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The Determination of Reference Evapotranspiration for Spatial Distribution Mapping Using Geostatistics

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Abstract The reference evapotranspiration (ET₀) is an essential variable in the agrohydrological systems and its estimation on a regional scale is limited to its spatial variability. This study compares two approaches for preparation of spatial distribution maps of ET₀ in Mazandaran province of Iran. In the first approach, ET₀ was calculated using climatic data and Hargreaves-Samani equation in weather stations locations and then were interpolated. In the second approach, the components of the Hargreaves-Samani equation were interpolated and then ET₀ maps were prepared by applying the Hargreaves-Samani equation and suitable commands in GIS. The 10-year climatic data for 51 weather stations (46 stations for preparing ET₀ maps and 5 stations as validation station) were gathered over Mazandaran province. Semivariograms were calculated and the best semivariogram model was selected on the basis of the least value of Residual Sums of Squares (RSS). The spatial correlation of the data was compared on the basis of Nugget to Sill ratio. The data were interpolated using Ordinary Kriging method and the interpolation error was computed by cross validation technique based on Root Mean Square Standardized Error (RMSE). The predicted ET₀ values were compared to the computed ET₀ in validation stations and sensitivity analysis was conducted. Results show the second approach had better spatial correlation and lower interpolation error and the difference between these two approaches were not significant. Therefore, the accuracy of the ET₀ maps is more related to the method of computing ET₀ than the type of climatic data is being interpolated.

Keywords Reference evapotranspiration · Geostatistics · Climate data interpolation · Ordinary kriging · Spatial distribution

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1 Introduction

It has been estimated that over 80 % of the developed freshwater resources around the world are used for irrigation (FAO 1994). However, only 45 % is used by crops and the rest are not effectively used in crops productions (FAO 1992). Hence, in order to improve water resources management, proper irrigation planning and scheduling is necessary. In irrigation scheduling, the determination of crops water requirement is indispensable, too. Crops water requirement is determined using both direct method (e.g., using lysimeter and water budget equation) and indirect method (by using climatic and crop data). Owing to the difficulty of obtaining accurate field measurements, crop water requirement is commonly computed from indirect method and is equal to crop evapotranspiration (ET) that is a function of reference evapotranspiration (ET₀) and crop coefficient (K_c) (Allen et al. 1998).

ET₀ is an essential variable in the agrohydrological systems and provides the evapotranspiration of a well-watered grass surface without any water stress (Rana and Katerji 2000; Kite and Droogers 2000). K_c depends on the crop and is obtained using crop parameters, though; ET₀ is computed from weather data which express the evaporating power of the atmosphere. Thus understanding ET₀ is so essential in planning and management the most effective use of water resources.

The climatic data are measured in weather stations. So, computing ET₀ by using weather data is only acceptable in the weather stations locations and as the position gets away from the stations, the accuracy is diminished because weather and climate vary from place to place. Although the prediction of ET₀ is very important for irrigation management and decisions making, the study on the prediction of ET₀ on a regional scale is limited due to its spatial variability (Zhao et al. 2005). Consequently, in order to predict ET₀ values in the locations without climatic data, a suitable interpolation method should be used. The past interpolation methods were classical statistics, arithmetic mean and regression methods that were quick and easy. But the lack of consideration given to the location and spatial correlation caused error in the interpolations. So, interpolating based on the spatially analyzed of the data was proposed by scientists.

