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Estimation models for precipitation in mountainous regions: the use of GIS and multivariate analysis

Jorge Marquínez*, Javier Lastra, Pilar García

INDUROT, University of Oviedo, Independencia 13, 33004 Oviedo, Spain

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Abstract

Using multiple linear regression and Geographic Information System techniques, we modelled the spatial distribution of mean monthly precipitation for the seasonal and annual periods in a mountainous region of 10,590 km^2, located in the central area of the Cantabrian Coast, Spain. We used precipitation data measured at 117 stations for the period 1966–1990, using 84 stations for function development and reserving 33 for validation tests. The best model developed used five topographic descriptors as independent variables: elevation, distance from the coastline, distance from the west, and a measurement of elevation and slope means into homogeneous areas. These topographic variables were calculated as raster models with 200 m resolution.

The model accounted for most of the spatial variability in mean precipitation, with an adjusted R^2 between 0.58 and 0.67. The standard error was approximately 10% and the mean absolute error ranged from 8.1 to 26.1 mm, which represented 13–19% of observed precipitation. Regression enabled us to estimate precipitation in areas where there are no nearby stations and where topography has a major influence on the precipitation.

Keywords: Regression analysis; GIS; Precipitation; Digital terrain model; Topographic variables; Multivariate analysis

1. Introduction

Spatial modelling of a climate variable is of interest because many other environmental variables depend on climate. Accurate climate data only exist for point locations, the meteorological stations, as a result of which values at any other point in the terrain must be inferred from neighbouring stations or from relationships with other variables.

Many studies (Kurtzman and Kadmon, 1999; Oliver and Webster, 1990; Philip and Watson, 1982; Mitas and Mitasova, 1988) model the spatial distribution of a climate variable using interpolation methods. These techniques can obtain satisfactory results from limited data, based mainly on the geographic situation of the sampling points, on the topological relationships between these points, and on the value of the variable to be measured. However, interpolation methods only consider spatial relationships among sampling points, and do not take into account other properties of the landscape.

Precipitation generally increases with elevation (Spreen, 1947; Smith, 1979), and so many authors have incorporated elevation into geostatistical approaches (Martínez-Cob, 1996; Prudhomme and

* Corresponding author.
E-mail address: jmarquin@indurot.uniovi.es (J. Marquínez).

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Duncan, 1999; Goovaerts, 2000). Others have developed relationships between precipitation and various topographic variables such as altitude, latitude, continentality, slope, orientation or exposure, using regression (Basist et al., 1994; Goodale et al., 1998; Ninyerola et al., 2000; Wotling et al., 2000; Weisse and Bois, 2001). Nevertheless, accuracy of the results obtained by these methods in mountainous regions is still very limited (Basist et al., 1994; Daly et al., 1994).

This study sought to develop the relationships between precipitation and a range of topographic variables in order to map precipitation across a mountainous region of Northern Spain. We chose topographic variables that had a great influence on precipitation within the area under study: previous climatic studies in the Cantabrian zone (Mounier, 1979; Sitges Menéndez et al., 1982; Felicísimo Pérez, 1992; Fernández Alvarez et al., 1996) point to the relevance of the position from the west and from the coastline as a predictor of precipitation, due to the dominance of fronts from the NW. We included two different measurements relative to these distances: a Euclidean length from each point to the coastline, and a Euclidean length from each point to a relative west. We also included commonly used topographic variables cited in the literature, such as elevation (Goodale et al., 1998; Katzfey, 1994; Basist et al., 1994; Bradley et al., 1998; Kurtzman and Kadmon, 1999; Wotling et al., 2000) and slope (Basist et al., 1994; Weisse and Bois, 2001), which we measured in a sub-basin area around each reference point, in order to integrate the effect of the orography on a local scale.

2. Methods and data

2.1. The study area

The study area is the Autonomous Region of Asturias in Northern Spain, covering an area of 10,590 km^2 (Fig. 1). This region is of special interest for the study of the relationships between precipitation and relief because of its climatic and topographic characteristics. The area has markedly seasonal rainfall and a very abrupt orography, with altitudes ranging from sea level to 2640 m within only 40 km.

Fig. 1. Location of the study area and the 117 meteorology stations used in the prediction function development and validation.

