

Araştırma Makalesi/Research Article (Original Paper)
Basic Kriging Methods in Geostatistics

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Abstract: Measurements of environmental, hydrological, agricultural and similar studies are based on point observations over the Earth. Precipitation and temperature values are measured from meteorological stations, soil characteristics are measured from soil samples, and pollution of a lake is measured by taking samples from lake. These are some examples from spatial point measurements. These variables can be measured by taking samples from a limited number of locations or from certain locations. However, it is logically impossible to measure a variable at all parts of globe or on a field of certain size. Instead of this it is possible to make some interpolation to map spatial distributions of that variable. Observation locations which are close to each other tend to have similar values, however the ones located farther apart from each other differ more. So this knowledge is used in prediction procedure (interpolation). Kriging which will be described here, is an interpolation method. Kriging makes optimal predictions: it provides the most likely value at any location of a variable. Methodologies of most commonly used kriging methods in geostatistics; Ordinary kriging, Regression kriging and Universal kriging have been described in this review work.

Keywords: Geostatistics, Interpolation, Ordinary kriging, Regression kriging, Universal kriging

Jeo-İstatistik'te Kullanılan Temel Kriging Yöntemleri

Özet: Çevresel, hidrolojik, tarımsal ve benzer çalışmalara ait ölçümler dünya üzerinde yapılmış noktasal gözlemlere dayanır. Yağış ve sıcaklık değerleri meteorolojik istasyonlarda, toprak karakteristiği toprak örneklerinden ve göl kirliliği gölden alınan örneklerden ölçülür. Bunlar noktasal olarak yapılan mekânsal ölçümlere örnektir. Belli noktalardan örnekler alarak veya belirgin yerlerden ölçüm yaparak sınırlı sayıda ölçüm yapabiliriz. Ancak ilgilendiğimiz değişkenin dünyanın her noktasında ya da belli büyüklükteki bir alan üzerinde ölçüm yapmak mantıksal olarak mümkün değildir. Bunun yerine bilim insanları bir değişkenin tüm alanda mekânsal olarak nasıl dağıldığını haritalamak için enterpolasyon yöntemini kullanmayı tercih ederler. Birbirine yakın olan gözlem noktaları benzer değerlere sahiptirler, ancak birbirinden uzak olan noktalar daha farklı değerler taşırlar. Bu bilgi tahmin prosedüründe (enterpolasyon) kullanılır. Burada bahsi geçen kriging yöntemleri de enterpolasyon yöntemlerindedir. Kriging en uygun tahmin değerleri verir: bir değişkene ait herhangi bir yerde en olası değeri üretir. Bu derleme çalışmasında jeo-istatistikte en çok kullanılan kriging metotlarından Sıradan kriging, Regresyon kriging ve Evrensel kriging yöntemlerine ait yöntemler anlatılmıştır.

Anahtar kelimeler: Jeostatistik, Enterpolasyon, Sıradan kriging, Regresyon kriging, Evrensel kriging

Introduction

In order to map the spatial distribution of a variable, we need to make some interpolation from a set of observations taken from specific locations. However direct measurement of environmental variables at every point on Earth or at every point within a region on the Earth is often an impossible task. This is the point where kriging comes in. We need spatially exhaustive information from a limited set of direct measurements to perform kriging analyses. Instead of obtaining direct measurements from a region, remotely sensed data is another alternative which also provides spatial information. However, its accuracy and spatial resolution may not be sufficient for the purpose of study. In addition, especially radar images of any meteorological variable is primarily used to figure out its motion instead of measuring the magnitude of variable. Therefore, it is a still valid method to make a measurement one to one over an area. Based on the need of obtaining predictions at unmeasured locations, many simple and complex spatial interpolation methods such as kriging have been developed to estimate the value of environmental variables at

unmeasured locations (Bostan 2012). In the past, these techniques only made use of direct measurements at point locations, but more recently many of these techniques have been extended such that spatially exhaustive information can be used as a covariate in spatial interpolation (e.g Knotters et al. 1995; Phillips et al. 1997; Hengl et al. 2004; Carrera-Hernández and Gaskin 2006; Heuvelink 2006; Grimes and Pardo-Iguzquiza 2010; Wang et al. 2010, Bostan 2012).

