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Evaluation of Precipitation Spatial Interpolation Techniques using GIS for Better Prevention of Extreme Events: Case of the Assaka Watershed (Southern Morocco)

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ABSTRACT

The spatial distribution of precipitation is a key data for the prevention and management of extreme events that threaten the Assaka watershed. This area is characterized by a scarcity of climatological data, an unevenly distributed rainfall observation network and low density. However, spatial interpolation methods of point precipitation measurements could overcome these aspects. For this reason, this research consists in determining the most adequate method in terms of efficiency and practical use in order to accurately map the maximum daily precipitation for a period of 30 years (1990 -2020). In this context four interpolation techniques (Thiessen polygons, inverse distance weighting, ordinary kriging and linear regression) were applied in a GIS environment. The cross-validation allows to evaluate the global performance of each method using statistical indicators (RMSE, MAE) as well as adjustment diagrams between observed and predicted values. Indeed, this analysis has allowed to qualify the method of multiple linear regression (MLR), as the best interpolator (RMSE=1.67mm and MEA=1.40mm). These results are judged by the fact that this technique integrates geographical factors (topography, latitude, proximity to the ocean) related to the formation of precipitation in the study area. Other methods are considered unsuitable in this anisotropic environment where the density of observation points is very low. These results constitute exploitable approaches by scientists and decision-makers in the prevention and management of extreme events (floods, landslides, water erosion) as well as land management (water resources, agriculture and environment).

Key words: *Assaka watershed, Spatial interpolation, Precipitation, Rainfall station, GIS.*

Introduction

In the field of prevention and management of extreme events, accurate precipitation mapping is of great importance, as it represents a key data for hydrological modeling and simulation of climatic scenarios necessary for the prevention of natural hazards such as floods, hydraulic erosion, desertification, and land movements (Caloiero *et al.,* 2021). However, these phenomena are often studied in very large areas where direct rainfall measurements from rainfall stations are spotty and poorly distributed. Therefore, a discrete spatial knowledge of extreme rainfall events is insufficient, or difficult to visualize (Joseph *et al.,* 2017). The observed values therefore need to be spatially interpolated if the "surface" rainfall is to be accurately known. Spatial interpolation is then the procedure that allows a continuous estimate over a territory from known observed neighbouring values (Mitas and Mitasova, 1999). A map with isolines that optimally estimate will therefore be the main objective of this process that plays a major role in decision making (Pellicone, 2018; Di Piazza *et al.,* 2011). In the literature, interpolation methods for rainfall spatialization are numerous, as well as of very variable complexity and efficiency (thiessen polygons, trend surfaces, splines, inverse distance weighting, geostatistical methods, artificial neural network and multiple regression ...). We therefore propose in this comparative study to determine the most suitable spatial interpolation method for the Assaka watershed, in terms of representativeness of the rainfall phenomenon, but also in terms of ease of use and reliability, with the aim of better knowledge and forecasting of intense rainfall events.

Presentation of the study area

The Assaka watershed, the subject of this study, which is located in the south of Morocco, in the Geulmim-Oued Noun region. It occupies an area of 6866 Km^2, corresponding to a perimeter of 750 km. It is located geographically between the two parallels 28.54° and 29.47°N and the two meridians 10.42° and 9.02°W (Fig. 1).

However, this study area is characterized by a severe aridity, due to the presence of the High Atlas Mountain range, which hinders rainy disturbances from the north. The average annual temperature is about 21 °C in Guelmim (Station Guelmim), while the average annual rainfall is about 115 mm, with a very significant random irregularity in the watershed. This fluctuation of rainfall in recent years, is the cause of the worsening of floods that have caused human damage, and very costly material in the watershed of Assaka (El Mahmouhi *et al*., 2016).

