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DAILY MAXIMUM ANNUAL RAINFALL STATISTICAL REGIONALIZATION IN ANDALUSIA

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ABSTRACT

The annual maximum daily rainfall (Amdr) is an important variable to model the runoff, justifying its study. This work aimed at regionalize the Amdr for the region of Andalusia through the spatialization of parameters of the probability distribution. Daily rainfall data between the years of 2001 and 2015 from 56 meteorological stations in Andalusia were evaluated and adjusted to ten probability distributions, as also the possibility of tendencies in the data was explored. The Gumbel II distribution was the one with better results for 20 of the 56 meteorological stations. Decreasing tendencies in three meteorological stations were verified. The Amdr was estimated for the payback periods of 10, 20, 50, 100 and 1000 years, obtaining average values of 76.76, 90.75, 110.79, 127.69 and 201.23 mm, respectively. Maps with the distribution of the parameters α and β of the Gumbel II distribution for Andalusia were obtained, apart from maps with the Amdr distribution for each payback period.

Keywords: Extreme events, geostatistics, Gumbel II

RESUMEN

La precipitación diaria máxima anual (Pdma) es una variable importante para la modelaje del escorrentía, justificando su estudio. Este trabajo objetivó regionalizar la Pdma para la región de Andalucía mediante la espacialización de parámetros de la distribución de probabilidad. Datos de precipitación diaria entre los años de 2001 a 2015 de 56 estaciones meteorológicas en Andalucía fueran evaluados y ajustados a diez distribuciones de probabilidad, bien como fue explorada la posibilidad de tendencias en las series. La distribución de Gumbel II fue la que presentó mejores ajustes para 20 de las 56 estaciones meteorológicas. Fue verificada tendencia decreciente en tres estaciones meteorológicas. La Pdma fue estimada para los períodos de retorno de 10, 20, 50, 100 e 1000 años, obteniendo valores medios de 76,76; 90,75; 110,79; 127,69 y 201,23 mm, respectivamente. Fueran obtenidos mapas de la distribución de los parámetros α y β de la distribución de Gumbel II para Andalucía, y mapas con la distribución de Pdma para cada período de retorno.

Palabras clave: Eventos extremos, geoestatística, Gumbel II

1. INTRODUCTION

The rainfall is one of the climatic factors that present higher spatiotemporal variability, justifying the study of extreme events of annual maximum daily rainfall

(Amdr) and its distribution in the space and time. The study of these extreme events is one of the main factors when dimensioning urban and rural drainage systems, contour farming and when rectifying waterways, once the Amdr is related to severe damages to the human activities, due to its potential to cause soil saturation, surface runoff and soil erosion (IPCC, 2007; Tammets & Jaagus, 2013).

Past extreme climatic events are studied to estimate the probability of future events to be equal to or greater than past ones, therefore being necessary to estimate its payback periods. Payback period is the average time needed, in years, for an event (Amdr) to be equaled or overcome, in any year (Naghettini & Pinto, 2007).

To estimate Amdr for different payback periods requires a dataset of at least 15 years without gaps, being preferable a dataset of 30 years. Due to the difficulty in obtaining data in certain regions, the geostatistics is used to allow the estimative of extreme events in not monitored areas, through the data from nearby meteorological stations.

Kriging is the generic name adapted by the geostaticians to the family of algorithms of generalized least squares regression (Goovaerts, 1997). The kriging methods use a spatial dependency expressed in the semivariogram between nearby samples to estimate values in any position of the region, without tendency and with a minimum variance, what makes them very good estimators in the study of the spatial distribution of the rainfall (Machado *et al*., 2010).

Many studies have used the quota as an auxiliary variable in the estimative of different main variables, with good results (Brito *et al*., 2010; Viola *et al*., 2010; Di Piazza *et al*., 2011). However, the quantification of its contribution in this aspect, regarding the interpolators still needs to be better determined.