Geostatistics is a branch of statistics which focuses on a subset of spatial and/or spatio-temporal data. It has the ability of the characterization of spatial variability which is quantified by semivariance, creation of prediction maps from point observations through spatial interpolation, and the quantification of the accuracy of interpolated maps (Heuvelink 2014). Kriging can be thought as synonym for geostatistical interpolation. The kriging is firstly used on mining industry in the 1950s on the purpose of improving ore reserve estimation introduced by a mining engineer, Daniel Krige from South-Africa (Hengl 2009). Since then it has been used also in other branches of the earth and environmental sciences, including soil science, hydrology and atmospheric science since 1980s (Heuvelink 2014).

Kriging which is an interpolation method makes optimal predictions: it yields the most likely value at any location. But it is only a prediction. The real value is uncertain as we did not measure it directly from the area, so it is treated as stochastic, and it has a probability distribution (Heuvelink 2014). In addition, errors are inevitable in prediction values, however by quantifying the spatial autocorrelation, it is possible to minimize and estimate the errors (Webster and Oliver 2007).

The aim of this review is to explain the methodologies and underlying statistical structures of the most widely used kriging methods as well as mentioning the previous studies. Most commonly used kriging method is Ordinary kriging (OK). In addition, it is convenient to understand kriging logic with OK method. Therefore OK methodology is explained more detailed. Then Regression kriging, and Universal kriging methods are examined.

Kriging

Kriging refers to a group of geostatistical interpolation methods in which the value at an unobserved location is predicted by a linear combination of the values at surrounding locations, using weights according to a model that describes the spatial correlation. Isaaks and Srivastava (1989), Bailey and Gatrell (1995), Lloyd (2007), and Webster and Oliver (2007) can be fundamental sources related with kriging. Kriging methods are widely applied for the interpolation of spatially distributed environmental variables. It provides a solution to the estimation problem based on a continuous model of stochastic spatial variation. Existing knowledge of data is ideally used through the variogram model by kriging. Kriging covers a range of least-squares methods of spatial prediction. These are: Ordinary kriging, Simple kriging, Lognormal kriging, Regression kriging, Universal kriging, Factorial kriging, Ordinary cokriging, Indicator kriging, Disjunctive kriging, Probability kriging, and Bayesian kriging (Webster and Oliver 2007).

Basic model of kriging is based on a stationary random function model is presented in Equation (1),

$$\hat{Z}(s) = m(s) + \varepsilon(s) \quad (1)$$

with s is the location of un-known point, $\hat{Z}(s)$ is the dependent target variable which will be estimated, $m(s)$ is the explanatory part and $\varepsilon(s)$ is the stochastic residual, un-explanatory part.

Almost all kriging methods calculate predictions based on weighted averages of data. The general kriging prediction formula is given in Equation (2):

$$\hat{Z}(s_0) = \sum_{\alpha=1}^n \lambda_{\alpha} z(s_{\alpha}) \quad (2)$$

Where $\hat{Z}(s_0)$ is target point which we want to predict, the $z(s_{\alpha})$ is the observation at location α , n is the number of observations and λ_{α} are the weights for each observation (Webster and Oliver 2007).

The underlying statistical theory of kriging enables to quantify accuracy of predictions by means of kriging variance. Kriging variance is a measure of uncertainty about true values, or, in other words, a measure of the accuracy of the interpolated values (Knotters et al. 2010).

The map of kriging variances characterizes the local accuracy of the spatial predictions. It should be noted that the kriging variance is based on various assumptions (the stationarity and isotropy assumption) and does not take the uncertainty about the model of spatial structure or variogram into account. A model-free assessment of the global uncertainty about the interpolation error can only be obtained by an independent validation study based on a probability sample (e.g., Brus and Heuvelink 2007).