There are two main groupings of spatially interpolation techniques: deterministic and geostatistical. Deterministic interpolation techniques create surfaces from measured data based on either the extent of similarity (inverse distance weighted) or the degree of smoothing (radial basis functions). A deterministic interpolation can either force the resulting surface to pass through the data values or not. However, geostatistical techniques quantify the spatial correlation among measured points and account for the spatial configuration of the sample points around the prediction location. Geostatistical interpolation techniques utilize the statistical properties of the measured data to produce the raster maps. This technique creates not only prediction maps but also error or uncertainty maps and implies how good the predictions are. Geostatistics is including different types of Kriging method such as Ordinary, Simple, Universal, Probability, Indicator, Disjunctive and Cokriging. Kriging quantifies the spatial correlation of the data which is called variography and then presents a prediction for the locations without any measured data (Matheron 1963). Variography is where it is fitted a spatial-dependence model to the data. To obtain a prediction for a location, Kriging uses the variogram model, the spatial correlation of the data, and the measured data around that location. Altogether, geostatistical methods can be used for producing spatial distribution maps of spatial data such as spatial variation analysis of major parameters which affect surface and groundwater quality (Masoud 2014), spatio-temporal maps of the water table depth in Italy (Barca et al. 2013), interpolating the snow water equivalent using ordinary kriging technique in Iran (Marofi et al. 2011), spatial analysis of rainfall in Nepal (Diodato et al. 2010), spatial

distributions of soil surface-layer saturated hydraulic conductivity in China (Zhang et al. 2010), estimating regional groundwater recharge in USA (Manghi et al. 2009), geostatistical assessment of Groundwater nitrate contamination in Lebanon (Assaf and Saadeh 2009), spatial distribution of rainfall in India (Basistha et al. 2008), ground water depth mapping in Iran (Ahmadi and Sedghamiz 2008), plotting the long-term mean daily ET₀ for each month in Greece (Mardikis et al. 2005), estimation of mean annual precipitation using geostatistics in Spain (Martinez-Cob 1996). New technologies like GIS allow us to use these methods and produce spatial distribution maps of spatial variables.

For preparing ET₀ maps, in common methods, ET₀ values are computed using meteorological data of each station and then they are interpolated; e.g., Dalezios et al. (2002) over Greece, Noshadi and Sepaskhah (2005) in the southern and central regions of Iran and Ganjizadeh et al. (2013) in Golestan province (Iran). However, in interpolating, the factor that may affect the interpolation results is the sequence of steps that are followed (Mardikis et al. 2005).

Two approaches, Interpolate-then-Calculate (IC) and Calculate-then-Interpolate (CI), were compared by many researchers for generating spatial ET₀ maps. Zhao et al. (2005) used IC procedure for preparing spatial distribution map of ET₀. Zhang et al. (2010) concluded for regions with isolated climate stations, 'IC' procedure by including topographic and geographic factors can effectively model spatially distributed ET₀'. Mardikis et al. (2005) conducted these two procedures when plotting the long-term mean daily ET₀ for each month in Greece using four interpolation methods including Ordinary Kriging (OK), Inverse Distance Squared (IDS), Residual Kriging (RK) and Gradient plus Inverse Distance Squared (GIDS). Their results revealed that GIDS method in IC procedure has the lowest mean absolute error (0.1207 mm) and root mean squared error (0.0367 mm) averaged over all months, but had a slight superiority over GIDS method in CI procedure. Altogether, they stated that procedures CI and IC did not differ for a given month and method and the interpolation of reference evapotranspiration were slightly affected by the sequence of steps. Bechini et al. (2000) stated that the IC procedure would increase the error of model application if the spatial and temporal structures of the model inputs were not reliable. They reported that for nonlinear models, IC procedure should be preferred but considerable attention should be paid in order accurate interpolation of inputs to be ensured. Ashraf et al. (1997) concluded that IC procedure provided lower Root Mean Squared Interpolation Error (RMSIE) of ET₀ than the CI procedure for ET₀, but the difference is small. Phillips and Marks (1996) and Bechini et al. (2000) concluded that the error of IC procedure is expected to be higher because it results from all interpolation errors of each individual input variable.

In all mentioned studies, FAO-Penman-Monteith equation was used and the researchers were worried about high input variables and their individual error effects on the interpolation accuracy. So, in this study, another suitable equation for Iran climate (Farshi et al. 1997; Noshadi and Sepaskhah 2005), Hargreaves-Samani equation, is tested. In addition, this equation has lower input variables. Also, the number of data is very important in interpolation. There are low synoptic weather stations in the study area for using FAO-Penman-Monteith equation; however, if it is used Hargreaves-Samani equation for computing ET₀, more weather stations could be used.

