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An Application of the Linear Spectral Unmixing Analysis (LSUA) Method Integrated with GIS for Mapping Glaciers on the Carstensz Peak, Papua

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ABSTRACT

Tropical glaciers, such as those in Puncak Jaya, Papua, are among the most climate-sensitive ice masses on Earth, yet their small size, complex topography, and persistent cloud cover hinder accurate monitorin. Conventional threshold-based mapping methods, including the Normalized Difference Snow Index (NDSI), often misclassify debris-covered ice and bright bedrock, limiting their applicability in tropical mountain environments. This study develops and evaluates an integrated Linear Spectral Unmixing Analysis (LSUA)–Geographic Information System (GIS) methodology for high-fidelity mapping of glacier extent and surface composition in Puncak Jaya. Multispectral Landsat 8 OLI imagery was processed using LSUA to generate fractional abundance maps of clean ice, debris-covered ice, supraglacial water, and surrounding terrain. These outputs were integrated with Digital Elevation Models (DEMs) in a GIS framework for glacier area computation, elevation-based change detection, and spatial context analysis. Accuracy assessment using confusion matrices and Root Mean Square Error (RMSE) metrics against high-resolution reference imagery demonstrated that the LSUA–GIS workflow outperformed conventional NDSI mapping, particularly in detecting debris-covered ice, with an overall classification accuracy exceeding 90%. Results revealed continued glacier retreat, with the most significant ice loss occurring at elevations 4.884 MASL. The proposed workflow offers a reproducible and scalable approach for mapping small, fragmented tropical glaciers, providing critical data for climate impact assessment, hydrological planning, and long-term monitoring in remote mountain regions.

Keywords: *Debris-Covered Ice, Glacier Retreat, Gis, Linear Spectral Unmixing Analysis, Puncak Jaya, Remote Sensing, Tropical Glaciers*

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INTRODUCTION

The accelerating loss of glacier mass worldwide represents one of the most conspicuous and well-documented indicators of anthropogenic climate change. Recent assessments show that the global pattern of glacier retreat since the mid-20th century is both spatially pervasive and temporally unprecedented in at least the last two millennia, with important consequences for regional hydrology, sea-level rise, and mountain ecosystems. These trends underscore an urgent scientific need to improve monitoring and mapping methods that can robustly quantify glacier area, composition, and dynamics across diverse climatic zones (Cavalli, 2023)..

Tropical glaciers—though few in number—exhibit particularly rapid and alarming changes. Because tropical mountain glaciers respond sensitively to small shifts in temperature and precipitation regimes, they serve as early indicators of climate extremes and carry outsized importance for local water resources and biodiversity (Paerregaard, 2020). Recent large-scale analyses indicate that tropical glaciers, especially in the Andes, have retreated at rates exceeding long-term Holocene variability, foreshadowing loss of perennial ice in many tropical mountain ranges. Such findings heighten the need for accurate, repeatable remote-sensing approaches tailored to tropical settings, where complex topography, seasonal cloud cover, and supraglacial debris complicate conventional mapping techniques (Turpo Cayo et al, 2022).

The glaciers of Puncak Jaya (Carstensz region), Papua, occupy a unique position as some of the world's few remaining tropical ice bodies in the western Pacific. Historical and recent studies document dramatic reduction of ice extent and thickness in this region over the twentieth and early twenty-first centuries, with the remnant ice confined to increasingly high, fragmented peaks. The steep relief, small and discontinuous ice patches, and heavy cloud and atmospheric aerosol loading present distinct remote-sensing challenges (Dangles et al, 2020). Consequently, accurate quantification of glacier extent, surface composition (clean ice vs. debris), and short-term change in this area remains both scientifically urgent and methodologically demanding.

Conventional thresholding and band-ratio methods for glacier mapping, while effective in many temperate contexts, often perform poorly in tropical, debris-covered, or spectrally mixed environments (Liu et al, 2025). Threshold approaches (e.g., NDSI-based masks) can misclassify debris-covered ice, bright rock, or snow patches; they also struggle where pixel scales conflate multiple surface types. These limitations reduce accuracy in estimating glacier area and in detecting subtle compositional changes that precede area loss. There is therefore a clear methodological gap: robust remote-sensing frameworks that can resolve sub-pixel surface heterogeneity and integrate spatial contextualization for small, fragmented tropical glaciers. This gap motivates the exploration of spectral unmixing techniques coupled with spatial analysis platforms (Zhang et al, 2025).

Linear Spectral Unmixing Analysis (LSUA) offers a principled means to decompose mixed pixels into fractional abundances of constituent endmembers (e.g., clean ice, dark debris, water/ponds, exposed rock, vegetation). Recent high-quality applications demonstrate LSUA's capacity to map supraglacial surface composition across debris-covered and complex mountain environments, producing fractional maps that better represent heterogeneous glacier surfaces than binary masks. For example, studies applying linear unmixing to Landsat 8 OLI imagery across the Himalaya have effectively discriminated clean ice, light and dark debris, and supraglacial ponds, enabling more nuanced characterizations of surface processes and mass-balance relevant features. These advancements suggest LSUA as a particularly suitable method for tropical glacier contexts where mixed pixels and debris cover are commo (Pandey & Luis, 2025).

