Climate change on the Quelccaya Ice Cap, Central Andes, and its relationship with the large-scale circulation

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CLIMATE CHANGE ON THE QUELCCAYA ICE CAP, CENTRAL ANDES, AND ITS
RELATIONSHIP WITH THE LARGE-SCALE CIRCULATION

by

Christian Pedro Yarleque Galvez

A Dissertation
Submitted to the University at Albany, State University of New York
in Partial Fulfillment of
the Requirements for the Degree of
Doctor of Philosophy

College of Arts & Sciences
Department of Atmospheric and Environmental Sciences
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DEDICATION

To my three loves,

My precious son Angel,

My beautiful daughter Paloma

and My lovely wife Maritza…

…and to my former mentors,

my dad the Principal Pedro Pablo Yarleque

and my mother the Artist Mercedes Galvez.
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The last lines are for the most important support that I had in every moment and in many ways, to my lovely wife Maritza Rodriguez. Thanks for being part of my life, without you and your help, nothing of this could be possible, I love you so much.
Statement of Publication and Contribution of Authors

I, Christian P. Yarleque Galvez, was the lead researcher for all material presented in this Thesis with the support of Dr. Mathias Vuille at the University at Albany, who contributed with the discussion, comments, advice, and edition of the thesis.

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The Chapters 2 of this dissertation include the following published material, with only minor changes to ensure continuity in tables, figure, and section numbering throughout the thesis. An
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ABSTRACT

Glaciated areas over the central Andes are highly sensitive to atmospheric forcings, as demonstrated by their current accelerated retreat in response to global warming. The present Thesis is focused on quantifying and assessing future climate change impacts over Quelccaya ice cap (QIC), the world-largest tropical ice body, which is considered as a representative case of the tropical Andean cryosphere. I focused my study on characterizing large-scale forcing and future changes of precipitation and temperature, since they represent the most important variables for accumulation and ablation processes in glaciated mountain regions. In my research I developed tools to overcome the lack of in-situ information over mountain regions; I addressed the challenge to obtain accurate precipitation estimates from coarse-resolution global climate models (GCM), and developed projection of the future state and evolution of the QIC.

A new high-resolution (~1 km² and 10 calendar days) precipitation reconstruction method was built and yielded data that improves information regarding precipitation over complex terrain and confirms that local precipitation over the central Andes is highly dependent on regional forcings. This relationship was quantified by a linear model relating local QIC precipitation to regional precipitation (mean of precipitation data from 9 in-situ weather stations surrounding QIC). In addition, an empirical statistical downscaling (ESD) multi-linear model was built to quantify the association between regional precipitation and large-scale atmospheric parameters. Both the linear and multi-linear models were used to calculate future QIC precipitation taking as input large-scale climatic parameters (zonal and meridional wind at 500 hPa, and omega at 700 hPa) from the CMIP5 model simulations for historical, RCP4.5 and RCP8.5 scenarios, across the 21st century.
The results do not show any major future changes for QIC precipitation regardless of scenarios. Instead the role of precipitation will be mediated through temperature, as changes in the (snow/rain/mixed) precipitation phase will likely be a major factor for the future QIC net mass balance.

Future projections of air temperature (Ta) and the equilibrium line altitude (ELA) at QIC summit were derived using the CMIP5 model simulations; with the ELA being derived indirectly through its linear association with the freezing level height (FLH). Results show that Ta at QIC will increase between 0.25 and 0.57 ºC/decade, resulting in a warming of 2.4ºC and 5.4ºC at QIC summit by the end of the 21st century in RCP4.5 and RCP8.5 scenarios, respectively. The critical value of Ta=−1ºC, where the precipitation phase will start to switch from solid to liquid and increasingly result in mixed precipitation will reach the summit around the year 2070 in the RCP8.5 scenario.

Based on the analysis of future ELA projections, the contribution of the elevation-dependent warming (EDW) effect to warming over the QIC is quantified and indicates that EDW adds about 7.6% and 9.9%, for RCP4.5 and RCP8.5, respectively, of extra ELA rise per decade. Finally, ELA projections under the high-emission scenario will rise continuously yielding an increasingly more negative mass balance of the QIC, thereby accelerating the ice cap retreat. It is estimated that starting around the 2055, for the RCP8.5 scenario, the ELA will be located at or above the QIC summit, thereby turning the entire ice cap into an ablation zone, which would lead to the eventual complete disappearance of the ice cap.
# TABLE OF CONTENTS

DEDICATION .................................................................................................................. ii
ACKNOWLEDGEMENTS ................................................................................................. iii
Statement of Publication and Contribution of Authors ....................................................... v
ABSTRACT ....................................................................................................................... vii
LIST OF TABLES ............................................................................................................. xii
LIST OF FIGURES .......................................................................................................... xili
ABBREVIATIONS ............................................................................................................ xviii

Chapter 1 ......................................................................................................................... 1
INTRODUCTION ............................................................................................................. 1
1.1. Motivation ............................................................................................................... 1
1.2. Objectives .............................................................................................................. 3
1.3. Background ............................................................................................................ 3
1.3.1. Quelccaya Ice Cap (QIC) and Central Andean climate ....................................... 3
1.3.2. Regional and Global Climate Models (GCM) ................................................... 8
1.3.3. Linking large-scale circulation with local-scale climate (Downscaling) .............. 10
1.3.4. Future projections over the Central Andes ......................................................... 12
1.4. Research structure and proposed hypotheses ....................................................... 13
1.5. References ............................................................................................................ 16

Chapter 2 ......................................................................................................................... 24
MULTISCALE ASSESSMENT OF SPATIAL PRECIPITATION VARIABILITY OVER COMPLEX MOUNTAIN TERRAIN USING A HIGH-RESOLUTION SPATIOTEMPORAL WAVELET RECONSTRUCTION METHOD ................................................... 24
Abstract ....................................................................................................................... 25
2.1. Introduction ......................................................................................................... 26
2.2. Study area and data used ..................................................................................... 30
2.2.1. Quelccaya Ice Cap Region ............................................................................. 30
2.2.2. Observed precipitation data around QIC ...................................................... 30
2.2.3. NDVI as a proxy for precipitation ............................................................... 32
2.2.4. Spatio-temporal rain rate satellite data ....................................................... 35
2.2.5. Elevation variable ......................................................................................... 36
2.3. Methods .............................................................................................................. 37
2.3.1. Spatial NDVI-precipitation lag calculation: Influence zone ............................ 37
2.3.2. High spatio-temporal precipitation reconstruction and cross validation .......... 37
2.4. Applying the spatio-temporal reconstruction method around QIC ...................... 39
2.4.1. Obtaining the influence zone matrix .............................................................. 39
2.4.2. Selection of the level of reconstruction .......................................................... 39
2.4.3. Precipitation reconstruction and cross-validation .......................................... 41
2.4.4. Assessing the spatial precipitation distribution .............................................. 42
2.4.4.1. Spatial aspects of the reconstructed precipitation ...................................... 42
2.4.4.2. Assessing the reconstruction over the eastern Andean slope ........................ 45
2.4.5. Comparison of reconstructed precipitation with snow accumulation at QIC ...... 46
2.5. Discussion and Conclusions .............................................................................. 48
2.6. Acknowledgements ............................................................................................ 54
2.7. Tables ................................................................................................................... 55
4.5. Acknowledgements ........................................................................................................... 140
4.6. Tables .................................................................................................................................. 141
4.7. Figures .................................................................................................................................. 143
4.8. References ............................................................................................................................. 150

Chapter 5 .................................................................................................................................... 156
FINAL CONCLUSIONS OF THE THESIS ................................................................................... 156
LIST OF TABLES

Table 2.1. Weather stations located in the study area (Figure 2.1) satisfying the criteria described in section 2.2.2. The lag and the maximum coefficient of determination (max. $R^2$) values correspond to the precipitation-NDVI dekadal time series comparison during the period 2000-2009 period.

Table 2.2. Shannon’s entropy ($E$), entropy difference ($\Delta E$), and the coefficient of determination ($R^2$) for NDVI and precipitation ($Prec$) for different wavelet decomposition levels ($i$). The precipitation time series is selected using the influence matrix to define which of the 13 station time series performed best at each location. The NDVI time series is corrected by applying a lag when compared with the precipitation time series. The entropy is calculated using a normalization unit for the corrected NDVI and precipitation. The absolute value ($|E|$) of the entropy difference between both signals is used for each level. The $R^2$ is calculated for each Trend of the wavelet decomposition process applied to the corrected NDVI and precipitation of each dekadal time series, but only the mean across the 13 station locations is shown for each decomposition level. An adjusted $R^2$ between reconstructed precipitation started in level $i$ ($Rec_i$) and measured Prec, is calculated per station location, but only the mean across the 13 station locations is presented.

Table 2.3. Cross validation of reconstruction model and statistical comparison using TRMM data. A cross validation was applied to reconstructed dekadal precipitation ($Rec$) using 6 randomly selected weather stations not included in the reconstruction process (Obs) starting at the 3rd level of decomposition, over the entire period 2000-2009. The indices used are the linear correlation ($r$), bias ($=\text{mean}(Rec)/\text{mean(Obs))}$), mean absolute error (MAE), and root mean square error (RMSE). Indices definitions were taken from (Dinku et al., 2008).

Table 3.1. In-situ weather stations (rows 1-9) used to calculate regional Andean precipitation between the 1st January 1979 and 28th February 2017, and AWS at QIC summit (row 10).

Table 3.2. List of the 16 CMIP5 models used.

Table 4.1. Landsat sensor and selected date for obtaining snow line altitude (SLA) by year between 1992 and 2017.

Table 4.2. List of CMIP5 models and attributes used in the present research.
LIST OF FIGURES

Figure 2.1. (a) The study area selected is highlighted by the black square, with coordinates 11.5°S - 15.5°S, and 72.5°W - 68.5°W. Weather station locations are shown with blue dots, including the AWS (red dot) located on QIC where snow accumulation was measured. Color shading represents the elevation in meters above sea level (masl). (b) USGS South America land cover version 2.0 map over the study area. The original land cover array is 446 rows and 452 columns, but was resampled to a 449 x 449 array using a bi-cubic interpolation technique to match the spatial scale of the NDVI data (~1km). Quelccaya ice cap location is indicated by the red dot.

Figure 2.2. NDVI dekad correction process using a smoothing methodology (section 2.2.3). The gray lines show the raw NDVI decadal data including extreme minimum values corresponding to periods of clouds and strong atmospheric scattering (noise). The bold black line corresponds to the filtered (corrected) NDVI data. Years on the x-axis are centered on the 3rd dekad of June. The NDVI values in the y-axis correspond to the original NDVI units from 0 to 255.

Figure 2.3. An example of the NDVI-lag determination and correction based on the station Sicuani. a) the optimal lag value (= 4 dekadals) as indicated by the maximum $R^2 = 0.66$ (red square) based on lagged correlation between precipitation and NDVI from Jan. 2000 to Dec. 2009. b) Precipitation – NDVI lag correction over the same period. Upper graph shows the dekad precipitation (blue line) and normalized and cloud corrected NDVI (green line) dekad time series. Lower graph shows same time series, but after shifting the NDVI data backward by 4 dekadals in order to remove the lag between precipitation and cloud-corrected NDVI data.

Figure 2.4. (a) Influence zone matrix derived from 7 out of 13 weather stations. The other 6 stations are retained for cross validation purposes (section 2.4.3). A topography mask was used to remove regions below 2500 masl (section 3.1). Numbers on the color bar correspond to the ID of each station in Table 2.3. (b) Influence zone matrix at ~1km² resolution, derived using 13 weather station locations with a $R^2$>0.35 and p-value<0.05, between NDVI(ST) vs. NDVI(x), where x represents locations over the study area, and ST the station locations above 2500 masl. Numbers on the color bar correspond to the ID of each station in Table 1. Black contours in (a) and (b) correspond to topography above 5000 masl, and white dot is representing QIC location.

Figure 2.5. Decomposition-Reconstruction Process based on the station Sicuani. Here the level 3 of reconstruction is shown (section 2.4.2). (a) Precipitation decomposition (downward arrows) using Symmlet-2 wavelet, until the level 3 is reached. (b) as in (a), but for the NDVI cloud (Figure 2.2) and lag-corrected data. (c) Reconstruction (upward arrows) from NDVI trend and precipitation detail signals at level 3, using a scaling factor (equation 3), and A’ means that A is previously normalized to 0-1 values. Precipitation details and reconstruction data are used for upper levels to obtain the final reconstruction at level 0 (i.e., at dekad time scale).

Figure 2.6. Reconstructed dekad precipitation (Rec.) for 1st dekad January 2000 based on 7 and 13 stations, respectively (left and middle figure), and the corresponding TRMM dekad precipitation (right figure) obtained from the raw TRMM v7 daily product. Gray, dark gray, and black contour lines indicate 3, 4 and 5 km elevation isolines, respectively. The red dot indicates the QIC location. A Lake Titicaca mask was applied.
Figure 2.7. (a) Reconstructed monthly precipitation climatology. Gray, dark gray, and black contour lines indicate 3, 4 and 5 km elevation isolines, respectively. The red dot indicates the QIC location. (b) As in (a), but for TRMM monthly precipitation climatology obtained from TRMM v7 daily product without any post-correction process (raw TRMM v7 product). A Lake Titicaca mask was applied.

Figure 2.8. Reconstructed precipitation (top row) and TRMM (bottom row) for dry (left), wet seasons (middle) and annual total (right) respectively. Gray, dark gray, and black contour lines indicate 3, 4 and 5 km elevation isolines, respectively. The red dot indicates the QIC location. A Lake Titicaca mask was applied.

Figure 2.9. Comparison of a) observed precipitation and b) NDVI seasonal cycle. Sicuani, Azangaro, Crucero, and Tambopata are located to the west, south, north and east of QIC, respectively. Sicuani, Azangaro and Crucero belong to the QIC system, while Tambopata is located on the eastern Andean slope (1340 masl), much below the Altiplano elevation.

Figure 2.10. Local analysis of reconstructed precipitation surrounding QIC, with a 0.0089° (or ~0.9805 km) resolution, for (a) dry and (b) wet periods, respectively. The black dot indicates the QIC location. The western and eastern QIC rectangles (10.79 km x 15.69 km or 0.0981° lat x 0.1426° lon or 11 rows x 16 columns), in red and blue, respectively, indicate the two regions selected over which precipitation was averaged to create time series from 2000 to 2009. Gray contour corresponds to 3 to 5.5 km elevation with a 0.5 km contour interval. White areas lack data as they are located below 2500 masl.

Figure 3.1. (a) South American topography from ETOPO2. (b) as in a) but for the regional study area (11.5°S to 15.5°S and 72.5°W to 68.5°W) indicated by black square in (a). Location of an automated weather station (AWS) on QIC summit (13.93°S, 70.82°W) is indicated by a red dot; 9 Andean stations are shown by blue dots. (c) Landsat 8 composite (bands 742) of QIC on 15th August 2016 with AWS location indicated by red dot. (d) Picture of the AWS on 10th July 2012.

Figure 3.2. (a) Monthly mean (calculated) precipitation derived from snow height data recorded by AWS at QIC summit (red dots), and monthly mean precipitation across 9 Andean stations (blue boxes); both plots were calculated over 2004-2017 period. Horizontal line in box represents the median precipitation averaged over the 9 Andean stations. The bottom and top box edges are indicating the 25th and 75th percentiles, and the whiskers are extended 1.5x(75th -25th percentiles) below the 25th percentile and up the 75th percentiles. (b) Scatterplot of DJF precipitation anomalies (z-scores) averaged across 9 Andean stations versus precipitation anomalies at QIC summit over the 2004-2017 period. Numbers indicate year of corresponding DJF wet season.

Figure 3.3. (a) Running mean Pearson’s correlation (gray dots) using 11-yr window, calculated using DJF regional precipitation anomalies (P, average of 9 weather stations around QIC) and DJF 200 hPa zonal wind anomalies (U200) aloft QIC from ERA interim reanalysis. Period of analysis is 1979-2017. Dashed line indicates correlation over the entire study period (r = -0.45). Anomalies are calculated with respect to the baseline period 1979-2005. Note that the scale of the y-axis is

xiv
reversed. (b) Wavelet coherence spectrum based on the same data as in (a). The Morlet wavelet was used in this analysis and only arrows with a squared coherence $>0.7$ were plotted.

**Figure 3.4.** Regression maps of DJF 200 hPa zonal (u) and meridional (v) wind and geopotential height (GPH) versus Andean precipitation (Prec.) for (a) 1979-2017, (b) 1979-1998, and (c) 1998-2017. (d), (e) and (f) as in (a), (b), and (c), respectively, but at 500 hPa. Wind field is only plotted where the correlation between either zonal or meridional wind component and Prec. is higher than 0.3 and it is significant at p-value<0.05. Scale for wind vector in m/s per std. dev., and the GPH contour range in m per std. dev. is indicated below (f) and are the same for all graphs. Positive, zero and negative GPH values are represented by black, bold, and dashed contours, respectively. Red dot indicates location of QIC summit.

**Figure 3.5.** Correlation map between DJF Andean Precipitation (P) and sea surface temperature (SST) from NOAA ERSST V5 over (a) 1979-2017, (b) 1979-1998, and (c) 1998-2017 periods. Correlations >0.2 and < -0.2 indicated color shading. Bold line indicates 0-contour. Positive and negative values are shown by continuous and dashed contours, respectively. Continental areas are shown in gray and elevation contour in black from 0 to 5 km by a step of 1 km, as indicated at bottom of (f). Red dot represents location of QIC summit.

**Figure 3.6.** (a) DJF 200 hPa geopotential height (GPH), zonal (u) and meridional (v) wind differences (1998-2017) – (1979-1998) in ERA-interim reanalysis. Contour interval is 5 m, colorbar (in m/s) indicates wind speed and reference wind vector is shown below the graph. (b) as in (a), but for DJF precipitation from GPCP product, with contours plotted every 20 mm, color bar in mm, and thick line indicates 0-contour. In both Figures, the black dashed rectangle delimits the area 5°N-25°S and 80°W-60°W, defining the large-scale forcing region influencing climate variability in the Central Andes and used to calculate climatic indices (or ESD predictors, section 3.3.2).

**Figure 3.7.** DJF meridional cross-section (as in Figure 10 from Vizy and Cook (2007)), averaged between longitudes 72.5°W and 70°W. The profiles contain the vertical component of the moisture flux “$wq$” (g Kg$^{-1}$ m s$^{-1}$), where q (g Kg$^{-1}$) as the specific humidity, and the vector field using the meridional wind component v (m s$^{-1}$) and scaled vertical velocity w (100 m s$^{-1}$) vectors for (a) 1979-1998, and (b) 1998-2017 periods. (c) shows the difference, (b) minus (a). Atmospheric variables were obtained from 2.5° ERA-interim products. Shaded values represent the $wq$ field. Vertical velocity was calculated transforming omega (Pa s$^{-1}$) with temperature and pressure fields. Location of AWS at QIC summit is shown by a red dot in each graph. Topography (black shaded area) from ERA-interim geopotential invariant field was added in each plot.

**Figure 3.8.** Comparison between observed and predicted precipitation. (a) Scatterplot (circles) and linear regression (black line) between predicted and observed DJF precipitation (in mm, equation 3.4). (b) Observed (blue line) and predicted ($P(U500, V500, W700)$, red line) DJF precipitation (in mm) between 1979 and 2017. The “Year” axis label indicates the DJF season, with the year label referring to the JF portion of the season. Additionally, the $P-U200$ linear model ($P(U200)$) is plotted as a black dotted line.
Figure 3.9. ESD Model cross-validation over the 1979-2017 period. (a) The residual (difference between observed and predicted DJF precipitation (in mm)). The x-axis ‘Year’ label is the same as in Figure 3.8b. (b) the RMSE$_{n-1}$/RMSE ratio, where the RMSE = 44.2 mm. (c) similar as (b), except for Pearson’s correlation coefficient (r), with gray line (r=0.82) indicating correlation coefficient of the full ESD model. (d) Histogram indicating the frequency of occurrence of each atmospheric index in the ESD$_{n-1}$ models. Only variables used at least once are plotted.

Figure 3.10. CMIP5 projections of DJF QIC precipitation anomalies. The ERA-interim reanalysis (1979-2017) fitted with observed data is shown in black; the historical CMIP5 simulations (1950-2005) are shown in gray, and the future CMIP5 projections are shown in blue (RCP4.5) and red (RCP8.5) for the period 2006-2100. Bold lines for CMIP simulations represent the mean of 16 models (Table 3.2). Shading represents the 95% confidence interval. The box plots indicate precipitation averaged over all 16 simulations over the period 2071-2100, with the horizontal line indicating the median, the bottom and top edges of the boxes indicating the 25th and 75th percentiles, respectively; and the whiskers are extended 1.5x(75th - 25th percentiles) below the 25th percentile and up the 75th percentiles. Anomalies are calculated with respect to the 1979-2005 baseline. The x-axis ‘Year’ label refers to the DJF season as in Figure 3.8b.

Figure 4.1. (left) Quelccaya Ice Cap image using Landsat 8 satellite data on 02-Aug-2017. (Upper right) South American country boundaries, and the red mark indicating QIC location at 13º56’S 70º50’W.

Figure 4.2. Snow line altitude using Landsat images. (a) Snow region in light blue, as a RGB composite using Landsat 5 (LT5) images of 5, 4, and 2 bands, applied histogram thresholds of 155 and 174 for bands 4 and 2, respectively. Snow line perimeter in yellow by date selected in 1998 (Table 4.1). The mean SLA is calculated as the average elevation of all DEM cells coinciding with the location of the snow line perimeter. (b) As in (a), but for the date selected in 2016, and bands 6, 5 and 3 from Landsat 8 (LC8), with histogram threshold 99 and 117 for bands 5 and 3, respectively. (c) Mean SLA obtained each year (i.e., mean elevation corresponding to yellow perimeter). The dashed line represents the linear trend with equation indicated in the legend. The non-zero trend was verified using an F-test (p-value<0.001), both with- and without outliers (strong El Niño years 1998, 2010, 2016) included.

Figure 4.3. Annual mean air temperature (Ta) from 2.5º ERA-interim reanalysis (thick black line, 1979-2016), historical (gray, 1950-2005) and future (2006-2100) RCP4.5 (blue) and RCP8.5 (red) simulations. Ta was calculated using lapse rate between 400 and 500 hPa level. Each curve was bias-corrected with AWS temperature data (2005-2016) at QIC summit. Colored thick lines represent the historical, RCP4.5 and RCP8.5 ensembles of 16 CMIP5 models (Table 4.2) and shading represents the 95% confidence interval.

Figure 4.4. Scatter plot between annual FLH and annual ELA at QIC. FLH is calculated by interpolating bias-corrected air temperature (Ta) and geopotential height between 500 and 600 hPa from ERA-interim. The bias-corrected Ta was obtained by fitting reanalysis air temperature with observed Ta from an AWS at QIC summit. ELA data were obtained from Landsat images at the end of the dry season (June to October, see Table 4.1). ELA and FLH were calculated for hydrologic years (September of previous calendar year to August). Pearson’s correlation
coefficient ($r$) and p-value are indicated in the Figure. The black dashed line indicates the QIC summit elevation (5680 m).

**Figure 4.5.** Equilibrium Line Altitude (ELA) calculated using the freezing level height anomaly projections at QIC (FLH$_{atm}$) from 16 CMIP5 models (Table 4.2) as input in equation (4.1). FLH$_{atm}$ was obtained by interpolating Ta and Zg between 500 and 600 hPa pressure levels. The black curve (OBS) represents the observed ELA obtained from Landsat satellite images over the 1992-2017 period (section 4.2.3). Bias-correction was applied to Ta and ELA for each CMIP5 model, using the observed Ta from the AWS at QIC. ELA represents the highest Snow-Line Altitude (SLA) from Landsat satellite images across each hydrological year, respectively. The hydrological year Sept.-Aug. was used for calculations. The ensemble of historical (1950-2005) simulations is represented with the gray line, while CMIP5 RCP4.5 and RCP8.5 future projections (2006-2100) are represented by green and orange lines, respectively. The shading represents the corresponding 95% confidence intervals. The blue dashed line indicates the QIC summit altitude (~5680 m). The mean observed ELA over the 1992-2017 period was 5435.7 m, and the mean annual ERA-interim ELA over the baseline 1979-2017 was 5416.5 m.

