GEAMA Journal

The Journal of environment Scientific Article

Mapping reference crop evapotranspiration in Bahia, Brazil, using Hargreaves-Samani method

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ABSTRACT

The objective of this work was to study the spatial behavior of the reference evapotranspiration (ET_0) in the state of Bahia according to the method of 1985 Hargreaves Samani. The study includes data from 452 meteorological weather stations managed by the National Institute of Meteorology (INMET) and the National Water Agency (ANA). These stations have data of maximum, minimum and average temperatures covering the period from 1965 to 2013. Monthly maps of spatial distribution of ET_0 were made by geostatistical techniques with ArcGIS 9.3 software. There is also predominance of higher evaporative demands in the north of the state. The month with the highest spatial dependence of ET_0 was the month of October, with similar results were observed for the months of May, July, August and September. The values of spatial dependence obtained in these respective months showed an average range of 1.07 degrees. The ET₀ rates corresponding to the Atlantic Forest areas near the Atlantic coast in the east are uniformly distributed where predominate Humid and Super-Moist climates. Alternative models to combination equations such as Penman-Monteith provide easier and reliable way to carry out studies on ET_0 estimation for water resources management. The geostatistical methods are important tools for regionalizing meteorological variables, including ET₀.

Keywords: Meteorology, GIS, geostatistic, evapotranspiration

INTRODUCTION

Evapotranspiration (ET) is one of the primary variables for most of hydrological processes in nature and its knowledge is crucial at any spatial scale for water resources management. Rates of ET at drainage basin levelare essentially determined by type of vegetation, soil moisture availability and meteorological conditions (SUN et al., 2004). In the context of water use in agriculture, the concept of a reference crop ET (ET_o) is related to the net water demand by other crops (ET_c) through a conversion factor called crop coefficient (K_c), which can generally vary from 0,1 to 1,3 according to crop type, frequency of wetting events (irrigation or rain) and crop development stage (SILVA et al, 2015; ROCHA et al, 2016).On the other hand, because ET_o essentially depends on atmospheric parameters, its concept is useful as an indicator of the general type of climate in a regionfrom humid (low ET_o) to arid (high ET_o) climate (ALLEN et al., 1998).

Reference ET rates can be determined by different methods generally classified into direct (measurement) and indirect (estimation) ones. Lysimeters measure ET_0 while mathematical models based on atmospheric variables are used to estimate it. The Penman-Monteith equation modified by the UN-FAO, known as FAO-56 Penman-Monteith equation (FAO-56 PM) (ALLEN et al., 1998), is considered a standard in providing quality estimations of ET₀ across different climates.

The FAO-56 PM method and other formulations of the so-called combination equations, require large amounts of reliable data on incident solar radiation, wind speed, air temperature, and relative humidity. Such demand for complete series of data imposes restrictions when one desires to generate maps of ET_0 for large areas due to the lack of enough information at the desired density. In such cases, equations based on fewer atmospheric parameters like the 1985-Hargreaves-Samani equation (HARGREAVES& SAMANI, 1985; HARGREAVES & ALLEN, 2003), which requires only air temperature as input variable, can be an alternative to the more data-demanding methods.

Geographic Information Systems (GIS) are powerful tools that allow spatial analysis of large sets of climatological data. In association to geostatistical techniques, GIS has presented interesting results in studies related to spatial variability, mapping and quantization of meteorological phenomena on monthly and annual basis (HASHMI et al., 1995; VIEIRA, 1997; SOUZA et al., 1998).

The usage of regionalized information on climate variables finds special applications in the field of water resources management. In this context, geostatistical techniques, particularly methods of interpolation such as Kriging have been applied with success on spatialization of meteorological variables, with superior results when compared to alternatives like inverse distance weighting, spline interpolation or natural neighbor (MELLO et al. 2003; ALVES et al. 2008; SILVA et al. 2010; GARDIMAN JUNIOR et al. 2012).

Many studies (BARBOSA et al., 2005, BELTRAME et al., 1994; CHUNG et al., 1997) have reported maps of reference ET from GIS techniques for many parts of the world. They concluded that their methodologies allowed them to acquire individual ET_0 values and, therefore, to make more accurate water demands evaluations in the region.

This paper aimed at analyzing the spatial distribution of reference ET in the state of Bahia by means of GIS and geostatistical techniques from historical series of weather data with the hope that such results can be useful for farmers at local level as well as for planners and decision makers at the government level.

