Climatic Change (2010) 102:595–623
DOI 10.1007/s10584-009-9753-5

Spline models of contemporary, 2030, 2060 and 2090 climates for Mexico and their use in understanding climate-change impacts on the vegetation

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Received: 11 June 2008 / Accepted: 27 August 2009 / Published online: 12 November 2009

Abstract Spatial climate models were developed for México and its periphery (southern USA, Cuba, Belize and Guatemala) for monthly normals (1961–1990) of average, maximum and minimum temperature and precipitation using thin plate smoothing splines of ANUSPLIN software on ca. 3,800 observations. The fit of the model was generally good: the signal was considerably less than one-half of the number of observations, and reasonable standard errors for the surfaces would be less than 1°C for temperature and 10–15% for precipitation. Monthly normals were updated for three time periods according to three General Circulation Models

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and three emission scenarios. On average, mean annual temperature would increase 1.5°C by year 2030, 2.3°C by year 2060 and 3.7°C by year 2090; annual precipitation would decrease −6.7% by year 2030, −9.0% by year 2060 and −18.2% by year 2090. By converting monthly means into a series of variables relevant to biology (e. g., degree-days > 5°C, aridity index), the models are directly suited for inferring plant–climate relationships and, therefore, in assessing impact of and developing programs for accommodating global warming. Programs are outlined for (a) assisting migration of four commercially important species of pine distributed in altitudinal sequence in Michoacán State (b) developing conservation programs in the floristically diverse Tehuacán Valley, and (c) perpetuating *Pinus chiapensis*, a threatened endemic. Climate surfaces, point or gridded climatic estimates and maps are available at http://forest.moscowfsl.wsu.edu/climate/.

1 Introduction

Biogeographers generally view climate as the primary factor controlling the distribution of plants (Brown and Gibson 1983; Tukanen 1980; Woodward 1987). Consequently, understanding plant–climate relationships is essential for designing comprehensive programs for the management and conservation of plant species, even without considering a change in climate. Comprehensive programs, however, require climate models, particularly for countries like México which have a large diversity of vegetation types (Rzedowski 1993) and high biodiversity (or megabiodiversity) (Mittermeier 1988; Ramamoorthy et al. 1993), particularly in forest trees such as the pines (Styles 1993), oaks (Nixon 1993) and legumes (Ricker et al. 2007).

Climate-change is expected to have negative impacts on food production, biodiversity, and conservation efforts, particularly in developing countries with tropic and subtropical climates that are expected to become more arid (Beg et al. 2002; Steffen 2008). Entire ecosystems will be decoupled of the climates that occur at their present distribution, and numerous tree species and populations will face extirpation unless they adapt or migrate (Rehfeldt et al. 1999, 2001, 2006; Hughes 2000; Tchebakova et al. 2005; Hamann and Wang 2006; Wang et al. 2006; Aitken et al. 2008). Expectations from climate-change in México include a substantial reduction of the present distribution of oaks and pines (Gomez-Mendoza and Arriaga 2007), and a shift or a decrease of the habitat distribution of several endemic and endangered species, both plants (Téllez-Valdés and Dávila-Aranda 2003; Téllez-Valdés et al. 2006) and wild animals (Peterson et al. 2002).

Developing strategies and programs for the management and conservation of genetic resources in forestry and agriculture for mitigating impacts of ongoing climatic change, such as selection of new crop varieties more resistant to drought stress (Pachauri 2004), redesign boundaries of existing natural protected areas for biological conservation (Téllez-Valdés and Dávila-Aranda 2003), assisted migration of plant populations northwards or to higher elevations (Hughes 2000; Tchebakova et al. 2005; Aitken et al. 2008), and increases in the genetic diversity of tree plantations to facilitate adaptative responses to climatic change (Ledig and Kitzmiller 1992; St Clair and Howe 2007), in a large extent are dependent on having future climate estimates (see Tchebakova et al. 2005). The traditional guidelines for the matching of genotypes to the climates for which they are adapted require adjustment to account for the fact that climate in any given geographical area will not be the same as in the near future (Hughes 2000; Rehfeldt et al. 2006; Sáenz-Romero et al. 2006; Gomez-Mendoza and Arriaga 2007; St Clair and Howe 2007; Aitken et al. 2008).

Developing a realistic climate model is challenging for countries like México where (1) physiography is complex, (2) weather stations are mainly distributed near agricultural areas, and (3) the stations are relatively poorly represented on the high mountains and remote areas where forest resources predominate, despite ongoing high rates of deforestation (see Sáenz-Romero et al. 2003). In this paper, we develop a climate model using thin plate smoothing splines, a relatively recent developed tool (Bates and Wahba 1982; Wahba 1985; Kohn et al. 1991) shown to have useful applications in the construction of climate models (Hutchinson 1993, 1995, 1998a, b; Hutchinson and Gessler 1994; Price et al. 2000). The splines can be viewed as an extension of multivariate regression, where the parametric regression model is replaced by a smooth non-parametric function and the splines fit a dependence on elevation (Hutchinson 2004). This technique, when applied to climate data from geographically complex regions, has proven to be superior to other extrapolation techniques like inverse distance weighted averaging (IDWA) or co-kriging (Hartkamp et al. 1999; Boer et al. 2001).

The ANUSPLIN software of Hutchinson (2004) has made the splining techniques readily accessible for climate modeling. For example, McKenney et al. (2001) have revised Canada's plant hardiness zones using Hutchinson's software. Rehfeldt (2006) has fit splines for the geographically complex western USA, and this work has recently been extended to all of western North America (see URL: http://forest.moscowfsl.wsu.edu/climate/). Although México is covered in a world-wide analysis (Hijmans et al. 2005), our analyses use an intensive distribution of samples for which an emphasis is placed on obtaining data for remote locations ordinarily not represented in largely agronomic databases, to provide point estimates of climate rather than gridded estimates. Other spline models for México tend to be regional: for Jalisco state, western México (Hartkamp et al. 1999; Boer et al. 2001), the Biosphere reserve of the Tehuacán Valley which lies at the border between the states of Puebla and Oaxaca (Téllez-Valdés and Dávila-Aranda 2003), and for habitats of *Fagus mexicana* (Téllez-Valdés et al. 2006).

Our contemporary spline climate model for México is based on an intensive sample of data from approximately 4,000 weather stations while projections use station data updated according to output of several General Circulation Models and emission scenarios for decades centered in the years 2030, 2060 and 2090. While the model is primarily for México, the geographic extent of the model includes southern USA (below the parallel 33° N), Belize, Guatemala and Cuba, and by extrapolation the Bahamas, Jamaica, and north of Honduras. Application of the model in programs designed to accommodate potential impacts of global warming is illustrated for genetic studies of Mexican pines in the western state of Michoacán, for the prediction of contemporary and future distribution of an endangered Mexican pine (*Pinus chiapensis)*, and for studies of the potential impacts of climatic change in a region with highly contrasting climate (the Tehuacán Valley and its neighboring slopes of Sierra Madre Oriental).

2 Methods

2.1 Spline surfaces for contemporary climates

We constructed a spline climate model using monthly averages of total precipitation, average temperature, maximum average temperature and minimum average temperature normalized for 1961–1990 period that we designated as the contemporary climate. The original raw data base consisted of more than 6,000 weather stations geographically limited in the North at 33° N latitude, in the South at 13° 54′ N latitude, in the West at 117° W longitude, and at the East at 74° W longitude (Fig. 1). USA data were obtained from the weather service (U. S. Department of Commerce 1994) and EarthInfo Inc. (1994); México data from Mexican Weather Service (personal request to Mexican Servicio Metereológico Nacional, México City) and Guatemala, Belize and Cuba from U.S. Department of Commerce (2008).

In assembling a dataset for analysis, we first constructed a list of standard stations, those with at least 20 years of observations in our 30-year period of normalization, ca. 2,600 stations of which 1,700 were Mexican. However, the distribution of standard stations tended to be skewed toward agricultural regions, particularly in México (Fig. 1b). To provide data points from remote areas, we assembled a list of candidate stations defined as those having at least 7 years of records for precipitation and 5 years for temperature variables. From this list, we eliminated the observations within 20 km and 50 m elevation of a standard station and those within the same distance of another candidate station with more years of observations. The remaining candidate stations totaled ca. 1,600 (Fig. 1b). This meant that the total number of stations supplying data was ca. 4,200, but all variables for all months were not necessarily available from each.

Data from the candidate stations were then adjusted to the period of normalization (1961–1990) by calculating and averaging monthly deviations for years in common between a candidate station and the four geographically proximal standard stations. The deviations were then used to estimate monthly normals for the candidate station from the mean of the four normals of the standard stations (see Rehfeldt 2006). To avoid the tacit assumption that deviations calculated in this manner were constant for all elevations, we used a set of rules that were applied sequentially until four stations were obtained: chose the closest stations from (1) within 100 km and 300 m elevation, (2) within 100 km and 600 m elevation, (3) within 300 km and 300 m elevation, and (4) within 300 km and 600 m elevation. Absolute values of the deviations were used for the calculation of temperature normals but ratios were used for precipitation.

As a result, our analyses are based on normalized monthly data from 3,971 stations for precipitation (Fig. 1b) and about 3,700 for the temperature variables. Approximately 78% of the stations were from México and about 20% from USA. There were 12 stations from Cuba, five from Guatemala, and four from Belize.

