

Article

Annual Variability in the Cordillera Blanca Snow Accumulation Area Between 1988 and 2023 Using a Cloud Processing Platform

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Abstract: Tropical glaciers are highly sensitive to climate change, with their mass balance influenced by temperature and precipitation, which affects the accumulation area. In this study, we developed an open-source tool to map the accumulation area of glaciers in the Cordillera Blanca, Peru (1988–2023), using Landsat images, spectral indices, and the Otsu method. We analyzed trends and correlations between snow accumulation area, meteorological patterns from ERA5 data, and oscillation modes. The results were validated using field data and manual mapping. Greater discrepancies were observed in glaciers with debris cover or small clean glaciers (<1 km²). The Amazonian and Pacific sectors showed a significant trend in decreasing accumulation areas, with reductions of 8.99% and 10.24%, respectively, from 1988–1999 to 2010–2023. El Niño events showed higher correlations with snow accumulation, snowfall, and temperature during the wet season, indicating a stronger influence on the Pacific sector. The accumulation area was strongly anti-correlated with temperature and correlated with snowfall in both sectors at a 95% confidence level ($\alpha = 0.05$). The highest correlations with meteorological parameters were observed during the dry season, suggesting that even minor changes in temperature or precipitation could significantly impact the accumulation area.

Keywords: El Niño—ENSO; glacial facies; tropical glaciers; climate change; Landsat

1. Introduction

Global climate change has intensified in recent decades, driven by increased greenhouse gas emissions from human activities [1]. In response, glaciers have been shrinking and losing volume at an accelerated pace [2]. Tropical glaciers are particularly sensitive to slight changes in climate, notably temperature changes [3]. Due to their location at low latitudes and particular climatic conditions [4,5], they react more rapidly to climatic changes [6]. High-altitude regions experience a more prominent increase in atmospheric temperature, especially in the Andean region (Ecuador, Peru, Bolivia, and northern Chile) [7]. Given

the acceleration of these changes in recent decades (since the middle of the 20th century), monitoring Andean glaciers is relevant for understanding the responses of tropical glaciers to climate change [8].

The Peruvian Andes have experienced accelerated glacier changes since the 1970s. Approximately 71% of the tropical glaciers lie in Peru, with the Cordillera Blanca (CB) exhibiting the largest glacierized area (527 km² in the 2000s) [9]. Glaciers in this cordillera are commonly small (<1 km²) [10] and are therefore overly sensitive to climate change [11]. Since 1930, CB glaciers have lost 46% of their glacial cover, with alternating periods of high retreat from 1930 to 1940 [12], followed by a slower retreat in the 1950s–1970s [13] and again a generalized retreat since the 1970s [10,14]. There was a particular increase in shrinkage rates between 2013 and 2016, with 177 CB glaciers disappearing [15], associated with El Niño oscillations [15]. South-facing glaciers with lower median elevations experience higher mass loss [15,16].

These climate-induced glacier changes impact water resources for downstream communities that depend on runoff from glacierized basins [4,17–20], with water discharge decreases ranging from 2% to 30%, depending on the basin [19]. Some studies have documented the substantial impact of such changes on the lives of local populations through interviews [17]. Water stress can lead to governance problems and enhance water competition in glacierized basins [20], further impacting local livelihoods. Furthermore, glacier retreat favors the growth of proglacial lakes and the risk of Glacier Lake Outburst Floods (GLOF) [21] (approximately 6.3% of the lakes are considered highly susceptible to a GLOF event [21]).

While recent studies have improved the understanding of glacier area changes and mass balance in the Andes, the relationship between climate variables and ablation patterns at interannual scales remains poorly understood. Vuille et al. (2003) showed that in the Peruvian Andes, ablation is primarily controlled by interannual variations in air temperature and humidity [22], which in turn determine the position of the snow line altitude (the line separating the ablation and accumulation area of glaciers). It is essential to understand how glacier surface facies, particularly the accumulation areas, fluctuate and determine the glacier mass balance [23], which, in turn, is an indicator of the interplay between glaciers and climate [4].

Semi-automated methods based on band ratios (simple band ratios or Normalized Difference Snow Index, NDSI) have been used to map clean ice glacier surfaces [24]. These methods have been applied to imagery from the Système Pour l’Observation de la Terre (SPOT), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), and the Landsat series, which are widely used for glacial inventories such as the Randolph Glacier Inventory RGI 7.0 (RGI) [25]. The NDSI uses spectral bands that respond differently to various observation targets [26]—the green and short-wave infrared (SWIR) bands—to differentiate between snow and ice from clouds and ice-free areas. This is based on the principle that snow and ice exhibit higher reflectance in the visible spectrum [10] and low reflectance in the electromagnetic spectrum range of 1.57 to 1.78 µm, which corresponds to the SWIR (band 5 in the Landsat TM and 6 in the OLI), while targets such as clouds exhibit significantly higher reflectance in the SWIR bands [10,27]. These semi-automated remote sensing methods are fast and reliable. Still, they are subject to classification errors owing to seasonal snow cover and the presence of debris cover [28], which cannot be effectively detected by these methods. Mountain glaciers located in steep terrain, including in CB, exhibit supraglacial coverage in their ablation areas owing to the erosive processes from surrounding slopes, which provide a large amount of debris through rockfall and avalanches [29].

However, systematically separating the accumulation and ablation remains a major challenge once the glacierized area has been delineated using automated methods. Glaciers' ablation and accumulation areas consist of various glacier facies, including ice and snow facies—specifically wet-snow, percolation, and dry-snow facies. In optical remote sensing, these facies can be distinguished using the snow grain size [30], but this approach is not frequently used. The presence of fresh snow, superimposed ice, and superficial melting complicates the distinction of different glacier facies [31] in optical imagery. Radar remote sensing allows for better identification of glacier zones, even in cloudy seasons [32]. In this study, we used the Otsu method [33] to identify the entire accumulation area of glaciers, with no distinction within the separate zones within it.

Previous studies have relied on the Otsu method to separate glacier facies. This is an unsupervised and non-parametric method in which a threshold is defined to discriminate between two classes with different gray levels [33]. This method helps to identify the bimodality of a class and allows for dividing between gray tones based on a histogram of a feature [33]. This method has already been applied to differentiate between wet snow and ice and to delineate snowlines in Landsat images with promising results for the Chandra basin (Western Himalaya) [34].

This study takes advantage of the Otsu method and the GEE platform and presents an algorithm for identifying the snow accumulation area from 1988 to 2023 for the Landsat series for (a) the automation of image processing using open-access data for the CB to obtain the interannual fluctuations in glacial accumulation and their related factors; (b) the investigation of the annual variation in glaciers facing the Amazon (eastern) sector and the Pacific Ocean (western) sector; and (c) its responses to the climatic parameters and the behavior of El Niño South Oscillation (ENSO) and Pacific Decadal Oscillation (PDO). The method is open source, allowing for the monitoring of glacial facies in the region to have temporal continuity.

2. Materials and Methods

2.1. Study Area

The CB ($8^{\circ}12' - 10^{\circ}01' \text{ S}$) is a subcordillera of the Andes located in Peru in the department of Ancash (Figure 1). This area has the highest concentration of glacial area in the tropical region; according to the MapBiomass Peru, the area of CB in 2020 was 453.21 km² [35], representing 32.17% of all tropical glaciers for the Andes in 2020.

Climatically, CB lies in the outer tropics, characterized by a dry season (May to August/September) and a wet season (October to April) [36], where the Intertropical Convergence Zone (ITCZ) controls the variation in humidity rates [11]. In this region, the mass balance of glaciers is closely related to the total amount and annual distribution of precipitation (December to February) [37]. At high elevations, precipitation is more abundant [38]. The intensity and pattern of the ITCZ, together with ENSO, influence temperature and precipitation on an interannual scale in the CB [39]. Most of the moisture in the CB originates from the Amazon Basin [40].

During the dry season, the ITCZ does not transport this moisture to the CB region, instead, it shifts towards the Northern Hemisphere [11]. In this season, turbulent fluxes play a significant role in the mass balance of small glaciers [40]. During the wet season, precipitation can occur even in the highest elevations and in the leeward areas of the CB. Thus, both the oscillation of the ITCZ and local topographical conditions influence the regional distribution of precipitation [11]. Accumulation primarily occurs during the wet period, while ablation continues year-round, with reduced ablation during the dry period [36,41].

