An update of high-resolution monthly climate surfaces for Mexico

Angela P. Cuervo-Robayo, Oswaldo Téllez-Valdés, Miguel A. Gómez-Albores, Crystian S. Venegas-Barrera, Javier Manjarrez and Enrique Martínez-Meyer

ABSTRACT: Climate surfaces are digital representations of climatic variables from a region in the planet estimated via geographical interpolation techniques. Climate surfaces have multiple applications in research planning, experimental design, and technology transfer. Although high-resolution climatologies have been developed worldwide, Mexico is one of the few countries that have developed several climatic surfaces. Here, we present an updated high-resolution (30 arc sec) climatic surfaces for Mexico for the average monthly climate period 1910–2009, corresponding to monthly values of precipitation, daily maximum, and minimum temperature, as well as 19 bioclimatic variables derived from the monthly precipitation and temperature values. To produce these surfaces we applied the thin-plate smoothing spline interpolation algorithm implemented in the ANUSPLIN software to nearly 5000 climate weather stations countrywide. As an additional product and unlike the previous efforts, we generated monthly standard error surfaces for the three climate parameters, which can be used for error assessment when using these climate surfaces. Our climate surface predicted slightly drier and cooler conditions than the previous ones. ANUSPLIN diagnostic statistics indicated that model fit was adequate. We implemented a more recent error assessment, a set of withheld stations to perform an independent evaluation of the model surfaces. We estimate the mean absolute error and mean error, with the withheld data and all the available data. Average RTGCV for monthly temperatures was of 1.26–1.12 ◦C and 24.67% for monthly precipitation, and a RTMSE of 0.48–0.56 ◦C and 11.11%. The main advantage of the surfaces presented here regarding the other three developed for the country is that ours cover practically the entire 20th century and almost the entire first decade of the 21st century. It is the most up to date high-resolution climatology for the country.

KEY WORDS ANUSPLIN; climate surfaces; temperature; precipitation; Mexico; 1910–2009

Received 27 June 2012; Revised 13 September 2013; Accepted 21 September 2013

1. Introduction

Climate surfaces have proven useful for several applications, including to understand the effect of climate change on various aspects of the environment, such as the distributions of species (Cuervo-Robayo and Monroy-Vilchis, 2012; Martinez-Meyer et al., 2004; Venegas-Barrera and Manjarrez, 2011), spatial epidemiology (Elliott and Wartenberg, 2004; Kuhn et al., 2003; Peterson et al., 2002), and productivity of forest plantations and agricultural crops (Geerts et al., 2006; Wang, 1994). They have also been useful for assessing the impact of climate change in water resources (Yatagai et al., 2008), agriculture, and biodiversity (Telléz-Valdés et al., 2006).

One of the first digital global climate datasets in the form of interpolated surfaces was generated by New et al. (1999), using 30-year climate records (1961–1990). A year later the same authors updated the temporal coverage of the database to a 96-year period (1910–1996), at a spatial resolution of 0.5◦. These climate datasets represented a step forward from previous products (Dai et al., 1997; Easterling et al., 1997; Hulme, 1995; Jones et al., 1999), mainly because they covered a much larger period of time and a larger number of stations (New et al., 2000, 2002). Later, Daly et al. (2008) generated a new climatology to properly represent the climatic conditions of the conterminous United States for a more recent period (1997–2000) and compared it with climate surfaces created with different interpolation methods.
There has been substantial progress in the development of climate surfaces for specific regions and worldwide (Funk and Richardson, 2002; Hutchinson, 1995; Kriticos et al., 2011). Hijmans et al. (2005) developed climate surfaces for the entire world that has been widely used because of their relatively high spatial resolution (30 arc sec $\approx 1$ km$^2$). Despite this, interpolations of climatic data have continued at regional-scale, since cleaning and interpolation of meteorological data at this level represent an opportunity to properly supervise the interpolation process. Regions like the United States and Canada (Daly et al., 2008; Hutchinson et al., 2009; McKenney et al., 2006), Europe (Haylock et al., 2008), Asia (Guan et al., 2009; Hong et al., 2005; Taesombat and Srixongsitanon, 2009), Middle East (Yatagai et al., 2008), Mexico (Saenz-Romero et al., 2009; Téllez-Valdés et al., 2011), among others, have continue to develop climate surfaces.

