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Modeling monthly mean air temperature for Brazil

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Abstract Air temperature is one of the main weather variables influencing agriculture around the world. Its availability, however, is a concern, mainly in Brazil where the weather stations are more concentrated on the coastal regions of the country. Therefore, the present study had as an objective to develop models for estimating monthly and annual mean air temperature for the Brazilian territory using multiple regression and geographic information system techniques. Temperature data from 2,400 stations distributed across the Brazilian territory were used, 1,800 to develop the equations and 600 for validating them, as well as their geographical coordinates and altitude as independent variables for the models. A total of 39 models were developed, relating the dependent variables maximum, mean, and minimum air temperatures (monthly and annual) to the independent variables latitude, longitude, altitude, and their combinations. All regression models were statistically significant ($\alpha \leq 0.01$). The monthly and annual temperature models presented determination coefficients between 0.54 and 0.96. We obtained an overall spatial correlation higher than 0.9 between the models proposed and the 16 major models already published for some Brazilian regions, considering a total of 3.67×10^8 pixels evaluated. Our national temperature models are recommended to predict air temperature in all Brazilian territories.

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1 Introduction

Air temperature is one of the major effects of solar radiation in the lower Earth atmosphere resulting from sensible heat transport, conduction and diffusion processes (Pereira et al. 2002). Air temperature controls the growth and development of most living organisms through its effect on enzymatic reactions that control physiological processes (Raven et al. 2007; Taiz and Zeiger 2009; Schmidt-Nielsen 2010). Extreme temperatures influence the geographical distribution of plants (Jeffree and Jeffree 1994; Larcher 2000), which makes possible classifying plants according to their thermal tolerance or requirement (Rizzini 1997). In agriculture and forestry, air temperature together with rainfall are the main factors defining crop zoning, sowing dates, and the expected yield levels.

Temporal and spatial variations of air temperature are regulated by solar radiation balance at the Earth's surface. On a geographical scale or macroscale, temperature is influenced by latitude (solar radiation), altitude, cloud cover, predominant winds, ocean streams, continentality, and air masses (Pereira et al. 2002; Dias and Silva 2009). Consequently, air temperature is traditionally measured in a standard condition, with the sensors inside a shelter at 1.5- 2.0 m height in a flat and lawn ground. These protocols are intended to minimize the influence of local conditions, with respect to topoclimate (relief) and microclimate (ground cover) factors, measuring the larger influences of macroclimate conditions to allow comparisons among locations (Pereira et al. 2002).

Proper measurement, interpretation, and prediction of weather conditions are essential to the success of agricultural activities, and national meteorological networks are important providers of reliable data. The recommended densities of weather stations in a network are 9,000 km^2 per station on the coast; 5,750 km^2 per station in flat and ondulate areas in the interior; and 2,500 km^2 per station in mountainous regions (WMO 1994). However, the density of weather stations in Brazil is very low, and in some areas there are no stations at all (Hijmans et al. 2005; Peel et al. 2007; Hamada et al. 2008; Rusticucci 2011).

Brazil has an area of 8,514,876.599 km^2 (IGBE 2002) and occupies nearly 48 % of South America, between the parallels 5°16′ N and 33°45′ S and between the meridians 34°47′ W and 73°59′ W, and is commonly referred to as a country of continental dimensions. Topography varies substantially and is classified as plateaus, plains, and depressions (Ross 1989). On average, Brazil is considered a low-lying country, where 41 % of its territory lies below 200 m, mainly in the plains of the Amazon River, Pantanal of Mato Grosso, Araguaia River, the Coastal Plains, and peripherical depression in the south. Only 7 % of the Brazilian territory is above 800 m, and these areas are concentrated in the mountains and highlands of the eastern and southeastern Atlantic regions, in the mountains and highlands of Goiás and Minas Gerais states, in the Borborema Plateau, and part of the plateau and table lands of the Parnaíba River basin.

The Brazilian territory has a wide climate diversity (Nimer 1979) and can be classified into five major areas: (1) the south (S) is dominated by a temperate climate of low diversity, but experiences notable thermal fluctuations throughout the year; (2) the southeast (SE) is a transitional region between the warm climates of low latitudes and the temperate climate of middle latitudes; (3) the central west (CW) presents a domain of high temperatures in spring and summer and mild in winter; (4) the northeast (NE) is where high temperatures are predominant throughout the year, but with two major climatic types (hot and warm); and (5) the northern region (N) is always hot, without seasonal temperature fluctuation.

Historical monthly air temperature data are not available for many locations in Brazil, primarily in the states within the CW and N regions. An alternative to make this data readily available is to estimate it with linear models considering geographical coordinates and altitude as independent variables (Varejão-Silva 2006). Since climate data exist as measurements at discrete points and many different methods have been developed to generate regional maps from point data, as complex interpolation methodologies, simple regression equations relating climate to grid position and elevation can summarize much of the spatial variation in climate data (Goodale et al. 1998). Usually, the normal monthly mean air temperature is estimated with the use of multiple linear regressions, and this method can be as effective as sophisticated local interpolation methods, especially when dealing with mean climatic data (Kurtzman and Kadmon 1999; Chuanyan et al. 2005). Such techniques have been applied in many parts of Brazil and around the world. The first study in Brazil that used topography to estimate meteorological parameters was done by Setzer (1946), in the state of São Paulo, using a simple regional temperature gradient as a function of altitude. In eastern Africa, regression equations to calculate the normal temperatures according to altitude were presented by Brow and Cocheme (1969). In the UK, Lennon and Turner (1995) developed models to estimate mean monthly temperature; however, they were very complex, limiting their application. In the northeastern USA, Ollinger et al. (1995) developed reasonable linear models to estimate the minimum and maximum air temperature. Similar models were developed by Goodale et al. (1998) for estimating maximum and minimum monthly temperatures in Ireland. In northeastern Spain, Ninyerola et al. (2000) applied multiple linear regression models to estimate maximum and minimum monthly temperatures using altitude, latitude, and longitude as independent variables. In Italy, Claps et al. (2008) calibrated equations for annual and monthly mean air temperature, and Boi et al. (2011) implemented a similar methodology in the study of monthly air temperature in Sardinia state. Lately, Gouvas et al. (2011) developed regression models for estimating monthly temperature for the whole Greece territory. In Lower Saxony, Germany, multiple linear regressions were also successfully used by Mues et al. (2002) to estimate air temperature. In the Durango region of Mexico, Gómez et al. (2008) presented reliable equations for estimating monthly mean temperature based only on altitude. In Asia, Chuanyan et al. (2005) and Guan et al. (2009) adjusted monthly equations for estimating the mean air temperature in the mountainous regions of China and Taiwan, respectively, based on the altitude, latitude, and longitude.

In Brazil, coefficients for linear models for estimating mean air temperature as a function of latitude, longitude, and altitude are available for approximately 50 % of the territory. Studies with this technique started in early 1970s, in the states of Rio Grande do Sul (Ferreira et al. 1971), Santa Catarina (Buriol et al. 1974), Paraná (Pinto and Alfonsi 1974), São Paulo (Pinto et al. 1972), and Goiás (Alfonso et al. 1974), and were used as a tool for the agroclimatic crop zoning programs which required growing degree days, minimum and maximum thresholds, and chilling hours (Mota 1975; Pereira et al. 2002; Mavi and Tupper 2004). Subsequently, air temperature linear models were applied in other Brazilian states such as Southeastern Bahia (Almeida and Sá 1984), Minas Gerais

(Sediyama and Melo Junior 1998); Piauí (Lima and Ribeiro 1998), Espírito Santo (Feitoza et al. 1979; Feitoza et al. 1980a; Feitoza et al. 1980b; Pezzopane et al. 2004), and Pará (Ferreira et al. 2006), with varying precisions and accuracies. Moreover, many of these studies were limited to capture the local variability completely, i.e., the estimates are not valid for the wide coastal ranges of the states of São Paulo (Pinto et al. 1972; Pedro Junior et al. 1991; Valeriano and Picini 2000), Paraná (Pinto and Alfonsi 1974), Rio Grande do Sul (Estefanel et al. 1973; Ferreira et al. 1971; Buriol et al. 1973), and Santa Catarina (Buriol et al. 1974; Ferreira et al. 1974). Another point is that a great part of the country does not yet have models developed to estimate temperature, limiting climatological and agrometeorological studies.

Based on the results found by previous studies and on the lack of temperature models for all countries, our study suggests that is possible to estimate historical monthly mean air temperatures for all Brazilian territories using multiple regression models, having as independent variables the geographical coordinates and altitude and their integration. In accordance with to that, our objectives were (1) to develop models for estimating monthly and annual maximum, minimum, and mean air temperatures for the whole Brazilian territory; (2) to evaluate the performance of the national models by comparing their results with those from regional models previously published and also with independent data; and (3) to elaborate annual air temperature maps based on the models and extracted information from all Brazilian capitals.

2 Material and methods

The study was conducted in several steps that included data compilation, exploratory analysis, data consistency, compilation in a geodatabase using a geographic information system, geoprocessing techniques, static descriptive analyzes, multivariate statistics, and geostatistics in a sequence of routine activities, as shown in Fig. 1.

The complete database used in this study comes from Brazilian institutions such as the National Institute of Meteorology (Brazil 1992), National Department of Works Against Droughts and Northeast Development Superintendency, and also the Food and Agriculture Organization of the United Nations (FAO 2001). At the beginning of the study, we compiled a total of 5,769 weather stations with data of the maximum, minimum, and mean monthly air temperature. Data were screened to filter out erroneous data of altitude, geographical coordinates, and normal monthly and annual temperature values. Meteorological stations were considered with historical series when presented more than 10 years of measurements for the period from 1950 to 1990. Based on this criterion, more than 50 % of weather stations presented more than 30 years of data. Thereby, the whole database can be considered long enough to ensure an appropriate climate modeling, according to results from Goodale et al. (1998), Marquinez et al. (2003), Rodríguez-Lado et al. (2007), Mello and Silva (2009), and Gouvas et al. (2011). Following the screening, we obtained a collection of 2,400 weather stations, titled consisted database, with monthly and annual maximum, mean, and minimum air temperature data to be used as the basis for the modeling process.

Weather stations are concentrated in densely populated regions of Brazil and also stratified by states for political and economic issues. In the Capricorn Tropic region, the amount is higher in the states of São Paulo and Paraná, where agriculture is older and more developed. Northeastern Brazil had large investments in the past for monitoring the drought in the semi-arid area, so there is a high spatial density of weather stations (Fig. 2). An important consideration is that the weather stations were located with a spatial distribution in heterogeneous areas regarding the relief, which allowed having high climate variabilities (Sparovek et al. 2007). On the other hand, the 2,400 weather stations selected for this study represent well the altitude strata of the Brazilian territory (Table 1). Finally, it is important to mention that the weather station of the consisted database represents an average density of one station for 3,533 km^2.

The consisted database was geographically divided randomly into two data sets. The first, referred to as the fitting set, with 75 % of weather stations, was used in multiple regression analyses in order to build models of air temperature. Another group, called the test set, with 25 % remaining data, was used to perform the first validation of the models for monthly and annual air temperature. Similarly, Calvo and Gregory (1994), Goodale et al. (1998), Ninyerola et al. (2000), Claps et al. (2008), and Gouvas et al. (2011) also used a portion of the data for model validation. Validation is essential for equations that are intended to be used for extrapolations. Therefore, we performed 39 geographically weighted random sampling to compose the data groups for fitting and test sets for maximum, mean, minimum, monthly, and annual air temperature data. Fitting and test sets are very similar in terms of average and standard deviation (Fig. 3). Fitting set was used to perform the first exploratory statistical analysis for obtaining the correlations between all dependent and independent variables.

