Linear and Nonlinear Statistical Downscaling for Rainfall Forecasting over Southeastern Brazil

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ABSTRACT

In this work linear and nonlinear downscaling are developed to establish empirical relationships between the synoptic-scale circulation and observed rainfall over southeastern Brazil. The methodology uses outputs from the regional Eta Model: prognostic equations for local forecasting were developed using an artificial neural network (ANN) and multiple linear regression (MLR). The final objective is the application of such prognostic equations to Eta Model output to generate rainfall forecasts. In the first experiment the predictors were obtained from the Eta Model and the predictand was rainfall data from meteorological stations in southeastern Brazil. In the second experiment the observed rainfall on the day prior to the forecast was included as a predictor. The threat score (TS) and bias, used to quantify the performance of the forecasts, showed that the ANN was superior to MLR in most seasons. When compared with Eta Model forecasts, it was observed that the ANN has a tendency to forecast moderate and high rainfall with greater accuracy during the austral summer. Also, when the observed rainfall of the previous day is included as a predictor, the TS showed the best performance in continuous rain and well-organized meteorological systems. On the other hand, in the austral winter period, characterized by slight rain, the ANN showed better forecasting ability than did the Eta Model. The obtained results also suggest that in the austral winter rainfall is more predictable because convection is less frequent, and when this occurs the forcing is dynamic instead of thermodynamic.

1. Introduction

The forecast of meteorological phenomena is a complex task. The mathematical, statistical, and dynamic methodologies developed help address the problem; however, there is still a need of exploring new techniques in order to improve the results. Currently, numerical weather prediction (NWP) models can forecast various meteorological variables with acceptable accuracy. Specifically, rainfall is of great interest as much for its climatic and meteorological relevance, as well for its direct importance to productive sectors of the society. However, it is one of the most difficult variables to forecast, because of its inherent spatial and temporal variability (Wilson and Vallée 2002; Antolik 2000). For this reason, temporal and spatial scales involved are not yet solved satisfactorily by the numerical models (Olson et al. 1995).

Because of the difficulties mentioned, the dearth of knowledge, and the high computational cost involved in rainfall modeling, postprocessing techniques of NWP output have been developed. One of these techniques is statistical downscaling, which involves the reduction of the model's spatial scale. There are two categories of downscaling techniques: dynamic, which focuses on numerical models with a more detailed resolution, and empirical (or statistical), which uses transfer functions between scales. The former involves the use of global- and regional-scale numerical models and requires detailed observed meteorological information (from the surface) and is computationally demanding. The latter employs statistical methods, the most commonly used being regression (linear and nonlinear: principal com-

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ponent analysis, canonical correlation analysis, composition technique, and artificial neural networks) and stochastic (fuzzy logic, genetic algorithms, etc.) (Wilby and Wigley 1997). Another downscaling method using wavelet transform was developed by Perica and Foufoula-Georgiou (1996). This method has the ability to reproduce, from a statistical point of view, the variability of a meteorological variable for small scales by a decomposition using a wavelet transform (Kumar and Foufoula-Georgiou 1993).

The advantage of using statistical downscaling is that it offers an immediate solution at low computational cost; consequently, it may be implemented easily in operational centers.

A statistical method of downscaling involving multivariate linear regression (MLR) methods is that of model output statistics (Glahn and Lowry 1972), which is used by many NWP centers worldwide. However, as the physical processes that govern rainfall are nonlinear, new techniques have appeared to address this problem. One of them currently in widespread use is the artificial neural network (ANN). This technique is an interesting tool because it has the capacity to identify patterns whose complexity is hard to define through more formal approximations. Hornik et al. (1989) describe ANN as a "universal approximator." That is, an ANN can approximate nonlinear relations and their derivatives without prior knowledge of a specific nonlinear function. Thus, it can be used to make accurate forecasts of highly nonlinear systems; rainfall is this type of system. In the Northern Hemisphere this technique has been widely used for several meteorological applications (Marzban and Stumpf 1996; Cavazos 1997; ASCE Task Committee on Application of Artificial Neural Networks in Hydrology 2000). Comparing the results of ANNs used for downscaling with other techniques (Koizumi 1999; Hall et al. 1999; Applequist et al. 2002) it was shown that ANN improved rainfall forecasts, mainly in situations associated with high and moderate rainfall rates. A detailed review of the different ANN applications for rainfall forecasting was documented by Maier and Dandy (2000).

In Brazil, the large spatial and temporal rainfall variability, added to a sparse rain gauge network and a lack of meteorological radars, hinders monitoring. The Brazilian Weather Forecasting and Climatic Studies Center [Centro de Previsão de Tempo e Estudos Climáticos (CPTEC)] works operationally with the regional Eta Model and with a global-scale model, which allows an overview of the different current synoptic systems. However, it has been observed that rainfall forecasts from these models need to be improved [i.e., the quality of initial conditions, problems of topography, and convection parameterization scheme treatment; Tippett and Da Silva (1999); Bustamante et al. (2005)]. In these cases, the application of postprocessing techniques becomes necessary. In this context, the objective of this study is to perform a statistical downscaling for rainfall forecasts over southeastern Brazil, based on outputs of the Eta Model. The aim is to make forecasts more accurate for the users (farmers, producers, business people, and the general public).

Two premises are important in the application of statistical downscaling (Hewitson and Crane 1996). 1) The NWP model used should be capable of producing fields of circulation at the synoptic scale and 2) the empirical approximation methodology should be capable of establishing a relationship between synoptic-scale and local-scale circulations. For the former, the Eta Model supplies the future behavior of the atmospheric circulation on the synoptic scale, and has recently been shown to be useful for supplying forecasts in South America for periods of up to 72 h. There have been studies that show the evaluation and expertise of the Eta Model (information online at http://www.cptec.inpe.br/projeta/avalmodelo.shtml) clearly indicating improvement in the quality of the forecasts generated. For the empirical methodology, there are studies in the Northern Hemisphere that have documented the great potential of ANNs in the use of statistical downscaling (Koizumi 1999; Hall et al. 1999; Applequist et al. 2002). In Brazil, this technique has been used successfully by Valverde Ramírez (2003) and Valverde Ramírez et al. (2005) for local rainfall forecasting in the state of São Paulo.

There are three important differences between the current study and the one employed by Valverde Ramírez et al. (2005). First, the methodology of the statistical downscaling was expanded to the southeastern region of Brazil, which includes the states of São Paulo, Rio de Janeiro, and Minas Gerais. Second, a new predictor is employed in this analysis, the real rainfall data of the previous day. There seems to exist in the rainfall process some kind of local persistence that presumably cannot be taken into account by the synoptic forcing process alone (Zorita and von Storch 1999). Third, a measure of performance, the threat score (TS), is used that is more suitable than the correlation and rmse skills. This parameter is the most common measure of accuracy for ranking predictions of interest (i.e., rainfall above a certain threshold). Rainfall forecasts, especially for heavy and moderate events, are better ranked using this measure (Yuval and Hsieh 2003). In this work a feed-forward ANN and the learning resilient back propagation (RPROP; Riedmiller and Braun 1993) were used. This ANN was previously used by

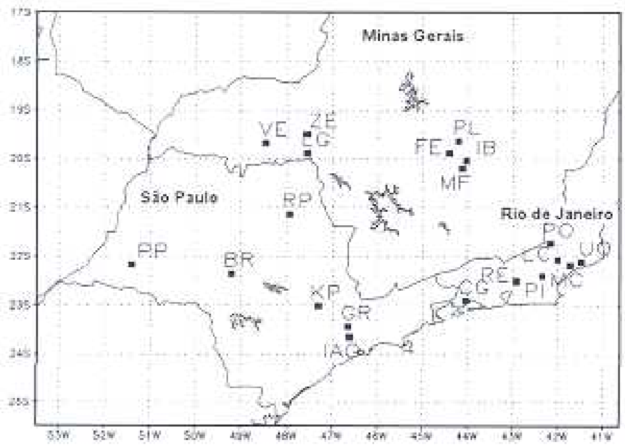

FIG. 1. Map of the southeastern region of Brazil and the geographical locations of the meteorological stations used.

Valverde Ramírez et al. (2005), and it has shown high adaptability in terms of training speed when compared with back propagation.

This paper is organized in the following manner. Section 2 describes the data and the Eta Model. Section 3 shows the basic structure of the ANN, the experiment, and the selection of the predictors. Section 4 describes the quantitative and qualitative results. Section 5 offers concluding remarks.

2. Data

This study used daily rainfall data at meteorological stations in the states of São Paulo, Rio de Janeiro, and Minas Gerais in southeastern Brazil (Fig. 1). The locations of meteorological stations are shown in Table 1. Output from the CPTEC regional Eta Model (Mesinger 1984; Chou et al. 2000) for the austral summer period between December and February (1997–2002) and for the austral winter period between June and August (1998–2002), and images from *Geostationary Operational Environmental Satellite-8* (*GOES-8*) for the period 1997–2002 were used. The meteorological stations analyzed were selected by the availability of a continuous series of data being concurrent with the operational Eta Model files stored by CPTEC.

The regional Eta Model was developed by the University of Belgrade (Mesinger 1984) and installed at CPTEC in 1996. The domain of the model covers approximately the region between latitudes 12°N and 45°S and longitudes 25° and 90°W.

The initial conditions were derived from the NCEP analyses, and the lateral boundary conditions from the CPTEC global forecast model. The analysis was performed on a grid corresponding to the global model and interpolated onto the Eta Model grid. The Eta Model has a horizontal grid length of 40 km and 38 layers in the vertical. The model is integrated twice a day using initial conditions at 1200 and 0000 UTC. The prognostic variables are air temperature, the zonal and meridional components of the wind, specific humidity, surface pressure, and turbulent kinetic energy. The convective rainfall of the model is produced by the Betts–Miller scheme (Betts and Miller 1986), while stratiform rain is generated via a cloud forecasting scheme (Zhao and Carr 1997).

TABLE 1. Geographical locations of the selected stations in São Paulo, Rio de Janeiro, and Minas Gerais.

State	Stations	Code	Lat (°S)	Lon (°W)	Alt (m)
São Paulo	Guarulhos	GR	23°26′	46°28′	803
	IAG	IAG	23°39′	46°37′	598
	Campinas	KP	23°00′	47°08′	661
	Bauru	BR	22°21′	49°03′	590
	Presidente Prudente	PP	22°10′	51°25′	435
	Ribeirão Preto	RP	21°08′	47°46′	621
Rio de Janeiro	Macabuzinho	MC	22°04′	41°43′	—
	Ponto de Pergunta	PO	21°44′	42°00′	61
	Leitão da Cunha	LC	22°04′	42°02′	425
	Usina Quissama	UQ	22°06′	41°29′	15
	Piller	PI	22°24′	42°21′	670
	Represa do Paraiso	RE	22°30′	42°55′	60
	Coroa Grande	CG	22°54′	43°52′05″	40
Minas Gerais	Lagoa	LG	19°53′	47°37′	—
	Zelândia	ZE	19°29′	47°33′	—
	Veríssimo	VE	19°41′	48°18′	—
	Melo Franco	MF	20°11′	44°07′	761
	Fazenda Escola	FE	19°53′	44°25′	745
	Ibirite	IB	20°01′	44°02′	1073
	Pedro Leopoldo	PL	19°37′	44°12′	698

In the operational version, the Eta Model has undergone some modifications. The new version of the model [Eta–Oregon State University (OSU)] has been operational at CPTEC since January 2000. This version has a more complex surface model than the "bucket," and was developed at OSU (Chen et al. 1997). In the modifications, the model's forecast period was extended by more than 12 h, generating forecasts of up to 72 h. With regard to this new version's convection parameterization, the mass flux convection scheme (Tiedtke 1989) was implemented in the regional model.