Modeling of Variogram

The variogram plays a central role in the interpolation of variable. A valid variogram model represents the spatial variation of geostatistical data. The suitable model is selected and the parameters of the model are estimated before spatial prediction (interpolation) is performed (Müller and Zimmerman 1997, Zimmerman and Zimmerman 1991).

Spatial variation can be quantified by using semivariance. The plot of semivariance as a function of distance is called semivariogram. The semivariance is the half the expected squared difference between the values of the variable of interest at two locations as presented in Equation (3) (Snepvangers et al. 2003, Heuvelink and Griffith 2010, Gething et al. 2007, Hengl 2009):

$$\gamma(h) = \frac{1}{2} \sum [(z(s) - z(s+h))^2] \quad (3)$$

where $z(s)$ is measurement at location s , $z(s+h)$ measurement at location $s+h$ (distance). These values can be plotted against spatial lag distance, and this plot is called “variogram cloud” which shows the spread of values at according to each lag. In principle, it is possible to fit a model by using variogram cloud, but in practice it may be completely impossible because it is difficult to evaluate the spatial correlation from variogram cloud as there is too many pairs of observation on the variogram cloud. Instead of using all variables, it is preferable to take averages of semi-variances at each lags. For a set of data $z(s_i)$, $i=1,2,\dots$, semi-variances can be computed as:

$$\gamma(h) = \frac{1}{2m(h)} \sum_{i=1}^{m(h)} [(z(s_i) - z(s_i+h))^2] \quad (4)$$

Where $m(h)$ is the number of pairs of data points separated by lag vector h . By changing h an ordered set of semi-variances are obtained which constitute the experimental or sample variogram. The average semi-variance for any lag can be obtained by grouping individual lag distances between point pairs into bins. The averaging is performed by choosing a set of lags, h_j , $j=1,2,\dots$, at constant increments d , and then correlating each h_j with a bin of width d and bounded by $h_j - d/2$ and $h_j + d/2$. Each pair of points separated by $h_j \pm d/2$ is used to estimate $\gamma(h_j)$. The lag distance and increment is important as it affects resulting variogram. The right decision depends on the number of data, distribution of it and form of the underlying variogram. As a rule thumb, each lag should include at least 30 pairs of observation, at least 10 lags should be kept, and maximum distance 1/2 of diagonal of study area (Heuvelink 2014). According to Webster and Oliver (2007), the starting point may be using the average separation distance between nearest neighbors as d . Semivariogram parameters which are identified as range, sill and nugget given in Figure 1. The curve of a variogram flattens out at a certain lag distance which is referred as “range”. Point pairs further apart than range are spatially independent and autocorrelation becomes zero. The variogram has the maximum value on the y axis is called in geostatistics as “sill”. Theoretically, at zero separation distance the variogram value should be zero. However, at small separation distance, the difference between measurements often does not tend to zero and called as the “nugget effect”.

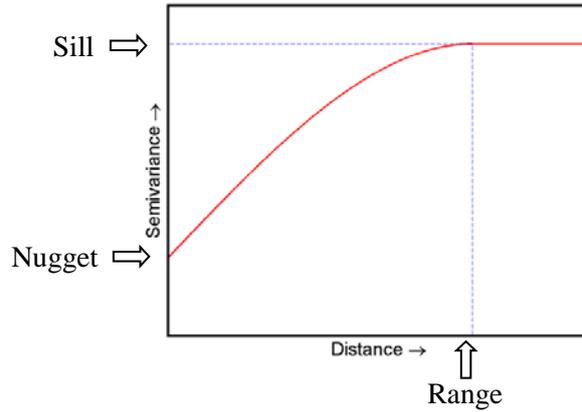


Figure 1. Semivariogram parameters.

When presenting the semivariogram, two assumptions were implicitly made:

1. Stationarity: the semivariance of $z(s)$ and $z(s+h)$ only depends on the distance h and not on the locations s and $s+h$. This means that distribution of the random process has certain attributes that are the same everywhere (Webster and Oliver 2007).
2. Isotropy: the semivariance is a function of the length of h , not of its direction (Heuvelink 2014). If the variation is isotropic, there are no directional differences on the semivariogram (Webster and Oliver 2007).