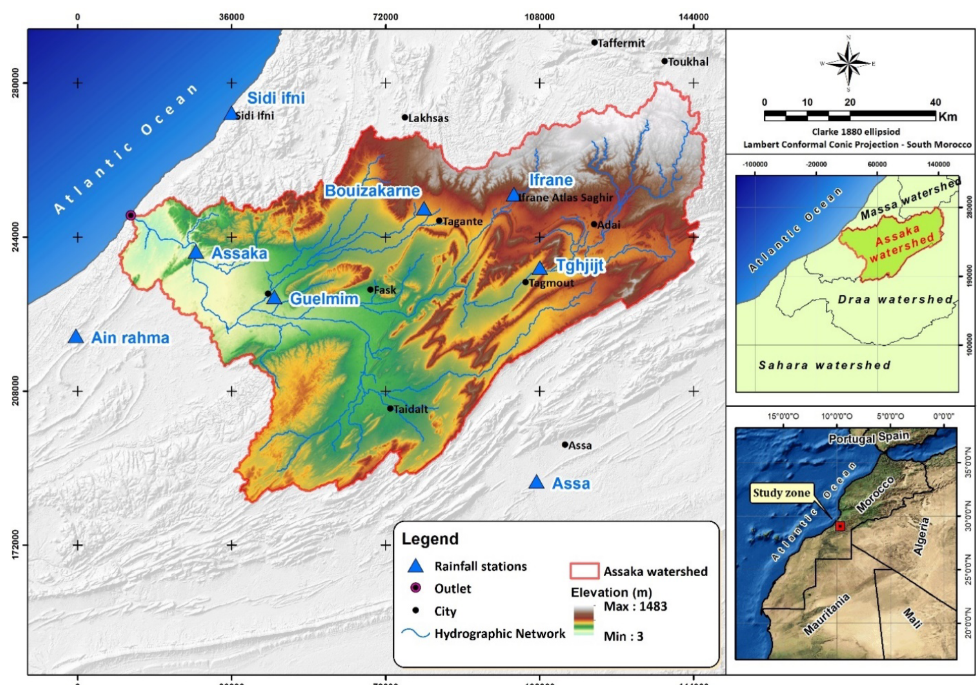

Fig. 1. Distribution map of rainfall stations in the vicinity of the Assaka watershed

Materials and Methods

Work methodology flowchart

The methodology adopted in this study consists of evaluating the performance of four of the most widely used interpolation methods in the field of climatology, in order to produce a low spatial distribution map of daily maximum precipitation for a 10-year return period (Fig. 2). This approach is based on daily precipitation data from 9 rainfall stations, for a period of 30 years (1990-2020). These data were provided by the Hydraulic Basin Agency of Draa Oued Noun (HBADON).

Although these series are spread over long periods of time (since 1975), it should be noted that they contain a large number of intervals without measurements, hence the interest in going through static processing of these data, in order to fill measurement gaps and eliminate all aberrant acquisitions. The analyses, statistical treatments and matrix corre-

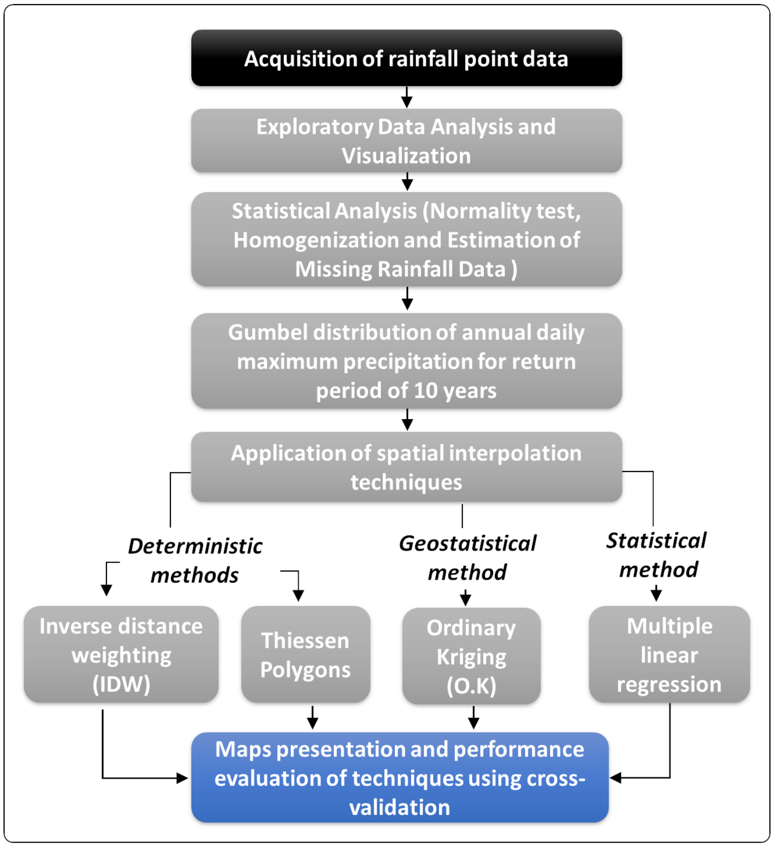

Fig. 2. Flowchart of the adopted methodology presenting the approach of the study

