THE IMPORTANCE OF SECONDARY VARIABLES FOR MAPPING OF METEOROLOGICAL DATA

Ismail Bulent GUNDOGDU, Omur ESEN

Abstract

Geographic Information System (GIS) is indispensable tool to analyze various and plenty of data. Generally, classical interpolation methods may not be sufficient to produce accurate maps. Geostatistical analyst (GA) is more considerable in this state. Secondary variables affect the precious of prediction models especially meteorological data mapping. In this study 200 meteorological data stations have been evaluated to produce precipitation model maps in Turkey. Long term (25 years) mean annual and monthly precipitation data from Turkish State Meteorological Service and elevation, slope and aspect values from Digital Elevation Model (DEM) were registered. Ordinary kriging (OK), Ordinary Co-kriging (OCK) and Geographically Weighted Regression (GWR) have been used as a method to compare the models. With the study if there are effects of secondary variables to precipitation models have been illustrated on the prediction maps. Besides comparing statistical values, regional effects of secondary variables have been determined and illustrated on the maps numerically. As a result to define precipitation distribution spatially R^2 values between measured and predicted values have been calculated 0.51 for kriging, 0.67 for OCK and 0.86 for GWR. Cross validation indicated that GWR interpolation yields the smallest prediction error with elevation, slope and aspect. So, It can be said that it is also important spatial distribution of meteorological stations.

Key Words: Geostatistical analyst, precipitation map, Ordinary Co-kriging, Geographically weighted regression, Meteorological data.

Assist. Prof. Dr. Ismail Bulent GUNDOGDU
Selcuk University
Department of Geomatic Engineering
Adress: Selcuk Universitesi, Müh-Mim. Fak. Harita Mühendisliği Bölümü, 42075 Selçuklu/Konya-Türkiye
Tel: +90 332 2231893
Fax: +90 3322410635
e-mail: bgundogdu@selcuk.edu.tr

Omur ESEN, MSc
Selcuk University
Office of Construction and Infrastructure
Adress: Selcuk Universitesi, Yapı İşleri ve Teknik Daire Bşk., Kampüs, 42075 Selçuklu/Konya-Türkiye
Tel: +90 332 2232509
Fax: +90 332 2410100
e-mail: omuresen@selcuk.edu.tr

1. INTRODUCTION

According to Turkish meteorologist severe unpredicted rainy days will be existed after severe hot climatic conditions, and the days will be existed frequently in future 5 years. At the scenario of future Turkey climate, aridity will be threatened to the south regions and torrents to the north regions. So It is the most important subject precision of precipitation maps performance must be increased with other effective factors.

Geostatistical analyst (GA) is one of the most effective method to analyse discrete data points in space both predict an unmeasured points' spatial positions and produce of prediction maps. GA is able to not only produce prediction or probability maps but also examine the precision of different models. GA has proved to be popular in many areas such as agriculture, hydrology, ecology, natural resource models, mining, geology, environmental science, building, cartography, risk management, and so on. The objective problem is to make a prediction at an unsampled location for a variable based on its relationship with one or more secondary variables. Several geostatistical data integration methods are available, and the choice depends on the type of the data available and the purpose of the study.

Briefly, the geostatistical method is a four-step procedure that calls on several geostatistical tools. These steps are: learn from the data through simple statistical analysis, find relationships between the data sets through cross plots, use what has been learned and found in the data to determine the spatial distribution of control points, and, finally, assess the accuracy/error/risk of the map using conditional simulation (Kok and Ulker,2008).

According to Goovaerts (2000) and Burrough (2001) a geostatistical approach is more effective because it has the advantage of using spatial context and external information as a random quantity in order to determine the change of scale most appropriate and possibly to improve the predictions or simulations required.

Perry and Hollis (2005) indicate in their study that climate data are often strongly related to topographic and geographic variables, and it is important to incorporate these factors.

Some recent studies have used topographical elevation as a source of secondary information to hydro meteorological variables, as referred to by Hevesi *et al*. (1992a,b), Raspa *et al*. (1997), Pardo-Igùzquiza (1998), Goovaerts (1999, 2000), Deirasme *et al*. (2001), Gomez-Hernandez and Cassigara (2001) and Diodato and Ceccarelli (2005). Several authors have shown the superiority of the GA methods over the conventional methods for estimation of rainfall at un-gauged locations with different secondary variables; with altitude Guler et al., (2007), with slope, aspect, distance to nearest river and solar radiation Erxleben et al. (2002), Bostan and Akyurek (2007), Akhtari *et al.,* (2009) besides elevation.