Thin plate splines were fit to normalized monthly means with the software ANUSPLIN v 4.3 (Hutchinson 2004) which fit smoothing parameters to the x-, y-, z-coordinates of geographic space. First, knots were generated using the SELNOT program. Output from the knots program was used for generating surfaces with the SPLINB option. We followed the recommendations of Hutchinson in using the output from the spline program to eliminate or add stations to the knots file. After

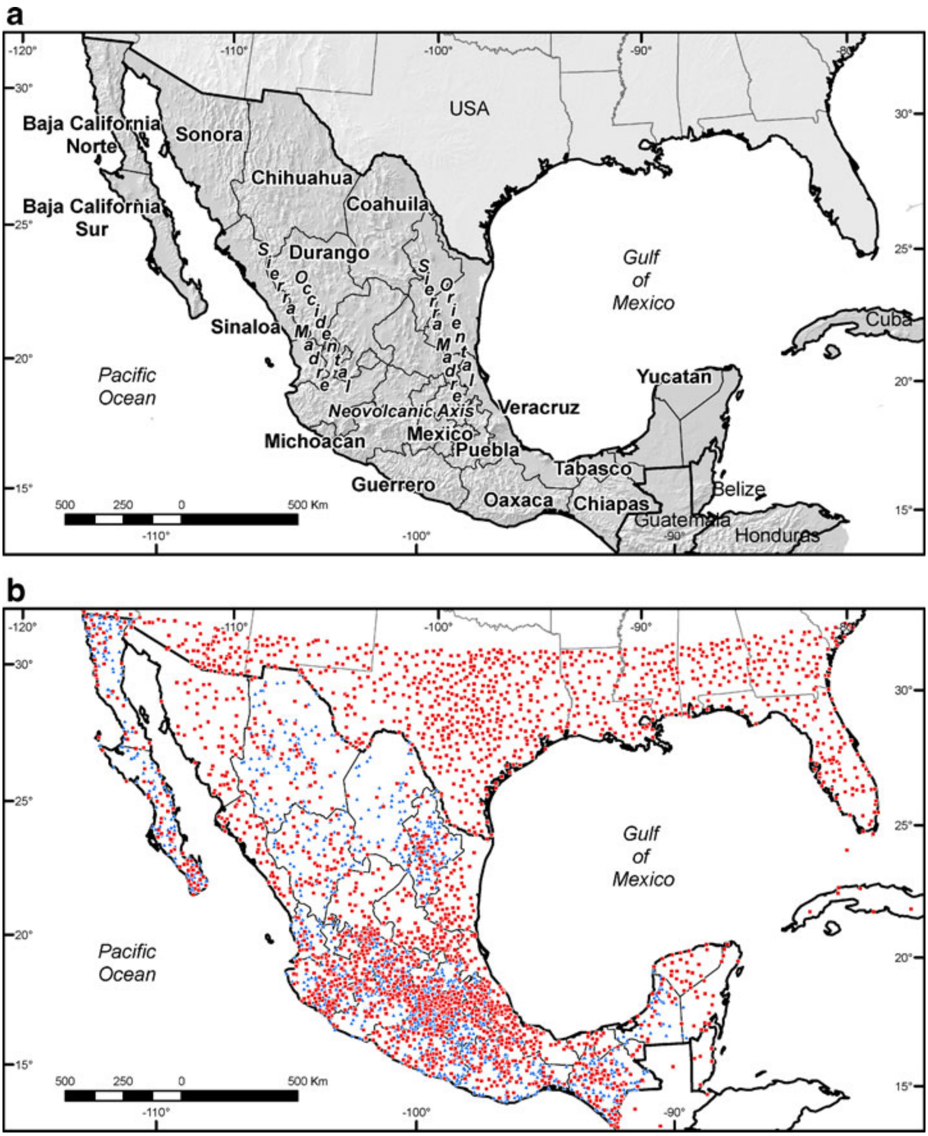


Fig. 1 Political divisions and prominent geographical regions of México referenced in text (**a**) and location of weather stations (standard = *red square*, normalized = *blue triangle*) used for the spline surfaces (**b**)

three iterations, the final surfaces were produced using 1,921 knots for precipitation and 1,703 for the temperature variables. The SPLINB program also accumulates in a ‘bad data flag file’ containing those monthly observations that lie more than 3.6 standard deviations off the surface. In the final model, these observations were not used to produce the climate surfaces. We fitted second order splines using latitude, longitude, and elevation as independent variables. Precipitation analyses used the square root transformation.

The statistical fit of the surfaces was assessed from three diagnostic statistics: the signal, root mean square error (RTMSE), and root of the generalized cross validation statistic (RTGCV). The signal is indicative of the degrees of freedom associated with the surface, which in a well fitting model should be no more than one-half of the number of observations; RTMSE is a measure of the standard error of surface values after the data error has been removed; and RTGCV is a spatially averaged standard error that reflects errors of prediction (Hutchinson 2004).

After fitting the splines, we explored their ability to provide reasonable estimations of temperature lapse rates using mean annual temperature for demonstration. Predicted temperatures were obtained for an altitudinal transect at 13 geographic locations. The locations represented the climatic diversity of México: moist and warm low lands with coastal Gulf of México influence (Tuxtepec, Oaxaca and Rio Blanco, Veracruz) and with coastal Pacific influence (Concordia, Sinaloa; Aquila, Michoacán); cold, high interior plateau (Toluca, Estado de México; Topilejo, Distrito Federal); cold, dry interior lands (Durango, Durango); very cold high mountains (El Salto, Durango); dry, warm interior lands (Oaxaca City and Tehuacán Valley, Oaxaca; Balsas Depression, Michoacán); dry, high inland plateau (Zacatepec, Puebla), and peninsular dry with Pacific influence (Santa Martha Mulege, Baja California). Transects were about 50 km in length, and consisted of 10–15 data points for which altitudes were obtained from GLOBE Task Team (1999). Altitudinal range of the transects was at least 1,500 m. Estimated mean annual temperatures by location were regressed on altitude using PROC REG of SAS (SAS Institute Inc. 1998).

Monthly estimates from the spline surfaces were converted into 19 variables of relevance to plants (see Tukanen 1980; Rehfeldt et al. 2006) according to the algorithms of Rehfeldt (2006). The variables were: mean annual temperature (MAT, degree Celsius), mean annual precipitation (MAP, mm), total precipitation in the growing season (April to September, GSP, millimeters), degree-days above 5°C (DD5), negative degree-days calculated from average temperature (DD0) or minimum temperature (MINDD0), mean temperature in the coldest month (MTCM, degree Celsius), mean minimum temperature in the coldest month (MMIN, degree Celsius), mean temperature in the warmest month (MTWM, degree Celsius), mean maximum temperature in the warmest month (MMAX, degree Celsius), Julian date of last spring frost (SDAY), Julian day of first fall frost (FDAY), length of frost-free season (FFP, days), degree-days above 5°C in the frost-free season (GSDD5), and Julian day on which DD5 sums to 100 (D100). Derived variables also included interactions among these variables such as the proportion of the total precipitation that falls during the summer (GSP/MAP), an annual aridity index ($AAI = DD5^{0.5}/MAP$), growing season aridity index ($GSAI = GSDD5^{0.5}/GSP$) and summer–winter temperature differential ($TDIFF = MTWM - MTCM$).

To illustrate the climate diversity of México as described by our surfaces, we estimated monthly average, minimum and maximum temperatures and precipitation for each cell of a digitized elevation model (GLOBE Task Team 1999) gridded at 0.5 min (0.008333° or approximately 1 km^2). For the study area, the total number of terrestrial cells was 4,630,997. The grids were then mapped with Geographical Information System software (Minami 2000).

2.2 Future climates and their surfaces

To estimate the future climates for the decades centered about years 2030, 2060 and 2090, we updated the monthly normals of precipitation, minimum, maximum and average temperatures of all weather stations with outputs from the following General Circulation Models (GCMs) and scenarios: (a) Canadian Center for Climate Modelling and Analysis (CCC), using the CGCM3 (T63 resolution) model, SRES A2 and B1 scenarios; (2) Met Office, Hadley Centre (HAD), using the HadCM3 model, SRES A2 and B2 scenarios; and (3) Geophysical Fluid Dynamics Laboratory (GFD), using the CM2.1 model, SRES A2 and B1 scenarios. Data, their descriptions, and explanation of the scenarios are available at the International Panel on Climate Change Data Distribution Center (URL: http://www.ipcc-data.org/). Weather station records were updated by using a weighted average of the monthly change in climate calculated for the GCM cell centers lying within 400 km of a station. The inverse of the square of the distance from the station to the cell center was used for weighting.

Of these emission scenarios, the A2 assumes high continued emissions from a continuously increasing population growth, with economic growth and technological change very heterogeneous among different regions and countries of the world; scenario B1 assumes a gradual reduction in emissions as rapid changes in economic structures are made toward a reduction in material intensity and introduction of clean technologies; scenario B2 assumes a continuous increasing population but at rate lower than scenario A2, intermediate levels of economic development and less rapid and more diverse technology change than B1 and A1. Scenario A1B assumes emissions intermediate between the A and B with a balanced fossil-intensive and non-fossil energy source in a world of very rapid economic growth as well as a rapid introduction of more efficient technologies (see URL: http://www.ipcc-data.org/; IPCC 2000).

The splines were then refit for each time period to produce monthly surfaces for the four climate variables for each scenario of all GCMs. Derived variables were then calculated as described above. Rather than updating grid cells of a fine resolution from the relatively coarse grids of the GCMs, our approach to downscaling begins anew the construction of spline surfaces from updated weather records. Either approach, however, tacitly assumes a constant relationship between elevation and the change in climate. Although this assumption is likely to be false, there are at present no reasonable alternatives. Our projections, therefore, are based on the differences in climate between that of a weather station and that of an average elevation of a GCM grid cell. Bias would occur if these differences were dependent on the elevation of the weather station.

For this paper, we illustrate projected changes in climate by mapping predictions for the A2 scenario of CCC for the decade centered in 2090. Other projections are available at http://forest.moscowfsl.wsu.edu/climate/.

2.3 Toward understanding plant–climate relationships

To illustrate the utility of the climate surfaces in biology, we consider (1) potential impacts of global warming on migration pattern of Mexican vegetation, (2) climatic niche analyses of a narrow endemic, *Pinus chiapensis*, (3) assisted migration in the botanical unique Tehuacán Valley as a management strategy for accommodating a changing climate, and (4) projection into future climate space the genetic differences occurring among populations within four species of pine inhabiting altitudinal transects in the Neovolcanic (also known as Transvolcanic) Axis (Fig. 1). For the latter analyses, genetic responses of populations separated by 100 m of elevation have been studied previously for *Pinus oocarpa* populations from 1,100 to 1,500 m (Sáenz-Romero et al. 2006); *P. devoniana* (also known as *P. michoacana*) populations from 1,600 to 2,400 m (Sáenz-Romero and Tapia-Olivares 2008); *P. pseudostrobus* populations from 2,100 to 2,800 m (Viveros-Viveros et al. 2005); and *P. hartwegii* populations from 3,000 to 3,600 m (Viveros-Viveros et al. 2009). Contemporary and 2,030 values of five derived variables, MAT, MAP, DD5, MTCM and AAI, were estimated using the A2 scenario of CCC. From these estimates we calculate the altitudinal distance that populations would need to be transferred if they were to occur in a climate similar to that inhabited today. The underlying assumption is that existing populations are genetically adapted to contemporary climates (Sáenz-Romero et al. 2006).

