Title: Maximum and Minimum Air Temperature Lapse Rates in the Andean region of Ecuador and Peru

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Abstract: To know the vertical distribution of air temperature is complex, and this is necessary for different applications. The main explanatory variable of air temperature is elevation above sea level, whose relationship with air temperature is measured by air temperature lapse rates (LRs). LRs can vary considerably spatiotemporally due to a wide spectrum of geographical, environmental, and other atmospheric factors. Our study presents the first comprehensive assessment of spatiotemporal changes of LRs over the Tropical Andes. Our study is focused on the Peruvian and Ecuadorian Andes, divided in two subregions by the parallel 9.5° (i.e. north and south). Maximum and minimum air temperatures were employed from 115 quality checked weather stations, for the period 1994-2011. Maximum ($LR_{\max}$) and minimum ($LR_{\min}$) air temperature lapse rates have been calculated for the whole study period. The effects of seasonality, humidity content and ENSO on the variability of LRs have been analyzed. Results show that LRs have large spatiotemporal variability, since references values of $LR_{\max}$ range from -3.57 (South, dry season) to -4.77 (North, wet season), and $LR_{\min}$ range from -3.78 (North, dry season) to -4.93 °C km⁻¹ (South, dry season), in function of season and subregion. Results indicate that the ENSO phases contribute significantly to the variability of southern subregion LRs. This study also presents that minimum air temperatures were more unpredictable than maximum air temperatures in terms of error and uncertainty, as a consequence of the larger spatial variability of nocturnal air temperatures, mainly influenced by local topography. In conclusion, this work goes deeper into the need to obtain precise LRs adapted to the study region, and shows that the use of standard LR values can cause significant failures in modeling air temperature in regions of complex terrain, such as the Andes.

Keywords: Air Temperature, Lapse rates, ENSO, Tropical Andes, Ecuador, Peru.

1. Introduction

Surface air temperature (measured at ~1.5 - 2.0 m height above ground) is a key climatic variable for a wide range of ecological (Hatfield and Prueger, 2015), environmental and economic applications (Moore and Diaz, 2015), among others. In regions of complex topography, air temperature varies considerably over space and time, even for short distances, which makes it necessary to use a dense network of meteorological information. Unfortunately, meteorological networks in mountainous regions are mostly characterized by uneven distribution of weather stations, especially in remote, elevated and less-populated sites (Barry, 2008). This is typical in the Andean region in Ecuador and Peru. To address this lack of information, some authors have installed their own weather station networks on the territory, mainly in reduced study areas (Lewkowicz and Bonnaventure, 2011; Bonnardot *et al.*, 2012; Appelhans *et al.*, 2016; Wang *et al.*, 2017). Alternatively, many investigations of air temperature in complex terrain regions deployed either reanalysis datasets (Alonso-González *et al.*, 2018) or interpolation techniques (Lussana *et al.*, 2018; Sadoti *et al.*, 2018). This has been evident for the Rocky Mountains (Whiteman *et al.*, 1999; Minder *et al.*, 2010), the Alps (Rolland, 2003), the Subarctic Scandinavia (Pike *et al.*, 2013) and the Ecuadorian Andes (Morán-Tejeda *et al.*, 2016), among others.

The elevational lapse rate (LR forward) is simply defined as the change in air temperature per elevation unit, measured in °C km⁻¹ (Fang and Yoda, 1988). In hydroclimatic research, it is

common to apply elevation-dependent LRs to interpolate air temperature. As such, they have been widely applied in various disciplines, such as glaciology, hydrology, and ecology (Immerzeel *et al.*, 2014; Hanna *et al.*, 2017; Kulshrestha and Ramsankaran, 2018). Amongst them, the most used LR is the fixed Mean Environmental Lapse Rate (hereafter MELR: $-6.5^{\circ}\text{C km}^{-1}$), which assumes free atmospheric conditions (Barry and Chorley, 1987). Nonetheless, the application of the fixed MELR has a degree of uncertainty, as it fails to adequately reveal the high variability of air temperature both vertically or horizontally (Kattel *et al.*, 2013; Miró *et al.*, 2017) and, accordingly, it does not represent the synoptic behaviors of temperature profiles (Pepin and Losleben, 2002; Du *et al.*, 2010). While the calculation of LRs can easily be accomplished, it requires high-resolution air temperature data over space and time, which allows for a more reliable diagnosis of air temperature variability at different scales.

Even under stable atmospheric conditions, LRs can vary considerably from one season to another for maximum and minimum air temperature (Pepin, 2001; Marshall *et al.*, 2007; Kattel *et al.*, 2013). This notion has been confirmed across the global mountain systems, including the Rocky Mountains (Kunkel, 1989; Pepin and Losleben, 2002), the Himalayas (Immerzeel *et al.*, 2014; Romshoo *et al.*, 2018; Ojha, 2019) and the Alps (Dumas, 2013; Nigrelli *et al.*, 2017), along with other regions (e.g. the Iberian Peninsula; (Navarro-Serrano *et al.*, 2018), as well as in the Antarctic Peninsula (Ambrozova *et al.*, 2019). In each region, the vertical distribution of air temperature varies between nighttime and daytime due to variations in heat fluxes between the atmosphere and the surface (Duane *et al.*, 2008; Gardner *et al.*, 2009). These diurnal variations demonstrated that MELR does not represent the regional annual average of LRs. Large errors may be introduced applying MELR on modelling temperature with diverse aims. Unfortunately, except for work at the local scale of Cordova *et al.* (2016) in a specific Ecuadorian valley over 12 months, the dependency between elevation and air temperature is still unexplored in this Andean region, which could have different implications in the countries of this region.

In Ecuador and Peru, the hydrological resources are needed for more than 40 million people, being originate mainly from the Andean mountains due to the strong lack of precipitation in

the coastal regions (Mortensen *et al.*, 2018). Water-dependent economic sectors in these countries (e.g. agriculture, energy production) are mainly based on the seasonal melting of glaciers (Bradley *et al.*, 2006; Mark *et al.*, 2017) which have undergone a marked retreat (Kaser, 1999; López-Moreno *et al.*, 2014). This makes the mountainous areas of the tropics amongst the regions most vulnerable to global warming (Bradley *et al.*, 2009; Vuille *et al.*, 2008). In the Tropical Andes, warming signals are stronger in the most elevated sites compared to low-elevationed locations (Morán-Tejeda *et al.*, 2016; Vicente-Serrano *et al.*, 2018), although there are also some world regions where this elevation-dependent warming has not been detected, due to diverse factors (Rangwala and Miller, 2012; Pepin *et al.*, 2015) in their global studies. Thus, a proper understanding of the spatial and temporal variability of air temperature LR is needed to improve the understanding of air temperature distribution over complex terrain in the Tropical Andes.

The Ecuadorian and Peruvian climate is influenced by the complex phenomenon of El-Niño-Southern-Oscillation (ENSO). In particular, changes in sea-surface temperatures (SSTs) of the Pacific Ocean can alter meteorological patterns of the South American coast. This phenomenon implies that, during the positive phase, the habitual and dominant trade winds from the east are weakened, allowing overheating of the sea surface and its larger influence on the continental zones from the west (inverse pattern in the negative phase), as Dijkstra (2006) explains. The impacts of the ENSO on the Andean region are assessed, including precipitation (Barros *et al.*, 2008; Grimm *et al.*, 2009), air temperature (Vuille and Bradley, 2000; Francou *et al.*, 2004; Vuille *et al.*, 2015), drought severity (Vicente-Serrano *et al.*, 2017), but with no investigation of their links to LR. This investigation is highly desired in the tropical Ecuadorian and Peruvian Andean regions, given the strong seasonality of their climate due to the shift of the Inter Tropical Convergence Zone (ITCZ) during the year.

Within this background, this study endeavored to assess the spatiotemporal characteristics of air temperature elevation LR in the Ecuadorian and Peruvian Andes, and their links to specific humidity and the ENSO during the period 1994-2011. The overriding objectives of this work are to (i) define annual, seasonal and monthly air temperature LR reference values; (ii) analyze the effects of seasonality, specific humidity, ENSO and topography on LR; and

(iii) identify subregional representative pair-stations, which allows for estimating air temperature LR in data-scarce areas.

2. Study Area

The Andean Mountains are located parallel to the Pacific coast of South America, extending for more than 7,000 km to the southern foothills of Cape Horn (Figure 1). The study area includes the Andean areas of Ecuador and Peru, disregarding Amazonian and coastal territories due to our special interest in mountainous regions, the uneven distribution of their weather stations, and their relatively low altitudes (Marengo *et al.*, 2016), affected by the usual coastal fogs. The study domain has a total area of almost 400,000 km², mostly above 3,000 m a.s.l., with its highest peaks in Huascarán Peak (Peru) at 6,768 m a.s.l. and Chimborazo volcano (Ecuador) at 6,267 m a.s.l. This steep slope represents almost a barrier for the Pacific and the Amazonian air masses. Here, the study area was divided into two subregions, separated by the latitude 9°30'S: namely the north and south domains. The northern territory (1°N-9°30'S) has a coastal plain that extends inland to the foothills, with widths varying from 10 to 150 km. Next, the land rises to the highlands (~3,000 m a.s.l.), where a large part of the population is located (García and Santiago Ochoa, 2012). The southern territory (9°30'-18°S) has a narrow coastal plain, which runs 15 km inland at most, generating a sudden rise in elevation from the sea to the highlands. The topographical gradient is very strong, particularly in the Peruvian Altiplano (~4,000 m a.s.l.), where elevation exceeds 5,500 m within only 85 km from the coast. While the climate of the northern and southern subregions of the study domain is generally tropical, some considerable differences exist due to the impact of latitude. Specifically, the northern subregion is typically equatorial (i.e. warm and rainy climate most of the year, especially on the coastal plain). Once the effect of elevation is removed, annual precipitation clearly decreases from North to South in the whole Tropical Andes, mainly driven by the ITCZ passage, shorter as it approaches the Tropic of Capricorn (Gruber, 1972). In the northern subregion, rainfall mainly occurs during March-April and October-November. The southern subregion is dryer, especially when approaching the Atacama desert in the extreme south (Cárdenas Gaudry *et al.*, 2017). The southern highlands show larger daily thermal amplitude

due to a combined impact of aerial extension and elevation, which enhance continental conditions (Vicente-Serrano *et al.*, 2018).

