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A Downscaling Technique for Climatological Data in Areas with Complex Topography and Limited Data

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Abstract: The current study describes a technique for downscaling climatological data in areas with limited or no grid data. In cases where grid data are unavailable and the researcher is called to operate on a regional or in the mesoscale and produce detailed and not coarse results, this technique can be a helping hand. It constitutes a combination of statistical downscaling through multi-linear regression techniques and dynamical downscaling by employing Geographical Information Systems, and it can be used in order to spatially interpolate with high resolution various climatological variables. The application of the described technique was applied on 3 agricultural areas that present different climate conditions and are characterised by complex topography. The results indicated that the current technique delivered very sufficient results as the adjusted coefficient (R^2) appears with high values in almost every case. Areas characterized by Mediterranean type of climate with hot summers (*Csa*) showed the strongest presumption against null hypothesis; while areas characterized by a combination of different Mediterranean climate types (*Csa* and *Csb*) used the most coefficients in the multi-linear procedure and produced relatively good results. Areas facing continental climate conditions delivered satisfactorily results, although most of the examined coefficients are presented with medium presumption against null hypothesis. Concluding, the described technique can be used for every type of climate in almost every terrain for the accurate representation of various climatological variables in the mesoscale.

Keywords: Downscaling; Climatological Data; Statistical Analysis; Geographic Information Systems; Greece.

I. INTRODUCTION

One of the biggest problems faced by atmospheric scientists nowadays is the accurate representation and prediction of various climatological parameters. In this direction, one of the most important observational tools that climatologists have in their service in order to collect data is the radar. Its applicability has been tested since the 1940's, mostly to detect and forecast extreme weather conditions, but also to contribute to the accurate knowledge of the climatic variations prevailing in and covering a certain area. In regions, however where radar grid observations are not available and the meteorological network does not have the density and thus is insufficient and unable to cover the whole area of study, downscaling through spatial interpolation is mandatory. Additionally, downscaling through spatial interpolation is useful when performing a future assessment of the spatial distribution of the climatic variables and hence there are no available radar grid observations.

A variety of interpolation methods have been developed for climatological data mapping. 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 [1-4]. Geostatistical Interpolation has become an important tool in applied climatology because it is based on the spatial variability of the variables of interest and makes it possible to quantify the estimation uncertainty [5-10]. In this latter case, the General Circulation Models, which according to Tolika et al. [11] although they remain, nowadays, the most appropriate tool for the development of future climate scenarios, nevertheless, they operate in macro-scale.

The need for regional projections of the changes in extreme meteorological parameters as well as the mismatch between spatial scale and the climate impact models – which operate on the meteorological mesoscale [12], lead to a wide development of several downscaling techniques. These downscaling processes are divided in two general subcategories: a) the dynamical approach, employing regional climate models (RCMs) and b) the statistical approach where empirical–statistical relationships are defined between the independent variables (predictors) and the dependent variables (predictants). Although RCMs are considered to be more promising at the evolution of downscaling, the statistical models present some advantages, which make them useful to the researcher. Also, they are transferable between different regions [13,14].

In the current study, a downscaling technique for the spatial interpolation of climatological data in the mesoscale is described and applied. The technique constitutes a coupling of statistical and dynamical downscaling and it can be applied in a grid starting from 1x1km through statistical analysis and the help of Geographic Information Systems. Additionally, an application of the technique is performed for 3 indicative climatological variables (i.e. precipitation, mean air temperature and potential evapotranspiration - PET) over 3 selected study areas widespread in Greece that present different climate conditions. It aims to prove that the certain technique can be efficiently used in order to describe the spatial interpretation of climatological data for every type of climate.

