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Citation (APA)

Zhang, G., Xie, H., Fernandez, A., Kinnard, C., & Lhermitte, S. (2025). Remote sensing of the global cryosphere: Status, processes, and trends. *Remote Sensing of Environment*, 334, Article 115220. <https://doi.org/10.1016/j.rse.2025.115220>

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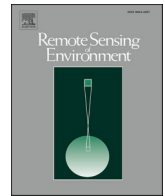
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Editorial

Remote sensing of the global cryosphere: Status, processes, and trends[☆]

ARTICLE INFO

Keywords:

Remote sensing
Glacier
Snow
Glacial lake
Permafrost
Ice sheet
Sea ice

ABSTRACT

Driven by rapid technological advances in cryospheric science and the emergence of new generations of remote sensing observations, this special issue of *Remote Sensing of Environment*, entitled “Remote sensing of the global cryosphere: status, processes, and trends”, brings together 23 studies published between 2023 and 2025. Collectively, these papers showcase how multi-sensor satellite observations, high-resolution digital elevation models (DEMs), and cutting-edge deep learning techniques are revolutionizing the monitoring of glaciers, snow, glacial lakes, permafrost, sea ice, and ice shelves across the Earth's three poles: the Arctic (including Greenland), Antarctica, and High Mountain Asia (the Third Pole). These studies integrate diverse datasets – including multisource DEMs, optical, thermal, and passive microwave imageries, as well as RADAR, LiDAR, and GRACE observations – to quantify glacier mass balance, map glacial lakes, assess permafrost thermal conditions, classify sea-ice types, and detect icebergs. We organize the publications by major cryospheric themes and their distribution across polar regions and summarize the dominant remote sensing datasets and methodologies employed. Finally, we outline future directions, emphasizing multi-sensor data fusion, physics-informed modeling, and AI-driven approaches to improve predictions of cryospheric change under a warming climate.

1. Introduction

The cryosphere — including glaciers, snow cover, ice sheets and ice shelves, sea ice, glacial lakes, river ice, and permafrost — plays a critical role in the global climate system, hydrological cycles, and natural hazard regimes. Yet it is experiencing widespread and rapid decline, evidenced by significant mass loss from glaciers and ice sheets, shrinking snow cover, thinning sea ice, and degrading permafrost. These transformations carry profound implications for water resources, sea-level rise, and cascading geohazards. Recognizing the urgency of these changes, the United Nations has declared 2025 as the *International Year of Glaciers' Preservation* and 2025–2034 as the *Decade of Action for Cryospheric Sciences* to raise global awareness of Earth's frozen regions.

Robust observation of cryospheric processes is essential, and remote sensing has become indispensable for monitoring changes across vast spatial and temporal scales, particularly in remote or inaccessible regions. Advances in high-resolution digital elevation models (DEMs), optical and radar satellite imageries, airborne and spaceborne Light Detection and Ranging (LiDAR), the Gravity Recovery and Climate Experiment (GRACE) and its successor GRACE Follow-On (FO), and Synthetic Aperture Radar (SAR), have revolutionized our ability to track cryospheric dynamics. Coupled with emerging deep learning techniques, these tools have greatly improved data analysis, image classification, and information extraction, helping to fill observational gaps where in situ measurements are limited. Collectively, these advances

enable assessments of glacier mass balance, estimates of fractional snow cover, evaluations of ice shelf stability, and deeper insights into permafrost thaw and its impact on ecosystems and infrastructure.

This special issue highlights recent progress in remote sensing, image processing, and deep learning to examine the status, processes, and trends of the global cryosphere (<https://www.sciencedirect.com/special-issue/104030VG1N3>). It focuses on five thematic areas:

- (1) Changes in mountain glaciers, snow, glacial lakes, ice sheets, ice shelves, and sea ice;
- (2) Hydrological and hazard impacts of climate-driven cryospheric changes;
- (3) Limitations in remote sensing data acquisition, retrieval, and uncertainty;
- (4) Mechanisms shaping present and future cryosphere evolution; and.
- (5) Impacts of cryospheric changes on local populations, environments, and ecosystems.