To illustrate the use of the climate surfaces in climate niche analyses, we used the Random Forest classification tree of Breiman (2001) and followed the procedures detailed by Rehfeldt et al. (2006) to develop a statistical model to predict presence–absence of *P. chiapensis* from contemporary climate variables and to project the climate niche according to the 2060 climate of the A2 scenario of HAD. Breiman's algorithm develops a classification tree from two-thirds of the observations selected randomly from a data set and uses the remaining observations to calculate error. The program then constructs a forest from a set of trees that use a recursive sample from the data set. For presence, we used all known locations inhabited by *P. chiapensis*, taken from Dvorak et al. (1996a), Newton et al. (2002), del Castillo and Trujillo (2008) and del Castillo et al. (2009), a total of 53. Because these observations constituted a census, we could assume that all other sites sampled from a digitized file of the Biotic Communities of North America (Brown et al. 1998) would not be inhabited by the pine. Technical procedures, described in detail in Rehfeldt et al. (2006), include devising a sampling procedure according to which the number of observations taken from a community was determined by the size and number of polygons representing a community in the digitized file, procuring a systematic sample of observations from each polygon on the file, associating with each observation an elevation from the digitized elevation model of GLOBE Task Team (1999), and estimating the climate of each location from the spline surfaces. These procedures produced a pool of about 56,000 observations for which the pine was absent.

Because the Random Forests algorithm is best suited to data in which the number of observations in classes is approximately equal (see Breiman 2001), only a small proportion of the number of observations without the pine could be used to construct a forest. In using the sampling protocol of Rehfeldt et al. (2006), we constructed 25 data sets, each with the 53 observations where the pine was present, weighted twice, and about 160 climatically diverse observations lacking the pine. Each data set was used in separate analyses to build a forest of 500 trees. This sampling protocol assures that 80% of the observations without the pine will be among those for which separating presence from absence is the most difficult.

The program started with 34 climate variables (19 derived variables previously described here plus additional interactions between them, such as DD5 × MAP) on which an iterative stepwise process eliminated one variable at each step according to the mean decrease in accuracy, a measure of variable importance. The process was halted with an eight-variable, shown previously to be robust for making projections. To make a prediction from the model, observation is run through all trees in all forests, with each tree contributing a vote, which in our case, would be whether or not the climate of an observation is suited for the pine. In making predictions for each cell of the GLOBE Task Team (1999) grid and, therefore, for gridded GCM projections, 12,500 votes were cast in each pixel. We assumed that the climate of a pixel was suited to the pine when a majority of the votes was affirmative.

3 Results and discussion

3.1 Spline surfaces for 1961–1990 normals

The signal averaged ca. 950 for monthly temperatures and 1,400 for precipitation. Because the signal was much less than the number of knots (ca. 1,700 for temperature variables and 1,900 for precipitation), our choice for the number of knots is adequate (see Hutchinson and Gessler 1994). The ratio of the signal to the total number of observations for the average, minimum and maximum temperatures averaged ca. 0.26, and those for precipitation averaged 0.36 (Table 1). Because the signal is much less than one-half of the number of observations, we conclude that models are a reasonably well fitting representation of the climatic variation in Mexico. These ratios are considerably less than those reported by McKenney et al. (2001) for Canada, Rehfeldt (2006) for northwest USA, and Boer et al. (2001) for western México. The signal was slightly higher in the summer months for the average and minimum temperatures, but showed no discernable pattern for maximum temperature and precipitation (Table 1), suggesting a greater instability in the temperature during the summer than during winter (Hutchinson and Gessler 1994).

The square root of the generalized cross validation statistic (RTGCV, Table 1), an conservative estimate of the predictive error (Hutchinson 2004) varied between 1.3°C and 1.6°C for the temperature variables and 7 mm in dry months to 34 mm in wet months (about 22% of the mean) for precipitation. The root mean square error (RTMSE), an optimistic estimate of the surface error, varied from 0.5°C to 0.75°C for the temperature variables and from 3 to 16 mm (3–10% of the mean) for precipitation. According to Hutchinson (2004), it would be reasonable to conclude that the standard errors for our surfaces are less than 1°C for temperature and 10–15% for precipitation. The ratio of RTMSE to RTGCV is about 0.5, suggesting that a substantial amount of data noise was overcome by fitting the spline model.

These surface errors are similar to those found for Canada (McKenney et al. 2001) and for western USA (Rehfeldt 2006), and seem typical of temperature and precipitation surfaces in general (Hutchinson 2004). While Hutchinson (2004) notes that a RTMSE value of 0.5 frequently results from fitting average temperature, the larger errors (Table 1) for minimum and maximum temperatures probably reflects

Table 1 Ratio of signal to the total number of observations, the square root generalized cross validation statistic (RTGCV), and the root mean square error (RTMSE) for spline monthly temperatures and precipitation surfaces

Month	Average temperature (°C)				Minimum temperature (°C)				Maximum temperature (°C)				Precipitation (mm)			
	Ratio	RTGCV	RTMSE	Mean	Ratio	RTGCV	RTMSE	Mean	Ratio	RTGCV	RTMSE	Mean	Ratio	RTGCV	RTMSE	Mean
1	0.22	1.26	0.53	14.8	0.22	1.69	0.70	7.2	0.24	1.53	0.66	22.6	0.36	8.39	4.04	34.2
2	0.24	1.26	0.54	16.0	0.22	1.69	0.70	8.0	0.26	1.56	0.69	24.1	0.35	7.44	3.57	29.0
3	0.25	1.28	0.56	18.5	0.23	1.68	0.71	10.2	0.26	1.61	0.71	26.8	0.35	7.31	3.51	28.7
4	0.27	1.33	0.59	21.0	0.23	1.67	0.71	12.8	0.26	1.68	0.75	29.3	0.31	8.55	3.98	32.6
5	0.29	1.34	0.61	22.9	0.25	1.60	0.70	15.1	0.28	1.67	0.75	30.7	0.33	13.40	6.31	61.0
6	0.30	1.28	0.59	23.8	0.27	1.51	0.67	16.9	0.27	1.61	0.72	30.7	0.34	27.00	12.90	134.8
7	0.29	1.24	0.56	23.7	0.25	1.39	0.61	17.3	0.27	1.55	0.69	30.0	0.36	33.50	16.20	155.0
8	0.29	1.22	0.56	23.5	0.26	1.39	0.61	17.2	0.27	1.53	0.68	29.9	0.35	32.90	15.80	153.8
9	0.29	1.20	0.54	22.6	0.25	1.40	0.61	16.3	0.27	1.51	0.68	28.8	0.34	33.00	15.70	157.3
10	0.27	1.21	0.53	20.4	0.26	1.46	0.65	13.5	0.27	1.51	0.67	27.4	0.38	19.40	9.44	79.1
11	0.24	1.22	0.53	17.7	0.23	1.62	0.69	10.2	0.25	1.51	0.66	25.3	0.37	10.50	5.06	39.2
12	0.23	1.24	0.53	15.6	0.22	1.67	0.71	8.1	0.25	1.51	0.66	23.1	0.37	8.88	4.31	35.7
Average	0.27	1.26	0.56	20.06	0.24	1.57	0.67	12.7	0.26	1.57	0.69	27.4	0.36	20.40	9.81	78.4

Number of observations was ca. 3,700 for the temperatures and 3,971 for precipitation the high variance in temperature in mountain systems in the arid north and humid systems in the south and east.

When expressed as a ratio to the mean, monthly RTMSE for western USA (Rehfeldt 2006) are quite similar as for Mexico. Largest errors tend to be associated with the wettest months, generally the winter in USA and summer in Mexico. Precipitation is generally higher in Mexico, and, therefore, inherently more variable during the summer monsoonal flow of moist air masses inland from the Gulf of Mexico.

In general, the signal, RTMSE, and RTGCV describe spline models that are well fit to the heterogeneous climates of Mexico. As discussed by Hijmans et al. (2005), uncertainty in the surfaces is directly related to, first, the number of observations and, second, variation in elevation. Because Mexico's physiognomy is a complex system of mountains and volcanoes, we addressed these sources of uncertainty by maximizing the number of observations particularly for remote locations.

