gondwana led to the isolation of Antarctica in a polar position (Storey et al. 2013). Thus, the consequences of the Gondwana separation on the hydrological settings can be illustrated by opened major oceanic gateways (Lawver and Gahagan 2003). These include Drake Passage and the Tasmanian gateway separating South America, Australia and Antarctica, which initiated modern circulation pattern around Antarctica (Bohoyo et al. 2016). Climate changes significantly affected glacial settings of Antarctica including the geometry and distribution of the ice sheets (Johnson et al. 2012).

The topography of Antarctica consists of several blocks which basement was formed in Precambrian (Dalziel 1992). West Antarctica includes two distinct large-sized topographic depressions covered by

ice shelves as West Antarctica basins: 1) Ross Ice Shelf, a southern depression in the Ross Sea; and 2) Ronne Ice Shelf, a northern depression in the Weddell Sea. The southern basin is considered as one of the world's largest crustal extensional areas (Behrendt 2013). The combined effects of the complex geological and geophysical processes resulted in significant extension of crust and magmatism in West Antarctica (Cande et al. 2000). The West Antarctic rift system, one of the largest active continental rift systems, was formed during late Mesozoic and Cenozoic extension of the West and East Antarctica (Cande et al. 2000). The topography of East Antarctica includes several ice sheets located along the coasts of the continents: Queen Maud Land, Enderby Land, Queen Mary Land, Wilkes Basin.

Geophysical processes, mechanisms of the geologic formation are still controversial and bring many disputes into the publications on Antarctic geology, tectonic formation, glacial distribution, and hydrological regime. This makes modelling of the Antarctica using high-resolution datasets to be actual contribution to the polar studies. Since the focus of this study is on Antarctic mapping by scripting cartography, this paper omits the additional details on tectonic evolution and geologic settings of Antarctica which can be found in the studies from last decade (see *e.g.* Gales et al. 2016, Leat et al. 2018, Flowerdew et al. 2012, Vaughan et al. 2012, Gibson et al. 2010).

Material and Methods

The maps presented in this research were made using GRASS GIS (Geographic Resources Analysis Support System) originally developed by M. Neteler (Neteler 2000, Neteler et al. 2008) and continuously supported by GRASS Development Team (2018 - [2]) since then.

Data

A range of geospatial data resources are now available including thematic websites on Antarctic and Polar research, PANGEA Data Publisher for Earth and Environmental Science, published datasets including those on Antarctica, and repositories with e-journals. The bathymetric data include GEBCO grid, and topographic regional improvements (*e.g.* Graham et al. 2011) of the selected areas in Antarctica and IBCAO for the North Pole.

The geophysical data include gravity grids (Smith and Sandwell 1995, Sandwell and Smith 2005, 2009; Sandwell et al. 2014), related datasets, such as EGM-96, EGM-2008, and archiving geophysical datasets (Hamilton et al. 2019). The sediment thickness is computed in global grid (Divins 2003), glacial sediment thickness grids cover selected regions of the World ocean (Lindeque et al. 2016, Wobbe et al. 2014) such approaches are used in existing practical applications (Rosenheim et al. 2008, Lemenkova 2020e). These data add to the general pool of Earth data resources which can also be used in regional studies of Antarctica.

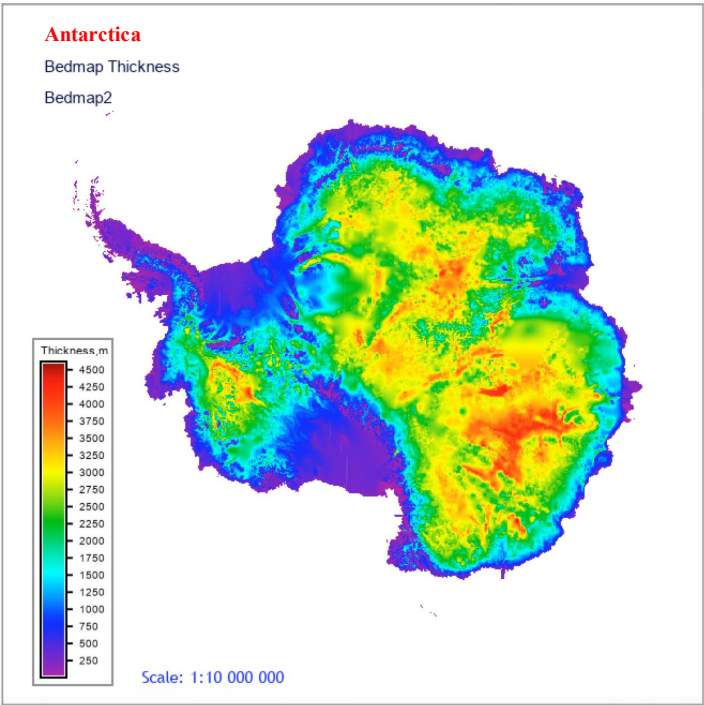


Fig. 2. Map of bed topography of Antarctica. Mapping: GRASS GIS.

Particularly, the data used in this paper include the bed grid of the Antarctica (Lythe et al. 2000, 2001), ETOPO1 global relief model of Earth's surface that integrates land topography and the ocean bathymetry with 1 arc-minute resolution (Amante and Eakins 2009). Other sources

are sediment thickness from the GlobSed-5 grid of total sediment thickness in the World's oceans (Straume et al. 2019), and geoid dataset available as a part of the Bedmap2 project (Fretwell 2012) which includes ice thickness, subglacial topographic model of Antarctica and geophysical data.

Methods

Various different GRASS GIS modules have been applied in scripting. The project was generated in GRASS GIS using following workflow. The folder was created for all stored files that GRASS used for creating maps in Polar stereographic projection. The the directory structure was assigned by GRASS and consisted from the main folder (location: Antarctica) and

subdirectories: mapsets. The mapset 'Permanent' was used as an archive for all maps, while other thematic mapsets were generated in the respective subdirectories, e.g.: 'Bathymetry', 'Bedmap', 'Surface Topography', 'Geoid', 'Sediment thickness', 'ETOPO1'). The workflow can be summarized as follows.

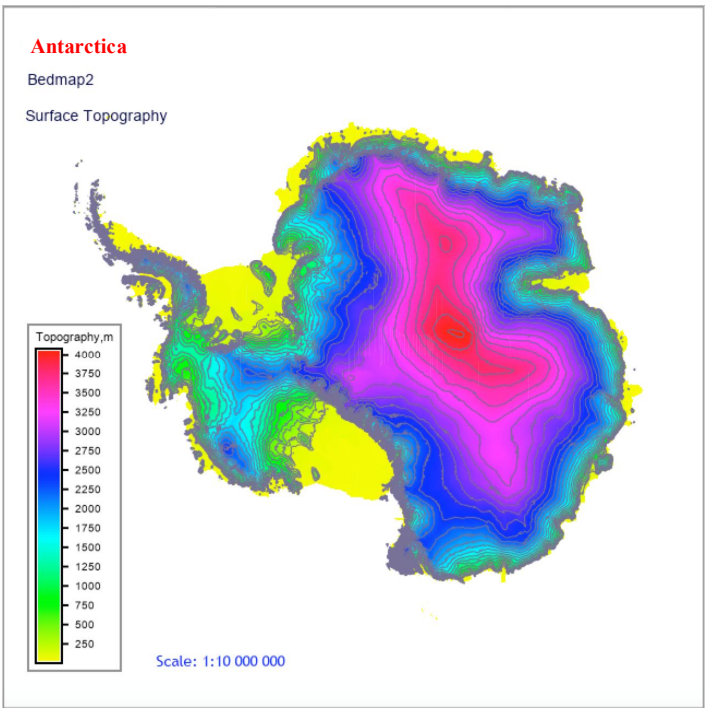


Fig. 3. Surface topography of Antarctica. Mapping: GRASS GIS.

First, the data using the GDAL library (Geospatial Data Abstraction Library - [3]) using a 'gdalwarp' utility to convert GeoTIFF file from XY Cartesian to WGS84, from NetCDF to GeoTIFF by following code (example for ETOPO1 grid converting):
gdalwarp -t_srs EPSG:4326 a_relief.nc a_relief_wgs84.tif -overwrite.

Second, the data were inspected for the extent, range and origin by metadata using 'gdalinfo' utility: `gdalinfo a_relief_wgs84.tif`. The unnecessary data were removed (those with not suitable spatial coverage or lack of data, such as 'bedmap2_rockmask.tif', 'grav_27.1.img' gravity data) and the following remained in the working folder: `bedmap2_bed.tif`, `bedmap2_coverage.tif`, `ETOPO1_Ice_g_gmt4.grd`, `bedmap2_grounded_bed_uncertainty.tif`, `bedmap2_icemask_grounded_and_shelves.tif`, `bedmap2_thickness.tif`, `bedmap2_surface.tif`, `gl04c_geiod_to_WGS84.tif`. The maps were generated using these data. The grids shown the extent of the data used for selecting the color palette and the step in the breaks useful in legends.

Third, the data were re-projected to the Universal Polar Stereographic (UPS) projection by the following code: `'gdalwarp -t_srs '+proj=ups +south +datum=WGS84' a_relief_wgs84.tif a_relief_ups.tif -overwrite` where the '+south' flag means the necessary remark for the South polar aspect, since the projection is suitable for the both poles.

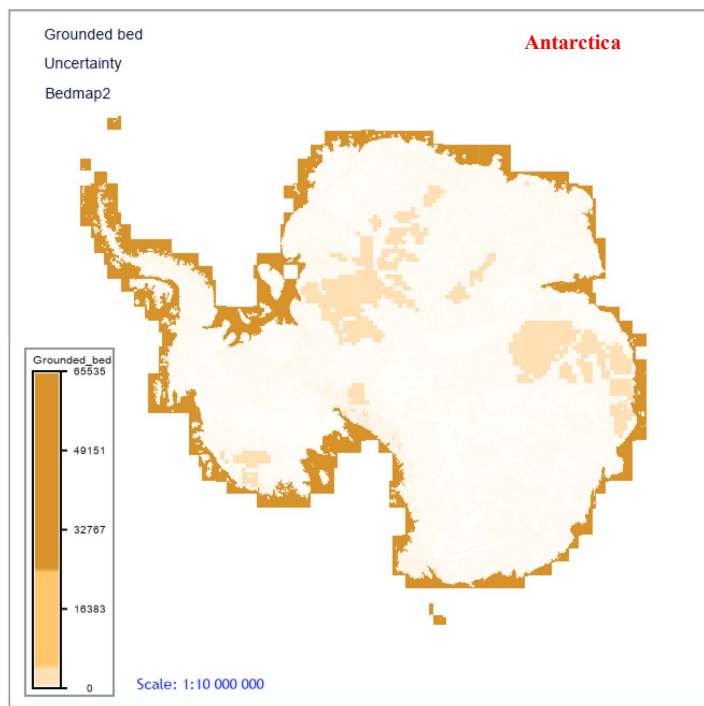


Fig. 4. Geoid undulations, Antarctic region. Mapping: GRASS GIS.

The data were then imported into a project using following code: `'r.in.gdal a_relief_ups.tif out=a_relief_ups title="Antarctic ETOPO1" -overwrite` and then inspected using the code `'r.info a_relief_ups'`. The boundary for the geographic region of Antarctica were defined by the 'g.region' module: `'g.region raster=a_relief_ups -p'`.

The next step included the preparation of the window for plotting using following codes: `'d.erase'`, `'d.mon wx0'`, `'r.colors a_relief_ups col=byr'`, `'d.rast a_relief_ups'`. These commands of GRASS GIS defined the color palette for the map (here: the topographic map based on the ETOPO1 shown in Fig. 7) and visualization is on the screen.

The cartographic elements are essential components of every map. They were plotted using special modules of GRASS GIS, explained as follows. The title was added using the module 'd.title' as follows: `d.title map=a_relief_ups | d.text text="Antarctica" color="red" size=3`. The legend was added using module 'd.legend' as follows: `'d.legend raster=a_relief_ups range=-7160,4763 -d title=Topography,m title_fontsize=8 font=Arial fontsize=7 -t -b bgcolor=white label_step=1000 border_color=gray thin=8'`.

The isolines were modeled from the raster grid every 2,000 meters using the 'r.contour' GRASS GIS module which plots a vector contour lines from a raster map, as follows: `'r.contour a_relief_ups out=reliefAnt step=2000 -overwrite'`. Then, the visualization was done (as additional elements) on the map by 'd.vect' module: `'d.vect reliefAnt color='100:93:134' width=0'`. The text annotations were added using following commands (here, the example of Scotia Sea): `'d.text text="Scotia Sea" color=blue size=2.0 font="Trebuchet MS" rotation=45'`.

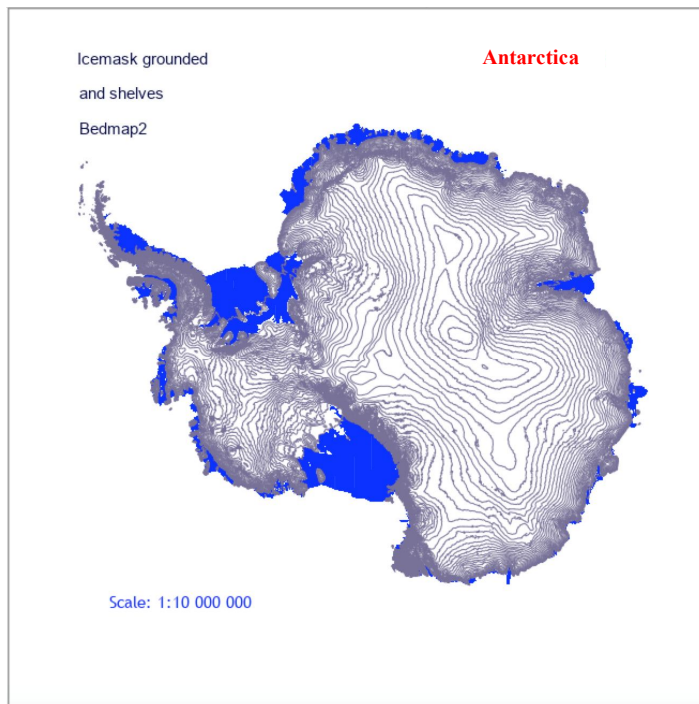


Fig. 5. Ice mask grounded and shelves in Antarctica. GRASS GIS.

Such technical cartographic approach of GRASS GIS syntax was followed for plotting of all the presented eight maps in this study. It should be pointed out that scripting techniques enable to reuse the script for the data processing which largely automates the workflow of the cartographer. Specifically, the machine and deep learning solutions of GRASS GIS enable to easy use of open source code to plot maps as smarter and faster Earth science workflow. Due to the automatization of the code, the shell script listings of the GRASS GIS can be reused for plotting similar maps, which makes the process of mapping more effective and fast. Along with open source availability and integration with GDAL/PROJ libraries and Python, it is one of the serious advantages of the GRASS GIS over the traditional commercial GIS.

Results and Discussion

The topographic and ice shelf maps were visualized using GRASS GIS for investigation of the geophysical settings of the region using scripting cartographic approach. Existing maps from previous studies played a critical role in visualizing Antarctic geology and geomorphic landforms, geologic modeling (*e.g.* basal ice age) and study of hydrosphere and cryosphere of the Southern Pole. However, the novelty of the present study is the new technical approach in GIS mapping by shell script without GUI. Such approach improved the methodological techniques of GIS, intended to contribute to the existing studies and add new results by visualizing thematic maps by high-resolution datasets on geo-

physical, geological (sediments), topographic and glaciological data.

The inspection of the data demonstrates following findings. The grid visualizing bed topography in Fig. 1 (r.info bedmap2_bed) shows the data range from -7,054 up to 3,972 including both bathymetric and topographic values. The complexity of the topographic settings formed as a result of long-term geologic and tectonic evolution of the continent is well reflected in its modern relief. The topographic elevations in Antarctica are largely controlled by the tectonic plate dynamics and the processes of their subduction and mass distribution. Fig. 1 shows the modern relief map of the Antarctica.

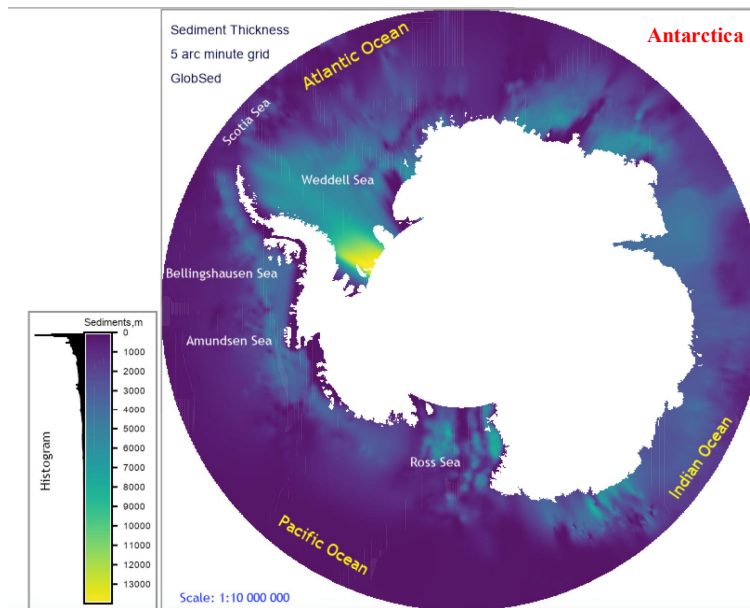


Fig. 6. Sediment thickness in Antarctic region. Mapping: GRASS GIS.

The map of the bed topography in Fig. 2 shows data distribution from 0 to 4,621 m which shows a subglacial topographic model of Antarctica. The inspection of grid showing surface topography in Fig. 3 (r.info bedmap2_surface) shows the data

range from 1 to 4,082 m heights. Therefore, the asymmetric distribution of the topography in West and East Antarctica mirrors general distribution of the continental and oceanic lithosphere types. East Antarctica and the Transantarctic Moun-

tain belt have higher elevation values while West Antarctica is notable by lower topographic heights, as can be noted in Fig. 3.

The bed map uncertainty in Fig. 8 reveals the unknown information on bed map data distribution and data coverage (certainty/uncertainty) corresponding to the grid of the Bedmap2 project (m). The ice shelves mask data distribution in Fig. 5 shows the present-day high-resolution ice map of the Antarctic ice sheet in the shelf areas with defined three data types: 0=grounded, 1=ice shelf, and the rest is the ocean. The isolines shown in grey refer to the elevations of the topographic relief.

The map of sediment thickness in Antarctic in Fig. 6 reveals the significant increase of the sediments in the Weddell Sea

which can be explained by the presence of the Ronne Ice Shelf largely contributing to the sediment accumulation and re-distribution in the shelf zone. Compared to other data from the published studies, analysis of the sediment distribution enables to better understand the ice sheet evolution and sedimentation history in Antarctica. Thus, total sediment volume in the Weddell Sea deep-sea basin is estimated by Lindeque et al. (2013) at $3.3\text{--}3.9 \times 10^6 \text{ km}^3$. According to findings of Rogenhagen and Jokat (2000), sediment thickness in the western Weddell Sea ranges from 4.8 ± 0.3 to $7.3 \pm 0.3 \text{ km}$, but is rather uniform in the eastern continental margin of the Antarctic Peninsula (ca. $52^\circ\text{--}35^\circ\text{W}$).

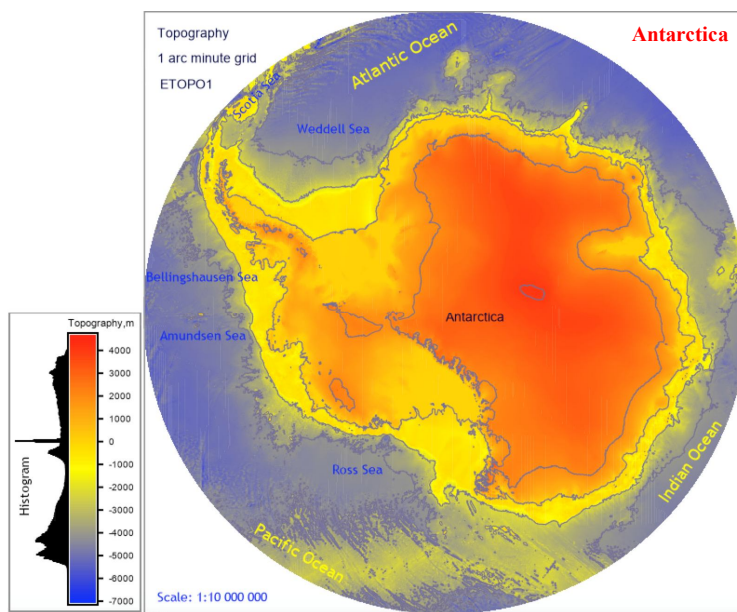


Fig. 7. ETOPO1 topography in Antarctic region. Mapping: GRASS GIS.

Previous studies also proved that the unique sedimentation environment of the SE Weddell Sea is explained by a large catchment area and fast paleo-ice streams that feed the Filchner Ronne Ice Shelf (Huang and Jokat 2016, Lemenkova 2021b). Other factors include turbidity/bot-

tom currents and sea level changes. They furthermore detected the sinuous, NE-SW-oriented turbidity-contourites that correlate with bathymetric highs over 150 km wide, 700 km long, and sediment thickness of up to 2 km. The Cretaceous proto-Weddell Gyre bottom current contributed to the sed-

iment accumulation as detected by the thick (up to 1130 m) pre-glacial seismic units which form a mound in the central Weddell Sea basin and in conjunction with the eroded flank geometry (Lindeque et al. 2013).

Sediment thickness and sedimentation rates are calculated and gridded using multichannel seismic reflection transects by Huang et al. (2014). They shown that

the pre-glacial deposition with thicknesses of up to 5 km was controlled by the tectonic evolution and seafloor spreading besides the terrigenous sediment supply. The data shown a high sedimentation rate in the Weddell Sea with thicknesses of up to 3 km. This may be caused by the formation of the East Antarctic Ice Sheet, which moved to the coast or inner Antarctic shelf (Huang et al. 2014).

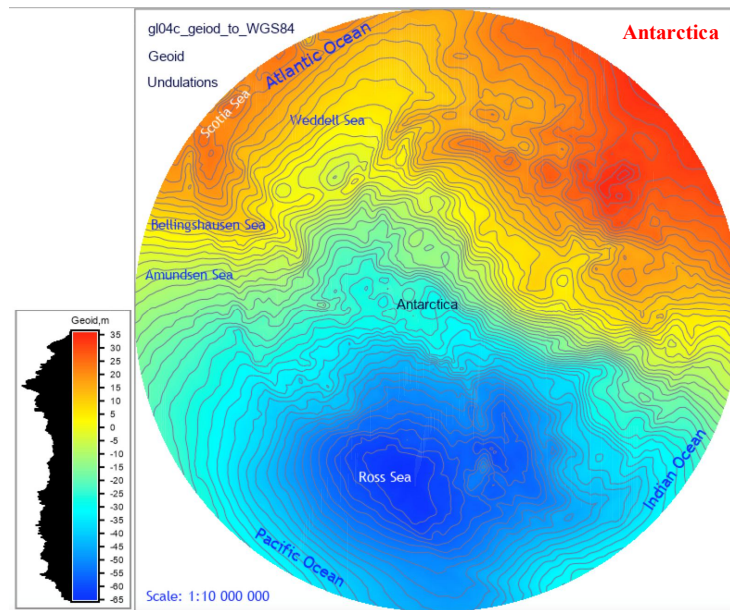


Fig. 8. Grounded bed uncertainty in Antarctica. Mapping: GRASS GIS.

The maximal values here reach up to 14,000 m of thickness according to the GlobSed5 project. The Ross Sea shows lesser amount of sediments though considerably higher comparing to the other seas of the Southern Ocean with the maximal values reaching 9,000 m. Both depressions of the Ross and Weddell seas have been isostatically readjusted and filled with deposited sediments which proves correlation between the topographic patterns affecting sediment distribution along with regional glacial settings.

The topographic map of Antarctic shown in Fig. 7 is based on the ETOPO1 project

with 1 arc min resolution grid. It is plotted using the modeled data of known topography and bathymetry, based on the ETOPO1 topographic compilation (Aman-te and Eakins 2009). The maps show the Antarctic topography with the isolines plotted every 2000 m and sidewise histogram on data distribution. The map of geoid undulations in Fig. 4 depicts the geophysical measurements performed in Antarctica and compiled in the Bedmap2 project. It is based on the high-resolution global mean gravity field model of the EIGEN-GL04C, derived from the combination of satellite tracking and surface data.

The model shows a combination of GRACE (Gravity Recovery and Climate Experiment, a joint mission of NASA and the German DLR) and LAGEOS (Laser Geodynamic Satellite) mission, gravimetry and altimetry surface data. The data show the rough sub-division of Antarctica into two large regions: the region with higher values from -15 to 35 m (corresponds to the northern part of Antarctica, Weddell

Sea and the south Atlantic Ocean, compare Fig. 1 and Fig. 4) and a region with lower values from -15 to -65 which corresponds to the very low negative values of geoid. This region includes the Ross Sea, South Pacific Ocean and south Indian Ocean. The variations in the data can be explained by the geophysical settings of the gravity anomalies in South Pole.

Conclusions

This paper presented an example of plotting series of the thematic maps of Antarctica using GRASS GIS based on open geophysical and topographic datasets. The compilation of the high-resolution datasets provides new insights into the topographic structure of Antarctica. It furthermore shows that a new approach of scripting cartographic workflow performs more effectively to create a series of maps than using traditional commercial GUI-based GIS with often perplexed interface. The scripting based cartography has a straightforward syntax which is user-oriented and direct in mapping techniques.

The attempts of combining logic of programming languages and machine learning approaches to cartography resulted in several outputs such as *e.g.* combination of machine learning classifiers along with GIS techniques (Motta et al. 2021), AWK language for processing tables from geo-data through conversion and formatting (Lemenkova 2019e), modeling links between environmental, biodiversity and climate change impacts (Walther and Huettmann 2021), integration of GRASS GIS, Python, TeX language, or artificial neural networks for geological engineering modeling (Bragagnolo et al. 2020, Lemenkov and Lemenkova 2021b), to mention a few of them.

Moreover, the use of coding marks the onset of scripting era in cartography that significantly facilitate mapping proc-

ess through fasten coding and absence of complex GUI with often useless and very specific functionality as in traditional GIS software. The main advantage of the shell scripts in cartography consists in their flexibility which is achieved in controlling utilities, using modules with their attributes (set up as 'flags'). The combination of the GRASS GIS codes in a script results in an effective and smooth mapping process that can be repeated for any other territories using flexible move of the coordinates and projecting transformations. A command syntax embedded in GRASS GIS offers a uniform shell programming structure within applications in a variety of tools in geospatial analysis, as demonstrated in this paper with a case study of Antarctica.

The high-resolution data from available sources (Bedmap2, *etc*) were processed and visualized to plot detailed maps of ice thickness and bed subglacial topography of Antarctica. The presented maps are accompanied with the scripts developed in GRASS GIS and described in Methodology section in detailed for repeatability. New cartographic visualization helps to gain a better understanding of the surface of the Antarctic topography in the regional studies on polar research, as well as the geophysical and glacial studies of the surrounding area which include sea of Antarctica.

Overall, the evolution of the Antarctic ice sheet thickness was fluctuating and mostly controlled by climatic drivers such as CO₂, and sea level forces with a period of ca. 100,000 yr. However, changes in ice sheet volume include a complex interplay of global and local, climatic, environmental and tectonic factors in Late Quaternary Antarctic ice sheet evolution (Tighe et al. 2018, Beltran et al. 2020, Halberstadt et al. 2021). Recently, the Antarctic ice sheet has been experiencing retreat and thaw. For example, the Reedy Glacier (southern Transantarctic Mountains) was significantly thicker multiple times during the mid-to-late Cenozoic, and the West Antarctic Ice Sheet was at least 500 m higher than today, as reported by Bromley et al. (2010). Furthermore, as reported by Hogg et al. (2017), the Antarctic ice shelves have retreated and suffered collapse in the period of 2010 to 2017. However, comparison of spatial variations shown that ice losses from West Antarctica are compensated by ice gains in East Antarctica. This resulted in the thickening of the ice shelves in Antarctica by an average of 1.3 m in the past two decades (Hogg et al. 2021).

This study demonstrated the ice sheet current view using recent data and modern

tools. The use of shell scripting in cartographic studies have only recently been actively used and this paper contributes to the technical advances of the mapping methodology. It should be also stressed that all the maps are made using available datasets and open source software which is valuable both for researchers and students with research in Antarctica and Southern Ocean. Examples of scripting cartography should include the Generic Mapping Tools (GMT) a cartographic scripting toolset widely used in geophysics. Lemenkova (2019c, d) undertook a cross-sectional survey of the submarine geomorphology of the selected deep-sea trenches and carried out a comparative analysis of their bathymetry in various regions of the Pacific Ocean using GMT scripting. The GRASS GIS, in contrast with GMT, has a graphical user interface (GUI) which enables to operate with data both from the console and using traditional GUI. Other differences between the two programs consists in GRASS having more functionality on remote sensing data processing (including satellite imagery) and spatial analysis (terrain geomorphometric analysis), while GMT is by far the best cartographic toolset for geophysical research and mapping.

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Machine learning-based field geological mapping: A new exploration of geological survey data acquisition strategy

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Human-computer interaction

ABSTRACT

Geological mapping, as the fundamental core of geological research and investigation, provides indispensable basic understanding and exploration data for mineral prospecting, disaster prevention and control, and other related fields. The emergence of big data algorithms and models, such as machine learning and deep learning, has brought new assistance to the task of geological mapping. By utilizing these advanced technologies, long-term accumulated exploratory data has been deeply mined and analyzed, significantly enriching the information obtained through conventional mapping methods and laying a solid foundation for subsequent research. However, challenges faced by machine learning in the field of geological mapping are gradually being recognized: the vast demand for data volume, interference from irrelevant information, the “black box” problem, limitations in computing power, algorithm applicability, and data security, among others. To address these challenges, this study takes the Duolong mineral district, Tibet, China, a region with a high degree of exploration, as an example, assuming it to be a blank area without mapping, and attempts to integrate the light gradient boosting machine (LightGBM) algorithm into the field geological mapping process. Firstly, based on remote sensing data, the distribution of alteration was identified to design the initial mapping route. Subsequently, geological units along the route were labeled, and the model was trained using geochemical sampling point data and remote sensing data as feature inputs. During the model prediction stage, the probability distribution obtained through the Softmax function was utilized to guide the subsequent design and planning of field mapping routes. After five iterations, based on field mapping that covers 20% of the entire area, 90% of the lithological units were successfully predicted. This study explores an effective combination of machine learning algorithms with field geological mapping that establishes a new method for field geological mapping based on machine learning. It not only improves the efficiency and accuracy of mapping but also provides a new strategy for balancing geological work with structured data acquisition.

1. Introduction

Geological mapping is an essential component within the field of geology, involving a systematic examination and analysis of geological features, structures, and formations (Cracknell and Reading, 2014; Miao et al., 2023; Pan et al., 2023). The primary objectives encompass identification and precise location determination of various rock types, minerals, fossils, and other geological features present in a specific region (Qiu et al., 2023). The valuable information serves to comprehend historical development and evolution of Earth's crust over time. By providing comprehensive and detailed information regarding the geological structure and composition of a specific area, it aids in

identifying potential mineral deposits and predicting their distribution (Jessell et al., 2021; Tang et al., 2023; Wang et al., 2018, 2022; Wang and Zhu, 2022). Through geological mapping, geologists can analyze the rock formations, faults, folds, and other features indicative of mineral presence. These geochemical properties of rocks and soils are further examined to ascertain the presence of elements or compounds associated with specific types of minerals (Wang et al., 2017b; Xiang et al., 2014). Additionally, geological mapping not only facilitates identification of potential mineral deposits, but also enhances precision and reliability of existing models by providing more precise data regarding the location and extent of known deposits (Cheng, 2007; Liu, 2022; Wang et al., 2015b). That can be utilized to update models and enhance

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their predictive capabilities. In the past few decades, both industry and academia, supported by governments worldwide, have been committed to providing comprehensive geological information. They have developed a diverse range of strategies to create all-encompassing geological maps that cover the vast majority of regions. These strategies involve utilizing advanced technologies, such as remote sensing and satellite imagery, to gather accurate data on various geological features (Chen and Zhang, 2022).

The accuracy and reliability of these maps are ensured through geological mapping expeditions to diverse terrains, such as mountains, deserts, and coastal areas (Chen et al., 2022). During these expeditions, meticulous observations and documentation of rock formations, sedimentary layers, fossils, mineral deposits, and other significant geological features are conducted. Specialized tools such as compasses, GPS devices, rock hammers, and cameras are broadly employed to accurately record field findings. Samples from the field or drilling cores from boreholes are then analyzed in state-of-the-art laboratories using advanced methodologies and techniques (e.g., petrography, geochemistry, paleontology, and geochronology) to determine composition, structure, and age of rocks and minerals found in each region (Zhang et al., 2023; Zhao and Chen, 2021). These analyses yield invaluable insights into the historical development and evolution of a region's geology. Furthermore, geological mapping consistently enhances its techniques by incorporating cutting-edge advancements in technology. The integration of field observations with existing maps and satellite imagery datasets obtained through remote sensing techniques such as LiDAR or aerial photography is crucial in modern geological mapping (Harris and Grunsky, 2015). For instance, the implementation of Geographic Information Systems (GIS) software facilitates the integration of multiple layers of data into geological maps. By utilizing GIS algorithms and models to integrate these diverse datasets, comprehensive and accurate topographic variation maps can be generated. In summary, the fieldwork of geological mapping coupled with laboratory analysis and data integration techniques generates intricate maps that offer a more comprehensive understanding of various factors influencing geology, including topography, hydrology patterns, seismic activities, and mineral resource distribution (Atta, 2023).

The flourishing of geological mapping theory and methodology worldwide has resulted in the rapid accumulation of related exploratory data, posing new challenges in data governance and management. Effectively utilizing and manipulating these “big data” has become a pressing focus within the geological mapping community. The application of machine learning (ML) techniques in geological mapping has emerged as a promising approach in recent years, enhancing the efficiency and accuracy of data acquisition strategies (Demir et al., 2010; Wang et al., 2021). These innovative methods utilize advanced algorithms and computational models to analyze large volumes of geological survey data, enabling geologists to gain valuable insights into the subsurface structure of the Earth. The field of mineral prospectivity prediction has witnessed significant advancements across multiple domains in previous research. State-of-the-art ML algorithms such as attention-based convolutional neural networks and Bayesian Decomposition have played a pivotal role in enhancing mineral prospectivity prediction, showcasing superiority over conventional methods (Li et al., 2023a; Mao et al., 2023). The integration of three-dimensional geological modeling with mineral prospectivity mapping has garnered increasing attention due to its ability to visually depict the spatial relationship between prospective domains and surrounding geological bodies (Li et al., 2022; Li et al., 2023b; Wang et al., 2024). Researchers have improved user-friendliness by integrating mineral prospectivity prediction workflows into widely used geological survey tools like ArcGIS (Brandmeier et al., 2020) or developing dedicated standalone tools for this purpose (Zuo et al., 2024). Overall, ongoing research in the field of mineral prospectivity prediction aims to enhance model predictive performance and interpretability while improving the intuitiveness and usability of both the prediction process and results (Zuo and

Carranza, 2023).

The application of ML methods in geological data analysis has achieved remarkable advancements in map accuracy, efficiency, and other critical aspects (Gasmi et al., 2016; Pan et al., 2023; Wang and Cheng, 2008). In terms of dimensionality reduction, state-of-the-art ML algorithms demonstrate exceptional prowess in reducing the complexity of voluminous geological datasets. These algorithms meticulously extract the most representative features, enhancing computational efficiency and precision in data processing. Furthermore, ML automates the intricate process of processing and interpreting geological data, ultimately minimizing the requirement for manual intervention. This automation enables generation of more precise maps in a fraction of the time, leading to optimized decision-making and resource allocation in mining and exploration industry. In the domain of classification and clustering, ML algorithms demonstrate remarkable capability to classify and organize geological data (Song et al., 2022). They facilitate the assembly of similar geological samples into distinct clusters, aiding in comprehensive understanding of distribution patterns and inherent characteristics associated with diverse types of geological bodies. These algorithms can be fine-tuned to automatically recognize and categorize diverse geological features in imagery and remotely sensed data (Xiang et al., 2014). This automation significantly reduces manual interpretation time and effort while enhancing feature identification accuracy and consistency. Moreover, in the realm of predictive analysis, ML algorithms demonstrate remarkable predictive capabilities regarding geological data. They can forecast spatial distributions of mineral resources or anticipate occurrences of geological disasters by analyzing historical data on mineral occurrences and associated geological features (Eskandari et al., 2023). These algorithms discern patterns and trends that enable more focused exploration efforts in unexplored regions, paving the way for more effective resource development. In conclusion, the integration of ML in geological mapping has revolutionized numerous aspects of the field (Wang et al., 2023). It has empowered mapmakers with powerful tools that automate time-consuming and error-prone tasks, enabling them to produce more accurate maps in a fraction of the time. The application of ML in geological mapping holds immense potential for further advancements and revolutionizing the field in the years to come.

While ML methods offer numerous advantages in geological mapping, it is crucial to be aware of their limitations and take appropriate measures to address them. Firstly, regarding data requirements, ML algorithms often require large amounts of data for training, yet geological data can be limited and difficult to acquire. This may result in models lacking generalizability to broader geological settings (Achu et al., 2022). Secondly, feature extraction from geological data can be challenging due to presence of noise and irrelevant information. Manual feature extraction requires expertise and may miss important information. Thirdly, traditional ML models such as decision trees and random forests provide some interpretability, but deep learning models often lack transparency, presenting a “black box” challenge. This can be problematic in geological mapping, as clarifying the model's decision-making process is essential for better understanding the geological context. Fourthly, processing and analyzing geological data often demands significant computing resources, including high-performance computers and large-scale storage systems. These resources may not be easily accessible to all geological research teams. Fifthly, selecting appropriate ML algorithms for a particular geological mapping task can be challenging, as different algorithms may be suitable for different geological data and objectives (Kumar et al., 2023). Finally, regarding data privacy and security, geological data may contain sensitive information such as location and mineral resources. It is crucial to protect sensitive information from unauthorized access or disclosure when using ML methods. In conclusion, while ML methods offer significant potential in geological mapping, it is essential to address these challenges to realize their full potential in this field. By considering these issues and taking appropriate measures to address them, ML can enable

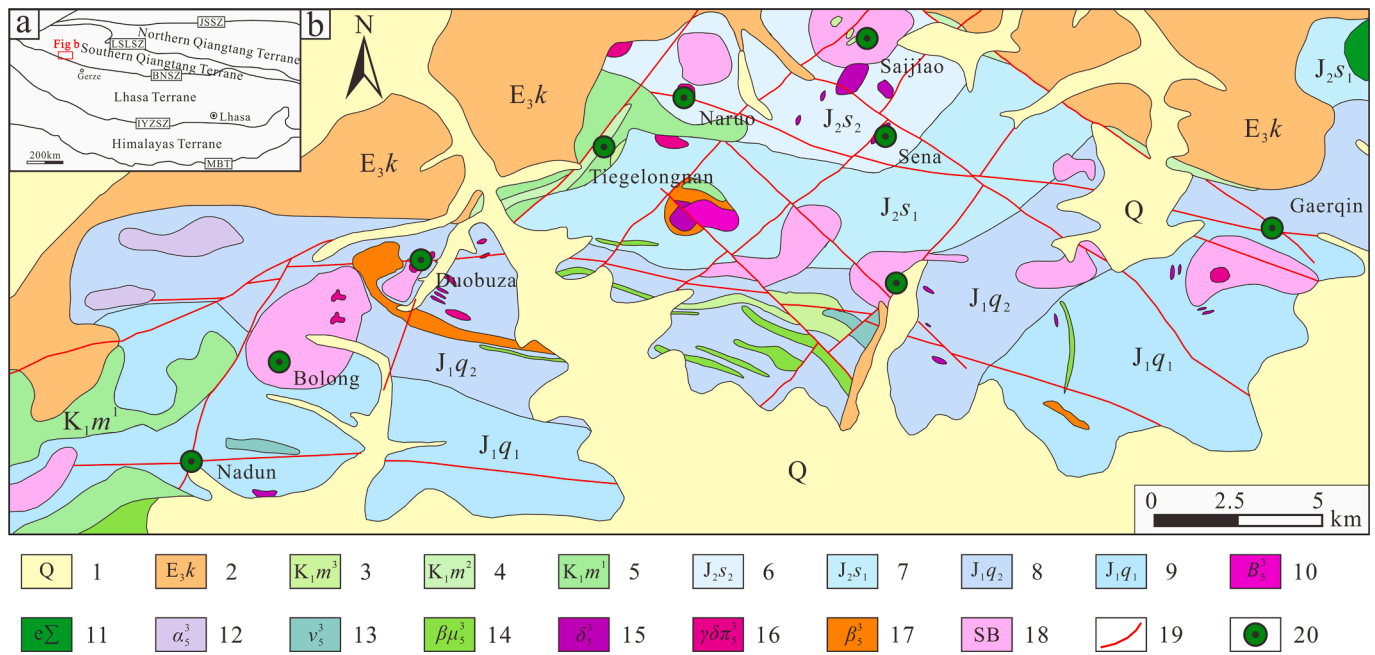


Fig. 1. Tectonic framework of Tibetan (a) (Zhu et al., 2011) and lithologic geological map of Duolong mineral district (b) (Ji et al., 2021). JSSZ: Jinshajiang suture zone. LSLSZ: Longmuco-Shuanghu-Lancangjiang suture zone. BNSZ: Bangongco-Nujiang suture zone. IYZSZ: Indus-Yalung Zangbo suture zone. MBT: Main Boundary thrust. 1: Quaternary residual slope deposits. 2: the Upper Oligocene Kangtuo Formation sandstone conglomerate. 3: Volcanic breccia in the upper member of the Lower Cretaceous Meiriquieuo Formation. 4: Volcaniclastic rock in the middle part of the Lower Cretaceous Meiriquieuo Formation. 5: Andesitic porphyrite and andesitic basalt in lower member of the Lower Cretaceous Meiriquieuo Formation. 6: Metamorphic quartz sandstone and metamorphic feldspar quartz sandstone in upper member of the Middle Jurassic Sewa Formation. 7: Metamorphic feldspar quartz sandstone is interspersed with metamorphic quartz siltstone in lower member of the Middle Jurassic Sewa Formation. 8: Metamorphic quartz sandstone in upper member of the Lower Jurassic Quse Formation. 9: Silty slate in lower member of the Lower Jurassic Quse Formation. 10: Volcanic breccia. 11: Serpentinized Peridotite. 12: Andesite. 13: Gabbro. 14: Diabase/Dolerite. 15: Diorite. 16: Granodiorite porphyry. 17: Basaltic andesite. 18: Altered rock. 19: Faults. 20: Deposits.

more accurate, efficient, and transparent geological mapping practices in the years to come.

Although ML has the capability to automate various aspects of field geological mapping, traditional field mapping remains a fundamental aspect of the discipline. It is crucial for understanding geological structures, mapping mineral resources, and studying environmental changes. It should always receive attention. Moreover, it is important to recognize limitations of ML methods applied in geological mapping. Striking a balance between traditional field mapping and utilization of ML methods is a critical aspect that requires rigorous consideration. Therefore, this study proposes a novel ML-based geological mapping model that integrates the light gradient boosting machine (LightGBM) method into the field mapping workflow in the Duolong mineral district, Tibet, China. Furthermore, a new exploration strategy for acquiring geological survey data will be introduced, encompassing multiple steps such as data collection, deployment, feedback, collaboration, and continuous learning. The modeling process unlocks new possibilities for enhancing efficiency, accuracy, and knowledge discovery in geological mapping and mineral exploration.

2. Study area and exploratory data

2.1. Geological background

The Duolong mineral district, situated on the southern margin of the Southern Qiangtang terrane, stands out as the most prominent porphyry Cu-Au deposit uncovered within the Bangongco-Nujiang metallogenic belt (Fig. 1a) (Qu and Xin, 2006; Tang et al., 2016; Zhu et al., 2011). The Bangongco-Nujiang suture zone (BNSZ), a vast geological feature traversing the Tibetan Plateau, extends from Bangongco westward, crossing Yunnan, and reaching as far as the Indochinese Peninsula spanning over 3000 km in length. Previous geological investigations

have firmly established that this suture zone marks the closure of the Bangongco -Nujiang Ocean (BNO) (Zhu et al., 2013), an event that has been a pivotal focus of research in the Tibetan Plateau. Evidence suggests that the initial stage of the BNO's disintegration can be traced back to the early Permian epoch (Metcalfe, 2013). This conclusion is supported by the presence of a divergent unconformity observed between the Upper Triassic flysch and the underlying ophiolite in the Baila area (Chen et al., 2005). Subsequently, during the Middle-Late Jurassic period, the BNO underwent expansion. This period was characterized by northward subduction, which triggered the formation of numerous intermediate-acidity intrusive bodies along the southern margin of the Southern Qiangtang terrane (Li et al., 2014; Shi et al., 2008). Consequently, a distinct continental-margin tectonic-magmatic arc emerged, spanning from Bangongco to the western reaches of the Nujiang River. However, despite extensive research, the timing of the BNO's closure remains a topic of debate. Initial hypotheses suggested that the event occurred during the Late Jurassic-Early Cretaceous period (Kapp et al., 2005; Zhu et al., 2013). In contrast, more recent geochronological investigations focusing on ophiolite and radiolarian fossils indicate a closure timeframe of approximately 100 Ma (Baxter et al., 2009; Liu et al., 2014; Zhang et al., 2012). This ongoing discussion highlights the complexity and evolving understanding of the geological history of the Tibetan Plateau and its adjacent regions.

The Duolong mineral district displays a prominent east-west trend, and it has been the site of multiple notable discoveries of porphyritic-epithermal and crypto-explosion breccia tube deposits (Ji et al., 2021; Li et al., 2012; Tang et al., 2016; Tang et al., 2021). Specifically, deposits like Naruo and Tiegelongnan have been identified as primarily forming between 116 and 122 Ma, marking a significant period of mineralization in the regional evolution (Tang et al., 2014). The rich endowment is further underscored by substantial copper reserves, which have been confirmed to exceed 20 million tons. As a result, the Duolong mineral

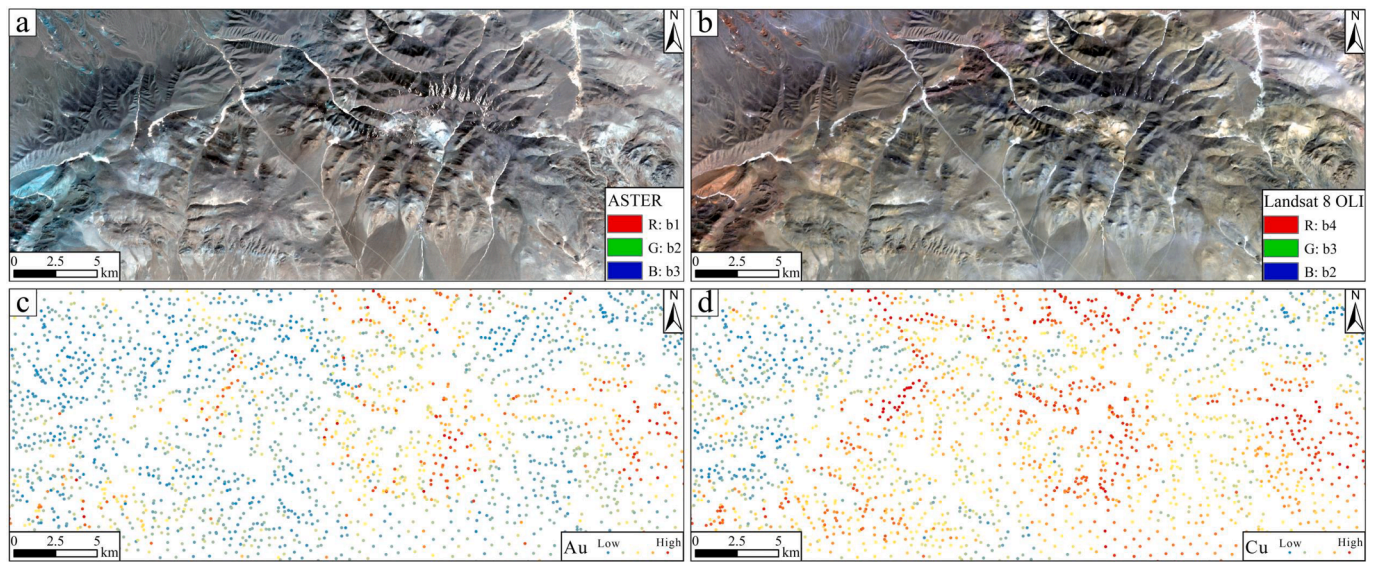


Fig. 2. Geo-exploratory datasets utilized in the current study. **a:** ASTER data. **b:** Landsat 8 OLI. **c:** Geochemical distribution of Au. **d:** geochemical distribution of Cu.

district has gained national and international prominence, establishing itself as the first world-class super large-scale copper–gold mineral district in China (Tang et al., 2016; Tang et al., 2021).

The Duolong mineral district is notably distinguished by the sequential deposition of Mesozoic marine sedimentary strata, overlaid extensively by Tertiary and Quaternary sediments. Stratigraphically, the district exposes a vertical succession encompassing the Lower Jurassic Quse Formation (J_1q), Middle Jurassic Sewa Formation (J_2s), and Lower Cretaceous Meiriquiecuo Formation (K_1m). These Paleozoic strata are capped by gravelly deposits of the Upper Oligocene Kangtuo Formation (E_3k) and Quaternary (Q) residual slope sediments (Fig. 1b) (Ji et al., 2021).

The Quse Formation, predominantly oriented northeastward, represents a sub-abyssal continental shelf environment characterized by flyschoid sedimentation. Lithologically, it is composed predominantly of feldspathic quartz sandstone, epimetamorphic argillaceous sandstone, intercalated mafic volcanic rocks (dated at 141–143 Ma) (Li et al., 2011b), and siliceous rocks. The overlying Sewa Formation, primarily distributed in the northern and northwestern sectors of the district, is composed of dark gray flagstones with interbedded sandstone layers. Partial metamorphism within the siltstone fraction has given rise to slate formation. Both the Quse and Sewa Formations exhibit conformable contacts, serving as pivotal wall rocks within the district's geological framework.

The Meiriquiecuo Formation represents a continental calc-alkaline volcanic sequence marked by multiple eruption-deposition cycles. This formation is attributed to the deposition of volcanic ejecta derived from terrestrial eruptions, encompassing a range of lithologies including andesite, andesitic diabase, and rhyolitic tuff. SHRIMP zircon dating of dacite yields an age of 111.1 ± 1.4 Ma (Li et al., 2011a), implicating its origin from a northward-dipping subduction margin arc that extends from Bangong Lake to Nuijiang (Wang et al., 2015a). These volcanic strata, exhibiting irregular and nodular distribution patterns, are widely superimposed upon sedimentary deposits such as the Tiegelongnan and Duobuzha formations, thereby playing a pivotal role in preserving mineralization within the district.

The Kangtuo Formation, predominantly distributed in the northeastern and northwestern regions of the district, is primarily composed of conglomerates and red mudstones. Quaternary residual slope sediments, predominantly composed of sandstone and siltstone, are primarily confined to the southern and northwestern gully areas of the district. This spatial distribution of sediments reflects the district's complex geological history and ongoing geomorphic processes.

The Duolong mineral district has undergone significant tectonic activity, characterized primarily by the development of fault structures, predominantly concealed faults, and localized fold structures that are observable. The fault structures exhibit characteristics of long-term and multi-stage secondary deformation, displaying a diamond-shaped structural framework oriented in the northeast direction as well as orientations in the northeast-west and near-east-west directions (Liu et al., 2017). Among these faults, the NE faults are identified as the primary ore-controlling structures within the ore concentration area with several deposits discovered along their traces.

Under the influence of intense tectonic processes, frequent magmatic activity occurs in the study area, resulting primarily in intermediate-acidity intrusive rocks, while mafic dikes are extensively developed within the middle Jurassic strata. The intermediate-acidity intrusive rocks primarily consist of granodiorite porphyry, diorite porphyry, and granite porphyry. These rocks exhibit elevated levels of calcium, potassium, and alkaline characteristics with a diagenetic age concentrated between 120 and 105 Ma (Li et al., 2014; Li et al., 2017; Lin et al., 2016; Lin et al., 2017; Wei et al., 2018). The granodiorite porphyries of the early Cretaceous, which intrudes the Quse and Sewa formations, are distributed along the northeast fault structure and serves as the primary rocks responsible for ore concentration in this area. Mineralization between 130 and 110 Ma (Lin et al., 2019) is associated with the northward subduction of BNO (Wang et al., 2015a). The mafic dikes, mainly consisting of gabbro, diabase, and pillow basalt, exhibit a predominant east-west orientation and display characteristics of alkaline and tholeiitic basalts. Volcanic rocks comprise a series of basalt-basaltic andesite assemblages that form the Lower Cretaceous Meiriquiecuo formation.

2.2. Geo-exploratory data

In the present study, the primary focus lies on machine learning-based geological mapping in an unexplored region, accompanied by introduction of a novel strategy for exploratory data acquisition. Within the scope of this study, it is crucial that the study area remains unexplored and devoid of any preliminary data. The Duolong mineral district has undergone extensive exploration and research, resulting in a wealth of geological knowledge and exploratory datasets. Consequently, it serves as an ideal area to demonstrate the modeling process under the assumption that it is unexplored; meanwhile, its existing geological mapping data and other exploratory resources (e.g., 18 lithologic units) can be utilized to validate our current geological mapping strategy.

The current study utilizes exploratory data (Fig. 2), which includes

Table 1

Characteristics of the ASTER and Landsat 8 OLI sensors.

Sensors	Subsystem	Band Number	Spectral Range (μm)	Spatial Resolution (m)
ASTER	VNIR	1	0.520 ~ 0.600	15
		2	0.630 ~ 0.690	
		3 N	0.780 ~ 0.860	
	SWIR	3B	0.780 ~ 0.860	30
		4	1.600 ~ 1.700	
		5	2.145 ~ 2.185	
		6	2.185 ~ 2.225	
		7	2.235 ~ 2.285	
		8	2.295 ~ 2.365	
	TIR	9	2.360 ~ 2.430	90
		10	8.125 ~ 8.475	
		11	8.475 ~ 8.825	
		12	8.925 ~ 9.275	
		13	10.250 ~ 10.950	
		14	10.950 ~ 11.650	
OLI	VNIR	8 (Pan)	0.50 ~ 0.68	15
		1	0.433 ~ 0.453	30
		2	0.450 ~ 0.515	
		3	0.525 ~ 0.600	
		4	0.630 ~ 0.680	
	SWIR	5	0.845 ~ 0.885	
		6	1.560 ~ 1.660	
		7	2.100 ~ 2.300	
		9	1.360 ~ 1.390	
	TIR	10	10.600 ~ 11.190	100
		11	11.500 ~ 12.510	

remote sensing, geological, and geochemical data. Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and Landsat 8 Operational Land Imager (OLI) data, as two highly accessible types of remote sensing data (Table 1), are employed as the primary datasets for geological mapping due to their global coverage in both well-explored and unexplored areas. Geological data at a scale of 1:50,000, including 18 identified lithologic units (Fig. 1), is used to simulate field-collected data for machine learning-based geological mapping, while the actual geological map is utilized to validate the accuracy of current mapping results. Geochemical data at the same scale is also incorporated to simulate geochemical measurements obtained through modern on-site chemical analysis equipment during geological route surveys. Concentrations of 15 trace elements are recorded at each sampling point. According to the national standard of geochemical sampling, a minimum of four samples are required for each 1 km² area in order to ensure a spatial resolution of 1:50,000 for the geochemical data at intervals of 500 m. For more detailed information on the currently utilized geochemical data, please refer to our previous publications (Wang et al., 2017a).

3. Methodology

The new data acquisition strategy for machine learning-based field geological mapping is designed by integrating the LightGBM algorithm with conventional geological survey methods, including field geological route surveys and remote sensing data analysis. The LightGBM serves as the core ML method, while the conceptual modeling process is introduced as follows.

3.1. LightGBM algorithm

The decision tree algorithm (Breiman et al., 1984) is a fundamental machine learning technique that performs classification and/or regression predictions on data by constructing a hierarchical structure of nodes (Debeljak and Džeroski, 2011). Each node represents a feature or attribute and splits the data into different sub-nodes based on the value of that feature until reaching a leaf node for prediction (Charbuty and Abdulazeez, 2021). Despite their interpretability and ease of

implementation, decision trees may suffer from limited performance when dealing with complex datasets. The gradient boosting algorithm was introduced to address limitations of decision trees, thereby enhancing their predictive capabilities by proposing the gradient boosting decision tree (GBDT) (Mayr et al., 2014). GBDT, as an ensemble learning technique, combines multiple weak learners, such as decision trees, to form a strong learner (Friedman, 2001). The fundamental idea is to progressively minimize the loss function by incorporating these weak learners during the learning process (Seto et al., 2022). In each iteration of the gradient boosting algorithm, a new weak learner is trained based on the residuals of the current model and subsequently added to the ensemble. The implementation of GBDT establishes several weak classifiers and reduces the model deviation effectively (Friedman, 2002; Zou et al., 2021). Through iterative training processes, a strong learner is eventually obtained that enables better data fitting and improved prediction performance. The GBDT algorithm achieves high classification accuracy and robustness while effectively handling various types of data (Lin et al., 2022).

Given a training dataset $T = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$, where x is a feature vector, $y = f(x)$ is the target function, and N is the number of samples. Given the loss function:

$$L(y, f(x)) = - \sum_{k=1}^K y_k \log p_k(x) \quad (1)$$

where, K is the number of classes and $p_k(x)$ is the predicted probability of the k^{th} class. A practical application of the GBDT algorithm (Yu et al., 2021; Zou et al., 2021) to analyze complex data is shown as:

(1) The initial step is to train a weak learner $f_0(x)$ using a regression tree in order to minimize the loss function.

$$f_0(x) = \underset{\gamma}{\operatorname{argmin}} \sum_{i=1}^N L(y_i, \gamma) \quad (2)$$

where, γ is a constant.

(2) The next step is to iteratively train additional regression trees. During each iteration, the negative gradient value of the loss function r_{im} , which represents the residuals of sample i , needs to be calculated.

$$r_{im} = - \left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)} \right]_{f(x)=f_{m-1}(x)} \quad (3)$$

where, m (1, 2, ..., M) is the number of training iterations, and $f_{m-1}(x)$ represents the $(m-1)^{\text{th}}$ regression tree.

(3) The predicted dataset and residuals are combined as training data for the next decision tree in order to obtain a new regression tree $f_m(x)$, where each leaf node region is denoted as γ_{jm} ($j = 1, 2, \dots, J$) and J represents the number of leaf nodes of the regression tree m . Subsequently, the best-fit value is calculated.

$$\gamma_{jm} = \underset{\gamma}{\operatorname{argmin}} \sum_{x_i \in R_{jm}} L(y_i, f_{m-1}(x_i) + \gamma) \quad (4)$$

(4) The contributions from all J nodes of the m^{th} classification and regression tree are summed up to provide an additive update to a strong learner.

$$f_m(x) = f_{m-1}(x) + \sum_{j=1}^J \gamma_{jm} I(x \in R_{jm}) \quad (5)$$

where, $I(x)$ is the indicator function, and if $x \in R_{jm}$ then $I = 1$, otherwise $I = 0$.