The special issue includes 23 studies covering a wide range of topics, collectively advancing our understanding of cryospheric processes and their impacts across the Earth's three poles: the Arctic (including Greenland), Antarctica, and High Mountain Asia (the Third Pole).

[☆] This article is part of a Special issue entitled: ‘Cryosphere remote sensin’ published in Remote Sensing of Environment.

2. Content of the special issue

This special issue showcases studies spanning a broad range of remote sensing applications in cryospheric research. Topics include changes in glacier mass balance and flow velocity, glacier surface temperature and albedo, glacial lakes, snow cover, and permafrost in high-mountain regions; sea ice, icebergs, and surface melt in Antarctica; sea ice, lake ice, and permafrost degradation in the Arctic; and glacier mass balance and surface water features such as supraglacial lakes, rivers, and water-filled crevasses in Greenland.

The studies draw upon extensive remote sensing datasets, including optical satellite imagery, multisource DEMs, GRACE and GRACE-FO observations, passive microwave data, SAR, Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature, and Atmospheric Infrared Sounder (AIRS) skin temperature (Fig. 1). These datasets are analyzed using advanced approaches such as deep learning, support vector machines, Bayesian methods, data assimilation, and radiative transfer models, often supported by cloud-computing platforms like Google Earth Engine.

Together, these tools enable the extraction of cryospheric information, the mapping of surface extent and properties, and the assessment of cryosphere dynamics and evolution.

2.1. Glaciers, glacial lakes, snow cover, and permafrost in high mountain regions (mainly the Third Pole)

Glaciers in high mountain regions provide essential freshwater resources for downstream populations, yet they are experiencing rapid thinning and retreat under global warming. These changes affect regional water availability, disrupt large-scale hydrological cycles, and heighten the risk of cryosphere-related hazards. Debris cover further complicates melt processes by modifying energy exchange at glacier surfaces, through advances in DEM differencing have improved the quantification of spatially heterogeneous changes in glacier elevation. For example, [Chen et al. \(2023a\)](#) estimated glacier surface elevation changes across the Himalaya between 2000 and 2013 using Shuttle

Radar Topography Mission (SRTM), Advanced World 3D (AW3D), and TerraSAR-X add-on for Digital Elevation Measurement-X (TanDEM-X) DEMs, revealing that ice cliffs play a dominant role in the ablation of

Table 1

A summary of the topics covered, the remote sensing data used, and the number of publications in this special issue.

Research topic	Primary remote sensing data used	Number of publications
Glacier mass balance (Chen et al., 2023a ; Li et al., 2023 ; Li et al., 2024 ; Wang et al., 2024)	SRTM DEM, AW3D DEM, TanDEM-X, KH-9 DEM, ASTER DEM, Sentinel-2, GRACE, GPS	4
Glacier surface temperature and albedo (Ren et al., 2024 ; Xie et al., 2024)	Landsat, MODIS	2
Glacial lake mapping, supraglacial lake, supraglacial river (Qiu et al., 2025 ; Tang et al., 2024 ; Wang and Sugiyama, 2024 ; Zhang et al., 2023)	Landsat, Sentinel-2	4
Snow over mapping and snowline, fractional snow cover (Chen et al., 2023b ; Xiao and Liang, 2024)	Landsat, MODIS	2
Permafrost extent (Kim et al., 2024)	MODIS, AIRS	1
Sea ice (Huang et al., 2024 ; Kim et al., 2023 ; Komarov et al., 2024 ; Qu et al., 2024 ; Rogers et al., 2024)	Sentinel-1, Advanced Microwave Scanning Radiometer 2 (AMSR2)	5
Iceberg (Braun and Andresen, 2024 ; Evans et al., 2023 ; Koo et al., 2023)	Sentinel-1, Worldview-2	3
Ice shelves (de Roda Husman et al., 2024)	Sentinel-1, Special Sensor Microwave Imager/Sounder (SSMIS), Advanced SCATterometer (ASCAT)	1
Melt pond (Lee et al., 2024)	MODIS	1