II. METHODOLOGICAL DESCRIPTION

In the current section the combination of dynamical and statistical approach is analysed in order to downscale and perform the spatial interpolation of selected climatological variables. The initial climatological data will be obtained from climatological (point) stations within or adjacent to the examined area. While mapping a climatological variable in a certain area, several factors that affect the certain climatological variable need to be taken into account. In order to depict the relationships of the examined climatological variable with the various factors that affect it, a multi-linear regression technique was performed including information from the climatological stations of each area, using as dependent factor the variable that needs to be spatially interpolated, and as independent all the factors that affect this certain variable. Following that procedure, an equation (Eq. 1) was created for this certain variable and study area:

$$x = b_o + b_1 a + b_2 b + \dots + b_n m \quad (1)$$

Where x represents the dependent variable at a certain point (climatological variable value); b_o is constant; $b_1 \dots b_n$ represent the coefficients obtained for each independent factor; $a \dots m$ represent the factors that were selected to be used in the multi-linear regression procedure and affect each time the certain climatological variable.

During the multi-linear regression and in order to observe the statistical significance of the examined factors, special attention needs to be given in the output p-value. P-value indicates the probability of obtaining a test statistic result at least as extreme as the one that was actually observed, assuming that the null hypothesis is true [15]. P-value also determines which factors will be used in the multi-linear regression in order to eliminate deficiencies. The preconditions that the output p-value should meet are:

- The output p-value should belong each time within the significance level ($p \leq 0.05$), in order for a strong presumption to exist against null hypothesis.
- In cases where the significance level of the examined factor is less than 95% during the multi-linear regression analysis, this factor should be eliminated from the procedure and the multi-linear regression needs to be re-performed.

This constitutes the statistical approach.

The methodology that was applied to the interpolation from irregularly distributed surface station data at coordinates x_i, y_i, z_i (where x_i = longitude, y_i = latitude and z_i = altitude from mean sea level of the i station) to surface gridded points X_j, Y_j, Z_j (where X_j = longitude, Y_j = latitude and Z_j = altitude from mean sea level of the j grid) was based on the Ordinary (spherical variogram) Kriging with the procedure of interpolation for geographical information systems [16] through ArcGIS 10.2.1 program.

Subsequently, through ArcGIS 10.2.1, in order to perform the Ordinary Kriging analysis, automatic points (x) within the basin were created within a 1x1km resolution grid and through the linear regression equation a value was given (according to the dependent variables) to every point by feeding them each time with different values from the independent factors. This constitutes the dynamical approach of the downscaling technique. Figure 1 gives a schematic representation and it is rather indicative of the procedure that was described above.

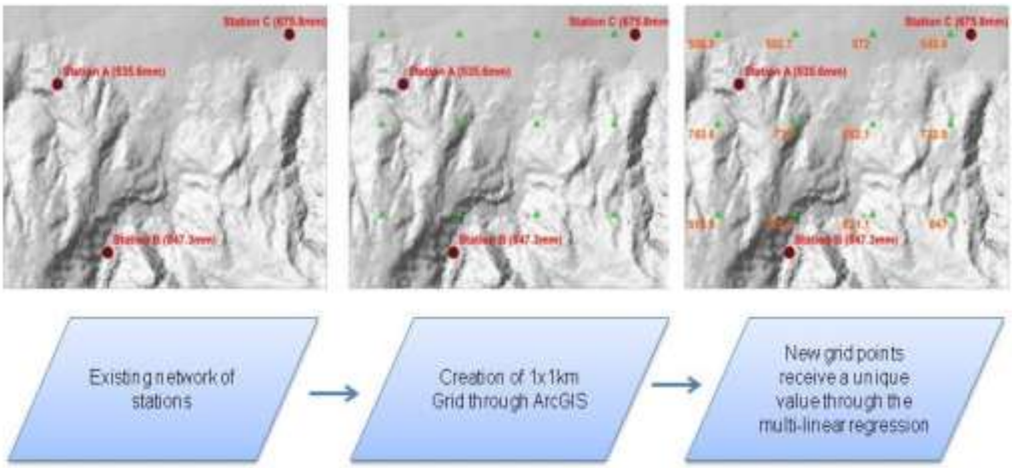

Fig.1: Dynamical and Statistical Downscaling Procedure

III. RESULTS AND DISCUSSION

The application of the current downscaling technique was conducted for 3 selected areas within Greece that present different climate characteristics and complex topography due to their location. The under investigation study areas are Ardas River basin in north-eastern Greece, Sperchios River basin in Central Greece and Geropotamos River basin in Crete island in South Greece. More information about the conditions prevailing in the study areas can be found in [17-21]. Figure 2 and Table 1 depict the general location and the characteristics of the stations that were used for the application of the described downscaling technique.