Interpolating climate datasets at a regional scale, rather than globally, has the advantage of including more information for that specific region, making a more thorough data cleaning and get a better control of source data, resulting in more robust and reliable products, which can be merged into a global dataset, as proposed by Hijmans et al. (2005). Furthermore, some countries have increased the number and type of information from weather stations (e.g. Klok and Klein Tank, 2009), which can be used to improve and extend the temporal coverage of the resulting climatologies (New et al., 2002). Besides, average global temperature has increased significantly since 1977 (Rahmstorf et al., 2007), so updating climate surfaces is necessary to generate reliable information to support scientific research and decision making (Kriticos et al., 2011).

Specifically for Mexico, we know two sets of regional climate surfaces (Saenz-Romero et al., 2009; Téllez-Valdés et al., 2011) and a third as a part of the global model WorldClim, generated by Hijmans et al. (2005). All of them were generated with the thin plate spline interpolation method, implemented in the ANUSPLIN software (Hutchinson, 2006; Hutchinson and Gessler, 1994), which fits smoothing spline surfaces to the longitude, latitude, elevation coordinates of geographic space and has shown better performance compared with others (Price et al., 2000). While these surfaces cover the entire country and contain the same type of climatic variables, except those from Saenz-Romero et al. (2009), their values are somewhat different because they cover different time periods and use different number of stations (e.g. Saenz-Romero et al., 2009). They also lack diagnostic statistics (e.g. Hijmans et al., 2005), making them difficult to evaluate critically to determine which is more reliable.

The climate surfaces developed in this work cover climatic records from 1910 to 2009, representing the most up to date and available information of this type for the country. This climate surfaces were also interpolated with ANUSPLIN at a spatial resolution of 30 arc sec, but with a larger number of meteorological stations compared with the other climatologies available for Mexico. We also included monthly surfaces of the model standard error, which can be useful to evaluate the uncertainty associated with the interpolation process in a spatially explicit fashion, or can be incorporated into the next generation of species distribution models (Parra and Monahan, 2008). One of the main reasons to develop these new climate surfaces was to make an accessible climatology that represents the entire 20th century and almost the entire first decade of the 21st century.

2. Methods

2.1. Climate data for Mexico

The National Meteorological Service has daily weather records for more than 5000 weather stations across the country, from 1910 to the present (Figure 1). However, some of the stations have observations for only a fraction of this period. We removed missing daily values with the NoData extension implemented in the Idrisi Taiga software (CRI-UAEMéx, 2007). The resulting datasets were averaged to obtain monthly values that cover most of the 20th century and early 21st century (1910–2009). This process was facilitated by the Structuration extension, also implemented in Idrisi (Quentin et al., 2007). These extensions are available for free on the website: http://idrisi.uaemex.mx/index.php?option=com_content&task=view&id=553&Itemid=114.

2.2. Climate data for the United States and Central America

The north and south of Mexico has low density of meteorological stations. In order to accurately interpolate and strengthen Mexico’s climate surfaces at north and south boundaries, we included weather data from the southern portions of the United States and northern Belize and Guatemala (Figure 1). The US data were collected from the United States Historical Climatology Network (USHC: http://cdiac.ornl.gov/epubs/ndp/ushcn/access.html). Rainfall data from Central America and the Caribbean were gathered by using the FAO-CLIM 2.0 software (http://geonetwork3.fao.org/climpag/agroclimd_en.php, FAO 2001), and temperature data were obtained from National Climatic Data Center (http://www.ncdc.noaa.gov/ol/ncdc.html) and from Colombia’s Centro Internacional de Agricultura Tropical (CIAT: http://ciat.cgiar.org).

