British Journal of Applied Science & Technology
3(4): 1286-1300, 2013

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Kriging Interpolation Method for Estimation of Continuous Spatial Distribution of Precipitation in Cyprus

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Authors' contributions

This work was carried out in collaboration between all authors. Authors FM, PA and SP designed the study and collected the data. Author KK performed the statistical analysis. All authors read and approved the final manuscript. All authors read and approved the final manuscript.

Research Article

Received 28th May 2013
Accepted 28th July 2013
Published 10th August 2013

ABSTRACT

Aims: Development of a precipitation prediction model for Cyprus.
Study Design: Precipitation data collected at 78 stations were used: data from 66 stations for model development and data from 12 stations for additional tests. Four topographic factors – altitude, slope, longitude, and latitude – were taken into account for model development.
Place and Duration of Study: All variables were obtained from the observation archives of the Water Development Department of the Ministry of Agriculture, Natural Resources and Environment of Cyprus, between 1961 and 1990.
Methodology: Multiple regression analysis, combined with residuals correction, was carried out to develop a precipitation prediction model.
Results: The multiple regression model can explain 61.3% of the spatial variability of precipitation over the whole year, 57.5% of variability in the wet season (October–April), and 99.6% of variability in the dry season (May–September). Interpolation-based

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residuals correction improved the accuracy of our model (*Adj_ R^2*=65.1%, 62.6% and 99.7%, respectively).
Conclusion: This approach, as presented in this paper, could potentially be applied to Cyprus' climate research.

Keywords: Cyprus; kriging interpolation; multiple regression; precipitation.

1. INTRODUCTION

Water balance (i.e. precipitation excess) directly affects nutrients concentration and biomass yield in a forest site [1,2,3]. However, precipitation is usually measured at a very limited number of stations, especially in mountain areas. As a result, accurate estimation and prediction of precipitation represents a great challenge due to lack or non-validity of observation data [4,5,6]. The development of geographic information systems (GIS) in recent years provides increased opportunities for precipitation modeling.

Interpolation methods have been developed for rainfall modeling. Most of them are based mainly on the similarity and topological relations of nearby sample points and on the value of the variable to be measured [7,8,9]. Interpolation can be achieved using simple methods (inverse distance weighting, trend surface analysis, splines and Thiessen polygons, etc.) or more complex methods (geostatistical methods, such as kriging). Geostatistical interpolation has become an important tool in climatology because it is based on the spatial variability of the variables of interest and makes it possible to quantify the estimation uncertainty [10,11,12,13,14,15]. However, interpolation methods only consider spatial relationships among sampling points, and do not take into account other important topographic variations. Consequently, the usual interpolation methods cannot provide researchers with adequate precision of precipitation estimation, especially in complicated terrains of mountainous regions [16,17].

In recent years, geographic and topographic factors have been integrated into the modeling of precipitation [18]. Some authors have attempted to incorporate local topographic factors, such as elevation, into geostatistical approaches [19], and others have developed models relating climate to site position and elevation [20]. Relationships between topography and the spatial distribution of precipitation have been analyzed for mountainous regions [21,22]. The precipitation-elevation regressions on independent slopes model brings a combination of climatological and statistical concepts to the analysis of orographic precipitation [4], and recently weighting functions to incorporate gauge data of neighboring topographic facets for regressions were used [23]. More recent studies have considered more refined topographic factors by using higher resolution digital elevation models (DEM) to predict the physical influence of topographic variables on precipitation patterns. Precipitation models integrating statistical and GIS techniques have become widespread and common [19,24]. Multiple linear [25,26,27,28] and non-linear [16,29] regression models have proved to be rather effective.

2. MATERIALS AND METHODS

2.1 Study Area

Cyprus is situated at latitude 35º and longitude 33º on average, and it is surrounded by the eastern Mediterranean Sea. The present study, focusing on Cyprus, was conducted to estimate precipitation in mountain regions, based on four topographic factors (altitude, slope, longitude, and latitude). It is worth noting that the rainfall network of Cyprus is quite dense (almost 1 gage each 69 km^2), which is not so usual in Mediterranean countries, and the data are regularly verified and published by a National Technical Service. In Fig. 1 the study area is shown; note that the area of interest is the area under the control of the Republic of Cyprus, comprising about 59% of the island's area, not the Turkish-controlled area in the north.