Kriging methods have been used some different area for example, they have been used for modelling the spatial variability of tropical rainforest soils Yemefack *et al.,* (2005), soil mapping (Leopold et al., 2005; Lopez-Granados et al., 2005), modelling the spatial distribution of human diseases Pleydell *et al.,* (2004), water table mapping (Desbarats et al., 2002; Finke et al., 2004), mapping the abundance of fish in the ocean Rivoirard (2002), rainfall mapping Lloyd (2005), and for detailed mathematical approaches Hengl (2007).

In recent years, a simple but powerful technique called GWR has been developed to explore the spatially varying relationships and to account for spatial autocorrelation Fotheringham *et al.,* (2002). This technique has been applied in some ecology Shi *et al.,* (2006), social Farrowet *et al.,* (2005), and urban studies Yu (2006), regional development Yu (2006), population segregation Yu & Wu (2004), the rainfall-altitude relationship Brunsdon *et al.,* (2001), relation between elevation and monthly precipitation amount is illustrated by Lloyd (2005), Brunsdon *et al*., (2001) regional analysis Ogneva-Himmelberger *et al.,* (2009), land use and water quality Tu & Zong-Guo (2008), water consumption Wentz & Gober (2007).

It is important to compare the statistical results obtained using alternative methods and different secondary variables applied to the same dataset or area , Because no single method or always the same secondary variable(s) is optimal for all regions or all seasons. For estimating long-year-average annual and monthly precipitation in Turkey, GWR has been compared with two alternative methods: OK and OCK. It is concluded that GWR has proved a robust and flexible interpolation method because it can also take into account auxiliary information in the form of smoothing the DEM besides secondary variable values.

2. STUDY AREA AND METHODS

Terrestrial climate conditions are effective in the area. In severe winter days soil freeze as 50 cm depth. Because of the loosen soil after warm days, precipitation become the most important factor for erosion and controlling of environmental changing. Mean annual precipitation is 720 mm. and maximum difference of elevation is 2500m. in the area. Precipitation records 200 meteorological stations' data for 25 years have been obtained from Turkish State Meteorological Service and input into the database using Ms Access to set up the Geographical Information Systems (GIS)-based application. In this process besides all monthly and mean annual precipitation values, times, elevation, slope and aspects values were recorded in the main dataset. DEM (25m X 25m) has been used to get values of secondary variables. Figure 1 shows the study area and network of stations.

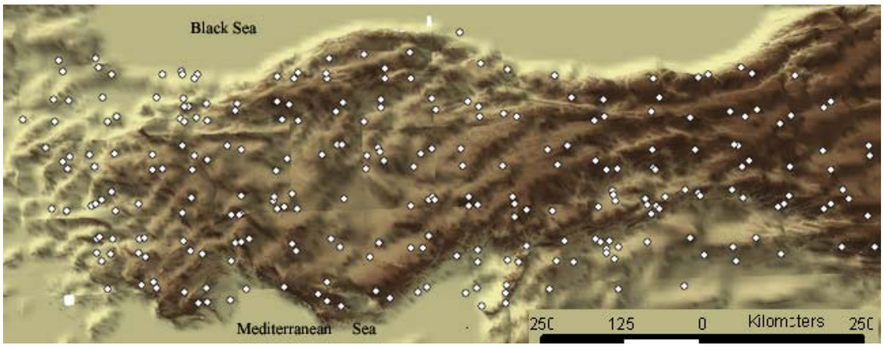


Figure 1. Spatial distribution of 200 meteorological stations.

For estimating 25-year-average annual and monthly precipitation in the area, data have been controlled by histogram values if there is necessary transformation than GWR, Kriging and OCK surfaces have been compared each other.

3. METHODOLOGY

3.1. Kriging Interpolation

Kriging takes into consideration weights the surrounding measured values to derive a prediction for an unmeasured location. The technique has proved to be popular in many areas such as agriculture, mining, geology, environmental science, building, cartography, risk management, and so on.

Calculating the variance is the most important and distinctive peculiarity of kriging in comparison with other techniques. The value is the criterion for the reliability of the estimated value. If the calculated variance is smaller than the variance of certain values, the estimated value is reliable for the unsampled point or area Kriging method is based on the autocorrelation of a variable between two points that is formulated as follows:

$$Z(s) = \mu + \varepsilon(s) \tag{1}$$

$Z(s)$ Consists of two parts: a deterministic trend $\mu(s)$ (i.e. flow direction) and a random auto correlated error $\varepsilon(s)$. The symbol s simply indicates the location of a point. Because $\mu(s)$ is a deterministic trend, the selection of a Kriging method is based on whether a directional trend exists or not.