Table 1. Characteristics of the 9 rainfall stations in the study area

Measuring stations	Coordinates X (m)	Coordinates Y (m)	Elevation (m)	Obeservation periods (year)	Year of registration
Ain rahma	-400	220850	70	1975 - 2020	45
Assa	107333	186790	370	1992 - 2020	28
Assaka	27700	240600	145	1983 – 2020	37
Bouizakarne	81000	250700	630	1989 – 2019	30
Guelmim	46000	230000	270	1973 – 2015	42
Ifrane	102000	254000	800	1989 – 2018	29
Pont_Draa	-42929	183398	58	1981 – 2012	31
Sidi ifni	36000	273000	59	1971 - 2020	49
Tghjijt	108100	236800	591	1975 - 2020	45

lations were performed using the XLSTAT tool. The spatial interpolation methods were applied in a GIS environment (ArcGis 10.4).

Presentation of rainfall data

Rainfall information on the surface of the study area comes from 9 rainfall covering variable periods from 1975 to 2020 (Table 1). They are relatively dense in the north and very sparse in the south of the Assaka basin (Fig. 1).

It is very important to mention the existence of discontinuities and gaps in the measurement series. The common monthly period between the stations is about 30 years (since 1990).

Statistical analysis of rainfall data

For an effective use of rainfall data, the primary analysis of these series is essential. It allows to control the plausibility of the information on the one hand and the spatial and temporal homogeneity of the data and the representativeness of the measurements on the other hand (López-Rodríguez *et al.*, 2019).

Review of precipitation normality

To know if this sample of 30 values follows the normal distribution, we used the Henry diagram. The latter allows it possible to assess the adequacy of an observed distribution (annual precipitation) to a normal distribution (Gaussian distribution), which will allow detecting where the deviations are located (Crépel, 1993). Thus, quantification of this normality using the Kolmogorov-Smirnov (K-S) test is still essential, in order to determine the probability of acceptance of the hypothesis that the distribution of annual values follows a normal distribution (Hassani *et al.*, 2015).

In addition, the examination of normality adjustment (Kolmogorov-Smirnov (K-S) test) confirms a probability value (p-value) of 0.749 and 0.799 respectively for the stations: Sidi Ifni and Taghjijt. These values are well above the alpha threshold =0.05.

Homogenization and estimation of missing data

This step consists in checking the homogeneity of the measured values of the station to be tested by correlating them with those of reference, that is why it is necessary to seek good coefficients of correlation existing between the stations of reference and the other neighboring ones, on the basis of the monthly water heights, with the aim of reducing the estimation error of missing measurements (Kessabi *et al*., 2022). These two reference stations (Tghjijt and Sidiifni) were chosen based on their long observation period (1971-2020). Inaddition these stations

