El Niño Enhances Snowline Rise and Ice Loss on the World's Largest Tropical Quelccaya Ice Cap, Peru

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Abstract. Tropical glaciers_are essential water resources in the central Andes ares vital water resources and crucial climate indicators, currently undergoing rapid retreat. However, understanding their vulnerability to the combined effects of persistent warming, short-term climate phenomena, and interannual fluctuations remains limited. Here we automate the mapping of key mass balance parameters on the Quelccaya Ice Cap (QIC) in Peru, one of the largest tropical ice caps, the world's largest tropical ice cap. Using Landsat's near-infrared (NIR) band, we analyze snow cover area (SCA) and total area (TA) and calculate the Accumulation Area Ratio (AAR) and Equilibrium Line Altitude (ELA) over nearly 40 years (1985-2023). Between 1985 and 2022, the QIC lost ~4658% and ~347% of its SCA and TA, respectively. We show that the QIC's loss-reduction in SCA and rise in ELA are exacerbated by El Niño events, which are strongly correlated to the preceding wet season's Ocean Niño Index (ONI). Further, While variance testing indicates El Niño years have a strong impact on the SCA and La Niña years all record significant SCA-expansion in the QIC's SCA is observed during all La Niña years, we observe that the QIC may be overwhelmed by anthropogenic climate impacts as it did not expand duringexcept for the 2021-2022 La Niña. Although a singular event, this could suggest an inability for SCA recovery and accelerated decline into the future, driven primarily by anthropogenic warming.

with current and ongoing warming we expect the decline to continue through the next La Niña and into the future We observe lower levels of correlation to more recent El Niño events as anthropogenic climatic impacts overwhelm the natural forcing and continue to exacerbate loss at the QIC.

25 1 Introduction

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Tropical glaciers are known to be especially sensitive to climate shifts (Kaser & Osmaston, 2002) and their accelerated decline has been well-documented in recent decades (Bradley et al., 2006; Braun et al., 2019; Hanshaw & Bookhagen, 2014; Hugonnet et al., 2021; Pepin et al., 2015, 2022; Seehaus et al., 2020; Thompson et al., 2011, 2021; Vuille et al., 2015). In the low latitudes and southern Andes, glaciers are projected to lose ~69-98% of their 2015 mass by 2100, respectively, depending on the emissions scenarios (i.e., RCP2.6 and RCP 8.5, respectively; -{Rounce et al., 2023}). The freezing level height

in the tropics is affected on an interannual basis by El Niño Southern Oscillation (ENSO) variations and follows the Multivariate ENSO Index (MEI) on a year-to-year basis (Bradley et al., 2009; Favier et al., 2004; Thompson, 2000; Vuille et al., 2000). The decline of the Quelcaya Ice Cap (QIC; the world's largest tropical ice cap; Fig. 1), located in the Cordillera Vilcanota (CV) range in the outer tropical region of the Andes, is one such concern with worst case (RCP8.5) projections suggesting the 'point of no return' suggesting (i.e., the rise of the ELA above the summit) its disappearance as early as 2050 (Yarleque et al., 2018), leading to the QIC's classification asleaving QIC a wasting ice field instead of an ice cap, similar to Kilimanjaro. -once, however due to its recent and is currently nowin (Kochtitzky et al., 2018)CC ontemporary changes in the QIC's outlet glaciers have been monitored frequently (Brecher & Thompson, 1993) and contextualized within a longer, millennial-scale timeframe (e.g., Mark et al., 2002; Lamantia et al., 2023). For example, Mark et al. (2022) combine moraine chronology with digital topography to model deglaciation rates during the Last Glaciation and Holocene and find that (Brecher & Thompson, 1993) with the QIC's most rapid deglaciation computed to retreat has have occurred over the most recent centuries modern retreat rates exceeding those reconstructed from Holocene moraines (Mark et al., 2002). Further, evidence of the QIC's past fluctuations has recently been placed within a longer term context using radiocarbon-dated plant remains from the QIC ice margin suggesting that the ice cap's retracted present-day magnitude of retreatmargin extent has not occurred since at least in the last 7,000 years (Lamantia et al., 2023) ago. In addition, the QIC's high-resolution ice-core records have proven invaluable for understanding of past climatic and environmental variability in the region (Thompson, 2000; Thompson et al., 1985, 2013, 2017, 2021). Thus, the ongoing loss of tropical glaciers will not only impact local communities that depend on glacial meltwater but has implications for the preservation of long-term climate records, essential for assessing the rate and magnitude of current changes (Thompson et al., 2021).

