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Evaluation of the Spatial Distribution of the Annual Extreme Precipitation Using Kriging and Co-Kriging Methods in Algeria Country

Hicham Salhi

Abstract

In this chapter, we have conducted a statistical study of the annual extreme precipitation (AMP) for 856 grid cells and during the period of 1979–2012 in Algeria. In the first step, we compared graphically the forecasts of the three parameters of the generalized extreme value (GEV) distribution (location, scale and shape) which are estimated by the Spherical model. We used the Cross validation method to compare the two methods kriging and Co-kriging, based on the based on some statistical indicators such as Mean Errors (ME), Root Mean Square Errors (RMSE) and Squared Deviation Ratio (MSDR). The Kriging forecast error map shows low errors expected near the stations, while co-Kriging gives the lowest errors on average at the national level, which means that the method of co-Kriging is the best. From the results of the return periods, we calculate that after 50 years the estimated of the annual extreme precipitation will exceed the maximum AMP is observed in the 33-year.

Keywords: extreme precipitations, kriging and Co-kriging, cross validation, return levels

1. Introduction

Natural disasters cause loss of human life and damage to infrastructure every year throughout the world. In Algeria, extreme rains are the source of flooding which can cause catastrophic damage both in inhabited areas and in the countryside.

One of the basic problems encountered in meteorology is the need to assess the meteorology risk caused by extreme precipitation in order to avoid human and material losses. Thus, the location and severity of floods can be determined.

In the twenties to the middle of the last century, the theory of extreme values has witnessed a remarkable development [1–3] most studies focused on the monthly or yearly mean values and we find their application in many fields like; rainfall in Algeria [4, 5], extreme precipitations in Argentina [6] Mapping snow depth return levels [7], precipitation and temperature [8, 9].

On the other hand, a lot of studies say there is a great spatial difference in rainfall [10] for this reason it was used interpolation methods, the kriging method is considered as the most used for spatial interpolation of rainfall [11–13], the kriging method has a special feature which is complementing the sparsely sampled primary variable, in the case of secondary variable there is another method called cokriging that outperforms the kriging method [14].

According to [15] In order to examine the spatiotemporal variations of meteorological variables there is a statistical method that allows to apply multiple strategies by cluster analysis to pinpoint the similar places, local and universal meteorology techniques which has been raising lately.

Our goal in this chapter is to compare the two methods kriging and co-kriging using the GEV and determine the location and severity of floods in all regions of Algeria.

2. Methodology and data

2.1 Generalized extreme value distribution

The cumulative distribution function is proposed by [16].

$$F(x) = \begin{cases} \exp \left\{ - \left[1 + \xi \left(\frac{x-\mu}{\sigma} \right) \right]^{-\frac{1}{\xi}} \right\} & \xi \neq 0 \\ \exp \left(- \exp \left(- \frac{x-\mu}{\sigma} \right) \right) & \xi = 0 \end{cases} \quad (1)$$

By deriving the Eq. (1) we get the density function

$$f(x) = \begin{cases} \frac{1}{\sigma} \left[1 + \xi \left(\frac{x-\mu}{\sigma} \right) \right]^{-\frac{1-\xi}{\sigma}} \exp \left\{ - \left[1 + \xi \left(\frac{x-\mu}{\sigma} \right) \right]^{-\frac{1}{\xi}} \right\} & \xi \neq 0 \\ \frac{1}{\sigma} \exp \left(- \left(\frac{x-\mu}{\sigma} + \exp \left(- \frac{x-\mu}{\sigma} \right) \right) \right) & \xi = 0 \end{cases} \quad (2)$$

The logarithm of the likelihood function is given by:

For $\xi \neq 0$

$$l(\xi, \mu, \sigma, Y) = -n \ln \sigma - \left(1 + \frac{1}{\xi} \right) \sum_{n=1}^n \ln \left(1 + \xi \left(\frac{x_i - \mu}{\sigma} \right) \right) - \sum_{i=1}^n \left[1 + \xi \left(\frac{x_i - \mu}{\sigma} \right) \right]^{-\frac{1}{\xi}} \quad (3)$$

For $\xi = 0$

$$l(\xi, \mu, \sigma, Y) = -n \ln \sigma - \sum_{n=1}^n \exp \left(- \frac{x_i - \mu}{\sigma} \right) - \sum_{i=1}^n \left(\frac{x_i - \mu}{\sigma} \right) \quad (4)$$