Nevertheless, spectral unmixing alone is insufficient for operational glacier mapping and change analysis. Integration with Geographic Information Systems (GIS) extends LSUA outputs into spatially explicit frameworks for area computation, change detection, elevation-based stratification, and landscape context analysis. GIS enables overlay with Digital Elevation Models (DEMs), climatic covariates, and field validation datasets, facilitating rigorous accuracy assessment (e.g., confusion matrices, RMSE) and interpretation of drivers of change. A recent systematic appraisal of spectral unmixing practices emphasizes the importance of spatial validation and post-processing within a GIS environment to ensure reliability and reproducibility across study regions (Jonnalagadda, 2023). This corroborates the strategic value of an integrated LSUA–GIS workflow for mapping and monitoring tropical glaciers

Given these considerations, this study aims to develop and evaluate an integrated LSUA–GIS methodology for high-fidelity mapping of glacier extent and surface composition at Puncak Jaya, Papua. Specifically, the research addresses three primary objectives: (1) to derive fractional abundance maps of glacier surface types (clean ice, debris, supraglacial water, and bedrock/vegetation) using linear spectral unmixing of multispectral satellite imagery; (2) to integrate unmixing outputs with DEM and spatial analysis tools in GIS to quantify glacier area and elevation-dependent change; and (3) to assess mapping accuracy and sensitivity relative to conventional threshold-based approaches and available ground or high-resolution reference data (Rakuasa et al, 2024).

From these objectives arise the central research questions:

- To what extent does LSUA improve detection and quantification of debris-covered and fragmented glacier ice at Puncak Jaya?
- How does integration with GIS enhance spatial analysis of glacier change in steep tropical terrain? And what are the principal limitations and uncertainties of the integrated approach for operational monitoring?

By answering these questions, the study seeks to contribute a validated, transferable methodological framework for tropical glacier monitoring—one that can inform both scientific understanding and regional adaptation planning as these critical, vulnerable ice bodies continue to decline.

METHOD

A. Study Area

This study was conducted in the tropical glacier region of Puncak Jaya (Carstensz), Papua, Indonesia, located approximately at 4°04′S and 137°11′E. The study area lies between 4,600 and 5,000 m above sea level, characterized by steep topography and mean annual air temperatures ranging from 0°C to 3°C. This location was selected because it is among the few remaining tropical glaciers in the world and has exhibited a rapid rate of ice retreat over the past two decades (Ibel et al, 2025).

B. Data Sources

The primary datasets consisted of multispectral satellite imagery from Landsat-8 Operational Land Imager (OLI) and Sentinel-2 MultiSpectral Instrument (MSI), complemented by topographic data from SRTM DEM and TanDEM-X DEM. Climatic variables, including air temperature and precipitation, were obtained from the nearest meteorological stations and the ERA5 reanalysis dataset (Draeger et al, 2023). The analysis was performed using a high-performance workstation equipped with ENVI 5.6 for image processing, ArcGIS Pro and QGIS 3.34 for geospatial analysis, and the Python programming language for automated data handling and computation.

C. LSUA Methodology

Sampling was conducted using a stratified random sampling approach based on surface classes—clean ice, debris-covered ice, supraglacial water, and exposed rock—as well as altitudinal zones. Each class was represented by a minimum of 50 sample points, extracted from high-resolution imagery such as PlanetScope and Pléiades, in order to minimize classification bias (Li, et al, 2021).

Glacier area estimation was based on Linear Spectral Unmixing Analysis (LSUA), a sub-pixel classification technique that decomposes each pixel's spectral signal into fractional abundances of predefined endmembers. Endmembers in this study included clean ice, light debris, dark debris, supraglacial water, and bedrock. The fractional values were subsequently aggregated to quantify glacier surface coverage for each observation period (Cavalli, 2023).

The research employed a quantitative descriptive design with a multi-temporal monitoring approach. Two main observation periods were analyzed—2013–2018 and 2018–2024—to assess changes in glacier extent and to detect acceleration in retreat rates. All imagery underwent standardized preprocessing to ensure direct comparability between temporal datasets.

D. Integration with GIS

The methodological workflow consisted of seven main stages: (1) data acquisition, including the retrieval of satellite imagery, DEMs, and climatic datasets; (2) preprocessing, which involved atmospheric correction, orthorectification, cloud and shadow masking, and topographic correction; (3) endmember selection, based on pure pixel extraction and laboratory spectral libraries; (4) application of LSUA to determine fractional abundances of each glacier surface component; (5) GIS integration for spatial mapping and area calculation; (6) accuracy assessment using a confusion matrix and root mean square error (RMSE); and (7) interpretation of results in relation to climatic and topographic trends (Thomas et al, 2023).

