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RESEARCH ARTICLE

Meteorological Applications RMetS

Time-lagged inverse-distance weighting for air temperature analysis in an equatorial urban area (Guayaquil, Ecuador)

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Abstract

It is well known that sudden variations of air temperature have the potential to cause severe impacts on human health. Therefore, it becomes necessary to provide information capable of quantifying the severity of the problem, considering that the continuous increase of temperature due to global warming and urban development will cause more intense effects in heavily populated areas. Due to its geographical location and local characteristics, Ecuador, a country located on the western coast of South America, is characterized by a high vulnerability to climatic extremes. The present research develops an evaluation of urban climate change effects through the analysis of extreme temperature indices using four meteorological stations situated in the city of Guayaquil (southwest Ecuador). Since the available data are not adequate for extreme temperature indices criteria, it was necessary to employ an infilling method for times series in an innovative way that can be applicable at the small scale. Thus, a cross-correlation-enhanced inverse distance weighting (CC-IDW) method was proposed. The method entails a spatial interpolation based on data of urban stations situated outside of Guayaquil by taking into account cross-correlation among times series at precise lags that leads to an improvement in the way of estimating the missing values. Subsequently, a homogeneity test, data quality control and the calculation of extreme temperature indices chosen from those proposed by the World Meteorological Organization (WMO) were implemented. The results show that there is a general tendency of warming with quite homogenous temperatures for all considered stations. However, it should be recognized that the climate pattern of this region is strongly modulated by the El Niño Southern Oscillation (ENSO) cycle. Only for two extreme indices: the highest maximum temperature (TXx) and the warm days (TX90p), are the resulting trend co-efficients statistically significant. The study suggests a deteriorated climatic condition due to heat stress that warrants further study using the available database for the city of Guayaquil.

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KEYWORDS

cross-correlation, Ecuador, extreme temperature indices, inverse distance weighting (IDW), missing data, urban area

1 | INTRODUCTION

Climate change and variability (especially expressed in terms of temperature fluctuations) play an essential role in human life, and with the current and projected trends of climate change this link has become more influential. In essence, one of the United Nations' (UN) Sustainable Development Goals "[to] ensure healthy lives and promote well-being for all at all ages" (SDG 3) is closely related with SDG 13 on climate change: "[to] take urgent action to combat climate change and its impacts" (Pezzoli *et al*., 2016). A landmark report of the UN's Intergovernmental Panel on Climate Change (IPCC) paints a far more severe picture of the immediate consequences of climate change than previously thought by expressing the need to transform the world economy "at a speed and scale that has no documented historic precedent" in order to mitigate the adverse impacts (Allen *et al*., 2018). The IPCC authors report that if greenhouse gas emissions continue at the current rate, the atmosphere will warm up by as much as 1.5°C above preindustrial levels by 2040, inundating coastlines and intensifying climate extremes (IPCC, 2014; Allen *et al*., 2018).

In particular, a worrying aspect concerns the increase in the frequency and intensity of heatwaves, especially in large urban areas that present higher risks of exposure than suburban and rural areas. These effects are due to the urban heat island (UHI) that is more intense during the night (Hass *et al*., 2016). Indeed, Hass *et al*. (2016) studied the fact that urban areas exhibit asymmetries in daily maximum temperatures (daytime) and daily minimum temperatures (night-time) cycles compared with the surrounding areas. Thermal stress in cities increases with high levels of night-time temperatures, reducing the possibility for the population to refresh itself. Many studies have noted not only the difference when comparing urban and rural areas but also a possible increase of the UHI effects between neighbouring urban areas (Luber and McGeehin, 2008; Hass *et al*., 2016). As Nakata-Osaki *et al*. (2018) reported, this characteristic is the result of a local microclimate due to urban features that modify the climate variables and their perception by the population, and it demonstrates that the phenomenon of the UHI has regional variability (Nakata-Osaki *et al*., 2018). Additionally, scientists have shown that tropical cities observe different temporal developments of the UHI and that it occurs more intensely during the daytime; this is one of the more considerable differences from mid-latitudes (Dias *et al*., 2009). The research published by Hannel (1976) on the temperatures recorded in the equatorial city of Quito (Ecuador) suggested the need to develop detailed studies of the features that influence the UHI in several other equatorial towns, which have to be weighted differently under various macroclimatic and topographic conditions.

Moreover, it has been assessed that tropical climates are more critical because of the higher health risk to which the population is exposed, especially where there is more urbanization (Johansson *et al*., 2018). For example, the strong impact of high temperatures on vector-borne diseases as dengue transmission, a mosquito-borne viral tropical disease, can be mentioned. Stewart Ibarra *et al*. (2013) evidenced the increasing risk of dengue transmission due to gradual growing minimum temperatures as a consequence of climate warming in Ecuador.

South American countries have perceived for some time the importance of the analysis and comprehension of climate extremes. One important actor in weather risk management in this region is the Centro Internacional para la Investigación del Fenómeno de El Niño (CIIFEN) which has supported decision-makers on the planning of adaptation and mitigation politics to climate change since 2003. The CIIFEN has suggested the use of models and software for the calculation of climatic indices and that trends at local scales should be observed (Martínez Guingla and Mascarenhas, 2009). One of the first attempts to collect climate information in South America is the analysis conducted by Vincent *et al*. (2005), the result of a workshop held in Maceiò, Brazil, in August 2004 that aimed at improving the research on changes in climate extremes. The study considers times series (1960–2000) belonging to meteorological stations situated all around the continent of South America in order to analyse climate change indices. The trends resulting from this analysis showed relevance in the indices based on daily minimum temperature, with high percentages of warm nights in many stations (Vincent *et al*., 2005). Another study by Skansi *et al*. (2013), resulting from a regional workshop in Guayaquil (Ecuador) in 2013, provides a more complete analysis compared with the workshop held in Brazil in 2004, which had limitations regarding the space–time availability of high-quality daily times series. In the later study, daily maximum and minimum temperatures and precipitation series were assessed

over South America for two different periods: 1950–2010 and 1960–2009. The results of the extreme indices calculation provided evidence of warming and wetting signals since the mid-20th century (Skansi *et al*., 2013). Further analysis including those of Cáceres *et al*. (1998) and Nieto *et al*. (2002) underline a general trend of temperature increases in Ecuador (Cáceres *et al*., 1998; Nieto *et al*., 2002). The emerging tendency is to deepen the analysis focused on variability of temperature and precipitations and their links to the El Niño southern oscillation (ENSO), because of its significant influence on the climate of South America and especially in the coastal region of Ecuador and Peru (Vicente-Serrano *et al*., 2017). The ENSO phenomenon, when it occurs, includes many variables that exhibit changes under normal conditions. In the specific case of Ecuador, it provides a series of damaging impacts on human health and society, particularly regarding the effects due to changes in rainfall regimes and oscillation of temperatures (Mora and Willems, 2012; Morán-Tejeda *et al*., 2016).