Therefore, this study compared two approaches of creating ET₀ maps using climatic data. In the first approach, (Calculation-then-Interpolate), the ET₀ values are computed using climate data of each station by Hargreaves-Samani equation and then they get interpolated. In the second approach, (Interpolate-then-Calculate), the components of the Hargreaves-Samani equation get interpolated and then ET₀ maps get prepared by using suitable commands in GIS. The specific objective is to evaluate these two approaches of creating spatial distribution map of ET₀ in Mazandaran province (Iran) for improving evapotranspiration estimation and evaluate the performance of these

approaches. Since, in the estimation of reference evapotranspiration (ET₀) in the regional scales, last studies used field data for FAO-Penman-Monteith equation, in this study another suitable equation for Iran climate aimed to be used. Also, FAO-Penman-Monteith equation components are just calculated in synoptic weather stations and the number of them is low in the study area. By changing FAO-Penman-Monteith equation with Hargreaves-Samani equation, the dataset from different weather stations (e.g., Synoptic, Rain-gauge, and climatological stations) can be used and it has positive effect on the interpolating accuracy. This method is really suitable for regions with lack of data such as Iran.

2 Materials and Methods

2.1 Study Area

The study area, Mazandaran province, is located in the north of Iran between 50° 34' E to 54° 10' E and 35° 47' N to 36° 35' N. The province has a total area of 23,756.4 km². The precipitation is varied 600 to 1200 mm throughout the province and is increasing from east to west. Agriculture is the biggest water user in this province. This area is a region where irrigation has been practiced for centuries in small fields dispersed through a number of valleys.

2.2 GIS Database

As mentioned before, current study compared two interpolation approaches for preparing spatial distribution map of reference evapotranspiration (ET₀) in Mazandaran province. In the first approach, Calculate-then-Interpolate (CI), the ET₀ values were calculated using climatic data by Hargreaves-Samani equation and then these values were interpolated. In the second approach, Interpolate-then-Calculate (IC), all components of the Hargreaves-Samani equation, including maximum air temperature, minimum air temperature and extraterrestrial radiation (Ra), were interpolated and then ET₀ maps were prepared by using these maps and suitable commands in GIS. For this purpose, a 10-year data series (2001–2010) of 51 weather stations (including 11 synoptic stations, 11 climatology stations and 29 evaporation stations) in Mazandaran province were gathered. Among these stations, 46 stations were used for preparing the maps and 5 stations were used as validation stations.

The location of the study area, stations and validation stations are shown in the Fig. 1. The validation stations are distributed in the upper, middle and lower elevations.

In every station, mean daily ET₀ was calculated for each month by using Hargreaves-Samani equation (Hargreaves and Samani 1985):

$$ET_0 = 0.0023Ra (T + 17.8)TD^{0.5} \quad (1)$$

$$TD = T_{max} - T_{min} \quad (2)$$

$$T = (T_{max} + T_{min})/2 \quad (3)$$

Where, T_{max} and T_{min} are maximum and minimum air temperature (°C). Ra is also Extraterrestrial radiation (MJ m⁻² min⁻¹) which is obtained as follows:

$$Ra = 37.586dr(W_s \sin \varnothing \sin \delta + \cos \varnothing \cos \delta \sin W_s) \quad (4)$$