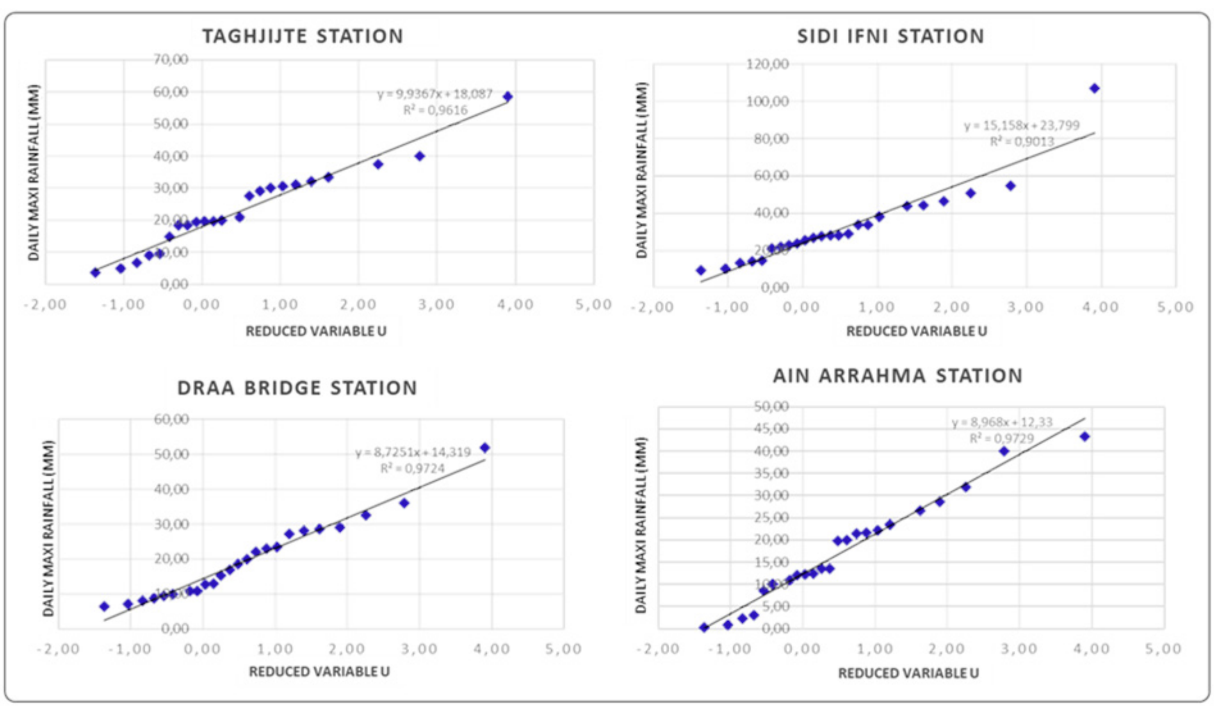

Fig. 3. Adjustment of maximum daily precipitation measurements for a 10-year return period by Gumbel's law

showed the most significant correlations with the other stations ($0,76 \leq R^2 \leq 92$).

Adjustment of maximum daily rainfall to Gumbel distribution

For the prediction of extreme values of precipitation, we use Gumbel's law (Gumbel, 1960) which presents a distribution function with the advantage of simplicity of calculation and the possibility of identifying the temporal distribution of extreme values for several return times (Abu Hammad, 2022).

The application of the Gumbel frequency analysis was performed in the XLSTAT tool, which allows the calculation of the annual maximum of the total precipitation on 4 consecutive days of each rainfall station, for a return period of 10 years. We present the adjustment results of four stations for illustrative purposes (Fig. 3). They show a relatively adequate fit to the Gumbel law. In addition, the chi-square test accepts this adjustment at the 5% threshold.

Application of spatial interpolation methods

In literature one can find a multitude of spatial interpolation methods, ranging from the most basic to the most advanced (Borges *et al.*, 2016).

The first category includes deterministic/statistical interpolation methods (Splines, Thiessen polygons, inverse distance weighting, trend surfaces and multiple regression...) based on the application of polynomial mathematical functions, weighting or statistical analysis, which allow to interpolate known measurement points in space. However, the second category of probabilistic methods (Kriging, Co- Kriging and artificial neural network...), model the regionalized variable by a random function or still use backpropagation algorithms for probabilistic type learning (Paraskevas *et al.*, 2014; Cerón *et al.*, 2021).

This study does not consist in making an exhaustive presentation of each interpolation method. Indeed, we have chosen to evaluate four methods most commonly used in the development of precipitation maps (Thiessen polygon method, Inverse distance weighting, multiple linear regression and ordinary kriging)

Thiessen polygon method

The principle of this technique is to assign to each observation (rainfall station) a polygon of influence, constructed so that each point of the polygon is closer to its observation site than to any other site. The polygons are obtained by drawing the bisectors of the segments connecting the observation sites (Thiessen, 1911). The result of this method depends only on the spatial distribution and density of the observation sites. It yields small area polygons for clustered data, in contrast to isolated data that will produce large area polygons (Olawoyin and Acheampong, 2017). This method assumes that each precipitation gauge does not have the same weight, and for each observation in a watershed one can assign precipitation equal to that of the nearest gauge by constructing influence polygons.