The purpose of this study is the regionalization of the annual maximum daily rainfall (Amdr) in the autonomous community of Andalusia. It also aims to research the contribution of the longitude and latitude and the covariate altitude as auxiliary in the determination of estimatives of the parameters of the chosen probability distribution, allowing the representation, through maps, of the distribution of extreme events for different payback periods.

2. MATERIAL AND METHODS

Andalusia is the second largest autonomous community of Spain in extension, with approximately 87600 km^2, between the longitudes of 07º 31’ W and 01º 38’ W, and between the latitudes of 38º 44’ N and 36º 00’ N. Around 31.42% of the territory has altitude between 0 and 200 m; 39.38% of the territory between 200 and 600 m of altitude; 25.94% between 600 and 1400 m of altitude and 3.27% higher than 1400 m.

According to the Köppen & Geiger (1928) climate classification, the climate Csa prevails in the region of Andalusia, characterized as temperate with hot and dry summer. Except for one area of the province of Almeria that presents a climate BWh (hot desert) and for the region of Sierra Nevada, that presents a climate Dsc (cold with dry and fresh summer).

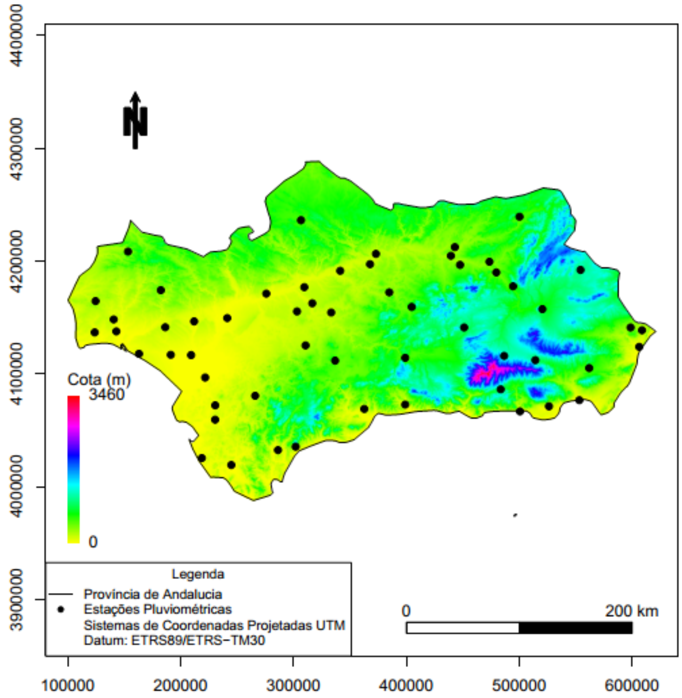

Fig. 1: Digital Model of the Terrain (DMT) and distribution of the meteorological stations studied, in the Andalusia Autonomous Community, Spain

The used dataset is constituted by the annual maximum daily rainfall (Amdr) of 56 meteorological stations (Figure 1 and Table 1), the datasets with an extension of 15 years (from 2001 and 2015, both included).

Based on the Amdr data series, from the respective stations, the data were adjusted to ten probability distributions, as follows: (*i*) Lognormal, (*ii*) Weibull, (*iii*) Gamma, (*iv*) Cauchy, (*v*) Normal, (vi) Logistic, (vii) Birnbaum-Saunders, (*viii*) Gumbell-II, (*ix*) Gumbel and (*x*) Rayleigh generalized. To adjust the parameters of the distributions the maximum likelihood method (ML) and the Akaike Information Criterion (AIC) were used to choose the distribution that better adjusted to the data, through the least AIC value. Therefore, the distribution that presented better adjusts to the Amdr data of most of the meteorological station was chosen to represent all studied region and, thus, the parameters of the chosen distribution were obtained and the Amdr was estimated for the payback periods (T) of 10, 20, 50, 100 and 1000 years.