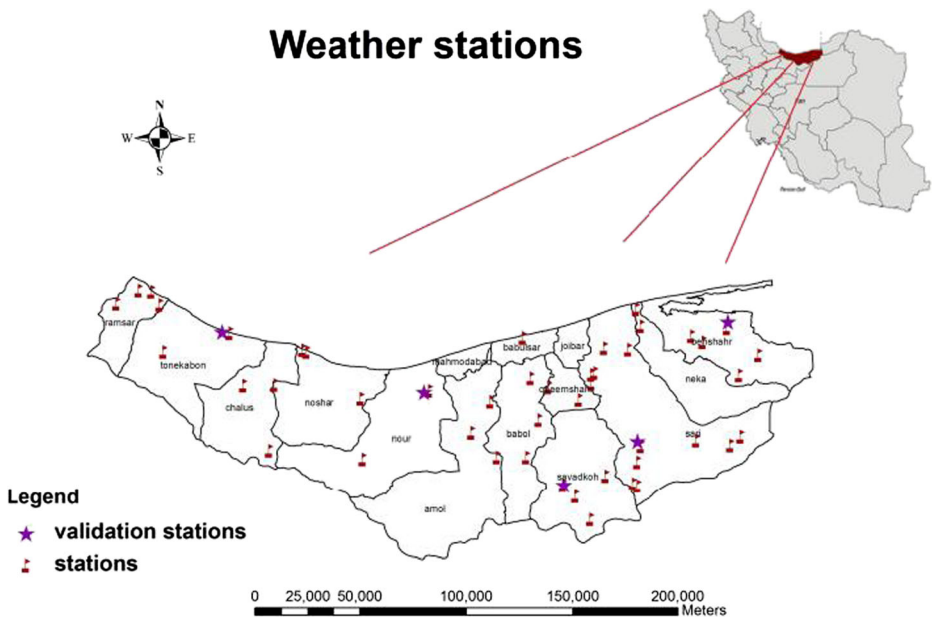


Fig. 1 The location of the study area, stations and validation station

$$Ws = \arccos(-\tan(\varphi) \tan(\delta)) \tag{5}$$

$$dr = 1 + 0.033 \cos(0.0172J) \tag{6}$$

$$\delta = 0.409 \sin(0.0172J - 1.39) \tag{7}$$

$$J = \text{Integer}(30.5M - 14.6) \tag{8}$$

Where, *dr* is inverse relative distance Earth-Sun, *Ws* is sunset hour angle, φ is latitude (rad), δ is solar declination and *J* is Julian day. After that, the related information layers were created in GIS and the necessary data were imported.

2.3 Geostatistical Analysis

As we wanted to consider the spatial correlation among measured data and also the geostatistical method has been considered appropriate, so Kriging (Matheron 1963; Delhomme 1978) was selected since it has been proved already for preparing ET₀ maps (Zhao et al. 2005; Dalezios et al. 2002; Ashraf et al. 1997; Cuenca and Amegee 1987). It should be noted that in order to use Ordinary Kriging, the data series should have a normal distribution; otherwise the non-linear Kriging should be used or the data have to be turned into a normal distribution using convertor functions, and then the Linear Kriging can be used (Webster and Oliver 2001). Therefore, the distribution function of the data must be checked. Also, the spatial correlation of the data is evaluated by semivariogram which is as follows (Matheron 1963):

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

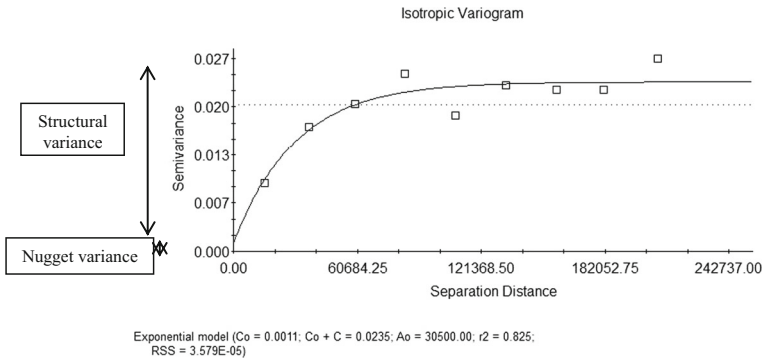


Fig. 2 Semivariogram values and the fitted model (Exponential model) for the ET0 in December

Where:

- $Z(x_i)$ value of the variable in the location x_i
- $Z(x_i+h)$ value of the variable in the location x_i+h
- $N(h)$ the number of pairs of observation separated by a distance h
- γ semivariogram