3. Methodology

a. ANN

The ANN is an attempt to imitate or reproduce the operation of the human brain. The brain is made up of neurons that interact in an intensely parallel manner, receiving and combining signals from various other neurons. The intensity of the signal that a neuron receives at its entry (dendrite) depends on the physical proximity of this entry to the neuron's exit (axon), which sends it the stimulus. This proximity determines the intensity of the connection (synapse) and is modified when the brain learns (Haykin 1998).

Analogously, the ANN is characterized by the coming together of a large quantity of processing units (neurons) interconnected by a large quantity of connections, each one with an associated weight. Preparing an ANN for a task involves submitting it to a learning process. The learning is achieved by adjusting the intensity of the connections between the processor units. An advantage of ANNs is their capacity to generalize, supplying rapid and meaningful responses, even when submitted to a situation not considered during training.

In this study, we used the feed-forward ANN. In this network the neurons from each layer are connected and propagated forward to all the neurons of the following layer. Figure 2 illustrates a feed-forward network with three layers: input, hidden (nonlinear), and output. In the mathematical notation, Yuval and Hsieh (2003) show that a matrix $\mathbf{X} = (x_{jk})$ is defined by $j = 1, \ldots, N$ and $k = 1, \ldots, L$, where N is the number of entry variables (predictands or data from the Eta Model) and L is the longitude of the entry series, respectively; h_i is referred to as the hidden layer of the model and it produces a weighted sum of its inputs (x_{jk}) with $\hat{w}_{ij}$ (elements $M \times N$ from the matrix of weights $\hat{\mathbf{W}}$); and $\hat{\mathbf{b}}$ is a vector column of $M \times 1$ elements. The vector column $\mathbf{F}$ with the elements f_k $(k = 1, \ldots, L)$ is the output series (predictor or rainfall), $\tilde{w}_i$ are the elements of a $1 \times M$ row vector $\tilde{\mathbf{W}}$ from the matrix of weights, and $\tilde{b}$ is a scale. The elements of vector $\hat{\mathbf{b}}$ and $\tilde{b}$ are called biases and they are additional entries. The function g is the activation of the hidden layer that in this study was the logistical function. The convergence of the neural network is linked to the best possible choice of the set of weights $\hat{\mathbf{W}}$.

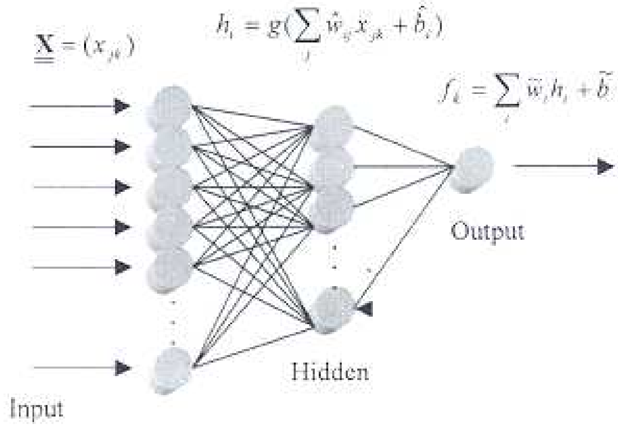

FIG. 2. The feed-forward neural network scheme with one hidden layer and the notation of connection between neurons for the present ANN.

The Stuttgart Neural Network Simulator, version 4.1 (Zell et al. 1995), was used for the ANN simulation for the nonlinear downscaling. The RPROP learning algorithm implemented in this simulator and the logistic activation function were used to train the ANN. RPROP performs a local adaptation of the weight updates according to the behavior of the error function and adds a weight decay term α to the error function expressed by

$$E = \sum_k [t_k - f_k(w_{ij})]^2 + 10^{-\alpha} \sum_{i,j} w_{ij}^2, \qquad (1)$$

where t_k is the desired output from the unit j, f_k is the actual output, and w_{ij} are the weights. The parameters of RPROP were the initial update value Δ_0, the maximum limit for the size of the step Δ_{max}, and the weight decay exponent α. Term α determines the output error reduction and the size of the weights needed to improve the generalization. The main advantage of RPROP is that it eliminates the undesirable effects of large partial derivatives in the calculation of the error reduction. Several tests indicated that the values of the parameters $\Delta_0 = 0.001$, $\Delta_{max} = 10.0$, and $\alpha = 6$ were more adequate. A complete formulation of the learning algorithm can be found in Riedmiller and Braun (1993) and Valverde Ramírez et al. (2005). The stopping criterion was determined by the behavior of the training process. The training was stopped when the error [Eq. (1)] reached a value less than 10^{-4}, or when the error function presented a constant value at each 100 consecutive

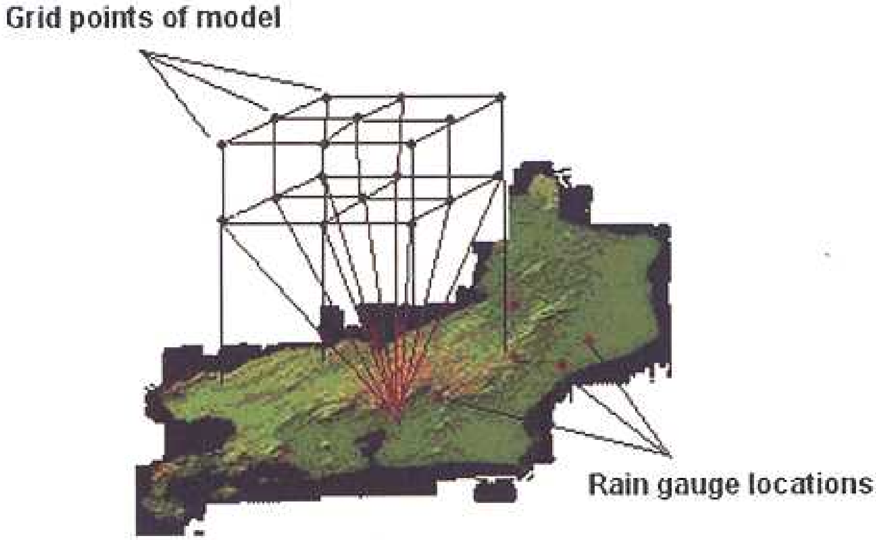

FIG. 3. Map of the state of Rio de Janeiro, illustrating the position of seven stations (rain gauges) analyzed in this study and the nine grid points of the model closest to the Represa do Paraíso (RE) station selected for statistical downscaling.

iterations, even if it had not reached the value 10^{-4}. The best results for the training were obtained with this criterion.

b. MLR

The linear downscaling used the MLR method (Neter et al. 1989) and was trained by the same data as the ANN. The MLR was programmed using the Matlab, version 5.1 (Misiti et al. 1997), toolbox.

c. Application of downscaling

To carry out statistical downscaling for each meteorological station, the predictors and predictands were supplied to the models (MLR and ANN). The predictors were taken from the 0000 UTC Eta Model initial conditions for the nine grid points closest to each station (Fig. 3) at four times, namely 0600, 1200, and 1800 UTC from the day before the forecast and 0000 UTC from the day of the forecast. The predictand was the daily rainfall (accumulated from the four synoptic times) at the corresponding station. The dataset was divided into two periods: austral summer (December–February) and austral winter (June–August). For each station a dataset was selected for training and another one for testing. The test set served to assess the performance of the ANN and the MLR after training.

d. Experiments

Table 2 illustrates the different experiments performed with the data series. One of the experiments used as a predictor the observed rainfall on the day before forecasting and the other experiment used the data series from the years 2000–02 (once during the year 2000 the Eta Model underwent changes to its code, which positively influenced the rainfall field). In the existing literature on the application of downscaling it is recommended that a homogenous data series be used to enable better learning and, consequently, better forecasts (Kumar et al. 1999).

TABLE 2. Dates of experiments.

	Summer period			Winter period		
Sets	Training	Testing	Predictors	Training	Testing	Predictors
ANN1	1997–98, 1998–99, 1999–2000, 2000–01	Dec 2001, Jan 2002, Feb 2002	Output model	1998, 1999, 2000, 2001	Jun 2002, Jul 2002, Aug 2002	Output model
ANNP	Idem ANN1	Idem ANN1	Output model and obs rainfall	—	—	—
ANNN	1999–2000, 2000–01	Feb 2002	Output model	2000, 2001	Aug 2002	Output model

e. Selection of predictor sets

The predictors commonly used for rainfall forecasting are geopotential height (Zorita and von Storch 1999), sea level pressure (Cavazos 1997), geostrophic vorticity (Wilby and Wigley 1997), humidity and vertical velocity (Kuligowski and Barros 1998), and wind speed (Murphy 1999). However, as this selection depends on the place and time of year, a synoptic climatological study of southeastern Brazil was included in this work. Consequently, the predictors were selected based on synoptic features and the rainfall distribution analysis.

To select the best predictors, there are also statistical techniques that link a set of predictors with the predictand through cross correlations, but these techniques do not necessarily include the theoretical or physical foundations. The best known techniques for this purposes are stepwise analysis and principal component analysis (Maier and Dandy 2000). However, the predictors selected by these techniques are not always the best because these methods only evaluate linear relationships between the predictor and the predictand. In fact, little is known about how to choose the best predictor for a neural network before the training process (Koizumi 1999). In this work, the selection of predictors was based on the identification of synoptic systems that were dominant during the period of study (see section 4a).

f. Quantitative verification

To determine the performance of the models (ANN, MLR, and Eta Model) in relation to the observed series, the statistical indices TS and bias score (BIAS; Antolik 2000) were used. The TS is defined as the ratio of the number of correctly predicted events (or forecast "hits"), and the sum of all outcomes incorrectly predicted. The BIAS is defined as the ratio of the total number of events forecast and the number of events actually observed; this variable gives the tendency to overforecast (BIAS > 1.0) or underforecast (BIAS < 1.0) a particular category. A BIAS of 1.0 indicates neither overforecasting nor underforecasting and that events are forecasted with the same frequency as they occur. The classification of rain and its thresholds used to calculate the BIAS and TS are presented in Table 3. Perfect forecasting is indicated by a TS = 1 and a BIAS = 1. It is important to note that all measurements of forecast performance (for the downscaling: from an area up to a point) include a "representativeness error" that is dependent of the model scale (resolution). Zepeda-Arce et al. (2000) indicate a reduction of the error when the model resolution is increased (i.e., high resolution).

TABLE 3. Rain classifications and thresholds.

