Evaluation of space-time dynamics in extreme precipitation frequency using geostatistical cosimulation with elevation

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Abstract: This study evaluates local dynamics in extreme precipitation frequency from 1940 to 1999 in the South of Portugal. The analysis is based on a climate index defined by the annual count of days with precipitation above the 30 mm threshold (R30mm). The space-time scenarios of this index, and their uncertainty evaluation, were produced through direct sequential cosimulation (coDSS) with elevation. The methodology incorporates space-time models that follow the premises that elevation and precipitation extremes may interact differently both in time and space. The results indicate that the relationship between elevation and the R30mm index has decreased through time over the study region, especially in the southeast area. Furthermore, the spatial patterns of the extreme precipitation index have become more homogenous during the last decades of the twentieth century. The more frequent heavy rainfall events occur in the mountainous areas of the South, which are desertification prone areas at risk of water erosion and floods. As expected, the space-time scenarios have greater spatial variability at regions less densely sampled. However, the uncertainty in mountainous regions is noticeably small given that elevation was used as secondary exhaustive information. The coDSS proved to be a valuable tool to deepen the knowledge on the local dynamics of the extreme precipitation frequency.

Key-Words: Climate dynamics; direct sequential cosimulation; geostatistics; precipitation indices; space-time patterns; stochastic simulation; uncertainty; local trends.

1 Introduction

The precipitation regime in southern Portugal is Mediterranean, thus highly variable in both the spatial and temporal dimensions. It is characterized by scarce rainfall, little runoff and water availability [1], frequent drought periods, and intense flood peaks. The most southern region (Algarve) is the one where episodes of heavy precipitation are most frequent and exhibit the strongest torrential character [2], [3]. Moreover, the South of the country has extensive areas highly vulnerable to desertification [4].

Climate has an important role on desertification processes through its impacts on dryland soils and vegetation. During wetter periods, high intensity rainfall is the most important contributor to erosion in drylands [5]. Therefore, research on the spacetime patterns of heavy rainfall events is an important contribution to evaluate desertification dynamics and to identify areas potentially at risk from land degradation. However, studies focusing on the role of regional climate changing on erosive factors are lacking for Portugal, especially at the local scale [4], [6].

In mountainous regions, physiographic features responsible for considerable spatial are heterogeneity of the precipitation distribution at the local scale. [7] and [8] verified that, in general, no more than four morpho-topographic parameters are necessary to reach a good explanation of the spatial variability of rainfall fields in complex mountainous terrain. According to [9], the main physiographic features affecting spatial patterns of climate are terrain (i.e., orography) and water bodies. [10] investigated the contribution of many physiographic features to the prediction of precipitation fields in continental Portugal, including: elevation, slope, dominant orientation of the hillsides, counting of blockages to the advance of the air masses, shortest distance to the coastline, and distance to the coastline measured according to the W, NW and SW directions. [10] concluded that elevation was the most important variable to explain the variability of precipitation fields when analyzed on restricted neighbourhoods, whereas the remaining attributes had low correlations with the precipitation variables.

The relationship between elevation and precipitation is complex and highly variable in space. Nevertheless, in general, precipitation increases with elevation, mainly because of the orographic effect of mountainous terrain [7], [11], [12]. On the windward side, forced lifting of approaching air masses causes the release of rainfall and an increase in precipitation with elevation.

Depending on the mountain size and the efficiency of the release processes, precipitation will decrease on the leeward side, hence the leeward slopes are drier and warmer (Föhn effect) than windward slopes. Moreover, it has also been noticed that the correlation between elevation and precipitation is stronger for averaged elevation over a larger area (usually a window with square shape) surrounding the observation point, than the effective elevation [7], [13], [14]. On the other hand, the correlation between elevation and precipitation decreases with increasing time resolution, thus it is less useful for estimation purposes [15], [16], [17].