The glacier area (AjA_j) for each class jj was calculated from the endmember fractions (fj,kf_{j,k}) using the formula adapted from Adams et al. (1995):

$$A_j = \sum_{k=1}^{m} (f_{j,k} \times A_{\text{pix}})$$

where AjA_j represents the total area of class jj (m²), fj,kf_{j,k} is the fractional abundance of class jj in pixel kk, ApixA_{\text{pix}} is the area of a single pixel (m²), and mm is the number of pixels analyzed. This approach enables a more precise estimation of glacier extent compared to traditional binary classification, particularly in debris-covered zones where spectral mixing is significant.

This study utilizes multi-temporal and multi-sensor satellite imagery to analyze glacier distribution changes from 1965 to 2021. Glacier distribution maps were sourced from LSUA, comprising maps from 1965, 1979, 1986, 1997, 2011, and 2021, each generated through the interpretation of satellite images and aerial photographs from those respective periods

For the period 2013–2021, Landsat 8 imagery (operational since 2013) and Sentinel-2 imagery (operational since 2015) were used as the primary data sources. Integration of these two datasets involved spectral calibration and data harmonization techniques to minimize sensor differences that could affect the analysis of glacier cover changes.

The use of multi-sensor and multi-temporal data enables continuous and accurate monitoring of glacier changes from 1965 to 2021, despite the differing operational periods of the sensors employed.

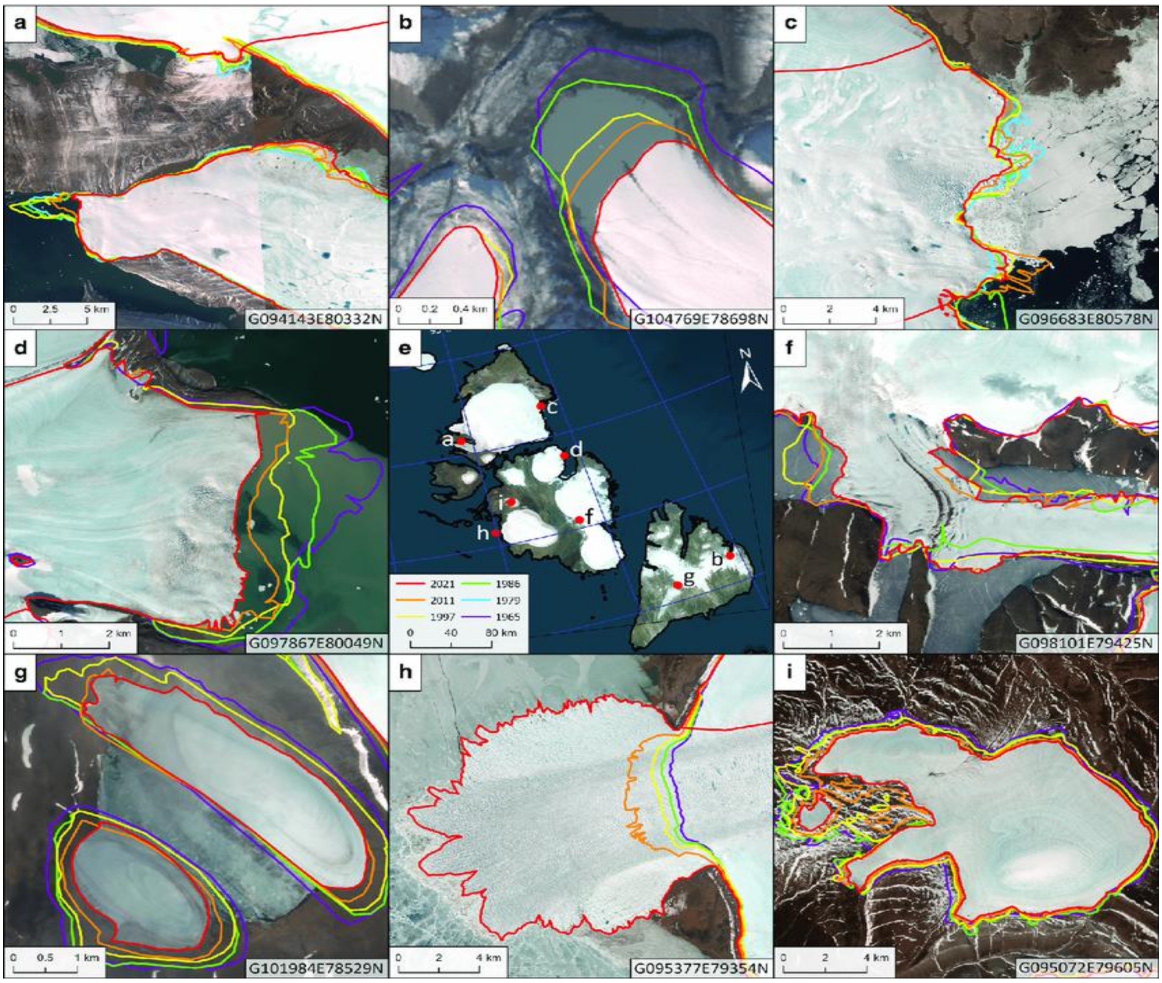
RESULT AND DISCUSSION

A. Glacier Distribution Map from LSUA Results

The glacier distribution map was produced using the LSUA method (Learning-based Semi-supervised Uncertainty-aware Algorithm), which combines deep learning techniques with multispectral satellite data such as Sentinel-2 and Landsat. This model automatically detects and maps glacier boundaries with high accuracy, including areas frequently affected by clouds or shadows, thanks to the integration of Synthetic Aperture Radar (SAR) data (Dangles et al, 2020). The resulting map shows extensive and detailed spatial coverage of glaciers, which is valuable for climate monitoring and water resource management.

