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ESTIMATION OF RAINFALL BY NEURAL NETWORK OVER A NEOTROPICAL REGION

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ABSTRACT: Rainfall is the key element in regional water balance, and has direct influence over economic activity. Quantifying rainfall at spatial and temporal scales in regions where meteorological stations are scarce is important for agriculture, natural resource management and land-atmosphere interactions science. Thus, we evaluated neural network performance for rainfall estimates over Mato Grosso State located in the Brazilian Midwest region. A dataset of 12 meteorological stations was used to train the neural network, and then was run to perform estimates, which allowed comparing with TRMM satellite estimates. Rainfall estimates were performed by neural network as a function of latitude and longitude for model 1 (NN1), and latitude, longitude, and altitude for model 2 (NN2). In general, rainfall values were higher overestimated by NN1 in January (18.7%), and September (119.2%) than by NN2 in January (6.8%), and September (0%). While NN2 had rainfall pattern closer to TRMM both in January and in September, NN1 rainfall estimates captured a small amount of the rainfall pattern over Mato Grosso state. There was no higher difference between NN1 and NN2 rainfall estimates in January. On the other hand, rainfall estimates had better performance in NN2 than NN1 in September. Bad rainfall estimates using neural network in Mato Grosso state were due to (i) a short temporal dataset, (ii) few stations with poor spatial variability, (iii) few auxiliary variables to build neural network, which could better capture the rain phenomenon over Neotropical regions. The next step will be to analyze the rainfall and other climatic estimates performed by neural network for the whole year for several years on the Central-West Region of Brazil including other auxiliary variables besides latitude, longitude, and altitude.

KEYWORDS: spatio-temporal dynamics, satellite observations, artificial intelligence, precipitation.

ESTIMATIVA DE CHUVAS PELA REDE NEURAL SOBRE A REGIÃO NEOTROPICAL

RESUMO: A precipitação é o elemento chave no balanço hídrico regional, e tem influência direta sobre a atividade econômica. Quantificar precipitação em escalas espaciais e temporais em regiões onde as estações meteorológicas são escassas é importante para a agricultura, gestão de recursos naturais e terra-atmosfera interações ciência. Assim, avaliamos o desempenho da rede neural para estimativas de precipitação mais de Mato Grosso localizadas na região Centro-Oeste brasileira. Um conjunto de dados de 12 estações meteorológicas foi usado para treinar a rede neural, e em seguida foi executado para realizar estimativas, o que permitiu a comparação com as estimativas TRMM satélite. Estimativas de precipitação foram realizadas pela rede neural em função da latitude e longitude para o modelo 1 (NN1) e latitude, longitude e altitude para o modelo 2 (NN2). Em geral, os valores de precipitação foram mais superestimados em NN1 em janeiro (18,7%) e setembro (119.2%) do que por NN2 em janeiro (6,8%) e setembro (0%). Enquanto NN2 tinha padrão de chuvas mais perto de TRMM se em janeiro e, em setembro, as estimativas de precipitação NN1 capturou uma pequena quantidade do padrão de precipitação ao longo do estado de Mato Grosso. Não houve diferença entre as estimativas de precipitação NN1 e NN2 em janeiro. Por outro lado, as estimativas de precipitação com NN2 tiveram melhor desempenho do que com NN1 em setembro. Os baixos desempenhos dos modelos em estimar a precipitação usando a rede neural em estado de Mato Grosso foram devido a (i) uma série temporal curta, (ii) algumas estações com baixa variabilidade espacial, (iii) poucas variáveis auxiliares para construir uma rede neural, o que poderia capturar melhor o fenômeno da precipitação ao longo de regiões neotropicais. O próximo passo será analisar a precipitação e outras variáveis climáticas com rede neural para todo o ano por vários anos sobre a Região Centro-Oeste do Brasil, incluindo outras variáveis auxiliares, além de latitude, longitude e altitude.

PALAVRAS-CHAVE: dinâmica espaço-temporal, observações de satélite, inteligência artificial, precipitação.