Fitting set was used to establish the relationships between the dependent (maximum, mean, and minimum, monthly, and annual air temperatures) and independent (altitude, latitude, longitude, and their combinations) variables (Eq. 1). Although other studies used several other independent variables to predict air temperature, we prefer to consider only the relevant variables that define the macroclimate such as altitude, latitude, and longitude for both small and large spatial scales (Oliveira Neto et al. 2002; Rodríguez-Lado et al. 2007; Bardin et al. 2010).

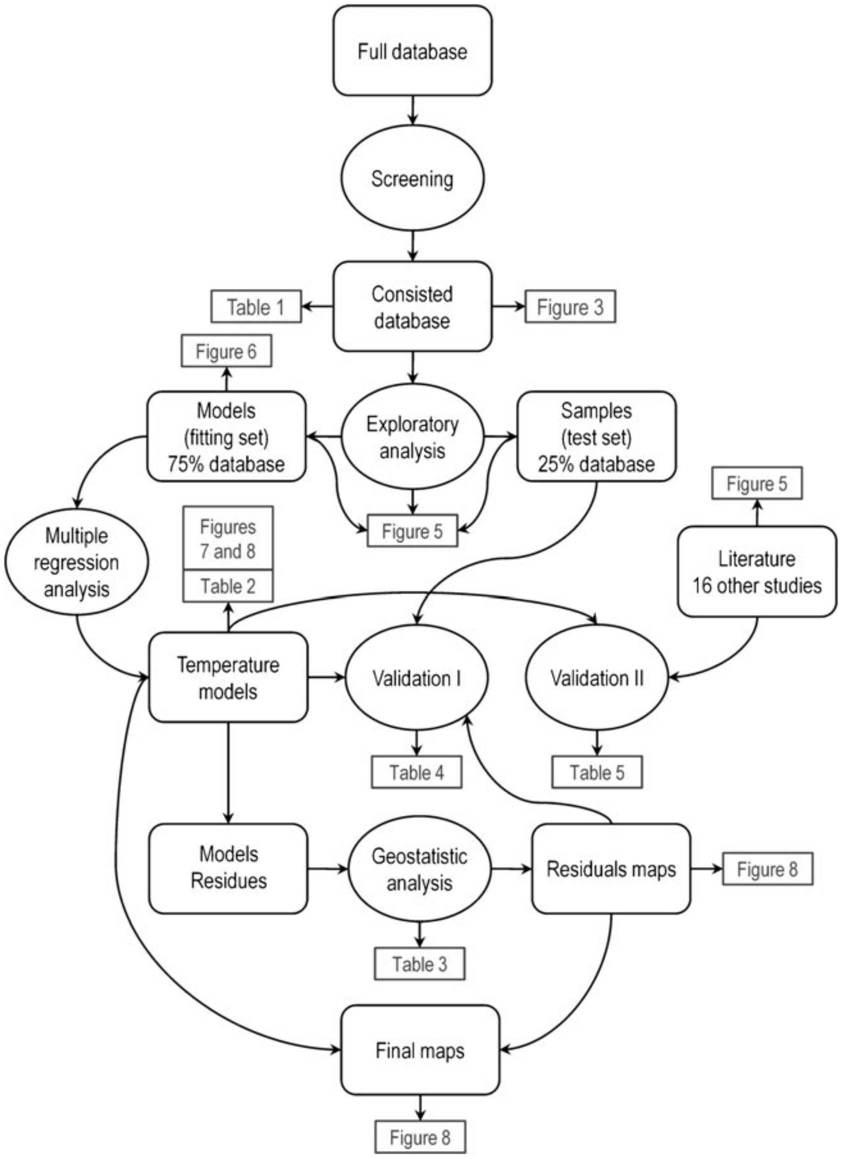

Fig. 1 Flowchart of the air temperature modeling processes: descriptive and multivariate statistical analyses and geostatistical and geoprocessing steps

Considering that only the linear model is not good enough to express the relationship between the air temperature and macroclimatic factors in a continental country like Brazil, we apply to the fitting test data a general multivariate nonlinear regression model (Eq. 1).

$$T_i = a_0 + a_1\varphi + a_2\lambda + a_3h + a_4\varphi\lambda + a_5\varphi h + a_6\lambda h + a_7\varphi^2 + a_8\lambda^2 + a_9h^2 \quad (1)$$

where T_i is the maximum, minimum, or mean, monthly (i=1, 2,…, 12) or annual (i=13) temperature; φ is the latitude in decimal degrees (positive values in the northern hemisphere and negative in the southern hemisphere); λ is the longitude in decimal degrees (negative values); h the altitude in meters; and a_0 to a_9 the coefficients of the multivariate regression equation.

An important recommendation in the multiple regression analysis is that the number of observations should be at least five to ten times greater than the number of independent variables (Draper and Smith 1981). As we have a total of 1,800 stations, such consideration is not a limitation for our study. Regression models were developed using the software XLSTAT v. 2011 (Addinsoft 2011) with the model selection by the backward method using multivariate regression technique, considering a 5 % probability. The motivation to eliminate variables is based on the residuals and loss of predictability that are introduced when irrelevant variables are added to the model. The objective was to reach a compromise where the final equation satisfies the purpose of the study (Rawlings et al. 1998). We used the criterion of highest R^2_{adj} (R^2 adjusted) for the selection of the best models. Unlike R^2, R^2_{adj} does not always increase as

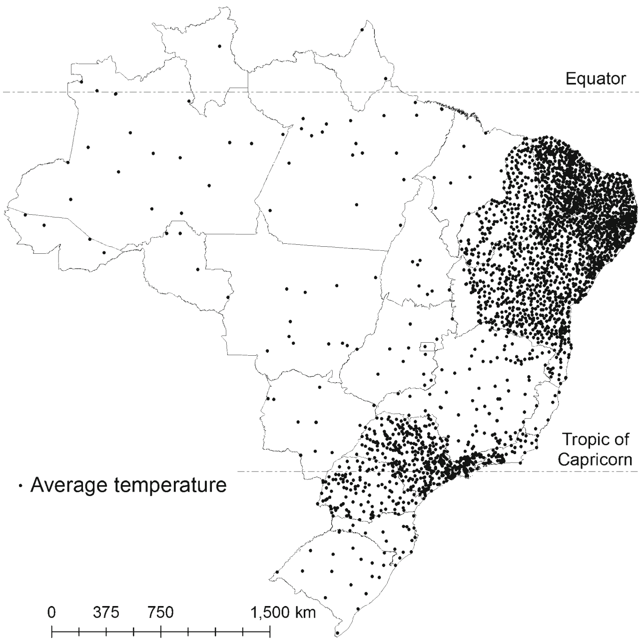

Fig. 2 Location of the Brazilian weather stations used for air temperature modeling

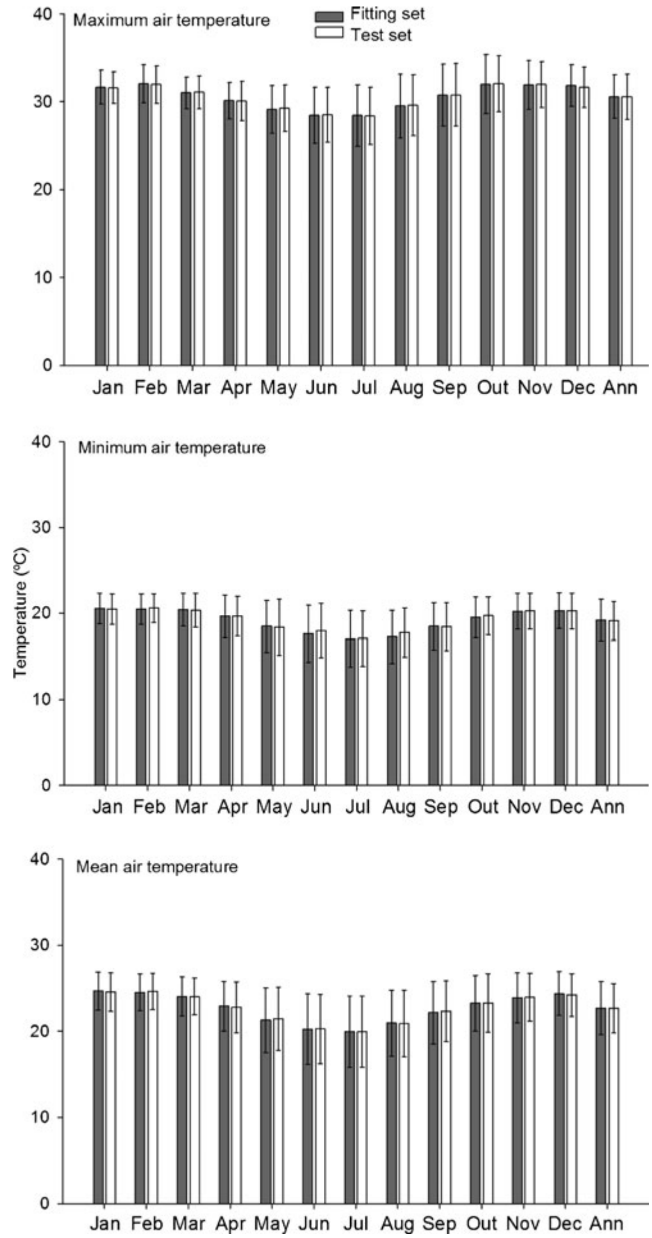

Fig. 3 Mean monthly maximum, minimum, and mean air temperature from 2,400 Brazilian weather stations, 1,800 for fitting test and 600 for test set. *Bars* represent data variability (±standard deviation) among the weather stations

variables are added to the model because it removes the impact of degrees of freedom and gives a quantity that is more comparable than R^2 over models involving different numbers of parameters (Rawlings et al. 1998). The value of R^2_{adj} will tend to stabilize around some upper limit as variables are added, and the simplest model with R^2_{adj} near this upper limit can be chosen as the "best" model. The method of multivariate regression was chosen for its simplicity and for being one of the most widely used techniques for developing empirical models (Lanzante 1996). Except for Medeiros et al. (2005), it is unusual to employ combined variables among geographic coordinates and altitude as independent variables in models to estimate air temperature. However, this technique was considered to optimize the precision and accuracy of the results. Analysis of variance was applied in the unfolded R^2_{adj} values, which allowed calculating the contribution of each significant independent variable in the estimation of air temperature.

Table 1 Distribution of weather stations in the Brazilian territory according to their altitude

Altitude (m.a.s.l.)	Relative area of altitude (%)	Absolute number of stations	Relative proportions of stations (%)	Density of stations (km^2 per station)
<100	21.0	479	20.0	3,729
100–200	20.2	351	14.6	4,912
200–400	28.0	624	26.0	3,826
400–800	23.6	787	32.8	2,520
800–1,200	6.7	149	6.2	3,831
>1,200	0.4	10	0.4	3,776
Total	100	2,400	100	3,533

Once a model is specified and its best-fitting parameters are found, one is in a position to assess the performance of the model with independent data. Researchers have proposed a number of criteria that were thought to be important for model evaluation; among them are included qualitative criteria (explanatory adequacy, interpretability, faithfulness) and quantitative criteria (falsifiability, goodness of fit, simplicity/complexity, generalizability; Myunget al. 2003). Besides R^2_{adj}, the following errors and indices were used to evaluate the air temperature models: root mean square error (RMSE), mean absolute percentage error (MAPE), Durbin–Watson statistic (DW), and Mallows' Cp coefficient (Cp). RMSE and MAPE were used to estimate the differences (in degree Celsius and percent, respectively) between values predicted by models and the values measured from the consisted database, which allows aggregating them into a single measure of predictive power. The Durbin–Watson test was used to detect the presence of serial correlation in the residuals, which was also evaluated visually (Bussab 1986). Mallows' Cp coefficient is an estimate of the standardized total mean squared error of estimation for the current set of data. When the model with $p+1$ (p') explanatory variables is correct, the residual sum of squares is an unbiased estimate of $(n-p')\sigma^2$; in this case, Cp is close to p' (Rawlings et al. 1998). Usually, small values of Cp are desirable. When important independent variables have been omitted from the model, the residual sum of squares is an estimate of $(n-p')\sigma^2$ plus a positive quantity reflecting the contribution of the omitted variables; in this case, Cp is expected to be greater than p'. Regression models with Cp values close to the top and below it are candidates for the best model.