Within this context, a small-scale analysis conducted on the warm–humid city of Guayaquil may be useful to understand the climatic variability within the town under the current climate change scenarios. The goal of the research is the analysis of extreme temperature indices variability of daily temperature time series referred by four meteorological stations located in the urban area of Guayaquil, on the southwest coast of Ecuador. It was decided to study the pattern of extreme temperature considering several stations across the city instead of one. This choice was derived by the failure of previous studies on temperature analysis in urban areas in the identification of the small-scale climatic variability associated with land use within a metropolitan area (Hass *et al*., 2016). This made possible the fact that, for the first time in this region, there is an intent to determine the extreme temperatures trends in an urban area to comprehend whether the output could give some information about climate change. This allows a better representativeness of climatic events, and thus increasing knowledge to support mitigation and/or adaptation actions. Considering that the available data, measured by the four meteorological stations in the urban area, is] not sufficient to evaluate the extreme temperature indices, an innovative methodology to build a "virtual database" in a metropolitan area is developed in the present research. The cross-correlation-enhanced inverse distance weighting (CC-IDW) method consists of a spatial interpolation method based on urban stations situated outside of Guayaquil that takes into account cross-correlations (similarity) among lagged-times series as described in Section 2. This technique performs well when the neighbouring stations are closer to the target station, such as in the present case (Shabalala *et al*., 2019). The infilling method for the times-series IDW, especially for daily temperature data, is usually developed for macro-scale analysis (Ahrens, 2006; Morales-Moraga *et al*., 2019). The novelty presented here is that this research employs the IDW method merged with the CC to develop the spatial interpolation for urban climate analysis, allowing the calculation of extreme indices and at the same time reducing the high costs to maintain the dense urban meteorological stations network. The obtained "virtual" series corresponding with the four meteorological stations situated in Guayaquil were used to calculate the extreme temperature indices chosen among those proposed by the World Meteorological Organization (WMO) Commission for Climatology (CCl)/World Climate Research Programme (WCRP) Climate Variability and Predictability project (CLIVAR)/Joint Commission for Oceanography and Marine Meteorology (JCOMM) Expert Team on Climate Change Detection and Indices (ETCCDI). Data quality control (QC) and analysis of the selected climatic indices were carried out using the computer program RClimDex Software v.1.1 freely available at http://etccdi.pacificclimate.org/software.shtml. The results and discussion are summarized in Section 3. Conclusions and future evolution are described in Section 4.

2 | MATERIALS AND METHODS

2.1 | Study area

Due to its geographical location, Ecuador is a country characterized by a high vulnerability to climatic extremes (CIIFEN, 2012). The city of Guayaquil (located at 2° 12′ S, 79° 54′ W) has a relatively smooth topography, with the lowest points of the city located at 4 masl and the highest at around 100 masl. Moreover, it is surrounded by two bodies of water: the Guayas River and an estuary (Estero Salado), which connects directly with the Pacific Ocean. Guayaquil is the largest city in Ecuador, with a population of about 2.6 million inhabitants when considering the entire conurbation (Delgado, 2013). In the stereotype of most South American metropolises, Guayaquil presents large areas reserved for a few wealthy families, in contrast to several crowded areas where the most impoverished population lives. The typical landscape is characterized by regular orthogonal streets lined mostly with low buildings, which are frequently constructed from a material with a high albedo and which are not capable of insulation, and which are responsible for high temperatures due to energy storage (Dias *et al*., 2009).

Although the city is part of the coastal region of Ecuador, with a stable warm–humid climate, the area is moderated by the cooling effect of the Humboldt Current along the coast. There are two seasons: the rainy season from December to April (with 80% of the annual rainfall and mean temperature of 26.4°C), due to the presence of

both the El Niño current that warms the western coast of South America and the latitudinal migration of the Intertropical Convergence Zone (ITCZ), which produces an excess of humidity; and the dry season from May to November (mean temperature of 23.6°C), modulated by the Humboldt Current which introduces cold air (Rossel and Cadier, 2009). Overall, the temperatures do not show extreme variations to clearly distinguish the seasons (Morán-Tejeda *et al*., 2016). It should be kept in mind that this typical pattern can be drastically altered with the presence of the ENSO events (Shabbar, 2006).

2.2 | Data description

Data on maximum and minimum temperatures (°C) were obtained from the Instituto Nacional de Meteorología e Hidrología (INAMHI), which is the institution that manages weather stations in Ecuador. The four stations inside Guayaquil present a registry activity that covers the period 2013–2014. Although the INAMHI was founded in 1961, it exhibits huge deficits due to the undeveloped infrastructures of the country (roads, media and specialised staff) (Emck, 2007). Thus, given that the available time series are incomplete and short for the calculation of accurate ETCCDI extreme temperature indices, it is necessary to find other data sets from urban weather stations situated outside of Guayaquil to create a "virtual data set" inside the metropolitan area. The spatial distribution of weather stations available is not optimal since they are located far from each other, thus generating spatial gaps. Thus, the working radius to search for suitable meteorological stations was extended to 80 km from Guayaquil when in the presence of areas with a similar topography and climatic dynamics. Only three times series associated with meteorological stations located outside Guayaquil in three different cities are incorporated into the analysis because their eligibility threshold of missing data is acceptable (not exceeding 25% of not available—n.a.). Another station within Guayaquil (located at the Universidad Estatal named Guayaquil U.E.) was considered to check the indices, even though the temporal coverage was different. Tables 1 and 2 give an overview of the stations considered in the present research; Figure 1 shows the area of study and the location of all stations.

2.3 | Descriptive statistical analysis and missing data imputation strategy

Figure 2 shows the pattern of the overall methodology implemented in this analysis.

The time-series were subjected to a preliminary descriptive statistical analysis using R software (R Core Team, 2016). This involved obtaining an overview of the series patterns and identifying anomalies and potential outliers (through, for instance, graphical output such as monthly box plots). Data series gathered from all considered weather stations were studied through descriptive statistical analysis of maximum and minimum temperatures. The intent is to understand the dynamism and composition of missing values, and eventually to underline the periodicity, namely the constancy of seasonality seen as a repetition of phenomena through time. From this first analysis emerges a significant deficiency of minimum temperatures series concerning the meteorological archive, which provides only integer and not decimal values. In such a situation, it is difficult to obtain a reliable variability's estimate of temperatures, and it is symptomatic of the bad quality and low reliability of measurements.

Among the several techniques for missing data imputation available to overcome this lack of useful data within urban areas (e.g. Donders *et al*., 2006), the site-dependent effect method (SDEM), introduced by Plaia and Bondì (2006) in research concerning the spatio-temporal variability of PM_{10} concentration due to meteorological variables, was evaluated. Those authors focused on the importance of each monitoring site's effect, considering its space and time information: weekly, daily and hourly impact depending on the site, and summarizing them to achieve the evaluation of missing values. The performance of this method was tested through a simulation of one incomplete data set. However, the method was not entirely satisfactory for the present research because it allows only for the input of missing data inside the temporal domain of the considered series, while with a spatial interpolation technique it is possible to obtain a value outside the temporal domain of a series (if data in close sites are available). Therefore, a strategy of imputation suitable for spatio-temporal data with a small number of nearby sites where data are available for a longer period of time is proposed. This provides a technique to build the "virtual data" for four urban stations in Guayaquil, taking advantage of the available information close in both space and time, even for a sub-period. In more detail, a two-step procedure is proposed: (1) analysis of cross-correlation functions (CCFs) in the temporal subdomain with data available at urban sites (both in Guayaquil and outside the city); and (2) spatial interpolation at urban sites in Guayaquil of temporally lagged data with the lag chosen in order to maximize the observed cross-correlations in the first step. This proposal was named the cross-correlation-enhanced inverse distance weighting method (CC-IDW), since the CCF estimation is used to improve the IDW spatial interpolation in the second step.