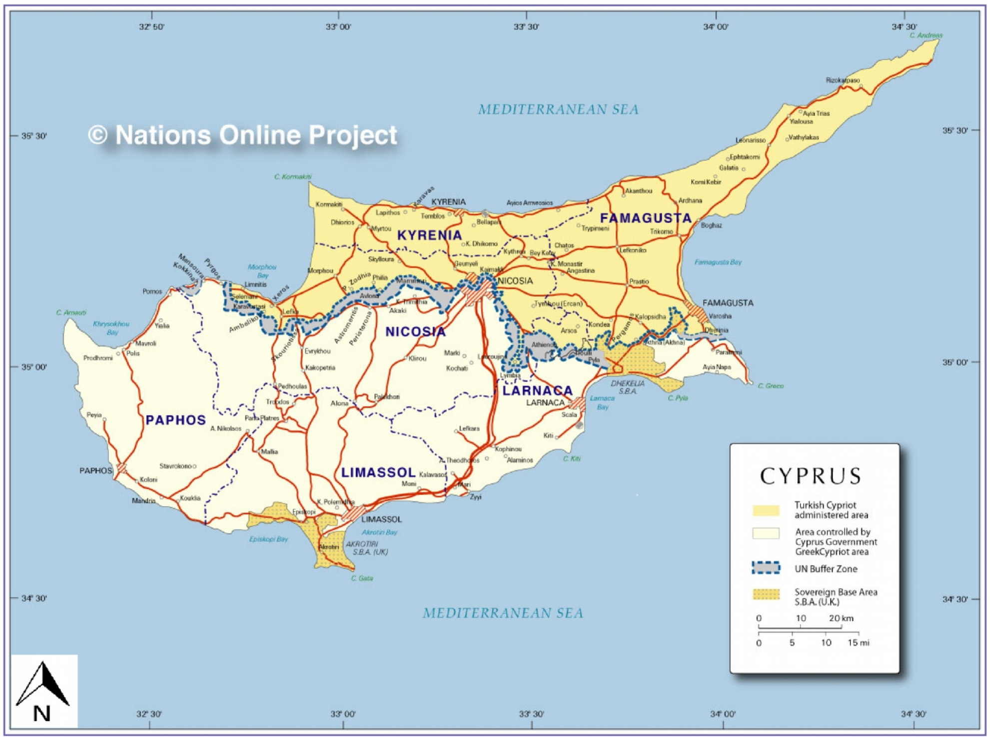

Fig. 1. Political map of Cyprus

Cyprus has an area of 9251 km^2 area and is the third largest Mediterranean island. Hydrographically, the island is divided into 9 hydrological regions composed by 70 watersheds and 387 sub-basins (according to Water Framework Directive 2000\60, as published by the Ministry of Agriculture, Natural Resources and Environment, 2005 [30]).

In the middle of the southwest part of Cyprus the Troodos mountain is located (maximum altitude = 1953 m), which is composed mainly of volcanic and some limestone rocks. At the North coast we find the mountainous region of Pentadaktylos (maximum altitude = 1000 m). Most rivers flow from the Troodos mountain. The lakes are mainly located in lowland areas.
Cyprus has a Mediterranean climate, with a typical seasonal variation particularly wide concerning temperature, precipitation and the weather generally. Hot, dry summers from mid-May to mid-September and rainy, rather unstable, winters from November to mid-March are interrupted by short autumn and spring periods characterized by sudden weather changes.

The average annual rainfall is about 500 mm, with a significant decrease in 1972-73 (182 mm) and a significant increase in 1968-69 (759 mm) [31]. The average annual rainfall increases from the southwest windward slopes (450 mm) to the Troodos mountain (about 1100 mm at the top). Rainfall increases during winter (December-February). The seasonal distribution of surface runoff follows the seasonal distribution of precipitation, with minima during summer and peak during winter. As a result of the East Mediterranean climate, which is characterized by prolonged hot summers and low average annual rainfall; there are no rivers with continuous flow throughout their entire length. Most rivers flow for 3 to 4 months and dry up the rest of the year. Only parts of some rivers that are located upstream of the Troodos mountain have continuous flow.