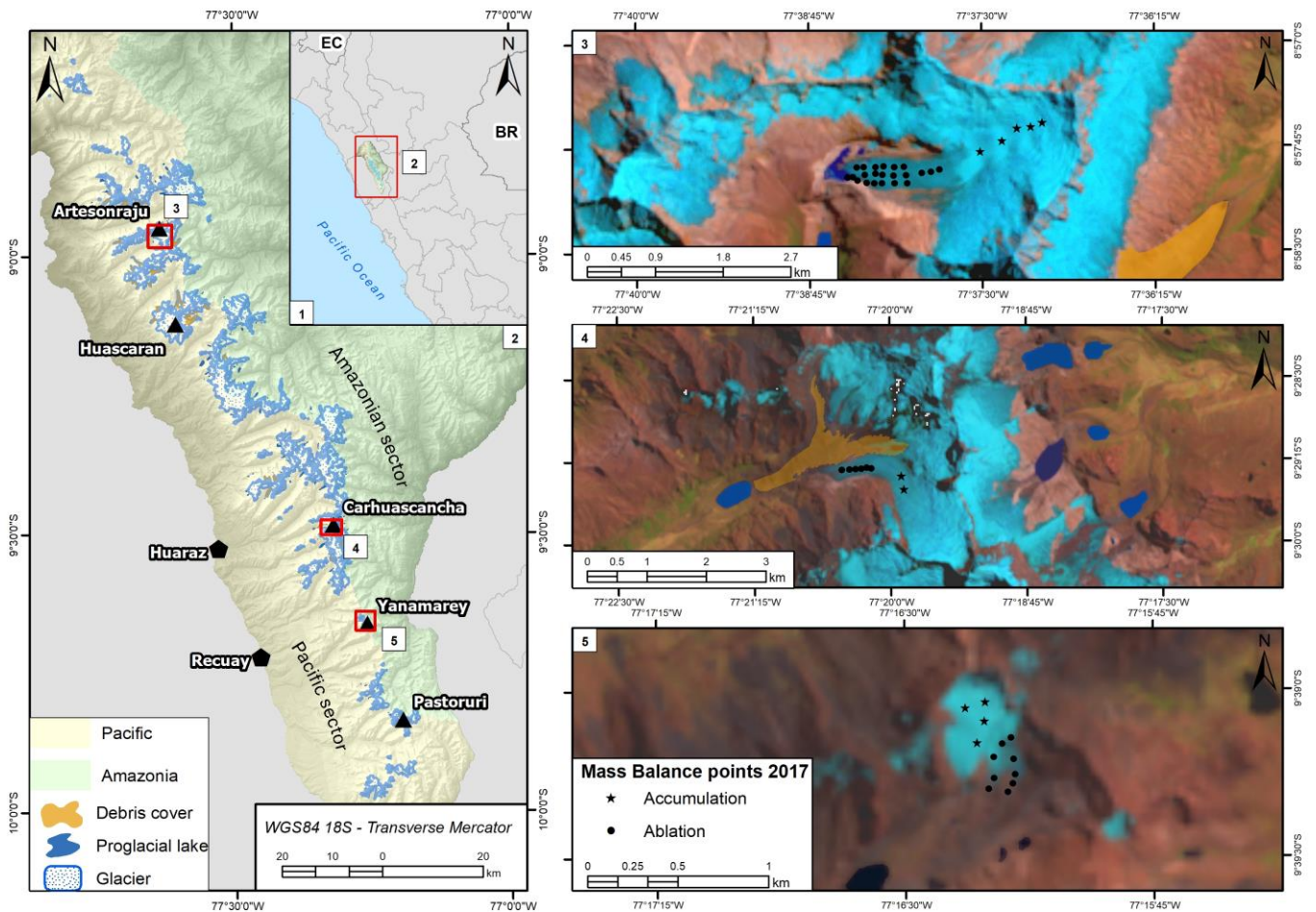


Figure 1. Cordillera Blanca study area (2) with emphasis on the glaciers Artesonraju (3), Shallap (4), and Yanamarey with mass balance stakes from Autoridad Nacional del Agua. Landsat image from 22 August 2023 (false-color composite). The debris cover outlines from 2003 represented in the map are from Global Land Ice Measurements from Space, the Amazon and Pacific drainage are from Autoridad Nacional del Agua, and the digital elevation model is from the NASA Shuttle Radar Topography Mission.

In the CB, an increase in air temperature of approximately $0.31\text{ }^{\circ}\text{C}$ per decade was observed between 1969 and 1998, followed by a slowdown in the warming trend during the period 1983–2012, although a general warming trend of $0.13\text{ }^{\circ}\text{C}$ per decade persisted [38]. A rise in the daily minimum temperatures primarily drove this warming [38]. Additionally, an increase in precipitation of approximately 60 mm per decade was recorded from 1980 to 2012 [38].

Previous studies have indicated a warming trend of $0.2\text{--}0.3\text{ }^{\circ}\text{C}/\text{decade}$ for the Amazonian region [42]. Future scenarios for the biogeographic region of the Amazon rainforest indicate a 44% decrease in average annual rainfall and a 69% increase in dry season length by 2100 [43]. For the western side of the CB in the Santa River Basin, there was an increase of $2\text{ }^{\circ}\text{C}$ compared to pre-industrial levels under the RCP2.6 scenario, while the RCP8.5 scenario suggests a $3\text{ }^{\circ}\text{C}$ rise by 2050 [44].

2.2. Data

2.2.1. Satellite Images

We used 130 optical satellite images from the Landsat series at 30 m (Landsat 5 TM and Landsat 8 OLI) complemented with PlanetScope data (3 m) covering the study area

between 1988 and 2023 (see Table 1, Figure 2, and Supplementary Materials). We did not use Landsat ETM+ because of the stripes. The data processed using GEE are listed in Table 1.

Landsat images are acquired every 16 days, and for this study, we selected annual images with low cloud cover ($\leq 45\%$) that were preferably captured during drier weather conditions. This approach aimed to avoid the refreezing of supraglacial water and ice and/or fresh seasonal snow outside the glacier ablation zone.

Table 1. Data collection was performed using GEE.

Collection Name	GEE Image Collection ID	Analysis Period	Spatial Resolution
Landsat 5	LANDSAT/LT05/C01/T1_L2	1 April 1988–31 August 2011	30 m
Landsat 8	LANDSAT/LC08/C01/T1_L2	1 April 2013–31 August 2023	30 m
ERA5—Monthly	ECMWF/ERA5_LAND/MONTHLY_AGGR	1 April 1988–31 August 2023	~1.1 km
ERA5—Daily	ECMWF/ERA5_LAND/DAILY_AGGR	1 April 1988–31 August 2023	~1.1 km
NASA SRTM	USGS/SRTMGL1_003	11 February 2000	30 m

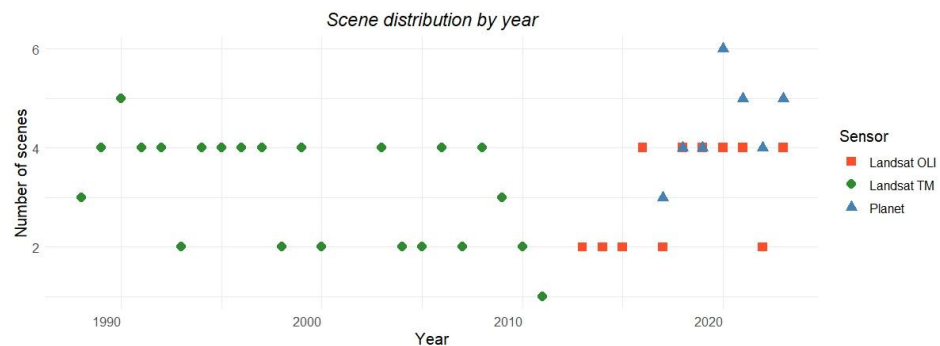


Figure 2. Yearly number of images and corresponding sensors analyzed for snow accumulation area assessment and product validation.

For this analysis, the CB was divided into two sectors—Pacific and Amazonian—based on the drainage divides provided by the Autoridad Nacional del Agua (ANA). Owing to the spatial extent of the Cordillera, at least two Landsat scenes (with a swath width of 185 km) were required each year to ensure full coverage. Consequently, the drainage divides from the RGI [25] were subdivided accordingly.

We used Landsat Level 2, Collection 2 Tier 1 images, which consist of calibrated scaled Digital Numbers (DN), providing orthorectified, atmospherically corrected data with a spatial resolution of 30 m [45]. These were not subjected to radiometric corrections. Two scenes per year were required to ensure total coverage of the study area. The period from May to August, which corresponds to the dry season in the outer tropics, is the time when the highest snow line altitude occurs [36], and the accumulation area with the minimum snow cover outside the glaciers is extracted. Within this time window, we applied filtered cloudy images and meteorological filtering using ERA5-Land, i.e., eliminating images for the dates of precipitation in the five days before acquisition. In addition, for the period 2017 to 2023, we obtained the PlanetScope Ortho Analytic Scene Product from the Planet Explorer website [46]. These have four spectral bands (464–888 nm) with a spatial resolution of 3 m and a frame size of 24 km × 16 km. For this research, we selected Level 3B analytic products that provide orthorectified, radiometrically, geometrically, and atmospherically corrected data. For elevation data, we used the NASA Shuttle Radar Topography Mission (SRTM) DEM (version 3) [47] to compute the slope gradient and orientation of the glaciers.