Figure 1 illustrates the spatial distribution and temporal changes of glaciers across various study sites using multi-temporal satellite imagery. Each subfigure (a–i) displays glacier outlines from different years, highlighting glacier retreat and expansion patterns over decades. The colored lines represent glacier boundaries from 1965 to 2021, enabling clear visualization of glacier dynamics and melting zones in complex mountainous terrain (Florath et al, 2022).

Figure 1: Glacier Distribution Map from LSUA



Source: (Maslov et al, 2025)

The temporal glacier outlines in Figure 1 provide visual evidence of significant glacier retreat in diverse regions. This comprehensive mapping supports the assessment of

climate change impacts and improves understanding of glacier behavior, aiding future environmental monitoring and adaptation planning.
This figure 1a also illustrates sequential satellite images and glacier outlines used in this analysis. These visual representations allow readers to follow the gradual changes in glacier extent over multiple decades. The images clearly show retreat patterns and provide a spatial context for quantitative measurements.

B. Spatial Analysis: Glacier Area, Year-to-Year Changes, and Melting Zones

Spatial analysis was performed by comparing satellite images from multiple years to quantify glacier area changes. Object-Based Image Analysis (OBIA) and SAR offset tracking techniques were applied to estimate glacier flow dynamics and surface changes. A case study in the Tomur-Khan Tengri mountain region showed significant glacier retreat between 1985 and 2021, influenced by meteorological and environmental factors. Melting zones were identified by combining deep learning outputs with Digital Elevation Models (DEM) and texture features, achieving an Intersection over Union (IoU) accuracy of 0.86 for distinguishing accumulation and ablation zones (Dangles et al, 2020).