2.2. The dependent variable: precipitation data

Precipitation is strongly seasonal (Fig. 2), and so in the analysis we calculate mean monthly precipitation for the dry season (June–September), and for the wet season (the rest of the year), as well as for the annual average.

2.2.1. Collection and processing of climate data

Precipitation data were obtained from 212 meteorology stations of the National Meteorological Institute (INM), and from 38 additional stations belonging to other organizations, irregularly dispersed throughout the Autonomous Community. Most of these stations are located in the central, relatively flat part of the region, while a small number of stations are in

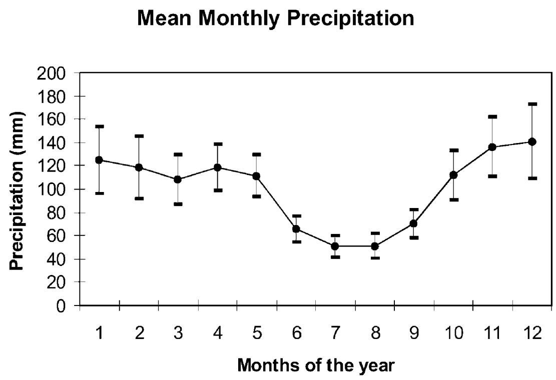

Fig. 2. Mean monthly precipitation of the stations used in the function development. Bars represent standard deviation.

areas of complex topography in the south of the region (Fig. 1).

The process for determining the polynomial functions began with the organization of the original station data into annual and seasonal series, followed by an analysis of the quality of the rainfall series: sample size and data homogeneity.

The World Meteorological Organization (WMO) recommends using 30 year means, although other authors have used shorter series with satisfactory results (Fernandez and Galán, 1996; Kurtzman and Kadmon, 1999; Goovaerts, 2000). We used a common period of 25 years, between 1966 and 1990, due to the limitations in the length of the rainfall series.

Only five of the 250 stations have complete data series for 1966–1990. We used two criteria to select the most appropriate meteorology stations: a minimum threshold of 0.8 in the Pearson correlation coefficient and the existence of at least 189 months in common between the stations. Of the total of 250 meteorological stations, only 117 reach the previously cited criterion. In consequence the remaining 133 stations were rejected for the purposes of this analysis.

We determined whether there were temporal trends within the rainfall series using the rachas test of homogeneity (Thom, 1966), and the results showed that none existed. Once the suitability of the sample length and homogeneity had been checked, we proceeded to fill in the gaps in the series which were incomplete for the study period.

To complete gaps in the data, we developed regression equations between stations with incomplete and complete data. The gaps completed by this methodology constituted 22.2% of the total data used in the development of the prediction function, and the spatial distribution of the 117 stations used is strongly biased towards lower elevations (Table 1), with 86% of measurement stations located below 600 m, 12 stations (10.3%) between 600 and 1000 m, and only four stations over 1000 m (3.4%). This is a handicap in a region where almost 20% of the territory is located over 1000 m.

The gaps in the data in the rainfall series, together with the irregular distribution of the stations, pose a problem common to the construction of such prediction models.

Table 1
Elevations of the meteorological stations in the area under study

Elevation (m)	Meteorological stations		
	Absolute frequency	Relative frequency (%)	Relative Asturias area (%)
<50	13	11.1	2.5
51–200	35	29.9	15.3
201–600	53	45.3	35.8
601–1000	12	10.3	26.4
>1000	4	3.4	19.8

2.3. The independent variables

We hypothesized that certain variables derived from topography, such as altitude, slope, distance from the coastline and from the west, could be used to predict precipitation. We used a digital elevation model (DEM) derived from the digitalization of the contour lines of the national topographical map 1:200.000 of the IGN (National Geographic Institute). This DEM (Fig. 3A) was made with Hutchinson's (1989) algorithm, also known as ANUDEM. This model and all its derivatives have a cell size of 200 m and their georeference system is UTM, zone 30, international ellipsoid. This refers to a rectangle covering the whole of the territory of Asturias.