Interpolation of climate data making use of physiographic information has been a subject of much research in hydrologic and climatic studies. In mountainous areas, interpolation techniques that make use of explanatory physiographic variables (e.g., elevation or distance to the coastline) have the potential to better represent the actual climate spatial patterns [7], [9]. Areas of great topographic complexity and regions with contrasting atmospheric or oceanic influences present more problems than flatter areas or regions with constant atmospheric patterns [18]. Interpolation methods performance depends strongly on the region, the variable under study, the data's spatial configuration and density, etc. Consequently, the superiority of a particular interpolation method is difficult to establish, since an interpolation method may be the 'best' for some specific situation and not for others [19], [20]. For example, [16] mapped monthly precipitation for 1999, in Great Britain, using five interpolation schemes and concluded that kriging using elevation as external drift provided the most accurate estimates from March to December. whereas for January and February ordinary kriging performed better. Therefore, when elevation was used as a secondary variable, the accuracy of precipitation estimates increased for most months, but the increase of complexity introduced in the estimation method did not payoff in all situations.

There are numerous successful applications of kriging interpolation described in the literature (e.g., [21], [22], [23]). [11] and [24] compared the application of different geostatistical (i.e. kriging) interpolators to precipitation fields in Portugal. [2] and [25] analysed the patterns of precipitation indices in southern regions of Portugal using direct sequential simulation (DSS).

The main objectives of this study are to evaluate the spatial and temporal local dynamics of extreme precipitation frequency from 1940 to 1999, in the South of Portugal, and to provide an uncertainty evaluation of the produced maps. A common approach to understand and assess the rainfall patterns over a region is based on the analysis of changes in climate indices, which are estimated from the empirical distribution of the daily observations [26], [27], [28]. The R30mm index was chosen to characterize the frequency of heavy precipitation events in the South of Portugal for the 1940–1999 period.

Geostatistical simulation methods generate a set of alternative realizations of the spatial distribution of an attribute that allow characterizing the spacetime uncertainty of physical phenomena [2], [25]. Annual scenarios of the R30mm index were produced for the 1940–1999 period using direct sequential cosimulation (coDSS) with elevation. Those scenarios were then used to produce an additional set of maps of indicators summarizing the scenarios' underlying local dynamics and uncertainty.

The methodology is described in Sect. 2, and the study region and data are detailed in Sect. 3. The main results are presented and discussed in Sect. 4, including the relationship between elevation and the R30mm index, the space-time dynamics of the index in 1940–1999, and the uncertainty evaluation of the produced maps. Finally, Sect. 5 states the major conclusions.

2 Methods

Consider the two dimensional problem of estimating a primary variable z at an unsampled location u_0 . Let $\{z(u_{\alpha}), \alpha=1, ..., n\}$ be the set of primary data measured at n locations u_{α} . Most of geostatistics is based on the assumption that each measurement $z(u_{\alpha})$ is a particular realization of the random variable $Z(u_{\alpha})$. Kriging uses a linear combination of neighbouring observations to estimate the unknown value at the unsampled location u_0 . This problem can be expressed in terms of random variables as:

$$\hat{Z}(u_0) = \sum_{\alpha=1}^{n} \lambda_{\alpha} Z(u_{\alpha})$$
(1)

The optimal kriging weights λ_{α} are determined by solving the kriging equations that result from minimizing the estimation variance while ensuring unbiased estimation of $Z(u_0)$ by $\hat{Z}(u_0)$. When developing the kriging equations the model of spatial covariances, or the semivariogram (inverse function of the spatial covariances), is assumed known. Typically, a mathematical semivariogram model is selected from a small set of authorised ones (e.g. exponential) and is fitted to experimental semivariogram which is computed as half the average squared difference between data pairs belonging to a certain angular and distance class:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[Z(x) - Z(x+h) \right]^2$$
(2)

where h is a vector defining the distance and direction.

In transition models (e.g., spherical and exponential), semivariogram functions increase with distance until they reach a maximum, named *sill*, at an approximate distance known as the *range*. The range is the distance h at which the spatial (or temporal) correlation vanishes, i.e. observations separated by a distance larger than the range are spatially (or temporally) independent observations.

Let $\{z(u_{\alpha}, t_i): \alpha=1,...,n; i=1,...,T\}$ be the set of climate data measured at *n* locations u_{α} and in t_i time instants (years). The n monitoring stations do not have to be all informed at the same T time instants (i.e., a number of z-values can be missing). The set of climate observations correspond to outcome values (realizations) of a spatiotemporal random variable Z(u, t) that can take a series of values at any location in space *u* and instant in time *t* according to the sequence of the direct sequential cosimulation (coDSS) algorithm for the joint simulation of different variables is described by [29]. This algorithm uses collocated simple cokriging to estimate local means and variances, incorporating the secondary information and the relationship between secondary and primary variables.