The Water Development Department of the Ministry of Agriculture, Natural Resources and Environment, is authorized to keep hydrologic records and write annual hydrologic reports.

2.2 Data Collecting and Processing

Precipitation data from 78 stations were obtained from the observation archives of the Ministry of Agriculture, Natural Resources and Environment of Cyprus. For each station, the annual average amount of precipitation for the period 1961-1990 was used. Measurements are related to the capacitive regions, as defined by the administrative boundaries of cities and villages. Most of these stations were located at low altitude, lower than 300 m (Table 1). Stations covered areas between 4.6 and 260 km^2, with an average of 69 km^2.

Table 1. Vertical distribution of precipitation stations in Cyprus

Altitude (m)	**Number of stations**	**Station proportions (%)**	**Area (km^2)**	**Area proportions (%)**
<=100	25	32.1	2422.5	44.9
(100,300]	32	41.0	2166.2	40.2
(300,600]	15	19.2	742.5	13.8
(600,900]	5	6.4	57.7	1.0
>1200	1	1.3	5.0	0.1
Total	**78**	**100.0**	**5393.9**	**100.0**

For the wet season (October–April), mean measured precipitation was 619.31 mm, for the dry season (May–September) 456.00 mm, and for the whole year, 601.59 mm.

There are many factors which affect precipitation and its spatial distribution. Usually, precipitation increases with growing elevation and it varies depending on slope [32]. Factors closely related to precipitation include not only rugged topography, but also geographical location, as rainfalls are mainly due to moisture-laden air masses from the southeast. Therefore, latitude and longitude should be considered in the development of precipitation modeling.

2.3 Calculation

The combination of models development (multiple regression models) and spatial interpolation methods (ordinary kriging) has been demonstrated to be effective in modeling precipitation [26]. Topographic variables, if considered on their own, are poorly related to rainfall statistics in our data, as shown in Table 2. In other words, none of the topographic variables could be used by itself to appropriately explain the precipitation pattern.

Table 2. Pearson correlation coefficient matrix for independent variables and precipitation data

Variable	Annual	Wet season	Dry season	Altitude	Slope	Longitude
Altitude	0.674**	0.626**	0.630*			
Slope	0.563*	0.646**	0.767**	0.541**		
Longitude	0.282*	0.312*	-0.302	0.071	0.052	
Latitude	-0.046	-0.090	-0.388	0.176	0.234*	-0.034

*** Significant at α = 0.01.*
** Significant at α = 0.05.*

In order to depict the relationships of precipitation and topographic variables, we tried to model precipitation with multiple linear stepwise regression, as follows:

$$P = b_0 + b_1 h + b_2 h^2 + b_3 h^3 + b_4 slp + b_5 slp^2 + b_6 slp^3 + b_7 X + b_8 X^2 + b_9 X^3 + b_{10} Y + b_{11} Y^2 + b_{12} Y^3 \tag{1}$$

where P represents precipitation (mm); b_0 is constant; b_1,...b_{12} represent the coefficients obtained for each independent variable, h, slp, X, Y represent the variables of altitude (m), slope (%), longitude (º), and latitude (º).

From the 78 precipitation stations, a total of 66 (about 85%) were selected for modeling by random sampling, and the remaining 12 stations (about 15%) were used for validation (stations 16, 26, 37, 42, 46, 52, 58, 64, 71, 75, 76, and 77). The split of the fitting and testing data was done by applying repeated random grouping for the number of experimental data (78 times) [33]. The constants were acquired by means of the least squares method in the regression module of SPSS software, and all the regression statistics were also created by the software.

Kriging belongs to the family of linear least squares estimation algorithms [34,35,36]. The aim of kriging is to estimate the value of an unknown real-valued function f at a point x^* given the values of the function at some other points, x_1, …, x_n. A kriging estimator is said to be linear because the predicted value $\hat{f}(x^*)$ is a linear combination that may be written as

$$\hat{f}(x^*) = \sum_{i=1}^{n} w_i(x^*) f(x_i).$$

The weights w_i are solutions of a system of equations which is obtained by assuming that f is a sample-path of a random process $F(x)$, and that the error of prediction

$$\varepsilon(x) = F(x) - \sum_{i=1}^{n} w_i(x) F(x_i)$$

is to be minimized in some sense. Depending on the stochastic properties of the random field different types of kriging apply. The type of kriging determines the linear constraint on the weights w_i implied by the unbiasedness condition; i.e. the linear constraint, and hence the method for calculating the weights, depends upon the type of kriging. Ordinary kriging is the most commonly used type of kriging, assuming a constant but unknown mean.