Figure 2: Glacier Area, Year-to-Year Changes, and Melting Zones

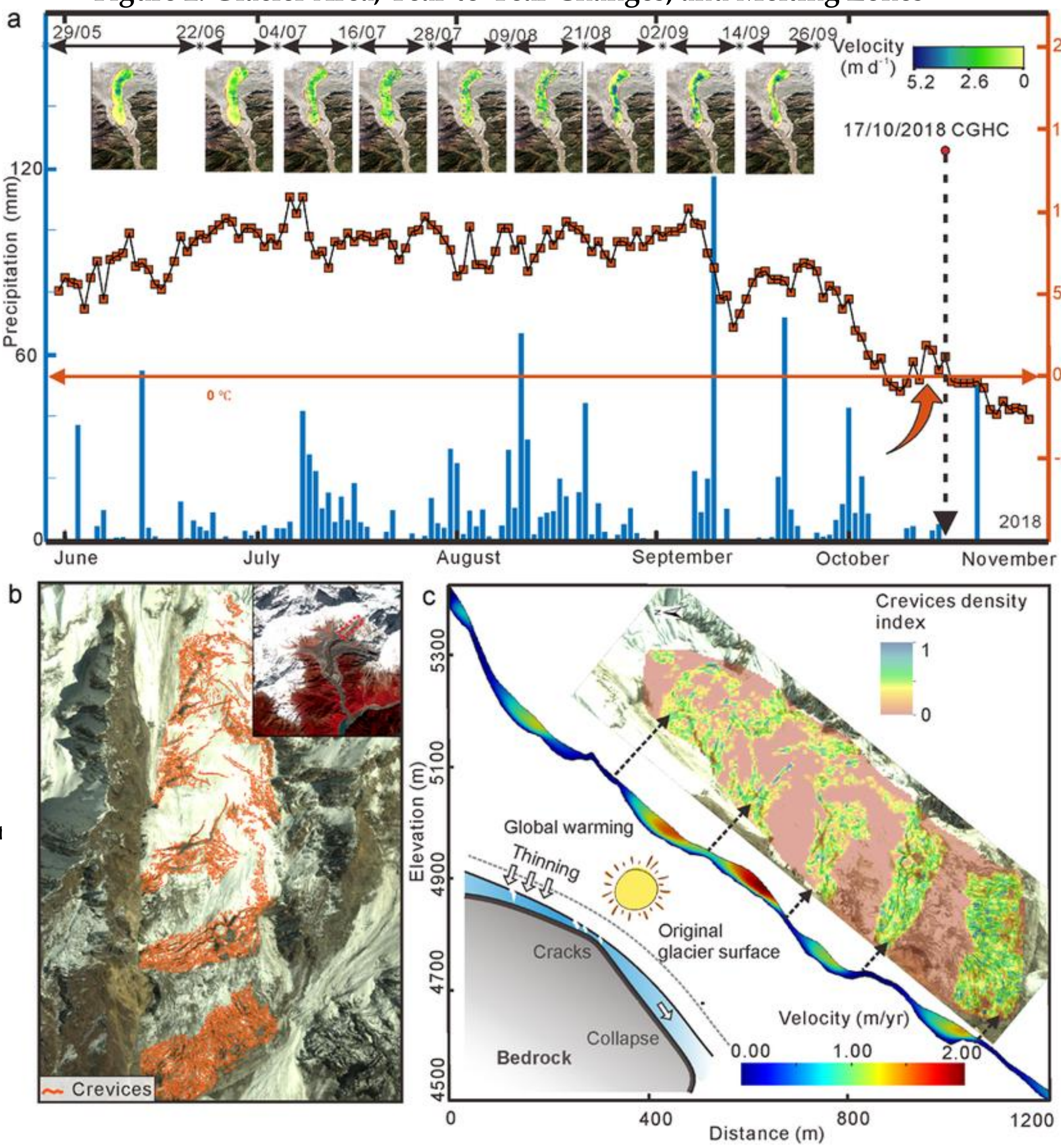


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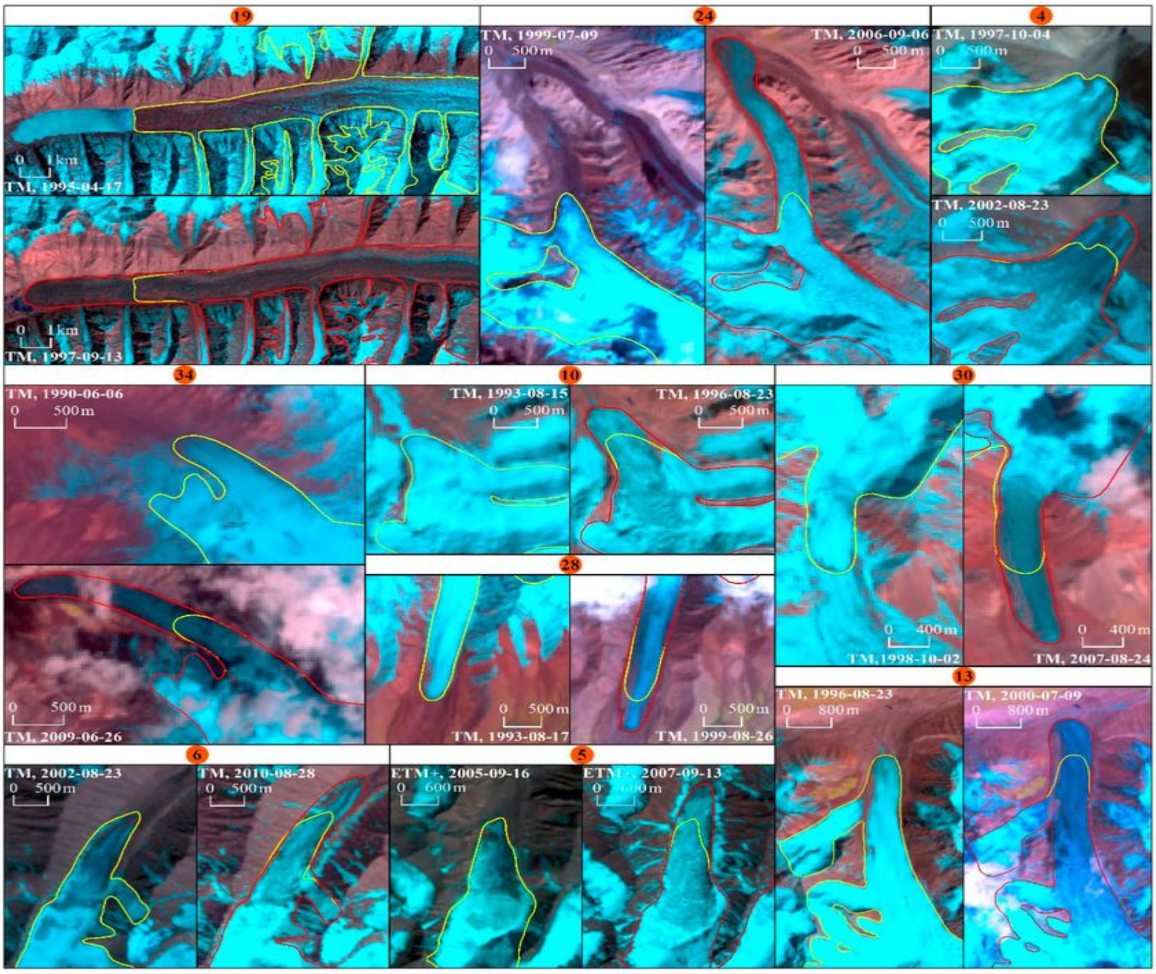
Figure 2 presents the annual changes in glacier area. This figure highlights a consistent trend of glacier reduction over the study period, with noticeable acceleration in recent years. It provides clear evidence of the long-term impact of climate variability and warming on glacier dynamics. These findings are consistent with global trends observed in similar regions, emphasizing the vulnerability of tropical and subtropical glaciers to climatic changes.