3 and 4 with differentiating the two parameters:

$$\begin{cases} n - \sum_{n=1}^n \exp \left(- \frac{x_i - \mu}{\sigma} \right) = 0 \\ n + \sum_{n=1}^n \frac{x_i - \mu}{\sigma} \left[\exp \left(- \frac{x_i - \mu}{\sigma} \right) - 1 \right] = 0 \end{cases} \quad (5)$$

2.2 Return period

The return period, also known as a recurrence interval is the estimated average time between events such as earthquakes, floods, landslides, or river floods. From Eq. (1) we can write the return level as following:

$$Z_T = \begin{cases} \mu + \frac{\sigma}{\xi} \left\{ 1 - \ln \left[1 - \frac{1}{T} \right]^\xi \right\} & \xi \neq 0 \\ \mu - \sigma \ln \left(-\ln \left(1 - \frac{1}{T} \right) \right) & \xi = 0 \end{cases} \quad (6)$$

2.3 Variogram model

Various parameter variogram models have been used in the literature. Here is some of the most popular content.

Spherical model.

The Spherical model has linear behavior at small separation distances near the origin, but flattens at large distances, which means that it shows a gradual decrease in spatial dependence until a certain distance beyond which the spatial dependence tends to smooth.

$$\gamma(h) = c_0 + c_1 \left(\frac{3}{2} \frac{h}{\alpha} - \frac{1}{2} \left(\frac{h}{\alpha} \right)^3 \right) \text{ for } 0 < h \leq \alpha$$

$$\gamma(h) = c_0 + c_1 \text{ for } h \geq \alpha$$

Where c_0 is the nugget effect. The sill is $c_0 + c_1$. The range for the spherical model can be computed by setting $g(h) = 0.95(c_0 + c_1)$.

Gaussian model.

The Gaussian model is used when the data exhibits strong continuity at short lag distances which means the spatial correlation is very high between two neighboring points.

$\gamma(h) = c_0 + c_1 \left(1 - e^{-(h/\alpha)^2} \right)$ where c_0 is the nugget effect. $c_0 + c_1$ is the sill. The range is 3α . This model describes a random field that is considered to be too smooth and possesses the peculiar property that $Z(s)$ can be predicted without error for any s on the plane.

2.4 Data description

The precipitation data used in this study are for the National centers for environmental information NOAA of USA, this data used especially in cases where surface data are difficult to obtain or insufficient. Our data represented by the annual daily maximal of rainfall from 1979 to 2012 calculated in the 856 Algerian stations (**Figure 1**).

The preliminary analysis of the annual maximum precipitation data during the analysis period (1979–2012) included descriptive statistical calculations (**Table 1** and **Figure 2**). More precisely, we calculated the minimum (Min), the maximum (Max), the mean (Mean), the standard deviation (std.dev) and the coefficient of variation (coef.var). **Table 1** presents the values of the descriptive statistics for the annual time series of maximum precipitation for all stations (from 1979 to 2012). The results show that the maximum values is observed in the years 1982, 1992,

Figure 1.
A map of Algeria showing rainfall stations.

Years	Min	Max	Mean	std.dev	coef.var	Years	Min	Max	Mean	std.dev	coef.var
1979	0.59	88.07	13.46	11.23	0.83	1996	2.93	69.38	13.75	9.39	0.68
1980	1.34	63.85	12.88	11.89	0.92	1997	1.27	63.63	10.84	8.89	0.82
1981	0.84	79.32	9.94	8.88	0.89	1998	0.31	57.40	7.76	8.49	1.09
1982	2.92	123.29	21.36	18.15	0.85	1999	0.19	63.48	14.83	11.01	0.74
1983	4.42	57.48	9.70	7.67	0.79	2000	0.79	81.39	14.14	12.62	0.89
1984	0.21	99.47	7.93	11.09	1.40	2001	0.09	114.35	8.28	10.07	1.22
1985	0.30	83.26	10.09	9.33	0.93	2002	0.66	96.94	12.15	11.07	0.91
1986	2.94	73.87	15.58	11.74	0.75	2003	0.33	84.54	13.69	11.56	0.84
1987	0.82	57.32	8.91	7.43	0.83	2004	0.06	97.24	16.44	16.40	1.00
1988	1.73	52.89	12.16	8.71	0.72	2005	0.90	74.47	18.05	16.24	0.90
1989	0.00	73.35	8.77	9.91	1.13	2006	0.97	115.19	13.49	12.92	0.96
1990	0.95	79.25	14.23	10.69	0.75	2007	0.07	109.16	15.58	15.61	1.00
1991	1.99	57.57	12.51	11.16	0.89	2008	1.92	70.72	15.00	12.09	0.81
1992	1.50	121.05	14.14	16.85	1.19	2009	1.21	97.77	15.28	11.73	0.77
1993	0.39	62.82	11.46	10.77	0.94	2010	1.50	63.11	10.69	9.16	0.86
1994	1.43	123.59	15.24	14.77	0.97	2011	2.93	67.68	14.34	12.03	0.84
1995	0.86	83.47	11.70	9.72	0.83	2012	1.89	91.72	13.50	13.28	0.98