The ability of the analyst to estimate variogram parameters efficiently is affected significantly by the sampling design, the spatial configuration of sites where observations are taken (Müller and Zimmerman 1997).

Ordinary Kriging (OK)

The Ordinary Kriging (OK) is the most common type of kriging. OK is used if the mean of the variable varies across the region of the interest. The mean is considered constant within a moving window. Since the mean is allowed to vary across the region, OK method can be considered a nonstationary method. The estimates are weighted averages of neighbouring data attributes (Lloyd 2005 and 2006). This model assumes that there is no trend in the data. For OK data should have these three requirements: trend function should be constant, variogram should be constant over the whole study area, and data variable should have approximately normal distribution (Hengl 2009).

The OK estimate is a linear weighted moving average of the available n observations defined in Equation (5) as:

$$\hat{Z}_{OK}(s_0) = \sum_{\alpha=1}^n \lambda_{\alpha}^{OK} z(s_{\alpha}) \quad (5)$$

$\hat{Z}_{OK}(s_0)$ is the OK estimation at location (s_0) , λ_{α}^{OK} is the OK weights, (s_{α}) is the observation location and n is the number of observations. Weights are derived from the kriging equations by means of the semivariance function. Parameters of the semivariance function can be estimated from the empirical semivariogram (Boer et al. 2001). The sum of the OK weights should be equal to 1.

The important part of OK is to define weights which are obtained such that the estimation error is unbiased and estimation variance is minimised. The estimation variance (σ_{OK}^2) is defined in Equation (6) as:

$$\sigma_{OK}^2(s_0) = 2 \sum_{\alpha=1}^n \lambda_{\alpha}^{OK} \gamma(s_{\alpha} - s_0) - \sum_{\alpha=1}^n \sum_{\beta=1}^n \lambda_{\alpha}^{OK} \lambda_{\beta}^{OK} \gamma(s_{\alpha} - s_{\beta}) \quad (6)$$

Where $\gamma(s_\alpha - s_\beta)$ is the semi-variance of Z between locations s_α and s_β , and $\gamma(s_\alpha - s_0)$ is the semi-variance between s_α and target location s_0 .

It is possible to estimate $\hat{Z}(s_0)$ in a block B which may be a line, an area, or a volume instead of a point. The kriged estimate in B is still a weighted average of the data represented in Equation (7).

$$\hat{Z}_{OK}(B) = \sum_{\alpha=1}^n \lambda_\alpha^{OK} z(s_\alpha) \quad (7)$$

Its variance is expressed in Equation (8),

$$\sigma^2_{OK}(B) = 2 \sum_{\alpha=1}^n \lambda_\alpha^{OK} \bar{\gamma}(s_\alpha - B) - \sum_{\alpha=1}^n \sum_{\beta=1}^n \lambda_\alpha^{OK} \lambda_\beta^{OK} \gamma(s_\alpha - s_\beta) - \bar{\gamma}(B, B) \quad (8)$$

The quantity $\bar{\gamma}(s_\alpha - B)$ is the average semivariance between the α th sampling point and the block B , and it is calculated with integral,

$$\bar{\gamma}(s_\alpha - B) = \frac{1}{|B|} \int_B \gamma(x_i, x) dx \quad (9)$$

Where $\gamma(x_i, x)$ denotes the semivariance between the sampling point x_i and a point x describing the block. $\bar{\gamma}(B, B)$ is the double integral, which represented in Equation (10),

$$\bar{\gamma}(B, B) = \frac{1}{|B|^2} \int_B \int_B \gamma(x, x') dx dx' \quad (10)$$

Where $\gamma(x, x')$ is the semivariance between two points x and x' that sweep independently over B (Webster and Oliver 2007).