TABLE 1 Meteorological stations used in the study and their locations

Station	Locality	Region	Latitude (° N, ′, ″)	Longitude (° E, ′, ″)
EMA DURAN-RADIOSONDEO	Guayaquil	Guayas	2° 10′ 10.20″ S	79° 50′ 0.24″ W
EMA_COE MONTEBELLO	Guayaquil	Guayas	2° 5′ 20.86″ S	79° 56′ 25.63″ W
EMA PUERTO HONDO	Guayaquil	Guayas	2° 11′ 26.43″ S	80° 1′ 26.59″ W
EMA SONGA	Guayaquil	Guayas	2° 5′ 20.86″ S	79° 56′ 25.63″ W
GUAYAQUIL UNIVERSIDAD ESTATAL (RADIO SONDA)	Guayaquil	Guayas	2° 10′ 50″ S	79° 53′ 59″ W
MILAGRO (INGENIO VALDEZ)	Milagro	Guayas	2° 8′ 1″ S	79° 36′ 1″ W
BABAHOYO-UTB	Babahoyo	Los Rios	1° 47′ 49″ S	79° 32′ 0″ W
INGENIO AZTRA (LA TRONCAL)	La Troncal	Cañar	2° 26′ 15″ S	79° 21′ 09″ W

TABLE 2 Observations, missing data and temporal length of the reference stations

Station	Observations	"n.a." T_{max}	% "n.a." T_{max}	"n.a." T_{min}	% "n.a." T_{min}	Period
DURAN	423	178	42%	178	42%	2013/03–2014/03
MONTEBELLO	423	173	41%	173	41%	2013/03–2014/03
PUERTO HONDO	423	172	41%	172	41%	2013/03–2014/03
SONGA	423	172	41%	172	41%	2013/03–2014/03
GUAYAQUIL U.E.	8,583	910	11%	942	11%	1992/02–2015/07
MILAGRO	16,649	2,325	14%	2,453	15%	1970/01–2015/07
BABAHOYO	12,358	2,596	21%	2,664	21.5%	1980/06–2014/03
INGENIO AZTRA	9,620	1,276	13%	1,264	13%	1989/05–2015/08

With the intent to observe the similarity in temperatures patterns between four urban stations and those three outside of Guayaquil and to study the dynamic evolution of times series, it is then necessary to consider the aspect of correlation having to deal with data observed in different moments. In this specific case, the CCF is used to analyse the relationship between two times series at several lags (Chatfield, 2004). Therefore, using the open-source R software, the CCFs are estimated for each urban series in couple with the other three out of Guayaquil on both variables (daily maximum and minimum temperatures). The results show positive correlation co-efficients, implying that when one series increases/decreases, the other increases/decreases with a certain delay in time (lag). In particular, it was observed that all the evaluated CCFs have a peak at lag $h = 1$, meaning that one series has the highest linear correlation co-efficient with the other one considered one day before. A one day lag refers to one day before, and it means that the data series is regarded at time $t - 1$.

For the second step, given the small number of sites close to the urban area considered, the IDW method was chosen for spatial interpolation (Shepard, 1968). Data at time $t - 1$ for the three urban stations out of Guayaquil were weighted depending on distance (Figure 3) to each of the four urban sites (Duran, Montebello, Puerto Hondo and Songa) and averaged to obtain a spatial prediction for the urban site at time t. It is important to remember that the IDW is not a stochastic spatial prediction method so that there is no variance associated with the prediction. For this reason, in order to assess the goodness of this spatial prediction, it was realized that a comparison between original data and interpolated ones (Figure 4) showed a good correlation. It was then possible to rebuild the four data sets through the IDW prediction over 24 years (a common period among the considered stations: January 2, 1990–January 1, 2014). For maximum temperatures series, this imputation was conducted on missing values; meanwhile, for minimum temperatures, it was performed on entire data sets because of their limited reliability.

2.4 | Descriptive statistical analysis, time-series quality control (QC) and homogeneity testing

After a preliminary descriptive statistical analysis, data were ready for examination under the QC criteria by

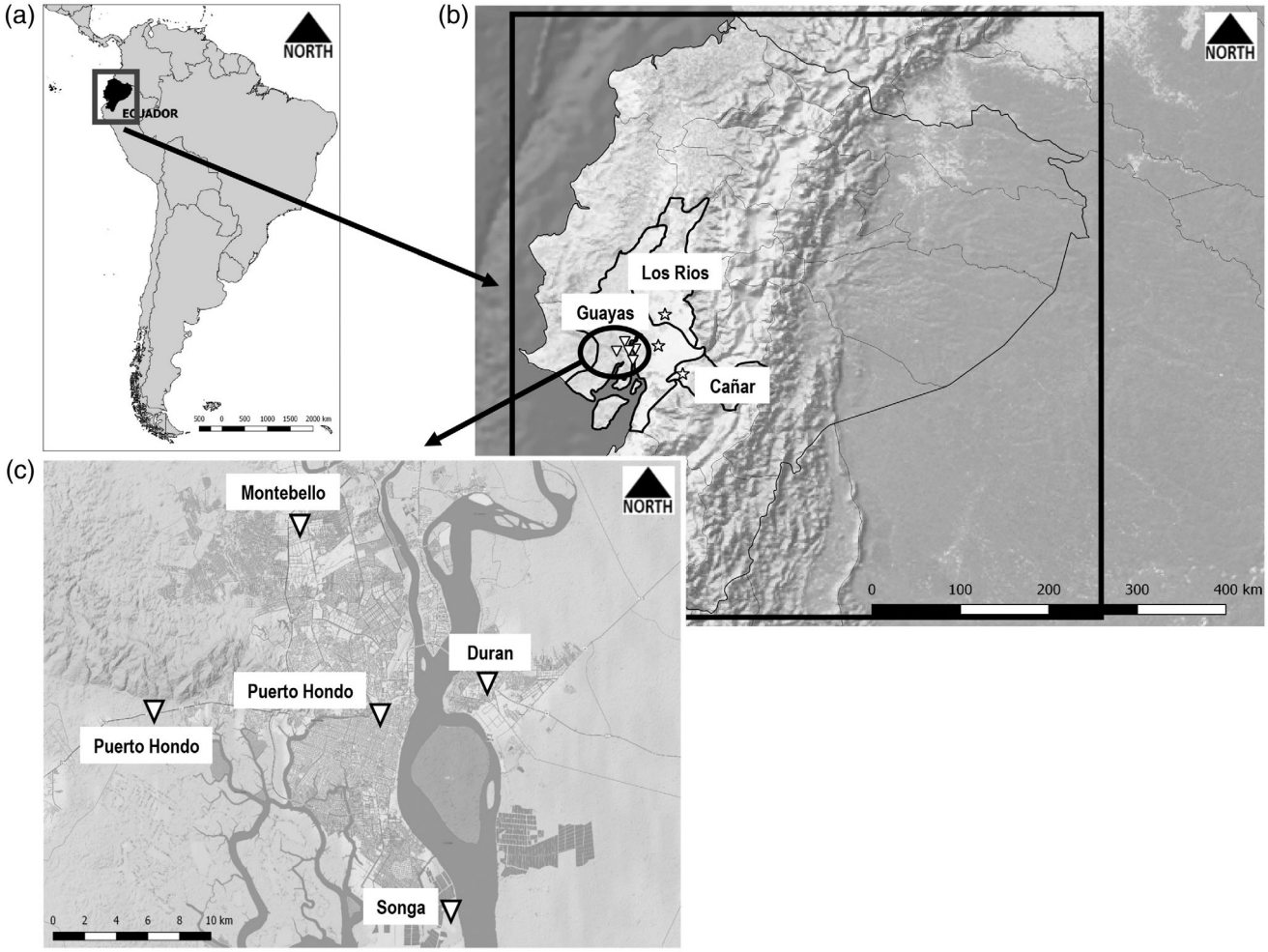


FIGURE 1 (a) Location map of Ecuador; (b) focus on the provinces (Guayas, Los Rios, Cañar) considered in the analysis (stars show the urban stations used to create the "virtual data set"); and (c) triangles show the urban weather stations of the city of Guayaquil