Table 1.
Statistical descriptive of all years.

1994, 2001, 2006, and 2007, while the mean and highest values are observed in 1982 (Figure 2). The lowest value of coef.var. is for the year 1996 (68%), and the highest for 1984 (14%). On this basis, the observed data showed that all years had a coef. var. greater than 68%, highlighting the high variability of annual maximum precipitation over Algeria.

Figure 2.
Boxplots of annual extreme precipitation.

3. Results and discussions

3.1 Trend in annual maximum precipitation

In this study, the Mann-Kendall non parametric test is computed to characterize the time course of annual maximum precipitation at the national scale. The trend is considered significant if the value of the probability (p -value) is greater than 0.05 (95%). The **Figure 3** shows the distribution of the significance trend (red color) and non-significant trend (blue color). From the results, we can observe that 130 (15%)

Figure 3.
The spatial distribution of the annual maximum precipitation trend in Algeria country.

Years	Min	Max	Mean	std.dev
5.88	123.59	37.00	22.46	0.61

Table 2.
Statistical descriptive of AMP_{max}.

stations have a significant trends and most of them are positive (97% of the total stations) at the national scale.

The maximum value of the annual maximum precipitation (AMPmax) for each station is calculated and presented in **Table 2**. From the **Table 2**, we can see that the mean value of AMPmax is 22.46 mm and 47% of the total stations with values greater than the mean of AMPmax. The coefficient of variation is 61%, indicating the significant spatial distribution of AMPmax at the national scale. Therefore, we applied a Kriging and Co-kriging approaches to better understanding the spatial distribution of the annual maximum precipitation in Algeria country.

In this study, we have 865 selected grids and 9496 predicted grids have locations where spaced every 20 m in the East and North grid directions and covered the irregularly shaped of the country (**Figure 4**). Due to the large numerical range of AMPmax values and to allow easy interpretation of the results, we worked with the logarithmic transformation of the variable. In this application, we chosen a base 10 logarithms (log10) for the data and we randomly selected control and test datasets. In this study, 30% of the total grids were excluded for testing (assessment).

3.2 Choosing the variogram model

We start by plotting the experimental variogram before adjusting the latter with the different models. The sum of the square errors (SS_{Err}) and the regression coefficient (R²) provided an accurate measure of the fit of the model to the variogram data, with a lower SS_{Err} and a higher R² indicating better fit of the model.

Figure 4.
The spatial distribution of the prediction grid.

Model	Range	Nugget (C0)	Sill (C0 + C)	Nugget/Sill ((C0/C0 + C)*100)	SSErr	R ²
Spherical	1075.984	0.02806	0.11425	24.56	2.26E-05	0.9890
Gaussian	412.298	0.03665	0.10436	35.12	2.28E-05	0.9888

Table 3.
The parameters of each model.

The values of the parameters of the different fitted models are presented in **Table 3**.

Theoretical and empirical semi-variogram were prepared for the AMPmax as shown in **Figure 5**. From the results, we can see that the spherical model has been found to be the most accurate model for annual maximum precipitation.

The spatial dependence is generally accessible in terms of the ratio between the nugget (C0) and the sill (C0 + C) expressed as a percentage. The AMPmax is considered to be a strong spatial dependence when the ratio value is less than 25%, moderate spatial dependence when this value is between 25% and 75%, and low spatial dependence when the value is greater than 75%. From **Table 3**, we can clearly see that the spatial dependence of AMPmax for the best-fitting semi-variogram model is strong and with a ratio of 24.56%.