1. INTRODUCTION

Rainfall is one of the most variable atmospheric parameters in space and time that has a direct impact on human life (MISHRA et al., 2011). The rainfall as the most influential meteorological element (RAMÍREZ et al., 2005; DALLACORT et al., 2011) has a direct effect on the water balance (THIEMIG et al., 2013), and an indirect effect on relative humidity, air and soil temperature, which affect plant growth (BROCCA et al., 2013), and human development (Santos, 2005). Rainfall characterization allows better planning of agricultural practices, soil conservation structures (contour lines and terraces), constructions (channel drains and dams), and weather forecasts (BAZZANO et al., 2007).

Quantifying rainfall at spatial and temporal scales in regions where meteorological stations are scarce is important for agriculture, natural resource management and land-atmosphere interactions science (QUIROZ et al., 2011). Economy based on agribusiness involving production chain of agricultural and cattle raising can be directly influenced by the excess or lack of rainfall causing partial and total losses such as in the economy of Mato Grosso state in Brazil (DALLACORT et al., 2011). These effects on agribusiness have caused an increasing demand about climatic and meteorological data in large spatial and temporal scales. Accurate rainfall data with sufficient spatial resolution are important, but adequate gauged data is seldom available in many developing countries (QUIROZ et al., 2011). Thus, the problem of rainfall estimation has been widely studied in recent years (UNAL et al., 2004; JAKOB et al., 2007; XU and TUNG, 2009; SARKER et al., 2010; LEE et al., 2010).

Analyses of pluviometric regime demand long data series (MARCUZZO et al., 2012), which can be obtained by remote sensing (SIMPSON et al., 1988; THIEMIG et al., 2013) and computational techniques (ARKIN, 1979; HSU et al., 1997; KULIGOWSKI, 2002). The monitoring of rainfall by ground stations and satellite sensors has been well established for many years even though it still suffers from several limitations (CROW et al., 2011), i.e., the spatial representativeness of rain gauge stations and the quantitative accuracy of radar, passive microwave, thermal and infra-red sensors on-board several satellites (BROCCA et al., 2013).

Remote sensing and computational techniques are advantageous because they allow the monitoring on a regional scale of the energy partitioning, carbon and water cycle with low operating costs and greater data acquisition (COURAULT et al., 2005; ALLEN et al., 2011). Development of satellite remote sensing techniques provides a unique opportunity for better observation of precipitation for regions where ground measurements are limited (JENIFFER et al., 2010). Satellites obtain information about the distribution and amounts of precipitation (ARKIN, 1979; QUIROZ et al., 2011). Several methodologies have been proposed for rainfall estimation using neural network (FRENCH et al., 1992; RAMÍREZ et al., 2005) and satellite images such as– Tropical Rainfall Measuring Mission (TRMM) Satellite (SIMPSON et al., 1988; YANG et al., 2014).

A neural network model is a mathematical construct whose architecture is essentially analogous to the human brain, which is represented by the network topology and pattern of connections between the nodes, its method of determining the connection weights, and the activation functions that it employs (DIBIKE and COULIBALY, 2006; SILVA et al., 2010; SHIRGURE, 2013; HAYKIN, 1998). Nevertheless, the interest in artificial neural networks (ANNs) is nowadays increasing because of their high potential for complex, non-linear and time-varying input-output mapping (DIBIKE and COULIBALY, 2006). Recently, artificial neural networks have been applied in meteorological and agroecological modeling and applications (HOOGENBOOM, 2000). Kumar et al. (2002) applied neural networks for estimation of daily evapotranspiration and compared the performance neural networks with Penman-Monteith method. Most of the applications reported in literature concern estimation, prediction and classification problems (SHIRGURE, 2013).