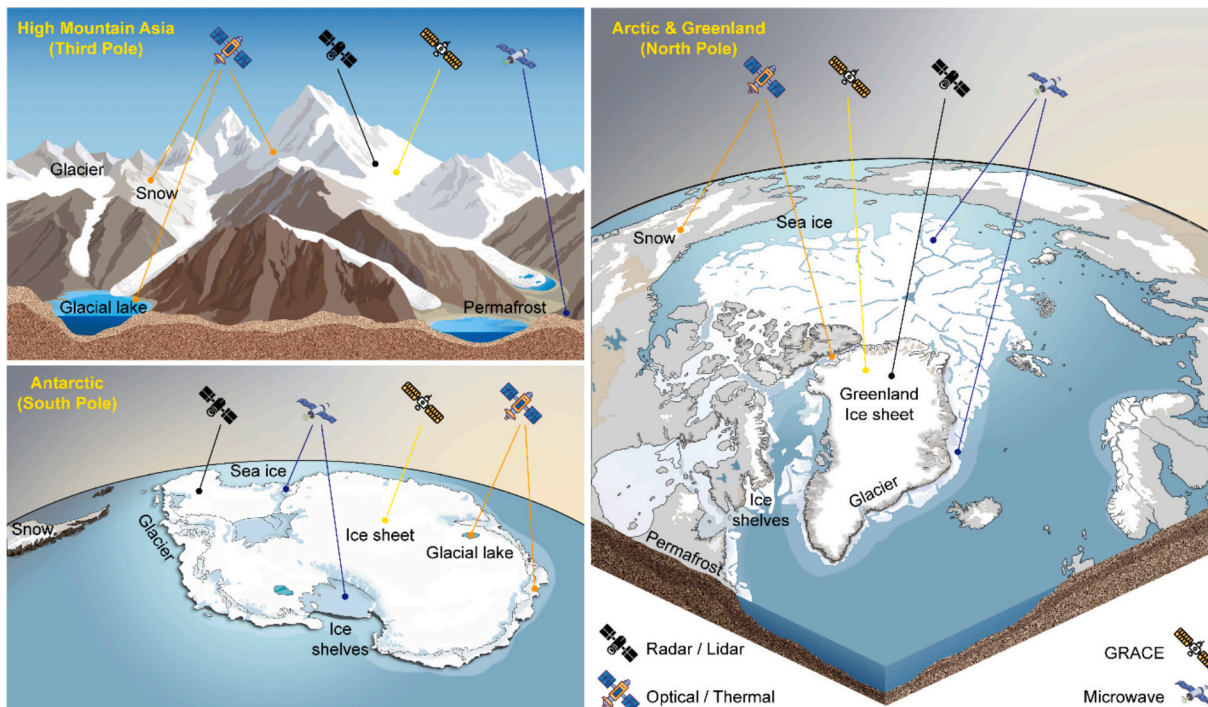


Fig. 1. Schematic illustration of remote sensing observations of cryosphere changes across the Earth's three poles. The components of the cryosphere monitored by satellites are connected by indicative lines.

debris-covered glaciers (Table 1). Similarly, Wang et al. (2024) assessed glacier melt rates in the Ak-Shyrak massif, central Tien Shan, from 1973 to 2023 using Key Hole-9 (KH-9), SRTM, and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) DEMs, detecting melting throughout the whole analyzed period, although with fluctuating rates.

Glacier flow velocity is another critical indicator of ice dynamics and stability, informing processes such as surging, basal sliding, and the potential initiation of ice avalanches. However, limited in-situ observations, signal decorrelation, and steep phase gradients that hinder the Differential Interferometric Synthetic Aperture Radar (D-InSAR) processing make accurate monitoring difficult. Using Sentinel-2 imagery, Li et al. (2024) produced quasi-monthly glacier velocity fields across the “Karakoram–Pamir anomaly” region and identified two distinct surging mechanisms: (a) with short surging phase and no seasonal flow rates' variation and (b) with advancing glacier front and seasonal acceleration.