The variables that were spatially interpolated were precipitation, potential evapotranspiration and mean air temperature. As described above, all the factors which affect a certain climatological variable need to be included in the multi-linear regression procedure. These factors can be separated to physical factors that affect the type, occurrence, and amount of the variable and environmental factors that affect their composition. In this certain case, the following available factors were taken into account: latitude, longitude, presence of mountains and their elevation, slope, prevalent wind speed, distance from a body of water, air temperature (for PET), etc.

A noteworthy fact is that the selection of the factors that will be included in the regression procedure is not determined as each climatological variable is influenced by various factors, thus the selection of the factors that will be used every time lies within the responsibilities of the researcher and the availability of the data. Figure 3 depicts the spatial interpolation of precipitation, PET and mean air temperature for the examined study areas, while Table 2 presents the p-values that were occurred through the multi-linear regressions. The categorization of the output p-values has been made in accordance with the significance level of 95% ($p \leq 0.05$). The dark and light green values indicate that the certain factor has in this specific case a (very) strong presumption with the examined dependent variable, the orange ones that it is very close to the limits of the significance level of 95% and it can be potentially used (in cases where all the factors are outside the significant level, etc.), and the red values indicate that there is no presumption between the examined climatological variable and the certain factor and thus they are eliminated from the regression procedure. Finally the light grey values indicate that in the certain case the data are either insufficient to be used, or irrelevant (they do not influence the examined variable).

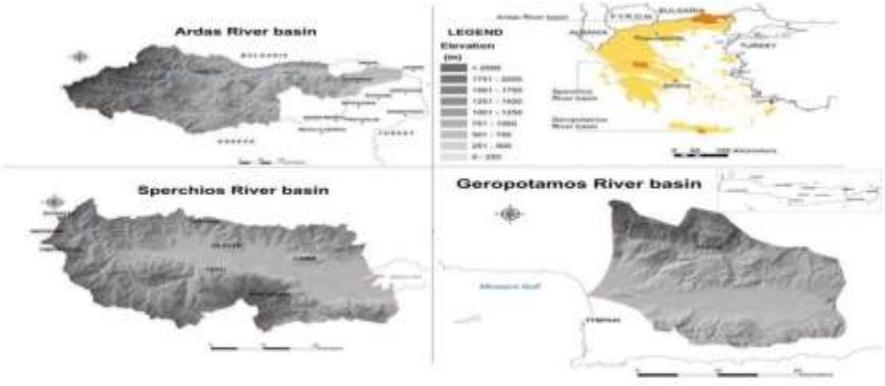

Fig. 2: Location of the Study Areas in Greece

Table 1: Climatological Stations and their Characteristics

Study area	Stations	Lat.	Long.	Elevation (m)	Years
Ardas River basin	Dikaia	41.7	26.3	90.7	1985-2000
	Kuprinos	41.58	26.23	51.2	
	Sitoxori	41.46	26.35	112.4	
	Mikr. Dereio	41.31	26.1	129.2	
	Meg. Dereio	41.23	26.01	401.4	
	Protoklisi	41.3	26.25	55.1	
	Didimoteixo	41.35	26.5	48.4	
	Metaxades	41.41	26.23	129	
	Orestiada	41.5	26.51	39.2	
	Edirne	41.66	26.56	50	
	Kurdjali	41.65	25.36	273.3	
Sperchios River basin	Neoxori	38.96	21.86	800	1981-2000
	Pitsiota	39.01	21.9	800	
	Zileuto	38.93	22.26	120	
	Lamia	38.9	22.43	144	
	Trilofos	39	22.21	580	
	Timfristos	38.91	21.91	850	
	Ypati	38.86	22.23	286	
	Duo Vouna	38.79	22.38	460	
Geropotamos River basin	Souda	35.54	24.1	106.4	1981-2000
	Irakleio	35.32	25.17	68.3	
	Ierapetra	35.01	25.72	24.2	
	Siteia	35.19	26.09	25	
	Rethimno	35.34	24.5	118	
	Tympaki	34.99	24.74	33.7	
	Palaioxora	35.23	23.68	25	
	Anogeia	35.28	24.95	823.7	
	Fourni	35.25	25.66	500	
	Kastelli	35.12	25.2	350	
	Zaros	35.13	24.9	322	