TRMM as a remote sensing technique with the specific purpose of measuring rainfall in the tropics (COLLISCHONN et al., 2007) has been used to investigate pluviometric regime dynamics for many purposes such as: assessing the spatiotemporal dynamics of two sub-regions of the Pantanal (ADAMI et al., 2008); studying daily variability of rainfall in the Amazon basin (SILVA et al., 2011); identifying warm season in urban regions of some cities in USA (SHEPHERD et al., 2002); and investigate flooding causes in a city in south Brazil (COLLISCHONN, 2010). Rainfall estimated by TRMM was validated over the Ethiopian highlands (DINKU et al., 2011) and the Central-West Region of Brazil (DANELICHEN et al., 2013). TRMM precipitation dataset is now considered by the Earth science community as the most accurate rain observations from space (YANG and NESBITT, 2014). These data sets have been widely applied in Earth science applications, such as weather forecast and hydrology (KRISHNAMURTI et al., 2001; SU et al., 2008; JENIFFER et al., 2010).

Therefore, computational techniques and remote sensing for climatic and meteorological estimation in large areas with small dataset are growing around the world. The objective of this paper is to evaluate neural network performance for rainfall estimates over a Neotropical region.

2. MATERIAL AND METHODS

2.1. Study area

Mato Grosso is one of the Brazilian states, the third largest by area, located in the western part of the country (latitude from 7º to 18º S and longitude from 50º to 62º W) (Figure 1). A state with a flat landscape, alternating plateaus and plain areas, which presents three different ecosystems: Amazon forest, Cerrado (Brazilian savanna) and the Pantanal (wetland) (COSTA et al., 2010). According to Köppen, the regional climate is Aw (SOUZA et al., 2013), with a dry season from May to September and a wet season from October to April (DANELICHEN et al., 2013). The annual temperature average ranges from 23°C to 26.8°C and the annual rainfall average ranges from 1,200 to 2,000 mm (SOUZA et al., 2013). Mato Grosso contributes to form three basins: Paraguay (176,800.60 km^2), Amazon (592,382.54 km^2) and Tocantins (132,237.56 km^2) (MATO GROSSO, 1995).

