Journal of Iberian Geology **42 (1) 2016:** 113-124
http://dx.doi.org/10.5209/rev_JIGE.2016.v42.n1.49120

www.ucm.es/info/estratig/journal.htm
ISSN (print): 1698-6180. ISSN (online): 1886-7995

Journal of Iberian Geology
AN INTERNATIONAL PUBLICATION OF EARTH SCIENCES

Estimate of the (R)USLE rainfall erosivity factor from monthly precipitation data in mainland Spain

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Received: 14 May 2015 / Accepted: 13 April 2016 / Available online: 30 April 2016

Abstract

Calculation of the rainfall erosivity factor (R-factor) of the (R)USLE model requires continuous recording rain gauges, which may limit its use in areas without good temporal data coverage. In mainland Spain, the Nature Conservation Institute (ICONA) determined the R-factor at few selected pluviographs, so simple estimates of the R-factor are definitely of great interest. The objectives of this study were: (1) to identify a readily available estimate of the R-factor for mainland Spain; (2) to discuss the applicability of a single (global) estimate based on analysis of regional results; (3) to evaluate the effect of record length on estimate precision and accuracy; and (4) to validate an available regression model developed by ICONA. Four estimators based on monthly precipitation were computed at 74 rainfall stations throughout mainland Spain. The regression analysis conducted at a global level clearly showed the modified Fournier index (MFI) ranked first among all assessed indexes. Applicability of this preliminary global model across mainland Spain was evaluated by analyzing regression results obtained at a regional level. It was found that three contiguous regions of Eastern Spain (Catalonia, Valencian Community and Murcia) could have a different rainfall erosivity pattern, so a new regression analysis was conducted by dividing mainland Spain into two areas: Eastern Spain and Plateau-lowland area. A comparative analysis concluded that the bi-areal regression model based on MFI for a 10-year record length provided a simple, precise and accurate estimate of the R-factor in mainland Spain. Finally, validation of the regression model proposed by ICONA showed that R-ICONA index overpredicted the R-factor by approximately 19%.

Keywords: rainfall erosivity, R-factor, Universal Soil Loss Equation, modified Fournier index, soil erosion, Spain

Resumen

La necesidad de disponer de un registro continuo de la precipitación dificulta el cálculo del índice de erosión pluvial (factor R) del modelo (R)USLE en zonas sin un buen registro temporal. En la España peninsular, el Instituto para la Conservación de la Naturaleza (ICONA) determinó el factor R en un reducido número de pluviógrafos, por lo que es de gran interés disponer de una herramienta que permita estimar el factor R de manera sencilla. Los objetivos de este estudio fueron: (1) identificar un estimador del factor R en la España peninsular; (2) discutir la aplicabilidad de un único modelo de estimación global a partir de los resultados obtenidos a nivel regional; (3) analizar el efecto de la longitud del intervalo de cálculo en la precisión y exactitud de las estimaciones; y (4) evaluar el modelo de regresión disponible propuesto por ICONA. Para ello se calcularon cuatro estimadores basados en la precipitación mensual en 74 estaciones pluviométricas repartidas por la geografía peninsular. El análisis de regresión llevado a cabo demostró que el índice de Fournier modificado (MFI) es el mejor estimador. La aplicabilidad del modelo global generado inicialmente se evaluó mediante la comparación con resultados obtenidos a nivel regional. Se observó que tres comunidades autónomas del este peninsular (Cataluña, Comunidad Valenciana y Región de Murcia) presentaban un régimen de precipitaciones diferente al resto de la Península, por lo que se efectuó un nuevo análisis de regresión dividiendo el territorio en dos zonas: zona Este y resto de la península. A partir del estudio comparativo de los resultados, se concluyó que el modelo bizonal basado en el índice de Fournier modificado para un intervalo de 10 años permite obtener, de manera sencilla, una estimación lo suficientemente precisa y exacta del factor R en la España peninsular. Finalmente, se determinó que el modelo disponible propuesto por ICONA tiende a sobreestimar el factor R en aproximadamente un 19%.

Palabras clave: erosión pluvial, factor R, Ecuación Universal de Pérdida de Suelo, índice de Fournier modificado, erosión del suelo, España

1. Introduction

The Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1961, 1965, 1978) and its revised version (RUSLE) (Renard et al., 1991, 1997), commonly referred together as (R)USLE model, constitute a valuable tool for the study of soil erosion. (R)USLE is a simplistic empirical model that predicts long-term average annual soil loss based on six factors associated with rainfall erosivity, soil erodibility, topography (slope length and gradient), vegetation and management. Despite the simplicity of the (R)USLE model, its application is still limited in many regions because of the difficulty in computing the rainfall erosivity factor (R-factor).

The R-factor for a single storm was defined as the product of the total kinetic energy (E) multiplied by the maximum 30-minute rainfall intensity (I_{30}) (Wischmeier, 1959). The R-factor at a particular location is computed as the average of annual $E \cdot I_{30}$ values over long time intervals (over 20 years) to include apparent cyclical rainfall patterns (Wischmeier and Smith, 1978). Although several equations have been proposed for calculating the kinetic energy of a storm (Wischmeier and Smith, 1978; Brown and Foster, 1987), all of them require continuous recording rain gauges with time resolution of at least 15 minutes. This need for continuous recording makes it difficult to obtain the R-factor in some areas. This is the case for Spain, where rainfall data with good temporal coverage are still scarce.

There have been many attempts worldwide to establish correlations between the R-factor calculated by the prescribed method and more readily available rainfall data, such as daily and monthly precipitation (Renard and Freimund, 1994; Yu and Rosewell, 1996; Loureiro and Coutinho, 2001; Yu et al., 2001; Colotti, 2004; Diodato, 2004; Petkovšek and Mikoš, 2004; Diodato and Bellochi, 2007; Salako, 2008; Angulo-Martínez and Beguería, 2009; Bonilla and Vidal, 2011; Lee and Heo, 2011). Nonetheless, most of the obtained equations have limited application outside of the areas in which they were developed without a thorough validation analysis. In Spain, the Nature Conservation Institute (ICONA, 1988) performed a regression analysis that resulted in an isoerodent map and three equations to estimate the R-factor throughout the country. However, previous results reported by Hernando and Romana (2015) in central Spain suggested that the aforementioned equations may overpredict the R-factor.

The objectives of this study were: (1) to identify a readily available estimate of the R-factor for mainland Spain; (2) to discuss the applicability of a single (global) estimate by means of comparison with regional results; (3) to evaluate the effect of record length on estimate precision and accuracy; and (4) to validate the existing regression model developed by ICONA.

2. Material and methods

2.1. Rainfall erosivity estimators

Based on the literature review, four estimators of rainfall erosivity were selected for this study: total annual rainfall (P), Fournier index (Fournier, 1960), modified Fournier index (Arnoldus, 1980) and a regression model proposed by the Spanish Nature Conservation Institute (ICONA, 1988). Other factors such as Hudson's KE>25 index (Hudson, 1971), Lal's AI_m index (Lal, 1976), Onchev's P/St universal index (Onchev, 1985), and Burst factor (Smithen and Schulze, 1982) were not considered since they still require continuous recording. In addition, Oliver's precipitation concentration index (Oliver, 1980) was discarded after poor results obtained in a preliminary screening. A further description of selected estimators is provided below.

Fournier (1960) found a high correlation between the total annual erosion and the distribution coefficient of rainfall or, most commonly named, Fournier index:

$$F = \frac{p^2}{P} \tag{1}$$

where F is the Fournier index, p is the maximum monthly precipitation and P is the total annual rainfall.

A major difference between calculation of the R-factor and F is that the latter only considers those storms out of the month with the highest precipitation within the denominator. For this reason, Arnoldus (1980) proposed a modification of the Fournier index so that the storms that occur outside the month of maximum rainfall increase the overall value of the index:

$$MFI = \sum_{i=1}^{12} \frac{p_i^2}{P} \tag{2}$$

in which MFI is the modified Fournier index, p_i is the monthly rainfall and P is the total annual rainfall. Ferro et al. (1991, 1999) reported better estimates of the R-factor when the annual values of MFI were averaged over a period of several years.