(5) The final learner (strong learner) is obtained through summation after M iterations.

$$f_M(x) = \sum_{m=1}^M \sum_{j=1}^J \gamma_{jm} I(x \in R_{jm}) \quad (6)$$

The GBDT model, developed in the preceding steps, is commonly

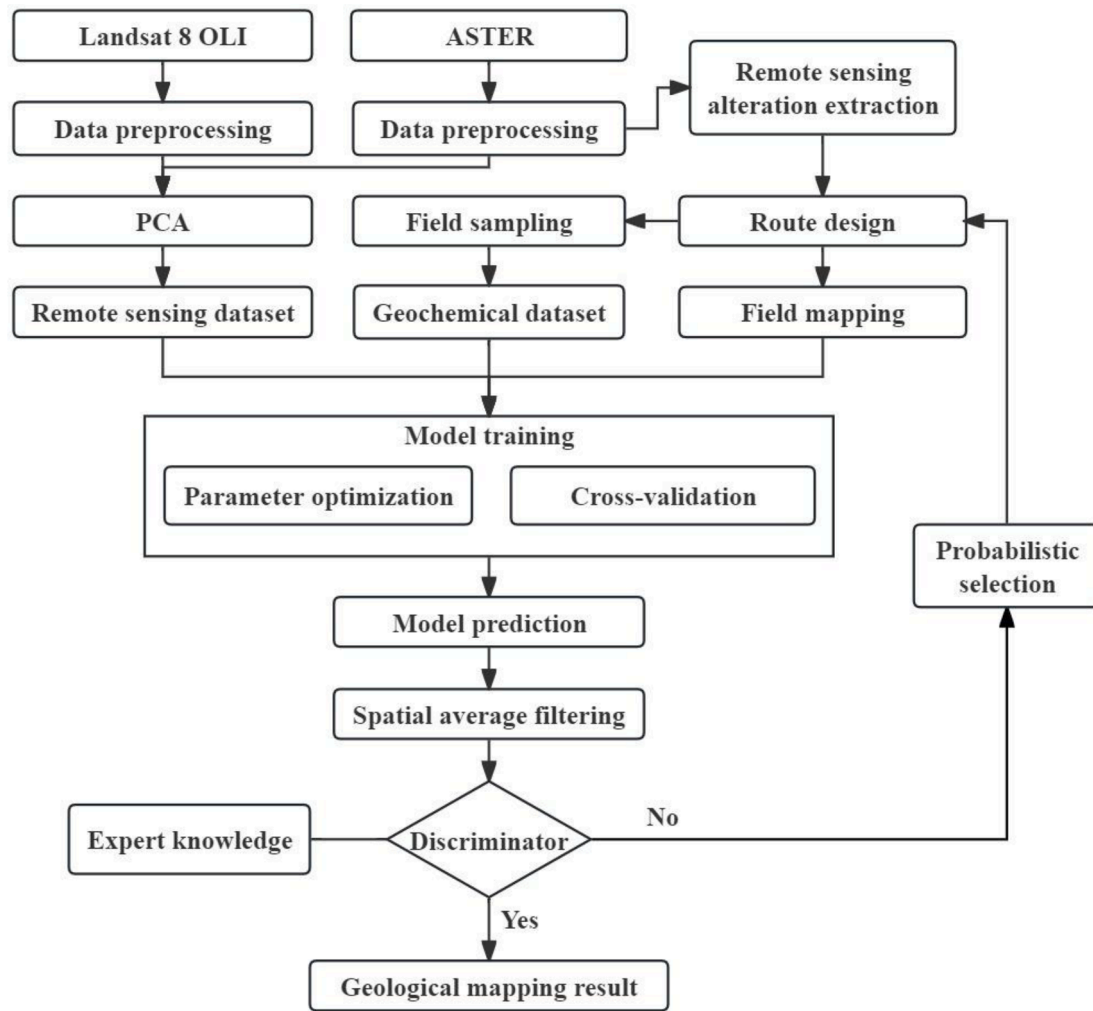


Fig. 3. The technical flow and framework of the current machine learning-based field geological mapping method.

applied to tackle classification problems. In such cases, a normalized exponential function, Softmax, is typically employed to calculate probability values $p_k(x)$ for multiple classification outcomes.

$$p_k(x) = \frac{e^{f_k(x)}}{\sum_{l=1}^K e^{f_l(x)}} \quad (7)$$

where, the predicted probability value of feature vector x being classified into class k (where $k = 1, 2, \dots, K$) is denoted as $p_k(x)$. Ultimately, the model evaluates and compares the predicted values for each category of feature vector x and selects the category corresponding to $p_k(x)_{\max}$ as its final prediction.

The LightGBM algorithm (Ke et al., 2017) is an enhanced model derived from GBDT to address issues such as high memory consumption and slow processing speed. Firstly, LightGBM employs an improved histogram-based segmentation algorithm for efficient traversal of optimal segmentation points, resulting in significant reductions in memory usage and computational costs (Zhang et al., 2019). Moreover, it adopts a leaf-wise leaf growth strategy with depth constraint to strike a balance between ensuring high efficiency and preventing overfitting (Dai et al., 2023; Zhang et al., 2019). Additionally, LightGBM incorporates exclusive feature bundling (EFB) and gradient-based one-side sampling (GOSS) techniques to enhance performance (Song et al., 2021). In summary, the LightGBM algorithm offers faster training speeds with lower memory consumption compared to GBDT, making it well-suited for geological mapping using multiple geoscience data.

3.2. Machine learning-based geological mapping

Conventional approaches to geological mapping primarily employ two strategies for route design. The first strategy is the traverse method, which involves designing field routes that are approximately perpendicular or at oblique angles to strikes of geological bodies or fault traces, thereby traversing various lithological units. This method is particularly suitable for mapping areas with limited lithological variation and uncomplicated structures. The second method is known as the tracing method, which involves designing field routes along boundaries of geological bodies (e.g., rock formations, ore bodies, or structural extension directions). It is commonly utilized for tracking significant geological phenomena and delineating geological bodies.

The LightGBM algorithm is currently utilized in the design of field geological mapping routes and analysis of on-site structured data acquisition, aiming to enhance the accuracy and input–output ratio of conventional geological mapping. The new strategy is illustrated in a schematic flowchart (Fig. 3) and implemented through detailed steps as:

- (1) **Alteration information extraction:** Prior to field mapping, globally available remote sensing data without blind spots are initially employed to extract information on alteration minerals in the area. The spatially diverse alterations can provide initial indications of areas with variations in lithologic units.
- (2) **Initial mapping route design:** Based on identified alteration information, the traverse method is employed as the primary

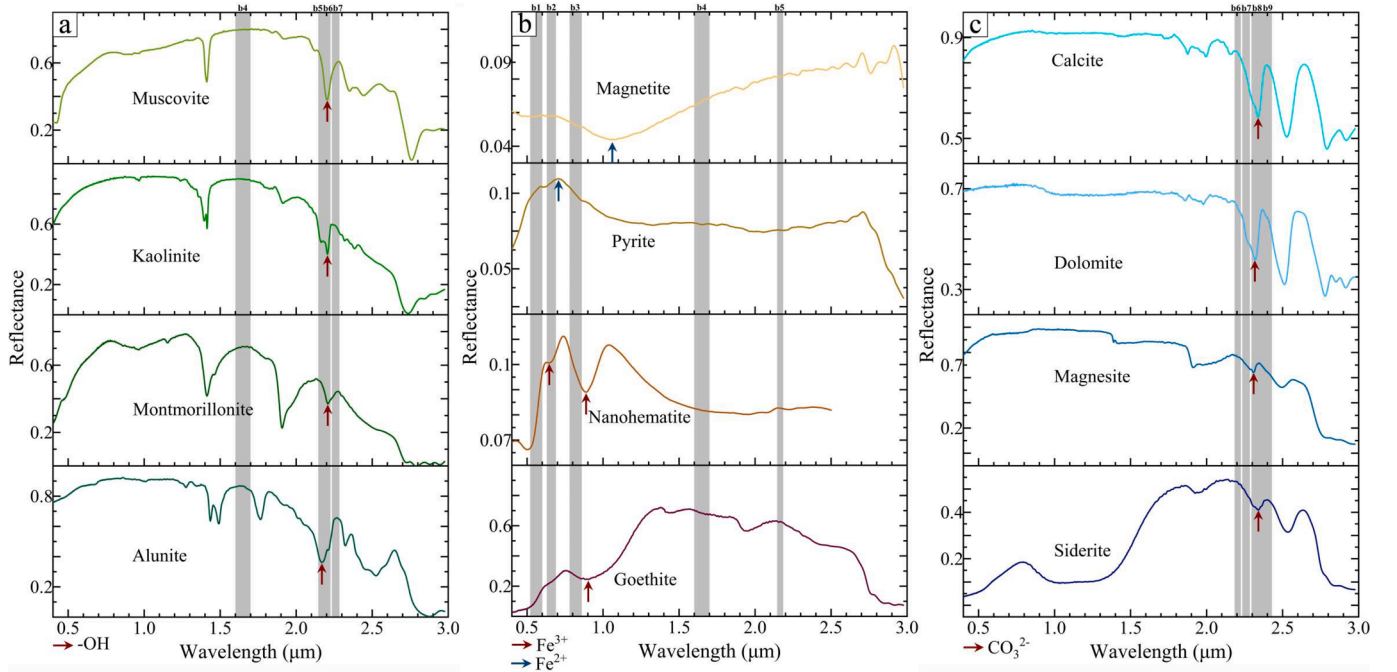


Fig. 4. Spectral curves of typical alteration minerals collected from the USGS spectral library. **a:** Silicate and clay minerals. **b:** Fe-bearing minerals. **c:** Carbonate minerals.

approach, complemented by the tracking method, to establish the initial field mapping routes. In addition to identifying and recording geological units during field mapping, exploratory geochemical samples are collected within a predefined buffer zone along the mapping routes. The concentrations of 15 elements can be measured using advanced on-site equipment. In the context of the current study, lithological units and sampling locations within the buffer zone are selected from the geological map (Fig. 1) and previously collected geochemical data (Fig. 2) to simulate the manipulation of field mapping and on-site chemical analysis.

- (3) **Training and prediction dataset construction:** Principal component analysis (PCA) is employed to reduce the dimensionality of remote sensing data (Bro and Smilde, 2014). The concentrations of 15 elements sampled along the initial field routes are interpolated, providing an initial representation of the geochemical distributions across the entire study area. Subsequently, the feature data is constructed by combining geochemical and remote sensing information. Additionally, geological information such as identified geological units along the field routes can be spatially correlated and connected with their corresponding feature data to generate the training dataset. The exclusion of certain lithologic units along the initial mapping route during the training procedure should be acknowledged; however, additional units will be incorporated as the iteration progresses.
- (4) **Model training and prediction:** Utilizing the aforementioned training data, employ either random search or grid search techniques in conjunction with K-fold cross-validation to optimize the parameters of the LightGBM algorithm and successfully accomplish model training. The LightGBM algorithm is then utilized to generate a classification map and a predicted probability map of geological units within the study area.
- (5) **Iterative mapping:** The predicted probability map undergoes spatial average filtering to mitigate influence of factors that introduce bias, such as noise. A judicious selection of a reasonable probability threshold can be made to define the target area for

subsequent iterative mapping as the region where the prediction probability is below this threshold.

- (6) **Result discrimination:** The subsequent iterative mapping areas should be determined based on the predefined threshold established in step 5. If deemed necessary, the iteration shall continue; otherwise, the geological mapping can be finalized and generate output prediction results. Within the current context, the predicted geological map will be compared with the previously produced geological map to verify the effectiveness of the new strategy.

3.3. Evaluation metrics

The commonly employed evaluation metrics in machine learning-based geological mapping include accuracy (Ac), macro-averaged precision (Pr), recall (Re), and F1-score ($F1$) (Ji et al., 2021). The Accuracy (Ac) represents the ratio of correctly classified samples to the total number of samples, while Precision (Pr_{macro}) indicates the proportion of samples accurately categorized within a specific category by the model's classification. Additionally, Recall (Re_{macro}) signifies the proportion of samples correctly classified in a particular category. Lastly, $F1_{macro}$ is an amalgamation that combines precision and recall into a single metric (Ji et al., 2021). Suppose the confusion matrix G :

$$G = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1K} \\ g_{21} & g_{22} & \cdots & g_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ g_{K1} & g_{K2} & \cdots & g_{KK} \end{bmatrix} \quad (8)$$

The formulas for the four evaluation metrics are presented as follows (Dev and Eden, 2019; Ji et al., 2021):

$$Ac = \frac{1}{\sum_{a=1}^K \sum_{b=1}^K g_{ab}} \times \sum_{a=1}^K g_{aa} \quad (9)$$

$$Pr_{macro} = \frac{\sum_{b=1}^K \frac{g_{aa}}{\sum_{a=1}^K g_{ab}}}{K} \quad (10)$$

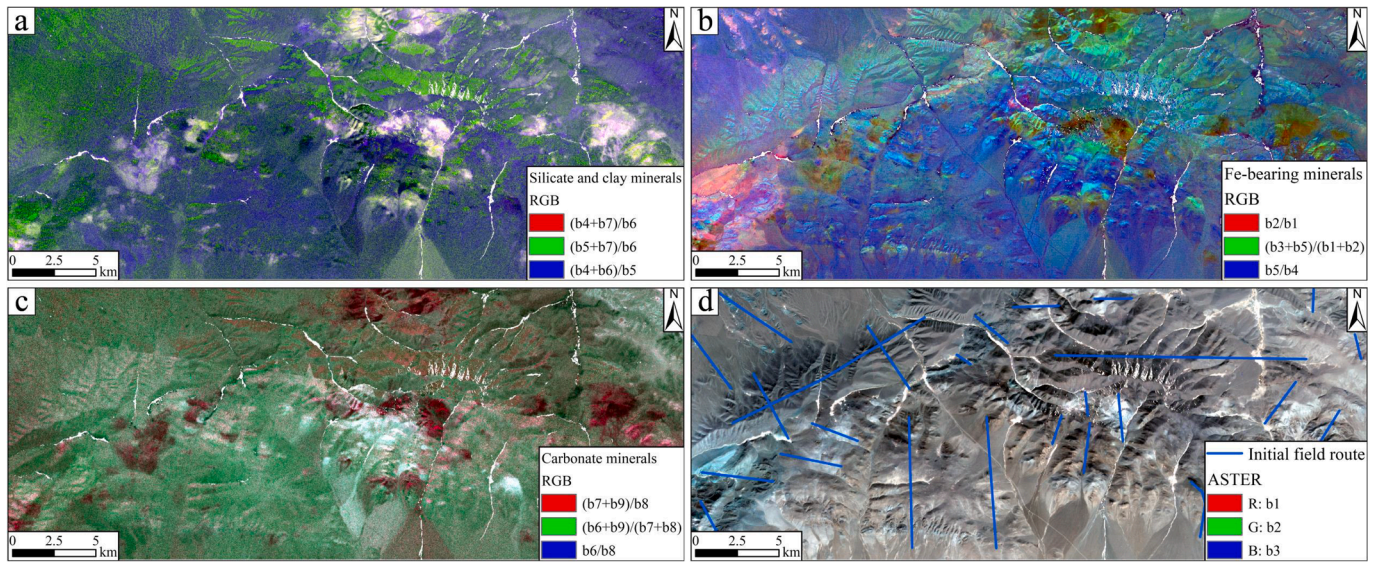


Fig. 5. The typical alterations in the Duolong mineral district were identified through analysis of ASTER data, and the route design was based on these identified alterations. **a:** Silicate and clay minerals. **b:** Fe-bearing minerals. **c:** Carbonate minerals. **d:** The initial field geological route design.

$$Re_{macro} = \frac{\sum_{a=1}^K \frac{g_{aa}}{\sum_{b=1}^K g_{ab}}}{K} \quad (11)$$

$$F1_{macro} = \frac{2 \times Pr_{macro} \times Re_{macro}}{Pr_{macro} + Re_{macro}} \quad (12)$$

where, K denotes the number of classes, g_{aa} represents the count of accurate predictions for samples belonging to class a , and g_{ab} represents the count of instances predicted as class b when they actually belong to class a . Considering the interplay between precision and recall, it may not be meaningful to solely prioritize increasing either precision or recall (Yu et al., 2021). Hence, the current study employs two metrics, namely Ac and $F1_{macro}$, for evaluating geological mapping classification outcomes.

4. Results and discussions

4.1. Alteration extraction

The spectral and spatial characteristics of ground objects in remote sensing images serve as a theoretical foundation for the identification of these objects. In practical applications within geology, identification of minerals and lithological units are closely interconnected. Each mineral exhibits distinct spectral characteristics concerning absorption and reflection peaks, which can be attributed to variations in physico-chemical properties such as crystal lattice structure, elemental compositions, and optical attributes (Hunt, 1977). Each lithological unit comprises diverse minerals (e.g., native elements, halides, oxides and hydroxides, oxyalts), resulting in blended spectral features encompassing reflection, absorption, and emission properties when exposed to electromagnetic waves by its constituent minerals (Clark and Roush, 1984).

A commonly employed technique for alteration extraction is the band ratio method, which effectively enhances spectral information of target minerals and enables their differentiation from other features by leveraging distinctive absorption and reflection bands exhibited in their spectral characteristics (Ninomiya et al., 2005; Sengar et al., 2020). Among 14 bands in the ASTER data, SWIR and TIR bands are widely utilized for lithological identification due to their rich spectral information (Fig. 4) (Kokaly et al., 2017). Since this study assumes that the study area is unexplored, applying the band ratio method to the ASTER

data allows for tentative identification of silicate and clay minerals, Fe-bearing minerals, and carbonate minerals that provide a preliminary understanding of lithological units within the study area.

Silicate and clay minerals: Clay minerals predominantly composed of aluminum and magnesium are hydrous silicate minerals. The spectral characteristics of these minerals are primarily influenced by hydroxyl groups and water molecules (Fig. 4a). In previous studies, three band ratios were applied to ASTER data for identification of silicate and clay minerals: $(b4 + b7)/b6$ for sericite alteration, $(b5 + b7)/b6$ for geological bodies with high concentrations of illite, montmorillonite, and muscovite, and $(b4 + b6)/b5$ for geological bodies with elevated levels of kaolinite and alunite. When applied to the Duolong mineral district, these three ratios effectively delineate the spatial distribution of clay minerals in the color composite image using red, green, and blue colors (Fig. 5a).

Fe-bearing minerals: The diverse spectral characteristics of Fe-bearing minerals arise from the presence of two primary valence states, namely Fe^{2+} and Fe^{3+} (Fig. 4b). Band ratios commonly employed for identifying Fe-bearing minerals include $b2/b1$ for geological formations with higher concentrations of trivalent iron, $(b3 + b5)/(b1 + b2)$ for geological formations with elevated levels of divalent iron, and $b5/b4$ for Fe-bearing silicates. In practical application within the study area, these three ratios are represented by red, green, and blue in the color composite image illustrating the spatial distribution of Fe-bearing minerals (Fig. 5b).

Carbonate minerals: Based on spectral characteristics of commonly occurring carbonate minerals, their absorption and reflection peaks primarily correspond to bands 7 and 8, as well as bands 6 and 9 in the ASTER data (Fig. 4c). In this study, the ratios $(b7 + b9)/b8$, $(b6 + b9)/(b7 + b8)$, and $b6/b8$ are utilized for identifying information related to carbonate minerals and propylitic alteration (red), calcite (green), as well as geological bodies containing higher concentrations of hornblende (blue). The spatial distribution of carbonate minerals can be visualized in the form of white or light gray regions within the composite image (Fig. 5c).

The initial understanding of the distribution of minerals and/or mineral assemblages within the study area can be gained through the extraction of remote sensing alteration information. Shifting our focus back to the primary objective of machine learning-based field geological mapping, it becomes imperative to design an initial field geological route utilizing the traverse method (Fig. 5d). A comprehensive field geological survey, encompassing both altered and unaltered regions

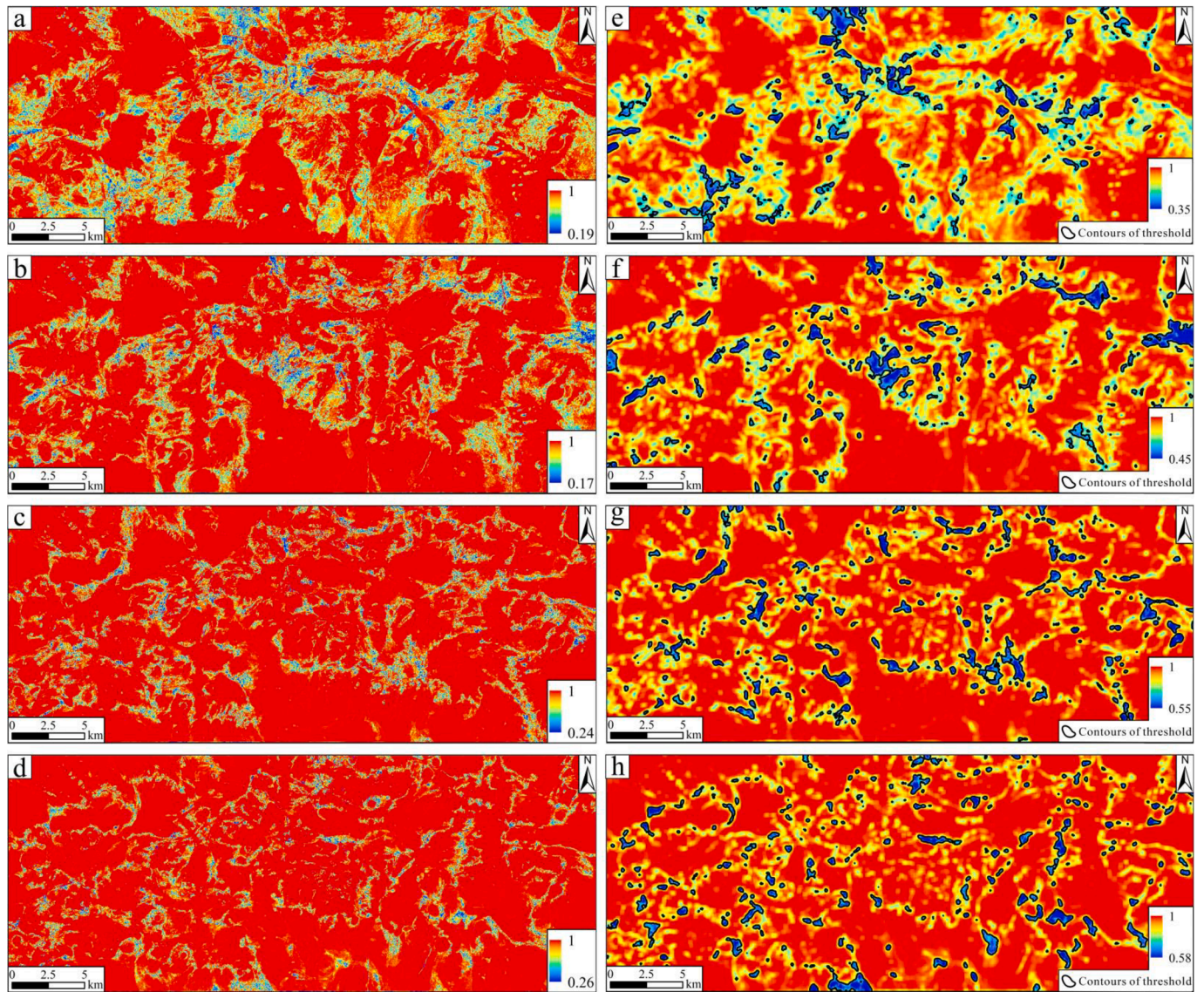


Fig. 6. The predicted probability patterns of the first four iterations. **a** to **d**: The original patterns obtained from the first and fourth iterations. **e** to **h**: the processed patterns after applying spatial average filtering across the iterations.

within the Duolong mineral district, can be conducted to acquire crucial information pertaining to the distribution of geological units, along with the collection of geochemical samples (Fig. 5d).

4.2. Geological mapping

4.2.1. Data preprocessing

The raw data acquired from ASTER and Landsat 8 OLI necessitates preprocessing procedures including radiometric correction, atmospheric correction, layer stacking, masking, mosaicking, and clipping. The application of Principal Component Analysis (PCA) is employed to mitigate information redundancy in visible-short wave infrared bands of ASTER and Landsat 8 OLI datasets, specifically targeting bands 1–9 of ASTER data and bands 1–7 of Landsat 8 OLI data. The first nine principal components with the highest amount of information are retained and further combined with thermal infrared bands from both ASTER and Landsat 8 OLI datasets. That results in the construction of a remote sensing dataset comprising a total of 16 bands.

For the construction of the geochemical dataset, it is crucial to process the acquired small volume geochemical data containing outliers and convert discrete element concentrations into a comparable form and

scale as that of the remote sensing dataset. Utilizing the inverse distance weighted (IDW) interpolation method, a comprehensive geochemical dataset consisting of 15 bands is generated, encompassing the entire Duolong mineral district with a spatial resolution aligned with that of the remote sensing dataset (Bokati et al., 2020).

The feature dataset, comprising 31 bands, is established by pre-processing geochemical and remote sensing data at this stage. The labels for model training are derived from the geological units extracted from the existing 1:50,000 regional geologic map, which also serve as a reference basis for model evaluation.

4.2.2. Field mapping route design

In this study, we employed an exploratory approach to conduct the geological mapping experiment in the Duolong mineral district. The machine learning-based geological mapping incorporates geo-exploratory datasets, which consist of labeled geological units, geochemical data capturing concentrations of 15 trace elements at various sampling locations, and remote sensing data encompassing ASTER and Landsat 8 OLI data. The current strategy for acquiring new geo-exploratory data is based on experiments conducted in the well-explored Duolong mineral district. Each iterative geological mapping,

Table 2
Key parameters of the LightGBM-based geological mapping model.

Iterations	Percentage of training data	Geochemical sampling points	Accuracy	F1-score	Threshold
1	5.2 %	157	57.3 %	37.3 %	0.68
2	9.6 %	273	73.1 %	57.5 %	0.75
3	14.4 %	399	83.5 %	67 %	0.81
4	18.9 %	485	89.1 %	74.7 %	0.84
5	21 %	540	91.6 %	77.9 %	—

utilizing the LightGBM algorithm, necessitates the collection of geochemical and geological data within a 150 m buffer area along designated field routes. Within the experimental context, these data are obtained from existing geochemical and geological records that simulate practical field data collection. The fact that only units within the

mapping routes of each iteration will be utilized as labels is worth reiterating. Specifically, for this particular study, certain units may be excluded in the initial iterations, particularly those rarely exposed units covered by the mapping routes.

When designing the initial field mapping route (Fig. 5d), buffer zones extending 150 m are deliberately outlined to represent the areas designated for practical field mapping and geochemical sampling. Geological and geochemical data points within these predefined zones are carefully selected. Adhering to the systematic flowchart (Fig. 3), an innovative strategy is executed through iterative modeling. For each iteration, a predicted probability map, generated by the Softmax function (Fig. 6a), facilitates the classification assessment of these feature datasets. Furthermore, this probability map proves invaluable in guiding the design of subsequent field mapping routes. Routes are strategically planned within regions exhibiting lower probabilities, thereby ensuring targeted data supplementation aimed at enhancing model accuracy. The training dataset can be enhanced by incorporating the uncovered geological units of the 18 units (Fig. 1) accordingly.

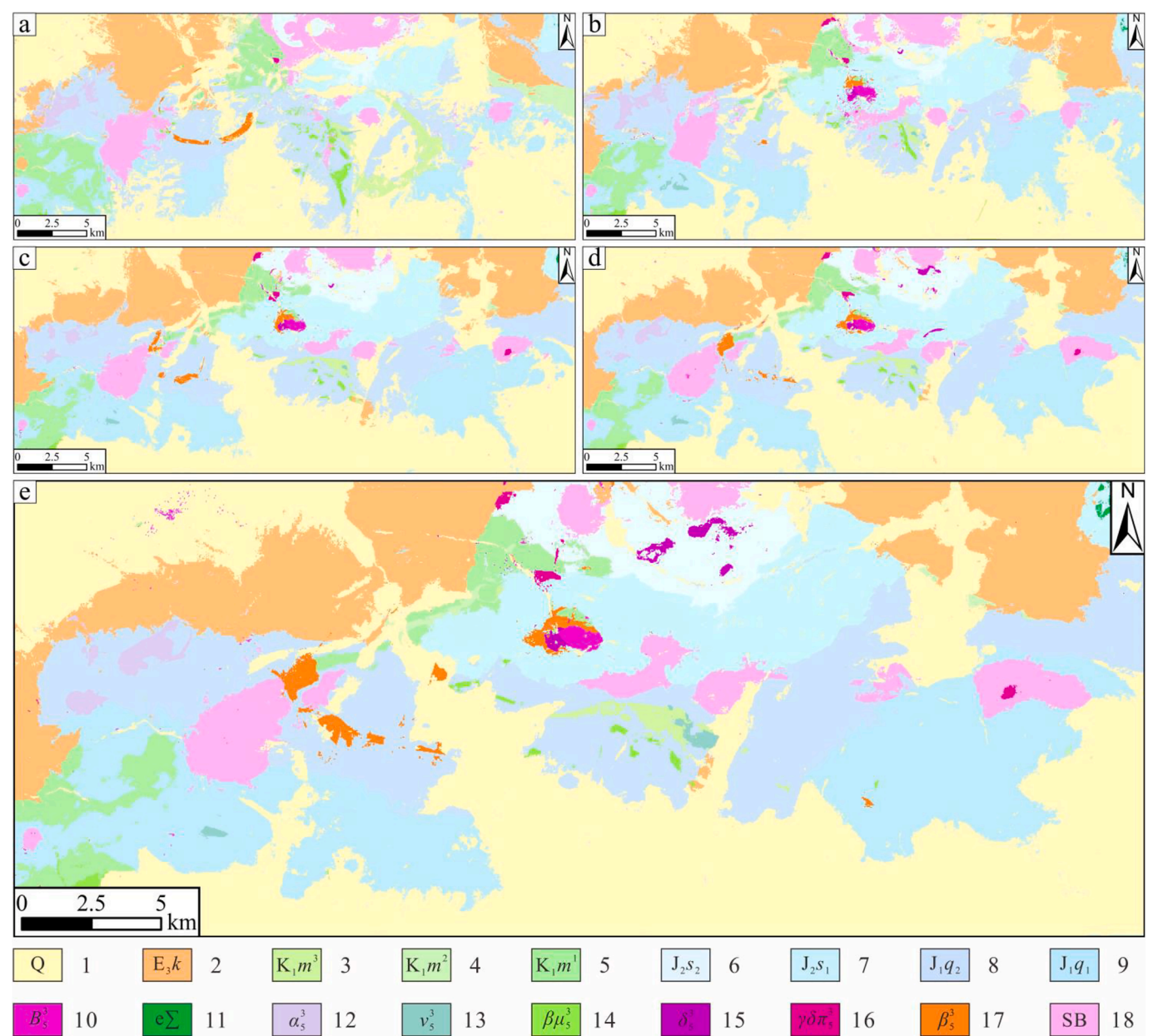


Fig. 7. Iterative field geological mapping results in the Duolong mineral district. a to e: Identified lithological units by the first iteration to the fifth iteration.

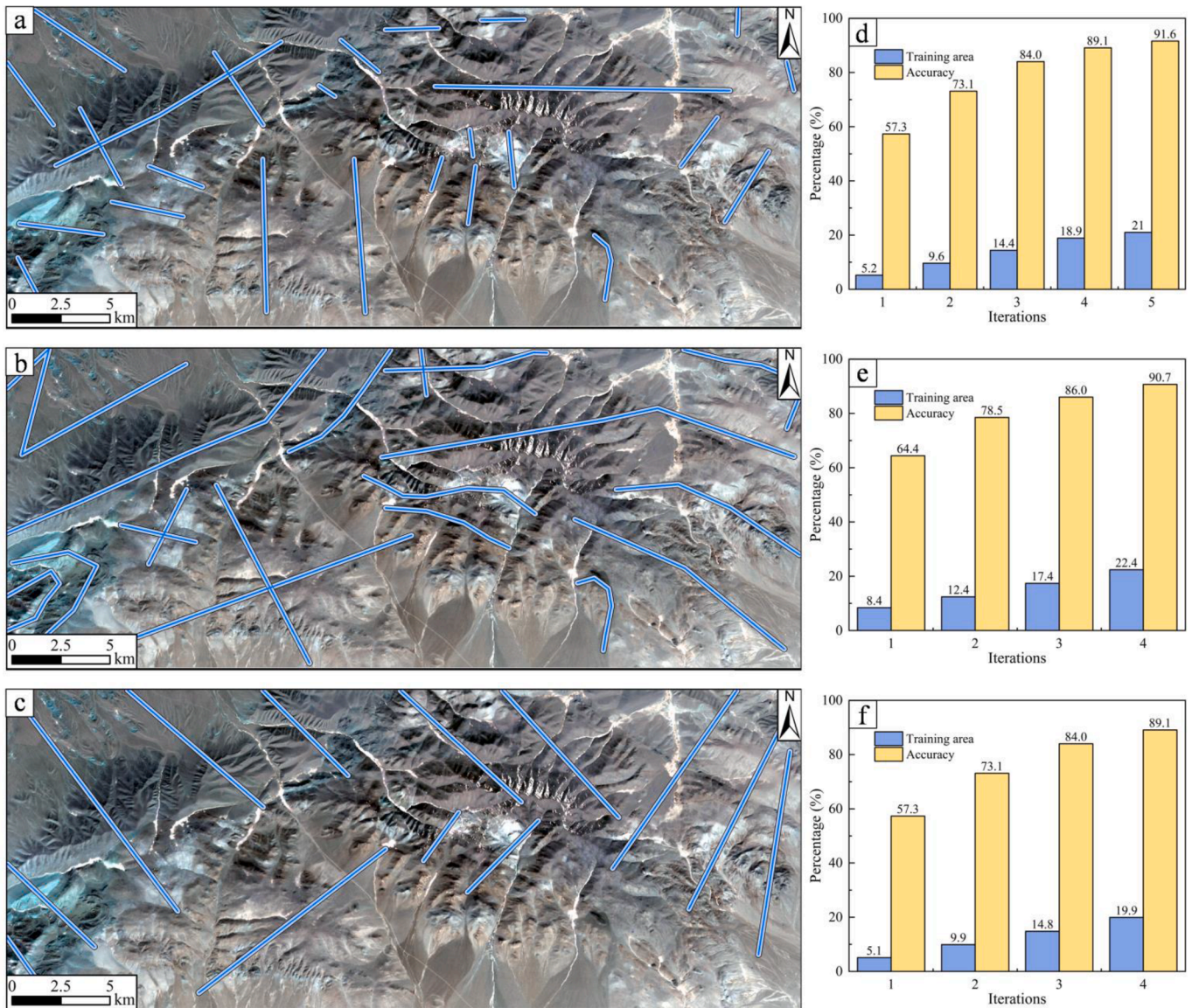


Fig. 8. Comparison of results among different schemes for the initial mapping route design. a to c: three different design schemes; d to f: Iterative prediction results.

To operationalize this approach, a threshold is established to pinpoint areas with comparatively lower probabilities. In our current study, the 5th percentile of the probability distribution serves as an exemplary threshold, guaranteeing that each iterative field geological mapping encompasses approximately 5 % of the total study area. Future investigations could delve into more nuanced criteria for determining this threshold. However, after the first four iterations, notable challenges emerge. While the predicted probability maps (Fig. 6a to 6d) broadly identify low-probability areas, their inherently discrete and chaotic patterns somewhat impede efficient route planning for subsequent iterations. Therefore, to enhance the clarity and continuity of the predicted probability patterns, a spatial average filtering technique employing a 10×10 kernel is utilized. This results in smoother, more coherent visualizations as exemplified (Fig. 6e to 6h). Consequently, the design of field mapping routes is significantly improved. Specifically, the grid (i.e., blue regions in Figs. 6e to 6h) generated by the threshold, which denotes regions with relatively low predicted probabilities, serves as a guide for selecting optimal areas for subsequent field mapping iterations.

4.2.3. Iterative mapping results

After five rounds of model iteration optimization, remarkable results have been achieved (Table 2). The proportion of training data in the study area has significantly increased from the original 5.2 % to 21 %, indicating a substantial improvement in data utilization. Meanwhile, the accuracy of the model has steadily risen with each iteration, escalating from an initial 57.3 % to an impressive 91.6 %, demonstrating a remarkable enhancement in model performance. It is worth to note that throughout the iterative process, the required amount of geochemical data has only increased from 157 to 540, highlighting the model's ability to achieve performance gains while maintaining conciseness and efficiency in data usage and acquisition. Furthermore, the progress is of great significance for geological mapping, as the substantial improvement in prediction performance has greatly reduced the workload in the field. Furthermore, the gradual increase in threshold values during the iteration process, specifically, 0.68, 0.75, 0.81, and 0.84, not only validates the effectiveness of the iterative mapping but also provides strong evidence of the model's continuously enhancing classification reliability. Together, these achievements showcase the dual advancement in both model performance and quality achieved through the new strategy.

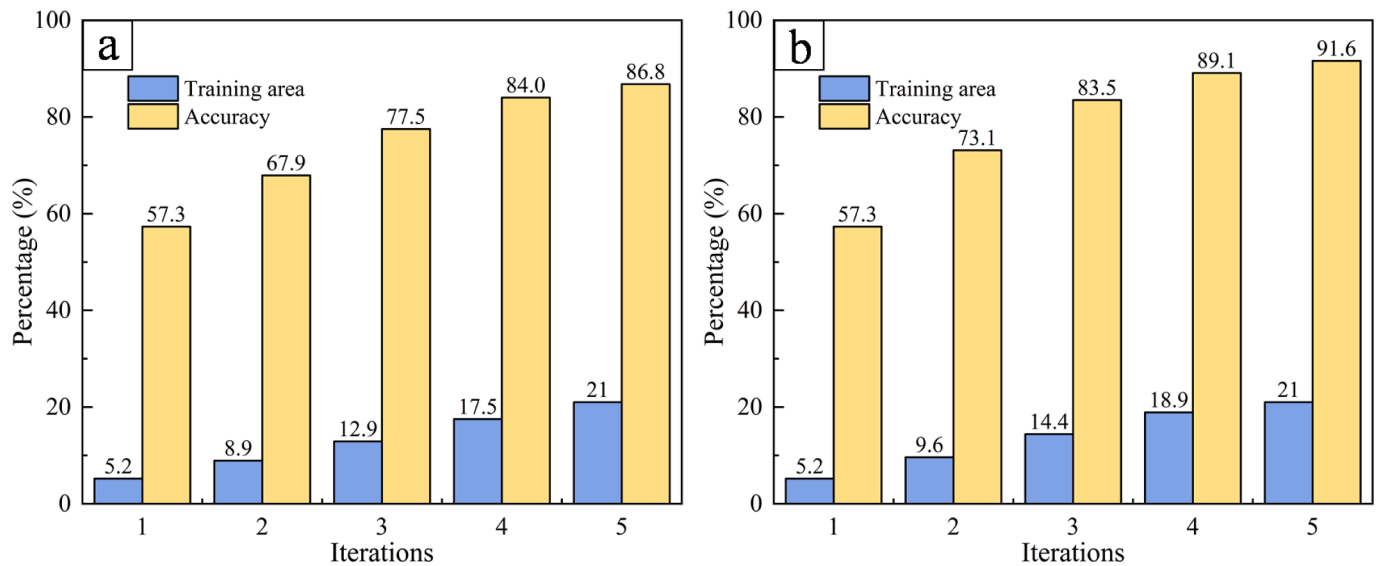


Fig. 9. Comparison of results among the initial mapping route and areas designed by expertise (a) and model selection (b).

After undergoing five rounds of model iterations, geological mapping outcomes were derived for the study area (Fig. 7). A rigorous statistical analysis was conducted that incorporated known lithological units sourced from the 1:50,000 geological map, resulting in a distinct classification accuracy distribution across the 18 lithologic units. Specifically, four units exhibited classification accuracy exceeding 90 %, five fell within the range of 80 % to 90 %, and eight ranged between 70 % and 80 %. Notably, diorite was an outlier with a relatively lower classification accuracy of only 58 %. This diminished performance might be primarily attributed to the limited outcrops of diorite within the study area and the scarcity of available sample data.

4.3. Model validation

The initial round of mapping route design is a critical and somewhat empirical step in the current machine learning-based geological mapping model, which may be influenced by expertise. During the modeling process, experts are required to design the initial field routes based on the identified alteration. Due to variations in experience and judgment among different professionals, discrepancies may arise in route design. To investigate the impact of these discrepancies on the final mapping results, multiple experiments were conducted wherein different designing schemes for the initial route were considered. The experimental results (Fig. 8) demonstrate that despite variations in selecting the initial route design, there is remarkable similarity observed in the final mapping outcomes. By practically mapping approximately 20 % of the area, a prediction accuracy of around 90 % can be achieved. This not only highlights the robustness of our proposed mapping method but also effectively mitigates influence from expertise during the modeling process. Thus, the current model provides a more objective and reliable strategy for field geological mapping.

An improved method for selecting field mapping areas is currently proposed, offering notable enhancements in both objectivity and efficiency compared to traditional expertise-based selection. The latter often relies directly on predictive probability maps for route design, with expert experience and subjective judgments playing a dominant role. By contrast, the new approach introduces spatial average filtering to preprocess the predictive probability maps, followed by the use of thresholds to determine subsequent mapping areas. This not only minimizes the influence of human factors but also enhances the scientific rigor of the selection process. Furthermore, the method provides crucial location information to the model, which serves as a vital basis for supplementing label and feature data. This contribution proves instrumental in boosting

the model's prediction accuracy. A comparative analysis between expertise-based selection (Fig. 9a) and model-based selection (Fig. 9b) reveals that, despite maintaining consistency in initial mapping areas, geological, and geochemical data, the model-based approach outperforms expertise-based selection by achieving a 4.8 % higher prediction accuracy in the fifth iteration of mapping, when both methods utilize the same mapping area. The results obtained from our proposed method demonstrate its superiority over the conventional approach in mapping area selection, thereby enhancing the model's predictive capabilities, as evidenced by more detailed findings presented in expertise-based route selection (Figs. S1 and S2, Table 1).

5. Summaries and preliminary conclusions

The present study introduces a geological mapping workflow that integrates fieldwork, remote sensing data, and a limited collection of geochemical samples. The workflow incorporates the LightGBM algorithm, which demonstrates superior performance in both mapping efficiency compared to traditional geological mapping methods. According to practically mapping only 21 % of the study area and utilizing 540 geochemical samples, along with data sources such as ASTER and Landsat8, the workflow achieves a lithological prediction accuracy of 91.6 % for the entire region. This approach not only reduces the workload of field mapping but also ensures high accuracy.

Within the framework, mapping results obtained from different initial mapping areas and route design schemes are generally similar and maintain high precision. That helps to address inconsistencies in mapping results arising from variations in expert or mapper knowledge backgrounds and experiences. Furthermore, the use of spatial average filtering to process probability maps effectively obtains critical training data and feature data for improving model classification performance, further reducing workload of actual field mapping. The model-based selection approach also enhances the objectivity of the entire process, minimizing influence of uncertain factors.

It is worth noting that the current exploratory experimental research successfully integrates machine learning methods into conventional field geological mapping workflows, fully leveraging advantages of innovative spatial quantitative algorithms and significantly improving efficiency of field mapping. Additionally, the machine learning-based field mapping method proposed in the current study offers a new strategy for acquiring exploratory data and positively impacts subsequent data management and mining utilization in geological survey. While completing field mapping tasks, structured geological data is

directly obtained, and collection and analysis of geochemical data are also considered, laying a solid foundation for subsequent mineral prospecting predictions.

However, this study primarily focuses on the identification of lithological units, while geological units such as structures (e.g., fault and fold), which are crucial components of mapping, are not fully represented in the model. Therefore, future research will further explore and investigate how to effectively incorporate these geological units into the model. Simultaneously, more data are necessary to be considered and introduced that can be collected and analyzed on-site, such as gravity, magnetic, and other geophysical data, as well as structural measurement and other field record data. By exploring feasibility and effectiveness of more diversified exploratory data in field mapping, it is expectable to continuously update the model along with its associated feature and label data, ultimately achieving the goal of predictive mapping for all key elements in geological maps.

CRedit authorship contribution statement

Wenlei Wang: Conceptualization, Funding acquisition, Data curation, Writing – original draft, Writing – review & editing, Visualization, Investigation, Validation, Formal analysis, Methodology, Supervision, Resources, Project administration, Software. **Congcong Xue:** Conceptualization, Data curation, Visualization, Investigation, Validation, Formal analysis, Methodology, Project administration, Software. **Jie Zhao:** Conceptualization, Writing – review & editing, Methodology, Supervision. **Changjiang Yuan:** Data curation, Visualization. **Jie Tang:** Visualization, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.oregeorev.2024.105959>.

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ARTICLES FOR FACULTY MEMBERS

REMOTE SENSING BIG DATA ANALYTICS FOR DETAILED GEOLOGICAL MAPPING IN EXPOSED ZONES OF DRY VALLEYS, SOUTH VICTORIA LAND, ANTARCTICA

Remote mapping of bedrock for future cosmogenic nuclide exposure dating studies in
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Article

Remote Mapping of Bedrock for Future Cosmogenic Nuclide Exposure Dating Studies in Unvisited Areas of Antarctica

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Abstract: Cosmogenic nuclide exposure dating is an important technique for reconstructing glacial histories. Many of the most commonly applied cosmogenic nuclides are extracted from the mineral quartz, meaning sampling of felsic (silica-rich) rock is often preferred to sampling of mafic (silica-poor) rock for exposure dating studies. Fieldwork in remote regions such as Antarctica is subject to time constraints and considerable logistical challenges, making efficient sample recovery critical to successful research efforts. Remote sensing offers an effective way to map the geology of large areas prior to fieldwork and expedite the sampling process. In this study, we assess the viability of multispectral remote sensing to distinguish felsic from mafic rock outcrops at visible-near infrared (VNIR) and shortwave infrared (SWIR) wavelengths using both the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and very high-resolution Worldview-3 (WV-3) imagery. We applied a combination of spectral mapping and ground truth from spectral measurements of 17 rock samples from Mount Murphy in the Amundsen Sea sector of West Antarctica. Using this approach, we identified four dominant rock types which we used as a basis for felsic–mafic differentiation: felsic granites and gneisses, and mafic basalts and fragmental hydrovolcanic rocks. Supervised classification results indicate WV-3 performs well at differentiating felsic and mafic rock types and that ASTER, while coarser, could also achieve satisfactory results and be used in concert with more targeted WV-3 image acquisitions. Finally, we present a revised felsic–mafic geological map for Mt Murphy. Overall, our results highlight the potential of spectral mapping for preliminary reconnaissance when planning future cosmogenic nuclide sampling campaigns in remote, unvisited areas of the polar regions.

Keywords: Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER); cosmogenic nuclide surface exposure dating; Mount Murphy; multispectral; spectral mapping; supervised classification; WorldView-3



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1. Introduction and Rationale

Rock outcrops that are presently exposed above the ice sheet surface in Antarctica can provide direct evidence for past ice thickness by using cosmogenic nuclide surface exposure dating of their surfaces [1–3]. Quartz is often the preferred target mineral for extraction

of cosmogenic nuclides because the most commonly measured cosmogenic nuclides (e.g., ^{10}Be , ^{26}Al , ^{14}C) are produced within quartz. Felsic rocks are typically preferred over mafic rocks for cosmogenic nuclide exposure dating studies because felsic rocks are silica rich and often contain minerals such as quartz, feldspars and micas, whereas mafic rocks are iron and magnesium-rich and generally contain little or no quartz. There is, however, potential for extraction of cosmogenic nuclides from other minerals, including those common in mafic rocks such as olivine (in situ ^{14}C ; [4]) and pyroxene (^{10}Be ; [5]). Developing the ability to remotely differentiate felsic from mafic rocks would enable identification of areas where bedrock lithologies are likely to be favourable for application of a specific target mineral and/or nuclide, permitting forward planning for future exposure dating field campaigns. The geology of the polar regions, especially Antarctica is, however, often sparsely mapped, and many outcrops are extremely challenging to access [6]. Thus, in some areas, virtually nothing is known about the composition of the outcropping rocks.

Remote sensing is an effective alternative way to characterise the geology of such areas because it is capable of covering large areas and can be undertaken both rapidly and safely in regions where it is logistically challenging to conduct fieldwork [7]. It therefore has the potential to be used to make a preliminary determination of an area's suitability for retrieval of samples suitable for cosmogenic nuclide analysis. However, remote sensing in polar regions faces numerous challenges, including steep topography combined with low elevation sun angles [8], limited and varied exposure of rock outcrops, and persistent cloud cover [7]. Despite these challenges, medium-resolution imagery acquired from the Antarctic Peninsula by the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) has demonstrated that remote sensing can refine existing geological knowledge in sparsely mapped polar regions [9,10]. The launch of the very high-resolution Worldview-3 (WV-3) satellite in 2014 permits mapping at a spectral resolution that rivals ASTER, but in much better spatial resolution at both visible-near infrared (VNIR) and shortwave infrared (SWIR)—1.24/3.7 metres per pixel [11], enabling more detailed lithologic mapping of smaller nunataks that previously could not be well-resolved using lower resolution ASTER imagery (VNIR/SWIR—15/30 metres per pixel).

In this study, we focus on Mount Murphy, a large volcanic edifice located in the Amundsen Sea Sector of the West Antarctic Ice Sheet (WAIS) adjacent to Pope Glacier (Figure 1a). This peak comprises lithologies ranging from felsic to mafic and covers an area of $\sim 35 \times 45$ km [12]. Mt Murphy was visited in 2015–16 for a cosmogenic nuclide sampling campaign [2] and much of its geology is well-described from earlier visits [13–16], providing reliable ground truth for this study. Some areas of the Mt Murphy massif, however, remain sparsely mapped, providing an opportunity to refine existing geological knowledge. This study therefore aims to assess the potential of spectral mapping for characterising the suitability of unvisited outcrops for cosmogenic nuclide exposure dating and improve our existing knowledge of Mt Murphy's geology. Its objectives are fourfold:

- (i) Obtain spectral reflectance measurements from previously collected rock samples from Mt Murphy to provide ground truth for satellite-based spectral mapping results.
- (ii) Investigate the capabilities of ASTER and WV-3 imagery for spectral geological analysis, with focus on specific areas of Mt Murphy.
- (iii) Assess supervised classification techniques for felsic-mafic rock separation at Mt Murphy using endmembers extracted from the imagery and from laboratory spectra.
- (iv) Produce a revised felsic-mafic geological map of Mt Murphy through integration of supervised classification, manual mapping techniques and existing ground truth.

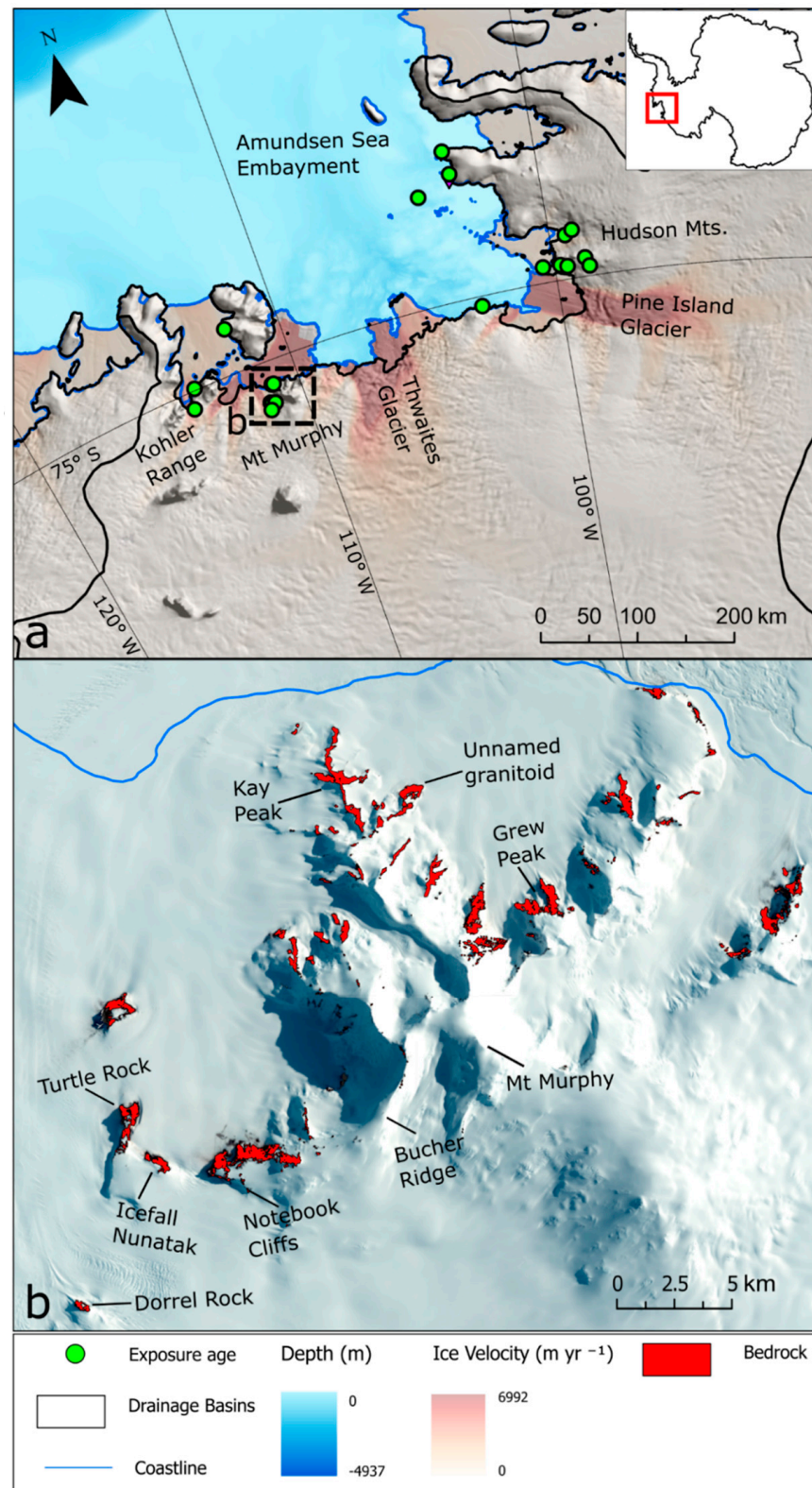


Figure 1. (a) Map showing locations of major glaciers and nunataks previously visited on cosmogenic nuclide sampling campaigns. Green dots indicate the locations of samples collected on previous fieldwork which have provided exposure ages. Hillshade is derived from the Reference Elevation Model of Antarctica (REMA) [17]. Regional bathymetry from [18] and Antarctic coastline sourced from the Antarctic Digital Database (ADD), v 7.7. Black lines depict ice sheet drainage basins and grounding line position [19]. Map of Antarctica (inset) showing location of Amundsen Sea Embayment. (b) Landsat-9 image of Mt Murphy highlighting exposed rock outcrops (shown in red), along with key locations mentioned in the text. Rock outcrop extents are from the ADD [20].

2. Background

2.1. Remotely Sensed Datasets

ASTER VNIR-SWIR and WV-3 VNIR and SWIR datasets were selected for this study due to their proven superior spectral coverage and spectral resolution over SWIR wavelengths compared to other optical satellites such as Landsat-9 and Sentinel-2 [11,21,22].

ASTER is a polar orbiting imaging system aboard the Terra spacecraft, with a 60 km image swath with three subsystems operating in VNIR, SWIR and Thermal Infrared (TIR). It possesses three bands in the VNIR wavelength region with a spatial resolution of 15 m, six bands in the SWIR region at 30 m spatial resolution, and five bands in the TIR region at 90 m spatial resolution (Table 1). Since its launch in 1999, ASTER has been used routinely for lithologic mapping [21,23–26], including in remote polar regions [10,24,27]. ASTER has also proven effective for separating felsic intrusive and extrusive rock types from more mafic and sedimentary lithologies, improving existing geological mapping coverage [9,10,27]. However, these previous geological mapping studies relied on the full suite of ASTER instruments including the TIR which is not feasible for mapping smaller (<100 m) rock exposures. Sub-pixel techniques have had some success in classifying felsic (Al-rich) minerals in polar regions at VNIR-SWIR wavelengths, but resolving Fe³⁺, Fe²⁺ and Mg-rich mafic pixels has proven more challenging [24].

Table 1. Characteristics and wavelengths detectable by the Advanced Spaceborne Thermal Emission and Reflection Radiometer. After [28].

Sub-System	Band No.	Band Name	Wavelength (μm)	Spatial Resolution (m)
VNIR	1	VNIR-1	0.52–0.60	15
	2	VNIR-2	0.63–0.69	15
	3N	VNIR-3N	0.78–0.86	15
	3B	VNIR-3B	0.78–0.86	15
SWIR	4	SWIR-1	1.60–1.70	30
	5	SWIR-2	2.15–2.19	30
	6	SWIR-3	2.19–2.23	30
	7	SWIR-4	2.24–2.29	30
	8	SWIR-5	2.30–2.37	30
	9	SWIR-6	2.36–2.43	30
TIR	10	TIR-1	8.13–8.48	90
	11	TIR-2	8.48–8.83	90
	12	TIR-3	8.93–9.28	90
	13	TIR-4	10.25–10.95	90
	14	TIR-5	10.95–11.65	90

WorldView-3 (owned by Maxar and launched in 2014) is a very-high resolution sensor (Tables 2 and S1) supplying commercial imagery, with a narrow 13 km swath. WV-3's capabilities include at nadir 1.24 m per pixel spatial resolution in eight VNIR bands and 3.7 m per pixel resolution in eight SWIR bands (often re-sampled to 2 m and 7.5 m per pixel resolution, respectively). VNIR bands of both ASTER and WV-3 sensors are positioned to resolve spectral absorption features of minerals containing ferric (Fe³⁺) iron, such as goethite, and ferrous (Fe²⁺) iron, such as chlorite (see Figure S4). In addition, Al-OH, Fe/Mg-OH and CO₃^{2−} spectral absorption features can be discriminated across several narrow SWIR wavelengths enabling differentiation of the minerals muscovite, epidote, chlorite, and calcite [11,21,22]. One key spectral difference between the two sensors is the position of the WV-3 SWIR band 1 at 1.2 μm (Table 2), effective for identifying minerals with Fe²⁺ absorption features [29]. Assessments of spectral mapping capabilities of WV-3 have

validated its potential for discriminating between lithological units based on their Fe^{3+} , Fe^{2+} , Al-OH , Fe/Mg-OH and CO_3^{2-} absorption [11,22]. WV-3 VNIR-SWIR imagery has been used in commercially focused mineral mapping studies at mid-low latitudes [30,31], but WV-3 imagery has not been used extensively in polar environments because commercial prospecting is either not permitted there (Antarctica) or is less common. Worldview VNIR imagery has, however, been applied in Antarctica to delineate land cover areas such as snow/ice, water bodies and landmass, and for vegetation mapping [8,32] and mapping of glacial landforms [33].

Table 2. Characteristics and wavelength ranges detectable by WorldView-3. After [11].

Sub-System	Band No.	Band Name	Wavelength (μm)	Spatial Resolution (m)
VNIR	1	Coastal	0.40–0.45	2
	2	Blue	0.45–0.51	2
	3	Green	0.51–0.58	2
	4	Yellow	0.59–0.63	2
	5	Red	0.63–0.69	2
	6	Red Edge	0.70–0.75	2
	7	Near-IR1	0.77–0.90	2
	8	Near-IR2	0.86–1.04	2
SWIR	9	SWIR-1	1.12–1.23	7.5
	10	SWIR-2	1.55–1.59	7.5
	11	SWIR-3	1.64–1.68	7.5
	12	SWIR-4	1.71–1.75	7.5
	13	SWIR-5	2.15–2.19	7.5
	14	SWIR-6	2.19–2.23	7.5
	15	SWIR-7	2.24–2.29	7.5
	16	SWIR-8	2.30–2.37	7.5

In summary, using ASTER in conjunction with WV-3 SWIR is a useful approach. ASTER's 60 km swath and open-source imagery mean it can be applied cheaply to map large areas but lacks the spatial resolution to discern smaller outcrops. WV-3 has a narrow 13 km swath and is only commercially available, but its high spatial resolution means it can be deployed to acquire targeted spectral information which may be challenging to extract from an ASTER image.