The geostatistic analysis was performed using the parameters of the distribution that presented better adjust to the Amdr data, aiming at regionalizing the Amdr for the studied area.

Initially, an exploratory analysis of the variables to be interpolated (parameters of the best distribution for most of the stations) was performed, aiming at confirming some presuppositions assumed by the geostatistic model, among them: (*i*) normality, (*ii*) no spatial tendentiousness, and (*iii*) outliers removal.

The parameters of the function of the chosen distribution were analyzed according to the approach of the geostatistics models (Diggle & Ribeiro Junior, 2007). This way, we sought to adjust the model's parameters (Equation 1) by the maximum likelihood method.

$$Y(Xi) = \beta + S(Xi) + \varepsilon i \quad (1)$$

In which, $Y(Xi)$ is the annual maximum daily rainfall in the i line of the matrix of X coordinates; β is the global average of a specific area; $S(Xi)$ is a Gaussian process with a function of a mathematical model with variance parameter σ^2 and reach parameter φ; εi is the random noise normally distributed with average zero and variance τ^2.

Different tendency models were tested, defined by linear and quadratic relations between the covariates X, Y and quota in the location of the meteorological stations.

Station	Pr.	Lat.	Long.	Q (m)	Station	Pr.	Lat.	Long.	Q (m)
1-Adra	AL	36.75	2.99	42	29-Aroche	HU	37.96	6.95	299
2-Almería	AL	36.84	2.40	22	30-El Campillo	HU	37.66	6.60	406
3-Cuevas de Almanzora	AL	37.26	1.80	20	31-El Tojalillo-G	HU	37.32	7.03	52
4-Fiñana	AL	37.16	2.84	971	32-Gibraleón	HU	37.41	7.06	169
5-Huércal-Overa	AL	37.41	1.88	317	33-La Condado	HU	37.37	6.54	192
6-La Mojonera	AL	36.79	2.70	142	34-Guzmán	HU	37.55	7.25	288
7-Tabernas	AL	37.09	2.30	435	35-Lepe	HU	37.30	7.24	74
8-Virgen F.C. Almanzora	AL	37.39	1.77	185	36-Moguer	HU	37.15	6.79	87
9-Basurta-Jerez de la Frontera	CA	36.76	6.02	60	37-Alcaudete	JA	37.58	4.08	645
10-Conil de la Frontera	CA	36.33	6.13	24	38-Chiclana de S.	JA	38.30	3.00	510
11-Jerez de la Frontera	CA	36.64	6.01	32	39-Huesa	JA	37.75	3.06	793
12-Jimena de la Frontera	CA	36.41	5.38	53	40-Linares	JA	38.06	3.65	443
13-Vejer de la Frontera	CA	36.29	5.84	24	41-Mancha Real	JA	37.92	3.60	436
14-Villamartín	CA	36.84	5.62	171	42-San José P.	JA	37.86	3.23	509
15-Adamuz	CO	38.00	4.45	90	43-Torreblasco	JA	37.99	3.69	291
16-Baena	CO	37.69	4.31	334	44-Ubeda	JA	37.94	3.30	358
17-Bélmez	CO	38.25	5.21	523	45-Estepona	MA	36.44	5.21	199
18-Córdoba	CO	37.86	4.80	117	46-Málaga	MA	36.76	4.54	68
19-El Carpio	CO	37.91	4.50	165	47-Sierra Yeguas	MA	37.14	4.84	464
20-Hornachuelos	CO	37.72	5.16	157	48-Veléz-Málaga	MA	36.80	4.13	49
21-Santaella	CO	37.52	4.89	207	49-Aznalcazar	SE	37.15	6.27	4
22-Baza	GR	37.56	2.77	814	50-Ecija	SE	37.59	5.08	125
23-Cadiar	GR	36.92	3.18	950	51-La Luisiana	SE	37.53	5.23	188
24-Iznalloz	GR	37.42	3.55	935	52-La Rinconada	SE	37.46	5.92	37
25-Jerez de Marquesado	GR	37.19	3.15	1212	53-Lebrija I	SE	36.98	6.13	25
26-Loja	GR	37.17	4.14	487	54-Lora del Río	SE	37.66	5.54	68
27-Puebla Don Fradique	GR	37.88	2.38	1110	55-Osuna	SE	37.26	5.13	214
28-Almonte	HU	37.15	6.48	18	56-Sanlúcar M	SE	37.42	6.26	88