**Figure 4.6.** Tropical SST forcing of FLH at QIC during 1980-2017 (hydrologic years). Annual FLH anomalies (FLHA) at QIC were calculated by interpolating bias-corrected air temperature (Ta) and geopotential height (Zg) from ERA-interim reanalysis, between 500 and 600 hPa pressure levels at QIC summit location (red curve). The bias-corrected Ta was obtained fitting the ERA-interim Ta product with observed Ta data from an AWS at QIC summit. The annual tropical (spatially averaged across 28.75°N to 28.75°S) SST anomalies were calculated from ERSST data (blue curve). Anomalies were calculated using the baseline 1979-2005 period. A linear relationship between FLHA and tropical SST anomalies was calculated resulting in FLHA = 286.4xSSTA+1.4, with $r=0.84$ and p-value<0.001.

**Figure 4.7.** Annual mean ELA derived from FLH at QIC calculated by linear regression (equation 4.1) with annual mean tropical SST from ERSST dataset as predictor (FLH$_{SST}$ using equation 4.2), compared with ELA derived by interpolating air temperature (Ta) and geopotential height (Zg) from ERA-interim reanalysis between 600 and 500 hPa levels (FLH$_{atm}$) (black dots). The same approach is applied to the ensemble mean of annual FLH$_{SST}$ and ELH$_{atm}$ obtained from 16 CMIP5 models (Table 4.2) for Historical (gray dots), RCP4.5 (blue dots) and RCP8.5 (red dots) scenarios. Historical and future simulations were analyzed over the periods 1951-2005 and 2006-2100, respectively. Dashed line represents the 1:1 line. A bias-correction was applied to Ta and ELA, using data from the AWS at QIC summit elevation (5680 m) and estimated highest annual snowline altitude from Landsat images, respectively.
<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tr>
<td>CC</td>
<td>Climate Change</td>
</tr>
<tr>
<td>TG</td>
<td>Tropical Glaciers</td>
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<td>SA</td>
<td>South America</td>
</tr>
<tr>
<td>BH</td>
<td>Bolivian High</td>
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<tr>
<td>SASM</td>
<td>South American summer monsoon</td>
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<td>ITCZ</td>
<td>Inter-tropical convergence zone</td>
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<td>ENSO</td>
<td>El Niño – Southern Oscillation</td>
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<td>SST</td>
<td>Sea surface temperature</td>
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<td>QIC</td>
<td>Quelccaya ice cap</td>
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<td>GCM</td>
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<td>ESD</td>
<td>Empirical Statistical Downscaling</td>
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<td>Equilibrium-line altitude</td>
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<td>EDW</td>
<td>Elevation-dependent warming</td>
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Chapter 1.

INTRODUCTION

1.1. Motivation

Many studies in recent years have focused on Climate Change (CC) impacts on society, principally over regions where the population is highly sensitive to climate variability as is the case for the Andes mountains in western South America (SA) (e.g., Rabatel et al., 2013). This climate dependence of the population living along the Andean foothills can be associated with the continuous loss of snow and ice, since glaciated bodies act as source of (melted) freshwater, which is distributed as runoff to lowland populations (Viviroli et al., 2011). This process is relevant principally in dry seasons (May to September for the tropical Andes) when the ablation processes play an important role (Rabatel et al., 2013), affecting the hydrology and socio-economic sector of the region.

About 99% of the world’s tropical glaciers are located over the Andes, with Peru alone containing about 70% of them (Kaser, 1999; Vuille et al., 2008a; Rabatel et al., 2013). Quelccaya ice cap (QIC), located in the Cordillera Vilcanota in southern Peru (13º56’S, 70º50’W), with a median area of about 50.2 km² over the 1975-2010 period, and an approximate summit elevation of 5680 meters above sea level (masl) (Bradley et al., 2009; Thompson et al., 2006; Thompson et al., 2013; Hanshaw & Bookhagen, 2014), is the largest tropical ice cap (Buffen et al., 2009; Thompson et al., 2006; Thompson et al., 2013), and representative of many tropical glaciers in the Andes with a relatively low summit elevation.
While both anthropogenic and natural forcings may affect mass balance variability on QIC on interannual timescales (e.g., Thompson et al., 2006; Vuille et al., 2015), the accelerated rate of retreat observed over the last decades (Hanshaw & Bookhagen, 2014), is consistent with the gradual disappearance of lower lying Andean glaciers such as being observed for example in Bolivia, Colombia and Venezuela (Ramirez et al., 2001; Braun & Bezada, 2013; Rabatel et al., 2017). Modeling studies suggest continued future shrinkage of tropical Andean glaciers, with some completely disappearing by the end of the 21st century (Schauwecker et al., 2017; Vuille et al., 2018), thereby significantly reducing dry season runoff (e.g. Juen et al., 2007; Kaser et al., 2010; Baraer et al., 2012).

Hence a more thorough understanding of future glacier retreat rates in the tropical Andes is critical, given their prominent role in dry season water supply, ecosystem services, and impacts on tourism, natural hazards and cultural values and belief systems of local populations (e.g., see review in Vuille et al., 2018). Thence, the relevance of studying the Andean cryosphere system is multifaceted, but fundamentally relates to the importance of anticipating its future changes, since it is highly sensitive to climate change (Vuille, 2011a, 2011b), and its potential impacts as they relate to being a source of (melted) freshwater for lowland populations (Viviroli et al., 2011).
1.2. Objectives
This study focuses on assessing how CC affects the Peruvian Andes region, and the main aim of the present Thesis is to contribute to a better understanding of some of the more important problems scientists are faced with when studying glaciers and ice caps in the central Andes. Several problems are presented that relate to assessing climatic conditions in the Central Andes, with three of them being addressed in the present Thesis. The first problem is the lack of in-situ climatic information (e.g., Nesbitt and Anders, 2009), since glaciated bodies across the tropics and subtropics are located at the highest location of mountain peaks in often remote and inaccessible terrain. This environment leads to prohibitive costs for supporting a dense weather station network and hence a low number of stations and other measurements over these regions (Salzmann et al., 2013; Viviroli et al., 2011). A second problem is the poor representation of mountain climate in climate models. This failure is due principally to the high spatio-temporal variability of mountain climate, modulated by the complex Andean topography, which remains unresolved in the coarse resolution of Global Climate Models (GCM) (Baron et al., 2005). Similar uncertainties exist even in Regional Climate Models (RCM) over the Andes region (e.g., Chou et al., 2012). The third issue is the uncertainty of how imminent the threat of a future disappearance of the QIC really is and to what extent the timing depends on the choice of emission scenario.

1.3. Background

1.3.1. Quelccaya Ice Cap (QIC) and Central Andean climate
The climate of the tropical Andes can be divided into two zones (Kaser et al., 2005): the inner tropical climate or inner tropics with continuous wet conditions, where humidity remains almost
unchanged throughout the year and more or less continuous precipitation occurs throughout the year (Rabatel et al., 2013); and the outer tropical climate or outer tropics with wet and dry seasons from October to March and May to September, respectively (Rabatel et al., 2013). QIC belongs to the outer tropics, where the environment is defined as arid and semi-arid (Quiroz et al., 2011). QIC has been reduced by about 30% in surface area between 1980 and 2010, covering an area of ~44 km² in 2010 (Hanshaw & Bookhagen, 2014).

The extent of the QIC has been affected by the increase in Andean surface temperature (Bradley et al., 2009; Vuille & Bradley, 2000), but potentially also by variations in precipitation (Rabatel et al., 2013; Salzmann et al., 2013). The El Niño - Southern Oscillation (ENSO) (e.g., Thompson et al., 2013), the South American Summer Monsoon (SASM) (e.g., Vuille and Werner, 2005), and cold air incursions from the extratropics (Hurley et al., 2015) also affect the conditions on QIC on interannual time scales. However, no continuous mass balance measurements exist on QIC; hence the relationship between the reduction in surface area and loss of glacier mass is not known.

The tropical Andes are a mountain region with complex topography, where turbulent mixing occurs over the eastern Andes slope (or Andes barrier). Moreover, orographic precipitation is mainly sustained by humid air advection during the SASM season (Oct.-April). The large-scale mechanism that produces precipitation over the central Andes (more than 70% of which falls during the austral summer monsoon season) is related to upper-air easterlies, which enhance near-surface upslope flow of moist air through downward entrainment of easterly momentum over the Andean ridge (Vuille, 1999; Vuille and Keimig, 2004; Falvey and Garreaud, 2005; Garreaud et al., 2003; Garreaud, 1999, 2009). Complementary to this convective mechanism, Perry et al.
(2014) and Perry et al. (2017) have been pointing out that much of the precipitation over the Central Andes is the result of nocturnal stratiform precipitation, which is in concordance with radar observations (Romatschke and Houze, 2010). Thus, the intense convection over QIC has been linked to increased mid-tropospheric humidity. For instance, snowfall at the QIC occurs in conjunction with the SASM during November to April (Thompson et al., 1985), but several meso-scale circulation systems influence the local climate. Specifically, over the Peruvian central Andes, the Bolivian High (BH), an upper-level anticyclone that develops in response to latent heat release over the Amazon basin (Lenters and Cook, 1997) plays an important role in the transfer of momentum. On the other hand, mid-tropospheric westerly flow, originating over the Pacific generally leads to very dry conditions over the Central Andes, although occasional embedded cut-off lows can lead to massive austral winter snowfall (Vuille and Ammann, 1997). In general, however, the ‘easterly/wet’ and ‘westerly/dry’ relationship holds on intraseasonal, seasonal and interannual time scales and has been used to infer projected future changes in rainfall over the region from CMIP3 models (Minvielle and Garreaud, 2011). Additionally, the periodic occurrence of ENSO affects precipitation over South America (Garreaud et al., 2009) and leads to positive (negative) precipitation anomalies over the southern Peruvian Andes during La Niña (El Niño) (e.g. Vuille et al., 2008b). The ENSO phenomenon is also of utmost importance as it perturbs the atmospheric circulation, reducing (increasing) upper-level easterly flow, moisture influx and precipitation during the warm (cold) ENSO phase. The exact mechanism by which ENSO affects snowfall in the QIC region is not well understood but is assumed to also be related to anomalous atmospheric circulation linked to the anomalous warming or cooling of the tropical Pacific (Vuille and Werner, 2005). More recently Hurley et al. (2015) showed that more than 70% of the total snow accumulation measured at QIC summit by an automated weather station (AWS), is tied to
convection along the leading edge of extratropical cold air incursions of mid-latitude air advected equatorward from southern SA, with precipitation along the leading edge of northward propagating cold fronts. Moreover, long-term changes in precipitation in the region are also not well understood. For instance, Seth et al. (2010) analyzed precipitation trends at Patacamaya (17.24°S, 67.92°W) located south of QIC, at 3799 masl. They found a trend toward drier conditions in spring and increased rainfall during summer, over the 1960-2008 period. In contrast, using a station located closer to QIC, Salzmann et al. (2013) presented a precipitation analysis from Santa Rosa (14.6°S, 70.8°W, 3940 masl), which shows a slight decrease in precipitation for all seasons, over the 1965-2009 period.

On the other hand, air temperature has been increasing over the Peruvian Andes over the last six decades (Bradley et al., 2009; Casimiro et al., 2013; Salzmann et al., 2013), in agreement with the regional increase of temperature over the whole tropical and sub-tropical Andes (Rabatel et al., 2013). As shown by Vuille et al. (2015), the increasing temperature trend is a combined effect of natural multidecadal variability (i.e. the Pacific Decadal Oscillation or PDO) and anthropogenic radiative forcing. Due to this warming, QIC is retreating at an accelerated pace, as shown by Hanshaw and Bookhagen (2014), who document a shrinking of the QIC at a rate of \(0.57\pm0.10\) km\(^2\) yr\(^{-1}\) over the 1975-2010 period. This retreat is consistent with the reduction in glacierized surface area observed throughout the tropical Andes, including in the Cordillera Blanca and the Cordillera Ampato (Rabatel et al., 2013; Vuille et al., 2008a), located to the north and south of the Cordillera Vilcanota, where QIC is located, respectively. Although, the rate of warming tends to be amplified with elevation in many mountain regions (Diaz et al., 2014), an effect referred to as elevation-dependent warming (EDW) (e.g., Pepin et al., 2015), its causes and possible mechanisms are not
well understood, due to the lack of climate information over mountain regions (Pepin et al., 2015; Rangwala and Miller, 2012). Similarly, this EDW has been documented over the tropical Andes, based both in modern observations and future model scenarios (Vuille & Bradley, 2000; Urrutia & Vuille, 2009; Vuille et al., 2015).

A fairly simple diagnostic that can be calculated from reanalysis and model data, and is more relevant for glacier mass balance than surface temperature, is the freezing level height (FLH). The increase of the FLH in the Central Andes negatively affects the mass balance of glaciers by changing the rain/snow ratio and increasingly exposing lower reaches of glaciers to rain as opposed to snow (Rabatel et al., 2013). Hence a rise in the FLH does not only indirectly affect mass balance through higher temperatures, leading to more melt, but also impacts accumulation and ice albedo (Francou et al., 2004). Rabatel et al. (2013) documented that the FLH increased by approximately 160 m over the last five and a half decades over the Cordillera Blanca and Cordillera Real, located to the north and south of QIC, respectively. Schauwecker et al. (2017) showed that the mean annual FLH in the Cordillera Vilcanota was 5010 m asl over the 1980-2015 period, consistent with results in Rabatel et al. (2013), with a higher FLH during the warmer wet season and a lower FLH during the slightly colder dry season, respectively. Bradley et al. (2009) have shown that historically the increase of the FLH in the tropics can be empirically described as a linear response to the increase of tropical sea surface temperature (SST). Moreover, Diaz et al. (2003) have shown that the FLH over this region is dependent on the phase of ENSO and responds to both interannual and decadal-scale changes in tropical Pacific SST.
1.3.2. Regional and Global Climate Models (GCM)

GCMs simulate large-scale circulation features and dynamic aspects associated with the SASM reasonably well (e.g. Carvalho and Jones, 2013a; Lenters and Cook, 1997; Jones and Carvalho, 2013; Vuille and Werner, 2005). Precipitation, however, is the one atmospheric variable that is not well reproduced over the Andes by GCMs (e.g., Minvielle and Garreaud, 2011). This failure is due principally to the high spatio-temporal variability of precipitation, modulated by the complex Andean topography, which remains unresolved due to the coarse resolution of GCMs (Baron et al., 2005). Similar uncertainties exist even in RCMs over the Andes region (e.g., Chou et al., 2012).

In the Coupled Model Intercomparison Project Phase 3 (CMIP3) model simulations, seasonal precipitation over the Andes contained a large positive bias during the rainy season (December to February), and a smaller positive bias during the dry season (June to August), when compared with station data (Seth et al., 2010). Surface temperature shows a positive (warm) bias with respect to station data throughout the year in CMIP3 models (Seth et al., 2010). This behavior is expected due to the lower topography of the Andes in CMIP3 models. Over tropical latitudes, some improvements were made with the Coupled Model Intercomparison Project Phase 5 (CMIP5) in comparison with CMIP3 (e.g., Grose et al., 2014). Moreover, several studies documented how CMIP5 models include improved ENSO physics (e.g. Yeh et al., 2012), SASM dynamics (Jones and Carvalho, 2013), and cold air incursion characteristics (Yin et al., 2013), all affecting Andean precipitation. However, large discrepancies are still detected in the spatial variability of historical CMIP5 simulations for mean daily rainfall, South Atlantic Convergence Zone (SACZ) and ITCZ characteristics (Carvalho and Jones, 2013a). Miller et al. (2014) further demonstrated how historical CMIP5 simulations realistically represent the twentieth-century annular trends toward reduced surface pressure at southern high latitudes and a poleward shift of the mid-latitude
westerlies, consistent with observations. Because RCMs rely on GCM output as boundary conditions when simulating future scenarios, the same problems are inherited from GCMs, which can also be detected to a varying degree in dynamical downscaling exercises. For example, the RCM used by Urrutia and Vuille (2009) nicely reproduced 30 years of temperature variability observed over the Andes on interannual time scale, but precipitation was highly overestimated over the eastern Andean slope; a problem of orographic precipitation overestimation that is common in many RCM studies (Buytaert et al., 2010; Chou et al., 2012).

On the other hand, it is important to keep in mind that GCM output aside from precipitation also contain biases when compared to observed data, primarily due to their parameterization systems and large grid size (Sharma et al., 2007). Similar to what happens in a GCM grid cell, such errors can grow when climate data are aggregated spatially or in time, resulting in loss of relevant variation (Baron et al., 2005). Similar errors also occur in RCMs (Bordoy & Burlando, 2013). The regional Eta model (Chou et al., 2012), forced by ensembles of the UK Met Office Hadley Centre HadCM3 global model, for example, reproduced precipitation and temperature anomalies over South America, but with large overestimation of both fields over the Andean region. Removing this bias from the RCM, GCM, reanalysis, and/or satellite products, is crucial and can be achieved by applying several techniques. Sharma et al. (2007) for example used a bias-correction, applying a Gamma-gamma transformation method, while Wood et al. (2004) used a quantile-based mapping method. The most trivial case (and involving the assumption which is most commonly made) is assuming a constant bias through time (Fowler et al., 2007). Over the Central Andes, most reanalysis products present systematic biases for temperature and humidity (Hofer et al., 2010). In the case of rain rate satellite products over southern Peru (Blacutt et al., 2015), the bias portrays a
heterogeneous space-time distribution, but it can still be corrected, for example by applying a wavelet correction method (Heidinger et al., 2012).

1.3.3. Linking large-scale circulation with local-scale climate (Downscaling)

A crucial issue when analyzing mountain climate is how to adequately project future changes in precipitation, which plays a key role in several research areas and is highly relevant to society (Viviroli et al., 2011). Precipitation is the most complex variable to predict, given its stochastic nature (Yarleque et al., 2016). Although this complexity can be further increased in mountain regions by orographic forcing, empirical results have shown that in the Central Andes the in-situ measured precipitation exhibits considerable spatial covariance on a regional scale (Quiroz et al., 2011; Yarleque et al., 2016) and is closely related to the large-scale circulation on multiple time scales (e.g. Garreaud et al., 2003).

One way of evaluating future precipitation variability over the Central Andes by means of GCMs, is to empirically derive precipitation based on the observed close linear relationship between precipitation ($P$) and upper-level (usually at 200 hPa) zonal wind ($U$), hereafter referred to as $P$-$U_{200}$ linear model (Minvielle and Garreaud, 2011; Neukom et al., 2015), thereby taking advantage of the significant linear relationship that exists between both variables over the Central Andes (Garreaud et al., 2003; Vuille et al., 2008b). However, the strength of this linear relationship varies in space and time across the Andes. For instance, the $P$-$U_{200}$ relationship over the Cordillera Blanca, located to the north of the QIC, changed after the mid-1990s as shown by Schauwecker et al. (2014), who documented a shift toward larger precipitation and stronger easterlies around the mid-1990s. This shift is coincident with the La Niña-like SST pattern that emerged around 1997.
(Zhang et al., 2016). Hence precipitation projections based on assumptions of stationarity of the 
P-U200 model may generate ambiguous results, depending on the time period considered for 
calibrating this linear relationship. Nonetheless it is important to emphasize that the underpinning 
mechanism that determines the zonal flow aloft is related to the change in meridional baroclinicity 
off the west coast of South America (Garreaud and Aceituno, 2001) and the projected enhancement 
of westerly flow in the future is dynamically consistent with expected stronger future upper-
tropospheric warming in the tropics, as opposed to mid latitudes. Hence the results by Minvielle 
and Garreaud (2011) and Neukom et al. (2015) who project decreasing precipitation over the 
Central Andes over the course of the 21st century may be sensitive to the choice of calibration 
period, but are nonetheless physically plausible given the projected anomalous upper-tropospheric 
warming in the tropics.

Empirical-statistical downscaling (ESD) methods have made a lot of progress over the Andean 
region, in particular based on studies in the northern Cordillera Blanca (Hofer et al. 2015), and 
specifically over the tropical glaciers Artesonraju (Hofer et al., 2010) and Shallap (Maussion et 
al., 2015). In these instances, the large-scale predictors were related to local-scale predictand 
variables based on multiple linear regression models. In the tropical glacier Artesonraju study the 
observed air temperature and specific humidity over the glacier were considered as predictands, 
and several variables from reanalysis products as predictors. Moreover, Maussion et al. (2015) 
show how several atmospheric variables have a high skill to predict precipitation over glaciated 
regions (such as the Cordillera Blanca) using a multi-linear model, in contrast to the simpler P-
U200 linear model, which has stronger skill over the western Andean Cordillera (Minvielle &
Garreaud, 2011). Moreover, Hofer et al. (2017) listed and compared ESD models used to downscale several atmospheric variables in tropical environments.

1.3.4. Future projections over the Central Andes

Several analyses of 21st century climate projections are indicating a substantial future increase of temperature across the central Andes regions (Bradley et al., 2006; Urrutia and Vuille, 2009). For instance, for the end of the 21st century, the CMIP3 projections are in agreement in indicating that temperature over the Altiplano region is likely to increase by about 4°C under an A2 emission scenario (Seth et al., 2010). Using a high-emission representative concentration pathway 8.5 (RCP8.5) CMIP5 ensemble mean, Carvalho and Jones (2013b) calculated an increase in the lower troposphere (850 hPa) temperature (T850) 85th percentile of around 4.8°C over SA by 2095 relative to 1955, in agreement with CMIP3.

Additionally, using the CMIP3 models, Seth et al. (2010) pointed at a future intensification of the SASM. Similar results have been shown for the RCP8.5 CMIP5 simulations for the twenty-first century (Jones and Carvalho, 2013a). This notion is supported by the projected increase of specific humidity in the lower troposphere (Q850) as seen in the RCP8.5 CMIP5 ensemble mean (Carvalho and Jones, 2013a, 2013b). Seth et al. (2010), using CMIP3 simulations, further suggested that precipitation over the Central Andes region will increase, due to the future intensification of the SASM. This aspect, however, is difficult to verify due to the poor representation of precipitation over the Andes in historical CMIP5 simulations (Carvalho and Jones, 2013a), and these results are in stark contrast to the decrease in precipitation over the Central Andes over the course of the 21st century projected by Minvielle and Garreaud (2011) and Neukom et al. (2015). Seth et al. (2010)
further reported that soil moisture is projected to significantly decrease, despite the expected increase in precipitation. A caveat in all these analyses is that the thermodynamic mechanisms that determine precipitation amounts over the Andes region are not well simulated in CMIP3 models, and not well represented by CMIP5 either. In Urrutia and Vuille (2009) temperature projections for the end of the 21st century also portrayed a significant warming in the tropical Andes, which was amplified at higher elevation, but changes in precipitation in their simulations were spatially much less coherent.

1.4. Research structure and proposed hypotheses

To confront the key problems indicated previously (section 1.2), three research components were proposed to improve our understanding of the QIC climate system. First, generating a new precipitation database at local to regional scales can help overcome the lack of available climate information. Several processes overlap and interact at multiple spatial and temporal scales, resulting in very complex precipitation dynamics at QIC as it was discussed previously. On the other hand, precipitation has a spatially fairly homogeneous behavior over the (semi-)arid Central Andes (e.g., Quiroz et al., 2011), thus the few stations available over our study area may contain enough information to validate newly generated, independent precipitation data in space. Given the above observations and existing studies, I postulated a null hypothesis hereafter called “Local-regional precipitation hypothesis”: local QIC precipitation variability is independent of regional-scale precipitation variability surrounding the QIC. If this hypothesis is rejected, this means that precipitation on QIC can be evaluated and potentially estimated through a precipitation reconstruction at the regional scale, which does not depend on local on-site information and might be generated from a limited number of surrounding in situ stations or based on data sensed from
remote platforms. In Chapter 2, a test of this hypothesis is presented, with results indicating that it should be rejected.

Second, the current understanding of the linkages between large-scale forcing and local precipitation on Quelccaya is insufficient. Precipitation over the Central Andes is concentrated during the austral summer; hence major changes in seasonal precipitation should be related to interannual variations in austral summer circulation. Thus, one way to summarize forcing effects over QIC is assessing the seasonal precipitation variability and how it is conditioned by the atmospheric variability. In this case, a second null hypothesis is proposed called “Large-scale forcing QIC hypothesis”: Large-scale atmospheric forcings are not significantly related with the amount of precipitation falling locally on QIC. If this hypothesis is not rejected, then the precipitation should to be driven mainly by local factors and show little dependence on the large-scale circulation. If, however, the hypothesis is rejected, then precipitation changes on QIC can be assessed through a transfer (information) function between large-scale atmospheric variables and local-regional scale precipitation on QIC and surrounding regions. Chapter 3 presents the testing procedure for this hypothesis, concluding that it should be rejected.