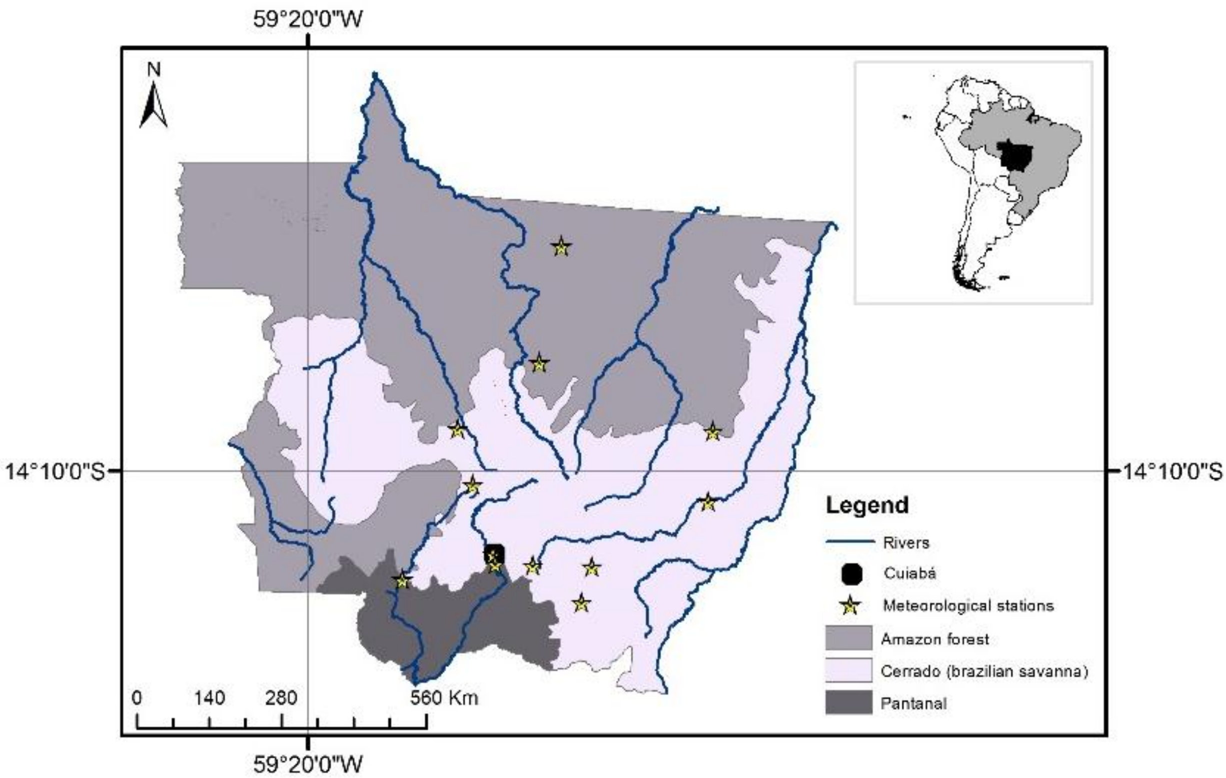

Figure 1. Location of Mato Grosso state, Brazil.

2.2. Meteorological data

Rainfall data were obtained from 12 meteorological stations (Figure 1 and Table 1) provided by the "Instituto de Controle de Espaço Aéreo" (ICEA) of "Comando da Força Aérea" available on the website [http://clima.icea.gov.br/clima/] and TRMM satellite provided by Distributed Active Archive System (DAAC) available on the website [http://disc2.nascom.nasa.gov/Giovanni/tovas/TRMM].There were 2 meteorological stations in Amazon forest, 8 in Cerrado and 2 in Pantanal (Table 1). The pixel size of TRMM is 25 km². We used data from 3B43 V6 products. We chose TRMM satellite estimates because it has estimated appropriately the annual accumulated rainfall in the Central-West Region of Brazil (DANELICHEN et al., 2013).

Table 1.Meteorological stations in Mato Grosso state, Brazil.

Stations	Code	Biome	Longitude	Latitude	Altitude (m)
Cáceres	83405	Pantanal	-57.68	-16.05	118
Canarana	83270	Cerrado	-52.27	-13.47	430
Cuiabá	83361	Cerrado	-56.10	-15.61	145
Diamantino	83309	Cerrado	-56.45	-14.40	286
Gleba Celeste	83264	Amazon forest	-55.29	-12.28	415
Matupá	83214	Amazon forest	-54.91	-10.25	285
Nova Xavantina	83319	Cerrado	-52.35	-14.70	316
Padre Ricardo Remetter	83364	Pantanal	-56.06	-15.78	140
Poxoréu	83358	Cerrado	-54.38	-15.83	450
Rondonópolis	83410	Cerrado	-54.56	-16.45	284
São José do Rio Claro	83267	Cerrado	-56.71	-13.43	350
São Vicente	83363	Cerrado	-55.41	-15.81	800

2.3. Artificial neural network

A dataset of 12 meteorological stations were used to train the neural network and then was run to perform estimates, which allowed comparing with TRMM satellite estimates. The input dataset contained 360 ground measurements of daily accumulated rainfall for January (wet season) and 372 September (dry season) for year 2010. Rainfall estimates were performed by neural network as a function of latitude and longitude for model 1 (NN1), and latitude, longitude and altitude for model 2 (NN2). Altitude data were obtained from SRTM (Shuttle Radar Topographic Mission) available at [http://www.dpi.inpe.br/Ambdata/altitude.php]. We generated 1,158 random points and extracted rainfall values from TRMM dataset to compare with the neural network estimates (Figure 2).