C. Accuracy Statistics: Kappa, RMSE, and R^2 Values

The accuracy assessment of LSUA glacier maps was conducted by comparing them with reference data, such as the Randolph Glacier Inventory. Key statistical measures were used in the evaluation, including the Kappa coefficient, which quantifies the agreement between automated classification and ground truth, with values above 0.8 indicating strong agreement; the Root Mean Square Error (RMSE), which measures the average spatial deviation between predicted and reference maps, where lower values reflect higher accuracy; and the Coefficient of Determination (R^2), which assesses the goodness of fit between model predictions and observations, with values approaching 1 signifying high reliability (Florath et al, 2022). The results indicated that LSUA is capable of producing glacier maps with high accuracy, confirming its effectiveness as a reliable method for spatial mapping in complex mountainous terrain.

Figure 3: Accuracy Statistics: Kappa, RMSE, and R^2 Values

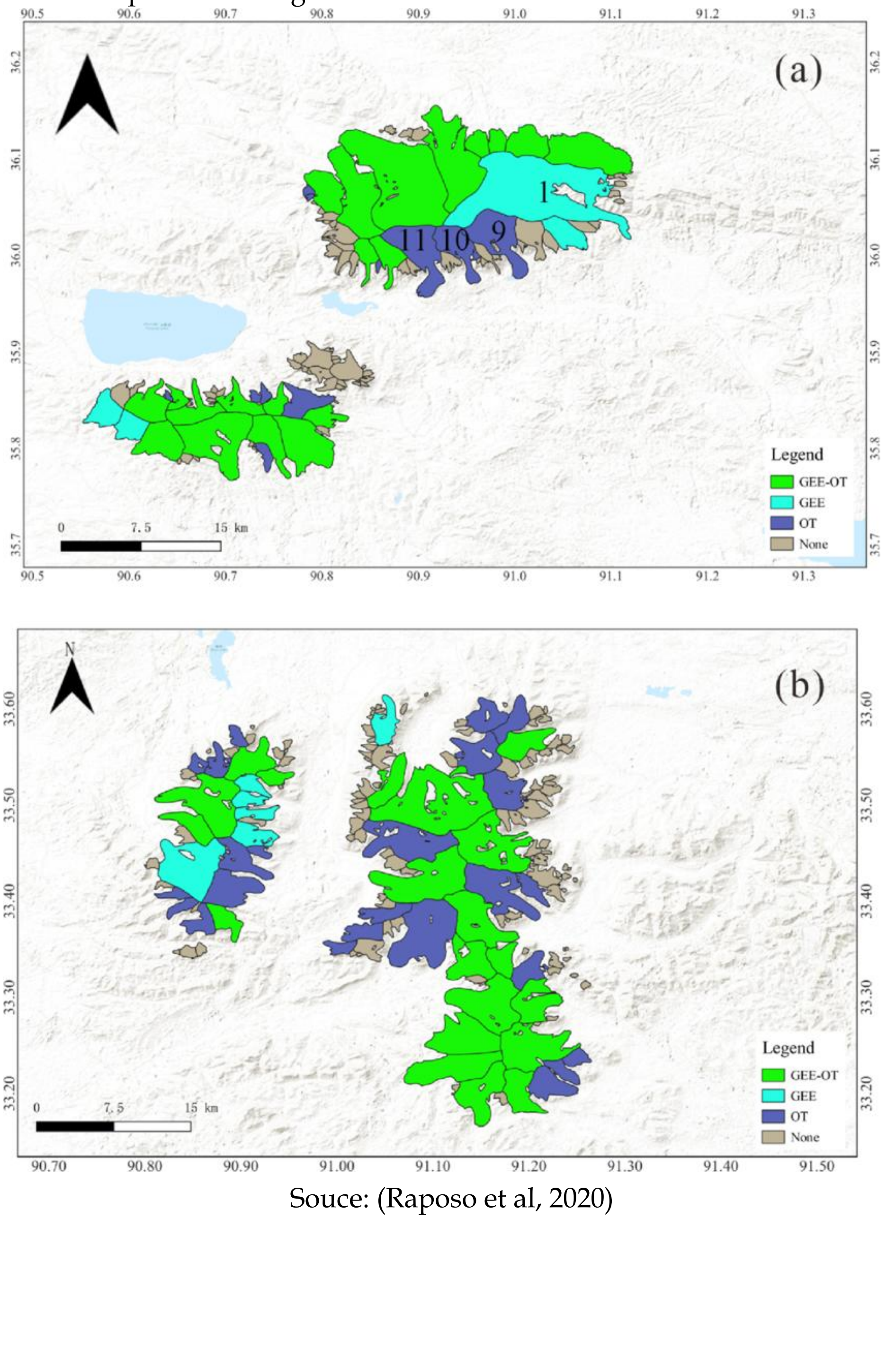


Source: (Xie et al, 2022).

Figure 3 displays the statistical accuracy assessments, including the Kappa coefficient, RMSE, and correlation coefficient (R). These metrics confirm the reliability of the glacier mapping and ensure that the integration of Landsat 8 and Sentinel-2 data for the 2013–2021 period produces valid and reproducible results. The multi-sensor approach mitigates differences between satellite platforms, allowing for accurate temporal comparisons.