In this study, the coDSS algorithm is applied in order to obtain a set of *m* equally probable realizations of Z(u, t) at all grid nodes and all instants in time: { $z^{s}(u_{\alpha}, t_{i})$: s=1,...,m; α =1,...,N; i=1,...,T}, where N is the total number of grid nodes to be simulated for each instant in time. For a given instant in time t_{0} , the set of *m* simulated values { $z^{s}(u_{0}, t_{0})$: s=1,...,m} defines the local histogram at the location (grid node) u_{0} for that instant. The collocated cokriging was applied with a Markovtype approximation [30] for cross-continuity model.

To reproduce the spatial distribution and uncertainty of a climate index characterizing extreme precipitation frequency, m=100equiprobable simulated realizations were generated through the coDSS algorithm on 800m×800m grids (N=74683), one for each year (T=60).

2.1 Space-time models

For each decade, the coDSS algorithm used a different space-time semivariogram model of the primary variable (R30mm index) and a different correlation model between primary and exhaustive secondary data (elevation), as proposed by [2]. The inferred semivariograms and correlation models are detailed in Sect. 4.

2.1.1 Correlation models

The local correlation models were computed as follows. First, for each decade, local correlations were calculated using a search neighbourhood centred at each station's location. To reproduce the spatial distribution of the relationship between elevation and the R30mm index, the second stage used the *direct sequential simulation* (DSS) algorithm [29] to interpolate the local correlations. In this stage, 50 equiprobable simulated realizations of the local correlations were generated through the DSS algorithm for each decade on 800m×800m grid cells. Finally, the correlation models were determined by computing the mean of the distribution of the 50 simulated values at each grid node, by decade.

2.1.2 Semivariogram models

In this study, we selected exponential models that capture the major spatial features of the climate index within each decade [25]. The spatial variability is assumed identical in all directions (i.e. isotropic) within each decade.

The exponential model approaches the sill (*C*) asymptotically, with *a* representing the practical range (distance at which the semivariance reaches 95% of the sill value):

$$\gamma(\mathbf{h}) = \mathbf{C} \left(\mathbf{l} - \mathbf{e}^{(-3\mathbf{h}/\mathbf{a})} \right) \quad , \quad \mathbf{h} \neq \mathbf{0} \tag{3}$$

2.2 Space-time dynamics

The space-time scenario for a given year t_0 corresponds to the average of the local histograms that were computed for all grid cells u_a :

$$z^{M}(u_{\alpha},t_{0}) = \frac{1}{m} \sum_{s=1}^{m} z^{s}(u_{\alpha},t_{0})$$
, $\alpha = 1,...,N$ (4)

Similarly, the uncertainty of the space-time scenario for a given year t_0 was evaluated by both the standard deviation and the coefficient of variation of the local histograms.

Let { $z^{M}(u_{\alpha}, t_{i})$: $\alpha=1,...,N$; i=1,...,T} be the set of T=60 annual gridded datasets of the climate index (denoted by I_{Z}). At each grid node u_{α} , the probability of exceeding a given value z_{k} was evaluated as the proportion of the *T* estimated values $z^{M}(u_{\alpha}, t_{i})$ that exceed that threshold:

$$P[I_{Z}(u_{\alpha}) \ge z_{k}] \approx \frac{1}{T} \sum_{i=1}^{T} w(u_{\alpha}, t_{i}) , \alpha = 1, ..., N \quad (5)$$

where $w(u_{\alpha}, t_i)$ are indicator data defined as

$$w(u_{\alpha}, t_{i}) = \begin{cases} 1 & \text{if } z^{M}(u_{\alpha}, t_{i}) \ge z_{k} \\ 0 & \text{otherwise} \end{cases}, \qquad (6)$$
$$\alpha = 1, ..., N; \quad i = 1, ..., T$$

The nonparametric yearly trend map is based on the nonparametric estimates of the trend slope magnitude [31], computed at each grid cell u_{α} :

$$b(u_{\alpha}) = Median\left[\frac{z^{M}(u_{\alpha}, t_{j}) - z^{M}(u_{\alpha}, t_{i})}{(t_{j} - t_{i})}\right], \quad (7)$$
$$\forall t_{i} < t_{j}, \quad \alpha = 1, ..., N$$

3 Study region and data

The study region is located in the South of continental Portugal (Fig. 1) and includes the Algarve region, in the far South, and most of the Alentejo region (limited in the North by the Tejo River).