In Spain, ICONA (1988) conducted research to evaluate the R-factor throughout the entire country. The research covered rainfall data from 1950 to 1985 and was based on the analysis of 162 pluviographs, supported by 809 additional rainfall stations due to the reduced number of continuous recording rain gauges. Regression analysis resulted in an isoerodent map and a regression model consisting of three equations to estimate the R-factor in the three zones that divided the country:

Zone 1:

$$R_{ICONA} = e^{-0.834} \cdot PMEX^{1.314} \cdot MR^{-0.388} \cdot F_{24}^{0.563} \tag{3}$$

Zone 2:

$$R_{ICONA} = e^{-1.235} \cdot PMEX^{1.297} \cdot MR^{-0.511} \cdot MV^{0.366} \cdot F_{24}^{0.414} \tag{4}$$

Zone 3:

$$R_{ICONA} = e^{0.754} \cdot T_2^{1.031} \cdot T_{10}^{-0.828} \cdot F^{-0.482} \cdot PMEX^{1.628} \cdot MR^{-1.22} \cdot MV^{0.536} \cdot F_{24}^{0.8} \cdot e^{0.211 \cdot a - 0.157 \cdot b} \quad (5)$$

where,

R_{ICONA} is the rainfall erosivity index as estimated by ICONA (MJ·cm·ha^{-1}·h^{-1}·year^{-1}), PMEX is the maximum monthly precipitation (mm), MR is the total rainfall from October to May (mm), MV is the total rainfall from June to September (mm), F is the Fournier index (mm), F_{24} is the ratio of the square of the maximum annual rainfall in 24 hours (mm) to the sum of the maximum monthly rainfall in 24 hours (mm):

$$F_{24} = \frac{\left(P_{24h,annual}\right)^2}{\sum_{i=1}^{12} P_{24h,i}} \quad (6)$$

T_2 represents the maximum annual rainfall in 24 hours for a 2-year recurrence interval, T_{10} is the maximum annual rainfall in 24 hours for a 10-year recurrence interval, and a and b are two parameters that can take the values of zero or one depending on the location.

Annual values for the period covered by each rainfall station were calculated for the four estimators. A series of values for each estimator were then obtained by averaging annual values over time intervals. These series were used to evaluate the effect of record length through regression analyses. The effect of record length on each estimator was studied using the following time intervals: 1, 2, 5, 10, 15 and 20 years, as described by Eq. 7:

$$X_N = \frac{1}{N}\sum_{i=1}^{N} X_i \quad (7)$$

where X_N represents the value of the estimator (R-ICONA, P, F and MFI) for a record length of N consecutive years, and X_i is the annual value of the estimator in year i. Eq. 7 was applied to all consecutive 1, 2, 5, 10, 15 and 20-year intervals within the period covered by each rainfall station.

2.2. Study area

This study covered mainland Spain, which refers to the regions located in the Iberian Peninsula. It is bordered to the north by the Cantabrian Sea and France, to the east and south by the Mediterranean Sea, and to the west by the Atlantic Ocean and Portugal. The total area of mainland Spain is 492,175 km^2, divided into 15 administrative regions (Fig. 1). The orography is dominated by a central vast plateau around 600 m above sea level (a.s.l.), surrounded by a series of mountain ranges with elevations from 1,500 to 3,400 m.a.s.l. Three major climatic zones can be distinguished in mainland Spain. Most of the study area (from the central plateau to the east and south) is dominated by a Mediterranean climate, characterized by seasonal temperatures, summer drought, erratic rainfall and annual precipitation between 400 and 800 mm. A semiarid climate covers the southeastern corner of the country, defined by an extended dry season and less than 400 mm of annual precipitation.

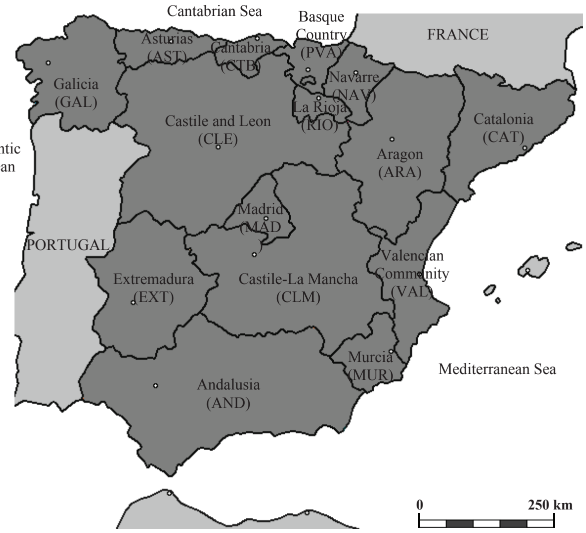

Fig. 1.- Fifteen administrative regions of mainland Spain (study area)

Finally, an oceanic climate extends through the north and northeastern portion of the country, characterized by no seasonal drought and more than 800 mm of annual rainfall.

2.3. Database

The rain gauge network provided by the Spanish Meteorological Agency (AEMET) in mainland Spain consists of more than 9,000 rainfall stations. In 1988, the R-factor at approximately 850 locations was published as part of the rainfall erosivity evaluation conducted by ICONA (1988). However, only a limited number of those stations (approximately 10%) were actual pluviographs with complete and continuous rainfall data series over 20 years. Rainfall erosivity was found to vary widely across the country since the reported values ranged from 21 to 550 MJ·cm·ha^{-1}·h^{-1}·year^{-1}. To date, no more attempts to complete the national network have been published and the R-factor values reported by ICONA (1988) are still considered a reference for the study of rainfall erosivity in Spain.

In this study, rainfall stations were selected on the basis of geographic location, elevation, record of complete years and reported R-factor. The goal was not only to obtain a representative sample of the geography throughout mainland Spain, but also to characterize the broad rainfall erosivity range previously identified by ICONA. A total of 74 rainfall stations were chosen, which translated into approximately 4,400 annual rainfall data sets (74 stations times 60 years on average). For each station, monthly rainfall and maximum monthly rainfall in 24 hours were provided by AEMET. Locations of the 74 stations considered in this study are shown in Fig. 2. Table 1 includes the station name, region, elevation, available R-factor, analysis period covered and number of complete years.

Rainfall data were employed to perform a regression analysis between R-factor values reported by ICONA and the

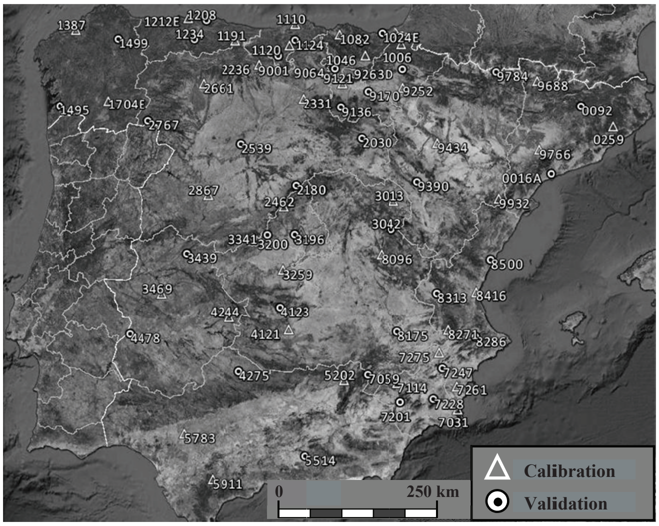

Fig. 2.- Location of selected rainfall stations

four estimators presented in Section 2.1 (R-ICONA, P, F and MFI). The regression analysis was divided into three stages:

First, 37 stations were used to develop a regression model for each estimator and record length characterizing the entire mainland Spain, i.e., a regression analysis at a global level. Models obtained from these 37 calibration stations were then validated in 37 additional stations. Both calibration and validation stations are identified in Figure 2 and Table 1.

Second, rainfall data were used to establish a regression model for each estimator and record length in each of the 15 administrative regions that compose mainland Spain, i.e., a regression analysis at a regional level. Given the relatively reduced number of rainfall stations in each region, all stations were considered for model calibration and no validation was conducted at a regional level.

Finally, results obtained at a regional level were used to discuss the applicability of a single model for estimating R-factor throughout mainland Spain.