A semivariogram reveals the spatial structure of a variable and how it varies in different directions. In order to investigate geostatistical analysis and spatial correlation of the data, their semivariograms were calculated and different common semivariogram models (e.g., Spherical, Exponential, Gaussian and etc.) were fitted on them (Delhomme 1978) which an example one is shown in Fig. 3. To conduct geostatistical analysis GS+ software was used. For each model, Sill, Range and Nugget would be calculated. When the distance between the samples (h) increases, the value of semivariogram increases to a certain distance and then graph levels off which is called Sill (the model asymptote). The distance between the samples from which the variable values in adjacent areas have little effect on each other and with further increase the samples become independent, is called the Range or Radius of Influence. Also, the semivariogram value for $h=0$ is called Nugget (Isaaks and Srivastava 1989). Ideally, the Nugget should be zero, but in reality this status does not happen due to sampling, measurement and analysis errors of the data (Delbari et al. 2004). As shown in Fig. 2, the Nugget is the

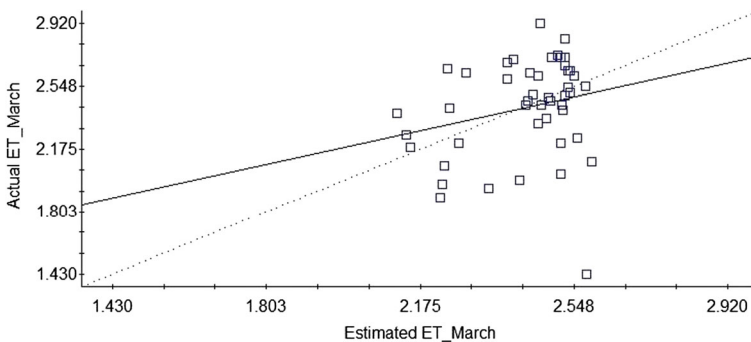


Fig. 3 Cross validation Diagram for the ET0 data in March

Table 1 Spatial correlation for ET0, Tmax and Tmin data in different months (Str=Strong, Mod=Moderate)

Parameter	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
ETo	Str	Mod	Mod	Mod	Mod	Mod	Str	Str	Mod	Mod	Mod	Str
Tmax	Str	Str	Mod	Str	Mod	Str	Str	Str	Str	Str	Str	Str
Tmin	Str	Str	Str	Str	Str	Str	Str	Str	Str	Str	Str	Str
Ra	Str	Str	Str	Str	Str	Str	Str	Str	Str	Str	Str	Str

randomized variance of the variable (the y-intercept of the model) which its consideration in the geostatistical interpolation method is the advantage of this model over the deterministic interpolation method. On the other side, the N/S index is used to determine the correlation of the data, which is:

$$N/S = \text{Nugget/Sill} = C0/(C + C0) \tag{10}$$

For N/S index values less than 0.25, between 0.25 and 0.75 and higher than 0.75, the spatial correlation is strong, moderate and weak, respectively (Cambardella et al. 1994).

The best one is selected based on the lowest Residual Sums of Squares (RSS) values. RSS provides an exact measure of how well the model fits on the variogram data so that the lower residual sums of squares, the better the model fits (Fig. 2).

Data anisotropy has also been studied in the model fitting. Spatial correlation may depend only on the distance between two observations, which is termed isotropy. However, it is possible that the same correlation value may occur at different distances when considering different directions, which is termed anisotropy. This matter effects the geostatistical prediction. In order to check for data anisotropy, semivariogram are plotted in different directions and are checked.