Summer		Winter	
Rain intensity	Threshold (mm)	Rain intensity	Threshold (mm)
Slight	3–10	Slight	0.1–3
Moderate	15–30	Moderate	5–15
High	40–60	High	20–30
Intense	>60	Intense	>30

4. Results and discussion

a. Synoptic study

In this section a summary of the climatological synoptic study corresponding with the occurrence of rainfall over southeastern Brazil is presented. In the austral summer, the South Atlantic convergence zone (SACZ) and frontal systems (FSs) were associated with rainfall. It has been observed that most SACZ events are associated with upper-level cyclonic vortices (ULCVs) in the vicinity of northeast Brazil (SACZ–ULCV pattern; Valverde Ramírez et al. 2004). The interaction of the Bolivian high (BH) with all of the aforementioned meteorological systems also stood out.

Figure 4 shows a typical case of SACZ–ULCV and BH interaction on 10 January 1999. It is observed in the satellite image (Fig. 4a), and in the streamline (Fig. 4b) and vorticity fields (Fig. 4c), that the location of the ULCV inland (Bahia and Tocantins states), and the anticyclonic circulation located south of ULCV indicate the existence of the SACZ (Valverde Ramírez et al. 1999). In the vorticity field a band of intense anticyclonic vorticity is observed over the SACZ region. In this case the presence of the BH interacting with the SACZ–ULCV pattern of cloudiness over the southeast region is evident. Figure 5 illustrates another typical austral summer case involving an FS and the ULCV farther north, and the interaction of these systems enhances the cloud over the states of Rio de Janeiro, Minas Gerais, and northeastern Brazil.

In the austral winter period the rains decrease considerably, the tropospheric circulation is more zonal at high levels and the convective activity in the Tropics decreases considerably. The prevailing weather systems over the southeastern region were the FSs (Fig. 6), the midlatitude ULCVs, and the troughs in high and middle levels originating from the subtropical latitudes. During this season, FSs displaced inland do not have

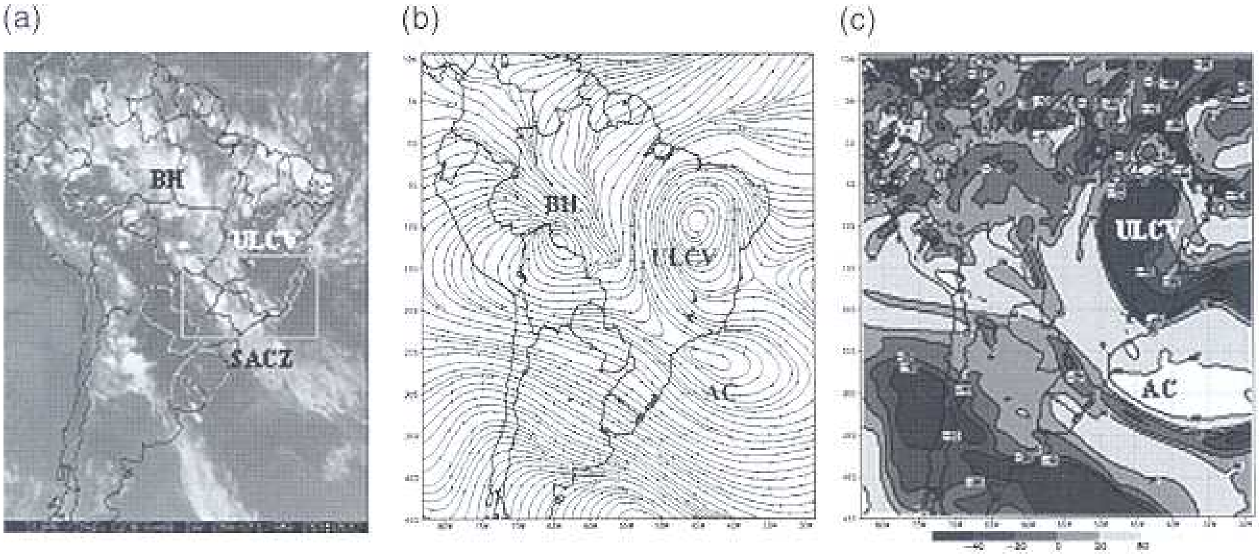

FIG. 4. (a) *GOES-8* image for 0000 UTC 10 Jan 1999, (b) streamlines at the 200-hPa level, and (c) the vorticity at 250 hPa. The dark area (light) indicates values less (greater) than $-3 \times 10^{-5}\ s^{-1}$ ($3 \times 10^{-5}\ s^{-1}$).

feedback from the tropical convection associated with the BH or the ULCV from the northeast. On the other hand, as the flow pattern is more zonal, its role in terms of convective activity is less significant. During this period some cases of cyclogenesis were also observed to be interacting with the FSs over the southeast region. Also, the presence of the subtropical jet operating in conjunction with these systems supported the instability in the southeast region. After identifying the synoptic systems associated with rainfall, and based on related observational studies (Kousky and Gan 1981; Oliveira 1986; Kodama 1992; Valverde Ramírez et al. 1999; Lourenço 1996), the predictors derived from the Eta Model were selected for statistical downscaling (Table 4).

b. *Qualitative forecast analysis*

In this section analyses of the forecasts from the different models (ANN, MLR, and Eta Model) and the observed rainfall for some stations from the regions of study are presented. Although various ANN experiments were carried out, only the best performances are presented.

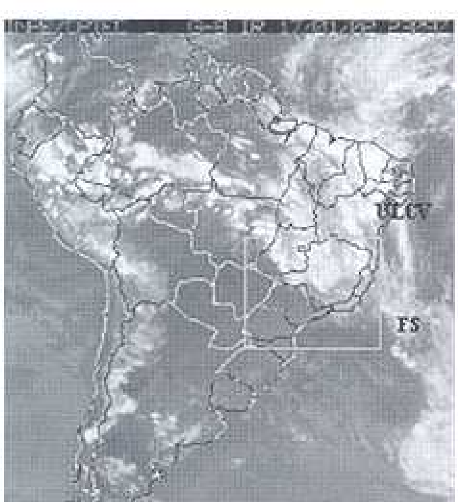

FIG. 5. *GOES-8* image for 2309 UTC 17 Jan 2002.

FIG. 6. *GOES-8* IR channel image for 0300 UTC 30 Aug 2002.

TABLE 4. Predictors used for statistical downscaling during the summer and winter periods.

Predictors	
Austral summer	Austral winter
Specific humidity (700 hPa)	Relative vorticity (500 and 250 hPa)
Moisture flux divergence (850 and 500 hPa)	Air temperature (850 and 500 hPa)
Relative vorticity (250 hPa)	Meridional and zonal wind components (850 hPa)
Air temperature (850 hPa)	Sea level pressure
Potential temperature (850 hPa)	Moisture flux divergence (850 and 500 hPa)
Precipitable water	
Vertical component of the wind (850 hPa)	

1) AUSTRAL SUMMER PERIOD

(i) *São Paulo region*

Figure 7a shows the observed rainfall at IAG and the corresponding rainfall predicted by the different models for January 2002. It is observed that the MLR forecast overestimated rainfall, showing a tendency to generate rain on days when it did not occur (e.g., days 1, 3, 16, 28, 29, and 31). Eta Model forecasts underestimated rainfall, although it captured most of the rainy days. ANN1 unrealistically estimated rain on day 31 and it had difficulty in capturing some periods of rain (days 8, 18, 24, and 27). The ANNP was better at reproducing the daily rainfall than ANN1. ANNP predicted rainfall for days 8 and 27 and on day 31 the rain forecast overestimate was less than that of ANN1. In other periods (days 12, 22, 27, and 30) the ANNP rain forecast was close to the observed values. In this month the rain events were produced by FSs.

Figure 7b shows the forecast results for KP for the month of February 2002. The MLR forecasts overestimated rainfall in comparison with the Eta and ANN

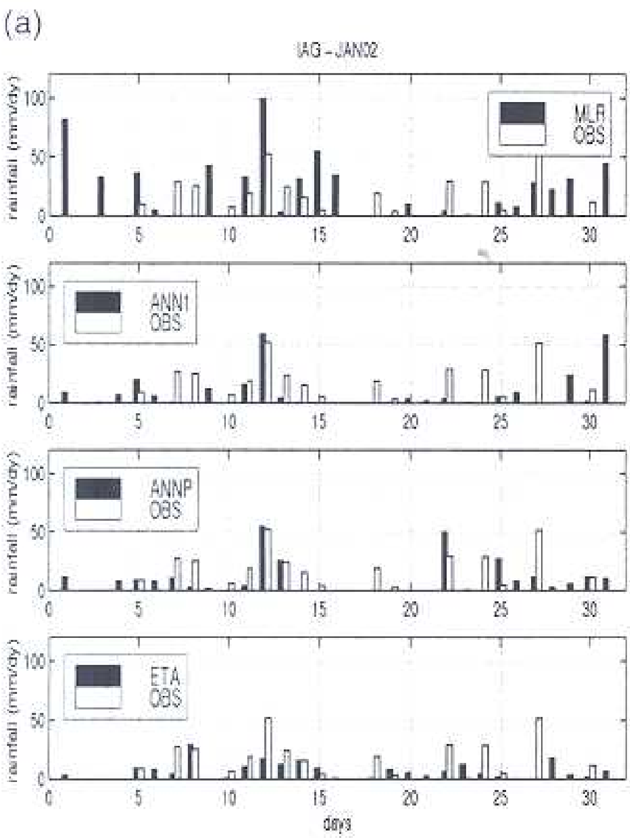

FIG. 7. Observed and forecast rainfall from the ANN1, ANNP, MLR, and Eta models for (a) Jan 2002 at IAG and (b) Feb 2002 at KP. The blank bars represent observed rainfall, and the filled ones the rainfall forecast by the models.

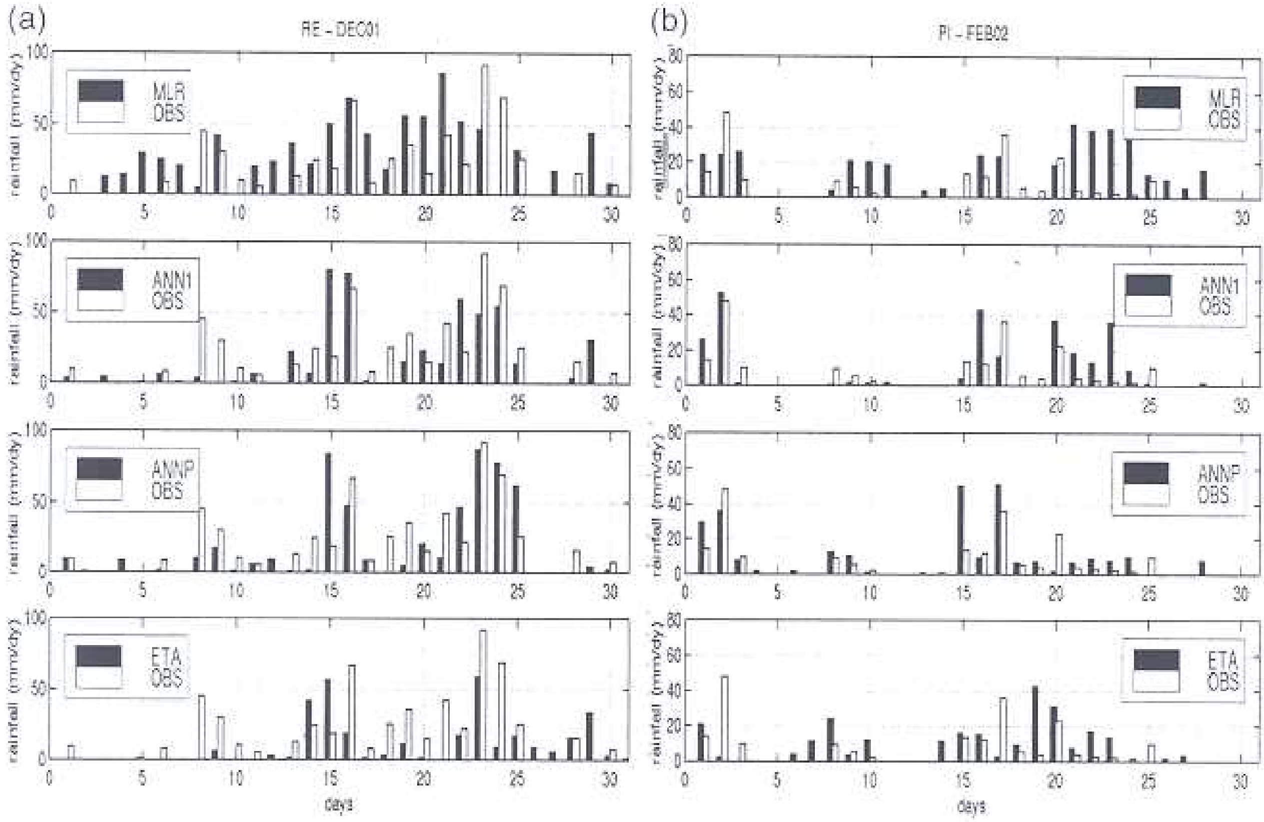

FIG. 8. Same as Fig. 7 but for (a) Dec 2001 at RE and (b) Feb 2002 at PI.