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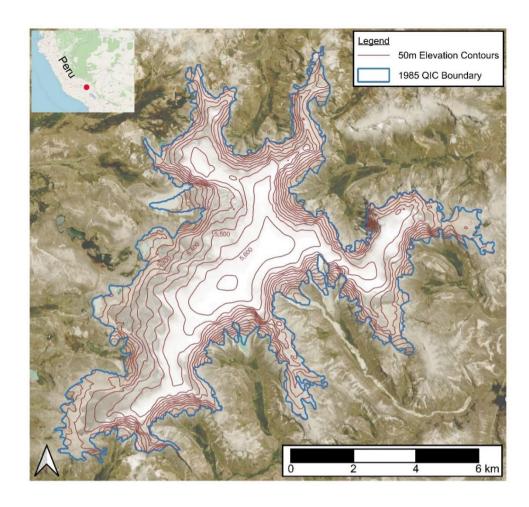


Figure 1: Aerial view of the Quelccaya Ice Cap (13°56'S; 70°50'W) from October 11, 2023. The summit of the QIC reaches 5,670 m a.s.l with a handful of outlet glaciers to the west and a steep-sided eastern portion. Base Imagery was obtained from Planet Labs Dove Satellite with 3-meter resolution and inset (top left) was obtained from the OpenStreetMap database (© OpenStreetMap contributors 2023. Distributed under the Open Data Commons Open Database License (ODbL) v1.0.)

In the tropics, there is no seasonal snow cover beyond the glacierized area that would provide an additional buffer to the ice cap's decline (Vuille et al., 2018). Quelccaya's snowfall is largely controlled by the South American Summer Monsoon (SAMS) with the snowfall peak in December and moisture transport from the Amazon is influenced by ENSO variations (J. V. Hurley et al., 2015). The southern wet outer tropics are climatically controlled by fluctuations in the Intertropical Convergence Zone (ITCZ) and glaciers such as the QIC have enhanced temperature sensitivity relative to those in the dry outer tropics (Veettil et al., 2017). There has been no significant change in precipitation around the QIC over the last fifty years, with 10% of stations in the CV recording only a slight decrease in rainfall (Casimiro et al., 2013). However, but ice core records from the QIC core reveal the net accumulation in the region has been above average for the last century (Thompson L.G., 2017). In the Peruvian Amazon—Andes basin, The average mean annual temperature has increased by ~0.09°C per decade over the last sixty years, while withmaximum the summer temperature time series in the Andes show an even higher magnitude

trend (0.15°C per decade; months recording a higher magnitude increase in maximum summer temperature (Casimiro et al., 2013). Additionally, and ice cores from multiple locations in Peru recording documenting thise accelerating enrichment (Thompson, 2017; Thompson et al., 2013). Nearby mountain ranges such as the Cordillera Blanca and Real have experienced an increase in the freezing level height (FLH) by 160 m over the last five and a half decades with implications for not only where snow can survive and accumulate (Bradley et al., 2009; Schauwecker et al., 2014; Seehaus et al., 2020) but also increased albedo in the ablation zone influenced by a rise of the rain/snow line (Rabatel et al., 2013). High-resolution ice core records show that the QIC is an excellent recorder of the El Niño and La Niña events that create elevated sea surface temperatures (SSTs) in the Eastern Pacific Ocean, recording years of strong El Niño events with isotopically enriched δ¹⁸O (Thompson et al., 2011, 2017). Alongside these ice core records, the QIC's contemporary and past margins have has been monitored and reconstructed, but its_has yet to be evaluated for ice losssensitivity and response to multiple short-term climate phenomena over recent decades have yet to be extensively evaluated that may play a role in its current decline. Thus, the QIC is an ideal setting to assess the combined effects of sustained warming and short-term climate variations, such as ENSO, on tropical glacier vulnerability.

Since routine ground-based measurements in a remote location such as south-central Peru are difficult to maintain, using satellite imagery to estimate the Equilibrium Line Altitude (ELA) has become a viable solution for long-term glacier monitoring. Previous studies have shown that the end of dry season (September) location of the snowline altitude (SLA) can act as a proxy for the ELA and ultimately be used to infer the mass balance of a glacier or ice cap (Fang et al., 2011; Hu et al., 2020; Liu et al., 2021; Racoviteanu et al., 2019). Initial studies in the Andes involved a manual assessment of the Artesonraju and Zongo glaciers via Landsat and SPOT imagery compared against field measurements (Rabatel et al., 2012). Yarleque et al., (2018) most recently analyzed the QIC's response to warming scenarios based on the FLH/ELA relationship and future ELA projections. Here, we useemploy cloud-based analysis of satellite imagery a suite of imagery spanning 1985 to 2023 to assess the QIC at the end of the dry season between 1985 and 2023 through a cloud based analysis of satellite imagery. We automate not only the detection of the snow-covered area (SCA) and total area (TA), but also the calculation of the accumulation area ratio (AAR), the median elevation of the SCA, and the SLA as a proxy for the ELA. Changes to the ELA, SCA, and AAR are analyzed alongside ERA5—Land Reanalysis Climate Data from the European Centre for Medium Weather Range Weather Forecast (ECMWF) including total precipitation and surface temperature as well as multiple ENSO Indices including the MEI, the Ocean Niño Index (ONI), and the Southern Oscillation Index (SOI). We additionally focus on the strongest most recent El Niño events (1998, 2016, and& 2023) and the QIC's response to these short-term climate anomalies.