2.4. Statistical models

Two statistical models were selected for this study. The first one was a simple linear regression with intercept term, as defined by equation 8:

$$R = \beta_0 + \beta_1 \cdot X + \varepsilon \tag{8}$$

where R is the rainfall erosivity factor, β_0 is the intercept term, β_1 is the slope, X is the estimator (R-ICONA, P, F and MFI) and ε represents the error.

It should be noted that the intercept term β_0 is just a fitting parameter which has no physical meaning since no erosion should occur for zero rainfall. Therefore, a simple linear regression through the origin (no intercept term) was defined as the second statistical model:

$$R = \beta_2 \cdot X + \varepsilon \tag{9}$$

in which R is the rainfall erosivity factor, β_2 is the slope, X is the estimator and ε represents the error.

The assumptions for both models were that errors are independent of each other and normally distributed with a mean of zero and constant variance. Based on available rainfall data, a series of values for each estimator (R-ICONA, P, F and MFI) and record length (1, 2, 5, 10, 15 and 20 years) were determined. These values were then correlated with the single computed R-factor reported by ICONA (1988) for each station.

3. Results and discussion

3.1. Regression analysis at a global level

Model calibration

Regression results obtained at a global level from 37 calibration stations in mainland Spain are presented in Table 2. These results include regression equation, coefficient of determination (r^2) and root mean squared error (RMSE) for each estimator and record length. Assumptions of the statistical models were successfully validated. It was observed that the regression model through the origin (Eq. 9) provided r^2 and RMSE values rather close to those provided by the regression model with intercept term (Eq. 8). In fact, the intercept term was found not to be statistically significant in the regression analysis. Therefore, the simpler regression model without intercept term was proposed in Table 2 for most record lengths and estimators.

Good results were obtained for R-ICONA, P, F and MFI; around 70% of the total variability (r^2=0.70) was explained for record lengths as short as 5 years. MFI clearly ranked first among the assessed indexes in terms of r^2 and RMSE for any record length. R-ICONA and F were the worst estimators for record lengths lower than 5 years, whereas they ranged between MFI and P for record lengths of 5 years or more. The slope obtained for R-ICONA suggests that the current regression model proposed by ICONA (Eqs. 3-5) may overpredict the R-factor by approximately 19%. These results support previous observations by Hernando and Romana (2015) who reported an average overestimate of 16% in the central part of Spain (Madrid Region).

Effect of record length on estimate precision and accuracy

As can be inferred from Table 2, record length had a direct effect on regression models: as record length increased, r^2 increased and RMSE decreased. A possible explanation is that as record length increased, the annual values of the estimators were averaged over a longer time interval as defined by Eq. 7. Thus, this 'smoothing' effect translated into less dispersion and, consequently, a better fit.

In order to further analyze the effect of record length on the precision and accuracy of the estimates, two additional

Code	Station name	Region[(a)]	Elev. (m.a.s.l.)	R-factor ($MJ·cm·ha^{-1}·h^{-1}·year^{-1}$) (ICONA, 1988)	ICONA Zone	Period covered	Complete years	App[(b)]
5202	Beas de Segura	AND	577	90	1	1955-1981	27	Cal.
5783	Seville-San Pablo Airport	AND	26	182	1	1951-2009	59	Cal.
5911	Grazalema	AND	823	540	2	1939-2009	70	Cal.
4275	Pozoblanco	AND	649	81	1	1940-2009	70	Val.
5514	Armilla Air Base (Granada)	AND	687	43	1	1940-2009	70	Val.
9434	Zaragoza Airport	ARA	247	50	3	1941-2009	69	Cal.
9932	Peña Dam	ARA	620	131	3	1946-2009	64	Cal.
9390	Daroca	ARA	779	55	3	1940-2009	70	Val.
9784	Barrosa Dam	ARA	1200	186	3	1942-1993	52	Val.
1191	Restaño (Amieva)	AST	700	275	1	1956-2009	53	Cal.
1212E	Asturias Airport	AST	127	123	1	1969-2009	40	Cal.
1208	Gijón	AST	3	115	1	1977-2000	24	Val.
1234	La Foz de Morcín	AST	260	162	1	1948-1985	38	Val.
0259	Turó de l'Home (Montseny)	CAT	1706	385	3	1956-2000	43	Cal.
9688	Estany Gento (lake)	CAT	2120	254	3	1926-1984	58	Cal.
9766	Els Omellons	CAT	386	96	3	1945-2009	65	Cal.
0092	Berga	CAT	730	160	3	1956-1993	38	Val.
0016A	Reus Airport	CAT	68	228	3	1946-2009	62	Val.
2236	Cervera Dam	CLE	1000	154	1	1940-2009	70	Cal.
2331	Burgos-Villafría Airport	CLE	890	77	1	1944-2009	66	Cal.
2661	Leon Airport	CLE	916	31	1	1940-2009	70	Cal.
2867	Salamanca-Matacán Airport	CLE	790	47	1	1945-2009	65	Cal.
2030	Soria	CLE	1082	67	1	1951-2009	59	Val.
2180	Matabuena	CLE	1154	111	1	1939-2009	68	Val.
2539	Villanubla	CLE	846	73	1	1940-2009	70	Val.
2767	Requejo	CLE	1006	324	1	1943-2009	67	Val.
3013	Molina de Aragón	CLM	1063	80	1	1951-2009	59	Cal.
3259	Toledo (Lorenzana Palace)	CLM	540	52	1	1910-1981	70	Cal.
4121	Ciudad Real	CLM	627	49	1	1971-2009	39	Cal.
8096	Cuenca	CLM	956	75	1	1951-2009	59	Cal.
3042	Vega del Codorno	CLM	1345	152	1	1956-2009	54	Val.
4123	Los Cortijos de Arriba	CLM	775	106	1	1948-2009	58	Val.
7059	Arguellite	CLM	980	195	2	1940-2009	70	Val.
8175	Los Llanos Air Base	CLM	704	74	1	1940-2009	70	Val.
1110	Santander	CTB	64	200	1	1926-1996	70	Cal.
1120	Sel de la Carrera	CTB	537	224	1	1939-1987	49	Cal.
1124	Villacarriedo	CTB	212	318	1	1947-2009	62	Val.
9001	Reinosa	CTB	855	128	1	1923-1994	70	Val.
3469	Cáceres	EXT	459	75	1	1917-1986	70	Cal.
4244	Herrera del Duque	EXT	465	144	1	1948-2009	62	Cal.
3439	Barrado	EXT	796	286	1	1946-2009	64	Val.
4478	Badajoz	EXT	195	100	1	1915-1984	70	Val.
1387	A Coruña	GAL	58	125	1	1940-2009	70	Cal.
1704E	Junqueira de Espadañedo	GAL	700	332	1	1949-2001	49	Cal.
1495	Vigo-Peinador Airport	GAL	255	353	1	1951-2009	59	Val.
1499	Punto Centro	GAL	443	145	1	1964-1984	21	Val.
2462	Navacerrada	MAD	1890	194	1	1947-2007	61	Cal.
3195	Madrid (Retiro)	MAD	667	65	1	1941-2008	68	Cal.
3196	Cuatro Vientos Airport	MAD	687	74	1	1946-2007	62	Val.
3200	Getafe Air Base	MAD	617	53	1	1951-2007	57	Val.
3341	San Juan Dam	MAD	540	105	1	1952-1999	47	Val.
7031	Murcia-San Javier Airport	MUR	2	135	2	1945-2009	65	Cal.
7114	Moratalla	MUR	680	109	2	1943-2001	58	Cal.
7275	Yecla	MUR	605	82	2	1939-2009	69	Cal.
7201	Doña Inés	MUR	786	63	2	1937-1990	53	Val.
7228	Alcantarilla	MUR	85	95	2	1941-2009	69	Val.
1006	Santesteban	NAV	131	237	1	1939-2009	67	Cal.
9252	Olite	NAV	390	50	3	1940-2009	67	Cal.
9263D	Pamplona-Noáin Airport	NAV	452	94	3	1975-2009	35	Val.
1046	Sanctuary of Arantzazu	PVA	770	236	1	1949-1989	41	Cal.
1082	Bilbao Airport	PVA	39	203	1	1948-2009	61	Cal.
1050	Eibar	PVA	121	241	1	1951-1996	46	Val.
9064	Salinas de Añana	PVA	566	90	1	1940-2009	70	Val.
1024E	San Sebastián (Monte Igueldo)	PVA	252	308	1	1940-2009	70	Val.
9121	Haro	RIO	479	54	1	1940-2007	67	Cal.
9136	Monastery of Valvanera	RIO	1020	111	1	1950-2009	60	Val.
9170	Logroño-Agoncillo Airport	RIO	352	33	1	1951-2009	59	Val.
7261	Almoradí	VAL	11	70	2	1939-1999	61	Cal.
8271	La Matea (Sierra de Enguera)	VAL	865	129	3	1949-1979	31	Cal.
8416	Valencia	VAL	11	175	3	1940-2009	70	Cal.
7247	Pinoso	VAL	574	65	2	1964-1993	30	Val.
8286	Les Planises (Beniatjar)	VAL	841	256	3	1950-2009	60	Val.
8313	Requena	VAL	693	116	3	1949-2009	61	Val.
8500	Almazora	VAL	31	210	3	1950-2002	52	Val.

