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Comparative Analysis of Different Interpolation Methods in Modeling Spatial Distribution of Monthly Precipitation

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Abstract

For many water resources planning and management studies such as water budget and hydrological modeling, it is very important to estimate areal precipitation from point observation stations. There are many deterministic and geostatistical methods for determining the spatial distribution of precipitation. In this study, the most widely used methods, inverse distance weighting (IDW), Simple Kriging (SK) and Co-Kriging (CK) are applied. It is the main objective of the study that Geographic Information Systems (GIS) techniques are used to compare widely preferred interpolation methods and to model the spatial distribution of monthly precipitation values for prediction in ungauged areas in Akarcay Sinanpasa and Suhut sub-basins, Turkey. At the same time, the effects of number of stations, basin area, characteristics and secondary data usage such as elevation on model performance are investigated. The IDW, a deterministic method and the SK-CK, geostatistical methods are compared with each other by cross validation technique and the applicability of the interpolation techniques for the study areas is analyzed. According to the cross validation test results of IDW, SK and CK methods, the mean RMSE (root mean square error) values of Sinanpasa sub-basin are respectively 13,76 mm, 9,32 mm and 8,72 mm while these values are 9,43 mm, 7,82 mm and 7,90 mm for Suhut sub-basin. Then, uncertainty analysis by means of PSE (prediction standard error) is applied to SK-CK methods with clear advantages over the IDW method and with the close RMSE values. In consideration of the results of the uncertainty analysis, the SK method with the mean PSE values 10,30 mm and 8,54 mm has a little superiority to the CK method whose average PSE values are 11,03 mm and 9,02 mm for both Sinanpasa and Suhut sub-basins, respectively. When the findings are evaluated, it can be seen that all three methods can be used for the study areas. The determination of the spatial distribution of precipitation in this way is considered to be beneficial for many water resources engineering studies in areas of ungauged/sparsely gauged.

Keywords

Areal Precipitation, Spatial Interpolation, GIS, IDW, Kriging

Aylık Yağışın Konumsal Dağılımının Modellenmesinde Farklı Enterpolasyon Yöntemlerinin Karşılaştırmalı Analizi

Özet

Su bütçesi ve hidrolojik modelleme gibi birçok su kaynakları planlama ve yönetim çalışmaları için noktasal yağış gözlemlerinden alansal yağışın tahmin edilmesi çok önemlidir. Yağışın konumsal dağılımının belirlenmesi için deterministik ve jeoistatistik birçok yöntem bulunmaktadır. Bu çalışmada en yaygın kullanılan uzaklığın tersi ile ağırlıklandırma (IDW), Simple Kriging (SK) ve Co-Kriging (CK) yöntemleri uygulanmıştır. Akarçay Sinanpaşa ve Şuhut alt havzalarında, Coğrafi Bilgi Sistemleri (CBS) teknikleri ile yaygın olarak tercih edilen enterpolasyon yöntemlerinin karşılaştırılması ve aylık yağış değerlerinin konumsal dağılımının ölçüm yapılmayan alanlarda tahmin yapılması için modellenmesi çalışmanın ana amacını oluşturmaktadır. Aynı zamanda istasyon sayısı, havza alanı, karakteristikleri ve yükseklik gibi ikincil veri kullanımının model performansları üzerindeki etkileri araştırılmıştır. Deterministik bir yöntem olan IDW ve jeoistatistik yöntemler olan SK-CK yöntemlerinin çapraz doğrulama tekniği ile performansları test edilerek karşılaştırılmış ve çalışma alanları için enterpolasyon tekniklerinin kullanılabilirliği incelenmiştir. IDW, SK ve CK yöntemlerinin çapraz doğrulama test sonuçlarına göre Sinanpaşa alt havzası için sırasıyla RMSE (karesel ortalama hata) değerleri 13,76 mm, 9,32 mm ve 8,72 mm iken; Şuhut alt havzası için 9,43 mm, 7,82 mm ve 7,90 mm'dir. IDW yöntemine kıyasla açık üstünlükleri olan ve yakın RMSE değerlerine sahip SK-CK yöntemlerine, ek olarak PSE (tahmin standart hatası) ile belirsizlik analizi uygulanmıştır. Belirsizlik analizi sonuçlarına göre hem Sinanpaşa hem de Şuhut alt havzaları için SK yöntemi sırasıyla 10,30 mm ve 8,54 mm PSE değerleriyle, 11,03 mm ve 9,02 mm PSE değerlerine sahip CK yöntemine az da olsa üstünlük sağlamıştır. Elde edilen bulgulara göre her üç yönteminde çalışma alanları için kullanılabilir olduğu görülmektedir. Bu şekilde yağışın konumsal dağılımının belirlenmesinin ölçüm yapılmayan veya kıt ölçüm yapılan alanlarda birçok su kaynakları mühendisliği çalışmaları için faydalı olacağı düşünülmektedir.

Anahtar Sözcükler

Alansal Yağış, Konumsal Enterpolasyon, CBS, IDW, Kriging

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1. Introduction

Precipitation is the main input data for many hydro-meteorological studies. In this respect, the accurate representation of spatial precipitation is very important in terms of the success of the studies. Precipitation has much more spatial variance than other meteorological phenomena. Establishment of rainfall observation stations in everywhere which is necessary for reliable representation of precipitation by point measurements, is not possible economically and geographically. In this context, it is important to model the areal rainfall. The amount of rainfall can be estimated in ungauged areas by areal rainfall modeling using spatial interpolation methods. Especially in areas where measurement is not performed, determination of the spatial distribution of precipitation has vital importance for many water resources planning and management studies such as water budget, hydrological modeling, and the investigation of the effects of climate-land use change on water resources.

In this study in general terms, the performance of the most widely used IDW, SK and CK interpolation methods in determining the spatial distribution of point measured rainfall data is compared and it is determined which method is more suitable for study basins with different characteristics. The spatial interpolation study of rainfall in Akarcay Sinanpasa and Suhut sub-basins consists of pre-process (exploratory analysis), modeling and validation phases.