The total glacier area in the CB region from 1988 to 2022 was obtained annually from MapBiomass-Peru [48]. These data are presented until 2022 because of the unavailability of cover and land use maps for after 2022. The MapBiomass glacial coverage is based on the methodology proposed by Turpo et al. (2022), who used masks for cloud and shadow zones, NDSI, annual mosaics for the Landsat series, and annual glacier classification [35]. The results of the post-classification and accuracy verification provided for MapBiomass results indicate an omission error of the glacial area of 11.46%, and the commission error was 2.44% for the glacial coverage in the tropics [35]. The data are available on the MapBiomass sites through the cover and land use maps, which consist of rasters classifying their class (e.g., glacier, river, grazing, etc.).

2.2.2. Meteorological Parameters

We used ERA5 reanalysis data for air temperature 2 m above ground level, snowfall, and total precipitation. Although the data have a relatively coarse resolution (~1.1 km), there is a strong correlation between data from automatic weather stations installed on glaciers, such as Artesonraju, and reanalysis products from ERA5-Land, particularly for hourly T air ($r > 0.80$) in the outer tropics [49]. We extracted the climatic parameters for the Pacific and Atlantic hydrographic regions separately and clipped them for the CB area. We analyzed the ERA5 data for the wet and dry seasons [11]. The annual anomaly was used for correlations, and the monthly anomaly was used to analyze trends in the Mann–Kendall test at a 0.05 significance level.

Additionally, we obtained data from the El Niño 3.4 region (comprising portions of Niño regions 3 and 4, from 170° W to 120° W longitude) from the National Oceanic and Atmospheric Administration (NOAA) [50]. The central months were considered for temperature anomaly values. We used the classification from Servicio Nacional de Meteorología e Hidrología del Perú (SENAMHI) [51], i.e., El Niño events in zone 3.4 of the Pacific are defined as positive temperature oscillations above 0.5 °C, while La Niña events are defined as temperatures less than −0.5 °C, with the interval between the two being a neutral phase. Pacific Decadal Oscillation data were obtained from the ERSST PDO Index provided by the NOAA.

The annual and seasonal average values of El Niño 3.4, PDO, and meteorological variables were subjected to the Shapiro–Wilk test and presented p -values > 0.05 , indicating normality. The meteorological parameters and oscillation mode series were generated for the period 1987/88 to 2022/23, considering the start and end of the hydrological years. Climatic parameters (temperature, snowfall, and precipitation), the automated accumulation area, El Niño 3.4, and PDO data were correlated for each region (Amazonian and Pacific). Statistical significance was assessed using $\alpha = 0.05$ (95% confidence level).

2.3. Methods

2.3.1. Processing and Identification of the Snow Accumulation Area by Automatic Method in Google Earth Engine

This study presents a semi-automatic workflow for processing Landsat imagery using GEE to extract snow accumulation areas during the dry season across the entire CB for the period 1988–2023. Image processing refers to an approach that combines filtering steps, a cloud cover mask, other masking steps, spectral indices (NDVI and NDSI), snow patch classification, and the application of the Otsu method in the NIR band (Figure 3). The application of the Otsu band in the NIR band builds on the existing workflow processing, including the use of NDSI and the snow patches [52] and the implementation of the Otsu algorithm in the GEE [53].

The filtering steps included temporal, meteorological, and cloud cover filtering. The following steps included applying the NDSI index (Equation (1)) [27] with a threshold

of ≥ 0.15 , from which we excluded slopes $> 60^\circ$, vegetated areas, and proglacial lakes mapped using the Normalized Difference Vegetation Index (NDVI) (Equation (2)) [54] ($\text{NDVI} \geq -0.3$ to ≤ 0), as performed by others [55]. The drainage divides of the RGI were used as the limit of the extent for extracting the entire glacier area.

$$\text{NDSI} = \frac{(\text{Green} + \text{SWIR})}{(\text{Green} - \text{SWIR})} \quad (1)$$

$$\text{NDVI} = \frac{(\text{NIR} + \text{Red})}{(\text{NIR} - \text{Red})} \quad (2)$$

Subsequently, based on the mapping of glacier facies, the snow accumulation areas were automatically distinguished from other glacier facies using the Otsu method. As previously performed, a global threshold for the Otsu method was established to identify snow accumulation zones [52].

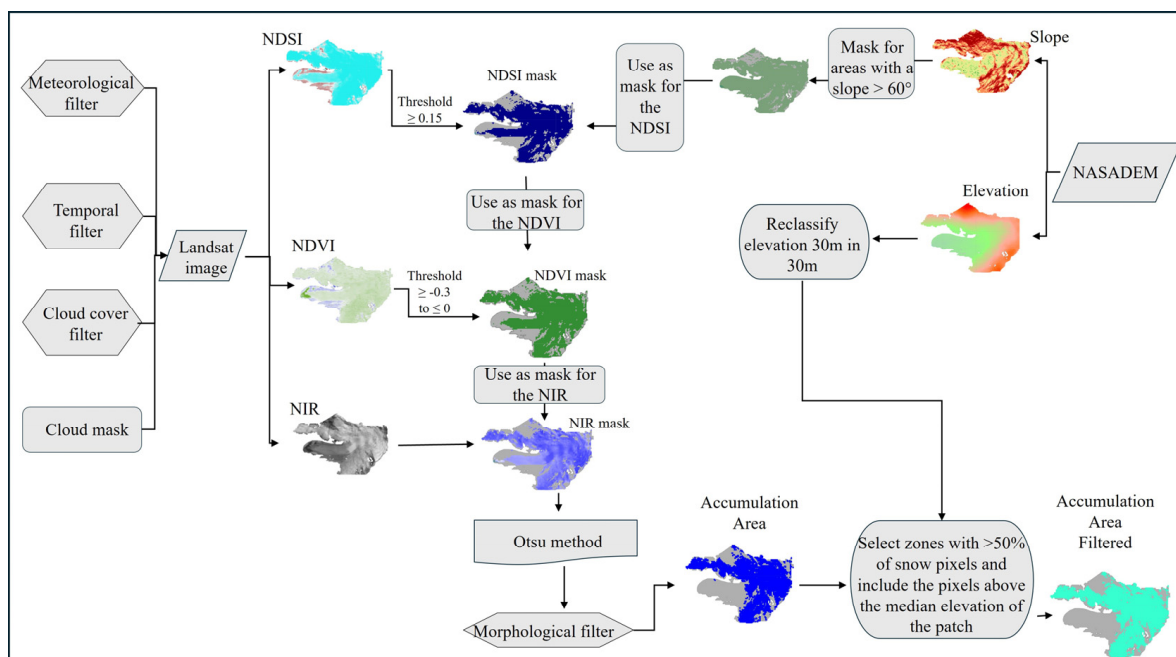


Figure 3. Methodological steps for snow-covered area calculation in Google Earth Engine.

Morphological filters were applied using a focal mode operation with a kernel radius of 1 (3×3 window) to reduce the salt-and-pepper effect in classifying the snow-accumulation area [56]. The altitudinal zoning method [52] was employed to determine the snow cover percentage within each 30 m elevation band. In this step, areas with more than 50% snow cover were classified as accumulation zones, and the median elevations of these areas were extracted. To minimize classification noise, exposed ice pixels above the median elevation of the zones with more than 50% snow cover—which were not masked or filtered out by cloud cover, NDVI, or slope—were also included in the accumulation class. Zones with more than 50% exposed ice were considered ablation sectors, and snow pixels within this zone were incorporated into the exposed ice class.

Accumulation areas were then generated for each sector (Pacific and Amazon) using GEE (Figure 3). Through cloud data processing, it is possible to perform large-scale digital image processing and obtain data on glacier facies variation promptly and automated processing, as well as extract facies over large glaciated areas, such as the CB.

2.3.2. Validation and Accuracy Assessment

Three control glaciers were used to validate the approach: Artesonraju ($08^{\circ}57' \text{ S}$, $77^{\circ}38' \text{ W}$), Shallap ($9^{\circ}20' \text{ S}$, $77^{\circ}20' \text{ W}$), and Yanamarey ($9^{\circ}39' \text{ S}$, $77^{\circ}16' \text{ W}$) (Figure 1). These glaciers were chosen for validation because their mass balance has been monitored since 2004/05, and they are also spatially distributed in the CB and are therefore not in the same sector. We assessed the uncertainty in our method on three control glaciers (Artesonraju, Shallap, and Yanamarey) using (i) yearly manually mapped snow areas and (ii) a comparison of accumulation areas and mass balance.