Coastal fogs occur in both the northern and southern subregions. This phenomenon has been studied in depth (Pinche Laurre, 1986; Schemenauer and Cereceda, 2006) and is persistent from June to September, occasionally from April to November and, exceptionally, it can appear in the rest of the year. Fogs are important due to their impact modulating coastal air temperature. This phenomenon is generally affected by the existence of the cold Humboldt Current which laps the coasts, especially the Peruvian coasts, but also those of Ecuador, although it can be generated by other diverse factors. The frequency of coastal fogs increases gradually to the south, causing a marked diurnal cooling in the affected areas.

3. Raw dataset description

3.1. Observed air temperature data

A daily raw maximum and minimum air temperature database of 694 manually observed weather stations across Ecuador and Peru was provided by the governmental meteorological services of Ecuador (INAMHI) and Peru (SENAMHI). Analysis was restricted to stations located along the highlands, western slopes and those situated along the continental coastlines. First, our analysis selected 363 stations in the northern subregion and 164 stations in the southern subregion. Air temperature data have been measured following World Meteorological Organization guidelines (WMO, 2014), i.e. at ~1.5-2.0 m height above the ground and protected with naturally-ventilated Stevenson screens against solar radiation and weather (van der Meulen and Brandsma, 2008). Air temperature data were subjected to a robust quality-control and homogenization protocol detailed in Section 4. Analysis was restricted to the period October 1994 to September 2011, given that this study period guarantees the highest density of climate records. In contrast, the 1970s and 1980s show a relatively lower data density, especially in the northern subregion. Finally, following the quality control and homogeneity testing, data from 76 and 93 weather stations in the northern and southern subregion, respectively (see Supplementary Material – Table 1 and Supplementary Material – Figure 1) were retained. The final dataset includes high quality,

quasi-complete, and homogenous time series, which were used for the subsequent analysis. Weather stations have been classified depending on their relative position in relation to elevation within 25 km in the surroundings: Bottom (0 to 33.3%), Slope (33.3 to 66.6%), and Summit (66.6 to 100%).

3.2. El Niño Southern Oscillation (ENSO)

In order to analyze the influence of the ENSO phenomenon from different locations, it has been analyzed by two different indexes: El Niño 3.4 and El Niño 1+2 (i.e. ONI and ICEN, respectively). The widely known Oceanic Niño Index (ONI) has been used to synthesize the behavior of sea surface temperature in the 3.4 Pacific region, defined by Rasmusson and Carpenter (1982) and showed in Supplementary Material – Figure 2. Data has been provided by the NOAA - Climate Prediction Center (https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php, last accessed on 19th January 2020) at three-months moving average resolution (Huang *et al.*, 2017), based on ERSSTv5 data. To synthesize the behavior of sea surface temperature in the 1+2 coastal Pacific region the Índice-Costero-El-Niño (ICEN) was chosen on a monthly basis, used previously in the Ecuadorian territory (Morán-Tejeda *et al.*, 2016). ICEN has been provided by the Peruvian Government (<http://www.met.igp.gob.pe/variabclim/indices.html>, last accessed on 19th January 2020), based on ENFEN (2012) and updated by Takahashi *et al.* (2014). Following the different criteria of the original authors, the El Niño positive phases are identified as follows: (ONI): five consecutive three-months moving average above +0.5 (below -0.5 are identified as La Niña negative phases); (ICEN): three consecutive three-months moving average above +0.4 (below -1.0 are identified as La Niña negative phases).

Following the methodology outlined in ENFEN (2012) and Huang *et al.* (2017), the monthly ONI and ICEN values were computed to determine the positive (El Niño), neutral (Neutral) and negative (La Niña) phases of the ENSO phenomenon, as well as intensity. The ICEN and ONI phases showed some common features. However, some differences due to the use of two different thermal anomalies in the Pacific sector were found. This refers to weak differences in the transition from the neutral phases to the positive and negative phases, as well as delays in the start of significant anomalies, which could slightly alter the results. In any case, the two

indices identified similar strong and very strong El Niño events (>1.5 ONI; >1.7 ICEN), such as 1972, 1982-1983, 1987, 1992 and 1997-1998). Likewise, strong La Niña events (<-1.5 ONI; <-1.4 ICEN) were also identified by the ICEN and ONI indices, but with weak differences, in which La Niña events were less frequent using the ICEN index. Nonetheless, strong and very strong La Niña events were detected by both indices (e.g. 1973-1976, 1988-1989, 1998-2001, 2007 and 2010).

3.3. Specific atmospheric humidity

Specific atmospheric humidity (g kg^{-1}) was analyzed to delimitate wet and dry seasons. It has been extracted from the ERA-Interim reanalysis (Berrisford *et al.*, 2011) at 500 hPa geopotential height at 6-hourly intervals (<https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim>, last accessed on 19th January 2020) from the start of available data (January 1979). The spatial horizontal resolution is about 0.7° degrees. The 500 hPa geopotential height (i.e., $\sim 5,500$ m a.s.l.) is above the average elevation of the region but affects surface conditions, while at higher geopotential heights (e.g. 100-300 hPa), the effects of specific humidity on surface air temperature would not be so obvious and direct due to its approximate correspondence with $> 9,000$ m a.s.l.

Raw 6-hourly (UTC+0) 500 hPa specific humidity data were aggregated to daily scale. Later, two subregional series were created for the northern and southern subregions using an arithmetic average of daily specific humidity for all pixels belonging to each subregion. In this process, raw 6-hourly (UTC+0) specific humidity data were adapted to local time zone (UTC-5), at the same time as air maximum and minimum daily temperature measurements.

4. Methods

4.1 Quality control and homogenization protocol

The raw dataset (694 weather stations) was subjected to a robust quality control (QC) and homogenization (Hom.) process, which consisted of six defined steps (Figure 2):

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- Step 1 (QC) consisted of discarding weather stations without metadata (i.e. latitude, longitude, elevation and recognized identifier), in addition to those located in the Amazon and insular territories, out of the analyzed study areas.
 - Step 2 (QC) consisted of data screening using the protocol proposed by Tomás-Burguera et al. (2016), which removes questionable samples according to Durre et al. (2010). This step aims to detect codification errors and extreme outliers to ensure data accuracy. The codification errors were: samples recorded on erroneous dates; seven or more consecutive days with identical value; write “0 °C” when NA corresponds; invalid data units; $T_{min} \geq T_{max}$; and diurnal variation larger than 35 °C. The outliers were identified by comparing with the extremes of the study area to maintain reliable values (i.e. between -35 and 50 °C). Step 2 does not imply a reduction in the number of weather stations but a reduction in the amount of daily records.
 - Step 3 (QC) consisted of discarding stations with less than 20% daily samples, referred to original temperature raw database period (1 January 1971 – 31 December 2012), which means 3,068 days (> 8 complete years).
 - Step 4 (QC) consisted of discarding weather stations affected by continuous and recurrent gaps, despite achieving Step 3, due to doubts about the quality of the data.
 - Step 5 (QC) consisted of removing daily records above percentile 99 (P_{99} , extreme warming) and below percentile 1 (P_{01} , extreme cooling) of change in relation to the previous day, along complete weather stations that experienced these repeated problems. During the QC process, it was preferred to remove weather stations of uncertain quality and keep only the truly reliable ones.
 - Step 6 (Hom.) consisted of homogenizing air temperature by applying relative homogeneity statistics, following the procedure described by Domínguez-Castro et al. (2018) at a daily scale. Daily missing data were not filled using available data from neighbouring stations, due to large variability of temperature even over short distances. Also, this reconstruction process may introduce new inhomogeneities into the series from the candidate closing series, which can add further challenges to LR calculation.

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Finally, weather stations without any data in the definitive study period, 1 October 1994 – 30 September 2011, and those weather stations located in the coastal areas, where coastal fog exists were discarded. Low-stratiform clouds and coastal fogs have large influences on near-surface air temperatures, leading to noticeable thermal inversion at coastal areas. The inclusion of these coastal areas generates serious noise problems in LR calculations outside the fog layer. Therefore, aiming to know the air temperature distribution in the mountainous area (where air temperature modelling is mainly needed), makes its elimination appropriate. As such, to determine the definition of coastal areas, the elevation threshold based on Pulgar-Vidal (1987) (i.e. 500-600 m a.s.l). and the height of the thermal inversion layer based on cloudiness were analyzed. Therefore, August MODIS-Terra satellite daily imagery from 2000 to 2012 was analyzed to detect coastal foggy days for the northern and southern subregions (e.g. in the Figure 3). August was chosen due to its central position in the dry and coastal foggy season. The corrected reflectance (True Color) product was analyzed (<https://earthdata.nasa.gov/faq#ed-CRvsSR>, last accessed on 19th January 2020) in addition to air temperature values of the weather station network to determinate the thermal inversion thresholds. Although there is certain variability in the daily thermal inversion high, 400 m (northern subregion) and 600 m (southern subregion) were defined as the best and conservative thresholds to determine the height of the thermal inversion layer. After applying the coastal fog-elevation threshold filter, a total of 115 stations were used in this study (37 in the northern subregion and 78 in the southern subregion). The vertical distribution of the final dataset is shown in Figure 4. A quick inspection of Figures 1 and 4 reveals that the elevation range between 1,000 and 2,000 m a.s.l is poorly represented in the final dataset. This lack of observations is due to the location of the main cities either below (coastal plain) or above (highlands) these elevation bands.