The ordinary Kriging formula is generally given by:

$$Z^*(u) = \sum_{a=1}^{n(u)} \lambda_a(u) Z(u_a) + \left[1 - \sum_{a=1}^{n(u)} \lambda_a(u)\right] m \tag{2}$$

where, $Z^*(u)$ is the ordinary Kriging estimate at spatial location u, $n(u)$ is the number of the data used at the known locations given a neighbourhood, $Z(u_a)$ are the n measured data at locations u_a located close to u, m is mean of distribution, $\lambda_a(u) =$ weights for location u_a computed from the spatial covariance matrix based on the spatial continuity (variogram) model, which is given by:

$$\lambda(h) = \frac{1}{2n} \sum_{i=1}^{n} \left(z(u_i) - z(u_i + b) \right)^2 \tag{3}$$

Where, n is the number of data pairs separated by distance b, $z(u_i)$ and $z(u_i + b)$ are the data values at locations separated by distance b.

3.2. The multivariate geostatistical approach

Geostatistical methods for interpolation start from recognizing that spatial variation of any continuous attribute is often too irregular to be modelled by one simple, smooth mathematical function. On the contrary, variation can be better described by a stochastic surface. Each measurement *z*(s) is thus interpreted as a particular realization of a random variable *Z*(s) and kriging is a generic name adopted by the geostatisticians for a family of local least-squares regression algorithms. The basic idea is to estimate the unknown rainfall value at the unsampled location s as a linear combination of same neighbouring observations. A kriged estimate of the variable at location s_0 is given by:

$$Z_{OCK}(s_0) = \sum_{i=1}^{n} \lambda_i z_i(s_i) + \sum_{j=1}^{m} \lambda_j z_2(s_j) \tag{4}$$

Where z_i is a vector of the observed primary data (in our case corresponding to precipitation) selected in the s_0 neighbourhood observation s_i, z_2 is a vector of the observed secondary data (in our case corresponding to elevation) selected in the s_0 neighbourhood observation s_j, λ_i and λ_j are weights associated with the distance $h_{0(i)}$ (between s_0 and s_i and $h_{0(j)}$ (between s_0 and s_i), respectively, calculated during the solution of the kriging simultaneous equation system (Johnston *et al*., 2003; Diodato and Ceccarelli, 2005).

3.3. Geographically Weighted Regression

GWR is thus a newly developed statistical methodology that extends an ordinary linear regression model by allowing estimation of local, rather than global, parameters. Coefficients are specific to location *i*, rather than assumed to be constant. The calibration of the GWR model relies on a sequence of locally linear regressions to produce estimates for each point in space by using weighted subsamples of data information from nearby observations. For each observation *i*, the model computes a matrix of weights in which the largest values are assigned to the corresponding nearest observations of *i*.

Geographically weighted regression is used to estimate locally linear coefficients and estimates of the dependent variable. The GWR model is formally defined as:

$$P_i = \beta_{0i} + \sum_k \beta_{ki} X_{ki} + \varepsilon_i \tag{5}$$

where P_i is the *i*th observation of the dependent variable. X_{ki} is the *i*th observation of the *k*th independet variable, ε_i is the *i*th value of a normally distributed error vector with mean equal to zero, β_{0i} is the constant estimated for local regression *i*, and β_{ki} is the regression coefficient estimated for regression *i* and varibale *k*. This differs from ordinary least squares regression by utilizing distinct constants and regression parameters for each point, rather than a single set of global parameters. The estimation algorithm essentially iterates through *n* weighted least square regression, each one modified by a unique distance-decay weight matrix. Estimation for point i thus takes the form:

$$\mathbf{B_i} = (\mathbf{X^T W_i X})^{-1} \mathbf{X^T W_i P}. \tag{6}$$

where $\mathbf{B_i}$ is the vector of estimated coefficients for observationi, **P** is the vector of observed dependent variables, **X** is the $n \times k$ matrix of explanatory variables, and $\mathbf{W_i}$ is a diagonal distance-decay weight matrix specific to *i*'s location relative to the surrounding observations (Fotheringham *et al.,* 2002).

