Geographically Weighted Regression and Secondary Variables for Mapping of Meteorological Data

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Abstract: GA (geostatistical analyst) is an indispensable tool to analyze various and plenty of data in GIS (geographic information system). Spatial distribution is the most effective factor for predicting of meteorological maps at the point of performance or reliability of the model. Generally, classical interpolation methods may not be sufficient to produce accurate maps. GA is more considerable in this state. Secondary variables affect the precious of prediction models especially meteorological data mapping. In this study 245 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 DEM (Digital Elevation Model) were registered. OK (Ordinary Kriging), OCK (Ordinary Co-Kriging) and GWR (Geographically Weighted Regression) 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 0.55 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. Spatial distribution of meteorological stations is also other important factor for similar studies.

Key words: Geostatistical analyst, precipitation map, ordinary Co-Kriging, geographically weighted regression, meteorological data.

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.

GA (geostatistical analyst) is one of the most effective methods to analyse discrete data points in space both predict an unmeasured points' spatial positions and produce 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 [1].

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According to Goovaerts and Burrough [2, 3], 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 [4] 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 Goovaerts [2, 5], Deirasme et al. [6], Gomez-Hernandez and Cassigara [7] and Diodato and Ceccarelli [8]. 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 [9], with slope, aspect, distance to nearest river and solar radiation [10-14], besides elevation.

Kriging methods have been used in some different areas for example, they have been used for modelling the spatial variability of tropical rainforest soils [15], soil mapping [16, 17], modelling the spatial distribution of human diseases [18], water table data mapping [19, 20], mapping the abundance of fish in the ocean [21], rainfall mapping [22], and for detailed mathematical approaches [23].

In recent years, a simple but powerful technique called GWR (Geographically Weighted Regression) has been developed to explore the spatially varying relationships and to account for spatial autocorrelation [24]. This technique has been applied in some ecology [25], social [26], and urban studies [27], regional development [27], population segregation [28], the rainfall-altitude relationship [29], relation between elevation and monthly precipitation amount is illustrated by Lloyd [22], Brunsdon et al. [29], Gundogdu [30], Okwuashi [31], Taghipour [32, 33]

Xu et al. (2015), regional analysis [34], land use and water quality [35], water consumption [36].

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 (Ordinary Kriging), and OCK (Ordinary Co-Kriging). 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 (Digital Elevation Model) besides secondary variable values.

2. Study Area and Methods

Continental climate conditions are effective in the area. In severe winter days soil freezes as 50 cm depth. Because of the loosen soil after warm days, precipitation becomes the most important factor for erosion and controlling of environmental changing. Mean annual precipitation is 720 mm and maximum difference of elevation is 2,500 m in the area. Precipitation records of 245 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 GIS (geographical information systems)-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 (25 m $\times$ 25 m) has been used to get values of secondary variables. All computations have been performed using the Geostatistical Analyst which was integrated into ArcGIS 10.0-ESRI software. Fig. 1 shows the study area and network of 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.

2.1 Kriging Interpolation

Kriging takes into consideration weights of 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 Eq. (1):

$$Z(s) = \mu + \varepsilon(s) \quad (1)$$

$Z(s)$ 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 Eq. (2):

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

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 Eq. (3):

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

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 .

2.2 The Multivariate Geostatistical Approach

Geostatistical procedures, known as Kriging, 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

Fig. 1 Spatial distribution of 245 meteorological stations.

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 Eq. (4):

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

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_j), respectively, calculated during the solution of the Kriging simultaneous equation system [8, 37].

2.3 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 the dependent variable. The GWR model is formally defined as Eq. (5):

$$P_i = \beta_{oi} + \sum_k \beta_{ki} X_{ki} + \varepsilon_i \quad (5)$$

where P_i is the i th observation of the dependent

variable. X_{ki} is the i th observation of the k th independent variable, ε_i is the i th value of a normally distributed error vector with mean equal to zero, β_{ki} is the constant estimated for local regression i , and β_{ki} is the regression coefficient estimated for regression i and variable 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 shown in Eq. (6):

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

where B_i is the vector of estimated coefficients for observations, P is the vector of observed dependent variables, X is the $n \times k$ matrix of explanatory variables, and W_i is a diagonal distance-decay weight matrix specific to i 's location relative to the surrounding observations [24].

3. Assessment of Data

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. 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.