Table 1: Location of the studied meteorological stations in the autonomous community of Andalusia, Spain; Pr. – Province; Long. – Longitude; Lat. – Latitude; Q – Quota; AL – Almeria, CA – Cadiz, CO – Cordoba; GR – Granada, HU – Huelva; JA – Jaen; MA – Malaga; SE – Seville.

To adjust the model's parameters the ML (maximum likelihood) method was used. Therefore, the assessment of the performance of each model, with and without spatial factor, in the interpolation of Amdr and of the parameters of the chosen distribution was performed through the AIC method.

Therefore, the best trend withdrawal method was chosen, characterized by the least value of AIC, and thus six models of covariance functions were tested, being them: (*i*) exponential; (*ii*) Gaussian; (*iii*) spherical; (*iv*) circular and; maternal with softness parameters equal to (*v*) 1.5 and (*vi*) 2.5. The evaluation of each model's performance in the estimative of the parameters of the chosen distribution was performed by the AIC.

Considering the geostatistic model's components (Equation 1), the selection of the model according to AIC followed the steps: (*i*) for the βxi component, firstly the S(xi) component was considered constant and then the best tested trend model was chosen; (*ii*) for the S(xi) component, once modeled the βxi component, it was fixed, and thus the best covariance function tested was chosen. After the choice of the model and estimative of its parameters, the ordinary kriging was used to interpolate the studied variables.

The data reading and handling to elaborate the Amdr data series (package hydroTSM – "Hidrologic Time Series Managemet"), as also the adjust of the distribution models (package fitdistrplus – "Parametric Distribution to Non-Censored or Censored Data"), the goodness of fit test (package (ADGofTest), among other calculations regarding statistics, geostatistics (packages geoR, MASS, rgdal and raster), the plots (package RColorBrewer, maptools and SDMTools) and the data series trend analysis (package Kendall) were performed in the statistical open software R Statistical 3.1.2 ® (R CORE TEAM, 2014).

3. RESULTS

The trends of the extreme events for each meteorological station were assessed by the test of Mann-Kendall (Table 2). From the 56 trend values, 36 were negative (a negative value indicates a decreasing trend of Amdr over time) and 20 were positives (increasing trend). However, when the significant values (p-value < 0.05) were considered, it was observed that only three stations presented significant values (emphasized in bold in Table 2), with decreasing trend (negative values). The others, that did not presented statistic significance, are explained by the natural variability of the rainfall. Therefore, world and regional climate changes that could be associated, for example, with the urban heating, did not affect significantly the rainfall records.

In Table 2 it is shown the obtained parameters for the chosen probability distribution for each station, emphasizing that both ten probability distributions were accepted according to the Anderson-Darling goodness of fit test ($p<0.05$). The distributions that presented the best adjusts for most of the Amdr data were Gumbel II (20 stations) and Birnbaum-Saunders (14 stations) The Normal and Cauchy distributions did not presented the best fit for any of the stations. Therefore, the distribution which presented the best fit for most of the Amdr data was the Gumbel II being chosen to represent the whole region of the present study. Thus, the scale (α) and shape (β) parameters of the chosen distribution were obtained for the remaining stations. The chosen distribution was evaluated by the Anderson-Darling test ($p<0.05$); the obtained values for this test were much lower than the critic values, being this distribution considered adequate in the 56 meteorological stations.