[(a)] AND=Andalusia; ARA=Aragon; AST=Asturias; CAT=Catalonia; CLE=Castile and Leon; CLM=Castile-La Mancha; CTB=Cantabria; EXT=Extremadura; GAL=Galicia; MAD=Madrid; MUR=Murcia; NAV=Navarre; PVA=Basque Country; RIO=La Rioja; VAL=Valencian Community.
[(b)] Application of rain gauge station for the regression analysis at a global level: 'Cal.' denotes calibration whereas 'Val.' denotes validation.

Table 1. Characteristics of rainfall stations selected in this study

Estimator / Record length	Regression equation	r^2	RMSE ($MJ \cdot cm \cdot ha^{-1} \cdot h^{-1} \cdot year^{-1}$)
R_{ICONA} ($MJ \cdot cm \cdot ha^{-1} \cdot h^{-1} \cdot year^{-1}$)			
1 year	$R = 0.32 \cdot R_{ICONA} + 92.83$	0.37	86
2 years	$R = 0.46 \cdot R_{ICONA} + 70.01$	0.52	74
5 years	$R = 0.62 \cdot R_{ICONA} + 43.11$	0.71	58
10 years	$R = 0.81 \cdot R_{ICONA}$	0.81	47
15 years	$R = 0.82 \cdot R_{ICONA}$	0.86	39
20 years	$R = 0.82 \cdot R_{ICONA}$	0.89	37
Annual rainfall, P (mm)			
1 year	$R = 0.15 \cdot P + 25.42$	0.59	69
2 years	$R = 0.18 \cdot P$	0.62	66
5 years	$R = 0.18 \cdot P$	0.67	62
10 years	$R = 0.18 \cdot P$	0.69	60
15 years	$R = 0.18 \cdot P$	0.71	58
20 years	$R = 0.18 \cdot P$	0.72	58
Fournier index, F (mm)			
1 year	$R = 1.22 \cdot F + 86.61$	0.37	86
2 years	$R = 1.72 \cdot F + 62.21$	0.52	75
5 years	$R = 2.29 \cdot F + 34.35$	0.70	59
10 years	$R = 2.80 \cdot F$	0.76	53
15 years	$R = 2.80 \cdot F$	0.81	47
20 years	$R = 2.80 \cdot F$	0.86	41
Modified Fournier index, MFI (mm)			
1 year	$R = 0.98 \cdot MFI + 33.87$	0.62	67
2 years	$R = 1.23 \cdot MFI$	0.71	59
5 years	$R = 1.28 \cdot MFI$	0.81	47
10 years	$R = 1.28 \cdot MFI$	0.84	42
15 years	$R = 1.28 \cdot MFI$	0.87	39
20 years	$R = 1.28 \cdot MFI$	0.89	37

Table 2. Regression results for R-factor ($MJ \cdot cm \cdot ha^{-1} \cdot h^{-1} \cdot year^{-1}$) at a global level from 37 calibration stations

statistics were evaluated: coefficient of variation (CV) and mean absolute percentage error (MAPE). This approach was previously used by the authors (Hernando and Romana, 2015) to assess the effect of record length at a local level (regional scale). CV is defined as the ratio of the standard deviation to the mean of a sample, expressed as a percentage. This statistic represents the variability of an index about its mean value and indicates the precision of the estimator. MAPE is a measure of the error estimating the R-factor (i.e., accuracy) and is determined as follows:

$$\text{MAPE (\%)} = \frac{1}{N}\sum_{j=1}^{N}\left|\frac{R-\hat{R}_j}{R}\right| \qquad (10)$$

in which R is the known value of the R-factor (Table 1), $\hat{R}_j$ is the estimated value from the regression model, and N is the number of data points for a given record length.

Fig. 3 plots CV for each estimator and record length. As clearly shown, P and MFI were the estimators with the lowest CV for any record length. R-ICONA and F nearly doubled the CV values obtained for P and MFI. The overall trend of the four estimators showed a substantial decrease in CV from 1 to 5 years of record length, followed by a slight reduction over 10 years.

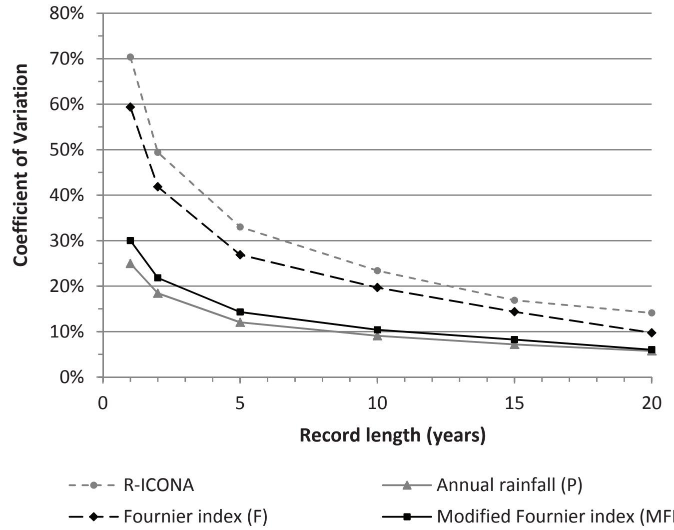

Fig. 3.- Coefficient of variation for each estimator and record length (global model calibration)

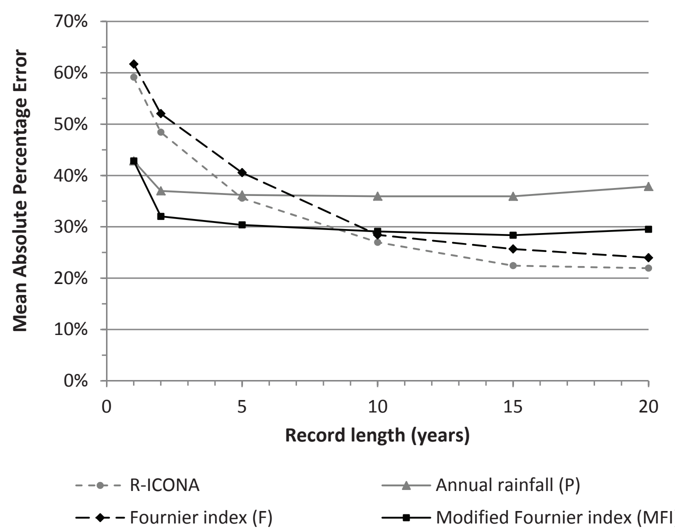

Fig. 4.- Mean absolute percentage error for each estimator and record length (global model calibration)

As depicted in Fig. 4, the overall trend of MAPE was clearly different from that of CV. P and MFI initially showed a moderate decrease in MAPE, but the values quickly leveled out at 30-35% for record lengths over 2 years. As for R-ICONA and F, a steep decline in MAPE was observed up to 10 years, followed by a small decrease for record lengths over 10 years.

These results confirmed that record length increased both precision and accuracy of the estimates when time intervals up to 10 years were considered, but slight improvement was obtained beyond that. A record length of 10 years seemed adequate to estimate the R-factor in mainland Spain at a global level. Therefore, regression results in Table 2 were reduced to one single equation for each estimator, as summarized in Table 3.