115 **2 Methods**

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2.1 Current Analysis Techniques

Manual snowline tracing is often limited to high quality imagery to determine scern between snow versus and ice presence. However, recent advances in image analysis have included allowed for the automation of snowline detection via satellite imageryas often manual tracing is limited to higher quality imagery to determine snow versus ice presence. Typically, a suite of images, often from Landsat satellites, are paired with one or more Digital Elevation Models (DEMs) and a glacier outline from the beginning of within the temporal scale of interest (Li et al., 2022). From there, a variety of thresholds are evaluated and set for the area of interest to separate snow from ice, and extract the position of the transition with the SLA extracted from automated calculations to be used as the ELA (Racoviteanu et al., 2019) or manual tracing of outputs (Liu et al., 2021). There are challenges in this process including the adjustment of ing surface reflectance from the for varying topographiesy, occurrence of patchy snow cover on thea glacier surface, and highly variable atmospheric conditions that require the algorithm to be adjusted to customized for the location of interest (Racoviteanu et al., 2019). Previous studies on Andean glaciers have used included a handful of techniques to extract the location of the snowline and to overcome some of the aforementioned challenges, -including satellite imagery analysis and spectral mixing analysis from the Landsat short wave infrared (SWIR) and near infrared (NIR) bands (Klein & Isacks, 1999), simple as well as satellite imagery band ratios and filtering, hillshade mask shadow removal, and manual editing (Hanshaw & Bookhagen, 2014; Klein & Isacks, 1999). Here we a-implement an automated approach that employsing athe necessary topographic correction, and followed by image segmentation via the OTSU method of the NIR band via the OTSU method, which we describe in further detail in section 2.3, below.

2.2 Data Collection

To automate the SCA detection and ELA calculation, the following data inputs were required: an annual satellite image, a DEM, and the 1985 outline of the QIC. Using the Google Earth Engine platform (GEE) we selected annual Landsat images as close as possible to September 15thst with clear visibility of the QIC from 1985 to 2023 (Table S1). September 1st Mid to end September marks the end of the dry season in the CV, which enabled analysis of the ice cap without extraneous snowfall around the perimeter. Imagery from each year was on average ±23 days within the target date and was manually inspected to ensure no recent snowfall events occurred. Additionally, Lif September imagery was not available. October and November images were collected, and if imagery was still not available August and July were collected with the intention to collect the closestbest to end of dry season conditions at the QIC. No images were used and were not used if a recent snowfall event was evident. Sentinel-2 imagery was used in 2021 and 2023, due to a lack of cloudless images from Landsat 8/9. As one of our aims was to analyze the 2023 El Niño event, a separate Scripts were adapted for each satellite (i.e., Landsat or Sentinel-2-set of) imagery. script was adapted for the higher resolution and alternate detail of Sentinel 2 processing. We note that the 2023 results are not included in our initial analysis of QIC's ELA change as it is part of an incomplete El Niño event. No imagery was collected for the years 1987, 19943, 20042, and 2012, and 2018 due to high cloud cover and/or visible snowfall

events. We used two DEMs tousage accounted for changes in ice elevation over time and any down wasting of the QIC. I, and initially the NASADEM, created from the Shuttle Radar Topography Missions (SRTM), was implemented from 1985 to 2005. Post 2005, the COP30 DEM, released in 2010, was implemented following an assessment of surface difference-differences in both DEMs between 2005 to 2015. Additionally, throughout and following the two largest El Niño events (1997-1999 and 2015-2017). He and 18-multiple images (16 and 18, respectively) from June of the first year to November of the last year, respectively, were collected, from June of the first year to November of the last year, to assess short-term change and response of the OIC to El Niño events.

2.3 Satellite Analysis for Snow Cover Area

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To begin, the least cloudy image from the end dry season target year closest to the end of dry season is clipped to the region of interest (ROI), the delineated OIC boundary (Step 1; Fig. S1). Pre-processing of each image included calculating the slope and aspect of the ROI from the DEM (Step 2). We-then implemented the Ekstrand Correction (Ekstrand, 1996) to account for topographic effects such as shadowing, due to differences int sun elevation s-and incidence angle (Step 3) rather thanillumination condition, which for the detection of the same features under different sunlight conditions (Step 2; Martín Ortega 160 et al., 2020). We use the Minnaert Correction (Ge et al., 2008), which assumes the reflectance of a surface is proportional to the cosine of the angle of incidence. Both are used to topographically correct for variability of observed reflectance and apply such to the selected annual image (Step 3; Ge et al., 2008). The QIC's low sloping topography works well with this method instead of a pixel-based Minnaert Correction method (Ge et al., 2008) which resulted and set band coefficients as it results in the the over-correction of the steeper eastern side of the OIC. is an excellent ease study for this method as the low-sloping 165 topography does not create as many shadows as a steep mountain glacier. To delineate the snow cover area (SCA), the NIR band was assessed with an image segmentation algorithm, the OTSU method (Gaddam et al., 2022). This results in . The NIR band records a bimodal frequency histogram where an of snow and ice and the OTSU method is designed to automatically detected the threshold separates snow from ice (Step 4; Fig. S2). Once calculated, it is applied to the NIR band to create a binary mask of snow and ice (Step 4). The annual image and DEM are then clipped to the snow mask creating the SCA, and 170 the DEM data is extracted (Step 5). Following this, and the SCA is calculated based on the number of pixels and image resolution, and the median elevation of the SCA is determined are calculated. SCAs are exported to shapefiles and the DEM data is exported as a histogram in 50-meter elevation bins (Step 6).

