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IMPROVEMENT THE EVAPOTRANSPIRATION ESTIMATES USING REMOTE SENSING TECHNIQUES AND FUZZY REGRESSION

SUMMARY
Through the use of remote sensing techniques, multiple regression analysis is related to evapotranspiration computed from two components: thermal infrared and spectral reflectance bands. Improvement the regression analysis with emphasis on the used components is the aim of this research which the vegetation indices is the desired one. In this regard, the performance of Soil Adjusted Vegetation Index (SAVI) in some synoptic stations of East Azarbaijan Province (Ahar, Tabriz and Mianeh stations) was compared with Normalized Difference Vegetation Index (NDVI) performance. Increasing of L in the SAVI calculation caused the increasing of estimated evapotranspiration. The change of vegetation index led to error decreasing for example the value of RMSE decreasing was 14.29% and 9.9% in case of Mianeh and Ahar stations, respectively. The vegetation cover was the main factor in improvement of evapotranspiration estimates using SAVI. The precise estimation of fuzzy regression parameters is more important which the variation of confidence level had no effect on the center of fuzzy number but the increasing of confidence level parameter led to increasing the spread of fuzzy number.

Keywords: Remote Sensing, Evapotranspiration, SAVI, NDVI, Fuzzy Regression

INTRODUCTION
Evapotranspiration with representation the water loss by evaporation and plants transpiration is the main factor in the climate change, land use, water budget and irrigation studies (Soskic et al., 2001; Dragovic et al., 2009). Over the past years, several evapotranspiration estimation methods are divided into four groups such as: the hydrological method (using the principle of water balance), micro-meteorological method (using the equations of energy balance and aerodynamic), combinations approach (Thornthwaite) and measurement into directly (lysimeter) (Matinfar, 2012).

In some ways, the application of methods is associated with a problem for example difficulty in making public the micro-meteorological method due to great cost of instrument manufacturing and small scale of evapotranspiration estimation using lysimeter (Lingling et al., 2013).

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Remote sensing methods have already reached a significant level of accuracy and reliability over the last forty years, thus becoming attractive for evapotranspiration estimation, since they have a very high resolution and cover large areas (Blanta et al., 2011; Djurovic and Nikolic, 2016; Chivulescu and Schiteanu, 2017). Empirical models with discovering the relationship between evapotranspiration and vegetation indices derived from satellite images and physical models with solving the energy balance equations using the surface temperature of satellites images are the evapotranspiration models with the information of satellite images. The empirical approach needs lesser additional information and rather to the physically models is simpler (Helman et al., 2015).

The relationship between evapotranspiration flux and Normalized Difference Vegetation Index (NDVI), surface temperature derived from satellite images have been analyzed in the variety studies. Surface temperature data modify the evapotranspiration flux with incorporating the effects of topography, surface water and wind (Di Bella et al., 2000).

Anbazhagan and Paramasivam (2016) investigated the correlation between NDVI and land surface temperature from thermal bands of Landsat TM. The results indicated the negative anomaly of vegetation index with increasing of emissivity. The standardized regression coefficient value derived from the statistical regression analysis of NDVI and land surface temperature was negative. The results of research emphasized the importance of land surface temperature (Anbazhagan and Paramasivam, 2016). Di Bella et al. (2000) using NDVI and surface temperature data of the Advanced Very High Resolution Radiometer (AVHRR) sensor have been applied the predictive power of models for evapotranspiration estimation in the Argentine Pampas. Based on the approach, the reliable evapotranspiration estimation was obtained using remotely sensed data. In order to generate the models, the high sensitivity of relation between spectral data and evapotranspiration was related to the dates (Di Bella et al., 2000).

Han et al. (2006) explained the spatial relationships of NDVI and land surface temperature in the form of triangular or trapezoid. For explication the existent meaning of a triangular space, the Temperature Vegetation Dryness Index (TVDI) has been used. Occurrence of that can be done after reaching NDVI to the saturated state with applying the relationships of NDVI, leaf area index (LAI) and evapotranspiration. The validation and updating of land surface models can be done accurately using the relations of NDVI and land surface temperature (Han et al., 2006).

Zhang et al. (2009) obtained the correlation of the groundwater use efficiency estimation derived from eddy covariance tower with vegetation index and ground micro-meteorological data. The correlation coefficient of water use efficiency and the Enhanced Vegetation Index (EVI) of moderate resolution imaging spectrometer (MODIS) (r = 0.82) was more than NDVI (r = 0.64). The annual curves illustrated the better correspondence between the values of

observed and predicted water use efficiency and evapotranspiration in 8 days temporal resolution (Zhang et al., 2009).

Chang and Sun (2013) have been applied the Adaptive Network based Fuzzy Inference System (ANFIS) for modeling the regional evaporation in Taiwan using EVI and land surface temperature of Landsat image products. The better results were related to the EVI and land surface temperature regard to evapotranspiration estimation, therefore improvement of estimation was linked to EVI (Chang and Sun, 2013).

Helman et al. (2015) estimated the actual evapotranspiration with a model basis on the relation of NDVI, EVI derived from MODIS and annual evapotranspiration at 16 FLUXNET sites with diversity of plant functional. The dominant variance was explained with vegetation indices also the regression (multiple variables) and the Temperature and Greenness model (modified version) with land surface temperature did not improve the correlations. The intra-annual relationships had high mean relative error rather than the interannual relationships (Helman et al., 2015).