About 72% of the weather stations have records of temperature and precipitation for 20 years or more, only 5% hold records for less than 5 years. We included these low-record stations because they are distributed in the northern part of the country, where the density of stations is already low (Diaz et al., 2001), thus any information is useful to improve the interpolation. More station data are preferred even if the period of record is incomplete. Hopkinson et al. (2012) showed that the use of larger datasets with incomplete record or adjusted data was superior in supporting climate interpolation for Canada, than using only less climate stations, with a complete record. Also, ANUSPLIN has demonstrated to
be very effective in reducing errors in short-period means (Hutchinson, 1995). Although, short-period stations had the largest residuals from the fitted surfaces (see methods below).

Weather stations were geographically confined to 13°00′00″–33°59′57″N and 79°00′06″–122°00′00″W (Figure 1).

2.3. Interpolation
Monthly climate surfaces of precipitation, maximum, and minimum temperature were generated with the thin-plate spline interpolation technique, implemented in the ANUSPLIN software version 4.3 (Hutchinson, 2006), which fits smoothing parameters to the longitude, latitude, and elevation coordinates in geographic space. The partial spline model for $N$ observed data values $z_i$ is given by:

$$z_i = f(x_i) + b^T y_i + e_i (i = 1, \ldots, N)$$

where each $x_i$ is a $d$-dimensional vector of spline of independent variables, $f$ is an unknown smooth function of the $x_i$, each $y_i$ is a $p$-dimensional vector of independent covariates, $b$ is an unknown $p$-dimensional vector of coefficients of the $y_i$, and each $e_i$ is an independent, zero mean error term. The $e_i$ accounts for measurement error as well as deficiencies in the spline model such as local effects below the resolution of the data network. The $e_i$ is assumed to have a covariance matrix $\sigma^2 V$ where $V$ is a known positive definite $n \times n$ matrix, usually diagonal, while $\sigma^2$ is usually unknown (McKenney et al., 2011a, 2011b). A more detailed description of the model can be found in Wahba (1990). Here we did not use any covariates, so the model is reduced to an ordinary thin plate spline model ($p = 0$), then $x_i$ represents the three coordinates: longitude, latitude, and appropriately scaled elevation (Hutchinson, 2006).

We fitted a second-order spline, using longitude, latitude, and elevation as independent variables as described by Hijmans et al. (2005). The value of the smoothing parameter is normally determined by minimizing a measure of predictive error of the fitted surface given by the generalized cross-validation (GCV). The GCV is calculated by implicitly removing each data point in turn and summing, with appropriate weighting, the square of the difference of each omitted data point from the spline fitted to all other data points (Hutchinson, 2006; McKenney et al., 2011a, 2011b). We used a square root transformation to reduce positive skewed values and ignore all negative values in precipitation data (Hutchinson, 1998, 2006). The square root transformation applies more smoothing to large precipitation values and less smoothing to small precipitation data values (Hutchinson et al., 2009). We used SPLINB, as recommended by Hutchinson (2006) when there were more than 2000 stations, and used SELNOT to select a set of knots to reduce the complexity of the fitted spline (Hutchinson, 2006).

SPLINB produces a list of the largest data residuals (abnormal stations). With this list we detected errors in the stations’ data. Residuals with large values usually indicate errors in the geographic position or variable values. We corrected the geographic positions and/or elevations for a hundred of erroneous stations by using online gazetteers and Google Earth; however, about 200–300 stations had to be excluded since these remained as residuals indicating some error. Properly referenced stations that kept high residual values were removed from the data because probably the records were erroneously captured; also we notice that some of them were the stations...
with low record (<5 years), as mentioned above. This significantly reduced data errors, which were then evaluated with the diagnostic statistics provided by ANUSPLIN and by withheld stations.