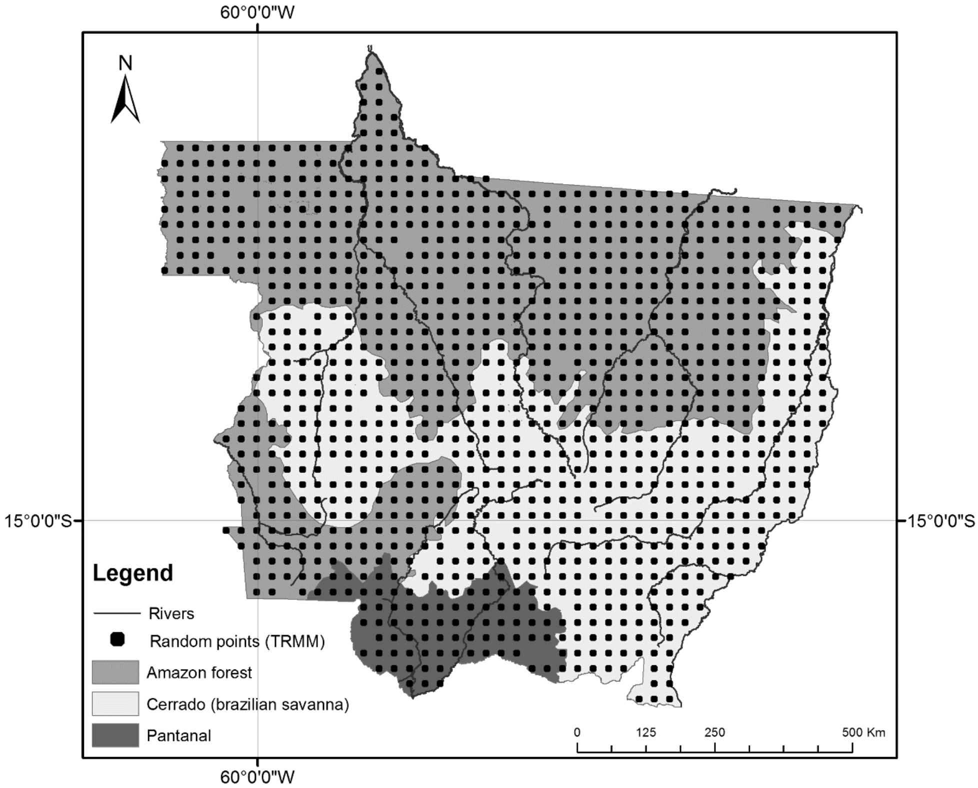

Figure 2. Random points from TRMM in Mato Grosso state, Brazil.

2.4. Statistical analysis

The evaluation of rainfall estimates from neural network data in relation to TRMM data was performed by these statistical indices: accuracy of Willmott index "d" (eq. 1), root mean square error "RMSE" (eq. 2), mean absolute error "MAE" (eq. 3), and Spearman's Rank correlation "r" (eq. 4).

The accuracy is related to the distance of the estimated values from those observed. Mathematically, this approximation is widely applied to the comparison between models (WILLMOTT et al., 1985). Their values range from the value of 0, representing no agreement, to value of 1 representing perfect agreement.

$$d = 1 - \left[\sum (P_i - O_i)^2 / \sum (|P_i - O| + |O_i - O|)^2\right] \quad (1)$$

where P_i is the estimated value, O_i the value observed and O the average of observed values.

The RMSE indicates how the model fails to estimate the variability in the measurements around the mean and measures the change in the estimated values around the measured values (WILLMOTT et al., 2005). The lowest threshold of RMSE is 0, which means there is complete adhesion between the TRMM estimates and measurements.

$$EQM = \sqrt{\frac{\sum (P_i - O_i)^2}{n}} \quad (2)$$

The MAE indicates the mean absolute distance (deviation) of values estimated from the values measured. The MAE and RMSE values should be close to zero (WILLMOTT et al., 2005).

$$EMA = \sum \frac{|P_i - O_i|}{n} \quad (3)$$

Spearman's Rank correlation coefficient is used to identify and test the strength of a relationship between two sets of data (ZAR, 2010).

$$r = 1 - \frac{6\sum d^2}{n\,(n^2 - 1)} \quad (4)$$

where $d_i = x_i - y_i$ is the difference in the ranks given to the two variable values for each item of data.