Glacier surface temperature and albedo strongly influence melt rates, surface energy balance, and overall ice dynamics, yet remain poorly constrained across the Third Pole (High Mountain Asia) due to sparse ground observations. Ren et al. (2024) quantified glacier surface temperature changes from 2000 to 2021 using an altitudinal area-weighting method based on Landsat thermal data, highlighting substantial spatial variability in surface warming. Xie et al. (2024) retrieved glacier surface albedo in the Karakoram using Landsat reflectance and the MODIS MCD43A3 product, a Bidirectional Reflectance Distribution Function (BRDF)/Albedo dataset, combined with random forest and back-propagation neural network regression methods. Their results show that surge-type, advance-type, and debris-covered glaciers exhibit slower albedo decline, offering new insights into the mechanisms behind the Karakoram anomaly.

Accelerated glacier retreat has led to the rapid expansion of glacial lakes, posing significant hazards. Glacial lake outburst floods (GLOFs), for example, can cause devastating impacts due to large elevation gradients between high-altitude lakes and downstream settlements. Accurate and comprehensive glacial lake inventories are therefore essential for regional hazard assessment. Automatic mapping remains challenging because of mountain shadows, wet or frozen lake surfaces, and snow-covered boundaries. Tang et al. (2024) evaluated several deep convolutional neural networks and found that DeepLabv3+ with a MobileNetv3 backbone performed best in the Third Pole, successfully overcoming terrain-related challenges.

Declining snow cover impacts ecosystems, water resources, winter tourism, and hydropower generation. Yet automated snowline extraction in mountainous terrain remains difficult when using Landsat reflectance data. Xiao and Liang (2024) assessed eight snow-cover mapping algorithms and applied them to automated snowline delineation in 15 catchments across the United States, providing practical approaches for estimating snowline elevations in complex terrain. In parallel, accurate representation of snow–vegetation radiative interactions remains limited by the complex scattering processes within snow-covered forests. Chen et al. (2023b) addressed this gap by developing a new bidirectional reflectance model for snow-covered conifer forests, enabling improved satellite-based retrievals and more accurate assessments of surface radiation processes.

Thawing permafrost poses major risks to infrastructure, alters hydrological pathways, and accelerates carbon release, reinforcing positive climate feedback. Yet limited in-situ observations make it difficult to quantify permafrost extent and thermal dynamics in remote mountain regions. Kim et al. (2024) integrated MODIS and AIRS surface temperature records, both often affected by cloud cover, to derive long-term subsurface thermal conditions. Their work provides a comprehensive assessment of permafrost extent across the Third Pole and establishes a robust framework for evaluating climate-sensitive hydrological and ecological impacts.

2.2. Sea ice, icebergs, and ice shelves in Antarctica

Sea ice plays a crucial role in regulating climate, supporting ecosystems, and stabilizing ice shelves, making its monitoring essential for understanding polar environmental change. SAR imagery is a primary data source for sea ice mapping because it is unaffected by cloud cover and illumination conditions. However, ambiguous signals and noise in SAR data complicate automatic mapping. To address this, Rogers et al. (2024) developed a tool trained on concurrent multispectral visible and SAR imageries for sea ice detection. Their approach outperformed U-Net and other networks, providing a robust method for accurate polar sea ice mapping.

Understanding iceberg dynamics is equally important, as icebergs influence ocean circulation, marine ecosystems, freshwater fluxes, and pose navigation hazards. While large icebergs have been extensively examined via remote sensing, medium-sized icebergs in the Southern Ocean remain under-monitored. Koo et al. (2023) created an open-source tool using Sentinel-1 imagery in Google Earth Engine to detect and track medium and large icebergs, enabling investigation of iceberg distribution and drift patterns. A persistent challenge, however, is the lack of fully automated methods capable of detecting icebergs under diverse environmental and backscatter conditions. Evans et al. (2023) addressed this gap by proposing a fully automated Sentinel-1 SAR framework that adapts to inter-scene variability and accurately distinguishes icebergs within complex sea-ice and ocean environments, laying a foundation for estimating near-shore iceberg populations.