2.2. Geology of Mount Murphy

This study focuses on Mount Murphy, a volcano located on the eastern periphery of Marie Byrd Land in the Amundsen Sea sector of West Antarctica. Marie Byrd Land comprises a ~50 km thick attenuated continental lithosphere [34] and is one of several uplifted crustal blocks intersected by the West Antarctic Rift system, which together make up the geologically complex region of West Antarctica [35]. During the Palaeozoic, regional convergence of oceanic and continental crust and resultant subduction led to several pulses of granitoid magmatism and metamorphism within Marie Byrd Land [14,36]. More recent Cenozoic magmatism formed Mt Murphy and 17 other large volcanoes distributed over a 500×800 km volcanic dome at the centre of Marie Byrd Land [37].

Mt Murphy consists of a main volcanic edifice emplaced over a north sloping block of much older pre-volcanic basement [15]. The site has been mapped and described in previous work focused on Mt Murphy's eruptive and tectonic history [12,13,15,16,37] and more recently with focus on its glacial history [2,38–40]. Observations from field expeditions associated with these studies provide a good measure of Mt Murphy's general geological characteristics. Mt Murphy's northern section, including Kay Peak (Figure 1b), consists

of a pre-volcanic metamorphosed basement and at least one large granitoid intrusive [14]. Outcrops surrounding Mt Murphy on its west and southwest flanks (Hedin Nunatak, Turtle Rock, Icefall Nunatak and Notebook Cliffs; Figure 1b) are all composed of mafic basalt lava flows and hydrovolcanic fragmental rocks, formed during volcanic eruptions dating from 9.5–0.6 Myr ago [12]. An additional large mafic intrusive to the south of Mt Murphy, Dorrel Rock, is composed of Oligocene gabbro [16]. Several smaller mafic parasitic cones formed of tuff and scoria are also present at the site [15]. The upper reaches of Mt Murphy (above 1900 m elevation) are comprised of volcanic rocks of intermediate-to-felsic composition [12,37]. However, much of the edifice remains sparsely mapped, especially at higher elevations, where many outcrops have never been visited and whose observation has previously relied on binocular observations.

2.3. Reference Geological Framework

We now describe mineral absorption and emissivity features, how they are discernible to the satellite sensors used in this study, and how these factors influenced our approach to compiling a reference geological map to validate remote sensing-based results. The mineral quartz (desirable for cosmogenic nuclide exposure dating; Section 1) is directly detectable by spectral absorption features at TIR wavelengths (8–14 μm) caused by asymmetric Si-O stretching vibrations within the mineral lattice [41]. However, the high latitude of Mt Murphy ($>75^\circ\text{S}$) results in a weak emissivity signal, leading to TIR images with poor signal-to-noise ratio (SNR). As such, discrimination of quartz by the ASTER and WV-3 sensors is restricted to characterising felsic rock (silica/quartz-rich) at VNIR-SWIR wavelengths.

Felsic minerals such as muscovite can be distinguished at VNIR-SWIR wavelengths due their high reflectance and the vibrational transition of hydroxyl (OH^- ions) resulting in an Al-OH absorption feature at 2.2 μm [42]. Conversely, mafic rocks display low albedo because they are composed largely of dark coloured minerals such as olivine, amphibole/hornblende, pyroxene, chlorite, and biotite which have distinct absorption features at VNIR-SWIR wavelengths. Chlorite and epidote can be detected by their ferrous iron (Fe^{2+}) absorption due to crystal field effects [9]. Chlorite, epidote, and hornblende also display an absorption feature at a wavelength of 2.33 μm , centred on ASTER band 8 [21] and WV-3 SWIR band 8 [11]. Additionally, a charge transfer feature enables detection of ferric iron (Fe^{3+}) at VNIR wavelengths from 0.5 to 0.7 μm [43]. Iron oxides and hydroxides are associated with weathering of both felsic and mafic minerals and can help identify weathered mafic rocks based on their high iron content [44].

To provide an effective validation tool for lithologic differentiation based on ASTER and WV-3 VNIR-SWIR imagery, we compiled a reference geological map (Figure 2) based on a geological map updated from field observations and previous studies [2,13–15,37]. We simplified current understanding of Mt Murphy's geology into two fundamental classes: felsic (silica-rich) and mafic (silica-poor). We follow a felsic-mafic classification scheme to categorise rock types based on their percentage silica content where we separate felsic rock types which are $\geq 65\%$ silica content (basement lithologies) and/or $>58\%$ (Mt Murphy felsic-intermediate volcanics) from mafic rock types $\leq 45\%$ silica content. Our felsic-mafic classification scheme is a useful metric because felsic and mafic minerals can be discriminated from each other based on their spectral properties [42,45]. Rock types at Mt Murphy that fall into the felsic class include previously mapped basement rocks such as granite and gneiss, and previously mapped felsic-intermediate volcanic rocks such as trachyte, which is mostly found at high elevations (>1900 m asl). The mafic class broadly contains igneous rocks with higher ferromagnesian mineral content (Fe, Mg) including volcanics such as basalts and hyaloclastites, pyroclastic cones consisting of scoria and tuff,

and mafic intrusive rocks such as gabbro. We classified unvisited outcrops or those not previously identified as felsic or mafic as a third category.

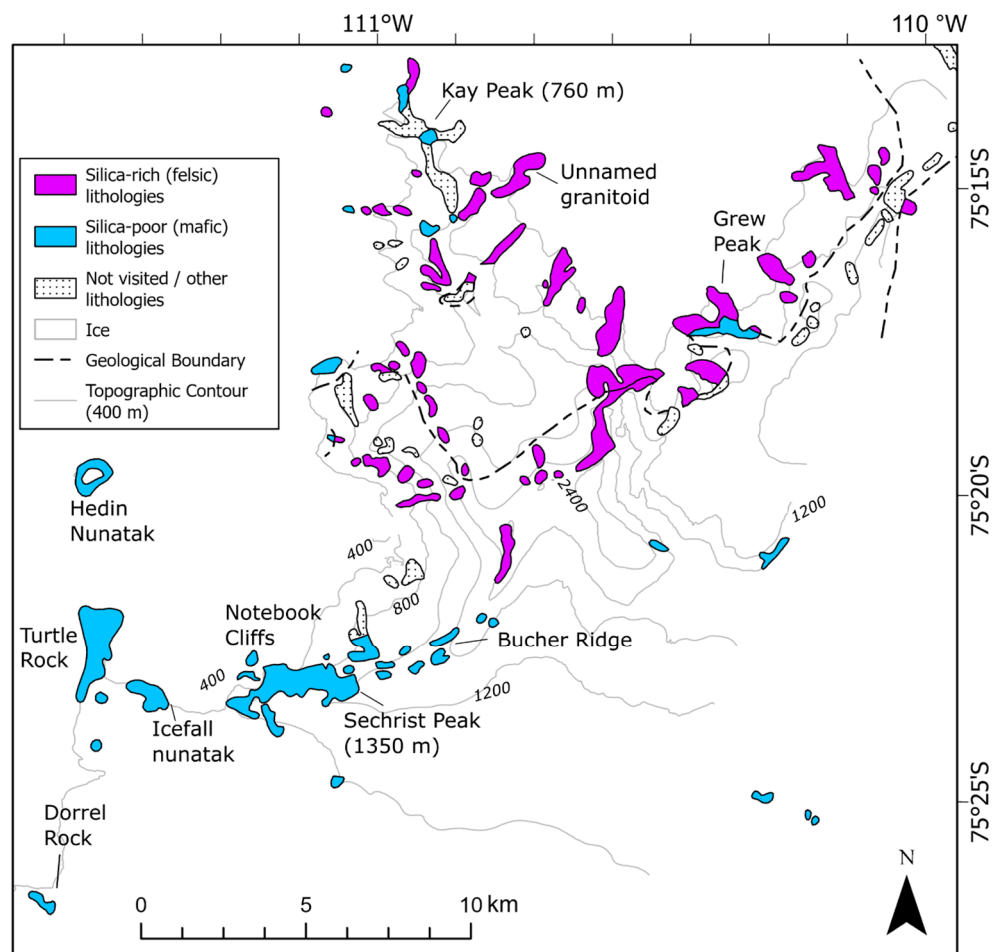


Figure 2. Mount Murphy reference geological map which represents ground truth at Mt Murphy, serving as a basis for remote sensing results in the present study. Nomenclature has been adapted and simplified to differentiate silica-rich (felsic) from silica-poor (mafic) lithologies using spectral mapping techniques in the VNIR-SWIR range (0.4–2.5 μm). Rock polygons downloaded from ADD. Contours (400 m) generated using the REMA [17]. Some geological units previously distinguished separately as evolved volcanic rocks and pre-volcanic basement are here combined as silica-rich (felsic) units.

We focused our spectral mapping predominantly on two areas of Mt Murphy: Kay Peak and an un-named granitoid outcrop to the north, and the area of Notebook-Icefall-Turtle Rock to the southwest of the main edifice (Figure 2). The motivation for selecting these areas for more detailed spectral analysis is twofold: (1) there is full cover of medium resolution ASTER and very-high resolution WV-3 VNIR and SWIR imagery across these areas, and (2) the case study locations have been the subject of previous fieldwork (Figure 3). Rock samples from these locations already exist, and they can be measured for spectral reflectance to validate remote sensing observations without the need for additional fieldwork. The Kay Peak area is lithologically complex, comprising felsic, intermediate and mafic rock types including intrusive granite and gneiss basement, a yellow diamict and basalt emplaced over lighter felsic basement rock (Figure 3a). The gneiss (Figure 3b) is also intersected by microgranite sheets [14]. To the southwest of the main Mt Murphy volcanic edifice, the mafic nunataks Turtle Rock, Icefall Nunatak and Notebook Cliffs (Figure 3) have been well mapped by previous fieldwork [13,15]. Mafic rocks are challenging to distinguish from each other and other rock types with low albedo (including sedimentary rocks) using

remote sensing-based techniques [10,46]. From field observations [15] and field photos (Figure 3c,d) we know there are sequences of basalt and fragmental hydrovolcanic rocks present in the study area, and so we also investigated the feasibility of differentiating these two lithologies at VNIR-SWIR wavelengths.

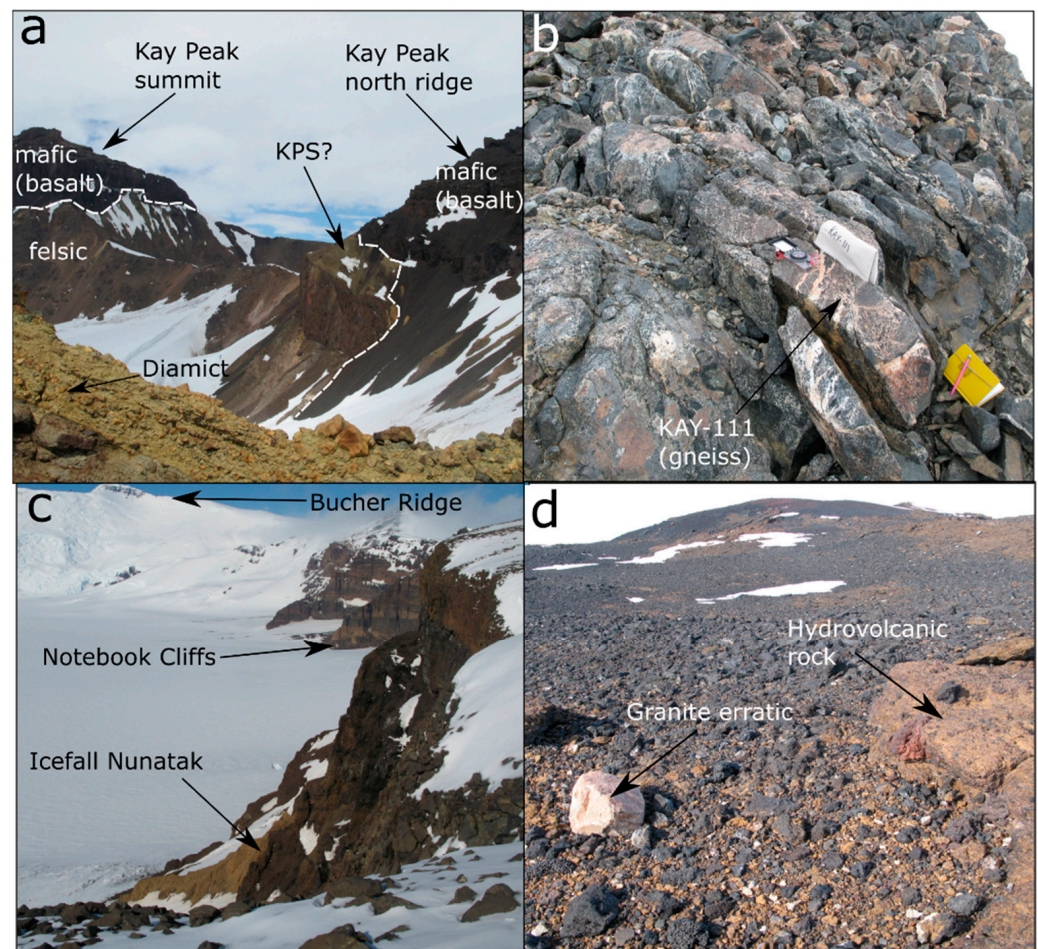


Figure 3. Field photos of Mt Murphy showing Kay Peak (a,b) and Turtle Rock, Icefall Nunatak and Notebook Cliffs areas (c,d). (a) Kay Peak viewed facing south from the ridge extending northward from Kay Peak showing darker mafic/basalt volcanic rock emplaced over lighter felsic/gneiss basement; contact is indicated by white dashed lines. (b) Outcrop of felsic gneiss at Kay Peak ridge (north), including sample KAY-111. (c) View from Icefall Nunatak (foreground) looking eastwards to Notebook Cliffs and Bucher Ridge. Distinctive light orange bands visible at Notebook Cliffs are similar to hydrovolcanic/hyaloclastite deposits described elsewhere [47] (d) Summit of Notebook Cliffs showing a mixture of light-orange hyaloclastite breccia, darker basalt, and a granite erratic. Images from ANiSEED 2015–2016 Field Report [2].

3. Methods

3.1. Reflectance Spectroscopy of Mount Murphy Rock Samples

Directly measuring the reflectance properties of rock samples recovered from Mt Murphy provides ground truth to inform spectral analysis of both ASTER and WV-3 imagery. We acquired reflectance spectra of 17 rock samples from Mt Murphy (Figure 4). We selected rock samples representative of Mt Murphy’s previously described geology which had been collected on previous field expeditions to Mt Murphy in the 2015–16 and 1990–91 field seasons as part of the ANiSEED and SPRITE projects [2,14,15]. Most samples ($n = 13$) had been collected during the ANiSEED project with the position of each sample recorded using a Trimble 5700 GPS receiver set at the same height as the sample’s

upper surface. Our rock samples consisted of granites, gneisses, and basalts, and a fourth group incorporating tuffs and hyaloclastite, which we broadly grouped as ‘fragmental hydrovolcanic’ rocks.

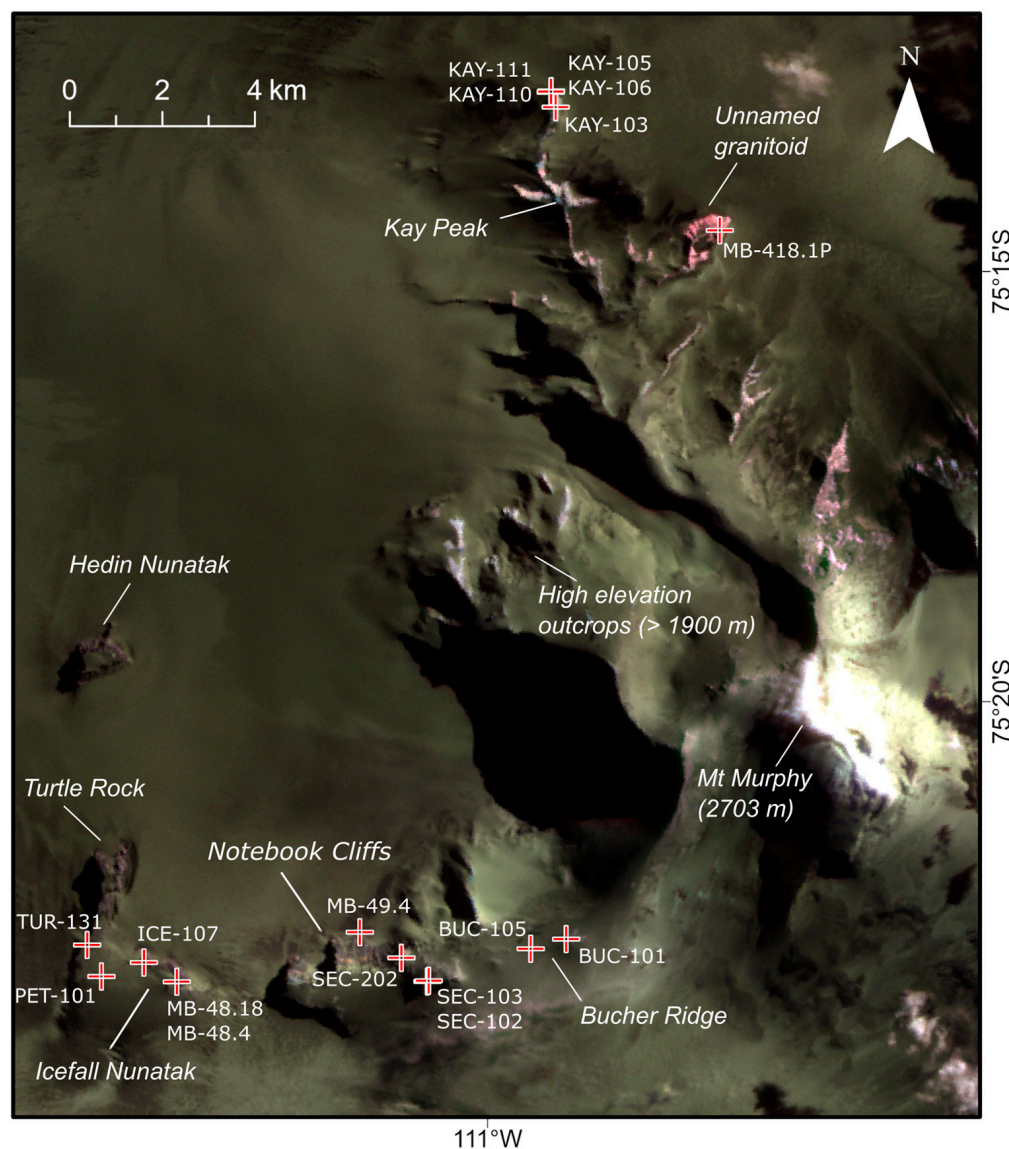


Figure 4. Locations of Mt Murphy rock samples measured for spectral reflectance (red crosses) overlain on ASTER SWIR false colour composite (468). Field locations discussed in the text are also indicated.

We measured rock sample reflectance spectra using a Spectral Evolution PSR 3500+ spectroradiometer [48] in a dark optical calibration laboratory at the NERC (Natural Environment Research Council) Field Spectroscopy Facility (FSF). The PSR 3500+ provides a high-resolution spectral range from 0.35 to 2.5 μm and is compatible with ASTER and WV-3 VNIR and SWIR band coverage (for detailed methods see Supplement S1). We performed post-processing of laboratory spectra using SpectraGryph v1.2.15—Optical Spectroscopy Software [49] and Python 3—Jupyter Notebooks, generating 17 reflectance profiles which were compiled into a new spectral library for Mt Murphy [50]. To provide mineralogic context for rock spectra, we inspected thin-section photomicrographs of selected samples in plane-polarised and cross-polarised light to identify the mineralogical composition of each sample, which also served as further validation for our satellite-based observations. Finally, we convolved the spectral profiles of Mt Murphy samples to the system response functions

of both the ASTER VNIR/SWIR and WV-3 VNIR/SWIR band passes, permitting analysis of characteristic mineral absorption features from the Mt Murphy laboratory spectra visible to the WV-3 and ASTER sensors.

3.2. Multispectral Image Pre-Processing

We purchased commercial WV-3 L2a VNIR and SWIR imagery from DigitalGlobe products, © WorldView-3 DigitalGlobe, Inc. (London, UK), a Maxar company, Westminster, Colorado. WV-3 VNIR imagery was acquired from the DigitalGlobe archive and WV-3 SWIR imagery was specifically tasked. We downloaded open-source ASTER 07XT crosstalk corrected surface reflectance imagery from the online Data Pool courtesy of the NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC), USGS Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota [51]. Image metadata including image acquisition dates are specified in Table S1. Image pre-processing steps, delineation of rock outcrops and subsequent techniques applied to ASTER 07XT and WV-3 L2a VNIR and SWIR imagery are outlined in Figure 5. We performed image pre-processing using ENVI and ArcGIS Pro v3.3 software. A detailed description of the image pre-processing steps can be found in Supplement S1.

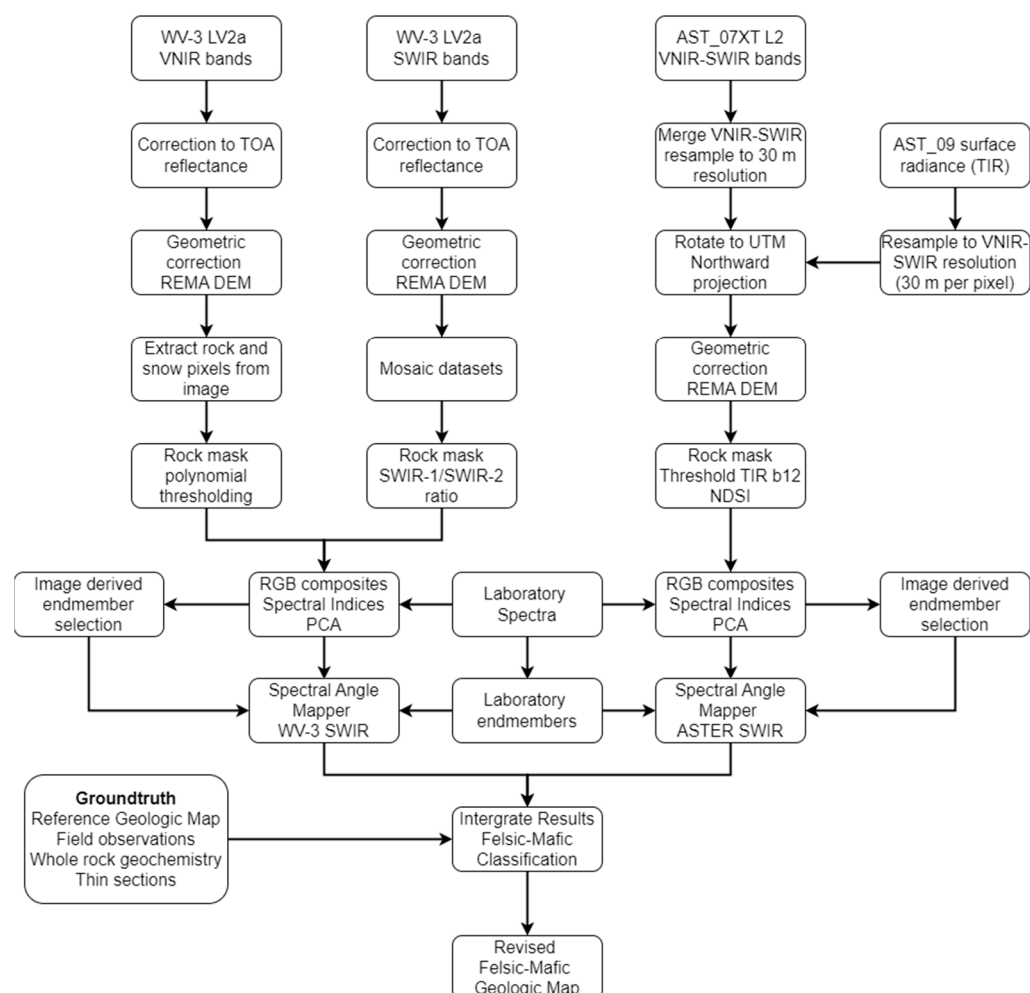


Figure 5. Flow chart summarising pre-processing steps and spectral analysis of laboratory spectra, WV-3 and ASTER datasets for mafic-felsic classification and mapping of Mt Murphy. Spectral mapping and classification techniques are explained in Section 3.3 and in detail in Supplement S1.

3.3. Spectral Mapping and Classification Methods

Following pre-processing, we used spectral mapping techniques to identify felsic-mafic endmember pixels from the imagery before correlating these pixels to our geolocated laboratory spectra. Spectral mapping refers to a set of statistical and algebraic methods used to classify and extract different classes of materials in an image based on their image spectral signature [7]. When using ‘broad band’ imagery such as WV-3 and ASTER VNIR-SWIR, such classification is limited to discrimination of lithologies based on distinct spectral absorption features caused by major mineral groups, most of which are wavelength dependent. Prior to spectral mapping, we applied a linear contrast enhancement to stretch image pixel values and make use of the full data value range for each image. Subsequent spectral mapping techniques included commonly adopted image processing techniques such as colour composites, applying spectral indices including Relative absorption Band Depth (RBD) [11,21] and Principal Component Analysis (PCA) [23]. A detailed explanation of the spectral mapping techniques applied in this study is provided in Supplement S1.

To classify image pixels with similar spectral signatures in ASTER and WV-3 imagery, we applied the Spectral Angle Mapper (SAM) algorithm [52] to the previously identified endmember felsic (granite, gneiss) and mafic (basalt, hydrovolcanic) reference spectrum. SAM is a supervised classification technique that determines the spectral similarity between two spectra by calculating the angle between them, permitting the rapid mapping of image spectra to reference spectra. The SAM algorithm utilises the vector direction and not the length of the vector to determine its classification (Figure S2), resulting in spectral classifications that are less impacted by variations in absolute illumination (sun angle/slope/detector/off-nadir angle or shading) than classifications made using other spectral matching algorithms [53]. Output class images, representing spectral angular similarity between reference and target spectra, were generated using both endmember pixels extracted from the image and endmember laboratory reflectance spectra.

4. Results

4.1. Mount Murphy Reflectance Spectroscopic Analysis

First, we describe the spectral profiles of rock samples previously collected from the Mt Murphy study area (Figures 4 and 6, Supplement S4) which provide ground validation for remotely sensed results and interpretations. Photomicrographs of thin sections from selected samples provide additional context for interpretation of mineral assemblages (Figure 7). The spectra we derived from felsic rocks from Mt Murphy, such as granite sample MB.418.1P and the granite/aplite KAY-103, display high to moderate albedo, indicating the presence of felsic minerals, and a strong Al-OH absorption feature at 2.2 μm associated with the mineral muscovite (Figure 6a, Supplement S4). Muscovite occurs in association with quartz and plagioclase in MB-418.1P (Figure 7c,d), with some mineral grains displaying evidence of alteration. In the spectra of gneisses, KAY-106 and KAY-111, a steep increase in reflectance from 1.2 to 1.8 μm wavelength is associated with a broad ferrous (Fe^{2+}) charge transfer feature. Spectra from these samples also display moderate absorption features at 2.33 μm and 2.4 μm (Figure 6b). The spectral profile of KAY-111 closely resembles biotite from 0.5 to 1.9 μm , which exhibits a relatively steep increasing slope from 1.2 to 1.8 μm , and so we attribute the Fe^{2+} charge transfer feature to numerous dark brown biotite crystals observed in thin sections of sample KAY-111 (Figure 7a,b). The presence of biotite is also consistent with previous observations describing Kay Peak ridge gneiss as a biotite gneiss (see Figure 3b). The Fe/Mg-OH absorption feature observed at 2.33 μm in the gneiss rock spectra could be associated with chloritization of primary biotite grains and the presence of hornblende (Figure 7a). The moderate absorption features at 2.33 μm and 2.4 μm also closely resemble the spectral profile of plagioclase [54]. Plagioclase is also observed in the

gneiss thin sections (Figure 7a,b). Therefore, it is likely a combination of both biotite and plagioclase which contribute to the spectral signature of whole rock samples.

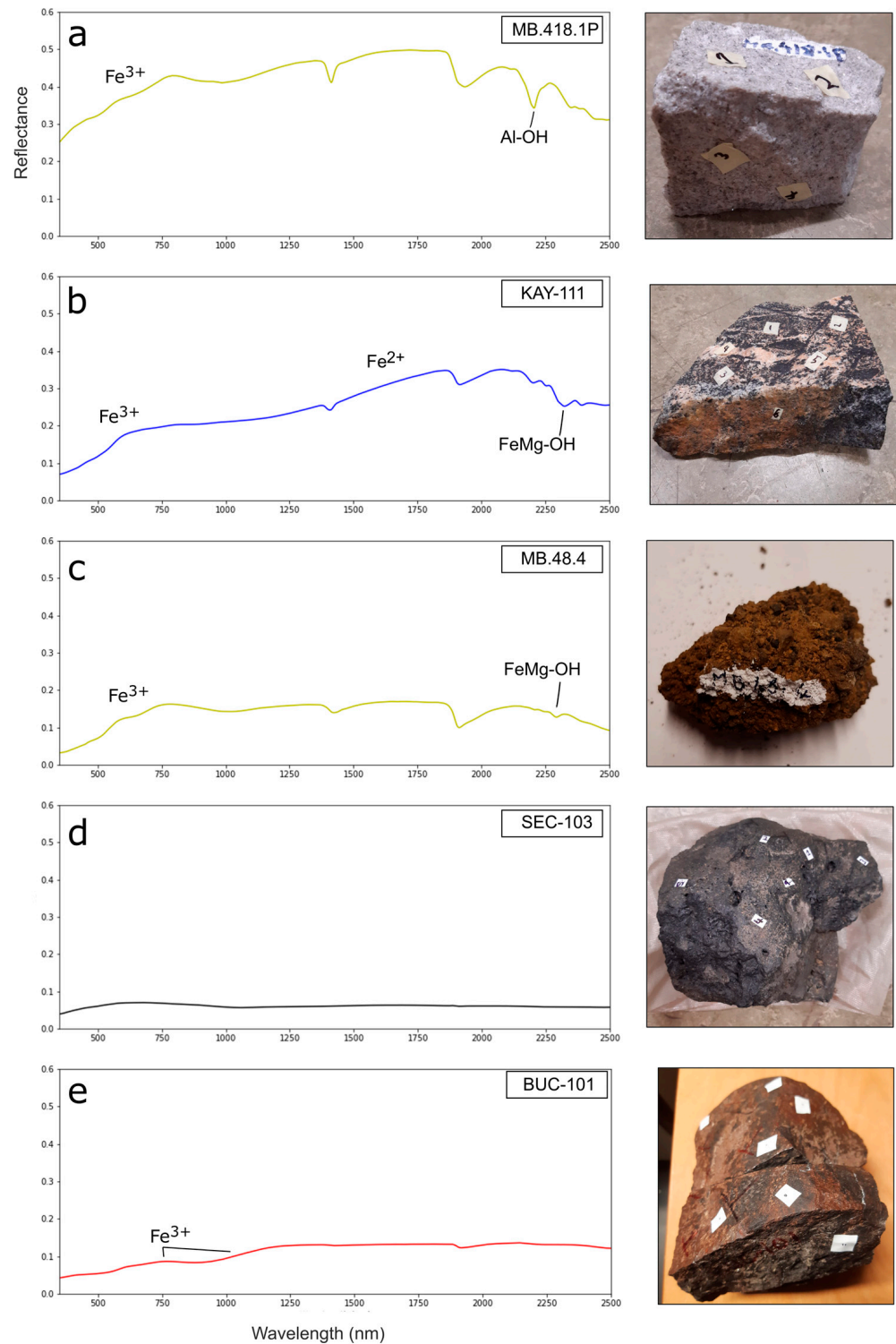


Figure 6. Spectral profiles and sample photos of the main rock types identified at Mt Murphy highlighting key spectral features used for lithologic discrimination of granite (a), gneiss (b), hydro-volcanic rock (c), basalt (d), and weathered basalt (e). Spectral profiles and associated whole rock photos of all Mt Murphy specimens can be viewed in Supplement S4.

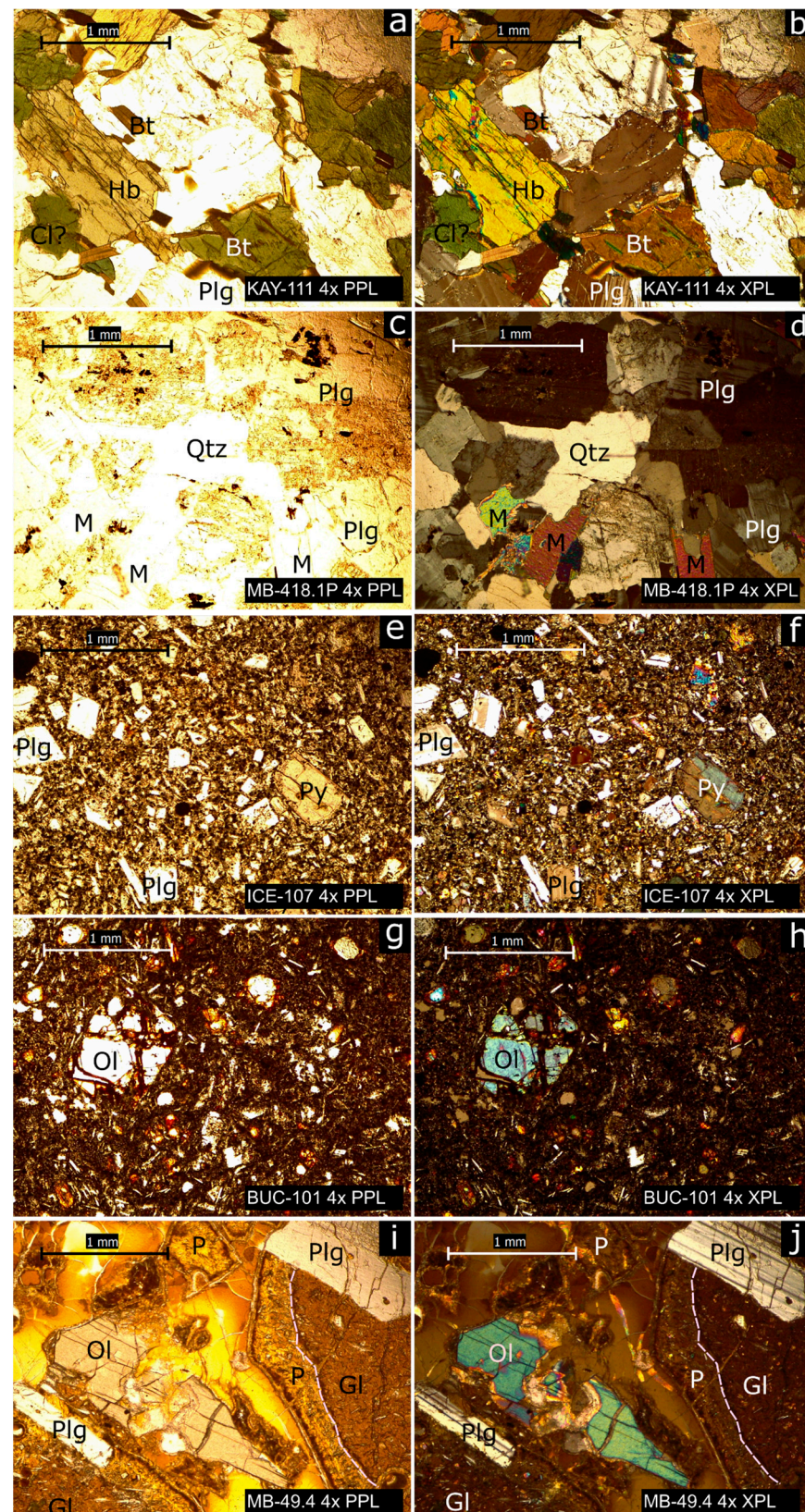


Figure 7. Photomicrographs of Mt Murphy rock specimens: gneiss—KAY-111 (a,b), granite—MB-418.1P (c,d), basalt—ICE-107 (e,f), weathered basalt—BUC-101 (g,h), and fragmental hydrovolcanic rock—MB-49.4 (i,j) in plane-polarised (PPL) and cross-polarised light (XPL). Bt—biotite, Cl—chlorite, Gl—glass, Hb—hornblende, M—muscovite, Ol—olivine, P—palagonite, Plg—plagioclase, Py—pyroxene and Qtz—quartz. Sample name, polarisation and scale shown on each panel. The white dashed lines in panels (i,j) indicate the border between fresh glass (Gl) and altered glass/palagonite (P).

Rock spectra profiles of the basalt samples (SEC-103, SEC-102 and TUR-131) are flat and exhibit low albedo (Figure 6d) due to the relative abundance of darker mafic minerals including pyroxenes and olivine (Figure 7e,f). Basalt samples SEC-202 and ICE-107 show a moderate increase in reflectance from 0.5 to 0.7 μm wavelength, indicative of ferric iron (Fe^{3+}) which is associated with oxidation products such as the mineral goethite. SEC-202 and ICE-107 are slightly weathered and have glacial striae on their surfaces, showing evidence of glacial polish. BUC-101—a heavily weathered basalt containing large fragmented olivine phenocrysts set within a reddish groundmass (Figure 7g,h)—displays a prominent stepped rise in reflectance from ~ 0.5 to $0.7 \mu\text{m}$ and from ~ 0.85 to $1.2 \mu\text{m}$, indicative of more intense Fe^{3+} absorption in these parts of the spectrum. In the present study, the fragmental hydrovolcanic rock spectra exhibit a more marked rise in reflectance from VNIR to SWIR wavelengths than the fresh and weathered basalts. Our spectroscopy results also indicate that polished basalt samples have a spectral profile similar to that of fresh basalt (Figure S3). Fragmental hydrovolcanic spectra also display stronger absorption features at wavelengths of $1.4 \mu\text{m}$ and $1.9 \mu\text{m}$. These are likely associated with the presence of hydrated minerals. Notably, sample MB 48.4 has an absorption feature at $\sim 2.29 \mu\text{m}$ (Figure 6c), suggesting the presence of nontronite, an Fe-rich smectite [55]. This is consistent with petrographic examination of this hydrovolcanic sample, MB.49.4, which shows alteration of darker volcanic glass to orange-brown palagonite (Figure 7i,j), an alteration product of basalt which contains smectite [56]. For an in-depth discussion of the impact of weathering on spectral profiles of Mt Murphy samples, refer to Supplement S2.

Results of Convolving Mt Murphy Rock Spectra

Mt Murphy rock spectra were convolved to the ASTER and WV-3 waveband ranges to enable comparison of endmember spectra from Mt Murphy rock types (granite, gneiss, hydrovolcanic rocks, and basalt) at the resolution of ASTER and WV-3 sensors. Certain mineral absorption features and variations in albedo are resolved by ASTER and WV-3 wavebands (Al-OH absorption feature and overall brightness) and serve as a basis for discrimination of felsic and mafic endmember lithologies. When resampled to ASTER and WV-3 wavebands (Figure 8a,c), the granite, gneiss, fragmental hydrovolcanic rock, and basalt rock spectra are still distinguishable from one another (Figure 8b,d). The double absorption feature observed in the gneiss rock spectra when resampled to WV-3 wavelengths is visible as a decrease in reflectance at $2.2 \mu\text{m}$, steepening at $2.3 \mu\text{m}$ (Figure 8c), while at ASTER wavelengths, it remains distinguishable as a single absorption feature (Figure 8d). The most notable feature in the gneiss spectrum, however, is the large Fe^{2+} charge transfer feature from 1.2 to $1.8 \mu\text{m}$ retained in WV-3 and to a lesser extent ASTER spectral profiles, indicating that gneiss samples from Kay Peak are iron-rich and that this is detectable in both the ASTER and WV-3 imagery. Discrimination of the mafic endmember lithologies (basalt and hydrovolcanic rock) is more challenging because they display similar absorption features at WV-3 and ASTER wavelengths. The broad rise in reflectance from 0.5 to $0.7 \mu\text{m}$ in moderately weathered basalt (SEC-202, ICE-107) and 0.85 to $1.2 \mu\text{m}$ in heavily weathered basalt (BUC-101) is well-resolved in the convolved WV-3 spectral profiles due to the relatively high spectral resolution of the WV-3 sensor at VNIR wavelengths. The moderate absorption feature at $2.29 \mu\text{m}$ associated with Fe-rich phyllosilicates such as smectite [55] is discernible as a broadband Fe/Mg-OH absorption feature in broadband WV-3 imagery and can potentially serve as a means to discriminate fragmental hydrovolcanic rock from basalt.

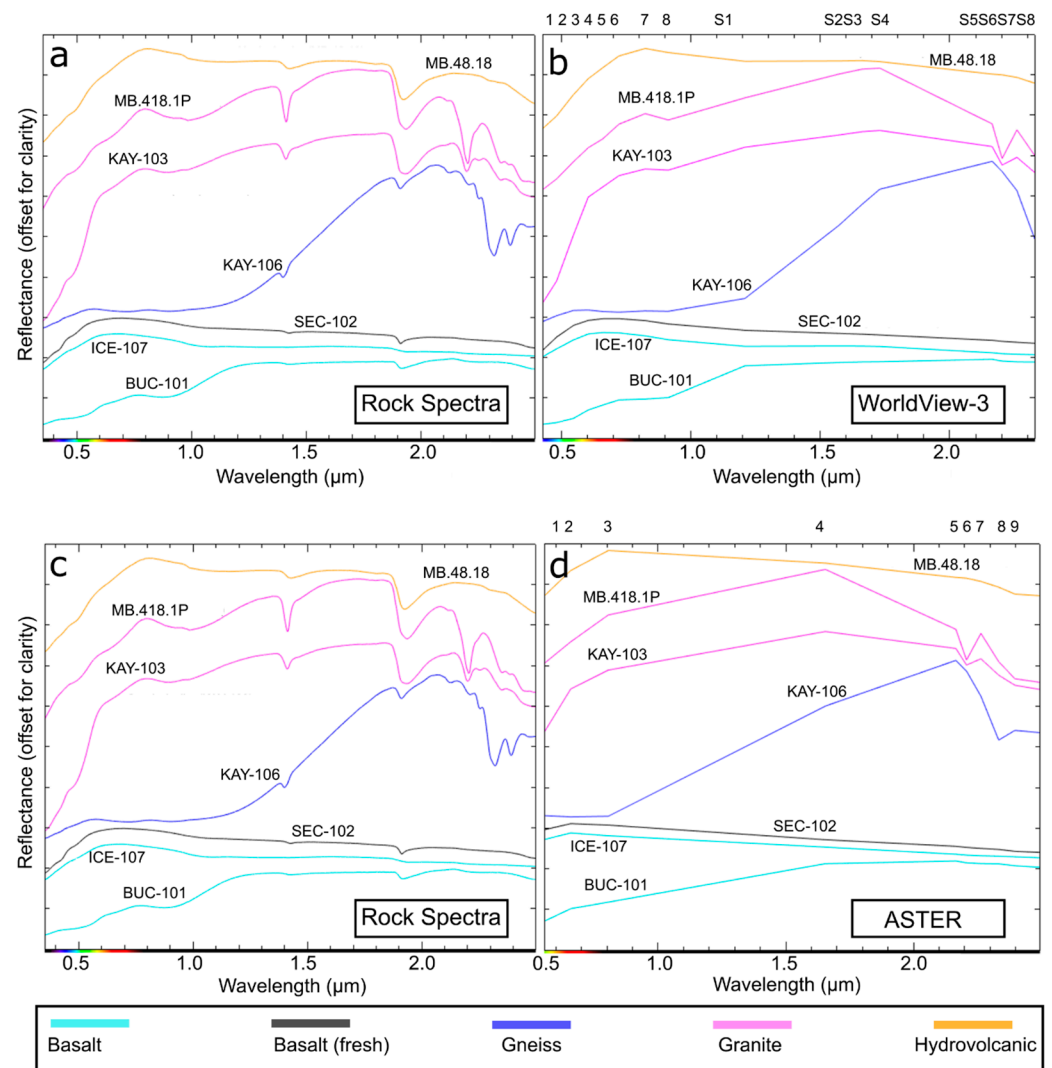


Figure 8. Mt Murphy sample rock spectra profiles (a,c) resampled to VNIR-SWIR Worldview-3 sensor bandpass (b) and ASTER bandpass (d). Panel (a) and Panel (c) show the same spectral profiles to make comparisons to WV-3 and ASTER convolved spectra clearer.

In summary, our observations from the resampled spectral rock profiles have the following implications for remote mapping of Mt Murphy rock types using WV-3 and ASTER multispectral imagery:

- Spectral discrimination of granitic rock from mafic rock is achievable due to the high albedo of granitoids and the Al-OH mineral absorption feature at 2.2 μm, associated with muscovite.
- Gneiss can be detected using its increased reflectance at 1.2–1.8 μm wavelengths, associated with increased Fe²⁺ absorption (produced by the presence of biotite) and a broadband Fe/Mg-OH absorption feature at 2.33 μm, which implies the presence of chlorite and hornblende (both minerals are common in gneissic rocks).
- Basalt has low reflectance in general, but weathered basalt exhibits raised reflectance at 0.5–0.7 μm associated with increased Fe³⁺, and so can be distinguished from fresh/polished basalt.
- Combined mapping of Fe³⁺ at VNIR wavelengths and detection of Fe-rich smectite (nontronite) ~2.29 μm as a broadband Fe/Mg-OH absorption feature provide a basis for successful differentiation of basalt and fragmental hydrovolcanic rock.

4.2. Mount Murphy Spectral Mapping Case Studies

To identify endmember pixels suitable for spectral classification, we applied spectral mapping techniques to ASTER and WV-3 VNIR/SWIR imagery from two sites at Mt Murphy: Kay Peak and Turtle Rock (see Figures 1 and 4). These techniques included generating targeted colour composites, spectral indices such as RBD ratios, and PCA (see Supplement S1 for detailed methods).

4.2.1. Case Study 1: Kay Peak and Granitoid Outcrop

Here, we describe remote sensing results from the Kay Peak study area, consisting of Kay Peak, its surrounding ridges and an unnamed granitoid outcrop 3 km southeast of Kay Peak (see Figure 4). Contrast-enhanced red-green-blue (RGB) composites helped identify the main lithologic groups in the Kay Peak study area. The most useful RGB colour composites were WV-3 VNIR 732 and WV-3 SWIR 368 false colour composites (FCC) and ASTER SWIR 468 FCC. Band ratios were useful for displaying the intensity of ferric (Fe^{3+}) and ferrous (Fe^{2+}) absorption, and targeted RBD ratios pinpointed Al-OH and Fe/Mg-OH absorption features at 2.2 μm and 2.33 μm , respectively (Figures 9 and 10).

Spectral mapping of the unnamed granitoid reveals that the outcrop exhibits high albedo, especially in the SWIR wavelength range, and strong Al-OH absorption (Figure 9). Remote sensing observations are consistent with lab spectroscopy results, which also show strong Al-OH absorption (sample MB-418.1P, previously collected from the outcrop) and the presence of muscovite, quartz, and feldspar in sample thin section. The geology of Kay Peak is more complex, with evidence for a variety of mafic and felsic rock types (Figure 10). The northernmost section of the ridge extending north from Kay Peak is characterised by very high reflectance, Fe/Mg-OH absorption (Figure 10e) and high Fe^{2+} spectral index values (Figure 10f). The combined spectral signatures of high Fe^{2+} values and Fe/Mg-OH absorption indicate the presence of biotite and Fe and Mg-rich hydrated secondary mafic minerals, such as chlorite and hornblende, consistent with the mineralogy of gneiss photomicrographs (Figure 7). Previous whole rock geochemistry results from Kay Peak reveal that the silica content of gneiss varies from felsic to intermediate, and that there is evidence of other mafic rock such as diorite/gabbro (Table S3 from [14]). The ridges running west and south from Kay Peak are visible in WV-3 VNIR imagery as distinct light-brown orange banding indicative of goethite Fe^{3+} iron absorption (Figure 10a), which coincides with very strong Al-OH absorption in WV-3 SWIR imagery (Figure 10c,d). However, it is unclear if Al-OH absorption detected in broadband SWIR imagery from ridges extending south and west from Kay Peak is due to the presence of primary muscovite or secondary clay alteration minerals.

North of Kay Peak, a distinct conglomeration of bright pixels is visible in both WV-3 and ASTER VNIR-SWIR imagery, hereby referred to as the Kay Peak spot (KPS). Reflectance values of the KPS at SWIR wavelengths are the highest at Mt Murphy, increasing to 60% reflectance in the 1.4–1.7 μm wavelength range. Field observations and photos indicate the presence of a yellow diamict in the vicinity of the KPS which is unique to this part of Mt Murphy (see Figure 3a). A targeted RBD expression (see Section 3.3) highlighted an absorption feature in WV-3 SWIR imagery centred at 2.16 μm and Al-OH absorption at 2.2 μm (Figure 10e). This double absorption feature is indicative of other Al-rich clay minerals such as kaolinite and alunite [11], and WV-3 and ASTER PC images suggest the KPS is spectrally distinct from the unnamed granitoid (Figure 10g,h). For a detailed breakdown of PCA results see Supplement S3.

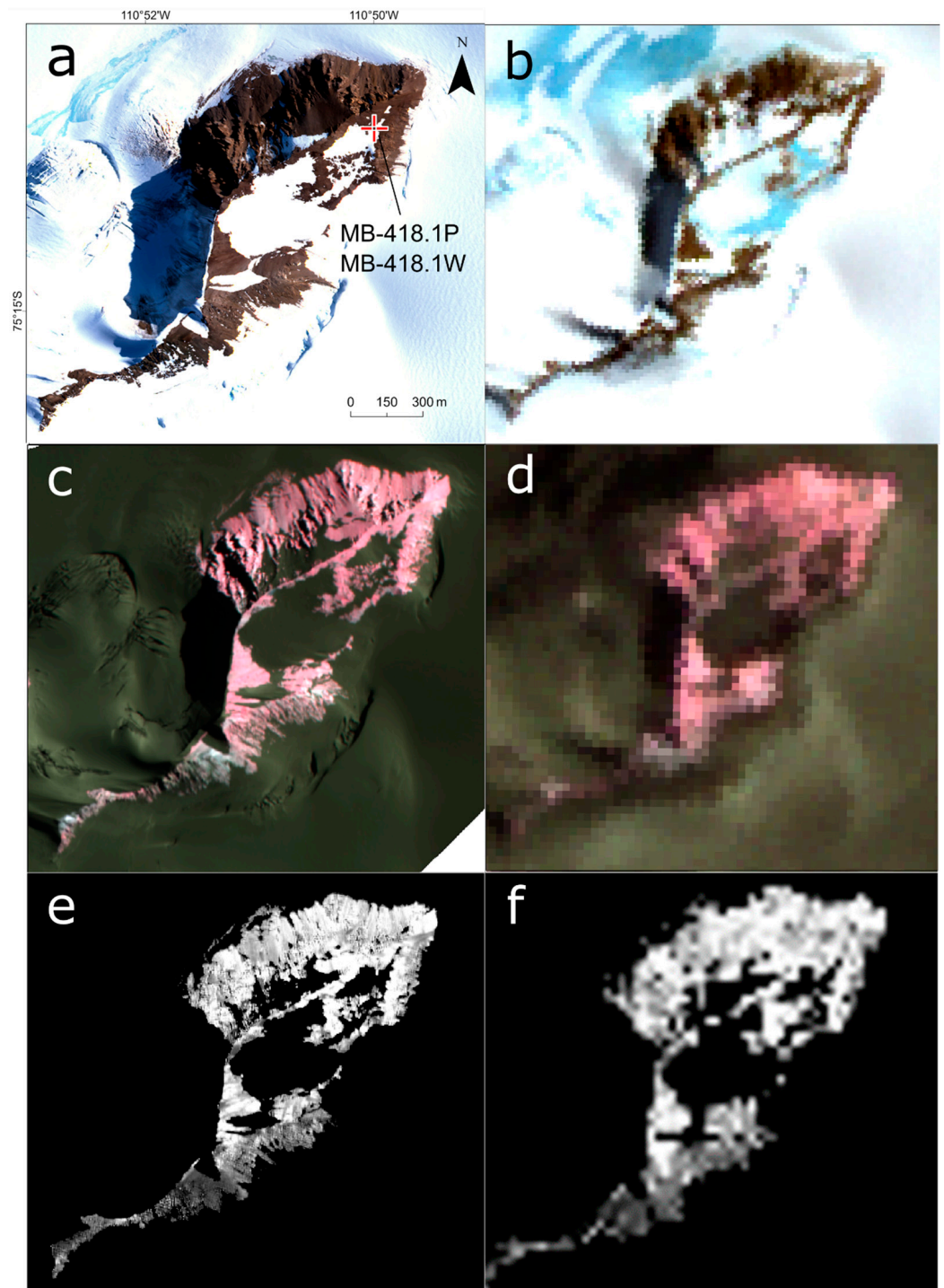


Figure 9. (a) WV-3 VNIR 532 contrast-enhanced true colour composite showing approximate GPS location (red cross) of MB-418.1P and MB-418.1W. (b) ASTER VNIR 321 image (15 m resolution). (c) WV-3 SWIR 368 false colour composite (contrast-enhanced). (d) ASTER 468 false colour composite showing equivalent to (c) at ASTER spatial resolution; the pink tone in both images is associated with intense hydrated mineral absorption from the Al-OH bond stretch. (e) WV-3 Al-OH RBD index $(bS5 + bS7)/bS6$, bright pixels indicate intense absorption at $2.2 \mu\text{m}$ associated with muscovite. (f) ASTER Al-OH RBD index $(b5 + b7)/b6$ showing equivalent to (e) at ASTER 30 m spatial resolution.

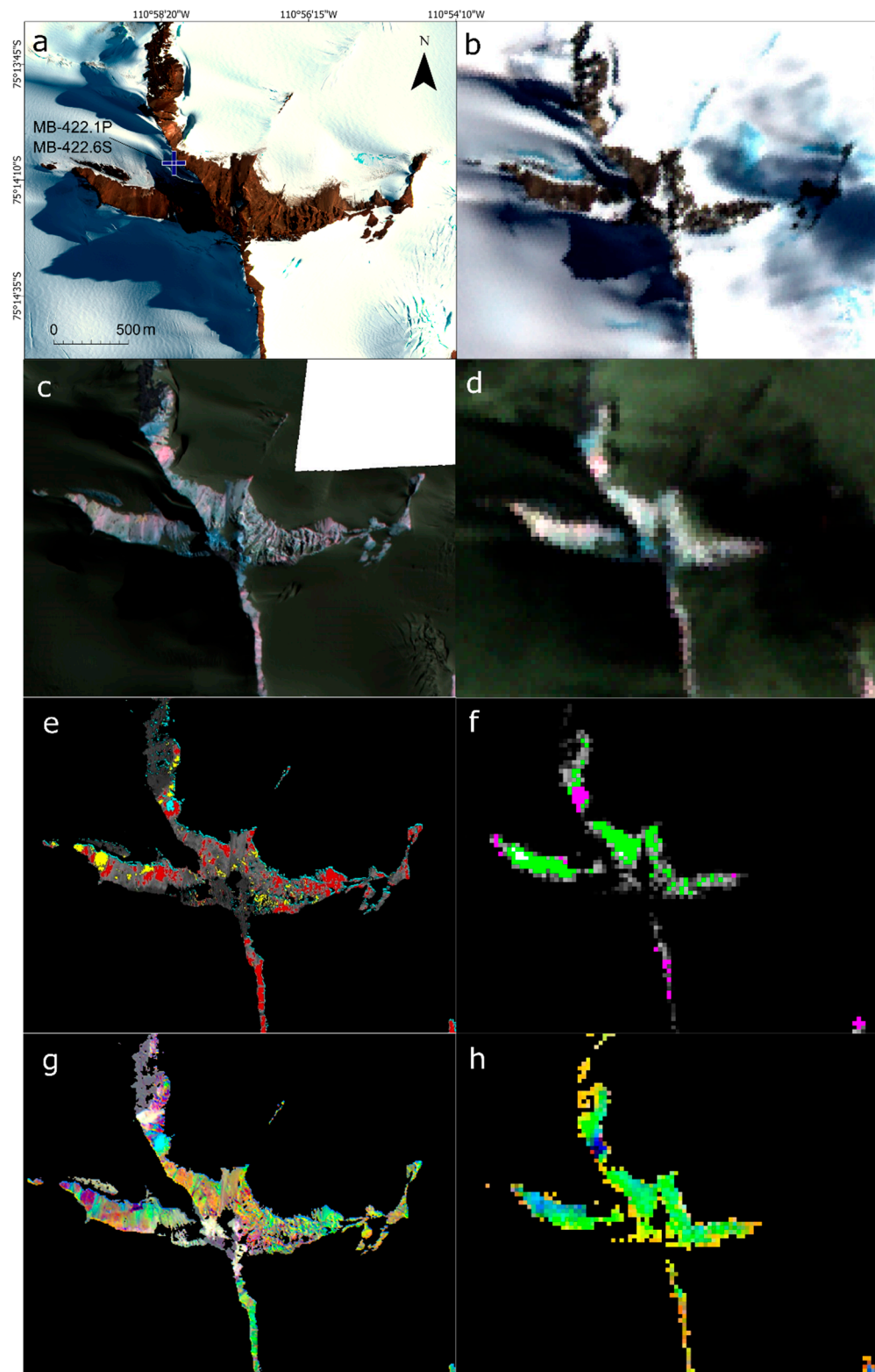


Figure 10. Kay Peak composite including (a) WV3-VNIR 732 FCC, displaying scale and approximate GPS location of rock sample (blue cross) for which whole rock geochemical analysis has been performed in a previous study. (b) ASTER 321 FCC. (c) WV3-SWIR 368 FCC. (d) ASTER 468 FCC (showing hydrated minerals in pink tones and mafic rocks in blue tones). (e) WV-3 SWIR spectral index composite (thresholded to show 90th percentile) of Al-OH (red), Fe/Mg-OH (yellow) and hydrated minerals with absorption centred around $2.16\ \mu\text{m}$ (blue). (f) ASTER spectral index composite (thresholded to show 90th percentile) of hydrated minerals (pink) and ferrous minerals (green). (g) WV-3 SWIR PCA composite of PCs 568 (Table S4) and (h) ASTER FCPS image (bands 1469) targeting smectite/kaolinite (Tables S6 and S7).

To summarise, the composition of the unnamed granitoid is well characterised by strong Al-OH absorption corresponding to muscovite, high albedo and high silica content and serves as a good endmember for supervised classification. In contrast, spectral analysis of WV-3 SWIR and ASTER imagery indicate the lithological variation of ridges neighbouring Kay Peak is complex, comprising a mixture of felsic and intermediate to mafic rock types (Figure 10, Table S3). Felsic lithologies at Kay Peak with strong Al-OH absorption such as granites and aplites can be distinguished from mafic rocks which exhibit low albedo such as the basalt at Kay Peak summit. Despite a relatively high silica content (Table S3), felsic gneiss is challenging to classify at VNIR-SWIR wavelengths, as it lacks an Al-OH absorption feature. Instead, gneiss displays strong Fe^{2+} and Fe/Mg-OH absorption at $\sim 2.33 \mu\text{m}$, akin to more mafic rocks, making differentiation using VNIR-SWIR imagery challenging in areas where ground truth is poor.

4.2.2. Case Study 2: Turtle Rock, Icefall Nunatak and Notebook Cliffs

We used subtle differences in spectral profiles of fresh/polished basalt, weathered basalt and hydrovolcanic rock (Figure S3) as a basis for spectral mapping of the mafic outcrops, Turtle Rock, Icefall Nunatak and Notebook Cliffs. The Turtle Rock, Icefall Nunatak and Notebook Cliffs outcrops are all low albedo (Figures 11 and S6), indicating that these outcrops contain an abundance of fresh and polished basalt, which is consistent with lab spectroscopy results (see Figure 6 and Supplement S4). A contrast-enhanced WV-3 368 FCC SWIR image also revealed zones of comparatively higher reflectance at SWIR wavelengths at all three outcrops relative to the low reflectance of fresh/polished basalt (Figure S5). Applying a WV3-VNIR 5/2 band ratio to WV-3 imagery indicates an Fe^{3+} signature that is suggestive of the presence of goethite, an Fe^{3+} rich mineral associated with basalt weathering. The remote sensing-based observations of the spatial distribution of Fe^{3+} at Icefall Nunatak are consistent with GPS locations of fresh and weathered basalt samples (Figures 5 and 11). For instance, sample ICE-107, which exhibits glacial polish and slight-moderate weathering, was collected from an area lacking an Fe^{3+} signature in WV-3 imagery (Figure 11a).