If Ai is the area assigned to station i, then the area precipitation can be estimated as follows (equation 1)

$$\bar{P}_{av} = \sum_{i=1}^{m} \frac{A_i}{A} P_i \quad .. (1)$$

$\bar{P}_{av}$: the area average of precipitation

P_i: the observed precipitation at this station or outside the watershed.

A_i: part of the polygon area surrounding station i located in the region.

M : the number of areas

Inverse Distance Weighting (IDW) method

It is a deterministic method commonly used in the spatial interpolation of climate data. This classic technique consists in calculating, for each point to be estimated, the average of the experimental values of its neighbors, favoring the closest points. The weighting factors are therefore calculated proportionally to the inverse of the distance (Lu and Wong, 2008). The general formula is expressed as follows (equitation 2):

$$\bar{Z}_{(s0)} = \sum_{i=1}^{n} \lambda_i Z_{(si)} \quad .. (2)$$

With :

$\bar{Z}_{(s0)}$: The estimated value of Z in S_0

λ_i : The weight of $Z_{(si)}$

n : The number of measurements used for the estimate

Then the weights are calculated as follows (equitation 3):

$$\lambda_i = \left(\frac{1}{d_i^P}\right) / \left(\sum_{i=1}^{n} \frac{1}{d_i^P}\right) \quad .. (3)$$

Where d_i is the distance between S_0 and Si, with P being a power parameter.

From the mathematical expression of this method, it is clear that the main parameter that defines the quality of the results is the power factor (Nalder and Wein, 1998).

Ordinary kriging method

Ordinary kriging is a probabilistic technique most used in geostatistics. It is a linear estimation method guaranteeing the minimum variance. Kriging performs the spatial interpolation of a regionalized variable using statistical adjustments through a semi-variogram that allows evaluating the spatial autocorrelation of the observation points (Dobesch *et al*., 2007). The method, in general, is built in 5 steps: i) exploratory analysis of the data; ii) construction of an experimental variography; iii) elaboration of a variogram model; iv) choice of the interpolation method (ordinary kriging in this case); v) evaluation of the quality of the interpolation by a cross validation. Since, the construction of the variogram is the most important step of a geostatistical study because it is from this that the spatial continuity can be modeled.

The experimental variogram is calculated empirically from the observations of the regionalized variable. This is why by admitting that the semi-variogram function $y(x,h)$ depends only on the translation vector h and not on the point x for the study of the regionalized parameters of precipitation. The formulation to estimate this variogram is (equation 4):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=h}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \quad .. (4)$$

With:

$\gamma(h)$: semivariogram

E: mathematical expectancy.

Z(x) : random variable representing z(x)

$Z(x_i) - Z(x_i + h)$: two measurements of the studied variable located at any two points distant from the vector h

N(h) : number of pairs of points distant from h, equal to $n(n-1)/2$, n being the number of measurement points of Z.

The experimental variogram allows the estimation of the theoretical variogram for a defined number of distances, ie only point values. Moreover, it does not necessarily respect the theoretical properties of the variogram. The idea is therefore to adjust a classic variographic model presenting the necessary characteristics and defined for a set of elements (Ly *et al*., 2011).

Then, the kriging, allows to provide a better linear estimator, without bias and with a minimum estimation variance (Goovaerts, 2000). In this case we use ordinary kriging because it is the most robust to stationarity errors. For this method, let us suppose that we want to estimate a block v centered at the point xi. Let us note Zv the true (unknown) value of this block and Zv the estimator that we obtain (equation 5).

$$Z_V^* = \sum_{i=1}^{n} \lambda_i Z_i \quad .. (5)$$

With: λ_i: is the weight to be assigned to the data $Z(xi)$ for i =1, ..., n. It is the interpolation algorithm that determines the value of the weights.

The Geostatistical Analyst tool of ArcGis 10.4 allowed us to carry out all the steps mentioned above, from adjusting the model to spatial interpolation using ordinary kriging. Table 2 presents the model parameters as well as the statistical criteria for the cross-validation.