models, mostly on days 25–27. The Eta Model predicted almost all rainfall periods, with the exception of day 5. However, it considerably overestimated the rain rates compared with the observations during days 13–15 and 19–21. In addition, ANN1 did not capture all of the periods of rainfall, specifically days 5 and 6, and it did not considerably overestimate the values for days 19–21 (like Eta) and 25–28 (like MLR). On the other hand, ANN1 had a better rainfall forecast performance on day 8. For this location, experiment ANNN presented improvements compared with ANN1. ANNN did not forecast the absence of rainfall on days 12, 15, and 28, as was estimated by ANN1 and other models, and it reduced the amount of rain forecast on days 1 and 27, where, in reality, no rain was measured. In this month there were two SACZ events (days 4–8 and 16–24) that affected the stations for short periods. Specifically, the second event affected KP such that moderate rains rates were observed for 4 days (20–23).

(ii) Rio de Janeiro region

Figure 8a shows rainfall observations for an austral summer period (December 2001) versus ANN1, ANNP, and Eta Model forecasts at RE. It is observed that ANN1 captured most of rain periods with values closer to those observed when compared with the Eta Model forecast, except for the period from days 8 to 10. An exception occurred on day 15, when there was a notable overestimation of rainfall. ANNP had better performance than ANN1; on days 1 and 9, and for the period from days 22 to 25, the forecast was very close to the observations. Compared with the ANNP forecasts the Eta Model underestimated the rain rates for days 16–20 and 23–24. The MLR generated unrealistic rain events in the first week of the month. The rains during this month were associated with two SACZ events (days 16–21 and 23–28).

Figure 8b illustrates the forecast at PI during February 2002; it is observed that ANN1 depicted most of the rain episodes despite having considerably overestimated the rainfall on day 23. ANNP improved the rain forecast for day 3 and days 8–10 and 21–24. However, on day 15 ANNP considerably overestimated the observed rainfall. The MLR considerably overestimated the rainfall for days 21–24. The Eta Model also forecasted the periods of rain, but underestimated the extreme peaks on days 2 and 17, and overestimated the rain on day 19. In this month there were two SACZ

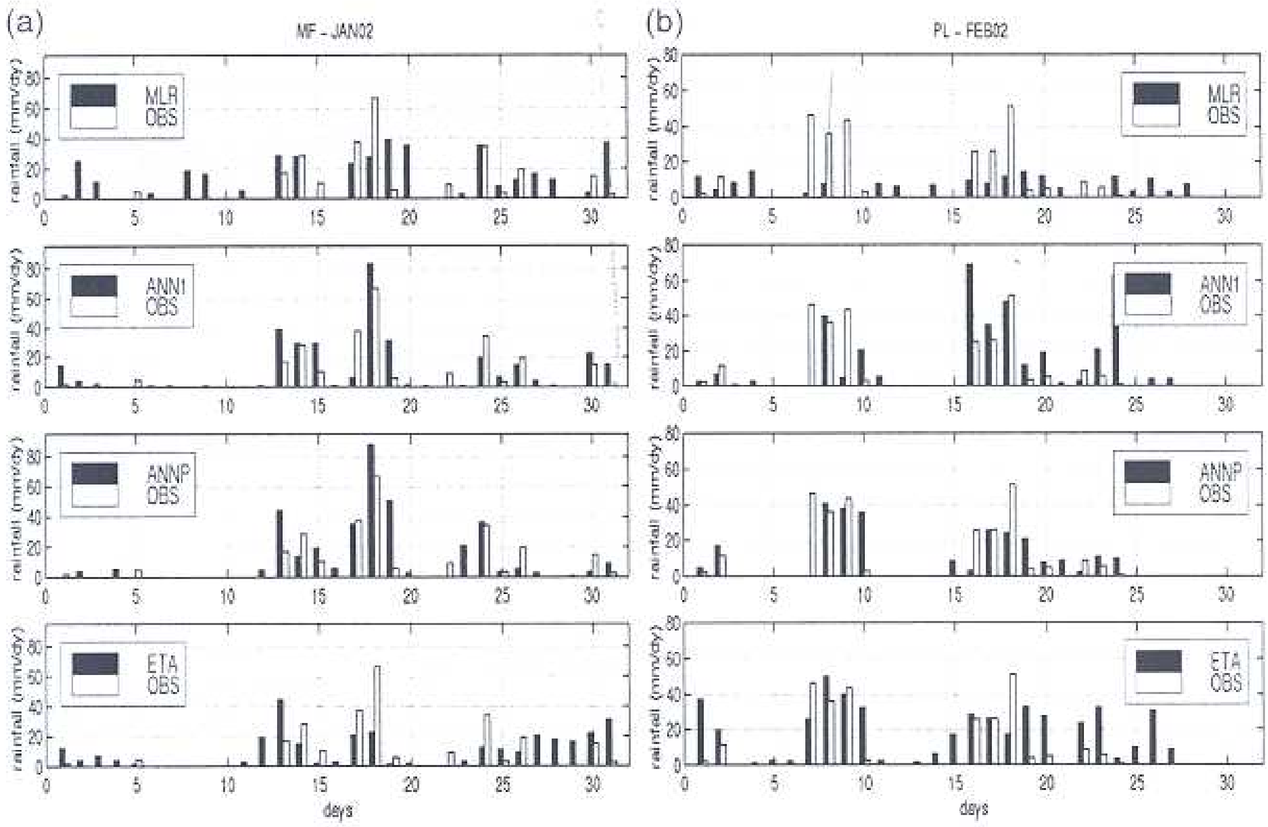

FIG. 9. Same as Fig. 7 but for (a) Jan 2002 at MF and (b) Feb 2002 at PL.

events (days 4–7 and 16–24), and moderate rainfall rates were observed at station PI during the second event. The first SACZ event was located over the São Paulo region.

(iii) Minas Gerais region

In this region, represented by MF (January 2002), it was observed that ANN1 predicted the heavy rain on day 18 (Fig. 9a). In the ANNP forecasts similar behavior is observed; however, during days 17 and 24 the rainfall values were closer to those observed. The Eta Model also forecast the periods of rain; however, there was a greater tendency to generate nonexistent rain (in the first and last weeks) and to underestimate the high rainfall (day 18). The MLR results showed skill in capturing periods of rain, but the generation of nonexistent rain was observed, specifically in the first days and in the last week. In this month there were no SACZ events; however, the periods of continuous rain were associated with FSs (Fig. 5; section 4a) over that region.

In February 2002 it is observed that the MLR forecasts for PL (see Fig. 9b) considerably underestimated periods of moderate rain (e.g., on days 7–9). In this case, ANN1 had difficulty in forecasting moderate rain in some periods (days 7 and 9), while in other periods (days 16 and 24) it produced a large overestimation. However, for the remaining rainy days its forecasts were closer to the observed value. Forecasts by ANNP were an improvement; it did not produce the extreme overestimates (days 16 and 24). On days 8–9 and 20–23 the predicted rainfall was close to the real values. On the other hand, the Eta Model forecasts captured the periods of rain, as well as predicting some other periods of rain that did not occur (days 25–27). Moreover, it overestimated rainfall compared with other models during the periods of days 1–2, 19–20, and 22–23. In this month, two SACZ events occurred, but only the second one (days 16–24) affected PL (Fig. 9b).

2) AUSTRAL WINTER PERIOD

This section describes the rainfall distribution of the three stations in the studied region. This period is characterized by few rain events, with those being of short duration (2–3 days).

Figure 10 shows the PP rainfall distribution in the São Paulo region during August 2002. At PP rainfall was sparse, with just one significant event on day 28 that was captured by the three models. In this case, the

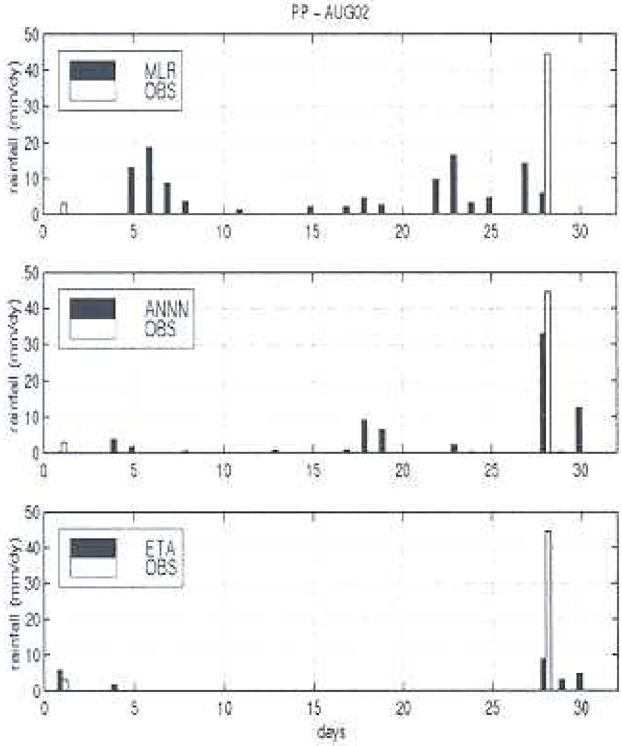

FIG. 10. Same as Fig. 7 but for for Aug 2002 at (a) RP and (b) PP.