2.3 Calculation of Total Area, AAR, and ELA, and Uncertainty

As the SLA is a proxy for the ELA, we will use the term ELA from this point forward. In pursuit of the ELA, we calculated the Accumulation Area Ratio (AAR). The AAR is defined as: AAR = Ac/(Ac +Ab) where Ac is the accumulation area, Ab is the ice covered area, and Ac + Ab is the total area (TA) (Meier, 1962). In this case, Ac is the SCA and Ac+Ab is the TA (both ice and& snow). To calculate the TA, we automated the calculation of the Normalized Difference Snow Index (NDSI), which leverages the reflectance of snow and ice in the green and SWIR spectra compared to other land cover types. The NDSI is

calculated by the following equation: NDSI = $(\rho_G - \rho_{SWIR})/(\rho_G + \rho_{SWIR})$, where ρ_G and ρ_{SWIR} are the reflectance of the green and shortwave infrared bands, respectively (Dozier, 1989; Hall & Riggs, 2007). We used the same OTSU thresholding method to calculate the NDSI threshold, typically set around 0.4 (Dozier, 1989; Hall & Riggs, 2007; Sankey et al., 2015). The number of snow- and ice-covered pixels is multiplied by the appropriate pixel resolution to obtain the TA. By applying the threshold to each image, we obtained a binary image of snow and fice versus land coverneither and used this to calculate the TA (Step 7). The AAR is calculated by dividing the SCA by the TA (Step 8). The ELA is calculated using the DEM and the AAR by taking the 1 – AAR percentile of all elevations in the TA (Step 9: Fig. S3). For example, if the AAR is 0.8, we assume the ELA is located at the 20th percentile of elevations in the TA. In summary, for each image analyzed, we obtained the SCA, the median elevation, the TA, the AAR, and the ELA. Calculated results for the SCA and TA via our automated methods are in good robust agreement with seven-manual digitizations (of the ELA SCA resulting in an error of SCA withinwithin ±3%) of the automated SCA and TA calculations. Other studies have shown manual and automated detection of snowlines produces similar results to manual digitization and low level of error (Hanshaw & Bookhagen, 2014) with automated detection being preferable to manual as repetition is simpler and any error is likely to be more consistent (Paul et al., 2013).

2.4 Renanalysis Data and ENSO Correlation

To observecompare the QIC's SCA and ELA alongside with climate, ie variables we used daily and monthly averaged data from the ERA5—Land Reanalysis Climate Data from the European Centre for Medium—Weather—Range Weather Forecasts (ECMWF), including total precipitation and surface 550mb temperature. Initially, we divided the data into wet (October to April) and dry (May to September) seasons based on precipitation records and past literature (Kaser & Osmaston, 2002; Veettil et al., 2017). To observe changes in climate at the QIC over time we calculated the average precipitation and temperature in five-year intervals, and the number of average number of days above and below freezing for each season from 1985 to 2023. Finally, tTo analyze assess the QIC's interannual response to climatic anomalies we paired detrended ELA, SCA, and median elevation with the MEI, SOI, and ONI indices for correlation. As such, the variables for each year were correlated with the preceding months' indices, for one year before the annual September observation date.

3 Results

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3.1 Ice Loss and Multi-Decadal Climate Trends

Over the observation period (1985 toand 2022), the QIC lost ~347% of its TA and ~5846% of its SCA (1985: TA=~598.76 km², SCA=~46.38 km²; 2022: TA=~369.67 km², SCA=~25.319.7 km²; (Table S2). Average loss Bbetween the first and last five observed years of observation, the QIC's and the last five recorded an SCA and TA declined by of ~38% and the TA by ~29%, respectively... This SCA-TA loss is concurrent with a retreat of the TA-SCA to higher elevations (Fig. 2). We observed a 168-209 m and 84-112 m rise of the ELA and median elevation of the SCA, respectively. In 1985, 90% of the SCA existed above 5,250 m a.s.l., and in 2021, 90% of the SCA shifted to elevations above 5,350 m a.s.l. Further, and by 2022, 90% of

210 the SCA shifted even higher, to elevations above 5,350 400 m a.s.l. On average, tThe SCA and TA record an average loss ofdecreased by ~0.72 km² and ~0.59 km² per year, with an average yearly ELA rise of ~5.65m. On average L, linear regression models suggest a loss of $0.3947\pm0.09 \text{ km}^2 \text{ yr}^{-1}$ (R²=0.3644, p<0.001) in the QIC's SCA; an average loss of $0.4948\pm0.023 \text{ km}^2$ yr^{-1} (R²=0.9389, p<0.001) in the QIC's TA; and an average rise of $\frac{2.963.61\pm0.759}{2.963.61\pm0.759}$ m yr^{-1} (R²=0.3240, p<0.001) in the QIC's ELA, However, the removal of the three largest El Niño influenced years (1998, 2016, and 2023) indicate indicates resulted 215 ined slower average losses in QIC's SCA and TA, and a slower average rise in QIC's ELA: -0.3642±0.077 km² yr⁻¹ (R²=0.580, p<0.001); $0.47\pm0.03 \text{ km}^2 \text{ vr}^{-1} (R^2=0.89, p<0.001)$; and $\pm2.723.25\pm0.59-64 \text{ m vr}^{-1} (R^2=0.472, p<0.001)$, respectively (Table S3). The QIC's average AAR (minus not including El Niño and La Niña years) is 0.74 throughout over the study period. Conversely, during, with the strongest El Niño years (1998, 2016, and 2023) the QIC's AAR was (0.320, 0.4501, and & 0.522, respectively) and during the strongest La Niña years (1999 and 2011) the OIC's AAR was (0.83, and 0.82), as the exceptions. 220 If we consider the 2023 El Niño, between 1985 to 2023, we observed a 60% decline in the QIC's SCA in just under 40 years (Fig. 4). Our measured variables show significant correlation to each other. For example, we find a strong positive correlation between the median elevation and the ELA (0.98), a strong negative correlation between the ELA and the SCA (0.98) and a strong positive correlation between the SCA and AAR (0.84, Table S4).