We used this DEM to provide estimates of elevation, and to derive other topographic indices. We computed the Euclidean distance from the coastline to each point (*dsea*), and the shortest distance to an arbitrary line further west than any point in the area (*dwest*). For some variables, the mean value in homogeneous setting close to a given point allows local effects to be smoothed, and has a greater significance than the value at the point itself (Daly et al., 1994; Wotling et al., 2000). We built these homogeneous settings by dividing the region into sub-basins. These were calculated using the *basin* function of Arc-Info GIS 7.1.2. grid module (ESRI, 1997), a function which establishes the drainage basin by identifying ridge lines between basins. Because of this, the flow-direction grid (Jenson and Dominge, 1988) was used to find all sets of connected cells that belong to the same drainage basin. These sub-basins have surface areas between 5 and 382 km^2, with an average of 32 km^2 (Fig. 3C), so additional variables

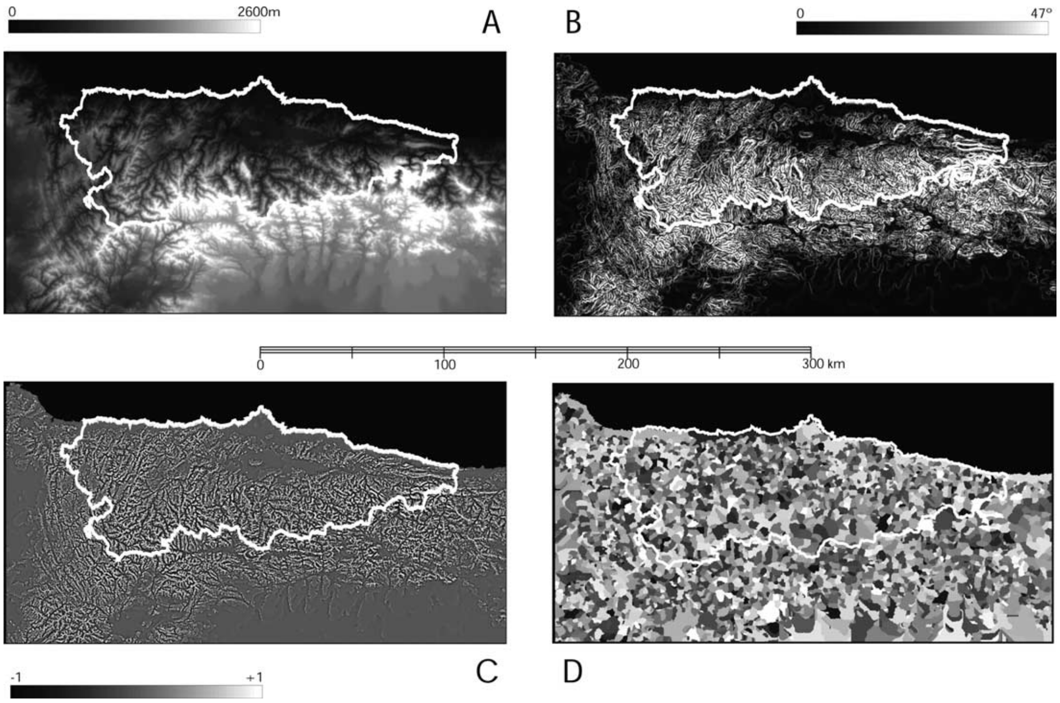

Fig. 3. Some digital terrain models used as independent variables. (A) DEM, (B) slope. We divided the region into sub-basins (C).

were incorporated as mean values of the 'sub-basins'. In this way, we obtained the mean sub-basin elevation (*DEMb*) and the mean sub-basin slope (*slopeb*) (Borrough, 1986).

2.4. Statistical analysis

We used data from the 117 complete stations described previously. Of these, 84 stations were used to derive the polynomial functions and 33 stations were reserved to validate these functions. The statistical method used to relate the rainfall variable to topographic variables was multiple linear regression.

The function has a *determination coefficient* (R^2) as a measure of the goodness of fit of the model, and this represents the proportion of the variation of the dependent variable (annual and seasonal mean monthly precipitation) explained by the regression model. Since the parameter R^2 tends to over-estimate the goodness of fit of the model in the population, we also calculated an *adjusted determination coefficient* (*adj-*R^2), which compensates for this optimistic trait in the determination coefficient, by taking into account the size of the sample and the number of prediction variables. Unlike R^2, the adjusted determination coefficient does not necessarily increase when additional variables are added to an equation.