2.4. Assessing primary climate surfaces

We assessed the accuracy of the fitted model surfaces in three ways: (i) we examine ANUSPLIN diagnostics measures (Hutchinson, 2006), (ii) the difference between the predicted value of each monthly variable and observed climate dataset, and (iii) in order to have an independent evaluation of data use to create climate surface for Mexico, we also partitioned the stations into a test (withheld) and training set and developed an additional climate surfaces with the training data and interrogated them for the locations of the withheld data (Hijmans et al., 2005). Because these second set of climate surface were only exploratory, ANUSPLIN statistics are not shown. With the last two tests we were able to compare the values of interpolation back to the original weather stations, and evaluate the accuracy and bias relative to the available weather stations (Parra and Monahan, 2008).

ANUSPLIN provides several measures to assess model quality (Hutchinson, 2006). The signal indicates the degrees of freedom associated with the surfaces (Hutchinson, 2006). It indicates the complexity of the surface and varies between a small positive integer and the number of stations used to generate the surface (McKenney et al., 2006). Hutchinson and Gessler (1994) suggest that the signal should be no greater than about half the number of data points. Models with a signal below these thresholds tend to be more robust and reliable in regions where data are scarce (McKenney et al., 2006). Higher signals can indicate that the climate field being analysed is too complex to be adequately represented by the data (Hutchinson et al., 2009). When monthly data is interpolated, there should be a steady progression in the signal values from month to month, indicating that there are no errors or outliers in the monthly values used (Téllez-Valdés et al., 2011). The RTGCV is robust measure of predictive performance. It is a spatially averaged standard error that reflects errors of prediction (Hutchinson, 2006) and it is calculated as the square root of the GCV.

We also withheld as test data a set of 850 and 600 stations of maximum and minimum temperature surfaces, and 900 stations for the precipitation. To select the withheld data we used SELNOT. We then calculated the mean error (ME) and the mean absolute error (MAE) of the differences between the fitted surface and the withheld data (Hutchinson et al., 2009; McKenney et al., 2006, 2011b, 2011a). Mean error is used in forecast analysis, because it can denote if the model is biased, and the mean absolute error describes the accuracy at specific spatially representative locations of the model (McKenney et al., 2011a, 2011b). In addition, we also calculated MAE and ME to the difference between the predicted value of each monthly variable and observed climate dataset. The final climate surfaces were created using all the available weather stations.

2.5. Monthly climate surfaces

Gridded monthly climate values and model standard error estimates for each surface were generated with the function LAPGRD, using coefficients defining the partial spline surface and the error covariance matrices (Hutchinson, 2006). Unlike the other climate surfaces for Mexico, this is the first time that spatially explicit standard errors are available for the country hence it represents a significant contribution. The model standard error relates to the error in the interpolation process, which can be useful to evaluate uncertainty in the climate surfaces. It is estimated using the derived covariance structure of the surface coefficients as described by (Hutchinson, 1995). All gridded climate values were derived using the elevation values from the 30 arc sec resolution (approximately 1 km²) GTOPO30 digital elevation model (http://eros.usgs.gov/#/Find_Data/Products_and_Data_Available/gtopo30_info). With the ANUCLIM software (Xu and Hutchinson, 2009) and the climate surface coefficients we derived 19 bioclimatic variables that represent more biologically meaningful combinations than the original climate variables and have been broadly used in different research areas (Hijmans et al., 2005).