When the semivariance values are defined in Equation (4), average semivariances versus average distance of the lags are plotted onto a graph to obtain the empirical semivariogram [Figure 2(a)]. However the empirical semivariogram values cannot be used directly in the Γ matrix (matrix required to solve kriging equation) because negative standard errors for the predictions can be achieved. Therefore a model should be fitted to the empirical semivariogram [Figure 2(b)]. Then, the fitted model will be used to determine semivariogram values for various distances. The formula to determine the semivariance at any given distance is represented at Equation 11.

$$\text{Semivariance} = \text{Slope} * \text{Distance} \quad (11)$$

Slope is the slope of the fitted model. In order to explain in more detail, an example semivariogram is given in Figure 2. In this example, slope of the fitted model is calculated approximately as 13.3 (when the value on the x axis is 6, then the corresponding value on the y axis according to the blue line -fitted model- is about 80; so slope is equals to $80/6= 13.3$).

Distance is the distance between pairs of locations and is symbolized as h . The semivariance values are calculated by multiplying the slope of the fitted model and the distance (Düzgün 2008).

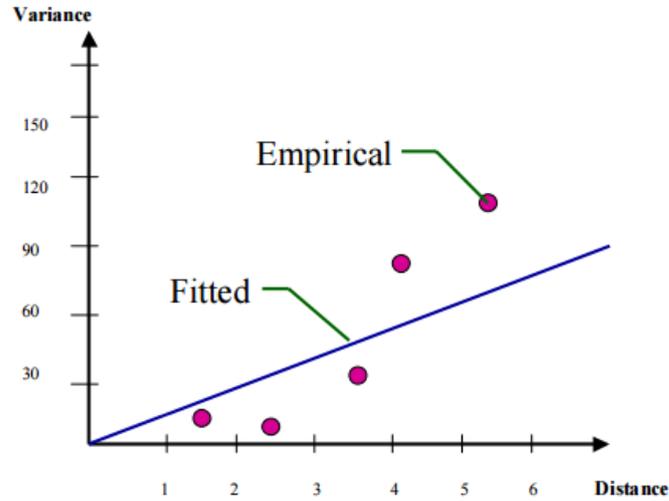


Figure 2. Empirical semivariogram and fitted model (URL1).

Next step in kriging is to calculate weights of each observation, subject to the constraint that they sum to 1. In order to define weights, the matrix Γ has to be defined. Γ matrix is composed of semivariance values created by Equation 11. An example to Γ matrix is given in Table 1. Suppose that the distance between observation-1 (Obs.1) and observation-2 (Obs.2) point pairs is 2.3 km and slope of the fitted model is taken as 13.3 (calculated from semivariogram example; Figure 2); then semivariance is 30.6 (=13.3*2.3). On average, the difference between predictions and original measurements should be zero. This condition ensures that predictions are unbiased. The 1 and 0 records in the bottom row and the right most column arise due to the unbiasedness constraints.

Table 1. An example to Γ matrix ('Obs.' refers to 'observation')

Pairs of obs. locations	Obs.1	Obs.2	
	Γ Matrix		
Obs.1	0.00	30.6	1.00
Obs.2	30.6	0.00	1.00
	1.00	1.00	0.00

The matrix formula for ordinary kriging is represented in Equation (12):

$$g = \Gamma * \lambda \quad (12)$$

where g is vector of unmeasured location which we want to predict. The g vector is calculated in the following way; the distances from observation locations to the unmeasured location is multiplied with slope of the fitted model (the value given here as 13.3) (Table 2). The value "1" at last row enables unbiasedness condition.

Table 2. g vector of unmeasured location based on distances of observations

Observations	Distance of observations to the unmeasured location	g vector of unmeasured location
Obs. 1	1.00	13.3
Obs. 2	2.00	26.6
		1.00

In order to calculate weights, simple matrix algebra is performed to Equation 12 and get the following Equation (13):

$$\lambda = \Gamma^{-1} * g \quad (13)$$

where Γ^{-1} is the inverse matrix of Γ . By performing basic linear algebra, the inverse of Γ is obtained (Düzgün 2008). When the Equation (13) is solved, weights of each observation location are obtained. Measurements of each observation locations are multiplied by their weights and products are summed according to Equation 5. Finally, aggregated value constituted the prediction value of unmeasured location (s_0).