The performance of the temperature models was also evaluated using the performance index "P_{i}" (Eq. 4). This new index is an update of the confidence index "c" (Sentelhas and Camargo 1997), which is the product of the coefficient of correlation "r" (Pearson's correlation coefficient) and the agreement index "d" (Willmott et al. 1985). The performance index, P_{i}, is the product of the coefficient of correlation "r" (Eq. 2) and refined agreement index "d_{r}" (Eq. 3; Willmott et al. 2012), combining accuracy and precision. Precision is provided by the coefficient of correlation "r" which indicates the dispersion degree of data from the mean, i.e., the random error. Accuracy is related to the disengagement of the estimated values from those observed and is estimated by the refined agreement index "d_{r}". The criteria for interpreting the performance index, P_{i}, is: $P_{\mathrm{i}}\geq 0.75$, optimum performance; $0.6\leq P_{\mathrm{i}}<0.75$, very good performance; $0.45\leq P_{\mathrm{i}}<0.6$, good performance; $0.3\leq P_{\mathrm{i}}<0.45$, tolerable performance; $0.15\leq P_{\mathrm{i}}<0.3$, poor performance; $0\leq P_{\mathrm{i}}<0.15$, bad performance; and $P_{\mathrm{i}}<0$, very bad performance.

$$r=\frac{(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\left[(x_i-\bar{x})^2\right]\left[(y_i-\bar{y})^2\right]}} \tag{2}$$

$$d_{\mathrm{r}}=\begin{cases}1-\dfrac{\sum|y_i-x_i|}{c\sum|y_i-\bar{y}|}, & \text{when} \sum|\mathrm{y_i}-\mathrm{x_i}|\leq \mathrm{c}\sum|\mathrm{y_i}-\bar{\mathrm{y}}| \\ \dfrac{\mathrm{c}\sum|\mathrm{y_i}-\bar{\mathrm{y}}|}{\sum|y_i-x_i|}-1, & \text{when} \sum|\mathrm{y_i}-\mathrm{x_i}|>\mathrm{c}\sum|\mathrm{y_i}-\bar{\mathrm{y}}|\end{cases} \tag{3}$$

$$P_{\mathrm{i}}=r\,d_{\mathrm{r}} \tag{4}$$

where r is the Pearson's correlation coefficient, x_i is ith measured value, y_i is the ith predicted value, $\bar{x}$ is the mean of all measured values, $\bar{y}$ is the mean of all predicted values, P_{i} is the performance index, and d_{r} is the refined agreement index; c=2.

The combination of kriging and multivariate models has been demonstrated as an effective way for modeling air temperature spatially (Goodale et al. 1998; Rodriguez-Lado et al. 2007; Claps et al. 2008). For this, the residues from the 1,800 weather stations of the test fitting database, resulted from the multivariate regression analyzes, were interpolated using geostatistical techniques. Normality hypothesis of fitting test residuals was tested according to the W test at 5 % (Shapiro and Wilk 1965). Experimental omnidirectional semivariograms were adjusted by the geostatistic program GS+ v.9 considering geometric field of until 50 % range fitting set (latitude and longitude) since after this value the semivariogram does not seem to be correct (Guerra 1988). Theoretical models such as spherical, exponential, Gaussian, and linear were considered since they usually cover the general dispersion situation of environmental science spatial events (Burrough and McDonnell 1998; Soares 2006). Through GS+ v.9 cross-validation, the correlation coefficients of the selected models were obtained. The spatial dependence index (SDI) was used according to Alvares et al. (2011), which measures the structural variance effect on the total variance (sill) of the sample. SDI comprises the following interpretation break: weak SDI≤25 %, moderate SDI between 25 and 75 %; and strong SDI≥75 %. Through structural parameters obtained from experimental semivariograms, residue maps were created with the geographic information system ArcGIS v.10 (ESRI 2010). A punctual ordinary kriging estimator was used for geostatistic interpolation.

The temperature values of 600 weather stations of the test set were compared against the estimates done by the multivariate equations, and this represents the first validation of temperature models. First validation has been divided into two parts, before and after kriging. Thus, the effect of the sum of the residue in the quality models and in the final temperature maps can be observed. For evaluating the performance of the temperature models in a first validation, the following errors were considered: mean error (ME), mean absolute error (MAE), RMSE, and MAPE according to the equations below:

$$\mathrm{ME} = \frac{1}{N}\sum(y_i - x_i) \tag{5}$$

$$\mathrm{MAE} = \frac{1}{N}\sum|y_i - x_i| \tag{6}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}(y_i - x_i)^2} \tag{7}$$

$$\mathrm{MAPE} = \frac{100}{N}\sum\left|\frac{y_i - x_i}{y_i}\right| \tag{8}$$

where x_i is the ith measured value, y_i is the ith predicted value, N is the number of samples considered, $\bar{x}$ is the mean of all measured values, and $\bar{y}$ is the mean of all predicted values.

Using map algebra techniques (Tomlin 1990; Burrough and McDonnell 1998), the results from the multivariate regression models for the maximum, minimum, and mean annual air temperatures were converted into maps using ArcGIS, processing the independent variables as raster layers. The altitude layer (in meters) was obtained from the digital elevation model (DEM) provided by the Shuttle Radar Topography Mission (SRTM; Farr and Kobrick 2000) in its current fourth version (Jarvis et al. 2008). Subsequently, ArcGIS was used to build the DEM for Brazil at 1,000 m resolution (pixel 1 km^2; Fig. 4). Latitude and longitude layers were obtained in decimal degrees using the central coordinates of each pixel corresponding to the DEM. Using geoprocessing techniques (Theobald 2007; Ormsby et al. 2010; Allen 2011), all temperature models were programmed and run in ArcGIS.

Unlike similar studies, in the present study, the models were evaluated by comparing them with results from 16 major publications presented in Brazil (Fig. 5), constituting the second validation of the temperature models. These papers were published in the last four decades since the pioneer one in the Rio Grande do Sul State (Ferreira et al. 1971) to the most recent publication for the microregion of Jundiaí, in São Paulo State, Brazil (Bardin et al. 2010). Among these, two papers that covered wide areas, covering more than one state, as presented by Oliveira Neto et al. (2002) for the "Midwest" region, between latitudes 16° and 24° S and longitudes 48° and 60° W, and by Medeiros et al. (2005) to the northeast region of Brazil, were also considered. All equations were programmed in ArcGIS 10 using

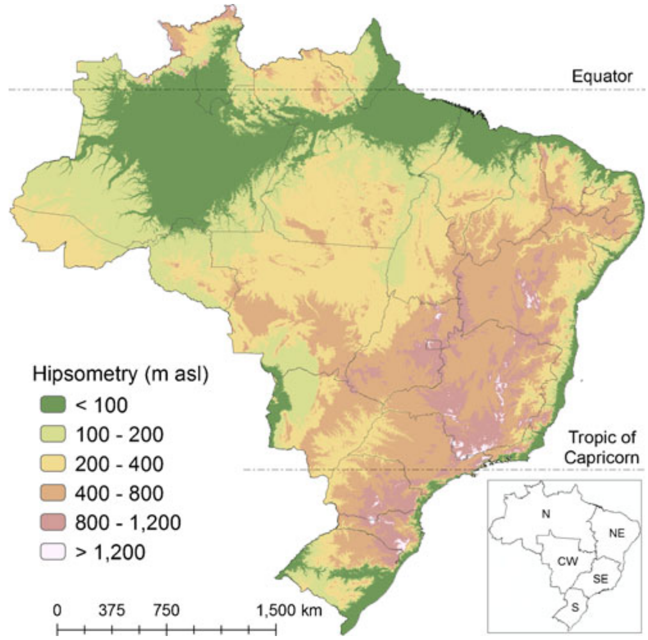

Fig. 4 Digital elevation model of Brazil. Mosaic composed by SRTM tiles

the tool "ModelBuilder" (Allen 2011), and DEM was used for each state and region to obtain altitude layers, as mentioned previously. Comparisons between air temperature values estimated with the previous models and with the models proposed in this study were evaluated using the Pearson's correlation coefficients of the maps compared using the tool "Band Collection Statistics" (ESRI 2010).

Finally, using the tool "Zonal statistics as table" (Theobald 2007), the descriptive statistics of the maximum, minimum, and mean air temperature were calculated for monthly and annual timescales for Brazilian state capitals using the official digital network (IBGE 2007).

3 Results and discussion

Exploratory data analysis showed that the maximum, minimum, and mean air temperatures showed strong relationships with geographic coordinates and altitude (Fig. 6). The correlations between air temperature and geographical coordinates and altitude were well defined, as observed by Pereira et al. (2002): higher latitude, lower temperature because of the seasonal variation of incoming solar radiation; higher altitude, lower temperature due to atmospheric pressure reduction and air rarefaction of the air. Longitude showed less effect on temperature variation since its effect on air temperature amplitude is associated with the position of the area in relation to the ocean, which varies with the regions of the country. About this, Driscoll and Yee Fong (1992) stated that longitude or continentality effect is

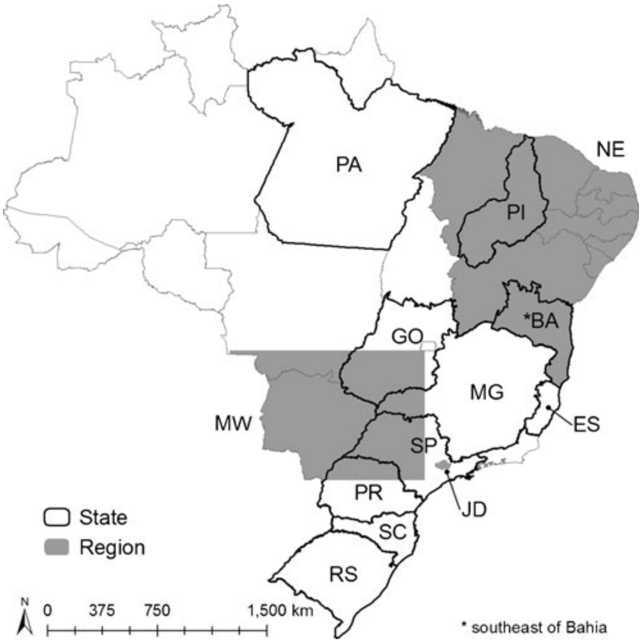

Fig. 5 Location of all studied areas used in the evaluation of the equations obtained in this study. *RS* Rio Grande do Sul (Ferreira et al. 1971; Buriol et al. 1973; Estefanel et al. 1973), *SC* Santa Catarina (Buriol et al. 1974; Ferreira et al. 1974), *PR* Paraná (Pinto and Alfonsi 1974), *SP* São Paulo (Rodríguez-Lado et al. 2007), *JD* Jundiaí micro-region (Bardin et al. 2010), *MG* Minas Gerais (Sediyama and Melo Junior 1998), *ES* Espírito Santo (Pezzopane et al. 2004), *MW* Midwest (Oliveira Neto et al. 2002), *GO* Goiás (Alfonsi et al. 1974), *NE* Northeast (Medeiros et al. 2005), *BA* Bahia (Almeida and Sá 1984), *PI* Piauí (Lima and Ribeiro 1998), *PA* Pará (Ferreira et al. 2006)

a variable very difficult to model since in some cases this effect can be related to the latitude when the ocean is north or south of the region considered.