Estimator	Record length	Regression equation	r^2	RMSE ($MJ \cdot cm \cdot ha^{-1} \cdot h^{-1} \cdot year^{-1}$)	CV (%)	MAPE (%)
R_{ICONA}	10 years	$R = 0.81 \cdot R_{ICONA}$	0.81	47	23	27
P	10 years	$R = 0.18 \cdot P$	0.69	60	9	36
F	10 years	$R = 2.80 \cdot F$	0.76	53	20	28
MFI	10 years	$R = 1.28 \cdot MFI$	0.84	42	10	29

Table 3. Simplified regression models obtained from 37 calibration stations (global analysis)

Validation

The simplified regression models obtained from 37 calibration stations (Table 3) were used to estimate the R-factor in 37 additional stations. Results are illustrated in Fig. 5, in which the vertical axis represents measured R-factor reported by ICONA (Table 1) and the horizontal axis represents predicted R-factor. The four estimators provided acceptable results for the proposed record length of 10 years. Overall, a good fit was observed for R-factor values under 200 $MJ \cdot cm \cdot ha^{-1} \cdot h^{-1} \cdot year^{-1}$, while some scattered data points appeared above this value, especially for R-ICONA and F.

RMSE and MAPE were also evaluated in the validation stations. Fig. 6 shows that RMSE values obtained from validation were rather close to those previously obtained from calibration, except for R-ICONA, which experienced a moderate increase. MFI was the estimator with the lowest RMSE. Regarding MAPE, Fig. 7 indicates that validation results were fairly similar to those observed from calibration. F and MFI showed the lowest MAPE values (25%).

These results clearly showed that MFI was the best estimator of the R-factor at a global level in mainland Spain. The simple regression equation:

$$R = 1.28 \cdot MFI_{10} \tag{11}$$

in which R is the rainfall erosivity factor ($MJ \cdot cm \cdot ha^{-1} \cdot h^{-1} \cdot year^{-1}$) and MFI_{10} is the modified Fournier index (mm) for a 10-year record length, not only yielded the best calibration results compared to the other estimators, but also minimized both RMSE and MAPE in the validation analysis.

3.2. Regression analysis at a regional level

A regression analysis was independently conducted for each of the 15 administrative regions that compose mainland Spain. Regression models at a regional level were developed for each estimator and record length following the procedure described in Section 3.1. One single regression equation was then selected for each region, based on the combined analysis of r^2, RMSE, CV and MAPE. Regression results are summarized in Table 4.

As shown in Table 4, excellent results in terms of r^2 were obtained in all regions (87% of total variability explained on average). The intercept term was again found not to be statistically significant, so regression models through the origin were chosen. Selected record lengths varied from 5 to 20 years, with the longest record lengths consistently located in the eastern part of the country (Catalonia, Valencian Community, Murcia and Castile-La Mancha). Eastern Spain is known for a marked erratic rainfall pattern, which may explain why

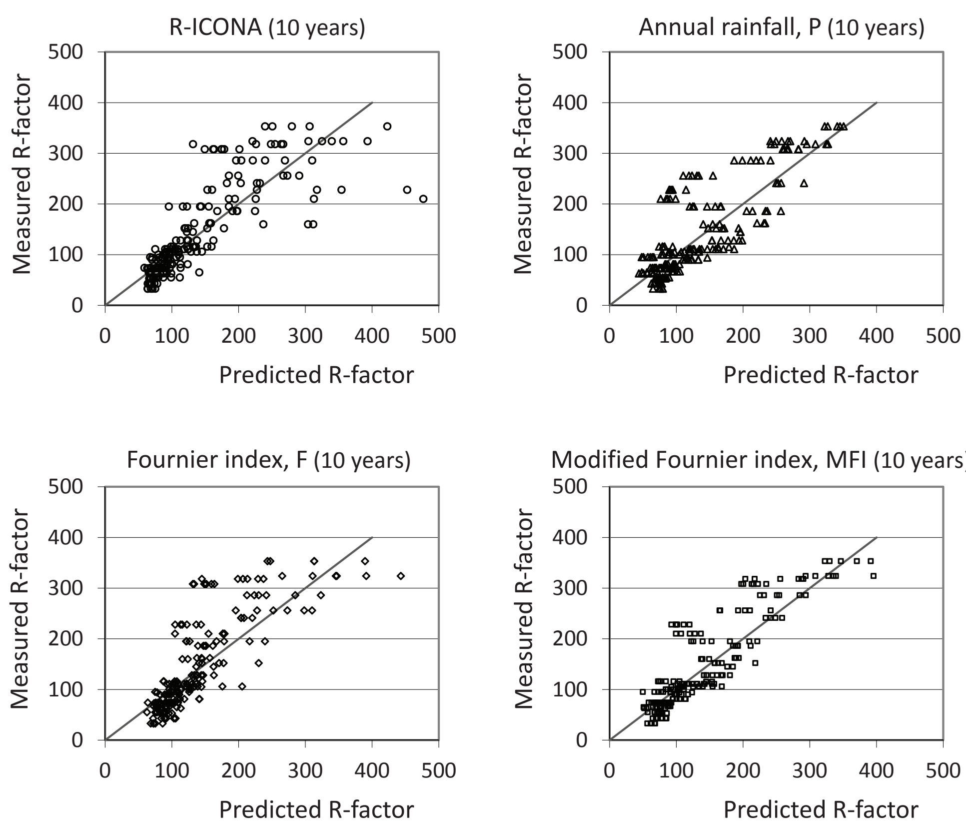

Fig. 5.- Scatter plot of R-factor measured by ICONA vs. R-factor predicted by estimates for proposed record length (10 years) in $MJ \cdot cm \cdot ha^{-1} \cdot h^{-1} \cdot year^{-1}$ (global model validation)

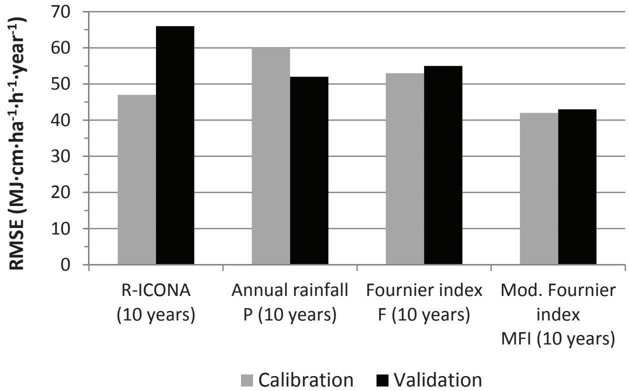

Fig. 6.- Comparison of root mean squared error (RMSE) results for calibration and validation (global model)

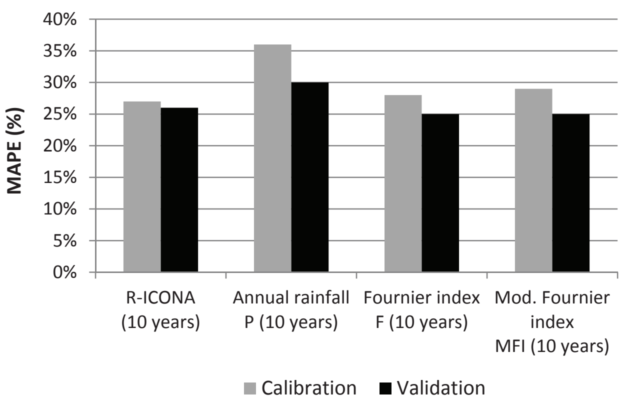

Fig. 7.- Comparison of mean absolute percentage error (MAPE) results for calibration and validation (global model)