As would be required in a well fitting climate model, altitudinal lapse rates for mean annual temperature depicted by the spline surfaces produced linear regressions that were statistically strong (Fig. 2). Simple correlations of temperature on elevation

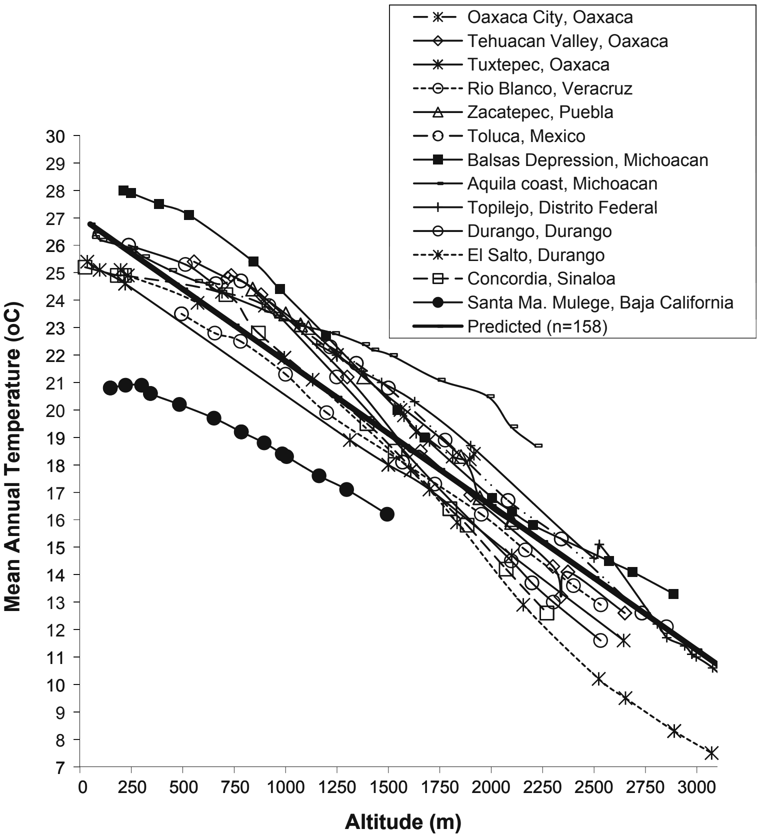


Fig. 2 Plots of predicted mean annual temperature across an altitudinal gradient for 13 locations with contrasting climates

averaged $r = -0.99$ ($P = 0.0001$) for the 13 altitudinal transects when analyzed separately, and -0.85 ($P = 0.0001$) for pooled data. As shown by the regression coefficients, lapse rates for these diverse locations varied from 3.4°C to 6.8°C per 1,000 m. As shown in Fig. 2, the relationship between mean annual temperature and elevation tends to flatten at elevations <500 m. Nonetheless, an average of 5.2°C per 1,000 m for the 13 transects is in close agreement with adiabatic lapse rates which are generally 5.0–5.5°C per 1,000 m (see Rosenberg 1974).

3.2 Projected climates and their spline surfaces

Weather station records updated for GCM output show in general that mean annual temperatures should increase steadily in Mexico, by 1.5°C in the decade surrounding 2030, 2.3°C in 2060, and 3.7°C by 2090 (Fig. 3). Projections, however, increasingly diverge among models and scenarios during the course of the century. For 2030, all the models and scenarios were similar, with the largest difference (0.5°C) between model CCC scenario A2 (increase of 1.7°C) and model GFD scenario B1 (increase of 1.2°C). By 2060, differences increased, with the largest difference (1.2°C) being between the most pessimistic scenario, A2 of HAD, which predicted a temperature increase of 2.8°C; the most optimistic was the B1 scenario of GFD which predicted an increase of 1.6°C. By year 2090, however, the differences among projections became even more pronounced, with model HAD scenario A2 projecting an increment of 5.0°C while GFD scenario B1 projecting 2.3°C. The 2090 projected increases shown in Fig. 3 are well within the range summarized for 21 global models for México and Central America for the period 2080–2099 Christensen et al. (2007). Figure 3 also shows that estimates for 2090 differ more between scenarios than between GCMs.

The GCMs and their scenarios unanimously project a decrease in precipitation across the century (Fig. 4), averaging −6.7% by 2030, −9% by 2060, and −18.2% for 2090. Variation among the GCMs and scenarios, however, was large. Projections

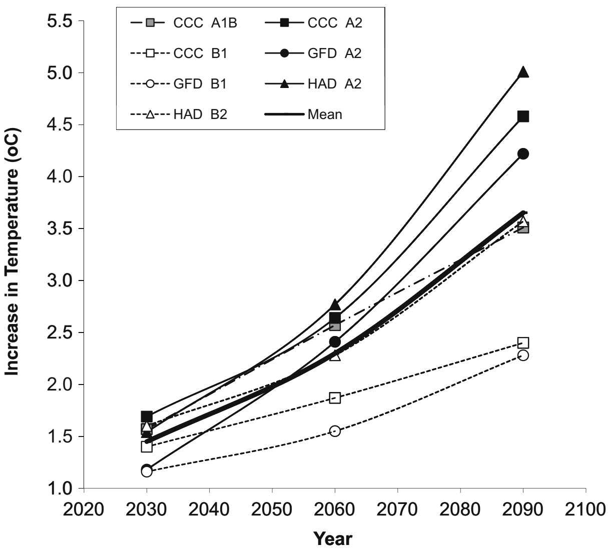


Fig. 3 Mean increment of average annual temperature (degree Celsius) in comparison to contemporary climate (1961–1990) from 3,700 weather stations updated by an inverse distance weighting for GCMs from the Canadian Center for Climate Modeling and Analysis (CCC, scenarios A2, B1 and A1B), Hadley Center (HAD, scenarios A2 and B2) and Geophysical Fluid Dynamics Laboratory (GFD, scenarios A2 and B1), for decades centered in years 2030, 2060 and 2090

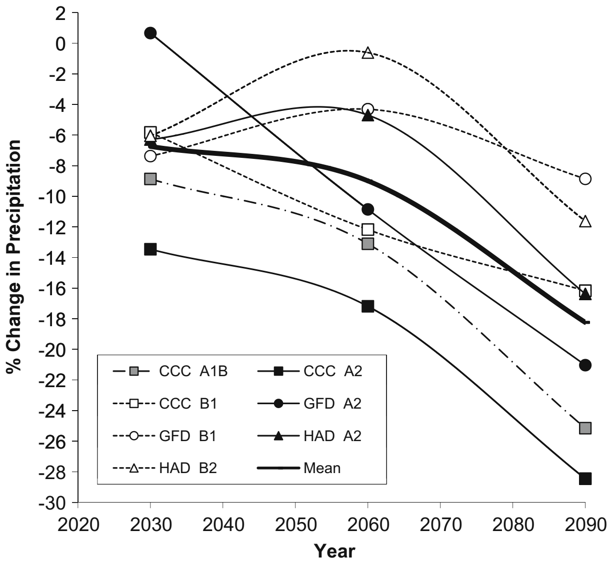


Fig. 4 Mean change in annual precipitation (percent) in comparison to contemporary climate (1961–1990) from 3,971 weather stations updated by an inverse distance weighting for GCMs from the Canadian Center for Climate Modeling and Analysis (CCC, scenarios A2, B1 and A1B), Hadley Center (HAD, scenarios A2 and B2) and Geophysical Fluid Dynamics Laboratory (GFD, scenarios A2 and B1) for decades centered in years 2030, 2060 and 2090

for 2030, for instance, varied between +0.7% and −13.5%, but for 2060, three of the projections predict increased precipitation in comparison to 2030, but with still an overall decrease from the present (ca. −3%), while four of the projections suggest a continued decline from 2030 to ca. −12% of the present. By 2090, all projections predict that precipitation should decrease, by −8.9% to −28.5% of the present. These results are similar to those of Christensen et al. (2007) who calculated reductions ranging from −9% to −48% for México and Central America between 2080 and 2099 from 21 global models.

Differences projected for precipitation between the A and B scenarios increase considerably in time. Although the two scenarios purport a similar reduction in precipitation for 2030 of about −6.5%, by 2060 the reduction for the A scenario is expected to be about −10.9% while that for the B scenario is −5.7%. By 2090, the reduction in precipitation under the A scenario (−22%) is projected to be nearly twice that of the B scenario (−12.2%).

In using updated weather records to develop climate surfaces for the future, we examined 21 sets (seven model-scenarios by three time periods) of spline output statistics such as those of Table 1. Although the monthly means changed, the signal, RTMSE, and RTGCV remained similar. The fit of the models, therefore, was also similar.

3.3 Mapped climate surfaces

To illustrate the tremendous climatic variability in México, we mapped predicted mean annual temperature, mean annual precipitation, and the annual aridity index of the contemporary period and for 2090, the latter using the A2 scenario of CCC (Figs. 5, 6, 7). As expected, geographic patterns in mean annual temperature reflect altitudinal differences between the mountain systems and the lowlands. In the contemporary climate, the coolest regions (<12°C) are concentrated along the

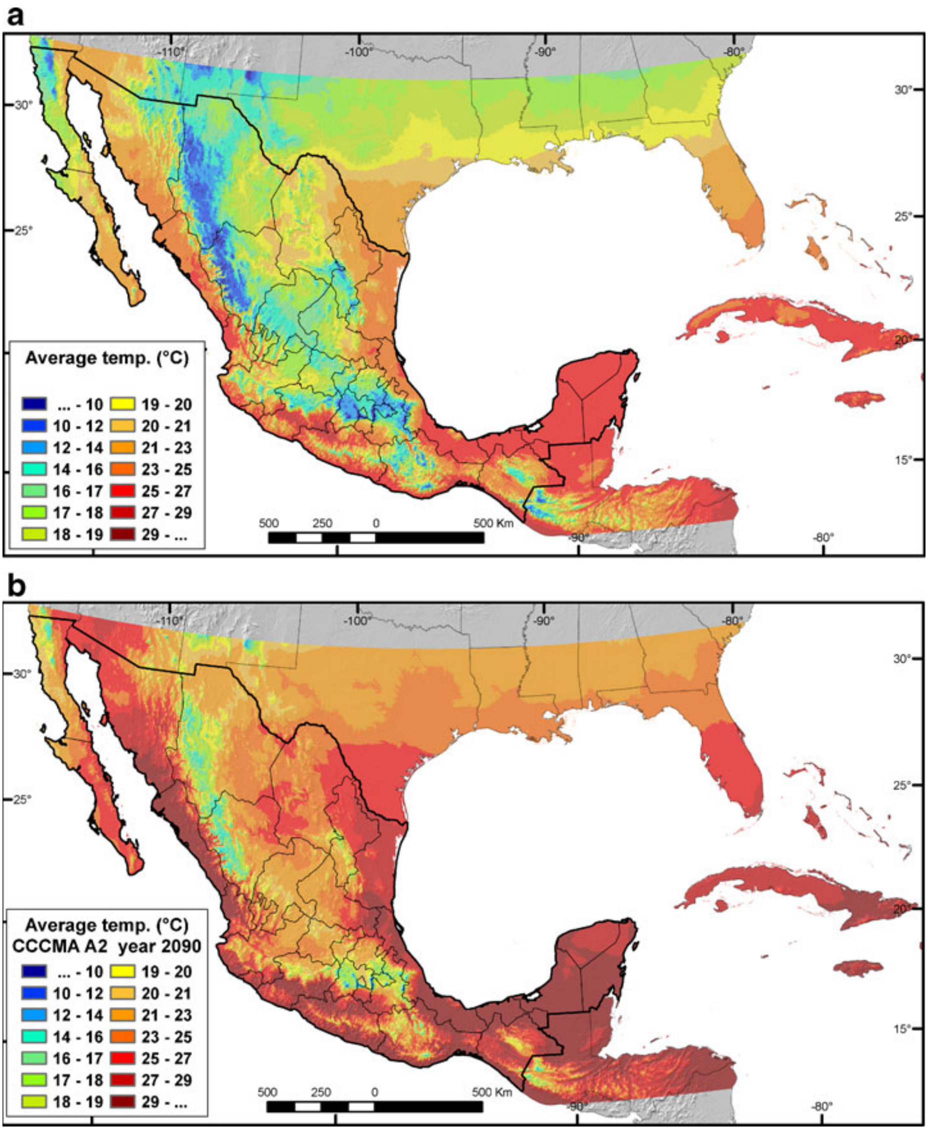


Fig. 5 Mapped predictions of mean annual temperature (degree Celsius) for digitized elevations on a 0.5 min (about 1 km) grid, for contemporary climate (**a**) and 2090 climate (**b**), using output from the Canadian Center for Climate Modeling and Analysis model, scenario A2