testing for the presence of possible extreme values (outliers), inhomogeneity (sudden changes in the trend of a variable) or absence of measurements in the series due to changes in the detecting instruments, relocation of tools, measurement error, activity pauses, change in land use, and so on (García-Garizábal and Romero, 2016). Through the use of the RClimDex software, this assessment allows for the identification and documentation of potential non-systematic errors and ensures that the data series are free of gross errors (Skansi *et al.*, 2013). For the elimination of outliers, a reception region was first defined as [mean – n*std, mean + n*std], namely the mean $\pm$ n times the standard deviation of the daily value. It was used $n = 3$ for this study. Some studies use $n = 4$ to reduce the detection of outliers (Zhang *et al.*, 2005; Keggenhoff *et al.*, 2015). On the other hand, many researchers prefer $n = 3$ to guarantee a more accurate and finer analysis (Aguilar *et al.*, 2005). The outliers identified were replaced with not available (n.a.) values. This pre-processing data analysis is a very tricky phase for the consecutive steps of the analysis so that it is considered appropriate to follow the automatized process QC in Rclimdex. Having removed the outliers, it is possible to test the time series for homogeneity and, if necessary, run a homogenization technique. This step is necessary because it allows the elimination of irregularities in the time series due to non-weather factors that could invalidate the results of the climatic analysis. These irregularities are called "changepoints" and are caused by many anthropic causes, as stated above. For example, in urban areas such as Guayaquil, with a high concentration of vehicles, industries, construction, pollution, and so on, temperatures tend to reach extremes as the UHI effect. Aguilar *et al.* (2003) identified 14 assessment methods available in the literature for the homogeneity test proposed in the World Climate Data and Monitoring Programme (WCDMP). The selection of an appropriate homogenization technique depends on the climatic variables and time scale (annual, monthly or daily times series). The homogeneity testing chosen in the present

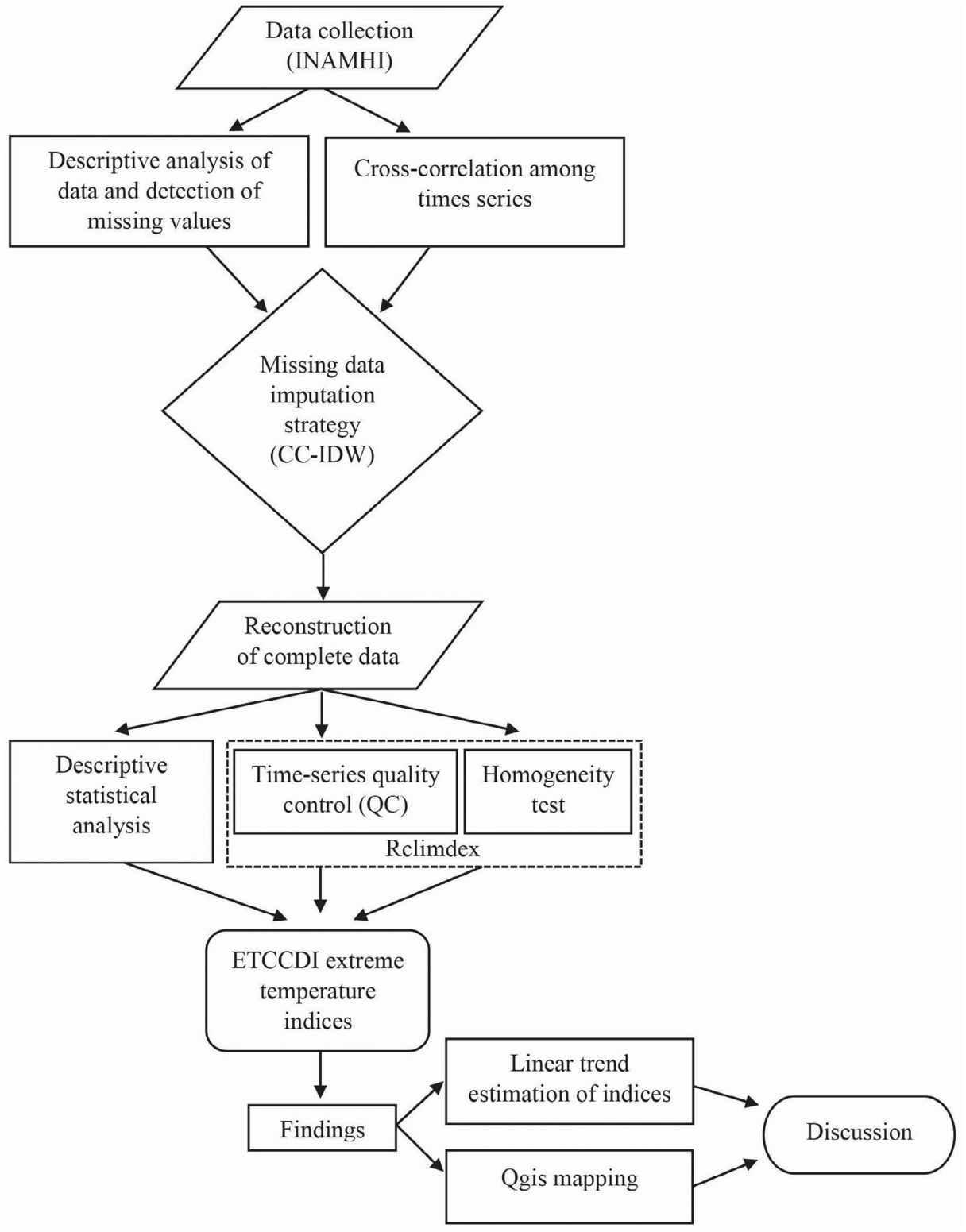


FIGURE 2 Flowchart of the methodology

study is an indirect method: the penalized maximal *F*-test (PMFT) which works through the opensource software RH_Test_V4 (freely available at http://etccdi.pacificclimate.org) provided by ETCCDI (2013). This method requires two distinct phases: first, detecting (which deals with the identification of changepoints); and second, adjustment (which sees the homogenization with the correction of breakpoints identified). The PMFT proposed by Wang (2008) is more desirable than the other tests because it considers the existence of linear