4.2 Daily air temperature LR

Maximum (LR_{max}) and minimum (LR_{min}) daily air temperature LR were calculated separately for the northern and southern subregions for the period October 1994 – September 2011 with all selected series. Since the number of available series varies daily, the mean number of weather stations used in the regressions was 31 for the northern subregion and 65 for the

southern subregion. Following Rolland (2003) and Navarro-Serrano et al. (2018) procedures, multiple daily regressions were used to compute daily air temperature LR. This was conducted by removing the effect of other topographic and geographic variables (i.e. latitude and sea distance), formulated as:

$$T'_{max} \text{ or } T'_{min} = a_0 + a_1 \text{Elev} + a_2 \text{Lat} + a_3 \text{Sea} + e$$

where T'_{max} and T'_{min} are the daily maximum and minimum air temperatures (in °C), respectively; Elev, Lat and Sea are elevation above sea level (in m a.s.l.), latitude (in decimal degrees), and distance to the sea (in km), respectively; e is the regression error; and a_1 , a_2 and a_3 are the regression coefficients, a_1 corresponding to the daily maximum (LR_{max}) or minimum (LR_{min}) lapse rate. These daily LR_s were aggregated to months and seasons, and by ENSO phases, in order to develop reference LR_s for the northern and southern subregions. LR_s at daily, monthly, and seasonal scales have been compared by the Wilcoxon-Mann-Whitney test to identify statistically significant differences among groups (i.e. ENSO phases, seasons, subregions, and maximum-minimum). The Wilcoxon-Mann-Whitney (Wilcoxon, 1945) is a nonparametric statistical test that allows for testing the similarity/differences between two independent samples. Differences were tested at 0.05 level of significance.

A validation process was implemented to assess the accuracy of the computed monthly LR_s. Herein, 90% of weather stations was randomly selected and the remaining 10% was used for validation purposes. Daily and monthly MAE statistics were computed from the residuals between maximum and minimum air temperature observed and the estimated by the regression model derived from 90% of weather stations, and were summarized at monthly basis (in absolute °C).

4.3 Local vs. subregional LR_s

The possibility of estimating subregional air temperature LR using data from only two representative weather stations at large elevational ranges (difference, in meters, between the elevation above sea level of the two weather stations) was also tested. Then, the LR obtained from those pairs was compared with the LR obtained from all stations. For this purpose, the

same equation (Section 4.2) was used to calculate daily air temperature LR for all combinations between pairs of weather stations, regardless of elevation range. Next, these daily ‘pair lapse rates’ were aggregated at a seasonal scale, compared with those calculated from all stations. A similar procedure for LR calculation from two weather stations was adopted by Holden and Rose (2011) in England and Nigrelly et al. (2017) in the Alps, in addition to other old works, due to the absence of a wide observational network or long-term air temperature series. The absolute residuals were summarized by seasons. The Mean Absolute Error (MAE) statistics were computed and correlations between the two LRs were analyzed. MAE was tabulated in relation to the elevation range between each pair using different categories of this range, i.e. less than 500 m, 500-999 m, 1,000-1,499 m, 1,500-1,999 m, and higher than 2,000 m. In addition, the effect of horizontal distance between pairs was analyzed.

4.4 Wet/dry season definition

Two seasons were identified as a function of the 500 hPa specific atmospheric humidity and frequency of coastal fogs as a sign of seasonal change (Supplementary Material – Figure 3): (a) Dry Season (June-September) and (b) Wet Season (October-May). Dry season corresponds to the four months with smaller atmospheric humidity content. In addition, the dry season corresponds to a more frequent coastal foggy period as shown by MODIS-Terra satellite imagery (Paniagua-Guzmán, 2017), being a clear seasonal signal. The wet and dry seasonal specific atmospheric humidity content was statistically different ($p < 0.05$), for both the northern and southern subregions.

5. Results and discussion

5.1 Air temperature LR validation

Figure 5 summarizes two basic patterns: (1) MAE was larger ($p < 0.05$) for minimum than maximum air temperature in the two subregions, and (2) MAE was larger ($p < 0.05$) in the northern subregion for both maximum and minimum air temperatures. These results agree with earlier works that suggest more uncertainty modelling minimum/nocturnal air temperatures, especially in mountainous regions. Dodson and Marks (1997) indicate that

interpolation methods based on statistical approaches (e.g. IDW, or kriging) have worse yields at nocturnal air temperatures due to specific local topography and aspect.

We also noted that the impact of seasonality is more pronounced in the southern subregion, as MAE increases mainly during the dry season (May-November is ~ 2 °C in maximum and ~ 3 °C in minimum air temperatures). In the northern subregion seasonality is much less pronounced than in the southern region. Larger differences between the northern and southern subregions were identified during the wet season (October-May), while the dry season (June-September) balances both study areas (although the whiskers are larger in the northern subregion). The differences between MAEs of maximum and minimum air temperatures were larger in the north (~ 2 °C difference), while in the southern subregion they were similar during some wet season months (December-March); these differences increase (~ 1.5 °C) in the dry season. Non-absolute residuals were compiled in Supplementary Material – Table 2, and they were around 0 °C. The significant differences in LRs as a function of the subregion and season are relevant. The spatial uncertainty and spatial distribution of LRs have already been evident in several studies, coming mainly from environmental factors such as specific humidity (Bolstad *et al.*, 1998; Du *et al.*, 2017), topography, continentality (Lewkowicz and Bonnaventure, 2011), distribution, and representativeness of weather stations (Navarro-Serrano *et al.*, 2018), etc.

5.2 Air Temperature LR, specific humidity and ENSO phases

Figure 6 illustrates the data period October 1994 – September 2011 (all available data from 1971 are shown in Supplementary Material – Figure 4). Monthly LR peaks varied from -5.1 and -2.8 °C km $^{-1}$ for the southern LR $_{\max}$; -6.2 and -3.9 °C km $^{-1}$ for the southern LR $_{\min}$; -5.7 and -3.8 °C km $^{-1}$ for the northern LR $_{\max}$; and -5.2 and -2.7 °C km $^{-1}$ for the northern LR $_{\min}$. This supposes a small and reduced range between the steepest and weakest values in comparison with previous works, such as Blandford *et al.* (2008) in the Rocky Mountains, or Li *et al.* (2013). A fact which could be due to reduced thermal range and a climate less variable than the present on mid-latitude territories. This stresses that the use of a fixed MELR (i.e., -6.5 °C km $^{-1}$) might lead to gross errors (i.e. slightly during the wet season and strongly in the dry season). A similar finding in relation to MELR has been confirmed in

previous studies (e.g. Blandford et al., (2008), Gardner et al., (2009), Hubbart et al., (2007), Kulshrestha and Ramsankaran, (2018), Minder et al., (2010)). All these studies (located in Rocky Mountains, Arctic or Western Himalayas) showed different values (generally weaker) than $-6.5\text{ }^{\circ}\text{C km}^{-1}$. Indeed, the marked seasonal variability in the calculated LR reference values would be missed when applying a fixed MELR. This was also confirmed by Dumas (2013) for the Alps and Heynen et al. (2016) for the Himalayas. The northern LR_{max} showed the smallest difference between maximum and minimum values. LR_{max} was affected largely by seasonality, as LRs exhibited steeper values during the wet season, compared to the dry season. These seasonal patterns were less evident for LR_{min} . The error of regression over the period has been constant (not shown in the figure), responding to the seasonal variability shown in the validation experiment (Figure 5).

Specific atmospheric humidity showed a marked seasonal pattern, with its highest values during the wet season (almost 3 g kg^{-1} in the northern and southern subregions), while its lowest values were recorded during the dry season ($\sim 1\text{ g kg}^{-1}$ in both subregions). Nonetheless, the two subregions show statistically significant differences in their specific atmospheric humidity ($p < 0.05$), particularly in terms of seasonality. Seasonality is more marked in southern subregion. The interannual variability is relatively small in the two subregions during the wet and dry seasons, being remarkable only during some very wet periods (i.e. 1997 – 1998).

A quick inspection of Figure 6 (and Supplementary Material – Figure 4) reveals that the strong El Niño events (i.e. positive phases) were often followed by an increase of specific atmospheric humidity and an enhanced increase of LR_{max} and LR_{min} at a monthly scale. A representative example is the El Niño event in 1997-1998, especially in the southern subregion. Contrarily, the strong La Niña events (e.g. 1973-1976 or 2007) did not show significant impact on LR variability. Overall, this behavior may be expected, given the low interannual variability of specific humidity. As such, specific humidity is more likely to increase during an El Niño positive phase.