The climate of southern Portugal is characterised by a dry and very hot season, and a very irregular distribution of precipitation over the wet season, as well as over the years, with very intense flood peaks and with frequent drought periods. Whenever the precipitation variability is associated with extreme phenomena, such as intensive rainfall events or drought situations, it may cause soil degradation and vegetation loss that contribute to the desertification of the most vulnerable regions (e.g., [32], [33]). The heaviest and most frequent extreme precipitation events occur in the Algarve region [2], [3]. The Alentejo area, north of Algarve, is mainly an agrosilvo-pastoral region and the most affected by desertification and drought [34].



Fig. 1 – Elevation of the study region in the South of Portugal and stations' locations

For this study, 105 monitoring stations with daily precipitation data were selected (Fig. 1) and each station series data was previously quality controlled and studied for homogeneity [28], [35].

To gain a uniform perspective on observed changes in climate extremes, a core set of standardized indices was defined by the joint CCI/CLIVAR/JCOMM Expert Team on Climate Change-Detection and Indices (ETCCDI,

http://www.clivar.org/organization/etccdi/etccdi.php ; [36], [26]). Among those indices, we selected the R30mm index to evaluate the local dynamics of extreme precipitation frequency in southern Portugal. The R30mm index is defined as the annual count of days with rainfall above the 30 mm threshold.

Elevation data were taken from a digital elevation model with a grid resolution of 20m×20m and resampled to an 800m×800m grid mesh. The topographic variable derived is defined as the elevation of the nearest grid point to the meteorological station location.

4 Results and discussion

4.1 Space-time continuity

The parameters for each exponential semivariogram of the R30mm index, used in the coDSS algorithm, are summarized in Table 1.

In what concerns the temporal component, there are no relevant tendencies. However, the range of the models' spatial component shows a strong increase in the spatial continuity of the frequency of heavy precipitation events on the last two decades. These findings are consistent with the results of [2] for a precipitation index that characterizes the magnitude of extreme precipitation events (named R5D), and the results of [37] for the Simple Daily Intensity Index.

Table 1 – Parameters of the space-time exponential
semivariograms for the R30 index, by decade

Decade	Spatial range (m)	Temporal range (years)	Sill
1940–49	40000	2.5	13.314
1950–59	50000	1.3	8.561
1960–69	65000	1.5	9.981
1970–79	100000	2.5	9.510
1980–89	145000	5.0	13.089
1990–99	160000	4.5	8.984

4.2 Relationship with elevation

The yearly relationships between the extreme precipitation index and elevation were evaluated through Pearson's correlation coefficients (Fig. 2). Elevation was measured by the station's grid point elevation.



Fig. 2 – Regional correlations between the R30mm index and elevation, by year

The correlations are not constant through time, but rather show a negative trend during the study period, although not statistically significant. Because of the sparse coverage of meteorological stations in some areas, especially until the 1970s, the local relationships between elevation and extreme precipitation were assessed by decade. Hence, the coDSS algorithm used a different correlation model between the R30mm index and elevation within each decade.

The estimated correlations between elevation and the R30mm index range from moderately weak (-0.45) to strong (0.86) across the region and along decades. For illustration purposes, only the

correlation models of the 50s, 70s and 90s decades are presented in Fig. 3. The decreasing relationship between R30mm and elevation is evident over the southeast region (Caldeirão mountains).



Fig. 3 – Local correlation models between elevation and R30mm values for the a) 1950s, b) 1970s, and c) 1990s decade

4.3 Local dynamics

For illustration purposes, two scenarios for the frequency of extreme precipitation events are shown in Fig. 4, as well as their uncertainty evaluation measured by the standard deviation. As expected from the space-time continuity analysis, the spatial patterns of extreme precipitation became more homogenous in the last decades of the twentieth century, while the levels of local variability decreased. Only a few stations are located at medium (>400m) and high elevations, thus greater uncertainty would be expected at those regions. However, the uncertainty in the mountainous regions of the South is often small (Fig. 5), because of the use of elevation as secondary exhaustive information in the spatial interpolation procedure.