MATERIALS AND METHODS

Region of interest

Due to the large natural variability and complexity of the Bahia territory, it is common to classify its sub regions according to a set of different criteria such as major natural biomes, drainage basins and hydrogeological domains. The state area can then be divided into four major natural biomes: tropical savannah, semi-arid, mountain ranges and Atlantic forest. There are also thirteen major drainage basins: São Francisco (42% of the Bahia territory), Vaza-Barris, Real, Itapicuru, Inhambupe, Recôncavo Norte, Paraguassu, RecôncavoSul, Contas, Leste. Pardo, Jequitinhonha

andExtremoSul, and five hydrogeological domains: DetritalCoverings, Sedimentary basin, Limestones, Metasediments, Crystalline fissure (SEI, 2012).

Meteorological data his study is based on monthly averages of meteorological data collected at weather stations of the Brazilian National Institute of Meteorology (INMET) and the Brazilian National Water Agency (ANA) networks. There are altogether 452 meteorological stations in Bahia providing records for maximum, minimum and average temperature. The records used in this work range from 1965 to 2013 with an average of 45 years per station and





Hargreaves-Samani (1985) estimation method

The Hargreaves &Samani (1985) model is shown in Equation 1.

$$ET_o = 0,0023 \cdot (T_m + 17,18) \cdot \sqrt{(T_x - T_n)} \cdot Ra$$
 (1)

where,

ET_o– reference evapotranspiration (mmd-1);

 T_m – mean air temperature (°C);

T_x- maximumair temperature (°C);

 T_n – minimum air temperature (°C);

 R_a – extraterrestrial solar radiation (mmd⁻¹).

Geostatistical tools

A series of maps was initially built using the Geostatistical Analyst tool in the ArcGIS 9.3 software. Ordinary Kriging was used as interpolation method. Its general formula is presented on Equation 2:

$$Z_{\nu}' = \sum_{i=1}^{n} \lambda_i Z_{\nu i} \tag{2}$$

where,

 Z'_v – the ordinary kriging estimator for a point v; λ_i – ith weight; Z_{vi} – value of the ith observation for the regionalized variable, collected on point x_i ;

n – number of weights.

According to LANDIM (2003), a semivariogram is an important tool for determining weights for spatial continuity and represents a quantitative variation of the regionalized spatial phenomenon. It allows determining and analyzing the dependency between spatialized points (JOURNEL & HUIJBREGTS, 1978). A semivariogram for kriging regressions is presented on Equation 3:

$$y(h) = \frac{1}{2N(h)} \cdot \sum_{i=1}^{n} \left[Z(x_i) - Z(x_i + h) \right]^2$$
(3)

where,

y(h) – estimation; Z(x) – position of the elements; N(h) – observation pairs; h – distance.

After adjusting the semivariograms the Nugget Effect (Co), sill (Co+C1) and range (Ao) parameters were calculated. When the distance h reaches its maximum value the sill parameter, which represents the maximum limit distance of spatial dependency, is determined (ISAAKS & SRIVASTAVA 1989).

An evaluation of spatial dependency is relevant once it provides another parameter for map interpretation. Equation 4, as proposed in CAMBARDELLA et al. (1994), was used in this process. The level of spatial dependence (GD) was classified as: strong, when GD < 25%, moderate, when 25%<75%, and weak, when GD > 75%.

$$GD = \left(\frac{C_0}{C_0 + C_1}\right) \cdot 100 \tag{4}$$

where,

GD – dependence level; C_0 – nugget effect; $(C_0 + C_1)$ – sill.

Model performance

The performance of models and methods for ETo is evaluated using Root Mean Square Error (RMSE) (Equation 5), which is considered an efficient statistical indicator for calibration and evaluation (GAVILÁN et al., 2006; LOPEZ-URREA et al., 2006, JABLOUN & SAHLI, 2008, KUMAR et al., 2002; and AHMADI & FOOLADMAND, 2008) and the Mean Bias Error (MBE) is calculated in Equation 6.

The precision of the kriging interpolation on a monthly basis was quantified using the Pearson's correlation coefficient (r) (Equation 7), and the Willmott index of agreement (d) (WILLMOTT, 1982), Equation 8.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (ET_{oEi} - ET_{oOi})^{2}}{n}}$$
(5)

$$MBE = \frac{\sum_{i=1}^{n} \left(ET_{oEi} - ET_{oOi} \right)}{n}$$
(6)

$$r = \frac{\sum_{i=1}^{n} (ET_{oOi} - \overline{ET_{oOi}}) \cdot (ET_{oEi} - \overline{ET_{oEi}})}{\sqrt{\sum_{i=1}^{n} (ET_{oOi} - \overline{ET_{oOi}})^{2} \cdot \sum_{i=1}^{n} (ET_{oEi} - \overline{ET_{oEi}})^{2}}}$$
(7)

$$d = 1 - \left[\frac{\sum_{i=1}^{n} (ET_{oEi} - ET_{oOi})^{2}}{\sum_{i=1}^{n} \left[\left(ET_{oEi} - \overline{ET_{oOi}} \right) + \left(ET_{oOi} - \overline{ET_{oOi}} \right) \right]^{2}} \right]$$
(8)

where,

r - Pearson's correlation coefficient;

d - Willmott index of agreement;