For the regression, we followed the criterion of the *stepwise approach*, selecting the variables backwards. This method has the advantage that a variable selected in one step can be eliminated in another later step. In this way, initially all the variables are introduced in a single step and after they are discarded one by one basing on the outset criteria. In order to avoid the possibility of any of the variables being a linear combination of the rest, the tolerance criterion is followed: the tolerance of a variable X_j with the other variables is defined as

$$\mathrm{Tol}_j = 1 - R_j^2 \tag{4}$$

where R_j is the multiple correlation coefficient between variables X_j and X_1, X_{j-1}, $X_{j+1},\ldots,X_p$. If the tolerance is close to 0, the variable X_j is a linear combination of the others and is removed from the equation. The tolerance criterion is additional to the probability of entry in the equation. Each time a variable is removed from the function, the model is recalculated so the variance must be explained globally.

The relationships between precipitation and the independent topographic variables described above generally fit squared or cubic models better than linear ones. Consequently, we introduced the squared and cubic values of the independent variables to achieve a better fit of the theoretical curve to the data.

3. Results and discussion

3.1. The regression model

Pearson correlation coefficients for the relationships between precipitation and the independent topographic variables are shown in Table 2, whilst the models developed are shown in Table 3. The best mean monthly precipitation function was predicted with model 4, which shows the following expression

$$F(x) = b_1 DEM + b_2 DEM^2 + b_3 DEM^3 + b_4 DEMb + b_5 DEMb^2 + b_6 DEMb^3 + b_7 slopeb + b_8 slopeb^2 + b_9 slopeb^3 + b_{10} dwest + b_{11} dwest^2 + b_{12} dwest^3 + b_{13} dsea + b_{14} dsea^2 + b_{15} dsea^3 + b_0 \quad (5)$$

where $b_1, \ldots, b_n$ represent the coefficients obtained for each independent variable for the dry season, the wet season, and the annual period, that best predict the value of the dependent variable (Table 4).

There are three topographic variables significant at a level of $p < 0.05$ (Table 2): *DEM*, *DEMb* and *slopeb*, although model 2, when developed with these variables, only accounted for 10–41% of the spatial variability of mean precipitation (Table 3). Front associated variables, *dwest* and *dsea*, raise the accountability to 47–58% of the spatial variability of the mean precipitation in model 3, which has been developed using non-sub-basin derived variables. However, the accuracy of this model is approximately 10% poorer than that of model 4, which uses sub-basin derived variables.

Table 2
Bivariate correlation coefficients for the independent variables and precipitation data

	DEM	DEMb	slopeb	dwest	dsea
Annual	*0.39*	*0.41*	0.26	−0.22	0.15
Dry season	0.06	0.04	0.01	0.02	−0.23
Wet season	*0.44*	*0.47*	*0.30*	−0.26	0.23
DEM		*0.88*	*0.58*	*−0.25*	*0.75*
DEMb	*0.88*		*0.76*	*−0.24*	*0.85*
slopeb	*0.58*	*0.76*		*−0.21*	*0.65*
dwest	*−0.25*	*−0.24*	*−0.21*		−0.18
dsea	*0.75*	*0.85*	*0.65*	−0.18	

Statistically significant relationships at the 0.05 level are italicised.

In the model 4, topographic variables accounted for 67% of the spatial variability of the mean annual precipitation at the 84 measurement stations (Table 4). Topographic variables explained 58% of the spatial variability of precipitation in the dry season and 67% for the wet season. Standard errors of prediction ranged from 6.2 to 13.1 mm, corresponding to 10.1–10.8% of the magnitude of mean precipitation.

By applying model 4 function to the topographic indices derived from the DEM we mapped mean monthly precipitation for the dry and wet seasons, as well as for the whole year, for the period between 1966 and 1990 (Fig. 4).

It is difficult to interpret the relationships between precipitation and each of the terrain derived variables quantitatively but independently, due to the nature of multivariant analysis. Nevertheless, in Fig. 5 the regression coefficients for the independent variable used are shown. The *Y*-axis only indicates the partial contribution of each variable to the equation, the form of each function offering greater information. *Dwest* and *dsea* variables describe U-form precipitation patterns (Fig. 5), the estimated total precipitation diminishing approximately 90–100 km from the chosen reference point to the west and 45 km from the coast, in other words, in the western, inland basins. Both variables describe a high precipitation in the NW and in the NE of the region, as a result of the dominance of fronts from the NW. Elevation displays an increase in