To produce distance-weighted neighbourhoods with each containing *q* nearest neighbours, Fotheringham et al. (2002) suggests using the following bi-square function:

$$W_{ij} = \left[1 - \left(d_{ij}/b\right)^2\right]^2 \quad \text{if } d_{ij} < b \text{ and } \mathbf{0 \ otherwise.} \tag{7}$$

This function produces numbers that are near-normal in their distribution for $d_{ij} < b$, and 0 for distances greater than or equal to *b*. The key to remember fort his function is that *b* adapts from observtion to observation since it is defined as the maximum of the distances between observation *i* and its *q* nearest neighbours (Farber and Paez, 2007).

4. ASSESSMENT OF DATA

Table 1. Statistical values to describe mean annual precipitation, elevation, aspect and slope

Statistics	***Mean annual precipitation (cm)***	***Elevation (m)***	***Aspect***	***Slope***
Min value	2.00	1.68	1	2
Max value	15.38	2400	353	90
Mean value	6.17	706.66	193.81	79.12
Std. dev.	2.55	584.50	10.12	20.12
Skewness	1.12	0.908	0.945	1.06
Kurtosis	3.68	2.17	2	5.44
1st quartile	4.02	7.25	122.24	67.25
Median value	5.36	774	195	82
3rd quartile	7.51	1111.5	281.20	84

Table 1 shows general statistical information of data. These values must be controlled if these are normal distribution before geostatistical application. If the mean and median values are close, it can be said that the data have a normal distribution. A histogram shows whether distributions of data are symmetrical or not. Normal distribution of data can be realised with a skewness value close to one. According to the values in Table 1, the data are normally distributed. However, a normal QQPlot also allows us to compare the data with a normal distribution.

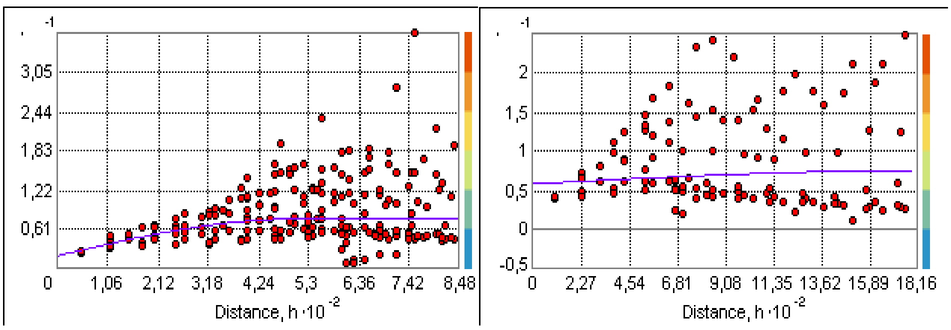
4.1. Interpolator performance:

Table 2 Statistics of the experimental errors computed from mean annual precipitation data (Kriging, OCK_{EAS}: Ordinary co-kriging with elevation, aspect and slope, GWR with elevation $_{(E)}$, aspect $_{(A)}$, slope $_{(S)}$, elevation-aspect($_{EA}$), elevation-slope ($_{ES}$), aspect-slope ($_{AS}$), elevation-aspect-slope($_{EAS}$))

	kriging	OCK(EAS)	GWR(EL)	GWR(A)	GWR(S)	GWR(EA)	GWR(ES)	GWR(AS)	GWR(EAS)
Mean	0,00191	-0,13390	-0,00190	-0,00206	0,00825	-0,00190	0,00172	0,00750	0,00046
RMS	1,65300	1,94300	1,00600	0,50400	0,56140	1,05600	1,08300	0,71170	1,12000
RMSS	0,94560	0,77620	1,03300	1,15500	1,18100	1,01500	1,06900	1,40100	1,05100
T Test	0,03063	2,65602	0,02789	0,02705	0,10594	0,02839	0,02439	0,08119	0,00664

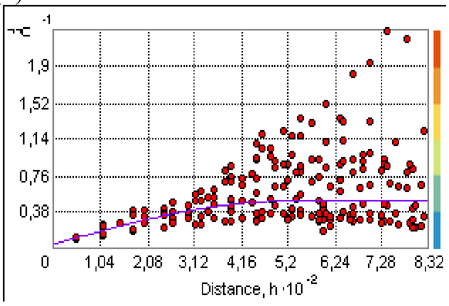
Generally, the best model is the one that has the standardized mean nearest to zero, the smallest root-mean-square prediction error, the average standard error nearest the root-mean-square prediction error, and the standardized root-mean-square prediction error nearest the one (Johnston et al. 2003). The best statistical results in GWR_{EAS} column at the Table 2.