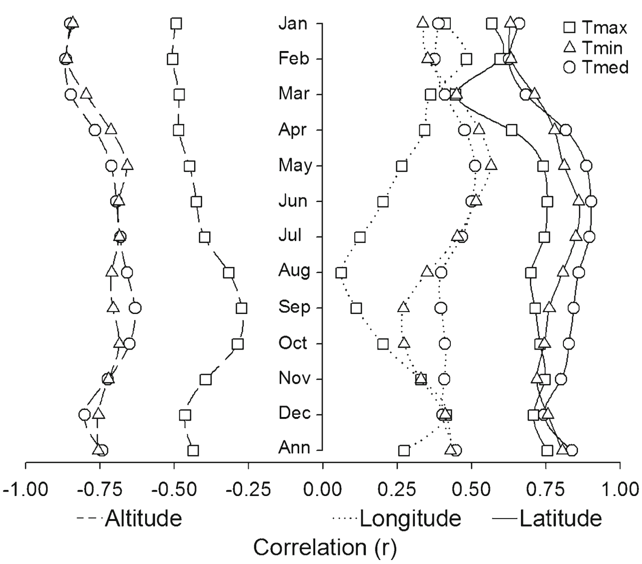

Fig. 6 Pearson's correlation coefficients for the relationships between maximum, minimum, and mean (monthly and annual) air temperatures and altitude, longitude, and latitude

Compared with the minimum and mean temperature, the maximum temperature showed the lowest correlations with altitude, longitude, and latitude (Fig. 6). During winter (July and August) and spring (September and October), the correlation between maximum temperature with altitude and longitude were the lowest ($r<0.25$). The correlation between maximum temperature and latitude was above 0.5 in all months, but still smaller than the values obtained for the minimum and mean temperatures. This is likely because in most parts of Brazil, the maximum temperatures are influenced by other variables besides latitude, longitude, and altitude, such as rainfall patterns and cold front influence. In Brazil, cold fronts are seasonal and occur more frequently from May to September, with approximately 45 crossings per year in the south and southeast regions and up to 10 crossings in the lower latitudes, until 15° S (Cavalcanti and Kousky 2009). During wintertime, cold air incursions have a profound impact upon the grass temperature and extreme episodes can produce freezing conditions in southern and southeastern Brazil (Garreaud 2000). During the warm season, these episodes produce less dramatic variations of temperature. The coastal region of northeastern Brazil, which receives maximum rainfall from May to July, normally experiences an increase in rainfall associated with the cold fronts (Kousky 1979), and in this season, there is high temperature variability. Additionally, Andrade (2005) noted that years with greater rainfall totals corresponded to those with a greater number of cold front crossings. The high air relative humidity in the rainy season causes less temperature fluctuations during the day, with the maximum temperature remaining mild. In most regions of the country, the dry season, which usually coincides with the winter and spring, has temperatures that vary more over the day, reaching quite high values in several days, increasing the average, and reducing the concordance in relation to the time of year and location when modeled. Furthermore, Barros et al. (2002) showed that in southern Brazil, the interannual variability of temperature is higher in colder months, with a standard deviation of approximately 2 °C. Minimum temperatures showed better correlations than maximum temperatures, with r greater than 0.6 for latitude and less than −0.7 for altitude in all months. It was also observed that for most of the year, except for March, latitude explains at least 50 % ($r>0.71$, $R^2=0.5$) of the variability of the maximum, minimum, and mean air temperatures in both monthly and annual timescales (Fig. 6). The same relationship was found between altitude and the mean annual temperature for the state of São Paulo by Rodríguez-Lado et al. (2007).

The square of altitude (h^2) was not significant at 5 % and thus did not contribute to predicting the maximum, minimum, and mean temperatures both in monthly and annual timescales (Table 2). Similar results were obtained by Ranhao et al. (2008) since the inclusion of squared altitude in the models was not significant in both annual and seasonal timescales. However, in northeastern Brazil, this variable was important for determining the maximum and mean temperatures during the summer months (Medeiros et al. 2005). In the microregion of Jundiaí, in the state of São Paulo, Bardin et al. (2010) concluded that latitude and longitude were not significant due to the reduced dimension of the studied area. In the state of Espirito Santo, Brazil, longitude was not significant in the estimation of air temperature since the entire state territory is very close to the Atlantic Ocean (Pezzopane et al. 2004). On the other hand, Buriol et al. (1974) showed that the maximum temperature variation in Santa Catarina State, Brazil, had a greater influence of longitude and altitude than latitude.

All regression models were significant ($\alpha \leq 0.01$), as well as all independent variables, at 1 and 5 %. The monthly and annual temperature models presented adjusted determination coefficients between 0.51 and 0.96 (Table 2). The better fitting equations were obtained for the mean (R^2_{adj}=0.87–0.96) and minimum (R^2_{adj}=0.84–0.94) temperatures. However, the equations for maximum temperature showed adjusted determination coefficients between 0.51 and 0.81, which are still good enough for temperature estimates considering that they presented statistical significance. Therefore, models of maximum temperature presented the worst indices, with RMSE above 1 °C and MAPE higher than 2.5 %, reaching 4.8 % for August. These results are expected since the maximum values are more difficult to predict due to the fact that they are influenced by factors other than latitude, longitude, and altitude, mainly during the rainy season in low latitudes, as previously discussed. Zheng and Basher (1996) have also found that their regression equations give slightly worse results when used to estimate the mean summer maximum temperature. Similar results were obtained by Boi et al. (2011) in the summer months. Minimum temperature was accurately estimated (R^2_{adj}>0.9) between the fall and winter, in the months from March to July. In the case of mean temperature, the R^2_{adj} was lower than 0.9 in the warmer months: December, January, and February.

To check the quality of the temperature estimates, the DW test for residue estimation was conducted. The DW test showed that for most of the models (21 equations), the residues are not autocorrelated, i.e., DW values are close to 2 (Table 2). For two other equations (mean temperature for October and annual minimum temperature), the autocorrelation was identified as inconclusive, i.e., DW test points to an indecision zone and cannot rule out an autocorrelation. Other models presented a slight autocorrelation and thus showed DW below the critical value for the significance level of 5 %. However, analyzing the residue plots, there is no clear trend of autocorrelation (Bussab 1986). Thus, it demonstrates that the models proposed are of good quality and able to predict most of the spatial variability of air temperature in the Brazilian territory.

Mallows' Cp coefficient showed that the models were well selected since they presented Cp values very close to p' (Table 2). The new index for evaluating the models' quality, named performance index (P_i), showed that most equations had optimum or very good performance, presenting high accuracy and precision on estimating the air temperature for Brazil. RMSE and MAPE were generally higher in the winter months (June to September), which may indicate that the models have higher difficulty of capturing the spatial variability of air temperature this time of year, which is probably related to the sporadic incursions of cold air masses in the Brazilian territory.

Altitude was the most important independent variable to estimate the average and minimum temperature. It was present in most models, representing more than 45 % of the temperature variability in the models in which it was significant (Fig. 7), mainly in the summer months. As observed in the general analysis, altitude also showed lower contribution in the estimates of the mean and maximum temperatures in the coldest months of the year, between June and September. Latitude was also important in the mean and maximum temperature models. It had a tendency to have greater contribution during the coldest months. Considering all the months when this variable was significant, it had an overall contribution of 40 %. In the case of minimum temperature, latitude had a large contribution (>65 %) in April and May. Finally, longitude was the independent variable which was present in the majority of the models, but with weight contribution not exceeding 12 %. It was more important in the winter months to estimate the mean and maximum temperature (Fig. 7).

The combined variables were important in different periods of the year and contributed differently in the estimation of the maximum, mean, and minimum temperatures. The variable "altitude×latitude" ($h\varphi$) had moderate contribution to the models, with more expression to the minimum temperature in May, explaining 16 % of T_{min} variability. For the other models, it explained no more than 5 % of temperature variability. The combination of "altitude×longitude" ($h\lambda$) was significant in the majority of the models; however, in the models of maximum and mean temperatures, their contribution was limited to no more than 8 %. On the other hand, their greatest effect occurred in January, April, and December, explaining respectively 51, 25, and 31 % of the variability. In northeastern Brazil, the combined variable $h\lambda$ was not significant (α=0.05) for any model of air temperature (Medeiros et al. 2005). The variable "latitude×longitude" ($\varphi\lambda$) contributed 22 % to estimate the maximum temperature in April. Estimates of the mean temperature in July, August, September, and October were explained by $\varphi\lambda$ in at least 25 %. This combined variable was responsible for explaining 23 % of the annual mean temperature.

Table 2 Coefficients of the monthly and annual air temperature models and statistical performance indices