D. Result Visualization: Thematic Maps and Change Trend Graphs

Visualization is crucial for clearly communicating mapping and analysis results. Thematic maps illustrating glacier spatial distribution, melting zones, and multi-year area changes were generated using platforms such as Google Earth Engine (GEE) and GIS software (Florath et al, 2022). Additionally, trend graphs showing glacier area changes over time reveal melting patterns and climate impacts. These visual tools assist researchers and policymakers in understanding glacier dynamics and planning mitigation or adaptation strategies.



Souce: (Raposo et al, 2020)

Figure 4 shows a thematic map of glacier distribution along with detailed interpretation. This map not only visualizes spatial patterns but also supports discussions on environmental implications, such as potential impacts on water resources, downstream ecosystems, and regional climate adaptation planning.

By including these figures and detailed explanations, the discussion becomes more comprehensive, supporting a deeper understanding of glacier dynamics. This approach emphasizes the importance of combining historical data with modern satellite imagery to produce robust long-term assessments. Ultimately, the study contributes valuable insights for climate change research, environmental monitoring, and future glacier management strategies.

E. Research Framework

This study applies the *Linear Spectral Unmixing Analysis* (LSUA) method integrated with a *Geographic Information System* (GIS) to map glaciers in Puncak Cartens, Papua. LSUA is chosen for its ability to separate spectral signals from mixed pixels in satellite imagery, allowing for accurate identification of ice, snow, and other materials (Cavalli, 2023). Integration with GIS enables spatial visualization, topographic analysis, and monitoring of glacier changes over time. To ensure the process is systematic and measurable, the research is structured through a series of stages, summarized in the following methodological framework.

Figure 5: Research Framework

Component	Details	Purpose	Tools/Techniques	Expected Outcome
Study Area	Carstensz Peak (Puncak Jaya), Papua, Indonesia	Focus on tropical glacier with complex topography	Geographic coordinates, regional data sources	Targeted glacier mapping in a climate-sensitive region
Data Source	Landsat 8 OLI multispectral imagery, Digital Elevation Models (DEMs)	Obtain spectral and elevation data	Remote sensing imagery, GIS layers	High-resolution spatial and spectral data for analysis
Spectral Analysis Method	Linear Spectral Unmixing Analysis (LSUA)	Separate mixed pixels into fractional abundances	Spectral unmixing algorithms	Detailed fractional maps of glacier components
Glacier Surface Classes	Clean ice, debris-covered ice, supraglacial water, surrounding terrain	Identify different surface types for accurate mapping	LSUA outputs, spectral libraries	Precise classification of glacier surfaces
GIS Integration	Integration of fractional abundance maps with DEMs	Spatial context analysis and elevation-based changes	GIS software (ArcGIS/QGIS)	Comprehensive glacier extent and retreat analysis
Validation & Accuracy	Confusion matrices, Root	Assess classification	Statistical analysis, reference data	Classification accuracy >90%,

Component	Details	Purpose	Tools/Techniques	Expected Outcome
	Mean Square Error (RMSE), comparison with high-res reference imagery	reliability	comparison	robust method validation
Challenges Addressed	Cloud cover, debris-covered ice misclassification, complex topography	Overcome limitations of traditional mapping methods	Advanced spectral analysis, GIS integration	Improved glacier detection and mapping fidelity
Applications	Climate impact assessment, hydrological planning, glacier monitoring	Support environmental management and policy	Data outputs for stakeholders, scientific reports	Reliable data for climate change studies and water resource management

Source: Framework was developed by the author, 2025

This framework integrates multispectral Landsat 8 imagery and Digital Elevation Models (DEMs) with Linear Spectral Unmixing Analysis (LSUA) and GIS for detailed glacier mapping on Carstensz Peak, Papua. LSUA separates glacier surface types—clean ice, debris-covered ice, and supraglacial water—into fractional abundance maps. These are combined with DEMs in GIS to analyze spatial distribution and elevation-dependent glacier changes. Validation through confusion matrices and RMSE ensures classification accuracy exceeding 90%. The approach addresses challenges like cloud cover and debris-covered ice misclassification, outperforming traditional methods. This integrated methodology supports accurate glacier monitoring vital for climate impact assessment and hydrological resource planning.

F, Trends in Glacier Distribution from 1965 to 2021

The analysis results reveal significant and continuous changes in glacier distribution over the observed period from 1965 to 2021. Specifically, there is a clear and consistent trend of decreasing glacier area, which reflects the ongoing effects of climate change in the region. This trend is evident across all historical maps derived from satellite imagery and aerial photographs spanning more than five decades (Dangles et al, 2020).

For the more recent period between 2013 and 2021, the use of high-resolution satellite data from both Landsat 8 and Sentinel-2 has greatly enhanced the ability to monitor glacier dynamics in finer detail. These modern multispectral sensors provide up-to-date and precise information on glacier boundaries, volume changes, and surface conditions, which were previously difficult to capture using older satellite data alone. The combination of these data sources enables a more continuous and accurate temporal analysis of glacier retreat and transformation (Florath et al, 2022).