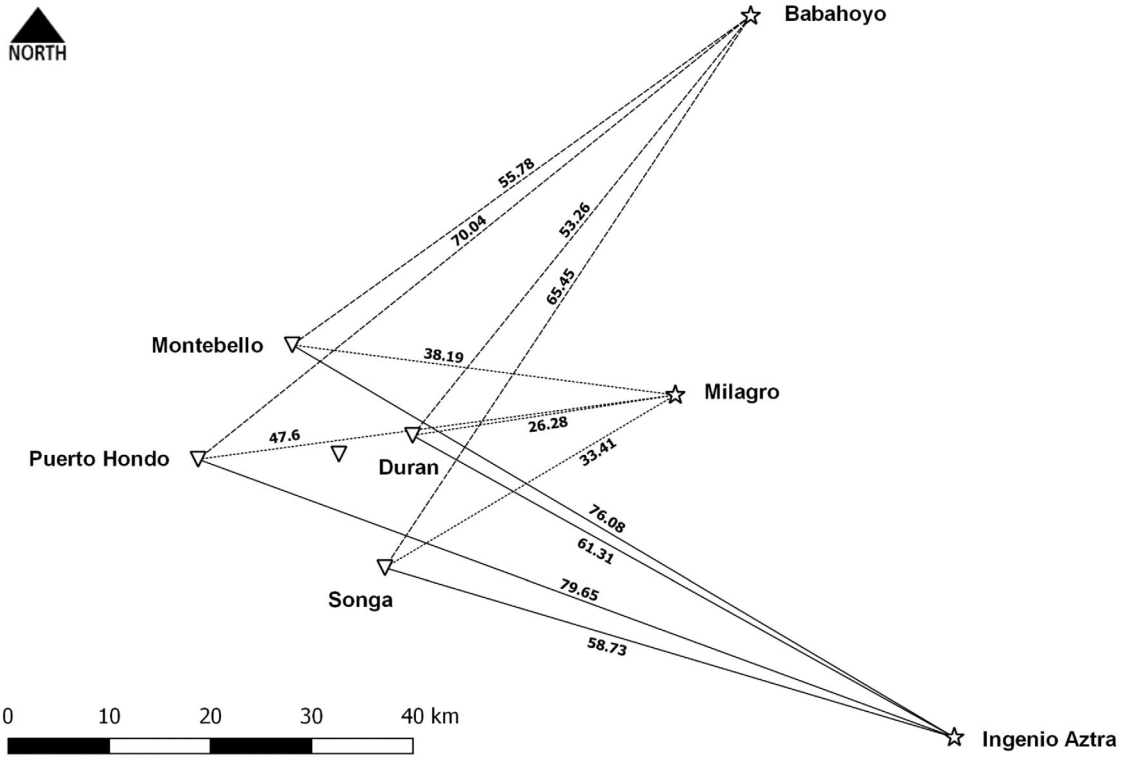


FIGURE 3 Distance between stations (km)

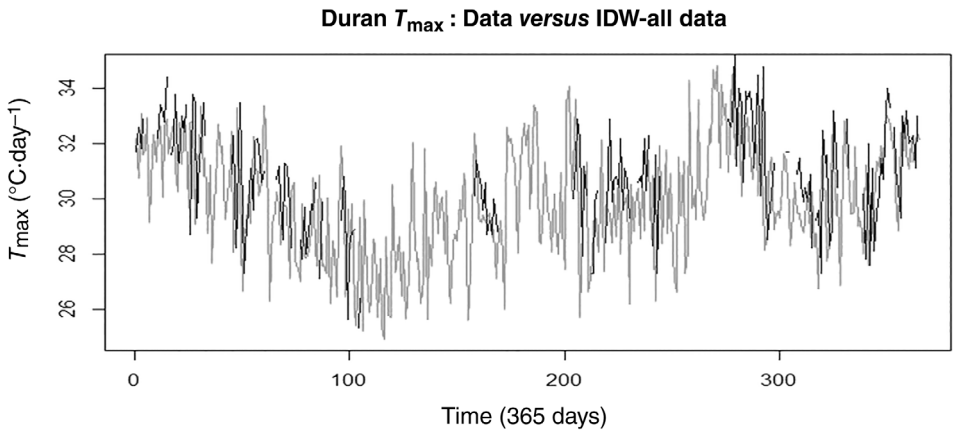


FIGURE 4 Spatial prediction at time $t - 1$ (light) *versus* original data set at time t (dark) with missing values (for Duran station) for maximum temperatures

autocorrelation of a time series at a specific delay (lag 1) when the changepoint was identified. The results of the homogenization are analysed to understand the origin of changepoints.

After verifying with the INAMHI that there were no changes in the measurement instruments or relocation of meteorological stations during the period considered, and not having enough and reliable metadata, it was believed that there could be external causes, probably natural causes. Besides, this hypothesis is strengthened by the fact that the number of changepoints is the same for the maximum and minimum temperature series of all four stations, and there is not a unique situation for each station. For this reason, and because Ecuador is an area subjected to a critical regional climate forcing (the ENSO cycle), the dates at which changepoints occurred for each meteorological station and the dates at which occurred El Niño and La Niña (ENSO phenomena) were compared. For this comparison, the values from the Indice Costero El Niño (ICEN), the index provided by the Instituto Geofisico del Perù (http://www.met.igp.gob.pe/variabclim/indices.html), were considered. These data are divided into two categories: "hot condition" and "cold condition." The first, which includes four levels (extraordinary, substantial, moderate and weak), is associated with positive values of the ICEN (i.e. El Niño events), while negative values of the ICEN

TABLE 3 Extreme temperature indices from the Expert Team on Climate Change Detection and Indices (ETCCDI) analysed in this assessment with associated definitions, index typology and units

ID	Index	Index definition	Typology	Units
SU25	Number of summer days	Annual count of days when TX > 25°C	Threshold index	Days
TR20	Number of tropical nights	Annual count of days when TN > 20°C	Threshold index	Days
TXx	Highest T_{max}	Annual highest daily maximum temperature	Absolute index	°C
TXn	Lowest T_{max}	Annual lowest daily maximum temperature	Absolute index	°C
TNx	Highest T_{min}	Annual highest daily minimum temperature	Absolute index	°C
TNn	Lowest T_{min}	Annual lowest daily minimum temperature	Absolute index	°C
TmaxMean	Mean T_{max}	Mean annual monthly mean of maximum daily temperature	Absolute index	°C
TminMean	Mean T_{min}	Mean annual monthly mean of minimum daily temperature	Absolute index	°C
TN90p	Warm nights	Percentage of days when TN > 90th percentile for the referenced period	Percentile-based index	% days
TX90p	Warm days	Percentage of days when TX > 90th percentile for the referenced period	Percentile-based index	% days
DTR	Daily temperature range	Annual mean difference between TX and TN	Other indices	°C

correspond to La Niña events, or "cold condition" (strong, moderate and weak). The aim of this passage is the assessment of a possible correspondence between the intensity level of the ENSO phenomena and the occurrence of changepoints (Takahashi *et al.*, 2014). The analysis revealed that a large number of identified breakpoints follow the succession of two ENSO events, mainly for minimum temperatures. For just a few changepoints not associated with the ENSO (especially for maximum temperatures), it was assessed that there were no anomalies. After this process, the maximum and minimum temperatures series were now homogeneous and suitable for computing extreme temperature indices.

2.5 | The ETCCDI extreme temperature indices

To calculate the ETCCDI extreme temperature indices, data should have a long, continuous, QC and homogeneous daily time series. However, this is not the only condition, because the implementation in the RClimDex software requires, for instance, no more than 15% of missing values in one year to calculate the annual value for an index. The percentile-based indices are also computed if there are at least 80% of the data in the considered period (Zhang and Yang, 2004). These constraints had an impact on the final number of calculated indices. Table 3 contains a brief description of the computed indices, which includes threshold indices, absolute indices and percentile-based indices, among others. The results obtained were represented in a Qgis map, which helps to make a more intuitive interpretation as commented in the "Results and discussion" (Section 3) where the two cases are analysed.