Region	Record length	Regression equation	r^2	RMSE ($MJ \cdot cm \cdot ha^{-1} \cdot h^{-1} \cdot year^{-1}$)	CV (%)	MAPE (%)
AND	10 years	R = 1.27·MFI	0.97	37	10	33
ARA	5 years	R = 1.22·MFI	0.84	21	15	20
AST	5 years	R = 1.18·MFI	0.82	30	9	14
CAT	20 years	R = 4.79·F	0.92	28	5	16
CLE	5 years	R = 1.14·MFI	0.88	30	12	35
CLM	20 years	R = 1.18·MFI	0.82	22	7	17
CTB	15 years	R = 0.16·P	0.79	33	7	13
EXT	5 years	R = 1.29·MFI	0.84	32	16	20
GAL	10 years	R = 1.25·MFI	0.88	38	9	16
MAD	5 years	R = 1.05·MFI	0.93	14	11	11
MUR	20 years	R = 2.93·F	0.84	10	11	9
NAV	5 years	R = 0.14·P	0.94	22	12	20
PVA	10 years	R = 0.17·P	0.80	36	7	16
RIO	5 years	R = 0.11·P	0.88	11	11	19
VAL	20 years	R = 1.71·MFI	0.81	30	10	21
		Average	0.87	26	10	18

Table 4. Regression models proposed for mainland Spain (regional analysis)

a short record length did not provide an adequate estimate of the long-term rainfall erosivity. Outcomes from regression analysis showed that MFI was the best performing estimator in most regions (9 out of 15). P was chosen at four northern regions, characterized by a relatively high annual rainfall. These results are supported by Ferro et al. (1999), who previously reported that P was a robust estimator of the R-factor in regions where high rainfall erosivity corresponded to high annual rainfall. F was only selected at two of the eastern regions. The average CV value (10%) was exactly the same obtained at a global level, whereas the average MAPE value of 18% was substantially lower than that determined from global analysis (28%). Because of the relatively reduced number of stations in each region, all stations were used for model development and no validation analysis was conducted at the regional level.

3.3. Applicability of a single (global) estimate model

Result comparison

Results obtained at the regional level were used in this section to discuss the applicability of a single (global) model for estimating the R-factor across mainland Spain. Fig. 8 plots the slope of the regression through the origin obtained for each estimator and region (note that Section 3.2 only presented the slope for the selected estimator). For comparative purposes, a constant record length of 20 years was considered for all regions. Regions were sorted by slope from smallest to largest. In addition, the slope previously determined from the global analysis is depicted in Fig. 8 as a horizontal line.

As can be seen in Fig. 8, Catalonia, Valencian Community and Murcia, three contiguous regions of Eastern Spain, seemed to provide extreme slope values for the four estimators, which could be an indication of a different rainfall erosivity pattern. These three regions had the highest slope coefficients for both P and MFI. In addition, Catalonia presented the highest slope for F, and both Valencian Community and Catalonia were two of the regions with the lowest slope for R-ICONA. A closer look at the initial regression model at a global level (Fig. 5) revealed that most of the discordant rainfall stations identified for rainfall erosivity values over 200 $MJ \cdot cm \cdot ha^{-1} \cdot h^{-1} \cdot year^{-1}$ happened to be located in this three regions. These observations were supported by an analysis of the variance (ANOVA), which confirmed that the values obtained in Catalonia, Valencian Community and Murcia were statistically different from those obtained in the rest of mainland Spain, for a significance level of 5%. After this important finding, the decision was to conduct a new regression analysis by dividing mainland Spain into two areas (Fig. 9):

a) Eastern Spain, composed of Catalonia, Valencian Community and Murcia; and b) Plateau-lowland area, which included the rest of mainland Spain.

Bi-areal regression model

Regression equations were developed in both areas for each estimator and record length. Calibration and validation stations previously used for the initial regression analysis at

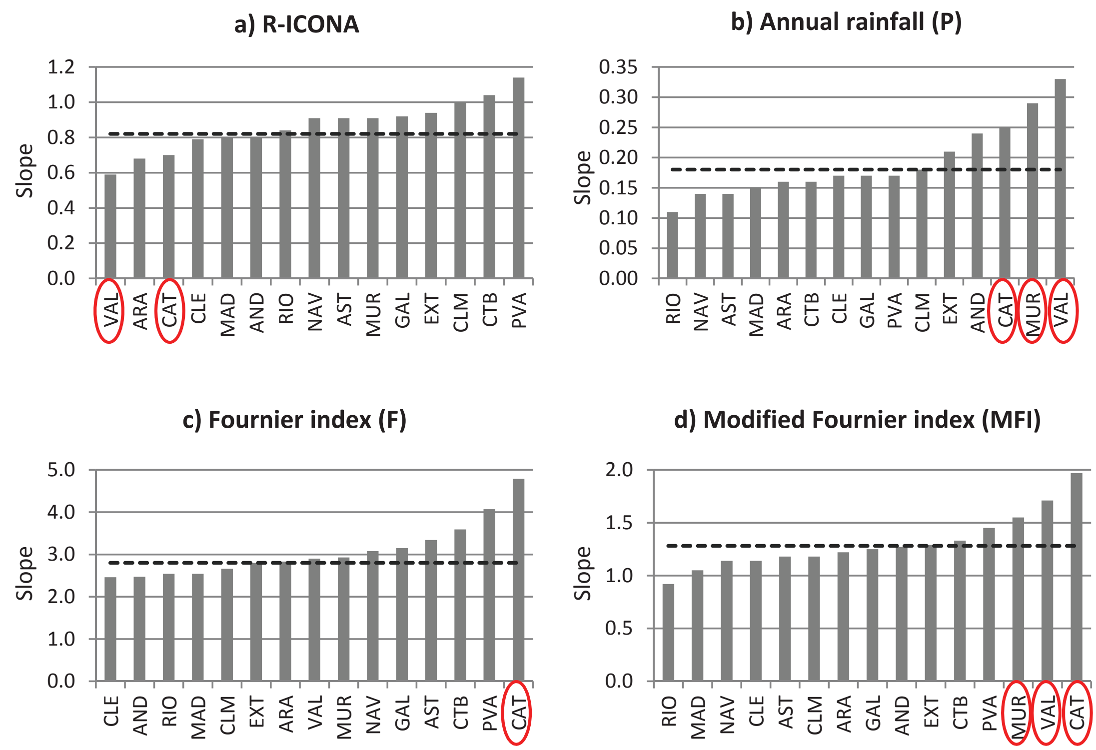

Fig. 8.- Slope coefficients obtained for regressions through the origin from analysis at the regional level (20-year record length)

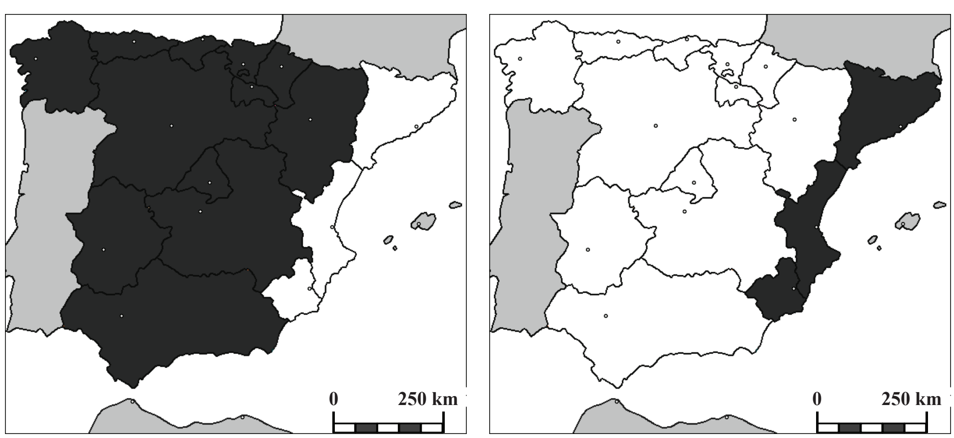

Fig. 9.- Areas defined for bi-areal regression model: Plateau-lowland area (left); Eastern Spain (right)

a global level were respectively maintained for the two new areas into which mainland Spain was divided. This means that 28 calibration stations and 29 validation stations were used for the Plateau-lowland area, while 9 stations were used for calibration and 8 for validation in Eastern Spain (Table 1, Fig. 2). A record length of 10 years was selected based on the analysis of r^2, RMSE, CV and MAPE results from the calibration stations. Validation results confirmed that MFI outperformed the rest of estimators in both areas. The regression equation obtained for each area is as follows:

Plateau-lowland: $$R = 1.22 \cdot MFI_{10} \qquad (12)$$

Eastern Spain: $$R = 1.80 \cdot MFI_{10} \qquad (13)$$

where R is the rainfall erosivity factor ($MJ \cdot cm \cdot ha^{-1} \cdot h^{-1} \cdot year^{-1}$) and MFI_{10} is the modified Fournier index (mm) for a 10-year record length. Compared to the single (global) model, the slope coefficient for the Plateau-lowland area slightly decreased from 1.28 to 1.22, whereas the slope for Eastern Spain experienced a substantial increase to 1.80. An increase in the slope coefficient for Eastern Spain was expected, since most of the rainfall stations from this area fell above the identity line defined in Fig. 5.