A third research component was to assess the relevance and rate of change in air temperature and FLH over the QIC climate system. In contrast to precipitation, free-air temperature is quite accurately simulated by GCMs, and very well represented by reanalysis. Temperature is also well reproduced by most GCMs although there is a substantial warm bias in surface temperature due to the reduced topography in the models. Thus, using a few local in-situ stations with monthly air temperature data, it should be possible to assess the quality of reanalysis and GCM output for
creating future scenarios at QIC, as well as for some other atmospheric variables which depend on air temperature. A very important variable to assess is the FLH, which is closely linked with the equilibrium-line altitude (ELA, the elevation where the accumulation equals ablation, when averaged over the year). On QIC, as everywhere else in the tropical Andes, the FLH (Schauwecker et al., 2017) and the ELA (Vuille et al., 2018) have risen over the past decades, consistent with the widely reported negative mass balance recorded from glaciated bodies (Rabatel et al., 2013; Hanshaw and Bookhagen, 2014). Here the interest is to learn more about the future state of the QIC: how much ice will potentially be lost or when will the ice cap lose its accumulation zone (and eventually disappear) under a future warming scenario? Hence the null hypothesis called “Future changes at QIC system” was postulated: The future increase of air temperature will lead to the disappearance of QIC. If the hypothesis is not rejected, it will be interesting to assess when in the 21st century the ELA will rise above the QIC summit. If this hypothesis is rejected, the location of the ELA by the end of the 21st century can be assessed for different scenarios. In Chapter 4 results of this hypothesis testing are presented, indicating that acceptance or rejection of this hypothesis depends on the emission scenario considered.
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Chapter 2.

MULTISCALE ASSESSMENT OF SPATIAL PRECIPITATION VARIABILITY OVER COMPLEX MOUNTAIN TERRAIN USING A HIGH-RESOLUTION SPATIOTEMPORAL WAVELET RECONSTRUCTION METHOD

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Abstract

Studying precipitation variability in the Peruvian Andes is a challenge given the high topographic variability and the scarcity of weather stations. Yet previous research has shown that a near-linear relationship exists between precipitation and vegetation in the semi-arid central Andes. We exploit this relationship by developing a new, spatially highly resolved spatio-temporal precipitation reconstruction method, using daily precipitation time series from in situ weather stations, and dekadal (10 calendar days) normalized difference vegetation index (NDVI) fields. The two data sets are combined through a wavelet decomposition method. A 4° x 4° region around Quelccaya ice cap (QIC), the world’s largest tropical ice cap located in the central Peruvian Andes, was selected as study area, due to its importance for climatic, glaciologic and paleoclimatic research. The reconstructed end product, a ~1 km² gridded precipitation data set at dekadal temporal resolution, was validated against independent rain gauge data and compared with the Tropical Rainfall Measuring Mission (TRMM) 3B42 version 7 product. This validation showed a better overall performance of our own reconstruction than the TRMM data. Additionally, a comparison of our precipitation product with snowfall measurements at the QIC summit (5680 m) shows a regionally coherent signal at the dekadal scale, suggesting that the precipitation falling at QIC is driven by regional- rather than local-scale convective activity. We anticipate that this methodology and the type of data generated in this study will be useful for hydrological and glaciological studies, as well as for validation of high-resolution downscaling products in mountain regions.
2.1. Introduction

The Andes mountain chain, extending along western South America from Venezuela to Chile, affects climate and the atmospheric circulation of the entire region (Garreaud, 2009), primarily in lower tropospheric levels. Modeling studies show that the Andes affect first and foremost the tropical precipitation distribution in the interior of the continent (Lenters and Cook, 1999), and the Intertropical Convergence Zone (ITCZ) north-south asymmetry (Takahashi and Battisti, 2007). The Andes are home to a large number of tropical glaciers and ice caps, which are sensitive to the current climate warming (Schauwecker et al., 2014; Vuille et al., 2015), negatively affecting their energy and mass balance (Vuille et al., 2008a; Rabatel et al., 2013). The warming has led to rapid shrinkage of many tropical glaciers (Vuille et al., 2008a), affecting the regional hydrology (e.g. Baraer et al., 2012). Atmospheric warming is considered to be the main factor explaining the current retreat observed on tropical glaciers and ice caps, with higher freezing levels increasingly exposing the ablation zones to rain as opposed to snow (L'hôte et al., 2005; Bradley et al., 2009; Rabatel et al., 2013).

While the temperature increase in the Andes is well documented (Vuille and Bradley, 2000; Vuille et al., 2015), the role that changes in precipitation amount or in the rain/snow ratio might play in negative glacier energy and mass balance is not nearly as well understood. Lack of a dense station network, the complex topography leading to sharp precipitation gradients over short distances and the logistical difficulties in obtaining accurate measurements of snow accumulation on tropical glaciers have prevented a thorough analysis of spatiotemporal precipitation patterns at high resolution. Here we focus on quantifying precipitation and its variability, at high spatial resolution, in a region of southern Peru, surrounding the world’s largest tropical ice cap, Quelccaya.
An automated weather station has been recording continuous in-situ climatic information at the summit of the Quelccaya Ice Cap (QIC) for over a decade (Bradley et al., 2009; Hurley et al., 2015). Thus, the QIC region is an ideal natural laboratory to evaluate tropical mountain atmosphere-cryosphere interactions.

On interannual time scales, the occurrence of the El Niño - Southern Oscillation (ENSO) phenomenon affects precipitation over the southern tropical Andes (Vuille, 1999; Vuille et al., 2000; Garreaud and Aceituno, 2001; Garreaud et al., 2003). In general the amount of precipitation increases (decreases) over the southern Peruvian Andes during La Niña (El Niño) (Vuille et al., 2008b). The exact mechanism by which ENSO affects precipitation over the QIC region is not very well studied, although the main large-scale forcing factor appears to be the meridional baroclinicity and the resulting change in the strength of the upper-level westerlies over the Andes region, induced by the anomalous SST change over the eastern Pacific (Garreaud and Aceituno, 2001). The upper-level winds affect the strength of the upslope flux of humid air from the lowlands to the east. Studies on the ENSO footprint over the broader Altiplano region show, however, that the eastern Andean region where the QIC is located, is not as strongly affected by this forcing as the more arid western cordillera (Vuille et al., 2000).

The upper-level easterlies are established on the northern side of the Bolivian High (Lenters and Cook, 1999) as part of the South American monsoon system during austral summer and lead to a wet season on QIC that starts around October and November, and lasts until March or April (Hurley et al., 2015). The clear spatial precipitation gradient across the southern Andes, ranging
from the more humid northeast to the arid southwestern part of southern Peru, as measured for example by the Tropical Rainfall Measuring Mission (TRMM) products during the wet season (Mohr et al., 2014), is a clear testament to an easterly moisture source. While the moisture is provided by evaporation over the tropical Atlantic and recycled over the Amazon basin, recent studies on the synoptic conditions associated with snowfall over Quelccaya highlight the importance of cold air incursions, embedded in extratropical Rossby wave activity. Snowfall on QIC appears to be related to uplift of moist air along the leading edge of these northward propagating cold air masses to the east of the Andes (Hurley et al., 2015). Hence the moisture is of tropical origin and associated with deep convective storms (e.g. Bookhagen and Strecker, 2008; Casimiro et al., 2009; Casimiro et al., 2013; Casimiro et al., 2012), but uplift and condensation are triggered by northward moving cold fronts. In fact more than 70% of snowfall on Quelccaya is tied to the leading edge of northward propagating cold air incursions (Hurley et al., 2015).

While this larger-scale forcing is fairly well established, the interaction of easterly flow and northward penetrating cold frontal systems with the Andean orography are not well understood, due principally to the scarcity of observational data and the complex topography affecting the precipitation distribution around QIC (Quiroz et al., 2011; Heidinger et al., 2012; Espinoza et al., 2015). As a result little is known regarding the small-scale variability of precipitation in this region, even though it is likely to be strongly modulated by topography. Some preliminary analyses on the spatial distribution of precipitation in this region have been performed by means of high-resolution satellite data. For instance, Bookhagen and Strecker (2008) used TRMM data to analyze how the Andean orography affects the precipitation distribution. Hunink et al. (2014) combined satellite data, data from local weather stations and reanalysis products to reconstruct precipitation at high
resolution in the Andes of Ecuador using a multi-linear model. Quiroz et al. (2011) reconstructed daily precipitation over the Peruvian Andes by combining the Normalized Difference Vegetation Index (NDVI) and data from a few local weather stations. Other studies based their spatial reconstructions on interpolation techniques (Wilks, 2011), but those techniques do not permit a correct (local) representation unless topography is implicitly included in the interpolation algorithm (Bookhagen and Strecker, 2008; Posadas et al., 2015). An alternative approach is to use geographically-dependent land surface information from satellites, as is the case when using NDVI data (Quiroz et al., 2011; Hunink et al., 2014).

Here we analyze the local- to regional-scale precipitation distribution over the broader QIC region, taking into account the topography of the central Andes, and the fact that the availability of station data in this region is very limited. Building on the one-dimensional precipitation reconstruction method established by Quiroz et al. (2011), we develop a new method to obtain a high-resolution, spatio-temporally complete precipitation reconstruction using NDVI data and a few rain-gauge stations. The resulting NDVI-derived precipitation product allows analyzing precipitation in this region at a much higher spatial and temporal resolution than what was previously possible. Section 2.2 presents the study area, the in-situ and satellite-derived data used, and how the data were pre-processed. In Section 2.3 the high-resolution precipitation reconstruction method is discussed in detail. Section 2.4 includes a discussion of the results, and a validation of their representativeness using a set of independent stations. TRMM and topographic data are used alongside the reconstruction in interpreting local conditions and the rain-snow line around QIC. Section 2.5 contains a discussion of the potential and caveats of our method and ends with conclusions and an outlook on further studies.
2.2. Study area and data used

2.2.1. Quelccaya Ice Cap Region

Quelccaya Ice Cap (QIC) is the largest tropical ice cap, located in the Cordillera Vilcanota of southern Peru (13°56'S, 70°50'W, Figure 2.1a), with an approximate summit elevation of 5680 masl (Thompson et al., 2013). The ice cap is undergoing an accelerated retreat at a rate of 0.57±0.10 km² yr⁻¹ since 1980, as evidenced in a study by Hanshaw and Bookhagen (2014). This retreat is consistent with the retreat occurring throughout the tropical Andes, including in the Cordillera Blanca and the Cordillera Ampato (Rabatel et al., 2013; Vuille et al., 2008b), to the north and south of the Cordillera Vilcanota, respectively. A land cover map (Figure 2.1b) presents the main land surface characteristics of the study area, which is dominated by dry grassland (puna) and shrubland.

2.2.2. Observed precipitation data around QIC

Daily precipitation data from 13 weather stations were used over the period 2000 to 2009. The stations were selected from a network of 29 initial stations belonging to the Peruvian Servicio Nacional de Meteorologia e Hidrologia (SENAMHI, see Table 2.1) and available from the Autoridad Nacional del Agua (ANA) official webpage (www.ana.gob.pe). The stations are labeled with an ID, following the nomenclature of ANA. The 13 precipitation records (Table 2.1 and Figure 2.1a) were selected and pre-processed as follows: 1) the stations had to be located above 3000 m and contain more than 75% complete data, 2) precipitation for each station was summed up over periods of 10 calendar days, to create precipitation dekadals, to allow a comparison with the 10 day NDVI unit calendar time scale, 3) a moving average with an 11-day window size was
applied to fill gaps and obtain 100% continuous data, 4) a strong linear relationship between precipitation and NDVI (max. $R^2_{NDVI\text{-}precipitation} > 0.35$ with p-value < 0.05) was required by all stations to guarantee a physical relationship between NDVI and precipitation. The NDVI product is calculated over all land surfaces including bare rocks, ice or lakes, where no vegetation is present. In our study area a weak NDVI-precipitation relationship is mainly due to such elements other than vegetation, which do not respond to precipitation variability in the way that vegetation does. Since we are trying to generate a spatial precipitation product based on a vegetation index, it is important to remove such negative non-vegetation effects by only including stations with a strong linear NDVI-precipitation relationship. Thus, removing stations with a low $R^2$ ensures that the NDVI-precipitation relationship really represents statistically and physically the vegetation response to precipitation. Here one station was discarded for this reason. More details and a discussion of this point are given in section 2.2.3 and section 2.5) Vegetation (the NDVI signal) responds to precipitation with a lag, but since the study region represents fairly homogeneous precipitation (Quiroz et al., 2011) and land surface characteristics (Figure 2.1b), the lag values should be comparable across station locations. Therefore, stations with an excessive NDVI response time ($\geq 7$ dekadal) were omitted as they point toward non-climatic factors affecting the NDVI response (three stations were discarded for this reason). Similar to criteria 4 above, non-vegetated surfaces can influence the lag calculation and vegetation can also respond to non-precipitation effects such as irrigation, river runoff, etc. More in-depth environmental monitoring based on data from others satellite products might aid in exploring spatial variability in this lag in response to varying land-surface conditions, but this aspect is beyond the scope of the present study. This issue is discussed in more detail in section 2.2.3.
Data from an additional weather station, Tambopata (14.22°S, 69.15° W, 1340 m asl), were used at a later stage in the validation process to highlight the fact that our method is not applicable over lower-elevation forested terrain (section 2.4.4.2). Note that Tambopata is a low-elevation station, which does not satisfy the selection criteria discussed above and applied to the 13 precipitation stations on the Central Andes plateau.

Continuous hourly snow height change (m) data between June 2005 and December 2009, obtained from an automated weather station (AWS), located at QIC summit (5680 m asl, 13.9°S, 70.8°W) (Hurley et al., 2015), were summed up to 10-day (dekadal) snow height totals. Since positive and negative snow height change represent accumulation (precipitation) and ablation, respectively, only positive dekadal snow height values were used and multiplied with the mean snow density (0.236, or 263 kg m⁻³) measured near the AWS, to calculate the equivalent precipitation on QIC. The same data-smoothing process used for the 13 precipitation stations (step 3) was applied to this calculated precipitation data as well.

2.2.3. NDVI as a proxy for precipitation

The linear relationship between grassland vegetation and precipitation is documented in recent studies over the Andes (Hunink et al., 2014; Quiroz et al., 2011), as well as in other mountain areas, such as Tibet (Immerzeel et al., 2005). This relationship can be observed in arid or semi-arid regions such as the Altiplano, where annual precipitation ranges from 50-400 mm in the west to 600-1000 mm in the east (Vuille and Keimig, 2004) and vegetation is mainly dominated by grassland and shrubland, as is the case in our study area (Figure 2.1b), which responds to the amount of precipitation (Quiroz et al., 2011), or on the Tibetan plateau, where vegetation greening
is linked with the occurrence of the monsoon (Immerzeel et al., 2005). This linear relationship can be quantified using the Normalized Difference Vegetation Index (NDVI), which is calculated as the ratio between the difference and the sum of spectral reflectance measurements in the visible and near-infrared portion of the electromagnetic spectrum. The NDVI varies between -1.0 and 1.0, with a value of 1.0 indicating maximum biomass. The NDVI dekadal and ~1 km spatial resolution synthesis data from SPOT-VEGETATION Products (VGT-S10) are used in the present analysis. The dekadals are defined according to the legal calendar: The first dekadal labeled 1 corresponds to the period from the 1st to 10th day; the second dekadal labeled 11, from the 11th to 20th day; and the third dekadal labeled 21, from the 21st day to the end of each month. Each pixel of VGT-S10 products contains the maximum NDVI value recorded over the period of 10 days, to ensure a minimal effect of cloud cover. Original NDVI digital values range between 0 and 255, but were re-scaled to 0-1 values.

The present study focuses on the precipitation reconstruction process over the 2000-2009 period, but the NDVI data were selected from 2000-Jan-1st to 2010-Dec-21st, because the NDVI lags precipitation (Quiroz et al., 2011). Details of this lag-correction, as well as the NDVI noise correction pre-processing, are explained in the next paragraphs.

Satellite measurements of land cover are often disturbed by the intermittent optical depth in the atmosphere, sensor instability or orbit deviations (Immerzeel et al., 2005). In this context a cloud or noise correction is the most important pre-processing step to be applied to NDVI data. There exist several methodologies to remove the noise from NDVI signals (e.g. Hird and McDermid, 2009; Hunink et al., 2014), but the best methodology depends on the NDVI signal (location,
climatic conditions, etc.) and its application. Because we are interested in using the low frequency NDVI signal, we removed the cloud/atmospheric noise by applying a running average filter, which we applied three times, over the 1st, 2nd, and 3rd forward-backward neighboring dekadal NDVI data (i.e. without taking the central value) consecutively. An example of the NDVI filter result is given in Figure 2.2.

The NDVI field corresponding to the present study area (section 2.2.1) is given by a matrix of 449 rows x 449 columns x 360 dekadal with a grid length of approximately 1 km. The linear dependence of NDVI on precipitation (Table 2.1), is phase-lagged (i.e. vegetation responds with a delay to precipitation), therefore the NDVI signal was shifted in time in order to remove the lag between both signals for each station location, thereby maximizing the $R^2$ value between both signals (Figure 2.3a). In order to maintain the length of the time series post lag-correction, the NDVI data period was selected from 1 January 2000 to 21 December 2010. An example is given in Figure 2.3b for Sicuani station, showing a comparison between NDVI and precipitation, both without and after (Figure 2.3b) applying such a lag correction. Lags between NDVI and precipitation, however, do not in every case correspond to a delayed vegetation response to rainfall, since other surface characteristics can also affect the NDVI (reflectance) measure. At four stations (Ramis, Pomacanchi, Colquepata and Paucartambo) out of the group of 17 initially selected, conditions 4 and 5, as indicated in the section 2.2.2, were not met. At the station Ramis the NDVI data is uncorrelated with precipitation ($\max R^2_{\text{NDVI,precipitation}} = 0.03$). This lack of correlation is likely caused by the location of Ramis at the shore of Lake Titicaca, leading to a mixed spectral NDVI signal that includes lake water and bare, non-vegetated shoreline. The stations Pomacanchi, Colquepata, and Paucartambo portrayed significant relationships between NDVI and precipitation.
(max. $R^2_{\text{NDVI, precipitation}} = 0.47, 0.56$ and $0.56$, respectively), but at lags (12, 8, and 7 dekadals, respectively) that are physically implausible and much longer than at the rest of the stations, all characterized by lags of either 4 or 5 dekadals (Table 2.1). Again the location of the stations is likely to blame for these unreasonable lags as Pomacanchi station is located along a river mouth draining into Lake Titicaca, Colquepata station is located on a ravine where the field is dominated by farms that are using a channelized rill, and Paucartambo station is located next to a river and a ravine (all verified with Google Earth). In all cases, the channelized water likely affected the spectral signal measured by the SPOT sensor. Hence these four stations were not considered for the calibration and validation process. Some additional considerations and caveats regarding spatial variations in NDVI-precipitation lags due to varying terrain and land surface characteristics are given in section 2.5.

There is considerable interannual variability in the NDVI signal (e.g. Figure 2.2), mostly driven by the South American Summer Monsoon (SASM) and ENSO, which both influence precipitation over the central and southern Peruvian Andes (Vuille and Werner, 2005). While the NDVI – SASM/ENSO dependence is an interesting area to investigate in more detail, it is not the aim of the present study. Instead here we focus on the methodological aspects of the precipitation reconstruction by means of the NDVI and on the analysis of the spatial precipitation variability in the region surrounding Quelccaya.

2.2.4. Spatio-temporal rain rate satellite data

Over the 2000-2009 period, the reconstruction results are compared with the Tropical Rainfall Measuring Mission (TRMM) 3B42 version 7 (v7), obtained from the Goddard Earth Science Data
and Information Services Center (GES DISC) of NASA. The TRMM Multisatellite Precipitation Analysis is a dataset, which merges the microwave and infrared precipitation estimates computed every 3 hours with 0.25° x 0.25° latitude-longitude resolution (Huffman et al., 2007). The TRMM v7 product is pre-processed by combining a monthly multi-satellite product with rain gauge data. Hence the final TRMM v7 product is a gauge-corrected product, but we did not further correct this data set with our own station data. This version of TRMM was selected because it has shown a good rain representation over the Andes region, improving on other satellite and reanalysis products (Zulkafli et al., 2014; Blacutt et al., 2015; Mantas et al., 2015; Satgé et al., 2015; Zubieta et al., 2015; Manz et al., 2016; Mourre et al., 2016). It is worth noting that the precipitation rate obtained by this TRMM product includes only the liquid phase precipitation, but is not taking into account the solid phase (snow).

2.2.5. Elevation variable

To analyze the topographic characteristics of the study area (Figure 2.1a), the 2-minute Gridded Global Relief Data (ETOPO2v2) database (U.S. Department of Commerce, 2006) from the National Oceanic and Atmospheric Administration and the National Geophysical Data Center (NCAR/NGDC) was used. This database has WGS-84 horizontal projection and is in cylindrical-equidistant projection (sometimes called Latitude-Longitude, or Geographic). The ETOPO2v2 data have a horizontal grid spacing of 2 minutes of latitude and longitude, and its vertical precision is 1 meter. The data were re-scaled to the NDVI grid resolution (1 km x 1 km, section 2.2.3).
2.3. Methods

2.3.1. Spatial NDVI-precipitation lag calculation: Influence zone

For locations where both NDVI and precipitation data (weather stations) exist, a correlation criterion was used to calculate the most appropriate lag to be applied to the NDVI data (section 2.2.3, Table 1). To apply such a lag correction over each NDVI grid cell, first requires identifying which of the 13 base locations best represents the NDVI characteristics at each individual cell. Hence a spatial correlation map was created for each station location, correlating its NDVI with the NDVI at each grid cell. In the end at each grid cell the station with the highest correlation coefficient was selected. This procedure allowed the creation of ‘influence zones’ for each weather station, highlighting which precipitation station data are most pertinent to use in remote locations where weather stations do not exist. Note that the lag value calculation, which will be used in the reconstruction process with the precipitation time series (i.e. the lag obtained by comparing NDVI with precipitation at the same station), is independent from the influence zone calculation (i.e. each grid cell in the domain is attributed to a zone by comparing its NDVI with the NDVI at the 13 stations). The lag calculation details were given in section 2.2.3 and will be discussed in section 2.5.

2.3.2. High spatio-temporal precipitation reconstruction and cross validation

Here the temporal reconstruction method using wavelet as described by Quiroz et al. (2011) and Heidinger et al. (2012) was modified and adapted to include a spatial dimension, with the aim of producing a spatially complete gridded precipitation field derived from NDVI data and precipitation recorded at local stations near QIC.
The reconstruction is based on the decomposition-reconstruction process of each signal (NDVI and precipitation data) in each location (of the NDVI grid field), using the dyadic Wavelet Orthonormal Multi-resolution Analysis (WOMA) and Symmlet wavelet mother (Quiroz et al., 2011). Here we used the Wavelet tool in the Matlab software. The wavelet-decomposition is given as:

\[
\begin{align*}
NDVI(x,t) &= A_{NDVI}(x,t) + D_{NDVI}(x,t), \\
Prec(x,t) &= A_{Prec}(x,t) + D_{Prec}(x,t),
\end{align*}
\]

(2.1)

where \(A\) and \(D\), are understood as the “Trend” (or low frequency) and “Detail” (or high frequency) wavelet decomposed signals, respectively, \(x = (\text{latitude}; \text{longitude})\), and \(t\) is the time variable. Since NDVI and precipitation signal are linearly correlated (Table 2.1, \(R^2\) values between precipitation and NDVI lagged), it is possible to find the state where \(A_{NDVI}\) and \(A_{Prec}\) have a good correlation as well (Quiroz et al. 2011; Heidinger et al. 2012). Then the wavelet reconstruction model can be written as

\[
Rec(x,t) = C(x) \times A'_{NDVI}(x,t + \text{lag}) + D_{Prec}(x,t),
\]

(2.2)

Here the \(A_{NDVI}\) is obtained from \(NDVI(x,t+\text{lag})\) in equation 2.1 with a lag value corresponding to the ID number given by the influence matrix at \(x\) location (section 2.2), after which the trend signal is rescaled to 0–1 values (\(=A'\)), \(Rec\) is the reconstructed precipitation, and \(C\) is a scaling factor at each location \(x\). Several studies have used linear models such as \(Rec = C \times A_{NDVI}\), but this kind of model does not preserve the high-frequency precipitation variability (\(D_{Prec}\)), where a large fraction of this high frequency signal information is concentrated. The present study is focused on a reconstruction that maintains the precipitation variability and stochasticity properties. The value of \(C\) (scaling factor) is defined as

\[
C(x) = \frac{A'_{Prec}(x)}{A_{NDVI}(x)},
\]

(2.3)
where the overbar indicates the mean value over time.