5.3 Reference Air Temperature LR

Table 1 shows the monthly and seasonal LR_{max} and LR_{min} values for each subregion. In the northern subregion, the steepest LR_{max} (LR_{min}) are during December (March), while the weakest LR_{max} (LR_{min}) are during June (September). In the southern subregion, the steepest LR_{max} (LR_{min}) are during February (May), while the weakest LR_{max} (LR_{min}) are during July (December). The main seasonal reference values for LR_{max} (LR_{min}), in $^{\circ}C\ km^{-1}$, were: -4.77 (-4.10) for North-Wet; -4.26 (-3.78) for North-Dry; -4.16 (-4.74) for South-Wet; and -3.57 (-4.93) for South-Dry. This implies that LR_{max} was steeper in the northern subregion than in the southern subregion ($p < 0.05$), shared by a larger atmospheric instability and lower air pressure, which prevents air subsidence in the northern subregion. The effect of atmospheric instability and synoptic conditions on LRs has been previously indicated by Blandford et al. (2008), Gardner et al. (2009), Bonnardot et al. (2012) and Hanna et al. (2017) in different mountain areas of the globe. Thus, the larger instability throughout the year due to the proximity of the ITCZ has been proved analyzing atmospheric pressure values, and the more progressive relief towards the highlands might cause steeper values of LR_{max} .

In contrast, LR_{min} was steeper in the southern subregion ($p < 0.05$), but with slight seasonal variations. LR_{min} was also affected by these north-south differences by the same phenomenon during the unstable and low-pressure characterized wet season. In contrast, during the stable dry season, unexpectedly LR_{min} is steeper than LR_{max} in the southern subregion. It is widely accepted that LR_{min} are weaker than LR_{max} , since they are generally impacted by several processes (e.g. cold air pool formations, thermal inversions in lowlands (Kattel and Yao, 2018)), which can weaken LR, as pointed out by many authors (Bonnardot *et al.*, 2012; Hanna *et al.*, 2017). However, the specific pattern found in the southern subregion could be attributed to some local factors of the database. The topographical position of the weather stations, which can induce the formation of nocturnal cold air pools at the position of the highest weather stations of the network (above 3,000 m a.s.l.), steepening the calculated LR (Duane et al., 2008). This hypothesis has been analyzed through the topographical position (bottom – slope – summit) of weather stations as a function of their elevation in relation to the surrounding areas. It has been observed (not shown in the results) that there are few weather stations located at summit topographical positions, being mainly located at the

bottom of high valleys, or on sloped areas. In addition, the lower atmospheric humidity content at high elevation leads to steeper values of LR in response to night overcooling in these higher locations. Moreover, the enhanced continentality condition in the southern subregion increases the daily thermal amplitude, and favors a steeper LR_{min} compared to LR_{max} . Continentality, low specific humidity, and location of weather stations could favor the diurnal heating at higher weather stations, usually located at the bottom of high valleys, thus weakening the whole subregional LR_{max} . This feature was less evident in the northern subregion, where there is lower air pressure, more atmospheric instability and higher specific humidity due to the proximity to the ITCZ (Takahashi *et al.*, 2007), in addition to the lower continentality of northern weather stations, causing that LR_{max} and LR_{min} were more balanced to the habitual pattern.

The weakening of LRs during the dry season when the atmosphere is rather stable has been reported in previous works (Richardson *et al.*, 1999; Pepin and Losleben, 2002; Harlow *et al.*, 2004; Marshall *et al.*, 2007), although this is not always valid, as Kattel *et al.* (2015) and Kattel and Yao (2018) show in their Himalayan works; and Córdova *et al.* (2016) in a specific Ecuadorian valley for a 12-month period. Moreover, LR_{max} was more intensified during the wet season. The dispersion of LR values is synthetized by showing values corresponding to the 25 and 75 quantiles. The percentiles are close to the mean values, suggesting low interannual LR variability. LR_{max} and LR_{min} were significant different in the south and in the north ($p < 0.05$), and northern and southern LRs were significantly different analyzing LR_{max} ($p < 0.05$) and LR_{min} ($p < 0.05$) data.

5.4 Links between ENSO and LRs

Table 2 shows the LR_{max} and LR_{min} as a function of the subregion, seasons and ENSO phases. For the ENSO phases, more complex patterns were found:

- LR – ONI: In the northern and southern subregions, the steepest LR_{max} during the wet season occur during La Niña phases, although they were only statistically significant ($p < 0.05$) in the northern subregion; during the dry season in the south, the steepest LR_{max} occurred during El Niño phases ($p < 0.05$) and in the northern subregion no

statistical significant ($p > 0.05$) ENSO phase differences were found. In terms of LR_{min} , the only statistically significant differences ($p < 0.05$) were found analyzing the northern subregion during the wet season, with steepest values during La Niña phases.

- LR – ICEN: In the northern subregion, no statistically significant ($p > 0.05$) differences between ENSO phases and LR_{max} and LR_{min} were found. In the southern subregion, the steepest LR_{max} ($p < 0.05$) occurred during El Niño phases in the wet and dry seasons.

Figure 7 illustrates the seasonal differences found in all combinations between ENSO indices, seasons and subregions. The differences between ONI and ICEN (comparing the lapse rates during the same ENSO phase calculated from both indices) were weak and statistically non-significant for El Niño ($p > 0.05$, with the exception of south LR_{min}), while being weak and statistically significant for La Niña ($p < 0.05$, with the exception of north LR_{min}) phases. However, the differences among the ENSO phases were statistically significant ($p < 0.05$), with the exception of ICEN phases in the northern subregion ($p > 0.05$), and ONI phases ($p > 0.05$) for the southern LR_{min} , in addition to ONI phases during the dry season. The differences between ENSO phases were smaller than the seasonal variability. In the southern subregion, it was possible to detect a weak and statistically significant steepness of LRs when the El Niño phase occurs, especially following ICEN phases. In the northern subregion, only ONI phases and during the wet season was statistically significant, showing a steepness during La Niña phases. In summary, it seems that ENSO effects were more detectable in the southern subregion, compared to the northern subregion, showing better response of the southern subregion to ICEN phases, and northern subregion to ONI phases, although with nuances in relation to El Niño and La Niña effects.

Therefore, similar to other studies (Bennett *et al.*, 2016; Morán-Tejeda *et al.*, 2016) in Puna (Bolivia and Chile) and Ecuador, respectively, the dependency between air temperature and the ENSO was not statistically significant in all cases. Moreover, ENSO effects are spatially variable and not equal over the whole south American coast (Morán-Tejeda *et al.*, 2016). The ENSO effects were stronger in the southern subregion, since its low variability and high

temporal stability facilitate strong air mass irruptions from the west (i.e. strong positive ENSO episodes). This relationship only during extreme episodes implies that the neutral and weak positive ENSO episodes fail to penetrate inland sufficiently (Dijkstra, 2006) to affect the weather station network and change the subregional LRs. Contrarily, during strong and very strong El Niño episodes, the west-to-east associated pattern could reach the mainland and the Andean lands in Ecuador and Peru, largely covering the weather station network and, thus, could alter air temperature conditions over the whole study area. Comparative analysis between ENSO indices has shown that the ICEN index is more appropriate for the southern subregion, as ENFEN (2012) and Takahashi et al. (2014) actively seek with the development of this index for the Peruvian territory, while ONI has higher influence in the northern subregion.

5.5 Comparison of Local and regional lapse rates

Figure 8 depicts the MAE between seasonal LRs calculated from the pairs of weather stations and those calculated using the whole network. Box-plots illustrate that MAE is less when elevation range between pairs is larger than 1,500 m, as their vertical range allows for properly detecting the vertical air temperature profile. On the other hand, box-plots showing extremely higher values ($> 20\text{ }^{\circ}\text{C km}^{-1}$) when elevation range is $< 500\text{ m}$. For all situations, the differences between the wet and dry seasons were detected, but with no clear pattern. MAE for LR_{max} was lower than LR_{min} for the northern and southern subregions. It can be observed that the median MAE tended to stabilize around $1\text{ }^{\circ}\text{C km}^{-1}$ for elevation ranges larger than 1,500 m. Euclidean distance between the most representative pairs (Supplementary Material – Figure 5) have been analyzed, but no significant patterns were found. The topographic position of pairs in relation to MAE have been analyzed (Supplementary Material – Figure 6.a.b), showing that it is not appropriate to choose only bottom located weather stations, since these pairs are not usually representative of the general behavior. The most representative pairs (shown in Supplementary Material – Figures 7.a.b) in almost all combinations had MAE values $< 0.3\text{ }^{\circ}\text{C km}^{-1}$. Seasonally, the wet season had better scores, in terms of MAE.

The findings suggest that there is a possibility to properly estimate the subregional seasonal LR using only a pair of stations. These findings imply that previous works carried out with few data can incur errors of low representativeness of the regional LRs. In the southern subregion, the most representative territory was the southeast, which has a large number of the most representative pairs. This allows for obtaining the subregional seasonal LR behavior for both the coastal and highlands territories. However, in all cases, the errors obtained using these representative stations were lower than those derived from the use of a fixed LR (e.g. the MELR). The low correlations in the majority of the selected pairs occurred due to the compensation between weak underestimations and overestimations of LRs along the study period. The remarkable low MAE values inform the reliability of the paired LRs. According to our findings in both northern and southern subregion, the calculation of LR from only two stations is possible, although it is necessary to choose weather stations representative of regional behavior, in addition to choosing weather stations with a minimum elevation range of at least 1,500 m; and studying the minimum number of weather stations needed to better represent lapse-rates.

To conclude, our findings indicate that due to various geographic, climatic, and topographic variables, LR is highly variable over space and time in the Andean region in Ecuador and Peru. This stresses the need to consider specific LRs rather than universal and fixed LRs (e.g. the MELR). However, it is noteworthy that the reference LR values are regionally specific and cannot be extrapolated to other regions, considering the large spatial and seasonal variability of air temperature on one hand and the possible impacts of local environmental factors on the other hand (Marshall *et al.*, 2007). It is not recommended to use the MELR, as it introduces large biases to air temperature estimations. Increasing the number of weather stations in mountain areas can improve estimation of air temperature LRs. This study contributes to better understanding of the factors controlling snow hydrology and water resources availability in dry areas. In this way, it has been possible to advance knowledge of the explanatory factors for its variability.