mountainous Sierra Madre Occidental and the central Neovolcanic Axis (Figs. 1a and 5a), where the highest Mexican volcanoes occur. Areas with >25°C occur along much of the coastal regions south of 25° N as well as in the Yucatán Peninsula (Fig. 5a). Because the mean annual, maximum, and minimum temperatures and degree days >5°C are correlated, their geographic patterns are all similar to those of Fig. 5a.

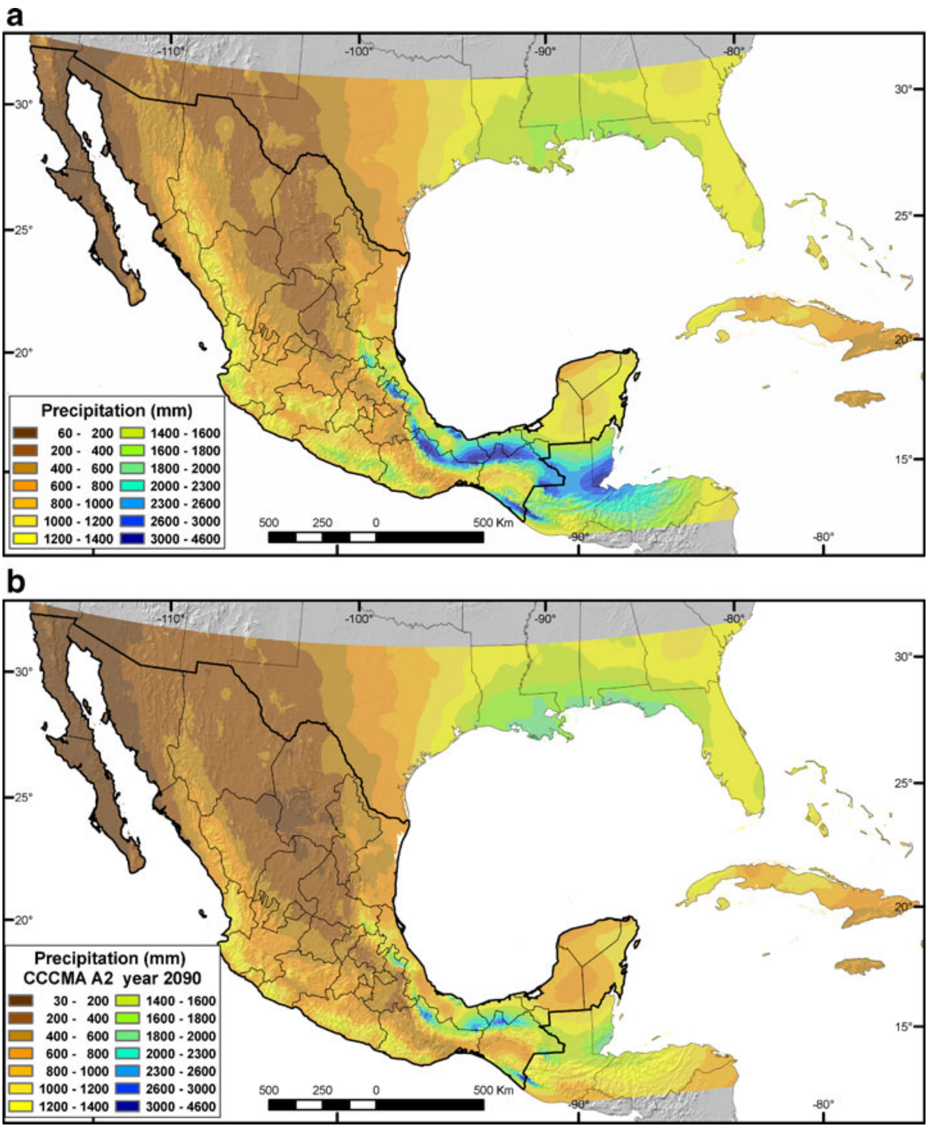


Fig. 6 Mapped predictions for mean annual precipitation (millimeters), for contemporary climate (**a**) and 2090 climate (**b**), using output from the Canadian Center for Climate Modeling and Analysis model, scenario A2

The 2090 temperature projections show that areas with the coolest climates (<12°C) should largely disappear, being restricted to only the highest volcanoes (dark blue, Fig. 5b). In addition, portions of the Veracruz coast, Tabasco, Yucatán Peninsula, large parts of Pacific Coast and Balsas Depression (central-south of Michoacán State and western Guerrero State) became very warm, with average annual temperatures >29°C (darkest red shades, Fig. 5b).

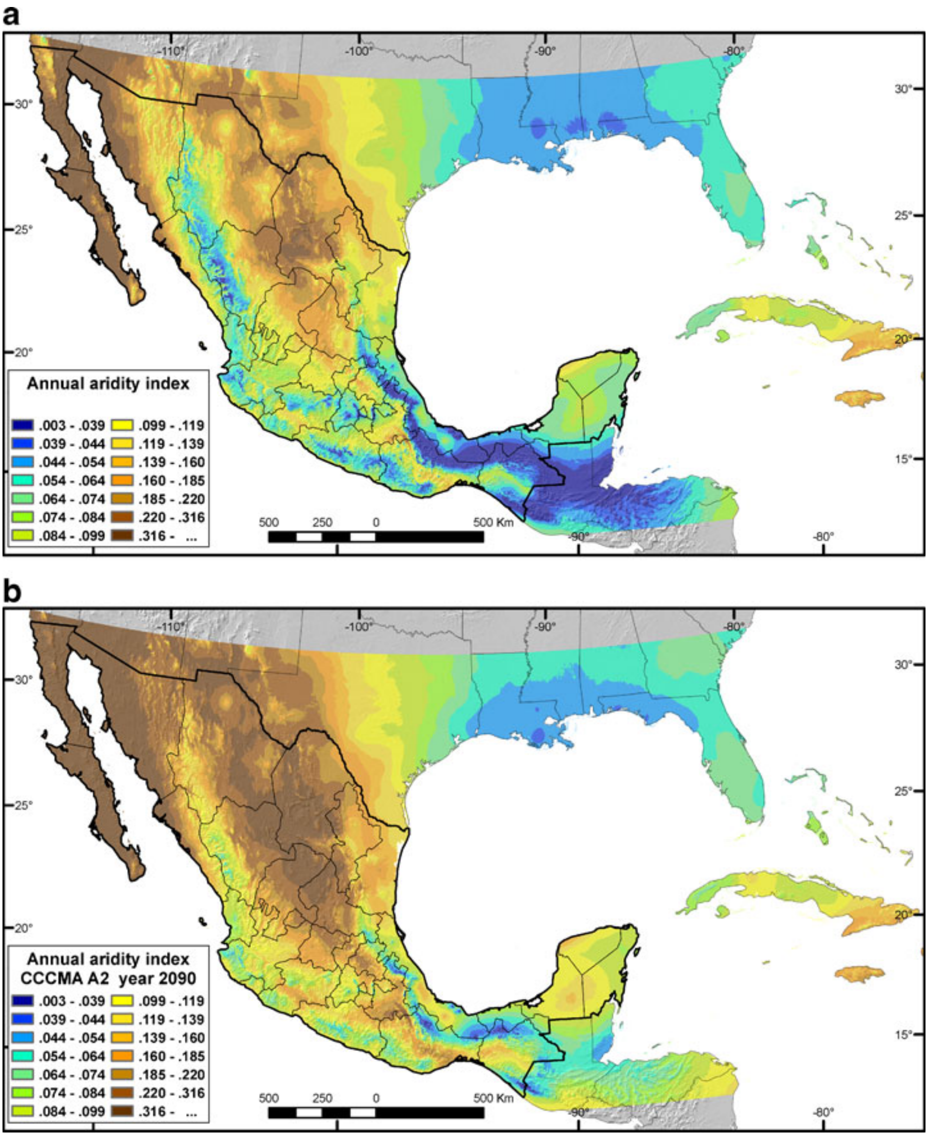


Fig. 7 Annual aridity index (ratio of square root of degree days >5°C to precipitation) for contemporary climate (**a**) and 2090 climate (**b**), using output from the Canadian Center for Climate Modeling and Analysis model, scenario A2

Highly variable contemporary precipitation (Fig. 6a) results from both altitudinal effects and the differential impacts of arid westerly air masses from the Pacific Ocean and moist monsoonal flows from the Gulf of México and the Caribbean Sea. In the Mediterranean climate of Baja California in northwest México, for example, annual precipitation may be only 200 mm, coming mostly in winter months. Yet, 3,000 mm or more may fall at localities in the tropical rain forest along Tabasco and

Veracruz slopes, northeastern Oaxaca and northern Chiapas in southeast México. This region is strongly influenced not only by monsoonal flows but also by occasional hurricane landfalls which contribute to the high variability in precipitation (Table 1, Fig. 6a). Climate-change, however, is expected to progressively reduce the amount of area receiving more than 2,300 mm of rain (blue tones of Fig. 6b) and expand arid and semiarid regions receiving <400 mm (brown tones) in the north and northwest of México. Also, precipitation in much of the Yucatán Peninsula which currently receives 800–1,400 mm (yellow tones of Fig. 6a) should drop by about 17% (Fig. 6b).