Table 2. Variogram model parameters and statistical criteria for cross-validation to develop a maximum precipitation map

Parameter	Variogram model parameters				Statistical parameters of the cross-validation			
	Model	Nugget effect (m^2)	Sill (m^2)	Range (m)	Mean Standardized Error	Root	Average meansquare error	Standard Error
Expression	Gaussian : y(h)=[1–exp(–3(h/a)^2]	C0	σ1	a	$\frac{1}{N}\sum_N \frac{(Z^* - Z)}{\sigma}$		$\sqrt{\frac{1}{N}\sum_N (Z^* - Z)^2}$	$\sqrt{\frac{1}{N}\sum_N \sigma^2}$
Results	-	9.48	150.1	140943	0.106	4.02	6.56	

Explanation: *N*: number of samples; *Z*: real value of the variable; *Z**: estimated value of the variable; σ : The standard deviation

Table 3. Regression model for the annual maximum total precipitations over 4 consecutive days for a 10-year return period

Source	Regression coefficient	Standard error	t	Pr > ǀtǀ	Terminal	Source
Z	0,2324	0,0057	1,3516	0,2344	0,0196	0,0677
Y	0,9595	3,8933	1,5155	0,0729	-2,2208	14,0219
d_ocean	-0,4424	0,00004	-2,2654	< 0,0001	-0,0008	-0,0006
Model parameters	Value			Model expression (Eq. 7)		
R^2	0,9650					
R^2 adjusted	0,9439					
MSE	5,0576	Pdmax_10 yrs= -738,247 + 0,0076*Z + 26,7208*Y - 0,0001*d_ocean				
RMSE	2,2489					
F	45,8898					
Pr > F	< 0,0005					

Explanations: Z- elevation of station, X- Longitude, Y- Latitude, d_ocean- Proximity to the ocean Atlantic, Pdmax_10 yrs- Annual maximum total precipitations over 4 consecutive days for a 10-year return period, R^2- coefficient of determination, MSE- Mean squared error, RMSE- Root Mean Square Error, F- Fisher test, t- coefficient divided by its standard error, Pr- statistical test

Multiple linear regression method

The multiple regression method is a statistical technique that expresses the relationship between several independent variables and the dependent variable. This technique has shown very satisfactory results in rainfall mapping, because it takes into account the factors influencing the spatial distribution of rainfall (elevation, longitude, latitude, distance to the ocean, exposure and slope) (Hay *et al*., 1998; Yun *et al*., 2009). The MLR model consists of finding the relationship between the dependent value (y) and several independent variables (xi), using the following expression (equation 6):

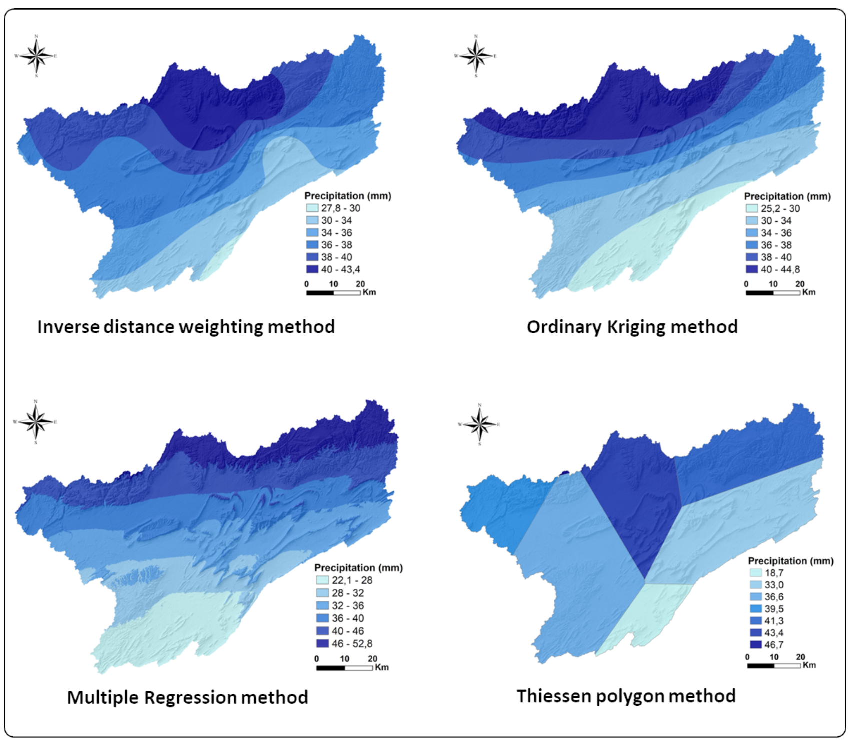

Fig. 4. Maps of total daily maximum precipitation (1990 – 2020) for a return period of 10 years according to the different spatial interpolation methods

$$y = C + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots \beta_k x_k \quad .. (6)$$

Where y: denotes the dependent variable; β_i (i=1,2,...,k) represents a regression coefficient for the independent variables xi (i=1,2,...,k), and C: is a constant of the regression.