Ind.	Trend	Model	Parameter		Payback period (years)					Ind.	Trend	Model	Parameter		Payback period (year)				
			Par1	Par2	10	20	50	100	1000				Par1	Par2	10	20	50	100	1000
1	0.14	Bisa	37.951	0.437	65.54	76.11	89.67	99.74	132.58	29	0.11	Gamma	13.924	0.247	76.25	83.15	91.38	97.15	114.52
2	-0.09	Genray	28.671	1.983	49.34	54.91	61.44	65.93	79.00	30	-0.20	Weibu	3.886	68.189	84.51	90.43	96.86	101.01	112.12
3	0.37	Genray	42.236	1.864	71.94	80.21	89.89	96.55	115.90	31	-0.38	Bisa	53.317	0.302	78.28	87.12	98.11	106.08	131.28
4	-0.25	Gumb2	29.462	2.776	66.26	85.88	120.12	154.47	354.58	32	-0.28	Gumb	12.560	51.951	129.47	166.86	215.27	251.54	371.40
5	-0.18	Lnorm	3.821	0.608	99.58	124.21	159.30	188.04	299.32	33	-0.37	Bisa	52.585	0.263	73.55	80.79	89.69	96.09	116.11
6	0.009	Gumb2	31.518	3.615	58.73	71.67	92.74	112.50	212.96	34	0.11	Bisa	55.949	0.275	79.48	87.67	97.77	105.06	127.93
7	-0.13	Gumb2	30.160	3.021	63.52	80.61	109.72	138.25	296.67	35	-0.32	Bisa	46.937	0.288	67.76	75.07	84.12	90.66	111.29
8	0.12	Gamma	4.601	0.099	75.42	86.79	100.81	110.90	142.42	36	**-0.52**	Bisa	53.418	0.349	83.20	94.06	107.72	117.72	149.76
9	0.12	Bisa	55.095	0.334	84.34	94.91	108.16	117.84	148.73	37	-0.03	Gamma	10.686	0.257	58.44	64.43	71.61	76,67	92.05
10	0.14	Lnorm	3.804	0.599	96.63	120.11	153.43	180.64	285.40	38	0.30	Gumb	8.766	34.453	86.30	111.10	143.20	167.26	246.74
11	0.12	Gumb2	54.729	4.328	92.05	108.70	134.81	158.41	269.94	39	0.10	Gamma	17.232	0.565	40.20	43.50	47.40	50.13	58.29
12	0.12	Gumb	17.023	57.069	145.45	186.53	239.70	279.55	411.21	40	-0.04	Bisa	34.949	0.391	57.40	65.80	76.48	84.36	109.84
13	0.31	Gumb2	49.182	3.775	89.26	108.01	138.25	166.34	306.47	41	0.10	Gamma	12.516	0.348	49.47	54.17	59.80	63.75	75.69
14	-0.05	Gumb2	46.208	4.892	73.20	84.80	102.59	118.32	189.62	42	-0.02	Gamma	9.778	0.326	42.72	47.28	52.77	56.64	68.44
15	-0.04	Genray	51.700	2.320	91.24	101.09	112.65	120.63	143.92	43	-0.09	Weibu	2.929	44.792	59.55	65.14	71.36	75.45	86.65
16	0.009	Gumb2	33.669	3.338	66.07	81.98	108.37	133.59	266.66	44	-0.01	Gumb2	32.408	4.152	55.73	66.28	82.95	98.15	171.09
17	-0.28	Logis	46.127	8.138	64.01	70.09	77.80	83.52	102.33	45	0.20	Gumb2	55.087	3.089	114.15	144.11	194.85	244.27	515.54
18	-0.15	Gumb	14.528	49.397	125.69	161.25	207.27	241.76	355.72	46	-0.21	Gumb2	42.442	2.809	94.57	122.19	170.26	218.30	496.34
19	0.09	Bisa	52.299	0.441	91.39	106.45	125.81	140.20	187.23	47	0.03	Gumb2	38.001	3.056	79.36	100.44	136.24	171.21	364.23
20	0.09	Gumb2	49.119	3.891	87.58	105.38	133.88	160.20	289.83	48	0.01	Weibu	3.277	75.699	97.64	105.80	114.78	120.64	136.52
21	-0.18	Gumb2	39.411	3.850	70.71	85.25	108.59	130.18	237.02	49	**-0.40**	Bisa	51.619	0.421	88.02	101.89	119.63	132.78	175.61
22	-0.78	Gumb	7.727	27.986	70.71	90.85	116.93	136.47	201.03	50	-0.18	Gumb2	37.827	3.378	73.64	91.13	120.07	147.64	292.28
23	0.05	Gumb2	40.556	5.380	61.62	70.44	83.76	95.37	146.44	51	0.13	Lnorm	3.888	0.478	90.12	107.22	130.37	148.51	213.98
24	0.16	Gumb2	38.202	3.149	78.07	98.12	131.91	164.65	342.59	52	**-0.39**	Gumb2	46.355	4.580	75.77	88.66	108.67	126.56	209.45
25	-0.15	Bisa	27.878	0.377	44.99	51.34	59.38	65.30	84.39	53	-0.09	Gumb2	46.031	3.856	82.51	99.44	126.62	151.75	276.04
26	0.24	Gumb2	31.403	4.338	52.75	62.28	77.20	90.68	154.34	54	0.03	Bisa	54.403	0.293	79.06	87.74	98.51	106.31	130.92
27	-0.05	Bisa	32.452	0.339	49.98	56.34	64.32	70.15	88.79	55	-0.29	Gumb2	34.881	3.888	62.22	74.88	95.16	113.88	206.13
28	-0.14	Bisa	50.235	0.446	88.35	103.08	122.02	136.12	182.24	56	-0.35	Weibu	4.815	75.699	64.73	68.37	72.27	74.76	81.32