Table 3
Models developed, and R^2, adjusted R^2 (adj-R^2) and standard error (SE) coefficients. Linear, squared and cubed terms of each variable were used

	Topographic variables					Annual			Dry season			Wet season		
						R^2	Adj-R^2	SE	R^2	Adj-R^2	SE	R^2	Adj-R^2	SE
Model 1	DEM	DEMb				0.31	0.29	15.0	0.11	0.08	9.2	0.36	0.29	18.7
Model 2	DEM	DEMb	slopeb			0.39	0.36	14.2	0.17	0.10	9.1	0.44	0.41	17.6
Model 3	DEM			dwest	dsea	0.61	0.58	11.5	0.51	0.47	6.9	0.63	0.59	14.6
Model 4	DEM	DEMb	slopeb	dwest	dsea	0.71	0.67	10.3	0.65	0.58	6.2	0.72	0.67	13.1

precipitation with elevations up to 400 m, at which point the slope curve drops virtually to zero, with the intensity of the rainfall remaining constant. Above 1000 m precipitation increases once more with altitude. The *DEMb* variable behaves in much the same way for the dry season, whilst acquiring a linear pattern for the wet season and the annual average, with a continual increase in precipitation with the altitude of the sub-basin. The *Slopeb* variable function grows rapidly above 12 degrees, increasing its importance in the absolute value of the total function. This variable appears to regulate the rainfall predicted by the model on steep slopes to the south of the region.

3.2. Error estimation: residual analysis

The analysis of regression residuals is the first validation test of the model. If the fitted model is appropriate, the residuals should be normally distributed, and should not correlate with each other or with the independent variables:

Table 4
Coefficients and regression statistics obtained for the prediction function of the mean precipitation

Coefficients and regression statistics	Variable	Annual	Dry season	Wet season
b_0	Constant	106.397	73.026	131.108
b_1	DEM	0.127	7.84×10^{-2}	0.147
b_2	DEM^2	-2.05×10^{-4}	$-1.42 \times {}^{-4}$	-2.33×10^{-4}
b_3	DEM^3	1.01×10^{-7}	7.41×10^{-8}	1.13×10^{-7}
b_4	DEMb	4.99×10^{-2}	0.109	6.33×10^{-2}
b_5	DEMb^2		-1.18×10^{-4}	
b_6	DEMb^3		4.76×10^{-8}	
b_7	slopeb	-5.997	-3.444	-7.32
b_8	slopeb^2	0.955	0.487	1.169
b_9	slopeb^3	-3.98×10^{-2}	$-1.9 \times {}^{10-2}$	-4.89×10^{-2}
b_{10}	dwest	-3.74×10^{-4}	-7.24×10^{-4}	-5.22×10^{-4}
b_{11}	dwest^2	1.80×10^{-9}	6.88×10^{-9}	$2.40 \times {}^{10-9}$
b_{12}	dwest^3		-1.81×10^{-14}	
b_{13}	dsea		$-1.30 \times {}^{10-3}$	
b_{14}	dsea^2	-6.92×10^{-8}		-8.32×10^{-8}
b_{15}	dsea^3	1.02×10^{-12}	1.95×10^{-13}	1.25×10^{-12}
R^2		0.72	0.65	0.72
Adj-R^2		0.67	0.58	0.67
SE (mm)		10.26	6.19	13.15
SE (%)		10.18	10.39	10.83
Mean (mm)		100.79	59.57	121.41
N		84	84	84

N is the number of meteorological stations used in the regression, R^2, determination coefficient, adj-R^2, adjusted determination coefficient, and SE is the standard error.