6. Conclusions

This study assessed, for the first time, changes in air temperature LRs over the Andean region in Ecuador and Peru using in situ temperature data from 1994 to 2011. The major findings of this study can be summarized as follows:

- (i) It is more complex to estimate LR_{min} than LR_{max} , given that T_{min} has more spatial heterogeneity and is more influenced by local meteorological processes.
- (ii) The calculated LR_{max} and LR_{min} are weaker than the fixed Mean Environmental Lapse Rate (MELR $-6.5\text{ }^{\circ}\text{C km}^{-1}$), which has been widely used to interpolate and extrapolate air temperatures with multiple aims. Importantly, the calculated LRs are spatiotemporally more variable. This study stresses the need to calculate specific LR for each study area and season, as the fixed and standard MELR cannot adequately reveal the large spatial and temporal variability of air temperature in regions of complex topography.
- (iii) LR_{max} and LR_{min} show steeper values during the wet season (October-May), with the exception of LR_{min} in the southern subregion, where continentality, topography, and specific humidity content could influence air temperature conditions.
- (iv) The ENSO phenomenon significantly influences LR variability in the southern subregion, while its impact is more variable in the north. In some exceptional events corresponding mainly to the strong and very strong positive ENSO (El Niño) events (e.g. 1997-1998), LRs can support an intense steepness.
- (v) LRs can be calculated using limited data (i.e. pair of weather stations); however, this was mainly restricted to weather stations with an elevation range over 1,500 m, where MAE is generally around $1^{\circ}\text{C km}^{-1}$.

These findings show the need to continue researching this issue for other spatial scales and geographical areas, so observed variability and patterns might be larger than commonly assumed by lapse rate users. In the future, it is necessary to advance in the assessment of the spatiotemporal variability and causes of LRs for other regions. Thus, based on our findings, the extrapolation of air temperature from lowlands to summits would be not recommended. In addition, an increase in the number of weather stations located in the summits is crucial to retrieve air temperature data over miles of km^2 in which they are generally extrapolated

without using empirical data. Thus, a comprehensive monitoring of highest elevation areas and summits are needed to better obtain LR_s for the whole study region, which may indirectly influence common human activities (e.g. water resources) or climate products as air temperature grid datasets.

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References

- Alonso-González E, Ignacio López-Moreno J, Gascoin S, García-Valdecasas Ojeda M, Sanmiguel-Vallelado A, Navarro-Serrano F, Revuelto J, Ceballos A, Esteban-Parra MJ, Essery R. 2018. Daily gridded datasets of snow depth and snow water equivalent for the Iberian Peninsula from 1980 to 2014. *Earth System Science Data*, 10(1). <https://doi.org/10.5194/essd-10-303-2018>.
- Ambrozova K, Laska K, Hrbacek F, Kavan J, Ondruch J. 2019. Air temperature and lapse rate variation in the ice-free and glaciated areas of northern James Ross Island, Antarctic Peninsula, during 2013-2016. *International Journal of Climatology*. John Wiley & Sons, Ltd, 39(2): 643–657. <https://doi.org/10.1002/joc.5832>.
- Appelhans T, Mwangomo E, Otte I, Detsch F, Nauss T, Hemp A. 2016. Eco-meteorological characteristics of the southern slopes of Kilimanjaro, Tanzania. *International Journal of*

Climatology. John Wiley & Sons, Ltd, 36(9): 3245–3258. <https://doi.org/10.1002/joc.4552>.

Barros VR, Doyle ME, Camilloni IA. 2008. Precipitation trends in southeastern South America: relationship with ENSO phases and with low-level circulation. *Theoretical and Applied Climatology*. Springer-Verlag, 93(1–2): 19–33. <https://doi.org/10.1007/s00704-007-0329-x>.

Barry R. 2008. *Mountain weather and Climate*. Cambridge University Press.

Barry R, Chorley R. 1987. *Atmosphere, Weather and Climate*. Taylor & Francis.

Bennett M, New M, Marino J, Sillero-Zubiri C. 2016. Climate complexity in the Central Andes: A study case on empirically-based local variations in the Dry Puna. *Journal of Arid Environments*. Academic Press, 128: 40–49. <https://doi.org/10.1016/J.JARIDENV.2016.01.004>.

Berrisford P, Dee D, Poli P, Brugge R, Fielding K, Fuentes M, Kallberg P, Kobayashi S, Uppala S, Simmons A. 2011. The ERA-Interim archive, version 2.0. *ERA report series*. ECMWF, 1: 23.

Blandford TR, Humes KS, Harshburger BJ, Moore BC, Walden VP, Ye H, Blandford TR, Humes KS, Harshburger BJ, Moore BC, Walden VP, Ye H. 2008. Seasonal and Synoptic Variations in Near-Surface Air Temperature Lapse Rates in a Mountainous Basin. *Journal of Applied Meteorology and Climatology*, 47(1): 249–261. <https://doi.org/10.1175/2007JAMC1565.1>.

Bolstad P V., Swift L, Collins F, Régnière J. 1998. Measured and predicted air temperatures at basin to regional scales in the southern Appalachian mountains. *Agricultural and Forest Meteorology*, 91(3–4): 161–176. [https://doi.org/10.1016/S0168-1923\(98\)00076-8](https://doi.org/10.1016/S0168-1923(98)00076-8).

Bonnardot V, Carey V, Madelin M, Cautenet S, Coetzee Z, Quénot H. 2012. Spatial variability of Night temperatures at a fine scale over the Stellenbosch Wine District, South Africa. *J. Int. Sci. Vigne Vin*, 46(1): 1–13.

Bradley RS, Keimig FT, Diaz HF, Hardy DR. 2009. Recent changes in freezing level heights in the Tropics with implications for the deglaciation of high mountain regions.

Geophysical Research Letters. John Wiley & Sons, Ltd, 36(17): L17701.

<https://doi.org/10.1029/2009GL037712>.

Bradley RS, Vuille M, Diaz HF, Vergara W. 2006. Climate change. Threats to water supplies in the tropical Andes. *Science (New York, N.Y.)*, 312(5781): 1755–6.

<https://doi.org/10.1126/science.1128087>.

Cárdenas Gaudry MM, Gutknecht D, Parajka J, Perdigão RAP, Blöschl G. 2017. Seasonality of runoff and precipitation regimes along transects in Peru and Austria. *J. Hydrol. Hydromech*, 65: 347–358. <https://doi.org/10.1515/johh-2017-0018>.

Córdova M, Céleri R, Shellito CJ, Orellana-Alvear J, Abril A, Carrillo-Rojas G. 2016. Near-surface air temperature lapse rate over complex terrain in the Southern Ecuadorian Andes: Implications for temperature mapping. *Arctic, Antarctic, and Alpine Research*. Institute of Arctic and Alpine Research, 48(4): 673–684. <https://doi.org/10.1657/AAAR0015-077>.

Dijkstra HA. 2006. The ENSO phenomenon: theory and mechanisms. *Advances in Geosciences*, 6: 3–15. <https://doi.org/10.5194/adgeo-6-3-2006>.

Dodson R, Marks D. 1997. Daily air temperature interpolated at high spatial resolution over a large mountainous region. *Climate Research*, 8(1): 1–20. <https://doi.org/10.3354/cr008001>.

Domínguez-Castro F, Vicente-Serrano SM, López-Moreno JI, Correa K, Ávalos G, Azorin-Molina C, El Kenawy A, Tomas-Burguera M, Navarro-Serrano F, Peña-Gallardo M, Gimeno L, Nieto R. 2018. Mapping seasonal and annual extreme precipitation over the Peruvian Andes. *International Journal of Climatology*. John Wiley & Sons, Ltd, 38(15): 5459–5475. <https://doi.org/10.1002/joc.5739>.

Du M, Liu J, Zhang X, Li Y, Tang Y. 2010. Changes of spatial patterns of surface-air-temperature on the Tibetan Plateau. *Latest Trends on Theoretical and Applied Mechanics, Fluid Mechanics and Heat & Mass Transfer*.

Du M, Zhang M, Wang S, Zhu X, Che Y. 2017. Near-surface air temperature lapse rates in Xinjiang, northwestern China. *Theoretical and Applied Climatology*, 1–14.

<https://doi.org/10.1007/s00704-017-2040-x>.

Duane WJ, Pepin NC, Losleben ML, Hardy DR. 2008. General characteristics of Temperature and Humidity Variability on Kilimanjaro, Tanzania. *Arctic, Antarctic, and Alpine Research* 2, 40(2): 323–334. [https://doi.org/10.1657/1523-0430\(06-127\)](https://doi.org/10.1657/1523-0430(06-127)).

Dumas MD. 2013. Changes in temperature and temperature gradients in the French Northern Alps during the last century. *Theoretical and Applied Climatology*. Springer Vienna, 111(1–2): 223–233. <https://doi.org/10.1007/s00704-012-0659-1>.

Durre I, Menne MJ, Gleason BE, Houston TG, Vose RS, Durre I, Menne MJ, Gleason BE, Houston TG, Vose RS. 2010. Comprehensive Automated Quality Assurance of Daily Surface Observations. *Journal of Applied Meteorology and Climatology*, 49(8): 1615–1633. <https://doi.org/10.1175/2010JAMC2375.1>.

ENFEN. 2012. *Definición operacional de los eventos El Niño y La Niña y sus magnitudes en la costa del Perú*. Lima.

Fang J-Y, Yoda K. 1988. Climate and vegetation in China (I). Changes in the altitudinal lapse rate of temperature and distribution of sea level temperature. *Ecological Research*, 3(1): 37–51. <https://doi.org/10.1007/BF02348693>.