In the literature, there are many studies aimed at determining the spatial distribution of precipitation in various parts of the world. Ball and Luk (1998) stated that developing computer technology and hydroinformatics tools facilitated the application of precipitation estimation models, an important component of the basin simulation process and reliably predicted the spatial distribution of precipitation in Upper Parramatta by using a GIS software (ArcInfo). It was emphasized that it is possible to predict accurately real-time precipitation using GIS. Carrera-Hernandez and Gaskin (2007) used Kriging (K) methods to perform spatial and temporal analysis of daily precipitation and temperature in the Mexican basin, and stated that elevation data increases interpolation performance as a secondary variable. Bostan and Akyurek (2007) used CK and geographically weighted regression (GWR) methods to model the spatial distribution of mean annual precipitation for Turkey using secondary data such as elevation, aspect and stream network and investigated the effects of secondary data on model performance. They pointed out that GWR gave better results than CK method. Bostan et al. (2012) performed a similar study for the mean annual precipitation in Turkey using multiple linear regression (MLR), Ordinary K (OK), Regression K (RK), Universal K (UK) and GWR methods. In order to compare the performance of interpolation techniques, the data set was randomly divided into ten equal parts, 90% of each part being used as training data set (calibration) and the rest as test data set (validation). The predictions of the interpolation model established with the training data were compared with the test data set using various performance criteria. According to the verification results, UK is the most accurate method and MLR is the worst method. In addition, for the eastern of Turkey, extrapolation of the annual rainfall estimates was made using observation stations in the western part of the country and it was expressed that MLR, GWR and RK methods gave the best results with close error values. It was also stated that the auxiliary variables increase the interpolation and extrapolation performance greatly. Saghafian and Bondarabadi (2008) studied the spatial distribution of rainfall in mountainous areas, which are insufficient in number and distribution of observation stations. They investigated the validity of interpolation-extrapolation techniques in mountainous areas using spline, weighted moving average, OK and CK methods in the south-western part of Iran. Although the spline method is the most accurate method in the study, it was stated that the CK method is more consistent with the land topography. Aly et al. (2009) evaluated deterministic and stochastic interpolation techniques to fill gaps in daily precipitation records. Di Piazza et al. (2011) also used different spatial interpolation techniques (IDW, linear and multi regression, GWR, artificial neural networks (ANN) and K) to complete the deficiencies in the monthly rainfall time series for Sicily, in some techniques the elevation was input as secondary data, they did not include a part of data set into the model for using in the validation process and compared the model performances with different techniques in this way. It is stated that methods that do not consider elevation in the study have bigger errors, OK shows the best performance. Aydin and Raja (2016) modeled the annual mean precipitation of East African Mauritius Island with deterministic (Thiessen polygon and IDW) and OK methods and compared the models by cross validation method and found that OK method has the highest performance. Adhikary et al. (2016) used OK methods based on genetic programming (GP) and ANN to determine the spatial distribution of precipitation and showed that OK method based on GP gave better results than ANN based and conventional OK methods. Aslantas et al. (2016) used the OK and UK methods to analyze the annual precipitation values of the Euphrates river basin using secondary variables as elevation, aspect, land cover, surface roughness, distance to the coast and river network and used cross validation method to compare methods. Gonga-Saholiariliva et al. (2016) estimated geostatistics of daily monsoon precipitation using the Ordinary CK (OCK) method, which uses elevation as an auxiliary variable in the Koshi river basin, a mountainous region of Nepal where the precipitation is highly changeable. The OCK results were compared with the data sets produced by the Aphrodite Project (Asian Precipitation-Highly Resolved Observational Data Integration Towards Evaluation of Water Resources) and it was stated that OCK grids (1 km resolution) were better than the Aphrodite grids (25 km resolution) in terms of fit performance with observed data. It was also emphasized that the higher resolution of OCK product is an advantage. Citakoglu et al. (2017) predicted properly the spatial variation of seasonal precipitation using K method embodied Gaussian type semivariogram through the instrument of monthly mean rainfall data of 200 observation stations located in Turkey with a minimum observation period of 20 years.

Except for the above studies, examples of spatial analysis of precipitation are Aydin and Cicek (2013), Turkoglu et al. (2016) and Shi et al. (2016). Examples of the use of secondary variables in the spatial analysis of precipitation are Putthividhya and Amto (2016) and Jin et al. (2016).

The main objective of this study is to compare in spatial modeling of the monthly rainfall of two agricultural sub-basins (Sinanpasa and Suhut) differing in terms of basin characteristics in the semi-arid Akarcay basin using GIS techniques and to determine the optimum technique in prediction of the rainfall in the ungauged areas. The secondary purpose of the study is to investigate the effects of station number, basin area, characteristics and the use of auxiliary variables on model performance. It is thought that determining the regional precipitation distribution of the relevant sub-basins, which are important for agriculture in the region, can be useful for hydro-meteorological studies and facilitate decision-makers.

2. Materials and Methods

2.1. The Study Area

This study is carried out in Sinanpasa and Suhut sub-basins of Akarcay that is agricultural catchments (Figure 1). Akarcay river basin is located between 38°-39° north latitudes and 30°-32° east longitudes; in the western part of Turkey, at the junction of Aegean, Mediterranean and Central Anatolian Regions. Although the eastern part of Akarcay basin, which is the closed watershed of the Eber and Aksehir Lakes, enters in Konya province borders, most of it is in the borders of Afyonkarahisar province. Eber and Aksehir Lakes are ecologically wetlands of international importance and protected under the Ramsar Convention. The altitude of Akarcay basin, which has 7993 km^2 basin area, varies between 905-2561 m. The mean slope of the basin with an average altitude of 1207 m is about 10%. The mean annual precipitation of the basin is in the range of 400-450 mm and it has annual average temperature of 11 °C. Mean annual flow volume of Akarcay river with an average slope of 2% is around 0,49 km^3.

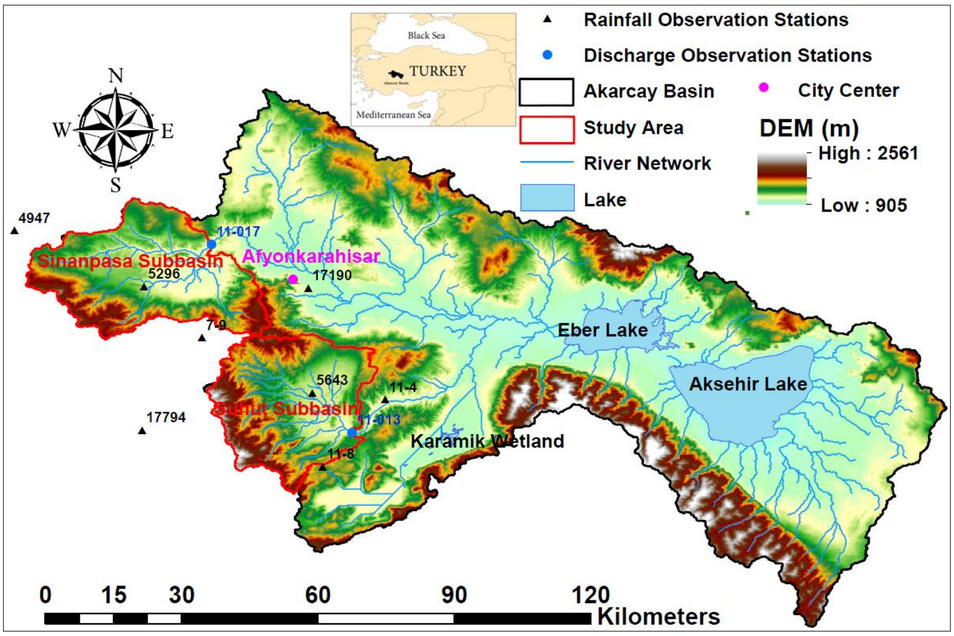

Figure 1: The geographical location of the study area and the position of the meteorological stations

Sinanpasa and Suhut sub-basins are the precipitation catchments of the flow observation stations 11017 and 11013 respectively. Aksu creek, the main river of the Sinanpasa sub-basin, has mean monthly discharge of 1,98 m^3/s according to the flow data of 11017 with maximum value 85,3 m^3/s on 28.03.2015. According to Kali creek -main stream line of Suhut sub-basin- observation station 11013, mean monthly flow rate is observed as 1,51 m^3/s and on 11.03.1968 maximum discharge of its was 270 m^3/s. Sinanpasa and Suhut sub-basins are rich catchments of Akarcay basin in terms of rainfall and agricultural area. Hydrometeorological values are obtained from the Ministry of Forestry and Water Affairs, State Hydraulic Works and Turkish State Meteorological Service.

2.2. The Data Used

In the context of modeling the spatial distribution of precipitation in Akarcay Sinanpasa and Suhut sub-basins, monthly precipitation data of 8 meteorological observation stations (Figure 1) located in and around the study area is used as input for interpolation methods. The details of meteorological stations used in the study are presented in Table 1. The spatial precipitation distribution model is applied for the 1988-1989 period (Figure 2), which is the paired data of 8 meteorological observation stations. The altitudes of the observation stations vary between 1034-1310 m and the average annual precipitation is in the range of 350-550 mm.

Before the modeling, a number of GIS techniques are performed for identification of study area. DEM (Digital Elevation Model) conditioned with HydroSHEDS data is provided from SRTM (Shuttle Radar Topography Mission) database whose spatial resolution is approximately 90 m (3 arc-second). DEM is used to derive various layers related to basin characteristics as slope, aspect and river network by spatial analysis. Land cover data of the basin is taken from EEA (European Environment Agency) CORINE data base and reclassified appropriately.