2.6. Comparison with earlier works

Our climate surfaces differ from early works (Hijmans et al., 2005; Saenz-Romero et al., 2009; Téllez-Valdés et al., 2011) in three ways: the temporal coverage, number, and set of climate stations (Table 6). These differences can lead to non-objective comparisons among them; therefore we only compared all climatologies using standardized z-scores. Moreover, z-scores allow analysing differences between surfaces and help to avoid including spatial variations on precipitation and temperature. To calculate z-scores, for each month (12 months) and variable (precipitation, minimum, and maximum temperature), we obtained the average and standard deviation from the four climatologies. For example, for the monthly data we created an average January, an average February and so on. Then we substracted the long term average from each month. The result was divided by the standard deviation to create a z-score (Eastman, 2009). In this new system, positive z-scores of one surface are related to warmer or wetter conditions than the average of the four surfaces, negative z-scores to colder or driest conditions than average, and values near to zero represents monthly surface closest to the average. We performed Function Discriminant Analysis (Statistica 10, StatSoft 2013) to estimate if the four climate surfaces differ statistically depending on z-scores of precipitation, minimum and maximum temperature on February, May, August and November, which represent seasonal climatic variations. Discriminant analysis is a descriptive version of multivariate analysis of variance for two or more groups, which find linear combinations of the variables that separate the groups (James and McCulloch, 1990). The analysis estimate the optimal combination of variables that maximizes the differences between groups.
and minimizes the differences within groups, so the first function (root) provides the most overall discrimination between groups, the second provides second most, and so on. Moreover, the functions will be orthogonal; their contributions to the discrimination between groups will not overlap. Also, this test identifies which variables has the greatest contribution to discrimination between groups (factor structure), by means of estimating the correlation between the variables in the model and the discriminant function (values from 1.0 to −1.0).

Finally, we determine the number of significant roots, which account significant variance to discrimination between groups, with the Chi square test of successive roots removed. With the module SAMPLE of the Idrisi Taiga software (Eastman, 2009), we randomly selected 937 pixels from Mexico. Comparisons were made only for the area of Mexico, because higher model standard error occurred in the US and Central America (Figure 2). Finally, when available, we also compared the diagnostics statistics produced by ANUSPLIN.

3. Results

Final surface of precipitation, maximum and minimum temperature were generated with 4966, 4851, and 4602 weather stations, respectively. All monthly surfaces of precipitation, minimum and maximum temperature, their respective standard error surfaces and the 19 bioclimatic parameters are freely available to download at: http://idrisi.uaemex.mx. Finer-resolution climate surfaces for a specific location can be generated upon special request.

3.1. Model assessment

For the final fitted model the average ratio of the signal to the number of data points was 0.24 for monthly temperatures and 0.27 for precipitation (Table 1). Minimum values of the signal were similar for both temperatures (0.22), however the maximum signal ratio was slightly higher for minimum temperature (0.26). Because ratio signal are below the maximum value recommended by Hutchinson and Gessler (1994), the surfaces are robust. Also, as mentioned by Téllez-Valdés et al. (2011) there is a steady progression in the signal values from month to month (Table 1). This indicates no systematic errors or outliers in the monthly values and an appropriate degree of smoothing. The monthly average RTGCV for minimum temperature was 1.26 °C, and 1.12 °C for maximum temperature. For precipitation (Table 1) it was of 11.11 mm (24.67%). Maximum temperature RTMSE (0.48 °C) was slightly less than minimum temperature (0.54 °C), and of 8.65 mm (11.1%) for precipitation (Table 1). In general, real error deviance should be a value between RTGCV and RTMSE (Hutchinson, 2006).

Considering the degree of error of the diagnostic statistics these surfaces represent a good fit between the data and the modelled surface, this also indicates that the model is reliable (McKenney et al., 2006). Like the signal, the RTGCV values for precipitation were higher during the summer months, mainly from July to September. The RTGCV values for maximum temperature were smallest from June to November, as for minimum temperature (Table 1). ANUSPLIN diagnostic measures described spline models that fit well to the diverse climates of Mexico.
Residuals from the surfaces minus the full dataset were generally small, indicating that the model was close to the observed stations (Table 2), and the magnitude of the errors was close to those of the RTMSE (Table 1). Mean absolute error for both temperatures were $<$1°C, and $<$15 mm for precipitation. MAE showed the similar season variation as RTGCV (Tables 1 and 2). Mean errors for the three variables were small and slightly underestimated (Table 2). On average, precipitation has the highest values of mean error ($\sim$0.37).