Francou B, Vuille M, Favier V, Cáceres B. 2004. New evidence for an ENSO impact on low-latitude glaciers: Antizana 15, Andes of Ecuador, 0°28'S. *Journal of Geophysical Research*. John Wiley & Sons, Ltd, 109(D18): D18106. <https://doi.org/10.1029/2003JD004484>.

García D, Santiago Ochoa W. 2012. Relación entre crecimiento económico y medio ambiente en Ecuador a nivel provincial (Promedio 2010-2015). *Revista Amazónica Ciencia y Tecnología*. Universidad Estatal Amazónica, 6(2): 99–112.

Gardner AS, Sharp MJ, Koerner RM, Labine C, Boon S, Marshall SJ, Burgess DO, Lewis D. 2009. Near-Surface Temperature Lapse Rates over Arctic Glaciers and Their Implications for

Temperature Downscaling. *Journal of Climate*, 22(16): 4281–4298.

<https://doi.org/10.1175/2009JCLI2845.1>.

Grimm AM, Tedeschi RG, Grimm AM, Tedeschi RG. 2009. ENSO and Extreme Rainfall Events in South America. *Journal of Climate*, 22(7): 1589–1609.

<https://doi.org/10.1175/2008JCLI2429.1>.

Gruber A. 1972. Fluctuations in the Position of the ITCZ in the Atlantic and Pacific Oceans. *Journal of the Atmospheric Sciences*. American Meteorological Society, 29(1): 193–197.

[https://doi.org/10.1175/1520-0469\(1972\)029<0193:fitpot>2.0.co;2](https://doi.org/10.1175/1520-0469(1972)029<0193:fitpot>2.0.co;2).

Hanna E, Mernild S, Yde J, Villiers S. 2017. Surface Air Temperature Fluctuations and Lapse Rates on Olivares Gamma Glacier, Rio Olivares Basin, Central Chile, from a Novel Meteorological Sensor Network. *Advances in Meteorology*. Hindawi, 2017: 1–15.

<https://doi.org/10.1155/2017/6581537>.

Harlow RC, Burke EJ, Scott RL, Shuttleworth WJ, Brown CM, Petti JR. 2004. Research Note: Derivation of temperature lapse rates in semi-arid south-eastern Arizona. *Hydrology and Earth System Sciences*, 8(6): 1179–1185.

Hatfield JL, Prueger JH. 2015. Temperature extremes: Effect on plant growth and development. *Weather and Climate Extremes*. Elsevier, 10: 4–10.

<https://doi.org/10.1016/J.WACE.2015.08.001>.

Heynen M, Miles E, Ragetti S, Buri P, Immerzeel WW, Pellicciotti F. 2016. Air temperature variability in a high-elevation Himalayan catchment. *Annals of Glaciology*, 57(71): 212–222.

<https://doi.org/10.3189/2016AoG71A076>.

Holden J, Rose R. 2011. Temperature and surface lapse rate change: a study of the UK's longest upland instrumental record. *International Journal of Climatology*, 31(6): 907–919.

<https://doi.org/10.1002/joc.2136>.

Huang B, Thorne PW, Banzon VF, Boyer T, Chepurin G, Lawrimore JH, Menne MJ, Smith TM, Vose RS, Zhang H-M, Huang B, Thorne PW, Banzon VF, Boyer T, Chepurin G,

Lawrimore JH, Menne MJ, Smith TM, Vose RS, Zhang H-M. 2017. Extended Reconstructed Sea Surface Temperature, Version 5 (ERSSTv5): Upgrades, Validations, and Intercomparisons. *Journal of Climate*, 30(20): 8179–8205. <https://doi.org/10.1175/JCLI-D-16-0836.1>.

Hubbart J, Kavanagh K, Pangle R, Link T, Schotzko A. 2007. Cold air drainage and modeled nocturnal leaf water potential in complex forested terrain. *Tree Physiology*. Oxford University Press, 27(4): 631–639. <https://doi.org/10.1093/treephys/27.4.631>.

Immerzeel WW, Petersen L, Ragetti S, Pellicciotti F. 2014. The importance of observed gradients of air temperature and precipitation for modeling runoff from a glacierized watershed in the Nepalese Himalayas. *Water Resources Research*, 50(3): 2212–2226. <https://doi.org/10.1002/2013WR014506>.

Kaser G. 1999. A review of the modern fluctuations of tropical glaciers. *Global and Planetary Change*. Elsevier, 22(1–4): 93–103. [https://doi.org/10.1016/S0921-8181\(99\)00028-4](https://doi.org/10.1016/S0921-8181(99)00028-4).

Kattel DB, Yao T. 2018. Temperature-topographic elevation relationship for high mountain terrain: an example from the southeastern Tibetan Plateau. *International Journal of Climatology*. John Wiley & Sons, Ltd, 38: e901–e920. <https://doi.org/10.1002/joc.5418>.

Kattel DB, Yao T, Yang K, Tian L, Yang G, Joswiak D. 2013. Temperature lapse rate in complex mountain terrain on the southern slope of the central Himalayas. *Theoretical and Applied Climatology*, 113(3–4): 671–682. <https://doi.org/10.1007/s00704-012-0816-6>.

Kattel DB, Yao T, Yang W, Gao Y, Tian L. 2015. Comparison of temperature lapse rates from the northern to the southern slopes of the Himalayas. *International Journal of Climatology*. John Wiley & Sons, Ltd, 35(15): 4431–4443. <https://doi.org/10.1002/joc.4297>.

Kulshrestha S, Ramsankaran R. 2018. Investigating the performance of snowmelt runoff model using temporally varying near-surface lapse rate in Western Himalayas. *Current Science*, 114: 808–813. <https://doi.org/10.18520/cs/v114/i04/808-813>.

Kunkel KE. 1989. Simple Procedures for Extrapolation of Humidity Variables in the Mountainous Western United States. *Journal of Climate*, 2(7): 656–670.

[https://doi.org/10.1175/1520-0442\(1989\)002<0656:SPFEOH>2.0.CO;2](https://doi.org/10.1175/1520-0442(1989)002<0656:SPFEOH>2.0.CO;2).

Lewkowicz AG, Bonnaventure PP. 2011. Equivalent Elevation: A New Method to Incorporate Variable Surface Lapse Rates into Mountain Permafrost Modelling. *Permafrost and Periglacial Processes*. John Wiley & Sons, Ltd, 22(2): 153–162.

<https://doi.org/10.1002/ppp.720>.

Li X, Wang L, Chen D, Yang K, Xue B, Sun L. 2013. Near-surface air temperature lapse rates in the mainland China during 1962–2011. *Journal of Geophysical Research: Atmospheres*, 118(14): 7505–7515. <https://doi.org/10.1002/jgrd.50553>.

López-Moreno JI, Fontaneda S, Bazo J, Revuelto J, Azorin-Molina C, Valero-Garcés B, Morán-Tejeda E, Vicente-Serrano SM, Zubieta R, Alejo-Cochachín J. 2014. Recent glacier retreat and climate trends in Cordillera Huaytapallana, Peru. *Global and Planetary Change*. Elsevier, 112: 1–11. <https://doi.org/10.1016/J.GLOPLACHA.2013.10.010>.

Lussana C, Tveito OE, Uboldi F. 2018. Three-dimensional spatial interpolation of 2 m temperature over Norway. *Quarterly Journal of the Royal Meteorological Society*. John Wiley & Sons, Ltd, 144(711): 344–364. <https://doi.org/10.1002/qj.3208>.

Marengo JA, Williams ER, Alves LM, Soares WR, Rodriguez DA. 2016. Extreme Seasonal Climate Variations in the Amazon Basin: Droughts and Floods. Springer, Berlin, Heidelberg, 55–76.

Mark BG, French A, Baraer M, Carey M, Bury J, Young KR, Polk MH, Wigmore O, Lagos P, Crumley R, McKenzie JM, Lautz L. 2017. Glacier loss and hydro-social risks in the Peruvian Andes. *Global and Planetary Change*. Elsevier, 159: 61–76. <https://doi.org/10.1016/J.GLOPLACHA.2017.10.003>.

Marshall SJ, Sharp MJ, Burgess DO, Anslow FS. 2007. Near-surface-temperature lapse rates on the Prince of Wales Icefield, Ellesmere Island, Canada: implications for regional

downscaling of temperature. *International Journal of Climatology*, 27(3): 385–398.
<https://doi.org/10.1002/joc.1396>.

Minder JR, Mote PW, Lundquist JD. 2010. Surface temperature lapse rates over complex terrain: Lessons from the Cascade Mountains. *Journal of Geophysical Research*, 115(D14): D14122. <https://doi.org/10.1029/2009JD013493>.

Miró JR, Peña JC, Pepin N, Sairouni A, Aran M. 2017. Key features of cold-air pool episodes in the northeast of the Iberian Peninsula (Cerdanya, eastern Pyrenees). *International Journal of Climatology*. John Wiley & Sons, Ltd. <https://doi.org/10.1002/joc.5236>.

Moore FC, Diaz DB. 2015. Temperature impacts on economic growth warrant stringent mitigation policy. *Nature Climate Change*. Nature Publishing Group, 5(2): 127–131.
<https://doi.org/10.1038/nclimate2481>.

Morán-Tejeda E, Bazo J, López-Moreno JJ, Aguilar E, Azorín-Molina C, Sanchez-Lorenzo A, Martínez R, Nieto JJ, Mejía R, Martín-Hernández N, Vicente-Serrano SM. 2016. Climate trends and variability in Ecuador (1966-2011). *International Journal of Climatology*. Wiley-Blackwell, 36(11): 3839–3855. <https://doi.org/10.1002/joc.4597>.