2.6 | Linear trend estimation of indices

The extreme temperature index time series, given as the RClimDex software output, were regressed against time by using a linear regression model (with co-efficients estimated by ordinary least squares—OLS) to analyse the temporal evolution of extreme temperature indices. To simplify this analysis, it is possible to observe the graphical outputs (Figure 5) with each index time series plotted, the estimated regression line and a curve obtained by locally weighted regression (LWR). The latter is a regression model where the predicted value at a point of interest is achieved by using only training data that are in proximity ("local") to that point (Cleveland, 1979). The LWR curve considers the correlation of the temperatures in time and shows the influence of close values on the estimated trend. Other four values that resume the regression are shown on the graphics: R^2, p-value, slope estimate and slope error. As is well known, the R^2 of a linear regression permits one to assess how well the estimated straight line describes the data. Meanwhile, the p-value is the observed statistical significance level, and it has to be compared with theoretical one that, in the study, it is chosen at the 5% level ($\alpha = 0.05$). When statistically different from zero, the sign of the estimated trend

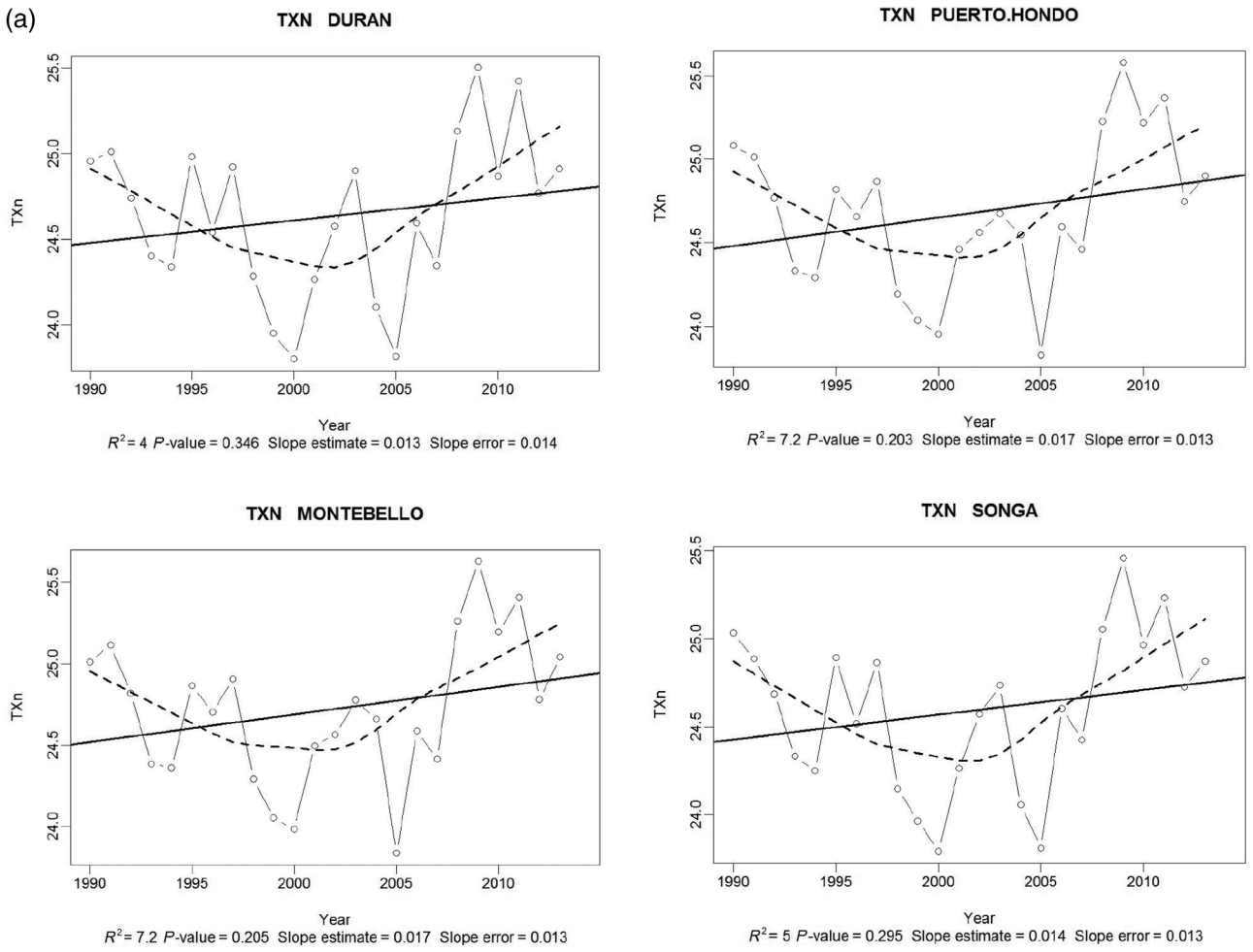


FIGURE 5 Outputs of the indices: (a) lowest maximum temperature (TXn); (b) mean maximum temperature (TmaxMean); and (c) daily temperature range (DTR) for each meteorological station. Reproduced is a curve representing the annually temporal evolution of the index, with the continuous line showing the estimation trend and the dotted line the locally weighted linear interpolation (locally weighted regression—LWR)

co-efficient allows one to highlight an increasing or a decreasing trend. Finally, the slope error defines the estimation of the standard error of the trend co-efficient (if this value is the lower, the slope of the estimated regression line will be more reliable).

3 | RESULTS AND DISCUSSION

This section shows the results of the analysis used to assess the climatic variability over the city of Guayaquil, where urbanization has grown over time. Table 4 shows that the estimated trend co-efficient of each index is positive/negative when maximum and minimum temperatures are increasing/decreasing along the reference period 1990–2014. This output suggests that most of the trend co-efficients are not statistically significant, and therefore no great changes in temperature trends during these 24 years can be detected. At the same time, there are a few co-efficients (Table 4) that prove statistically significant at the 5% and 10% levels. The results highlight a general situation of growing warming signals. The Rclimdex outcomes of simple linear regression suggest that the times series of extreme temperatures do not show essential variations. Instead, when looking at the LWR regression, it is possible to observe increasing and decreasing trends in time, as in Figure 5 (shown are only some interesting cases because of limited space).

The threshold indices SU25 and TR20 have both non-statistically significant co-efficient trends, meaning that there are no important variations in the number of days in each year with a maximum temperature $> 25°C$ (SU25) or with a minimum temperature $> 20°C$ (TR20).

Significant co-efficient trends emerged among the absolute indices. Indeed, for the highest maximum temperature (TXx), three out of four meteorological stations