Figure 2 shows semivariances (a) with OK, (b) with OCK and (c) with GWR. Ideally the value of the semivariogram for precipitation should be zero when the separation vector is zero. Since measurement error exists this is not true in the study. In this case Diodato and Ceccarelli (2005) declared that it can be assumed that the phenomenon to be estimated is smooth (i.e. annual precipitation values change gradually with the distance). In this respect the exponential semivariogram for precipitation with small nugget effect and cross-covariance function was selected as the base model for calculations.



(a) (b)

(b)



(c)

Figure 2. Experimental semivariance and their coregionalization model (continuous line) for (a) kriging, (b) OCK_{EAS} and (c) GWR_{EAS}.

In this phase, absolute error values were re estimated using seasonal precipitation (Table 3) for controlling accommodation between yearly and seasonal values.

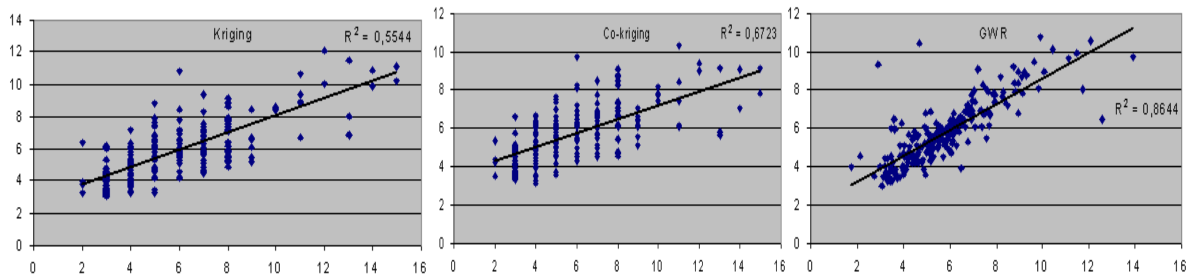
Table 3: Mean absolute error prediction (cm) computed from seasonal precipitation data

Algorithms	Spring	Summer	Autumn	Winter
Kriging	2.170	2.223	2.181	**2.761**
OCK_{EAS}	3.125	3.163	3.662	**3.988**
GWR_{EAS}	**0.146**	**0.153**	**0.445**	**0.112**

The influence of the topographic conditions is essentially sensitive on mean, root mean square and average standard errors. Root mean square is close to the average standard errors mean correctly assessing the variability in prediction. There is clearly a significant improvement in the estimation performance when taking into account $_{EAS}$ as a secondary variables through GWR: the mean absolute error decreases from 2.980-3.160 to 0.012 cm.

5. RESULT MAPS AND CONCLUSIONS

Before mapping of precipitation, all measured and prediction R^2 values have been shown in Figure 3.



(a) (b) (c)

Figure 3. Measured and predicted correlation graphics (a) with OK, (b) with OCK, (c) with GWR.

The techniques were illustrated by using annual and monthly precipitation observations collected at 200 climatic stations in Turkey. In the case study, cross-validation was used to compare the prediction performances of the three methods. GWR_{EAS} gave the best performance in the statistical sense. For result maps figure (Figure 4) 3 types of maps were produced to compare the precipitation distribution visually with 3 methods. After decision that GWR is the best method for precipitation modelling, secondary variables were used one by one and two by two and trio (Elevation, aspect, slope, elevation-aspect, elevation-slope, aspect-slope and elevation-aspect-slope). The R^2 maps of secondary variables can be produced by GWR result tables. The maps show which points are affect to model in which quantity at the side of secondary variables. It is also indicates the more priority regions to take precautions for watererosion. Indeed, the spatial distribution of station points and the number of them is also effective the performance of the precipitation models.