The semivariogram/covariance cloud allows us to examine the spatial autocorrelation between the measured sample points. In spatial autocorrelation, it is assumed that things that are close to one another are more alike than those further apart. The semivariogram/covariance cloud lets us examine this relationship. To do so, a semivariogram value, which is the squared difference between values at paired locations, is plotted on the y-axis relative to the distance separating the two observations. Semivariogram values are averaged within classes of distance to facilitate the visualization of how the semivariogram value increases with distance. However, a certain distance is reached where the cloud flattens out, indicating that the relationship between the pairs of locations beyond this distance is no longer correlated.

3. RESULTS

3.1 Regression Model

It has been shown that when the fit set accounts for more than 80% of the whole set, the adjusted determination coefficient (*adj_ R^2*) tends to remain stable [37]. Hence, it is reasonable to select 85% (66 stations) of the whole set as the fit set (Fig. 2).

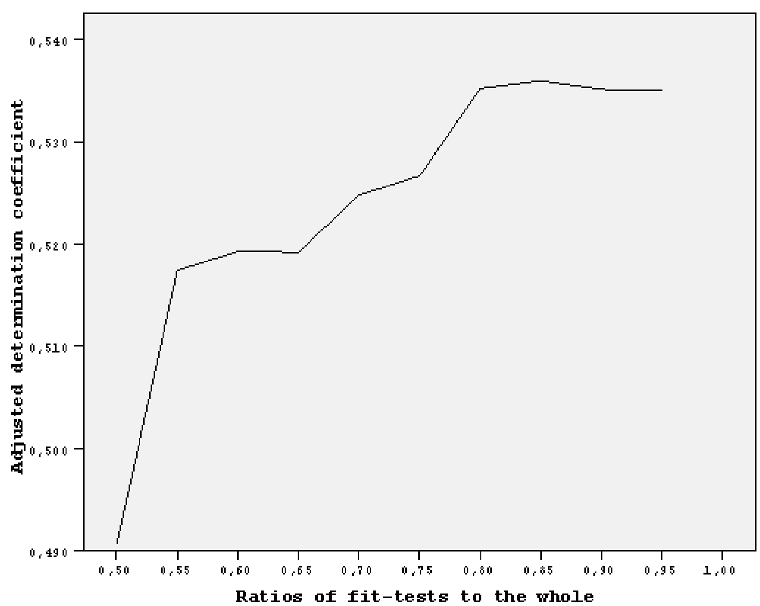

Fig. 2. Error stability of the precipitation prediction model

Using stepwise method, model (1) took the following form, for annual and wet season precipitation:

$$P = b_0 + b_1 h + b_2 h^2 + b_3 h^3 + b_4 slp + b_5 slp^2 + b_6 slp^3$$
$$+ b_7 X + b_8 X^2 + b_9 X^3 + b_{10} Y + b_{12} Y^3$$

As for the dry season, the precipitation model is:

$$P = b_0 + b_1 h + b_3 h^3 + b_4 slp + b_6 slp^3$$
$$+ b_7 X + b_9 X^3 + b_{10} Y + b_{12} Y^3$$

Statistics for these models are given in Table 3. Standardized regression coefficients are calculated, in order to determine the relative importance of the significant predictor variables. Multiple R^2 is calculated, since the regression was conducted for a series of fits sets, as the proportion of variance in the dependent variable that is explained by the additive combination of effects of the independent variables; *Adj_* R^2 is the adjusted determination coefficient, which compensates for the limitation of the determination coefficient by taking into account the size of the sample and the number of prediction variables, and it exactly represents the proportion of variation of the dependent variable (i.e. annual mean precipitation) explained by the multiple regression model; *RMSE* is the root mean squared error, which describes the error of prediction in the modeling of precipitation; *F* is the value of the *F* statistical test; *DW* is the value of the Durbin-Watson statistic – a test statistic used to detect the presence of autocorrelation in residuals, based on regression analysis.