Table 1: The information of the meteorological stations used

Station		Altitude (m)	Annual precipitation (mm)						
No	Name		Min	Mean	Median	Max	Std. dev.	Skewness	Kurtosis
17190	Afyon	1034	238	435	445	679	92	0,22	0,10
4947	Dumlupinar	1250	428	521	493	669	90	0,96	0,01
17794	Sandikli	1100	320	471	485	669	89	0,04	-0,89
5296	Sinanpasa	1130	344	542	534	760	99	0,13	-0,33
5643	Suhut	1130	212	383	394	540	88	-0,29	-0,87
11008	Kulak	1310	320	467	494	640	98	0,00	-1,34
11004	Selevir	1130	194	352	351	464	73	-0,15	-0,80
07009	Serban	1215	317	505	481	794	115	0,85	0,26

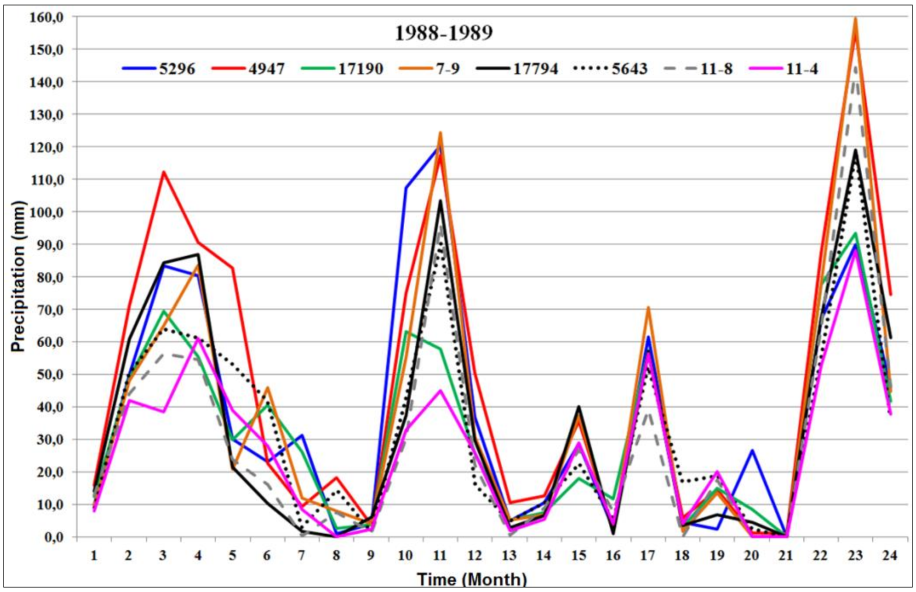

Figure 2: The monthly precipitation of the meteorological stations during the application period

2.3. Interpolation Methods

There are many deterministic and geostatistical methods for determining the spatial distribution of rainfall. In this study, the spatial distribution of rainfall is modeled in GIS environment by applying the most widely utilized IDW, SK and CK interpolation methods. ArcGIS, a GIS software developed by ESRI (Environmental Systems Research Institute, California, USA) is used in this study.

For processes such as acquisition, organization, storage, spatial query, analysis and presentation of data, GIS is a crucial decision support system that provides great convenience in the planning and management of water resources as well as many other areas. Mapping, geographical analysis, data editing and management, visualization can be performed on ArcGIS platform using its integrated interfaces (Icaga et al. 2016).

ArcGIS incorporates many interpolation methods that use different properties of the sample data. Some of these methods are based on some assumptions about the sample data. These methods, which include typical parameter sets for model calibration, derive a continuous surface from the sample points and are considered as mathematical functions and stochastic processes in two classes. Deterministic methods are based on the degree of similarity of measured values. On the contrary, geostatistical techniques use the statistical properties of measurement points to measure spatial autocorrelation and assess the uncertainty of estimations (ESRI 2001). While the IDW, a deterministic method, interpolates with a mathematical formula considering the distance from the stations only, the K which is a geostatistical method, takes into account the spatial distribution of the stations besides the distance. The mathematical general expression of interpolation methods is as follows (ESRI 2001):

$$P = \sum_{i=1}^{n} \lambda_i P_i \tag{1}$$

P: Predicted value at the interpolation point
P_i: Observed value at point i
n: Number of sample points
λ_i: Weight of the observed value at point i

The weights used during the interpolation usually are based on the distance of each control point (sample value) from the target location (grid node). Control points closer to the target receive the larger weights; however, if the data exhibit strong anisotropy, it does not necessarily hold true that the closest control point should receive the greatest weight. Rather, more distant control points along the axis of maximum correlation should have greater influence on the interpolated value. In search of neighborhood or ellipse, the unique neighborhood (global neighborhood) is the simplest type, uses all the data, and has an infinite radius. A moving neighborhood is a search strategy that uses only a portion of the total number of control points. Typically, the modeler must specify the radius length, the number of sectors, and the number of control points per sector. During variographic analysis, the spatial model requires an anisotropic covariance function. Therefore, the search neighborhood should be designed with radii lengths that are similar to the correlation scales (or their relative ratios), with its longest axis aligned with the direction of maximum correlation (Chambers et al. 2000).

2.3.1. IDW

In the IDW method, which is based on the distance of the observation stations to the point at which precipitation is estimated, closer observation points have more influence on the interpolation point. Spatial rainfall is estimated by weighting inversely proportional to the square of the distance of the observation points to the predicted point. The equation of the IDW method is as follows (Watson and Philip 1985):

$$P = \frac{\sum_{i=1}^{n} \frac{1}{d_i^2} P_i}{\sum_{i=1}^{n} \frac{1}{d_i^2}} \tag{2}$$

P: Estimated value at the interpolation point
P_i: Observed value at point i
n: Number of sample points
d_i: Distance between interpolation and observation points

2.3.2. SK and CK

Unlike deterministic methods, the K-an advanced geostatistics technique is associated with spatial distribution analysis of sample points. The K method considers spatial correlation and statistical relationships between observation points (Krige 1951). Several types of the K methods are available, and they are distinguishable by how the mean value is determined and used during the interpolation process (Journel 1986; Deutsch and Journel 1998). The K methods assume that the data has normal distribution and needs de-trending and de-clustering processes. In the K method, a spatial dependent model is constructed by semivariogram and covariance analysis to measure the spatial structure of the data (ESRI 2001). In K techniques, normal score transformation is applied by ranking the values in the dataset from lowest to highest and matching these ranks to equivalent ranks generated from a normal distribution.

Besides of the SK method, the CK method is considered and the effect of secondary data usage on model performance is examined in the paper. When using the auxiliary variable in the K method, the method is called the CK. If the correlation coefficient between main data and co-data is less than 0,5; the co-data has less influence during the estimation process (URL-1 2018). As it is well known, there is generally a strong physical relationship between the precipitation and the elevation. In this study, SRTM DEM as the elevation data is used as co-variable for the orographic representation of the precipitation. Goovaerts (2000) stated that using multiple secondary variables can lead to unstable the CK systems. Thus, only the elevation data is used in the CK method in this study.

SK and CK methods are respectively generalized forms of univariate and multivariate linear regression models. The expression of the best linear unbiased estimator is used for the K algorithm which is a robust technique (i.e., small changes in variogram parameters equate to small changes in the results) and minimizes the error variance associated with the estimate. Unbiasedness is assumed for all the interpolation algorithms, and means simply that, when mathematically interpolating, it is expected to overestimate as often as underestimate. Thus, it can be visualized the error in estimation as a bell-shaped curve with a mean of zero. It is this assurance of a balanced distribution of error variance. In addition, the practical strength of the K as an interpolation method lies in its ability to capture anisotropy of the variables through the spatial semivariogram/covariance model (URL-1 2018).