The annual aridity index (ratio of square root of degree days >5°C to precipitation) expresses an interaction of temperature with precipitation that better illustrates the remarkable climatic variability in México than either component separately (Fig. 7). By reflecting the amount of growing season heat received for each mm of annual precipitation, this ratio represents the potential for moisture stresses to develop in the vegetation. In the contemporary climate (Fig. 7a), lowest index values are associated with the southern tropical forests, while the highest values occur in the deserts of the north. This map is strikingly similar to vegetation maps of México (e.g., Rzedowski 1978, 1993; Brown et al. 1998). However, according to the A2 scenario of CCC, the arid regions (brown tones of Fig. 7a) of north-central México, encompassing the States of Chihuahua, Durango, Coahuila, should expand toward both coasts and toward the southeast by 2090 (Fig. 7b). At the same time, the moist regions of Veracruz, Tabasco and northern Oaxaca and Chiapas would be reduced greatly (blue tones), and much of the Sierra Madre Occidental and the Neovolcanic Axis would become more arid while the deserts of the northwest in Sonora and Sinaloa expand.

The maps of Figs. 5–7 and many additional maps are available at http://forest.moscowfsl.wsu.edu/climate/.

3.4 Applications in plant–climate relationships

3.4.1 Assessing impacts of climate-change on vegetation

Projected impacts of climate-change on the vegetation, such as those for western Canada (Rehfeldt et al. 1999; Hamann and Wang 2006; Wang et al. 2006), western USA (Rehfeldt et al. 2006), and Siberia (Tchebakova et al. 2005), commonly show that the climate now inhabited by local populations, species, and ecosystems generally will shift toward the north and to higher elevations. Paleoecological evidence alone suggests that natural systems will respond to change such that a semblance of equilibrium is maintained between plant distributions and climate (e.g., Rehfeldt et al. 1999, 2002; Tchebakova et al. 2005; Aitken et al. 2008). Although factors such as soils, insects and disease also affect the distribution of plants, one can assume that during times of change, plants seemingly will attempt to track the climate in which they now occur, a premise that is basic to paleoecology. Based on projected responses elsewhere, the intuitive expectation for Mexico, subject to the lag in response expected between migration and the change in climate (see Davis 1989; Davis et al. 2005), therefore, would be for a general migration of vegetation toward higher elevations in a northerly direction.

Our results for Mexico, however, suggest that potential migration in Mexico would be much more complex. Arid climates currently occupy northern México, and projections are for these arid climates to expand in all directions (Fig. 7b).

These expanding arid climates would act as a barrier to the northward migration of species attempting to track the climate they now inhabit. For species that presently inhabit climates of least aridity at intermediate and high altitudes, the only routes available for a progressive northward migration would be through the Sierra Madre Occidental and Sierra Madre Oriental. Both routes, however, are dead ends because both mountain ranges dissipate south of the USA border. Even though mountain islands exist in the deserts of southwest USA, the possibilities of a stepping stone path of migration from mountain peak to mountain peak are problematic. Projections for these mountain islands is for their vegetation to be pushed upwards and north (Rehfeldt et al. 2006), presumably being supplanted by the vegetation of the arid climates now at lower elevations. Stepping-stone migrations also require periods of trial and error in the dispersion of propagules, and time is not a commodity available in the scenarios we use. Our conclusion for Mexico's vegetation is that the expansion of the arid climates in the north will force plant migrations upwards and to the south, toward the Neovolcanic Axis (Fig. 1). This would mean that possibilities for the migration of Mexican flora into USA would be greatest during cooling trends rather than warming trends.

An increase in aridity also should impact agriculture. Crop production most certainly will be affected, particularly in such areas where a lack of irrigation makes corn production in marginal areas dependent on the rainy season. Also, a decrease in forage production for cattle consumption can be expected as well as the decrease of 5% to 30% in cereal yield that has already been forecast for México by 2080 (Parry et al. 2004). Wild animals will suffer from increasingly poor adaptation as the climate for which they are physiologically attuned and the vegetation within which they are dispersed appears at novel and distant locations. It is estimated that by 2055, 40% of fauna species will be occupying suboptimal habitats (Peterson et al. 2002). Climate-change therefore will force tree species to adapt, migrate or be extirpated (Davis 1989; Rehfeldt et al. 2001; Davis et al. 2005; Aitken et al. 2008). The distribution of Mexican oaks might decrease by 7% to 48% while that of Mexican pines may decrease by up to 64% by 2050, depending of the scenario used for estimating effects (Gomez-Mendoza and Arriaga 2007). Whether agriculture, wood production, or conservation, it seems obvious that the assistance of mankind will be needed to assure the perpetuation of the goods and services demanded from natural ecosystems (see Tchebakova et al. 2005).

3.4.2 Predicting the contemporary climatic niche of Pinus chiapensis

Classification errors from the Random Forests analysis averaged 4.7% across the 25 forests. All errors resulted were errors of commission, predicting that the climate was suitable for *P. chiapensis* when it was not present. The two most important climate variables for predicting the occurrence were (1) an interaction between the summer–winter temperature differential and mean annual precipitation, and (2) the mean minimum temperature in the coldest month. Figure 8a shows the location of pixels predicted to have a climate suitable for this species in the contemporary climate, with the insert in the upper right locating the observations where the species was present. Notice that all actual locations are inside the contemporary predicted habitat (Fig. 8a), which is an indication of the goodness of fit of the model and its power for prediction. Pixels colored yellow received 50–75% of the votes; those colored red

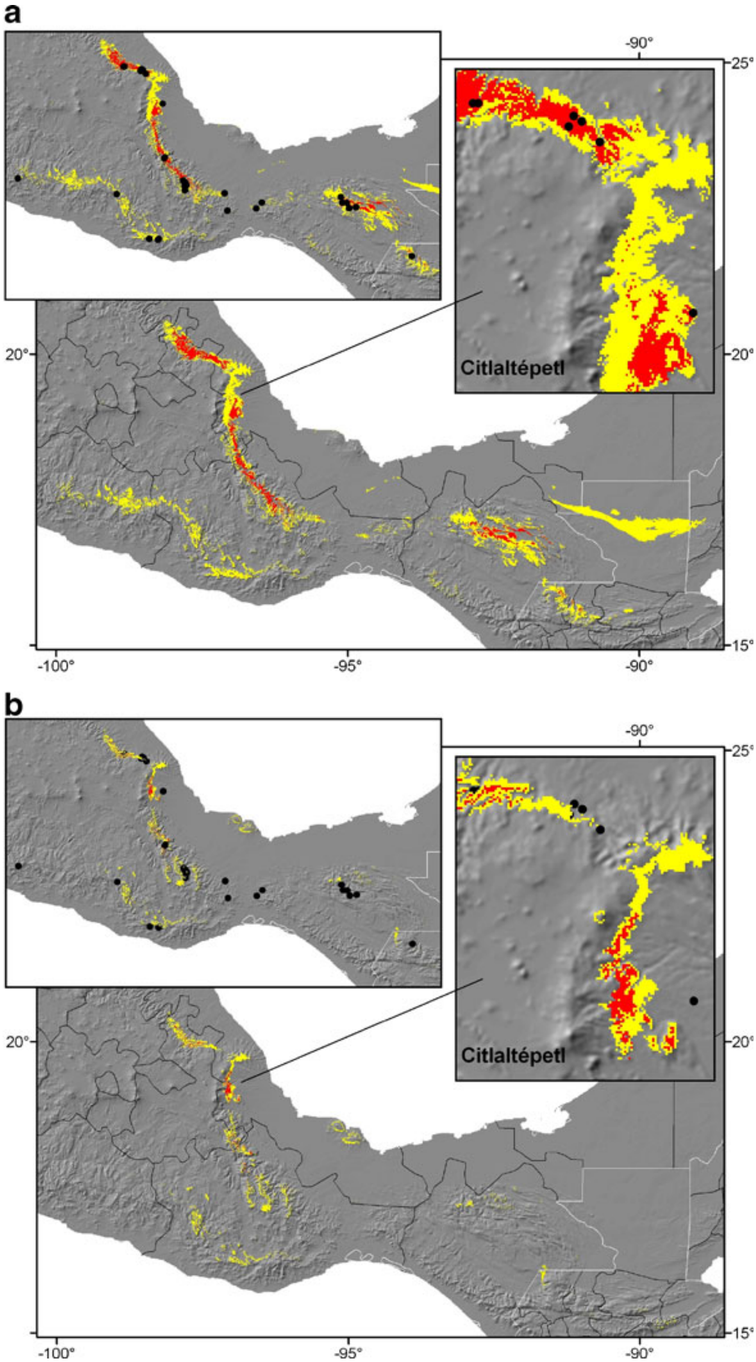


Fig. 8 Predicted climatic niche of *Pinus chiapensis* (*yellow and red pixels*) for the contemporary climate (**a**) and the 2060 climate according to A2 scenario of the Hadley Centre (**b**). *Dots in upper left insert* of (**a**) show inhabited locations of today. *Inserts in upper right* of (**a**) and in (**b**) show predicted climatic niche in relation to two of the easternmost volcanoes in the Neovolcanic Axis. *Yellow*, 50–75% of the votes; *red*, 75–100% of the votes

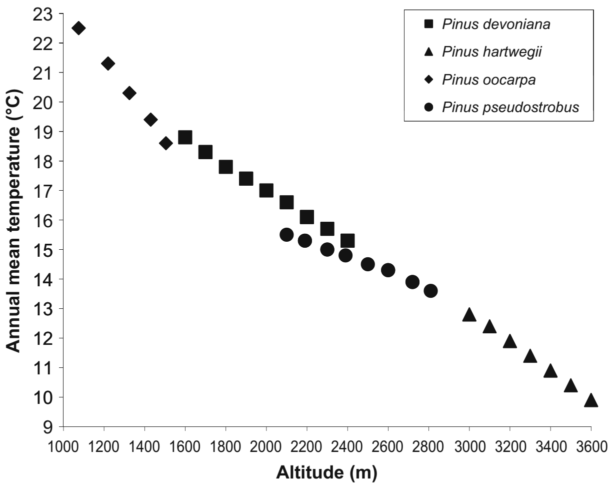
received >75%. Figure 8b shows the projected 2060 climate niche according to the A2 scenario of HAD.