For the first validation, the annual snow accumulation areas were manually mapped at least once per year (see Supplementary Materials). The exclusion of 2002, 2011, and 2012 occurred due to cloud cover or lack of satellite images. For Landsat, mosaics of false-color composites (RGB of SWIR, NIR, and green bands) (1988–2023) were used [36]. For PlanetScope images, we mapped the 2017–2023 period. Following the recommendations of previous research [57], we utilized high-resolution imagery to enhance mapping accuracy; thus, PlanetScope images with a resolution of 3 m were used for detailed manual delineation from 2017 to 2023. Mapping uncertainty was estimated using the buffer method with ± 1 pixel [58]. The mapping error was calculated based on the Root Mean Square Error (RMSE), derived from a comparison between the automatically obtained data and the manually mapped data using PlanetScope images.

Second, the automated snow accumulation area was validated by comparing it with specific net mass balance data. Mass balance was collected in the field using the glaciological method by the Unidad de Glaciología y Recursos Hídricos (UGRH) of ANA. Mass balance data were available for the Artesonraju Glacier (2006/07–2022/23). For the Yanamarey Glacier, we used the years 2004/2005–2018/2019, and for the Shallap Glacier, we used the years 2004/05–2018/19. The 2011/12 hydrological year was excluded for all three glaciers because of a lack of information on the accumulation area caused by the transition between the Landsat TM and OLI sensors. Additionally, the year 2010/11 was not used for the Yanamarey Glacier because of excessive cloud cover in the images. The mass balance and automatic accumulation area variables for Artesonraju, Shallap, and Yanamarey were correlated using a coefficient of determination test (R^2).

3. Results

3.1. Accuracy Assessment of Snow Accumulation Areas

The accuracy assessment that followed was validated with the manual delineation of the accumulation area using Landsat and PlanetScope imagery performed for the three reference glaciers, and the results were compared to the automatic delineation to support the validation (Table 2 and Figure 4). Additionally, the accumulation area was compared with field data from the mass balance of glaciers.

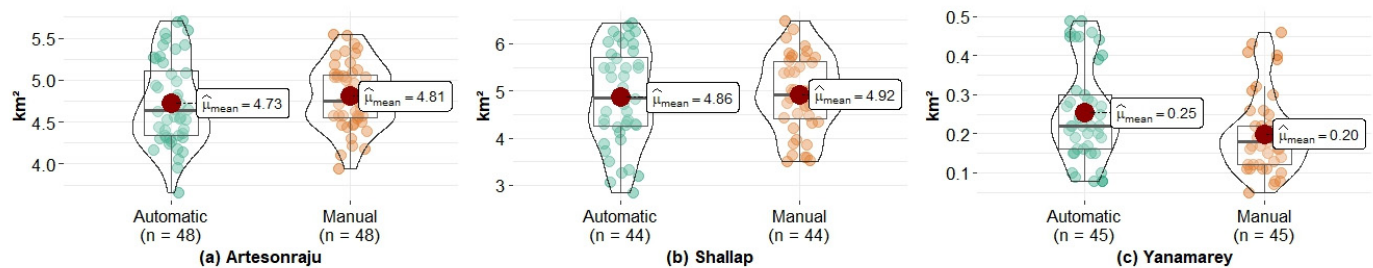
Table 2. Differences between the accumulation area obtained using the automatic method and PlanetScope.

Glacier	Manual Planet Scope (km ²)				Automatic Method (km ²)				RMSE (km ²)	Relative Uncertainty (%)	R ²
	Mean	Min	Max	STD	Mean	Min	Max	STD			
Artesonraju (<i>n</i> = 9)	4.50	4.18	4.81	0.2	4.4	4.16	4.91	0.24	0.16	3.55	0.71
Shallap (<i>n</i> = 9)	4.37	3.58	4.79	0.41	3.90	3.19	4.39	0.43	0.51	11.67	0.76
Yanamarey (<i>n</i> = 10)	0.15	0.09	0.20	0.04	0.16	0.06	0.22	0.04	0.01	6.67	0.81

The relative uncertainty of the RMSE for the manual PlanetScope mapping ranged from 3.55% to 11.67%. The Yanamarey Glacier had the lowest RMSE value at 0.01 km² deviation from the control data, while the Shallap Glacier showed the worst RMSE with a value of 0.51 km². The smallest glacier, Yanamarey, showed residual errors closer to zero, but the method overestimated its area. The brightness characteristics of snow patches in optical images can influence automatic methods and contribute to misclassification of pixels at lower elevations.

In contrast, the Shallap Glacier showed a positive residual error distribution, indicating an underestimation of its accumulation area compared to that obtained from the PlanetScope images. This underestimation may result from sources of error, such as shadows or steep slopes, which are exclusion areas in this method. The *t*-test reinforces the significant difference between the mean values. Nevertheless, the positive correlation values for the Shallap Glacier between the manual vectorization from the PlanetScope images and the automatic method demonstrate that the glacier exhibits the same signal in both methods. The F-test further supports this, which indicates that the glaciers have the same variance.

Automatic method x Landsat images



Automatic method x Planet images

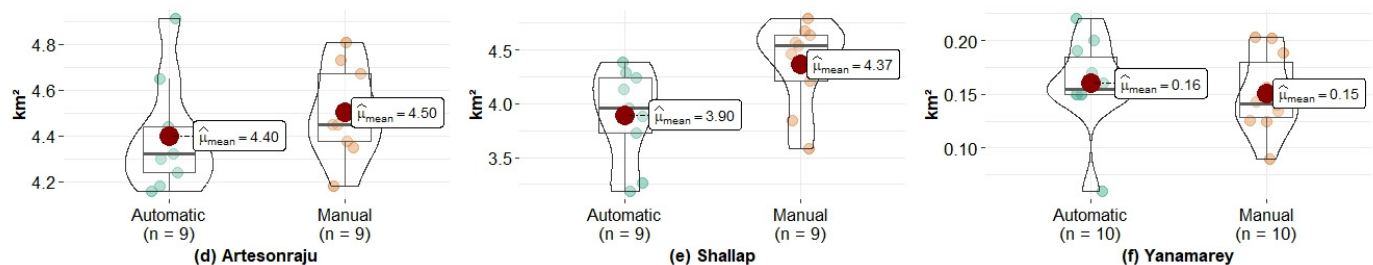


Figure 4. Differences in the accumulation area (km²) between the same dates with the automated and manual methods for Landsat images (a–c), and the differences in the accumulation area from Planet images for available dates (d–f).

For the Artesonraju and Shallap glaciers, the manually delineated accumulation areas using Landsat TM and OLI imagery exhibited equal variances compared to the automatic accumulation area, as determined by an F-test, assuming a parametric *p*-value at a 95% confidence interval. Additionally, the *t*-test did not identify any significant differences between the mean values of the two methods. For the Yanamarey Glacier, although the F-test exhibited equal variances at a 95% confidence interval, the *t*-test showed that the means were different (*p*-value < 0.05).

The automatic method generally showed the highest standard deviation values compared with the Landsat images, as shown in Table 2 and Figure 4. Despite this, in general, considering the values of the automatic accumulation area for the three glaciers, the algorithm agrees with those values obtained manually from the Landsat images ($R^2 = 0.98$).

The automated method also yielded satisfactory results compared to the manual accumulation area of the Planet images. Considering the three glaciers, no differences in variance were observed when subjected to the F-test at a 95% confidence interval. The *t*-test showed no difference between the averages (*p*-value > 0.05).

The correlations with the specific net mass balance further support the RMSE data between the Planet images, as higher correlation values were obtained between the glacier mass balance and accumulation area for the Artesonraju and Yanamarey glaciers. For the Shallap glacier, an underestimation of the accumulation area was observed when compared with the mass balance (Figure 5e).