3. RESULTS AND DISCUSSION

Rainfall ground measurements were higher in January than in September (Table 2), following the seasonal trends of the region (DANELICHEN et al., 2013; BIUDES et al., 2015). In general, rainfall values were higher overestimated by NN1 in January (18.7%), and September (119.2%) than by NN2 in January (6.8%), and September (0%) (Table 2). The higher overestimated rainfall values by NN1 in January occurred in Pantanal (33.9%), and Amazon forest (20.9%) than in Cerrado (13.4%); while the higher overestimated values in September occurred in Cerrado (185.3%) than in Amazon forest (94.6%), and Pantanal (90.1%). NN2 rainfall values were more overestimated in Pantanal (41.4%) than in Amazon forest (13.1%) in January, and underestimated in Cerrado (- 6.9%). On the other hand, NN2 rainfall values were underestimated in Pantanal (-55.6%), and Cerrado (-50.4) in September, but they were overestimated in Amazon forest (54.6%).

Table 2. Spatial and temporal variability of rainfall estimates by meteorological stations, TRMM and neural networks in Mato Grosso state, Brazil. MS = Meteorological Stations. NN1 = Neural Network for model 1. NN2 = Neural Network for model 2. MT = Mato Grosso state. AF = Amazon forest. CE = Cerrado. PN = Pantanal.

Sites	MS (mm)		TRMM (mm)		NN1 (mm)		NN2 (mm)	
	Jan	Sep	Jan	Set	Jan	Sep	Jan	Sep
MT	345.33	11.45	368.04	20.14	436.86	44.14	393.05	24.16
AF	376.15	36.35	398.70	24.92	482.28	48.49	451.01	38.48
CE	346.90	5.92	354.01	13.97	401.58	39.87	329.73	6.93
PN	308.25	8.65	214.24	18.15	286.97	34.52	303.02	11.06

Mato Grosso state is located in the Central-West Region of Brazil, which is mainly controlled by large, and mesoscale systems. According to Alves (2009), the Central-West Region of Brazil, a subtropical area, is under climatic influence of tropical and subtropical atmosphere systems. During wet season, South Atlantic Convergence Zone (SACZ) is associated to a humidity convergent outflow from Amazonia to Brazilian Southeast, which is responsible by rain extreme events. On the other hand, SACZ absence can cause rain suppression and long periods of drought (CARVALHO and JONES, 2009). During dry season, convection and precipitation are suppressed due to anticyclonic outflow from an upper-level high pressure system ("Bolivian high") (HARDY et al., 1998). A warm core below about 150 mb, capped above by a cold top (VIRJI, 1981; SILVA DIAS et al., 1983), characterizes Bolivian high, generated from strong convective heating (latent heat release) from the atmosphere during the summer months in the Amazonia (Alves, 2009). As consequence of this anticyclone circulation, a low pressure region is formed in the low levels of the atmosphere, and air convergence occurs (VIRJI, 1981), causing the dry season in the Central-West Region of Brazil (KOUSKY and KAYANO, 1994). There are still cold surges, or friagem, caused by outbreaks of polar air during wintertime (May–August) low temperatures in mid-latitudes, which affect southern Brazil with considerable cooling in central and northern Amazonia (PARMENTER, 1976; MARENGO et al., 1997).

There was a geographical pattern of rainfall from higher to lower values from North to South in January (Figure 3) in Mato Grosso state as found by DANELICHEN et al. (2013). However, NN1 rainfall estimates captured a small amount of the rainfall pattern over Mato Grosso state (Figure 4). NN2 had rainfall pattern closer to TRMM both in January and in September (Figure 5).