2.4. Applying the spatio-temporal reconstruction method around QIC

2.4.1. Obtaining the influence zone matrix

For the cross validation process (section 2.4.3) 6 randomly selected weather stations were withheld (Table 2.3) and the remaining seven weather stations were used to calculate the influence zone matrix (Figure 2.4a). Additionally, a second influence zone matrix using all 13 weather stations (Figure 2.4b) was developed. A topography mask was applied to each influence matrix masking data below 2500 masl. This was done for several reasons: a) the vegetation cover to the northeast (forested region) is completely different from the vegetation over the Andes (grassland and shrubland), hence the linear (or otherwise) association between precipitation and vegetation is lost over the forested region (results not shown, but this can be deduced from Figure 2.8 and section 2.4.4.2), making our approach unsuitable; b) The atmospheric conditions are distinctly different in the tropical forested lowland areas when compared to the semi-arid conditions in the Andes, that are required to successfully apply the reconstruction technique by Heidinger et al. (2012) and Quiroz et al. (2011).

2.4.2. Selection of the level of reconstruction

Although the equation (2.1) and equation (2.2) are given for one step of decomposition (Figure 2.5a and Figure 2.5b) and reconstruction (Figure 2.5c), respectively, those can be applied several times (Quiroz et al., 2011; Heidinger et al., 2012). For instance, applying the decomposition (equation 2.1) five times (or 5 levels of decomposition) to $A_{NDVI}$ and $A_{Prec}$, results in new trends and detailed signals for each application. We can also start the reconstruction process (i.e. use the
equation 2.2) in the decomposition level that we have selected from 5 to 1 (i.e. the process starts in reverse order). But what is the adequate level of decomposition to start the reconstruction process? To answer this question we analyzed the decomposition results up to level 5 in Table 2.2. Level zero corresponds to the original precipitation and NDVI corrected data, for each NDVI grid location. The precipitation time series were extracted from the group of 13 stations selected previously for each NDVI grid influence zone matrix (Figure 2.4b), with the corresponding lag applied to the NDVI time series at each grid location. In the first column of Table 2.2, levels 1-5 indicate the number of times the wavelet decomposition process was applied over the Trend (A). Using the Shannon’s entropy (E) and the coefficient of determination ($R^2$) we evaluated which level of decomposition ($i$) should be used to start the reconstruction process. Table 2.2 shows a natural behavior of entropy (based on the mean across all grid locations), with an exponential decay (column 6) across the levels $i$, without any clear breaking point, unlike in Quiroz et al. (2011) or Heidinger et al. (2012). $R^2$ values between NDVI and precipitation trends portray similar values at all levels (Column 7), increasing in concordance with the decomposition levels. Additionally, observed and reconstructed precipitation based on several decomposition levels were compared (column 8), using the adjusted $R^2$ as metric (since the reconstruction’s degrees of freedom are increasing at each level). The $R^2$ suggests that a better precipitation reconstruction can be achieved when a higher level of decomposition is used. But in general the entropy, (ordinary) $R^2$, and adjusted $R^2$ are showing that further gains after the 3rd level of decomposition are much smaller than at lower levels. Thus, hereafter we will work with the reconstruction process starting at level 3.
2.4.3. Precipitation reconstruction and cross-validation

An example of the reconstruction process is presented in Figure 2.5, adjusting the space dimensions to the Sicuani station location. Here one level of decomposition was applied. This model was applied to each NDVI grid cell, using the appropriate influence zone matrix. The resulting reconstructed precipitation data array has dimensions corresponding to 449 rows x 449 columns x 360 dekadals, including the 1 January 2000 to 21 December 2009 dekadals.

A cross-validation is applied to test the reconstruction results. Here 7 stations were randomly chosen to generate the influence zone matrix and its respective precipitation reconstruction, while the remaining 6 stations were withheld to validate the results. This random separation is appropriate as the study region has a homogenous precipitation behavior. As was demonstrated in Quiroz et al. (2011), using a different station subset would not yield significantly different results. Afterward the reconstructed precipitation was compared with the observed precipitation at the location of the 6 weather stations that had been withheld from the reconstruction process. The statistics of this comparison are presented in Table 2.3, and were calculated using the definitions given in Dinku et al. (2008). A comparison of the reconstructed precipitation results against the 6 independent precipitation records from the stations not included in the reconstruction process (Table 2.3, Rec. vs. Obs. dekadal), shows high linear correlation coefficients (r > 0.68); bias values between 1.19 and 0.84, indicating a moderate over- and underestimation, and a low Mean Absolute Error (MAE) with values between 8 and 13 mm/dekadal. This comparison indicates that the reconstruction model produces an acceptable precipitation reconstruction over this area on the dekadal scale. Similarly, Table 2.3 shows the statistics of the comparison between TRMM and precipitation at the 6 independent stations. The correlation, MAE and RMSE over the dekadal time
scale show similar performance for TRMM as for the reconstructed precipitation. This indicates that the reconstruction using just 7 stations produces an acceptable spatial representation of precipitation, but with a higher resolution.

Additionally, a comparison between the reconstruction using 7 and 13 weather stations was developed to show the advantage in the use of more stations for the spatial reconstruction, taking as reference the observed TRMM dekadal satellite precipitation field. Figure 2.6 shows a representative example for the 1st dekadal in January 2000. The reconstruction (rec.) using 13 weather stations presents a more homogeneous behavior than the one using only 7 stations. The reconstruction based on 13 stations displays intense precipitation to the west of Lake Titicaca (e.g., Mohr et al., 2014) with more intense precipitation at lower elevation regions across our study area, while the reconstruction using 7 stations is characterized by more intense localized precipitation to the southwest of the QIC and the northwest of Lake Titicaca. When compared with the corresponding TRMM dekadal field, both reconstructions fail to reproduce the intense precipitation over the Andean slope, although the known large bias of TRMM over the Andean slope prevents a detailed comparison. Thus we infer that the reconstruction based on all 13 stations contains an even more detailed and reliable reconstruction.

2.4.4. Assessing the spatial precipitation distribution

2.4.4.1. Spatial aspects of the reconstructed precipitation

The seasonal cycle with enhanced precipitation over the October-April months (wet season), and less precipitation between May and September (dry period) is well known for the central Andes (Vuille, 1999; Vuille et al., 2000; Garreaud et al., 2003). Bookhagen and Strecker (2008) show
how the topographic relief plays an important role associated with orographic precipitation, but their analysis focused mainly on the eastern Andean slope, with tropical forest cover. Our precipitation reconstruction at approximately 1 km resolution allows for a more detailed local analysis of precipitation variability around QIC.

Figures 2.7a and 2.7b show the reconstructed precipitation and TRMM climatologies, respectively. The reconstructed climatology (Figure 2.7a) presents a homogeneous but much more detailed precipitation pattern during DJFM (austral summer) and JJAS (austral winter), and a more heterogeneous pattern in April-May and October-November, which correspond to the transition seasons. During the wet periods the lower elevations receive more precipitation (<140 mm/month). An unrealistic pattern with reduced wet season precipitation, when compared with the Altiplano region, was found over the eastern Andean slope (see section 2.4.4.2).

The TRMM data in Figure 2.7b portray a homogeneous pattern except to the north and northeast of QIC and along the eastern Andean slope, where precipitation is enhanced. In fact precipitation is overestimated by a factor of 1.5 or more by TRMM over regions with high elevation, such as QIC and the eastern Andean ridge and slope areas. This bias may be due to stratiform clouds associated with deep convection, producing ice bands at high tropospheric levels that can perturb the satellite measurements (Mohr et al., 2014). In the case of the overestimation in the neighborhood of Lake Titicaca by TRMM (Figure 2.7b for DJF and Figure 2.8 for wet and annual), the lake itself could have an impact on precipitation formation (Giovannettone and Barros, 2009). This overestimation is consistent with the observations at Taraco station, located close to Lake Titicaca, which features a bias value of 1.33 (TRMM vs Obs dekadal, Table 2.3). The problem
along the eastern Andean slope is assessed separately in section 2.4.4.2. The fact that TRMM overestimates precipitation over the Peruvian Andes has been documented in previous studies, and several (linear and non-linear) techniques have been proposed to correct for this bias (e.g., Condom et al., 2011; Heidinger et al., 2012; Satgé et al., 2015). Here we do not apply such a post-processing to TRMM as such corrections could also be applied to the reconstructed precipitation data. We are more interested in the direct comparison between our reconstruction method and raw TRMM data, as applied in most tropical precipitation studies.

Figure 2.8 shows the ~1km Dry, Wet, and Annual reconstructed precipitation distribution over the study area. The reconstructed precipitation during the dry period shows a homogeneous behavior, with enhanced precipitation over the northeastern slopes and around some of the localized peaks with more than 5 km height, such as QIC. The wet season precipitation portrays a more heterogeneous behavior with increased precipitation at lower elevations, principally west of Lake Titicaca. The reconstruction, however, also produces reduced precipitation along the eastern Andean slopes when compared to the Altiplano itself, which is unrealistic. When the data are aggregated to annual precipitation totals, the reconstruction presents relatively homogeneous precipitation amounts, oscillating around 600 to 800 mm, but with increased precipitation at lower elevations, west of Lake Titicaca and to the southwest of QIC in particular.

The more homogeneous precipitation characteristics during the dry period may be indicative of the influence of large- to meso-scale circulation systems which may play a more dominant role (Vuille and Ammann, 1997) than local- or regional-scale convective processes, dominating during
the wet season summer months and being more strongly modulated by the complex topography (Garreaud et al., 2003).

Figure 2.8 also displays the Dry, Wet and annual TRMM distributional analysis. The TRMM v7 data were not corrected with the in situ station data, as this product already includes a correction process based on local station data. Studies by Scheel et al. (2011) and Heidinger et al. (2012), show a large overestimation of precipitation by TRMM products over high-elevation locations, and details of the TRMM version 6 and 7 bias are discussed in Zulkafli et al. (2014).

The Wet and Annual reconstruction patterns are comparable to the TRMM cases (Figure 2.8). Across the eastern Andean ridge, however, our reconstructed precipitation pattern is contrary to the well-known northeast-southwest decreasing precipitation trend (e.g., Figure 3 in Mohr et al., 2014; and Figure 2 in Satgé et al., 2015) with the precipitation gradient being reversed. This problem is assessed in more detail in the following section.

2.4.4.2. Assessing the reconstruction over the eastern Andean slope

The reconstruction represents precipitation over the Andes quite well, when compared to the TRMM data (Figure 2.7 and Figure 2.8). However, the reconstruction shows an unrealistic behavior over the eastern Andean slope during the wet season. The eastern Andes region is a highly complicated region to obtain accurate precipitation information, be it from satellite, reanalysis or weather station measurements (Blacutt et al., 2015; Espinoza et al., 2015). During December, for instance, the reconstructed precipitation over this slope is about 30 mm/month, much lower than the amount on the Altiplano, which ranges between 80 to 120 mm/month. To assess this problem
over the Andean slope, we used data from an additional independent station, Tambopata (~1340 masl), not used in the reconstruction and located at a much lower elevation on the Andean slope (Figure 2.1a).

We selected four locations for this additional analysis: Sicuani, Azangaro, Crucero, and Tambopata. Sicuani and Azangaro are located on the Altiplano, while Crucero is located close the eastern Andean ridge (~3042 masl), and Tambopata, as discussed, at a much lower elevation on the eastern slope. The seasonal cycle of precipitation (Figure 2.9a), is similar at all stations, but with much higher values in all months at Tambopata. Moreover, intense precipitation events are not uncommon in Tambopata, as occurred during the July 2009 dry season, when more than 250 mm of precipitation fell within a week. This amount is similar to the maximum monthly precipitation over the Central Andes region during the wet season. In the case of NDVI (Figure 2.9b), the Andean precipitation seasonality is well reproduced by Sicuani, Azangaro and Crucero, but completely lost in the case of Tambopata, likely because of orographic precipitation enhancement along the Andean slope throughout the year (Figure 2.9a). In addition the lack of clear days during the wet season produces extremely perturbed NDVI measurements around Tambopata. As a result the precipitation-NDVI relationship as derived from Andean stations, is not representative over the Andean slope region.

2.4.5. Comparison of reconstructed precipitation with snow accumulation at QIC

In Figure 2.10, dry and wet season average reconstructed precipitation data are shown over a smaller domain centered on QIC. Precipitation around QIC is distributed rather uniformly, but there is a clear enhancement of precipitation over the higher topography of QIC, especially on its
eastern flank. While this is consistent with the notion of easterly moisture advection during the wet season, dry season precipitation on QIC itself is significantly overestimated by our reconstruction in Figure 2.10a.

At the QIC summit (5680 masl) snowfall has been routinely measured at hourly resolution since 2004 (Hurley et al., 2015). Hence it is worth investigating the spatial coherence between these measurements with our reconstructed precipitation using NDVI. However, our reconstruction lacks physical representation or definition of objects where vegetation is absent, as is the case on QIC and its surroundings, which are covered by ice and bare rocks. Thus, the precipitation values produced by our reconstruction on the QIC itself are unrealistic, with dry season values of approximately 200 – 300 mm (Figure 2.10a), when in reality snowfall during the dry season is limited in magnitude (Hurley et al., 2015). We can therefore not directly compare calculated precipitation (from snowfall totals measured by the AWS, section 2.2.2) on QIC with estimated values from our precipitation reconstruction.

Since we cannot compare AWS snowfall totals with our reconstructed precipitation totals on QIC itself, we instead average the reconstructed precipitation over the eastern and western sides of QIC (blue and red rectangles, respectively, in Figure 2.10; 10.79 km x 15.69 km or 0.0981º lat x 0.1426º lon each). The two dekadal precipitation time series obtained in this way are highly correlated with r = 0.95 (p-value<0.0001). Hence the temporal precipitation variability is almost identical on both sides of QIC. If we compare the observed snowfall totals at QIC (converted into water equivalent precipitation) against reconstructed precipitation to the west and east of QIC at the dekadal scale between 2005 and 2009, we obtain correlation coefficients of 0.85 and 0.79, respectively, in both
cases with p-value<0.0001. This suggests that precipitation at QIC is regionally homogeneous and that snowfall at Quelccaya is spatially representative, in terms of amount and in terms of variability, of a larger surrounding region. On the other hand, this result also indicates that snowfall variability at dekadal scale at QIC summit may be estimated from nearby precipitation at lower levels.

2.5. Discussion and Conclusions

A spatio-temporal precipitation reconstruction model using NDVI data was built, validated with an independent set of data and used to describe the climatology and spatio-temporal variability of precipitation in the Cordillera Vilcanota region, surrounding the QIC at dekadal scale. This model is based on stochastic variability inheritance from daily precipitation data of local stations and a vegetation index, applying the WOMA and Symmlet wavelet mother, which maintain the local variability and internal information (entropy) of the precipitation data from neighbor locations.

The reconstruction method uses the low-frequency NDVI data, incorporated as a proxy for low frequency precipitation, removing cloud-related errors and high-frequency local noise caused by various different sources (i.e. non-vegetation elements such as bare soil or snow). Vegetation responds to precipitation with a lag, which varies depending on ground water recharge and discharge, soil properties, land cover, topography, and others (Quirroz et al., 2011). A detailed quantification of this lag is beyond the scope of this study, since it would require more detailed in situ measurements at and below the ground level. However, based on the empirically established lags (Table 2.1), we can infer that the soil properties are inducing a delay on the order of 4-5 dekadals between precipitation and the corresponding vegetation response. This is consistent with
the semi-arid climatic conditions of the study area. In the Andes of Ecuador, for example, where conditions are humid all year, the NDVI-precipitation lag is between 1 and 2 dekadals (Hunink et al., 2014). Our lag values are also consistent with the delay found in Quiroz et al. (2011) over a similar study region located nearby. Immerzeel et al. (2005) showed that the NDVI-precipitation response on the Tibetan plateau, an ecosystem that is comparable to the Altiplano in terms of altitude, vegetation and climate, is also delayed by approximately 5 dekadals (see Figure 6 in Immerzeel et al., (2005)).

Our reconstruction method implicitly accounts for the stochastic nature of precipitation by incorporating the high-frequency precipitation signal, which is locally unique. High-frequency precipitation variability has a complex (chaotic) behavior, and is retained in our reconstruction, unlike any method that would rely on a spatial interpolation technique. As such our reconstruction method is divided in two parts; the low-frequency precipitation, modeled by means of the low-frequency NDVI signal, and the high-frequency, chaotic precipitation variability. Moreover, since NDVI is taken as precipitation proxy, it carries some constraints about the local precipitation behavior. For example the lag between NDVI and precipitation portrays a quasi-linearity, without consideration of non-linear factors in the reconstruction model. These constraints can be relaxed when a higher decomposition level is used, allowing the use of more information from high-frequency precipitation (detail signals) than is available from NDVI alone. Here we use the 3rd decomposition level to start the reconstruction process, based on the entropy comparison between different decomposition levels.
We have calculated the explained variance that is simply due to the annual cycle by correlating the reconstructed mean annual cycle (climatology) vs. the observed precipitation at all 13 stations ($R^2_{\text{annual}}$) and then repeated this analysis with the intraseasonal and interannual variability included ($R^2_{\text{interannual}}$). The mean $R^2_{\text{annual}} = 0.61$ is quite high, indicating the strong role played by precipitation seasonality. When using the actual reconstruction, including variability at intraseasonal and interannual timescales, $R^2_{\text{interannual}} = 0.87$ (as it was presented in Table 2.2 for the 3rd level of reconstruction), highlighting the added skill of our model. Indeed at 11 out of the 13 stations the $R^2_{\text{interannual}} \geq 0.90$.

It is important to note, that the NDVI data were filtered to obtain a low-frequency (more periodic) NDVI signal. This filtering effectively removes noise from clouds, but also from several other biophysical mechanisms, such as photosynthesis, transpiration, soil moisture, or objects that lack vegetation (open water, bare soil and rocks, roads, etc.). Thus, the pre-processing of the NDVI signal depends on the kind of information (frequency) that one wishes to retain in the final results. For our case, since we only assessed the reconstruction method over a period of 10 years, long-term NDVI variability and trends cannot be assessed (for instance, the El Niño impacts on NDVI). In the present study we focused on removing a major part of the high-frequency NDVI variability. Hence the reconstructed precipitation carries more weight from the high-frequency component observed in precipitation at in-situ stations. Future research will be oriented on the use of low-frequency NDVI models, such as a statistical NDVI model generation, or a functional composition model based on several environmental variables. Moreover, other environmental data from satellites, besides NDVI, might be used to further improve the precipitation reconstructions. By changing the satellite product the same method can be used for other process studies, as was done,
for example, by Heidinger et al. (2012) who used the one dimensional reconstruction method of Quiroz et al. (2011) to correct the TRMM product over the Central Andes.

One of the advantages of our method is that spatial lags associated with spatial precipitation variability are inherently included and accounted for in our reconstruction method as it forms part of the NDVI response. For example, a meso-scale disturbance moving across the region over the course of several days will lead to rainfall on different days at different points of its trajectory. An in-situ network may not detect this spatial lag if it is not sufficiently dense. The vegetation and hence the NDVI, however, will respond accordingly, showing an increasing lag along the disturbance’s trajectory when compared to the region where the disturbance first emerged, in accordance with the duration of the storm travel time.

The spatial variability of the reconstruction was compared against TRMM 3B42 v7 data, which confirmed the robustness of the reconstruction model to generate realistic spatio-temporal characteristics, although the comparison with TRMM was hampered by TRMM overestimation in this region. In general, TRMM shows a positive precipitation bias around high elevation areas (more than 5000 masl), but over lower elevation Andean regions (between 3000 and 5000 masl) the two products showed similar results.

Several important conceptual assumptions have to be considered to fully appreciate the high-resolution precipitation results obtained in this study: 1) the reconstruction is based on surface observations, i.e. in contrast to TRMM products, which are derived from infrared, thermal and microwave spectral exitance from clouds, the NDVI-precipitation measurements are obtained from
sensing dynamical land cover on the ground; 2) the NDVI field contains topographic information and variability, and this property is inherited to the precipitation reconstruction; 3) the precipitation variability used in the reconstruction process incorporates in-situ weather station data; 4) the spatial resolution is constrained by the spatial scale of the NDVI data; 5) the 10 day temporal (dekadal) scale was selected here to maintain the same time scale as the NDVI data and therefore we did not take into consideration higher frequency events in the analysis of our results. But since the NDVI data are only used as a “trend”, the high frequency information is retained by the local precipitation measurements from the weather stations (the “details” in equation (2) of the reconstruction process). Hence it would be possible to extend the reconstruction process to a daily (Quiroz et al., 2011, Heidinger et al., 2012), or even higher temporal resolution, as long as precipitation data were available, for example at hourly resolution. 6) A limitation of our reconstruction results is lack of a physical representation or definition of objects where vegetation is absent, as is the case on the QIC and other glaciated areas, lakes, bare ground, rocks, etc. Similarly precipitation over the eastern Andean ridge and slope is not well represented by the reconstruction. This limitation was to be expected since station data over the eastern Andean slope were not used in the reconstruction process, and since the vegetation – precipitation relationship breaks down at lower elevations over forested terrain. Here other types of (vegetation-) indices and/or satellite data may be used in the future to obtain a more reliable representation. 7) As is visualized in Table 2.3, the reconstruction does not show superior skill when compared to TRMM at capturing temporal variance. This is to be expected, given that the reconstruction is based on a vegetation-derived proxy, while TRMM includes information on rain rate from satellite and rain gauge measurements.
The spatial reconstruction model presented here may be extended to correct satellite products over other, similar mountain regions where TRMM products may be questionable. In addition, our NDVI-derived product significantly improves the spatial resolution when compared to the much coarser spatial scale of many satellite products such as TRMM (about 0.25° or 27 km in the case of TRMM v7).

Our high-resolution precipitation product may also permit a better validation of numerical model results obtained from global and regional climate models, reanalysis, and satellite data. Such data sets may also prove valuable for forecasting and prediction studies or for developing climate change scenarios over mountain regions at a much finer resolution.

The main goal of this study was to generate high-quality regional precipitation information over a mountain region with a low density of weather stations. We acknowledge that several caveats exist, that have to be considered in more detail in future studies. In particular the model could benefit from the inclusion of a denser surface station network or from a modification that would allow taking into account topography, land cover, soil moisture and type and other important surface characteristics. Moreover, additional tests evaluating the reconstruction sensitivity to varying environmental boundary conditions (e.g. ENSO) would be desirable. Nonetheless, the high spatial resolution of our spatio-temporal reconstruction model makes our results appealing to a variety of applications over semi-arid mountain regions, especially given its good performance compared to other spatial precipitation products, such as TRMM 3B42 v7.
2.6. Acknowledgements

We are grateful for the comments from 3 reviewers (Bodo Bookhagen and 2 anonymous) who helped to significantly improve the quality of the manuscript. This study was supported by the US Department of State as part of the ACCION project (award S-LMAQM-11-GR-086), by the National Science Foundation programs P2C2 (award AGS-1303828) and Paleoclimate (9909201 and 0402557), and by the NOAA Global Climate Observing System. Co-authors of CIP acknowledge the contribution of the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). Data generated as part of this study is available from the authors upon request. The reconstruction algorithms are available in Matlab format at http://www.atmos albany.edu/student/yarleque/.
2.7. Tables

Table 2.1. Weather stations located in the study area (Figure 2.1) satisfying the criteria described in section 2.2.2. The lag and the maximum coefficient of determination (max. $R^2$) values correspond to the precipitation-NDVI dekal time series comparison during the period 2000-2009 period.