Table 2: Parameters of the most appropriate distribution models in the determination of the probability of happening the maximum daily rainfall in the Andalusia autonomous community, Spain; Ind. – Identification of the stations; Trend – tendency values (τ); Bold – There is tendency in the data series ($p<0.05$) by the Mann-Kendall's test; Lnorm – Lognormal; Weibu – Weibull; Gamma – Gamma; Cauchy – Cauchy; Norm – Normal; Logis – Logistic; Bisa – Birnbaum-Saunders; Gumb2 – Gumbel-II; Gumb – Gumbel; Genray – generalized Rayleigh

One of the presuppositions of geostatistics is the existence of data normality thus, the Box-Cox family test was performed for the Gumbel II parameters, obtaining values of 0.97 and 0.99. Indicating that the parameters present tendency to a normal distribution.

Twelve types of spatial trend were considered, combining algebraically the longitude, latitude and quota. Among the tested spatial trend models, those who presented greater prediction precision are emphasized in Table 3, as the estimatives of the parameters (τ^2, σ^2 e ϕ).

The circular model considers the trends of latitude with the covariate quota and can be used to estimate β. For the variable α it was not necessary to include the covariance function S(xi), it was adjusted only with the spatial trend of latitude. Representing the best model that explains the spatial variability of the Gumbel II parameters.

The semivariogram range parameter indicates the maximum distance where the sampling points are correlated between them, in other words, the points located in an area which radius is the range parameter are more similar between them than between the ones that are separated by greater distances. The range of 68.63 km for the β parameter shows that all the nearby stations inside this radius can be used in the estimative of values in smaller distances (Table 3).