Precipitation map with kriging
2,000000 - 2,773296
2,773296 - 3,432320
3,432320 - 4,205615
4,205615 - 5,112997
5,112997 - 6,177714
6,177714 - 7,427049
7,427049 - 8,893013
8,893013 - 10,613169
10,613169 - 12,631591
12,631591 - 15,000000
250 125 0 Kilometers 250

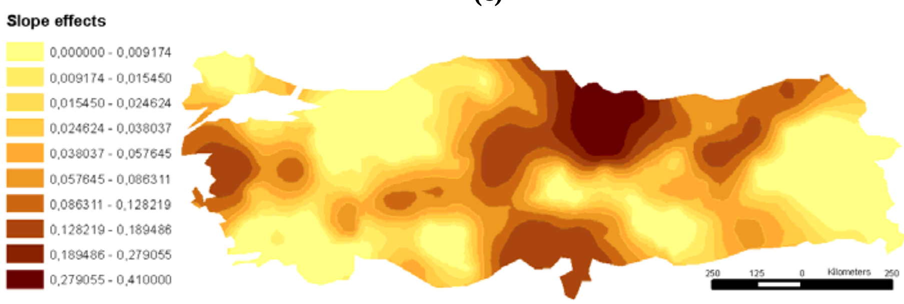
(a)


Precipitation map with Co-kriging
2,000000 - 2,773296
2,773296 - 3,432320
3,432320 - 4,205615
4,205615 - 5,112997
5,112997 - 6,177714
6,177714 - 7,427049
7,427049 - 8,893013
8,893013 - 10,613169
10,613169 - 12,631591
12,631591 - 15,000000
Kilometers
250 125 0 250

(b)


Precipitation map with GWR
1,743083 - 3,852485
3,852485 - 4,859367
4,859367 - 5,339983
5,339983 - 5,569396
5,569396 - 5,678902
5,678902 - 5,908315
5,908315 - 6,388930
6,388930 - 7,395812
7,395812 - 9,505214
9,505214 - 13,924376
Kilometers
250 125 0 250

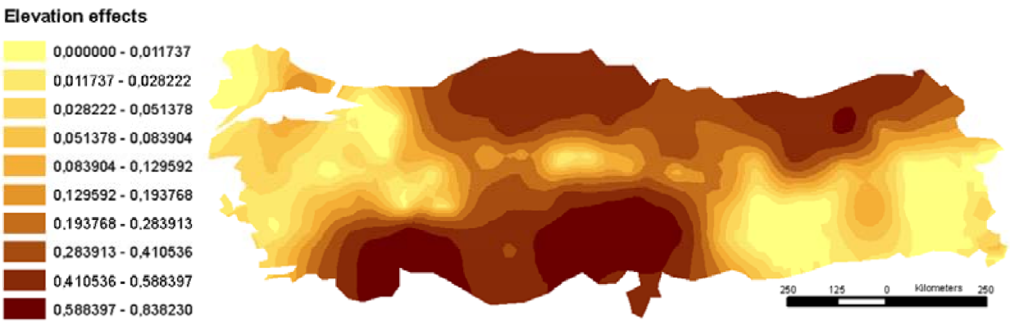
(c)


Slope effects
0,000000 - 0,009174
0,009174 - 0,015450
0,015450 - 0,024624
0,024624 - 0,038037
0,038037 - 0,057645
0,057645 - 0,086311
0,086311 - 0,128219
0,128219 - 0,189486
0,189486 - 0,279055
0,279055 - 0,410000
250 125 0 Kilometers 250

(d)


Aspect effects
0,000002 - 0,001552
0,001552 - 0,004056
0,004056 - 0,008101
0,008101 - 0,014636
0,014636 - 0,025195
0,025195 - 0,042254
0,042254 - 0,069814
0,069814 - 0,114340
0,114340 - 0,186276
0,186276 - 0,302496
250 125 0 Kilometers 250

(e)



(f)

Figure 4. (a) Precipitation maps with OK, (b) with COK_{EAS}, (c) with GWR_{EAS}.(d) R^2 value distribution with slope, (e) R^2 aspect (f) R^2 with elevation values.

Turkey has been effected cold air mass from north and warm air mass from south at side of geographical location. Since the area in centre climatic zone, four seasons have been existed explicitly. However the area is take part in the warm climatic zone, it has some different climatic properties. The reasons of these differences are: -to be surrounded with seas at 3 sides. -to be lied parallel mountains to seasides. -prevented sea effects to interior area because of mountains. -increasing elevation from west to east.

As a result Ordinary kriging is not able to use secondary variables. A recently developed technique, GWR, is used to examine the relationships between precipitation and other secondary variables. The results of the study suggest that GWR technique has abilities to evaluate which secondary variable is more effective in the area for each point. The method can be used for similar studies of precipitation management models at global scales.

6. REFERENCES

Akhtari, R., Morid, S., Mahdian, M., H., and Smakhtin, V., 2009. Assessment of areal interpolation methods for spatial analysis of SPI and EDI drought indices. International Journal of Climatology. pp.135-145.