Month	Temp	Coefficients of the multivariate regression equation									Goodness-of-fit statistics					Performance index			
		a (°C)	*h* (°C m^{-1})	φ (°C per degree)	λ	*h*φ (°C m^{-1} per degree)	*h*λ	φλ	$φ^2$ (°C per square degree)	$λ^2$	R^2_{adj}	RMSE (°C)	MAPE (%)	DW	Cp	*r*	d_r	P_i	Performance
Jan	Max	29.22	1.22×10^{-2}	0.659	−0.252	-1.08×10^{-4}	4.02×10^{-4}	1.99×10^{-2}	-1.47×10^{-2}	-3.84×10^{-3}	0.51	1.33	3.3	1.76	9.0	0.72	0.77	0.55	Good
	Min	18.44	–	0.3	−0.245	–	1.19×10^{-4}	4.13×10^{-3}	–	-2.85×10^{-3}	0.84	0.69	2.2	1.96	7.0	0.92	0.86	0.79	Optimum
	Mean	20.17	-5.56×10^{-3}	0.308	−0.385	–	–	9.23×10^{-3}	-8.52×10^{-3}	-4.78×10^{-3}	0.87	0.82	2.6	1.84	6.0	0.93	0.86	0.80	Optimum
Feb	Max	43.21	6.88×10^{-3}	0.851	0.231	-8.97×10^{-5}	2.7×10^{-4}	2.31×10^{-2}	-1.34×10^{-2}	–	0.55	1.45	3.7	1.72	7.9	0.75	0.77	0.58	Good
	Min	18.11	-1.96×10^{-3}	0.144	−0.228	–	7.7×10^{-5}	2.82×10^{-3}	-3.62×10^{-3}	-2.55×10^{-3}	0.89	0.58	1.9	1.93	7.8	0.94	0.88	0.83	Optimum
	Mean	23.06	-7.45×10^{-3}	8.83×10^{-2}	−0.214	–	-3.99×10^{-5}	6.43×10^{-3}	-1.05×10^{-2}	-2.85×10^{-3}	0.87	0.76	2.3	1.98	7.5	0.93	0.86	0.81	Optimum
Mar	Max	21.03	1.04×10^{-2}	-9.98×10^{-2}	−0.387	-1.26×10^{-4}	3.75×10^{-4}	1.12×10^{-2}	-2.64×10^{-2}	-4.0×10^{-3}	0.56	1.21	2.8	1.85	9.0	0.75	0.79	0.59	Good
	Min	19.19	1.23×10^{-3}	-6.09×10^{-2}	−0.135	–	1.49×10^{-4}	–	-7.42×10^{-3}	-1.29×10^{-3}	0.90	0.60	2.0	2.01	6.9	0.95	0.92	0.87	Optimum
	Mean	21.45	-5.77×10^{-3}	−0.106	−0.219	–	–	4.7×10^{-3}	-1.5×10^{-2}	-2.59×10^{-3}	0.90	0.70	2.2	1.95	7.5	0.95	0.89	0.85	Optimum
Apr	Max	15.02	3.57×10^{-3}	–	−0.637	–	1.76×10^{-4}	1.3×10^{-2}	-2.95×10^{-2}	-6.61×10^{-3}	0.70	1.17	2.9	1.98	6.9	0.84	0.83	0.70	Good
	Min	25.27	–	−0.237	0.143	–	1.19×10^{-4}	-4.54×10^{-3}	-8.60×10^{-3}	1.6×10^{-3}	0.91	0.71	2.8	1.96	8.0	0.95	0.93	0.88	Optimum
	Mean	14.62	-9.87×10^{-3}	−0.275	−0.481	3.38×10^{-5}	-1.04×10^{-4}	–	-1.72×10^{-2}	-4.88×10^{-3}	0.94	0.69	2.3	2.02	7.1	0.97	0.92	0.89	Optimum
May	Max	−6.98	–	0.157	−1.594	–	9.86×10^{-5}	1.14×10^{-2}	-2.76×10^{-2}	-1.60×10^{-2}	0.78	1.28	3.6	1.83	7.0	0.88	0.86	0.76	Optimum
	Min	40.19	–	−0.125	0.759	5.51×10^{-5}	1.02×10^{-4}	-5.05×10^{-3}	-5.41×10^{-3}	7.49×10^{-3}	0.90	0.97	3.7	1.83	7.9	0.95	0.92	0.87	Optimum
	Mean	10.08	-1.23×10^{-2}	−0.279	−0.674	5.46×10^{-5}	-1.67×10^{-4}	-3.62×10^{-3}	-1.57×10^{-2}	-6.65×10^{-3}	0.95	0.81	2.9	1.94	9.0	0.98	0.93	0.90	Optimum
Jun	Max	−23.67	-4.56×10^{-3}	0.266	−2.314	–	–	1.12×10^{-2}	-2.82×10^{-2}	-2.31×10^{-2}	0.81	1.42	4.1	1.75	8.0	0.90	0.87	0.78	Optimum
	Min	26.03	-2.66×10^{-3}	6.61×10^{-2}	0.127	4.29×10^{-5}	5.94×10^{-5}	-4.31×10^{-3}	-3.07×10^{-3}	1.11×10^{-3}	0.94	0.80	3.4	2.03	9.0	0.97	0.95	0.92	Optimum
	Mean	3.18	-1.48×10^{-2}	−0.167	−0.971	5.54×10^{-5}	-2.20×10^{-4}	-4.59×10^{-3}	-1.29×10^{-2}	-9.52×10^{-3}	0.96	0.85	3.3	1.91	9.0	0.98	0.92	0.90	Optimum
Jul	Max	−26.04	-7.99×10^{-3}	0.677	−2.487	–	-8.92×10^{-5}	1.56×10^{-2}	-2.33×10^{-2}	-2.49×10^{-2}	0.80	1.54	4.5	1.71	8.0	0.90	0.84	0.75	Optimum
	Min	22.95	-3.96×10^{-3}	0.254	–	–	4.09×10^{-5}	-2.86×10^{-3}	–	–	0.90	1.00	4.2	2.02	6.0	0.95	0.92	0.87	Optimum
	Mean	−2.36		–	−1.211	–			-1.38×10^{-2}		0.94	0.98	3.9	1.94	6.3	0.97	0.91	0.89	Optimum

Table 2 (continued)

Month	Temp	Coefficients of the multivariate regression equation									Goodness-of-fit statistics					Performance index			
		a (°C)	h (°C m^{-1})	φ (°C per degree)	λ	hφ (°C m^{-1} per degree)	hλ	φλ	φ^2 (°C per square degree)	λ^2	R^2_{adj}	RMSE (°C)	MAPE (%)	DW	Cp	r	d_r	P_i	Performance
			-1.39×10^{-2}				-1.81×10^{-4}	-1.47×10^{-3}		-1.19×10^{-2}									
Aug	Max	−32.46	-7.94×10^{-3}	0.897	−2.827	–	-1.03×10^{-4}	2.1×10^{-2}	-2.54×10^{-2}	-2.87×10^{-2}	0.77	1.72	4.8	1.7	7.2	0.88	0.80	0.70	Very good
	Min	7.39	-6.92×10^{-3}	0.193	−0.64	-5.37×10^{-5}	–	-2.24×10^{-3}	-3.33×10^{-3}	-6.22×10^{-3}	0.88	1.06	4.2	1.98	7.0	0.94	0.91	0.85	Optimum
	Mean	−13.3	-1.48×10^{-2}	–	−1.66	–	-2.09×10^{-4}	1.19×10^{-3}	-1.81×10^{-2}	-1.63×10^{-2}	0.92	1.10	4.1	1.88	7.9	0.96	0.90	0.86	Optimum
Sep	Max	−27.46	-2.07×10^{-3}	0.999	−2.649	4.99×10^{-5}	–	2.72×10^{-2}	-3.11×10^{-2}	-2.73×10^{-2}	0.78	1.64	4.4	1.66	7.0	0.88	0.82	0.72	Very good
	Min	−3.31	-1.05×10^{-2}	0.17	−1.109	–	-1.03×10^{-4}	–	-7.02×10^{-3}	-1.1×10^{-2}	0.87	1.00	3.9	1.95	8.0	0.93	0.89	0.83	Optimum
	Mean	−15.17	-1.13×10^{-2}	–	−1.762	–	-1.38×10^{-4}	4.11×10^{-3}	-2.19×10^{-2}	-1.75×10^{-2}	0.90	1.14	4.1	1.78	6.0	0.95	0.89	0.85	Optimum
Oct	Max	−19.07	4.06×10^{-3}	0.983	−2.348	9.19×10^{-5}	1.36×10^{-4}	2.84×10^{-2}	-3.1×10^{-2}	-2.47×10^{-2}	0.76	1.61	4.0	1.73	9.0	0.87	0.84	0.73	Very good
	Min	−5.88	-5.36×10^{-3}	–	−1.179	–	–	–	-1.08×10^{-2}	-1.14×10^{-2}	0.84	0.93	3.6	2.01	6.1	0.92	0.90	0.83	Optimum
	Mean	−6.09	-1.02×10^{-2}	–	−1.402	–	-1.12×10^{-4}	6.39×10^{-3}	-2.33×10^{-2}	-1.41×10^{-2}	0.90	1.05	3.5	1.89	6.0	0.95	0.90	0.85	Optimum
Nov	Max	15.32	1.36×10^{-2}	1.204	−0.935	-9.17×10^{-5}	4.23×10^{-4}	3.11×10^{-2}	-2.22×10^{-2}	-1.1×10^{-2}	0.69	1.53	3.8	1.82	9.0	0.83	0.80	0.66	Very good
	Min	1.96	1.77×10^{-3}	7.56×10^{-2}	−0.868	–	1.66×10^{-4}	2.9×10^{-3}	-9.70×10^{-3}	-8.58×10^{-3}	0.84	0.84	3.0	2.0	8.0	0.92	0.88	0.81	Optimum
	Mean	6.36	-8.35×10^{-3}	0.277	−0.946	–	-6.92×10^{-5}	9.93×10^{-3}	-1.66×10^{-2}	-1.01×10^{-2}	0.90	0.91	2.9	1.97	7.0	0.95	0.89	0.84	Optimum
Dec	Max	33.72	1.37×10^{-2}	1.189	−0.18	-8.36×10^{-5}	4.24×10^{-4}	2.87×10^{-2}	-1.39×10^{-2}	-3.81×10^{-3}	0.63	1.43	3.5	1.65	9.0	0.80	0.78	0.63	Very good
	Min	11.29	–	0.119	−0.518	–	1.18×10^{-4}	1.45×10^{-3}	-5.71×10^{-3}	-5.35×10^{-3}	0.88	0.72	2.7	1.99	6.6	0.94	0.91	0.85	Optimum
	Mean	17.58	-7.89×10^{-3}	0.393	−0.514	–	-5.25×10^{-5}	1.1×10^{-2}	-1.10×10^{-2}	-6.11×10^{-3}	0.89	0.84	2.6	2.0	7.3	0.94	0.88	0.83	Optimum
Year	Max	3.22	2.49×10^{-3}	0.64	−1.307	–	1.42×10^{-4}	1.99×10^{-2}	-2.35×10^{-2}	-1.4×10^{-2}	0.75	1.25	3.3	1.88	7.1	0.87	0.83	0.73	Very good
	Min	14.22	-2.1×10^{-3}	0.103	−0.371	–	7.8×10^{-5}	–	-5.53×10^{-3}	-3.82×10^{-3}	0.93	0.63	2.3	1.9	8.0	0.96	0.93	0.89	Optimum
	Mean	5.12	-9.63×10^{-3}	–	−0.93	–	-8.97×10^{-5}	3.2×10^{-3}	-1.55×10^{-2}	-9.5×10^{-3}	0.93	0.80	2.7	2.01	6.6	0.96	0.91	0.88	Optimum

Missing values of coefficients were not significative at 5 %

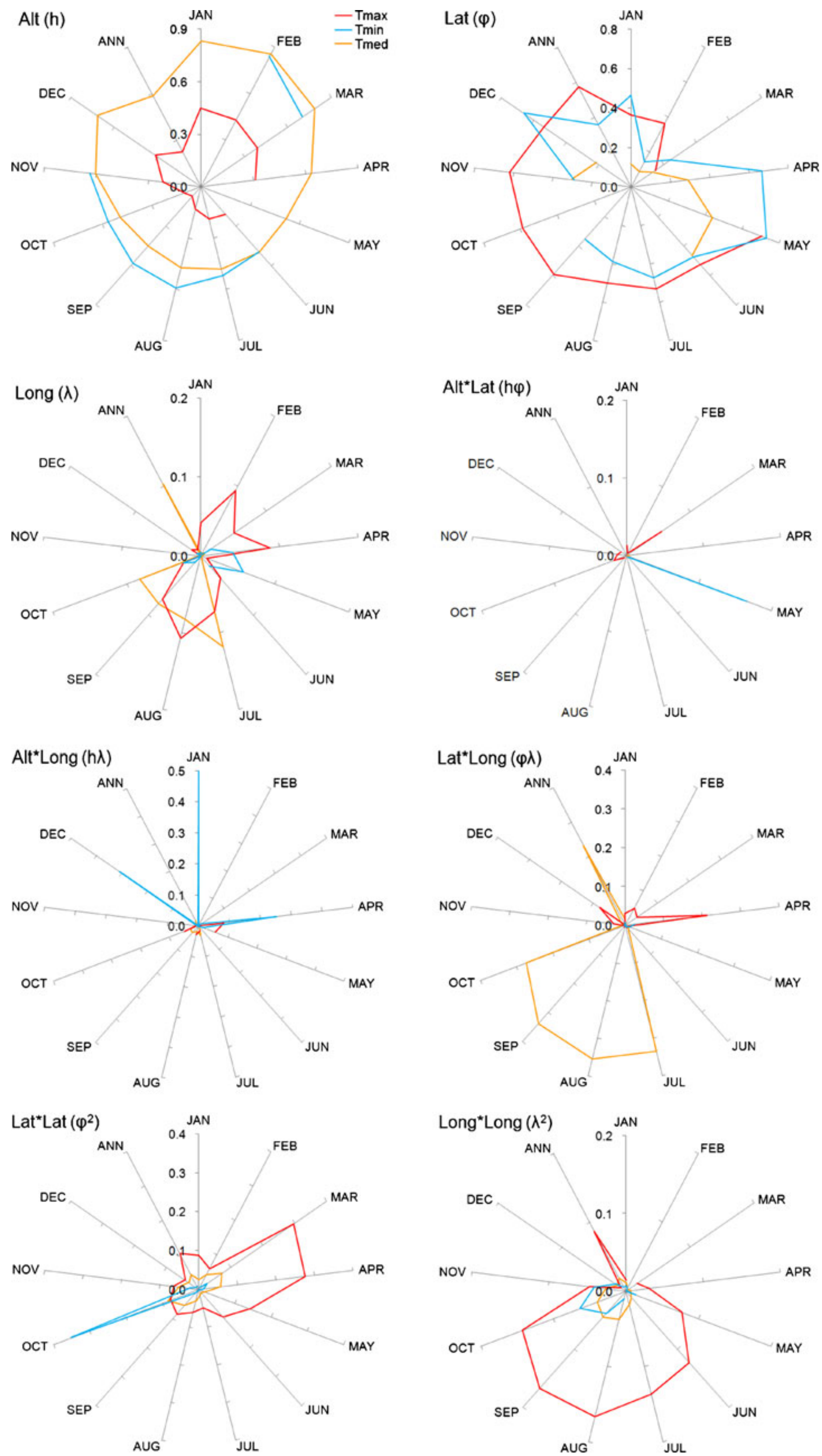

Fig. 7 Monthly distribution breakdown of the sum of squares for the contribution of significant independent variables (in percent) for the air temperature models

The quadratic interaction of latitude (φ^2) contributed in all models of maximum and mean temperature, being more important in March and April to the maximum temperature, explaining more than 25 % of its variability. Approximately

35 % of the estimated minimum temperature for October was explained by φ^2. Finally, the quadratic interaction of longitude (λ^2) was significant for all temperature models, except for maximum temperature in February and for minimum temperature in July. This independent variable showed the highest contribution to maximum temperature estimates, between 12 and 18 %, during the months from June to October (Fig. 7).