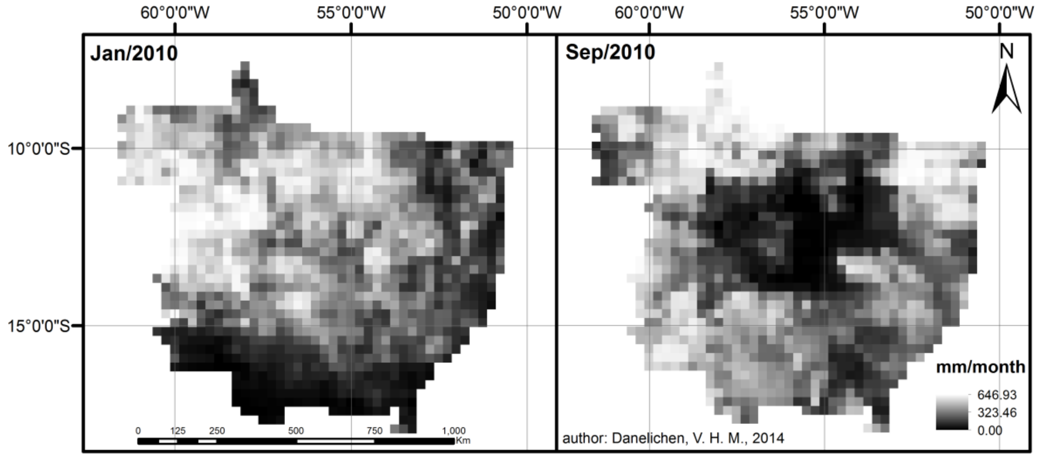

Figure 3. Rainfall map using TRMM estimates in Mato Grosso state, Brazil.

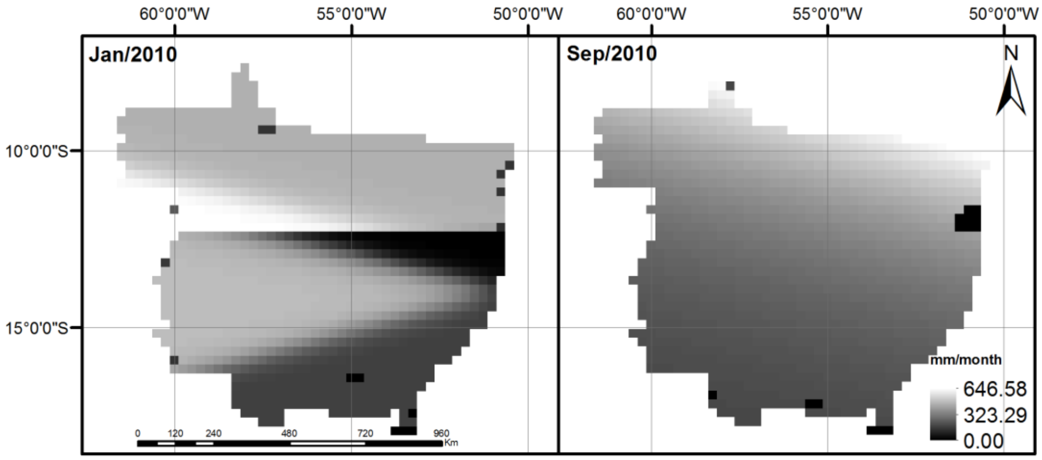

Figure 4. Rainfall map using Neural Network for model 1 (NN1) estimates in Mato Grosso state, Brazil.