225 The QIC's Delaily and monthly variations recorded atby the QIC summit and bottom margin weather stations from Bradley et al., (2009) are well correlated with the ERA5 surface 550mb temperature dataset, which was analyzed used to determine changes in meteorological temperature variables through the observation period. Analysis of the ERA5 Between the first and last five years in our observational period, surface the reanalysistemperature data records recorded a 0.60°C increase in wet season (October-April) temperature and 46% of the wet season (October April) and 11% of the dry season (May 230 September) with mean daily temperatures above 0°C. Tthe average temperature of the first five and last five years a show an increase increasing of 0.5960°C in the wet season (October April) and 1.124°C increase in the dry season (May – September) temperature. Similarly, the number of days above 0°C rose from 321% to 506% in the wet season and from 50.5% to 478% in the dry season between ever the first five and last five years. These results are consistent with previous studies discussing that suggest a ~0.1°C/decade rise in upper air temperature, and a rise in the height of the freezing leveline (~45 m between 1977-235 2007) in the tropics near the QIC (Bradley et al., 2009; Vuille et al., 2008). We observe no significant change in a linear regression for precipitation in both the wet and dry seasons (wet: R²=0.02, p=0.05; dry; R²=0.03, p=0.01) with 73% of the precipitation occurring during the wet season.

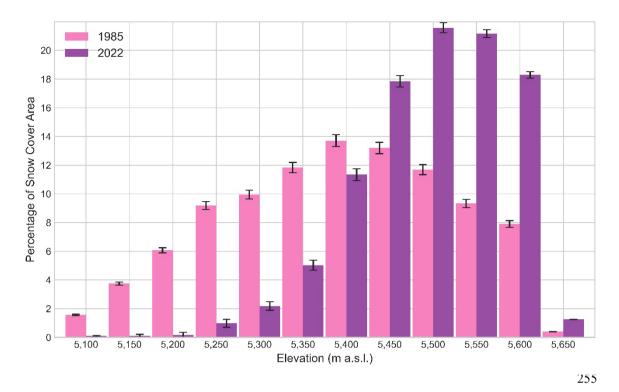


Figure 2: Percentage of snow cover area (SCA) in 50-meter elevation bins, demonstrating the shift to higher elevations.

3.2 QIC Response to Short-Term Climate Phenomena

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The strongest El Niño events (1998, 2016, and 2023) coincide with a large decrease in the QIC's SCA. We observed a 6352% reduction loss in SCA from 1997 to 1998 and a 4048% reduction loss from 2015 to 2016. In 1999, a rebound of the SCA was observed back to 1997 conditions however, in 2017 the SCA only reaches reached about 760% of its 2015 value (~32km²) following the 2016 El Niño (Fig. 3). A small increase in the SCA is observed in 2019 (no imagery was available for 2018), however, to date the SCA has notever returned to its pre-El Niño 2015 eoverageextent and has continued to decline up through 2022, full rebound in the SCA is not observed until two years following the event, in 2018. To better determine the patternsQIC changes during the El Niño events, high frequency sampling was conducted around the complete El Niño events, consisting of 16 and 18 images collected between 1997—1999 and 2015—2017, respectively. In both cases, the lowest SCA during El Niño is observed in the annual mid—September measurement, with a steady decline occurring from the prior year's September measurement over the three consecutive years. In addition, correlation between the monthly ELA and monthly ONI index during the two El Niño events (1997-1999 and 2015-2017) are 0.68 and 0.26, respectively. The 1997 to 1998 QIC's AAR decreasedrops from 0.715 to 0.310 from 1997 to 1998 and from 0.76 to 0.41 from 2015 to 2016. from 0.786 to 0.451. During these El Niño events, noticeable spikes are recorded in ERA5 temperature recordsdata recordedshows increased air temperatures while precipitation patterns and magnitude remain largely unchanged. For instance, during the dry season from