Mortensen E, Wu S, Notaro M, Vavrus S, Montgomery R, De Piérola J, Sánchez C, Block P. 2018. Regression-based season-ahead drought prediction for southern Peru conditioned on large-scale climate variables. *Hydrology and Earth System Sciences*, 22: 287–303.
<https://doi.org/10.5194/hess-22-287-2018>.

Navarro-Serrano F, López-Moreno J, Azorin-Molina C, Alonso-González E, Tomás-Burguera M, Sanmiguel-Valladolid A, Revuelto J, Vicente-Serrano SM. 2018. Estimation of near-surface air temperature lapse rates over continental Spain and its mountain areas. *International Journal of Climatology*. Wiley-Blackwell. <https://doi.org/10.1002/joc.5497>.

Nigrelli G, Fratianni S, Zampollo A, Turconi L, Chiarle M. 2017. The altitudinal temperature lapse rates applied to high elevation rockfalls studies in the Western European Alps. *Theoretical and Applied Climatology*, 1–13. <https://doi.org/10.1007/s00704-017-2066-0>.

Ojha R. 2019. Identification of homogeneous regions of near surface air temperature lapse rates across India. *International Journal of Climatology*. John Wiley & Sons, Ltd. <https://doi.org/10.1002/joc.6073>.

Paniagua-Guzmán LJ. 2017. Condiciones microclimáticas en las lomas costeras y riesgos a la salud de los pobladores en Lima Metropolitana. In: Observatorio Geográfico de América Latina (ed) *Actas del EGAL XVI*. La Paz (Bolivia), 15.

Pepin N. 2001. Lapse rate changes in northern England. *Theoretical and Applied Climatology*, 68(1–2): 1–16. <https://doi.org/10.1007/s007040170049>.

Pepin N, Bradley RS, Diaz HF, Baraer M, Caceres EB, Forsythe N, Fowler H, Greenwood G, Hashmi MZ, Liu XD, Miller JR, Ning L, Ohmura A, Palazzi E, Rangwala I, Schöner W, Severskiy I, Shahgedanova M, Wang MB, Williamson SN, Yang DQ. 2015. Elevation-dependent warming in mountain regions of the world. *Nature Climate Change*. Nature Publishing Group, 424–430.

Pepin NC, Losleben M. 2002. Climate change in the Colorado Rocky Mountains: free air versus surface temperature trends. *International Journal of Climatology*, 22(3): 311–329. <https://doi.org/10.1002/joc.740>.

Pike G, Pepin NC, Schaefer M. 2013. High latitude local scale temperature complexity: the example of Kevo Valley, Finnish Lapland. *International Journal of Climatology*. John Wiley & Sons, Ltd, 33(8): 2050–2067. <https://doi.org/10.1002/joc.3573>.

Pinche Laure C. 1986. Estudio de las condiciones climáticas y de la niebla en la costa norte de Lima. Universidad Nacional Agraria La Molina, Lima (Perú).

Pulgar-Vidal J. 1987. Geografía del Perú: las ocho regiones naturales, la regionalización transversal, la microregionalización. .

Rangwala I, Miller JR. 2012. Climate change in mountains: A review of elevation-dependent warming and its possible causes. *Climatic Change*, 114(3–4): 527–547. <https://doi.org/10.1007/s10584-012-0419-3>.

Rasmusson EM, Carpenter TH. 1982. Variations in Tropical Sea Surface Temperature and Surface Wind Fields Associated with the Southern Oscillation/El Niño. *Monthly Weather Review*, 110(5): 354–384. [https://doi.org/10.1175/1520-0493\(1982\)110<0354:VITSST>2.0.CO;2](https://doi.org/10.1175/1520-0493(1982)110<0354:VITSST>2.0.CO;2).

Richardson S, Brock F, Semmer S, Jirak C. 1999. Minimizing Errors Associated with Multiplate Radiation Shields. *Journal of Atmospheric and Oceanic Technology*, 16(11): 1862–1872. [https://doi.org/10.1175/1520-0426\(1999\)016<1862:MEAWMR>2.0.CO;2](https://doi.org/10.1175/1520-0426(1999)016<1862:MEAWMR>2.0.CO;2).

Rolland C. 2003. Spatial and Seasonal Variations of Air Temperature Lapse Rates in Alpine Regions. *Journal of Climate*, 16(7): 1032–1046. [https://doi.org/10.1175/1520-0442\(2003\)016<1032:SASVOA>2.0.CO;2](https://doi.org/10.1175/1520-0442(2003)016<1032:SASVOA>2.0.CO;2).

Romshoo SA, Rafiq M, Rashid I. 2018. Spatio-temporal variation of land surface temperature and temperature lapse rate over mountainous Kashmir Himalaya. *Journal of Mountain Science*. Science Press, 15(3): 563–576. <https://doi.org/10.1007/s11629-017-4566-x>.

Sadoti G, McAfee SA, Roland CA, Fleur Nicklen E, Sousanes PJ. 2018. Modelling high-latitude summer temperature patterns using physiographic variables. *International Journal of Climatology*. John Wiley & Sons, Ltd, 38(10): 4033–4042. <https://doi.org/10.1002/joc.5538>.

Schemenauer RS, Cereceda P. 2006. Meteorological conditions at a coastal fog collection site in Peru. *Atmósfera*. Universidad Nacional Autónoma de México, 6(3).

Takahashi K, Battisti DS, Takahashi K, Battisti DS. 2007. Processes Controlling the Mean Tropical Pacific Precipitation Pattern. Part I: The Andes and the Eastern Pacific ITCZ. *Journal of Climate*, 20(14): 3434–3451. <https://doi.org/10.1175/JCLI4198.1>.

Takahashi K, Mosquera K, Reupo J. 2014. El Índice Costero El Niño (ICEN): Historia y actualización. *Boletín Técnico del Instituto Geofísico del Perú*, 1(2): 8–9.

Tomás-Burguera M, Jiménez Castañeda A, Luna Rico MY, Morata A, Vicente Serrano S, González-Hidalgo JC, Beguería S. 2016. Control de calidad de siete variables del banco nacional de datos de AEMET. In: Asociación Española de Climatología Congreso (10. 2016.

Alicante) (ed) *X Congreso Internacional AEC: Clima, sociedad, riesgos y ordenación del territorio*. Alicante, Spain, 407–415.

van der Meulen JP, Brandsma T. 2008. Thermometer screen intercomparison in De Bilt (The Netherlands), Part I: Understanding the weather-dependent temperature differences). *International Journal of Climatology*. John Wiley & Sons, Ltd, 28(3): 371–387. <https://doi.org/10.1002/joc.1531>.

Vicente-Serrano SM, Aguilar E, Martínez R, Martín-Hernández N, Azorin-Molina C, Sanchez-Lorenzo A, El Kenawy A, Tomás-Burguera M, Moran-Tejeda E, López-Moreno JI, Revuelto J, Beguería S, Nieto JJ, Drumond A, Gimeno L, Nieto R. 2017. The complex influence of ENSO on droughts in Ecuador. *Climate Dynamics*. Springer Berlin Heidelberg, 48(1–2): 405–427. <https://doi.org/10.1007/s00382-016-3082-y>.

Vicente-Serrano SM, López-Moreno JI, Correa K, Avalos G, Bazo J, Azorin-Molina C, Domínguez-Castro F, Kenawy A El, Gimeno L, Nieto R. 2018. Recent changes in monthly surface air temperature over Peru, 1964–2014. *International Journal of Climatology*, 38: 283–306. <https://doi.org/10.1002/joc.5176>.

Vuille M, Bradley RS. 2000. Mean annual temperature trends and their vertical structure in the tropical Andes. *Geophysical Research Letters*. John Wiley & Sons, Ltd, 27(23): 3885–3888. <https://doi.org/10.1029/2000GL011871>.

Vuille M, Francou B, Wagnon P, Juen I, Kaser G, Mark BG, Bradley RS. 2008. Climate change and tropical Andean glaciers: Past, present and future. *Earth-Science Reviews*. Elsevier, 89(3–4): 79–96. <https://doi.org/10.1016/J.EARSCIREV.2008.04.002>.

Vuille M, Franquist E, Garreaud R, Lavado Casimiro WS, Cáceres B. 2015. Impact of the global warming hiatus on Andean temperature. *Journal of Geophysical Research: Atmospheres*. John Wiley & Sons, Ltd, 120(9): 3745–3757. <https://doi.org/10.1002/2015JD023126>.

Wang G yi, Zhao M fei, Kang M yi, Xing K xiong, Wang Y hang, Xue F, Chen C. 2017.

Diurnal and seasonal variation of the elevation gradient of air temperature in the northern flank of the western Qinling Mountain range, China. *Journal of Mountain Science*. Science Press, 14(1): 94–105. <https://doi.org/10.1007/s11629-016-4107-z>.

Whiteman CD, Bian X, Zhong S, Whiteman CD, Bian X, Zhong S. 1999. Wintertime Evolution of the Temperature Inversion in the Colorado Plateau Basin. *Journal of Applied Meteorology*, 38(8): 1103–1117. [https://doi.org/10.1175/1520-0450\(1999\)038<1103:WEOTTI>2.0.CO;2](https://doi.org/10.1175/1520-0450(1999)038<1103:WEOTTI>2.0.CO;2).

Wilcoxon F. 1945. Individual Comparisons by Ranking Methods. *Biometrics Bulletin*. International Biometric Society, 1(6): 80. <https://doi.org/10.2307/3001968>.

WMO. 2014. *Guide to Meteorological Instruments and Methods of Observation*. Geneva, Switzerland.