Results of r^2, RMSE, CV and MAPE for the bi-areal model proposed in this section (Plateau-lowland and Eastern Spain) were compared to those previously obtained for the global model in Section 3.1. Fig. 10 shows a significant improvement in the variability explained by the regression model

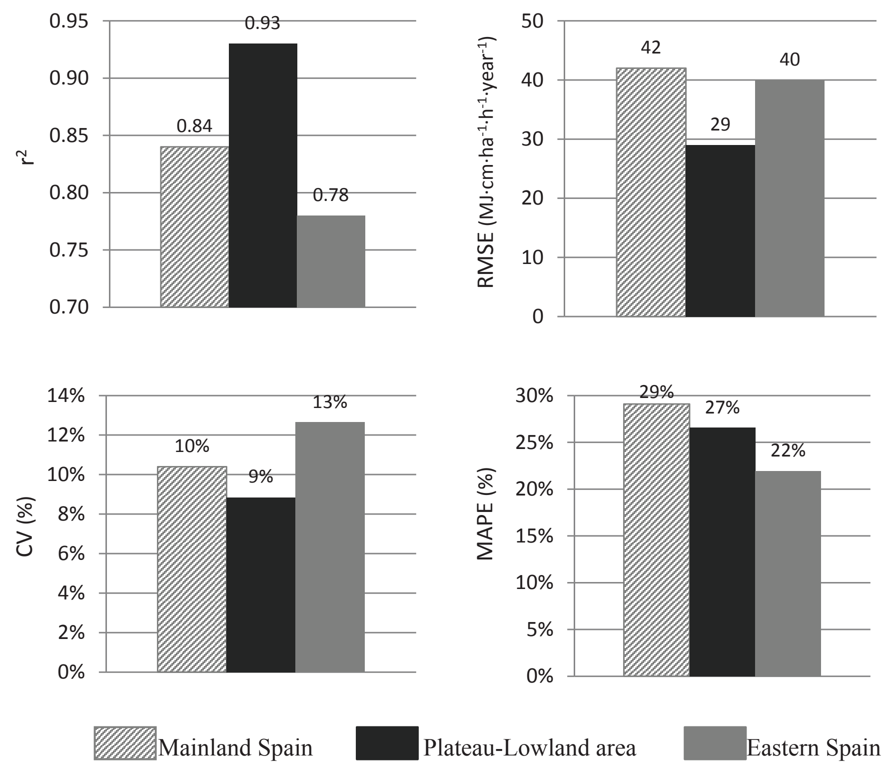

Fig. 10.- Comparison of r^2, RMSE, CV and MAPE results for the single and the bi-areal models (Plateau-Lowland area and Eastern Spain) in mainland Spain

when the Plateau-lowland area was studied independently of Eastern Spain (r^2 increased from 0.84 to 0.93). However, r^2 for Eastern Spain decreased moderately. As previously stated, this area is characterized by a strong erratic rainfall pattern, which means higher variability in rainfall erosivity. In fact, this higher variability was observed by an increase in CV from 10 to 13%. At this point, it was not clear whether the division of mainland Spain into two areas (bi-areal model) really provided better estimates as compared to the single model. However, the analysis of RMSE and MAPE clearly showed improvement. The original RMSE of 42 $MJ \cdot cm \cdot ha^{-1} \cdot h^{-1} \cdot year^{-1}$ obtained for the global model was reduced to 40 $MJ \cdot cm \cdot ha^{-1} \cdot h^{-1} \cdot year^{-1}$ in Eastern Spain and, especially, to 29 $MJ \cdot cm \cdot ha^{-1} \cdot h^{-1} \cdot year^{-1}$ in the Plateau-lowland area (31% reduction). Furthermore, RMSE decreased from 29% for the global model to 27% for the Plateau-lowland area and 22% for Eastern Spain. Therefore, these results confirmed that the rainfall erosivity pattern of Eastern Spain is different from that of the Plateau-lowland area, and the use of the bi-areal model clearly improves the estimate of the R-factor in mainland Spain.

3.4. Validation of the regression model proposed by ICONA

The regression model proposed by ICONA (Eqs. 3-5) was validated by computing R-ICONA in the 74 rainfall stations considered in this study. A regression model was then established between R-ICONA and the reported values of the R-factor. The parameter used for validation analysis was the slope obtained from the regression-through-the-origin model. Since the R-factor represents the long-term average value of rainfall erosivity, a record length of 20 years was assumed to be the most representative for this analysis.

Fig. 11 depicts the relationship between R-ICONA (in the horizontal axis) and reported R-factor (in the vertical axis) for 74 rainfall stations in mainland Spain. It was found that most of the points fell below the identity line, which indicated the regression model proposed by ICONA overpredicted the R-factor. A slope of 0.81 was obtained for the regression through the origin, which meant an overall overprediction of 19%. Note that Fig. 8.a depicts how the slope of the regression between R-ICONA and R-factor varied from region to region. From this figure one can see that only Castile-La Mancha presented a slope value close to 1.0. Cantabria and Basque Country yielded slope values above 1.0, while slope coefficients below 1.0 were obtained in most of mainland Spain (12 out of 15 regions).

4. Summary and conclusions

A detailed linear regression analysis of 74 rainfall stations throughout mainland Spain resulted in the identification and validation of a readily available estimate of the (R)USLE rainfall erosivity factor. The conducted analysis clearly showed the modified Fournier index (MFI) ranked first among the assessed indexes. In an initial attempt to provide a simple estimate of the R-factor, a single global regression equation was developed for mainland Spain. Thirty-seven calibration stations showed that MFI provided the best results in terms of coefficient of determination (r^2) and root mean squared er-

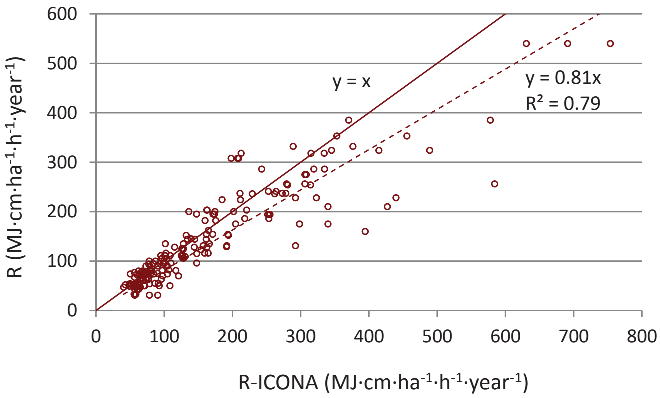

Fig. 11.- Scatter plot of R-factor vs. R-ICONA for 74 rainfall stations in mainland Spain

ror (RMSE). Two additional statistics, coefficient of variation (CV) and mean absolute percentage error (MAPE), were used to evaluate the effect of record length on estimate precision and accuracy. A record length of 10 years seemed to provide adequate estimates, since little improvement was obtained for longer records. Subsequently, the regression equation obtained for a 10-year record length was subjected to a validation analysis in 37 additional rainfall stations. Validation results confirmed MFI as the best estimator.