ANNN forecast was closest to the observed value and the Eta Model underestimated it. However, the rain estimates generated by MLR did not occur in reality. In this period, the rainfall was associated with the passage of an FS at the end of the month, and an ULCV originating in midlatitudes slightly affected PP on the first day of the month. Figure 11a illustrates the rainfall distribution for the Usina Quissama (UQ) station (in Rio de Janeiro) during July 2002. In this case, ANN1 forecasts were near the observed rainfall values only on days 2 and 3. Also, the Eta Model overestimated rainfall on days 11 and 22, and the MLR underestimated it on days 3 and 11. In this month, the isolated rainfall events were produced by the instability associated with moving FSs. For the Minas Gerais region (Fig. 11b) the forecasts were compared with the observations from Lagoa station (LG) during August 2002. At this station the observed rainfall was sparse, characterized by just 1 day of rain on day 31, due to an FS (Fig. 6). The ANN1 forecasts were accurate, as it predicted the only day of rain with a forecast amount close to the observed value. On the other hand, the Eta Model generated unrealistic rain (days 1–2), and captured the peak in the rain but overestimated it. The forecasts by MLR considerably underestimated the rain at the end of the month, and generated rain in intermittent periods.

c. Statistical analysis of the forecast

To quantify the performance of the forecasts by the models, the BIAS and TS indices were calculated. The BIAS and TS were analyzed jointly. When analyzed jointly, it is easy to check when the underestimates or overestimates are really associated with the days when it actually rained and are not affected by periods of nonexistent rain that the model may have generated.

1) AUSTRAL SUMMER PERIOD

(i) São Paulo region

To facilitate the analysis of the results and to get an overview of the behavior of each model, the average of the TS (Fig. 12) and BIAS (Fig. 13) for six stations in the São Paulo region were calculated for each month of the austral summer. Figure 12a shows that in December 2001 the average TS for the six stations indicate that the Eta Model performed the best for all the thresholds. During this period only ANN1 forecasts for KP and GR were better than the Eta Model. The performance of ANN1 was closest to that of the Eta Model for the 30-mm threshold. It is observed that largest TSs occurred for the thresholds of 3 mm (slight rain) and for those of 30 mm (moderate rain). The MLR result was close to that of ANN1 and ANNP for the ≤15 mm threshold, while for the ≥20 mm threshold the TS was low. The BIAS (Fig. 13a) shows that the MLR overestimated, by up to four times, the moderate and high rainfall thresholds; however, as the TSs (Fig. 12a) were low, many of the rainfall events forecast by the MLR happened on days in which it did not rain. On the other hand, the Eta Model produced small overestimates for slight rainfall events, and for high rainfall (40- and 50-mm thresholds) the BIAS reached a value of 2. However, these forecast rainfalls were not observed, as the TSs were equal to zero. ANN1 and ANNP underestimated slight rainfall events, which justified low TSs, and ANNP overestimated the thresholds of 30, 40, and 50 mm just as the Eta Model did.

For the month of January 2002 (Fig. 12b), the TSs of the Eta Model, ANN1, and ANNP did not show significant differences for the 3-, 10-, 15-, and 20-mm thresholds. For the moderate (30 mm), high (40–50 mm), and intense (≥to 60 mm) rainfall, ANN1 and ANNP showed TSs above the Eta Model and MLR. It was also observed that for high values of rainfall, forecasts by ANNP were better than by ANN1. The BIAS (Fig. 13b) also showed that MLR overestimated rainfall more than the other models; however, the difference was not as great in December. The Eta Model underestimated the high and intense rainfalls (40- and 60-mm

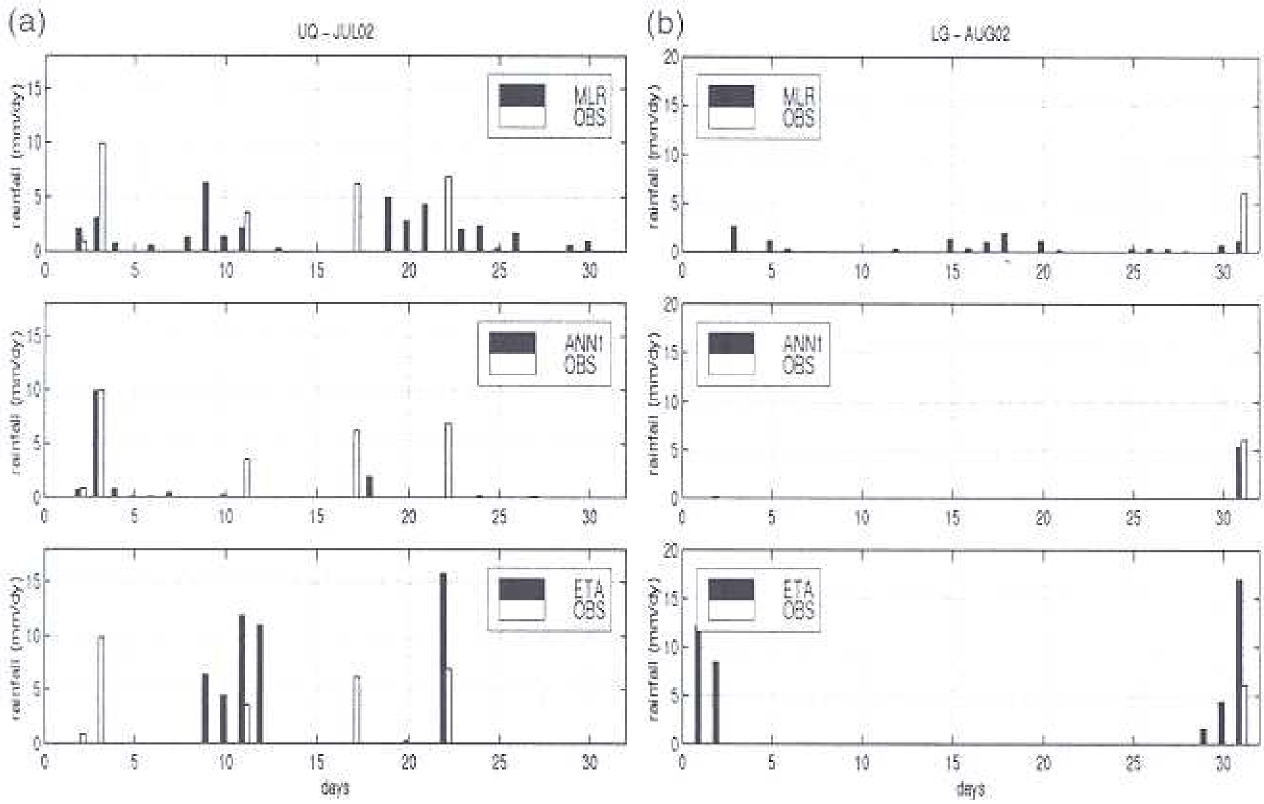

FIG. 11. Same as Fig. 7 but for (a) Jul 2002 at UQ and (b) Aug 2002 at LG.

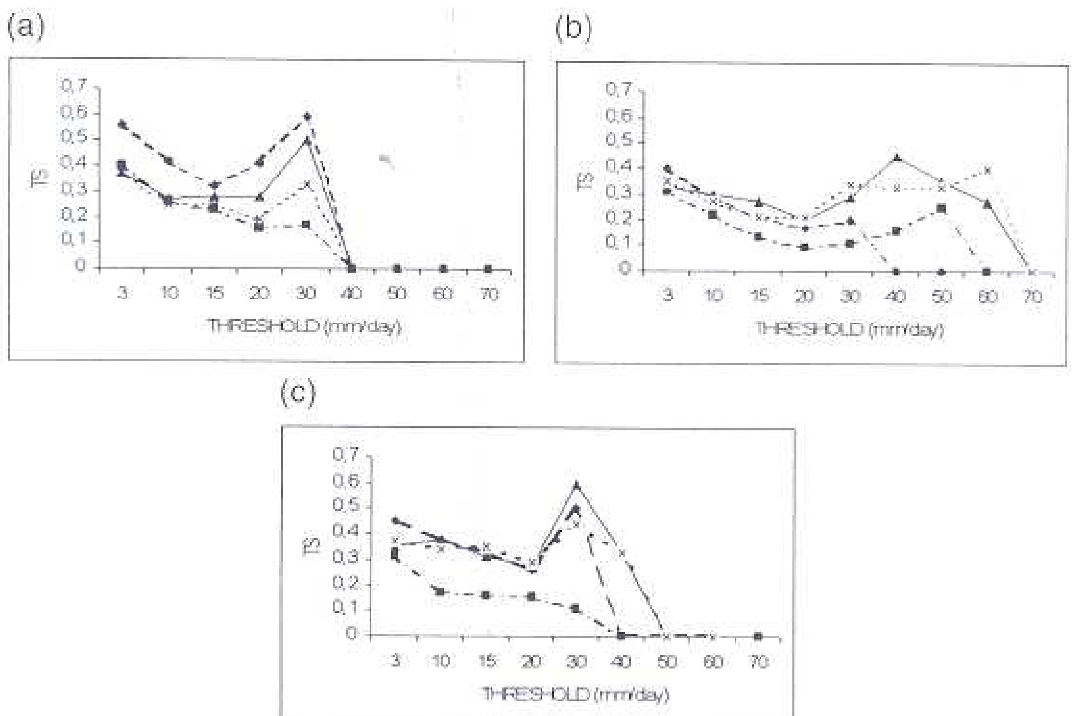

FIG. 12. Average TSs for the stations in the São Paulo región for the austral summer months (a) Dec 2001, (b) Jan 2002, and (c) Feb 2002 for ANN1 (filled triangles), Eta Model (filled diamonds), MLR (filled squares), and ANNP (Xs).

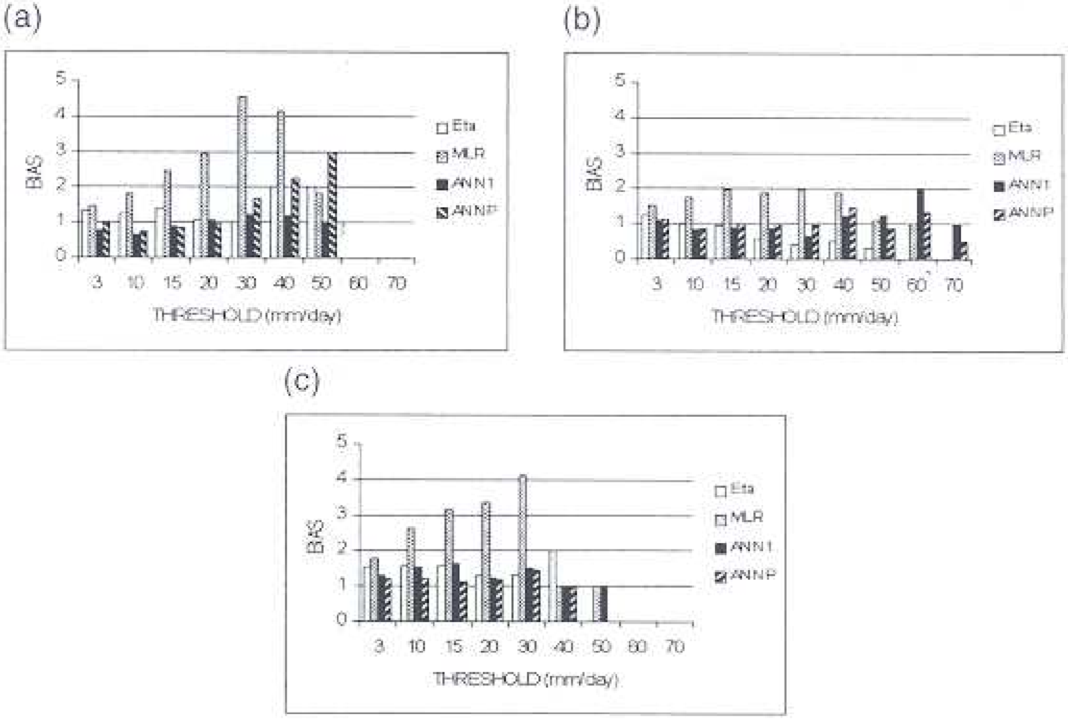

FIG. 13. Average BIAS from the stations in the São Paulo region for the months of (a) Dec 2001, (b) Jan 2002, and (c) Feb 2002.

thresholds). On the other hand, ANN1 and ANNP slightly overestimated high rainfall, with ANN1's overestimate being greater. In the qualitative analysis (section 4b), the observed and forecast rainfall amounts for IAG (Fig. 7a) clearly show that ANNP was much more accurate in forecasting moderate (30 mm) and high (40–50 mm) rainfall than was the Eta Model.