After geostatistical analysis, the Ordinary Kriging method was used for interpolation of the data as follows (Matheron 1963):

$$Z^*(x) = \sum_{i=1}^n \lambda_i Z(x_i) \tag{11}$$

Where:

- Z*(x) the estimated value of the variable Z in a point with coordinates x_i
- Z(x_i) observed value of the variable Z in a point with coordinates x_i
- λ_i weight assigned to the variable Z at the point x_i

Table 2 RMSSE values for interpolation of ET0, Tmax and Tmin data in different months

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
ET0	1.80	1.50	1.11	1.14	1.17	1.14	1.10	1.06	1.11	1.13	1.25	1.56
Tmax	1.44	1.16	1.40	1.12	0.99	1.05	0.98	1.01	1.06	1.15	1.33	1.40
Tmin	0.95	0.97	0.98	0.97	0.95	0.97	1.00	1.02	1.00	0.98	0.96	0.97
Ra	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01

Table 3 Error percentage for the computed ET0 compared with ET0 from CI and IC approaches

Month Approach	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CI	0.06	0.05	0.11	0.09	0.09	0.12	0.12	0.12	0.10	0.11	0.10	0.05
IC	0.05	0.06	0.08	0.09	0.11	0.11	0.12	0.12	0.09	0.11	0.09	0.05

Kriging provides a minimum error-variance of any unsampled value and is described as the Best Linear Unbiased Estimator (B.L.U.E). It is best because it tries to minimize the variance of error; It is linear because its estimations are weighted linear combinations of the data; It is unbiased because it tries to have the mean residual of error equal to 0 (Noshadi and Sepaskhah 2005).

In E. 11, λ_i are determined so that the mean squared prediction error is minimized. In order to test the variogram models and to determine the interpolation error, a cross validation has been used (Isaaks and Srivastava 1989). In this technique each data is omitted and then is predicted using the Kriging method. The point values being predicted are then compared with their measured values (an example is shown in Fig. 3) and their differences were considered as error where in this study we used Root Mean Square Error (RMSE).

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^n \left\{ \frac{Z^*(x_i) - Z(x_i)}{\sigma(x_i)} \right\}^2 \right]^{0.5} \tag{12}$$

Where $Z^*(x_i)$ is the predicted value for a given $Z(x_i)$ with standard deviation $\sigma(x_i)$. The RMSE provides a great measure of how closely two independent data sets match (Ventura et al. 1999). Since in this study the considered parameters were different, the standardized RMSE values were used to present error.

In order to verify the interpolation, interpolated ET0 values of the both approaches were compared with the computed ET0 values in validation stations and the amount of error was calculated based on the Error Percentage and Mean Absolute Error (MAE) as follows:

$$ErrorPercentage = \left| \frac{Z(x_i) - Z^*(x_i)}{Z(x_i)} \right| * 100 \tag{13}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |Z(x_i) - Z^*(x_i)| \tag{14}$$

Where $Z^*(x_i)$ are predicted values, using both IC and CI approaches, and $Z(x_i)$ is the computed value at the location of validation stations.

Table 4 MAE values for the computed ET0 compared with ET0 from CI and IC approaches

Month Approach	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CI	0.07	0.10	0.27	0.27	0.34	0.52	0.53	0.52	0.34	0.26	0.16	0.06
IC	0.07	0.11	0.20	0.29	0.44	0.49	0.55	0.49	0.31	0.25	0.15	0.06