The semivariogram and covariance functions quantify the assumption that things nearby tend to be more similar than things that are farther apart. Semivariogram and covariance both measure the strength of statistical correlation as a function of distance. The semivariogram depicts the spatial autocorrelation of the measured sample points. The experimental semivariogram is defined as (ESRI 2001):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \tag{3}$$

$\gamma(h)$: Semivariance function
$N(h)$: Number of data pairs ($Z(x_i)$ and $Z(x_i+h)$)
h: Euclidean distance vector-semivariance
$Z(x_i)$: Observed value at point i
$Z(x_i+h)$: Observed value at h distance from point i

If two locations are close to each other in terms of the distance measure, then it is expect that they are similar, so the difference in their values will be small. As they get farther apart, they become less similar, so the difference in their values will become larger as shown in Figure 3 which is a typical graph of theoretical semivariogram. The sill, range, and nugget are the important characteristics of the model. The nugget effect can be further divided into measurement error and microscale variation. The nugget effect is simply the sum of measurement error and microscale variation and, since either component can be zero, the nugget effect can be comprised wholly of one or the other (ESRI 2001).

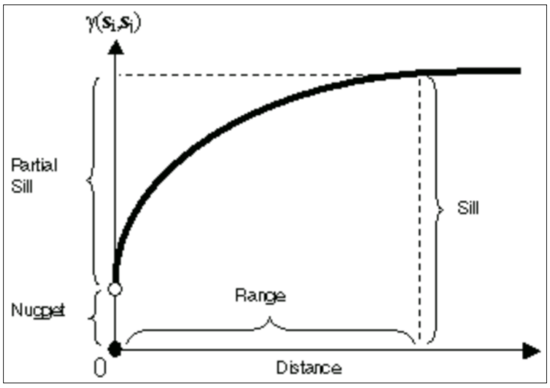

Figure 3: The structure of a typical semivariogram (ESRI 2001)

Semivariogram/Covariance modeling is a key step between spatial description and spatial prediction. Modeling semivariograms and covariance functions fit a semivariogram or covariance to sample data. The goal is to fit the best model to the semivariogram. The model will then be used in predictions. The weights are calculated from the theoretical (estimated) variogram that they depend not only on distance, but also on the direction and orientation of the neighboring data to the unsampled location. The selected model influences the prediction of the unknown values, particularly when the shape of the curve near the origin differs significantly. The steeper the curve near the origin, the more influence the closest neighbors will have on the prediction. For fitting a theoretical semivariogram (model) to the experimental semivariogram (binned dots), many functions are used. In this study, stable model is used as semivariogram type that equation with a nugget component is presented below (ESRI 2001).

$$\gamma(h) = c_0 + c_1 \left[1 - \exp\left(-\frac{3h^w}{r^w} \right) \right] \tag{4}$$

c_0: Nugget effect
c_1: Partial sill-contribution (c_0+c_1=c (Sill))
r: Effective range parameter-distance at which 95% of sill reached
h: Distance between points
w: A coefficient ($0 < w \leq 2$; w=1 exponential model; w=2 Gaussian model)

In order to test the spatial dependence, spatial dependence index (SDI) is performed, which is the ratio representing the percentage of data variability explained by spatial dependence. The SDI is calculated with the following expression (Biondi et al. 1994):

$$SDI = \left(\frac{c_1}{c_0 + c_1}\right)100 \tag{5}$$

Classification of dependency: Strong (SDI>75%), medium (25%<SDI≤75%), and low (SDI≤25%).

The SK assumes that the observed values are realizations of a stationary random function with a global (constant) mean. In the SK technique, the global mean is known and is held constant over the entire area of interpolation. The estimation value is a linear combination of the sample values by weighting. The values of weights are determined according to three criteria: the weights sum to 1; the estimate is unbiased; and the estimation variance is minimized. The general equation is presented below (Journel 1986):

$$z_0^* = \sum_{i=1}^{n} \lambda_i z_i \tag{6}$$

z_0^*: The value at an unsampled location to be estimated from a linear combination of n values of a regionalized variable z_i
λ_i: The weight of the regionalized variable z_i
z_i: The regionalized variable at a given location

The K estimation variance provides the narrowest confidence interval about the estimate and thus produces the best estimate, but only under conditions of multivariate normality; however, if the distribution of data values departs from multivariate normality (a frequent occurrence), the K variance might not be precise and might only represent a measure of the relative goodness of the estimate. The K variance is a relative index of the reliability of estimation in different regions and a good indicator of data geometry. In addition, the K variance is written as (Journel 1986):

$$\sigma_k^2 = c_{00} - \sum_{i=1}^{n} \lambda_i c_{0i} + \mu \tag{7}$$

σ_k^2: The K variance whose units are in terms of the regionalized variable, squared
c_{00}: The sill of the variogram
λ_i: The weight assigned to a given sample
c_{0i}: The covariance between a sample at a given location and the target location
μ: A Lagrange multiplier

The common CK methods are multivariate extension of the basic K algorithm and use two or more additional attributes. In the CK method, the prediction value is a linear combination of the values of two or more regionalized and spatially correlated variables. The CK methods are used to take advantage of the semivariogram/covariance between two or more regionalized variables that are related, and are appropriate when the main attribute of interest is sparse, but related secondary information is abundant. In the case of sparse data, the variance model is inferred from the co-variable. The mean is specified explicitly and assumed to be a global constant in the simple CK method. The general equation for two variables is given as (Deutsch and Journel 1998):

$$z_0^* = \sum_{i=1}^{n} \lambda_i z_i + \sum_{j=1}^{n} \beta_j t_j \tag{8}$$

z_0^*: The estimate at the interpolation point
λ_i: The undetermined weight assigned to the primary sample z_i

z_i: The regionalized variable at a given location
t_j: The secondary regionalized variable that is co-located with the primary regionalized variable z_i
β_j: The undetermined weight assigned to t_j

In the CK, the cross-covariance/cross-semivariogram model of primary and secondary data is required besides of the semivariogram models of primary and secondary data. By using a cross-covariance model, the influence of the secondary variable can be calibrated and controlled (Deutsch and Journel 1998). Modeling the co-regionalization between two variables involves choosing and fitting theoretical models to two direct semivariograms and plus the cross-semivariogram. The difficulty lies in the fact that the three models cannot be built independently from one another. The easiest approach consists of modeling the three semivariograms as linear combinations of the same set of basic semivariogram models. The experimental cross-semivariogram is computed as (Goovaerts 1998):

$$\gamma_{ZY}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)][Y(x_i) - Y(x_i + h)] \tag{9}$$

$\gamma_{ZY}(h)$: Cross-semivariance function
N(h): Number of data pairs
h: Euclidean distance
$Z(x_i)$: Observed primary data value at point i
$Z(x_i+h)$: Observed primary data value at h distance from point i
$Y(x_i)$: Observed secondary data value at point i
$Y(x_i+h)$: Observed secondary data value at h distance from point i

In the study, the interpolation models are optimized by applying manual calibration in analysis of neighborhood, function type and degree; and automatic calibration to parameters and semivariogram model.

2.4. Cross Validation Test

After the modeling, the validity of the models is tested by leave one out-cross validation method. So that IDW, SK and CK methods are compared in terms of model performance and the optimal method is determined for the modeling period in the study area.

The cross validation test, which is a statistical technique applied to evaluate the accuracy of interpolation models, involves analysis of the errors between observation and prediction values in terms of various performance criteria for choosing the most appropriate method. In the phase of the leave one out, a station is eliminated every time from the observation data, and the value of relevant station (the witness observation station) is estimated using the remaining observation data with the interpolation model. In this way, estimates are made at all observation points and errors between observation and estimation values are analyzed (Isaaks and Srivastava 1989).