<table>
<thead>
<tr>
<th>Order</th>
<th>ID (by ANA)</th>
<th>Name Stations</th>
<th>Elev. (masl)</th>
<th>Latitude (º)</th>
<th>Longitude (º)</th>
<th>Lag (dekalals)</th>
<th>max. $R^2$: Prec. vs. lagged NDVI</th>
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<tr>
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Table 2.2. Shannon’s entropy (E), entropy difference (ΔE), and the coefficient of determination (R²) for NDVI and precipitation (Prec) for different wavelet decomposition levels (i). The precipitation time series is selected using the influence matrix to define which of the 13 station time series performed best at each location. The NDVI time series is corrected by applying a lag when compared with the precipitation time series. The entropy is calculated using a normalization unit for the corrected NDVI and precipitation. The absolute value (|E|) of the entropy difference between both signals is used for each level. The R² is calculated for each Trend of the wavelet decomposition process applied to the corrected NDVI and precipitation of each dekadal time series, but only the mean across the 13 station locations is shown for each decomposition level. An adjusted R² between reconstructed precipitation started in level i (Rec_i) and measured Prec, is calculated per station location, but only the mean across the 13 station locations is presented.

| Level (i) | Time scale | E(AN_DVI_i) | E(APrec_i) | ΔE = |ΔE/max(ΔE)| \times 100\% | R² from AN_DVI_i vs APrec_i | Adjusted R² from Rec_i vs Prec |
|-----------|------------|-------------|------------|-------|----------------|-------------------------|-----------------------------|
| 0         | 1 dekadal  | 3.12        | 2.85       | 0.27  | 100            | 0.57                    | ---                         |
| 1         | 2 dekadal  | 3.13        | 2.88       | 0.25  | 94             | 0.67                    | 0.69                        |
| 2         | 4 dekadal  | 2.86        | 2.75       | 0.11  | 41             | 0.76                    | 0.79                        |
| 3         | 8 dekadal  | 2.52        | 2.51       | 0.01  | 4              | 0.85                    | 0.87                        |
| 4         | 16 dekadal | 2.15        | 2.15       | 0.00  | 1              | 0.80                    | 0.91                        |
| 5         | 32 dekadal | 1.75        | 1.78       | 0.03  | 10             | 0.53                    | 0.92                        |
Table 2.3. Cross validation of reconstruction model and statistical comparison using TRMM data. A cross validation was applied to reconstructed dekadal precipitation (Rec) using 6 randomly selected weather stations not included in the reconstruction process (Obs) starting at the 3rd level of decomposition, over the entire period 2000-2009. The indices used are the linear correlation (r), bias (= mean(Rec)/mean(Obs)), mean absolute error (MAE), and root mean square error (RMSE). Indices definitions were taken from (Dinku et al., 2008).

<table>
<thead>
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<th>TRMM vs Obs dekadal</th>
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</thead>
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<td>bias</td>
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<td>Crucero</td>
<td>0.76</td>
<td>1.01</td>
</tr>
</tbody>
</table>
2.8. Figures

Figure 2.1. (a) The study area selected is highlighted by the black square, with coordinates 11.5°S - 15.5°S, and 72.5°W - 68.5°W. Weather station locations are shown with blue dots, including the AWS (red dot) located on QIC where snow accumulation was measured. Color shading represents the elevation in meters above sea level (masl). (b) USGS South America land cover version 2.0 map over the study area. The original land cover array is 446 rows and 452 columns, but was resampled to a 449 x 449 array using a bi-cubic interpolation technique to match the spatial scale of the NDVI data (~1km). Quelccaya ice cap location is indicated by the red dot.
Figure 2.2. NDVI decadal correction process using a smoothing methodology (section 2.2.3). The gray lines show the raw NDVI decadal data including extreme minimum values corresponding to periods of clouds and strong atmospheric scattering (noise). The bold black line corresponds to the filtered (corrected) NDVI data. Years on the x-axis are centered on the 3rd decadal of June. The NDVI values in the y-axis correspond to the original NDVI units from 0 to 255.
**Figure 2.3.** An example of the NDVI-lag determination and correction based on the station Sicuani. a) the optimal lag value (= 4 dekadals) as indicated by the maximum $R^2 = 0.66$ (red square) based on lagged correlation between precipitation and NDVI from Jan. 2000 to Dec. 2009. b) Precipitation – NDVI lag correction over the same period. Upper graph shows the dekal precipitation (blue line) and normalized and cloud corrected NDVI (green line) dekal time series. Lower graph shows same time series, but after shifting the NDVI data backward by 4 dekadals in order to remove the lag between precipitation and cloud-corrected NDVI data.
Figure 2.4. (a) Influence zone matrix derived from 7 out of 13 weather stations. The other 6 stations are retained for cross validation purposes (section 2.4.3). A topography mask was used to remove regions below 2500 masl (section 3.1). Numbers on the color bar correspond to the ID of each station in Table 2.3. (b) Influence zone matrix at ~1km² resolution, derived using 13 weather station locations with a $R^2>0.35$ and p-value<0.05, between NDVI(ST) vs. NDVI(x), where x represents locations over the study area, and ST the station locations above 2500 masl. Numbers on the color bar correspond to the ID of each station in Table 1. Black contours in (a) and (b) correspond to topography above 5000 masl, and white dot is representing QIC location.
Figure 2.5. Decomposition-Reconstruction Process based on the station Sicuani. Here the level 3 of reconstruction is shown (section 2.4.2). (a) Precipitation decomposition (downward arrows) using Symmlet-2 wavelet, until the level 3 is reached. (b) as in (a), but for the NDVI cloud (Figure 2.2) and lag-corrected data. (c) Reconstruction (upward arrows) from NDVI trend and precipitation detail signals at level 3, using a scaling factor (equation 3), and A’ means that A is previously normalized to 0-1 values. Precipitation details and reconstruction data are used for upper levels to obtain the final reconstruction at level 0 (i.e., at dekadal time scale).
Figure 2.6. Reconstructed dekadal precipitation (Rec.) for 1st dekadal January 2000 based on 7 and 13 stations, respectively (left and middle figure), and the corresponding TRMM dekadal precipitation (right figure) obtained from the raw TRMM v7 daily product. Gray, dark gray, and black contour lines indicate 3, 4 and 5 km elevation isolines, respectively. The red dot indicates the QIC location. A Lake Titicaca mask was applied.
Figure 2.7. (a) Reconstructed monthly precipitation climatology. Gray, dark gray, and black contour lines indicate 3, 4 and 5 km elevation isolines, respectively. The red dot indicates the QIC location. (b) As in (a), but for TRMM monthly precipitation climatology obtained from TRMM v7 daily product without any post-correction process (raw TRMM v7 product). A Lake Titicaca mask was applied.
Figure 2.8. Reconstructed precipitation (top row) and TRMM (bottom row) for dry (left), wet seasons (middle) and annual total (right) respectively. Gray, dark gray, and black contour lines indicate 3, 4 and 5km elevation isolines, respectively. The red dot indicates the QIC location. A Lake Titicaca mask was applied.
Figure 2.9. Comparison of a) observed precipitation and b) NDVI seasonal cycle. Sicuani, Azangaro, Crucero, and Tambopata are located to the west, south, north and east of QIC, respectively. Sicuani, Azangaro and Crucero belong to the QIC system, while Tambopata is located on the eastern Andean slope (1340 masl), much below the Altiplano elevation.
Figure 2.10. Local analysis of reconstructed precipitation surrounding QIC, with a 0.0089° (or ~0.9805km) resolution, for (a) dry and (b) wet periods, respectively. The black dot indicates the QIC location. The western and eastern QIC rectangles (10.79km x 15.69km or 0.0981° lat x 0.1426° lon or 11 rows x 16 columns), in red and blue, respectively, indicate the two regions selected over which precipitation was averaged to create time series from 2000 to 2009. Gray contour corresponds to 3 to 5.5 km elevation with a 0.5 km contour interval. White areas lack data as they are located below 2500 masl.
2.9. References


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Chapter 3

FUTURE PROJECTIONS OF PRECIPITATION VARIABILITY OVER THE CENTRAL ANDES

Christian Yarleque, Mathias Vuille, Douglas R. Hardy, Oliver Elison Timm, and Hugo Ramos
Abstract
Precipitation is an important variable determining snow accumulation over glaciated mountain regions and affecting the hydrologic cycle downstream, but the lack of data, inaccurate precipitation estimates due to complex mountainous terrain, and the coarse resolution of global climate models (GCM) present major hurdles when modeling snowfall and its future changes. Here wet season precipitation over the Central Andes is simulated with an empirical-statistical downscaling (ESD) model, employing long-term regional precipitation data from in-situ observations as predictand and large-scale atmospheric circulation indices derived from reanalysis products as predictors. Our ESD model has the skill to predict austral summer precipitation over the central Andes despite multi-decadal Pacific climate variability modulating the relative importance of individual predictors over time. Our analysis shows how Central Andean precipitation is associated with both zonal and meridional wind at 500 hPa, and vertical velocity at 700 hPa (predictors). As an application of this model, future precipitation on Quelccaya Ice Cap (QIC) is projected, using QIC as a representative case study for low-elevation glaciated areas over the Central Andes. Future projections of wet season (DJF) precipitation at QIC, using 16 CMIP5 models, do not show any statistically significant change for either a medium emission scenario (RCP4.5), or a high emission scenario (RCP8.5), during the twenty-first century.
3.1. Introduction

A crucial issue when analyzing mountain climate is how to adequately project future changes in precipitation, which plays a key role in several research areas and is highly relevant to society (Viviroli et al., 2011). Precipitation is the most complex variable to predict, given its stochastic nature (Yarleque et al., 2016). Although, this complexity can be further increased in mountain regions by orographic forcing, empirical results have shown that in the central Andes the in-situ measured precipitation exhibits considerable spatial covariance on a regional scale (Quiroz et al., 2011; Yarleque et al., 2016) and is closely related to the large-scale circulation on multiple time scales (e.g. Garreaud et al., 2003).

Precipitation over the Central Andes is the result of austral summer deep convection and downward mixing of easterly momentum over the eastern Andean ridge (Garreaud et al., 2003; Vuille and Keimig, 2004), thereby enhancing near-surface and mid-tropospheric easterly flow of moist air to higher levels. The daytime heating of near-surface levels is a vital destabilization mechanism, triggering deep convection once dynamical forcing has lifted moist near-surface air parcels above the level of free convection. Due to this diurnal mechanism, precipitation above 3000 meters above sea level (masl) occurs frequently in the evening (e.g., Garreaud, 1999). Complementary to this convective mechanism, Perry et al. (2014) and Perry et al. (2017) have been pointing out that much of the precipitation over the Central Andes is the result of nocturnal stratiform precipitation, which is in concordance with radar observations (Romatschke and Houze, 2010).
Austral summer precipitation over the Central Andes is typically associated with anomalous upper-air easterly winds, which enhance the upslope flow of moist air from the boundary layer through downward entrainment of easterly momentum over the Andean ridge (Vuille, 1999; Vuille and Keimig, 2004; Falvey and Garreaud, 2005; Garreaud et al., 2003; Garreaud 1999, 2000b, 2009). These easterly winds occur in response to an intensification and southward displacement of the Bolivian High (BH), an upper-level anticyclone that develops in response to latent heat release over the Amazon basin (Lenters and Cook, 1997). In addition intense convection over the Central Andes has been linked to increased mid-tropospheric humidity (Falvey and Garreaud, 2005). For instance, snowfall at the Quelccaya ice cap (QIC), in the Cordillera Vilcanota of southern Peru (Figure 3.1), occurs in conjunction with the South American Summer Monsoon (SASM) season between November and April (Thompson et al., 1985; Vuille and Werner, 2005; Mohr et al., 2014). Monsoon-related convection is often enhanced during periods when extra-tropical cold air incursions propagate northward from southern South America (SA) and lead to significant rain and snowfall in the Andes. Hurley et al., (2015) recently documented that up to 70% of the total snow accumulation measured on the QIC summit is tied to convection and uplift of warm tropical air masses along the leading edge of such extratropical cold surges. On the other hand, mid-tropospheric westerly flow, originating over the Pacific, generally leads to very dry conditions over the central Andes, although occasional embedded cut-off lows can lead to massive austral winter snowfall (Vuille and Ammann, 1997). On interannual timescales the El Niño - Southern Oscillation (ENSO) leads to positive (negative) precipitation anomalies over the Central Andes during La Niña (El Niño) by increasing (reducing) moisture influx and upper-level easterly flow over the Central Andes. The mechanism by which ENSO affects snowfall in the Central Andes is
first and foremost related to changes in meridional baroclinity driven by the anomalous warming or cooling of the tropical Pacific (Garreaud and Aceituno, 2001).

Long-term changes in precipitation in the region are not well understood. The few existing studies have suffered from the lack of a long and dense high-quality observational network in the region. For instance, Seth et al. (2010) analyzed precipitation trends at Patacamaya (17.24ºS, 67.92ºW) located south of QIC, at 3799 masl. They found a trend toward drier conditions in spring and increased rainfall during summer, over the 1960-2008 period. In contrast, using a station located closer to QIC, Salzmann et al. (2013) presented a precipitation analysis from Santa Rosa (14.6ºS, 70.8ºW, 3940 masl), which shows a slight decrease in precipitation for all seasons, over the 1965-2009 period.

Global Climate Models (GCM) simulate large-scale circulation features and dynamic aspects associated with the SASM reasonably well (e.g. Lenters and Cook, 1997; Carvalho and Jones, 2013; Vuille and Werner, 2005; Jones and Carvalho, 2013). Precipitation, however, is the one atmospheric variable that is not well reproduced over the Andes by GCMs (e.g., Minvielle and Garreaud, 2011). This failure is due principally to the high spatio-temporal variability of precipitation, modulated by the complex Andean topography, which remains unresolved due to the coarse resolution of GCMs (Baron et al., 2005). Similar uncertainties exist even in regional climatic models (RCMs) over the Andes region (e.g., Chou et al. 2012). In the Coupled Model Intercomparison Project Phase 3 (CMIP3) model simulations, seasonal precipitation over the Andes contained a large positive bias during the rainy season (December to February), and a smaller positive bias during the dry season (June to August), when compared with station data.
(Seth et al., 2010). Surface temperature shows a positive (warm) bias with respect to station data throughout the year in CMIP3 models (Seth et al., 2010). This behavior is expected due to the lower topography of the Andes in CMIP3 models. Over tropical latitudes, some improvements were made with the Coupled Model Intercomparison Project Phase 5 (CMIP5) in comparison with CMIP3 (e.g., Grose et al., 2014). Moreover, several studies documented how CMIP5 models include improved ENSO physics (e.g. Yeh et al., 2012), SASM dynamics (Jones and Carvaho, 2013), and cold air incursion characteristics (Yin et al., 2013), all affecting Andean precipitation. However, large discrepancies are still detected in the spatial variability of historical CMIP5 simulations for mean daily rainfall, South Atlantic Convergence Zone (SACZ) and ITCZ characteristics (Carvalho and Jones, 2013). Miller et al. (2014) further demonstrated how historical CMIP5 simulations realistically represent the twentieth-century annular trends toward reduced surface pressure at southern high latitudes and a poleward shift of the mid-latitude westerlies, consistent with observations. Because RCMs rely on GCM output as boundary conditions when simulating future scenarios, the same problems are inherited from GCMs, which can also be detected to a varying degree in dynamical downscaling exercises. For example, the RCM used by Urrutia and Vuille (2009) nicely reproduced 30 years of temperature variability observed over the Andes on interannual time scale, but precipitation was highly overestimated over the eastern Andean slope; a problem of orographic precipitation overestimation that is common in many RCM studies (Urrutia and Vuille, 2009; Buytaert et al., 2010; Chou et al., 2012).

One way of evaluating future precipitation variability over the Central Andes by means of GCMs, is to empirically derive precipitation based on the observed close linear relationship between precipitation ($P$) and upper-level zonal wind (usually at 200 hPa), hereafter referred to as $P-U200$
linear model (Minvielle and Garreaud, 2011; Neukom et al., 2015), thereby taking advantage of the significant linear relationship that exists between both variables over the Central Andes (Garreaud et al., 2003; Vuille et al., 2008b). However, the strength of this linear relationship varies in space and time across the Andes. For instance, the \( P-U200 \) relationship over the Cordillera Blanca, northern QIC, changed after the mid-1990s as shown by Schauwecker et al., (2014), who documented a shift toward larger precipitation and stronger easterlies around the mid-1990s. This shift is coincident with the La Niña-like SST pattern that emerged around 1997 (Zhang et al., 2016). Hence precipitation projections based on assumptions of stationarity of the \( P-U200 \) model may generate ambiguous results, depending on the time period considered for calibrating this linear relationship. Nonetheless it is important to emphasize that the underpinning mechanism that determines the zonal flow aloft is related to the change in meridional baroclinicity off the west coast of South America (Garreaud and Aceituno, 2001) and the projected enhancement of westerly flow in the future is dynamically consistent with expected stronger future upper-tropospheric warming in the tropics, as opposed to mid latitudes. Hence the results by Minvielle and Garreaud (2011) and Neukom et al. (2015) who project decreasing precipitation over the Central Andes over the course of the 21st century may be sensitive to the choice of calibration period, but are nonetheless physically plausible given the projected anomalous upper-tropospheric warming in the tropics.

Empirical-statistical downscaling (ESD) methods have made a lot of progress over the Andean region, in particular based on studies in the northern Cordillera Blanca (Hofer et al., 2015), and specifically over the tropical glaciers Artesonraju (Hofer et al., 2010) and Shallap (Maussion et al., 2015). In these instances, the large-scale predictors were related to local-scale predictand
variables based on multiple linear regression models. In the tropical glacier Artesonraju study the observed air temperature and specific humidity over the glacier were considered as predictands, and several variables from reanalysis products as predictors. Moreover, Maussion et al. (2015) show how several atmospheric variables have a high skill to predict precipitation over glaciated regions (such as the Cordillera Blanca) using a multi-linear model, in contrast to the simpler $P-U_{200}$ linear model, which has stronger skill over the western Andean Cordillera (Minvielle and Garreaud, 2011). Moreover, Hofer et al. (2017) listed and compared ESD models used to downscale several atmospheric variables in tropical environments.

The purpose of this study is to assess and describe the Central Andes wet season precipitation and its association with the large-scale circulation in view of a changing climate. In order to quantify this association, DJF seasonal precipitation (predictand) was modeled using an ESD model, where several climatic indices were built and combined to implement a predictor array. This model succeeds in generating regional precipitation over the Central Andes; results that are subsequently used to calculate the QIC precipitation through a local-regional precipitation relationship. The ESD model obtained in this way is statistically significant, physically plausible, and shows climate-sensitivity across the changing climate, making it a robust application for future projections. Here we used observations and reanalysis products to build the ESD model, CMIP5 model output from historical simulations to test its performance in a model environment and RCP4.5 and RCP8.5 scenarios to establish future projections of precipitation. This study shows how Central Andean precipitation is linked to convective activity over the western Amazon basin and documents the necessity to use several climatic variables to fit an ESD model that can adequately characterize climatic forcing factors of precipitation over the eastern Andean ridge.
Section 3.2 introduces the data used, while section 3.3 discusses the methods and presents the results of our model validation. Section 3.4 discusses results related to future projections of DJF precipitation on QIC. The main conclusions of the current study are presented in section 3.5.

3.2. Data used and study area

3.2.1. Precipitation from station data

The Central Andes are home to about 99% of all tropical glaciers (Kaser, 1999; Rabatel et al., 2013), with Peru alone containing about 70% of them (Vuille, 2011). Quelccaya ice cap (QIC), the world’s largest tropical ice cap, can be considered a representative case study for the response of the Andean cryosphere to 21st century climate change (Buffen et al., 2009; Thompson et al., 2006; Thompson et al., 2013; Hanshaw and Bookhagen, 2014). It is located in the Cordillera Vilcanota in southern Peru (13°56’S, 70°50’W, Figure 3.1), with an approximate summit elevation of 5680 masl. QIC undergoes pronounced wet and dry seasons from October to March and May to September, respectively, associated with the build-up and demise of the South American monsoon season (Hurley et al., 2015). The QIC surface area has been reduced by about 30% between 1980 and 2010, covering an area of ~44 km² in 2010 (Hanshaw and Bookhagen, 2014). This loss of surface area is consistent with the retreat of tropical Andean glaciers from Bolivia to Venezuela (Rabatel et al., 2013). This retreat is driven by the increase in Andean surface temperature (Bradley et al., 2009; Vuille and Bradley, 2000; Vuille et al., 2015), although precipitation also plays a key role as higher temperatures lead to rain as opposed to snow thereby affecting melt rates and glacier surface albedo (Rabatel et al., 2013; Salzmann et al., 2013).
The study area is the same as in Yarleque et al. (2016), where a regional-scale precipitation reconstruction from NDVI data was presented, with coordinates 11.5°S to 15.5°S and 72.5°W to 68.5°W (black box in Figure 3.1a). In this study daily precipitation from 9 in-situ weather stations (blue dots in Figure 3.1b) belonging to the Servicio Nacional de Meteorologia e Hidrologia del Peru (SENAMHI) were used. The data selection was performed according to the following criteria: a) more than 90% of available daily data between 01-01-1979 and 28-02-2017, b) only station located above 3000 masl (hereafter called Andean stations), and c) rejection of sites with large number of data errors (i.e., with several outliers overpassing 3 standard deviations, and with visual periods of inconsistent regional behavior). The period of analysis starts in 1979, to coincide with the period when reanalysis products started to assimilate satellite data. The study focuses exclusively on the DJF wet season, when 50% - 70% of the total annual precipitation falls on QIC (Hurley et al., 2015).

3.2.2. Quelccaya ice cap precipitation

QIC precipitation was calculated at QIC summit (5680 masl, Figure 3.1c) using the snow height change (in meters) measured by an automated weather station (AWS, Figure 3.1d). For the present study, continuous hourly snow height change data between 1st August 2004 and 30 June 2017, were summed up to daily snow height totals. Since positive and negative snow height changes represent accumulation (precipitation) and ablation, respectively, only non-negative snow height values were used for precipitation calculation following the relationship:

\[ P_{AWS} = \text{snow height} \times \left( \frac{\text{snow density}}{\text{water density}} \right) \times 1000 \text{mm}, \]

where, \( P_{AWS} \) is the calculated precipitation at QIC in mm, snow height is the positive value of daily snow height in meters (m), (mean) snow density is 0.236 or 263 kg m\(^{-3}\) with a standard deviation
of 40.3 kg m$^{-3}$, based on few in-situ snow density measurements near the AWS on QIC between 2005 and 2014 (Appendix A), and water density at 0ºC is taken as 999.84 kg m$^{-3}$. The factor 1000 is the conversion factor of m to mm. The calculated daily QIC precipitation was summed up to obtain monthly totals.

3.2.3. Reanalysis data

Hofer et al. (2012) evaluated the skill of several reanalysis products as predictors for daily air temperature at high elevation on a glaciated mountain in the Central Andes. That study was used as reference to select reanalysis products for our analysis, since temperature is more faithfully represented in climate models and reanalysis than precipitation. The monthly reanalysis products used were the NCEP-DOE AMIP-II (Kanamitsu et al., 2002), MERRA-2 (Gelaro et al., 2017), and ERA-interim (Berrisford et al., 2011), containing a lower, medium and higher skill in reproducing climate variability over the Central Andes, respectively (Hofer et al., 2012). This sample of reanalysis products was chosen for the purpose of covering a wide variety of skillfulness to represent climate variability over the Central Andes, mimicking the selection of a set of GCMs when assessing the climate behavior in a multi-model ensemble. Moreover, Hofer et al. (2012) demonstrated that a reanalysis ensemble presents higher skill when compared to individual reanalysis products. Reanalysis data were selected with monthly temporal and 2.5º x 2.5º spatial resolution, respectively.

3.2.4. Model simulations

The model data used were obtained from 16 CMIP5 models (Table 3.2) at monthly scale, for historical (1950-2005), and future RCP4.5 and RCP8.5 projections (2006-2100). The atmospheric
variables, pressure levels, and others sub-products obtained from CMIP5 data are the same as for the reanalysis data (section 3.2.3).

3.3. Methods and results

3.3.1 The link between QIC and the regional Andean precipitation signals

Precipitation seasonality on QIC between 2004 and 2017 is consistent with the precipitation climatology derived from the 9 Andean stations surrounding QIC (Figure 3.2a) during this same time interval. Two major seasons can be distinguished: the austral summer wet (ONDJFMA) and austral winter dry (MJJAS) seasons, respectively. Andean precipitation (derived as the mean of the 9 long-term Andean weather stations, i.e. blue dots in Figure 3.1b) is less than QIC precipitation except for the month of February. While there is some uncertainty in this east-west gradient, introduced by the snow-water equivalent conversion of the snow height data at the QIC, it is consistent with the horizontal gradient detected in satellite measurements (e.g., Mohr et al., 2014).