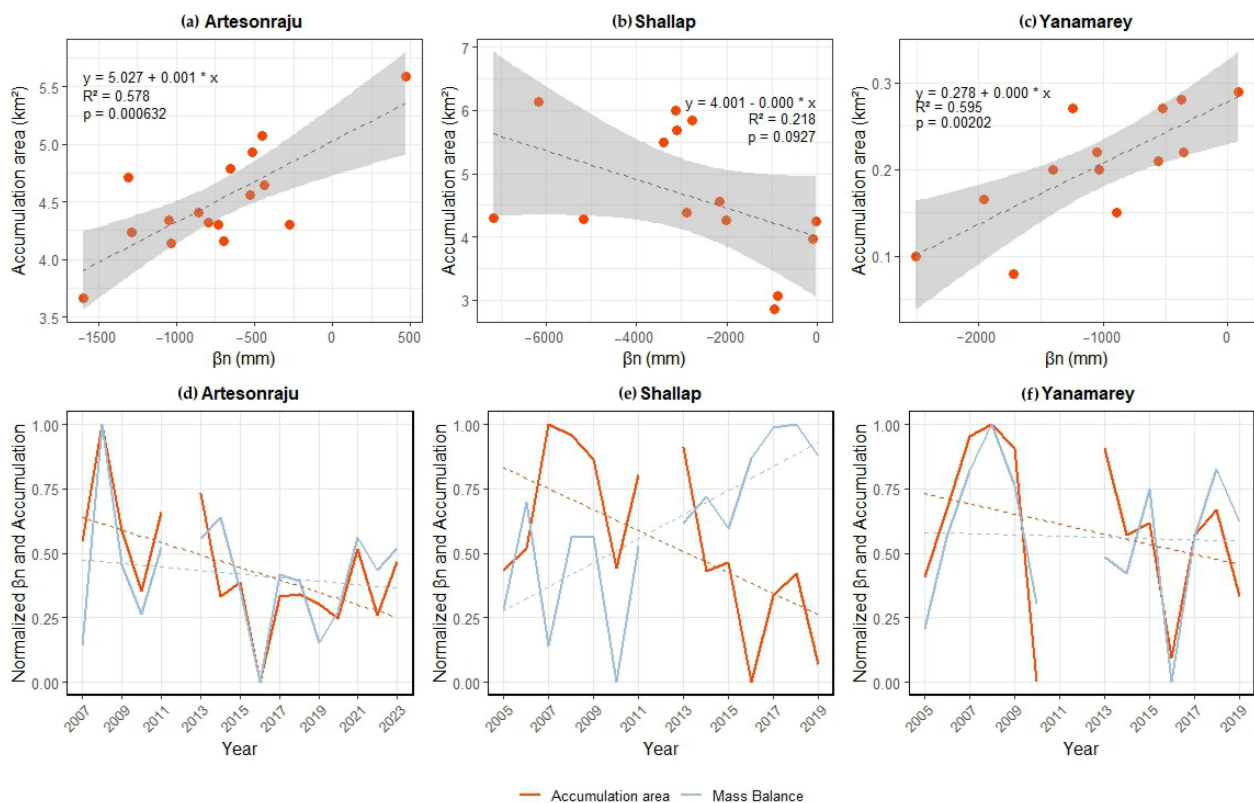


Figure 5. Correlations between the accumulation area (km²) and mass balance data (βn) (a–c), and trends over the years in the automated accumulation area and mass balance (d–f).

3.2. The Accumulation Area Variability in the Two Cordillera Blanca Sectors

The Amazonian sector showed a significant decreasing trend in the accumulation area in the series (Z-score: -2.6186 , $p < 0.05$) from 1988 to 2023. The mean value of the accumulation area for the series was 106.89 km². Furthermore, the mean accumulation area for the first period of the series (1988–1999) was the highest, with a decrease in all series, representing a decline of 8.99% from the first to the last period (Figure 6c).

The eastern face presented 15 years with values lower than the mean in the series. Four were between 1988 and 2000, three from 2000 until 2009, and lower-than-average values were from 2010 to 2023 (eight years). Seven of these years were concentrated before 2015 (Figure 6).

Based on the long-term mean value for the Amazonian sector, the accumulation area experienced a significant reduction (-16.56%) in 1997/98, and the decrease was -18.84% in 2015/16 from the long-term mean. For the year 2019/20, the decrease reached -20.89% . Regarding the total area, the hydrological years of 1997/98 and 2015/16 were marked with a low value of accumulation area, both years with noted strong ENSO events.

Similarly to the eastern face, the Pacific sector exhibited a significant decreasing trend in the accumulation area (Z-score: -2.8045 , $p < 0.05$). The mean snow accumulation area on the western face throughout the series was 227.6 km^2 . Notably, the lowest accumulation area was recorded in 2015/16, reaching 165.56 km^2 . Furthermore, from 2010 to 2023, eleven years exhibited accumulation area values below the mean of 227.6 km^2 .

Considering the average accumulation area on the western face, an even stronger reduction was observed in years marked by strong El Niño events. For example, the year 1997/98 showed a decrease of 22.73% in its accumulation area. Meanwhile, 2015/16 presented a shrinkage of 27.26%.

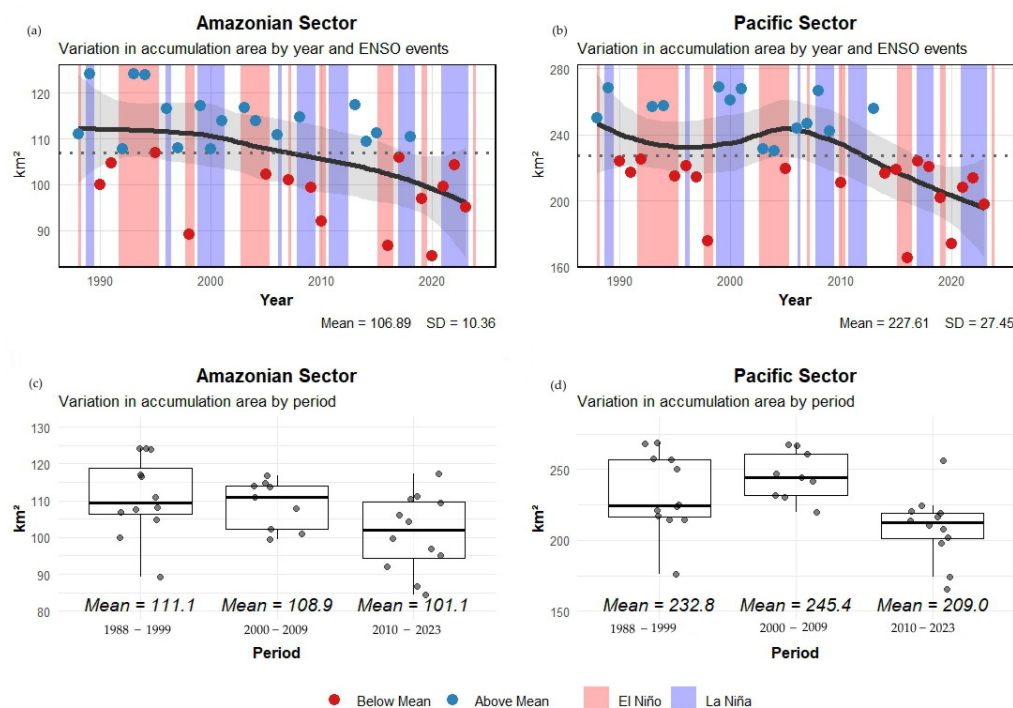


Figure 6. Fluctuations in the total snow accumulation area (km^2) and ENSO events for the Amazonian (a) and Pacific sectors (b) from 1988 to 2023. The red dots represent the years below the mean accumulation area value for the period, and the blue dots represent the years with higher accumulation area values. The variation in the accumulation area by period is represented in (c,d).

For the western face, contrasting with the eastern face, the Pacific sector experienced an increase in the average accumulation area during the second period (2000–2009), reaching 245.44 km^2 . After this, a marked decrease in the values was observed, with the lowest rates of accumulation area in the last period (2010–2023), representing a decrease of 10.24% from the first to the last period.

3.3. The Total Glacial Area Variation

The Amazonian sector exhibited a significant reduction in the glacial area obtained from MapBiomas data (Z-score: -8.1656 and $p < 0.05$). The eastern face experienced an area loss of 21.3% from 1988 to 2022, equating to an average loss of 0.70% per year over this period (Figure 7).

On the eastern face, as shown in Figure 7, glacier loss between 1988 and 2022 occurred primarily within the 4200–5000 m elevation range, with only minor changes observed above this elevation. By 2022, no glacier area remained below 4400 m, and elevations up to 4700 m had lost 71.86% of their glacier coverage during the analysis period.

Between 1988 and 1998, a reduction of 13.38 km^2 was recorded within the altitudinal range of 4300–5000 m, corresponding to a 7.62% decrease in the total area. In the more recent

period (2016–2022), losses have extended to higher altitudinal ranges, such as 4500–5300 m a.s.l.

The Pacific sector exhibited a significant reduction in glacial areas, as indicated by the MapBiomass data (Z-score: -8.1656 and $p < 0.05$). Between 1988 and 2022, the western face lost 22% of its glacial extent, corresponding to an average annual decrease of 0.75%. This sector has glaciers at higher altitudes, distributed over a greater range than the Amazonian glaciers. Most losses were concentrated between 4300 and 5600 m (Figure 7), with a particularly sharp 78.96% reduction observed within the 4300–4700 m range. Despite these declines, a comparison of the total area revealed that the Pacific sector exhibited the greatest mean value of total glacial coverage (339.64 km^2) over the study period (1988–2022). By 2022, this value had decreased to 300.86 km^2 .