Antarctica's ice shelves are critical for predicting sea-level rise, yet they are increasingly vulnerable to atmospheric and ocean-driven melting and structural weakening under climate change. Capturing ice shelf melt events is difficult due to their short duration, limited spatial extent, and the trade-off between spatial and temporal resolution in satellite observations. To overcome these limitations, de Roda Husman et al. (2024) generated a comprehensive Antarctic ice shelf surface melt record using a deep learning U-Net model implemented in Google Earth Engine. Their approach enables detection of surface melting across Antarctica at fine spatial scales while maintaining high temporal resolution, offering new insights into ice shelf responses to changing atmospheric forcing.

2.3. Sea ice and permafrost in the Arctic

Arctic sea ice is a critical component of the Earth system, strongly influencing climate processes and reflecting rapid environmental changes in the polar region. Satellite remote sensing, particularly SAR, enables accurate year-round monitoring of sea ice variability and dynamics. Yet, high accurate classification of Arctic sea ice using high-resolution imagery remains challenging. To address this, Huang et al. (2024) developed a dual-branch encoder U-Net deep learning model for classifying sea ice types in the Beaufort Sea using SAR data. Their approach outperformed traditional methods — including support vector machines, random forests, and conventional convolutional neural networks — in distinguishing multi-year ice, first-year ice, and open water.

Sea ice leads, narrow openings in the ice cover, play a key role by disrupting insulation, intensifying atmosphere-ocean exchanges, and influencing heat fluxes, ice production, upper-ocean mixing, and Arctic amplification processes. Parameterizing sub-kilometer lead distributions and associated dynamics remains a major challenge for numerical models. Qu et al. (2024) addressed this gap with an optimized random forest approach that integrates SAR polarization and texture features with geometric screening to detect narrow leads and track their evolution using SAR, buoy, and atmospheric reanalysis data. Their results reveal enhanced lead opening as sea ice motion shifted from the Beaufort Gyre to the Transpolar Drift. Komarov et al. (2024) further demonstrated that assimilating high-resolution ice concentration data from the RADARSAT Constellation Mission, combined with beam-specific wind retrievals and improved quality control, substantially

enhances Arctic ice analyses, particularly in coastal regions, lakes, marginal ice zones, and areas lacking chart coverage.

Pan-Arctic measurements of summer sea ice thickness are essential for understanding and predicting climate and weather processes. However, passive microwave observations only sense the upper tens of centimeters of ice, limiting retrievals to thin ice while leaving thicker summer ice largely unobserved. Kim et al. (2023) developed a method to estimate pan-Arctic ice draft from satellite microwave brightness temperatures, producing daily fields that reliably capture seasonal thinning.

Arctic landscapes are heterogeneous, with diverse patches varying across space and time. Melt ponds strongly influence summer ice energy balance, under-ice light availability, biological activity, and ice persistence. Comparative analyses of melt pond datasets help guide the selection of appropriate products. Lee et al. (2024) compared three publicly available melt pond datasets and found that they generally agree early in the melt season but diverge later, largely due to limitations of coarse-resolution satellite data. They also showed that higher melt pond fractions on first-year ice are generally negatively correlated with surface albedo.

Permafrost degradation reshapes landscapes, alters ecosystems, and amplifies global climate feedback. Accurately characterizing permafrost dynamics remains difficult due to high spatial heterogeneity. Braun and Andresen (2024) demonstrated that ice-wedge degradation on the Arctic Coastal Plain is highly variable across scales, with advanced degradation occurring locally in low-elevation troughs and regionally in higher-elevation clusters. Their findings, derived from sub-meter satellite imagery validated with LiDAR, drone, and in-situ observations, highlight the complexity and scale-dependent nature of permafrost change in the Arctic.