The models for both annual and seasonal precipitation pass the *F* test at 0.05 significance level. The determination coefficients (multiple R^2 and *adj_* R^2) show the goodness-of-fit of the annual and seasonal models (Table 3). The capability of the model to explain the spatial variability of precipitation varies depending on the period: its accuracy is 99.6% for the dry season, and 61.3% for the whole year, but only 57.5% for the wet season. The root mean squared error (*RMSE*) – an index for estimating relative error – is 5.95%, 62.24%, and 65.20% for the three periods, respectively. The low R^2 and high RMSE for the wet season show that our multiple regression model does not work well. The values of the Durbin-Watson test show positive autocorrelation among the residuals for both annual and wet season models and a negative autocorrelation for the dry season model.

We could also note that, even though h^3 has a small coefficient compared to the other predictors, in all three models, h^3 actually has a more important contribution because it has a large absolute standardized coefficient.

3.2 Ordinary Kriging

In order to improve the results of the regression model, we adopted ordinary kriging. An exponential semivariogram model was used for predicting the residuals of the 66 precipitation stations. Statistics of the kriging interpolation model are given in Table 4. The model for both annual and seasonal (wet – dry season) precipitation passes the *F* test at 0.05 significance level. The higher determination coefficients (R^2) and *adj_* R^2 show the better goodness-of-fit of the kriging model (Table 3). The capability of the model to explain the spatial variability of precipitation is 99.7% for the dry season, 65.1% for the whole year, and 62.6% for the wet season. The root mean squared error (*RMSE*) – an index for estimating relative error – is 5.60%, 59.09%, and 61.15% for the three periods, respectively. This shows that our kriging interpolation method really improves the multiple regression model.

Table 3. Regression statistics and evaluation of the multiple regression model (including 66 stations used for modeling)

	Whole season		Wet season		Dry season	
	Unstandardized coefficients	Standardized coefficients	Unstandardized coefficients	Standardized coefficients	Unstandardized coefficients	Standardized coefficients
b_0	498.383		316.393		530.347	
$b_1(h)$	0.286	0.388	0.676	0.857	0.215	0.246
$b_2(h^2)$	0.001	0.767	-0.001	-1.036	-	-
$b_3(h^3)$	-8.23E-007	-0.741	1.12E-006	0.836	-7.03E-006	-0.946
$b_4(slp)$	77.573	1.590	71.916	1.471	-14.424	-0.214
$b_5(slp^2)$	-7.796	-2.214	-6.039	-1.746	-	-
$b_6(slp^3)$	0.275	1.064	0.114	0.461	2.273	1.140
$b_7(X)$	-3.811	-0.664	-3.685	-0.653	-12.537	-2.619
$b_8(X^2)$	0.176	3.264	0.176	3.357	-	-
$b_9(X^3)$	-0.001	-2.515	-0.001	-2.628	0.001	2.824
$b_{10}(Y)$	-4.212	-0.378	0.098	0.009	10.114	1.221
$b_{12}(Y^3)$	0.000	0.135	0.000	-0.235	-0.001	-1.708
Multiple R^2	0.678		0.668		1.000	
Adj_ R^2	0.613		0.575		0.996	
RMSE **(mm)**	98.193		102.464		5.484	
RMSE **(%)**	62.24%		65.20%		5.95%	
F **(sig<0.05)**	10.345		7.147		317.608	
DW	1.564		1.593		3.050	

Adj_ R^2 is the adjusted determination coefficient.
RMSE is the root mean squared error.
DW is the value of the Durbin-Watson statistic.

Table 4. Statistics and evaluation of the kriging interpolation model (including 66 stations used for modeling)