To discriminate fragmental hydrovolcanic rock from basalt we applied a $b6/(b7+b8)$ RBD index to WV-3 SWIR imagery, which revealed strong Fe/Mg-OH absorption overlapping with Fe^{3+} rich zones at both Icefall Nunatak and Notebook Cliffs (Figures 11 and S6). We interpret zones of corresponding Fe^{3+} and strong Fe/Mg-OH absorption as evidence of Fe-rich smectite (nontronite). This is based on evidence from hydrovolcanic rock spectra (Figure 6) which show absorption at $2.29 \mu\text{m}$ (appearing as an Fe/Mg-OH absorption at broadband WV-3 wavelengths) and supported by thin sections of Icefall Nunatak and Notebook Cliff samples showing that volcanic glass has been palagonitized (Figure 7). Areas of overlapping Fe^{3+} and Fe/Mg-OH absorption are most prominent at Notebook Cliffs (Figure S6, Supplement S3) and are supported by previous field observations and the GPS location of fragmental hydrovolcanic rock samples (MB 48.4, Figure 6). At Turtle Rock, areas of increased Fe^{3+} on the upper Turtle Rock platform also indicate the presence of goethite associated with basalt weathering. However, it is challenging to differentiate hydrovolcanic rocks from weathered basalt at Turtle Rock because geometric correction has distorted some image pixels, leading to incidences of extreme reflectance values. In addition, the vertical viewing angle of the satellite emphasises the capping lava while the underlying fragmental hydrovolcanic rock visible in the field is partially obscured.

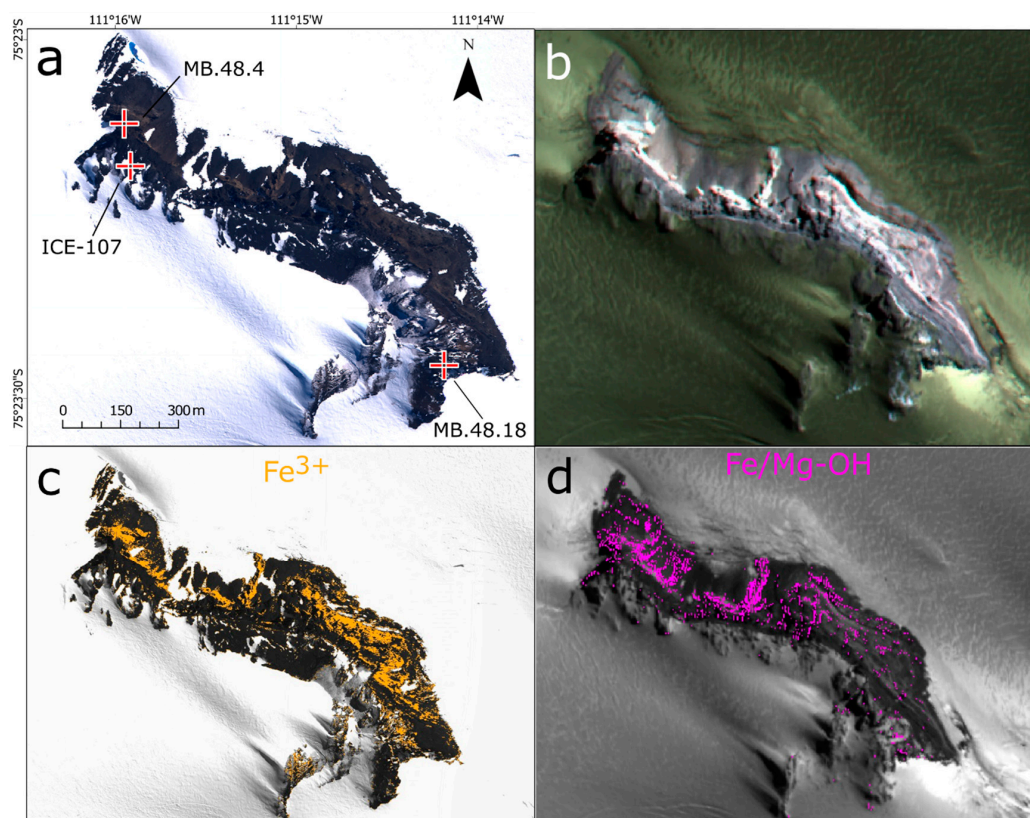


Figure 11. Icefall Nunatak (a) WV-3 VNIR 732 FCC showing GPS locations of Mt Murphy spectra (red crosses) collected from Icefall Nunatak. (b) WV-3 SWIR 368 false colour composite (contrast-enhanced) showing VNIR Fe-O dominated pixels are consistent with uniform high SWIR band reflectance. (c) WV3-VNIR band 5 overlaid with upper 90th percentile thresholded pixels from 5/2 (red/blue) Fe-O ratio (orange). (d) Upper 90th percentile thresholded pixels SWIR Fe/Mg-OH index overlaid on greyscale image of WV-3 SWIR band 1 (purple).

In summary, our assessment of ASTER and WV-3 spectral mapping capabilities at the mafic outcrops; Notebook Cliffs, Icefall Nunatak and Turtle Rock, establishes that areas of increased Fe^{3+} signal distinguish both hydrovolcanic rock and weathered basalt from fresh basalt. Hydrovolcanic rock at Notebook Cliffs and Icefall Nunatak is mapped separately from weathered basalts using the combined spectral signals of Fe/Mg-OH absorption and increased Fe^{3+} absorption. Gneiss also exhibits broadband Fe/Mg-OH absorption due to the presence of chlorite and hornblende (Figure 10), but in conjunction with increased Fe^{2+} absorption from biotite rather than increased Fe^{3+} due to weathering of mafic minerals. Fe-rich smectite in hydrovolcanic rocks can therefore be mapped manually, but this may be more challenging if there is a lack of geological context from previous observations.

4.3. Supervised Felsic-Mafic Classification

We now describe felsic-mafic classification results using the spectral angle mapper (SAM) algorithm. The best classification results were achieved using endmember image pixels identified from spectral mapping at locations where rock samples had also been collected. SAM image-based classification using WV-3 correctly mapped the granite outcrop and areas of Kay Peak but required a spectral angle threshold of ~ 0.1 to achieve a high classification rate (Figure 12a). The requirement of a broader angle threshold points towards further potential mineralogical differences between the unnamed granitoid and other locations with strong Al-OH absorption such as the KPS (see Section 4.2.1). Using all four rock types (granite, gneiss, basalt, fragmental hydrovolcanic) as endmember image classifiers (see Figure S7) increased the amount of classified rock, particularly around Kay

Peak and the ridge extending northward from Kay Peak (Figure 12c). A lower threshold angle of 0.04 radians was relatively consistent at classifying mafic rock for both WV-3 and ASTER SWIR imagery at Notebook-Icefall-Turtle Rock outcrops (Figure 13a,b). Classification of fragmental hydrovolcanic rock and basalt is, however, more difficult because the VNIR part of the spectrum (useful for discrimination of Fe^{3+}) and SWIR part of the spectrum (useful for discriminating hydrated minerals, e.g., $\text{Fe}/\text{Mg-OH}$) exist as separate WV-3 datasets collected at different dates. Despite this, SAM successfully classified the portions of Icefall Nunatak and Notebook Cliffs corresponding to increased Fe^{3+} absorption and $\text{Fe}/\text{Mg-OH}$ absorption as hydrovolcanic rock (Figure 13c).

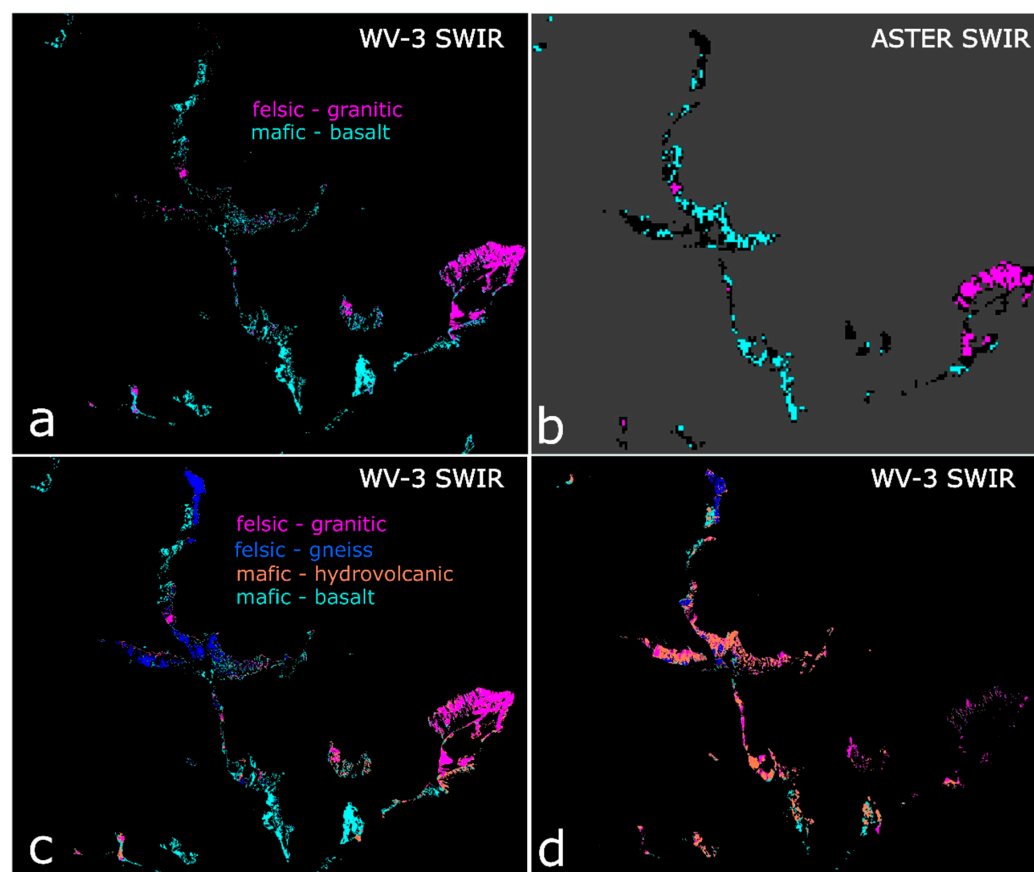


Figure 12. Supervised classification of key lithological groups at Kay Peak showing (a) WV-3 image endmember derived felsic-mafic classification (0.1 rad). (b) ASTER image endmember derived felsic-mafic classification (0.04 rad). (c) WV-3 image derived endmembers; granite, gneiss, hydrovolcanic rock and basalt (0.1 rad), and (d) laboratory spectra derived classification with all 17 samples simplified to four endmember types (0.1 rad).

Simplified felsic-mafic classification results using ASTER SWIR imagery were cruder but displayed relatively good coverage (Figures 12b and 13b). ASTER based classification captures more exposed rock at Mt Murphy using smaller angular thresholds of ~ 0.04 . A larger pixel means spectral vectors are more likely to be apart from one another, i.e., the size of the spectral angle is larger, so despite the larger size of ASTER SWIR pixels (30 m), there is less spectral variation within them. Notably, the KPS, which amounts to a few pixels at ASTER-SWIR spatial resolution, is successfully classified as felsic, and pixels at scoria cone are classified as mafic (Figure 12b), demonstrating that medium resolution ASTER-SWIR imagery using endmembers extracted from the image as training data can achieve a broad mafic-felsic differentiation. Classifications produced using subsampled laboratory reflectance spectra measured from endmember samples (Figures 8d and 12d) are less reliable (for further results see Supplement S3). However, the gneiss endmember is

consistently classified on the well illuminated slope of Kay Peak north ridge using both image-derived and laboratory spectra as classification inputs (Figure 12c,d).

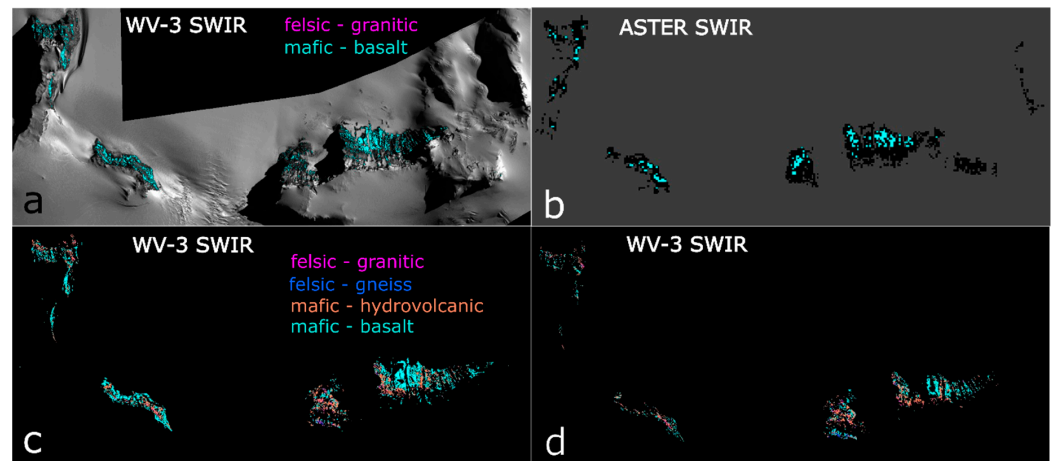


Figure 13. Supervised classification of key lithological groups at Turtle Rock area showing (a) WV-3 image endmember derived felsic-mafic classification (0.04 rad). (b) ASTER image endmember derived felsic-mafic classification (0.03 rad). (c) WV-3 image derived endmembers; granite, gneiss, hydrovolcanic and basalt (0.1 rad) and (d) laboratory spectra derived classification using all Mt Murphy samples simplified to four endmember types (0.1 rad).

5. Discussion

5.1. Assessment of Mapping and Supervised Classification Performance

Differentiation of felsic and mafic lithologies at Kay Peak and the unnamed granitoid was possible due to the high albedo of paler felsic minerals such as quartz and feldspars, and detection of the Al-OH absorption feature at 2.2 μm associated with muscovite which is commonly found in granite. Gneiss is distinguishable at Kay Peak due to (i) the presence of biotite causing a rise in reflectance from 1.2 to 1.8 μm , and (ii) secondary alteration minerals such as chlorite and hornblende which manifest as an Fe/MgOH absorption feature at 2.33 μm . Differentiation of mafic rocks into fresh/polished basalt, weathered basalt, and fragmental hydrovolcanic rock at Icefall Nunatak and Notebook Cliffs is possible due to a combination of Fe^{3+} and Fe/Mg-OH absorption at 2.33 μm . Applying these assumptions to mapping mafic rock types in unvisited areas with no ground truth is more challenging, as mafic minerals such as chlorite and hornblende also display an Fe/Mg-OH mineral absorption signal. Spectral mapping of certain areas of Mt Murphy is impacted by illumination with sensors detecting anomalously high reflectance on sun facing slopes and low reflectance on shaded slopes, sometimes leading to a spectral signature that does not accurately reflect the true reflectance signature of the rock in question.

Following spectral mapping, we assessed the performance of SAM for classifying felsic-mafic rock types using (i) both ASTER-SWIR and WV-3 SWIR imagery based on endmember pixels identified from spectral mapping (see Section 4.2), and (ii) GPS locations of rock reflectance spectra profiles from Mt Murphy samples (see Section 4.1). SAM performs better at classifying poorly illuminated pixels than other algorithms [53] but may be prone to over-classification of basalt/hydrovolcanic rock pixels in our WV-3 scenes, especially when the spectral angle is relaxed. Laboratory endmembers performed poorly compared to image-based endmembers, which may be due to differences in overall spectral shape between image and laboratory spectra, particularly impacting the spectral profile of image derived relative to rock spectra derived basalt (Figure S7). Poorer spectral matching between ASTER SWIR imagery and laboratory spectra may also be due to differences in spectral shape due to a lack of pure endmember pixels because of ASTER's 30 m spatial resolution but could

also be due to limitations of the AST_07XT product associated aerosol model. The Antarctic atmosphere is clean, cold and dry with minimal aerosol levels [57], and a correction to top-of-atmosphere (TOA) reflectance has proven sufficient for obtaining robust SAM results in other studies [58]. Applying a TOA correction to ASTER L1T (Level 1 Precision Terrain Corrected Registered At-Sensor Radiance) imagery could therefore potentially yield better classification results.

The selection of training pixels for the image-based SAM classification approach combined a degree of reliable ground truth, validation, and pre-existing knowledge of the site in question. Differentiation of felsic-mafic rock types could feasibly rely on comparison of image spectra to known spectra from existing spectral libraries [24] including our new spectral library. However, differentiation of fragmental hydrovolcanic rock from basalt without ground truth would be more challenging [46]. SAM classifies pixels independent of albedo, but this can be disadvantageous in some cases, as relative albedos need to be considered when classifying different types of volcanic rock, i.e., trachyte (high albedo) vs. basalt (low albedo), which otherwise have a similar spectral profile at VNIR-SWIR wavelengths [54]. Despite these limitations, by applying the SAM algorithm at Mt Murphy, we were able to differentiate felsic-mafic endmember spectra on the ground in very-high-resolution WV-3 SWIR imagery and medium-resolution ASTER SWIR imagery. SAM can therefore be applied to classify felsic and mafic rock types in polar regions using WV-3 SWIR imagery and open-source medium-resolution ASTER imagery for larger outcrops.

5.2. Revised Geological Map of Mount Murphy

Our remote sensing-based mapping has enabled the differentiation of four principal rock types (granite, gneiss, fragmental hydrovolcanic rock, and basalt), which, along with ground truth and existing observations allows us to produce a revised felsic-mafic geological map of Mt Murphy (Figure 14). This map was produced by combining spectral classification (SAM) results with other metrics, including spectral absorption features and albedo. Where possible, we compared classified SAM pixels against GPS locations of our laboratory spectra and previous field observations to check their accuracy. Previous field expeditions observed minimal deposits of surficial glacial till and colluvium on Mt Murphy's ridges and surrounding nunataks [2,15]. In addition, any erratic boulders and cobbles transported by ice and emplaced on bedrock are too sparse to impact the spectral signal from the underlying bedrock [2]. We therefore interpret spectral mapping and classification results to reflect signal from bedrock. Our new map is more comprehensive than existing published maps of Mt Murphy [12,37], refining and improving detail of the east, west and south ridges extending from one of the northern outcrops of the massif, Kay Peak, where supervised classification results are largely consistent with existing field observations (Figure 15). We also mapped the high elevation rock outcrops (>1900 m asl) adjacent to Mt Murphy summit and Grew Peak.

Based on remote sensing evidence (Figures 9 and 12), ground truth (Figures 6 and 7) and previous observations (Figure 2), the unnamed granitoid is mapped as felsic, supported by previous geochemical analysis of samples from this outcrop which are over 70% silica (Table S3 from [14]). The presence of gneiss at Kay Peak north ridge based on Fe^{2+} and Fe/Mg-OH absorption is also in agreement with the existing geological map, field observations, and laboratory spectra, as is the boundary between gneiss and basalt observed at the summit of Kay Peak and the ridge extending north from Kay Peak (see Figure 3a). Spectral classification results suggest that much of the Kay Peak south ridge may be composed of basalt (or another mafic lithology), potentially indicating more extensive emplacement of volcanic rock at Mt Murphy than previously thought. A large portion of Kay Peak west ridge is mapped as felsic-gneiss interspaced with areas of increased Al-OH

absorption, potentially corresponding to previously described microgranite sheets [14]. Strong Fe/Mg-OH absorption observed at Kay Peak west ridge is indicative of gneiss with higher MgO content or diorite (Table S3 from [14]).

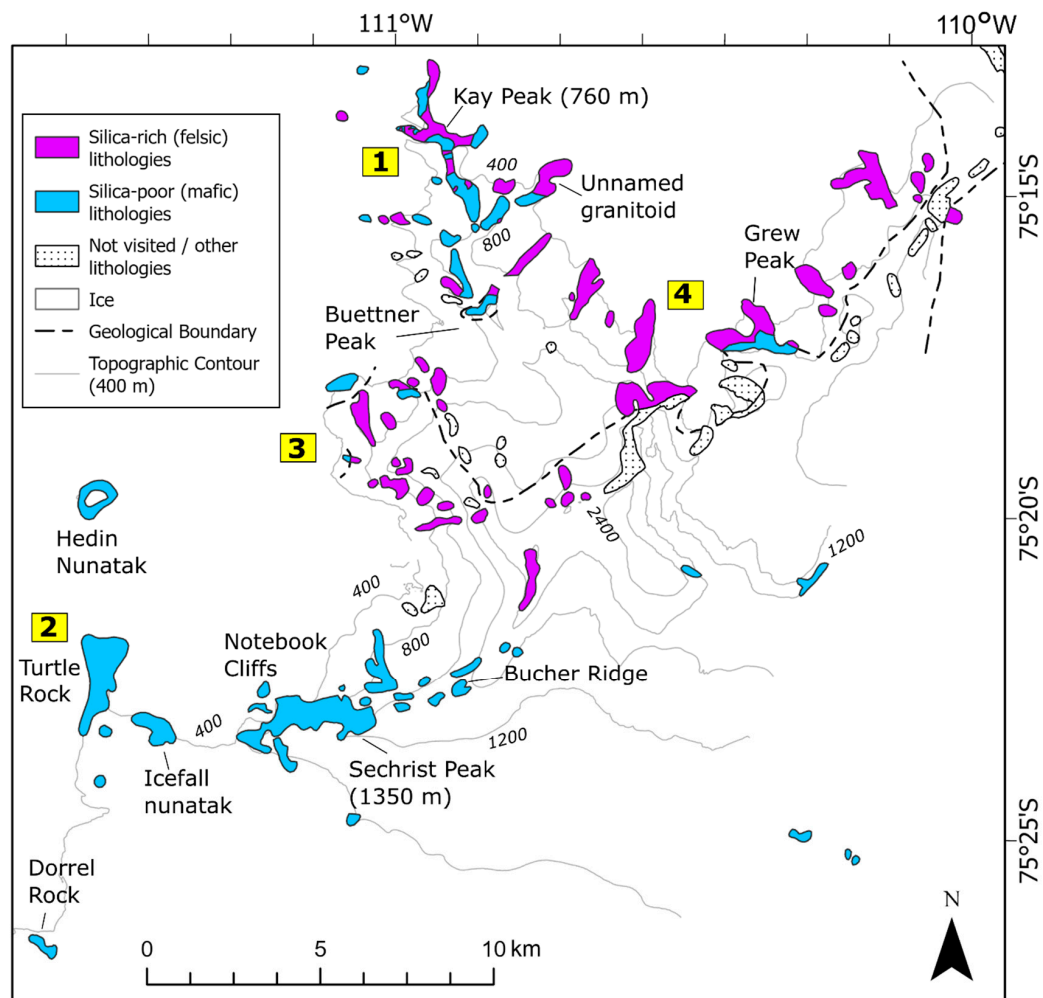


Figure 14. Revised felsic-mafic geological map of Mount Murphy based on the original reference geological map (Figure 2), spectral mapping (Section 4.2), and SAM classification (Section 4.3) results using ASTER and WV-3 VNIR-SWIR imagery. Note that shadowed outcrops (75°20'S, 111°00'W) and outcrops east of Grew Peak could not be reclassified due to shadow or cloud cover and remain the same as in the original reference geological map. Numbered locations correspond broadly to areas: Kay Peak (1), Turtle Rock, Icefall Nunatak and Notebook Cliffs (2), high elevation rock outcrops (3) and Grew Peak (4). Nomenclature is the same as in the reference geological map (Figure 2).

Classification results for Notebook-Icefall-Turtle Rock outcrops are consistent with existing observations that these outcrops are composed of mafic rock types [2,13,15]. The differentiation of basalt from fragmental hydrovolcanic rock using WV-3 imagery has permitted more detailed mapping of these nunataks, with remote mapping of their eruptive composition being broadly consistent with field observations [15]. These outcrops are simplified to mafic outcrops in the revised geological map and are consistent with the original reference geological map (Figure 2).

The KPS displays absorption at 2.16 μm and 2.2 μm indicating the presence of Al-rich clay minerals, potentially kaolinite or alunite. The yellow diamict observed in field photos (see Figure 3a) is distinct from the unnamed granitoid. The limited spectral resolution of the WV-3 sensor, however, means there is some confusion between alunite, kaolinite, and muscovite [11]. Diamict observed at the KPS could contain material from silicic boulders to phyllosilicates, making it challenging to specify its composition further without either

hyperspectral imagery or dedicated geochemical analysis. Despite its classification as a felsic outcrop by SAM, we have mapped one outcrop as gabbro (Figure 15d), consistent with field mapping of the locality. The outcrop may have been misclassified by SAM, as it displays moderate Al-OH absorption and moderate albedo (Figure 15b).

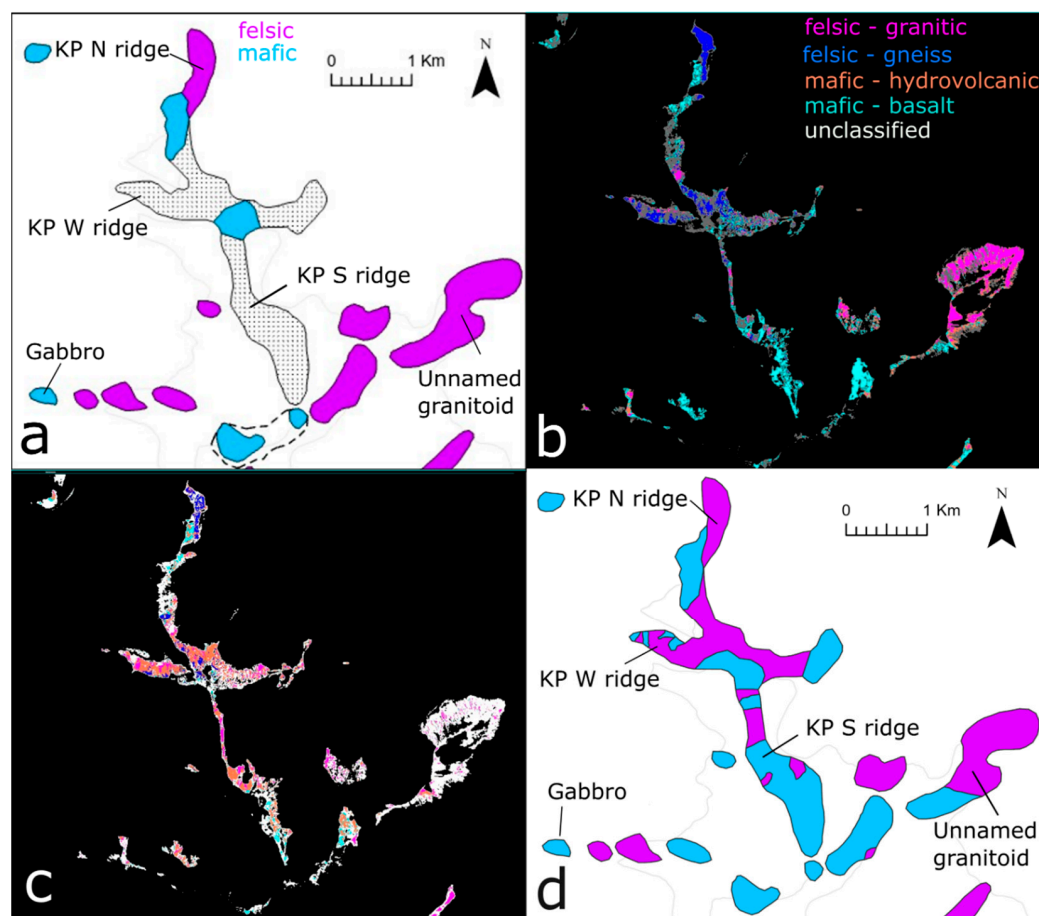


Figure 15. Example of revised classification at Kay Peak based on WV-3 imagery showing (a) original reference felsic-mafic geological map (Figure 2). (b) SAM image endmembers (preferred classifier). (c) SAM laboratory endmembers with some clearly erroneous classifications, e.g., hydrovolcanic rock at Kay Peak (secondary classifier). (d) Revised felsic-mafic geological map based on new remote sensing observations. The boundary in panel (d) is removed because there is limited evidence for this based on our spectral mapping.

The high elevation outcrops at Mt Murphy (see Figure 4, elevations > ~1900 m asl) consists of felsic-intermediate lava types (trachyte and benmoreite flows; [37]) and some basalt. However, summit outcrops are incorrectly classified by SAM as basalt (0.1; see Supplement S1), conflicting with our original reference map (Figures 2 and S8). Trachyte exhibits a relatively flat spectral profile at SWIR wavelengths, but with higher reflectance values than basalt [54]. Therefore, it is unlikely an additional trachyte endmember would resolve SAM misclassification at the Mt Murphy summit, as its spectral profile and spectral angle are similar to basalt. We mapped Mt Murphy summit rocks as felsic, based on their relatively high albedo at SWIR wavelengths relative to basalt (see Figure 4), which is consistent with mapping of felsic intermediate lavas based on their relatively high reflectance values in previous studies [10]. Remaining outcrops at Mt Murphy summit which are in shadow, and for which there are no field observations, are mapped as unvisited.

Rock outcrops extending W-E from Kay Peak comprise an unnamed outcrop and Grew Peak (Figure 4). These outcrops are mapped as felsic in our revised geological map

based on rock spectra-based SAM classification, minor Al-OH absorption, and high albedo consistent with the original reference geological map. All three outcrops exhibit high albedo and moderately weak Al-OH absorption features suggestive of felsic intrusive rock. The northern part of Grew Peak displays high albedo and Al-OH absorption, and the southern portion displays low albedo, in agreement with the geological boundary between felsic and mafic rock types of the original reference geological map (Figure 2). Image-based classification results were mixed, with some pixels classified as basalt. Laboratory spectra-based classification was, however, consistent with spectral mapping results in agreement with previous observations that these outcrops are felsic. The less consistent image-based endmember classification results around Grew Peak cannot be explained by SAM's lack of sensitivity to albedo. We were unable to extend mapping east of Grew Peak due to cloud cover in the ASTER image and lack of WV-3 coverage, and so the lithology of these outcrops was not revised.

In summary, consistent spectral classification results (see Section 4.3) helped to both refine and extend mapping coverage of Kay Peak and surrounding ridges (area 1), with empirical division into mafic and felsic lithologies of particular use for planning cosmogenic nuclide exposure dating studies. Mapping of the Notebook-Icefall-Turtle Rock outcrops is also consistent with previous observations that this area consists solely of mafic outcrops. At both the high elevation outcrops adjacent to Mt Murphy summit (area 3) and outcrops extending eastwards to Grew Peak (area 4), there are minor inconsistencies between spectral classification results and the original reference geological map (Figure 2). The production of the revised felsic-mafic geological map was validated using sample reflectance spectra, photomicrographs, and whole rock geochemistry.

5.3. Implications for Future Cosmogenic Nuclide Sampling Campaigns

Our findings indicate remote sensing-based mapping can be applied as a preliminary site characterisation tool to discriminate outcrops of felsic bedrock (which are more likely to contain quartz needed to extract nuclides such as ^{10}Be , ^{14}C and ^{26}Al) from mafic bedrock. Distinguishing between silica-rich and silica-poor rock types using VNIR-SWIR imagery can, however, be more nuanced because Al-OH absorption features associated with granitic-felsic rock types are also observed in diamict at Kay Peak ridge (Figures 3a and 10e), a less optimal lithology for cosmogenic nuclide sampling. A preliminary differentiation of silica-rich and silica-poor rock types is useful for determining a site's suitability for different types of cosmogenic nuclide sampling in unvisited areas, but can be improved by photo geological interpretation, which can help to distinguish less well consolidated Al-rich clay diamict from suitable felsic bedrock [7]. The remote differentiation of basalt from weathered basalt and hydrovolcanic rock (Figures 11 and S6) can also aid future cosmogenic nuclide field sampling design. Existing capabilities to measure the stable nuclide ^3He in olivine and pyroxene [59] and the potential to further develop extraction of in situ ^{14}C from olivine [4] and ^{10}Be from pyroxene [5] require well-preserved mineral crystals. Olivine and pyroxenes are typically less altered in fresh basalt (see Figure 7), making it useful to separate fresh and polished basalt from weathered basalt and hydrovolcanic rock, which we have demonstrated at Icefall Nunatak and Notebook Cliffs.

The remote sensing-based method presented here could also be used to aid in preliminary identification of suitable sites for recovery of subglacial bedrock cores by identifying the lithology of exposed ridges prior to field-based radar surveys to trace their subglacial extension [40]. Subglacial bedrock is increasingly being targeted for cosmogenic nuclide analysis, as it can provide insight into times when ice sheets were smaller than present [40]. However, poorly consolidated material such as frozen sediment and clay severely impedes bedrock core recovery [60]. Remote differentiation of fresh basalt from weathered basalt

and hydrovolcanic rock is useful, as it can help determine if a potential site contains an abundance of weathered, degraded or predominantly clay-rich material. Future applications of our method to map areas potentially suitable for cosmogenic nuclide sampling and/or subglacial bedrock drilling can make use of a new publicly available spectral library of Mt Murphy rock samples [50], as well as existing rock and mineral spectra available from spectral libraries such as the USGS [54].

5.4. Study Considerations and Future Work

Our results show that the use of ASTER and Worldview-3 VNIR-SWIR imagery for mafic-felsic differentiation in polar regions is achievable but has some limitations which are described below.

- WV-3 VNIR and SWIR datasets were not acquired simultaneously, precluding combined spectral analysis from band ratios and PCA and limiting the use of the SAM classifier to either VNIR or SWIR wavelengths for WV-3 imagery. The use of only part of the VNIR-SWIR spectral profile negatively impacts automatic differentiation of basalt and hydrovolcanic rock, likely contributing to cases of misclassification of these two endmembers.
- ASTER 07XT imagery was supplied with a pre-applied atmospheric correction using a radiative transfer model, whilst WV-3 data were corrected to top-of-atmosphere (TOA) reflectance. Supervised classification of ASTER imagery yielded less consistent results than WV-3, perhaps due to WV-3's superior spatial resolution, but potentially also due to artefacts introduced to ASTER imagery during atmospheric correction.
- We found ASTER TIR imagery had a poor signal-to-noise ratio at very high latitudes, and rock outcrops are often too small to be captured at the spatial resolution of this sensor (90 metres per pixel), so we could not use ASTER TIR imagery to directly detect quartz. Instead, albedo and the Al-OH absorption feature associated with the presence of muscovite served as proxies for distinguishing silica-rich and silica-poor rock.
- A new VNIR-SWIR hyperspectral sensor—Environmental Mapping and Analysis Program (EnMAP)—with medium spatial resolution (30 metres per pixel) has been launched since we acquired imagery for this study. EnMAP possesses much improved SNR relative to older hyperspectral sensors [61] so has the potential to resolve ambiguities classifying primary muscovites in granites from Al-rich clay diamict.
- Illumination differences due to low sun angles and the steep topography of Mt Murphy, particularly of shaded slopes, impacted spectral shape and therefore SAM classification. SAM addresses topographic induced differences in albedo, but shade dampens the reflectance signal and thus suppresses the true spectral shape of the rock being classified.

To resolve some of the limitations of the study described above, we make the following recommendations for future work:

- Where possible, use simultaneously acquired WV-3 VNIR and WV-3 SWIR datasets. For Antarctica, this requires specific joint VNIR-SWIR tasking requests, as WV-3 SWIR is not readily available to download from Digital Globe archives at high latitudes.
- Use L1T (Precision Terrain Corrected Registered At-Sensor Radiance) ASTER data and correct manually to top-of-atmosphere (TOA) reflectance for consistency with WV-3 image analysis. This may improve spectral classification (SAM) results using ASTER imagery.
- Future mapping would benefit from complementing the use of multispectral ASTER and Worldview-3 imagery with the new ENMAP hyperspectral sensor, especially to resolve ambiguities in mapping granitic bedrock and Al-rich clays. Resampling of the WV-3 imagery to the 30-metre spatial resolution of EnMAP would be a useful starting point for testing the effectiveness of this approach.

- Perform additional mineral analyses to better understand and distinguish the mineral composition of our samples and compare these results to petrography and spectral studies already undertaken.

6. Conclusions

In this study, we set out to remotely distinguish felsic (silica-rich) from mafic (silica-poor) rock types at VNIR and SWIR wavelengths to characterise suitable sites for future cosmogenic nuclide sampling campaigns. The primary conclusions of the study are as follows:

- There are four spectrally distinguishable lithologic groups at Mt Murphy: granites, gneisses, basalts, and fragmental hydrovolcanic rocks. A comparison of spectral profiles of fresh, polished, and weathered surfaces indicates rock surfaces that are glacially polished are spectrally similar to fresh rock surfaces.
- Spectral classification performs well for identifying and separating silica-rich rock at the mixed felsic-mafic Kay Peak study area, and for classifying mafic outcrops to the southwest of Mt Murphy (Turtle Rock, Icefall Nunatak, Notebook Cliffs). More ambiguous spectral classification results from other parts of Mt Murphy can be resolved by using spectral mapping techniques to identify areas of Al-OH absorption and high albedo, as well as photo geological interpretation of WV-3 panchromatic imagery.
- Separation of granite and biotite gneiss lithologies from mafic lithologies at VNIR-SWIR wavelengths can serve as a proxy for silica content. Strong Al-OH absorption and high albedo (average reflectance across the VIS-SWIR range) are useful for detecting granite, while Fe^{2+} and Fe/Mg-OH absorption features are useful for detecting biotite-rich gneiss, demonstrating that separation of these lithologies at VNIR-SWIR wavelengths can serve as a proxy for silica content. This is useful because the ASTER TIR sensor can directly detect silica, but its spatial resolution is too coarse to identify silica at many rock outcrops, and its signal-to-noise ratio is often poor at high polar latitudes.
- Altered fragmental volcanic rock can be differentiated from basalt using remote sensing due to the increased Fe^{3+} and Fe/Mg-OH absorption signature of Fe-rich smectite that is present in fragmental hydrovolcanic rock but absent in basaltic rocks.
- Differentiation of felsic and mafic rock outcrops can be achieved with broadband WV-3 SWIR imagery, and similar (though coarser) results can be achieved with medium-resolution ASTER SWIR imagery.

Overall, we demonstrate at Mt Murphy that remote sensing-based mapping using multispectral satellite imagery can be used to preliminarily identify suitable sites for future cosmogenic nuclide sampling prior to undertaking more targeted fieldwork.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs17020314/s1>, Supplement S1, Detailed Methods; Supplement S2, Rock Weathering Studies; Supplement S3, Additional Spectral Mapping and Classification Results; Supplement S4, Spectral Profiles of Mount Murphy rock samples [62–74].

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Data Availability Statement: Laboratory spectral reflectance data of Mount Murphy rock samples used to ground truth remote sensing data for this study can be freely accessed from the UK Polar Data Centre [50].

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Conflicts of Interest: The authors declare no conflicts of interest.

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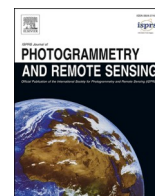
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REMOTE SENSING BIG DATA ANALYTICS FOR DETAILED GEOLOGICAL MAPPING IN EXPOSED ZONES OF DRY VALLEYS, SOUTH VICTORIA LAND, ANTARCTICA

Revealing critical mineralogical insights in extreme environments using deep learning technique on hyperspectral PRISMA satellite imagery: Dry Valleys, South Victoria Land, Antarctica / Habashi, J., Pour, A. B., Muslim, A. M., Afrapoli, A. M., Hong, J. K., Park, Y., Almasi, A., Crispini, L., Hashim, M., & Bagheri, M.

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Revealing critical mineralogical insights in extreme environments using deep learning technique on hyperspectral PRISMA satellite imagery: Dry Valleys, South Victoria Land, Antarctica

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ABSTRACT

Hyperspectral satellite remote sensing imagery is a state-of-the-art technique to obtain important information on the presence, distribution, and composition of crystalline weathering products and alteration minerals in extreme environments such as Antarctica. The Dry valleys (DVs) of South Victoria Land in Antarctica, one of the most extreme deserts on Earth, characterized by a cold, dry climate and minimal atmospheric moisture, provide a superlative analog to the landscapes of Mars and an important record of Earth's geological history; although they occupy only a tiny fraction of the continent's area, the DVs comprise approximately 25 % of all snow-free exposed lithology outcrops across Antarctica. In this study, hyperspectral PRISMA satellite images were meticulously analyzed using 3-dimensional Convolutional Neural Networks (3-D CNNs) to generate a regional mineral map for the DVs. To achieve accurate classification and mapping of minerals in the DVs, an innovative methodology combining Adaptive Vertex Component Analysis (AVCA), spectral augmentation, and 3-D CNNs was developed. Numerous endmember spectra extracted from the PRISMA datasets show a variety of important absorption and reflectance features associated with different mineral groups, such as biotite, calcite, corrensite, epidote, chlorite, jarosite, sericite, kaolinite/smectite, limonite/goethite/hematite, mirabilite/thenardite, montmorillonite/illite, nontronite, plagioclase, pyroxenes, vermiculite and zeolite. Mineral maps were then produced for several selected exposed zones and compared to lithological maps generated using the GeoMAP dataset (v.2022-08) of the DVs. The evaluation of the performance of the deep learning algorithm shows that 3-D CNNs exhibit high training and validation accuracy, with values between 0.994 and 0.997, besides training and validation loss values between 0.10 and 0.11, reflecting a robust and reliable performance. Consequently, a regional mineral map for the DVs was generated using the 3-D CNNs algorithm on hyperspectral PRISMA satellite imagery, accurately. This study demonstrates the great potential of hyperspectral PRISMA satellite imagery and deep learning techniques for mineralogical studies in extreme environments and provides valuable insights into the geological evolution of Antarctica and similar extraterrestrial terrains.

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1. Introduction

In Antarctica, spectral analysis of minerals could provide conclusive information on the presence, nature, distribution, and chemical composition of crystalline alteration products associated with exposed outcrops and provide perceptiveness into parent lithological units (Cox et al., 2012; Cox et al., 2023a,b). Nevertheless, fieldwork and the collection of rock samples for this purpose are very arduous due to the harsh conditions, logistical difficulties, inaccessibility, and isolation of many exposed zones in Antarctica.

Every day, a multitude of space-based satellite sensors provide an immense amount of remote sensing data for the whole world. These datasets include various spatial resolutions, dimensionality (spectral bandwidths), and radiometric resolutions that can be used to locate and map exposed outcrops and provide information on the presence, distribution, and composition of alteration minerals in exposed zones of Antarctica. Recently, some studies have focused on the application of remote sensing satellite imagery for geological and alteration mineral mapping in Antarctica (Haselwimmer et al., 2010, 2011, Pour et al., 2019, 2019a,b, 2021, 2018a, 2018b; Salvatore, 2015; Salvatore et al., 2014). In particular, some remote sensing studies have been conducted in Northern Victoria Land (NVL) in Antarctica, including regional-scale geological-lithological mapping in NVL, local-scale alteration mineral mapping in the Morozumi Range and Helliwell Hills areas of the Wilson Terrane, mapping of listvenite occurrences in the Wilson-Bowers and Bowers-Robertson Bay terrane boundaries, and identification of phyllosilicates in the Mesa Range, Campbell, and Priestley Glaciers (Pour et al., 2019a,b,b, 2021). In these investigations, multispectral images from Landsat-8 and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) sensors were used to obtain geological and mineralogical information.

The use of hyperspectral satellite remote sensing data can increase the prospects of detailed mineralogical information on weathering and alteration products associated with exposed lithologies in Antarctica. The recently launched Italian hyperspectral sensor PRISMA (Per-Spettrale della Missione Applicativa) offers a high capability to detect alteration minerals, crystalline weathering products, and lithological units with high accuracy compared to multispectral sensors (e.g., ASTER). PRISMA offers 234 spectral bands, 63 bands in the visible and near-infrared (VNIR), and 171 bands in the shortwave infrared (SWIR), covering the range of 0.4–2.5 μm with a spatial resolution of 30 m (Candela et al., 2016; Cogliati et al., 2021). Several studies confirmed the efficiency of PRISMA images for alteration mineral detection and lithological mapping (Agrawal et al., 2023; Bedini and Chen, 2020; Chirico et al., 2023; Habashi et al., 2024a; Shebl et al., 2023; Sorrentino et al., 2024; Tripathi and Garg, 2023). These studies support the high potential and great applicability of hyperspectral PRISMA satellite imagery for mineralogical mapping in Antarctic environments.

Besides, Artificial Intelligence (AI), especially deep learning, has recently revolutionized the analysis of hyperspectral images, which contain a wealth of spectral information in different bands. In this context, Convolutional Neural Networks (CNNs) play an important role as they are able to automatically extract hierarchical features from the image data, reducing the need for manual feature creation (LeCun et al., 2015; Li et al., 2022). The CNNs show optimal performance in classification, unmixing, and anomaly detection by exploiting spectral-spatial features to gain detailed insights into material compositions and environmental changes. CNNs can overcome challenges such as high-dimensional data, noise, and overlapping spectral signatures through various techniques, from dimensionality reduction to spectral feature fusion and spatial-spectral convolution (LeCun et al., 2015; Li et al., 2022). In the field of geological remote sensing, CNNs will soon play a crucial role in mapping and analyzing the Earth's surface to identify and classify rock types, minerals, and soil compositions. It utilizes spectral signatures and spatial patterns to accurately identify geological features, which helps in mapping alteration minerals and crystalline weathering

products (Li et al., 2024a; Pan et al., 2023; Shirmard et al., 2022). It facilitates the interpretation of complex spectral datasets by distinguishing materials with subtle spectral variations and reducing false positives. More advanced architectures such as 3-D CNNs and hybrid models further improve the extraction of spectral-spatial features to enable a breakthrough in mineral mapping (Belenguer-Plomer et al., 2021; Jan et al., 2024; Li et al., 2024b; Farahbakhsh et al., 2024).

The DVs region in South Victoria Land in Antarctica, covering an area of approximately 13000 km^2 , is an exceptional part of the Earth (terrestrial analog of Mars) located in the Transantarctic Mountains along the Ross Sea coast (Fig. 1). The DVs area is the most important ice-free sector of Antarctica and one of the coldest and driest places on Earth (the most extreme deserts in the world) with -20°C or less (mean annual temperature) and 100 mm or less (precipitation) (Doran et al., 2002). Although considerable remote sensing studies have focused on soil moisture properties, surface elevation mapping, snow distribution, and biomass estimations in the DVs (Fountain et al., 2017; Levy et al., 2014; Power et al., 2020, 2024, Salvatore et al., 2020, 2021, 2023; McNulty, 2023), Only a few geological remote sensing works have been conducted in the DVs (McMurdo) region using multispectral satellite imagery to characterize spectral and geochemical variability of the Ferrar Dolerite using Advanced Land Imager (ALI) and ASTER data, and mapping lithological compositional variability using Worldview-2 (Salvatore, 2015; Salvatore et al., 2014). Therefore, there is not yet a specific study on hyperspectral satellite remote sensing using PRISMA and deep learning techniques for mineral mapping in Antarctica, especially for the DVs. Consequently, the main objectives of this study are: (i) to develop an innovative method combining AVCA, spectral augmentation and 3-D CNNs applied to PRISMA hyperspectral satellite remote sensing for accurate classification and mapping of minerals in Antarctica; (ii) to detect the presence and distribution of crystalline weathering products and alteration mineral groups in DVs at local and regional scales; (iii) to verify the remote sensing results against documentary field data and existing/updated geological maps of DVs.

2. Geologic setting of the study area

The southern region of Victoria Land in Antarctica is bounded by the Ross Sea on the northern edge of the Ross Ice Shelf (Fig. 1). It embraces a fragment of the Transantarctic Mountains, which extend inland to the polar plateau. The region is bisected by the West Antarctic Rift System (WARS) under the western Ross Sea, whose uplifted western shoulder forms the escarpment of the Transantarctic Mountains (Behrendt, 1999; Busetti, 1999; Cox et al., 2012; Eagles et al., 2009; Wise et al., 2008). In the Transantarctic Mountains, Neoproterozoic and Paleozoic granitoids and the metasedimentary rocks that host them are superimposed by a thick sequence of sedimentary rocks interbedded with extensive dolerite sills and revealed in the outcrops of the ice-free Dry Valleys (DV) (Cook, 2007; Cox et al., 2012). The rocks and deposits of the DVs have been specifically divided and described into six main units, which differ in terms of lithostratigraphy, age, and tectonic history (Table 1) (Cox et al., 2012). Detailed information on the six most important lithological units can be found in Appendix 1.

3. Materials and methods

3.1. PRISMA data characteristics

The PRISMA satellite was launched by the Italian Space Agency (ASI) on March 22, 2019. This compact satellite features advanced hyperspectral imaging and a medium-resolution panchromatic imager. The PRISMA hyperspectral sensor uses prisms to scatter the incident light and employs the “push-broom” scanning technique. The resulting hyperspectral images comprise 239 bands ranging from the visible/near-infrared (VNIR) to the shortwave infrared (SWIR), with 66 bands in the VNIR range and 173 in the SWIR range, including nine overlapping

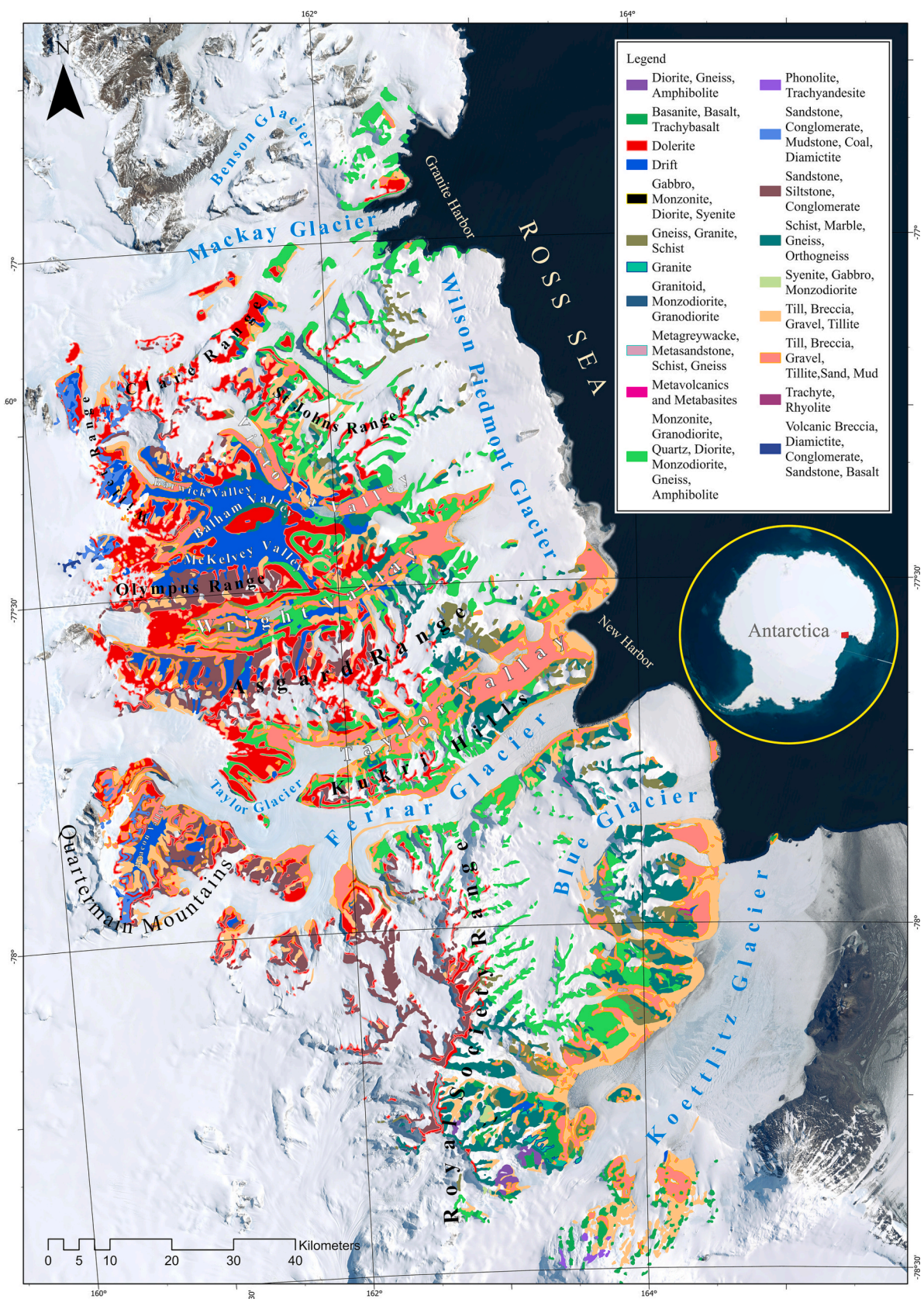


Fig. 1. Lithological map of the Dry Valleys, South Victoria Land, Antarctica (Generated using the GeoMAP (v.2022-08) dataset (<https://scar.org/library-data/map/s/geomap-geological-mapping>), (Cox et al., 2023a; Cox et al., 2023b).

Table 1

Reported mineralogical groups in the main lithological units of the DVs region.

Lithological units	Reported mineralogy
(1) Precambrian metasediments (Skelton groups)	Plagioclase, K-feldspar, quartz, clinopyroxene, amphibolite (hornblende and tremolite-actinolite), muscovite, biotite, wollastonite, epidote, chlorite, calcite, diopside, pyrite, phlogopite, and magnetite (Cox et al., 2012; Findlay et al., 1984)
(2) Late Precambrian-Early Ordovician granitoids (Granite Harbour Intrusive Complex)	Hornblende-biotite, plagioclase-quartz-biotite-amphibole-orthoclase-clinopyroxene, plagioclase-alkali feldspar-quartz-hornblende-biotite and feldspar-biotite-nepheline-calcite-fluorite with accessory titanite, fluorite, garnet, amphibole, zircon, allanite, rutile, actinolite, monazite, apatite, magnetite, allanite, and ilmenite, Secondary alteration minerals such as chlorite, actinolite, muscovite, epidote, and calcite (Cox et al., 2012; Jones, 1997)
(3) Devonian-Triassic conglomerate, sandstone, siltstone (Beacon Supergroup)	Mica, quartz, feldspar (Cox et al., 2012)
(4) Jurassic dolerite sills, breccia, and basalt flows (Ferrar Group)	Augite, pigeonite, plagioclase, orthoclase, apatite, biotite, sanidine, pyroxene, hornblende, iron oxides, quartz, zeolite, and stilpnomelane (Cox et al., 2012; Morrison and Reay, 1995).
(5) Eocene-Holocene sedimentary rocks (till and fluvioglacial sediments)	Quartz, mica, feldspar, mirabilite, volcanic ash, ferromagnesian minerals, and salt deposits (Abigail Patricia Lovett, 2011).
(6) Miocene-Holocene volcanic rocks (McMurdo Volcanic Group)	Feldspars, quartz, olivine, pyroxenes, spatter deposits, and scoria (Cox et al., 2012; Wright and Kyle, 1990)

bands between VNIR and SWIR. These images cover a 30 km × 30 km area with a spatial resolution of 30 m, and the spectral separation between the bands is less than 12 nm. In addition, the satellite provides panchromatic images with a spatial resolution of 5 m (Chiavetta et al., 2016; Loizzo et al., 2018; Vangi et al., 2021).

Fourteen Level 2D PRISMA scenes of the Dry Valleys, South Victoria Land, Antarctica, were acquired from ASI's eoPortal (<https://prisma.asi.it/>) for this study. The Level 2D scenes were obtained from geocoding (orthorectification) of Level 2C (bottom of atmosphere reflectance) PRISMA datasets. Detailed information on the PRISMA scenes can be found in Table 2. The coverage of fourteen PRISMA scenes of the Dry Valleys is shown in Fig. 2.

Table 2

The dataset attributes of PRISMA scenes used in this study.

Granule ID	Date of acquisition	Path/Row	Cloud Coverage
PRS_L2D_STD_20221104210732_20221104210737_0001	2022/11/04	1439/1417	free
PRS_L2D_STD_20230113211403_20230113211408_0001	2023/01/13	1447/1430	free
PRS_L2D_STD_20211203211113_20211203211118_0001	2021/12/03	1449/1433	free
PRS_L2D_STD_20221104210741_20221104210745_0001	2022/11/04	1450/1435	free
PRS_L2D_STD_20220130211244_20220130211248_0001	2022/01/30	1448/1432	free
PRS_L2D_STD_20210129210145_20210129210149_0001	2021/01/29	1445/1425	free
PRS_L2D_STD_20210129210149_20210129210153_0001	2021/01/29	1451/1438	free
PRS_L2D_STD_20201120205605_20201120205609_0001	2020/11/20	1447/1428	free
PRS_L2D_STD_20221121210051_20221121210056_0001	2022/11/21	1442/1424	free
PRS_L2D_STD_20201120205609_20201120205614_0001	2020/11/20	1448/1430	free
PRS_L2D_STD_20221121210056_20221121210100_0001	2022/11/21	1443/1424	free
PRS_L2D_STD_20221121210100_20221121210104_0001	2022/11/21	1445/1424	free
PRS_L2D_STD_20201125204247_20201125204251_0001	2020/11/25	1449/1435	free
PRS_L2D_STD_20201125204251_20201125204256_0001	2020/11/25	1449/1436	free

3.2. Methodology

This study uses a meticulously structured methodology involving several phases to process data from different sources. Each phase is specifically designed to ensure both accuracy and reliability and to contribute to a comprehensive understanding of the occurrence of alteration minerals in the Dry Valleys region, South Victoria Land, Antarctica. Fig. 3 shows the successive steps of this analysis. The software programs Environment for Visualizing Images (ENVI) version 5.6 (<https://www.exelisvis.com>, Harris Geospatial Solutions), ArcGIS Pro version 3.0.1 (Esri, Redlands, CA, USA), PyCharm Community Edition version 2024.2.4 (JetBrains, Czech Republic), and Anaconda Navigator version 2.6.3 were used to process the remote sensing datasets.

The three main phases of the methodology used in this study can be summarized as follows. (1) Pre-processing: For PRISMA data, this phase includes quality assessment, elimination of bad bands, implementation of a mask layer to exclude areas such as ice, water, clouds, and shadows, and dimensionality reduction by applying the Minimum Noise Fraction Transform (MNFT) to optimize the data (Green et al., 1988; Boardman and Kruse, 1994). (2) Spectral information extraction, augmentation, and classification: This phase involves the extraction of endmembers using the Adaptive Vertex Component Analysis (AVCA) algorithm, identifying endmember types, and aggregating similar mineral signatures from diverse spectral libraries corresponding to the extracted endmembers. Additionally, a spectral augmentation approach is applied to amplify the dataset up to 1000-fold, creating a robust training and testing dataset for implementing the convolutional neural network (CNN) algorithm for mineral distribution mapping. These techniques collectively enable the generation of detailed mineral distribution maps, effectively highlighting the presence and concentration of specific minerals in the region. (3) Accuracy Assessment: Evaluating the effectiveness of the results by examining the overall accuracy, precision, recall, and F1-score.

3.2.1. Pre-processing

3.2.1.1. Data quality assessment. In this study, the L2D PRISMA data were used; the provider, ISA (Italian Space Agency), has already made atmospheric corrections to the PRISMA L2D data. In addition, certain PRISMA bands were excluded due to their high sensitivity to water vapor, which can lead to absorption problems. In this analysis, the bands in the ranges 913–979 nm, 1078–1185 nm, 1317–1491 nm, and 1775–2044 nm were excluded in particular.