After these preliminary results at a global level, an individual regression analysis was conducted in each of the fifteen administrative regions that compose mainland Spain. The purpose of the regional analysis was to discuss the applicability of a single (global) estimate across mainland Spain. It was determined that three contiguous regions of Eastern Spain (Catalonia, Valencian Community and Murcia) consistently presented extreme slope values for the regression equations, which could indicate a different rainfall erosivity pattern. A further investigation of the global regression model revealed that most of the discordant data points happened to be located within these three regions. After this finding, a new regression analysis was conducted by dividing mainland Spain into two areas: Eastern Spain (containing Catalonia, Valencia Community and Murcia) and Plateau-lowland area (remaining regions of mainland Spain). The following equation was selected for each region:

Plateau-lowland: $R = 1.22 \cdot MFI_{10}$

Eastern Spain: $R = 1.80 \cdot MFI_{10}$

in which R is the rainfall erosivity factor ($MJ \cdot cm \cdot ha^{-1} \cdot h^{-1} \cdot year^{-1}$) and MFI_{10} is the modified Fournier index (mm) for a 10-year record length. Results of r^2, RMSE, CV and MAPE obtained for the bi-areal model were compared to those provided by the preliminary global equation. Unclear results were obtained from r^2 and CV. On the contrary, RMSE and MAPE clearly produced better results for the bi-areal model. Therefore, it was concluded that a bi-areal regression model based on MFI for a record length of 10 years provided a simple, precise and accurate estimate of the (R)USLE rainfall erosivity factor in mainland Spain.

Finally, the regression model proposed by ICONA was evaluated by estimating the R-factor in 74 rainfall stations. It was found that R-ICONA overpredicted the rainfall erosivity factor in almost all regions, obtaining an average overprediction of 19%. Thus, the bi-areal regression model developed in this study seemed to be the superior choice to estimate the rainfall erosivity factor in mainland Spain.

References

Angulo-Martínez, M., Beguería, S. (2009): Estimating rainfall erosivity from daily precipitation records: a comparison among methods using data from the Ebro Basin (NE Spain). *Journal of Hydrology* 379, 111–121. doi: 10.1016/j.jhydrol.2009.09.051.

Arnoldus, H.M.J. (1980): An approximation of the rainfall factor in the Universal Soil Loss Equation. In: De Boodt, M., Gabriels, D. (eds.), *Assessment of Erosion*. John Wiley & Sons, Chichister, 127–132.

Bonilla, C.A., Vidal, K.L. (2011): Rainfall erosivity in Central Chile. *Journal of Hydrology* 410 (1-2), 126–133. doi:10.1016/j.jhydrol.2011.09.022.

Brown, L.C., Foster, G.R. (1987): Storm erosivity using idealized intensity distributions. *Transactions of the American Society of Agricultural Engineers (ASAE)* 30 (2), 379-386.

Colotti, E. (2004): *Aplicabilidad de los datos de lluvia horaria en el cálculo de la erosidad*. [Applicability of hourly rainfall data to erosion analysis]. Fondo Editorial de Humanidades y Educación. Departamento de Publicaciones. Universidad Central de Venezuela. (In Spanish).

Diodato, N. (2004): Estimating RUSLE's rainfall factor in the part of Italy with a Mediterranean rainfall regime. *Hydrology and Earth System Sciences* 8 (1), 103–107.

Diodato, N., Bellochi, G. (2007): Estimating monthly (R)USLE climate input in a Mediterranean region using limited data. *Journal of Hydrology* 345, 224–236. doi:10.1016/j.jhydrol.2007.08.008.

Ferro, V., Giordano, G., Iovino, M. (1991): Isoerosivity and erosion risk map for Sicily. *Hydrological Sciences Journal* 36 (6), 549-564. doi:10.1080/02626669109492543.

Ferro, V., Porto, P., Yu, B. (1999): A comparative study of rainfall erosivity estimation for southern Italy and southeastern Australia. *Hydrological Sciences Journal* 44 (1), 3-24. doi:10.1080/02626669909492199.

Fournier, F. (1960): *Climat et érosion. La relation entre l'érosion du sol par l'eau et les précipitations atmosphériques*. [Relationship between soil erosion by water and rainfall] Presses Universitaires de France, Paris. (In French).

Hernando, D., Romana, M.G. (2015): Estimating the rainfall erosivity factor from monthly precipitation data in the Madrid Region (Spain). *Journal of Hydrology and Hydromechanics* 63 (1), 55–62. doi: 10.1515/johh-2015-0003.

Hudson, N. (1971): *Soil Conservation*. Cornell University Press, Ithaca.

ICONA. (1988): *Agresividad de la lluvia en España. Valores del factor R de la Ecuación Universal de Pérdidas de Suelo*. [Rainfall erosivity in Spain. R-factor values for the Universal Soil Loss Equation]. Ministerio de Agricultura, Pesca y Alimentación, Madrid. (In Spanish).

Lal, R. (1976): Soil erosion on alfisols in Western Nigeria III–Effects of rainfall characteristics. *Geoderma* 16, 389-401. doi:10.1016/0016-7061(76)90003-3.

Lee, J.H., Heo, J.H. (2011): Evaluation of estimation methods for rainfall erosivity based on annual precipitation in Korea. *Journal of Hydrology* 409 (1–2), 30–48. doi:10.1016/j.jhydrol.2011.07.031.

Loureiro, N., Coutinho, M. (2001): A new procedure to estimate the RUSLE EI_{30} index, based on monthly rainfall data and applied to the Algarve region, Portugal. *Journal of Hydrology* 250 (1-4), 12-18. doi:10.1016/S0022-1694(01)00387-0.

Oliver, J.E. (1980): Monthly precipitation distribution: a comparative index. *Professional Geographer* 32(3), 300-309.

Onchev, N.G. (1985): Universal index for calculating rainfall erosivity. In: El-Swaify, S.A., Moldenhauer, W.C., Lo, A. (eds.), *Soil Erosion and Conservation*. Soil Conservation Society of America, Ankeny, 424-431.

Petkovšek, G., Mikoš, M. (2004): Estimating the R factor from daily rainfall data in the sub-Mediterranean climate of southwest Slovenia. *Hydrological Sciences Journal* 49 (5), 869–877. doi:10.1623/hysj.49.5.869.55134.

Renard, K.G., Foster, G.R., Weesies, G.A., Porter, J.P. (1991): RUSLE — Revised Universal Soil Loss Equation. *Journal of Soil and Water Conservation* 46 (1), 30–33.

Renard, K.G., Foster, G.R., Weesies, G.A., McCool, D.K., Yoder, D.C. (1997): *Predicting soil erosion by water: a guide to conservation planning with the revised Universal Soil Loss Equation (RUSLE)*. Agriculture Handbook No. 703. U.S. Department of Agriculture, Washington D.C.

Renard, K.G., Freimund, J.R. (1994): Using monthly precipitation data to estimate the R-factor in the revised USLE. *Journal of Hydrology* 157, 287-306. doi:10.1016/0022-1694(94)90110-4.

Salako, F.K. (2008): Rainfall variability and kinetic energy in Southern Nigeria. *Climatic Change* 86, 151–164. doi:10.1007/s10584-006-9198-z.

Smithen, A.A., Schulze, R.E. (1982): The spatial distribution in Southern Africa of rainfall erosivity for use in the Universal Soil Loss Equation. *Water SA* 8 (2), 74–78.

Wischmeier, W.H. (1959): A rainfall erosion index for a Universal Soil-Loss Equation. *Soil Science Society of America, Proceedings* 23 (3), 246–249.

Wischmeier, W.H., Smith, D.D. (1961): *A universal equation for predicting rainfall-erosion losses – An aid to conservation farming in humid regions*. ARS Special Report 22-66. U.S. Department of Agriculture, Washington, D.C.

Wischmeier, W.H., Smith, D.D. (1965): *Predicting rainfall erosion losses from cropland East of the Rocky Mountains*. Agriculture Handbook No. 282. U.S. Department of Agriculture, Washington, D.C.

Wischmeier, W.H., Smith, D.D. (1978): *Predicting rainfall erosion losses. A guide to conservation planning*. Agriculture Handbook No. 537. U.S. Department of Agriculture, Washington, D.C.

Yu, B., Rosewell, C.J. (1996): A robust estimator of the R factor for the Universal Soil Loss Equation. *Transactions of the American Society of Agricultural Engineers (ASAE)* 39, 559–561.

Yu, B., Hashim, G.M., Eusof, Z. (2001): Estimating the R-factor with limited rainfall data: a case study from peninsular Malaysia. *Journal of Soil and Water Conservation* 56(2), 101–105.