2.4. Glacier and surface water in Greenland

Research on Greenland's surface mass balance has primarily emphasized decadal and longer-term variations, including prevailing trends, periodic oscillations, and the accelerating rate of mass loss. However, the individual components of surface mass balance – such as snowfall, rainfall, and runoff – and their spatial and temporal variability remain poorly constrained. Li et al. (2023) quantified the contributions of these components to seasonal and transient crustal deformation in Greenland using GPS networks, GRACE datasets, and regional climate models. Their study provides a valuable reference for advancing research on Greenland's surface mass balance and improving dynamic monitoring.

Supraglacial lakes, which form on the Greenland Ice Sheet during the melt season as surface meltwater accumulates in depressions, play a key role in modulating ice sheet dynamics. While Greenland's surface hydrology has been widely examined, the seasonal and interannual variability of supraglacial lakes remains insufficiently understood. Wang and Sugiyama (2024) mapped the distribution and temporal evolution of supraglacial lakes from 2014 to 2021 using a random forest-based machine learning approach applied to Landsat 8 and Sentinel-2 imagery within Google Earth Engine. Their results highlight the inland expansion of supraglacial lakes under a warming climate and their potential influence on glacier dynamics. Beyond long-term evolution, intra-annual fluctuations of supraglacial lakes are also critical yet understudied. Qiu et al. (2025) developed a deep learning approach to automatically map supraglacial lakes across Greenland during the 2017–2022 melt seasons using passive optical satellite imagery. Their study underscores the importance of high-frequency monitoring of supraglacial lake areas for understanding cryospheric hydrology dynamics.

Finer-scale surface water features on the Greenland Ice Sheet, including rivers, water-filled crevasses, and small ponds, are less well documented due to their narrower widths compared to supraglacial lakes. Zhang et al. (2023) quantified surface water extent and volume during the relatively cool summer of 2018 and the warm summer of

2019 using 10 m-resolution Sentinel-2 imagery, a semi-automated multi-scale water extraction algorithm, and a regional atmospheric climate model. Their study reveals significant temporal and spatial differences in surface water extent, volume, and drainage patterns, providing new insights into the hydrological processes shaping Greenland Ice Sheet.

3. Conclusions

This special issue highlights rapid advances in remote sensing and the growing integration of deep learning for monitoring cryospheric processes across glaciers, ice sheets, ice shelves, snow, sea ice, glacial lakes, and permafrost. Remote sensing provides multi-scale and multi-temporal observations, while deep learning enhances analysis by automating feature extraction, improving retrieval accuracy, and supporting interpretation in complex environments.

(1) Integration of remote sensing and deep learning.

Deep learning has become a cornerstone of cryospheric remote sensing, enabling automated and accurate analyses in challenging environments. Models such as DeepLabv3+, U-Net, and random forests have advanced the automatic mapping of glacial lakes, supraglacial water, and sea-ice features from optical and SAR data. By integrating multisource satellite observations, deep learning also improves retrievals of glacier surface albedo and permafrost ground temperatures. Unsupervised approaches support robust iceberg detection, while cloud platforms like Google Earth Engine facilitate efficient, large-scale applications.

(2) Applications of remote sensing in cryosphere studies.

Multi-source satellite data and DEMs enable detailed assessments of glacier mass balance, flow velocity, surface temperature, albedo, and glacial lake evolution. Snow cover dynamics are monitored through automated snowline mapping and radiative transfer models. Uncrewed Aerial Vehicle (UAV) imagery and high-resolution optical data enhance detection of permafrost conditions and associated landscape changes. SAR and passive microwave observations support sea-ice classification, lead detection, ice draft estimation, and melt pond mapping.

Overall, the integration of remote sensing and deep learning is transforming cryosphere research by enabling automated feature detection and supporting large-scale monitoring with greater accuracy and temporal continuity than traditional methods. Looking ahead, progress will increasingly rely on multi-sensor data fusion, physics-informed modeling, and AI-driven approaches. Together, these advances will improve the detection of subtle changes, reduce retrieval uncertainties, and strengthen predictions of cryospheric evolution under a warming climate.