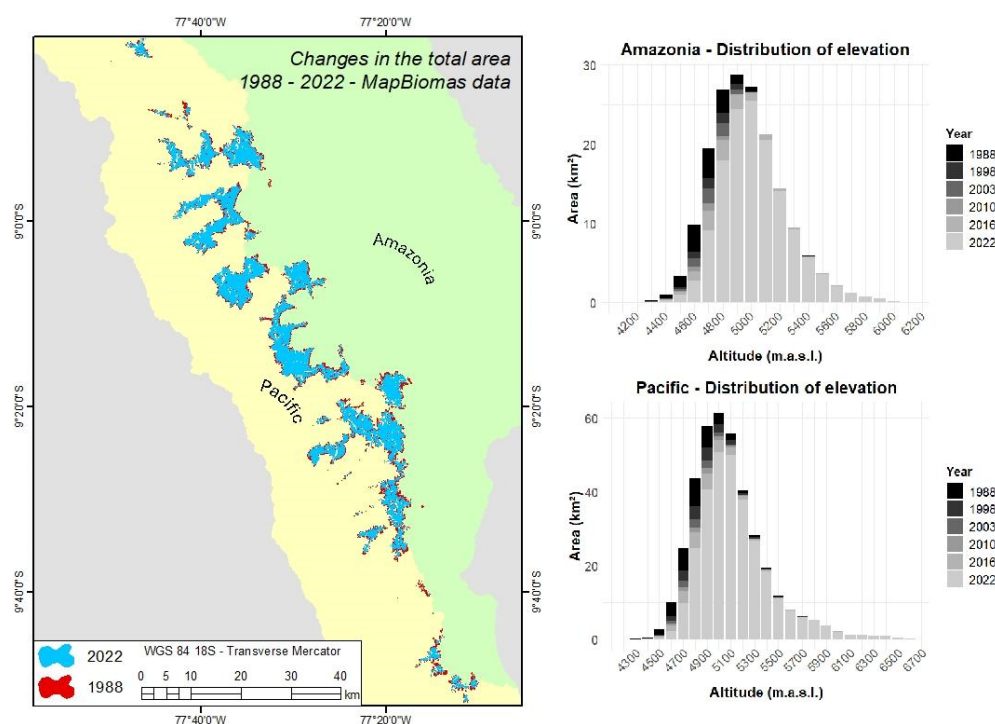


Figure 7. Changes in the total area for 1988 and 2022 were obtained through MapBiomass Peru for the Cordillera Blanca and the change in pixel frequency by elevation range over the years.

3.4. Correlation of El Niño, Accumulation Area, and Climatic Parameters

In the Amazonian sector, over the total period of analysis (1987/88–2022/23), both seasons presented a significant correlation between the annual accumulation area (p -value < 0.05) and total precipitation, snowfall, air temperature, and El Niño 3.4 (Figure 8). The correlations with accumulation area and temperature ($r = -0.83$) were strong, as was that with snowfall ($r = 0.77$). Our analysis revealed that the wet season had a higher number of significant correlations between the accumulation area and climatic variables (such as El Niño, climatic patterns, and PDO). The correlation between the annual accumulation area and snowfall, air temperature, and total precipitation was stronger in the dry season ($r = 0.7$, -0.79 , and 0.55 , respectively) than in the wet season ($r = 0.66$, -0.73 , and 0.34 , respectively).

In the wet season, a greater trend in the elevation of monthly anomaly temperature was observed in the eastern sector (Z-score = 2.411 and p -value < 0.05). There was a significant trend in decreasing the monthly anomaly of snowfall (Z-score = -4.885 and p -value < 0.05), with an increase after the 2000s (Z-score = -5.15 and p -value < 0.05).

In the Pacific sector, significant correlations were observed between the accumulation area and variables such as snowfall, temperature, and El Niño 3.4. Among these, snowfall ($r = 0.82$) and temperature ($r = -0.83$) showed the strongest relationships with the accumulation area. When comparing the correlations between snowfall and temperature across seasons, snowfall had a slightly greater influence on the accumulation area during the wet season ($r = 0.75$) than during the dry season ($r = 0.73$). In contrast, temperature had a stronger impact during the dry season ($r = -0.83$) than during the wet season ($r = -0.73$).

In the dry season, the western sector showed a greater trend in the elevation of monthly anomaly temperature (Z-score = 3.174 and p -value < 0.05). After the 2000s, there was a significant trend of decreasing the monthly anomaly of snowfall (Z-score = -5.24 and p -value < 0.05).

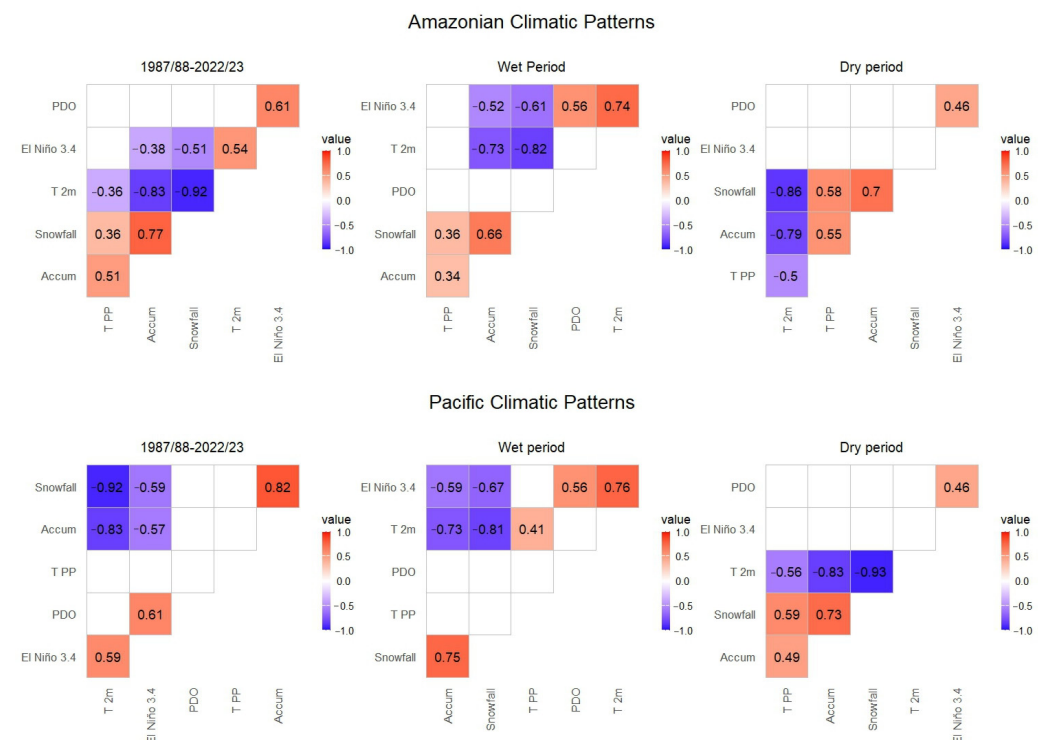


Figure 8. Correlation (r values) between the snow accumulation area (Accum), meteorological parameters (temperature 2 m—T2; total precipitation—T PP; and snowfall), and oscillation modes (El Niño zone 3.4 and Pacific Decadal Oscillation—PDO). The blanks indicate correlations with p -values > 0.05.

The climatic variables (temperature, snowfall, and precipitation) yielded robust correlations with each other during the dry period for both sectors. Temperature and snowfall were closely anti-correlated with each other ($r = -0.93$ for the Pacific and $r = -0.86$ for the Amazonian sector). El Niño 3.4 is closely anti-correlated with snow accumulation area, temperature, and snowfall in the Pacific sector. These values were lower in the Amazonian sector.

4. Discussion

4.1. Uncertainties of Automatic Glacial Area Accumulation

Our results demonstrated good agreement between the Landsat manual and automatic estimates of accumulation areas for the three glaciers from 1988 to 2023 ($R^2 = 0.98$), supported by the lower RMSE values observed for the Yanamarey and Artesonraju glaciers. This approach is considered to provide satisfactory results in identifying surface facies in glaciers with well-defined glacial morphologies, debris-free areas, and areas > 1 km² (e.g., Artesonraju Glacier), as shown by the difference between the automatic estimation and

manual delineation in PlanetScope images and the lowest relative uncertainty presented in the RMSE. The *t*-test and F-test regarding manual vectorization in Planet images and the automated method agreed with the RMSE results for the Artesonraju Glacier. Gaddam et al. (2022) obtained good correlation values between the manually determined glacier area and the area calculated using the corrected Otsu method [34]. They found an R^2 value of 0.73 for the glacier accumulation area derived from the Otsu method compared to the manual measurements, and we found similar correlations, with R^2 values above 0.71 between the manual and automated methods.