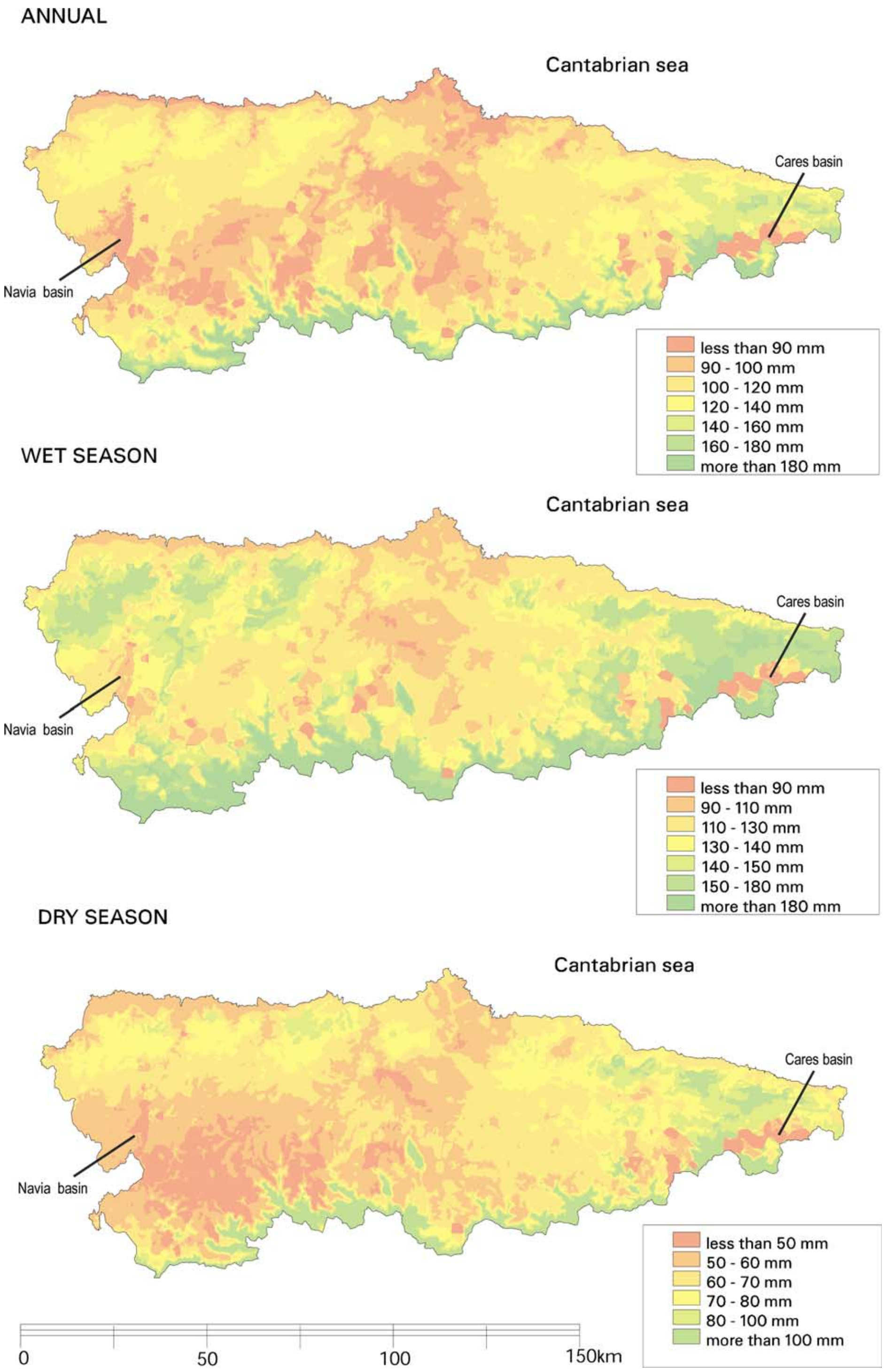

Fig. 4. Distribution model for the estimated mean precipitation in the Region of Asturias based on the prediction function.