These results are in agreement with Yarleque et al. (2016), who showed that precipitation variability on QIC is consistent with region-wide variations. Indeed, the correlation between the DJF seasonal Andean and QIC precipitation anomalies (Figure 3.2b) is highly significant with r=0.72 and p-value<0.02, over the 2004-2017 period, despite a few outliers, such as the strong 2015/16 El Niño season. The linear relationship between QIC and regional precipitation can be quantified as follows:

\[ P_{AWS} = 0.38 \times R + 2.28 \text{mm} \, , \]  
\[ (3.2) \]

where \( P_{AWS} \) and \( R \) represent the QIC and Andean DJF seasonal precipitation anomalies, respectively.
3.3.2. Assessing the large-scale circulation forcing

Since the QIC summit is located at 5680 m asl, representing a flat plateau without obstacles at about 500 hPa (the actual air pressure at the summit based on AWS measurements is approximately 515 hPa), it is directly exposed to the mid- and upper tropospheric zonal flow, commonly used as a proxy for precipitation (Garreaud et al., 2003; Vuille et al., 2008b; Minvielle and Garreaud, 2011). Predominant southeasterly flow recorded at the AWS during the wet season (not shown) is mainly a manifestation of the anticyclonic circulation associated with the Bolivian High (BH), but likely also influenced by extratropical cold air incursions propagating from southwest to northeast over the South American continent and leading to massive snowfall on the QIC (Hurley et al., 2015). On the other hand, prevailing westerly winds recorded at the AWS during the dry season (not shown) are consistent with the dominant upper-level westerly zonal flow during this season (e.g., Garreaud et al., 2003), minimizing precipitation over the Central Andes.

3.3.2.1 Multi-scale analysis of zonal wind – precipitation mechanism

We compare the DJF Andean precipitation vs. zonal wind or P-U200 linear model (Minvielle and Garreaud, 2011) over 1979-2017 period by means of a running correlation method with a 11-year window. The zonal wind at 200 hPa represents a spatial mean over the study area (Figure 3.1b). Here we show results based on ERA interim reanalysis, but the results do not change significantly when NCEP-DOE AMIP-II or MERRA-2 reanalysis products are used (results not shown). The results, displayed in Figure 3.3a, show a decline in the strength of the correlation over time from a significant negative correlation of <-0.6, to insignificant values after the mid-1990’s. When considering the entire period, the correlation is statistically significant with an r-value of -0.45 (p-
value<0.01, dashed line in Figure 3.3a). The same pattern is apparent in the wavelet coherence analysis (Figure 3.3b), indicating a strong anti-phased relationship between zonal wind and precipitation at high frequencies (interannual time scale) from 1979 to the mid-1990s, but a lack of such a relationship thereafter. In summary, it appears as if the P-U200 relationship was weak over the last decades, potentially modulated by strong interdecadal variability (Segura et al., 2016), although it remained significant overall when considering the entire period 1979-2017. The apparent non-stationarity of this relationship can generate considerable uncertainty for future precipitation projections (e.g., Minvielle and Garreaud, 2011; Neukom et al., 2015).

3.3.2.2. Large-scale circulation forcing of Central Andean precipitation

To clarify how the large-scale circulation affected QIC precipitation during different time intervals, we divided our analysis into three time periods: the entire 1979-2017 period, and the two sub-periods with strong (1979-1998) and weak (1998-2017) U200-precipitation relationships. Figure 3.4 shows DJF Andean precipitation regressed against upper-tropospheric wind and geopotential height (GPH). When considering the full period, upper-tropospheric easterlies emerge as dominant forcing over the Central Andes as expected and consistent with many previous studies. Between 1979 and 1998 (Figure 3.4b), this pattern is even more pronounced and a clear link to tropical Pacific forcing is evident, with the two tropical cyclones straddling the equator in each hemisphere in response to an anomalous heat source over the equatorial Pacific. But, for the most recent period, 1998-2017 (Figure 3.4c), this linear association is lost or at least not statistically significant, Similar patterns emerge at 500 hPa (Figure 3.4d, 3.4e, and 3.4f), but with the main difference in the most recent period, where the dominant wind direction over QIC is from the northwest (Figure 3.4f).
Since the tropical Pacific Ocean has been a key driver of tropical Andean precipitation on interannual timescales (e.g., Garreaud and Aceituno 2001; Vuille and Keimig 2004; Thompson et al. 2013), we assessed the relationship between tropical Pacific sea surface temperature (SST) and DJF precipitation over the same three periods as above. As shown in Figure 5 the strength of the ENSO-like pattern, with negative correlations over the central and eastern Pacific (indicating enhanced precipitation in the Andes during periods of negative SSTA, i.e. La Niña) varies considerable between periods. Most notably the most recent period shows teleconnections that are weaker, but also shifted spatially toward the eastern Pacific near the Peruvian and Ecuadorian coasts. Hence this suggests that eastern Pacific SSTA, associated with coastal or eastern Pacific El Niño’s (Takahashi et al., 2011; Takahashi and Martinez, 2017) may have been more dominant in forcing Andean precipitation over the past 2 decades. It is well known that the different flavors of ENSO lead to very different impacts on precipitation in the Andes of Peru (Sulca et al., 2018). Results presented in Figure 3.5 were generated using NOAA ERSST V5 data, but similar results were found using NOAA OI SST V2 data, but for 1982-2017, 1982-1998, and 1998-2017 periods (not shown).

Figure 3.6a presents the upper-level wind and GPH differences between the two 20-yr time periods. The main changes detected are related to an intensification of upper-level easterlies to the north of QIC on the order of 5 m/s, extending from the western Amazon to eastern Pacific, across the Andes. Moreover, the intensification of precipitation over the western Amazon basin (Figure 3.6b) also affects precipitation over the QIC region (Hurley et al. 2015). A meridional cross-section of moisture flux, near 70.8ºW where QIC is located, highlights the northerly moisture flux
exporting moisture from the Amazon toward the subtropics (Figure 3.7a). While most pronounced at lower levels, the moisture transported south to the east of the Andes is also contributing to the moisture lifted up to the QIC region. As shown by Espinoza et al. (2015) the northerly low-level flow impinging on the eastern foothill of the Andes, generates precipitation hotspots at the latitude of the QIC region. At mid-tropospheric levels, southerly winds dominate over the QIC region consistent with anemometer observations on the ice cap and the classic BH – easterly wind-precipitation mechanism (Garreaud et al. 2003). Figure 3.7b shows the same analysis but for the more recent 20-yr period and documents an intensification of the northerly winds and increased specific humidity to the east of the Andean at low and mid-tropospheric levels. The differences between the two periods are highlighted in Figure 3.7c, where the enhanced moisture flux, in particular at mid-tropospheric levels is evident. The notion that convective activity over the western Amazon basin is directly linked with precipitation over the QIC is not new, but was already pointed out by Hurley et al (2015). However, our results suggest that the southward transport of moisture at mid-tropospheric levels has increased over the past 2 decades, potentially contributing to the weakening of the relationship between snowfall on QIC and the upper-level zonal wind, as pointed out in the previous section.

3.3.3. Empirical statistical downscaling

A downscaling model was built to quantify the local QIC precipitation forced by the large-scale circulation following the results found in section 3.3.2. This was done in two steps: First, an ESD model was built using regional Andean precipitation as predictand, and an array of several atmospheric variables from reanalysis products as potential predictors. The aim of this model is to quantify the statistical relationship between large-scale forcing and regional precipitation
variability over the Central Andes for the DJF wet season. In a second step local DJF precipitation at QIC is derived from the Andean regional precipitation calculated in the first step. This step is based on the assumption that QIC precipitation variability is closely related to the regional-scale precipitation component \((R)\) as expressed in equation 3.2. Note that the main goal is to generate local DJF precipitation at QIC as an application of this downscaling process, but the same process can of course be applied to each Andean station in the study area (Figure 3.1b). The regional precipitation \((R)\) given in equation (3.2), can be summarized as:

\[
R = P(X) + \epsilon,
\]  

(3.3)

where, the \(P(X)\) is the predicted precipitation by the ESD model as a transfer information operator between the target variable or predictand \(R\), and \(X\), the large-scale array of atmospheric variables (predictors) from reanalysis or GCM data; while \(\epsilon\) represents a noise term. In this modeling approach \(X\) was based on an array of several time-dependent indices derived from atmospheric variables. The ESD coefficients are obtained by means of a forward stepwise multi-linear regression approach (Wilks, 2011).

### 3.3.3.1. The predictand

The predictand \((R\) in equation 3.3) is defined as the regional seasonal DJF precipitation anomalies, calculated as the mean from 9 in-situ weather stations located in the study area (blue dots in Figure 3.1b), hereafter referred to as Andean precipitation. Precipitation data were selected for the 1979-2017 period, since assimilation of observations into reanalysis are more consistent after 1979, when several satellite products were included (e.g., Hofer et al., 2012). Note that calculating the mean across 9 weather stations removes part of the local-scale signal while retaining the regional-scale variability representative of the synoptic scale. Additionally, the predictand was detrended
to avoid spurious correlation due to common trends in the data sets. This was achieved by removing the linear trend, computed by the least-square linear fit.

### 3.3.3.2. Predictor selection

Several methods and considerations to select the best predictors over the Central Andes are summarized in Hofer et al. (2017). The variables analyzed as potential predictors were: zonal ($U$) and meridional ($V$) wind, specific humidity ($q$), and omega ($W$), for 850, 700, 500, 400 and 200 hPa pressure levels. Climatic information from intermediate pressure levels were not considered since they contain largely redundant information and high correlation with variables from the selected levels, leading to potentially degenerate (or biased) coefficients in the regression model due to (multi-) collinearity between predictors (Wilks, 2011). Note that derived climate variables from the ones referenced above such as divergence and vorticity, were also considered. Relative humidity was not considered as a predictor, given its close correlation with specific humidity.

The spatial domain over which predictors were calculated was determined by taking into account the changing pattern of large-scale forcing related to QIC precipitation over the past 40 years, as discussed in section 3.3.2.2, in conjunction with the study of correlation maps between DJF seasonal Andean precipitation anomalies against each predictor variable (analysis not shown). Figure 3.6 shows this spatial domain, the large-scale forcing region (5°N - 25°S and 80°W – 60°W), encompassing the Central Andes and the western Amazon basin.

The predictor array ($X$ in equation 3.3) is defined as the array of several climate indices. Each index is given by an atmospheric variable at one specific pressure level, derived from reanalysis.
products. Its seasonality is removed to obtain anomalies using 1979-2005 as the baseline period. A spatial Hann filter is applied each time (here each DJF season) to minimize the boundary effects affecting the circulation over the predictor region (e.g., during the DJF season upper-level easterlies affecting snowfall at QIC may be neutralized by their westerly counterpart, depending on location of the BH, when calculating the zonal wind index). Afterwards a spatial average was calculated to obtain a time series index, which was standardized to allow comparison between indices.

3.3.3.3. Building the ESD model

The ESD model was built over the whole 1979-2017 study period, since one goal was to assure that the model remains applicable across periods with different large-scale forcing states, i.e., as the main forcing factors shift between past and more recent periods (section 3.3.2.2). Another aim was to develop an ESD model which is applicable across several reanalysis products (or several GCMs); hence predictors are averaged across reanalysis products (section 3.2.3) to build the model. Thereby model-intrinsic and not circulation-related variability will be removed from the reanalysis data. The final ESD model was built using the detrended DJF seasonal Andean precipitation and the array of detrended DJF seasonal climatic indices averaged across reanalysis products, as predictand and predictors, respectively, and modeled using a forward stepwise linear regression analysis, given by:

\[ P = -46.1 \times U_{500} - 68.7 \times V_{500} - 30.8 \times W_{700}, \]  

(3.4)

where the Pearson’s correlation between observed and predicted precipitation (Figure 3.8a) is \( r = 0.815 \) with a p-value<0.005; \( U_{500} \) and \( V_{500} \) are the zonal and meridional wind indices at 500 hPa, and \( W_{700} \) is the omega index at 700 hPa. The comparison between the predicted and the
observed precipitation is presented in Figure 8b. Additionally, the $P$-$U200$ linear model is plotted in Figure 8b, labeled as $P(U200)$, which results in $r=0.41$ (positive since $P(U200)$ is calculated as a negative model coefficient. Note that this $P(U200)$ model was obtained using the $U200$ index averaged over the large domain encompassing the tropical Andes and western Amazon basin as predictor (i.e., dashed area in Figure 3.6). The resulting correlation is similar when using -$U200$ defined over the QIC region only ($r=-0.45$ over region given by Figure 3.1b). Hence, the multivariate $P$ model (equation 3.4) has higher skill than the univariate $P$-$U200$ model, when considering the entire 1979-2017 period.

Note that the stepwise algorithm selection considered predictors from mid- to upper-tropospheric levels only. Hence the ESD model (equation 3.4) only incorporates variables that should be reasonably well reproduced in reanalysis and model output, unlike near-surface and lower tropospheric variables which are more strongly influenced by complex terrain and therefore not well represented in gridded reanalysis and model data (Reichert et al. 1999). The range of observed values were [-163.2; 155.2] mm, while for the simulated values using the ESD model values were [-145.6; 148.1.] mm/DJF (Figure 3.8b). Although it is well known that such linear regression-based reconstruction methods tend to underestimate the observed variance and are not well suited to reconstruct extremes, the range of $P$ values is quite consistent with the observed range of precipitation variability. Quantitatively, the three terms in equation (4), $U500$, $V500$ and $W700$ explain about 19%, 32%, and 13% of the observed variance, respectively (Figure 3.8a).
3.3.3.4. ESD model validation

The residual values (i.e., \( r = \text{observed} - \text{predicted} \), from equation 3.3) plotted in Figure 3.9a, scatter randomly around the zero mean, with a standard deviation of 43.6 mm, and a maximum absolute value in the DJF season 1998/99 (year 1999 in Figure 3.9a), which corresponds to a strong La Niña year.

Given the short-time period of available datasets, and with the goal in mind to conserve the maximum predictability on short time scales (DelSole and Tippett, 2017), the ESD model was validated using the “leave-one-DJF-season-out” cross-validation over the entire 1979-2017 period, rather than subdividing the data into independent calibration and validation periods (e.g., Hofer et al 2010). Hence, for each DJF season, an ESD\( _{n-1} \) model was generated, by omitting the data of the corresponding DJF season. In this way 38 ESD\( _{n-1} \) models were created, generating the same numbers of \( P_{n-1} \) similarly to equation (3.4). Figure 3.9b presents the root mean square error (RMSE) ratio between the RMSE\( _{n-1} \) for each \( P_{n-1} \) estimated for each year and the RMSE from the full \( P \) model including all DJF seasons (i.e., equation 3.4). As for the residuals, the ratio varies randomly, with a mean value of 1 (when RMSE\( _{n-1} = \text{RMSE} \)). Again, the largest outlier is observed in the 1998/99 DJF season. A similar random distribution is observed when comparing the Pearson’s correlation coefficient between observed and predicted precipitation with each \( P_{n-1} \) (Figure 3.9c). The horizontal black line in Figure 3.9c indicates the correlation when the full model is used. Note that for the season 1998/99 the correlation is higher, since the outlier data from this season was removed to calculate the \( P_{n-1} \) estimation. Figure 3.9d shows the number of times that each climatic index was used as a predictor to build each ESD\( _{n-1} \) model. Consistent with the full ESD model selected (equation 3.4), the \( U500, V500, W700 \) indices were always included to build
the cross-validated ESD_{n-1} models. On the other hand, q_{700} and q_{500} indices were selected only once or twice to build the ESD_{n-1}, suggesting that these indices do not contain relevant climatic information for the ESD model.

The previous analysis showed that the skill of reproducing DJF precipitation based on ESD of large-scale climate indices is high. Nonetheless, Figure 3.9 illustrates that the ESD model is somewhat sensitive to inclusion or exclusion of a few specific years. For instance, a better model skill is achieved when the DJF seasons 1993/94 (normal year), 1998/1999 (strong La Niña), 2009/10 (moderate El Niño) are removed, but the improvement is minor and appears to be independent of ENSO phase. In general, the ESD model reproduces Andean precipitation in a satisfactory way, with no major bias introduced by ENSO phase.

Physically, the predictors selected in equation (3.4), are representing well-understood mechanisms explained in section 3.1 and 3.3.2. The U_{500} index, for example, exerts a similar forcing as U_{200} in the P-U_{200} linear model, modulating the downward entrainment of easterly momentum over the Andean ridge (Falvey and Garreaud 2005; Garreaud et al. 2003), thereby regulating the upslope flow of moist air from the boundary layer. The V_{500} forcing was explained in detail in section 3.2.2 (Figure 3.7), essentially representing the strength of the moist air flux from the region of deep convection over the western Amazon. The W_{700} index represents a necessary mechanism to transfer water vapor from low- to mid-tropospheric levels, through deep convection over the western Amazon region. Interestingly the model incorporated three dynamic variables U_{500}, V_{500} and W_{700}, which are orthogonal in their planes, thereby representing the regional circulation in its 3 dimensions. It is also noteworthy that the best model relies on 3 dynamic variables, but does not
include a single thermodynamic predictor. This is consistent with the current understanding of climate variability in this region, which considers moisture transport to the high Andes, rather than moisture variations in the lowlands to the east, to be the limiting factor for precipitation in the central Andes (Garreaud, 2000).

3.4. QIC precipitation projections using CMIP5 simulations

In this section, the results of the future projections for precipitation on QIC are presented. These projections were calculated using the equations (3.4) and (3.3) in (3.2), where $R$ represents the regional projection of Andean precipitation obtained from equation (3.4) using the climatic index predictors from 16 CMIP5 models (Table 3.2) for RCP4.5 and RCP8.5 scenarios as input. The projected future changes in QIC precipitation in DJF are shown in Figure 3.10. The historical projections are consistent with the fitted reanalysis (black curve in Figure 3.10), in not showing any significative trend across 1950-2005. The future projections also do not significantly differ from present-day precipitation intensity and variability. For the RCP4.5 scenario the projections in 2071-2100 extend across the same range as during the present period (blue box plot in Figure 3.10). For the RCP8.5 scenario, projections suggest that precipitation may slightly increase by the end of the 21st century (red box plot in Figure 3.10).

3.5. Conclusions

Results show that decadal variability significantly affected the austral summer (DJF) precipitation – upper level zonal wind linear relationship over the QIC study area over the past 30 years. This relationship is usually applied to develop future precipitation projections (section 3.3.2.1) over the central Andes, assuming a stationary relationship. An alternative solution was presented here,
including additional, statistically significant, atmospheric parameters, resulting in an ESD model, which is more robust and less affected by non-stationarities introduced by Pacific decadal variability.

The 1979-2017 period saw a decadal-scale change in the relationship between QIC precipitation and the large-scale atmospheric circulation, rendering the establishment of an ESD model with high skill more difficult. The source of this decadal-scale climate variability likely lies in the tropical Pacific and is associated with multi-decadal SST variability (Figure 3.5), consistent with the PDO influence on Andean temperature as documented in Vuille et al. (2015), and on Bolivian precipitation as shown in Seiler et al. (2013).

The ESD model was used to generate regional Andean precipitation (equations 3.4 and 3.3) with predictors from CMIP5 simulations. The linear relationship between DJF regional Andean precipitation and QIC snowfall (equation 3.2) was applied to obtain projections of future QIC precipitation (Figure 3.10). In contrast to previous GCM- (e.g., Minvielle and Garreaud, 2011) and RCM- (e.g., Urrutia and Vuille, 2009) based approaches, which resulted in future precipitation projections with significant uncertainties, the ESD model presented here, has high skill in reproducing observed Central Andean precipitation, both in terms of amplitude and temporal variability (Figure 3.10). Our reconstructions and projections show no significant changes over time, neither in historical nor in future precipitation. The lack of a trend in the historical simulations is supported by observational evidence, at least over the past 5 decades. Seiler et al. (2013), for example, analyzed precipitation data from 68 weather stations distributed across Bolivia, to the south of QIC, and found no trends over the 1960-2010 period. Similarly, Heidinger et al. (2018),
using 47 precipitation time series from weather stations across the central and southern Peruvian Andes, i.e., located to the west and southwest of QIC, over the 1965-2010 period, found no significant trends in the regional mean and extreme precipitation. Finally, Casimiro et al. (2013) analyzing precipitation data over the Central and western Amazon, also did not detect a significant trend over the past several decades. Our results suggest that interannual variability will continue to dominate over a long-term precipitation trend on QIC going forward as well.

Increasing the confidence in our model is the fact that each variable included in the ESD model represents a physical mechanism related to the large-scale atmospheric forcing, known to affect Central Andean precipitation. Since our model projects no major changes in DJF QIC precipitation, the precipitation phase will instead become an increasingly important factor to assess. Future projections of air temperature, FLH (e.g. Schauwecker et al., 2017; Vuille et al., 2018) and hence the elevation at which snow transitions to rain (e.g., L'hôte et al., 2005) will become increasingly important, and need to be quantified to complement this study.

3.6. Acknowledgments

This study was produced under the umbrella of the Andean Climate Change Interamerican Observatory Network (ACCI0N, grant SLMAQM-11-GR-086), funded by the Bureau of Western Hemisphere Affairs of the United States Department of State. We acknowledge the World Climate Research Programme's Working Group on Coupled Modeling, which is responsible for CMIP, and we thank the climate modeling groups (listed in Table 3.2) for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software
infrastructure in partnership with the Global Organization for Earth System Science Portals.

3.7. APPENDIX A: Snow density measurements at Quelccaya Ice Cap

Six measuring campaigns of snow density on QIC summit were performed between 2005 and 2014, during the months of June to October. The lowest snow density was recorded in April 2012 with a value of 180 Kg m$^{-3}$. The highest snow density was measured in October 2014 with a value of 290 Kg m$^{-3}$. The mean snow density is $236.17 \pm 40.3$ kg m$^{-3}$. This value was divided by the density of water at 0 ºC, which is 999.84 kg m$^{-3}$, to obtain $23.6\pm4.05$% snow density percent. Since those measurements were obtained during the Central Andes dry season, when more of the accumulated snow comes from the previous austral wet summer season, the gauged snow density values could be underestimated, since the snow density is known to be higher during austral summer when the snow melts as it is falling due to the warm conditions in this season. To clarify how much significative is this underestimation and if the mean snow density at QIC is representative in a regional scale, this mean value is contrasted with other measurements performed on neighboring glacier locations.

Snow density measurements in the outer tropical locations of Chacaltaya and Zongo glaciers, in the Cordillera Real of Bolivia at 16ºS, are consistent with the values calculated here for QIC summit. Chacaltaya glacier, with a summit elevation at 5360 masl in the year 2000, was a glacier which by now has disappeared, but where snowfall occurred during the warm austral summer at temperatures near 0ºC (Francou et al., 2003). These warm conditions resulted in heavy, wet snow with a density close to 400 kg m$^{-3}$, with low variability. On Zongo glacier the measured snow
density was 250 ±50 kg m$^3$ (Sicart et al., 2002), obtained during a 2-year period with air temperature above -3°C during snowfall.

In summary the mean snow density at QIC is within the range of expected density values for the region, although more in-situ records are needed to further improve this estimate.
3.8. Tables

**Table 3.1.** In-situ weather stations (rows 1-9) used to calculate regional Andean precipitation between the 1st January 1979 and 28th February 2017, and AWS at QIC summit (row 10).

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Table 3.2. List of the 16 CMIP5 models used.