RMSE – Root Mean Square Error (mm d⁻¹);

MBE – Mean Bias Error (mm d⁻¹);

 ET_{oEi} – estimated(interpolated) ET_o (mm d⁻¹);

$$ET_{oOi}$$
 – observed(calculated) ET_o (mm d⁻¹);

 ET_{oEi} – mean estimated (interpolated) ET_o (mm d⁻¹);

$$ET_{oOi}$$
 – mean observed (calculated) ET_o (mm d⁻¹).

RESULTS AND DISCUSSION

The results of the application of the statistical indicators for mapping ET₀ over the entire state of Bahia are shown in Table 1. All models of monthly ET₀ mapping using kriging interpolation were satisfactory. A strong positive correlation was verified in all month estimations according to the Pearson's coefficient. Regarding the MBE and RMSE indicators, for all months these parameters presented positive values tending to zero. This behavior was also observed in several comparisons for different ET₀ estimation methods by researchers like AHMADI & FOOLADMAND (2008), LOPEZ-URREA et al. (2006), and GAVILÁN et al. (2006). The Willmott index of agreement (d) was also satisfactory in all months with values around 1, confirming the results reported by LOPEZ-URREA et al. (2006) and SULEIMAN & HOOGENBOOM (2007).

Negative values around -0.225 were found by Vilanova et al. (2012) and Lemos Filho et al. (2007) in studies of ET₀ spatialization for the state of Minas Gerais. The values reported in their work for MBE were all near zero, suggesting a super estimation by the model.

Table 1. Statistical indicators for ET_o estimation over the state of Bahia

Month	r	(MBE)	(RMSE)	d
January	0.851	0.00042	0.021	0.9988
February	0.853	0.00078	0.028	0.9975
March	0.847	0.00119	0.034	0.9954
April	0.887	0.0006	0.025	0.9983
May	0.916	0.00058	0.024	0.999
June	0.931	0.00072	0.027	0.999
July	0.937	0.00059	0.024	0.9993
August	0.947	0.00037	0.019	0.9997
September	0.953	0.00085	0.029	0.9994
October	0.936	0.00148	0.038	0.9986
November	0.911	0.00124	0.035	0.9981
December	0.885	0.00148	0038	0.9965

The Table 2 presents the geostatistical parameters of each ET_o monthly estimation model obtained by kriging. In this study, all ET_o spatialization models showed moderate dependence

Revista Geama, v.2, n.4, oct.-dec., 2016. Received: March 24, 2016 | Approved: August 06, 2016.

level. The spatial variability of meteorological variables may be influenced by different topographic and geographic aspects, specially altitude and proximity to the sea. It may also be affected by other climatic factors such as humidity, wind and vegetation (JIN et al., 2013). Nevertheless, the dominant influence seems to be land topography (BOTH et al, 2010) that affects air temperature in the sense that highest elevations tend to show the lowest values of ET₀. Normally the interpolation methods do not consider the altitude of the sample points, instead, like the kriging method for example, they are based on the distance between the samples and the point of the estimated value, lowering its spatial dependence (BURROUGH, 1986; BETTINI, 2007). According to Table 2, October was the month with the strongest spatial dependence with similar results found for the months of May, July, August and September.

 $\label{eq:table2} \begin{tabular}{ll} \textbf{Table 2.} Geostatistical parameters of mapping ET_o estimated \\ with the Hargreaves and Samani equation \\ \end{tabular}$

Month	C ₀	C1	C ₀ + C ₁	Ao (degree)	GD %	Class
January	0.0225	0.0211	0.0436	0.576	51.6	Moderate
February	0.0204	0.0231	0.0435	0.818	46.9	Moderate
March	0.0183	0.0201	0.0384	0.948	47.7	Moderate
April	0.0181	0.0271	0.0452	0.897	40.0	Moderate
May	0.0206	0.0404	0.0610	1.021	33.8	Moderate
June	0.0187	0.0438	0.0625	0.966	29.9	Moderate
July	0.0219	0.0597	0.0816	1.079	26.8	Moderate
August	0.0256	0.0612	0.0868	1.099	29.5	Moderate

September	0.0244	0.0620	0.0864	1.040	28.2	Moderate
October	0.0237	0.0679	0.0916	1.228	25.9	Moderate
November	0.0201	0.0346	0.0547	0.865	36.8	Moderate
December	0.0191	0.0267	0.0458	0.948	41.7	Moderate

The center part of Bahia, an area called Chapada Diamantina with the highest elevations in the state (Figure 1), is the limit between two major river basins, the São Francisco in the west (the largest) and the Paraguassu river basin in the east. The effect of elevation on air temperature can be appreciated from Figure 2A with the lowest values (18.9 to 22.4°C) found in the center-south part of the state. On the other hand, Figure 2B shows that the effect of proximity to the Atlantic Ocean is more important on the difference between the maximum and minimum air temperature, with the amplitude increasing from east to west.