Regression Kriging (RK)

The Regression kriging method combines regression and kriging by treating these as two separate, consecutive steps. At first part linear regression is applied to data. Regression coefficients and residuals are obtained. Regression model is obtained by multiplying the regression coefficients by each grid value of data which the predictions will be calculated on that surface. Next, a kriging step is done in which the regression residual is no longer treated as uncorrelated but allowed to be spatially correlated. When regression residuals are spatially correlated, the map may become more accurate by interpolating these residuals and adding them to the predicted values from the regression model. At this step, simple kriging is applied to the residuals (i.e., the differences between the observations and the predicted values with linear regression). Simple kriging is used instead of ordinary kriging because it can be assumed that the residual has a known mean (namely zero). Finally, the kriged residual is added to the regression model result. This method can thus be seen as an extension of Multiple Linear Regression (MLR) because by adding residual kriging to regression one has the ability to include additional information and gain more accurate predictions. This constitutes the Regression kriging (RK) (Knotters et al. 1995; Hengl et al. 2004; Brus and Heuvelink 2007).

The RK prediction formula is given by Equation (14):

$$\hat{Z}(s) = \hat{\beta}_0 + \sum_{k=1}^p \hat{\beta}_k X_k(s) + \sum_{i=1}^n \lambda_i \varepsilon(s_i) \quad (14)$$

where $\hat{Z}(s)$ is the prediction at location s , $\hat{\beta}_0$ is the estimated intercept, the $\hat{\beta}_k$ are estimated regression model coefficients, $X_k(s)$ are the values of independent variables, n is the number of observations, the λ_i are simple kriging weights derived from the spatial dependence structure of the residual and where $\varepsilon(s_i)$ is the (observed) regression residual at measurement locations s_i .

The accuracy of the RK prediction is quantified with the simple kriging prediction error variance, which is given by:

$$\text{Var}(Z(s) - \hat{Z}(s)) = C(s, s) - \sum_{i=1}^n \lambda_i \cdot C(s, s_i) \quad (15)$$

where $C(s, s)$ is the variance of $\varepsilon(s)$ and $C(s, s_i)$ is the covariance of $\varepsilon(s)$ and $\varepsilon(s_i)$.

Universal Kriging (UK)

In OK the mean is assumed to be constant within a moving window. However in some cases mean may not be constant. Under this circumstances the experimental variogram has concave upward form (smoothly changing in the underlying variable). This is resulted because of local *trend* or *drift*. In another instances, the experimental variogram increases sharply after reaching sill; this is often resulted because of long-range trend superimposed on relatively short-range random variation. In both circumstances the mean is not constant, but it is a function of local trend '*coordinates*' or external variable '*drift*' (Webster and Oliver 2007). In such cases, using Universal kriging (UK) (kriging with a trend model, or kriging with an external drift) is beneficial, as it takes into account of local trends in data while it minimizes the error associated with prediction. (Lloyd 2006). UK by using spatial coordinates is referred to as *kriging with a trend model*. In here, $Z(x)$ is modelled as deterministic function of spatial coordinates. Equation (16) represents this by,

$$Z(s) = u(s) + \varepsilon(s) \quad (16)$$

Where $u(s)$ is deterministic part which varies smoothly and replaces the mean $m(s)$ in Equation 1. The trend $u(s)$ can be represented as,

$$u(s) = \sum_{k=0}^K \beta_k f_k(s) \quad (17)$$

$$Z(s) = \sum_{k=0}^K \beta_k f_k(s) + \varepsilon(s) \quad (18)$$

Where $f_k(s)$ are functions of the coordinates and β_k are unknown coefficients.

Many scientists claim that if there is an obvious trend seen from experimental variogram, use of kriging with a trend model (UK with spatial coordinates) is favorable (Lloyd 2007).