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3.9. Figures

Figure 3.1. (a) South American topography from ETOPO2. (b) as in a) but for the regional study area (11.5°S to 15.5°S and 72.5°W to 68.5°W) indicated by black square in (a). Location of an automated weather station (AWS) on QIC summit (13.93S, 70.82W) is indicated by a red dot; 9 Andean stations are shown by blue dots. (c) Landsat 8 composite (bands 742) of QIC on 15th August 2016 with AWS location indicated by red dot. (d) Picture of the AWS on 10th July 2012.
Figure 3.2. (a) Monthly mean (calculated) precipitation derived from snow height data recorded by AWS at QIC summit (red dots), and monthly mean precipitation across 9 Andean stations (blue boxes); both plots were calculated over 2004-2017 period. Horizontal line in box represents the median precipitation averaged over the 9 Andean stations. The bottom and top box edges are indicating the 25th and 75th percentiles, and the whiskers extend to the maximum and minimum values. (b) Scatterplot of DJF precipitation anomalies (z-scores) averaged across 9 Andean stations versus precipitation anomalies at QIC summit over the 2004-2017 period. Numbers indicate year of corresponding DJF wet season.
Figure 3.3. (a) Running mean Pearson’s correlation (gray dots) using 11-yr window, calculated using DJF regional precipitation anomalies (P, average of 9 weather stations around QIC) and DJF 200 hPa zonal wind anomalies (U200) aloft QIC from ERA interim reanalysis. Period of analysis is 1979-2017. Solid line indicates correlation over the entire study period ($r = -0.45$). Anomalies are calculated with respect to the baseline period 1979-2005. Note that the scale of the y-axis is reversed. (b) Wavelet coherence spectrum based on the same data as in (a). The Morlet wavelet was used in this analysis and only arrows with a squared coherence $>0.7$ were plotted.
Figure 3.4. Regression maps of DJF 200 hPa zonal (u) and meridional (v) wind and geopotential height (GPH) versus Andean precipitation (Prec.) for (a) 1979-2017, (b) 1979-1998, and (c) 1998-2017. (d), (e) and (f) as in (a), (b), and (c), respectively, but at 500 hPa. Wind field is only plotted where the correlation between either zonal or meridional wind component and Prec. is higher than 0.3 and it is significant at p-value<0.05. Scale for wind vector in m/s per std. dev., and the GPH contour range in m per std. dev. is indicated below (f) and are the same for all graphs. Positive, zero and negative GPH values are represented by black, bold, and dashed contours, respectively. Red dot indicates location of QIC summit.
Figure 3.5. Correlation map between DJF Andean Precipitation (P) and sea surface temperature (SST) from NOAA ERSST V5 over (a) 1979-2017, (b) 1979-1998, and (c) 1998-2017 periods. Correlations >0.2 and <−0.2 indicated color shading. Bold line indicates 0-contour. Positive and negative values are shown by continuous and dashed contours, respectively. Continental areas are shown in gray and elevation contour in black from 0 to 5 km by a step of 1 km, as indicated at bottom of (f). Red dot represents location of QIC summit.
Figure 3.6. (a) DJF 200 hPa geopotential height (GPH), zonal (u) and meridional (v) wind differences (1998-2017) – (1979-1998) in ERA-interim reanalysis. Contour interval is 5 m, colorbar (in m/s) indicates wind speed and reference wind vector is shown below the graph. (b) as in (a), but for DJF precipitation from GPCP product, with contours plotted every 20 mm, color bar in mm, and thick line indicates 0-contour. In both Figures, the black dashed rectangle delimits the area 5°N-25°S and 80°W-60°W, defining the large-scale forcing region influencing climate variability in the Central Andes and used to calculate climatic indices (or ESD predictors, section 3.3.2).
Figure 3.7. DJF meridional cross-section (as in Figure 10 from Vizy and Cook (2007)), averaged between longitudes 72.5°W and 70°W. The profiles contain the vertical component of the moisture flux “$wq$” (g Kg$^{-1}$ m s$^{-1}$), where $q$ (g Kg$^{-1}$) as the specific humidity, and the vector field using the meridional wind component $v$ (m s$^{-1}$) and scaled vertical velocity $w$ (100 m s$^{-1}$) vectors for (a) 1979-1998, and (b) 1998-2017 periods. (c) shows the difference, (b) minus (a). Atmospheric variables were obtained from 2.5° ERA-interim products. Shaded values represent the $wq$ field. Vertical velocity was calculated transforming omega (Pa s$^{-1}$) with temperature and pressure fields. Location of AWS at QIC summit is shown by a red dot in each graph. Topography (black shaded area) from ERA-interim geopotential invariant field was added in each plot.
Figure 3.8. Comparison between observed and predicted precipitation. (a) Scatterplot (circles) and linear regression (black line) between predicted and observed DJF precipitation (in mm, equation 3.4). (b) Observed (blue line) and predicted ($P(U500, V500, W700)$, red line) DJF precipitation (in mm) between 1979 and 2017. The “Year” axis label indicates the DJF season, with the year label referring to the JF portion of the season. Additionally, the $P-U200$ linear model ($P(U200)$) is plotted as a black dotted line.
Figure 3.9. ESD Model cross-validation over the 1979-2017 period. (a) The residual (difference between observed and predicted DJF precipitation (in mm)). The x-axis ‘Year’ label is the same as in Figure 3.8b. Dashed lines represent the ±2 standard deviation of the residual. (b) the RMSE$_{\text{r-1}}$/RMSE ratio, where the RMSE =44.2 mm. (c) similar as (b), except for Pearson’s correlation coefficient (r), with gray line (r=0.82) indicating correlation coefficient of the full ESD model. (d) Histogram indicating the frequency of occurrence of each atmospheric index in the ESD$_{\text{r-1}}$ models. Only variables used at least once are plotted.
Figure 3.10. CMIP5 projections of DJF QIC precipitation anomalies. The ERA-interim reanalysis (1979-2017) fitted with observed data is shown in black; the historical CMIP5 simulations (1950-2005) are shown in gray, and the future CMIP5 projections are shown in blue (RCP4.5) and red (RCP8.5) for the period 2006-2100. Bold lines for CMIP simulations represent the mean of 16 models (Table 3.2). Shading represents the 95% confidence interval. The box plots indicate precipitation averaged over all 16 simulations over the period 2071-2100, with the horizontal line indicating the median, the bottom and top edges of the boxes indicating the 25th and 75th percentiles, respectively; and the whiskers extend to the maximum and minimum values. Anomalies are calculated with respect to the 1979-2005 baseline. The x-axis ‘Year’ label refers to the DJF season as in Figure 3.8b.
3.10. References


Chapter 4

HOW IMMINENT IS THE THREAT OF DISAPPEARANCE OF THE WORLD’S
LARGEST TROPICAL ICE CAP?

Christian Yarleque, Mathias Vuille, Oliver Elison Timm, Douglas R. Hardy, Jorge De la Cruz

and Hugo Ramos
Abstract

Populations living at high elevations in the tropical Andes depend on glacial meltwater for variety of socio-economic activities. Thus, quantifying cryospheric changes in the tropical Andes is a vital need for implementing adequate mitigation polices. Here we analyze the future state of Quelccaya Ice Cap (QIC), the largest tropical ice body as a representative case for many low-elevation glacierized sites in the tropical Andes. Future changes in air temperature (Ta), freezing level height (FLH) and equilibrium line altitude (ELA) at QIC summit were calculated using observations, reanalysis, and CMIP5 simulations for historical and future scenarios (RCP4.5 and RCP8.5). Our analysis corroborates that the elevation-dependent warming (EDW) effect is related to anthropogenic forcing over the Andes region, and will generate an additional rate of warming over the QIC system. Future projections of Ta at QIC indicate a warming of about 2.4°C and 5.4°C at 2100, for RCP4.5 and RCP8.5 scenarios, respectively, resulting in a much higher FLH by the end of the century. The direct impact of this warming on the QIC system was quantified using ELA projections for both RCP scenarios. The change in the ELA was calculated based on an empirical ELA – FLH relationship, calibrated with modern observations of the dry season snow line altitude (SLA) derived from Landsat data. Our result show that starting around the mid 2050s, the ELA will be located above the QIC summit in the RCP8.5 scenario. At that time, QIC and most tropical glaciers at similar elevations in the Cordillera Vilcanota, should be characterized by a continued negative specific mass balance even at their highest locations, leading to their eventual complete disappearance. Finally, here we show that the elevation–dependent warming (EDW) will amplify the anthropogenic warming at higher elevations, leading to a more rapid impact on glacier mass balance than would be expected otherwise.
4.1. Introduction

About 99% of the world’s tropical glaciers are located over the Andes, with Peru alone containing about 70% of them (Kaser, 1999; Vuille et al., 2008a; Rabatel et al., 2013). Quelccaya ice cap (QIC), located in the Cordillera Vilcanota in southern Peru (13°56’S, 70°50’W, Figure 4.1), with a median area of about 50.2 km$^2$ over the 1975-2010 period, and an approximate summit elevation of 5680 meters above sea level (masl) (Bradley et al., 2009; Thompson et al., 2006; Thompson et al., 2013; Hanshaw & Bookhagen, 2014), is the largest tropical ice cap (Buffen et al., 2009; Thompson et al., 2006; Thompson et al., 2013), and representative of many tropical glaciers in the Andes with a relatively low summit elevation. A more thorough understanding of future glacier retreat rates in the tropical Andes is critical, given their prominent role in dry season water supply, ecosystem services, and impacts on tourism, natural hazards and cultural values and belief systems of local populations (e.g., see review in Vuille et al., 2018).

The extent of the QIC has been affected by the increase in Andean surface temperature (Bradley et al., 2009; Vuille et al., 2015), but potentially also by variations in precipitation (Rabatel et al., 2013; Salzmann et al., 2013). The El Niño - Southern Oscillation (ENSO) (e.g., Thompson et al., 2013), the South American Summer Monsoon (SASM) (e.g., Vuille and Werner, 2005), and cold air incursions from the extratropics (Hurley et al., 2015) also affect the conditions on QIC on interannual time scales. However, no continuous mass balance measurements exist on QIC; hence the relationship between the reduction in surface area and loss of glacier mass is not known.

Air temperature has been increasing over the Peruvian Andes over the last six decades (Bradley et al., 2009; Casimiro et al., 2013; Salzmann et al., 2013), in agreement with the regional increase of
temperature over the entire tropical and sub-tropical Andes (Rabatel et al., 2013). As shown by Vuille et al. (2015), the increasing temperature trend is a combined effect of natural multi-decadal variability (i.e., the Pacific Decadal Oscillation) and anthropogenic radiative forcing. Due to this warming, QIC is retreating at an accelerated pace, as shown by Hanshaw and Bookhagen (2014), who documented a shrinking of the QIC area at a rate of 0.57±0.09 km\(^2\) yr\(^{-1}\) over the 1975-2010 period. This retreat is consistent with the reduction in glacierized surface area observed throughout the tropical Andes, including in the Cordillera Blanca and the Cordillera Ampato (Rabatel et al., 2013; Vuille et al., 2008a), located to the north and south of the Cordillera Vilcanota, where QIC is located, respectively.

Model projections of twenty-first century climate change indicate a substantial future temperature increase across the central Andes ranging anywhere between 3 and 5°C depending on region, model and emission scenario (Bradley et al., 2006; Urrutia & Vuille, 2009; Seth et al., 2010). It is important to note that the rate of warming tends to be further amplified with elevation in many mountain regions due to elevation-dependent feedbacks (e.g., Rangwala & Miller, 2012; Pepin et al., 2015). Given that coarse global models do not adequately resolve the Andean topography, this effect is likely underestimated in surface temperature estimates from global models (Russell et al., 2017), but likely less so when considering the free tropospheric temperature trends (Bradley et al., 2006). This elevation-dependent warming has been documented over the tropical Andes, both in modern observations and future model scenarios (Vuille & Bradley, 2000; Urrutia & Vuille, 2009; Vuille et al., 2015).
A fairly simple diagnostic that can be calculated from reanalysis and model data, and is more relevant for glacier mass balance than surface temperature, is the freezing level height (FLH). The increase of the FLH in the Central Andes negatively affects the mass balance of glaciers by changing the rain/snow ratio and increasingly exposing lower reaches of glaciers to rain as opposed to snow (Rabatel et al., 2013). Hence a rise in the FLH does not only indirectly affect mass balance through higher temperatures, leading to more melt, but also impacts accumulation and ice albedo (Francou et al., 2004). Rabatel et al. (2013) documented that the FLH increased by approximately 160 m over the last five and a half decades over the Cordillera Blanca and Cordillera Real, located to the north and south of QIC, respectively. Schauwecker et al. (2017) showed that the mean annual FLH in the Cordillera Vilcanota was 5010 masl over the 1980-2015 period, consistent with results in Rabatel et al. (2013), with a higher FLH during the warmer wet season and a lower FLH during the slightly colder dry season, respectively. Bradley et al. (2009) have shown that historically the increase of the FLH in the tropics can be empirically described as a linear response to the increase of tropical sea surface temperature (SST). Moreover, Diaz et al. (2003) have shown that the FLH over this region is dependent on the phase of ENSO and responds to both interannual and decadal-scale changes in tropical Pacific SST.

While both anthropogenic and natural forcings may affect mass balance variability on QIC on interannual timescales (e.g., Thompson et al., 2006; Vuille et al., 2015), the accelerated rate of retreat observed over the last decades (Hanshaw & Bookhagen, 2014), is consistent with the gradual disappearance of lower lying Andean glaciers as is being observed for example in Bolivia, Colombia and Venezuela (Ramirez et al., 2001; Braun & Bezada, 2013; Rabatel et al., 2017). Modeling studies suggest continued future shrinkage of tropical Andean glaciers, with some
completely disappearing by the end of the 21st century (Schauwecker et al., 2017; Vuille et al., 2018), thereby significantly reducing dry season runoff (e.g. Juen et al., 2007; Kaser et al., 2010; Baraer et al., 2012).

Here we assess the rate of change of surface air temperature and FLH over QIC, using CMIP5 projections based on two different emission scenarios. In contrast to variables related to the hydrologic cycle (e.g., precipitation), free-air temperature is quite accurately simulated by GCMs, and very well represented by reanalysis (e.g. Hofer et al., 2012). Surface temperature is also well reproduced by most GCMs, although there is a substantial warm bias over the Andes due to the reduced topography in the models. Here we rely on in-situ air temperature data recorded by an automated weather station (AWS) at the summit of QIC (Bradley et al., 2009; Hurley et al., 2015) to remove the temperature bias from both reanalysis and GCM output, allowing for an accurate future projection of changes in FLH. We further take advantage of the documented close empirical relationship between FLH and the glacier Equilibrium Line Altitude (ELA) on tropical Andean glaciers (Vuille et al., 2018) to project the future rise of the ELA on QIC under various emission scenarios. Although no in-situ ELA measurements exist on QIC, the ELA can be constrained by determining the snowline at the end of the dry season using satellite data (Rabatel et al., 2012). Hence the aim of this study is to determine how imminent the threat of a future disappearance of the QIC really is and to what extent the timing depends on the choice of emission scenario. We also consider the influence of EDW on the rate of the ELA rise, by comparing CMIP5 simulations with an empirical model that relates tropical SST to FLH assuming a constant lapse rate (Bradley et al., 2009).
4.2. Data and methods

4.2.1. Observational data

Daily mean non-aspirated temperature and snow height between 21-07-2004 and 22-07-2017 from an AWS installed at QIC summit (5680 m, 13.93ºS, 70.82W) was used to bias-correct air temperature from reanalysis and CMIP5 models, and in the process of Landsat image dates selection. As reference, the mean annual air temperature (Ta) at QIC from this dataset is about -3.99ºC over 2005-2016. Additionally, daily rainfall data from Ccatcca station (with coordinates 13.61ºS, 71.5603ºW, and 3693 masl) maintained by the Peruvian National Meteorological and Hydrological Service (Servicio Nacional de Meteorología e Hidrología del Perú, SENAMHI), being the closest station to QIC, over the period 1979-2016, were used to inform the Landsat image dates selection process (section 4.2.3). In addition, monthly mean SST data from the NOAA Extended Reconstructed Sea Surface Temperature v5 (ERSST) dataset (Smith et al., 2014) were extracted over the tropical belt (28.5ºS-28.5ºN) from 1950 to 2017. Anomalies were calculated using 1979-2005 as the reference period and then spatially averaged to obtain a tropical SSTA time series.

4.2.2. Ta and FLH calculation from reanalysis products

Several studies have shown that mid- and upper-tropospheric temperatures are fairly accurately reproduced by GCMs and reanalysis products over the central Andes (Hofer et al., 2012; Bradley et al., 2009; Russell et al., 2017). In the present study, we relied on ERA-interim reanalysis (Berrisford et al., 2011) since this dataset has higher skill in reproducing observed temperature variability over the central Andes region compared with other reanalyses (e.g., Hofer et al., 2012). Monthly Ta at the elevation of QIC (5680 masl) in the reanalysis data was calculated by
interpolating the Ta and geopotential height (Zg) from 400 and 500 hPa pressure levels, which are the nearest standard pressure levels below and above the QIC summit respectively. The reanalysis used were the monthly ERA-interim products, covering the 1979 to 2017 period, resampled to a 2.5º grid resolution to mimic the spatial scale of the majority of CMIP5 models. A bias correction was applied to the reanalysis Ta using as reference the observed data from AWS at QIC summit. Similarly, the FLH at QIC was calculated as the elevation of the 0ºC isotherm using a linear interpolation of ERA-interim Zg and (bias-corrected) Ta between 500 and 600 hPa. The same approach was applied to Ta and FLH from CMIP5 simulations to remove temperature biases from the simulations and to calculate historical and future FLH as simulated by the models.

As shown by Bradley et al. (2009) the FLH in the tropics can be estimated using an empirical linear relationship with tropical SST. Here, we followed this approach by comparing the QIC FLH derived from ERA-interim with ERSST data over the tropics for the period 1979-2017. This linear SST-FLH model was then applied to tropical SST simulated with CMIP5 models from both historic runs and future projections. Comparing FLH simulated directly by the CMIP5 models (henceforth labeled FLH$_{atm}$) with FLH estimated from a linear empirical dependency with SST (henceforth labeled FLH$_{SST}$) allows assessing the degree of EDW, since the lapse rate is allowed to adjust in the coupled CMIP simulations used to determine FLH$_{atm}$, but held fixed at observed present-day values in the latter empirical approach of calculating FLH$_{SST}$.

**4.2.3. Snowline altitude calculated using satellite data**

Since no mass balance measurements exist from QIC, we applied an indirect method to determine the ELA, following a procedure developed by Rabatel et al. (2012). This method is based on the
linear relationship that exists on glaciers in the outer tropics between the annual ELA and the highest snow line altitude (SLA) reached at the end of the dry season of the same hydrological year. Here, the annual SLA was determined using data from Landsat-6, -7 and -8 between 1992 and 2017, selecting one image (or date) per year (Table 4.1). The selection criteria for the Landsat data consist of choosing the date with the highest SLA across the hydrological year, and avoid dates with recent snowfall and rainfall events. As indicated in Table 1 the chosen Landsat images date to the end of the dry season and early wet season, i.e. from June to October. Images that postdate recent snowfall on QIC were flagged based on the daily snow height time series from the AWS at QIC, and daily rainfall data from Ccatcca station. Additionally, the ALOS PALSAR digital elevation model (DEM) with sensor FBS, path 101, 12.5 m² cell size, WGS 1984 UTM zone 19S projection, from 26. Oct. 2007 (ASF DAAC, 2005) was used to determine the elevation of the SLA pixels in the Landsat data, since its spatial resolution is superior to conventional products, and it includes terrain, radiometric and ortho-rectification corrections.

We followed the procedure described in Rabatel et al. (2012) to obtain the SLA, which first required displaying the Landsat data as RGB images using Shortwave Infrared 1 (SWIR), Near Infrared (NIR) and Green bands. A threshold was set to detect snow areas in NIR and Green bands (e.g. see Figure 4f in Rabatel et al., 2012) since lighting conditions vary through dates (e.g., Figure 4.2a and 4.2b). For the images listed in Table 4.1, thresholds between 80 and 180 were used in the histogram from NIR and Green bands. Finally, the perimeter of the snow-covered area above the SLA was hand-digitized and projected on the DEM to extract the corresponding elevation values of the SLA. A mean SLA was calculated for each date by averaging the elevation corresponding to all SLA pixels.
It is worth noting that the determination of the snowline altitude is threshold-selection sensitive. Determining this threshold is complicated by the fact that the ice edges or boundaries can change abruptly over complex terrain, affecting the rate of non-ice and ice regions. Measurement errors can also be produced by the debris located on the lower slopes of the ice cap. Moreover, the western side of the QIC has a higher sensitivity (and hence a lower uncertainty) in SLA detection than the eastern side since the western slope extends over flatter terrain covering a larger surface area per unit elevation change. In general, however, these errors introduced by complex topography, insolation or debris-covered ice are reduced when the SLA is measured at the end of the dry season, as the SLA reaches its highest location at that time of year, where the terrain is more symmetric and uniformly sloped on both sides (see vertical profiles in Thompson et al. (1982) and Thompson et al. (1985), and surface area measurements in Hanshaw & Bookhagen (2014)). Errors in hand-digitized SLA at QIC are comparable with those obtained through automated techniques (e.g., Hanshaw & Bookhagen, 2014), although some studies use hand-digitized SLA as a reference or true value, due to the scarcity of in situ data (e.g., Albert, 2012). Studies determining QIC surface area estimated the hand-digitized values to be 99.8% accurate (Albert, 2002), while Hanshaw & Bookhagen (2014), using an automated technique, estimated the uncertainty in their areal measurements to be 5%. For the current study, the mean SLA is obtained as the mean elevation of all cells corresponding to SLA pixels, along the entire ice cap perimeter (yellow perimeter in Figure 4.2a and 4.2b), which corresponds to approximately 800 to 1200 cells, depending on the year. The resulting mean SLA per year (or available date selected to obtain the approximated highest SLA each year) is plotted in Figure 4.2c. The 95% confidence interval ($±1.96 \sigma$) for the calculated mean SLA ranges between 4.4 and 8.7 m. It is worth noting that the SLA distribution
per date selected has an approximately Gaussian distribution, and the 95% confidence intervals calculated with t-distribution presented values similar to the ones calculated using bootstrap analysis. The non-zero trend presented in Figure 4.2c is statistically significant (F-test, p-value<0.001), regardless of whether the three outlier years associated with strong El Niño years (1998, 2010, 2016) are included or not.

4.2.4. Derivation of the ELA-FLH relationship

The SLA determined in the previous step can be considered a reasonable proxy for the ELA in each year, as outlined in Rabatel et al. (2012). To project the future change in the ELA on QIC over the course of the 21st century, we take advantage of the close linear relationship between ELA and FLH on tropical Andean glaciers as demonstrated by Vuille et al. (2018). We first establish the local slope of this relationship over QIC using bias-corrected reanalysis data (see section 4.2.2) over the period of overlap with satellite data. The FLH is calculated as the average of the hydrologic year, which runs from Sep. to Aug. Finally, projected future changes in the ELA were calculated by applying the present day FLH-ELA relationship to future FLH simulated by bias-corrected CMIP5 models, as outlined in section (4.2.2).

4.2.5. GCM simulation data

16 CMIP5 models for historical (1950-2005), RCP4.5 and RCP8.5 (2006-2100) scenarios (Taylor et al., 2012) were selected for our analysis (Table 4.2). The three variables of interest include air temperature (Ta), geopotential height (Zg), and skin or sea surface temperature (SST). From those variables we calculated the FLH\textsubscript{atm} and FLH\textsubscript{oce} and their corresponding ELA\textsubscript{atm} and ELA\textsubscript{oce}
projections in the same way as described for the reanalysis products (section 4.2.2 and 4.2.4 respectively), using the model or reanalysis grid cell encompassing QIC.

4.3. Results and Discussions

4.3.1. Future projections of air temperature and FLH over QIC

Figure 4.3 shows the annual Ta at QIC from 2.5º ERA-interim reanalysis and CMIP5 simulations calculated as indicated in section (4.2.2). The Pearson’s correlation coefficient between the annual mean Ta from ERA-interim and the AWS time series over the 2005-2016 period was 0.78, indicating that the reanalysis has a high skill in reproducing the annual Ta variability at QIC. As reference, the mean annual ELA ERA-interim Ta is about -4.4 ºC over the baseline 1979-2005. In the same Figure, the ensemble of 16 CMIP5 historical simulations (Table 4.2) and the reanalysis data present a common Ta warming rate of 0.14 ºC/decade over the periods 1950-2005 and 1979-2016, respectively. It is worth noting that the CMIP5 interannual variability is substantially muted due to the cancellation of internal variability once multiple models are averaged to obtain the mean (hereafter labeled as ensemble). Future ensemble projections of Ta using RCP4.5 and RCP8.5 emission scenarios indicate substantial warming over the 2006-2100 period of about 0.25 ºC/decade and 0.57 ºC/decade, respectively. Those future scenarios suggest that the mean Ta at QIC summit will increase by approximately 2.4ºC and 5.4ºC, respectively, by the end of the 21st century. This is consistent with results from previous studies over the tropical Andes using the older SRES scenario A2 (e.g. Bradley et al., 2006; Urrutia & Vuille, 2009). Maybe more relevant in this context is the fact that under the RCP8.5 scenario Ta at QIC summit will surpass 0ºC by ~2060, while under the RCP4.5 scenario Ta will start to stabilize around -2ºC by ~2070.
4.3.2. Calculation of the equilibrium line altitude (ELA) at QIC using satellite data

The SLA was determined as described in section 4.2.3. Its standard deviation (σ) calculated along the SLA perimeter every year, varied between 64 and 103 m across the 1992-2017 period, with largest spread in 1994 and lowest variance in 2010 (strong El Niño), respectively. The 95% confidence interval (CI) of the annual mean SLA uncertainty over the 1992-2017 period ranges between 25 and 40 m. Hence, following the analysis done by Rabatel et al. (2012), we consider that ELA≈SLA within the 95% confidence interval. Note that the dates used to calculate the SLA (Table 4.1) are concentrated between June to October, i.e., toward the end of the hydrological dry season on QIC. The calculated (annual) ELA is defined over the hydrologic year starting in September of the previous year and ending in the current August. Thus, the label year indicated in the x-axis in Figure 4.2c corresponds to the August’s years.