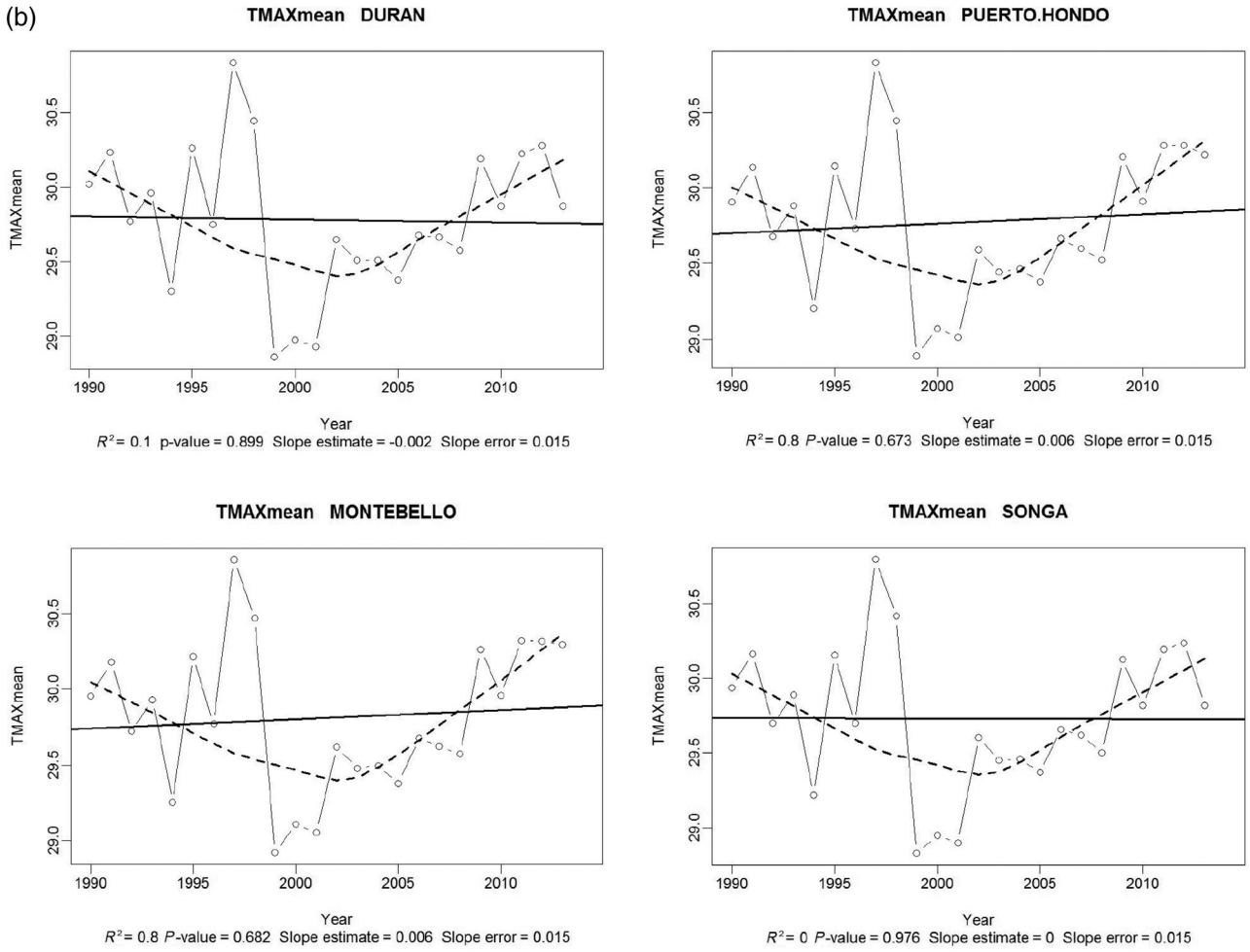


FIGURE 5 (Continued)

showed a slightly statistically consistent growth (Figure 6). In other words, there is a growing variety of the highest annual maximum monthly of maximum daily temperature during the referred period. On the other hand, the lowest maximum temperature (TXn) presents a co-efficient trend not statistically significant and shows a curious situation for analysis by observing the LWR regression (Figure 5a). This weighted interpolation indicates a decreasing trend up to 2002, which is followed by an increase in the number of the annual lowest daily maximum temperature in the consecutive period. This condition could be explained by the ENSO phenomenon, which shows one of the extraordinary events of La Niña during 1988. The effect appears as an intense and rapid cooling of temperature. Also, for the index concerning the highest minimum temperature (TNx), there are no significant results. On the other hand, it seems there is a definite variation in the number of annual lowest value in daily minimum temperature (TNn), as shown by the resulting trend co-efficient statistically significant at the 10% level (Table 4 and Figure 6). The two indices concerning the monthly mean maximum and minimum temperatures (TmaxMean and TminMean) do not reach statistical significance for Guayaquil. Still, again the LWR regression shows a decrease until about 2001 (in concordance with a La Niña event) followed by a constant growth for all meteorological stations (Figure 5b).

Among the percentile-based indices (TN90p for minimum temperatures and TX90p for maximum temperatures), only the percentage of days in the year with daily maximum temperatures > 90% percentile, that is, TX90p, shows a positive variation (an increase of warm days), with a significant co-efficient trend for two stations (Table 4).

Finally, the annual diurnal temperature range (DTR) is the index that shows in Figure 4 a moderate downward trend over all stations. Still, not one presents co-efficient trends that are statistically significant (Table 4). The locally weighted regression illustrates, however, a decrease until 2004, followed by a considerable growth of

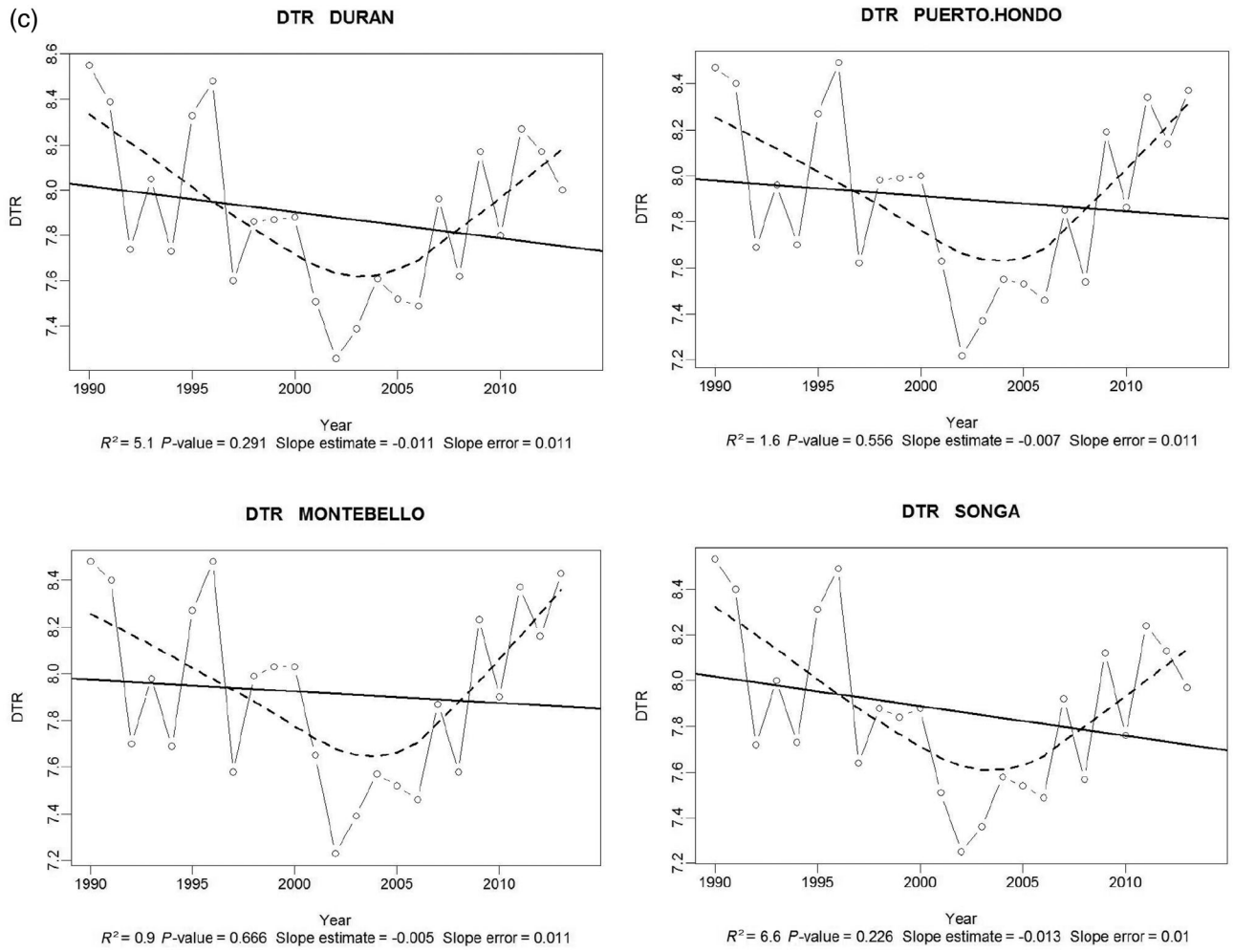


FIGURE 5 (Continued)

TABLE 4 Co-efficients' trend signs for the period 1990–2014 for average temperature indices using a robust linear trend estimate

	DURAN	MONTEBELLO	PUERTO HONDO	SONGA
SU25	+(0.424)	+(0.29)	+(0.489)	+(0.44)
TR20	+(0.382)	+(0.315)	+(0.253)	+(0.302)
TXx	+(0.082)	+(0.058)	+(0.035)	+(0.103)
TXn	+(0.346)	+(0.205)	+(0.203)	+(0.295)
TNx	+(0.245)	+(0.456)	+(0.324)	+(0.178)
TNn	+(0.092)	+(0.054)	+(0.057)	+(0.088)
TmaxMean	−(0.899)	+(0.682)	+(0.673)	0 (0.976)
TminMean	+(0.517)	+(0.455)	+(0.376)	+(0.389)
TN90p	+(0.944)	+(0.922)	+(0.892)	+(0.856)
TX90p	+(0.191)	+(0.043)	+(0.049)	+(0.118)
DTR	−(0.291)	−(0.666)	−(0.556)	−(0.226)

Note: Co-efficients' signs shown in dark grey are significantly different from zero at the 5% level, while light grey is assigned to values significant at the 10%. All the other co-efficients are not statistically significant at the 10% level. *p*-values are given in parentheses.