For the month of February 2002 (Fig. 12c), it was observed that up to the threshold ≤20 mm, the Eta Model, ANN1, and ANNP did not show significant differences among their TSs. On the other hand, for the 30-mm rainfall thresholds, ANN1 showed a higher TS, and for the 40-mm threshold the ANN1 and ANNP had the same performance. The Eta Model did not forecast rainfall ≥40 mm. In the qualitative analysis of KP station (Fig. 7b) it was shown that the forecasts by ANN1 and ANNP were more accurate, with a TS of 0.8 for moderate rainfall (≥15 mm; not shown). The MLR model showed itself to be inferior to the other models. On the other hand, the Eta Model overestimated slight, moderate, and high rainfall more than did ANN1 and ANNP (Fig. 13c). Specifically, for the threshold of 40 mm, Eta Model predicted these amounts on days when no rain was measured, as the TS was 0.

(ii) Rio de Janeiro region

In Figs. 14 and 15 the average TS and BIAS are shown for the Rio de Janeiro region in the three austral summer months. In December (Fig. 14a) it was observed that for moderate and slight rainfall, the TSs were similar for the Eta Model, ANN1, and ANNP. For high and intense rainfall thresholds, ANN1 and, above all, ANNP performed better than did the Eta Model. The MLR model again had a TS inferior to the other models. The BIAS (Fig. 15a) showed that the MLR overestimated rainfall for thresholds up to ≤50 mm more than did the other models. Conversely, MLR underestimated rainfall > 50 mm, while ANNP overestimated it (70-mm threshold).

In January 2001 (Fig. 14b) it was observed that the TS did not exceed 0.4. In this case, both ANN1 and ANNP showed slightly better performance than did the Eta Model for the 3-, 10-, and 20-mm thresholds. For moderate rainfall (30 mm) the Eta Model showed a slight superiority compared with the forecasts from ANN1, the BIAS (Fig. 15b) from the MLR showed large overestimates in the forecast, with ANN1 and ANNP also showing this behavior for the 20- and 30-mm thresholds, respectively. The behavior of the TS from February 2002 (Fig. 14c) showed that, for thresholds up to 30 mm, the forecasting by ANNP was slightly superior compared with the other models. At PI (Fig. 8b; see also section 4b) it was seen that the values for the slight (≥3 mm) and moderate (≥30 mm) rainfall events were better forecast by ANNP. The Eta Model overestimated these thresholds, but did capture some

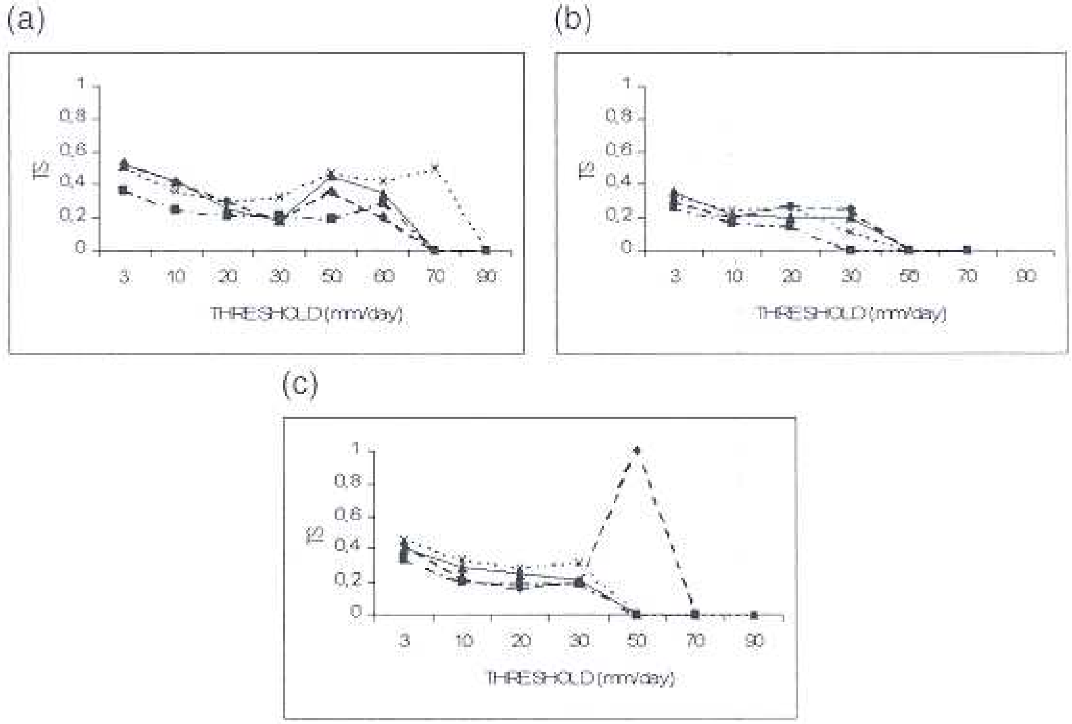

FIG. 14. Same as Fig. 12 but for the stations in the Rio de Janeiro region.

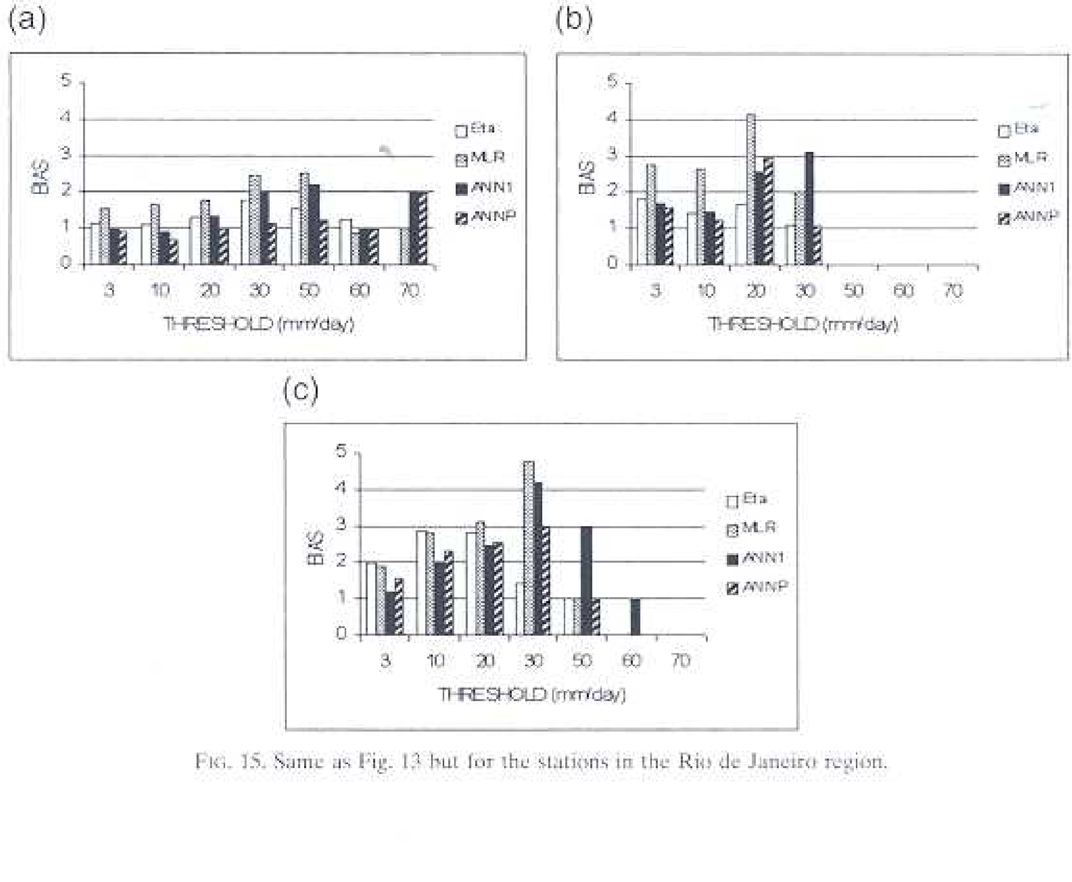

FIG. 15. Same as Fig. 13 but for the stations in the Rio de Janeiro region.

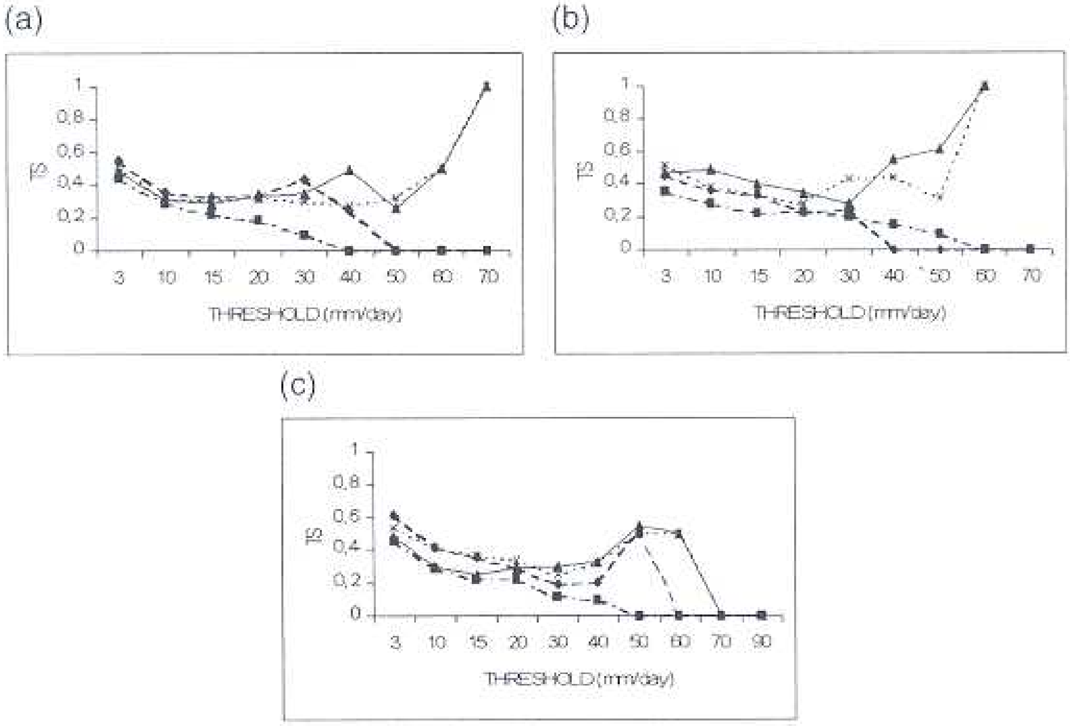

FIG. 16. Same as Fig. 12 but for the stations in the Minas Gerais region.

events. On the other hand, for high rainfall events (≥50 mm) the Eta Model had a TS = 1. However, this high rainfall event was only measured at Leitão da Cunha (LC; not shown). For this month the overestimates were also high for rainfall of up to 20 mm for both the MLR and the Eta Model (Fig. 15c). For rainfall amounts between 30 and 50 mm, MLR and ANN1 overestimated by a significant margin; however, as the TSs were 0, rain was forecast on the wrong days. For the 50-mm threshold Eta Model, the results show a BIAS = 1 and TS = 1 (Fig. 14c), indicating perfect forecasts for this threshold.