The annual maximum, minimum, and mean temperature maps for Brazil presented, as expected, a high range of variation (Fig. 8). The annual maximum temperature expressed extreme values between 11.4 and 34.7 °C. Much of central, northern, and northeastern Brazil presented annual maximum temperatures above 32 °C. The annual minimum temperature map showed that the classes were distributed in parallel to latitude and with remarkable influence of the relief (Figs. 4, 6, 7, and 8). The minimum annual temperature extremes were between 3.7 and 23.5 °C. The mean annual temperature had greater influence by longitude and altitude, with extremes of temperature between 8.4 and 28.2 °C.

In order to improve the results of the regression models, we adopted ordinary kriging to obtain a residue surface. Among the theoretical models tested (spherical, exponential, Gaussian, and linear), the spherical model was the best one to describe the experimental semivariograms (Table 3), according to the method used by the program geostatistic GS+ v.9, which is based on the smallest reduced sums of squares (RSS) and on the greatest determination coefficient (R^2; Robertson 2008). All spherical models presented R^2 higher than 0.9. Rodríguez-Lado et al. (2007) also found that spherical was the best model fitted to temperature residue equations for the state of São Paulo. We observed that the nugget effect was greater at residues of mean and maximum temperature. This means that there are components of variability in the regression models and that the semivariograms were not able to detect them. Semivariograms stabilize at approximately 5°, but values were observed between 2.95 and 8.53, with higher ranges in the winter months (June, July, and August). SDI indicated that temperature residue presented moderate to strong spatial dependence, showing that there are patterns of spatial distribution for all models (Fig. 8). In Midwest and northern Brazil, in the states of Mato Grosso, Pará, and Amazonas, the highest negative residues (less than −3 °C) were observed for the maximum, mean, and minimum temperatures. The largest positive residues in the maps were found in southeastern Brazil and far north to the maximum temperature and in the Midwest region (states of Goiás and Mato Grosso do Sul) to the mean temperature. The residues observed in the maps ranged from −3 to 3 °C, which is very similar to what was found by Rodríguez-Lado et al. (2007) in São Paulo state, Brazil. These residuals express the local temperature variation that was not adjusted by the regression models. Based on that, they were used to improve the accuracy of the temperature maps by adding the residue maps to the modeled temperature maps, obtaining corrected temperature maps (Fig. 8).

All the air temperature models (Table 2) were applied twice in the 600 weather stations from the test set to accomplish the first validation (Table 4). At the first round of tests, only the geographical coordinates and altitude of the weather stations were considered from the test set and then the results were compared with those observed in these same localities. This part, called "before kriging," showed MAE ranging from 0.4 to 1.4 °C, RMSE from 0.6 to 1.8 °C, and MAPE from 2.1 to 4.8 % (Table 4). The largest deviations were found in the winter months, mainly for maximum temperature, with MAE always >1 °C, RMSE>1.5 °C, and MAPE>4 %. In the second round of tests, the models were used to estimate temperatures for the 600 weather stations from the test set and then the values extracted from the residue kriging maps were added to them. When considering this procedure, named "after kriging," the estimated temperature values became very similar to the observed data, as demonstrated by ME, MAE, RMSE, and MAPE (Table 4). The overall ME was 0, the maximum MAE was lower than 0.4 °C, RMSE was no greater than 0.8 °C, and MAPE was lower than 2.8 %. Such results show that residues are random errors and that our regression model worked quite well for interpreting the spatial variability of air temperature throughout the Brazilian territory.

The final map of the annual maximum temperature (map regression+kriging map of residue) shows that a large portion of Brazil, above the Tropic of Capricorn, has an annual T_{max} greater than 29 °C, with the exception of the areas with altitude above 700 m. Below the tropic line, the annual minimum temperature is <14 °C, and in higher areas (up to 800 m) of the mountainous regions in the states of Paraná and Santa Catarina, this value is no more than 11 °C (Fig. 8). The peak of Bandeiras, on the border between the states of Minas Gerais and Espirito Santo, southeastern Brazil, is the coldest Brazilian area with a mean annual temperature below 8 °C. The peaks of Pedra da Mina and Agulhas Negras, both with altitude around 2,800 m, in Mantiqueira Mountains, near the triple border of the states of Minas Gerais, São Paulo, and Rio de Janeiro, are also very cold localities with mean annual temperatures between 8 and 11 °C (Fig. 8). The Serrano Plateau (Santa Catarina state), southern Brazil, with an altitude ranging from 1,200 to 1,800 m, is also one of the coldest regions of Brazil having a mean annual temperature between 11 and 14 °C. Within this same temperature class, we found a small area in the far north of the Rio Grande do Sul state, a plateau with altitudes between 1,000 and 1,200 m. A large part of Midwest and northeastern Brazil has a mean annual temperature between 23 and 26 °C. Some exceptions are found in the highlands and

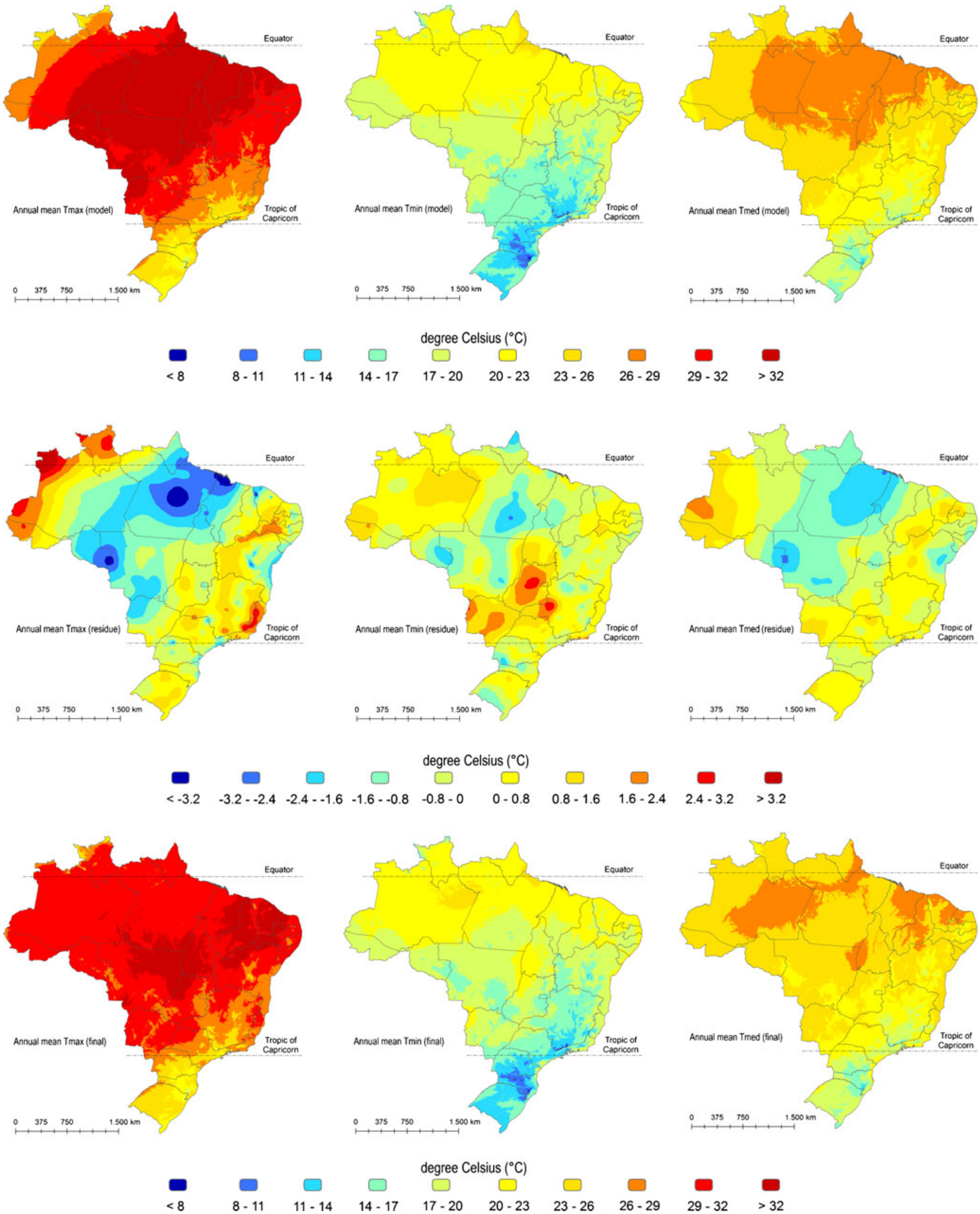

Fig. 8 Annual maximum, minimum, and mean air temperature maps for Brazil, generated by the regression models, their residues interpolated by kriging, and the final maps of air temperature

Table 3 Models, parameters, and quality of experimental semivariograms adjusted for fitting set residue