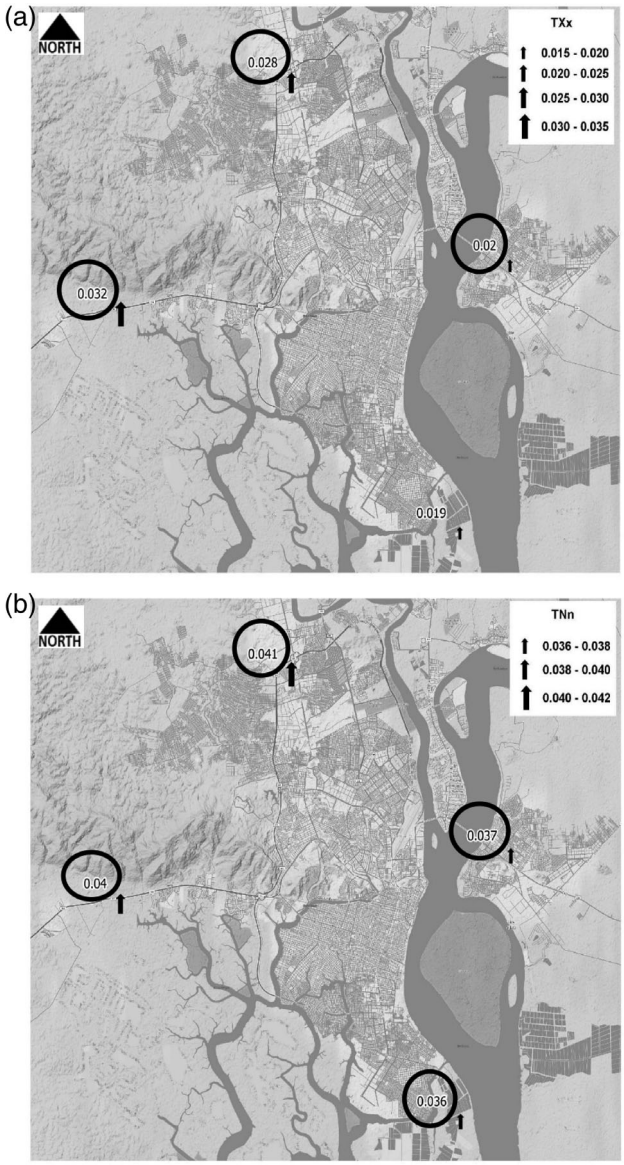


FIGURE 6 Qgis maps for the indices: (a) highest maximum temperature (TXx); and (b) lowest minimum temperature (TNn). Symbols represent the location of meteorological stations, and its dimension is proportional to the values of trend co-efficients (non-dimensional), within a circle for significant cases. Numbers near the symbols represent the estimated trend co-efficients, whereas in the legend are created intervals of trend co-efficients expressed in absolute values to define the dimension of the symbols proportionally

the pattern as a symptom of an increase of the DTR of the last years (Figure 5c). That difference between daily maximum and minimum temperatures could be caused by a rising TX and stability of TN, or the opposite, although this latter alternative should be discarded since the area of interest is hot.

In general, the evidenced results indicate warming temperatures up to 2004, and this situation reinforces the idea that more extreme events could occur, especially the occurrence linked to warm climate such as those of Guayaquil city. More specifically, the west and north sectors of the town—"Puerto Hondo Canton" and "Montebello Canton"—mainly suffered from the increasing air temperature (also evidenced in Figure 6). The present research contributes to maintaining information useful to sustainable urban planning adaptation policies since air temperature is one of the most important meteorological variables for evaluating the vulnerability of an urban area linked to its development (Norton *et al*., 2015). Norton *et al*. (2015) suggest mitigation measures for high temperatures in the urban landscape well known as urban green infrastructure (UGI), for example, street trees, parks, green roofs and facades. Therefore, it emerges how important could be the development of an appropriate strategy for the UGI implementation in Montebello Canton of Guayaquil (see also Figure 5). Otherwise, the warming situation in Puerto Hondo Canton is less worrying because this area is a completely green area with a low population density (Figure 1c). On the other hand, the slow growth of temperature (Table 4) associated with the high density and urbanized Duran Canton (Figure 1c) should be managed through the implementation of the UGI's strategy to reduce the vulnerability of this area in the face of climate change.

4 | CONCLUSIONS

The present research highlights the need to create and maintain an information system in order to implement adaptation policies for different districts' management within the city. It was possible to study the changes in temperature extremes through the "reconstruction" of data sets, even though the time series available presented many problems (i.e. lack of climate series completeness with large amounts of missing periods and values). In line with the latest Intergovernmental Panel on Climate Change (IPCC) reports, which suggest a possible increment on the number of warm days and nights, the results of this research evidence a deterioration of climatic conditions concerning the maximum and minimum temperature variables. This situation reinforces the idea that more extremes events could occur, especially those linked to warm climate such as presented in the study area.

For future efforts, it is necessary to consider the limits of this research. First, the simple linear regression model was fitted on indices with annual values for only 24 years. Greater data availability would allow one to specify and fit a non-linear model that could provide further insights into the analysis. Indeed, the analysed time series were collected in a too short a period and did not

show continuity in their measurements, presenting significant gaps. This issue is common for climate analysis, especially in South America and other developing regions.

To prepare adequately and effectively for the effects of climate change and their related extreme weather events requires long-term (strategic) thinking that is often well beyond any individual policy-maker's tenure in office. Strategic thinking about climate disaster risk reduction will be a precursor for goals concerned with planning for sustainable development, and these activities must be undertaken with the prospects of longer term, sustainable development in mind.

It should be noted that the aim of the study was not to define climate scenarios, but to evidence the temperature evolution in a specific equatorial city in the face of climate change and contributing to the literature by building the foundations for future research in urban areas. Indeed, the cross-correlation-enhanced inverse distance weighting (CC-IDW) methodology for obtaining more extended time series starting from data for one or two years of measurement could be useful for further analysis. Since dense detecting networks in urban areas demand high costs of maintenance, the use of methods such spatial interpolation to obtain more data for urban analysis in order to improve climate change knowledge is more sustainable in economic terms. In this way, small-scale studies should increase the assessment of the vulnerability of urban areas. It is certainly not easy to contribute to the awareness of policy-makers, considering that one's efforts aim to indicate structural actions to improve the management of data, which present high costs of implementation without direct benefits. This is because it is not easy to quantify the value of human life and health risks. As defined in the public volume concerning the politics of climate change in South America, each city has own microclimate due to all the urban characteristics that modify the weather elements, such as increases in population and use of vehicles, emission of pollutants, eradication of vegetation, presence of waterproof materials, and so on (Dias *et al.*, 2009).

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