	Whole season		Wet season		Dry season	
	Unstandardized coefficients	**Standardized coefficients**	**Unstandardized coefficients**	**Standardized coefficients**	**Unstandardized coefficients**	**Standardized coefficients**
b_0	523.983		226.376		531.444	
$b_1(h)$	0.274	0.381	0.918	1.134	0.215	0.245
$b_2(h^2)$	0.001	1.039	-0.002	-1.754	-	-
$b_3(h^3)$	-1.05E-006	-1.028	1.91E-006	1.386	-7.03E-006	-0.938
$b_4(slp)$	74.818	1.571	69.554	1.418	-14.427	-0.207
$b_5(slp^2)$	-7.336	-2.124	-4.694	-1.335	-	-
$b_6(slp^3)$	0.259	1.014	0.009	0.034	2.274	1.101
$b_7(X)$	-3.641	-0.704	-4.278	-0.860	-12.531	-2.361
$b_8(X^2)$	0.158	3.277	0.185	4.036	-	-
$b_9(X^3)$	-0.001	-2.498	-0.001	-3.113	0.001	2.425
$b_{10}(Y)$	-4.809	-0.445	1.857	0.186	10.078	1.173
$b_{12}(Y^3)$	0.000	0.211	0.000	-0.404	-0.001	-1.581
Multiple R^2	0.710		0.708		1.000	
Adj_ R^2	0.651		0.626		0.997	
***RMSE* (mm)**	2282.017		2309.718		145.1824	
***RMSE* (%)**	59.09%		61.15%		5.60%	
***F* (sig<0.05)**	12.014		8.611		358.186	
DW	1.450		1.680		3.049	

Adj_ R^2 is the adjusted determination coefficient.
RMSE is the root mean squared error.
DW is the value of the Durbin-Watson statistic.

The Durbin-Watson values in Table 4 show autocorrelation among the residuals also. Even though h^3 has a small coefficient compared to the other predictors, in all three models after kriging improvement, h^3 actually has a more important contribution because it has a large absolute standardized coefficient.

Looking at the semivariogram (Fig. 3), we can assume that the phenomenon to estimate is smooth (i.e., rainfall values change gradually with the distance). The semivariogram represents the continuity structure quite well also. The presence of locally changing linear drift in the data is indicated when the semivariogram has a gently parabolic concave-upward shape [38,39].

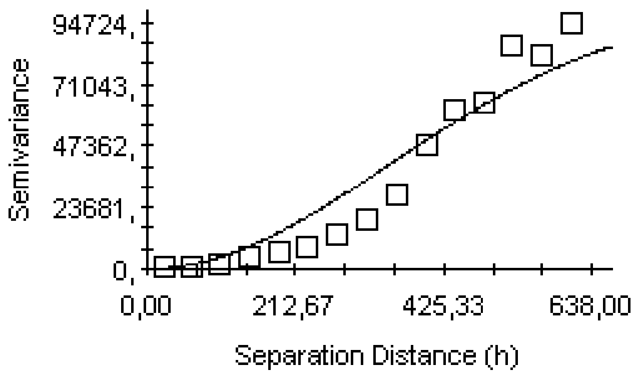

Fig. 3. Semivariogram of the ordinary kriging interpolation model

3.3 Validation of the Kriging Interpolation Model with 12 Test Stations

We calculated the mean *RMSE* of repeated (78 times) precipitation estimations for the 12 test stations. The *RMSE* for the whole year yielded a precipitation value of 1047.486 mm, accounting for 23.10% of measured precipitation. For the seasonal models, the variance-covariance matrices were singular. As a result, influence statistics could not be computed. Upon considering the kriged residuals grids, mean *RMSE* for validation data (repeated 78 times precipitation estimations) reduced considerably. This demonstrates that our kriging interpolation method works quite well for interpreting the spatial variability of annual precipitation.

Differences between the initial multivariate regression model and the kriging improvement are illustrated in Figs. 4a and 4b. Each figure is a rectangular map, in which the study area is defined by specifying the longitude/latitude of the lower left and upper right corners instead of the usual west, east, south, north boundaries. The reason for specifying the study area this way is that, lines of equal longitude and latitude are not straight lines, and are thus poor choices for map boundaries. By comparing the two figures, we can distinguish slight differences in colored areas, which correspond to annual predicted precipitations.