Variables Y(xi)	Parameters of the spatial trend $\beta(x)$	AIC test		Covariance function S(xi)	Parameters					
					Spatial trend β_n			Covariance S(xi)		Err.
		W/ S(xi)	W/o S(xi)		β_0	β_1	β_2	σ^2	ϕ	τ^2
Scale (α)	$\beta(x) = \beta_0 + \beta_1 x$	355.9	362.6	Circular	54.702	-0.04		24.92	68.63	10
Shape (β)	$\beta(x) = \beta_0 + \beta_1 x + \beta_{2Quota}$	132.8	132.3	Gauss	3.962	-2e-3	9e-4	0.343	14.56	0.2

Table 3: Evaluation of the best models with and without spatial trend and the covariance function for the scale (α) and shape (β) parameters of the Gumbel II distribution; Y(xi) – observed value in the position x; $\beta(x)$ – overall average of a specific area; S(xi) – random factor spatially correlated; AIC – Akaike Information Criterion; τ^2 – error; σ^2 - variance ; ϕ – reach; β_n – spatial trend component

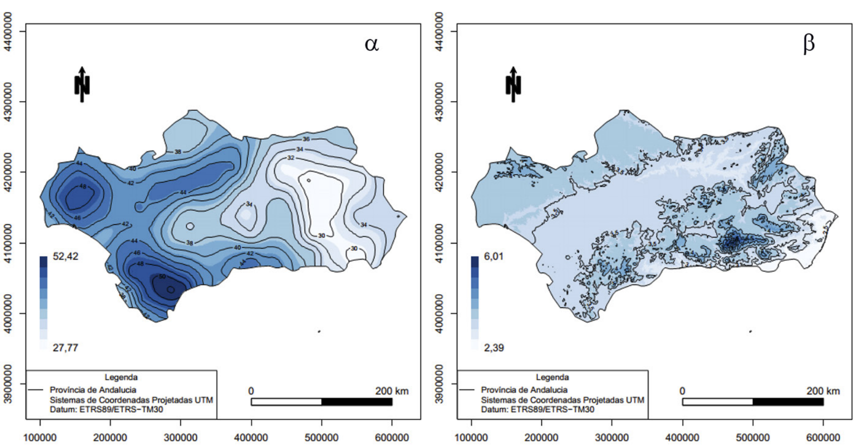

Figure 2: Maps of the scale (α) and shape (β) parameters of the Gumbel II distribution in the Andalusia autonomous community, Spain (2001-2015)

To estimate the Gumbel II parameters not sampled in locations maps of spatial distributions were generated (Figure 2), obtained by the interpolation by kriging method, from the parameters of the models fitted to the semivariograms (Table 3).

From the parameters of the Gumbel II distribution (Table 3) and from the maps of Figure 2, maps for each payback period were obtained (Figure 3).