Table 2: Output P-values of the Examined Coefficients

Ardas River basin	PREC	PET	T_{mean}
Regression - Statistics			
Adjusted coefficient	0.66	0.90	0.89
Observations	11	11	11
P - values			
Intersection	0.099	0.003	0.098
elevation (h)	0.047	0.020	0.003
Slope (%)	0.046		0.165
X	0.065		0.063
Y	0.096		0.097
Distance from Water (km)	0.097		0.048
PREC		0.046	
T_{mean}		0.003	
R_s		0.001	0.008

Sperchios River basin	PREC	PET	T_{mean}
Regression - Statistics			
Adjusted coefficient	0.71	0.83	0.75
Observations	10	10	10
P - values			
Intersection	0.034	3.4E-95	5.2E-56
elevation (h)	0.081	1.1E-92	4.3E-61
Slope (%)	0.063		1.4E-58
X	0.050		0.0634
Y	0.030		0.06069
Distance from Water (km)	0.039		0.01726
PREC		9.6E-91	
T_{mean}		5.4E-42	
R_s		0.118	0.015

Geropotamos River basin					
PREC		PET		T_{mean}	
Regression - Statistics		**Regression - Statistics**		**Regression - Statistics**	
Adjusted coefficient	0.91	Adjusted coefficient	0.84	Adjusted coefficient	0.89
Observations	11	Observations	11	Observations	11
P - values		**P - values**		**P - values**	
Intersection	0.040	Intersection	0.044	Intersection	0.048
elevation (h)	0.022	elevation (h)	0.083	elevation (h)	0.006
Slope (%)	0.016	Slope (%)		Slope (%)	0.253
X	0.190	X		X	0.230
Y	0.140	Y		Y	0.256
Distance from Water (km)	0.052	Distance from Water (km)		Distance from Water (km)	0.150
PREC		PREC	0.089	PREC	0.240
T_{mean}		T_{mean}	0.023	T_{mean}	
R_s		R_s	0.0008	Rs	0.240