UK incorporating secondary variables at the prediction procedure is referred as *kriging with an external drift*. The assumption is accepted that the drift is due to secondary variables. With this method, trend is explained by a function of secondary variables which are linearly related with target (primary) variable. Secondary variables have to be measured at the same locations of primary variable and all locations at which predictions are desired (Lloyd 2007, Knotters et al. 2010). At this method, predictions are a function of variogram model, neighboring primary variable measurements, and modelled relationship between primary and secondary variables locally. So Equations 17 and 18 are modified and the UK prediction is represented as,

$$\begin{aligned} Z(s) &= \sum_{k=0}^K \beta_k y_k(s) + \varepsilon(s) \\ &= \beta_0 + \beta_1 y_1(s) + \beta_2 y_2(s) + \dots + \beta_K y_K(s) + \varepsilon(s) \end{aligned} \quad (19)$$

Functions of the coordinates are replaced by the secondary variables measurements. $y_1(s), y_2(s), \dots, y_k(s)$ are known measurements of secondary variables, and $\beta_1(s), \beta_2(s), \dots, \beta_k(s)$ are unknown coefficients of these variables. The $y_k, k=1,2,\dots$, are secondary ‘external’ variables that are linearly related with primary variable (Webster and Oliver 2007; Lloyd 2007).

Application Example

Long-term mean monthly temperature values of Lake Van Basin measured at 12 meteorological stations were obtained from Turkish State of Meteorological Service. Long-term annual averages were used for kriging applications. OK method uses only observation values. RK and UK methods use observation values as primary variable and Z (elevation) and TWI (topographic wetness index) as covariates. Prediction maps were represented at Figure 3.

Performance assessments of methods were made by one-fold cross-validation. In this method, all observations were used once during testing procedure of method. For more detailed information, see e.g. Bostan (2013). According to the cross-validation results *Root Mean Squared Error (RMSE)*, *Coefficient of Determination (R^2)* and *correlation between observed and predicted values* were compared of the three kriging methods (Table 3).

According to the prediction maps represented at Figure 3, prediction map obtained with OK, does not show spatial detail, and negative temperature values could not be detected over the area. Prediction maps obtained from RK and UK have similar characteristics and have more detailed information. Generally, temperature is high around the lake. At the basin, surface topography is getting higher when going away from the lake. This situation can be seen from the temperature prediction maps, also. Temperature is dropping when going away from the lake.

Predicted long-term mean annual temperature of Van Lake Basin obtained with kriging methods