Implications of Fig. 8 are that the climates in which this species occurs today should be reduced greatly in area by 2060. For example, predicted suitable contemporary habitat in the states of Guerrero and Chiapas (southern México) mostly disappear by year 2060. According to HAD, a 2060 sanctuary would be nestled on the eastern slopes of the easternmost and highest volcano in the Neovolcanic Axis (Pico de Orizaba, also known as Citlaltépetl, 5,600 masl). This sanctuary is generally within the species contemporary climatic niche, although at higher altitudes than contemporary *P. chiapensis* predicted habitat (inserts of Fig. 8). Accordingly, conservation efforts for this threatened species would be to assure that native populations are perpetuated in this sanctuary, perhaps by assisted migration by establishing conservation *ex-situ* plantations upwards in altitude (del Castillo et al. 2009).

3.4.3 Migration and assisted migration of four Michoacán conifers

As many as 14 pine species inhabit Michoacán (Cué-Bär et al. 2006), more than in any other México state. As shown in Fig. 9 for four species, *Pinus hartwegii*, *P. pseudostrobus*, *P. devoniana* (also known as *P. michoacana*), and *P. oocarpa*, have distinctive altitudinal distributions in Michoacán (Viveros-Viveros et al. 2005, 2009; Saenz-Romero et al. 2006; Saenz-Romero and Tapia-Olivares 2008). Although altitude is commonly viewed as a surrogate for climate, particularly temperature (e. g., Fig. 2), the spline climate model allows the distribution of these pines to be ordinated in 2-variable climate space. Figure 10, for instance, shows that *P. hartwegii*, a species native to the highest mountains, occupies sites that are relatively cold and moist (low aridity index values), while on the other extreme, *P. devoniana* and *P. oocarpa* share the same range of relatively high values of the aridity index but are separated ecologically by cold temperatures. Although this ordination is a simplistic

Fig. 9 Distribution of provenances of four pine species from altitudinal transects in Michoacán plotted in relation to the mean annual temperature of the provenance



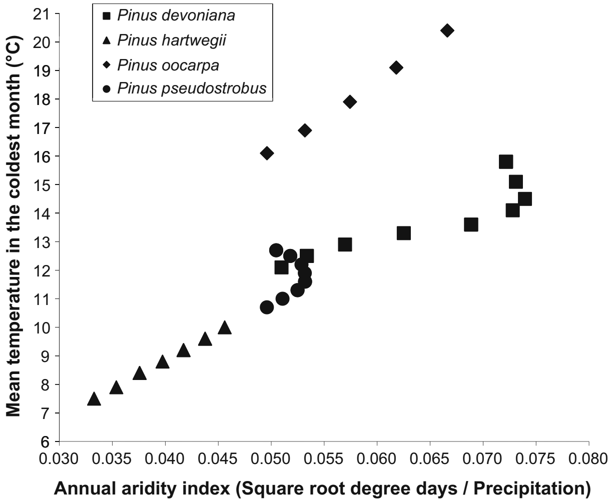


Fig. 10 Ordination of provenances of four pine species from an altitudinal transect in Michoacán according to the mean temperature of the coldest month and annual aridity index of the provenance

representation of the climate variables which act to separate the distributions of these species, Fig. 10 nonetheless illustrates the different climatic niches of these four species in Michoacán.

Annual aridity indices (AAI) estimated for contemporary climates and for year 2030, using the A2 scenario of CCC, suggest an increase of AAI of all sites now inhabited by these species in Michoacán (Fig. 11). These changes should have an impact on the distribution of these species. For example, for the site now inhabited by the population of *P. oocarpa* from the lowest elevation (1,075 m), AAI would change from 0.66 in the contemporary climate to 0.080 in 2030, a value that is far higher than climates inhabited by any of these species today. The arrow attached to this data point in Fig. 11 suggests that the AAI of this site today should recur at an

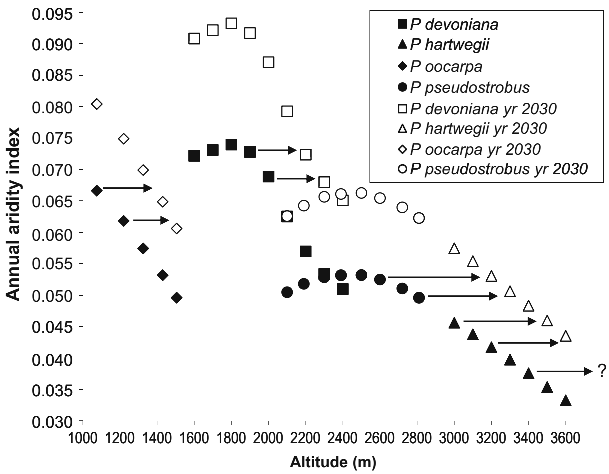


Fig. 11 Annual aridity index estimated for contemporary (*filled symbols*) and future climate (*empty symbols*, year 2030, Canadian model, scenario A2), for locations presently inhabited by *Pinus devoniana*, *P. hartwegii*, *P. oocarpa* and *P. pseudostrobus* in the central-west Mexican state of Michoacán. *Arrows* indicate suggested assisted migration upwards in altitude to match present genotypes with locations where will occur annual aridity values for which they are adapted

altitude about 300 m higher in 2030 than at present. Likewise, at the upper altitudes, the AAI of the site inhabited by *P. hartwegii* at 3000 m would increase from the 0.046 at present to 0.057 by 2030, a value seemingly better suited to *P. devoniana* and to *P. pseudostrobus* than the *P. hartwegii* that is there now, provided that the mean temperature in the coldest month would change by about 4°C (see Fig. 10).

By integrating the effects of temperature and precipitation, aridity indices tend to be closely related to the altitudinal distribution of species (see Rehfeldt et al. 2008). It is well known that increases in aridity decrease the carrying capacity of a site, increase moisture stress in plants, and eventually lead to mortality and extirpation. Because immigration is problematic in a rapidly changing climate (Rehfeldt et al. 1999, 2006; Tchebakova et al. 2005; Aitken et al. 2008), the species of pine in Figs. 10 and 11 undoubtedly will require human assistance if they are to inhabit a future climate that is similar to those inhabited today. A reasonable option would be to assist migration by moving the natural population—by artificial plantation programs—to the location at a higher altitude where the future aridity is expected to be equivalent to that where the populations grow today.

A program seeming suitable for Michoacán that targets the climate of 2030 would invoke a general upwards transfer pattern, with, for instance, lower altitudinal populations of *P. oocarpa* and of *P. devoniana* being planted in place of higher altitudinal populations of the same species; and high altitudinal populations of *P. psedostrobus* displacing low altitudinal populations of *P. hartwegii*; while the highest altitudinal distributions of the latter species would essentially be eliminated in Michoacán. The upward altitudinal migration would need to be between 300 to 450 m of altitudinal difference, with the larger interval suited mostly to populations at high elevation (Fig. 11). It also is expected (Fig. 11) that the present *P. oocarpa* populations would be extirpated at their lower altitudinal distribution, between 1,075 and 1,400 m. Abandoned niche space would be available for immigration tropical dry forest species (e. g., *Bursera* spp.), presumably because *P. oocarpa* currently is the only pine species able to survive in the low altitudinal ecotones with the tropical dry forest (Sáenz-Romero et al. 2006).

Particularly disconcerting are the upper altitudinal extremes of the pine distribution, which in Michoacán are at volcano Pico de Tancítaro. Here, the 2030 distribution of *P. hartwegii* would be reduced to only a portion of the contemporary, from 3,000–3,600 m at present (Viveros-Viveros et al. 2009) to approximately 3,500–3,600 m, with the populations at the highest elevations being lost. Although this volcano reaches 3,845 m, upper slopes are largely steep and rocky with little potential to support viable pine populations. The conclusion seems inescapable that the distribution of *P. hartwegii* will be greatly reduced in size. Consequently, a management option might be to transfer high altitudinal populations for which extirpation is imminent to volcanos of higher altitude in the same Neovolcanic Axis, like to Volcán de Colima (4,300 m), Popocatépetl (5,400 m), Iztaccíhuatl (5,220 m) and Citaltépetl (5,600 m) (Viveros-Viveros et al. 2009).

However, would it be sensible to begin now the transfer of populations of these four pine species to target future climates using only values of AAI? To be sure, additional climate variables (Fig. 10) undoubtedly should be considered after the completion of a thorough analysis of the climatic niche as presented above for *P. chiapensis* (Fig. 8). Other considerations would involve the question of which of the many GCMs and projections should be used for in a proactive program. Figure 3 shows clearly that projected temperatures for all models and scenarios are similar for 2030, but diverge considerably for 2060 and 2090. To this end, Rehfeldt et al. (2009) suggest using the consistency among GCM projections as a hedge against uncertainty; management should be encouraged in those areas where the projections concur. Another question must deal with the time frame: if managers plant altitudinally upwards now to match climates expected by years 2060 and 2090, they would risk frost damage on young seedlings and concomitant low survival (del Castillo et al. 2009); transferred populations would not yet be genetically suited to a climate targeted for so many decades in the future. Nonetheless, a lack of action puts natural populations at risk from physiological stresses (McLachlan et al. 2007) such that seed production could be insufficient to support large-scale planting programs. Inaction, therefore, is not a realistic option.