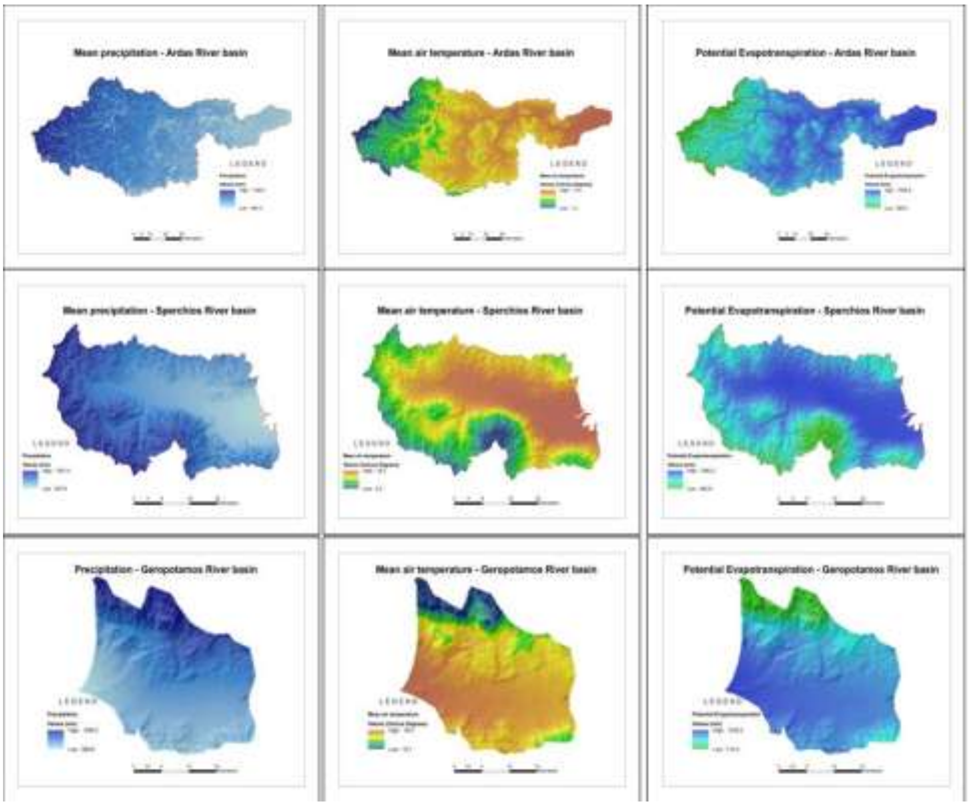

Fig. 3: Spatial Interpolation of the Examined Variables in the Study Areas

Following the application of the described technique, the results indicated that the adjusted coefficient delivered very satisfactory results. Regarding the study areas, the Sperchios River basin which is characterized by Mediterranean conditions with some variations on the rivers' springs where milder conditions occur (*Csa* and *Csb* according to Köppen-Geiger classification), used the most coefficients for the application of the multi-linear regression in every case. On the other hand the Geropotamos River basin that is characterized purely by Mediterranean conditions (*Csa*) used the least amount of coefficients during the multi-linear regression. The Ardas River basin that is characterized by continental conditions shows diversity and complexity with a significant amount of the examined coefficients to present medium presumption against null hypothesis. Regarding the examined variables, PET is appeared with the highest values of the adjusted coefficient in every study area, while precipitation is appeared with the lowest. Specifically, in order to downscale and map precipitation in a certain area, linear models are used which does not always deliver satisfactory or at least the expected results. Since thought grid radar data observations weren't available and the surrounding meteorological network was limited and unable to cover adequately the study area, the current technique constitutes the most optimum solution to interpenetrate precipitation.

Another noteworthy fact is that during the multi-linear regression of mean air temperature for the Geropotamos River basin, the only coefficient that was included after the regression procedure was the elevation. Nevertheless, the adjusted coefficient of T_{mean} was 0.89. This fact points out that it is not always necessary that the more coefficients there are, the better the results will be, as in the certain case and using only one coefficient (elevation) the achieved results were very adequate. Furthermore, Table 2 indicates that the other examined coefficients in the certain case not only appear no presumption against the null hypothesis, but if they had potentially been used in the multi-linear procedure, they could have negatively influenced the results of the spatial interpolation, producing overestimation, or even worse, underestimation of the results.

Attempts towards this direction have also been performed by [17,18,19,22,23,24,25]. Some of these studies have used data from the climatological stations as well as topographical parameters in order to describe the spatial interpolation of various climatological variables over a certain area. Nevertheless, these similar studies have been performed in areas with much greater extend (i.e. country level) in the macroscale and they didn't include a clear framework according to which parameters should be used every time, and how were the spatial relationships between the stations, the topography and the climate conditions were created.

IV. CONCLUSIONS

In the current note, a downscaling technique was presented that uses a combination of dynamical and statistical downscaling for climatological variables in areas with complex terrain and limited data. The results indicated that in areas where complex climate and topographic conditions exist, it is rather difficult to adjust and apply a method that is referred to regional case studies into a larger area, because the under examination coefficients present high variability and they are affected by various parameters each time. The described technique is referred and focused on the mesoscale and it constitutes a simple linear method, which in combination with the spatial interpolation technique through GIS programs can produce reliable maps that can be notified free of charge to farmers, researchers or various stakeholders. It can be a helping hand towards the accurate spatial representation of various climatological variables in future studies that deal with the agricultural production, or in studies that refer to the impacts of climate change.

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