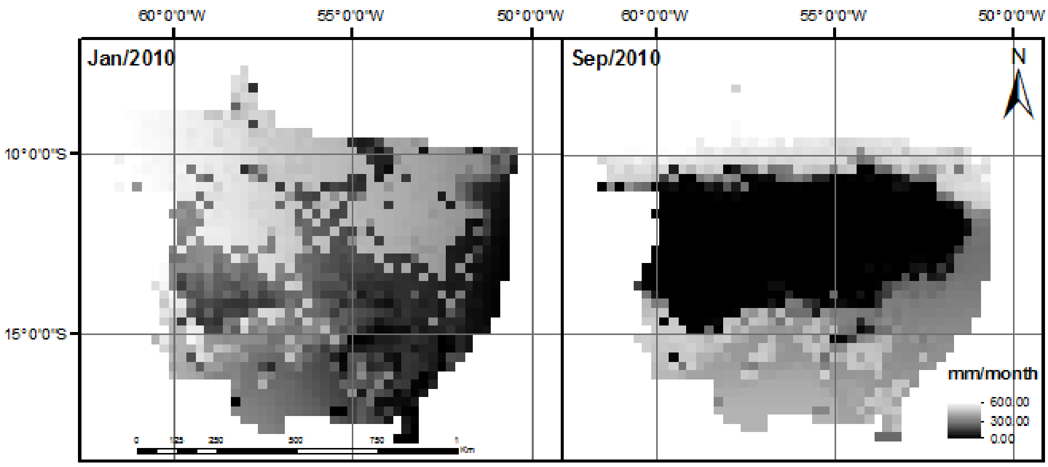

Figure 5. Rainfall map using Neural Network for model 2 (NN2) estimates in Mato Grosso state, Brazil.

There was no significant difference between NN1 and NN2 rainfall estimates in January (Table 3). The rainfall estimates had better performance in NN2 than NN1 in September (dry season). Anyway, rainfall estimates were worst in January than in September both in NN1 and in NN2.Considering biomes, rainfall estimates by NN1 and NN2 had better performance in Pantanal than in Amazon forest and Cerrado both in January and in September. Cerrado had the worst rainfall estimates.

Table 3. Statistical performance of neural network for estimating rainfall in Mato Grosso state, Brazil. MT = values including all biomes. AF = Amazon forest. CE = Cerrado. PN = Pantanal.

Time/Space	RMSE	MAE	D	R
Jan_MT (NN1)	124.47	103.70	0.67	0.55
Jan_MT (NN2)	125.34	104.59	0.59	0.34
Jan_AF (NN1)	141.19	120.97	0.47	0.20
Jan_AF (NN2)	125.09	104.53	0.54	0.26
Jan_CE (NN1)	102.65	85.16	0.74	0.68
Jan_CE (NN2)	127.66	106.01	0.20	-0.21
Jan_PN (NN1)	97.03	75.92	0.32	-0.16
Jan_PN (NN2)	113.28	96.79	0.30	-0.43
Set_MT (NN1)	30.4	27.3	0.50	0.36
Set_MT (NN2)	10.38	7.89	0.08	-0.23
Set_AF (NN1)	33.1	29.2	0.50	0.28
Set_AF (NN2)	37.33	23.44	0.59	0.46
Set_CE (NN1)	28.2	26.6	0.40	0.33
Set_CE (NN2)	48.59	33.40	0.61	0.49
Set_PN (NN1)	17.9	16.7	0.35	-0.02
Set_PN (NN2)	17.31	12.58	0.43	0.24

HIJMANS et al. (2005) obtained good estimates of monthly total precipitation, monthly mean, minimum and maximum temperature using latitude, longitude, and elevation as auxiliary variables in neural networks. DIBIKE and COULIBALY (2006) also obtained good estimates using temporal neural network as method for downscaling both daily precipitation as well as daily maximum and minimum temperature series. ANTONIC et al. (2001) obtained good results for modelling seven climatic variables using neural network with elevation, latitude, longitude, month and time series of respective climatic variable observed at two weather stations as auxiliary variables.

Thus, neural network has obtained good estimates of meteorological and climatological variables in several studies as shown previously. Despite the great popularity of the neural network models in many fields, Hsieh and Tang (1998) showed three obstacles to adapting the neural network method to meteorology and oceanography, especially in large-scale with low-frequency studies due to (a) nonlinear instability with short data records, and (b) large spatial data fields.

4. CONCLUSION

In general, we obtained bad rainfall estimates by neural network using just latitude and longitude in Mato Grosso state in the wet season due to (i) a short temporal dataset, (ii) few stations with poor spatial variability, and (iii) few auxiliary variables to build neural network, which could better capture rain phenomenon in Neotropical regions. On the other hand, rainfall estimates in September were better when altitude was included as auxiliary variable. The next step will be to analyze the rainfall and other climatic estimates performed by neural network for the whole year for several years on the Central-West Region of Brazil including other auxiliary variables besides latitude, longitude, and altitude.

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