3.4.4 Conservation programs in the Tehuacán Valley

Conservation biologists currently are faced with accommodating the impacts of climate-change on threatened and endangered species. The Tehuacán Valley (corner between Puebla, Veracruz and Oaxaca States, Fig. 1), for instance, is a semiarid, inland region extremely rich in endemic cacti for which a biosphere reserve, Tehuacán-Cuicatlan, has been established. This unique assemblage of vegetation occurs in a region where the transitions in climate are remarkable. As shown by the spline model (Fig. 12), for instance, a transect from northwest to southeast across this valley would begin on the warm interior slopes of the Sierra Madre Oriental, where the climate of today generally exceeds 7,000 degree-days>5°C, and end high in the Sierra Madre Oriental where degree-days may be <2,100 (Fig. 12a). Precipitation, moreover, may be as low as 200–400 mm on the west, but may be >3,000 mm in the mountains on the east (Fig. 13a).

A concern is that climate-change will initiate a dramatic reduction or even disappearance of cacti habitat within the reserve and that suitable habitats will appear elsewhere in the future (Téllez-Valdés and Dávila-Aranda 2003). For managers attempting to decide where to plant these endangered species to target future climates, our spline model can be a valuable tool. The models aptly illustrate the increase in aridity that is expected to occur in this valley by 2090. According to the A2 scenario of CCC, degree days >5°C should reach more than 8,000 in much of interior Tehuacán Valley and along the eastern slopes of Sierra Madre Oriental (Fig. 12b). Meanwhile, areas with annual precipitation of only 200–400 mm should expand significantly in this valley while a dramatic reduction in precipitation should occur along the eastern slopes of the Sierra Madre Oriental (Fig. 13b).

As shown above for *P. chiapensis* and for numerous North American species by Iverson et al. (2008) and Rehfeldt et al. (2006), species-specific guidelines can be developed that pinpoint future areas expected to have climates similar to those inhabited by species today. These predictions pertain to developing management strategies for assisting migration of threatened species. While our maps were made on a 1 km grid, the climate model itself describes climate on a continuous scale. Because soils, insects and disease are also important besides climate in determining suitable habitat, managers will need to superimpose intuitive decisions on

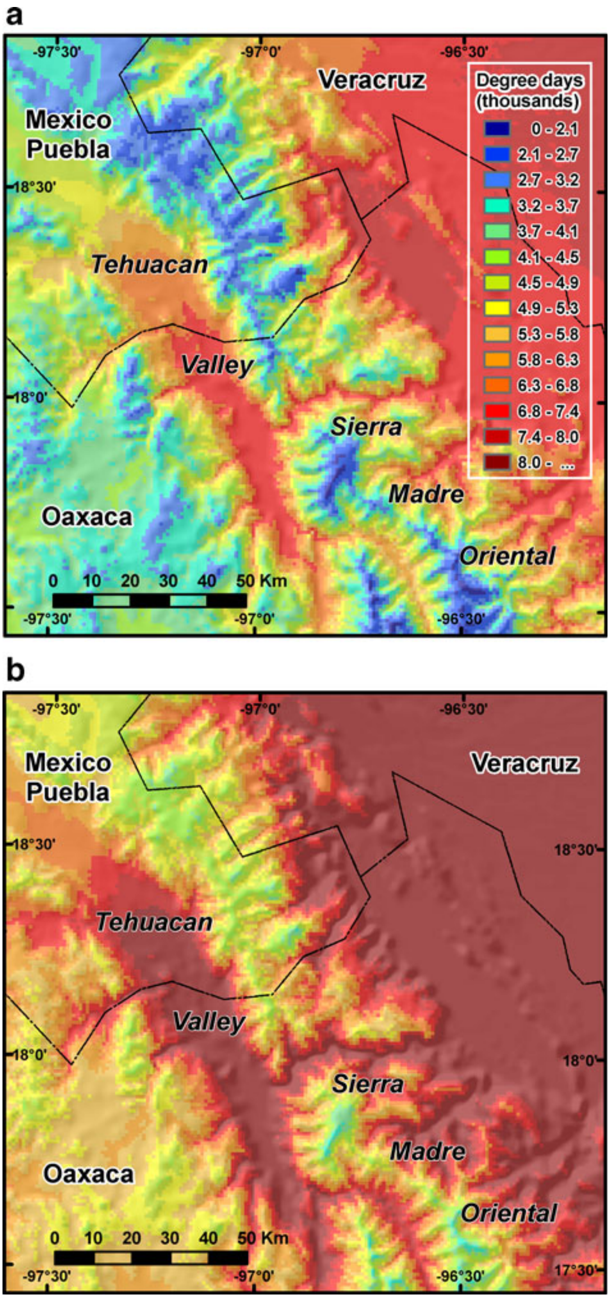


Fig. 12 Panels of the Tehuacán Valley showing the transition in degree-days across the desert into the high mountains for the contemporary climate (**a**) and that of 2090 (**b**) according to the A2 scenario of the Canadian Center for Climate Modeling and Analysis

predictions. Mapping can be done at fine resolutions that are dependent only on the resolution of the digitized elevations, thereby allowing managers to include local topographic (e.g., aspect, drainages, slope positions) effects into their guidelines.

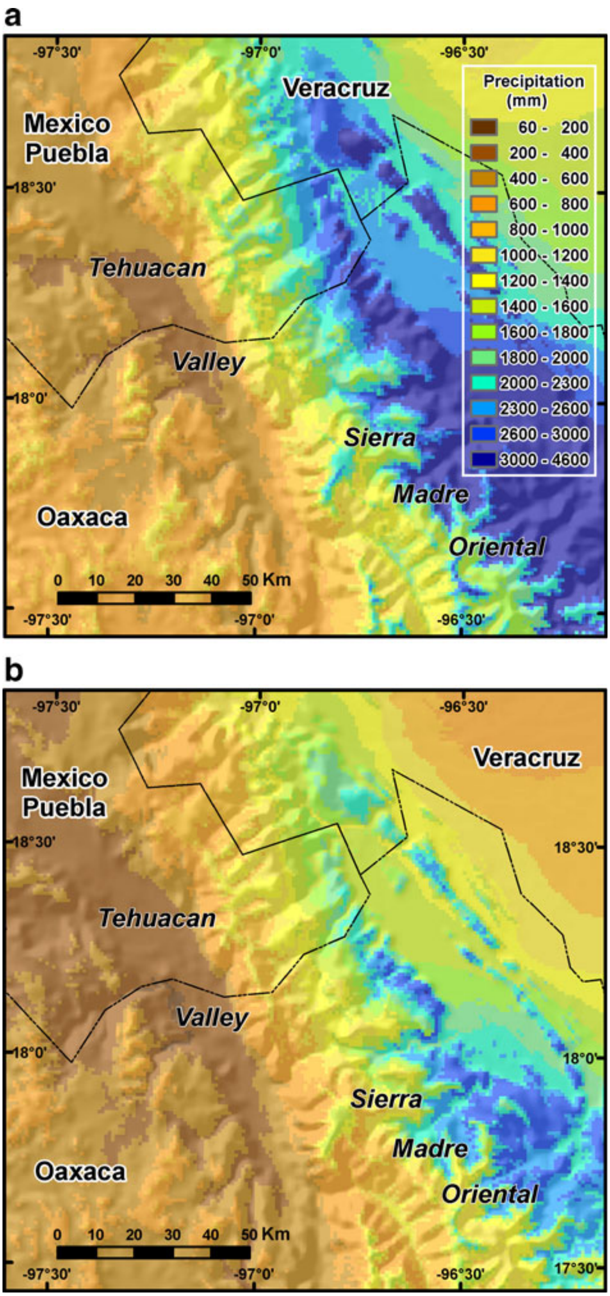


Fig. 13 Panels showing for the Tehuacán Valley the transition in annual precipitation from the desert of the valley floor into the moist eastern slopes of Sierra Madre Oriental to the east (Veracruz and Oaxaca States) for the contemporary climate (**a**) and that of 2090 (**b**) using output from the A2 scenario of the Canadian Center for Climate Modeling and Analysis

4 Conclusions

The climate surfaces are available for providing predictions of 1961–1990 monthly mean precipitation, temperatures (average, maximum and minimum averages), and variables derived therefrom (e.g., degree days, annual aridity index, etc.) at http://forest.moscowfsl.wsu.edu/climate/. Either point estimates, derived from the latitude, longitude, and elevation of an input dataset, or gridded estimates can be obtained. The estimates can be used as a powerful resource for making inferences about the distribution of species or ecosystems (Rehfeldt et al. 2006), understanding of genetic differentiation among populations for specific species distributed along climatic gradients (Sáenz-Romero et al. 2006), or developing climatically based seed transfer guidelines (Beaulieu et al. 2004; Rehfeldt 2004; St Clair and Howe 2007). While predicting the distribution of vegetation associations is feasible and useful, one should be aware that species respond individualistically to climate and, as a result, the disparate climatic variables often are of different degree of relevance for each plant species (Rehfeldt et al. 2008).

Geographic variables such as latitude and altitude frequently are correlated with different performance of plant populations when grown in the same environment, as, for example the pronounced differentiation between north–south *Pinus greggii* populations in México (Donahue and Lopez-Upton 1996; Dvorak et al. 1996b). Geographic variables, however, are surrogates for the climate variables operating in natural selection. Knowledge of climatic variables that drive genetic differentiation among plant populations facilitates the development of management guidelines for seed collection and seed transfer in reforestation based directly on, for example, annual aridity index values (Sáenz-Romero et al. 2006), instead on altitude or latitude. Although management strategies must consider variables such as potential negative interactions among species or forest fires dynamics (Pearson and Dawson 2003; van Zonneveld et al. 2009), the spline climate surfaces along with their derived variables provide a foundation for understanding the relationship between plants and climate and for developing strategies for accommodating projected impacts of climate-change.

Acknowledgements This research was conducted during a sabbatical year of CSR at the Centre canadien sur la fibre de bois, Service canadien des forêts, Ressources naturelles Canada, Québec, Québec, Canada. Financial support for the sabbatical was provided by Mexican Council of Science and Technology (CONACYT, fellowship 75831), the Universidad Michoacana de San Nicolás de Hidalgo (UMSNH) and Natural Resources Canada, and a research grant to CSR by the Coordinación de la Investigación Científica, UMSNH. We thank Rafael F. del Castillo for providing unpublished coordinates of *Pinus chiapensis* provenances. Three anonymous reviewers helped to improve significantly the manuscript.

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