(iii) Minas Gerais region

For December 2001 (Fig. 16a) the Eta Model produced slightly better results for the slight and moderate rainfall thresholds. For high and intense rainfall both ANN1 and ANNP performed better. Specifically for the 70-mm threshold, the TS was equal to 1 for the forecasts by ANN1 and ANNP. The BIAS (Fig. 17a) for this threshold and for these models was also 1, indicating a perfect forecast. The BIAS for MLR for this same threshold equaled 1, corresponding to a forecast of the same value of rainfall, but on a day where it was not observed. Additionally, the Eta Model and MLR overestimated rainfall more than did ANN1 and ANNP for the thresholds of up to 20 mm.

For the month of January 2002 (Fig. 16b) it was observed that ANN1 and ANNP performed better at all of the thresholds, especially for moderate and high rainfall, and the TS reached the value of 1 for the 60-mm threshold. The BIAS was also equal to 1, as is shown in Fig. 17b. This result was associated with MF, where rainfall exceeded 60 mm. It should be noted that rainfall from day 18 exceeded 60 mm (Fig. 9a) and was forecast with more precision by models ANN1 and ANNP. The MLR overestimated slight and moderate rainfall on days in which it did not happen; for this reason the TS for MLR was the lowest of all the models.

The behavior of the TS (Fig. 16c) and the BIAS (Fig. 17c) in February 2002 shows that ANNP and Eta Model had similar TSs for threshold values from 3- to 15-mm. For ≥20 mm, ANN1 showed slight superiority in relation to the other models. The Eta Model did not forecast above the 70-mm threshold. The BIAS (Fig. 17c) indicates that the Eta Model overestimated rainfall values more than the other models for the 3–30-mm thresholds and, for the 40-mm threshold, ANNP overestimated much more.

2) AUSTRAL WINTER PERIOD

(i) São Paulo region

In the month of June 2002 there were no rainfall measurements at the stations. In July 2002 there was

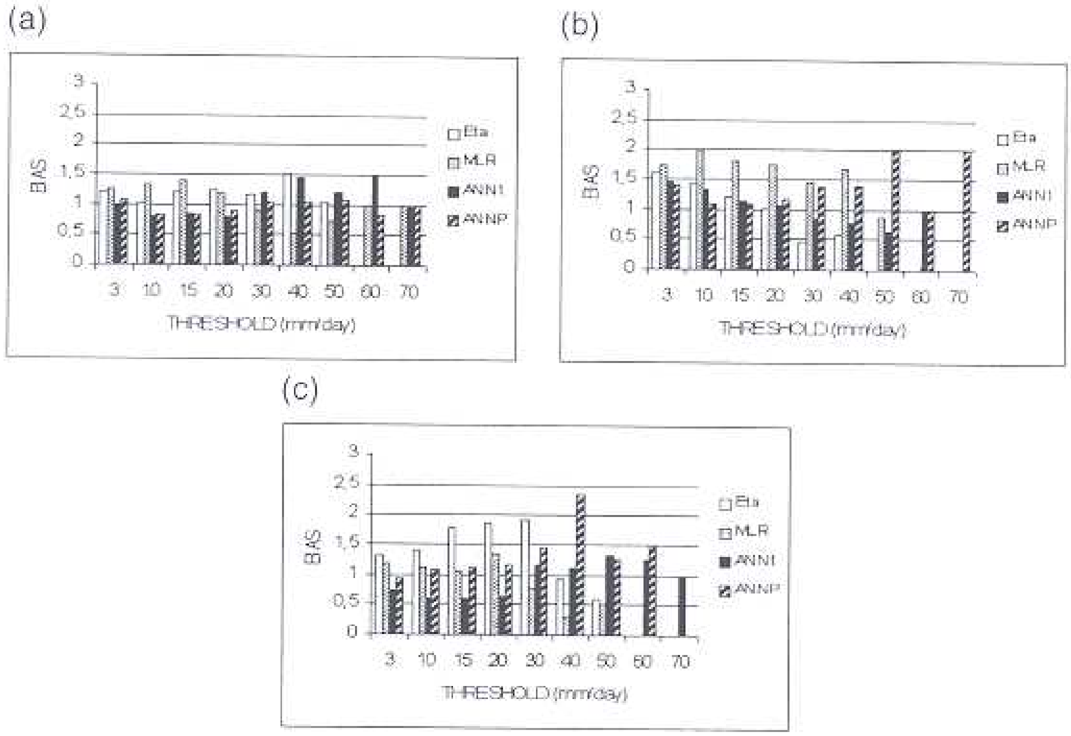

FIG. 17. Same as Fig. 12 but for the stations in the Minas Gerais region.

rainfall at the six stations; however, the average TS (Fig. 18a) shows that the Eta Model forecast was superior for all stations and for almost all of the thresholds, reaching TS = 1 for high rainfall events [Bauru (BR), IAG, and PP]. ANN1 is only close to the accuracy of the Eta Model for the 12-mm threshold. However, BIAS (Fig. 18b) shows that the Eta Model overestimated almost all of the thresholds (except for 20 mm) and ANN1 underestimated the thresholds for slight and moderate rainfall.

The average TS (Fig. 18c) for the month of August 2002 shows that the performance of ANN1 was better for the thresholds > 10 mm, and in the case of the 40-mm threshold the BIAS was equal to 1. The BIAS (Fig. 18d) confirms the perfect forecast by ANN1 with a score of 1 for the 40-mm threshold. MLR showed many predictions of nonexistent rain as the TS values were very low.

(ii) Rio de Janeiro region

Figure 19a shows the TSs for the month of June. The average Eta Model TSs are greater that those of ANN1 and MLR for almost all of the thresholds, because rainfall at four stations [UQ, PI, RE, and CG)] were better predicted by the Eta Model. Only for the 12-mm threshold did the ANN1 perform better. The BIAS (Fig. 20a) shows overestimates for ANN1, and specifically for the 25-mm threshold where the TS = 0, indicating forecasts of nonexistent rain. In July (Fig. 19b) it was observed that ANN1 produced superior results compared with the Eta Model, specifically for the 5-, 8-, and 10-mm thresholds, where the TS value was more significant. The BIAS (Fig. 20b) shows that the MLR produced extreme overestimates, especially for the 8–20-mm thresholds. In August 2002 (Fig. 19c) only station CG did not observed rain; however, the Eta and MLR models forecast excessive rain at this site, which is shown in the BIAS average (Fig. 20c). In the average TS, ANN1 performed best for the thresholds from 5 to 8 mm. The BIAS for ANN1 and Eta Model (for thresholds > 8 mm) was due to the prediction of nonexistent rain, as the TS was 0.

(iii) Minas Gerais region

In June 2002 there was no measured rainfall at the seven Minas Gerais stations. The ANN1 and Eta models also forecast no rain. However, the BIAS for MLR was 7 (not shown). For July 2002 it was not possible to train the models because of a lack of data from the Eta Model. Forecasts for August 2002 (Fig. 21a) show that ANN1 performed better than Eta Model for thresholds of 1, 3, and 5 mm. The Eta Model was the best model for the thresholds of 8 and 10 mm. In the qualitative analysis, station LG (Fig. 11b) was assessed, which reg-

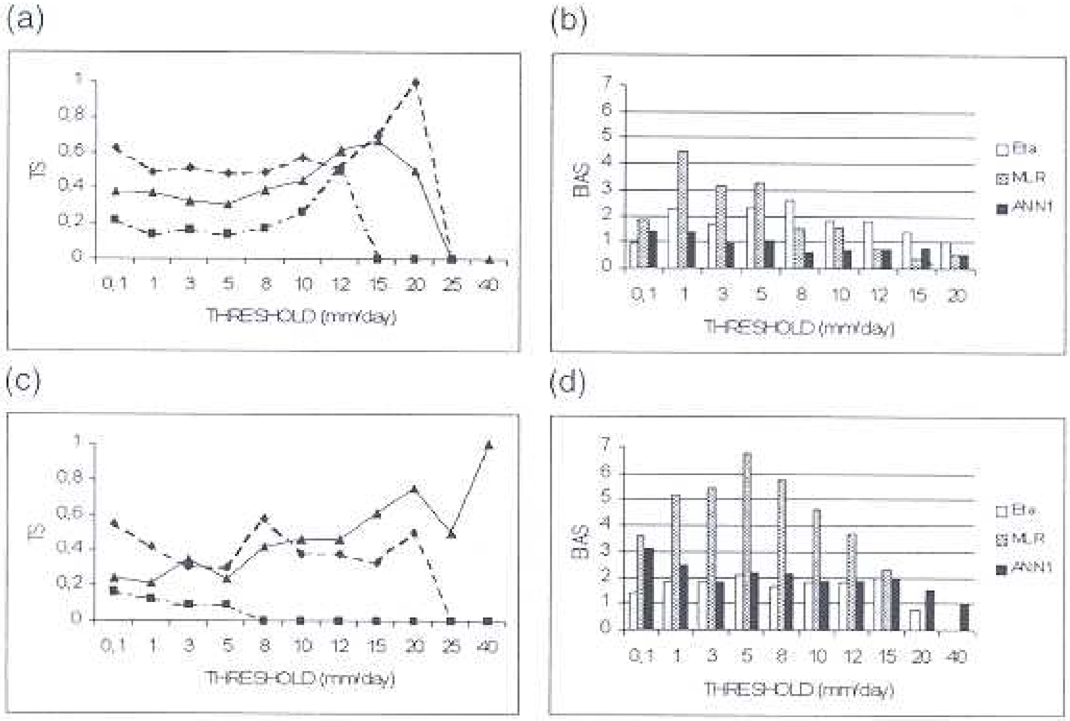

FIG. 18. Average TSs and biases for the São Paulo region stations for (a) Jul and (b) Aug 2002 for ANN1 (filled triangles), Eta Model (filled diamonds), and MLR (filled squares).