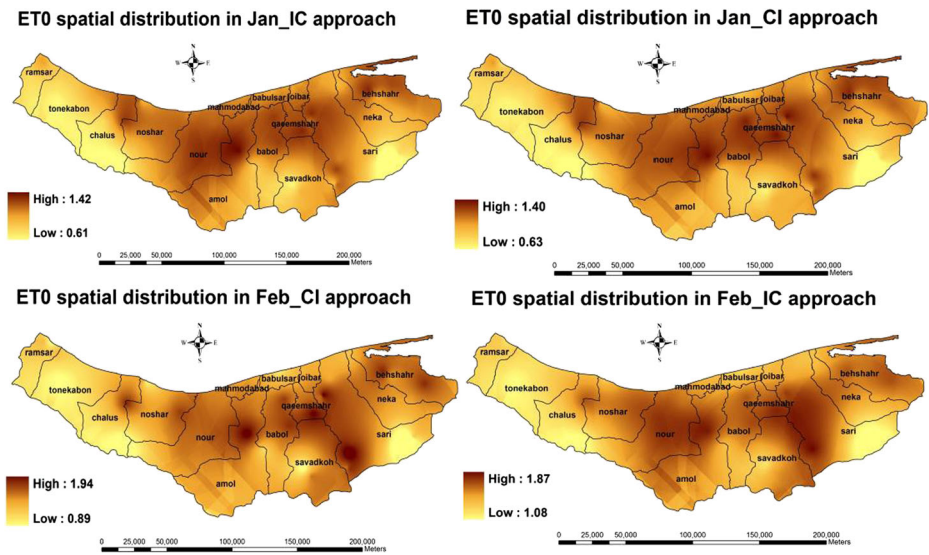


Fig. 4 ET0 spatial distribution maps resulted from CI and IC approaches in Jan and Feb in Mazandaran province

3 Results

As it was mentioned, for using Ordinary Kriging interpolation method, the distribution function of the data was analyzed using SPSS software and it was found that all the data had a normal distribution function at 95 % level by Kolmogorov-Smirnov method. Then, semivariogram values of the data were calculated and the best fitted models were determined based on RSS index which were Spherical for minimum air temperature data and were Exponential and Spherical in different months for maximum air temperature and ET0 and extraterrestrial radiation data. To investigate the anisotropy of the data, semivariograms were drawn in different directions (0, 45, 90, 135°) and it was found that the data did not have anisotropy. Also, by inspecting the fitted semivariogram models, no trend was observed.

ET0 spatial distribution in Oct_CI approach

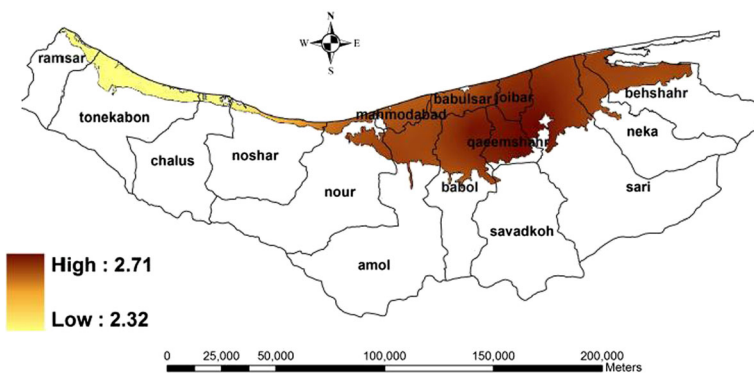


Fig. 5 ET0 spatial distribution Map resulted from CI approach in Oct in farming area of Mazandaran province

The Correlation of the data was investigated according to the Nugget to Sill ratio (N/S) and showed that the spatial correlation of maximum and minimum air temperature and extraterrestrial is stronger than that of ET₀ data (Tables 1, 2, 3 and 4). Then the data were interpolated by Ordinary Kriging method and spatial distribution maps of the reference evapotranspiration in different months were prepared for Mazandaran province by both approaches. For example some of them are shown in Fig. 4. In order to interpolate, 16 observed data in the surrounding areas were used. It should be cited that ET₀ spatial distribution maps in the second approach were prepared using maximum air temperature, minimum air temperature and extraterrestrial radiation maps and suitable commands in ArcGIS software according to Hargreaves-Samani method. Then cross validation diagrams were plotted and the amounts of errors were calculated based on Root Mean Square Standardized Error (RMSSE) for different months. Except for March and October, the interpolation errors of maximum and minimum air temperatures and extraterrestrial radiation were less than that of ET₀ data.

Also, in order to assess the accuracy of the predictions, the predicted ET₀ values from two interpolation approaches (ET_{0_{dir}} and ET_{0_{cal}}) were compared with the computed ET₀ values at validation stations.