The model performances are evaluated based on prediction pixels-stations validation with different benchmarks which are R^2 (coefficient of determination), RMSE, MAE (mean absolute error), ME (mean error) and NSE (Nash-Sutcliffe Efficiency) statistical comparison criterion. The performance criteria measure the power of the statistical relationship between observed and modeled values. The R^2, square of Pearson correlation coefficient is proportion of observed data total variance explained by predicted data and calculates as Equation 10. The value of the R^2 varies between 0 and 1. The RMSE (Equation 11), the standard deviation of prediction residuals, is used to analyze errors. The MAE (Equation 12) is mean of the absolute errors while the ME (bias) is mean of the errors that is given in Equation 13. To measure the success of the model results, the NSE criterion (Nash and Sutcliffe 1970), commonly used in the literature and given in Equation 14 is utilized. The NSE criterion ranges from $-\infty$ to 1, with 0 representing average model success. In evaluation process of sensitivity and reliability of the predictions, the values close to 1 for R^2 and NSE; and the less RMSE, MAE and ME values mean better model performance. The formulas of the model performance benchmarks for the cross-validation are presented below:

$$R^2 = \left\{ \frac{\sum_{i=1}^{n} \left[(P_{Observed,i} - \overline{P}_{Observed})(P_{Modeled,i} - \overline{P}_{Modeled}) \right]}{nS_{Observed}S_{Modeled}} \right\}^2 \tag{10}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_{Modeled,i} - P_{Observed,i})^2} \tag{11}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|P_{Modeled,i} - P_{Observed,i}\right| \qquad (12)$$

$$ME = \frac{1}{n}\sum_{i=1}^{n}(P_{Observed,i} - P_{Modeled,i}) \qquad (13)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(P_{Observed,i} - P_{Modeled,i})^2}{\sum_{i=1}^{n}(P_{Observed,i} - \overline{P}_{Observed})^2} \qquad (14)$$

$P_{Modeled,i}$: Modeled value at point i
$\overline{P}_{Modeled}$: Mean of modeled time series
$P_{Observed,i}$: Observed value at point i
$\overline{P}_{Observed}$: Mean of observed time series
$S_{Modeled}$: Standard deviation of modeled time series
$S_{Observed}$: Standard deviation of observed time series
n: Number of observations

In addition to the above benchmarks, the PSE is calculated for uncertainty analysis that is the square-root of the prediction variance and quantifies the uncertainty of the prediction. It indicates the level of uncertainty (ESRI 2001).

$$PSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_{Modeled,i} - \overline{P}_{Modeled})^2} \qquad (15)$$

3. Results and Discussion

Before the modeling of the spatial distribution of precipitation, pre-process analysis are carried out to prepare the data set and to form the base layers. Pre-process analysis include determination of meteorology observation stations to be used, dataset processing and transfer to GIS environment, determination of the basin boundaries and characteristics (elevation, slope, aspect, basin area, river network, land cover and some hydrological analyzes) via GIS.

In the GIS environment, many basin characteristics are derived from DEM through various surface and hydrological analyzes. The spatial hydrological analyzes carried out on the DEM to identify the basin boundary and river network. The basin area is calculated by determining the basin boundary. The process of the basin delineation and determining the river network respectively include the steps of filling of sink-peak values in the DEM data, the determination of the flow direction and accumulation, and defining the basin outlet point. In the same way, the boundaries of the sub-basins are determined. Drainage characteristics such as longest flow path length and main stream slope are calculated by measurements in the GIS environment with the help of river network and topography features. Then, the slope and the aspect of the study area are derived from the DEM data by raster surface analysis. Finally, the land cover layer, provided as vector data from the EEA CORINE database, is appropriately edited and the sub land cover groups are merged into 6 main land cover classes (Figure 4). GIS techniques are applied to define the study area hydrologically. The mean altitudes of Sinanpasa and Suhut sub-basins are 1279 m and 1362 m respectively. When we look at the slope and aspect maps derived from DEM dataset, the Sinanpasa sub-basin has a 9,9% mean slope and dominant northern group aspect; the southern group aspect is dominant in Suhut sub-basin, whose average slope is 15,1%. It can be said that Suhut sub-basin is a mountainous basin from the point of the average elevation and slope of the basin. The aspect is very important for basin hydrology because it affects factors such as sunshine duration, solar radiation and snowmelt. When viewed land cover layer, Suhut sub-basin consists almost entirely grassland and agricultural areas, whereas Sinanpasa sub-basin has also a fair amount of bare land and forest area beside agricultural land and pastures. In addition to these, the longest flow path length and the main stream slope reflect the hydrological characteristics of the basins. The characteristics of the Suhut sub-basin with a 677,1 km^2 precipitation area and the Sinanpasa sub-basin with an area of 765 km^2 are summarized in Table 2.

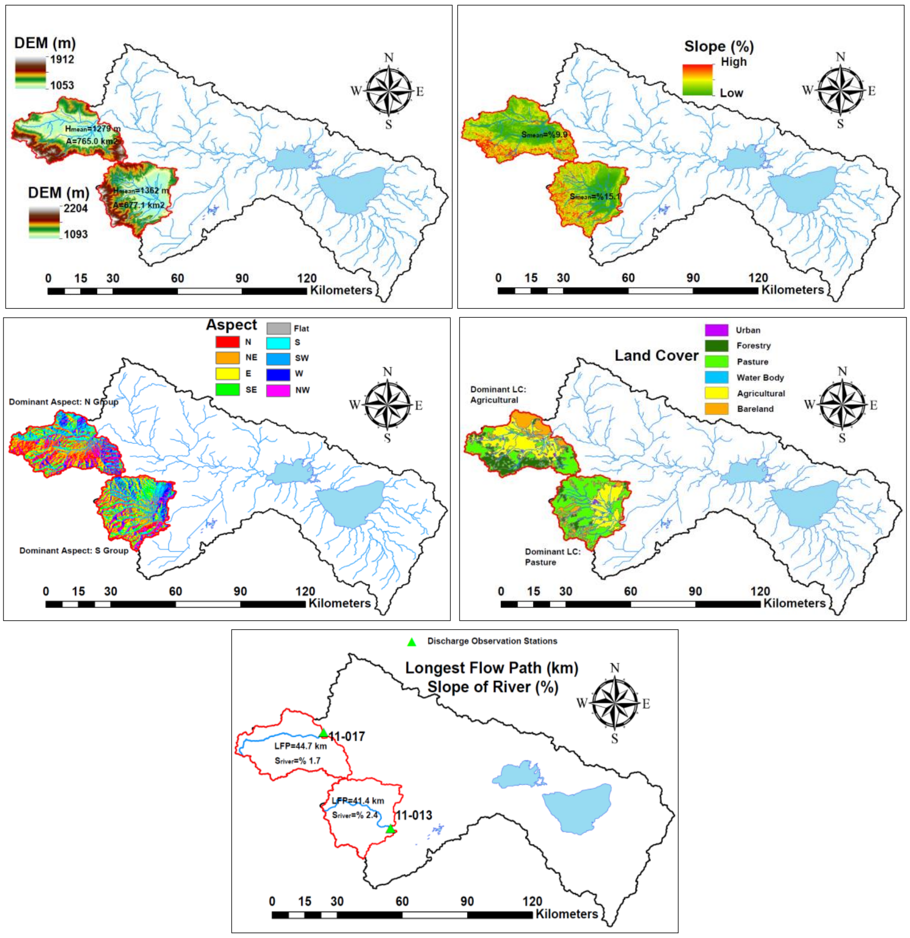

Figure 4: The output layers of GIS analysis: DEM, slope, aspect, land cover and drainage characteristics maps

Table 2: The characteristics of the sub-basins by GIS analysis

Properties of basin	**Subbasin name**	
	Suhut	**Sinanpasa**
Area (km^2)	677,1	765,0
Max elevation (m)	2204	1912
Min elevation (m)	1093	1053
Relief (m)	1111	859
Mean elevation (m)	1362	1279
Mean slope (%)	15,1	9,9
Dominant aspect	South Group	North Group
Dominant land cover	Pasture, Agricultural	Agricultural, Pasture
Length of longest flow path (km)	41,4	44,7
Slope of main river (%)	2,4	1,7

For the study area, the monthly RMSE and PSE results of IDW, SK and CK methods are shown in Table 3. For IDW, SK and CK methods, the mean RMSE values of Sinanpasa sub-basin are respectively 13,76 mm, 9,32 mm and 8,72 mm; for Suhut sub-basin, these values are 9,43 mm, 7,82 mm and 7,90 mm. Then, the uncertainty analysis by means of the PSE is applied to SK-CK methods with clear advantages over the IDW method and with the close RMSE values. When the results of the uncertainty analysis are considered, the SK method with the mean PSE values 10,30 mm and 8,54 mm has a little performance superiority to the CK method whose average PSE values are 11,03 mm and 9,02 mm for both Sinanpasa and Suhut sub basins respectively.