The annual ELA obtained as indicated above was then compared with its corresponding FLH, which was calculated for the same hydrological year for the 1992-2017 period. Figure 4.4 presents the ELA – FLH comparison obtained from satellite images and ERA-interim reanalysis (section 4.2.2), respectively. The FLH is characterized by a statistically significant linear association with the ELA, consistent with the results presented in Vuille et al. (2018), for several other glaciers in the inner and outer tropical Andes. The linear ELA – FLH relationship at QIC is quantified as:

\[ \text{ELA} \approx 0.56 \times \text{FLH} + 2610.1 \text{ m}, \]  

(4.1)

with \( r=0.82 \) and p-value<0.001, over the 1991-2017 period. This model was subsequently used to generate ELA projections using as input the FLH_{atm} and FLH_{sst} at QIC generated from CMIP5 historical and future scenarios.
4.3.3. Future ELA projections at QIC

Figure 4.5 presents observational (previously derived using SLA), historical and future annual ELA projections for QIC. The mean ELA from observations was 5435.7 m over the 1992-2017 period, and the mean ELA value from ERA-interim over the baseline 1979-2005 was 5416.5 m (data not shown). The increase in the ELA is 16.3 m, 13.6 m, 24.5 m and 58.4 m/decade, for reanalysis (1980-2017), historical (1950-2005), RCP4.5 and RCP8.5 (2006-2100), respectively. The dashed line in Figure 4.5 indicates the current QIC summit elevation (5680 m). Based on the multi-model mean estimate the ELA will remain below the QIC summit until the end of the 21st century in the RCP4.5 scenario, although some CMIP5 models are projecting a future ELA that is higher than the QIC summit.

For the RCP8.5 scenario the changes at QIC are going to be more impactful and occur much earlier than in the case of the RCP4.5 scenario. By the middle of the century the ensemble mean ELA is projected to reach the QIC summit, turning all of QIC into an ablation zone. A very important point is that the QIC summit at 5680 m will of course be continuously lowered once the ice cap starts to thin out more and more from its current thickness of approximately 150 m (Thompson et al., 1982; Thompson et al., 1985). Hence it will be exposed to higher temperatures at lower elevation (elevation feedback), as well as increasingly to edge effects and warm air advection from surrounding exposed bare rock areas as the ice cap shrinks in size (albedo feedback). These feedbacks are not accounted for in our analysis, suggesting that our results are likely err on the conservative side and that the ELA may in fact reach the QIC summit earlier than projected in our analysis.
Finally, the RCP8.5 Ta projections at QIC suggest that at the end of the 21st century temperature will have increased by about 5.4ºC (section 4.3.1). This implies that the ensemble mean Ta at the summit will be near +1ºC. Precipitation events at this temperature threshold will be divided in snow, rain and mixed precipitation in similar proportion (L’Hote et al., 2005). How long it will actually take for QIC to completely disappear is a different question and beyond the scope of this study, but it is evident that runoff from QIC during the dry season will eventually decrease significantly, although the enhanced melt water contribution from the receding ice cap may for a period of time contribute to enhanced runoff, following the peak water concept (Baraer et al., 2012).

4.3.4. On the relationship between FLH at QIC and tropical SST

The regional increase of temperature detected from observation and reanalysis over QIC (section 4.3.1) is consistent with the regional FLH increase reported in previous studies (e.g., Figure 3 in Bradley et al., 2009). On the other hand, a linear relationship between tropical SST and Andean climate was documented in several studies (Maussion et al., 2015; Thompson et al., 2013; Garreaud, 2009; Vuille et al., 2008b; Francou et al., 2003; Francou et al., 2004; Bradley et al., 2009). However, trends in tropical FLH have varied regionally over the past decades (e.g., Figure 2 in Bradley et al., 2009), as well as for the mean FLH (e.g., Figure 3 in Schauwecker et al., 2017). Here we calculate the FLH at QIC using reanalysis products, and linearly related it with tropical SST following the comparison in Bradley et al. (2009), to compare future FLH changes under such a fixed lapse-rate scenario with the FLH changes simulated by coupled ocean-atmosphere CMIP5 models.
The hydrologic year FLH at QIC was calculated from ERA-interim reanalysis products (section 4.2.2), and compared with tropical SST (spatially averaged from 28.75°N to 28.75°S, section 4.2.1). The resulting linear relationship between annual anomalies of FLH (FLHA) at QIC and tropical SSTA (ºC) (Figure 4.6) over the 1980-2017 period (38 hydrologic years), is expressed as:

\[ \text{FLHA}_{\text{SST}} = 286.4 \times \text{SSTA} + 1.4 \text{ m}, \]  

(4.2)

with, \(r=0.84\) and \(p\)-value<0.001. Note that FLH\textsubscript{SST} is obtained adding its seasonal component over the 1980-2017 period. This statistical relationship quantifies how tropical SST forces the atmospheric temperature at QIC under present conditions. How increasing tropical SST can affect the FLH (and in consequence the ELA) at QIC is not completely clear, nor do we know how this relationship will change in the future. The increase in tropical convection due to higher SST, however, will likely result in a transfer of latent heat to higher levels in the tropics as enhanced condensation will lead to stronger release of latent heat, thereby warming the upper troposphere. In addition, the increase in water vapor in the atmosphere will lead to a stronger warming at higher altitudes, where temperature is colder and the initial water vapor concentration is lower (e.g., Rangwala & Miller., 2012). Hence to a first approximation, the increase of upper-tropospheric temperature due to enhanced longwave downwelling radiation is likely a significant driver of the FLH increase, but several other feedbacks affecting elevated regions like QIC, such as clouds, albedo, and aerosols (Pepin et al., 2015; Rangwala & Miller, 2012) may also play a role.

### 4.3.5. Elevation-dependent warming (EDW) quantification at QIC

To verify and quantify how much the EDW (following the Pepin et al. (2015) nomenclature) will affect QIC going forward, we present a comparison between the ELA\textsubscript{SST} and ELA\textsubscript{atm} at QIC, both calculated based on equation (4.1), but using as input the FLH\textsubscript{SST} from equation (4.2), and FLH\textsubscript{atm}
derived by interpolating Ta and Zg, respectively, for 16 CMIP5 model simulations (Table 4.2). The ERSST and ERA-interim reanalysis products were used as a control case.

In Figure 4.7, the control case results (black dots) are consistent with the Historical comparison between the ELA_{SST} and ELA_{atm} ensembles from 16 CMIP5 historical simulations (gray dots). Future projections of ELA_{atm} ensembles, based on 16 CMIP5 RCP4.5 (blue dots) and RCP8.5 (red dots) simulations, however, are not following the expected ELA increase inferred from the ELA_{sst} model. For instance, in the RCP4.5 scenario, the increase of the ELA_{SST} ensemble is about 22.8 m/decade, slightly less than the ensemble ELA_{atm} increase of 24.5 m/decade. In the case of the scenario RCP8.5, this difference in ELA trends is larger, with 52.9 m/decade and 58.4 m/decade for ELA_{SST} and ELA_{atm}, respectively. This implies that CMIP5 simulations with 4.5 W/m² radiative forcing at the end of the 21st century generate an additional rise of the ensemble mean ELA at QIC of about 1.72 m/decade when compared to the tropical SST forcing, while the 8.5 W/m² radiative forcing generates an additional ELA rise of about 5.5 m/decade. This additional ELA rise can be understood as an EDW response, resulting from feedbacks that effectively leads to a flattening of the tropical lapse rate. Thus, for a more intense anthropogenic radiative forcing scenario, the EDW effect will increase. This analysis verifies and quantifies the projected EDW effect over the QIC environment and shows how the feedbacks associated with EDW will respond strongly (or with larger positive feedback) to changes in the future strength of the radiative forcing.

The difference between the ensemble mean ELA_{atm} and ELA_{SST} of about 5.5 m/decade for the RCP8.5 scenario implies that by 2055, the ensemble ELA_{atm} will reach the QIC summit level, while the ELA_{SST} ensemble will be 27.5 m below the QIC summit. Similarly the ELA_{atm} will reach
the QIC summit about 12 years earlier than the ELA_{SST}. Note that these calculations were done for the ensemble of 16 CMIP models, but that results for individual CMIP5 models vary considerably.

### 4.4. Conclusions

Here CMIP5 model simulations were applied to study changes in the tropical Andean mountain climate over the Quelccaya Ice Cap region, assessing the relationship between ELA and FLH and how these variables relate to tropical SST forcing in the past and the future. We did not consider the influence of ENSO on QIC climate, which is particularly relevant for understanding interannual variability and will be included in future work.

One important outcome of this study is that QIC will be strongly affected by future warming, and may completely lose its accumulation zone before the end of the 21\textsuperscript{st} century. The critical time when the ensemble RCP8.5 ELA will reach the QIC summit is around 2055 (Figure 4.5), concomitant with RCP8.5 Ta at QIC rising to approximately -1.8°C (Figure 4.3). From that point forward, the ELA will be permanently above the ice cap’s highest elevation, leaving the entire ice cap exposed to a permanently negative mass balance. However, other factors, not considered here can change this timing such as changes in the amount or seasonality of precipitation. Since changes in precipitation are a more complex issue to assess, it was dealt with in a complementary study, applying an empirical-statistical downscaling (ESD) model to evaluate the influences of atmospheric forcings affecting QIC precipitation. As far as precipitation phase is concerned, following L’Hote et al. (2005) Ta= -1°C is the critical threshold where precipitation starts to change phase in the tropical Andes; leading to a decline in snowfall and increasing mixed
precipitation. Based on our results, this threshold will be reach around 2070 for a few models in the RCP4.5 scenario and the ensemble mean Ta for the RCP8.5 scenario.

More research is needed to further clarify the nature of the feedbacks that lead to the anticipated EDW warming on QIC. In addition, it is critical to better quantify elevation feedbacks, edge effects, and the impacts of changing phase of precipitation with higher FLH on QIC’s mass balance. All those aspects would tend to lead to an even faster demise of the ice cap, hence our projections are likely conservative estimates of the future state of the QIC.

4.5. Acknowledgements

This study was produced under the framework of the Andean Climate Change Interamerican Observatory Network (ACCIION, grant S- LMAQM-11-GR-086 to M. Vuille); a project funded by the Bureau of Western Hemisphere Affairs of the United States Department of State. We acknowledge the World Climate Research Programme's Working Group on Coupled Modeling, which is responsible for CMIP, and we thank the climate modeling groups (listed in Table 4.2 of this document) for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.
4.6. Tables

Table 4.1. Landsat sensor and selected date for obtaining snow line altitude (SLA) by year between 1992 and 2017.

<table>
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<th>Sensor</th>
<th>Date</th>
<th>Sensor</th>
<th>Date</th>
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<td>LT5</td>
<td>17 Aug 2005</td>
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<tr>
<td>LT5</td>
<td>29 Jun 1993</td>
<td>LE7</td>
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<td>LT5</td>
<td>07 Jul 1996</td>
<td>LT5</td>
<td>15 Oct 2009</td>
</tr>
<tr>
<td>LT5</td>
<td>27 Aug 1997</td>
<td>LT5</td>
<td>16 Sep 2010</td>
</tr>
<tr>
<td>LT5</td>
<td>15 Sep 1998</td>
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<td>LC8</td>
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Table 4.2. List of CMIP5 models and attributes used in the present research.

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<th>Grid resolution (°)</th>
<th>Latitude</th>
<th>Longitude</th>
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</thead>
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4.7. Figures

**Figure 4.1.** (left) Quelccaya Ice Cap image using Landsat 8 satellite data on 02-Aug-2017. (Upper right) South American country boundaries, and the red mark indicating QIC location at 13°56’S 70°50’W.
Figure 4.2. Snow line altitude using Landsat images. (a) Snow region in light blue, as a RGB composite using Landsat 5 (LT5) images of 5, 4, and 2 bands, applied histogram thresholds of 155 and 174 for bands 4 and 2, respectively. Snow line perimeter in yellow by date selected in 1998 (Table 4.1). The mean SLA is calculated as the average elevation of all DEM cells coinciding with the location of the snow line perimeter. (b) As in (a), but for the date selected in 2016, and bands 6, 5 and 3 from Landsat 8 (LC8), with histogram threshold 99 and 117 for bands 5 and 3, respectively. (c) Mean SLA obtained each year (i.e., mean elevation corresponding to yellow perimeter). The dashed line represents the linear trend with equation indicated in the legend. The non-zero trend was verified using an F-test (p-value<0.001), both with- and without outliers (strong El Niño years 1998, 2010, 2016) included.
Figure 4.3. Annual mean air temperature (Ta) from 2.5° ERA-interim reanalysis (thick black line, 1979-2016), historical (gray, 1950-2005) and future (2006-2100) RCP4.5 (blue) and RCP8.5 (red) simulations. Ta was calculated using lapse rate between 400 and 500 hPa level. Each curve was bias-corrected with AWS temperature data (2005-2016) at QIC summit. Colored thick lines represent the historical, RCP4.5 and RCP8.5 ensembles of 16 CMIP5 models (Table 4.2) and shading represents the 95% confidence interval.
Figure 4.4. Scatter plot between annual FLH and annual ELA at QIC. FLH is calculated by interpolating bias-corrected air temperature (Ta) and geopotential height between 500 and 600 hPa from ERA-interim. The bias-corrected Ta was obtained by fitting reanalysis air temperature with observed Ta from an AWS at QIC summit. ELA data were obtained from Landsat images at the end of the dry season (June to October, see Table 4.1). ELA and FLH were calculated for hydrologic years (September of previous calendar year to August). Pearson’s correlation coefficient (r) and p-value are indicated in the Figure. The black dashed line indicates the QIC summit elevation (5680 m).
Figure 4.5. Equilibrium Line Altitude (ELA) calculated using the freezing level height anomaly projections at QIC (FLH$_{atm}$) from 16 CMIP5 models (Table 4.2) as input in equation (4.1). FLH$_{atm}$ was obtained by interpolating Ta and Zg between 500 and 600 hPa pressure levels. The black curve (OBS) represents the observed ELA obtained from Landsat satellite images over the 1992-2017 period (section 4.2.3). Bias-correction was applied to Ta and ELA for each CMIP5 model, using the observed Ta from the AWS at QIC. ELA represents the highest Snow-Line Altitude (SLA) from Landsat satellite images across each hydrological year, respectively. The hydrological year Sept.-Aug. was used for calculations. The ensemble of historical (1950-2005) simulations is represented with the gray line, while CMIP5 RCP4.5 and RCP8.5 future projections (2006-2100) are represented by green and orange lines, respectively. The shading represents the corresponding 95% confidence intervals. The blue dashed line indicates the QIC summit altitude (~5680 m). The mean observed ELA over the 1992-2017 period was 5435.7 m, and the mean annual ERA-interim ELA over the baseline 1979-2017 was 5416.5 m.
Figure 4.6. Tropical SST forcing of FLH at QIC during 1980-2017 (hydrologic years). Annual FLH anomalies (FLHA) at QIC were calculated by interpolating bias-corrected air temperature (Ta) and geopotential height (Zg) from ERA-interim reanalysis, between 500 and 600 hPa pressure levels at QIC summit location (red curve). The bias-corrected Ta was obtained fitting the ERA-interim Ta product with observed Ta data from an AWS at QIC summit. The annual tropical (spatially averaged across 28.75°N to 28.75°S) SST anomalies were calculated from ERSST data (blue curve). Anomalies were calculated using the baseline 1979-2005 period. A linear relationship between FLHA and tropical SSTA was calculated resulting in FLHA = 286.4xSST + 1.4, with r=0.84 and p-value<0.001.
Figure 4.7. Annual mean ELA derived from FLH at QIC calculated by linear regression (equation 4.1) with annual mean tropical SST from ERSST dataset as predictor (FLH\text{SST} using equation 4.2), compared with ELA derived by interpolating air temperature (Ta) and geopotential height (Zg) from ERA-interim reanalysis between 600 and 500 hPa levels (FLH\text{atm}) (black dots). The same approach is applied to the ensemble mean of annual FLH\text{SST} and ELH\text{atm} obtained from 16 CMIP5 models (Table 4.2) for Historical (gray dots), RCP4.5 (blue dots) and RCP8.5 (red dots) scenarios. Historical and future simulations were analyzed over the periods 1951-2005 and 2006-2100, respectively. Dashed line represents the 1:1 line. A bias-correction was applied to Ta and ELA, using data from the AWS at QIC summit elevation (5680 m) and estimated highest annual snowline altitude from Landsat images, respectively.
4.8. References


Chapter 5

FINAL CONCLUSIONS OF THE THESIS

This thesis presented the data analysis, methods and procedures to understand the local impacts of climate change (CC) on the cryosphere over the central Andes. Although here we used the world’s largest tropical ice cap, Quelccaya, as a local case study, it can be considered as a representative case for other lower-elevation glaciated mountain ranges, where similar processes are at play.

These local impacts were assessed across several spatiotemporal scales: from local (~1 km) to large-scale, and from dekadal (~10 calendar days) to multi-decadal, generating valuable new information. This information helped address three keys problems considered at the outset of this study (section 1.4): i) The lack of in-situ climatic information; ii) the poor representation of mountain climate in GCMs and RCMs; and, iii) how imminent the threat of a future disappearance of glaciers and ice caps in the Andes, specifically the QIC, really is. Three chapters of the present thesis address these problems in more detail.

Chapter 2 addressed the lack of in-situ climatic information over mountain regions, focusing on the generation of precipitation information, due to the importance of this climatic variable to several other study areas. The precipitation modelling is challenging because its high variability over short time and space dimensions in comparison to others climatic parameters, such as temperature. Moreover, precipitation variability is not well represented in GCMs and RCMs as discussed in section 1.3.2. In section 2.3 an alternative methodology to reconstruct high spatio-temporal precipitation using the relationship between precipitation and the NDVI vegetation index over the Peruvian Andes is presented. The final results include the generation of 10 years of
precipitation fields with ~1 km² and 1 dekadal of spatial and temporal resolution, respectively. This product was used to assess the local – regional precipitation relationship, documenting that precipitation at QIC is linearly related with regional-scale precipitation. The importance of this result consists in the realization that regional precipitation can be used to predict or reconstruct the local QIC snowfall totals with quite some confidence, which is an important result, given that modelling of regional-scale precipitation is much easier to achieve than directly predicting or reconstructing local, point-scale precipitation.

As was indicated previously (section 3.1), GCMs and RCMs show a large bias in their precipitation estimates over the Andes and their projections often indicate conflicting results. The main problem to generate accurate precipitation estimates is the insufficient understanding of the linkages between the large-scale forcing and local-regional precipitation. Chapter 3 addressed this issue, first by generating an empirical statistical downscaling (ESD) model based on a forward stepwise multilinear regression approach, whereby several atmospheric indices were selected as predictors, portraying high skill in reproducing the observed wet season (DJF) regional precipitation. In a second step, these results were complemented by the development of an empirical linear model that links local snowfall on QIC with regional-scale precipitation. These two models combined, allow linking the large-scale forcing with local precipitation, thereby enabling the transfer of future climate change information from coarse models to local hydrological conditions on the QIC.

To address the third problem discussed above, i.e., how imminent the threat of a future disappearance of the QIC really is, it was necessary to consider how air temperature, generally considered to be the main long-term forcing factor affecting the QIC, will change going forward.
This notion of temperature being the main driver of future ice retreat on QIC, is confirmed by my analysis of future changes in local precipitation at QIC summit based on the ESD model forced with CMIP5 model simulations (Table 3.2) for historical, RCP4.5 and RCP8.5 scenarios, which show that precipitation is not projected to change much for either RCP4.5 or RCP8.5 scenario during the 21st century. Hence the increase in air temperature (Ta) is considered to be the main factor that leads to the future shrinkage and eventual disappearance of the Andean glaciers such as QIC, although precipitation may also play a role in the sense that the future increase in air temperature will affect the precipitation phase (i.e. the partitioning into snow, rain or mixed precipitation). In Chapter 4, the impact of the future increase of Ta at QIC was quantified by documenting how fast the FLH will rise over QIC. Results show that the freezing level height (FLH) will increase by 24.5 m/decade and 58.4 m/decade, for RCP4.5 and RCP8.5 scenarios, respectively. These estimates are based on an ensemble of 16 CMIP5 model simulations (Table 4.2). These results further show that the current Ta (about -4°C) at the QIC summit (5680 m) will increase to approximately -1.6°C and +1.4°C, for RCP4.5 and RCP8.5 scenarios, respectively, by the last decade of the 21st century. Since the snow-mixed precipitation threshold over the Central Andes is near Ta = -1°C (section 4.3.1), changes in precipitation phase (decline in snowfall and increase in mixed precipitation frequency) is expected after ~ 2050 in the RCP8.5 scenario (Figure 4.2). Moreover, in Chapter 4 I show how the equilibrium line altitude (ELA) was obtained using satellite data of the latest available dry season snowline altitude and how the ELA can be linearly related to the FLH. The importance of studying this variable is that the ELA can be used as a proxy of the QIC mass balance (MB), where an ELA rise (lowering) indicates a trend toward a more negative (positive) MB. More importantly, if the ELA emerges above the highest point of a glacier, this by definition invokes that the glacier has lost its accumulation zone and will eventually
disappear, since mass balance is now negative over the entire extent of the glacier or ice cap. Future ELA projections using CMIP5 models (section 4.3.3) indicate a significant contribution from elevation-dependent warming (EDW). This effect was quantified (section 4.3.5), by comparing the future evolution of the ELA calculated using a fixed present-day lapse rate (ELA\text{SST}) with a freely changing lapse rate as simulated in CMIP5 models (ELA\text{atm}). Results show that the EDW is responsible for approximately 7.6% and 9.9% \(^1\) of additional ELA rise in RCP4.5 and RCP8.5 scenarios, respectively. Hence this EDW effect will further accelerate the QIC retreat. The ensemble mean projections indicate that the ELA will rise above the QIC summit by 2055 in the RCP8.5 scenario (section 4.3.3 and Figure 4.5). From this moment forward, the ELA will be permanently above the ice cap’s highest elevation, effectively rendering the entire remaining QIC into an ablation zone with net mass loss. Additionally, other factors can accelerate the timing of the ice cap losing its accumulation zone, such as the change of phase of precipitation, which will increasingly expose larger and larger areas of the ice cap to rain or mixed precipitation as opposed to snow, and the future reduction in ice thickness which will lead to a lowering of the summit elevation into a warmer atmosphere (elevation feedback).

The results presented in this thesis are based on a multi-scale analysis of a local system, the Quelccaya ice cap, and how it responds to current and future climate variability and change. It is anticipated that these results are useful for policy- and decision-makers but also for others research areas.

\(^1\) Percentage calculated as \([(\text{ELA}_{\text{atm}}-\text{ELA}_{\text{SST}}) / \text{ELA}_{\text{SST}}] \times 100\%\), taking the \text{ELA}_{\text{SST}} as the 100\% reference case, since it is obtained assuming an invariant lapse rate through time.
Some caveats of the present work need to be considered. Since this study was developed over an area that is located in the eastern Andes, its spatial representativeness is probably limited to this region. Previous studies related to precipitation downscaling in the Altiplano region, further to the southwest, have come to different conclusions regarding future changes in precipitation, which are best explained by the different regional focus. The methods and processes used for downscaling in this analysis are rooted in statistical tools; hence it would be informative to complement those results with output of high-resolution numerical models. The fate of the QIC was assessed here only by means of the rise of the ELA as simulated by the change of the FLH. While a useful metric, it does not consider potential future changes in snowfall amount (although our ESD-based results suggest these might be very minor), impacts of edge effects (albedo feedback) as the ice cap shrinks, or the increasing temperature at the summit as a result of the ice cap thinning (elevation feedback). Finally, I did not consider the unrealized response of the QIC, i.e. the fact that the QIC, as all large ice bodies, is not in steady state with its surrounding climate and therefore exhibits a delayed response to changes in the climate system. This makes it impossible to predict when exactly the mountain ridge on which QIC sits, will become completely ice free.

Future planned projects are focused on replicating this study over other cryospheric systems. The application of the high spatio-temporal reconstructed precipitation method over other Andean regions and semi-arid areas across the world is planned, as is the use of this kind of product to fit high-resolution numerical models. Applying the ESD model in other disciplines such as hydrology and agriculture, can provide critical information on future precipitation that is highly relevant over Andean regions where the population is dependent on rainfall for various socio-economic uses.
Finally, such ESD models should be refined to allow projections at higher temporal resolution than the seasonal scale, which was the focus of this research.