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TITLE: Maximum and Minimum Air Temperature Elevation Lapse Rates in the Tropical Andean region of Ecuador and Peru

RUNNING TITLE: Air temperature lapse rates over Ecuador and Peru

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Graphical abstract:

- LRmax and LRmin are weaker than the fixed Mean Environmental Lapse-Rate (MELR - $6.5\text{ }^{\circ}\text{C km}^{-1}$).
- The steepest lapse-rates are registered in the wet season (October to Mat), with the exception of the LRmin in the South.
- ENSO phenomenon influences the LR in the South significantly, whereas its effect is highly variable in the North.

	MONTH	NORTH LR _{max}		NORTH LR _{min}		SOUTH LR _{max}		SOUTH LR _{min}	
WET SEASON	Oct	-4.6 (-4.8/-4.5)	-4.77 (-4.97/-4.54)	-3.8 (-4.2/-3.5)	-4.10 (-4.41/-3.78)	-3.6 (-3.7/-3.4)	-4.16 (-4.56/-3.75)	-4.6 (-4.7/-4.4)	-4.74 (-4.84/-4.54)
	Nov	-4.8 (-4.9/-4.7)		-4.0 (-4.1/-3.8)		-3.6 (-3.6/-3.5)		-4.8 (-5.1/-4.6)	
	Dec	-5.0 (-5.1/-4.8)		-3.9 (-4.1/-3.7)		-3.9 (-4.0/-3.8)		-4.5 (-4.6/-4.3)	
	Jan	-4.9 (-5.1/-4.6)		-4.3 (-4.6/-4.0)		-4.5 (-4.6/-4.3)		-4.6 (-4.7/-4.5)	
	Feb	-4.8 (-5.2/-4.5)		-4.3 (-4.7/-4.1)		-4.8 (-5.0/-4.6)		-4.7 (-4.8/-4.6)	
	Mar	-4.9 (-5.1/-4.7)		-4.4 (-4.9/-4.3)		-4.7 (-5.0/-4.5)		-4.7 (-4.8/-4.5)	
	Apr	-4.7 (-4.8/-4.7)		-4.2 (-4.3/-3.9)		-4.3 (-4.4/-4.2)		-4.8 (-5.0/-4.6)	
	May	-4.5 (-4.6/-4.3)		-4.0 (-4.3/-3.7)		-4.0 (-4.1/-3.7)		-5.2 (-5.3/-5.0)	
DRY SEASON	Jun	-4.2 (-4.3/-4.2)	-4.26 (-4.37/-4.12)	-3.8 (-4.1/-3.5)	-3.78 (-4.13/-3.49)	-3.6 (-3.7/-3.5)	-3.57 (-3.72/-3.37)	-5.2 (-5.4/-5.0)	-4.93 (-5.12/-4.70)
	Jul	-4.2 (-4.3/-4.1)		-3.9 (-4.2/-3.7)		-3.5 (-3.7/-3.3)		-5.0 (-5.1/-4.7)	
	Aug	-4.3 (-4.4/-4.2)		-3.8 (-4.1/-3.5)		-3.6 (-3.8/-3.4)		-4.9 (-5.1/-4.7)	
	Sep	-4.3 (-4.6/-4.2)		-3.6 (-3.9/-3.3)		-3.6 (-3.8/-3.4)		-4.6 (-4.9/-4.4)	

Table 1. Reference monthly and seasonal mean (and 25th / 75th Percentile information) LR_{max} and LR_{min} (in °C km⁻¹) to northern and southern subregions.

SEASON	LR _{max} (in °C km ⁻¹)		ENSO Index Phase	
	NORTH	SOUTH		
WET SEASON (October-May)	-4.73 (-4.89/-4.55)*	-4.07 (-4.38/-3.79)	El Niño (+)	ONI
	-4.63 (-4.85/-4.43)*	-4.12 (-4.49/-3.71)	Neutral	
	-4.91 (-5.16/-4.67)*	-4.26 (-4.76/-3.73)	La Niña (-)	
	-4.68 (-4.85/-4.51)	-4.09 (-4.37/-3.78)*	El Niño (+)	ICEN
	-4.82 (-5.01/-4.62)	-4.25 (-4.69/-3.85)*	Neutral	
DRY SEASON (June-September)	-4.67 (-4.90/-4.52)	-3.63 (-3.74/-3.52)*	La Niña (-)	ONI
	-4.26 (-4.46/-3.99)	-3.95 (-4.07/-3.76)*	El Niño (+)	
	-4.19 (-4.28/-4.08)	-3.51 (-3.68/-3.35)*	Neutral	
	-4.37 (-4.54/-4.25)	-3.44 (-3.56/-3.36)*	La Niña (-)	ICEN
	-4.35 (-4.53/-4.19)	-3.76 (-3.98/-3.43)*	El Niño (+)	
	-4.22 (-4.34/-4.07)	-3.53 (-3.68/-3.46)*	Neutral	
	-4.23 (-4.33/-4.19)	-3.34 (-3.38/-3.31)*	La Niña (-)	
	LR _{min} (in °C km ⁻¹)		ENSO Index Phase	
	NORTH	SOUTH		
WET SEASON (October-May)	-3.99 (-4.36/-3.62)*	-4.76 (-4.86/-4.53)	El Niño (+)	ONI
	-4.04 (-4.31/-3.73)*	-4.76 (-5.03/-4.52)	Neutral	
	-4.23 (-4.61/-3.90)*	-4.70 (-4.82/-4.56)	La Niña (-)	
	-3.96 (-4.27/-3.70)	-4.87 (-5.16/-4.59)*	El Niño (+)	ICEN
	-4.17 (-4.50/-3.82)	-4.72 (-4.83/-4.55)*	Neutral	
DRY SEASON (June-September)	-3.99 (-4.38/-3.50)	-4.51 (-4.70/-4.33)*	La Niña (-)	ONI
	-3.67 (-3.94/-3.41)	-5.06 (-5.51/-4.42)	El Niño (+)	
	-3.80 (-4.15/-3.45)	-4.90 (-5.08/-4.70)	Neutral	
	-3.81 (-4.08/-3.60)	-4.91 (-5.12/-4.79)	La Niña (-)	
	-3.98 (-4.37/-3.69)	-5.24 (-5.48/-5.05)*	El Niño (+)	
	-3.66 (-3.90/-3.44)	-4.86 (-5.06/-4.68)*	Neutral	
	-3.92 (-4.14/-3.67)	-4.65 (-4.83/-4.42)*	La Niña (-)	

Table 2. Reference seasonal mean (and 25th / 75th Percentile information) LR_{max} and LR_{min} (in °C km⁻¹), as a function of the subregion and ENSO phases. Asterisk (*) represent significant (<0.05) LR_s differences between positive (El Niño) and negative (La Niña) episodes.

Figure 1. Topography of the study domain. The northern and southern subregions are delimited by the 9°30'S parallel. The available, selected (red dots), fog rejected (blue dots) and rejected (denoted with x symbol) weather stations are shown. Two cross-sectional elevation profiles for the northern and southern subregion are also included (solid grey lines).

210x297mm (200 x 200 DPI)

Figure 2. The total number of the selected meteorological observatories following the different steps of quality control and homogenization testing for both northern (green) and southern (golden) subregion. Raw database (grey) has not subregion distinction due to the location lags.

90x94mm (600 x 600 DPI)

Figure 3. Example of MODIS-Terra satellite images in two situations of (i) coastal fog-covered, and (ii) cloud-free days for both (a-b) northerh, and (d-e) southern subregions. The vertical distribution of air temperature is represented in lower panels. Coastal fog-free stations of the northern (> 400 m a.s.l.) and southern subregion (> 600 m a.s.l.) are represented in red, while weather stations located below the coastal fog elevation threshold were represented in blue. Lines represent the best linear fitted model between elevation and air temperature using all available weather stations (blue lines) and using only fog-free weather stations (red lines).

210x147mm (200 x 200 DPI)

Figure 4. Vertical distribution of the selected station network. Coastal fog-free stations of the northern (> 400 m a.s.l.) and southern subregion (> 600 m a.s.l.) are represented in red, while stations impacted by coastal fog are shown in blue.

Figure 5. Monthly MAE (October 1994 – September 2011) between the observed and estimated maximum and minimum air temperatures for the northern (green) and southern (orange) subregions. The median (black line) and the interquartile range (boxes; Y-axis) are shown.

210x147mm (200 x 200 DPI)

Figure 6. (a) Daily, monthly and seasonal North (a.1) and South (a.2) series of LRmax and LRmin. Mean Environmental Lapse-Rate (MELR $-6.5^{\circ}\text{C km}^{-1}$) was represented by dashed grey line; (b) Monthly and seasonal 500 hPa specific atmospheric humidity (in g kg^{-1}); (c) ENSO El Niño (red), Neutral (green) and La Niña (blue) phases based on the ICEN index (c.1) and the ONI index (c.2).

210x296mm (200 x 200 DPI)

Figure 7. LR_{max} and LR_{min} by means of the ENSO phases and indices distribution for both the wet (W) and dry (D) seasons during the common period October 1994 – September 2011. La Niña (blue), Neutral (green) and El Niño (red) are represented.

210x147mm (200 x 200 DPI)

Figure 8. Seasonal LR_{max} and LR_{min} MAE distribution by season (i.e. wet and dry) and elevation range between pairs (in meters) for both the northern and southern subregions. MAE is represented by a logarithmic y-axis from 0.1 to 100 °C km⁻¹ due to aberrant values found. The median (black line), the interquartile range (boxes), and whiskers are shown.

210x147mm (200 x 200 DPI)