The errors in small glaciers, even with lower RMSE values, could be amplified by their size. The Yanamarey Glacier has a relatively small total area (less than 1 km²), which results in a narrower range of variability between the highest and lowest values, as demonstrated by the minimal differences in standard deviation values (for PlanetScope and automatic, both values were 0.04 km²). However, the results in the *t*-test were worse than those of the automatic method and manual vectorization in the Landsat images. This might suggest that the differences observed between vectorization and automatic data (specifically for Landsat) were more pronounced in the Yanamarey Glacier, partly because it is smaller than the Artesonraju Glacier.

The estimation based on PlanetScope data for the Shallap Glacier exhibited the highest RMSE and the greatest relative uncertainty. Previous studies have reported substantial differences between automated and manual vectorization, with standard deviation values in debris-covered glaciers of approximately 30% [57]. In the *t*-test, the Shallap Glacier showed a significant difference in the mean values compared to the other two glaciers. While assessing the discrepancies between the automated method and manual vectorization using PlanetScope imagery, it also showed greater differences in the standard deviation. This highlights the importance of carefully evaluating glacier areas that are covered by debris. According to Rastner et al. (2019), when the Otsu method is applied and the amount of debris is small relative to the clean ice surface, the debris is classified alongside the exposed ice facies, as the method assumes two classes with a bimodal histogram [59]. However, extensive debris cover, shaded areas, and steep areas may introduce additional uncertainty in delineating the accumulation area.

Furthermore, the steep slope angles at higher altitudes (above 5000 m) of the Shallap Glacier contribute to the difficulty in accurately classifying the accumulation areas. The glacier has a steeper surface exposed to the southwest above 5000 m, and the higher altitudes receive slightly less incident solar radiation than the ablation zone. Furthermore, a slower decrease in snow albedo with altitude can reduce shortwave energy absorption [60]. These facts can cause difficulties because the algorithm uses the spectral behavior of the target to distinguish the classes.

4.2. Climatic Control of Changes in Snow Accumulation Areas at Regional Scale

Our results indicate that both the glacierized area and snow accumulation zones in CB have been reduced since 1988 in response to meteorological parameters. Precipitation has been identified as the primary driver of interannual glacier mass balance in the CB region [2]. During the wet season, snowfall significantly influences the variability of the snow accumulation area, as demonstrated by the strong correlations observed in the Pacific region. This pattern aligns with the typical accumulation pattern in the outer tropics, where glacial accumulation rates are higher during the wet season [41].

In the CB, the highest ablation rates are observed during the wet season [11]. During this period, ablation is primarily driven by shortwave radiation, which is particularly sensitive to reduced albedo values [60]. However, low cloud cover and humidity help

offset the shortwave energy input, resulting in increased latent heat flux and more negative net longwave radiation [61].

Nevertheless, the anti-correlation values between temperature anomalies, snowfall, and total precipitation were stronger during the dry season than during the wet season for both the Amazonian and Pacific sectors ($r = -0.86$ and -0.50 ; $r = -0.93$ and -0.56 , respectively). This suggests that even minor temperature variations can significantly influence precipitation patterns during the dry season.

Warming trends can cause precipitation to occur as rain rather than snow [61,62], which can impact the surface albedo. Schauwecker et al. (2014) observed an increasing trend in air temperature during the dry months (June, July, and August [38]), which may help explain this relationship. Additionally, the accumulation area showed a stronger correlation with air temperature and total precipitation during the dry period, reinforcing this interpretation.

This is particularly important because temperature increases during precipitation events may cause a corresponding rise in the snowline altitude [38]. Moreover, Representative Concentration Pathway 8.5 scenarios project a significant increase in the freezing level height in the CB region through the year 2100 [63]. These factors could lead to a reduced surface albedo during both the dry and wet seasons, enhancing energy absorption and consequently accelerating ablation.

The period of image acquisition can also influence the correlation values involving the accumulation area, temperature anomalies, snowfall, or total precipitation. However, this factor alone cannot account for the stronger temperature–snowfall correlations observed during the dry season. Given the high variability of total precipitation, lower correlation values would typically be expected. Furthermore, precipitation data from reanalysis products may present greater uncertainties because of the complex and dynamic meteorological conditions in high-altitude regions [64].

Despite projections of increased precipitation for the CB region [44], studies indicate that the runoff of glacierized catchments in this region is expected to decrease by 2080 [65]. This pattern suggests a continued decline in glacierized and accumulation areas, further supported by the anticipated rise in the freezing level [63]. The long-term trend of glacial retreat has been discussed in other studies [2]. Although precipitation increased between the 1980s and the 2010s, it was insufficient to compensate for the effects of atmospheric warming [38]. Although a non-significant increase in the freezing level height was noted on rainy days during this period, the overall warming trend persisted, contributing to ongoing glacier shrinkage [38].

The variation in the CB accumulation area since 1987/88 reflects the response to a warmer climate during this period [36,38], which could be associated with a notable reduction in snowfall after the 2000s. Both the Pacific and Amazonian sectors experienced significant reductions in accumulation area during 1997/98 and 2015/16, coinciding with strong ENSO events. These years recorded particularly low values for the accumulation areas. Previous studies have also detected a rise in the equilibrium line altitude (ELA) during the 1997/98 El Niño in tropical Andean glaciers [36], as well as a considerable decrease in the glacier mass balance [66]. The correlation between temperature anomalies for the El Niño 3.4 index reached $r = 0.74$ and 0.76 during the wet season. This pattern may help explain why accumulation area values tend to decrease during El Niño events that occur in the wet season, such as 1987/88, 2009/10, and 2015/16, compared to those associated with higher temperature anomalies during the dry season, such as 2014/15 and 2022/23. Furthermore, this affirmation is supported by the low significance of the correlations between the El Niño 3.4 index and meteorological factors during the dry season.

A higher anti-correlation was also found between El Niño and the accumulation area during the wet season (-0.52 to -0.59), which aligns with the findings of other studies [40].

The year 2019/2020 saw a significant reduction in snow accumulation areas (173.94 km^2 and 84.46 km^2 , respectively), presenting only a weak El Niño anomaly in the Niño 3.4 region during this period, with a temperature increase of $0.5 \text{ }^{\circ}\text{C}$ for four months. It is important to note that El Niño events do not always coincide with negative mass-balance anomalies in this tropical region [67]. Globally, 2020 was the second warmest year on record since 1880 [68]. Paleoclimate models indicate that under cooler climatic conditions, Walker circulation is stronger; thus, warming is expected to weaken the circulation, which may lead to a rise in the frequency and intensity of El Niño events [69]. This weakening of the Walker circulation under warmer conditions could amplify the impact of El Niño on the snow accumulation area in the CB, even during weak events. However, further research is required to confirm this relationship.

4.3. Contrasting Responses of Accumulation Area and Total Area Changes in Amazonian and Pacific Sectors

According to MapBiomas data, the total glacial area loss from 1988 to 2022 in the Pacific region was slightly higher (22%) than that in the Amazonian sector (21.3%). Although this difference was not statistically significant at a 95% confidence level ($p > 0.05$, with a mean difference of 0.028), similar patterns have been reported in previous studies [10]. The changes in the total area by elevation range from 1988 to 2022 are consistent with other studies, which reported higher losses in the range of 4800 to 5100 m [10]. Our analysis shows that the highest losses occurred between 4600 and 4700 m and 5100–5200 m, whereas higher elevations exhibited minor fluctuations. In 2022, the Amazonian sector did not present glaciers below 4400 m. The Pativilca Basin (Pacific region), which holds small glaciers, experienced the highest area loss, reducing 56.21% between 1987/88 and 2021/22. Regarding the snow accumulation area, both sectors experienced a significant reduction in the accumulation area between 1988 and 2023, with decreases of 14.38% and 20.81% in the Amazonian and Pacific sectors, respectively.

The smallest mean snow accumulation area value was observed in the CB on the Amazonian side. In this sector, total precipitation correlates strongly with the accumulation area, and other studies have found a decrease in annual precipitation from 1970 to 1999 [10]. The Amazonian sector presented the highest anti-correlation between accumulation area and temperature ($r = -0.73$ and $r = -0.79$ for the wet and dry seasons, respectively). It exhibited a general trend of rising temperatures throughout the study period, along with a decreasing trend in snowfall. This behavior was expected, as the Amazonian sector is at a lower elevation, ranging from 4200 to 6200 m. Consequently, it may have a smaller accumulation area above the $0 \text{ }^{\circ}\text{C}$ isotherm than the Pacific sector.