### 3.2. Model assessment – withheld data

Withholding data were used as a third test of the accuracy and bias. As expected, the mean absolute and mean withheld errors were higher (Table 3) than errors estimated from all the observed data from the fitted model (Table 2), mainly for precipitation. In Mexico, the operation of the weather stations has been very irregular, that is why it was not possible to withheld stations with a 100-year mean period, although 60% of the withheld data represent a period greater than 40 years. The use of withheld data with short period means can inflate the estimate errors, however we were also able to identify seasonal variations in MAE. Precipitation showed higher mean absolute error during summer months and both temperatures showed it during winter. The spatially standard error for the model created with withheld data was higher in the mountains, as for the surfaces interpolated with all the stations (Figure 2). Although greater models errors were distributed in the west of the US and Central America (>180 mm, and 1°C).

We chose the two extreme weather months, April as the driest and September as the wettest to exemplify the amount of standard error in these two seasons (Figure 2). Model standard errors were higher in the mountains and in the Gulf of Mexico, mostly in the Sierras of Chiapas, the Llanura Veracruzana and the swamps of Tabasco, as seen in the standard error surface, which provides insights into the spatial distribution of error of both the driest (Figure 2(c)) and wettest months (Figure 2(d)).
3.3. Comparison with earlier work

In general, our monthly surfaces represent drier and colder conditions than the other climatologies (Figure 3). We found that the four climatologies differ on z-scores of precipitation and temperatures (Wilks’ Lambda = 0.0009, \( F_{df} = 36,1148 = 15311.74, P < 0.0000 \), Table 4). Minimum and maximum monthly temperatures offer higher variations between surfaces than monthly precipitations (Table 5). The first root accounts 99.97% of variations, it discriminates Hijmans et al. (2005) surfaces from the other three climatologies, because it predicts higher values of minimum temperature on May, August and October. The second root accounts 0.02% of variations (Eigenvalue = 4.6), discriminates our climatologies from Télež-Valdés et al. (2011) and Saenz-Romero et al. (2009), which differ mainly because our climate surfaces predicts lower maximum temperatures on February. The third root accounts for 0.01% of variations, it differentiates Télež-Valdés et al. (2011) from Saenz-Romero et al. (2009), principally because the first one estimated higher maximum temperatures on August than the second one (Figure 3).

Previous climatologies assessed their model only with ANUSPLIN diagnostic statistics (Table 6); we used more recent error assessment like spatially representative withheld data to estimated MAE and ME, mainly because there are situations where the RTGCV may not be entirely reliable, due to the presence of data with significant short-range correlation or unevenly spaced data networks dominated by particular data-dense areas (McKenney et al., 2011a, 2011b), and RTMSE is considered an overoptimistic measure (Hutchinson 2006). Comparison of ANUSPLIN statistic was only possible for some of the months (Table 6). Saenz-Romero et al. (2009) report all monthly statistical values, and Télež-Valdés et al. (2011), only describe the inter-seasonal statistics. Monthly values of RTMSE and RTGCV of Saenz-Romero et al. (2009) are higher than ours, indicating higher error in their climate surfaces. The inter-seasonal monthly statistics of minimum temperature reported by Télež-Valdés et al. (2011) have slightly lower values than the ones that we obtained.

4. Discussion and conclusions

Climate is highly diverse at the global scale and its accurate representation is challenging, especially when the weather stations that provide source data are unevenly and insufficiently distributed in many regions of the world (Jones et al., 1999; New et al., 1999, 2000, 2002). Nonetheless, availability of climate surfaces and bioclimatic parameters is an invaluable source of information which has been widely used in diverse applications in the biological and agricultural sciences (Funk and Richardson, 2002; Haylock et al., 2008; Hijmans et al., 2005; McKenney et al., 2006; Saenz-Romero et al., 2009; Télež-Valdés et al., 2011). However, given the dynamic nature and rapid change of climate in the last century information needs to be updated to increase its reliability and usefulness (Jones et al., 1999; Kriticos et al., 2011; Rahmstorf et al., 2007). Climatic surfaces have been updated several times for the United States (New et al., 1999, 2000, 2002) and recently Mitchell and Jones (2005) and McKenney et al. (2006) produced historical and actual climate surface representing the entire 20th century. McKenney et al. (2006) also derived 29 bioclimatic parameters that play an important role controlling the abundance and distribution of plant and animal species (Nix, 1986; Xu and Hutchinson, 2009). Our goal was to develop reliable and robust climate surfaces that represent the 20th century, so that they could be helpful for stakeholders and decision makers.