1997 to 1998 there is a 1.35°C increase in temperature and a change inof total precipitation under of less than 0.025 meters. Additionally, If we fit linear regression models for the ELA and SCA that to linear regression include model with El Niño years as a binary predictor (i.e., yes or no), improve thethe R² valueseeefficients for the ELA and SCA from 0.39 to (R² = 0.67 (5) p<0.001) and; & 0.44 to R²=0.6772 (-p<0.001), respectively improve with statistically significant values. However Conversely, the R² value TA coefficient for the model predicting TA does not improve with the inclusion of the binary predictors (R²=0.903. p=0.73<0.001). Aan analysis of variance testing (ANOVA) with a post hoc test records shows a significant difference in the mean SCA and ELA from between El Niño andto neutral conditions years, as well asnd in the AAR between El Niño andto neutral years and between El Niño to La Niña years (Fig S41). There is no significantee difference in the mean TA TA does not record any significant differencet within between El Niño, La Niña, andte neutral conditions years (Table S45). As the 2023 measurements occur during an ongoing El Niño event, we initially compiled data from 1985 to 2022 and reported the 2023 data as an additional insight into the effects of El Niño events on the QIC. If we consider the 2023 El Niño, between 1985 to 2023, we observed a 61% decline in the OIC's SCA in just under 40 years (Fig. 4). The OIC's SCA observed during the onset of the 2023 El Niño is ~17.97 km²—, a 259% loss compared to that of 2022. The 2023 AAR is calculated at 0.532, well below the average (i.e. 0.74), and f. From 2022 to 2023, we observed a 31-15 m and 828 m rise of the ELA and median elevation with 90% of the SCA existing over 5,400 m a.s.l. as opposed to 5,350 m a.sl. in 2022. We intend to continue to monitor the QIC to determine the continued effects of the El Niño event and any possible rebound that could occur in 2024.

ENSO indices were are most strongly correlated with the QIC's ELA, SCA, and median elevation as they best represent the changing ice distribution and mass. We evaluated all three previously mentioned ENSO indices but have chosen to discuss the ONI as it presented the clearest patterns between ENSO and the assessed QIC variables (Table S56). The ONI is measured as sea surface temperature (SST) anomalies in the Niño 3.4 zone (5°N - 5°S and& 120°W - 170°W) and is mostly used to define El Niño and La Niño events. The ONI is most strongly correlated to the median elevation (Table 1Fig. 5) with a Pearson coefficient from the preceding April back through the previous September ranging from 0.489 46 to 0.644-61 (P<0.05). The ONI and ELA are similarly positively correlated (0.41 to 0.58 April-September), while ndthe ONI index and SCA exhibit a median elevation recorded negative correlation of similar strength a similar pattern with the prior wet season (March April through September (-0.44 to -0.60), recording the highest correlations (0.517 41 to 0.64458). The SCA recorded a similar pattern through a negative correlation from the prior wet season (0.555 44 to -0.6041).

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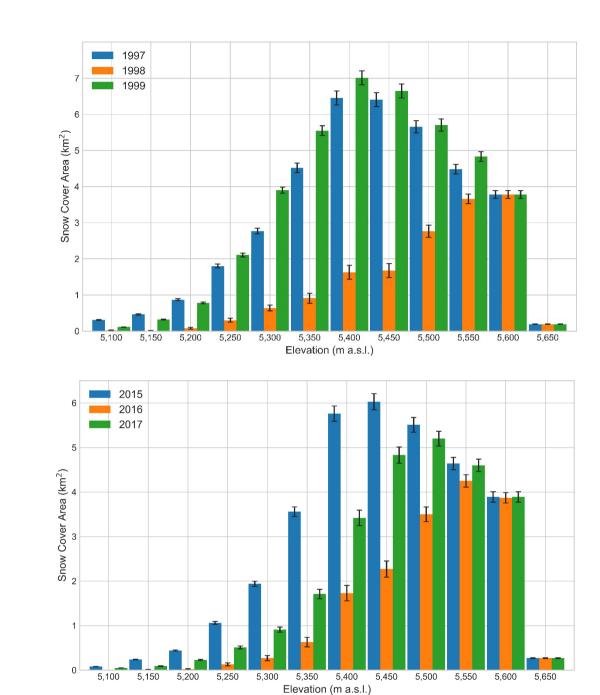


Figure 3: Percentage of snow cover displaying <u>reduction loss</u> and rebound of the SCA during the 1998 El Niño event (top) and incomplete recovery following the 2016 El Niño event (bottom).

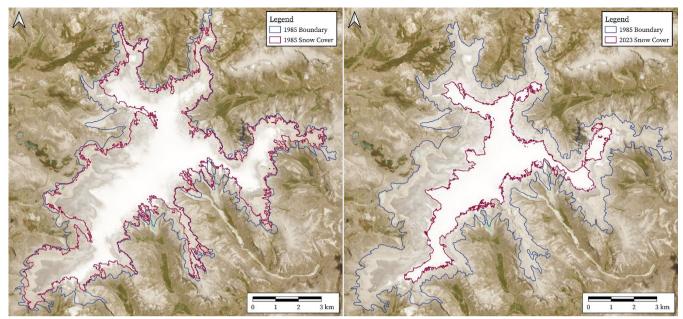


Figure 4: Decrease in the QIC's SCA (red) and TA (blue) at the end of the dry season from 1985 (left) to 2023 (right). Base Imagery obtained from Planet Labs Dove Satellite with 3-meter resolution, October 2023.