Month	Temp	Model	Co[a]	Co+C[b]	Ao[c]	C/(Co+C)	SDI	R^{2d}	RSS	r^e
January	Max	Esf.	0.130	2.174	4.630	94.0	Strong	0.96	1.41×10^{-1}	0.88
	Min	Esf.	0.050	0.368	4.710	86.4	Strong	0.96	4.07×10^{-3}	0.73
	Mean	Esf.	0.181	0.647	3.940	72.0	Moderate	0.99	1.96×10^{-3}	0.76
February	Max	Esf.	0.164	2.532	4.330	93.5	Strong	0.96	2.27×10^{-1}	0.89
	Min	Esf.	0.039	0.248	5.120	84.3	Strong	0.98	8.52×10^{-4}	0.73
	Mean	Esf.	0.170	0.556	4.580	69.4	Moderate	0.99	1.02×10^{-3}	0.76
March	Max	Esf.	0.202	1.627	4.430	87.6	Strong	0.95	8.72×10^{-2}	0.85
	Min	Esf.	0.070	0.265	4.070	73.7	Moderate	0.94	2.03×10^{-3}	0.61
	Mean	Esf.	0.152	0.489	4.600	68.9	Moderate	0.95	4.12×10^{-3}	0.73
April	Max	Esf.	0.238	1.588	5.020	85.0	Strong	0.97	5.55×10^{-2}	0.85
	Min	Esf.	0.031	0.450	4.910	93.1	Strong	0.98	4.08×10^{-3}	0.69
	Mean	Esf.	0.164	0.479	5.190	65.7	Moderate	0.93	5.78×10^{-3}	0.73
May	Max	Esf.	0.270	1.857	6.190	85.5	Strong	0.99	1.26×10^{-2}	0.86
	Min	Esf.	0.070	0.265	4.070	73.7	Moderate	0.94	2.03×10^{-3}	0.61
	Mean	Esf.	0.182	0.754	6.570	75.9	Strong	0.98	7.33×10^{-3}	0.75
June	Max	Esf.	0.256	2.197	6.030	88.3	Strong	0.99	3.09×10^{-2}	0.89
	Min	Esf.	0.048	0.515	7.450	90.7	Strong	0.99	7.44×10^{-4}	0.64
	Mean	Esf.	0.200	0.786	6.050	74.6	Moderate	0.97	1.06×10^{-2}	0.82
July	Max	Esf.	0.150	2.472	5.990	93.9	Strong	0.99	4.55×10^{-2}	0.89
	Min	Esf.	0.078	0.829	8.180	90.6	Strong	0.99	7.03×10^{-4}	0.63
	Mean	Esf.	0.153	1.018	5.010	85.0	Strong	0.94	3.57×10^{-2}	0.80
August	Max	Esf.	0.089	3.134	5.620	97.2	Strong	0.99	7.52×10^{-2}	0.92
	Min	Esf.	0.109	0.854	8.530	87.2	Strong	0.99	8.11×10^{-4}	0.58
	Mean	Esf.	0.164	1.299	5.260	87.4	Strong	0.99	1.57×10^{-2}	0.84
September	Max	Esf.	0.148	2.883	5.630	94.9	Strong	0.99	2.31×10^{-2}	0.91
	Min	Esf.	0.173	0.722	6.540	76.0	Strong	0.99	1.63×10^{-3}	0.66
	Mean	Esf.	0.285	1.395	5.740	79.6	Strong	0.99	9.25×10^{-3}	0.86
October	Max	Esf.	0.267	2.720	5.620	90.2	Strong	0.99	1.38×10^{-2}	0.90
	Min	Esf.	0.135	0.555	7.670	75.7	Strong	0.99	1.67×10^{-3}	0.58
	Mean	Esf.	0.280	1.152	5.590	75.7	Strong	0.94	5.40×10^{-2}	0.85
November	Max	Esf.	0.119	2.856	4.840	95.8	Strong	0.99	7.72×10^{-2}	0.89
	Min	Esf.	0.055	0.574	4.810	90.4	Strong	0.92	2.17×10^{-2}	0.70
	Mean	Esf.	0.163	0.792	3.240	79.4	Strong	0.95	1.06×10^{-2}	0.82
December	Max	Esf.	0.131	2.499	4.320	94.8	Strong	0.96	2.07×10^{-1}	0.89
	Min	Esf.	0.057	0.440	4.360	87.0	Strong	0.91	1.29×10^{-2}	0.71
	Mean	Esf.	0.139	0.668	2.950	79.2	Strong	0.95	6.26×10^{-3}	0.82
Year	Max	Esf.	0.172	1.701	4.900	89.9	Strong	0.99	3.01×10^{-2}	0.87
	Min	Esf.	0.037	0.282	4.920	86.8	Strong	0.97	2.05×10^{-3}	0.67
	Mean	Esf.	0.200	0.653	4.740	69.4	Moderate	0.98	2.34×10^{-3}	0.79

Sph spherical, *SDI* spatial dependence index, *RSS* residue sum of squares

[a] Co=nugget

[b] Co+C=sill (C structural variance)

[c] Ao=range (degrees)

[d] R^2 =model adjustment determination coefficient

[e] r=crossed validation correlation coefficient

plateaus of the states of Mato Grosso, Goias, and Bahia. A mean annual temperature above 26 °C was mapped in wide valleys of the Amazon, Tocantins, Araguaia, and Parnaíba Rivers. The extreme north of the Brazilian Northeast

Table 4 Errors of the temperature multivariate regression models using database from fitting and test sets considering kriging effects for the first validation

		Before kriging				After kriging			
		ME (°C)	MAE (°C)	RMSE (°C)	MAPE (%)	ME (°C)	MAE (°C)	RMSE (°C)	MAPE (%)
January	Max	−0.03	1.1	1.3	3.4	−0.04	0.3	0.6	1.1
	Min	−0.03	0.4	0.6	2.3	−0.02	0.2	0.4	1.1
	Mean	0.04	0.6	0.8	2.4	0.01	0.3	0.4	1.2
February	Max	0.04	1.1	1.4	3.5	0.01	0.4	0.6	1.2
	Min	−0.02	0.4	0.6	2.2	−0.01	0.2	0.5	1.2
	Mean	0.01	0.6	0.7	2.2	0.05	0.3	0.5	1.2
March	Max	0.01	0.9	1.2	2.9	≤ 0.01	0.4	0.6	1.2
	Min	0.02	0.4	0.6	2.1	0.02	0.3	0.5	1.4
	Mean	0.0[a]	0.5	0.7	2.1	0.03	0.3	0.5	1.4
April	Max	−0.02	0.8	1.1	2.8	≤0.01	0.3	0.6	1.2
	Min	−0.03	0.5	0.8	3.0	−0.01	0.3	0.6	1.6
	Mean	−0.02	0.6	0.7	2.4	−0.03	0.3	0.6	1.5
May	Max	0.04	1.0	1.3	3.7	−0.01	0.3	0.6	1.3
	Min	0.04	0.7	0.9	4.0	0.03	0.3	0.5	1.7
	Mean	0.02	0.6	0.8	2.9	0.03	0.3	0.5	1.5
June	Max	0.03	1.2	1.4	4.2	0.11	0.3	0.5	1.2
	Min	−0.09	0.5	0.7	3.1	−0.02	0.2	0.5	1.6
	Mean	−0.05	0.7	0.9	3.6	0.04	0.3	0.7	1.9
July	Max	0.06	1.2	1.5	4.3	0.06	0.4	0.7	1.5
	Min	−0.07	0.6	1.1	4.9	−0.06	0.3	0.8	2.8
	Mean	−0.12	0.7	1.0	3.8	−0.05	0.3	0.5	1.8
August	Max	−0.15	1.4	1.7	4.9	0.05	0.4	0.7	1.3
	Min	−0.01	0.6	1.1	4.0	0.03	0.3	0.8	2.3
	Mean	−0.07	0.9	1.1	4.5	−0.03	0.4	0.6	2.0
September	Max	−0.14	1.4	1.8	4.8	−0.04	0.4	0.8	1.5
	Min	0.02	0.7	1.1	4.3	0.05	0.4	0.8	2.4
	Mean	0.02	0.9	1.1	3.9	−0.02	0.4	0.5	1.7
October	Max	−0.11	1.3	1.6	4.2	−0.03	0.4	0.7	1.3
	Min	−0.05	0.6	0.8	3.3	−0.03	0.3	0.6	1.8
	Mean	−0.1	0.9	1.1	3.8	≤0.01	0.4	0.6	1.6
November	Max	−0.09	1.2	1.6	3.9	−0.03	0.4	0.8	1.3
	Min	0.03	0.5	0.8	2.8	0.04	0.3	0.6	1.5
	Mean	−0.12	0.8	1.0	3.2	−0.05	0.4	0.6	1.6
December	Max	−0.16	1.0	1.3	3.3	−0.03	0.4	0.7	1.3
	Min	0.03	0.5	0.7	2.6	0.03	0.3	0.5	1.5
	Mean	−0.05	0.7	0.9	2.8	−0.01	0.3	0.6	1.4
Year	Max	0.06	0.9	1.2	3.1	≤0.01	0.3	0.5	1.1
	Min	0.01	0.4	0.7	2.4	≤0.01	0.2	0.5	1.3
	Mean	−0.01	0.6	0.8	2.8	−0.01	0.3	0.5	1.5

ME mean error, *MAE* mean absolute error, *RMSE* root mean square error, *MAPE* mean absolute percentage error

[a] Less than 0.01

(latitude<9°), in the states of Maranhão, Piauí, Ceará, and Rio Grande do Norte, also presents a mean annual temperature greater than 26 °C, where there are altitudes no greater than 300 m.

After the first round of tests, 372 spatial correlations, evaluating a total of 3.67×10^8 pixels (1 km^2), were performed between the results provided by the proposed models and other studies (Table 5), which resulted in the second

Table 5 Pearson's correlation coefficient for the relationship between temperatures estimated by the models proposed and those published for some Brazilians regions and states, considering aspatial resolution of 1 km^2, for the second validation

Month	Temperature	RS	SC	PR	SP	FC	MG	ES	MW	GO	NE	BA	PI	PA
		Pearson's correlation coefficient (r)												
January	Maximum	0.91	0.89	0.99	–	0.99	0.92	0.97	0.92	–	0.83	–	0.88	–
	Minimum	0.90	–	0.97	–	0.99	0.97	0.99	0.96	–	0.99	–	0.99	–
	Mean	0.97	0.99	0.99	0.99	–	0.99	0.99	0.92	0.99	0.89	0.88	0.88	0.74
February	Maximum	0.88	0.95	0.98	–	0.99	0.93	0.99	0.99	–	0.66	–	0.91	–
	Minimum	0.95	–	0.97	–	0.99	0.98	0.99	0.98	–	0.98	–	0.99	–
	Mean	0.99	0.99	0.99	0.99	–	0.99	0.99	0.92	0.99	0.95	0.91	0.93	0.63
March	Maximum	0.96	0.92	0.99	–	0.99	0.96	0.99	0.91	–	0.78	–	0.92	–
	Minimum	0.96	–	0.96	–	0.99	0.96	0.99	0.99	–	0.97	–	0.99	–
	Mean	0.99	0.98	0.99	0.99	–	0.99	0.99	0.93	0.99	0.96	0.91	0.88	0.74
April	Maximum	0.94	0.94	0.99	–	0.99	0.96	0.99	0.96	–	0.87	–	0.88	–
	Minimum	0.98	–	0.95	–	0.99	0.95	0.99	0.93	–	0.98	–	0.91	–
	Mean	0.97	0.93	0.98	0.99	–	0.99	0.99	0.98	0.99	0.95	0.87	0.94	0.87
May	Maximum	0.95	0.91	0.98	–	0.98	0.96	0.99	0.95	–	0.89	–	0.70	–
	Minimum	0.94	–	0.89	–	0.99	0.93	0.99	0.92	–	0.86	–	0.96	–
	Mean	0.93	0.93	0.98	0.99	–	0.98	0.99	0.99	0.99	0.97	0.84	0.98	0.81
June	Maximum	0.97	0.85	0.98	–	0.98	0.95	0.98	0.92	–	0.88	–	0.77	–
	Minimum	0.82	–	0.85	–	0.99	0.96	0.99	0.92	–	0.99	–	0.99	–
	Mean	0.97	0.93	0.97	0.99	–	0.99	0.99	0.99	0.98	0.96	0.78	0.92	0.71
July	Maximum	0.94	0.78	0.96	–	0.96	0.91	0.97	0.97	–	0.90	–	0.81	–
	Minimum	0.81	–	0.87	–	0.99	0.96	0.99	0.93	–	0.99	–	0.99	–
	Mean	0.97	0.89	0.96	0.99	–	0.99	0.99	0.99	0.99	0.99	0.73	0.92	0.81
August	Maximum	0.92	0.77	0.95	–	0.95	0.91	0.94	0.87	–	0.88	–	0.80	–
	Minimum	0.80	–	0.88	–	0.99	0.96	0.99	0.94	–	0.98	–	0.84	–
	Mean	0.97	0.86	0.97	0.99	–	0.99	0.99	0.94	0.98	0.73	0.65	0.81	0.80
September	Maximum	0.90	0.82	0.94	–	0.94	0.93	0.92	0.94	–	0.85	–	0.65	–
	Minimum	0.88	–	0.92	–	0.99	0.98	0.99	0.97	–	0.95	–	0.78	–
	Mean	0.97	0.89	0.98	0.98	–	0.99	0.99	0.98	0.99	0.91	0.61	0.74	0.78
October	Maximum	0.91	0.88	0.97	–	0.97	0.93	0.95	0.84	–	0.84	–	0.64	–
	Minimum	0.95	–	0.98	–	0.99	0.99	0.99	0.97	–	0.93	–	0.83	–
	Mean	0.95	0.92	0.99	0.98	–	0.92	0.99	0.98	0.98	0.91	0.79	0.70	0.37
November	Maximum	0.84	0.88	0.97	–	0.99	0.87	0.87	0.88	–	0.84	–	0.84	–
	Minimum	0.90	–	0.97	–	0.99	0.98	0.99	0.95	–	0.96	–	0.82	–
	Mean	0.97	0.96	0.98	0.98	–	0.99	0.99	0.88	0.97	0.88	0.86	0.72	0.40
December	Maximum	0.90	0.87	0.96	–	0.99	0.92	0.94	0.87	–	0.82	–	0.92	–
	Minimum	0.94	–	0.99	–	0.99	0.96	0.99	0.97	–	0.96	–	0.87	–
	Mean	0.96	0.99	0.99	0.98	–	0.99	0.99	0.96	0.98	0.85	0.79	0.82	0.52
Year	Maximum	0.92	0.93	0.98	0.88	0.98	0.93	–	0.95	–	0.83	–	–	–
	Minimum	0.91	–	0.95	0.97	0.99	0.97	–	0.95	–	0.99	–	–	–
	Mean	0.99	0.96	0.99	0.99	–	0.99	–	0.98	0.99	0.93	0.80	–	–