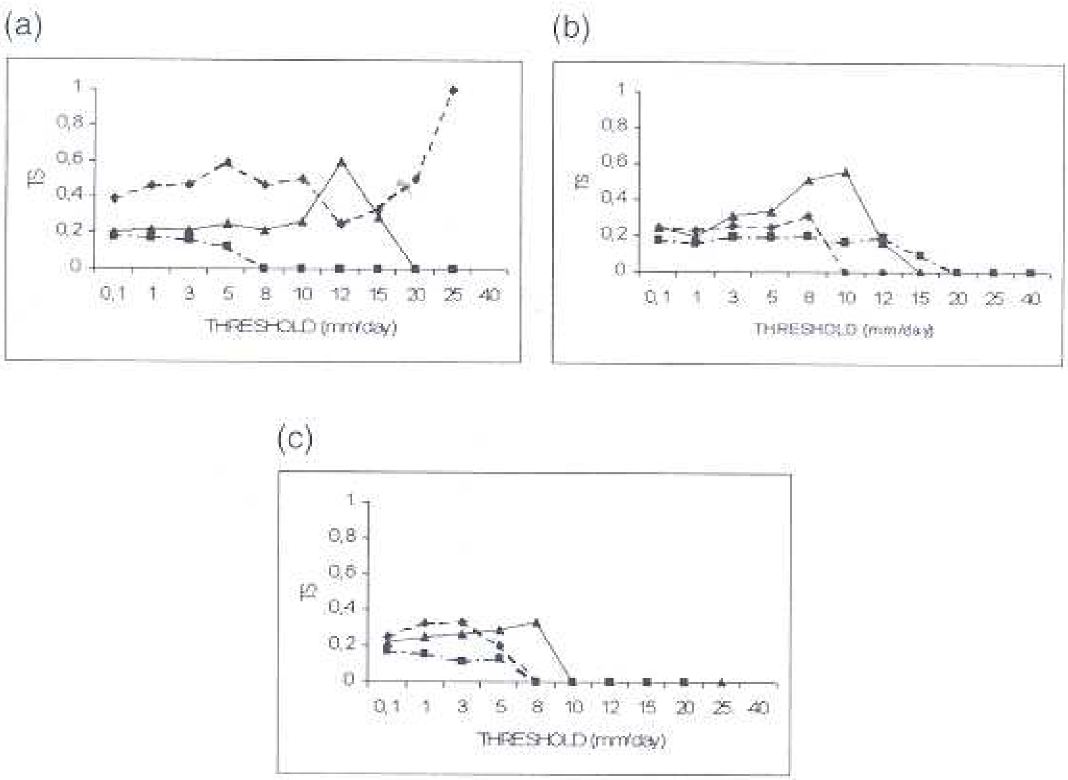

FIG. 19. Same as Fig. 14 but for (a) Jun 2002, (b) Jul 2002, and (c) Aug 2002.

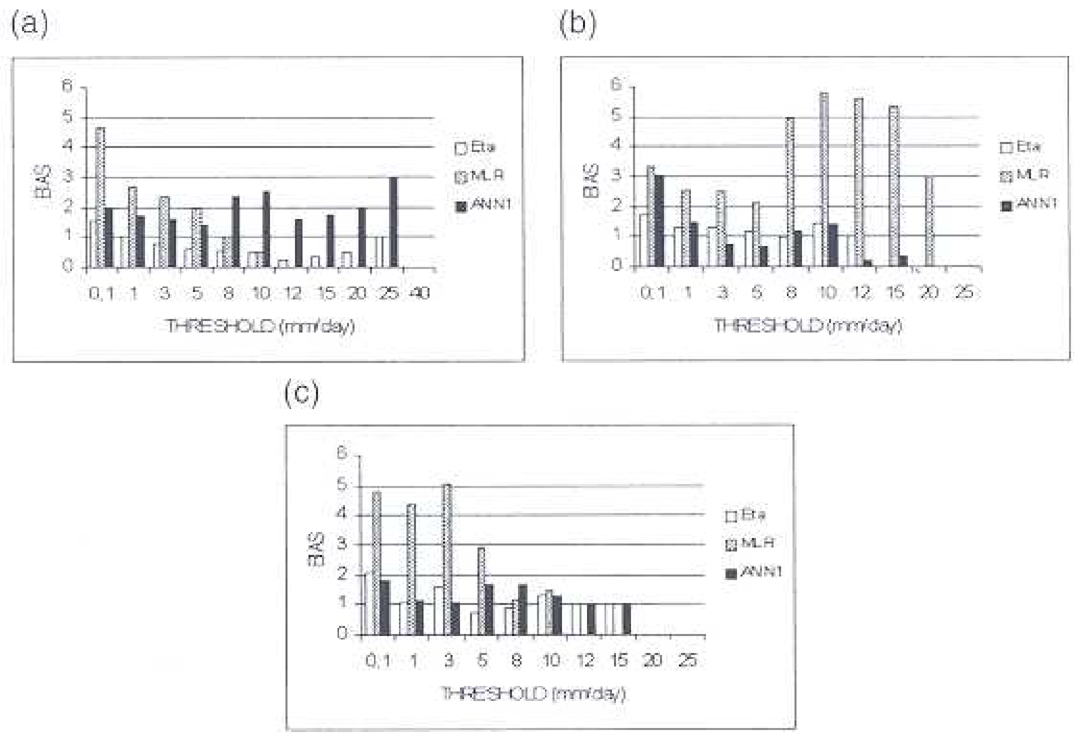

FIG. 20. Same as Fig. 15 but for (a) Jun 2002, (b) Jul 2002, and (c) Aug 2002.

istered just 1 day of rainfall (5.3 mm), and ANN1 captured this with great precision. The bias (Fig. 21b) generally showed that MLR overestimated rainfall significantly more than did Eta Model.

d. Discussion of the results

The statistical indices (TS and BIAS) show a significant difference in the performance of the different models used for statistical downscaling. Forecasts from the Eta Model were also evaluated because the objective of this study is to adjust these forecasts for specific points (meteorological stations) through statistical downscaling.

The MLR TS and BIAS show poor performance in the forecasting of rainfall. Extremely low TSs show the difficulty the linear model has in adjusting the Eta Model predictors to the values of the observed rainfall. However, the high overestimates indicated by the BIAS reveal that, in most cases, much of the rainfall forecast by the model did not actually happen, which explains the low TS values. In some cases MLR did forecast rainfall on the days it occurred at the stations. The use of a linear model does not allow for suitable adjustments between the rainfall and the associated dynamic variables.

The performance of the ANN shows superior behavior compared with MLR and shows encouraging results when compared with the Eta Model rainfall forecasts. The ANN was not uniformly superior for all of the stations and the periods studied; for each region and station it behaved differently. In the São Paulo region, the ANN had difficulty improving upon the forecasts by Eta Model, especially in December, as the TSs were very close to those for Eta Model and in some cases lower. In January and February, the performance improved, achieving a TS = 1 and a BIAS = 1 for moderate and high rainfall events (30–40-mm thresholds), indicating accurate forecasting.

In the Rio de Janeiro and Minas Gerais regions, it was observed that the performance of the ANN showed a similar improvement to the Eta Model as was observed in São Paulo. At most of the observation stations, ANN1 and ANNP presented a TS > 0.7 with a BIAS that did not present extreme over- or underestimates. Of the thresholds analyzed, it was also observed that moderate and high rainfall events show the highest TSs. In relation to intense rainfall, the ANNs also managed to capture the extreme values; however, it was noted that in some stations there were extreme overestimates.

For the austral winter period, it was observed that the ANN was better than the Eta Model at forecasting dry periods, especially in June. Only in July did the ANN not perform as well as the Eta Model. For the other

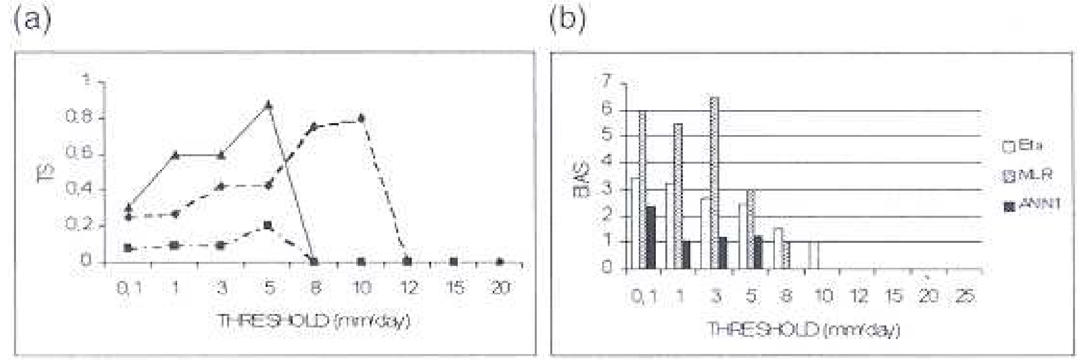

FIG. 21. Same as Fig. 18 but for the Minas Gerais region for Aug 2002.

stations in the states of Rio de Janeiro and Minas Gerais, the ANN performed better for most of the stations with a TS > 0.5.

Concerning the different temporal series (experiments), ANN1 and ANNP performed best. In some cases ANNN proved superior to the other models, showing that the modifications made to the parameterization improved the forecasts of the variables of the model. However, as there were few events to be trained and learned from (a short series of 2 yr), these results were not reproduced at all stations in the study. On the other hand, the ANN1 series is longer (five years; Table 2), therefore, this series included more rainfall events than the ANN can learn during training. However, changes in the model code meant that it was not homogeneous and therefore it was unstable. Inclusion of the variable rainfall from the previous day (ANNP) gave the network local information related to the event to be forecast in such a way that the forecasts were more specific and closer to the measured rainfall. Apparently, the inclusion of rain gave the network additional information (local persistence) that allowed it to discern more precisely the associated pattern. Generally, it was observed that at those stations in which ANN1 and ANNP had good rain forecast performance, the periods of rain were associated with well-defined SACZ events and FSs. This was more evident in the São Paulo and Rio de Janeiro regions. On the other hand, in Minas Gerais some stations did not perform well, despite the observed rain having been associated with synoptic-scale systems. This may be associated with local aspects such as topography, microclimate, and local convection, as these also influence the occurrence of rains but were not included as predictors in the ANN.

5. Concluding remarks

The comparison of point forecasts with those performed by the Eta Model (40 × 40 km) is justified, as the objective of this study is to adjust this forecast for specific points (meteorological stations) through statistical downscaling. The objective in using different temporal series to generate the prognostic tool was to find the best temporal series that represents the several rain patterns. Despite the limitation of having a relatively small series (5 yr) of Eta Model output, and having to use corresponding output every 6 h, it was observed that the ANN technique was effective at adjusting the rainfall forecasts to specific points. In general, the Eta Model and MLR forecasts become less accurate at higher thresholds; conversely, the forecast produced via the neural networks (ANN1 or ANNP) were more accurate in the case of heavier rain.

The results suggest that in the austral winter, rainfall is more predictable, because the synoptic forcing is stronger, and deep convective activity is less common. This would also explain why the forecasts by ANN1 were better in the austral winter than in the austral summer. It is important to stress that this technique is not intended as a substitute for the models (statistical or NWP) currently in use, but it may complement those currently used at CPTEC, providing more information as the basis for the issued forecast. Thus, the prognostic tools developed in this study are ready to be used and tested in operational weather forecasting centers, as they would make more specific forecasting possible for a certain locality. Currently, statistical downscaling is widely used in large operational centers around the world, using exclusively linear relations (MLR); this study is innovative in Brazil in having implemented a statistical downscaling methodology using a nonlinear technique known as ANNs.

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