This special issue would not have been possible without the collaborative efforts of all contributors. We sincerely thank Dr. Menghua Wang, Editor-in-Chief of *Remote Sensing of Environment*, for his invaluable guidance and support. We extend our sincere thanks to Di Wang and the journal management team for their professional assistance, and to all authors and reviewers for their active participation and contributions. We hope this special issue will serve as a valuable resource and provide guidance for future research in cryospheric remote sensing.

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.

References

- Braun, K.N., Andresen, C.G., 2024. Heterogeneity in ice-wedge permafrost degradation revealed across spatial scales. *Remote Sens. Environ.* 311, 114299. <https://doi.org/10.1016/j.rse.2024.114299>.
- Chen, F., Wang, J., Li, B., Yang, A., Zhang, M., 2023a. Spatial variability in melting on Himalayan debris-covered glaciers from 2000 to 2013. *Remote Sens. Environ.* 291, 113560. <https://doi.org/10.1016/j.rse.2023.113560>.
- Chen, S., Xiao, P., Zhang, X., Qi, J., Yin, G., Ma, W., Liu, H., 2023b. Simulating snow-covered forest bidirectional reflectance by extending hybrid geometric optical-radiative transfer model. *Remote Sens. Environ.* 296, 113713. <https://doi.org/10.1016/j.rse.2023.113713>.
- de Roda Husman, S., Lhermitte, S., Bolibar, J., Izeboud, M., Hu, Z., Shukla, S., van der Meer, M., Long, D., Wouters, B., 2024. A high-resolution record of surface melt on Antarctic ice shelves using multi-source remote sensing data and deep learning. *Remote Sens. Environ.* 301, 113950. <https://doi.org/10.1016/j.rse.2023.113950>.
- Evans, B., Faul, A., Fleming, A., Vaughan, D.G., Hosking, J.S., 2023. Unsupervised machine learning detection of iceberg populations within sea ice from dual-polarisation SAR imagery. *Remote Sens. Environ.* 297, 113780. <https://doi.org/10.1016/j.rse.2023.113780>.
- Huang, Y., Ren, Y., Li, X., 2024. Deep learning techniques for enhanced sea-ice types classification in the Beaufort Sea via SAR imagery. *Remote Sens. Environ.* 308, 114204. <https://doi.org/10.1016/j.rse.2024.114204>.
- Kim, J.-M., Kim, S.-W., Sohn, B.-J., Kim, H.-C., Lee, S.-M., Kwon, Y.-J., Shi, H., Pnyushkov, A.V., 2023. Estimation of summer pan-Arctic ice draft from satellite passive microwave observations. *Remote Sens. Environ.* 295, 113662. <https://doi.org/10.1016/j.rse.2023.113662>.
- Kim, K.Y., Haagenson, R., Kansara, P., Rajaram, H., Lakshmi, V., 2024. Augmenting daily MODIS LST with AIRS surface temperature retrievals to estimate ground temperature and permafrost extent in High Mountain Asia. *Remote Sens. Environ.* 305, 114075. <https://doi.org/10.1016/j.rse.2024.114075>.
- Komarov, A.S., Caya, A., Pogson, L., Buehner, M., 2024. Assimilation of RCM data in the Canadian ice concentration analysis system. *Remote Sens. Environ.* 306, 114113. <https://doi.org/10.1016/j.rse.2024.114113>.
- Koo, Y., Xie, H., Mahmoud, H., Iqrah, J.M., Ackley, S.F., 2023. Automated detection and tracking of medium-large icebergs from Sentinel-1 imagery using Google earth engine. *Remote Sens. Environ.* 296, 113731. <https://doi.org/10.1016/j.rse.2023.113731>.
- Lee, S., Stroeve, J., Webster, M., Fuchs, N., Perovich, D.K., 2024. Inter-comparison of melt pond products from optical satellite imagery. *Remote Sens. Environ.* 301, 113920. <https://doi.org/10.1016/j.rse.2023.113920>.