3.2.1.2. Build mask layer. Building a mask layer for ice coverage is another important pre-processing task, especially in regions with significant ice accumulation. A mask is created to exclude areas covered by ice, water, clouds, and shadows from the analysis to ensure that only relevant data is processed (Gupta et al., 2005). For this study, a masking

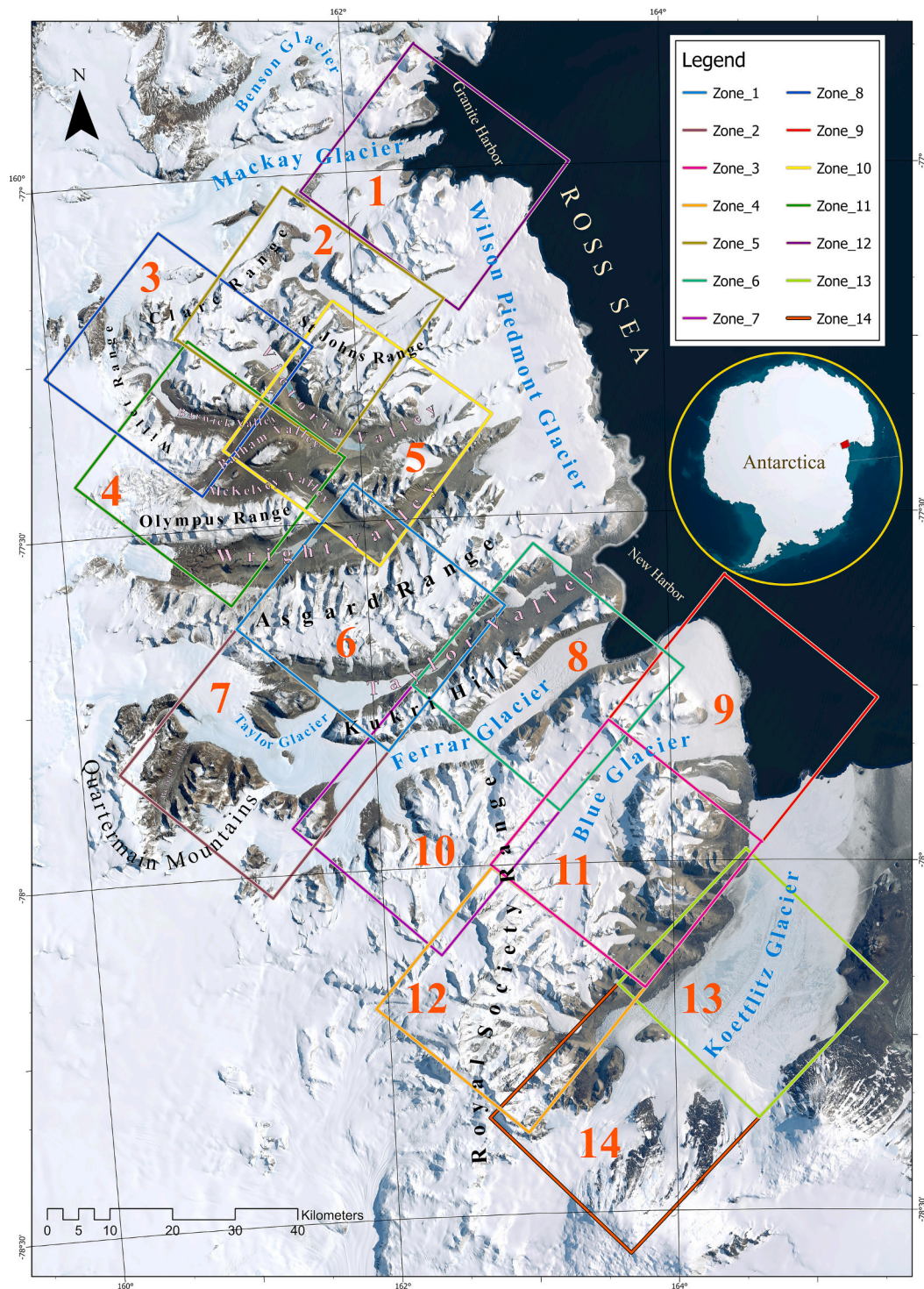


Fig. 2. The coverage of fourteen PRISMA scenes (zones 1 to 14) used in this study for the Dry Valleys, South Victoria Land, Antarctica.

procedure was implemented using the low-value thresholds of band four of the PRISMA data to mitigate the effects of snow, ice, clouds, and shadows.

3.2.1.3. Dimensional reduction. After preparing the data, the final pre-processing step was to choose the best possible dimensionality. Dimensionality reduction techniques are used to reduce the number of spectral bands while preserving the most relevant information, minimizing noise, and improving the efficiency of the analysis (Santos et al., 2022). The minimum noise fraction transform (MNFT) technique was

used to reduce dimensionality. The MNFT is a linear technique that maps the data to a lower-dimensional space and maximizes the variance of the data in the lower-dimensional representation (Green et al., 1988). Dimensionality reduction is crucial when analyzing hyperspectral data, as it helps to overcome the curse of dimensionality, where the efficiency and accuracy of algorithms decrease as the number of dimensions increases (Green et al., 1988). Reducing dimensionality reduces the computational complexity of subsequent analysis steps, making it easier to process and interpret the data (Rajabi et al., 2024).

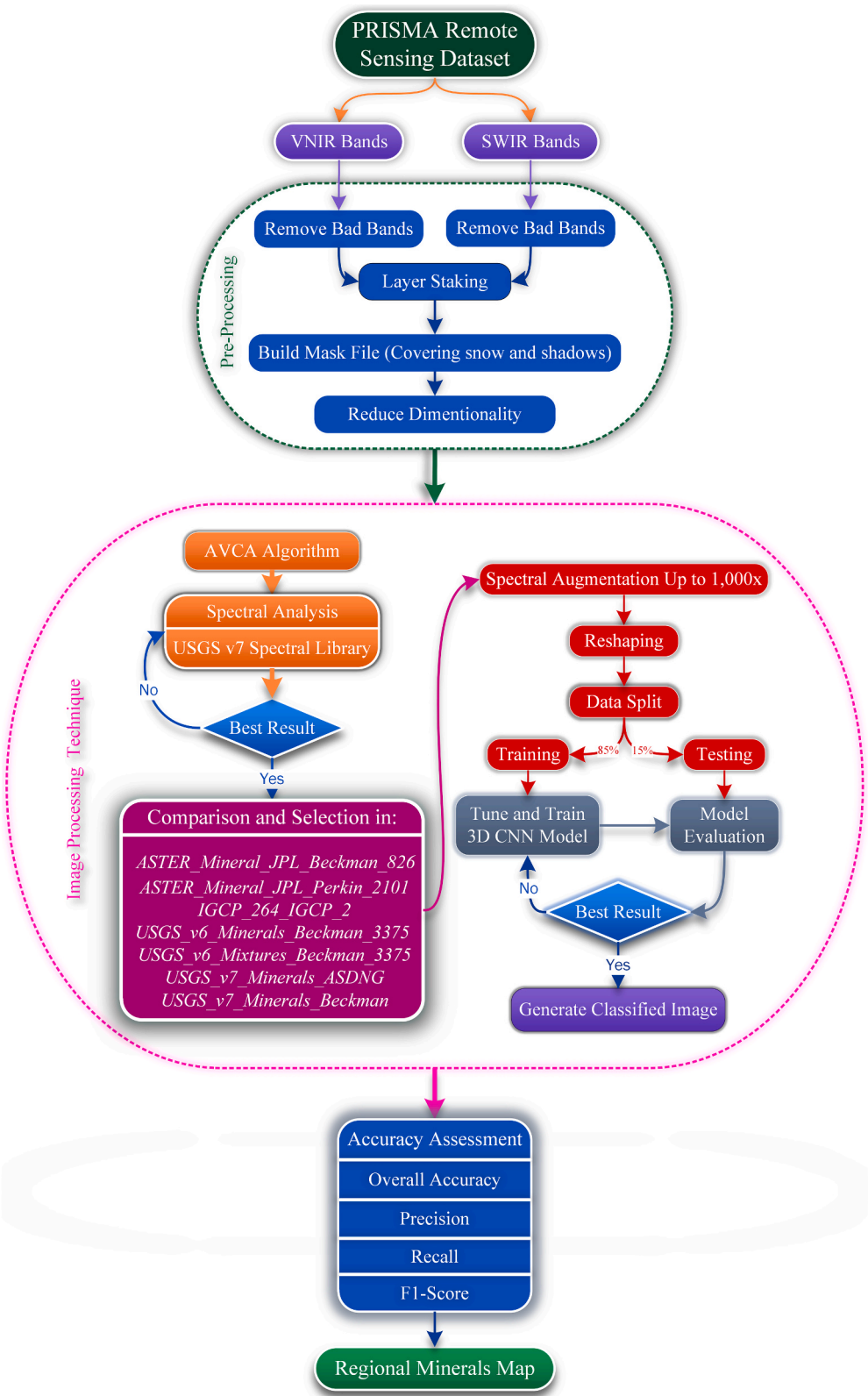


Fig. 3. Overview of the methodological flowchart used in this study.

3.2.2. Image processing techniques

3.2.2.1. Endmember extraction by adapted vertex component analysis. Vertex Component Analysis (VCA) is a widely used technique for identifying pure spectral signatures (endmembers) within hyperspectral

imagery. These endmembers are essential for separating the spectral contributions of different materials within a single pixel. VCA operates under the assumption that each pixel’s spectral signature is a combination of the spectra of the individual materials present (Nascimento and Dias, 2005).

To enhance VCA's applicability, we developed Adaptive Vertex Component Analysis (AVCA), which incorporates significant improvements, including robust handling of zero values in the input data, ensuring reliable and accurate results. Furthermore, AVCA supports using mask files, allowing users to selectively process specific regions of interest and exclude irrelevant areas. This mask functionality significantly improves its usability for analyzing large, uncropped datasets. VCA's core principle involves identifying the vertices of a geometric shape (simplex) that encompasses the spectral data in a lower-dimensional space (Heylen et al., 2017). These enhancements to AVCA significantly improve its robustness and practicality for real-world hyperspectral image analysis.

In this algorithm, the remote sensing data represented as a matrix Y of dimensions $L \times N$ (L is the number of spectral bands and N is the number of pixels), is first transformed into a zero-mean space (Nascimento and Dias, 2005). This is done by subtracting the mean spectrum r_m from all data points:

$$r_m = \frac{1}{N} \sum_{i=1}^N Y[:, i], Y_o = Y - r_m \quad (1)$$

The signal-to-noise ratio (SNR) is estimated to determine the dimensionality of the subspace. The SNR is calculated using the power of the original data (P_y) and the projected data (P_x):

$$P_y = \frac{1}{N} \sum_{i=1}^d \|Y[:, i]\|^2, P_x = \frac{1}{N} \sum_{i=1}^d \|x[:, i]\|^2 + \|r_m\|^2 \quad (2)$$

$$SNR = 10 \cdot \log_{10} \left(\frac{P_x - \frac{P_x P_y}{P_y}}{P_y - P_x} \right) \quad (3)$$

where x is the data projected into a lower-dimensional subspace, P is the number of endmembers, and l is the number of spectral bands.

Based on the estimated SNR, the algorithm projects the data into a subspace of dimension R (number of endmembers) or $R-1$. The projection matrix U_d , derived from the Singular Value Decomposition (SVD) of the covariance matrix of Y , is used for this dimensionality reduction:

$$x_p = U_d^T \cdot Y_o, Y_p = U_d \cdot x_p + r_m \quad (4)$$

Or for a higher SNR:

$$x_p = U_d^T \cdot Y, Y_p = U_d \cdot x_p \quad (5)$$

In the reduced-dimensional space, AVCA identifies the vertices (endmembers) by finding the extreme points of the data distribution. A random vector w is used to compute a direction f orthogonal to previously identified vertices:

$$f = w - A \cdot (A^+ \cdot w), f = \frac{f}{\|f\|} \quad (6)$$

The projection of f onto the data provides a measure ν , and the index of the maximum absolute value of ν corresponds to an endmember:

$$\nu = f^T \cdot x, \text{index}[i] = \text{argmax}|\nu| \quad (7)$$

The final step reconstructs the spectral signatures of the endmembers in the original space using the identified indices:

$$Ae = Y_p[:, \text{index}] \quad (8)$$

Ae is the matrix of extracted endmember spectra, where each column corresponds to a pure spectral signature.

This approach efficiently combines geometric and statistical principles to extract endmembers from remotely sensed data. Its ability to handle noisy datasets and its computational efficiency make it a

valuable tool for unmixing and classifying tasks.

3.2.2.2. Spectral analysis. Spectral analytic functions are critical to spectral analysis, especially for matching unknown spectra to materials in a spectral library such as the USGS Spectral Library, the ASTER Spectral Library, and the ECOSTRESS Spectral Library (Baldridge et al., 2009; Meerdink et al., 2019; Kokaly et al., 2017). These functions use different spectral similarity methods to quantify the similarity between an unknown spectrum and reference spectra. One of the most important strategies used in this process is the spectral angle mapper, which compares spectra based on their trends. Additionally, spectral feature fitting can extract absorption features that are useful for identifying alteration minerals using any spectral library. These methods enable rapid evaluation (Milliken and Mustard, 2007). Typically, spectral analysis features improve the accuracy of endmember identification (Clark et al., 1992, 1991, 1990; Clark and Swayze, 1995; Crowley and Clark, 1992; Swayze and Clark, 1995).

In this study, the spectra of the endmember minerals extracted from the PRISMA datasets using the AVCA method were compared with the USGS spectral library (version 7.0) (Kokaly et al., 2017). Furthermore, for the detailed analysis of the endmember spectra extracted by the AVCA method and the creation of comprehensive abundance mineral maps, the Dry Valleys region was divided into fourteen zones based on full scene coverage of the PRISMA images (see Fig. 2). For each extracted endmember spectrum, reference spectra of the endmember minerals from the USGS spectral library were provided for comparison. The lithological maps of each zone were also cropped and provided.

3.2.2.3. Spectral augmentation. Data augmentation is essential in deep learning, particularly when large, high-quality datasets are unavailable. It enhances the training process by artificially expanding the dataset, offering the model a greater variety of examples to learn from. This diversity not only reduces the risk of overfitting—where the model memorizes specific patterns in the training data—but also improves generalization, enabling the model to perform better on unseen data. Furthermore, augmentation simulates real-world scenarios by introducing variations such as offsets and noise, making models more robust to imperfections (Bjerrum et al., 2017; Chung et al., 2024; Passos and Mishra, 2021).

In the context of spectral data analysis, adding incremental offsets to reflectance values serves as a simple yet effective augmentation technique. This approach mimics natural variability and measurement noise, equipping the model to handle diverse and realistic datasets. By doing so, it enhances the model's ability to analyze spectral data under varying conditions, ensuring reliable performance in practical applications. Our spectral augmentation methodology enhances spectral data by introducing incremental changes, known as offsets, to the reflectance values. This process is performed iteratively, beginning with an initial offset and increasing it by a fixed step size in each subsequent iteration. For instance, if the original reflectance value is R , and the offset applied in the i -th iteration is O_i , the resulting augmented reflectance is calculated as $R + O_i$. The augmented reflectance data, generated through multiple iterations, is then combined with the corresponding wavelengths to ensure that the augmented dataset preserves its association with the original spectral references. This approach provides a robust and comprehensive dataset for model training and evaluation.

In this study, we did not directly process the endmembers identified by AVCA. Instead, our approach focused on identifying minerals with spectral characteristics similar to the endmembers from various established spectral libraries. These libraries included *ASTER-Mineral-JPL-Beckman-826*, *ASTER-Mineral-JPL-Perkin-2101*, *IGCP-264-IGCP-2*, *USGS-v6-Minerals-Beckman-3375*, *USGS-v6-Mixtures-Beckman-3375*, *USGS-v7-Minerals-ASDNG*, and *USGS-v7-Minerals-Beckman*. All spectra were resampled to match the spectral dimensions of the imagery used in our analysis.

Subsequently, to enrich the dataset, the proposed spectral augmentation techniques were applied, expanding each unique spectral library by up to 1000-fold. All augmented samples were subsequently resampled to align with the spectral bands of the PRISMA sensor. The augmented spectral profiles for each endmember are comprehensively detailed in Table 3, which delineates the initial sample counts, augmentation rates, and the resultant augmented spectral profiles across the aforementioned spectral libraries. This augmentation introduced controlled variations to emulate natural spectral heterogeneity, ensuring a more representative and diverse dataset for training and validating deep learning models in hyperspectral image analysis. This strategy mitigates overfitting risks and enhances model generalizability, addressing inherent challenges in complex hyperspectral data environments.

3.2.2.4. Convolution neural networks workflow. The methodological framework employed for the Convolutional Neural Networks (CNNs) involved specific preprocessing and computational techniques tailored explicitly for spectral data analysis, essential for hyperspectral image processing tasks. Initially, spectral signature data were reshaped into 3D cubes to leverage CNN's capability to extract spatial and spectral features simultaneously, enhancing data interpretability and classification accuracy (Egmont-Petersen et al., 2002; Ghosh et al., 2019; Schmidhuber, 2015). To ensure robust validation and reliable performance metrics, the dataset was partitioned into 85 % training and 15 % testing subsets. Detailed information on CNN architecture can be found in Appendix 2.

3.2.2.4.1. Loss function. Categorical cross-entropy (Eq. (16)) was used as the loss function to measure the discrepancy between the predicted probabilities and the true class distributions. It significantly penalizes incorrect predictions, thus guiding the model toward achieving high accuracy and confident classification results (Dunne and Campbell, 1997; Zhang and Sabuncu, 2018). The formula for categorical cross-entropy is:

$$L = - \sum_{i=1}^C y_i \log(\hat{y}_i) \quad (9)$$

where L is the loss, y_i is the true label for the class i (one-hot encoded), $\hat{y}_i$ is the predicted probability for the class i , and C is the total number of classes.

3.2.2.4.2. Model optimization. Model optimization was performed using the Adam optimizer (Eq. 10–12), known for its efficient handling of gradient variability and quick convergence by dynamically adjusting learning rates based on gradient moment estimations. The optimizer efficiently navigated the high-dimensional optimization space typical of 3D CNNs, crucial for handling the complexity inherent in hyperspectral image processing (Kingma, 2014; Zhang, 2018). The Adam optimizer's update rules are given by:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (10)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (11)$$

$$\hat{w} = \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \quad (12)$$

where g_t is the gradient of the loss for the weight at the time t ; m_t and v_t are moving averages of the gradient and its square; β_1 and β_2 are decay rates for the moment estimates. η is the Learning rate was set at 0.0001; ϵ is a small constant to prevent division by zero; $\hat{m}_t$ and $\hat{v}_t$ are bias-corrected versions of m_t and v_t , and $\hat{w}$ is the updated weight.

3.2.2.4.3. Training strategy. Training efficiency and robustness were enhanced using a custom early stopping strategy based on dual criteria, specifically set for simultaneous accuracy ≥ 99.4 % and loss ≤ 0.11 across training and validation datasets. This approach effectively minimized overfitting risks and optimized computational resources, leading

Table 3
Initial counts, augmentation factors, and final totals of augmented samples for each mineral endmember across seven compiled spectral libraries.

	aster_mineral_jpl_beckman_826	aster_mineral_jpl_perkin_2101	igcp_264	usgs_v6_minerals_beckman_3375	usgs_v7_minerals_asdng_beckman	Total Augmentation rate	Augmented spectral profiles
Biotite	3	3	0	0	3	12	500
Calcite	9	9	1	7	3	33	5973
Corrensite	3	3	0	0	1	8	750
Epidote + Chlorite	18	18	1	0	13	58	103
Jarosite + Sericite	12	12	2	0	23	79	76
Kaolinite / Smectite	2	2	5	6	8	34	177
Limonite + Goethite + Hematite	5	4	2	2	22	56	108
Mirabilite / Thenardite (or Evaporates)	0	0	0	0	3	6	1000
Montmorillonite + Illite	3	3	2	4	14	44	137
Nontronite	5	5	0	0	4	19	316
Plagioclase	0	0	0	0	3	6	1000
Pyroxene	4	4	0	0	17	42	143
Vermiculite	6	6	0	0	4	20	300
Zeolite	0	0	0	1	8	17	353

to adaptive, efficient training processes (Prechelt, 1998). Good fitting refers to the optimal balance where a model achieves low training loss and high accuracy on unseen data, effectively capturing underlying patterns without overly adapting to noise (Li et al., 2024c; Elharrouss et al., 2025). In contrast, overfitting occurs when the model learns the training data too closely, including noise, which leads to poor generalization and reduced performance on new, unseen data (Terven et al., 2025). Therefore, the custom early stopping mechanism used in this study significantly helps achieve good fitting by terminating training once optimal performance metrics are reached.

3.2.2.4.4. Model evaluation. To assess the CNN model effectiveness comprehensively, multiple metrics were applied. These included the confusion matrix and derived metrics such as overall accuracy (OA, Eq. (13), user's accuracy (UA, precision, Eq. (14), producer's accuracy (PA,

recall, Eq. (15), and F1-score (Eq. (16), calculated as follows:

$$OA = \frac{TP + TN}{N} \quad (13)$$

$$UA = \frac{TP}{TP + FP} \quad (14)$$

$$PA = \frac{TP}{TP + FN} \quad (15)$$

$$F1 = 2 \cdot \frac{UA \cdot PA}{UA + PA} \quad (16)$$

These measures facilitated nuanced evaluations of model performance,

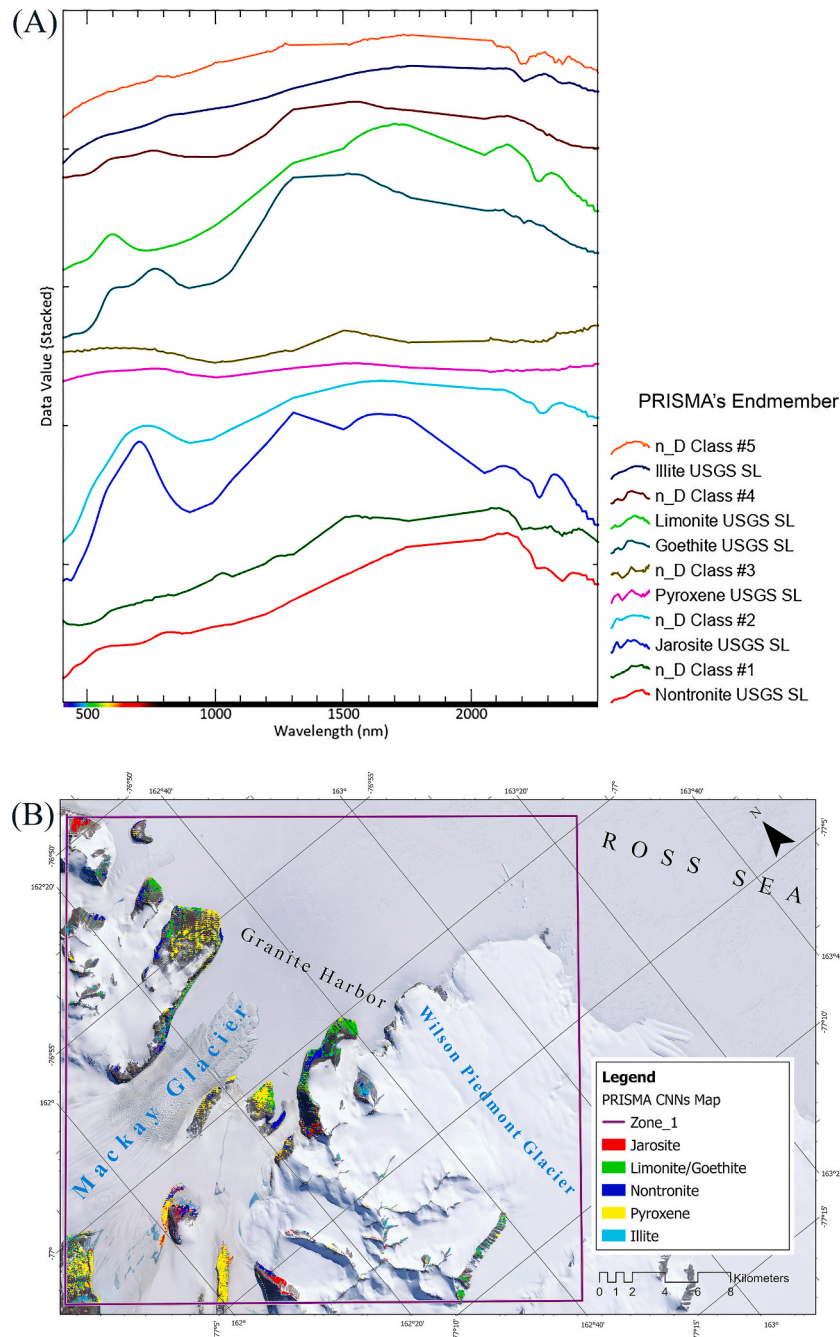


Fig. 4. (A) Endmember spectra derived from PRISMA data of Zone 1 and the USGS reference spectra of the endmember minerals. (B) Mineral map generated using the CNNs algorithm applied to PRISMA data of Zone 1.

accounting for both class-specific and overall predictive effectiveness, thus providing a balanced and realistic assessment of CNN model generalization capabilities (Mäyrä et al., 2021). After training and the model evaluation on the zone-specific training samples, each scene of PRISMA data is classified using the obtained model weights and resulting outputs.

4. Results and analysis

4.1. Mapping alteration minerals using the CNNs algorithm

In this study, the endmember spectra extracted from the PRISMA data for Zone 1 are shown in Fig. 4A. Five typical n_D classes were recognized for Zone 1. n_D Class #1 has spectral similarity to nontronite. It shows clear Fe absorption at 0.50 to 0.85 μm and an increasing

reflectance trend up to 2.15 μm . The spectral profile is typically oscillatory, with absorption features around 2.20 μm and 2.38 μm due to Al-OH and Fe-OH bonding. n_D Class #2 shows spectral features resembling jarosite. The most important absorptions occurred in the 2.2–2.35 μm range due to Al-OH and SO_4 bonding. In addition, $\text{Fe}^{3+}/\text{Fe}^{2+}$ electronic absorption features at 0.50 to 0.85 μm are also evident. n_D Class #3 is similar to the spectral features of pyroxene (Klima et al., 2008). It shows a sinusoidal trend in the range of 0.4 to 0.7 μm . A significant absorption occurs in the range of 0.85 to 1.2 μm due to the Fe^{2+} and other transition elements (e.g., Ti) (Klima et al., 2008). In addition, there was an increase in reflectance at 1.5 μm , followed by a decrease from 1.7 to 2.4 μm . n_D Class #4 could be limonite/goethite. It shows a broad absorption from 0.50 to 1.0 μm due to $\text{Fe}^{3+}/\text{Fe}^{2+}$ electronic absorption features, followed by an increasing trend from 1.5 to 2.0 μm . Slight OH absorption features are seen near 1.9 and 2.1 μm . n_D Class #5 shows the

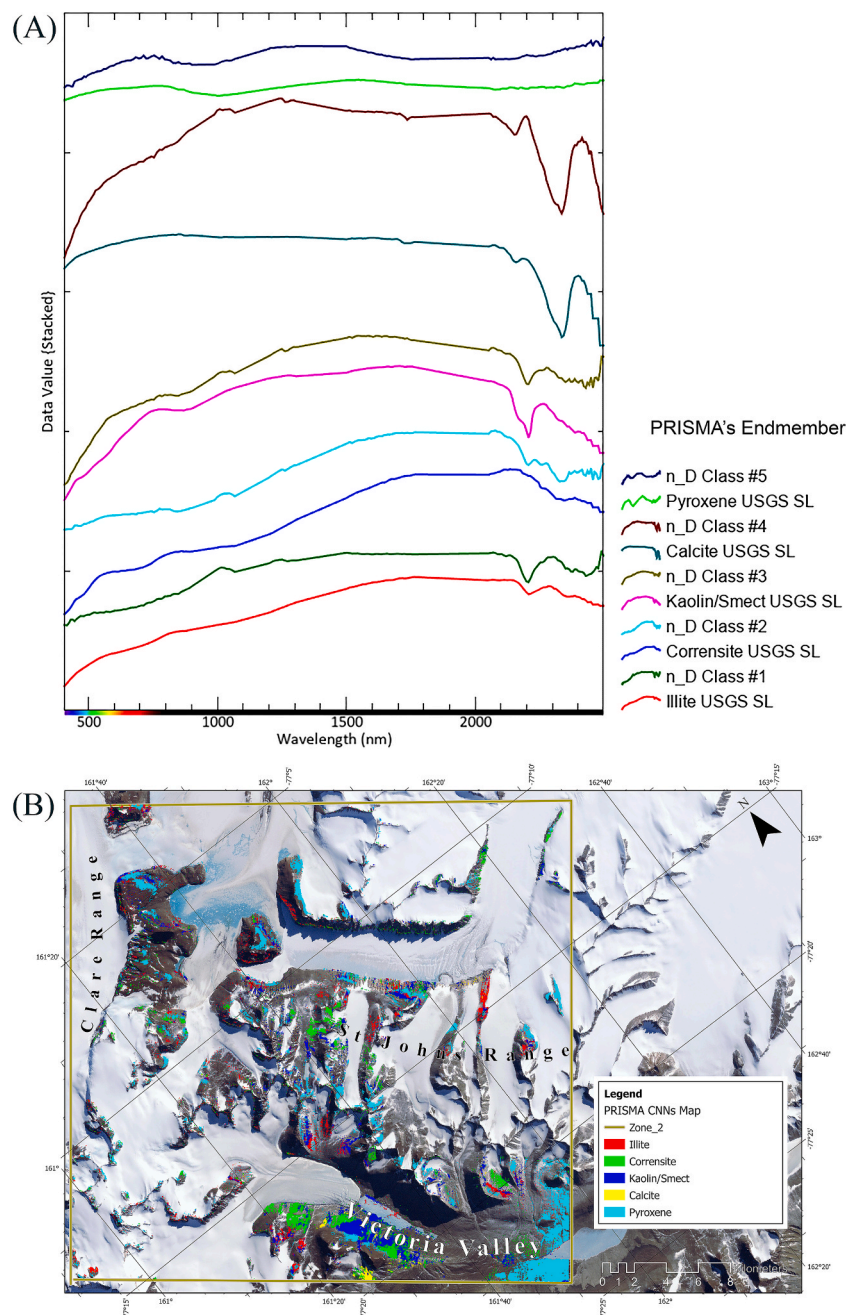


Fig. 5. (A) Endmember spectra derived from PRISMA data for Zone 2 alongside USGS reference spectra of the endmember minerals; (B) Mineral map generated using the CNNs algorithm applied to PRISMA data for Zone 2.

spectral properties of illite. It shows an increasing trend in VNIR to SWIR with pronounced absorption features at 2.2–2.25 μm due to Al-OH bonding (Fig. 4A).

Fig. 4B shows the mineral map produced using the CNN algorithm for the PRISMA data from Zone 1. The distribution of alteration minerals was compared to the lithological map of Zone 1 (see Appendix Fig. 1A). Nontronite was found mainly in Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss, and Amphibolite. Jarosite was found predominantly in Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss, and Amphibolite. It was also mapped in Till, Breccia, Gravel, and Tillite formations and Sand and Mud units. Pyroxene was mainly mapped in Diorite. In the central sector, particularly at Mackay Glacier and Granite Harbor, as well as in the southwest and western sectors it was also mapped in Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss and Amphibolite units, and Till, Breccia, Gravel, Tillite, Sand, Mud units. Limonite/goethite was identified mainly in Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss, and Amphibolite units. It was also commonly found in gneiss, granite, and schist formations. Jarosite was found in Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss, and Amphibolite. In the southern sector, particularly across the Wilson Piedmont Glacier. Illite was typically mapped in Gneiss, Granite, and Schist units and Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss, and Amphibolite units (Fig. 4B and Appendix Fig. 1A).

For Zone 2, the five endmember spectra extracted from the PRISMA data for Zone 2 are shown in Fig. 5A. n_D Class #1 shows reflectance, absorption, and spectral characteristics similar to illite. n_D Class #2 could be corrensite ($(\text{Mg}, \text{Fe})_9(\text{Si}, \text{Al})_8\text{O}_{20}(\text{OH})_{10}\cdot n\text{H}_2\text{O}$), a mixed-layered clay mineral consisting of chlorite and smectite. It has distinct absorption features due to its layered structure and the presence of OH groups, $\text{Fe}^{2+}/\text{Fe}^{3+}$, Mg, and Al. Corrensite typically shows low reflectance features associated with Fe^{2+} and Fe^{3+} , especially around 0.7–0.9 μm , an upward trend towards the near infrared, and strong absorption features near 2.2–2.3 μm due to Al-OH and Mg-OH bonds (Fig. 5A) (Bishop et al., 2008). n_D Class #3 shows spectral similarity to kaolinite/smectite. Absorption features primarily due to Al-OH bonding around 2.2 μm are evident, and a low reflectance with weak absorption around 0.50 μm to 0.90 μm is also obvious (Fig. 5A). n_D Class #4 shows a strong similarity to calcite with pronounced absorption features around 2.34 μm , which are due to the presence of carbonate ion bonding (CO_3^{2-}). A prominent absorption feature from 0.50 μm to 1.2 μm shows the presence of Fe^{3+} and Fe^{2+} in this n_D class. It indicates that dolomite may be associated with calcite because the presence of Fe^{2+} in dolomite causes a broad absorption in the range of 0.9–1.2 μm (Gaffey, 1986). In addition, a weak absorption feature near 2.17 μm indicates the mixing of the clay mineral groups with calcite (Fig. 5A). n_D Class #5 is similar to pyroxene in its spectral properties.

Fig. 5B shows the mineral map generated using the CNNs algorithm for the PRISMA data from Zone 2. The distribution of alteration minerals compared to the lithological map of Zone 2 (see Appendix Fig. 1B) is as follows. Illite was found in the Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss, and Amphibolite units, as well as in the Till, Breccia, Gravel, and Tillite units throughout the region and in the Syenite, Gabbro, and Monzodiorite units in the central sector of the St. Johns Range. Corrensite was found in the Drift unit, the Monzonite, Granodiorite, Quartzdiorite, Monzodiorite, Gneiss and Amphibolite units, the Schist, Marble, Gneiss, and Orthogneiss units, as well as the Till, Breccia, Gravel, and Tillite units and the Sand and Mud unit in Victoria Valley and the eastern sector of St. Johns Range. Kaolinite/smectite was mapped in the Drift unit, the Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss, and Amphibolite units, as well as in the Till, Breccia, Gravel, and Tillite units, and the Sand and Mud unit in the southern sector at Victoria Valley and the eastern sector of the St. Johns Range. Calcite was found in the Schist, Marble, Gneiss, and Orthogneiss units and the Till, Breccia, Gravel, and Tillite units in the southern sector at the Victoria Valley region. Pyroxene was found in the

Dolerite unit and the Drift unit, as well as in the Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss, and Amphibolite units (Fig. 5B and Appendix Fig. 1B).

In Zone 3, based on the analysis of the PRISMA datasets, six certain n_D classes could be distinguished for Zone 3 (Fig. 6A). n_D Class #1 could be considered for pyroxene. It shows pronounced absorption properties due to the presence of Fe^{2+} , especially between 0.9 and 1.2 μm (Klima et al., 2008). In addition, there are other broad absorption features in the range of 1.7–2.0 μm , which are due to increasing the amounts of Ca or non-quadrilateral elements (e.g., Cr, Al, Mn, and Fe^{3+}) in pyroxenes (Klima et al., 2008). n_D Class #2 could be hematite/goethite. It shows a broad absorption from 0.50 μm to 1.1 μm , which is due to the absorption features (electronic processes) of $\text{Fe}^{3+}/\text{Fe}^{2+}$ (Hunt and Ashley, 1979). In addition, a broad, slight absorption from 2.17 μm to 2.40 μm indicates the association of hematite/goethite with a background of Al-OH and Fe, Mg-OH minerals. n_D Class #3 shows spectral characteristics similar to kaolinite/smectite. n_D Class #4 could be considered plagioclase. A pronounced absorption around 1.3 μm , a mild absorption from 0.50 μm to 0.85 μm , and a weak absorption from 2.17 μm to 2.30 μm could indicate the presence of a background with Al-OH and Fe-OH minerals associated with plagioclase. n_D Class #5 could represent biotite. It has distinct broad absorption features mainly due to $\text{Fe}^{3+}/\text{Fe}^{2+}$ around 0.5–1.1 μm , as well as conspicuous Al and Fe-OH bonds absorption features at 2.1–2.2 μm . In addition, a weak absorption around 2.35–2.40 indicates the presence of Mg-OH bonds and the association of hornblende or actinolite-teremolite with biotite. n_D Class #6 could be epidote/chlorite/calcite. It has broad absorption characteristics due to the presence of iron ($\text{Fe}^{2+}/\text{Fe}^{3+}$) from 0.5 to 1.2 μm and a strong absorption at 2.35–2.45 μm because of Fe, Mg-OH, and CO_3 bonding (Bishop et al., 2008).

Fig. 6B shows the CNNs mineral map produced from the PRISMA data for Zone 3, which is compared to the lithological map of Zone 3 (see Appendix Fig. 1C). Pyroxene was found in the Drift unit in the Willet Range and the western sector, as well as in the Dolerite unit in the southeastern sector. Hematite/goethite was mapped in the Drift unit, the Sandstone, Siltstone, and Conglomerate units, and in the Schist, Marble, Gneiss, and Orthogneiss units in the Barwick Valley and the Willet Range. Kaolinite/smectite was found in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the Willet Range, in the Drift unit in the Barwick Valley, and in the Till, Breccia, Gravel, and Tillite units in the eastern and southern sectors. Plagioclase was found in the Dolerite unit in the western and southern sectors in the Willet Range and southern sector, in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the southern sector, and in the Drift unit in the southern sector and Barwick Valley. Biotite was found in the Drift unit in the western sectors and in the Sandstone, Conglomerate, Mudstone, Coal, and Diamictite units in the western and southwestern sectors of the Willet Range. Epidote/chlorite/calcite was found in the Drift unit in the southwestern sectors of the Willet Range; in the Sandstone, Conglomerate, Mudstone, Coal, and Diamictite units in the southwestern sectors of the Willet Range; in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the Willet Range; in the Drift unit in Barwick Valley and the western sector; in the Dolerite unit in the western sector; and in the Schist, Marble, Gneiss, and Orthogneiss units in the western sector (Fig. 6B and Appendix Fig. 1C).

For Zone 4, based on the analysis of the PRISMA datasets, three distinct n_D classes could be distinguished for Zone 4 (Fig. 7A). n_D Class #1 could be pyroxene, whose absorption and reflection properties are shown above. n_D Class #2 could represent zeolite. It shows strong absorption features mainly related to (OH) bonding is typically found around 1.5 μm and 2.0 μm . In addition, reflectance features are observed in the 1.6–1.8 μm and 2.1–2.3 μm ranges. Absorption features from 2.35 to 2.5 μm can be attributed to Al-OH, Si-OH, and Fe, Mg-OH bondings. n_D Class #3 shows epidote spectral features. Fig. 7A shows the CNNs mineral map for Zone 4 from the PRISMA data. For comparison, the lithologic map of Zone 4 (see Appendix Fig. 1D) is shown. Pyroxene was found in the Dolerite unit in Wright Valley in the southern, eastern, and

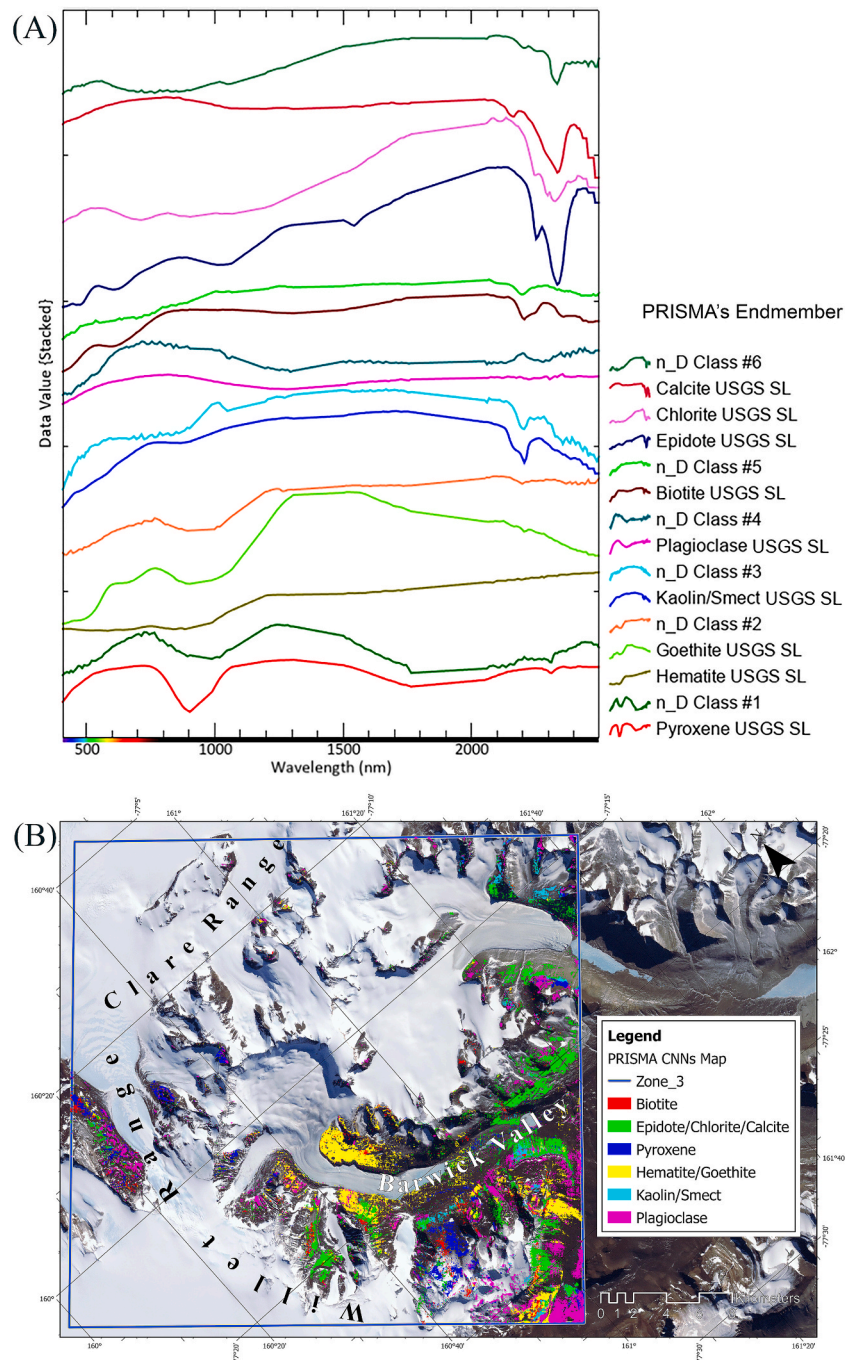


Fig. 6. (A) Endmember spectra derived from PRISMA data for Zone 3 alongside USGS reference spectra of the endmember minerals; (B) Mineral map generated using the CNNs algorithm applied to PRISMA data for Zone 3.

central sectors; in the Drift unit in Barwick Valley in the northern sector; in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in Wright Valley in the southern sector and in Barwick Valley in the northern and central sectors; and in the Sandstone, Siltstone, and Conglomerate units in the central sector. Zeolite was found in the Dolerite unit in the eastern sector and in the Balham Valley in the central sector; in the Till, Breccia, Gravel, and Tillite units in the Balham Valley in the central sector; in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the southern sector and in the Balham Valley in the central sector; in the Sandstone, Siltstone, and Conglomerate units in the eastern sector; and in the Drift unit in the southern sector. Epidote was found in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the northwestern sector; in the Drift unit in the northwestern sector; in the Gneiss, Granite, and Schist units in the

Balham Valley in the eastern sector; and in the Sandstone, Siltstone, and Conglomerate units in the Wright Valley in the southern sector (Fig. 7B and Appendix Fig. 1D).

In Zone 5, Analysis of the PRISMA datasets revealed four different n_D classes for Zone 5 (Fig. 8A). n_D Class #1 shows pyroxene spectral features. n_D Class #2 could be a mixture of jarosite, hydrous silica, and sericite. It shows two mild absorption features around 2.2 μm and 2.35 μm show the presence of Al-OH, Fe-OH, SO_4 , and Si-OH bonds. In addition, there is a strong increase in absorption from 0.50 to 1.1 μm due to the presence of $\text{Fe}^{3+}/\text{Fe}^{2+}$ (Hunt and Ashley, 1979) (Fig. 8A). n_D Class #3 could be mirabilite ($\text{Na}_2\text{SO}_4 \cdot 10\text{H}_2\text{O}$)/thenardite (Na_2SO_4) or evaporates. It shows a conspicuous absorption feature at 2.40 μm , which could be related to S-O bonding. n_D Class #4 shows a spectral feature

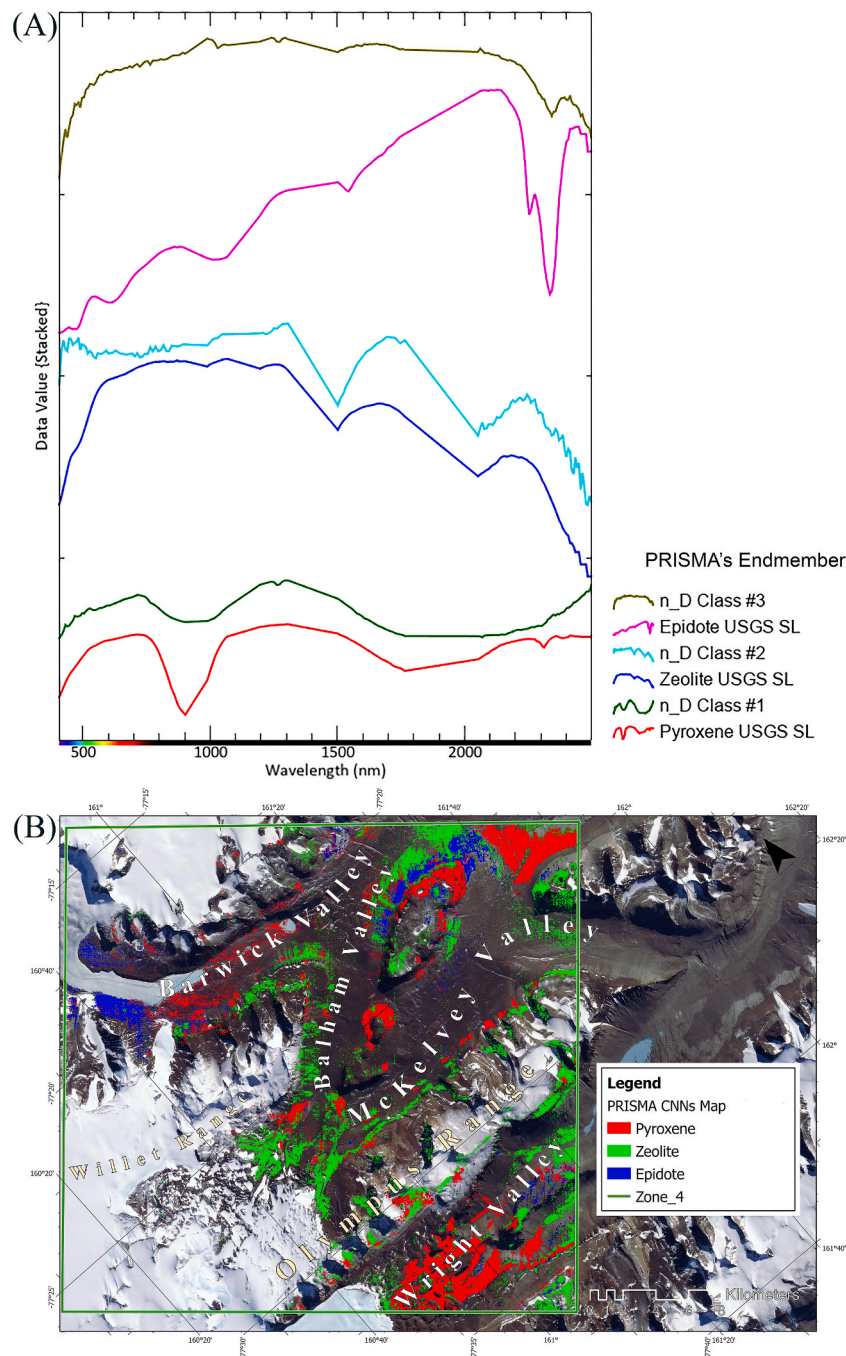


Fig. 7. (A) Endmember spectra derived from PRISMA data for Zone 4 alongside USGS reference spectra of the endmember minerals; (B) Mineral map generated using the CNNs algorithm applied to PRISMA data for Zone 4.

that could be a mixture of montmorillonite/illite and epidote. Notable absorption features at 2.2 and 2.35 μm , related to Al-OH and Mg-OH bonding, and a distinct reflectance feature at 2.28 μm are observed.

Fig. 8B shows the CNNs mineral map of the PRISMA data for Zone 5. Appendix Fig. 1E shows the lithological map of Zone 5. Pyroxene was found in the Dolerite and Till, Breccia, Gravel, Tillite, Sand, and Mud units in the central sector in Victoria Valley, as well as in the Monzonite, Granodiorite, Quartz, Diorite, Monzodiorite, Gneiss, Amphibolite, and Till, Breccia, Gravel, Tillite units in the northern sector of St. Johns Range. A mixture of jarosite, hydrous silica, and sericite was found in the Monzonite, Granodiorite, Quartz, Diorite, Monzodiorite, Gneiss, and Amphibolite units in the Victoria Valley in the central sector, as well as in the southern and southeastern sectors of the Wright Valley. It also

occurred in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the southern and southeastern sectors in the Wright Valley. Additionally, it can be located in the Drift unit in the southern and southeastern sectors in Wright Valley and the southwestern sectors in McKelvey Valley, as well as in the Basanite, Basalt, and Trachybasalt units in the eastern sector. Mirabilite (or evaporates) was found in the central sector in Barwick Valley, McKelvey Valley, and Victoria Valley in the Drift unit, as well as in the Basanite, Basalt, and Trachybasalt units. It is also present in the Till, Breccia, Gravel, Tillite, and Sand and Mud units. An admixture of montmorillonite/illite and epidote was found in the Drift unit in the central sector and McKelvey Valley in the southwestern sector. They are also present in the Till, Breccia, Gravel, and Tillite units in conjunction with Gneiss, Granite, Schist, and Dolerite in the central

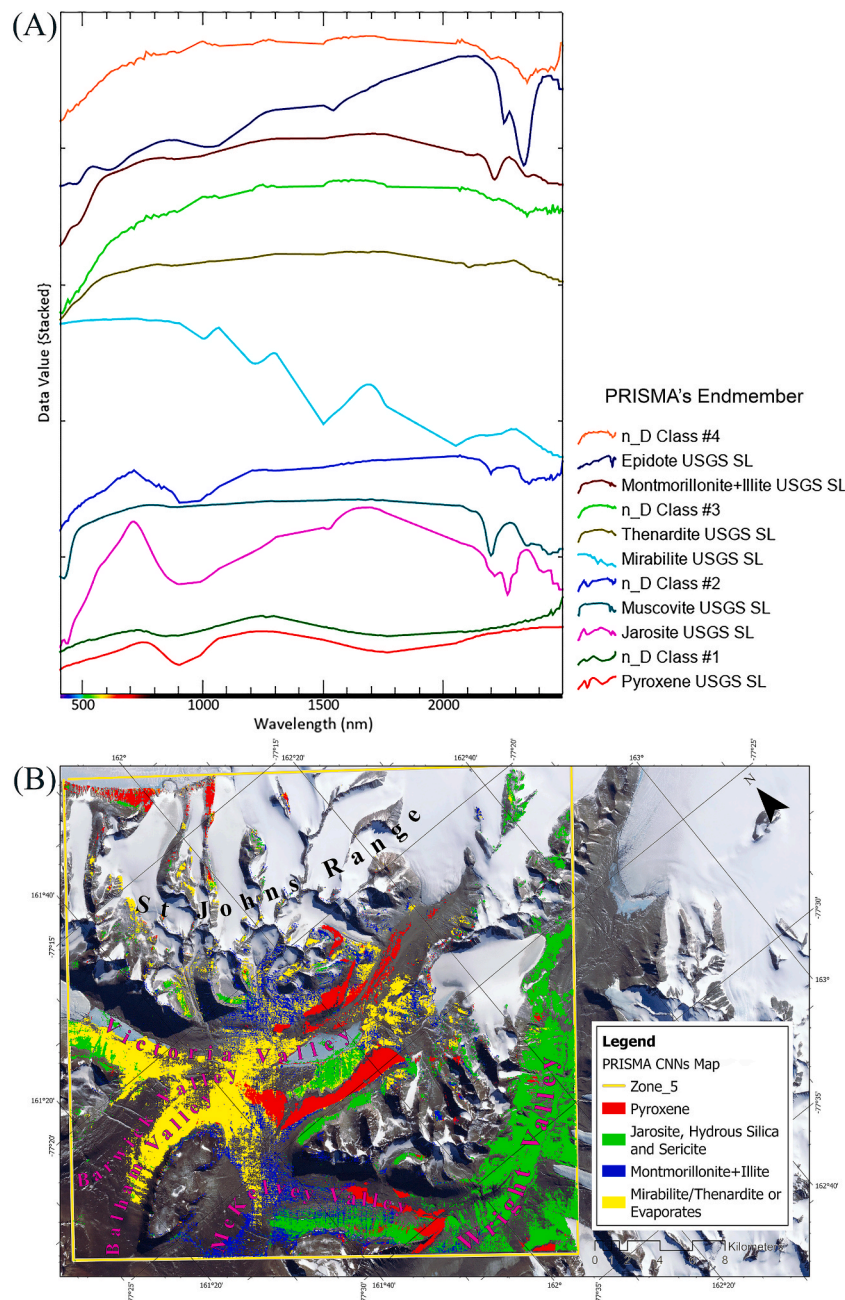


Fig. 8. (A) Endmember spectra derived from PRISMA data for Zone 5 alongside USGS reference spectra of the endmember minerals; (B) Mineral map generated using the CNNs algorithm applied to PRISMA data for Zone 5.

sector in Victoria Valley (Fig. 8B and Appendix Fig. 1E).

Analysis of the PRISMA results identified four distinct n_D classes for Zone 6 (Fig. 9A). n_D Class #1 shows spectral features associated with pyroxene, n_D Class #2 likely corresponds to illite, and n_D Class #3 is hematite. n_D Class #4 shows spectral features possibly indicative of pyroxene. It shows slight absorption features between 0.9 and 1.2 μm (attributable to Fe^{2+}) and a broad absorption feature from 1.7 to 2.0 μm , which is due to increasing Ca, Mg, and Fe^{3+} (Klima et al., 2008). Therefore, this n_D Class could be a clinopyroxene. Fig. 9B shows the CNNs mineral map of the PRISMA data for Zone 6, which is comparable to the lithological map for this zone (see Appendix Fig. 1F). Pyroxene was found in the Dolerite and Drift units in the northern sector in Wright Valley and in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in Taylor Valley and the southwestern sector. Illite was found in the Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss, and

Amphibolite units, and in the Till, Breccia, Gravel, and Tillite units in the northern sector in Wright Valley. It was also present in the Sandstone, Siltstone, and Conglomerate units in the Asgard Range, and in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in Taylor Valley. Hematite was found in the Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss, and Amphibolite units in the northern sector in Wright Valley and in the southwestern sector. It was also found in the Till, Breccia, Gravel, and Tillite units, and in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the Taylor Valley and southwestern sector. Pyroxene (clinopyroxene) was identified in the Dolerite, Quartz Diorite, Monzodiorite, Gneiss, and Amphibolite units, Drift units, and in the Till, Breccia, Gravel, Tillite, Sand, and Mud units (Fig. 9B and Appendix Fig. 1F).

Analysis of the PRISMA results determines five distinct n_D classes for Zone 7 (Fig. 10A). n_D Class #1 shows spectral features aligned with

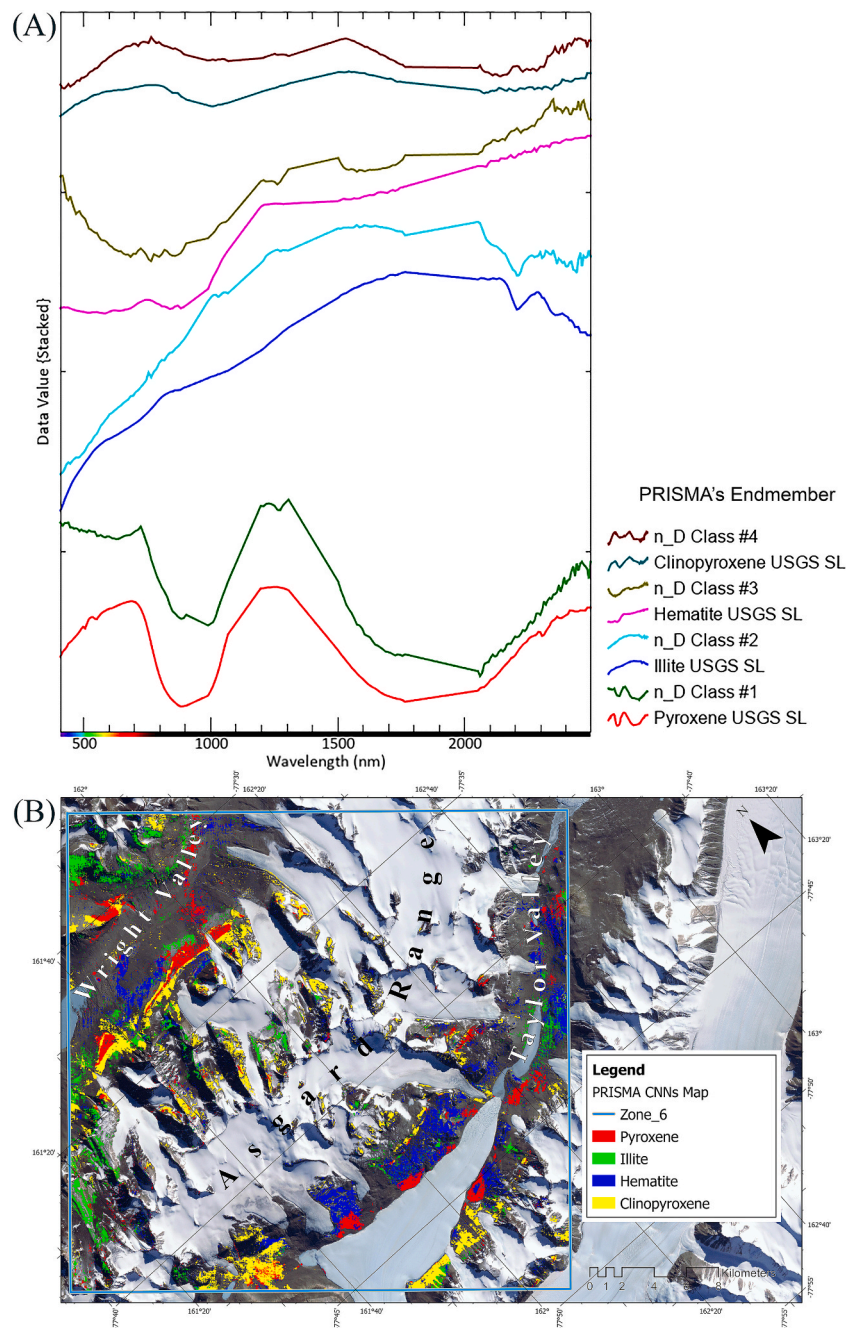


Fig. 9. (A) Endmember spectra derived from PRISMA data for Zone 6 alongside USGS reference spectra of the endmember minerals; (B) Mineral map generated using the CNNs algorithm applied to PRISMA data for Zone 6.

pyroxene. n_D Class #2 likely represents kaolinite/smectite. n_D Class #3 corresponds to illite spectral features. n_D Class #4 shows spectral features that could indicate montmorillonite, with distinct absorption features around 1.4 μm and 1.9 μm related to OH and water bonding, and notable Al-OH absorption around 2.2 μm . n_D Class #5 could be hematite/goethite. Fig. 10B and Appendix Fig. 1G show the CNNs mineral map from PRISMA and the lithological map for Zone 7, respectively. Pyroxene was found in the Dolerite unit in the northern and central sectors, at Taylor Glacier in the southeastern sector, and in the Quartermain Mountains. It was also identified in the Sandstone, Siltstone, and Conglomerate units in the central, southeastern, and western sectors, including the Quartermain Mountains. Additionally, pyroxene was present in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the central and southeastern sectors and in Beacon Valley.