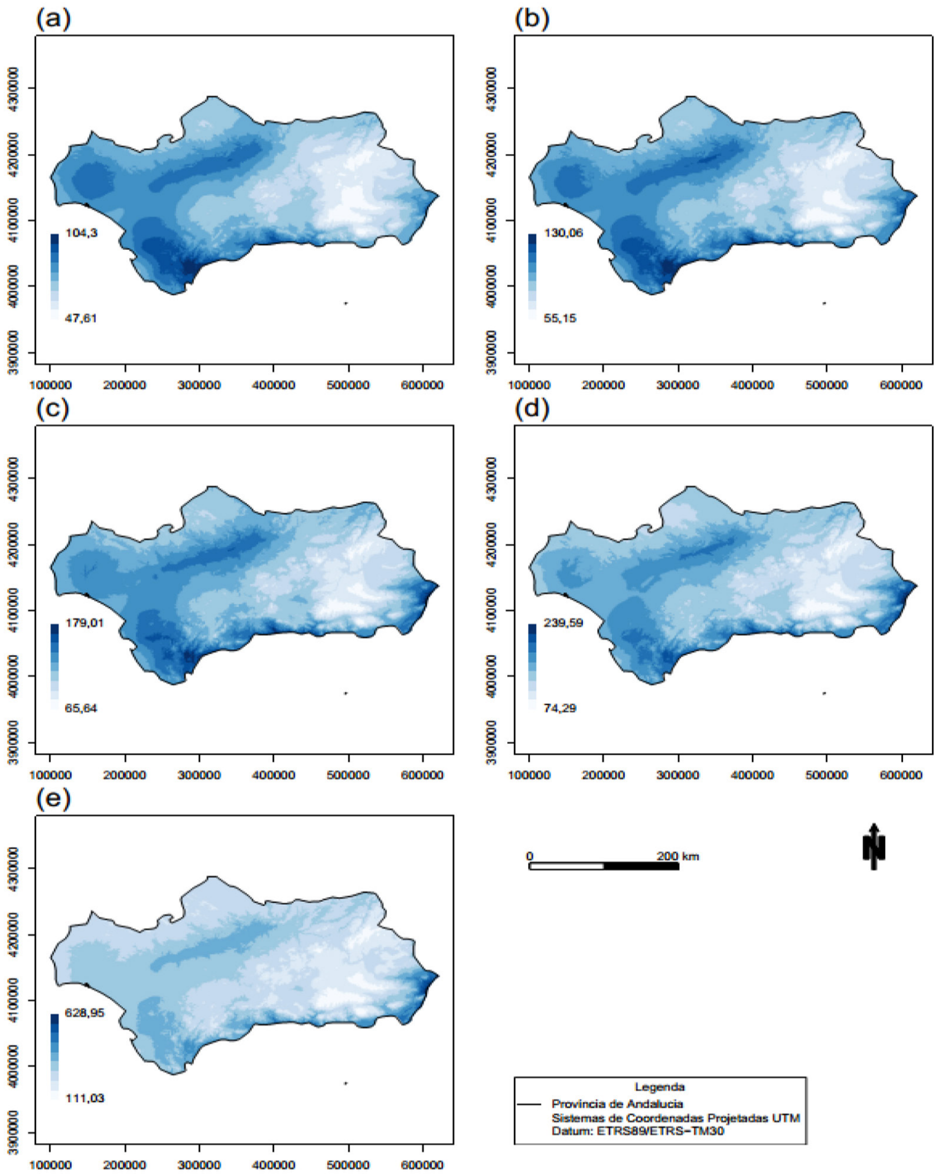

Figure 3: Maps of annual maximum daily rainfall, associated to the payback periods of 10 (a), 20 (b), 50 (c), 100 (d) and 1000 (e) years in the Andalusia autonomous community, Spain

4. DISCUSSION

Regarding the probability distributions that presented higher number of best fits for the meteorological stations, Almeida *et al*. (2014) obtained similar results, when studying the distribution of extreme events of daily rainfall in the state of São Paulo, Brazil. These authors verified that the Gumbel II distribution well represented the rainfall conditions of the region. The Gumbel II distribution is the one that is more frequently used in literature. José *et al*. (2014) obtained spatial distribution for the parameters of Gumbel II distributions associated to Amdr in the southeast region of Brazil.

Concerning the models of a trend, as discussed by Diggle & Ribeiro Junior (2007), it should ideally have a physical natural interpretation. Thus the choice of a simple model that explains most of the spatial variability would be ideal. More complex models are generally more difficult to interpret.

Observing Figure 3, it is possible to verify a trend of elevation of the rainfall in the region of the Guadalquivir Valley (Northeast-Northwest) and in the Mediterranean and Atlantic coasts, comprehending the quotas from 0 to 150 meters. The higher values are in the Mediterranean coast, the Cadiz coastline (Southeast) and the Almeria coastline (Southeast). This trend can be explained by the orographic effect, caused by the orientation of the Sierra de Roda in the Cadiz region and of the Cordillera Penibética in Almeria.

According to Muñoz-Díaz & Rodrigo (2004) this orographic region is influenced by the Atlantic and Mediterranean frontal systems, with a significant gradient of rainfall in the North-South direction.

5. CONCLUSION

The results revealed that the Amdr, associated to its respective payback periods and to the parameters of the Gumbel II distribution, present spatial tendency, from which Amdr maps were generated for the Andalusia autonomous community, Spain.

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