Initially, all data must be controlled if it is in normal distribution or not. Ideally, it must be in normal distribution or symmetrical. A histogram shows whether distributions of data are symmetrical or not. Fig. 2 shows the frequency distributions of data. However, the secondary variable's distributions are symmetric, but precipitation distributions draw away a little from normality, as it also results from skewness.

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	16.41	2,400	356	93
Mean value	7.17	776.11	194.41	79.12
Std. dev.	2.41	582.50	11.00	20.23
Skewness	1.21	0.978	0.967	1.03
Kurtosis	3.34	2.46	2	5.09
1 st quartile	4.07	7.62	121.09	73.88
Median value	4.31	774	194	83
3 rd quartile	7.44	1,111.4	281.34	82

(a)

(b)

(c)

(d)

Fig. 2 Histogram for the annual precipitation (a), aspect (b), elevation (c) and slope data (d).

Therefore, it was decided to work on data not transformed, which would not affect the estimate of the process.

3.1 Interpolator Performance

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 [37]. The best statistical results in GWR_{EAS} column are shown at the Table 2.

Fig. 3 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 [8] declared that it could be assumed that the phenomenon to be estimated was smooth (i.e. annual precipitation values changed 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.

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

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 variable through GWR: The mean absolute error decreases from 3.97 to 0.11 cm.

4. Result Maps and Conclusions

The aims of this study are modeling precipitation distribution by using spatial relationship between precipitation and secondary variables, and defining effects of secondary variables on modeling performance of precipitation. Taking into account the effect of geographic and topographic factors such as elevation, aspect, and slope can usually give better results in defining the spatial distribution of precipitation. Before mapping of precipitation, all measured and predicted R^2 values have been shown in Fig. 4. The diagrams show correlations of measured and predicted values.

The techniques were illustrated by using annual and monthly precipitation observations collected at 245 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. According to Table 2, when comparing three methods' statistical error values GWR_{EAS} yields the mean error nearest to zero, and RMSS nearest to 1. For result maps in Fig. 5, 3 types of maps were produced to compare the precipitation distribution visually with 3 methods. In Fig. 5 (a); (b); (c), maps show effective rainy regions in the area. 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).

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 (E)	GWR (A)	GWR (S)	GWR (EA)	GWR (ES)	GWR (AS)	GWR_{EAS}
Mean	0.19188	-0.00102	-0.00190	-0.00206	0.00825	-0.00640	0.03173	0.00993	0.00046
RMS	1.85300	1.12600	1.19600	1.50400	1.54140	1.23300	1.48300	0.71170	1.12000
RMSS	0.98880	0.75610	1.03200	1.15400	1.18600	1.01500	1.06400	1.42200	1.04400
T Test	0.03044	2.65322	0.02717	0.02746	0.10502	0.02848	0.02333	0.08348	0.00655

Fig. 3 Experimental semivariance and their coregionalization model (continuous line) for (a) Kriging, (b) OK and (c) GWR.

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

Algorithms	Spring	Summer	Autumn	Winter
Kriging	3.127	3.166	3.666	3.927
OCK _{EAS}	2.173	2.228	2.185	2.733
GWR _{EAS}	0.141	0.150	0.443	0.110

The R^2 maps of secondary variables can be produced by GWR results Tables 2 and 3. Fig. 5 (d); (e); (f) maps show high and low regression values distribution on the maps. The maps show that points are affected to model in which quantity at the side of

secondary variables. It also indicates the more priority regions to take precautions for water erosion. Indeed, the spatial distribution of station points and the number of them is also effective to the performance of the precipitation models.

Turkey has been effected by cold air mass from north and warm air mass from south at side of geographical location. Since the area is in centre climatic zone, four seasons have been existed explicitly. However the area has taken 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 seashores, prevented sea effects to interior area because of mountains, increasing elevation from west to east.

Actually OCK_{EAS} and GWR_{EAS} have approximate errors values; GWR_{EAS} yields more reliable and small

Fig. 4 Measured and predicted correlation graphics (a) with OK, (b) with OCK, (c) with GWR.

Precipitation map with kriging

(a)

Precipitation map with Co-kriging

(b)

Precipitation map with GWR

(c)

Slope effects

(d)

Aspect effects

(e)

Fig. 5 (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 [30].

prediction error values particularly in the seasonal evaluation.

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. Elevation effects on the north and south sea sides can be observed easily. According to result maps influence of slope is more effective on middle-north region. Aspect degree is more effective on south-west region. Some urgent precautions must be in agenda for these regions.

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