Kaolinite/smectite was found in the Sandstone, Siltstone, and Conglomerate units; the Till, Breccia, Gravel, and Tillite units; and the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the southeast sector and in the Quartermain Mountains. They were also identified in the Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss, and Amphibolite units in the northern sector, in the Sandstone, Conglomerate, Mudstone, Coal, and Diamictite units in the western sector, and in the Dolerite and Drift units in the southern sector. Illite was found in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the southeast and central sectors. It was also identified in the Dolerite unit in the central and northeastern sectors, as well as in the Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss, and Amphibolite units in the northeastern sector. Montmorillonite was found in the Dolerite and Drift units; the Sandstone, Siltstone, and Conglomerate units; the Till, Breccia,

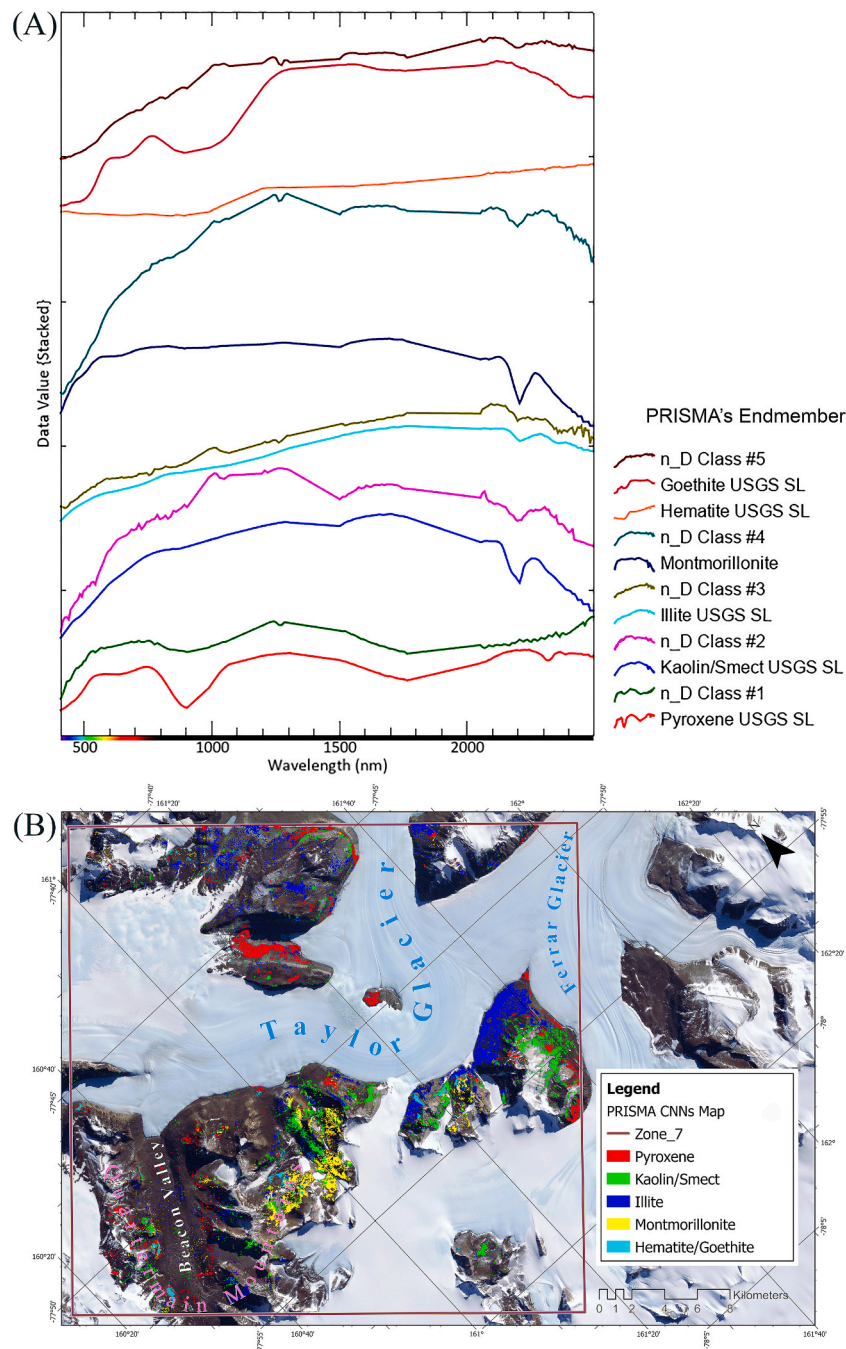


Fig. 10. (A) Endmember spectra derived from PRISMA data for Zone 7 alongside USGS reference spectra of the endmember minerals; (B) Mineral map generated using the CNNs algorithm applied to PRISMA data for Zone 7.

Gravel, and Tillite units; and the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the southeast sector at the Quartermain Mountains. Hematite/goethite was found in the Sandstone, Siltstone, and Conglomerate units in the western, Beacon Valley, and northeastern sectors. It was also identified in the Drift unit and the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the Quartermain Mountains (Fig. 10B and Appendix Fig. 1G).

Analysis of the PRISMA dataset shows four unique n_D classes in Zone 8 (Fig. 11A). n_D Class #1 resembles a mixture of mirabilite/thenardite or evaporates. n_D Class #2 shows spectral features of pyroxene (clinopyroxene). n_D Class #3 has spectral features that could indicate kaolinite/smectite. Comparison of the CNNs mineral map from PRISMA (Fig. 11B) with the lithological map (Appendix Fig. 1H) for Zone 8

shows that a mixture of mirabilite/thenardite or evaporates was found in the Till, Breccia, Gravel, Tillite, Sand, and Mud units; the Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss and Amphibolite units in Taylor Valley, the Kukri Hills and along the Ferrar Glacier boundary. Pyroxene was found in the Dolerite unit in Kukri Hills, in the Till, Breccia, Gravel, Tillite, Sand, and Mud units as well as in the Schist, Marble, Gneiss, and Orthogneiss units in Taylor Valley. Kaolinite/smectite was typically found in the Till, Breccia, Gravel, Tillite, Sand, and Mud units, in the Schist, Marble, Gneiss, and Orthogneiss units, in the Monzonite, Granodiorite, Quartz Diorite, Monzodiorite, Gneiss, and Amphibolite units, and in the Gneiss, Granite and Schist units in Taylor Valley, the Kukri Hills and along the Ferrar Glacier boundary (Fig. 11B and Appendix Fig. 1H).

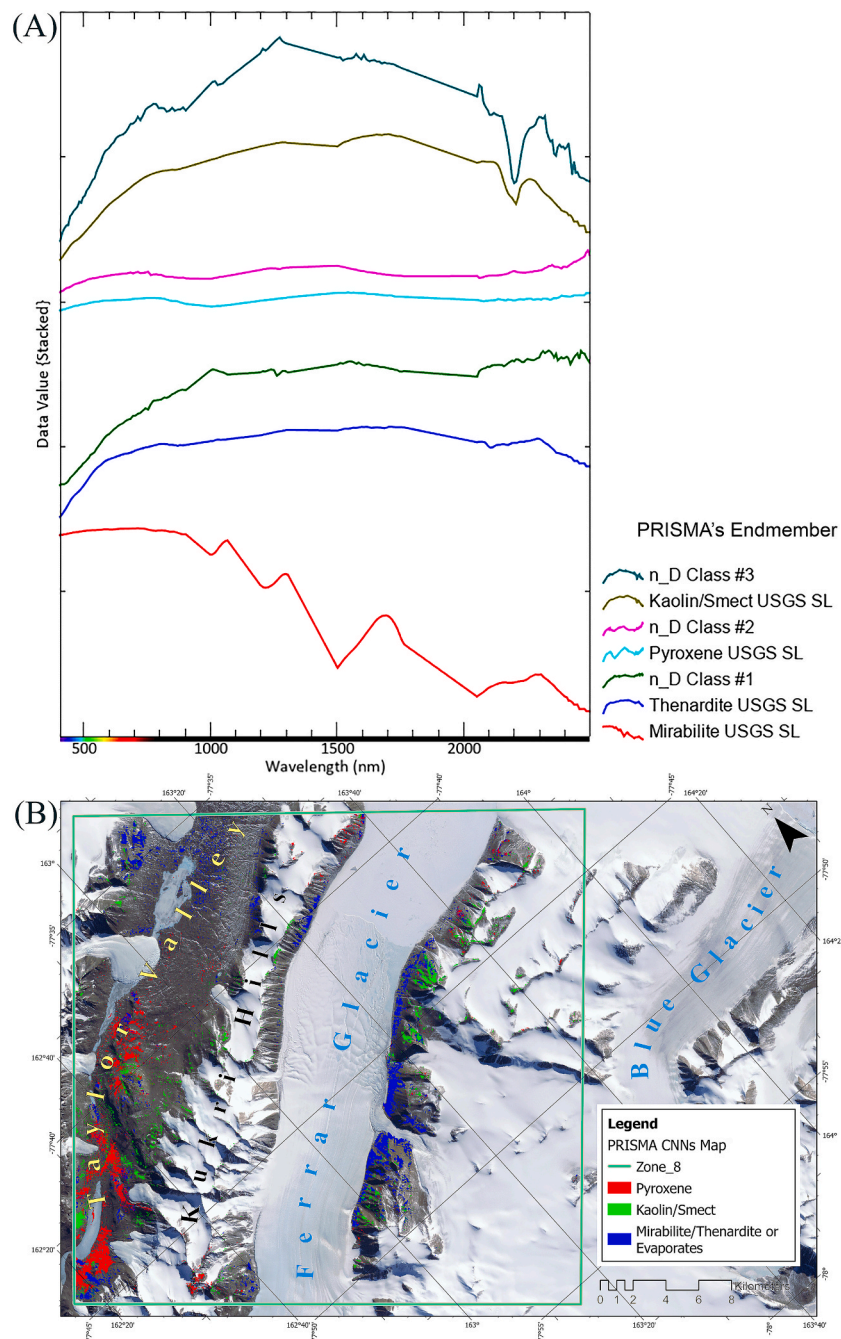


Fig. 11. (A) Endmember spectra derived from PRISMA data for Zone 8 alongside USGS reference spectra of the endmember minerals; (B) Mineral map generated using the CNNs algorithm applied to PRISMA data for Zone 8.

Based on the PRISMA results, three different n_D classes were identified for Zone 9, as shown in Fig. 12A. n_D Class #1 has spectral features that resemble illite and n_D Class #2 is similar to calcite. n_D Class #3 likely has spectral features that could be a mixture of hematite and goethite. Analysis of the CNNs mineral map (Fig. 12B) and the lithological map of Zone 9 (Appendix Fig. 2A) shows that illite occurs in the Schist, Marble, Gneiss, and Orthogneiss units, as well as the Till, Breccia, Gravel, Tillite, Sand, and Mud units exposed along the Blue and Koettlitz glaciers. Calcite was mapped in the Schist, Marble, Gneiss, and Orthogneiss units and in the Till, Breccia, Gravel, and Tillite units. An admixture of hematite and goethite was found in the Till, Breccia, Gravel, and Tillite units and in the Sand and Mud units associated with exposed lithologies in the Blue and Koettlitz glaciers (Fig. 12B and Appendix Fig. 2A).

The analysis of the PRISMA dataset reveals three distinct n_D classes in Zone 10 (Fig. 13A), namely n_D Class #1: kaolinite/smectite, n_D Class #2: corrensite, and n_D Class #3: illite. Comparison of the CNNs mineral map from PRISMA (Fig. 13B) with the lithological map (Appendix Fig. 2B) for Zone 10 shows that a Kaolinite/Smectite is identified in the Sandstone, Siltstone, and Conglomerate units; Till, Breccia, Gravel, and Tillite units; Till, Breccia, Gravel, Tillite, Sand, and Mud units specifically in the Kukri Hills, along the Ferrar Glacier boundary, and in the central sector. Corrensite was mapped in the Till, Breccia, Gravel, Tillite, Sand, and Mud units; Gneiss, Granite, and Schist units; Till, Breccia, Gravel, and Tillite units; and Monzonite, Granodiorite, Quartz, Diorite, Monzodiorite, Gneiss, and Amphibolite units in the western sector and Kukri Hills. It was also found in the Sandstone, Siltstone, and Conglomerate units in the southern sector in the Dolerite

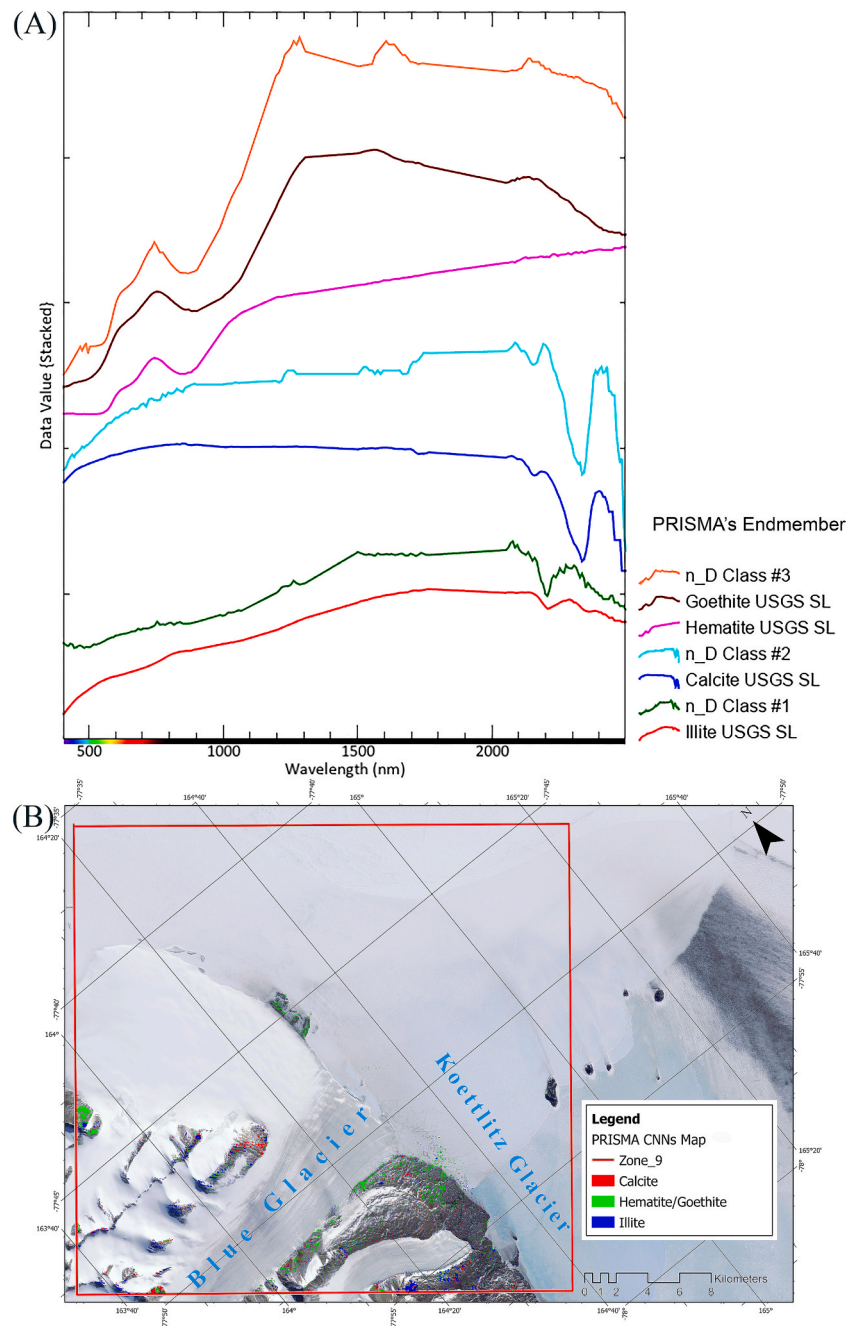


Fig. 12. (A) Endmember spectra derived from PRISMA data for Zone 9 alongside USGS reference spectra of the endmember minerals; (B) Mineral map generated using the CNNs algorithm applied to PRISMA data for Zone 9; (C) Lithological map of Zone 9.

unit in the western sector, and the Royal Society Range. Illite was identified in the Till, Breccia, Gravel, Tillite, Sand, and Mud units; Sandstone, Siltstone, and Conglomerate units; and Dolerite unit in the western sector, Kukri Hills, and along the Ferrar Glacier boundary. It also occurs in the Schist, Marble, Gneiss, and Orthogneiss units in Kukri Hills, and in the Monzonite, Granodiorite, Quartz, Diorite, Monzodiorite, Gneiss, and Amphibolite units in Kukri the Hills and central sector (Fig. 13B and Appendix Fig. 2B).

Analysis of the PRISMA dataset identifies six unique n_D classes in Zone 11 (Fig. 14A), that is n_D Class #1: chlorite, n_D Class #2: calcite, n_D Class #3: illite, n_D Class #4: plagioclase, n_D Class #5 goethite, and n_D Class #6 montmorillonite/illite. The CNNs minerals map derived from PRISMA (Fig. 14B) was compared to the lithological map (Appendix Fig. 2C) of Zone 11. It shows that chlorite was found in the

Monzonite, Granodiorite, Quartz, Diorite, Monzodiorite, Gneiss, and Amphibolite units, as well as in the Gneiss, Granite, and Schist units in the southern sector; in the Schist, Marble, Gneiss, and Orthogneiss units in the southeastern and eastern sectors; in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the eastern sectors; and in the Metavolcanics and Metabasites units in the eastern sectors. Calcite was typically found in the Till, Breccia, Gravel, and Tillite units in the southern sector, and in the Schist, Marble, Gneiss, and Orthogneiss units in the southern, southeastern, and eastern sectors. Illite was found mainly in the Monzonite, Granodiorite, Quartz, Diorite, Monzodiorite, Gneiss, and Amphibolite units in the southeastern sector; in the Gneiss, Granite, and Schist units in the southeastern and eastern sectors; in the Schist, Marble, Gneiss, and Orthogneiss units in the southeastern and eastern sectors; in the Drift unit in the eastern sector; and in the Till,

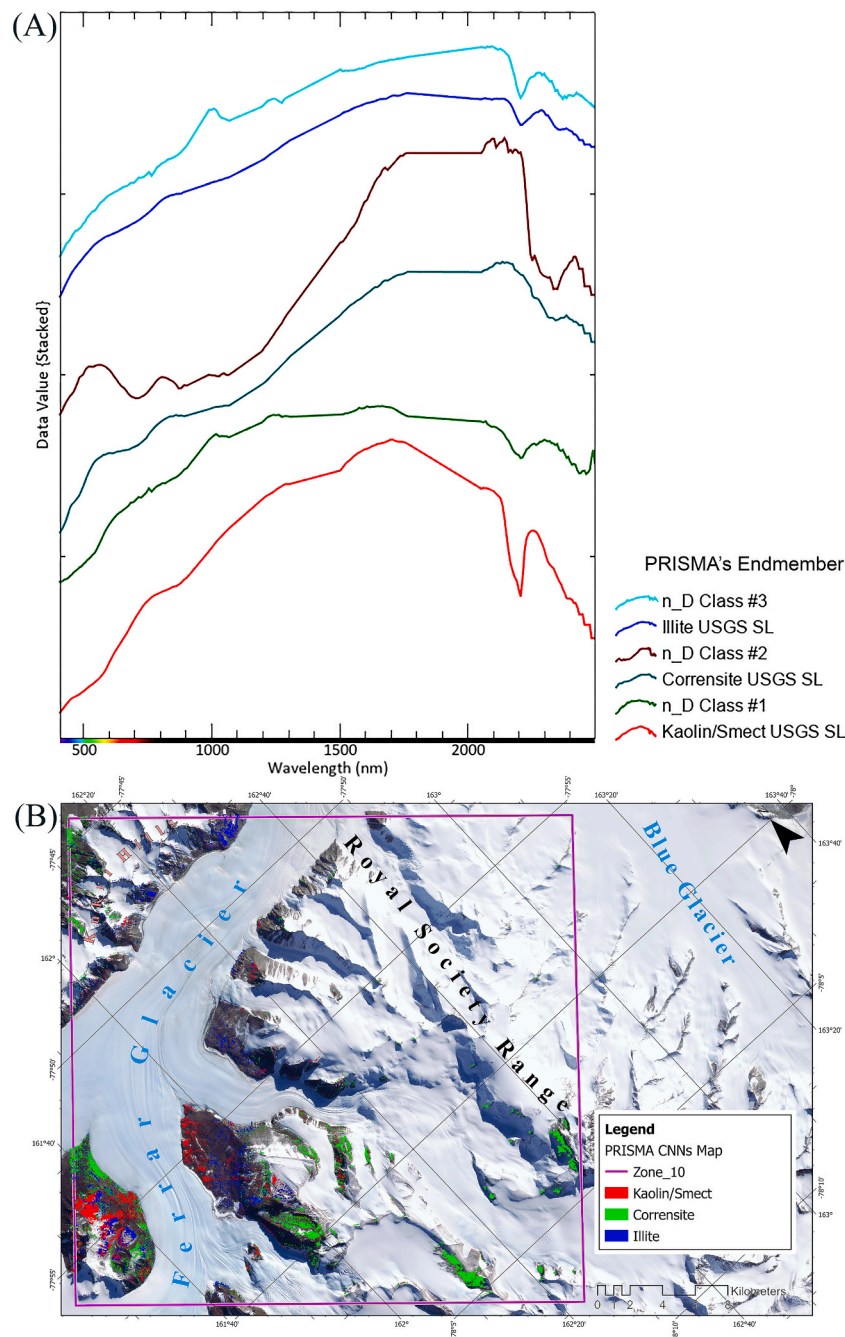


Fig. 13. (A) Endmember spectra derived from PRISMA data for Zone 10 alongside USGS reference spectra of the endmember minerals; (B) Mineral map generated using the CNNs algorithm applied to PRISMA data for Zone 10.

Breccia, Gravel, Tillite, Sand, and Mud units in the eastern sector. Plagioclase was mapped in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the eastern and central sectors, and in the Monzonite, Granodiorite, Quartz, Diorite, Monzodiorite, Gneiss, and Amphibolite units. Goethite was found in the Monzonite, Granodiorite, Quartz, Diorite, Monzodiorite, Gneiss, and Amphibolite units in the southern and central sectors; in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the central and eastern sectors; in the Till, Breccia, Gravel, and Tillite units in the southeastern and eastern sectors; and in the Schist, Marble, Gneiss, and Orthogneiss units in the southeastern sector. Montmorillonite/illite was found in the Schist, Marble, Gneiss, and Orthogneiss units in the northeastern and central sectors, and in the Gneiss, Granite, and Schist units in the southeastern and eastern sectors (Fig. 14B and Appendix Fig. 2C).

Analysis of the PRISMA dataset identifies four distinct n_D classes, including n_D Class #1: kaolinite/smectite, n_D Class #2: chlorite/epidote, n_D Class #3: hematite, and n_D Class #4: montmorillonite/illite in Zone 12 (Fig. 15A). Kaolinite/smectite was identified in the Schist, Marble, Gneiss, and Orthogneiss units in the southwestern sector of the Royal Society Range and in the eastern and southeastern sectors (Fig. 15B and Appendix Fig. 2D). It was also found in the Gneiss, Granite, Schist units, Monzonite, Granodiorite, Quartz, Diorite, Monzodiorite, Gneiss, Amphibolite units, Till, Breccia, Gravel, Tillite units, and Till, Breccia, Gravel, Tillite, Sand, Mud units in the eastern and southeastern sectors, as well as in the Diorite, Gneiss, Amphibolite units in the southern sector. Chlorite/epidote was detected in the Till, Breccia, Gravel, Tillite units and Till, Breccia, Gravel, Tillite, and Sand, Mud units in the southeastern and eastern sectors. In addition, it was mapped in the

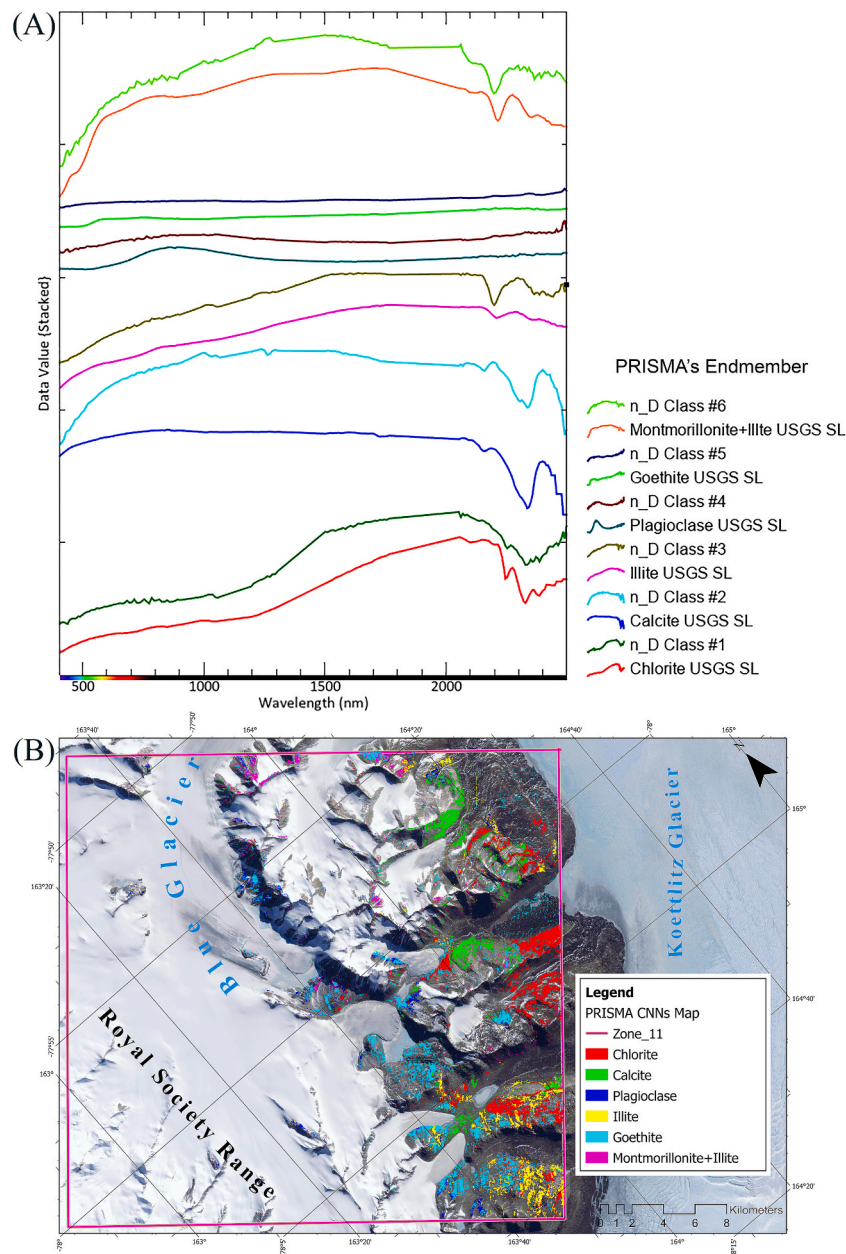


Fig. 14. (A) Endmember spectra derived from PRISMA data for Zone 11 alongside USGS reference spectra of the endmember minerals; (B) Mineral map generated using the CNNs algorithm applied to PRISMA data for Zone 11.

Granite unit and Drift unit in the southeastern sector, in the Sandstone, Siltstone, and Conglomerate units in the southern sector, and in the Dolerite unit in the northern sector (Fig. 15B and Appendix Fig. 2D). Hematite was observed in the Basanite, Basalt, and Trachybasalt units in the eastern and central sectors, as well as in the Schist, Marble, Gneiss, Orthogneiss units, and Diorite, Gneiss, Amphibolite units in the southern sector (Fig. 15B and Appendix Fig. 2D). Montmorillonite/illite was found in the Till, Breccia, Gravel, Tillite, Sand, and Mud units in the eastern sector, in the Till, Breccia, Gravel, Tillite units in the central sector, and in the Gneiss, Granite, Schist units and Schist, Marble, Gneiss, Orthogneiss units in the central and southern sectors (Fig. 15B and Appendix Fig. 2D).

Analysis of the PRISMA dataset reveals the presence of eight distinct n_D classes in Zone 13 (Fig. 16A). n_D Class #1 is calcite. n_D class #2 is illite. n_D Class #3 could be a mixture of hematite and goethite. n_D class #4 could be vermiculite $((\text{Mg}, \text{Fe}^{2+}, \text{Fe}^{3+})_3[(\text{Al}, \text{Si})_4\text{O}_{10}](\text{OH})_2 \cdot 4\text{H}_2\text{O})$. It shows two separate absorption features at 2.30 and 2.40 μm .

Additionally, H_2O absorption is seen at 1.9 μm and 1.4 μm . n_D class #5 is montmorillonite. n_D class #6 could be zeolite. n_D class #7 is corrensite. n_D class #8 is chlorite. Calcite was found in the Gneiss, Granite, and Schist units (Fig. 16B and Appendix Fig. 2E). Illite and a mixture of hematite and goethite were observed in the Monzonite, Granodiorite, Quartz, Diorite, Monzodiorite, Gneiss, Amphibolite units, Gneiss, Granite, Schist units, and Schist, Marble, Gneiss, Orthogneiss units (Fig. 16B and Appendix Fig. 2E). Vermiculite was identified in the Schist, Marble, Gneiss, Orthogneiss units, Till, Breccia, Gravel, Tillite, Sand, Mud units, and Gneiss, Granite, and Schist units. Montmorillonite was detected in the Till, Breccia, Gravel, Tillite, Sand, Mud units, Till, Breccia, Gravel, Tillite units, and Schist, Marble, Gneiss, Orthogneiss units (Fig. 16B and Appendix Fig. 2E). Zeolite was observed in the Monzonite, Granodiorite, Quartz, Diorite, Monzodiorite, Gneiss, Amphibolite units, and Schist, Marble, Gneiss, and Orthogneiss units. Corrensite was observed in the Gneiss, Granite, and Schist units, Schist, Marble, Gneiss, Orthogneiss units, and Till, Breccia, Gravel, Tillite,

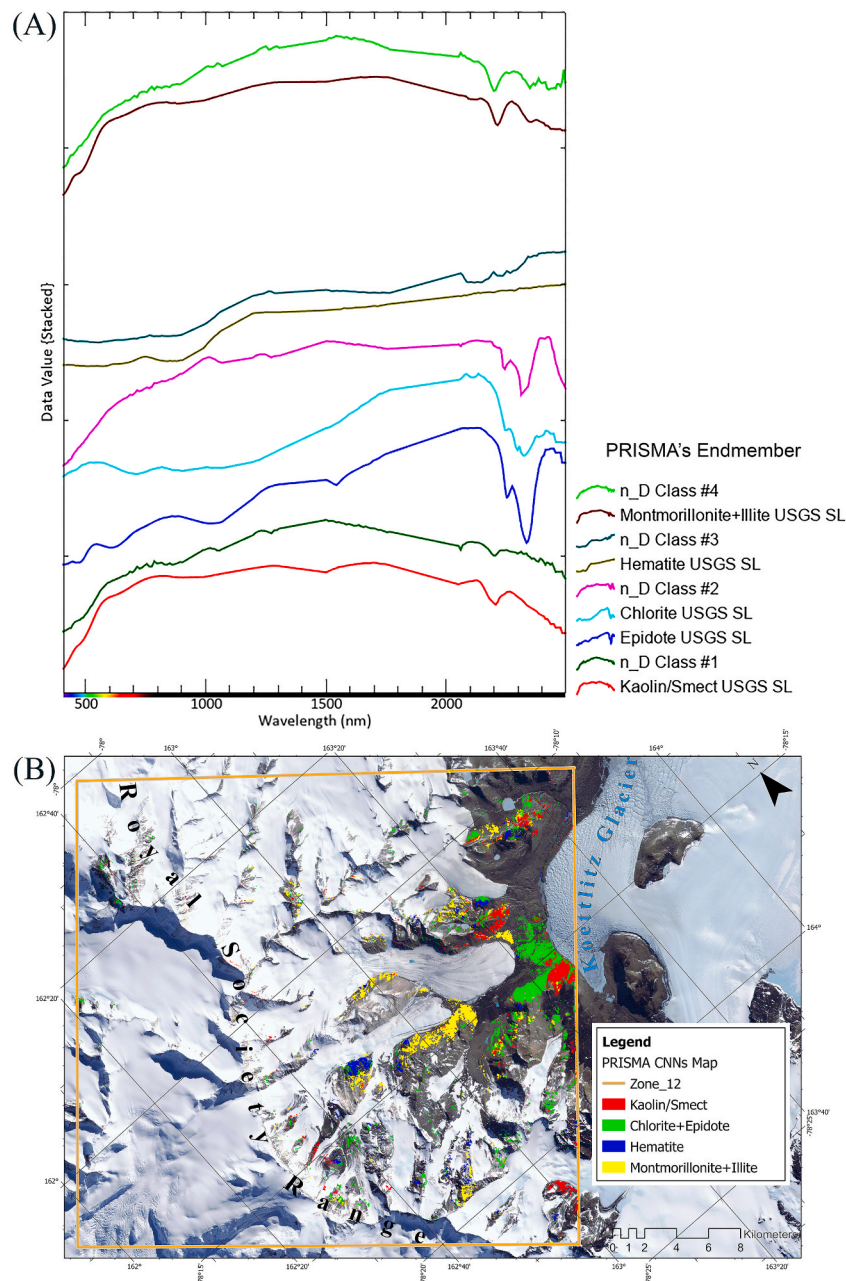


Fig. 15. (A) Endmember spectra derived from PRISMA data for Zone 12 alongside USGS reference spectra of the endmember minerals; (B) Mineral map generated using the CNNs algorithm applied to PRISMA data for Zone 12.

Sand, and Mud units. Chlorite was found in the Monzonite, Granodiorite, Quartz, Diorite, Monzodiorite, Gneiss, Amphibolite units, and Schist, Marble, Gneiss, Orthogneiss units (Fig. 16B and Appendix Fig. 2E).

Analysis of the PRISMA dataset shows five diverse n_D classes in Zone 14 (Fig. 17A). n_D Class #1 is Kaolinite/smectite. n_D Class #2 exhibits the spectral characteristic of hematite and goethite admixture. n_D Class #3 is hematite. n_D Class #4 could be zeolite. n_D Class #5 is calcite. Kaolinite/smectite was identified in the Schist, Marble, Gneiss, Orthogneiss units, Granite unit, Gneiss, Granite, Schist units, and Till, Breccia, Gravel, Tillite, Sand, Mud units in the northwest sector (Fig. 17B and Appendix Fig. 2F). In the northwestern sector, a mixture of hematite and goethite was observed in the Granite, Gneiss, Granite, and Schist units, and till, Breccia, Gravel, and Tillite units. Furthermore, hematite was found in the Basanite, Basalt, and Trachybasalt units and in the Trachyte and rhyolite units. Zeolite was detected in the Schist,

Marble, Gneiss, and Orthogneiss units in the northern and northwest sectors, in the Till, Breccia, Gravel, and Tillite units in the northern sector, in the Granite unit in the northwest sector, and in the Phonolite, Trachyandesite units in the southern sector (Fig. 17B and Appendix Fig. 2F). Calcite was found in the Schist, Marble, Gneiss, and Orthogneiss units in the northern and northwest sectors, and in the Till, Breccia, Gravel, and Tillite units in the northern sector (Fig. 17B and Appendix Fig. 2F).

4.2. Evaluation of CNNs models performance

The explanation of the performance analysis of the CNN models across epochs is presented in Appendix Figs. 3-6. Each subfigure shows the progression of training and validation accuracy along with the corresponding model loss, across various datasets and configurations. The training and validation accuracy remains consistently high, ranging

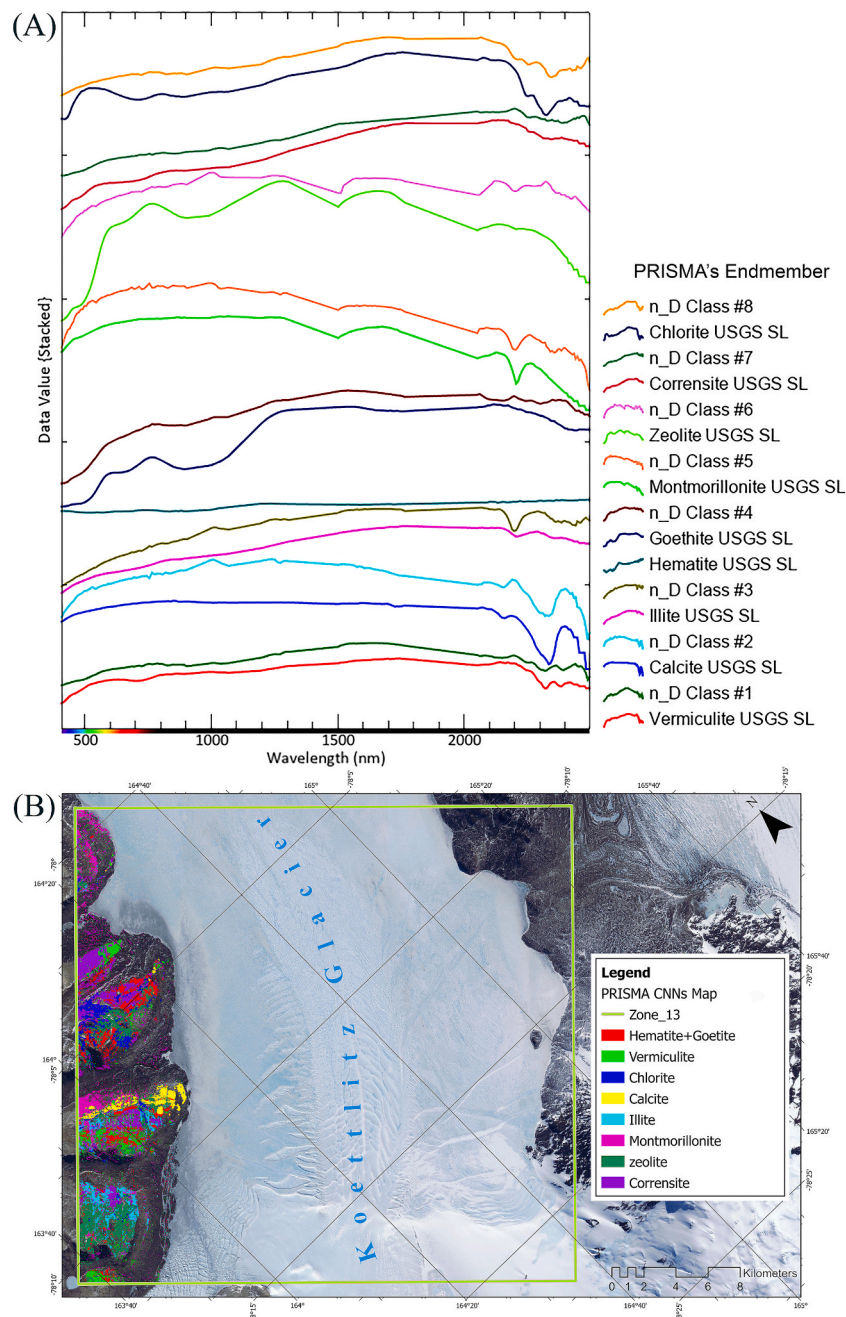


Fig. 16. (A) Endmember spectra derived from PRISMA data for Zone 13 alongside USGS reference spectra of the endmember minerals; (B) Mineral map generated using the CNNs algorithm applied to PRISMA data for Zone 13.

from 0.994 to 0.997, demonstrating robust performance. Furthermore, the loss curves exhibit convergence trends, with values between 0.10 and 0.11 indicating a good fit, as the validation and training losses are closely matched in all cases.

The assessment of accuracy involves examining and comparing the training and testing results for the datasets. It involves determining critical metrics, including overall accuracy, precision, recall, and the F1 score. These indicators reflect the validity and reliability of mineral identification and provide information on how well the datasets represent the mineralogical composition of lithological units. Table 4 provides a detailed comparison of the metrics of the confusion matrix in the datasets. The results show that the 3-D CNNs model achieves a precision of 0.981 to 0.994, a recall of 0.981 to 0.994, an F1-score of 0.982 to 0.994, and an overall accuracy of 0.981 to 0.994 (Table 4).

5. Discussions

In this study, hyperspectral PRISMA satellite images were successfully used to map the mineralogy of host rocks and their weathered/ altered/transported products in the DVs region (South Victoria Land, Antarctica) by implementing 3-D CNNs deep learning algorithm for accurate spectral analysis and classification. The main results demonstrate the ability of hyperspectral PRISMA data to produce detailed regional mineral map of the DVs region (Fig. 18). The most important advantage of the hyperspectral PRISMA satellite imagery enabled the recognition of minerals with a high overall accuracy of 0.981 to 0.994. The results highlight the originality of the application of 3-D CNNs in Antarctic remote sensing and emphasize their potential to overcome the traditional challenges of mapping minerals and lithologies in extreme

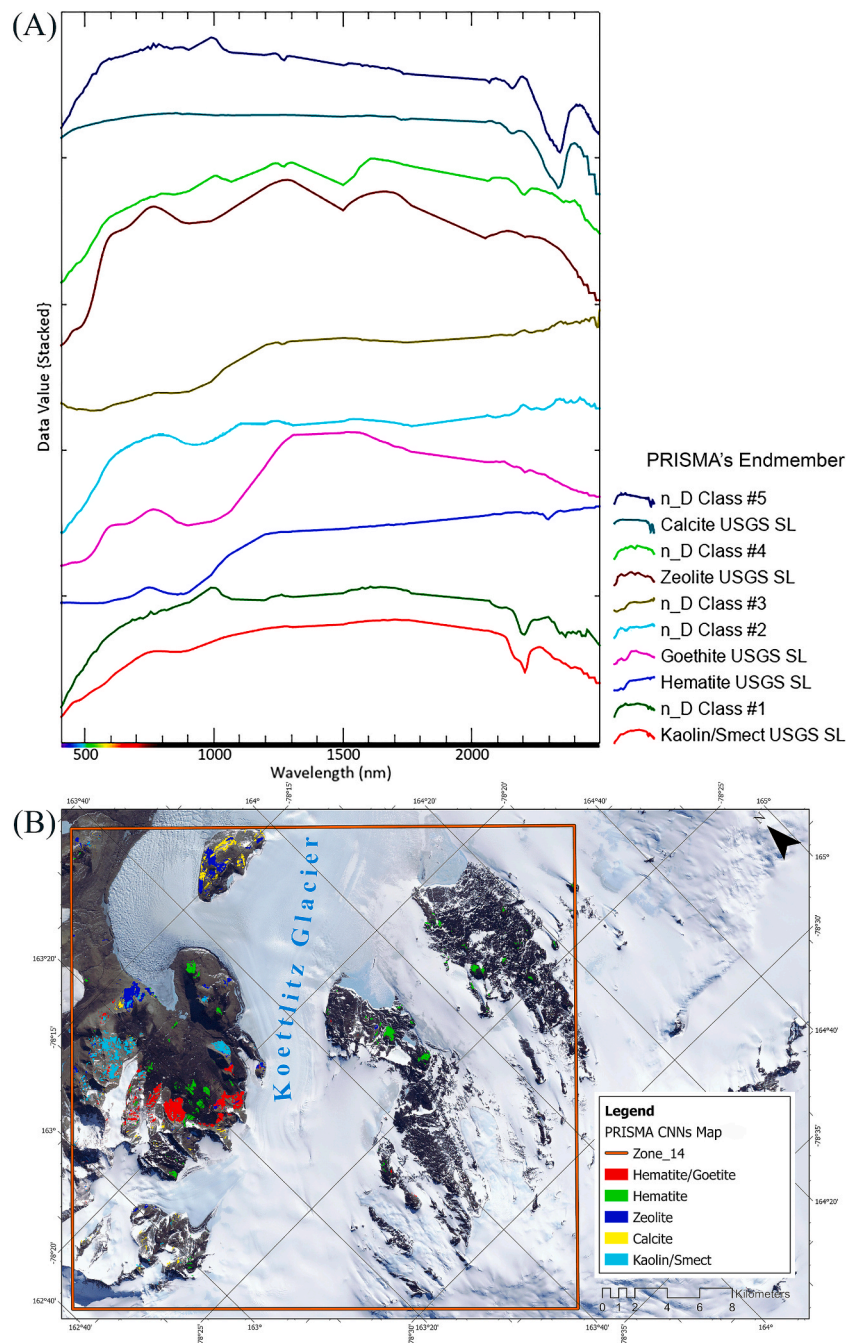


Fig. 17. (A) Endmember spectra derived from PRISMA data for Zone 14 alongside USGS reference spectra of the endmember minerals; (B) Mineral map generated using the CNNs algorithm applied to PRISMA data for Zone 14.

and inaccessible environments.

This research represents a significant advance in remote sensing analysis compared to previous studies that focused on the geological mapping of Antarctica. Previous works relied primarily on multispectral remote sensing data (Haselwimmer et al., 2010, 2011, Pour et al., 2019, 2019a,b, 2021, 2018a, 2018b; Salvatore, 2015; Salvatore et al., 2014), which limited the accuracy of mineral identification to some extent. By utilizing the hyperspectral capabilities of PRISMA, this study addresses these limitations and is consistent with recent findings that underscore the importance of hyperspectral imagery for geological and mineralogical investigations. Furthermore, the application of the 3-D CNNs deep learning algorithm in conjunction with the AVCA and spectral augmentation provides a robust and innovative framework for mineral classification in Antarctic geological research.

In recent research, CNNs are unanimously regarded as the most advanced method for geological remote sensing data processing (El-Omairi et al., 2025; Haidarh et al., 2025). Comparative research over the past decade shows that deep CNNs routinely outperform traditional pixel-based classifiers such as maximum-likelihood (MLC), spectral-angle mapper (SAM), support-vector machines (SVM), and random forests in geological satellite remote sensing, providing 5–20 % higher overall accuracy while capturing spatial context unavailable to purely spectral methods (Arun Solomon and Akila Agnes, 2023; Ortac and Ozcan, 2021; Wang et al., 2023). These gains have been demonstrated for lithological discrimination, mineral mapping, and hyperspectral scene interpretation, driving a paradigm shift toward AI-centred mineral-exploration pipelines (Agrawal and Govil, 2023; El-Omairi et al., 2025; Haidarh et al., 2025). Although, fusing multispectral (Landsat 8,

Table 4
Confusion matrix results for the CNNs model.

Sensor_Scene	Precision	Recall	F1-score	Overall Accuracy
PRISMA_scene 1	0.982	0.981	0.982	0.982
PRISMA_scene 2	0.988	0.983	0.985	0.985
PRISMA_scene 3	0.993	0.992	0.993	0.993
PRISMA_scene 4	0.981	0.983	0.982	0.982
PRISMA_scene 5	0.990	0.987	0.988	0.988
PRISMA_scene 6	0.994	0.993	0.993	0.993
PRISMA_scene 7	0.990	0.989	0.990	0.990
PRISMA_scene 8	0.985	0.984	0.984	0.984
PRISMA_scene 9	0.986	0.983	0.985	0.985
PRISMA_scene 10	0.988	0.987	0.987	0.987
PRISMA_scene 11	0.986	0.984	0.985	0.985
PRISMA_scene 12	0.994	0.994	0.994	0.994
PRISMA_scene 13	0.993	0.992	0.993	0.993
PRISMA_scene 14	0.989	0.991	0.990	0.990

ASTER, Sentinel-2) and hyperspectral (Hyperion, HyMap) imagery, the ANN outperforms every competing classifier—Minimum Distance (Min D), Mahalanobis Distance (Mah D), Parallelepiped (PP), Spectral Angle Mapper (SAM), Spectral Information Divergence (SID), and Maximum Likelihood (Max L)—by about 30 percentage points in overall accuracy (Habashi et al., 2024b).

On arid-terrain ASTER scenes, CNNs raised overall mapping accuracy from ~78 % with SVM to ~89 % by fusing spectral and texture cues (Lin and Wang, 2021; Yu et al., 2012). AdvSemi-OCNet further improved class separability in structurally complex belts, reducing ultramafic misclassification by 40 % relative to SVM baselines (Wang et al., 2023). Traditional statistical classifiers remain attractive when labels are scarce, yet semi-supervised CNNs now mitigate data hunger by exploiting unlabeled spectra (Shayeganpour et al., 2021; Wang et al., 2023). Benchmark datasets such as AVIRIS-Indian Pines and PRISMA have become standard testbeds for algorithm comparison (Ortaç and Özcan, 2021; Shebl et al., 2023). 3-D CNNs that learn joint spectral-spatial features outperform SVM, RF and XGBoost by 6–15 %, especially for spectrally similar silicate minerals (Arun Solomon and Akila Agnes, 2023; Shebl et al., 2023). Residual and recurrent CNN variants extend gains to fine-grained mineral species, pushing κ statistics above 0.90 while SAM plateaus near 0.75 (Agrawal and Govil, 2023; Paoletti et al., 2019). Hybrid CNN-SVM and CNN-LSTM schemes couple deep feature extraction with margin-based generalization, yielding the most robust shale-facies predictions reported to date (Agrawal and Govil, 2023; Li et al., 2024d). Comprehensive reviews concur that deep models excel at handling non-linear spectral mixtures, yet call for benchmark standardization and interpretability advances to address black-box critiques (Haidarh et al., 2025; Paoletti et al., 2019). Moreover, a comparative evaluation of target detection techniques for mineral mapping, including Orthogonal Subspace Projection (OSP), Matched Filtering (MF), Linear Spectral Unmixing (LSU), and Constrained Energy Minimization (CEM) with CNN for Zone 5 of DVs region is presented (see Appendix 3, Appendix Fig. 7 and Table 5).

This study also closes a crucial gap in our understanding of the distribution of mineralogy of host rocks and their weathered/alterated/transported products in the DVs region. Unlike previous geological, remote sensing, and environmental studies (Fountain et al., 2017; Levy et al., 2014; Power et al., 2020, 2024; Salvatore, 2015; Salvatore et al., 2014, 2020, 2021, 2023; McNulty, 2023), which primarily focused on limited areas or lacked comprehensive remote sensing spectral analysis, this work provides an advanced approach for mapping minerals on a regional scale (13000 Km², over 25 % of antarctica exposed lithologies). This study not only improves our understanding of the distribution of alteration minerals and tangible environmental processes but also lays the foundation for future studies of geochemical evolution in harsh environments such as Antarctica. Furthermore, this study lies in the innovative implementing of AVCA, spectral augmentation and then 3-D CNNs deep learning algorithm for mineral mapping, which has

significantly improved the accuracy of classification compared to other image processing techniques (e.g., Automated Spectral Hourglass (ASH)) approach (Kruse et al., 2003). This deep learning-based approach helps to alleviate one of the main limitations, namely the reliance on remote sensing data that needs to be validated by field surveys, which is a logistical challenge in Antarctic environments.

Analysis of the minerals identified in the various exposed lithological units in the DVs region (Fig. 19 A-F) reveals a variety of formation processes that are shaped by the environment, chemistry, and temperature conditions of the individual rock types. In the case of monzonite, granodiorite, quartz diorite, monzodiorite, gneiss, and amphibolite, several secondary minerals, including limonite, goethite, Fe-muscovite, kaolinite, jarosite, illite, and pyrophyllite, have been identified. These minerals are indicative of weathering, alteration, and hydrothermal processes. Limonite and goethite are iron oxides that typically form under oxidizing conditions in the presence of water, indicating that these rocks have been exposed to weathering in an oxygen-rich environment (Salvatore et al., 2013). Fe-muscovite is a type of mica that forms under low to moderate pressure during metamorphism, while kaolinite is a clay mineral that forms when feldspar or other aluminosilicates weather under acidic conditions. Jarosite and illite typically form under acidic, hydrothermal conditions or during weathering processes. The presence of nontronite, a type of smectite clay, is often associated with highly oxidizing conditions and the alteration of iron-bearing rocks, which was likely the case in this lithologic setting. Similar weathering and alteration processes can be observed in sedimentary units such as till, breccia, gravel, tillite, sand, and mud (Fig. 19 E and F). Minerals such as limonite, goethite, kaolinite, jarosite, and illite indicate that the sediments have undergone oxidation, clay formation, and acid weathering. These minerals typically form in environments where ferrous rock is exposed to fluctuating water conditions. The presence of nontronite indicates an environment with highly oxidizing conditions that were often influenced by ferrous fluids. The minerals found in these sediments, such as kaolinite and illite, typically form as a result of weathering of feldspar- and mica-rich parent rocks under moderately acidic conditions.

In metamorphic units such as schist, marble, and orthogneiss, the minerals epidote, chlorite, illite, kaolinite, goethite, jarosite, and calcite provide information about the conditions of metamorphism and alteration. Epidote and chlorite typically form during low to medium-grade metamorphism of mafic rocks such as those found in schist and gneiss. Calcite is a hallmark of metamorphosed limestone and indicates the formation of marble. Jarosite and goethite may form during the oxidation of sulfide minerals in hydrothermal alteration zones. The presence of smectite, illite, and kaolinite also indicates weathering processes that take place either in the parent rock or during later alteration stages. In sedimentary rocks such as sandstone, siltstone, and conglomerate (Fig. 19 D-F), the presence of epidote, chlorite, illite, kaolinite, jarosite, and calcite indicate both primary sedimentary and secondary alteration processes. Epidote, chlorite, illite, and kaolinite are products of the weathering and alteration of feldspar, mica, and other minerals in a slightly acidic environment. The occurrence of jarosite indicates that sulphurous, acidic conditions prevailed during the formation of the rock, which can probably be attributed to volcanic or hydrothermal activity. The presence of smectite and montmorillonite indicates that alkaline conditions during weathering or hydrothermal processes may have contributed to the formation of these clay minerals.

In dolerite (Fig. 19 C and D), secondary minerals such as goethite, jarosite, kaolinite, smectite, hydrous silica, and sericite reflect extensive alteration and weathering. These minerals usually form when basalts and other mafic igneous rocks are oxidized and acid-weathered. The primary minerals pyroxene, clinopyroxene, and epidote indicate that the original rock is of magmatic origin and formed under cooling conditions. Hematite and montmorillonite indicate both oxidizing conditions and clay formation in altered dolerite. The drift units (Fig. 19 B), which include minerals such as chlorite, muscovite, jarosite, hydrous silica,

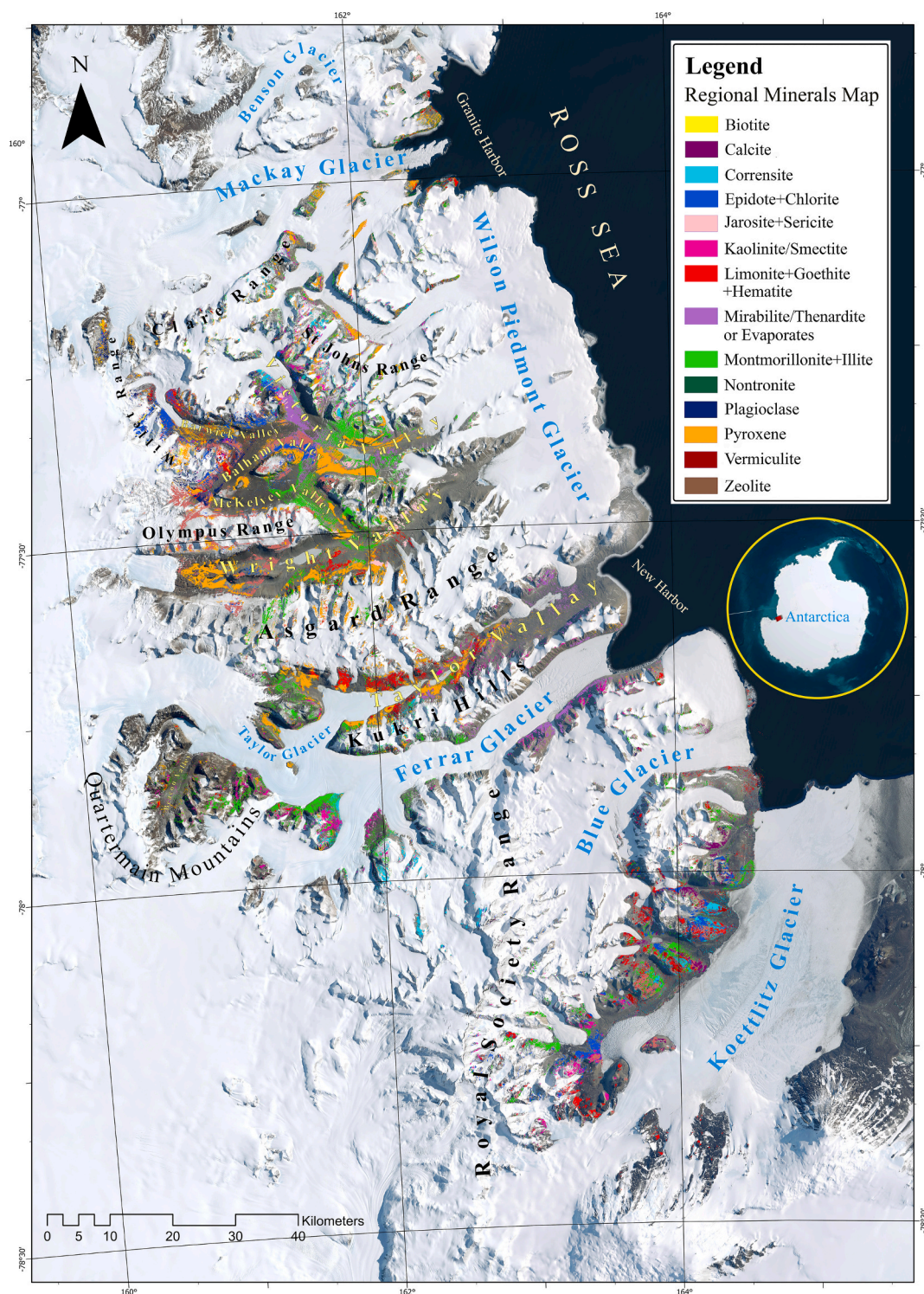


Fig. 18. Regional mineral map generated from the hyperspectral PRISMA satellite images for the DVs region, South Victoria Land, Antarctica.

and sericite, also indicate weathering and alteration processes. The presence of zeolite and corrensite in the PRISMA data indicates the alteration of volcanic rocks (volcanic ash) in the drift environment. In the case of basanite, basalt, and trachybasalt, the minerals jarosite, hematite, hydrous silica, sericite, kaolinite, smectite, hematite and goethite indicate that these volcanic rocks were altered under acidic, oxidizing conditions. Jarosite and hematite are usually associated with the oxidation of ferrous volcanic rocks in an acidic environment. The formation of clays such as kaolinite and smectite indicates that the

weathering processes in these environments were significant. Diorite and gneiss formations with minerals such as epidote, chlorite, illite, kaolinite, and jarosite reflect the conditions of low to medium-grade metamorphism. The presence of calcite, plagioclase, pyroxene, and clinopyroxene indicates that the original igneous character of these rocks has been preserved, indicating that they have undergone moderate metamorphism without complete alteration. In the phonolite and trachyandesite rocks, the identification of hematite and zeolite indicates oxidation during the alteration of the volcanic rocks. Zeolite forms

Table 5
Comparative assessment of the OSP, MF, LSU, and CEM classification maps with CNN map for Zone 5 of DVs region (Appendix Fig. 7, Panels A–E).