Bostan, P., A., Akyurek, Z., 2007. Spatial Modelling of the mean annual precipitation of Turkey by using secondary variables. Ulusal CBS kongresi KTU, Trabzon.

Brunsdon, C., McClatchey, J., & Unwin, D., J., 2001. Spatial variations in the average rainfall-altitude relationship in Great Britain: an approach using geographically weighted regression. International Journal of Climatology, 21, 455–466.

Burrough, P., A., 2001. GIS and geostatistics: essential partners for spatial analysis. Environmental and Ecolopical Statistics. 8: 361-377.

Deirasme, J., Humbert, J., Drogue, G., Freslon, N., 2001. Geostatistical interpolation of rainfall in mountainous areas. In Proceedings of meeting geoENV III – Geostatistics for Environmental Applications, Valencia, Spain, 18–20 November 1998, Gomez-Hernandez J, Soares A,Froideavux R (eds). Kluwer Accademic Publisher: Dordrecht; 57–66.

Desbarats, A., J., Logan, C., E., Hinton, M., J., Sharpe, D., R., 2002. On the kriging of the water table elevations using collateral information from a digital elevation model. Journal of Hydrology 255 (1-4), 25-38.

Diodato, N., Ceccarelli, M., 2005. Interpolation processes using multivariate geostatistics for mapping of climatological precipitation mean in the Sannio Mountains (southern Italy), Earth Surface Processes and Landforms. pp.259-268.

Erxleben, J., Elder, K., Davia, R., 2002. Comparision of spatial interpolation methods for estimating snow distribution in the Colorado Rock Mountains. Hydrological Processes, 16 3627-3649.

Farber, Steven, Paez, Antonio, 2007. A systematic investigation of cross-validation in GWR model estimation: empirical analysis and Monte Carlo simulations, J Geograph Syst, 9:371-396.

Farrow, A., Larrea, C., Hyman, G., Lema, G., 2005. Exploring the spatial variation of food poverty in Ecuador. Food Policy 30:510–31.

Finke, P., A., Brus, D., J., Bierkens, M., F., P., Hoogland, J., Knotters, M., de Vries, F., 2004. Mapping groundwater dynamics using multiple sources of exhaustive high resolution data. Geoderma 123 (1-2) 23-39.

Fotheringham, A., S., Brunsdon, C., & Charlton, M., 2002. Geographically weighted regression: The analysis of spatially varying relationships. John Wiley & Sons.

Gomez-Hernandez, J., J, Cassiraga, E., F., 2001. Incorporating information from a digital elevation model for improving the areal estimation of rainfall. In Proceedings of meeting geoENV III – Geostatistics for Environmental Application, Avignone, 2000. Kluwer Academic Publisher: Dordrecht; 67–78.

Goovaerts, P., 1999. Using elevation to aid the geostatistical mapping of rainfall erosivity. Catena 34: 227–242.

Goovaerts, P., 2000. Geostatistical approaches for incorporating elevation into the spatial interpolation of rainfall. Journal of Hydrology 228(1–2): 113–129.

Guler M., Cemek, B., Gunal, H., 2007. Assesment of some spatial climatic layers though GIS and statistical analysis techniques in Samsun Turkey. Meteorological applications, 14, 163-169.

Hengl, T., Heuvelink, G., B., M., Rossiter, D., G., 2007. About regression-kriging: From equations to case studies. Computers & Geosciences, 33 1301-1315.

Hevesi, J., A., Istok, J., D., Flint, A., L., 1992a. Precipitation estimation in mountainous terrain using multivariate geostatistics. Part I: Structural analysis. Journal Applied Meteorology 31: 661–676.

Hevesi, J., A., Flint, A., L., Istok, J., D., 1992b. Precipitation estimation in mountainous terrain using multivariate geostatistics. Part II: Isohyetal maps. Journal Applied Meteorology 31: 677–688.

Johnston, K., Ver Hoef, J., M., Krivoruchko, K., and Lukas, N., 2003. Using ArcGis Geostatistical Analyst, ESRI, 300 pp.

Kok, M., V., Ulker, B., 2008. Reserve Estimation Using Geostatistics, Energy Source Part A: Recovery, Utilization, and Environmental Effects, 30: 2, 93-100.

Leopold, U., Heuvelink, G., B., Tiktak, A., Finke, P., A., Schoumans, O., 2005. Accounting for change of support in spatial accuracy assessment of modelled soil mineral phosphorous concentration. Geoderma 130 (3-4) 368-386.