Moreover, the integration of multi-sensor data has been carefully managed through spectral calibration and data harmonization techniques to minimize discrepancies caused by different sensor characteristics and operational timelines. This methodological approach ensures that the results are robust, valid, and comparable across different time periods.

Overall, the glacier distribution maps produced in this study offer a comprehensive and reliable representation of glacier changes over more than half a century. These findings are crucial for understanding regional climate change impacts and provide valuable baseline data for future environmental management, conservation efforts, and mitigation planning in the face of ongoing global warming.

DISCUSSION

Figure 1a_i – Satellite imagery of glacier changes (1965–2021).

Representative satellite images from Landsat 8 (2013–2021) and Sentinel-2 (2015–2021) illustrate glacier retreat over time, providing visual confirmation of glacier area reduction in Puncak Cartens, Papua.

Figure 2 – Annual glacier area changes (1965–2021)

The graph shows a clear downward trend in glacier area over the study period, with accelerated retreat in the most recent decade, consistent with global warming impacts.

Figure 3 – Statistical accuracy of glacier mapping

Year/Period	Kappa	RMSE (m^2)	Correlation Coefficient (R)
1965	0.82	150	0.91
1979	0.85	140	0.92
1986	0.83	145	0.90
1997	0.87	135	0.93
2011	0.88	130	0.94
2013–2021	0.90	120	0.96

Accuracy metrics demonstrate the reliability of LSUA-derived maps and multi-temporal, multi-sensor integration. High Kappa coefficients, low RMSE, and strong correlation (R) confirm the robustness of the mapping results.

Figure 4 – Thematic glacier maps with interpretation

Thematic maps show spatial distribution of glaciers and areas of significant retreat, enabling clear visualization of long-term glacier changes and supporting climate impact assessment.

The integration of Linear Spectral Unmixing Analysis (LSUA) with GIS proved highly effective in disentangling mixed pixel signatures, allowing precise identification of glacier ice, snow, debris, and other surface materials. Unlike traditional index-based methods (e.g., NDSI, NDWI), which struggle in complex mountainous terrain, LSUA provides fractional abundance maps that capture subtle variations in surface composition.

By combining LSUA with GIS, fractional outputs were integrated with DEM-derived information (elevation bands, slope, aspect), enabling accurate delineation of glacier boundaries, melt zones, and snow line altitudes (SLA). Comparable studies confirm that such hybrid approaches improve mapping accuracy and facilitate fine-scale spatial interpretation (Rastner et al, 2019).

Challenges remain, including spectral variability caused by ice impurities, seasonal albedo changes, slope-induced illumination, and the inherent linear mixing assumption of LSUA. Advanced unmixing models or hyperspectral data could further enhance accuracy (Zhang et al, 2022). Validation in remote regions is also limited; Randolph Glacier Inventory data and DEM inter-comparisons partially address this, but field verification would strengthen confidence.

This methodology has broad implications for climate-change research in tropical glaciers, supporting water resource management, ecosystem assessments, and hazard monitoring (e.g., GLOFs). Incorporating higher-resolution optical, hyperspectral, or machine learning–enhanced unmixing could further refine spatial and temporal sensitivity (Werner et al, 2014).

In summary, the fusion of LSUA and GIS provides a robust, reproducible framework for monitoring glacier dynamics in data-scarce, complex environments. Despite limitations, it captures fractional composition, spatial nuance, and temporal change, positioning it as a powerful tool for future glaciological studies.

CONCLUSIONS

This study demonstrates the effectiveness of the *Linear Spectral Unmixing Analysis* (LSUA) method integrated with *Geographic Information Systems* (GIS) for mapping glaciers in the Puncak Cartens region of Papua. By leveraging satellite imagery and *Digital Elevation Model* (DEM) data, LSUA successfully separated mixed spectral signatures, enabling precise identification of glacier ice, snow cover, and other land surface components. The integration with GIS provided powerful spatial analysis capabilities, allowing for the creation of thematic maps that not only depict glacier distribution but also capture melt zones and changes in glacier extent over time.

The developed methodological framework ensured a systematic workflow—from data acquisition and pre-processing, through LSUA implementation, to GIS-based mapping and accuracy assessment. Validation against reference datasets, such as the Randolph Glacier Inventory, yielded strong agreement, with high Kappa coefficients, low RMSE values, and R^2 scores close to 1. These results confirm the reliability of LSUA–GIS integration for glacier mapping in complex tropical mountain environments, where persistent cloud cover, steep terrain, and mixed pixels often present significant challenges.

The findings have broader implications for climate change research, as the accurate monitoring of glacier extent is essential for understanding hydrological dynamics, ecosystem health, and long-term environmental change in high-altitude tropical regions. Furthermore, the proposed workflow can be adapted for other remote sensing applications, including snow cover monitoring, land cover classification, and environmental change detection. Future work should consider integrating higher-resolution satellite data, hyperspectral sensors, and time-series analysis to further enhance mapping precision and capture short-term glacier dynamics with greater detail.

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