- Li, W., Lei, J., Shum, C.K., Li, F., Zhang, S., Shu, C., Chen, W., 2023. Unraveling contributions of Greenland's seasonal and transient crustal deformation during the past two decades. *Remote Sens. Environ.* 295, 113701. <https://doi.org/10.1016/j.rse.2023.113701>.
- Li, G., Chen, Z., Mao, Y., Yang, Z., Chen, X., Cheng, X., 2024. Different glacier surge patterns revealed by Sentinel-2 imagery derived quasi-monthly flow velocity at West Kunlun Shan, Karakoram, Hindu Kush and Pamir. *Remote Sens. Environ.* 311, 114298. <https://doi.org/10.1016/j.rse.2024.114298>.
- Qiu, J., Ran, J., Tangdamrongsub, N., Fettweis, X., Ali, S., Feng, W., Wan, X., 2025. Recent significant subseasonal fluctuations of supraglacial lakes on Greenland monitored by passive optical satellites. *Remote Sens. Environ.* 328, 114896. <https://doi.org/10.1016/j.rse.2025.114896>.
- Qu, M., Lei, R., Liu, Y., Li, N., 2024. Arctic Sea ice leads detected using sentinel-1B SAR image and their responses to atmosphere circulation and sea ice dynamics. *Remote Sens. Environ.* 308, 114193. <https://doi.org/10.1016/j.rse.2024.114193>.
- Ren, S., Yao, T., Yang, W., Miles, E.S., Zhao, H., Zhu, M., Li, S., 2024. Changes in glacier surface temperature across the third pole from 2000 to 2021. *Remote Sens. Environ.* 305, 114076. <https://doi.org/10.1016/j.rse.2024.114076>.
- Rogers, M.S.J., Fox, M., Fleming, A., van Zeeland, L., Wilkinson, J., Hosking, J.S., 2024. Sea ice detection using concurrent multispectral and synthetic aperture radar imagery. *Remote Sens. Environ.* 305, 114073. <https://doi.org/10.1016/j.rse.2024.114073>.
- Tang, Q., Zhang, G., Yao, T., Wieland, M., Liu, L., Kaushik, S., 2024. Automatic extraction of glacial lakes from Landsat imagery using deep learning across the third pole region. *Remote Sens. Environ.* 315, 114413. <https://doi.org/10.1016/j.rse.2024.114413>.
- Wang, Y., Sugiyama, S., 2024. Supraglacial lake evolution on Tracy and Heilprin glaciers in northwestern Greenland from 2014 to 2021. *Remote Sens. Environ.* 303, 114006. <https://doi.org/10.1016/j.rse.2024.114006>.
- Wang, Y., Zheng, D., Zhou, Y., Nian, Y., Ren, S., Ren, W., Zhu, Z., Tang, Z., Li, X., 2024. Glacier mass change and evolution of Petrov Lake in the Ak-Shyrak massif, central Tien Shan, from 1973 to 2023 using multisource satellite data. *Remote Sens. Environ.* 315, 114437. <https://doi.org/10.1016/j.rse.2024.114437>.
- Xiao, X., Liang, S., 2024. Assessment of snow cover mapping algorithms from Landsat surface reflectance data and application to automated snowline delineation. *Remote Sens. Environ.* 307, 114163. <https://doi.org/10.1016/j.rse.2024.114163>.
- Xie, F., Liu, S., Zhu, Y., Qing, X., Tan, S., Gao, Y., Qi, M., Yi, Y., Ye, H., Afzal, M.M., Zhang, X., Zhou, J., 2024. Retrieval of high-resolution melting-season albedo and its implications for the Karakoram anomaly. *Remote Sens. Environ.* 315, 114438. <https://doi.org/10.1016/j.rse.2024.114438>.
- Zhang, W., Yang, K., Smith, L.C., Wang, Y., van As, D., Noël, B., Lu, Y., Liu, J., 2023. Pan-Greenland mapping of supraglacial rivers, lakes, and water-filled crevasses in a cool summer (2018) and a warm summer (2019). *Remote Sens. Environ.* 297, 113781. <https://doi.org/10.1016/j.rse.2023.113781>.

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