Table 3: The cross validation results in terms of the monthly RMSE and PSE of the study area during the application period

Year	Month	RMSE (mm)						PSE (mm)			
		Interpolation methods									
		IDW		SK		CK		SK		CK	
		Sub-basins									
		S.pasa	Suhut	S.pasa	Suhut	S.pasa	Suhut	S.pasa	Suhut	S.pasa	Suhut
1988	1	3,20	2,84	2,42	2,34	2,41	2,19	2,21	2,50	2,43	2,48
	2	11,21	6,84	7,73	6,56	1,08	6,71	4,23	2,37	5,57	4,17
	3	20,26	14,89	11,72	13,87	6,32	15,71	17,70	14,44	16,39	13,92
	4	15,97	11,95	15,70	9,37	13,91	9,49	13,64	10,48	13,09	12,86
	5	28,47	13,75	15,23	11,52	14,24	10,69	17,15	12,13	25,56	12,63
	6	13,48	17,03	10,48	14,49	9,83	14,15	12,99	14,80	13,31	15,03
	7	15,07	9,67	9,27	7,35	9,73	7,65	11,30	11,51	11,80	11,43
	8	9,24	7,09	7,22	5,11	7,16	5,31	8,88	5,60	8,84	5,89
	9	0,30	1,54	0,29	1,25	0,29	1,23	0,22	1,37	0,23	1,67
	10	31,00	12,21	19,84	6,55	19,85	6,92	22,21	11,46	23,23	11,78
	11	34,39	30,50	27,36	26,80	27,31	28,04	27,20	29,69	27,25	30,14
	12	9,71	5,44	2,17	4,91	3,40	4,65	6,43	5,37	9,42	5,53
1989	1	2,85	2,09	2,62	1,81	2,49	1,78	3,32	2,00	3,92	2,01
	2	2,71	2,17	2,22	1,62	1,61	1,62	2,89	1,76	2,68	1,82
	3	10,63	7,90	8,64	6,41	8,62	6,30	9,07	7,10	9,06	8,05
	4	5,21	4,21	4,20	3,94	4,22	3,90	4,60	3,31	4,88	4,16
	5	8,12	9,99	5,58	9,05	6,16	9,25	6,30	9,85	6,68	10,36
	6	1,85	7,82	1,54	5,57	1,49	5,23	1,87	6,48	1,92	7,02
	7	8,04	4,04	5,23	3,48	5,21	3,41	4,78	3,78	4,98	4,28
	8	17,77	3,84	10,61	3,65	10,61	3,45	12,25	3,41	12,78	3,45
	9	0,56	0,00	0,51	0,00	0,51	0,00	0,43	0,00	0,49	0,00
	10	10,79	9,82	7,22	8,97	7,05	8,89	8,33	10,19	8,33	10,81
	11	54,19	31,97	33,11	25,44	33,12	25,78	38,91	28,66	39,85	28,92
	12	15,16	8,70	12,86	7,57	12,70	7,18	10,20	6,67	12,05	8,18
TOTAL		330,18	226,30	223,77	187,63	209,32	189,53	247,11	204,93	264,74	216,59
MEAN		13,76	9,43	9,32	7,82	8,72	7,90	10,30	8,54	11,03	9,02

And in Figure 5, the change of the monthly RMSE over time is drawn as a graph. In 11. and 23. months, the all interpolation models give the high error due to high precipitation. In general, the curves of SK and CK methods are very similar in specially Suhut subbasin. When compared to the other models, the IDW has obvious high error in particular 5., 10., 20. and 23. months.

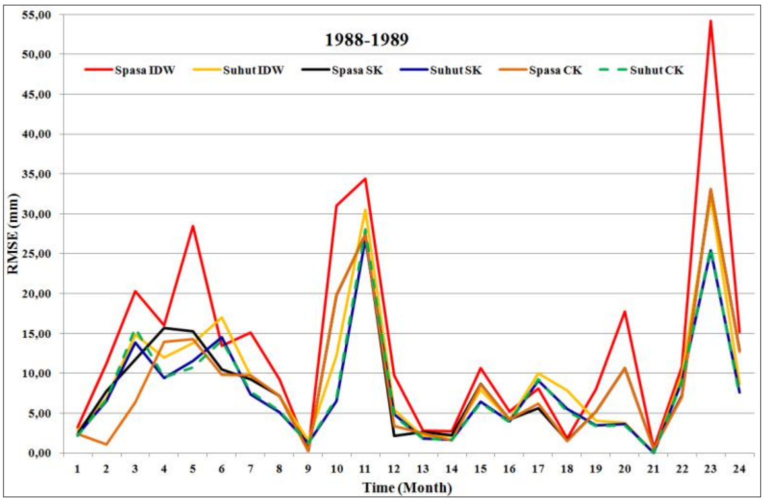

Figure 5: The monthly RMSE values of the study area

In Table 4, the model performance evaluation results are given for the meteorological stations and the sub-basins in terms of R^2, RMSE, MAE, ME and NSE criteria. With respect to these findings, SK and CK methods have an obvious performance superiority over the IDW that they have the close results in terms of model skill. In Sinanpasa sub-basin, the CK is slightly better than the SK, the exact opposite situation is true in Suhut sub-basin. However, SK is a bit better than the CK for both the sub-basins in consequence of the uncertainty analysis. This implies the importance of the uncertainty analysis. The performances of the all models are higher in Suhut sub-basin which has more stations.

Table 4: The model performance results of the interpolation methods

Interp. tech.	**IDW**					**SK**					**CK**				
Sta./Cri.	**R^2**	**RMSE**	**MAE**	**ME**	**NSE**	**R^2**	**RMSE**	**MAE**	**ME**	**NSE**	**R^2**	**RMSE**	**MAE**	**ME**	**NSE**
5296	0,79	13,22	10,32	-0,92	0,75	0,89	9,13	7,78	-0,92	0,89	0,89	8,72	7,51	-0,60	0,89
4947	0,84	15,05	14,51	9,33	0,78	0,96	9,52	9,29	6,11	0,92	0,95	8,26	7,78	4,43	0,93
17190	0,86	11,74	9,09	-3,84	0,66	0,90	9,50	7,58	-3,09	0,79	0,90	9,42	7,43	-3,24	0,79
7-9	0,89	12,66	10,45	3,76	0,84	0,95	9,09	7,63	3,09	0,92	0,95	8,99	7,76	3,03	0,92
17794	0,90	8,67	8,33	0,09	0,90	0,95	6,68	6,08	-0,24	0,94	0,95	6,35	5,75	0,01	0,95
5643	0,93	6,56	6,01	2,55	0,92	0,94	5,72	5,28	1,91	0,94	0,94	5,74	5,43	2,14	0,94
11-8	0,91	8,65	7,33	-1,39	0,89	0,95	6,59	6,08	-0,80	0,94	0,95	6,37	5,91	-1,58	0,94
11-4	0,87	10,80	8,01	-6,17	0,65	0,88	9,44	7,05	-4,45	0,73	0,88	10,03	7,63	-5,18	0,69
Mean	0,87	10,92	9,26	0,43	0,80	0,93	8,21	7,10	0,20	0,88	0,93	7,99	6,90	-0,12	0,88
Subbasins/Cri.	**R^2**	**RMSE**	**MAE**	**ME**	**NSE**	**R^2**	**RMSE**	**MAE**	**ME**	**NSE**	**R^2**	**RMSE**	**MAE**	**ME**	**NSE**
Sinanpasa	0,83	13,76	11,50	0,64	0,72	0,92	9,32	8,03	0,34	0,87	0,92	8,72	7,52	0,04	0,87
Suhut	0,90	9,43	7,93	0,13	0,83	0,93	7,82	6,64	0,04	0,88	0,92	7,90	6,72	-0,23	0,87

Figure 6 and Figure 7 illustrate the experimental and the theoretical semivariograms as examples. In the study area, the SDI results are mostly in classification of strong relation during the application period. The plus signs are the experimental semivariogram and the line is the theoretical semivariogram. The nugget effects are generally so little values (near-zero) for the precipitation.