Algorithm	Salt-and-pepper noise	Spatial coherence of classes	Delineation of <i>Pyroxene</i>	Separation of hydrous-silica alteration (blue)	Geological interpretability	Overall qualitative rating
Orthogonal Subspace Projection (A)	High	Fragmented	Faint and discontinuous	Chaotic	Heavy spectral spill-over into icefields produces false positives	Low accuracy – suitable only for a rough first pass
Matched Filtering (B)	Very high	Highly heterogeneous	Better than OSP but with broad halos	Strong over-estimation	Background spectral noise dominates detections	Poor signal-to-noise ratio
Linear Spectral Unmixing (C)	Low	Fairly uniform	Soft boundaries; fine detail lost	Conservative	Spectral averaging blurs genuine “edges”	Stable but low-detail output
Constrained Energy Minimisation (D)	Low	Uniform	Isolates <i>Zone 5</i> well, under-represents other minerals	Strongly suppressed	Single-target cost function neglects non-target classes	Good for single-mineral target mapping
Convolutional Neural Network (E)	Very low	Highly coherent	Sharp, continuous boundaries	Clear tracing of hydrous-silica veins	Reflects topographic and textural patterns realistically	Best balance of detail and noise reduction

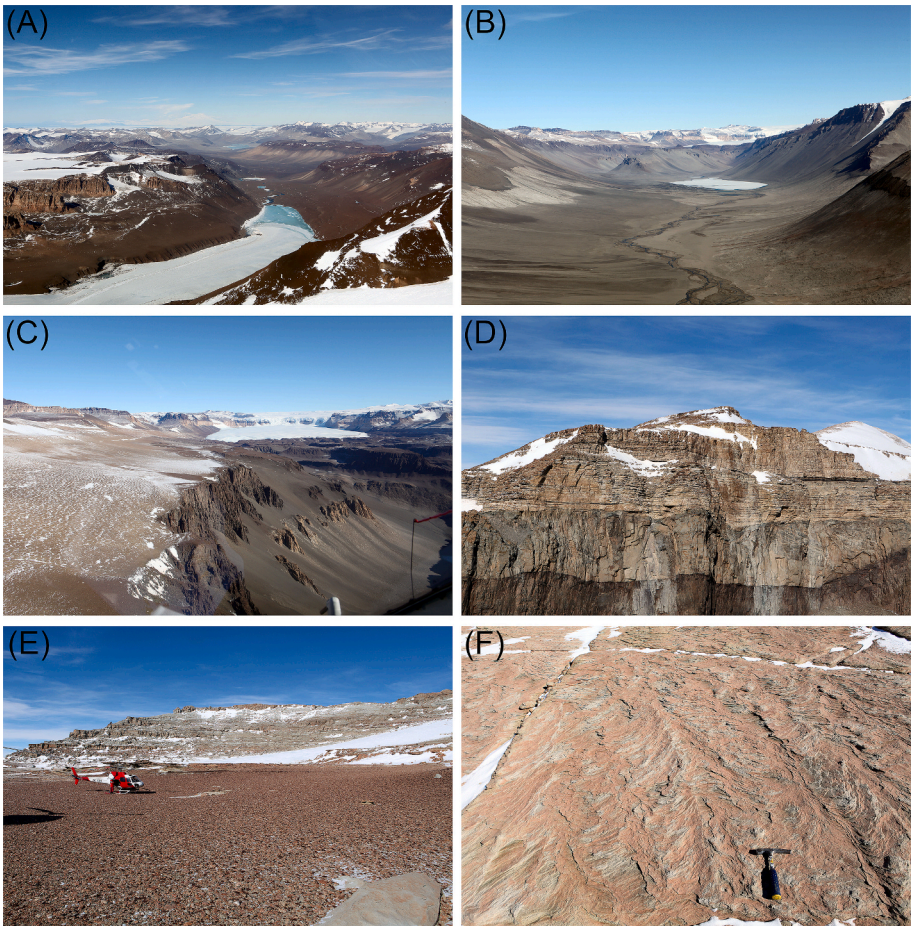


Fig. 19. Field images of various exposed lithological units in the DVs region (Summer season 2015–2016 geological expeditions by Korea Polar Research Institute (KOPRI)). (A) Helicopter synoptic view of the DVs region and the Transantarctic Mountains; (B) Regional view of the Wright Valley and exposed outcrops of alternating sandstone formations and dolerite sill complex, drifts, tills, and moraines, the Lake Vanda is visible as a white surface in the centre of the image; (C) Helicopter view of Victoria Valley and exposed outcrops of the Beacon Supergroup and Ferrar Group; (D) Regional view of outcrops of the Beacon Supergroup (upper parts), Pluton granite (middle parts), and Ferrar Dolerite (dark brown, lower parts) in the Asgard Range; (E) Regional view of outcrops of the Beacon Supergroup (upper part) and ventilated pavement of Beacon sandstone (lower parts); (F) Close-up view of rippled fine-grained sandstone or siltstone in the Quartermain Mountains.

typically in hydrothermal environments, while hematite indicates oxidizing conditions that promote the formation of iron oxides.

The accumulation of mirabilite/thenardite or evaporite salts was also discovered, particularly near Lake Vida in Victoria Valley, Barwick Valley, and Balham Valley. As mentioned in the geology section, several salt deposits have been documented near lakes and their margins in the DVs region (Bao and Marchant, 2006). In addition to numerous

geological studies of the lithologic units and mineralogy in the DVs (Cox et al., 2012), X-ray diffraction analysis of the soils and alteration mineral phases revealed the presence of feldspar, pyroxene, amphibole, mica, vermiculite, kaolinite, illite, pyrophyllite, laumontite, chlorite, hematite, anatase, and quartz (Quinn et al., 2010).

By consolidating the mineralogy of host rocks and their weathered/ altered/transported products within the identical family and

categorizing mixtures of multiple minerals into different mineral classes, a comprehensive regional map of minerals for the DVs region was developed in this study (see Fig. 18). This map shows the spatial distribution of minerals in the study area and provides important insights into the mineralogical composition of the area. These findings have implications for planetary research, particularly in the investigation of terrestrial analogs for the Martian environment. The detection of minerals under extreme Antarctic conditions provides valuable insights into similar processes that could occur on Mars. Furthermore, this research highlights the potential of hyperspectral PRISMA satellite data with deep learning methods to improve remote sensing analysis for extreme environments. To ensure robust mineral identification in the study area, we recommend validating spectral classifications through targeted field sampling complemented by proximal spectral measurements and X-ray diffraction (XRD) analysis. Building on this foundation, future research should integrate advanced hyperspectral sensors with state-of-the-art deep learning models and automated cross-verification workflows, thereby markedly enhancing both classification accuracy and processing speed. The combination of remote sensing satellite data and deep learning models offers transformative potential for mapping minerals in extreme environments. This approach not only advances Antarctic research but also sets a benchmark for the application of similar methods to planetary research and other challenging areas.

6. Conclusions

In this study, hyperspectral PRISMA satellite imagery combined with a robust and innovative framework of AVCA, spectral augmentation, and the 3-D CNNs deep learning algorithm were successfully used to achieve accurate and reliable mineral mapping in an extreme environment such as the DVs, despite sub-optimal solar irradiance at the edge of satellite remote sensing capabilities. By utilising hyperspectral PRISMA satellite data in combination with the advanced spectral-spatial feature extraction capabilities of 3-D CNNs, this analysis effectively overcomes the challenges presented by the extreme environmental conditions and remote, inaccessible terrain of Antarctica. The results revealed detailed mineralogical distributions and provided insights into the geological processes influencing these formations. They demonstrate the effectiveness of 3-D CNNs in automating and improving the accuracy of mineral recognition while reducing the reliance on extensive field surveys. These results highlight the potential of advanced hyperspectral satellite remote sensing techniques to revolutionize geological research, especially in regions where traditional methods face logistical and environmental limitations. The integration of AI-driven methods in this field not only accelerates mineral mapping but also expands the scope of remote sensing for Earth and planetary sciences. The implications of this research extend beyond mineral mapping, as the approach could be adapted to study other surface features and materials in similarly remote and extreme environments.

Future work could expand the scope of this study by incorporating multi-temporal and multi-sensor satellite data, such as radar and thermal imagery, to achieve even greater depth and accuracy in

mineralogical analyses. In addition, the application of hybrid neural network architectures or the exploration of transfer learning techniques could improve the generalizability of the models to other geological contexts. This study serves as a benchmark for hyperspectral satellite imagery with AI-assisted methods and paves the way for innovative research and practical applications in remote and challenging regions worldwide.

CRedit authorship contribution statement

Jabar Habashi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Amin Beiranvand Pour:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Aidy M. Muslim:** Writing – review & editing, Conceptualization. **Ali Moradi Afrapoli:** Writing – review & editing, Writing – original draft, Methodology. **Jong Kuk Hong:** Writing – review & editing. **Yongcheol Park:** Writing – review & editing. **Alireza Almasi:** Writing – review & editing. **Laura Crispini:** Writing – review & editing. **Mazlan Hashim:** Writing – review & editing. **Milad Bagheri:** Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: AMIN BEIRANVAND POUR reports financial support was provided by Yayasan Penyelidikan Antartika Sultan Mizan (YPASM). Reports a relationship with that includes: Has patent pending to. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Code availability

The developed Python codes for this project are publicly accessible and will be found in our GitHub repository. This repository includes the complete source codes, along with usage instructions. For access to the codes, please visit: <https://github.com/jabarhabashi1/Deep-Learning>.

Appendix 1. Detailed information on the six most important lithological units exposed in the DVs

A1.1 Characteristics of Lithological Units in the DVs

- (1) Precambrian metasediments (undifferentiated, schist, marble, metaconglomerate, greywacke and psammitic schist, calc-silicate schist, felsic gneisses, calc-silicate gneisses, argillite, and quartzite) and lesser metavolcanic and metabasites, referred to as Skelton groups (Fig. 1) (Allibone, 1992; Cox, 1992; Isaac et al., 1996; Turnbull et al., 1994). The mineralogical groups documented in the Skelton groups are listed in Table 1 (Cox et al., 2012; Findlay et al., 1984).
- (2) Late Precambrian-Early Ordovician granitoids and gneisses referred to as the Granite Harbour Intrusive Complex. It intrudes the metasedimentary rocks of the Neoproterozoic Skelton Groups. These intrusions can be assigned to four main petrogenetic suites, including the mafic Koettlitz Glacier Alkaline Suite, the Dry Valleys (DV) 1a Suite (hornblende-biotite granitoid rocks), the Dry Valleys (DV) 1b Suite (biotite

- granitoid rocks) and the younger Dry Valleys (DV) 2 Suite (unconformable granitoid plutons) (Fig. 1) (Read, 2010; Read et al., 2002). Table 1 shows the reported mineralogical groups in the Granite Harbour Intrusive Complex (Cox et al., 2012; Jones, 1997).
- (3) Devonian-Triassic conglomerate, sandstone, siltstone, and coal referred to as the Beacon Supergroup. The break-up of Gondwana was preceded by the deposition of layers from the Devonian to the Triassic. In the Antarctic, these rocks comprise the foreland deposits of the Beacon Supergroup (Boger, 2011; Collinson et al., 1994). It is found in large parts of the Transantarctic Mountains, partly originates from the Gondwanidean continental arc, and was deposited on its inner side (Elliot and Fanning, 2008). In the Beacon Supergroup, the mineralogical components are typically carbonaceous, micaceous, quartzofeldspathic, and lithic sandstone and siltstone with lesser amounts of conglomerate, mudstone, breccia, and thin coal seams the mineralogical components (Table 1). The rock fragments consist mainly of quartz, with a small proportion of metasedimentary rocks (Cox et al., 2012).
 - (4) Jurassic dolerite sills, breccia, and basalt flows referred to as the Ferrar Group. In southern Victoria Land, the Ferrar Group comprises volcanoclastic rocks, flood basalts (Kirkpatrick Basalt), and the voluminous sills of the Ferrar Dolerite (Airoldi et al., 2012; Muirhead et al., 2012), which extends along the Transantarctic Mountains. The Ferrar Dolerite sills intrude the basement, surface erosion, and the Beacon Supergroup rocks (Elliot and Fleming, 2004). Several mineralogical groups have been reported in the Ferrar Group (Table 1) (Cox et al., 2012; Morrison and Reay, 1995).
 - (5) Eocene-Holocene sedimentary rocks and sequences consist mainly of till and other fluvioglacial sediments (Fig. 1). The tills are typically derived from unconsolidated local bedrock lithologies and consist of a diverse admixture of clay, silt, sand, gravel, and boulders that vary greatly in size and shape (Hall et al., 1997; Prentice et al., 1993). The drift comprises unstratified material forming moraines and stratified deposits, forming outwash plains, eskers, kames, varves, lacustrine deposits, and fluvioglacial sediments (Hall and Denton, 2005). There are numerous lakes and ponds in the Dry Valleys region (Hendy, 2000). Continued periods of recurring melting and evaporation have accumulated dissolved salts in the lakes and evaporite salts at their margins. Several salt deposits are so dense that they can be mapped as evaporite deposits (Table 1). Mirabilite (sodium sulfate) is particularly common in the drift (Abigail Patricia Lovett, 2011). Additionally, numerous slightly weathered or unweathered deposits of volcanic ash, typically less than one meter thick, have been identified in the surficial sediments of the Dry Valleys (Marchant et al., 1996).
 - (6) Miocene-Holocene volcanic rocks known as the McMurdo Volcanic Group. In southern Victoria Land, basaltic and felsic alkali volcanic rocks of the McMurdo Volcanic Group form several large volcanoes in the east and south of McMurdo Sound and several small volcanoes in the eastern foothills of the Royal Society Range and the Taylor and Wright valleys (Martin et al., 2010). Numerous volcanic vents have erupted basanite lava and scoria in the eastern foothills of the Royal Society Range. Some eruptions occurred on or beneath glacial ice, as evidenced by the development of pillow lava and hyaloclastite (Wright, 1980). Several small basanite scoria cones and mounds are found in eastern Wright Valley and on the flanks and floor of Taylor Valley. They consist of bedded and welded spatter deposits, blocks, bombs, and scoria (Table 1) (Cox et al., 2012; Wright and Kyle, 1990).

Appendix 2. . Detailed information on CNN architecture implemented in this analysis

A2.1 CNN Architecture

A2.1.1 Convolution Operation

Central to CNNs' feature extraction was the 3D convolution operation (Eq. (1A)), utilizing a kernel to detect volumetric patterns across spatial and spectral dimensions, thus effectively modeling intricate interactions within hyperspectral data (Castleman, 1996; Schmidhuber, 2015). This three-dimensional analysis significantly augmented the network's ability to interpret complex patterns essential for accurate image classification, which is mathematically defined as:

$$y_{i,j,k}^{(l)} = \sum_{m=0}^{F-1} \sum_{n=0}^{F-1} \sum_{p=0}^{F-1} x_{i+m,j+n,k+p}^{(l-1)} \cdot w_{m,n,p} + b \quad (1A)$$

Here, $y_{i,j,k}^{(l)}$ represents the Output at the position (i,j,k) in layer l ; $x_{i+m,j+n,k+p}^{(l-1)}$ denotes the Input at the position $(i+m,j+n,k+p)$ from the previous layer; $w_{m,n,p}$ is the Weight of the filter (3D kernel) at position (m,n,p) ; b is the Bias term added to the output; and F represent the Filter size (e.g., $3 \times 3 \times 3$).

A2.1.2 Activation functions

Activation functions played a crucial role in modeling non-linear data relationships, preventing the CNN from linear behavior and addressing potential training challenges such as the vanishing gradient problem (Dubey and Jain, 2019). Specifically, the Leaky Rectified Linear Unit (Eq. (2A)) was employed due to its ability to mitigate the dying ReLU issue, ensuring neuron activation through maintaining non-zero gradients for negative inputs, hence preserving network trainability and adaptability to complex data patterns (Dubey and Jain, 2019; Mastromichalakis, 2020). The Leaky ReLU is mathematically defined as:

$$f(x) = \begin{cases} x, & x < 0 \\ \alpha x, & x \geq 0 \end{cases} \quad (2A)$$

where x represents the input, and α is a small positive constant that determines the slope for negative values and was set at 0.1.

A2.1.3 Pooling

Dimensionality reduction, crucial for computational efficiency and minimizing overfitting, was achieved using Max Pooling (Eq. (3A)). This method retained significant features by selecting the maximum value within pooling regions, thereby ensuring translation invariance and emphasizing salient patterns (A. Mohamed et al., 2022; Gholamalizadeh and Khosravi, 2020; Lecun et al., 1998). Max Pooling is expressed as:

$$y_{i,j,k} = \max\{x_{i+m,j+n,k+p} \mid 0 \leq m, n, p < P\} \quad (3A)$$

where P is the Pooling size, $x_{i+m,j+n,k+p}$ represents the input values in the pooling window. and $y_{i,j,k}$ is the Maximum value selected in the pooling

window. A pooling size of $(2 \times 2 \times 2)$ was adopted to balance detail preservation and feature simplification.

A2.1.4 Batch normalization

Batch normalization (Eq. (4A)) was integral in stabilizing and accelerating network training by normalizing layer outputs to zero mean and unit variance, thus mitigating internal covariate shifts and promoting efficient gradient flow. This normalization enhanced training stability, accelerated convergence, and provided inherent regularization effects, reducing the reliance on additional regularization methods (Ioffe and Szegedy, 2015). Batch normalization is defined as:

$$\hat{x} = \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}}, \quad y = \gamma \hat{x} + \beta \quad (4A)$$

where x represents the Input to the batch normalization layer; μ , and σ^2 are the Mean and variance of the batch; ϵ is the small constant to prevent division by zero, and γ and β are Learnable parameters for scaling and shifting.

A2.1.5 Fully connected layers

Post feature extraction, fully connected (dense) layers (Eq. (5A)) were employed to consolidate learned spatial-spectral features into final predictive outputs suitable for classification. Dense layers facilitated the transformation of high-level extracted features into compact, meaningful representations, effectively modeling complex interactions necessary for accurate predictions (Chen, 2014; Huang et al., 2017; Rumelhart et al., 1986; Schwing and Urtasun, 2015). The operation of the dense layer is mathematically expressed as follows:

$$z_i = \sum_{j=1}^n w_{ij} x_j + b_i \quad (5A)$$

where z_i represents the output of the neuron i , w_{ij} is the weight connecting the input x_j to neuron j , b_i is the bias term for the neuron i , and n is the number of inputs to the dense layer.

A2.1.6 Regularization

To further ensure generalization and prevent overfitting, L2 regularization (ridge regression, Eq. (6A)) was applied, penalizing larger weight values in the loss function and promoting smaller, evenly distributed weights. This regularization technique effectively balanced model complexity and performance, optimizing the network's predictive robustness (Hoerl and Kennard, 1970). The regularized loss function is given by:

$$L_{\text{regularized}} = L_{\text{original}} + \lambda \sum_{i=1}^n w_i^2 \quad (6A)$$

Here, (L_{original}) is the original loss (e.g., mean squared error or cross-entropy), (w_i) represents the weights of the model, (n) is the total number of weights, and (λ) the regularization strength controls the trade-off between fitting the training data and penalizing large weights. A higher (λ) increases the regularization effect, which in this study is set at 0.0001.

A2.1.7 Dropout

To further enhance generalization and mitigate overfitting, Dropout regularization was incorporated into the CNN model. Dropout randomly sets a fraction of input units to zero during training, effectively preventing the network from becoming overly dependent on specific pathways. This technique reduces co-adaptation of neurons and encourages the model to learn robust features that generalize better to unseen data (Srivastava et al., 2014). In this study, a dropout rate of 0.5 was applied to the fully connected layers to ensure effective regularization and optimal balance between model complexity and performance.

A2.1.8 Classification output

The final classification outputs were processed using the Softmax activation function (Eq. (7A)), converting logits into interpretable probabilities that summed to one. This probabilistic output enabled clear, confident classification decisions, essential for evaluating model performance and confidence in class assignments (Cox, 1958; Dunne and Campbell, 1997). The Softmax function is mathematically defined as:

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^C e^{z_j}} \quad (7A)$$

where $\hat{y}_i$ is the probability of the class i , z_i is the logit (raw output) for the class i , and C is the total number of classes.

Appendix 3. . Comparative assessment of the OSP, MF, LSU, and CEM classification maps with CNN map

The outputs of OSP, MF, LSU, and CEM classification maps for Zone 5 of DVs region are compared with the CNN map (Appendix Fig. 7 and Table 5). For each algorithm, the detection thresholds (e.g., target-abundance cut-offs) were established through an exhaustive grid search and intentionally set conservatively, ensuring that the map displayed represents the most favorable performance attainable under an identical preprocessing protocol.

Key Advantages and priorities of the CNN were achieved as follows:

(1) Marked noise suppression

OSP and MF display pronounced speckling in the highly reflective snow-ice environment, whereas the CNN's 3×3 spatial windows effectively suppress this artefact.

(2) Geologically credible boundaries

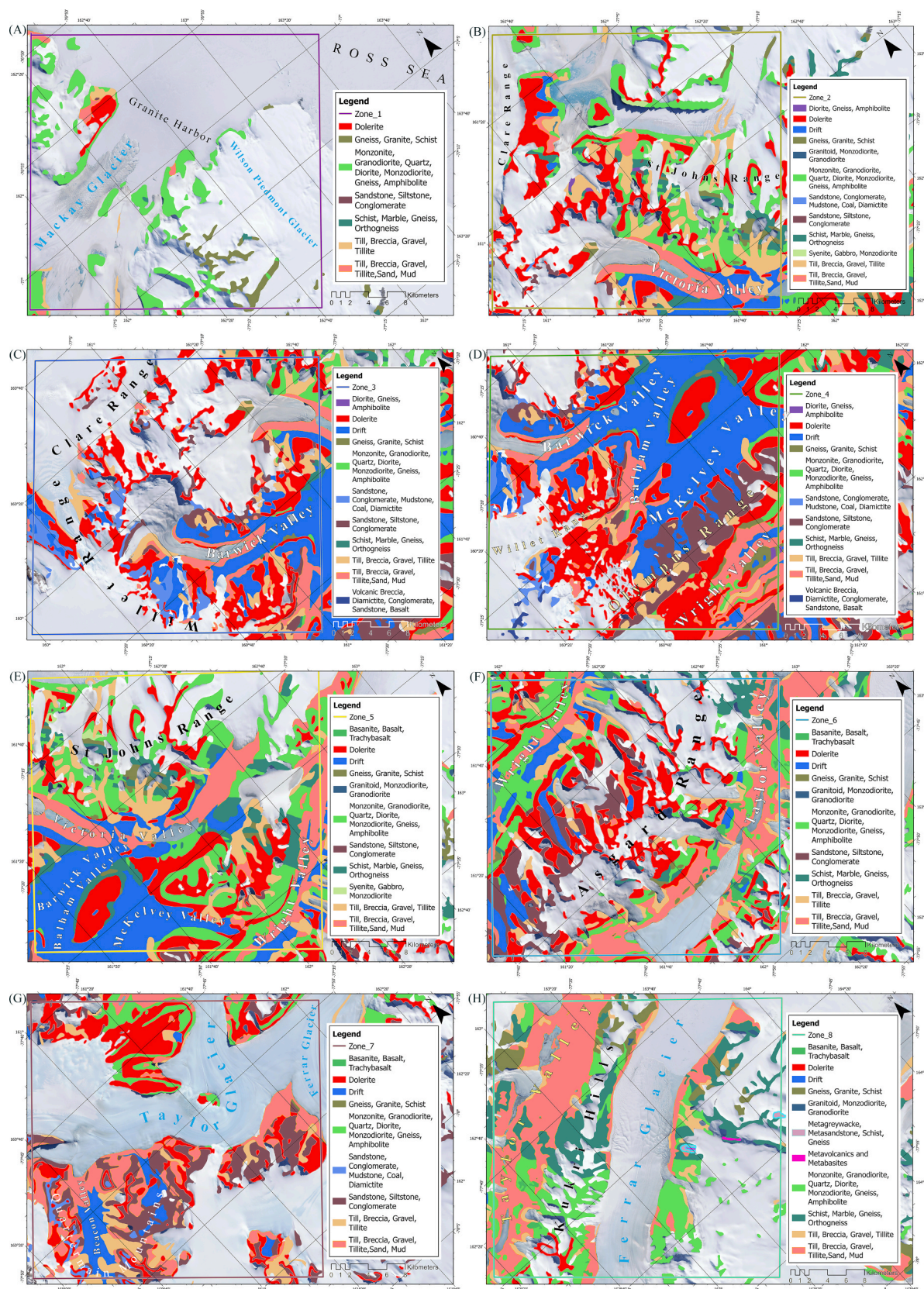
The CNN aligns the contacts of pyroxene (green) and evaporite zones (yellow) with valley floors and ridges; such coherence is blurred in LSU or incomplete in CEM.

(3) Accurate detection of subtle phases

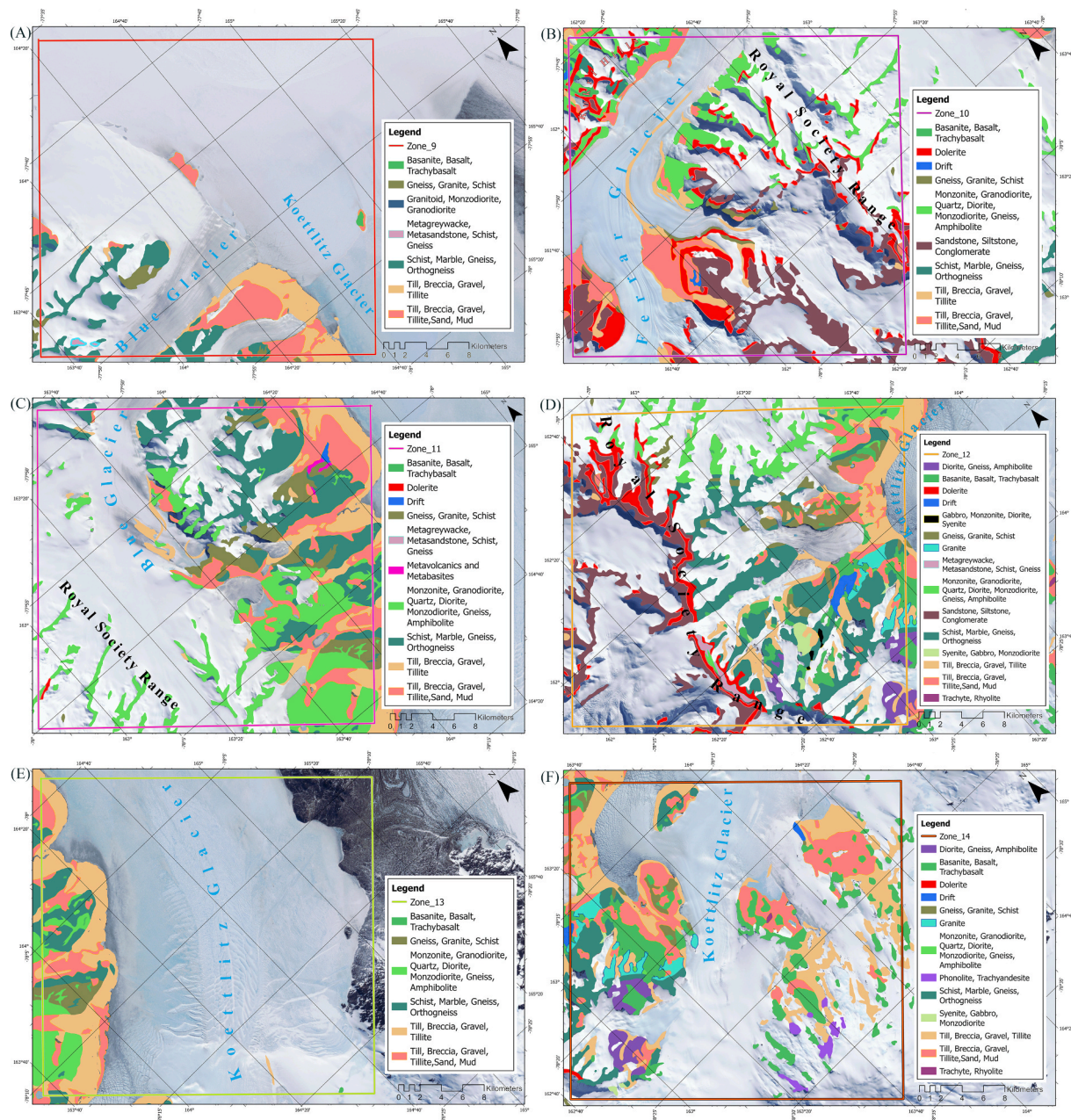
The mixed Jarosite-Hydrous Silica-Sericite phase (blue) is traced as continuous veins only by the CNN; classical algorithms either scatter or omit it.

(4) Retention of fine-scale detail (8–10 km)

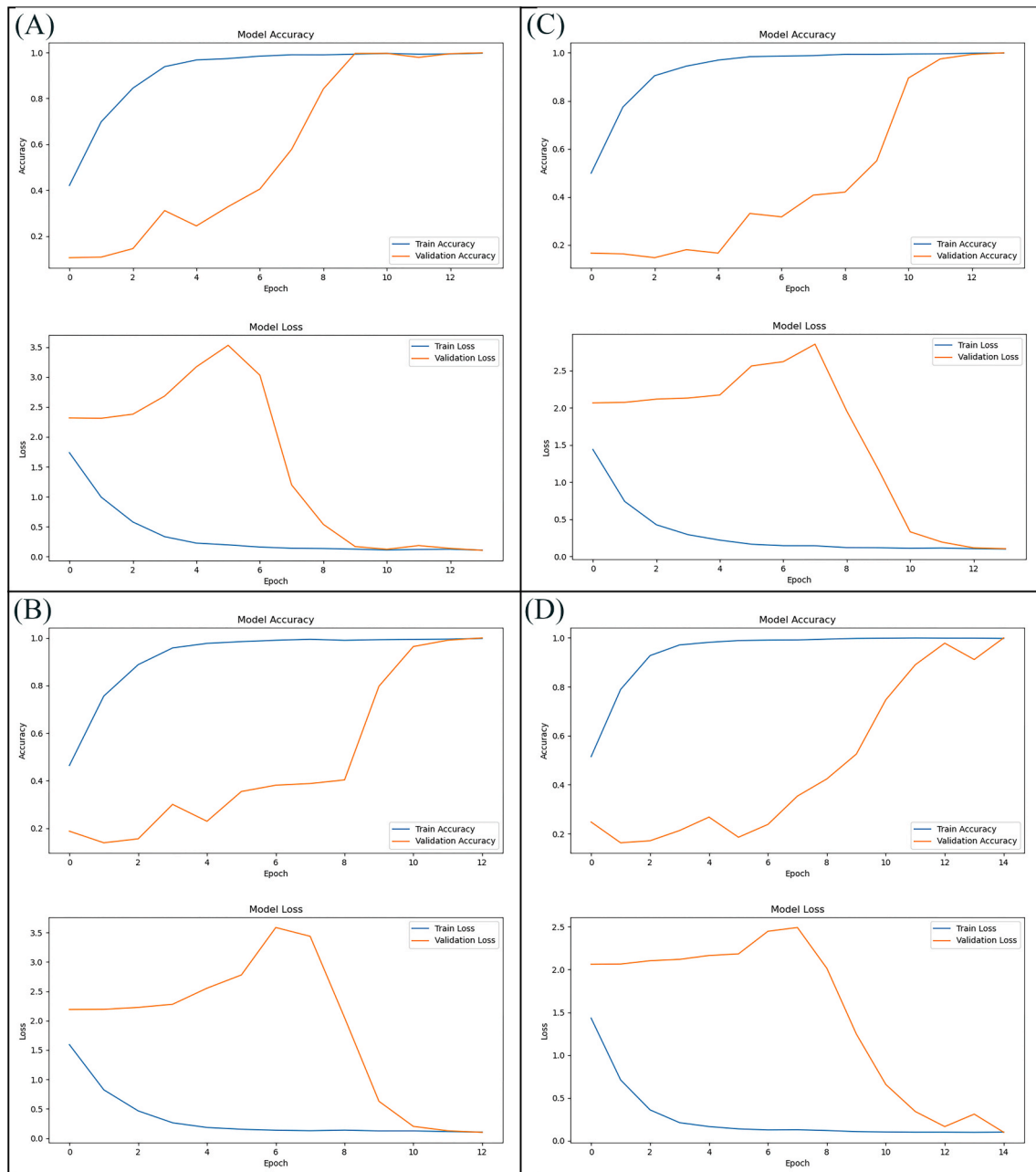
Unlike LSU, which smooths spectral variability, the CNN preserves subsidiary valleys and minor alteration fronts.



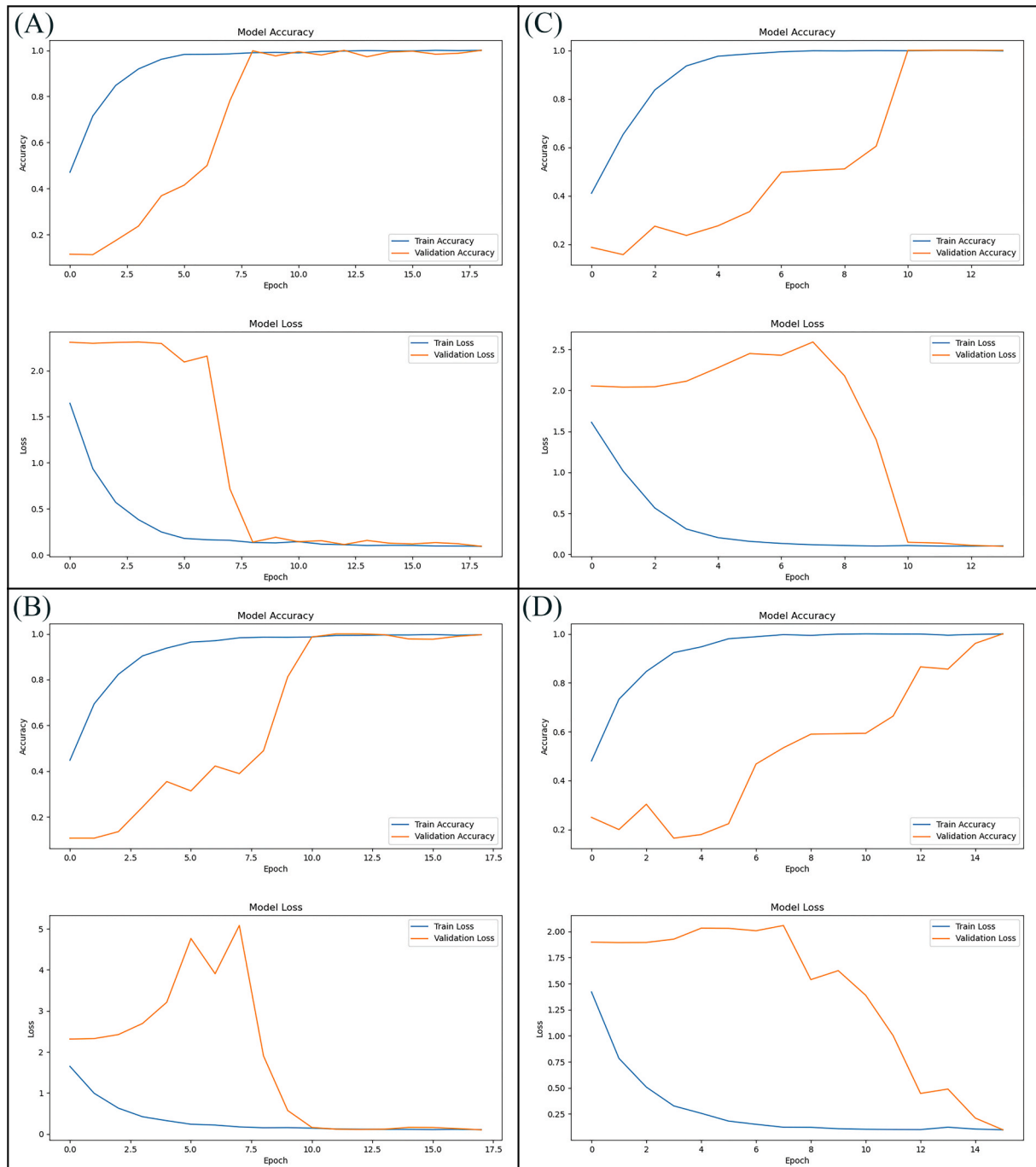
Appendix Fig. 1. Lithological map of (A) zone 1, (B) zone 2, (C) zone 3, (D) zone 4, (E) zone 5, (F) zone 6, (G) zone 7, (H) zone 8.



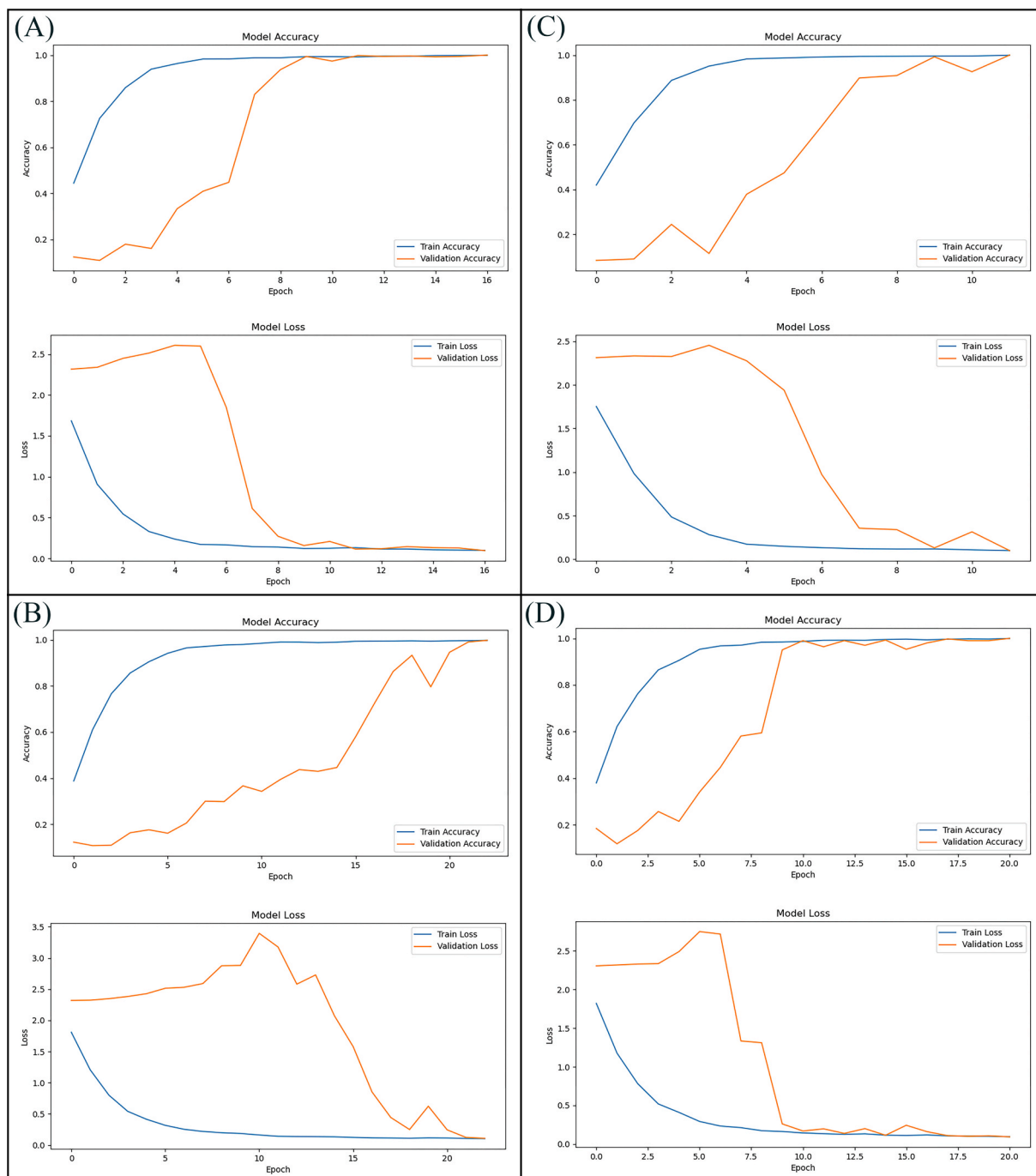
Appendix Fig. 2. Lithological map of (A) zone 9, (B) zone 10, (C) zone 11, (D) zone 12, (E) zone 13, (F) zone 14.



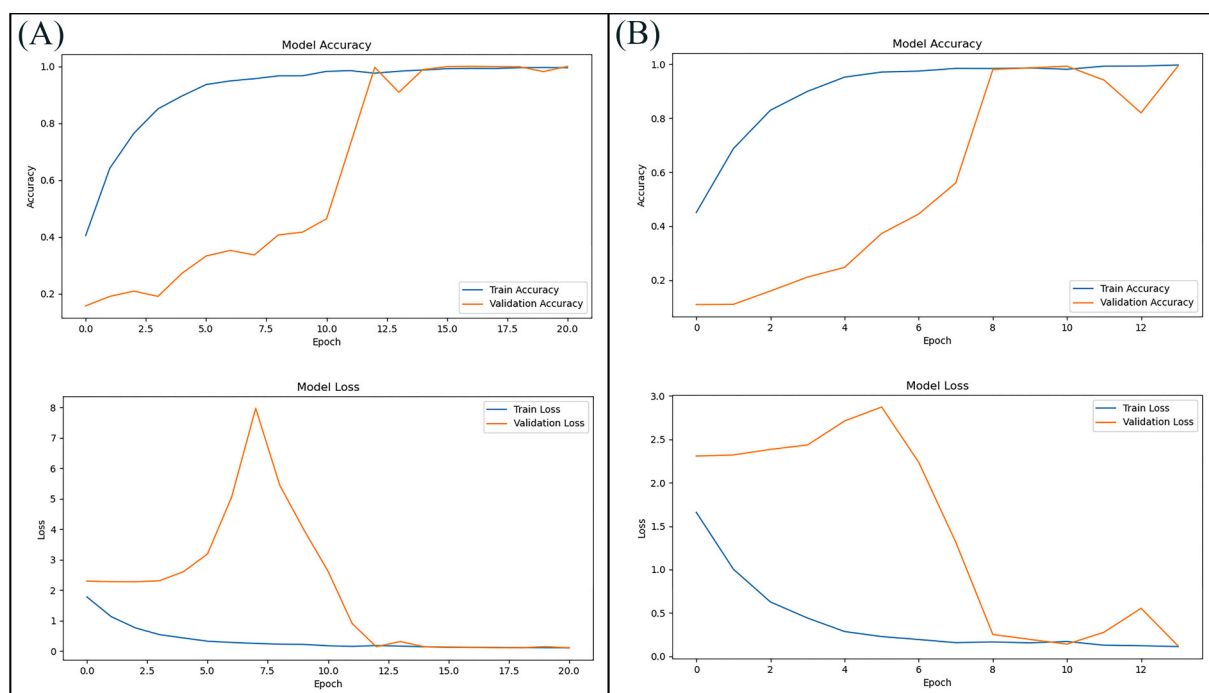
Appendix Fig. 3. Training and validation accuracy/loss of CNNs models over the epochs for (A) zone 1, (B) zone 2, (C) zone 3, (D) zone 4.



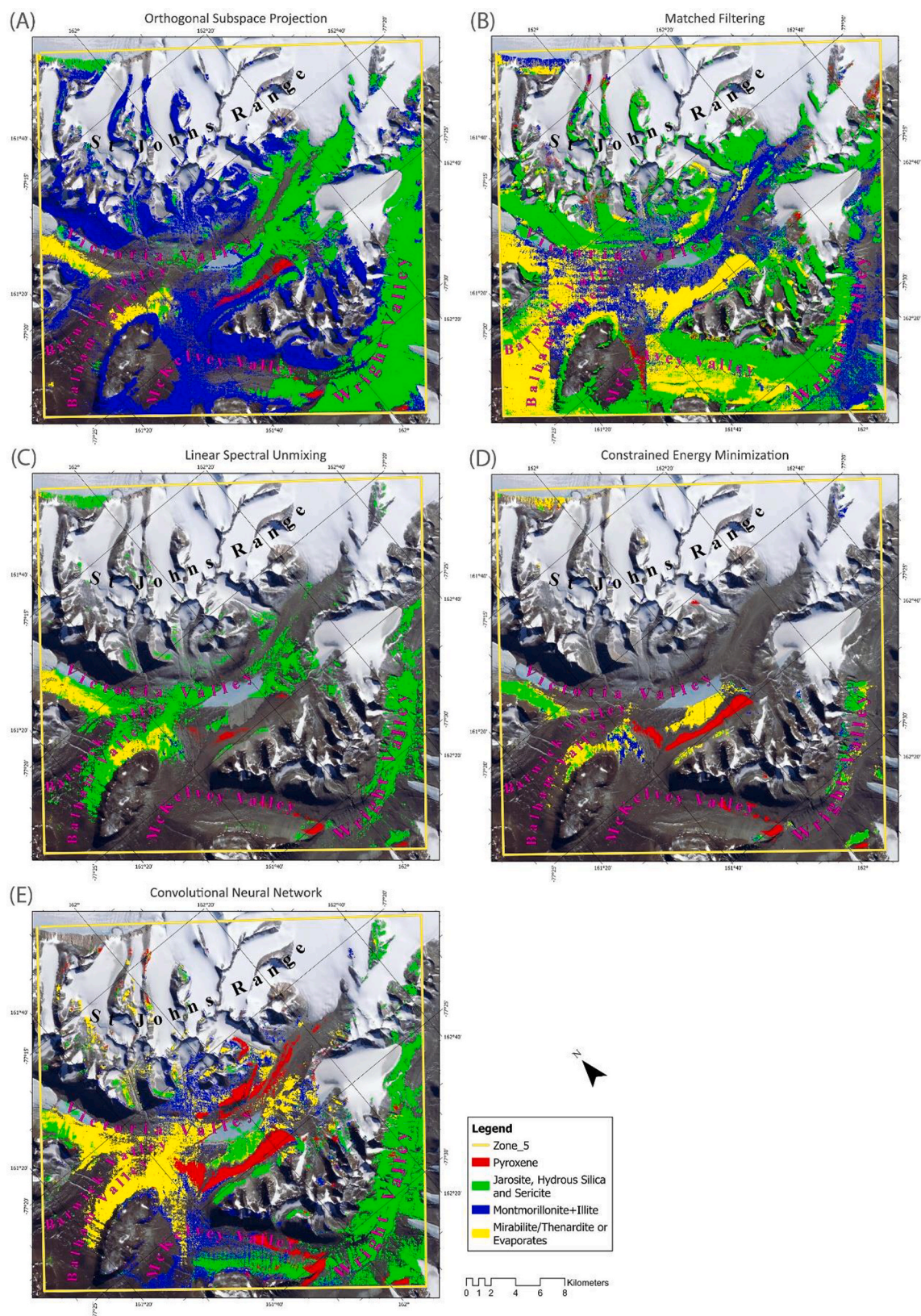
Appendix Fig. 4. Training and validation accuracy/loss of CNNs models over the epochs for (A) zone 5, (B) zone 6, (C) zone 7, (D) zone 8.



Appendix Fig. 5. Training and validation accuracy/loss of CNNs models over the epochs for (A) zone 9, (B) zone 10, (C) zone 11, (D) zone 12.



Appendix Fig. 6. Training and validation accuracy/loss of CNNs models over the epochs for (A) zone 13, (B) zone 14.



Appendix Fig. 7. Classification maps produced for Zone 5 of DVs region using: (A) Orthogonal Subspace Projection (OSP), (B) Matched Filtering (MF), (C) Linear Spectral Unmixing (LSU), (D) Constrained Energy Minimization (CEM), and (E) Convolutional Neural Network (CNN).

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Using deep learning and multi-source remote sensing images to map landlocked lakes in Antarctica

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Abstract. Antarctic landlocked lake open water (LLOW) plays an important role in the Antarctic ecosystem and serves as a reliable climate indicator. However, since field surveys are currently the main method to study Antarctic landlocked lakes, the spatial and temporal distribution of landlocked lakes across Antarctica remains understudied. We first developed an automated detection workflow for Antarctic LLOW using deep learning and multi-source satellite images. The U-Net model and LLOW identification model achieved average F_1 scores of 0.90 and 0.89 on testing datasets, respectively, demonstrating strong spatiotemporal robustness across various study areas. We chose four typical ice-free areas located along coastal Antarctica as our study areas. After applying our LLOW identification model to a total of 79 Landsat 8 Operational Land Imager (OLI) images and 330 Sentinel-1 synthetic aperture radar (SAR) images in these four areas, we generated high-spatiotemporal-resolution LLOW time series from January to April between 2017 and 2021. We analyzed the fluctuation of LLOW areas in the four study areas and found that during expansion of LLOW, over 90 % of the changes were explained by positive degree days, while during contraction, negative degree day changes accounted for more than 50 % of the LLOW area fluctuations. It is shown that our model can provide long-term LLOW time series products that help us better understand how lakes change under a changing climate.

1 Introduction

Antarctic lakes play a crucial role in the ecosystem of Antarctica and are reliable indicators of climate change (Lyons et al., 2006). These lakes can be divided into three main types: landlocked lakes, epiglacial lakes, and supraglacial lakes. Landlocked lakes, located in local depressions and usually free of ice during austral summer, primarily receive water inflow from the melting of seasonal snow cover (Shevnina et al., 2021). Epiglacial lakes are situated at the boundary between areas of rock and ice, and melting of the glacier ice is the main source of water inflow into them. Supraglacial lakes are found on the surface of ice sheets, glaciers, and ice shelves, forming during the summer melt (Hodgson, 2012).

Extensive research confirms diverse microorganisms in Antarctic lakes, including prokaryotes like bacteria and eukaryotes such as phytoplankton (Parnikoza and Kozeretska, 2020; Izaguirre et al., 2021; Keskitalo et al., 2013; Rochera and Camacho, 2019). Cyanobacteria play a crucial role in primary production and nutrient cycling, as highlighted by studies on their diversity and distribution (Taton et al., 2006; Komárek et al., 2012), alongside findings on unique microbial assemblages, such as *Hymenobacter* sp., and diverse bacterial communities (Koo et al., 2014; Huang et al., 2014; Carvalho et al., 2008; Papale et al., 2017). These studies underscore the ecological importance and high diversity of Antarctic lake ecosystems.

Antarctic lakes are rather sensitive to environmental change, especially under a warming climate (Quayle Wendy

et al., 2002). Seasonally ice-covered lakes magnify the warming trends observed in air temperature (Convey and Peck, 2019). Recent studies have highlighted the impact of increased temperature and melting of snowfields and glaciers on Antarctic lakes (Izaguirre et al., 2021; Stokes et al., 2019). In particular, the changes in the lake-ice and open water area can have significant implications for the lake environment, affecting both physical and biological aspects. Physically, alterations in lake-ice and open water area influence thermal stratification, leading to variations in heat distribution and vertical mixing within the water column (Preston et al., 2016; Lazhu et al., 2021). This, in turn, has implications for the biological effects observed. The occurrence peak of primary consumers (Hébert et al., 2021; Izaguirre et al., 2021), the nutrient regime (Prater et al., 2022; Yang et al., 2021), the development of a planktonic and benthic microbial population (Camacho, 2006), and the availability of a suitable oxythermal habitat for cold-water organisms (Pöysä, 2022) can all be influenced by the changes in lake-ice and open water area. Rising temperatures and stratification, coupled with reduced ice cover and increased nutrient inputs, may promote the growth of specific phytoplankton (Prowse et al., 2011). Landlocked lakes situated in coastal Antarctica typically undergo rapid species replacements during the active phytoplankton growth season, resulting in changes in plankton abundance (Izaguirre et al., 2021). For example, observations in Lake Limnopolar, Byers Peninsula, have demonstrated that temperature-induced warming significantly alters carbon flow, thereby impacting the abundance of plankton in the lake ecosystem (Villaescusa et al., 2016).

Over the past decade, thanks to the development of satellite remote sensing, there has been an increasing interest in the detection of Antarctic lakes. Compared to manual digitizing, an automated lake detection method is more suitable for larger-scale assessments because it can be automatically applied to hundreds of satellite scenes and can avoid user bias (Arthur et al., 2020). A number of methods have been developed to map Antarctic supraglacial lakes, including threshold-based lake classification methods (Fitzpatrick et al., 2014; Moussavi et al., 2020), adaptive classification methods (Johansson and Brown, 2013), and machine learning algorithms (Dirscherl et al., 2020, 2021a). Most previous works mainly focus on the detection of supraglacial lakes (Dirscherl et al., 2021a, b; Leeson et al., 2015; Li et al., 2021; Moussavi et al., 2020). Currently, a semi-automated algorithm has been developed for the detection of water bodies in Greenland (Miles et al., 2017). This method utilized Sentinel-1 synthetic aperture radar (SAR) and Landsat 8 Operational Land Imager (OLI) imagery to monitor surface and subsurface lakes on the Greenland Ice Sheet. As for Antarctic landlocked lakes, field surveys served as the primary method (Shevnina et al., 2021; Lecomte et al., 2016; Shevnina and Kourzeneva, 2017; Harris and Burton, 2010). Due to the limited study area scope and non-uniformity of field surveys, the spatiotemporal distribution of landlocked lakes across

Antarctica remains understudied. Unlike the identification of supraglacial lakes, the detection of landlocked lakes requires information on surrounding land covers. Optical remote sensing images are disturbed by frequent clouds in Antarctica, and SAR images have difficulty capturing the information on land covers around lakes. In addition, compared to single-polarization SAR images, the utilization of multi-polarization SAR images can improve the capability to distinguish LLOW from other ground objects (Zakhvatkina et al., 2019). However, high-resolution ground-range-detected (GRD) products only provide single polarization over the Antarctic continent. High-resolution multi-polarization SAR images are not available in Antarctica. Thus, to better understand the dynamics of landlocked lakes in Antarctica, more efficient and accurate methods are needed.

This study aims to apply a deep learning approach to detect the landlocked lake open water (LLOW) area in Antarctica by combining the Landsat 8–9 OLI and SAR imagery. Then, we aim to investigate the variations in LLOW and their relationship with environmental factors, such as temperature. To the best of our knowledge, this study represents the first attempt to map the open water area of landlocked lakes in Antarctica using remote sensing data.

2 Research data

2.1 Study area

Four typical ice-free areas distributed on coastal Antarctica were selected as study areas (Fig. 1). The Antarctic Peninsula has experienced the largest increases in near-surface air temperature in the Southern Hemisphere during the past few decades (Turner et al., 2016). As a representative site of the Antarctic Peninsula, Clearwater Mesa (CWM; 64.03° S, 57.71° W) on James Ross Island was chosen due to its high density of lakes, unique geomorphological setting, remote elevated position, and lack of previous human presence (Roman et al., 2019). In East Antarctica, we selected two large ice-free oases, the Larsemann Hills (LH; 69.41° S, 76.23° E) and the Vestfold Hills (VH; 68.58° S, 78.18° E). VH are a 400 km² area of ice-free rock (Seppelt and Broady, 1988), while LH are the second-largest ice-free oasis along East Antarctica with an area of about 50 km² (Shi et al., 2018). The Schirmacher Oasis (SO; 70.76° S, 11.65° E), which is an east–west trending narrow strip, with an ice-free area of about 35 km² (Srivastava et al., 2013), was chosen to represent the higher-latitude areas of Antarctica. Since the SO is located about 100 km from the coast, it can also represent the inland area of Antarctica. In these areas, the water source of landlocked lakes is mainly from the melting of seasonal snow cover.

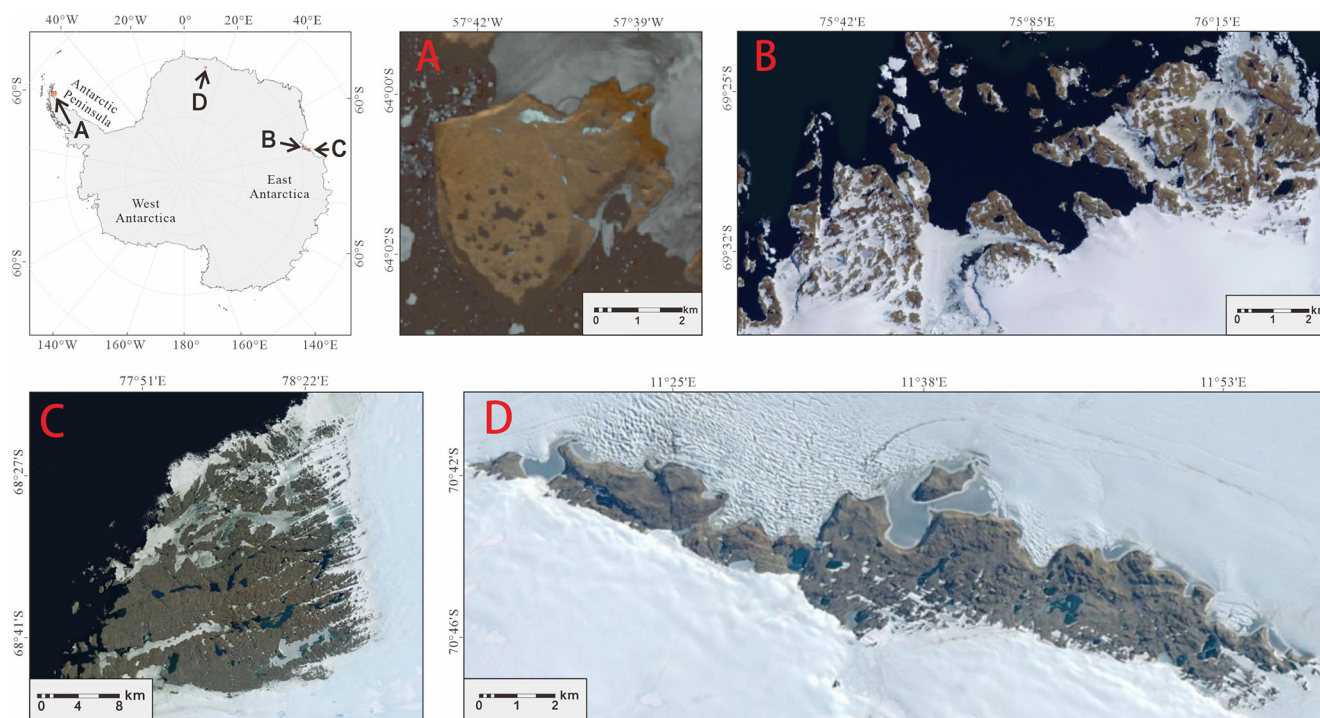


Figure 1. Map of study areas. Satellite images based on Landsat 8 and Esri World Imagery scenes show examples of landlocked lake occurrences. Scenes used for this figure include (a) Clearwater Mesa (CWM; Landsat 8; 2 February 2016), (b) Larsemann Hills (LH; Esri World Imagery; 7 April 2022), (c) Vestfold Hills (VH; Esri World Imagery; 7 April 2022), and (d) Schirmacher Oasis (SO; Esri World Imagery; 7 April 2022).

2.2 Dataset

The OLI on board the Landsat 8–9 satellite captures optical information in the visible and near-infrared (VNIR), near-infrared (NIR), and shortwave infrared (SWIR) portions, enabling the comprehensive assessment of diverse surface features. The Landsat 8–9 OLI data are superior in the enhanced radiometric capabilities and the expanded range of spectral bands (Gorji et al., 2020). Leveraging the capabilities of Landsat 8–9 OLI facilitates better monitoring of the LLOW. Thus, a total of 79 optical images of Landsat 8–9 Collection 1 with 30 m resolution between January and April from 2014 to 2022 were obtained from the United States Geological Survey (USGS) Global Visualization Viewer (GloVis) portal (<http://earthexplorer.usgs.gov/>, last access: 2 May 2022). The Landsat 8–9 satellite has a 16 d repeat cycle. However, cloud cover frequently hampers the detection through visible bands within the study areas. Whenever thick layers of clouds are present above our study areas in the Landsat images, those images are excluded from our study. As a result, the time interval between usable Landsat images can vary. In the Landsat OLI products, the optical bands 1–7 were utilized to identify the land cover in the study areas.