Figure 3 shows the distribution of annual ET_0 in Bahia. Due to the distribution patterns of mean air temperature and temperature amplitude, values of ET_0 based on the Hargreaves-Samani equation increases from southeast to northwest. The southeast is characterized by humid and super-humid climate. Topographic influences on ET_0 was also observed by McVicar et al. (2007) in some regions of China and by Latha et al. (2011) in India.

Figure 2. Distribution of the mean monthly air temperature (A) and the annual temperature amplitude (B) over the Bahia territory



Revista Geama, v.2, n.4, oct.-dec., 2016. Received: March 24, 2016 | Approved: August 06, 2016.





Figure 4 presents the ET_o distribution profile given in Figure 3 between the cities of Barreiras and Salvador, the capital of Bahia. The Tropical Savanna biome, on this profile, presents two types of climate: Semi-Humid and Semi-Arid. There are no considerable variations of ET_o on this biome (average 1810 mm), once its topography is very regular. In a study in an arid zone, Jin et al. (2013) found, on a similar ET_o profile, the lowest monthly ET_o values on desert and sand zones, while the highest ones on lake territories.

The savannah part of the profile has five sections of climatic typologies. There is also a considerable variation on ET_{0} in this region with values ranging from 1550 mm to 1770 mm annually. This happens especially due to the effects of altitude over the air temperature, which is a fundamental parameter for the Hargreaves-Samani method of estimating ET_{0} .



Figure 4. Annual average ET_o spatialization profile (SH: Semi-Humid; H: Humid; SpH: Super-Humid; SA: Semi-Arid).

The profile region corresponding to the Atlantic forest presents uniform ET_o with Humid and Super-Humid climates. In general, there is a decrease on ET_o values due to the influence of the ocean.

Table 3 presents annual ET_{\circ} values at drainage basins level. The São Francisco Basin presents the higher ET_{\circ} values, also with highest amplitude. Both the Real and the South Recôncavo drainage basins have similar spatial distribution. The Pardo basin presented the lowest maximum values of ET_{\circ} during the year. Meanwhile, the Vaza-Barris basin presented the highest minimum ET_{\circ} values annually. The Contas River basin presented the second highest amplitude, followed by the Paraguassu and the Far South basins. The lowest amplitude was observed for the Inhambupe basin.

Table 3. Annual values of ET_0 for the main drainage basins in Bahia

Danna							
River basin	Total annual of ETo (mm year ⁻¹)						
	Minimum	Maximum	Range	Average	SD		
Contas	1376.0	1631.2	255.2	1522	57.7		
ExtremoSul	1362.9	1564.7	201.8	1423	43.7		
Inhambupe	1513.5	1591.9	78.3	1550	20.7		
Itapicuru	1512.6	1688.3	175.7	1627	36.5		
Jequitinhonha	1394.9	1484.4	89.4	1444	21.1		
Leste	1444.9	1524.9	80.0	1475	13.8		
Paraguassu	1409.7	1653.4	243.6	1585	49.7		
Pardo	1368.4	1469.8	101.3	1420	26.6		
Real	1515.7	1633.0	117.2	1568	32.9		
Recôncavo Norte	1427.1	1588.1	160.9	1548	32.9		
Recôncavo Sul	1436.6	1578.7	142.1	1529	36.4		
São Francisco	1496.8	1977.6	480.8	1796	104.5		
VazaBarris	1520.8	1671.7	150.9	1611	38.4		

SD – Standard derivation

CONCLUSIONS

Alternative models to the combination equations for estimating ET_0 provide easier and more accessible ways of analyzing evapotranspiration in a wider range of study fields, with emphasis on management of water resources. Meanwhile, this work confirmed that geostatistical methods are important tools for regionalizing meteorological variables such as ET_0 .

One important observation was that the ET_o distribution presents spatial dependence in cold months of the year. This kind of analysis allows researchers to amplify their vision and, therefore, improve management of water resources on a larger scale.

The ET_0 profiles for the state of Bahia allow us to observe its distribution continuously, and associate it with corresponding biomes and climatic typologies. It also allows us to analyze its variations regarding other aspects like topography and distance to the sea. Additionally, considering the analysis for each specific drainage basin make it possible to better manage water resources with more efficient decisions.

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