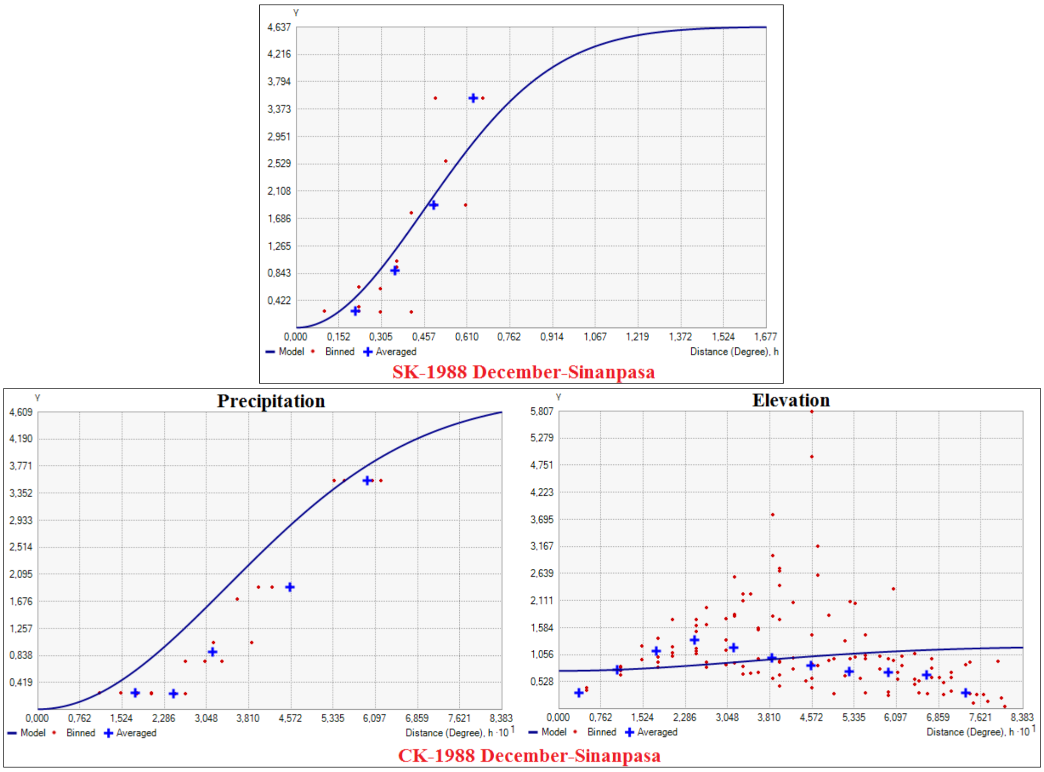

Figure 6: The experimental and the theoretical semivariograms of 1988 December for Sinanpasa sub-basin

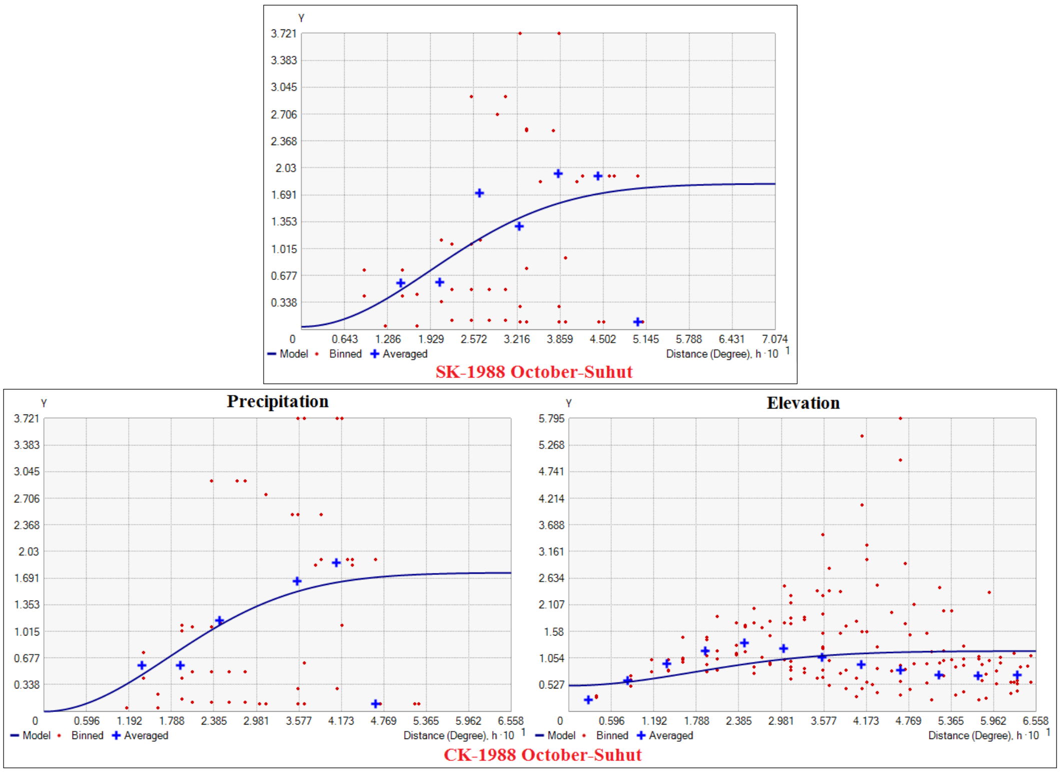

Figure 7: The experimental and the theoretical semivariograms of 1988 October for Suhut sub-basin

Figure 8 is given as an example in order to be seen the difference of the spatial distribution of precipitation of February 1988 produced by the three interpolation techniques (IDW, SK and CK) and it shows the PSE maps for the K methods. For 1988 February, the RMSE values of the Suhut sub-basin are too close but quite different in Sinanpasa sub-basin where the CK method with smooth transition surface has about 10 times better performance than the IDW in relevant month. When the PSE map is analyzed, it is seen that the uncertainty is higher in mountainous areas and for the CK.