Using the annual gridded datasets, probability maps of extreme precipitation were computed as described in Sect. 2.2. In order to determine appropriate threshold values, the regional histogram and its basic statistics were calculated using the values from the maps corresponding to the climate normal 1961/90 (Table 2).

Table 2 – Basic statistics of	of the R30mm index		
computed from the maps of 1961–1990			

Basic statistics	Regional values
Mean	4.3
Standard-deviation	2.3
Skewness	1.45
Kurtosis	4.22
Quantiles	
100% Max	23.0
99%	11.4
95%	8.3
90%	7.2
75% Q3	5.4
50% Median	3.8
25% Q1	2.6
10%	1.9
5%	1.5
1%	0.9



Fig. 4 – Scenarios for the R30mm index (top) and their corresponding uncertainty measured by the standard-deviation (bottom) for 1945 (left), and 1985 (right)



Fig. 5 – Probability of the uncertainty of the R30mm index scenarios, measured by the coefficient of variation, to be greater than 50%

The probability map corresponding to the threshold value equal to the median of R30mm (Fig. 6a) shows that the mountainous regions of the South (in Algarve), the northeast area, as well as the west coast have high probability of frequent extreme precipitation. On the other hand, the probability map for the third quartile (Fig. 6b) shows that the more frequent heavy rainfall events occur in the mountainous areas of Algarve.

The trend analysis of the R30mm index, performed by [28], revealed that the linear trend signals of this index were not statistically significant at the majority of stations in this region. In fact, our results for the local linear trends show that there is a pattern of weak trend signals in the extreme precipitation frequency over the study region (Fig. 7). Most of the region exhibits negative trends, while a small area in the northeast has the highest positive linear trends.

[28] also showed that the R30mm index has a cyclic pattern in many stations during the period 1955/1999. Hence, the local linear trends in Fig. 7 should be considered with caution, because the estimates of the linear trend slope might not capture accurately the local trend signal.



Fig. 6 – Probability of the R30 index values to be equal or greater than fixed thresholds



Fig. 7 – Local trends in the R30mm index

The results from [28] on the regional correlation analysis between precipitation indices, based on 15 stations data from 1955 to 1999, showed that the R5D and the R30mm indices were moderately positively correlated with each other. Using the 1940/99 scenarios of the R5D produced by [2] and the R30mm scenarios, a map of local correlations between them was obtained by computing the Pearson's correlation coefficient at each grid cell (Fig. 8). An interesting conclusion from this map is that increasing values of the R5D through time entail increasing values of R30mm in many areas that have low probabilities of extreme precipitation, and vice-versa. For example, many areas in the mountainous regions of Algarve have high probability of extreme precipitation events, but show weak correlations between the frequency of heavy precipitation (R30mm) and the intensity of mediumterm rainfall events (R5D).



Fig. 8 – Local correlations between the R5D and R30mm indices

5 Conclusion

The main objective of this paper is to assess spatialtemporal dynamics in the frequency of heavy precipitation events, in southern Portugal, through the analysis of the local patterns of the R30mm index from 1940 to 1999.

The results indicate that the spatial patterns of the extreme precipitation frequency have become more homogenous during the last decades of the twentieth century. This conclusion is also supported by the evidence that the relationship between elevation and the R30mm index has decreased through time over the study region. This is relevant information for the short- and medium-term management of Portuguese river basins.

The more frequent rainfall events occur in Algarve's mountainous regions, in the South. Accordingly, many areas of Algarve are at risk of water erosion and floods caused by extreme precipitation events.

The probability maps derived from the spacetime scenarios can be useful to identify regions at risk of water erosion caused by extreme precipitation events. A probability map could be combined with a vegetation cover map. This would allow the identification of regions at risk of water erosion corresponding to areas with little vegetation cover and high probability of extreme precipitation events. This could be a valuable improvement of the 'Erosion protection' map used to build the 'Vegetation quality index' used by the National Action Programme to Combat Desertification [38].

Regions where the distribution of precipitation extremes shows greater spatial variability, thus more uncertainty, correspond to regions less densely sampled. However, the uncertainty in mountainous regions is noticeably small given that elevation was used as secondary exhaustive information.

The existence of links between large-scale atmospheric mechanisms and the observed increase in the spatial homogeneity of the extreme precipitation index will be the subject of a future work, in order to obtain a complete understanding of its space-time variability.

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