In the context of this study area, the testing of a hypothesis that determines, among the parameters mentioned above, those that best explain the spatial variation of precipitation. The explanatory variables are: Station elevation: *Z*; Longitude: *X*; Latitude: *Y* and proximity to the Atlantic Ocean: *d_ocean.*

We present here the modeling of extreme daily rainfall for a return period of 10 years (Pdmax_10yrs). We start by evaluating the correlation between all the parameters, then we apply stepwise regression, using the XLSTAT tool. Table 3 presents the selected model equation and the adjustment parameters (equation 7).

Results and Discussion

Presentation of maximum precipitation maps for the period 1990-2020

The extreme rainfall event was spatially interpolated using the four spatialization methods from data collected by the 09 rain gauges during the period 1990 -2020 in the Assaka watershed (Fig. 4). These maps represent extreme daily rainfall for a return period of 10 years. Indeed, the spatial distribution of rainfall increases from south to north in the four interpolation methods with a minimum of 18.7 mm and a maximum of 52.8 mm. These results suggest that rainfall in the Assaka watershed is influenced by topography, which also increases from south to north, as well as latitude.

The inverse distance weighting (IDW) method illustrates circles around the measurement points (rain gauge stations), which reflects the fact that this technique depends greatly on the location of the data in relation to the node considered. In addition, the geostatistical interpolation method (ordinary kriging) shows a progressive graduation of precipitation that increases from south to north, which reflects certain "field logic" especially the influence of latitude. Concerning the Thiessen polygon method, we can clearly see the polygonal division of the basin into a number of distinct territories, centered on the measuring stations, this method suggests a total absence of rainfall graduation in space. However, the multiple linear regression method appears to be more representative because it has taken into account micro-scale changes in extreme precipitation.