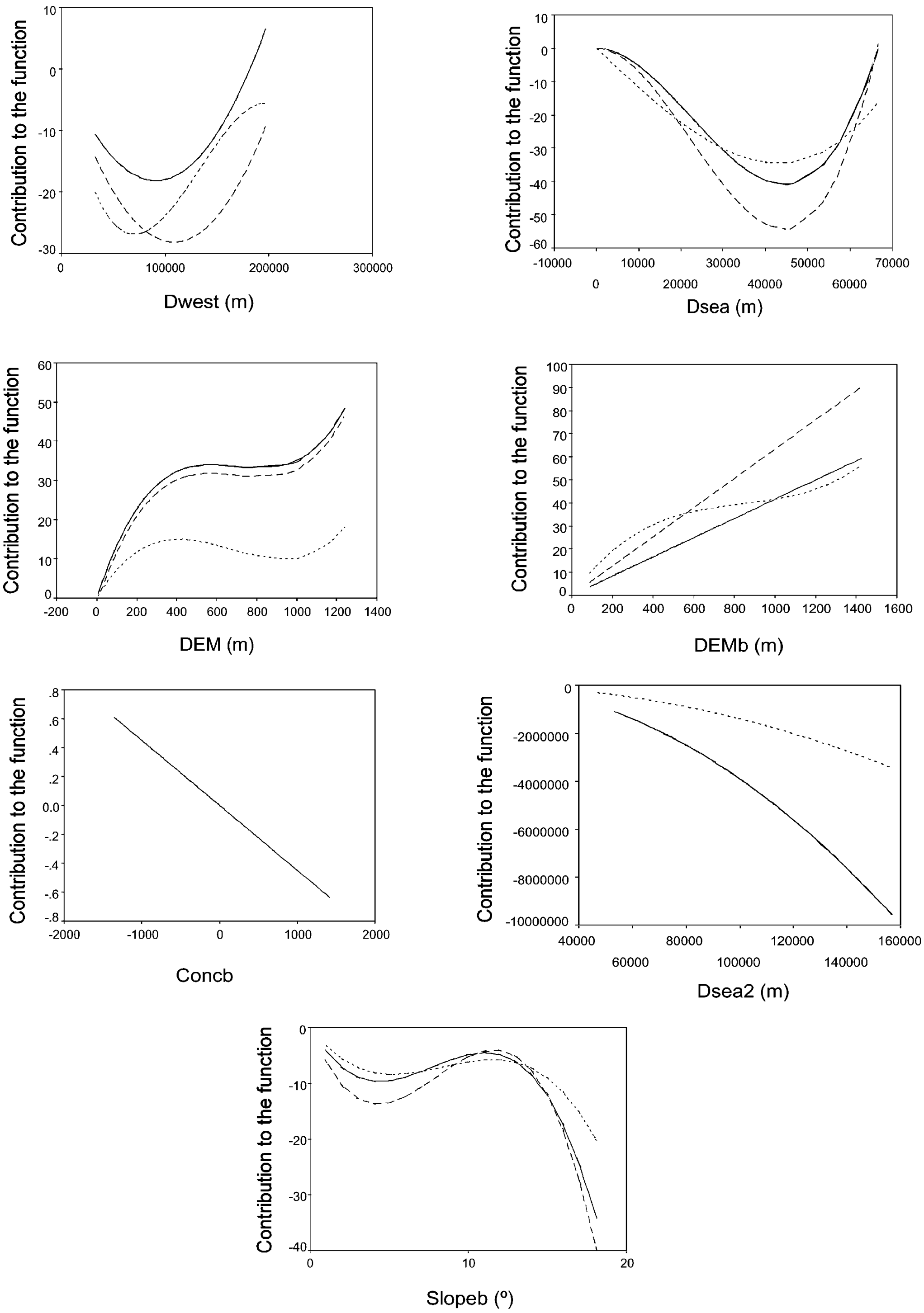

Fig. 5. Relationships between precipitation and independent variables for annual period (solid line), wet season (broken line) and dry season (dotted line).

Table 5
Results of the Kolmogorov–Smirnov and Durbin–Watson tests for the annual period, the dry and the wet seasons

	Annual	Dry season	Wet season
Kolmogorov–Smirnov's test			
Z-test value	0.831	0.731	1.063
Asinthotic significance	0.495	0.659	0.208
Durbin–Watson's test			
Test value	1.912	1.709	1.944

(1) We tested for normal distribution with the Kolmogorov–Smirnov test, and found that the non-standardised residuals can be considered as Normal at a level of significance of 0.05 (Table 5).
(2) The residuals should not present any systematic pattern with respect to the observation sequence (i.e. autocorrelation). We used the Durbin–Watson test to check for autocorrelation between the residual corresponding to each observation and the previous one. Durbin–Watson values range from 0 to 4, indicating a extremely positive or negative autocorrelation, respectively, in contrast to a value close to 2, which indicates little autocorrelation. We found Durbin–Watson values from 1.7 to 1.9, which confirms the independence of the residuals (Table 5).
(3) The residuals should not present a systematic pattern with respect to the independent variables. Fig. 6 reveals the lack of any clear trend between the residuals and predictions.

3.2.1. Error measured with other stations

Predictions from the linear regressions for each time period were compared with the data recorded in the 33 stations reserved for validation.