RS (T_{max}: Buriol et al. 1973; T_{min}: Estefanel et al. 1973; T_{med}: Ferreira et al. 1971); SC (T_{max}: Buriol et al. 1974; T_{med}: Ferreira et al. 1974); PR (Pinto and Alfonsi 1974); SP (Rodríguez-Lado et al. 2007); FC (Bardin et al. 2010); MG (Sediyama and Melo Junior 1998); ES (Pezzopane et al. 2004); MW (Oliveira Neto et al. 2002); GO (Alfonsi et al. 1974); NE (Medeiros et al. 2005); BA (Almeida and Sá 1984); PI (Lima and Ribeiro 1998); and PA (Ferreira et al. 2006)

validation of the models. The overall correlation obtained was 0.93, which considered all the states and regions and all months and years. The correlations between the annual temperatures from the proposed models and those obtained with the other regional models have reached the highest global precision, equal to 0.95. A high overall correlation

Table 6 Descriptive statistics of the monthly and annual maximum, minimum, and mean air temperatures in the Brazilian capitals, considering a resolution of 1 km^2

Capital	Area (km^2)	Maximum temperature (°C)				Minimum temperature (°C)				Mean temperature (°C)			
		Mn	Mx	Me	SD	Mn	Mx	Me	SD	Mn	Mx	Me	SD
Aracajú (SE)	174	29.3	29.6	29.4	0.1	20.4	20.7	20.6	0.0	25.0	25.3	25.3	0.0
Belém (PA)	1,065	31.2	31.6	31.4	0.1	22.8	23.3	23.1	0.1	25.7	25.9	25.9	0.1
Belo Horizonte (MG)	330	24.4	27.2	26.5	0.6	11.6	15.8	14.7	0.8	15.7	20.2	19.0	0.9
Boa Vista (RR)	5,687	29.8	32.1	31.4	0.3	20.5	22.5	22.3	0.1	24.0	25.5	25.1	0.1
Brasília (DF)	5,802	26.4	28.9	27.5	0.5	14.2	17.9	15.8	0.6	19.2	22.4	20.8	0.6
Campo Grande (MS)	8,096	27.8	30.2	29.1	0.4	16.3	19.0	17.4	0.4	22.1	24.4	23.0	0.3
Cuiabá (MT)	3,538	28.0	31.6	31.0	0.7	14.3	19.2	18.0	1.0	20.9	24.1	23.5	0.6
Curitiba (PR)	435	22.0	22.6	22.3	0.1	11.5	12.2	11.9	0.1	16.7	17.2	16.9	0.1
Florianópolis (SC)	433	21.8	24.1	23.6	0.4	14.3	16.8	16.4	0.5	17.9	20.2	19.9	0.4
Fortaleza (CE)	313	32.7	32.9	32.8	0.0	22.1	22.4	22.3	0.0	26.0	26.4	26.2	0.1
Goiânia (GO)	739	28.5	29.9	29.5	0.2	16.4	18.0	17.4	0.3	21.3	22.8	22.3	0.3
João Pessoa (PB)	211	30.1	30.3	30.2	0.0	20.8	21.2	21.0	0.1	25.2	25.7	25.5	0.1
Macapá (AM)	6,407	30.4	31.0	30.8	0.1	22.1	23.4	23.0	0.2	25.9	26.5	26.3	0.1
Maceió (AL)	511	29.9	30.4	30.1	0.1	19.3	20.5	20.2	0.2	23.5	25.1	24.6	0.2
Manaus (AM)	11,401	30.5	31.8	31.2	0.3	22.4	23.8	23.1	0.3	26.0	26.9	26.5	0.2
Natal (RN)	170	30.5	30.8	30.7	0.1	21.4	21.8	21.6	0.1	25.4	25.9	25.6	0.1
Palmas (TO)	2,219	30.6	32.9	31.9	0.7	18.0	21.1	19.7	1.0	23.4	26.2	25.1	0.9
Porto Alegre (RS)	497	23.6	25.0	24.6	0.3	13.5	15.3	14.8	0.3	17.8	19.2	18.8	0.3
Porto Velho (RO)	34,082	29.4	31.8	31.2	0.3	18.3	21.2	20.2	0.5	24.9	26.2	25.8	0.2
Recife (PE)	217	30.0	30.2	30.1	0.1	20.4	20.9	20.7	0.1	24.9	25.8	25.5	0.2
Rio Branco (AC)	9,223	30.0	31.6	31.0	0.3	17.1	18.9	18.1	0.4	24.2	25.7	25.1	0.3
Rio de Janeiro (RJ)	1,182	24.7	28.4	27.7	0.6	14.7	19.9	18.9	0.7	18.1	23.0	22.4	0.8
Salvador (BA)	707	28.2	28.9	28.6	0.2	20.1	20.6	20.5	0.2	24.2	24.9	24.7	0.1
São Luís (MA)	827	30.6	31.1	30.9	0.1	22.8	23.2	23.0	0.1	26.4	26.8	26.6	0.1
São Paulo (SP)	1,523	22.6	25.8	23.9	0.5	10.9	17.1	13.0	0.3	16.4	21.6	18.0	0.4
Teresina (PI)	1,756	33.0	33.6	33.4	0.1	20.8	21.9	21.5	0.2	26.2	27.3	27.0	0.2
Vitória (ES)	93	28.0	28.7	28.6	0.1	18.3	19.3	19.2	0.2	22.4	23.6	23.5	0.2

Mn minimum, *Mx* maximum, *Me* mean, *SD* standard deviation

was also obtained in January, February, and April, whereas in August, September, October, and November, the lowest correlations were found, equal to 0.90.

Brazilian southern states showed total correlation coefficients of 0.93 (RS), 0.91 (SC), and 0.96 (PR). The coefficients of correlation for minimum temperature in the states of RS and PR and maximum temperature in SC presented lower values during the coldest months of the year (Table 5). The same was observed in the original studies for these states (Estefanel et al. 1973; Buriol et al. 1974; Pinto and Alfonsi 1974).

In the Brazilian southeastern states, the total correlation coefficients were higher than 0.96. Similar results were obtained in São Paulo state (Rodríguez-Lado et al. 2007), in Espírito Santo state (Pezzopane et al. 2004), and in the micro-region of Jundiaí, in São Paulo state (Bardin et al. 2010), with Pearson's coefficients of 0.92, 0.86, and 0.85, respectively. In Minas Gerais state, the correlations for minimum temperature were smaller than those for the mean and maximum temperatures (Sediyama and Melo Junior 1998), which was also observed by Coelho et al. (1973) in the same state. Regarding Midwestern Brazil, the equations showed high correlation with the studies performed in the region by Oliveira Neto et al. (2002) and Alfonsi et al. (1974).

Considering the whole northeast region, the equations expressed good correlations with the results reported by Medeiros et al. (2005), showing an overall coefficient of correlation of 0.9, although the majority of the models proposed for the entire country of Brazil had better performance. The correlations between the equations for monthly minimum and mean temperatures were higher than the maximum temperature. Medeiros et al. (2005) reported that the correlation coefficients for maximum temperature were the lowest, which is related to the high maximum temperature variability in this region. The correlations for the southeast of Bahia were lower, especially in the winter months, a period when the adjustments obtained by Almeida and Sá (1984) were very low (r< 0.7). Also, in northeastern Brazil, in the state of Piauí, the correlations with the equations of Lima and Ribeiro (1998) were reasonable, with an overall correlation coefficient equal to 0.86. The majority of the temperature models presented by these authors were of low precision, mainly for minimum and maximum temperature.

In northern Brazil, the correlations were lower, with overall precision (r) equal to 0.68 in the state of Pará. This result was compromised because the equations published by Ferreira et al. (2006) presented poor quality for every month. Thus, the equations presented in the present paper are of higher precision and accuracy than those obtained by these authors.

Considering the application of these models to estimate the temperatures for the Brazilian capitals, the results are very coherent (Table 6). In Teresina (5°05′ S, 42°48′ W, 88 m), the capital of Piauí state, the annual temperatures were the highest, with a maximum of 33.4 °C, minimum of 21.5 °C, and mean of 27.0 °C considering the 1,756 pixels (1,756 km^2) of the municipality perimeter (Table 6). At the other extreme, the coldest capital was Curitiba (25°26′ S, 49°16′ W, 920 m), Paraná state, where annual temperatures were 22.3, 11.9, and 16.9 °C, respectively, for the maximum, minimum, and mean air temperatures. Belo Horizonte, Minas Gerais state (19°55′ S, 43°56′ W, 860 m); Cuiabá, Mato Grosso state (15° 36′ S, 56°06′ W, 180 m); Palmas, Tocantins state (10°10′ S, 48°20′ W, 250 m); and Rio de Janeiro, Rio de Janeiro state (22°54′ S, 43°12′ W, 10 m) had the greatest temperature spatial variability in their perimeters, with a standard deviation ranging from 0.6 to 1.0 °C, due to their vast territorial size or due to their irregular relief.

As agricultural businesses are responsible for a great part of the Brazilian gross domestic product (Brugnaro and Bacha 2009), we expect that the models generated in this study will become very useful for agricultural and livestock planning through their application in tools like crop zoning, animal comfort index mapping, determination of the best sowing dates, evapotranspiration estimates and irrigation planning, crop yield models, pest and disease risk zoning, and agricultural credit and insurance. On the other hand, we encourage state and federal governments in Brazil to invest in improvements and upgrades of the Brazilian Weather Stations Network, leading to an appropriate station density to provide high-quality data, especially in the less developed regions of the country.

4 Conclusions

Spatial and temporal variabilities of the monthly and annual temperatures in Brazil were properly modeled through the relations of latitude, longitude, altitude, and their combinations using multivariate regression equations, geostatistical analysis, and GIS. The models proposed in the present study showed, in general, better performance than the models previously published for several Brazilian states and regions. Therefore, the temperature models proposed in this study are recommended to accurately estimate air temperature for use in all Brazilian territories as well as the maps produced based on these models.

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