For Mexico, three digital climatologies have been produced before, covering different time periods: 1898–1995 (Télež-Valdés et al., 2011), 1960–1990 (Saenz-Romero et al., 2009), and 1950–2000 (Hijmans et al., 2005). Differences between the climatologies were expected, due to the difference in the data that was used for the interpolation (Hazeu et al., 2011). The climate surfaces generated by Télež-Valdés et al. (2011) extend...
Table 4. Mahalanobis distance (upper diagonal) and $F$ values (12, 3773) estimated from paired comparisons between four climatic surfaces derived from discriminate function analysis, all comparisons were statistically different ($P < 0.0000$).

<table>
<thead>
<tr>
<th></th>
<th>Cuervo-Robayo et al. (this study)</th>
<th>Téllez-Valdés et al. (2011)</th>
<th>Saenz-Romero et al. (2009)</th>
<th>Hijmans et al. (2005)</th>
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<td>3725202</td>
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<td>Téllez-Valdés et al. (2011)</td>
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<td>Saenz-Romero et al. (2009)</td>
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<td>1.16</td>
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<td>Hijmans et al. (2005)</td>
<td>95236.99</td>
<td>94683.74</td>
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</table>

Table 5. Factor structure matrix of $z$-scores of precipitation and temperatures derive from discriminate function analysis that represents the correlation of $z$-scores with canonical roots.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Root 1</th>
<th>Root 2</th>
<th>Root 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tmin8</td>
<td>-0.913</td>
<td>-0.011</td>
<td>-0.092</td>
</tr>
<tr>
<td>Tmax2</td>
<td>-0.005</td>
<td>0.733</td>
<td>-0.367</td>
</tr>
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<td>Tmax10</td>
<td>-0.001</td>
<td>0.010</td>
<td>-0.343</td>
</tr>
<tr>
<td>Tmax8</td>
<td>-0.001</td>
<td>0.002</td>
<td>-0.605</td>
</tr>
<tr>
<td>Tmin10</td>
<td>-0.621</td>
<td>-0.002</td>
<td>-0.068</td>
</tr>
<tr>
<td>Tmax5</td>
<td>0.000</td>
<td>0.013</td>
<td>-0.227</td>
</tr>
<tr>
<td>Tmin2</td>
<td>-0.014</td>
<td>0.003</td>
<td>-0.026</td>
</tr>
<tr>
<td>Prec2</td>
<td>0.001</td>
<td>0.081</td>
<td>0.429</td>
</tr>
<tr>
<td>Prec10</td>
<td>0.000</td>
<td>-0.012</td>
<td>-0.245</td>
</tr>
<tr>
<td>Prec8</td>
<td>0.000</td>
<td>0.073</td>
<td>0.338</td>
</tr>
<tr>
<td>Tmin5</td>
<td>-0.642</td>
<td>0.002</td>
<td>0.015</td>
</tr>
<tr>
<td>Prec5</td>
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<td>0.085</td>
<td>0.119</td>
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<td>Eigenvalue</td>
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<td>4.60</td>
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from 1898 to 1995 and used 6218 station for precipitation and 4262 for temperature. These were compiled from three sources: The Mexican Institute of Water Technology (1996), the International Center for Tropical Agriculture in Colombia (http://www.ciat.cgiar.org) and the National Climatic Data Center of the United States. Saenz-Romero et al. (2009) created monthly surfaces for a shorter period (1960–1990) and used data from 3971 stations for precipitation and about 3700 for temperatures. These data were collected from the National Weather Service of Mexico, the National Climate Center of United States (1994 and 2008), and from the EarthInfo Inc. (1994) database. The climate data source used by Hijmans et al. (2005) is diverse, cover an average period between 1950 to 2000, but the number and year of registration of stations used specifically for Mexico, were not reported (Table 2). They do not report the model’s diagnostic statistics, maybe because it is a global model, so the interpolation errors do not reflect the range of
error for a specific region. Even though they estimated that cross-validation errors for temperature were higher in some parts of the Americas and precipitation error was generally less than 10 mm/month in the vast majority of places within a 2-degree grid climate surfaces. They do not report the signal, RTGCV and RTMSE values, or standard error surfaces to compare for model assessment.