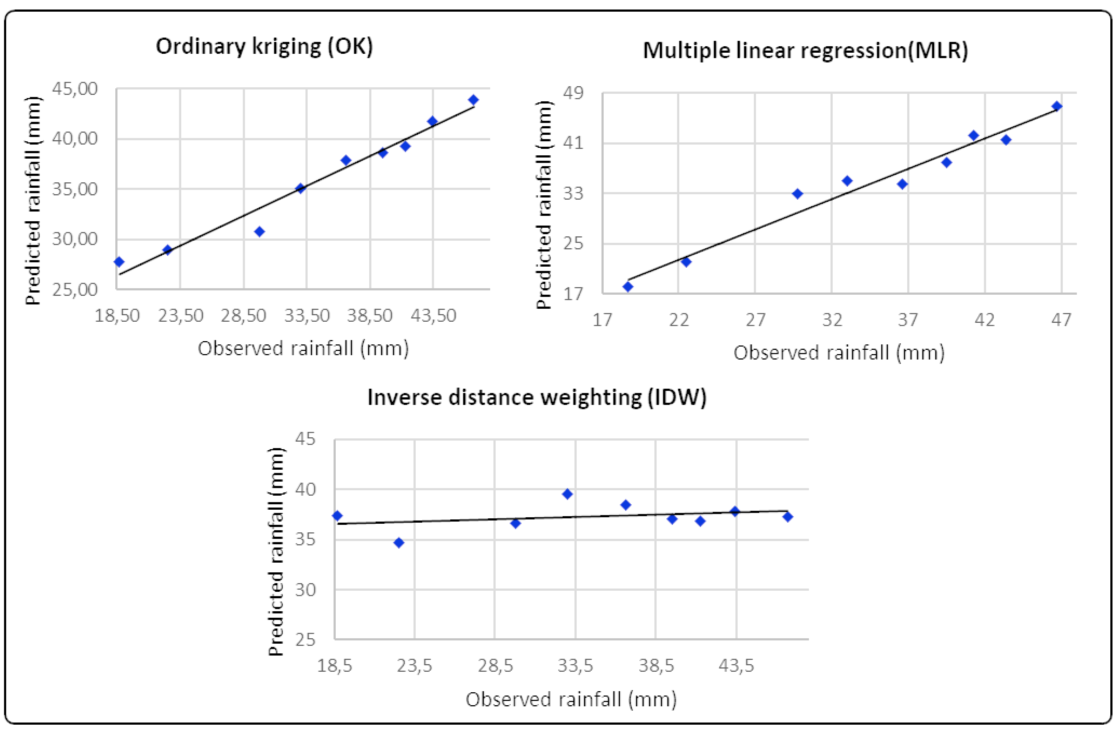

Fig. 5. Diagrams of adjustment of the observed values compared to the predicted values of the maximum daily precipitation for each interpolation method

Table 4. Cross validation performance of different interpolation methods

	Interpolation methods		
	Multiple linear regression	Ordinary kriging	Inverse distance weighting
RMSE	1.67	4.02	9.04
MAE	1.40	3.02	7.55

These are influenced by topography, latitude and distance from the ocean. All of these criteria were considered as independent variables for the multiple regression models to obtain a more accurate spatial distribution of precipitation.

Evaluation of Spatial Interpolation Methods (cross validation)

In order to evaluate the performance of the interpolation methods used in this study, cross-validation is the best known method. The latter consists in making a comparison between the observed values (rainfall stations) and the predicted values. The principle of this method is based on the fact of predicting at each known point the value from the neighbouring points, in order to calculate for all the observation points the errors between the predicted and observed values. The global evaluation of the performance of the interpolator is estimated by means of several statistical performance drivers. In this case we use two indicators, namely the root mean square error (RMSE) and mean absolute error (MAE). Their mathematical expressions are (equations 8 and 9).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Z^{*} - Z)^{2}} \quad .. (8)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|Z^{*} - Z| \quad .. (9)$$

With: N: number of samples; Z: actual value of the variable; Z^*: estimated value of the variable

The calculation of the statistical performance indicators for the three interpolation methods is as follows (Table 4).

The comparative analysis of the selected interpolation methods, both by visual analysis in Figure 4 and by cross-validation in Table 4, shows that not all models produce satisfactory estimates. This finding may be related to the low density of the rain gauge network in the area. For the Thiessen polygon method, its performance cannot be evaluated by the statistical indicators mentioned above, because this geometric method is based only on the distribution of stations, in order to assign a precipitation equal to that of the nearest gauge by drawing up influence polygons. The overall picture of this technique is far from being representative of reality. However, cross-validation showed that the MLR method performed better than the other two methods (RMSE=1.67 mm and MEA =1.40 mm), because this technique incorporates the relationship between precipitation and geographical site factors. In second place we find the O.K method, with a performance indication slightly lower than that of the MLR method (RMSE=4.02 mm and MEA =3.02mm). In addition, the deterministic IDW method still shows a lower representation quality in this study (RMSE=9.04 mm and MEA =7.55mm).

Another way to visualize certain trends between observed and predicted daily maximum precipitation, for the last three spatial interpolation methods (Fig. 5). This technique also illustrates that the MLR method and the O.K method show a strong linear correlation between predicted and observed precipitation, while the IDW method shows almost no correlation.

Conclusion

The fundamental interest of this work was to find the best method to spatialize the maximum daily rainfall in the Assaka watershed. The results showed that the extreme rainfall regime at the level of this study area is strongly influenced by the geographical factors of the site (Mountain, latitude and distance from the Atlantic Ocean). Indeed, the MLR statistical modeling method showed a better spatial prediction of extreme rainfall with a very low number of rainfall stations, which confirms that the secondary variables that condition the formation of rainfall have a great advantage in improving the results. these latter are considered encouraging for use in land use planning (water resources management, agriculture, environment), prevention and management of extreme events (floods, landslides, water erosion ...) which are based mainly on accurate precipitation mapping.

In this context this work must be considered as the first step of an interesting research perspective towards an improvement of the results, by integrating the data of the radar satellite imagery and their coupling with the ground measurements.

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