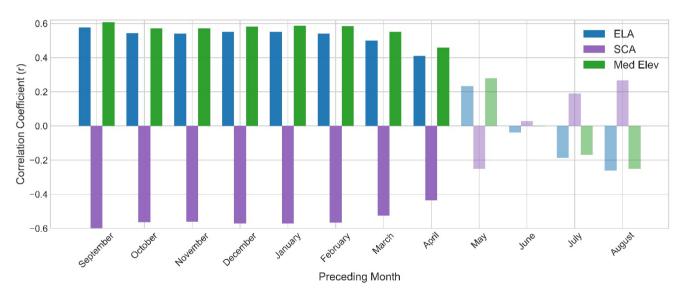


Table-Figure 51: Zero-order correlations (r) for QIC variables (ELA, SCA, and Median Elevation (Med Elev)) and the ONI Index. Correlation coefficients with non-statistically significant p-values (≥ 0.05) are indicated denoted in boldas semitransparent bars italies.

4 Discussion

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4.1 QIC Response to Short-Term Climate Variability

During El Niño events, the Peruvian Andes are often drier than average (Sulca et al., 2018), with on-site measurements at Quelccaya recording warmer and drier conditions (J. Hurley et al., 2019). Peru records higher precipitation along the northern coast, the Amazon, and the Andes (Lagos et al., 2008). To be considered an El Niño event, the SST anomalies must be high for at least four consecutive months (Lagos et al., 2008). Our results suggest? , and it is likely that these longer termlongerterm SST anomalies have a greater influence on the SCA than singular precipitation events (i.e., of which no correlation is observed between wet season precipitation and the SCA, ELA, and SCA median elevation), unlike the ONI index correlation. We see-demonstrateed evidence of these that the El Niño events in 1998 and 2016 impact correspond toing large reductions in OIC's the SCA and TA (Fig. 65). These SCA perturbations record Z scores of 2.3 and 2.11, are outliers from the observed declinemean SCA (z-score = -2.3 and -2.11, respectively; avg zZ-score = 0.12). These, and are evident in QIC shallow ice cores which display a 'smoothed' δ^{18} O signal during the El Niño instead of the usual high-resolution variability, indicating warm and dry conditions that lack accumulation and experience melt (Thompson et al., 2017). Linear rRegression analysis completed with and without El Niño event yearss show record recorded differing slope coefficients, indicating these events are associated with an enhanced reduction ining the OIC SCAice loss reduction. As noted in the the results, the SCA rebound from the 2016 El Niño did not fully occur until years later, unlike in 1999 which was one of the strongest La Niña events (ONI Index of -1.5) within the observation period, along with 1989 and 2011... This suggests the timing and magnitude of La Niña events are an additional factor influencing the year-to-year variability in SCA.

as 1999 (ONI Index of 1.5) was one of the strongest within the observation period, along with 1989 and 2011. In addition, Correlation during El Niño events between the monthly ELA and ONI index during. El Niño events (1997-1999 and 2015-2017) declines are from 0.65 and to 0.34, respectively, with respect to the 1998 and 2016 with the linear regression changing from an required of 0.434 (p<0.001) to R²r squared of 0.12-07 (p<0.0512) El Niños. If we consider El Niño and La Niña events that corresponding to ONI indexes greater than ±1.0, Tthe linear regression model with the an El Niño binary predictor records shows a strong and significant relationship between TA and year (R²=0.94, p<0.001). However, but variance testing analysis across the entire temporal scale indicates the presence of that El Niño years have provided a stronger impact onto the SCA, AAR, and ELA than on the TA (Fig. S4, Table S45). While the SCA is notably briefly impacted by these El Niño events, decline from anthropogenic warming has resulted in the long-term decline of the SCA and TA of the QIC (Bradley et al., 2009; Rounce et al., 2023; Thompson et al., 2021; Vuille et al., 2018; Yarleque et al., 2018). Further, during all previously noted La Niña events (Fig. 6), the SCA experienced some level of temporary expansion, but throughout the 2021-2022 La Niña, the SCA did not appear to rebound, but only declined further. While this is only one incidence, we expect this behavior to continue through the onset of the predicted upcoming 2024/2025 expected La Niña. The decrease in the percent-percentage of days at or below freezing during the wet season; will only exacerbate the decline in SCA. In addition, a recent study has

indicated projected the expectation of faster onsets and slower decline for of future El Niños future El Niños (Lopez et al., 2022). ; and Ceonsidering the current state of the QIC and the ongoing El Niño, a slow decline after of the current event will only delay recovery of in the SCA, and act to enhance mass loss, and continue to intensify its decline.

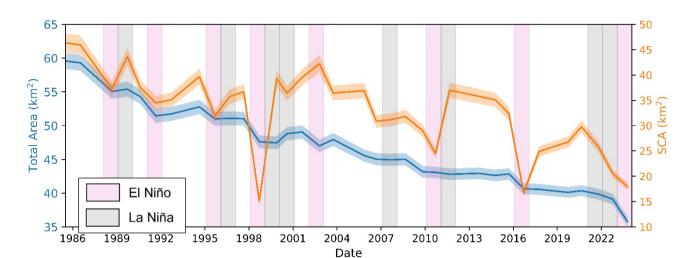


Figure 65: Decline of QIC's TA and SCA over the observational period (1985-2023). Timing of El Niño and La Niña events (recording anwith ONI indexes greater than ±1.0)- are noted in pink and gray colored coincide more readily with SCA than TA changes bars, respectively. Strongest events are denoted with stars (*).