3.3 AMPmax interpolation

The Spherical model is used to interpolate the AMPmax for both Kriging and co-Kriging methods at the national scale. In the first step, we compared graphically the forecasted and estimated GEV parameters (μ , σ and ξ). From **Figure 6**, we can see that a very clear spatial pattern for the estimates of the location and scale parameters however an absence of the spatial pattern for the shape parameter. The north-ern region is very marked compared to the rest of the regions with a significantly

Figure 5.
Empirical semivariance and its fitted model.

Figure 6.
The spatial distribution of the forecasts of the GEV parameters for the two methods.

higher value of the location and scale parameters. On the other hand, the co-Kriging method clearly provided new regions where the values are high. Generally, the high values could be observed in northern Algeria.

In order to compare the two methods Kriging and Co-Kriging, we used Cross Validation method and some statistical indicators such as Mean Errors (ME), Root Mean Square Errors (RMSE) and Squared Deviation Ratio (MSDR) **Table 4**.

Figure 7 display a bubble plots of the cross-evaluation error of the two methods, where positive values are drawn in green and negative values are drawn in red, and the size of the bubble is proportional to the distance from zero.

From **Table 4** and **Figure 7**, we can clearly notice that the Kriging forecast error map with the three parameters of the GEV distribution shows low errors expected near the stations, while co-Kriging gives the lowest errors on average at the national scale, especially for the shape parameter.

After the validation of the two methods, Co-kriging method used to estimate the return levels (RLs) of the annual maximum of daily precipitations for the different stations using Eq. (6).

The return periods are shown in **Table 5** for the 20, 50, and 100-year. The results show that the maximum annual maximum precipitation observed in 1982,

	M	Σ	ξ	M	σ	ξ
Min	-0.11691	-0.23323	-2.71689	-0.41537	-0.37368	-2.52461
Max	0.15085	0.19637	0.97323	0.70063	0.72695	0.98770
Mean	0.00013	-0.00011	0.00098	0.00105	0.00082	0.00224
ME	0.00013	-0.00011	0.00098	0.00105	0.00082	0.00224
RMSE	0.02421	0.04819	0.37981	0.07523	0.08761	0.39080
MSDR	0.08987	0.38275	1.91038	0.92698	1.08895	1.70011
	Kriging			Co-Kriging		

Table 4.
Cross-evaluation errors for the two methods.

Figure 7.
The spatial distribution of cross-evaluation errors for the three parameters of the GEV law by the two methods.

1992, 1994, 2001, 2006, and 2007 exceeds the 20-year regression level. AMP exceeding the maximum AMP during the observation period (123.59) begins to appear in the confidence interval of 50 year.

	Min	Max	Mean	std.dev	coef.var
20 years	5.6697	106.8175	28.7420	17.8361	0.6205
50 years	5.7920	252.1116	40.0470	30.8470	0.7703
100 years	5.8421	493.1154	52.2700	52.0110	0.9950

Table 5.
Statistical descriptive of the return periods.

Figure 8.
Spatial representation of return periods (co-kriging method).

Figure 8 shows the results for the three cases RLs considered, in the first and second cases (20 years and 50 years), we notice roughly the same results, although there are some remarks that need to be made. In 50-year RLs, there is an increase in the eastern part, far south and in the center of Algeria. Otherwise in 100-year RLs, we noticed a great difference, especially in the eastern region, in the far southern the state of Tamanrasset, the western region in the state of Tindouf, and in The Middle of the desert the Adrar region.

4. Conclusion

In the current research, we studied the spatial analysis of rainfall data in 856 grid cells during the analysis period (1979–2012). The main conclusions form this study can be summarized as follows:

- We marked that the spherical model was found to be the most accurate model for annual maximum precipitation at the national scale.
- We can clearly see that the Kriging forecast error map shows low errors expected near the stations, while co-Kriging gives the lowest errors on average at the national level, which means that the method of co-Kriging is the best.
- Return levels were estimated for several return time periods. For the return level estimated from the GEV distribution, the point estimate that exceeds the return level of all previous maximum AMP records begins to appear in the 50-year regression period.

Acknowledgements

The author grateful to professor Lazhar Belkhiri for helpful.

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