4 Conclusions

Since ET₀ play very important role in the distributed hydrological modeling, in this study two approaches for preparation of spatial distribution maps of ET₀ were compared. In the first approach (Calculation-then-Interpolate), ET₀ in every month was computed using climatic data and Hargreaves-Samani equation in weather stations locations and then were interpolated. In the second approach (Interpolate-then-Calculate), the components of the Hargreaves-Samani equation were interpolated and then ET₀ maps were prepared by applying the Hargreaves-Samani equation and suitable commands in GIS. Since, in the last studies FAO-Penman-Monteith was used, in this study another suitable equation for Iran climate aimed to be used. Also, FAO-Penman-Monteith equation components are just calculated in synoptic weather stations and the number of them is low in the study area. But, by using Hargreaves-Samani equation more weather station data can be used and it has good effect on interpolating.

The geostatistically results showed that the spatial correlation of maximum and minimum air temperature and extraterrestrial radiation is better than ET₀ and maximum and minimum air temperature and extraterrestrial radiation interpolation error was lower than ET₀. But the comparison of predicted ET₀ values resulted from two interpolation approaches with the computed ET₀ values in the validation stations locations showed that the differences were very low. Therefore, the significance of the differences between two approaches was evaluated using *t*-test analysis and showed that the differences were not significant in all months and all validation stations. So, we conclude that Interpolate-then-Calculate (IC) approach has no good effect on interpolation accuracy when Hargreaves-Samani equation is used for computing ET₀ and since the IC procedure is more complex and time consuming than Calculate-then-Interpolate (CI) procedure, the use of IC procedure is not justifiable. Also, it can be stated that the accuracy of ET₀ maps is more related to the method of computing of ET₀. This outcome is in accordance with Mardikis et al. (2005) and Ashraf et al. (1997) studies when FAO-Penman-Monteith was used for computing of ET₀. Also, this outcome is not similar to Phillips and Marks (1996) and Bechini et al. (2000) studies who stated that the error of IC may be higher because it results from all interpolation errors of each individual input variable. As

another result of this study, the ET₀ maps show temporal and spatial variation. Temporally, ET₀ values are rather low in the cool months (Jan, Feb, Oct, Nov and Dec), whereas they are rather high in the warm months (May, June, July and Aug) which express that in warm months, available energy primarily forces ET₀ as expected. Also, in the mentioned cool months, the spatial variation of ET₀ is small, whereas the spatial variation of ET₀ is high in the mentioned warm months. Spatially, ET₀ in the western part is lower than the other parts of the province. This condition is due to the narrower shape of the western part where mountain gets closer to the sea and air humidity increases and consequently air evaporability decreases. This outcome is in accordance with RahimZadeh and Khoshkam (2003) study. Furthermore, in this study, the interpolation approaches were applied on the whole area of the province, but it should be noted that the southern parts of the province are covered by Alborze mountainous region where there is no agricultural activities. Thus, in order to apply the results for irrigation management, ET₀ maps of the farmlands should be extracted (e.g., Fig. 5 shows the ET₀ maps of the farmlands in October). But, since this study was aimed to compare two approaches for preparing ET₀ spatial distribution maps based on computed ET₀ values at validation stations, the ET₀ maps for the whole province were shown. Results allow further developments in practical irrigation scheduling in the form of the development of regional distribution maps of ET₀ and crop water requirement. Besides the spatial distribution of ET₀, this study generates a series of spatial distributed maps such as maximum and minimum air temperature. These outputs could be used for other purposes like regional management and scheduling.

5 Discussion

Given that the differences between the interpolation methods are more depended strongly on the nature of the variables under study, data spatial configuration, number of available samples, the assumption drawn and the selected criteria for the interpolation than the method of interpolation (Creutin and Obled 1982; Isaaks and Srivastava 1989; Weber and England 1994; Martinez-Cob 1996; Caruso and Quarta 1998; Nalder and Wein 1998) and also different geostatistical methods have different precision, it is suggested to consider other geostatistical methods for interpolating and compare them with the results from the current study.

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