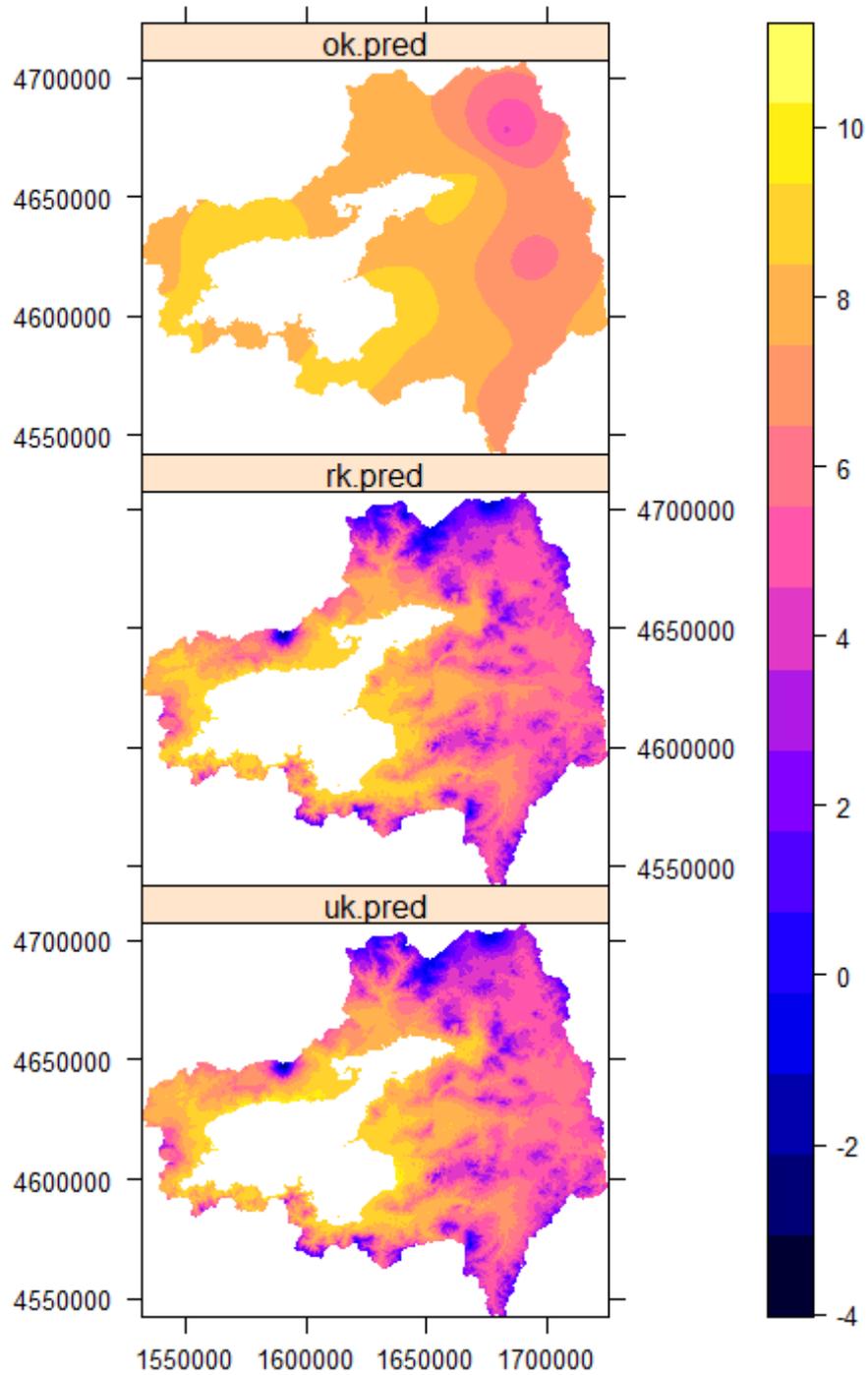


Figure 3. Prediction maps, “ok.pred” presents OK prediction, “rk.pred” presents RK prediction, and “uk.pred” presents UK prediction.

The lowest *RMSE* was obtained with RK (0.96⁰C), and the highest *RMSE* was obtained with OK (1.71⁰C). *RMSE* obtained by UK is moderately fine. Highest *R*² and highest *correlations between observation and prediction points* were obtained by UK method as 0.42 and 0.65, respectively.

Table 3. Performance comparison of kriging methods obtained with one-fold cross-validation

	OK	RK	UK
RMSE	1.71	0.96	1.29
Coefficient of Determination (<i>R</i> ²)	0.03	0.13	0.42
Correlation between observation and prediction	-0.16	0.36	0.65

Conclusion

The main purpose of this review is to explain the methodologies and statistical background of kriging method in terms of Ordinary Kriging (OK), Regression Kriging (RK) and Universal Kriging (UK). Kriging used for estimation of a variable at unknown locations based on a continuous model of stochastic spatial variation. It evaluates the existing knowledge of variable by taking into account the variogram model. Modelling the suitable variogram is the fundamental part of the kriging as it represents the spatial variability of data in space. OK is the most robust and most used method in geostatistics. In many studies, it is suggested that using OK is acceptable and easier than using RK and/or UK if there is no obvious trend within a local neighbourhood (Journel and Rossi 1989; Lloyd 2007; Bostan 2012). Bailey and Gatrell (1995) noted that local trend can be ignored within a smaller neighbourhood by applying OK. However, if there is a local trend between observation and covariates over the study area, then UK and RK give more acceptable results as represented with example application in here. UK and RK methods are more complicated interpolation methods than OK as they are adding more information to kriging procedure. Adding residual kriging improved the prediction performance as observed with the RK method (Table 3). UK and RK were the most reliable methods for spatial interpolation of the long-term annual temperature distribution of Van Lake basin according to the *RMSE*, *R*² and *correlations*. As a conclusion, kriging is an interpolation technique in which neighbouring observation values are weighted by means of semi-variogram, to obtain a prediction value of unmeasured location. In addition, it provides prediction variances as a measure of precision of estimates.

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