The decrease in the accumulation area is consistent with the findings of Racoviteanu et al. (2008) [10]. Lower accumulation area values lead to a reduction in glacier albedo, which affects the radiation balance [10]. This feedback mechanism is consistent with the decrease in the snow accumulation area in the Amazonian sector.

An increase of $2 \text{ }^{\circ}\text{C}$ in the central Peruvian Andes could result in a 50% to 10% reduction in solid precipitation [62]. This change may also result in higher humidity and cloud cover due to rising temperatures and topographic effects on the Amazonian side. Although the impact of cloudiness and its role are not fully understood, cloud cover and humidity have already been identified as key factors in the ablation rate in the CB [11]. Additionally, the steeper slopes on the eastern side [8] may contribute to lower values of the accumulation area for this sector.

According to MapBiomas, the highest average annual loss of the total glacial area in the Pacific sector occurred between 1987/88 and 1998/99, with a mean rate of -0.90% per

year. This was followed by the periods 2009/10–2021/22, presenting a rate of $-0.77\%/year$, and 1999/00–2008/09, with a rate of -0.51% . A similar temporal pattern was observed for the snow accumulation area, although the most recent period (post-2010) showed the lowest average accumulation area.

Previous studies have identified a warming trend in the CB from 1970 to 1999 [10] and an increase of approximately 0.10 – 0.11 °C per decade from 1939 to 1998 [70]. However, between 1999 and 2002, some glaciers in the CB experienced a re-advance of their termini [12]. This apparent pause or reversal in the warming trend aligns with the findings from other regions that noted a reduction or stabilization in warming during the early 2000s [71]. This cooling phase is further supported by a slowdown in warming observed by others between 1983 and 2012, following a more pronounced warming trend from 1969 to 1998 [38]. This pattern could explain the accumulation area rates for the first (1987/88–1998/99) and second periods (1999/00–2008/09).

During 2013–2016, CB presented a negative mass balance [15], consistent with the lower accumulation area rates observed during 2014–2016. The final period of the series (after 2010) depicts a return to higher retreat rates and lower values of the accumulation area compared to the previous period, which exhibited a reduction of 10.24% from the first to the last period. Therefore, it is possible to associate it with the end of the cooling period, observed for other regions from the early 2000s to the mid-2010s [72].

There are further implications for a reduction in glacier areas draining into the Amazon River Basin, which can result in alterations to river sedimentation and could impact geomorphological, biochemical, and ecosystem processes [73]. Other studies have indicated the relationship between changes in the Quelccaya Ice Cap and alterations in sedimentation in the Madeira River [74]. In the Pacific watershed region, such as the Santa River Basin, these changes in water availability may affect access to water resources for populations, such as upstream farmers and urban populations in poorer downstream areas, thereby exacerbating conflicts over water resources [20]. Furthermore, they may result in glacial hazards such as floods associated with the rupture of glacial lake dams [18].

4.4. Potential and Limitations of the Methodology

Automated mapping is essential because it maintains reliability according to the error presented and reduces processing time [57]. The generation of an open-source tool can improve the monitoring of fluctuations in accumulation areas. This initiative democratizes access to this information, which is easily verifiable. Automatic methods are especially recommended for identifying glacial areas in debris-free glaciers [57].

Cloudiness can be a limiting factor because it can influence optical images and limit the number of images available. Considering the temporal resolution of Landsat images, filtering applications that consider cloudiness and cloud masks for automatic classification methods are important for obtaining results that contain less noise. Therefore, the evaluation of images and cloud cover for the area covered by glaciers is relevant.

The division into patches of snow, as others have performed [52], helps to reduce noise and homogenize the classification of the accumulation area. This study used the Otsu method to discriminate between snow and ice targets, resulting in better outcomes owing to noise reduction. Gaddam et al. (2022) observed a strong correspondence between the targets when they applied a global threshold for classification [34]. However, the authors excluded snow pixels outside the glacier contour, retaining only continuous snow pixels. Therefore, the application of the Otsu method was deemed satisfactory.

However, identifying glacial zones using automated classification methods is challenging because of the spectral mixing of targets. Issues concerning the presence of surface glacial sediments are commonly reported, and measuring their impact on the results re-

mains difficult [59]. Thus, the spatial resolution of the TM and OLI sensors is a limiting factor for identifying details in the area of small glaciers and accurately indicating the accumulation area value (km^2). However, the approach was able to suggest fluctuations in mass balance, as indicated by the correlations between mass balance and accumulation area (Figure 5c).

Smaller glaciers may experience a more significant overestimation of both their accumulation and overall area measurements than larger glaciers. This discrepancy may arise because the Otsu method can misclassify areas as ice because of the limited snow cover of glaciers [52]. Underestimations of the snowline altitude were already noted in the OLI images, caused by the difference in the spectral reflectance of the snow pixels [55]. Consequently, this led to an overestimation of the accumulation area. Furthermore, it highlights the need to evaluate the total glacier area because the reduced sample size of pixels for automatic classification increases the likelihood of errors due to spectral mixtures [75]. This situation notably contributes to the measurement errors and uncertainties.

In the tropical Andes, particularly in the Zongo and Quelccaya Icecap Glaciers, spectral mixture analysis has been used to delineate glacial zones and assess transient snowlines. However, this method has limitations, particularly because of shading in the accumulation area [76]. A similar issue was evident in the Shallap Glacier, which features debris-covered and steeply sloped surfaces. In this instance, the accumulation area was underestimated compared to the PlanetScope imagery and mass balance data. These underestimations may be associated with shadowed areas that can be misclassified as classes that do not represent the snow. Moreover, it is important to highlight that debris-covered areas may affect this approach [59], as seen in the Shallap Glacier.

5. Conclusions

This study enabled an understanding of the fluctuations in the accumulation area of the glacierized CB from 1988 to 2023. In addition, it has contributed to the discussion of the differences in area between the western and eastern sectors. The automation of image processing for the CB provided spatial and temporal details regarding the glacier variations in each sector. The method applied in a cloud computing environment uses open-source code, ensuring the continuity of glacial facies monitoring in the region.

The proposed method for automating the identification of glacial zones is particularly significant because of the complexities involved in mapping mountainous environments. Our main findings are as follows:

- (a) There may be significant overestimations, particularly for smaller glaciers ($<1 \text{ km}^2$), because medium-resolution sensors (30 m) are not well-suited for capturing details in small glaciers such as Yanamarey. This limitation can increase the uncertainty due to spectral mixing. Furthermore, it is crucial to analyze the debris cover over glaciers and shadowed areas, as these factors may result in underestimating the accumulation area values.
- (b) Regarding the total area (MapBiomas data), the western and eastern sectors presented a significant decrease of 21–22% of the area (1988–2022), representing a mean loss of 0.74–0.75%/year. The most significant losses occurred in the first period of the series (1987/88–1997/98) for both sectors. The losses by elevation range are consistent with those of other studies. On the eastern side, no glaciers were observed below 4400 m after 2022.
- (c) In the Pacific sector, the decrease in the accumulation area over time was primarily driven by the rising temperature trend—particularly during the dry season—and by the variability of El Niño 3.4, PDO, temperature, and snowfall. The period between 1999/00 and 2008/09 presented lower rates of decrease as well as greater rates of

accumulation area. This could be associated with the low intensities of El Niño during this period, with lower warming trends and a decrease in snowfall trends after the 2000s. The anti-correlation between the accumulation area and El Niño 3.4 was stronger in this sector, with 1997/1998 and 2015/2016 showing some of the lowest recorded accumulation values.

- (d) The accumulation area in the Amazon has experienced a significant decrease in snowfall, correlated with rising temperatures. The eastern side, which has lower elevations, may be closer to moisture sources and potentially face higher levels of water vapor.
- (e) El Niño seems to lead to a greater decrease in accumulation during wet seasons. The year 2015/16, with high ENSO anomalies in the Pacific sector, presented the lowest accumulation area. Owing to the correlations between temperature, snowfall, and precipitation, even minor changes in temperature during the dry season could lead to changes in the accumulation area compared to the wet period.

Higher warming rates may have returned after the slowdown warming period, which is consistent with those observed in other regions. Additionally, the impact of El Niño events can be intensified in a warmer atmosphere, even for weaker events. The decrease in snow cover area, snowfall, and air temperature increase indicates risks to the socio-cryosphere present in this area. These factors may require greater attention to water resources and disaster prevention.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/geosciences15060223/s1>.

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Data Availability Statement: The following open-source tool for detection of the snow accumulation area and its source code are available at <https://ee-jlopeslorenz.projects.earthengine.app/view/accumulation-area-cb> (accessed on 2 June 2025). Landsat and PlanetScope scenes used for validation and to obtain the accumulation area are available in Supplementary Materials. The other data sources presented in this study are available upon request from the corresponding author.

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