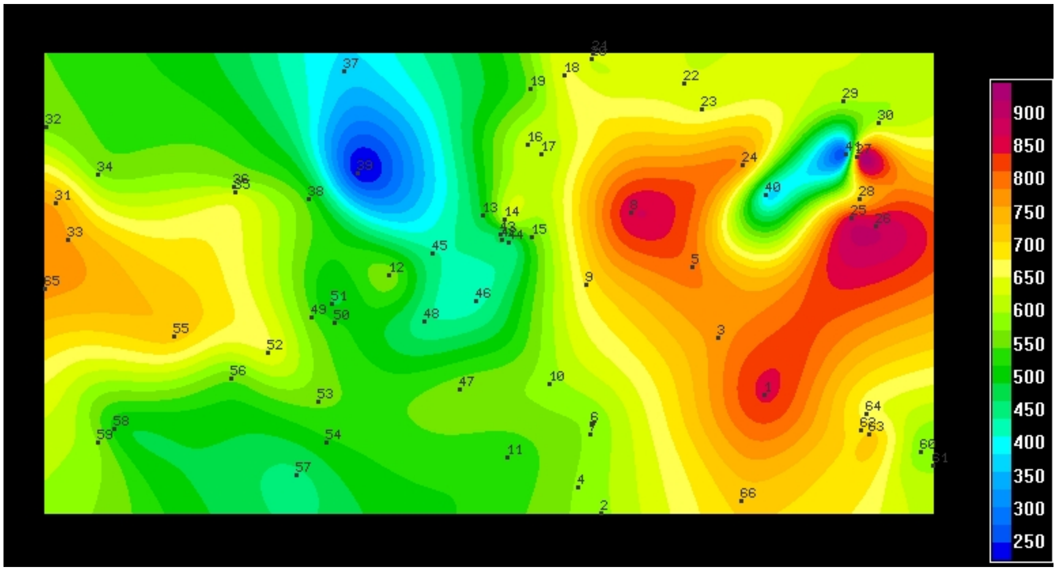

Fig. 4a. Predicted spatial distribution of annual precipitation in Cyprus, for the period 1961-1990 – multivariate regression model

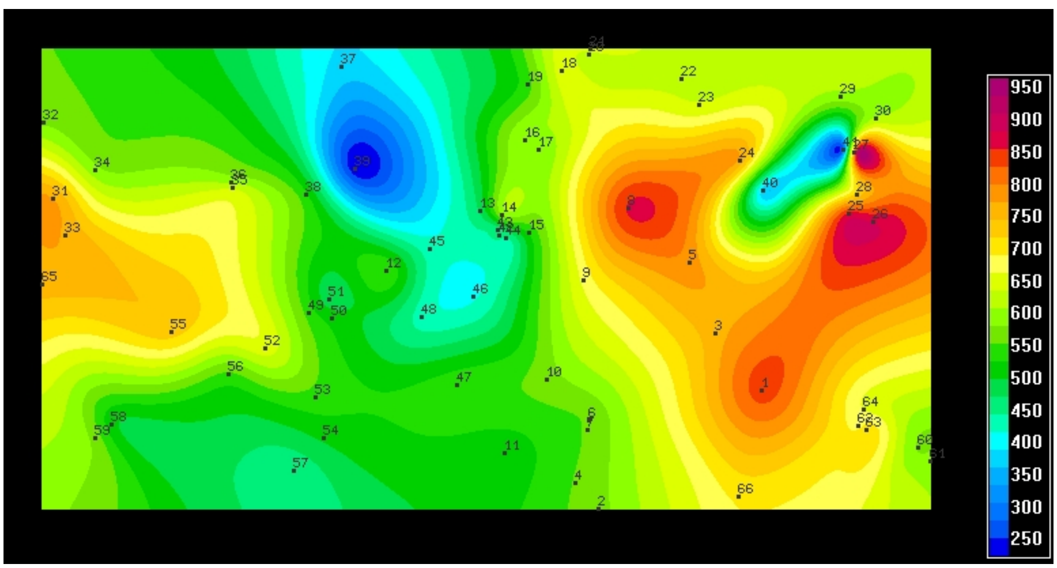

Fig. 4b. Predicted spatial distribution of annual precipitation in Cyprus, for the period 1961-1990 - kriging interpolation model

We can see an improvement in precipitation estimations with the kriging interpolation model, in relation to the multiple regression model in Fig. 5, where errors generally seem to be fairly smaller.