A source of error in all these climate surfaces is certainly the use of stations with poor data, however it has been estimated that the use of low quality stations does not have major negative effects or bias the results (Muller et al., 2013); however, we think if data is of extremely poor quality surely the results could also be poor quality. Instead, the use of more stations improves interpolations, especially in complex climatic areas like Mexico, where a low number of stations may not reflect climatic variations (Daly et al., 2008; New et al., 2002).

In this sense, the climatologies presented in this work represent a substantial upgrade to the climatic information for the country. Diagnostic statistics indicate that these new surfaces hold comparable errors to other climate surfaces developed for North America (Daly et al., 2008; Hutchinson et al., 2009; McKenney et al., 2006; Parra and Monahan, 2008; Saenz-Romero et al., 2009; Téllez-Valdés et al., 2011). The signal ratios for both temperature and precipitation were lower than the maximum indicating an appropriate degree of smoothing and that the surfaces are stable and robust. This is especially important for the north of Mexico, where coverage of weather station was scarce. The errors are directly related to the number of weather stations used for the interpolation (Hutchinson et al., 2009), on one hand, and on the other, to topographical complexity (Hijmans et al., 2005; Saenz-Romero et al., 2009), particularly so for precipitation.

Summer precipitation is difficult to model due to the high variability of rain in these months, and the result of convective processes that produce localized rainfall events (McKenney et al., 2006). For example in northwestern Mexico, there is a tendency for more winter precipitation, which has resulted in positive trends in river water levels (Dore, 2005). A general changing pattern shows that precipitation has increased in the Northern Hemisphere, but that in particular depends on the orientation of the catchment ( Jáuregui, 1979). Furthermore, few stations register differences in precipitations, associated to mountain barrier, slope, landform and mountain bridges (Gómez et al., 2008). In this sense, it is important to mention that the quality of the surfaces is spatially variable and depends on the local climate variability, and density of weather stations. In that sense, standard error surfaces are useful to assess the variability of the uncertainty within the monthly climate surfaces.

We recommend that future interpolations’ of climate for a specific region must consider variables that better explain climate variation at that local spatial scale. For example, for the region of Los Tuxtlas, southern Veracruz (Gutierrez-Garcia, 2011), additionally to longitude, latitude and elevation independent variables, used distance to the sea, the terrain’s slope, and the terrain’s aspect as covariates. Interpolations for conterminous parts of Mexico could be improved by including variables as those mentioned above (Daly et al., 2008). Also, future climate surfaces can be developed for different periods (i.e. annually and/or monthly) of the 20th century, which can be useful to define a baseline for climate change analysis.

In conclusion, the climatologies presented here represent significant progress regarding the climatic information available for Mexico, but additional efforts are needed to improve them (Mitchell and Jones, 2005). Evaluation of data sources, the amount of uncertainty and comparisons between datasets, as in this study, provides information on the geographical distribution of the error, as a starting point to improve areas where surfaces have more error. However, given the deficiency of climatic data in Mexico, we suggest using time periods covering at least 30 years of weather record, to produce climatologies that reflect climatic patterns of the country.

Acknowledgements

We would like to thank CONACyT for the Ph.D. scholarship number: 217650 to the first author. Dr. Janet Stein, from Fenner School of Environment and Society, Australian National University for reviewing and correcting the manuscript. To DGAPA-UNAM program (PAPIIT IN-216912) for financial support to carry out
projects for generating climatologies for Mexico. Servicio Meteorológico Nacional (SMN) for weather stations information. And to an anonymous reviewer who has made very valuable recommendations.

References