4.2 Equilibrium State of the QIC

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Glaciers in other locations such as the New Zealand Alps and the European Alps are considered in steady state with AARs of around 0.6 (Benn & Lehmkuhl, 2000), but tropical glaciers require an AAR of ~0.8 (Kaser & Osmaston, 2002). Discounting El Niño years (1998, 2016, &and 2023), the QIC average AAR is 0.744, indicating the QIC## is out of equilibrium, and likely somewhat lagging in response compared with with the pace of the ongoing changing climate change. The ice cap is pushed even more noticeably out of equilibrium during the observed El Niño events with AARs of 0.310, 0.541, and 0.523. These are far lower values than required for even high latitude glaciers, and far below the average for the QIC. Our results indicate the SCA has changed mores more dramatically on a year-to-year basis than the TA (Fig. 65), but the quick rebound of the AAR indicatinges rapid response of the SCA and thus the ELA to short-term climate variability, in addition to and its more recent decadal—scale changes (Zekollari et al., 2020). This is consistent with other studies that indicate thee QIC is likely responding to climate drivers within a few decades from the present, including the almost immediate response to El Niño events (Thompson, 2017; Veettil et al., 2017). Previous analyses of work on Quelccaya observed showed The median elevation of the entire QIC was recorded risingrose ~1.59 m per decade from 1975 to 2010 (Taylor et al., 2022) (Taylor et al., 2022), which is slightly less than ourthis estimate (~1.91 m/decade), although we note the different the temporal scale—observed was different.

400 Similarly, previous studies of the OIC note a mean ELA between 1992 and 2017 of ~5,436 m a.s.l. (Yarleque et al., 2018) while and our automated methods suggest a mean ELA of ~5,351 m a.s.l. for the same temporal scale. The OIC is likely responding to climate drivers within a few decades from the present, including the almost immediate response to El Niño events (Thompson, 2017; Veettil et al., 2017). This is evident in the regression analysis, when the El Niños are removed, the regression improves noticeably and variance testing to evaluate the mean of each variable during these different climatic 405 conditions Considering the QIC's likely continuation of the out of equilibrium state, as well as projections continuing along the linear continued decline of the SCA and rise of the ELA due to ongoing anthropogenic climate change, we suggest indicate the possiblethat the QIC will lose its stop receiving snow coverSCA before 2080 (-becominge a wasting ice field) and may and disappearance of the QIC completely melt away by 2090 prior to 2100 (assuming the rate of loss is constant; Fig. S5). Further However, with increasing ice loss, there is potential for an uneven ice surface with standing water to change the albedo. and thus affect the QIC's mass balance, enhancing its decline (Naegeli & Huss, 2017; Wang et al., 2015). As the ice continues 410 to retreat, an uneven ice surface, future El Niños, and anthropogenic warming will likely exacerbate the process, pushing its demise closer to the present than expected.

5 Conclusion

We automate the process of satellite-based collection of yearly OIC parameters variables important for mass balance 415 assessment and assess the ice cap's short-term fluctuations to local climate forcings, including temperature fluctuations and El Nino events. We observe and record decadal-scale change in TA, SCA, and ELA and high interannual variability in SCA and ELA. Specifically, we observe with staggering change in the QICloss over the last four decades including a \sim 42% TA loss in TA, a ~61%—SCA loss in SCA, and a ~224 meter rise of the ELA. In the height of the wet season, the ONI index is the determining factosignificantly correlated with for the QIC's SCA at the's end of dry season, with noticeable decreases of the 420 AAR during each El Niño event. While the SCA has responded rapidly to the ONI changes of the past, the SCA has declined through the most recent La Niña and is likely may to continue to do so during the next. condition, but as anthropogenic warming continues to overwhelm natural climatic signals the entire SCA continues to rapidly decline. Continued monitoring of the QIC will be vital, as the potential for surface processes and future El Niños to accelerate the ice loss rises with continued warming. The implications for Further, the OIC's future demise points towards water scarcity for the local population, creating uncharted 425 difficulties alongside the lessening of a water source, especially seasonally (Veettil et al., 2017; Vuille et al., 2018). With ongoing warming, we expect to see continued shrinkage of both the SCA and the entire QIC in the coming decades.

Code and Data Availability

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All calculated QIC variables from this study are provided within the supplementary information, detailed in Table S2. Annual SCA shapefile data and DEM bin distribution initially calculated within GEE is available at the following repository at https://doi.org/10.5281/zenodo.1126556810.5281/zenodo.10694300. A sample code for preprocessing and processing Landsat

8 images is available at the following url:

https://code.earthengine.google.com/72e85af2cc7c2e10482a939f7dd1cfe6?noload=true.

https://code.earthengine.google.com/cfcbd0780ff3f09b0698035cd6dd678a.

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Author Contribution

K.A.L. designed the study, developed the code, collected the snow cover data, and completed the analysis of the data and accompanying climate variables. K.A.L. wrote the manuscript. K.A.L., L.J.L, L.G.T., and B.G.M. contributed to the discussion of the results, editing, and revision of the manuscript.

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Competing Interests

The authors declare that they have no conflict of interest.

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