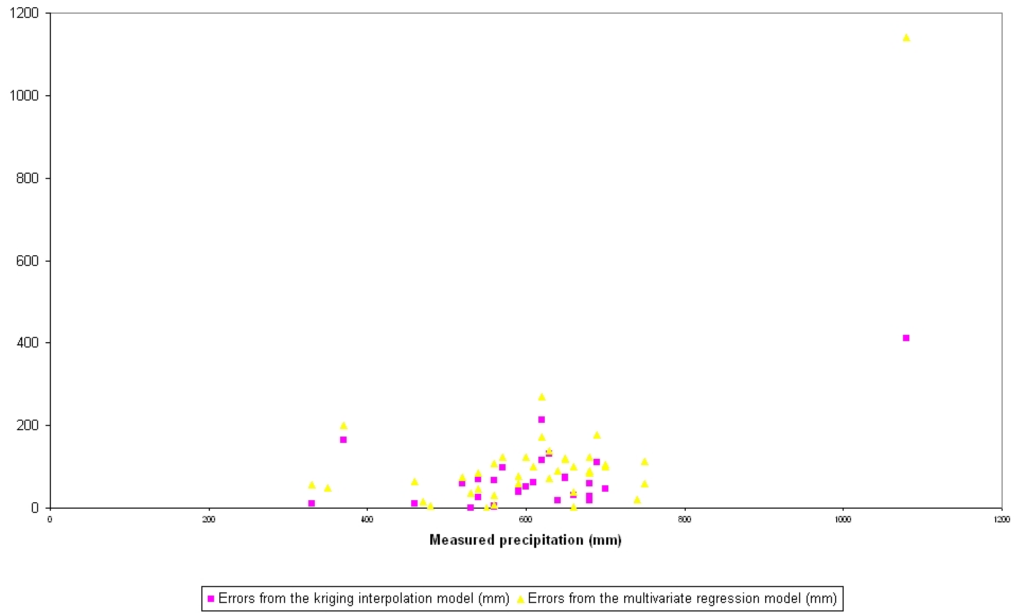

Fig. 5. Errors from the multivariate regression model and the kriging interpolation model

4. DISCUSSION

As a consequence of intense industrialization, rapid population growth and extensive changes in land use, the Eastern Mediterranean and the Middle East are expected to become a global climate change "hot spot", with much dryer and warmer climate conditions in the years to come, based on results of global climate models. Looking at climate models for Cyprus and the period from 2020 to 2050, one of the most remarkable results is an increase in extremely hot summer days with maximum temperatures exceeding 38ºC for an additional two weeks per year. Additionally, warm nights with minimum temperatures above 25ºC for an additional one month are expected. To make things worse, precipitation is expected to decline with reductions in mean annual rainfall of 10-15% over the 2020 to 2050 period, while most of the decrease in rainfall will be seen in the spring and summer seasons [40].

Now more than ever, there is a need for a reliable precipitation model, especially for the dry season, in order to have more dependable and consistent results in climate research [41,42]. Our precipitation model, which is proven to be particularly accurate for the dry season, can increasingly provide clues and insight into the likely impacts of climate change on Cyprus, especially for the dry season. By assessing these impacts and quantifying their economic and social costs, Cypriot government can be directed to more effective and more comprehensive adaptation strategies addressing the ever more pressing problems of climate change in the region.

5. CONCLUSION

The application of multiple regression analysis with kriging interpolation improvement, lead to the development of the following models, for precipitation estimation in Cyprus:

$$P = 523.983 + 0.274h + 0.001h^2 - 0.00000105h^3 + 74.818slp - 7.336slp^2 + 0.259slp^3$$
$$-3.641X + 0.158X^2 - 0.001X^3 - 4.809Y + 0.001Y^3$$

(annual, adjusted R^2=0.651)

$$P = 226.376 + 0.918h - 0.002h^2 + 0.00000191h^3 + 69.554slp - 4.694slp^2 + 0.009slp^3$$
$$-4.278X + 0.185X^2 - 0.001X^3 + 1.857Y + 0.001Y^3$$

(wet season, adjusted R^2=0.626)

$$P = 531.444 + 0.215h - 0.00000703h^3 - 14.427slp + 2.274slp^3$$
$$-12.531X + 0.001X^3 + 10.078Y - 0.001Y^3$$

(dry season, adjusted R^2=0.997).

Kriging interpolation methods can depict most of the spatial variability of precipitation. Our models, especially the dry season model, considering its effectiveness even though precipitation data came from a limited number of stations, could be applied to Cyprus' climate research.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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