Lloyd, C., D., 2005. Assessing the effect of integrating elevation data info the estimation of monthly precipitation in Great Britain. Journal of Hydrology 308 (1-4), 128-150.

Lopez - Granodos, F., Jurado – Exposito, M., Pena – Barragan, C., Garcia – Torres, L., 2005. Using geostatistical and remote sensing approaches for mapping soil properties. European Journal of Agronomy. 23 (33), 279-289.

Ogneva-Himmelberger, Yelena, Pearsall, Hamil, Raskhit, Rahul, 2009. Concrete evidence & geographically weighted regression: A regional analysis of wealth and the land cover in Massachusetts, Applied Geography, 29, 478-487.

Pardo-Igùzquiza, E., 1998. Comparison of geostatistical methods for estimating the areal average climatological rainfall mean using data on precipitation and topography. International Journal of Climatology 18(9): 1031–1047.

Perry, M., Hollis, D., 2005. The generation of monthly gridded datasets for a range of climatic variables over the UK. International journal of climatology. pp.1041-1054.

Pleydell, D., R., J., Rasul, F., Tourneux, F., Danson, F., M., Graham, A., J., Craig, P., S., Giraudoux, P., 2004. Modelling the spatial distribution of Echinococcus multilocularis infection in foxes. Acta tropica 91 (3), 253-265.

Raspa, G., Tucci, M., Bruno, R., 1997. Reconstruction of rainfall fields by combining ground raingauges data with radar maps using external drift method. In Geostatistics Wollongong '96, Baafi EY, Schofield NA (eds). Kluwer Academic Publishers: Dordrecht; 941–950.

Rivoirard, J., 2002. On the structural link between variables in kriging with external drift. Mathematical Geology 34 (7) 797-808.
Shi, H., Laurent, E., J., LeBouton, J., Racevskis, L., Hall, K., R., 2006. Donovan M, et al. Local spatial modeling of white-tailed deer distribution. Ecol Model 190:171–89.

Tu, Jun, Zong-Guo, Xia, 2008. Examining spatiallay varying relationships between land use and water quality using geographically weighted regression I: Model design and evaluation, science of the Total Environment 407, 358-378.

Wentz, Elizabeth, A., Gober, Patricia, 2007. Determinants of Small-Area Water Consumption for the City of Phoenix,Arizona,Water Resour Manage, 21:1849-1863.

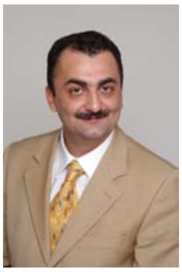
Yemefack, M., Rossiter, D., G., Njomgang, R., 2005. Multiscale characterization of soil variability within an agricultural landscape mosaic system in Cameroon. Geoderma 125 (1-2), 117-143.

Yu, D.,L., 2006. Spatially varying development mechanisms in the Greater Beijing area: a geographically weighted regression investigation. Annals of Regional Science, 40, 173–190.

Yu, D., & Wu, C., 2004. Understanding population segregation from Landsat ETMş imagery: a geographically weighted regression approach. GIScience & Remote Sensing, 41(3), 187–206.

Yu, D., 2006. Spatially varying development mechanisms in the greater Beijing area: a geographically weighted regression investigation. Ann Reg Sci, 40:173–90.

BIOGRAPHY



Dr. Ismail Bulent Gundogdu, born in 1968. Graduated in 1989 as first rank in Surveying and obtaining doctorate degree in 1997. 1991-1993 Lecturer, 1998- Assist.Prof.Dr. in Selcuk University, Engineering and Architecture Faculty, Konya/Turkey. More than 40 published paper,1 book, 2 CD about cartography, computer aided design and GIS. 2005-2006 Head of Cartography Department Division. Memberships of Chamber of Turkish Surveying Engineers. Interestings: Cartography, GIS, Geostatistical analyst, Delphi programming, Image proccessing. (http://www.bgundogdu.selcuk.edu.tr)

Omur Esen is a expert of Construction and Infrastructure Office at the Selcuk University of Konya, Turkey. He has been with Selcuk University since 2005. He completed his MSc thesis study at Selcuk University (2005), in tourism information systems and a BSc from Selcuk University (2001), in geomatic engineering. Now, He is a Ph.D. student at Selcuk University, Department of Geomatic Engineering. His research interests; Map projections, History of Cartography, Project planning and management and GIS.