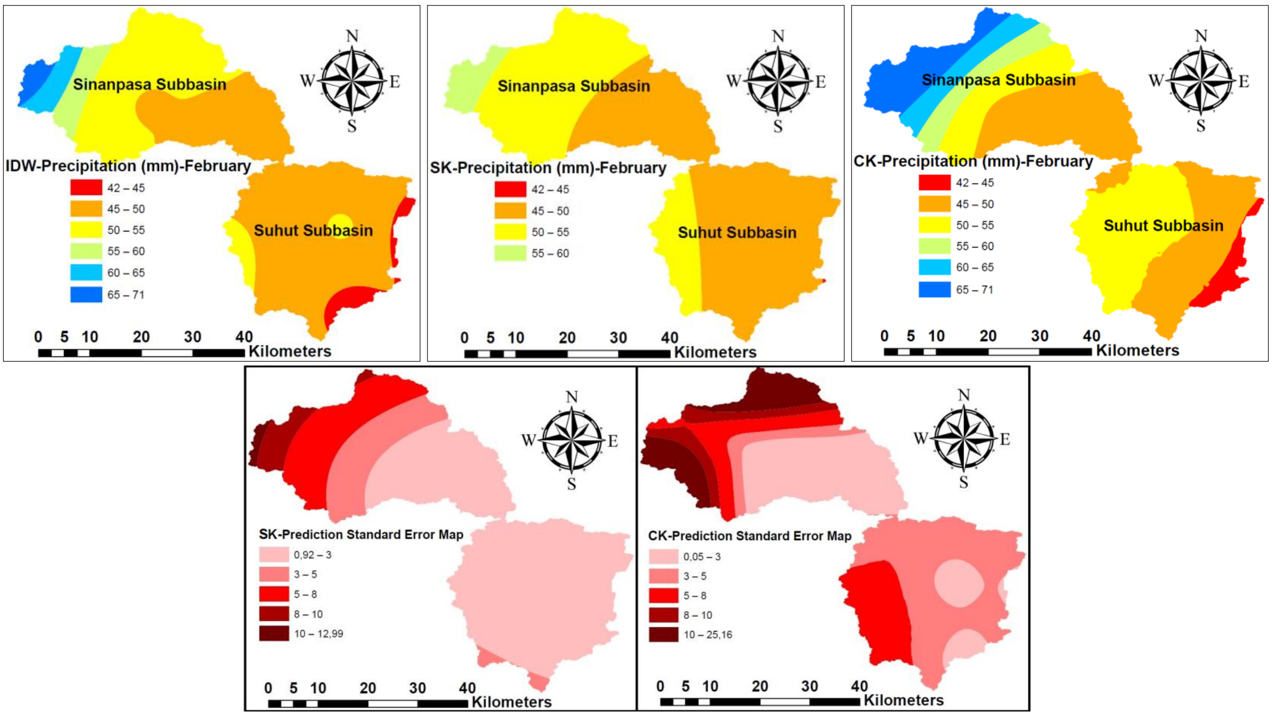

Figure 8: The maps of spatial distribution and PSE of the monthly precipitation (1988 February) by the interpolation methods used

In Figure 9, the NSE results are presented for the stations that the NSE is widely used for specially hydrological model performance. According to NSE values, SK and CK methods outdo the IDW method.

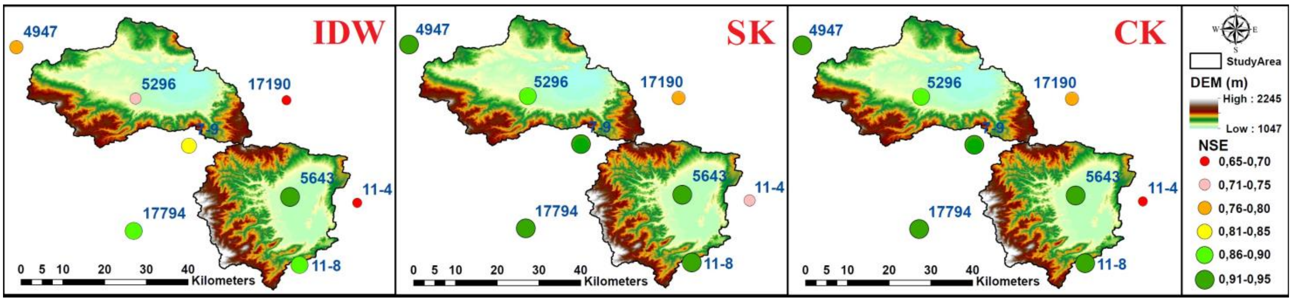

Figure 9: The NSE values of the interpolation methods used

4. Conclusion and Recommendations

In this study, the spatial precipitation in Akarcay Sinanpasa and Suhut sub-basins is modeled by IDW, SK and CK methods and the interpolation methods are compared. The accuracy and precision of interpolation methods are tested by cross validation in terms of various performance benchmarks. According to the results, SK and CK are clearly showed better performance than the IDW method for the application period in the study area with close and less error values. But the three models have enough model performance. In conclusion, the three models can be utilized to interpolate the precipitation in the study area. Advantage of the K methods in according to the IDW is to minimize the prediction error. In the K methods, the spatial variance model is required that it is difficult and time-consuming to set up accurately. From the point of simplicity, easiness, computation effort and time, the ranking of the methods used are respectively IDW, SK and CK.

The precipitation observation stations used in this modeling study are usually installed at low elevations. The absence of observation stations in mountainous areas in the study area increases uncertainty in the representation of precipitation in highlands. It is expected that the use of elevation auxiliary data reduces this uncertainty and increases the consistency. When the RMSE and the MAE values are examined, the elevation data increased a little model performance in Sinanpasa sub-basin, but slightly decreased in Suhut sub-basin. It is thought that the restricted number of observation stations can be a reason of this situation in the study area. In the study area, the correlation coefficient between the altitudes of the stations and the mean precipitation of 24 months (1988-1989) is 0,29 that is a little low value. This may have caused that the CK performance is not superior to the SK one, while expecting to improve the model performance by using co-variable. The SK could not represent well the local variation due to it relies on a global mean. For this reason, although the SK has a bit better performance, the CK can be considered and preferred for the representation of the orographic precipitation due to there is no observation station in highlands of the study area. In addition, north part of Sinanpasa watershed and south end of Suhut watershed are extrapolation areas in present condition of the stations. In the extrapolation areas, the CK method can be preferred because of the auxiliary data for more consistent estimation. These are advantages of the CK on the SK in case of sparse/missing primary data that the CK allows incorporation and integration of the correlated secondary data.

Furthermore, it is appeared that the CK method, supported with elevation data, provides a smoother transition surface in the spatial distribution of precipitation. In addition to the elevation data, the effects of secondary variables such as vegetation, temperature and aspect on the spatial precipitation can be investigated. The vegetation cover, NDVI (normalized difference vegetation index) and the temperature are closely related to the precipitation. In this context, many basin characteristics can be evaluated in the interpolation of the precipitation. The aspect may increase/decrease the orographic effect of the precipitation, so it can be important. In the modeling, it is expected that the use of the related auxiliary data increase the consistency in prediction of the spatial distribution of precipitation.

When we look at the ME values, the all methods slightly underestimate the precipitation except for the CK in Suhut watershed. In point of fact, the all ME values for the sub-basins are near-zero, in other words, it can be stated that the all predictions are unbiased. If the stations are assessed for the ME; 17190, 11-4, 11-8 and 5296 stations overestimate the precipitation ant the others excluding the 17794 station -which can be accepted unbiased estimation- underestimate.

When the performance results are considered for Sinanpasa and Suhut sub-basins, it is seen that the model performance in the Sinanpasa sub-basin, which is modeled with 4 observation station data (4947, 5296, 7-9 and 17190), is slightly lower than the Suhut sub-basin where 6 observational station data (5643, 11-8, 11-4, 7-9, 17794 and 17190) are used. The area per a meteorological observation station is 113 km^2 for Suhut sub-basin and 191 km^2 for Sinanpasa sub-basin that these values are suitable according to the recommendations of World Meteorological Organization. It is expected that the increase in the number of stations has a positive effect on the performance of the model.

Determination of the spatial precipitation distribution is useful for many hydrometeorological studies such as flood analysis, reservoir operation, hydropower generation, water supply and demand models, completing of missing data in the observation time series and prediction in ungauged basins. In the semi-arid Akarcay basin, Eber and Aksehir Lakes are very important for the ecological research and drought studies besides the irrigation activities of the two sub-basins which are important for agriculture. In this context, knowledge of the distribution of precipitation in water resources planning and management is vital for water authorities and decision makers.

The spatial distribution obtained from the point meteorological measurements by the spatial interpolation methods is used as the input data for the distributed hydrological models which are recently more interested in international studies. In this context, it is very important to produce the areal precipitation time series. In addition, the accuracy and reliability of rainfall raster data generated by interpolation can be tested by the performance of input hydrological models.

The spatial distribution of rainfall obtained by spatial interpolation methods can be compared with global databases and satellite based precipitation products. Furthermore it can be blended for better model performance. If available, it can also be evaluated with radar data.

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