We calculated the Bias as a measurement of the sign and magnitude of means errors

$$\text{Bias} = \frac{1}{n}\sum_{i=1}^{n}(P_i - O_i) \tag{6}$$

where: P_i is the predicted value at a given point, and O_i is the observed value at the same point and the mean absolute error (MAE) as a precision measurement:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|P_i - O_i|. \tag{7}$$

In Table 6 the results are shown. The MAE ranges from 8 to 26 mm which represents from 13.3 to 19.5% of the observed precipitation, an increment of less than 9% over the standard error estimated for the model of 10%.

The regression functions slightly overestimate mean precipitation by an average of 2.4 mm for the annual period, and underestimate 1.2 mm for the dry season, and 1.47 mm for the wet season. The error measurements in this study are similar to or an improvement over previous papers of mapping precipitation in mountainous regions using a regression approach (Basist et al., 1994; Daly et al., 1994;) or a geostatistical approach (Martínez-Cob, 1996).

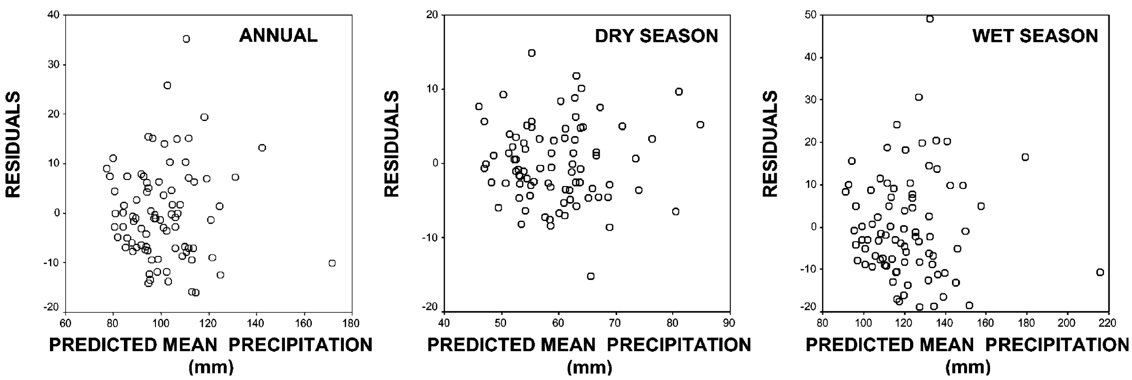

Fig. 6. Scattergrams relating the standard residuals compared to the standard estimates for the mean monthly precipitation for the three periods studied: annual period and dry and wet seasons.

Table 6
Errors measured when applying the prediction functions to the stations reserved for data validation

Period	MAE (mm)	Mean error (%)	Bias	Estimated average monthly precipitation (mm)
Annual	15.57	14.03	+2.40	108.13
Dry season	8.16	13.29	−1.18	60.95
Wet season	26.19	19.48	−1.47	130.12

4. Conclusions

The regression approach enabled us to describe 58–68% of the spatial variability of annual and seasonal mean precipitation. Using the five topographical variables (*DEM*, *DEMb*, *slopeb*, *dwest*, *dsea*) model 4, the results show an improvement over those from models developed using only altitude related variables (Table 3).

'Sub-basin' derived variables make a great contribution to the model, improving the results obtained by using only punctual topographical variables in 10%. This approach enabled us to identify the peculiarities of precipitation patterns with the variables *dwest* and *dsea*, which are related to the position of the dominant fronts, displaying a high precipitation in the NW and in the NE of the region, and a low precipitation in the inland basins. *DEM* and *DEMb* variables display an increase of precipitation with elevation, which is faster over 1000 m. *Slopeb* variable becomes an important factor in the function with slopes over 12 degrees.

This method also enabled us to estimate precipitation in areas where there is no nearby station, as the data are not inferred directly from the closest station, but rather from the topographic peculiarities of the terrain, as long as the topographic features are within the ranges used for the regression equation fit.

An advantage over interpolation methods is that the quality of estimated data does not depend on the density of measurement stations in the neighbouring area; it is enough to have stations in areas of similar topographic characteristics, even though they are relatively far apart. For the same reason, the area of estimation can also be extended beyond the last measurement station in the area as long as the topographic characteristics and the scale of work are similar.

5. Uncited reference

Fernández (1995).

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