The Sentinel-1 mission is dedicated to SAR imaging and provides all-weather day-and-night imagery in C-band. The SAR-based landscape detection offers a distinct ad-

vantage over optical approaches by mitigating the challenges posed by cloud interference. Consequently, it can offer datasets for obtaining long-time-series monitoring of the LLOW. Because of the advantages of SAR images, Sentinel-1 datasets have been widely used for Antarctic open water and snowmelt detection studies (Bowden et al., 2006; Liang et al., 2021; Dirscherl et al., 2021b). The European Space Agency (ESA) facilitates access to various Sentinel-1 products, including raw level-0 data, processed level-1 single-look complex (SLC) data, and level-1 ground-range-detected (GRD) data. To accurately determine the peak dates of landlocked lake area changes, the temporal resolution of area measurements needs to be at the weekly or daily timescale. Considering the high-temporal-resolution requirement of LLOW detection tasks, we used a total of 330 high-resolution Sentinel-1 SAR images from the interferometric wide-swath (IW) GRD products with about 10 m pixel space, which were acquired from the Alaska Satellite Facility (ASF) (<https://search.asf.alaska.edu/>, last access: 23 November 2022). All Sentinel-1 images are from the descending orbit in order to avoid geometric distortions and orthorectification limitations (Wangchuk et al., 2019). These selected Sentinel-1 images for CWM, LH, and VH span 2017 to 2021. However, for SO, where Sentinel-1 images are unavailable prior to 2019, only the images during 2020 and 2021 were obtained. The revisit period of Sentinel-1 satellites is 12 d.

By utilizing both Sentinel-1A and Sentinel-1B images, we obtained a shorter time interval of 6 d between consecutive Sentinel-1 images. These GRD products play a critical role in distinguishing the LLOW in the study areas.

Our dataset of wind speed for the four areas and daily-mean near-surface temperatures for CWM and SO came from the ERA5-Land dataset obtained from Google Earth Engine (Muñoz Sabater, 2019). The daily-mean air temperatures for LH and VH were derived from the weather stations at Zhongshan Station (Ding et al., 2022) and Davis Station. Hereafter, we use temperature to represent daily-mean air temperature and daily-mean near-surface temperature. To facilitate terrain correction, we employed the Copernicus 90 m global DEM data.

During the Antarctic summer, snow cover on lake surfaces undergoes melting, and consequently LLOW will be present, which can easily be observed through remote sensing techniques. The melting and freezing processes typically occur between September and April. However, the identification of LLOW is challenged by rising-temperature events during September and December. These occasional temperature increases can trigger relatively high temperatures and increased snow wetness. This wetness increase can reduce the backscatter of the snow surface (Shokr and Dabboor, 2020). These events lead to the lower backscatter of both snow and snow-covered ice, resulting in similar backscatter characteristics among ice, snow, and LLOW. During the melting period of landlocked lakes, which in general spans September to December, frozen landlocked lakes may be covered by wet snow due to rising-temperature events, resulting in low backscatter. Consequently, these frozen lakes are not LLOW but are incorrectly identified as LLOW. During January to April, the melted landlocked lakes have less snow cover and are less affected by the rising-temperature events. Thus, the identification of LLOW from January to April is much more accurate compared to September to December. To evaluate the influence of rising-temperature events from September to December, we sampled pixels of open water, land ice layers, and sea ice layers from several SAR images during this period. We also sampled LLOW pixels in January as the reference for backscattering analysis. We found that the backscatter of sampled land ice layers was as low as that of sampled LLOW in January in our study areas (Supplement Table S1). Consequently, our model cannot effectively distinguish between LLOW and ice layers in these images from September to December. Our analysis focuses on the changes in LLOW from January to April, when the identification accuracy is relatively high.

To train and validate the U-Net and the random forest (RF) models, we manually annotated ground truth labels from Landsat 8–9 OLI images and Sentinel-1 images. For the U-Net model, several Landsat images were selected, and the pixels in the images were annotated as “open water”, “ice”, and “rock” to serve as ground truth. To enhance the classification capability of U-Net in various scales, the side

lengths of Landsat images ranged from 30 pixels to 200 pixels. We annotated 23 patches with 17 100 pixels for U-Net. For the RF model, directly annotating the ground truth in SAR images is challenging and time-consuming, primarily due to their complex backscatter characteristics. Therefore, we conducted a visual interpretation of Sentinel-1 images with the assistance of Landsat images (Liang and Liu, 2020). To ensure that the Landsat images represent the surface of Sentinel-1 images, we selected the Landsat and Sentinel-1 images with the closest dates. Due to the limited availability of cloud-free Landsat images, we used all cloud-free Landsat images from 2017 to 2021 to generate the sample “open water” and “others”. In addition, to validate the accuracy of LLOW identification, we also annotated these Sentinel-1 images as “LLOW” and “others”. We annotated 46 patches with a size of 300×300 to train the RF model and validate the model accuracy. The 46 patches were randomly sampled at a 10 % ratio to generate a sample point set. These points were then randomly divided into 80 % for training and 20 % for testing to train and test the RF model. Additionally, we identified the LLOW with the 46 patches and then calculated the accuracy, F_1 score, and mean intersection over union (mIoU) to evaluate the identification accuracy.

3 Lake open water identification

The automated detection workflow for LLOW can be divided into three steps (Fig. 2): (1) pre-processing of Landsat and Sentinel input images, (2) open water identification, and (3) post-processing of extracted open water to generate the LLOW time series. To assess the accuracy of our LLOW detection workflow, we conducted a comparison between the identified LLOW and the labeled ground truth.

3.1 Pre-processing

Ensuring a consistent relative location of the study area in each image enhances the comparability of the detected LLOW within the study area across different images. To achieve this, predefined rectangular boundaries were established based on projected coordinates. We cropped images to fit within these specific boundaries, thereby unifying the relative location of the study area within the predefined boundaries. For Landsat images, we utilized specified coordinates to apply the resampling technique with a nearest neighbor (NN) algorithm and perform image cropping. For Sentinel-1 images, we performed orbital correction, thermal noise removal, radiometric calibration, speckle filtering, terrain correction, and decibel conversion on the Sentinel-1 level-1 GRD products using ESA's Sentinel Application Platform (SNAP) software. In addition, the incidence angles in SAR images were also extracted using SNAP. The corrected Sentinel-1 images were then reprojected and cropped to align with the spatial extent of the cropped Landsat images.

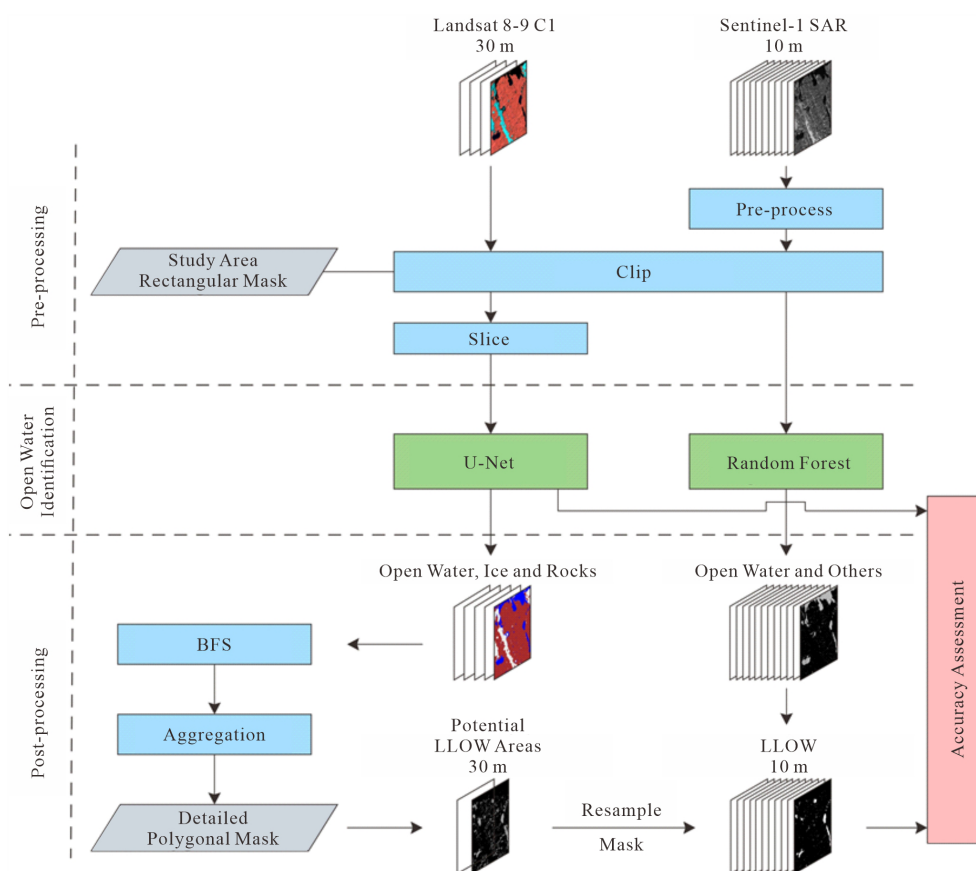


Figure 2. Workflow for detecting the landlocked lake open water (LLOW) in Antarctica.

It is necessary to expand the sample set using data augmentation to prevent the network from overfitting. Consequently, we augmented the annotated 23 sample images 20 times and obtained a total of 483 sample images. Our data augmentation methods include mirroring, translation, and rotation. Mirroring consists of three scenarios: vertical mirroring, horizontal mirroring, and vertical and horizontal mirroring. The translation involved a four-way translation up to $1/10$ of the side length. The range of the rotation angle was $0\text{--}360^\circ$. Any void pixels that arose after data augmentation were filled by the reflecting adjacent image pixels. Among the 483 sample images, 80 % were randomly assigned as the training set and the remaining 20 % as the validation set.

The use of an overlap-tile strategy for splitting large images into smaller patches has proven to be effective in overcoming GPU limitations (Ronneberger et al., 2015). Thus, this strategy was employed before using Landsat images in the U-Net. We sliced the input images into patches of 300×300 pixels. There are many small LLOW areas distributed across the four study areas, especially in LH and VH; however, the U-Net is not ideal for recognizing small-scale open water. Therefore, we resampled the patches with NN from 300×300 pixels to 1024×1024 pixels in order to magnify the small open water area. After land-cover classifica-

tion using U-Net, we again resampled these classified results of 1024×1024 pixels to 300×300 pixels with NN. To reduce the border effect caused by U-Net (Dirschler et al., 2021a), we only kept the result of 250×250 pixels in the center of the patch, while discarding the edge with a length of 25 pixels.

3.2 Open water identification

The U-Net neural network is a deep learning network for semantic segmentation based on a fully convolutional network (Ronneberger et al., 2015), which is faster to train due to its context-based learning approach (Siddique et al., 2021). In addition, it does not require the explicit specification of the input image size to achieve end-to-end semantic segmentation. For LLOW detection, the U-Net network can effectively fuse the spatial and spectral information. U-Net can process the spectral information for land-cover classification and can also consider the spatial contexts to effectively reduce the interference of shadows and clouds. Thus, we implemented a U-Net model to detect open water in Landsat images and classify the pixels into three types of land cover: ice, open water, and rock. The backscattering distributions of ice and rock are similar in single horizontal–horizontal (HH) polar-

ization, so we classified the pixels of Sentinel-1 images into only two types: open water and others.

U-Net consists of an encoder and a decoder (Fig. 3). The encoder and decoder are both mainly composed of double-convolutional (double-conv) layers and are used to enhance model depth (Wu et al., 2020). In the double-conv layers, the batch normalization layer and the leaky rectified linear unit (LeakyReLU) layer are added to re-correct the data distribution and achieve nonlinear computation. To avoid gradient vanishing and facilitate the deepening of the U-Net model network, we added a residual layer between the double-conv layers.

Open water bodies exhibit a smooth surface, resulting in weaker backscatters, while areas with rougher surfaces generate stronger backscatters. The backscatter of the surface varies across different incidence angles of SAR images (Wakabayashi et al., 2019). Thus, open water and other features can be distinguished based on backscatter and incidence angles. The RF model, a nonlinear modeling tool, can accurately predict open water and has a high tolerance of noise and outliers (Huang et al., 2021). We established the RF model for each study area to identify the open water in SAR images according to backscatter and incidence angles.

3.3 Post-processing

A landlocked lake is a water region surrounded by a rock region. Not all open water pixels extracted through the open water identification models are LLOW areas, such as glacial rivers and melted water from coastal glaciers. Moreover, LLOW may be indirectly surrounded by rocks. For example, LLOW may be enclosed by ice, which in turn is surrounded by rocks. In our classified results, a classified Landsat image consists of a connected non-rock area and interspersed rock areas containing LLOW. The breadth-first search (BFS) algorithm has been proven to be effective in removing the connected areas (Silvela and Portillo, 2001). Thus, the BFS algorithm can effectively eliminate the connected non-rock area while retaining the rock areas. BFS simulates the spreading of seawater in the Antarctic summer and leaves only rock areas where stable LLOW may exist. Supraglacial lakes, epiglacial lakes, and seawater are all removed during BFS. Finally, all the remaining open water pixels derived from Landsat images are extracted and marked as LLOW.

The use of Landsat images in the visible and near-infrared bands is significantly hindered by cloud interference, especially along the Antarctic coast. As mentioned in Sect. 2.2, within the four study areas over 2014–2022, a total of only 79 Landsat images are suitable for LLOW detection. Therefore, the number of Landsat images with low cloud cover in the study areas is insufficient for our time series analysis. To improve the temporal resolution of LLOW time series, we used Sentinel-1 SAR images as supplements. SAR images are not affected by clouds but have limited spectral information and lack accuracy in distinguishing ground objects

among open water, rocks, and ice. The open water identified solely from SAR imagery often includes substantial amounts of mountain shadows and numbers of lakes that were not surrounded by rocks. Without spatial information on rocks and ice, the BFS algorithm is invalid for extracting LLOW from open water. Consequently, SAR images enable the identification of only open water instead of LLOW. Using data from either Landsat 8–9 or Sentinel-1 alone cannot precisely capture the temporal variation in LLOW. However, combining the maximum lake area derived from Landsat with the results obtained from SAR images provides a better approach to achieving higher temporal resolution and more accurate results (Miles et al., 2017). Thus, for each study area, we defined the pixels that are classified as LLOW in multiple Landsat results as potential LLOW. Specifically, if a pixel was identified as LLOW two or more times from 2014 to 2022, it was considered a potential LLOW pixel. We aggregated all LLOW distribution images and obtained one potential LLOW area for each study area. According to the annotated sample set, some LLOW areas are not within the potential LLOW area range. To leverage the resolution advantage of Sentinel-1 and its potential for LLOW identification, we established a buffer zone for the potential LLOW area (Wangchuk et al., 2019). As shown in Fig. S1, the rate of decrease in the ignored LLOW area diminishes as the buffer radius increases. We selected a buffer radius of 20 m, where the reduction in LLOW area is most significant, and resampled the potential LLOW area into a 10 m resolution. After that, we combined the Landsat and Sentinel images, using the potential extents of LLOW and the open water derived from SAR, to generate the long-term time series of LLOW.

Because previous cropped images had wide rectangular boundaries, they still retained large non-research areas. To ensure consistency of the extracted LLOW in study areas, we delineated the more detailed coordinate boundaries according to the irregular shapes of the study area. The detailed boundaries were then used to narrow down potential LLOW regions. It is important to note that identifying LLOW in SAR images can be challenging due to various factors, such as strong wind, floating thin ice layers, and sensor speckle noise (Dirscherl et al., 2021a). These factors can impact the backscatter of LLOW and make accurate detection of LLOW difficult. For instance, congealed ice generates large bubbles, and the bubbles entrained within the ice layer enhance backscatters (Hirose et al., 2008). Consequently, LLOW covered by only a few floating ice layers or affected by strong winds may exhibit higher backscatter coefficients and cannot be detected by our threshold segmentation model. Instances of strong winds and floating ice have temporary effects on the entire study area and result in significant underestimation of LLOW. Therefore, we discarded the underestimated LLOW results and generated a total of 285 long-term time series images of LLOW. The LLOW time series with combined Landsat and Sentinel images have a spatial resolution of 10 m and a time resolution of ~ 6 d.

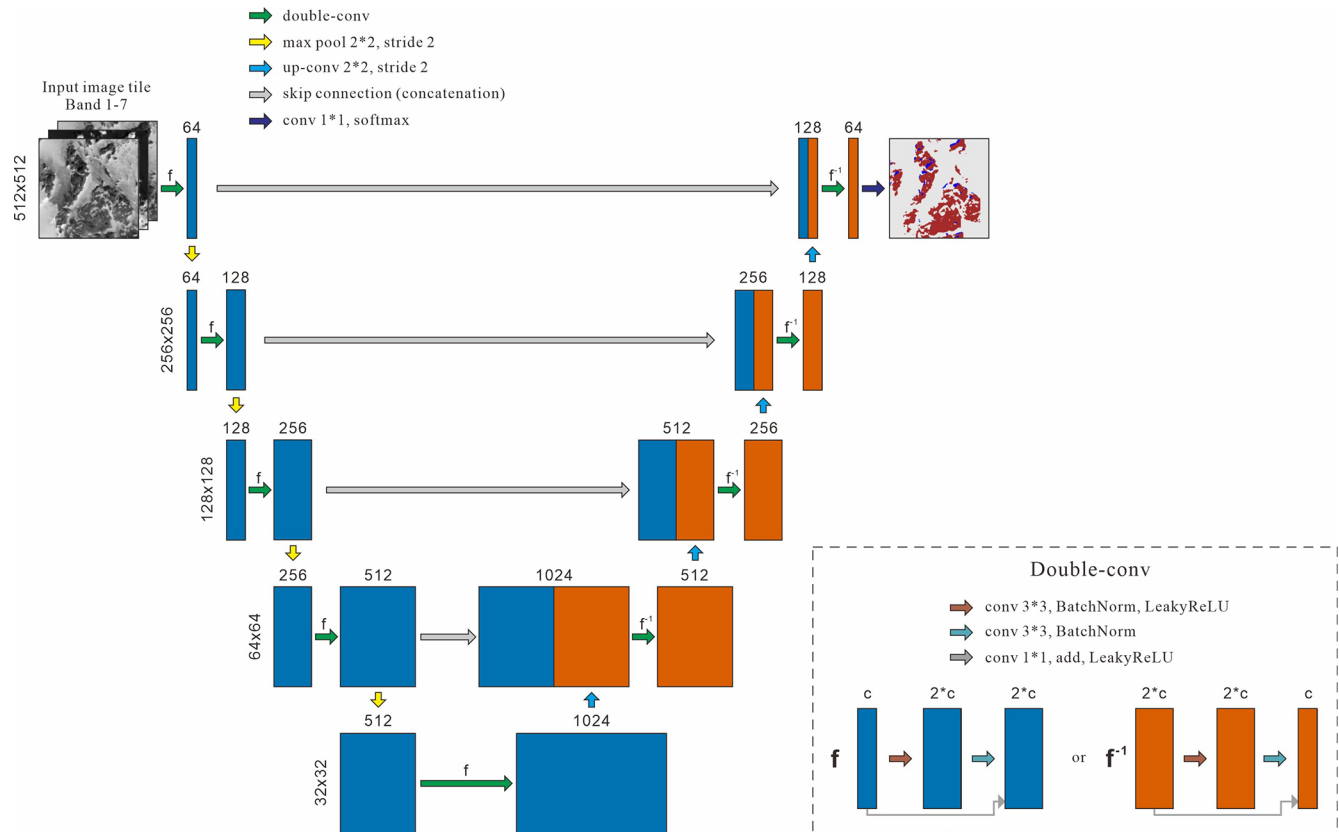


Figure 3. The structure of U-Net and the double-conv layer. The numbers on the left of the double-conv blocks represent the image sizes. The numbers above the double-conv blocks represent the feature channels after each operation. Double-conv blocks are able to double the feature channels in the encoder, while they halve the feature channels in the decoder.

3.4 Accuracy assessment

The accuracy of classification models is estimated by a confusion matrix, accuracy, an F_1 score, and a mean IoU. The formulas are presented in Eqs. (1), (2), (3), (4), and (5):

$$\text{Accuracy} = \frac{\text{TP}}{\text{TS}}, \quad (1)$$

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}, \quad (2)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad (3)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \quad (4)$$

$$\text{mIoU} = \frac{1}{N} \sum_{i=1}^N \frac{\text{TP}_i}{\text{TP}_i + \text{FP}_i + \text{FN}_i}, \quad (5)$$

where N is the number of categories, TS is the total number of samples, TP is the number of results classified as true positive, FP is the number of results classified as false positive, TN is the number of results classified as true negative, and FN is the number of results classified as false negative in the confusion matrix.

4 Results

4.1 Classification results

Figure 4 illustrates the process and intermediate results involved in the LLOW identification. The Landsat images were accurately classified into open water, ice, and rocks through the use of U-Net (Fig. 4e, f, g, and h). Compared to the images of the false color band combination, the results derived from threshold segmentation contained a large number of errors (Fig. 4m, n, o, and p). For example, smooth ice layers were misidentified as open water in Fig. 4p. However, we obtained information on potential LLOW areas through the results of U-Net. To rectify these errors, masking of potential LLOW areas was employed (Fig. 4q, r, s, and t), significantly improving the accuracy of LLOW identification based on SAR images.

Figure 5 shows the classification results obtained by U-Net for extracts from all Landsat test scenes. The U-Net network has generally shown good recognition performance across various terrains in all four study areas. Specifically, it effectively mitigates the impacts of diverse brightness and contrast levels in VH (Fig. 5a and b). Moreover, it accurately

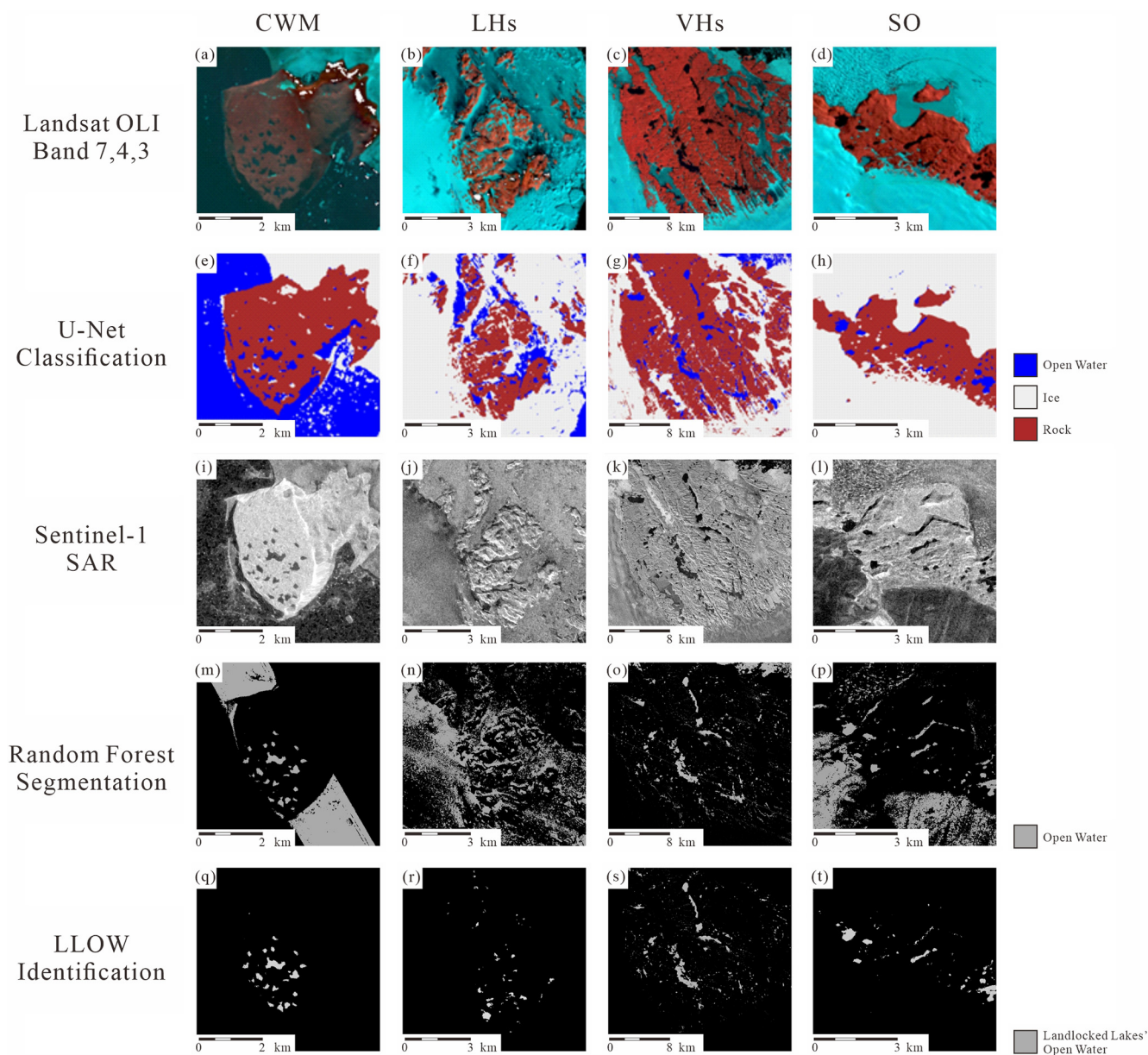


Figure 4. The intermediate images and results in the workflow of landlocked lake open water (LLOW) identification. The first row displays the Landsat images by the false color band combination 7–4–3 (RGB). The white regions in these images represent the void data in band 7, 4, or 3. The second row exhibits the classification results of U-Net. The third, fourth, and fifth rows represent the Sentinel images, the results of threshold segmentation, and the results of detected LLOW, respectively.

distinguishes mountain shadows from water bodies in LH without any misclassification (Fig. 5c and d). Notably, in SO, the presence of ice undulations causes numerous shadows. U-Net correctly identifies these shadows as ice (Fig. 5e), which can be a challenging task when using threshold methods. In addition, in both SO and CWM, there are partially melted lakes primarily composed of ice, which appears grayish (Fig. 5e and f). U-Net successfully identifies these lakes as ice surfaces, preventing any overestimation of open water areas.

Figure 6 displays LLOW results obtained through the fusion of Landsat and SAR images. A comparison within each row highlights differences between varied areas. For example, SO, the highest-latitude area, appears completely frozen in April (Fig. 6h), while the lower-latitude areas like CWM still exhibit LLOW during the same month (Fig. 6e). By contrasting the upper row with the lower row, temporal differences can be observed within the same area, where lakes show larger open water areas in the relatively warmer month of February (e.g., Fig. 6d and h).

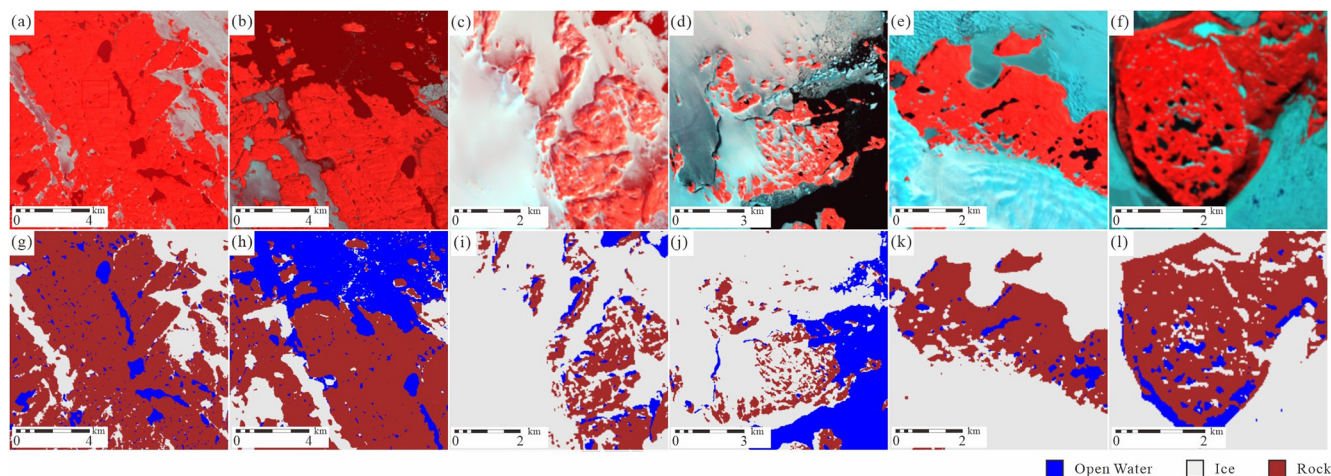


Figure 5. Comparison between the Landsat images and auto-generated classification examples of U-Net. The upper row displays Landsat 8 images, using the false color band combination 7–4–3 (RGB) to enhance feature distinction. The lower row shows the corresponding auto-generated classification results of U-Net. Panels (a) and (b) represent the Vestfold Hills (VH), panels (c) and (d) represent the Larsemann Hills (LH), panel (e) represents Schirmacher Oasis (SO), and panel (f) represents Clearwater Mesa (CWM).

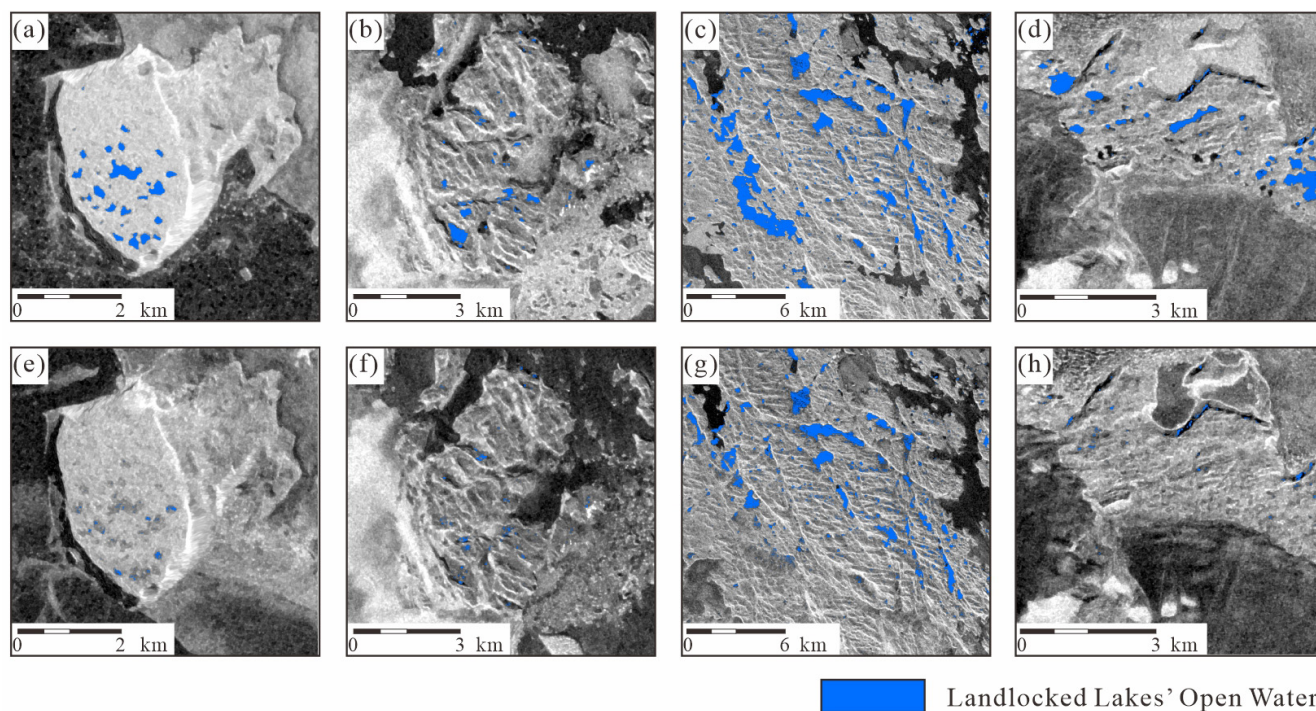


Figure 6. The landlocked lake open water (LLOW) area changes over time obtained through the fusion of Landsat and SAR images. The upper row shows the LLOW results in February, with the lower row representing the LLOW results in April. Panels (a) and (e) represent Clearwater Mesa (CWM), panels (b) and (f) represent the Larsemann Hills (LH), panels (c) and (g) represent the Vestfold Hills (VH), and panels (d) and (h) represent Schirmacher Oasis (SO).

4.2 Model validation

We compared the accuracy of LLOW identification between results obtained before applying the potential LLOW area mask and those obtained after applying the mask in LH

(Fig. 7). Prior to applying the mask, the RF model identified a large number of false LLOW instances in low-backscatter pixels. The LLOW identification only based on SAR images resulted in a mIoU value of only 0.29 when compared to the ground truth labels. However, the masking process based on

potential LLOW areas successfully reduced the majority of false LLOW instances and improved the mIoU value to 0.74. The increase in the mIoU suggests that masking using potential LLOW areas can compensate for the lack of spectral information in Sentinel-1 images, thereby enhancing the accuracy of the LLOW identification model.

Our land-cover classification model, based on U-Net, has achieved average accuracy, F_1 score, and mIoU values of 0.93, 0.90, and 0.82, respectively, on the test datasets, indicating reliable and accurate classification of land cover. The LLOW identification model yielded mean accuracy, F_1 score, and mIoU values of 0.94, 0.89, and 0.81, respectively, for four study areas on the test set. We further validated the model performance on four test patches (Fig. 8). The LLOW identification model yielded F_1 scores ranging from 0.88 to 0.95 and mIoU ranging from 0.81 to 0.90. Among the four areas, SO exhibited the highest mIoU value of 0.90, suggesting the most similar spatial distribution between the predicted LLOW and the ground truth. LH showed the lowest mIoU of 0.81, while CWM and VH showed mIoU values of 0.82 and 0.83, respectively. In VH and SO, the locations and areas of LLOW were well recognized (Fig. 8k and l). In LH, the spatial distribution of LLOW was also accurately detected, although there were some inconsistencies in the boundaries between the ground truth and the predicted lakes (Fig. 8j). In addition, in CWM, the model successfully identified all LLOW areas, but it misclassified the areas covered by floating ice with low backscatter (Fig. 8a) as LLOW. Overall, our model demonstrated proficiency in detecting LLOW areas, providing reliable information on the spatial distribution and extent of LLOW.

4.3 Seasonal variations in LLOW area

The study focused on changes in LLOW from January to April across four different areas in Antarctica. Figure 9 presents the spatial and temporal variations in the LLOW area during the study period. Our results indicate an initial increase followed by a decreasing trend in the overall LLOW area. Notably, the occurrence and duration of maximum LLOW areas varied among the study areas, with the highest value observed in early January in CWM, while SO in inland Antarctica experienced its peak LLOW area at the end of January, lasting for less than two satellite revisit cycles (12 d). The rate of decrease in LLOW area slowed down from late March, approaching a relatively stable low-value stage. By April, the LLOW areas had reduced to approximately 20 % of their maximum value for CWM, while LH and SO at higher latitudes decreased to 10 % of their maximum or approached zero.

In addition to seasonal variations, interannual variations in LLOW areas were observed. For example, LH exhibited significant variation in LLOW areas in different years, with the maximum recorded in 2018 being only 60 % of that in 2019 (Fig. 9b). Furthermore, CWM experienced a signifi-

cant freezing and thawing process in March 2017, when the LLOW area dropped to less than 50 % of its maximum before subsequently rebounding to the maximum value (Fig. 9a).

5 Discussion

The changes in LLOW areas can be categorized into two distinct phases: the growth phase and the decline phase (Fig. 9). The growth phase spans the initiation of our data collection until the maximum LLOW area is reached, while the decline phase extends from the maximum area to the minimum area after reaching the peak. In the following sections, we discuss these two phases separately.

5.1 Growth phase of LLOW area

With the onset of austral summer, lake surface ice and snow melt, resulting in the generation of meltwater, which contributes to an increase in the LLOW area. This process is closely associated with the changes in temperature, especially the occurrence of days with temperatures exceeding 0 °C (Braithwaite and Hughes, 2022; Li et al., 2021; Wake and Marshall, 2015; Maisincho et al., 2014; Barrand et al., 2013; Johansson et al., 2013). Thus, we evaluate the positive degree day (PDD) sum, which represents the cumulative sum of temperatures above the melting point during a specific period (Cogley et al., 2011). In this study, the PDD for a given day is calculated as the sum of temperatures exceeding 0 °C from 1 November of the previous year until the current day. It is important to note that we only analyzed the PDD for LH and VH in this study, considering that automatic weather station (AWS) data are only available at these two sites. The PDD is calculated using Eq. (6):

$$\text{PDD}_n = \sum_{i=0}^n \begin{cases} T_i, & T_i > 0 \\ 0, & T_i \leq 0. \end{cases} \quad (6)$$

Here, the positive degree day sum prior to the day n is denoted as PDD_n (°C), and T_i represents the station mean temperature (°C) measured on day i . Figure 10 illustrates the relationship between PDD and LLOW area change over time in LH and VH. During the growth phase of the LLOW area, the average R^2 value is around 0.9, indicating that PDD can explain ~90 % of the increase in LLOW area. However, there was a notable exception in LH in 2019, characterized by an unusual cooling event from middle to late January. This event persisted for several consecutive days with temperatures below 0 °C, resulting in a decline in the LLOW area. In addition, since the LLOW area had already reached its maximum at the beginning of January in LH in 2018, the growth phase was short and less discernible, leading to a lack of significant correlation between PDD and the LLOW area.

PDDs can also influence the year-to-year fluctuations in LLOW area, but the relationship between changes in PDD and LLOW area is nonlinear. For instance, the maximum

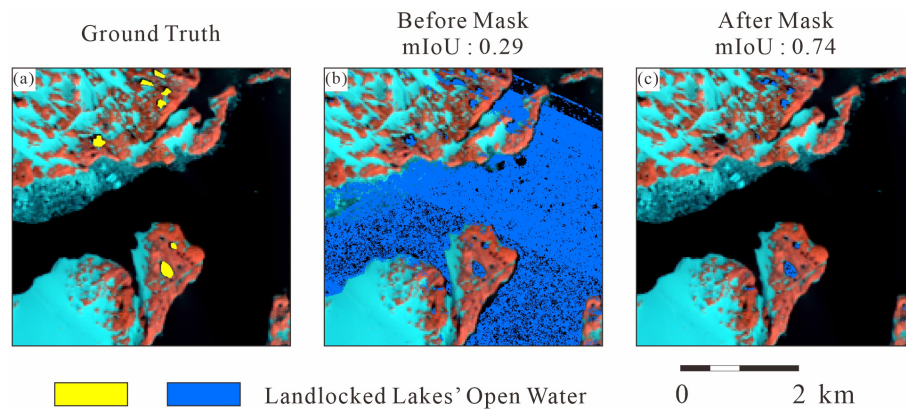


Figure 7. Accuracy comparison of LLOW identification before and after masking in LH. The background images are displayed from the false color combination of the 7–4–3 bands. The result before masking was derived from threshold segmentation.

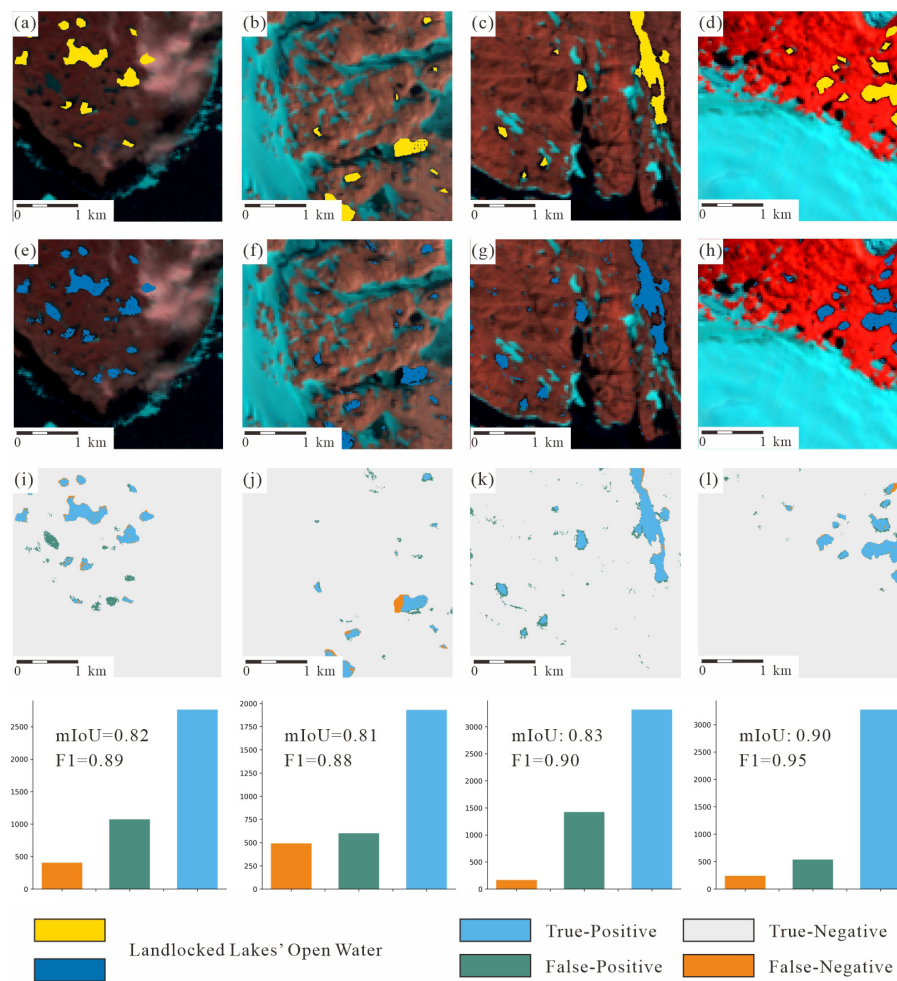


Figure 8. Validation of the landlocked lake identification model in the testing dataset for four areas. The four columns of images are validation images for CWM, LH, VH, and SO. The first, second, and third rows are ground truth, predicted, and spatial error images, respectively. The background images are displayed from the false color combination of the 7–4–3 bands. The spatial distribution of classification errors is obtained from overlapping ground truth and predicted images.

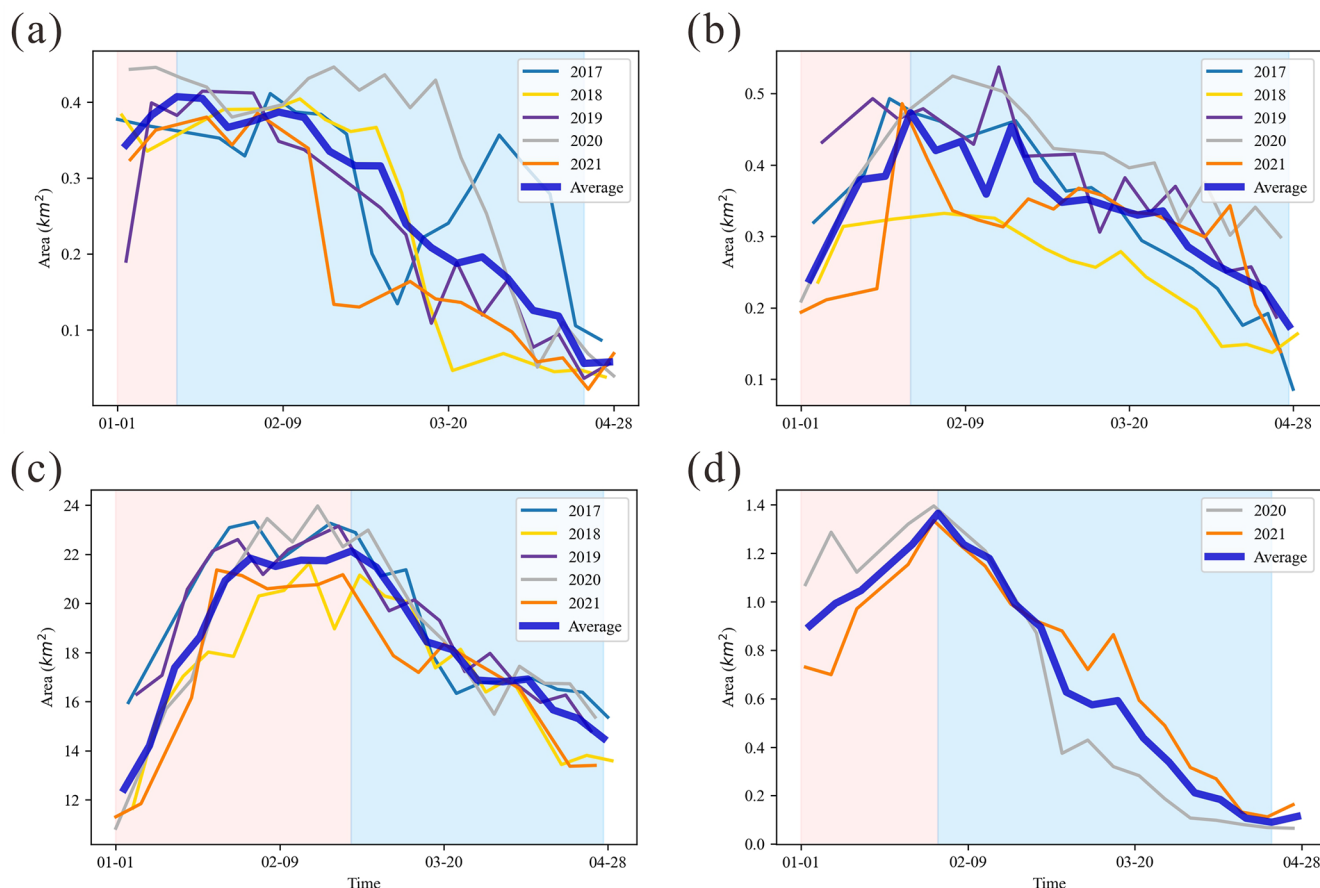


Figure 9. The landlocked lake open water (LLOW) area changes in CWM (a), LH (b), VH (c), and SO (d) from January to April. The red interval represents the growth phase of the LLOW area, while the blue interval represents the decline phase of the LLOW area.

PDD in 2017 was more than 2 times higher than that in 2018 in LH, yet the maximum area increased by 50 % (Fig. 10a and b). The maximum area of VH remained relatively stable over the 5 years. When PDD reaches a certain threshold, all LLOW areas have already melted, so further increases in PDD do not lead to changes in LLOW area. Therefore, across different years, significant differences in PDD can result in minimal variation in LLOW areas. Based on this, it can be inferred that the threshold for PDD in LH is likely between 25 and 35 °C. When PDD exceeds 35 °C, the maximum LLOW area stays relatively invariant at $\sim 0.5 \text{ km}^2$.

5.2 Decline phase of LLOW area

Cumulation of successive negative air temperature days contributes to the lowering of water temperature and the commencement of the water freezing process, i.e., the formation and longer-term persistence of ice cover (Graf and Tomczyk, 2018). Therefore, we calculate the negative degree day (NDD) sum by using Eq. (7), which represents the cumulative sum of temperatures below the melting point during a

specific period.

$$\text{NDD}_n = \sum_{i=0}^n \begin{cases} T_i, & T_i < 0 \\ 0, & T_i \geq 0. \end{cases} \quad (7)$$

Here, the negative degree day sum prior to the day n is denoted as NDD_n (°C), and T_i represents the station mean temperature (°C) measured on day i . The relationship between the LLOW area and NDD in each area during the freezing season is significant (Table 1). The calculation of the R^2 value was based on a linear fit of the NDD and the LLOW area, ranging from the maximum LLOW area to the minimum. In all four study areas, the R^2 values were found to be greater than 0.5. This indicates a strong response of the LLOW area to NDD changes during the decline phase of the LLOW area.

The relationship between the LLOW area and NDD in CWM in 2017 exhibited a relatively low R^2 value (0.52). During that year, sharp declines and subsequent rebounds of the LLOW area were observed (Fig. 11). As temperatures plummeted, the LLOW area decreased rapidly, nearly reaching its nadir simultaneously. Conversely, with rising temperatures, the LLOW area responded promptly, highlighting

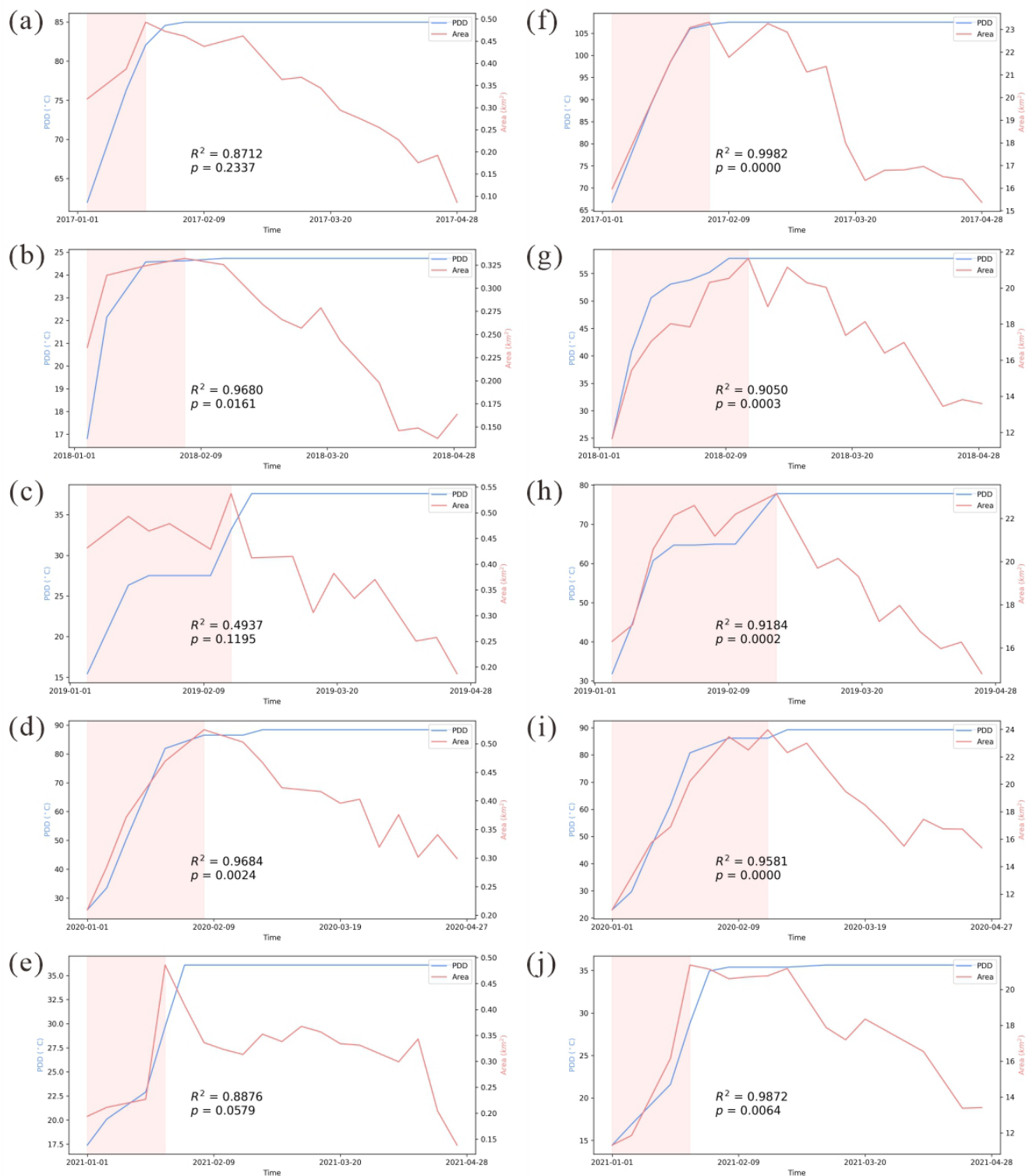


Figure 10. The positive degree day (PDD) sums and landlocked lake open water (LLOW) area change during the 2017 (a), 2018 (b), 2019 (c), 2020 (d), and 2021 (e) melt seasons in the Larsemann Hills (LH) and during the 2017 (f), 2018 (g), 2019 (h), 2020 (i), and 2021 (j) melt seasons in the Vestfold Hills (VH). In the figure, the red interval represents the growth phase of the LLOW area. The R^2 value in the figure is calculated from a linear fit of PDD and LLOW area during the growth phase.

Table 1. R^2 of the LLOW area and negative degree days in the freezing phase between 2017 and 2021.

Year	CWM	LH	VH	SO
2017	0.52**	0.95**	0.72**	
2018	0.84**	0.94**	0.85**	
2019	0.73**	0.75**	0.82**	
2020	0.88**	0.85**	0.78**	0.78**
2021	0.57**	0.59**	0.86**	0.97**
Average	0.71	0.82	0.81	0.88

** $p < 0.01$.

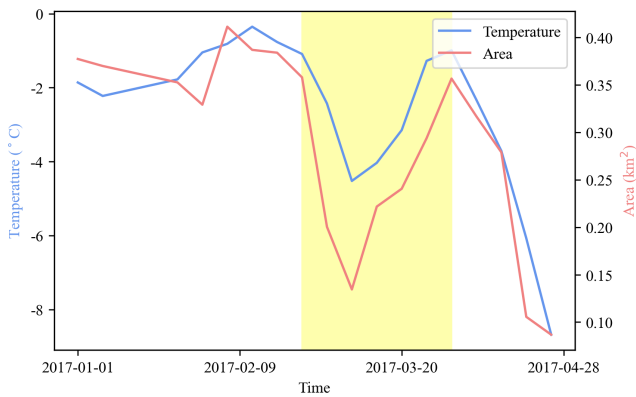


Figure 11. The temperature and the landlocked lake open water (LLOW) area in CWM in 2017. The yellow interval represents the declines and rebounds of lake area and temperature.

temperature’s predominant influence on fluctuations in the LLOW area. Therefore, using NDD instead of temperature to explain variations in the LLOW area during the freezing phase may overlook these instances of temperature-driven rebounds during the decline phase.

During the freezing stage, the depth of a lake will affect the time of lake-ice formation (Kirillin et al., 2012), which in turn affects the reduction in LLOW area. Shallower lakes tend to lose heat more quickly, leading to earlier ice cover formation. In contrast, deeper lakes possess greater heat capacity, resulting in a slower cooling process and delayed ice formation. For instance, VH and LH are close to each other with similar temperature conditions, so the LLOW area should begin to decrease around the same time. However, in LH, the LLOW area started to decrease continuously from late January, approximately 1 to 2 weeks earlier than in VH. This discrepancy may be attributed to the fact that the average lake depth in VH is ~ 30 m, with some lakes exceeding ~ 100 m in depth, whereas LH consist of lakes with an average depth of 10 m (Shevnina and Kourzeneva, 2017; Harris and Burton, 2010).

5.3 Model limitation

The backscatter of LLOW is mainly disturbed by two types of factors: the first is external factors, such as wind speed and direction, SAR image incidence angles, and mountain shadows; the second is the LLOW surface cover, such as floating ice and snow. Firstly, when the open water is disturbed by wind, the backscatter increases. Additionally, the incidence angles and topography also affect the backscatter of open water. Because the steep terrain yields mountain shadows and identification errors (Dirscherl et al., 2021a), we calculated the slopes from a DEM to evaluate the influence of topography. To evaluate the influence of wind, incidence angles, and topography, we sampled within the LLOW areas of the four study areas between 2017 and 2021 from the 46 sample patches (Figs. S3, S4, S5, and S6). However, there is no obvious linear correlation between LLOW backscatter and wind, incidence angles, or slope. Moreover, we added the wind speed, incidence angles, and slope as input features for the RF model in open water identification. However, only incidence angle yields a significant feature importance. This indicates that the incidence angle is much more important for open water detection compared to wind speed and slope. Thus, our RF model did not consider the wind features and slope. Secondly, unstable factors such as floating ice layers led to fluctuations of the LLOW area. The backscatter of LLOW can be influenced by the floating ice layer and snow covering open water, making accurate identification challenging. By comparing our spatial errors with input SAR images, we found that the floating ice layers directly caused the false positive errors (Fig. 8i). Furthermore, the presence of a blue ice layer with low backscatters can lead to overestimation of LLOW (Table S1). Despite our efforts to remove significantly underestimated results, as mentioned in Sect. 3.3, these factors remain the causes of fluctuations in the LLOW area time series.

Although the LLOW identification model has these limitations, our findings demonstrate its strong performance across the four study areas. The deep learning approach, namely U-Net, enhanced model robustness across diverse environmental conditions such as various surrounding features, cloud covers, lighting conditions, and mountain shadows. Using the RF model to identify open water in SAR images can also overcome unstable factors such as cloud cover, producing a stable high-resolution time series of open water areas. Therefore, our method has the potential to perform well in other regions, such as identifying the other landlocked lakes in Antarctica or detecting numerous landlocked lakes along the coastal areas of Greenland. Additionally, our proposed method for distinguishing between seawater, supraglacial lakes, and landlocked lakes can be applied to the identification of thermokarst lakes, such as the numerous thermokarst lakes on the Alaska North Slope. The BFS algorithm can distinguish between open rivers and closed lakes on plain permafrost. By utilizing BFS and the fusion of Land-

sat and Sentinel-1 images, we can differentiate thermokarst lakes and river drainages within an image. Consequently, the growth of thermokarst lakes and their integration into river systems can also be detected. Additionally, by combining Landsat and Sentinel-1 images, we overcame the severe cloud interference in the optical images in the Antarctic, significantly improving the detection frequency of landlocked lakes. We also addressed the challenge of obtaining surrounding land-cover information on water in SAR images, thereby successfully generating the high-resolution LLOW products. By providing reliable long-term LLOW time series products, our model contributes to a deeper understanding of the dynamic changes in LLOW under a changing climate.

6 Conclusion

We proposed an automated detection workflow for LLOW based on deep learning and multi-source satellite images. By utilizing the BFS algorithm and combining Landsat 8–9 OLI and Sentinel-1 SAR images, we successfully distinguished the LLOW from other open waters, overcoming the limitation of models based solely on optical or SAR images. In our model accuracy assessment, our U-Net model and LLOW identification model achieved average F_1 score values of 0.90 and 0.89, respectively, on the testing datasets. Our model accurately recognizes both large-scale and small-scale LLOW in the testing images. Applying our LLOW identification model to four typical coastal Antarctic areas, we mitigated cloud and shadow interference and generated high-resolution spatiotemporal LLOW area time series from January to April between 2017 and 2021.

The seasonal changes in LLOW area can be categorized into two phases: the growth phase and the decline phase. The growth phase includes the period from the initiation of our data collection until the maximum LLOW area is reached, while the decline phase extends from the maximum area to the minimum area after reaching the peak. We found that during expansion of LLOW area, $\sim 90\%$ of the changes are explained by PDDs. PDDs can also influence the interannual variations in LLOW area, but the changes in PDD and LLOW area are not proportional. Furthermore, during the decline phase, NDDs accounted for more than 50% of changes in LLOW area. Our model provides long-term LLOW time series products that help us better understand how lakes change under a changing climate.

Data availability. Data presented in this work are available at National Tibetan Plateau/Third Pole Environment Data Center (Shi, 2023; <https://doi.org/10.11888/Cryos.tpcdc.300665>).

Supplement. The supplement related to this article is available online at: <https://doi.org/10.5194/tc-18-5347-2024-supplement>.

Author contributions. GS conceived the study. XM designed the method and provided model data. AJ analyzed the data and interpreted the results. AJ and XM designed and wrote the paper with support from all co-authors. GS and YH improved the paper.

Competing interests. The contact author has declared that none of the authors has any competing interests.

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