Reyes-Gonzalez et al. (2018) estimated the crop evapotranspiration using vegetation index in northern Mexico during four growing seasons. The used index was NDVI. The results shows that Etc maps derived from multispectral vegetation indices are useful tool to find crop water consumption at regional and field scale (Reyes-Gonzalez et al., 2018).

The main objective of research is the evapotranspiration estimates improvement based on using land surface temperature and vegetation indices. Validation of evapotranspiration values related to the weather stations using the traditional method need to the large number of weather data which led to satellite data using in comparison to the other methods.

In this regard, we calibrated (16 data) and tested (8 data) the models which data of them derived from MODIS sensor to estimate evapotranspiration in some synoptic stations of East Azarbaijan Province (Ahar, Tabriz and Mianeh stations). In this regard, fuzzy regression models- symmetric and non symmetric- were used for modeling the relation between evapotranspiration and NDVI, land surface temperature. The improvement of evapotranspiration estimation was related to the vegetation index part which the Soil Adjusted Vegetation Index (SAVI) was applied instead of using NDVI.

MATERIAL AND METHODS
Vegetation index
Many studies indicated that NDVI and land surface temperature space can be representative of soil surface water content and vegetation coverage (Gilabert et al., 2002). Therefore, vegetation indices and land surface temperature are the most important component for evapotranspiration estimation.

The data derived satellite images in the form of vegetation indices can be monitored the variety of vegetation cover (Gilabert et al., 2002). NDVI is an important and applied vegetation index with combination of two spectral bands,

the visible and near-infrared bands of the electromagnetic spectrum in the form of numerical indicator. NDVI can be defined by equation 1.

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}} \tag{1}$$

Where ρ_{nir} and ρ_{red} are the near infrared and red reflectance band.

The range of NDVI is between -1 to 1 which higher value of NDVI is indicative of dense vegetation.

Despite the NDVI advantages for vegetation cover describing, the soil background brightness with separation the NDVI relationships with canopy biophysical properties limited the application of NDVI. In this regard, a soil-adjustment factor, L basis on the proposal of Huete (1988) was presented for description the first-order, non-linear, differential near infrared (Huete 1988) and red radiative transfer through a canopy, and obtained the SAVI with equation 2 (Jiang et al., 2008).

$$SAVI = (1+L)\frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red} + L} \tag{2}$$

Where ρ_{nir} and ρ_{red} are the near infrared and red reflectance band, L is a soil adjustment factor.

One source of error in NDVI calculation was related to the soil background, therefore SAVI have been used to get high accuracy calculation. Minimizing of brightness-related soil effects using SAVI can be conducted with considering the first-order soil vegetation interaction using L. Values for L range from 0 to 1. L varies with vegetation density which is zero for dense and 1 for low vegetation cover. The suggestion about the values of L is o.5 but prior knowledge about vegetation amounts is necessary, otherwise an iterative function would require (Qi et al., 1994). In this regard, the soil line has been used to describing the vegetation indices function. The soil line describes the variation of red and near infrared reflectance bands and for each soil types, the different soil line must be determined (Gilabert et al., 2002). L can be determined using the equation 3 and 4.

$$L = 1 - 2.a.NDVI.WDVI \tag{3}$$
$$WDVI = \rho_{nir} - \gamma\rho_{red} \tag{4}$$

Where ρ_{nir} and ρ_{red} are the near infrared and red reflectance band and L is a soil adjustment factor, a=1.6, γ is the soil line slope (Allen et al., 2010).

Land surface temperature

Two major factors that affected evpotranspiration is land surface temperature and vegetation index. Split window technique is used for land surface temperature estimation which based on differential absorption of two close infrared bands. In this case, the role of atmospheric gases in the absorption can be determined. In order to calculate land surface using brightness

temperature derived from multiple thermal bands, several split window algorithms are accessible. The algorithm of Price (1984) was applied in the study. Accurate performance of Price algorithm rather than to the other algorithms was stated by Vazquez et al. 1997 (Hong et al., 2009).

Fuzzy Regression

The development of the classical regression analysis was related to the suggestion of Asai et al. (1982) as the fuzzy linear regression. Describing the vague relationship of dependent and independent variables was developed using the fuzzy regression (Asai, 1982). In the regression, representation the some elements of the regression models is possible with imprecise data. The linear programming (LP) and the least-squares (LS) are the methods which used for the fuzzy regression coefficients estimation. The total spread of the estimated dependent variables was minimized using the LP methods. The constraint of optimization is related to the estimated dependent variables within a certain confidence level parameter (h). The LP computational complexity is low which led to method usefulness. Their sensitivity to outliers and growing the estimated intervals with more data collection are the thinking points of LP methods. To overcome the shortcoming of the LP methods, multi-objective fuzzy regression techniques were developed. Minimizing the total difference of estimated and observed dependent variables has conducted using the LS methods. The error comparison of LP and LS methods indicated that the LS methods have small error values but the computational complexity of the LS methods is high (Lu and Wang, 2009). The structure of describing the dependency between output and input variables in the fuzzy linear regression are brought in equation 5.

$$\tilde{Y} = \tilde{A}_0 + \tilde{A}_1 x_1 + \ldots + \tilde{A}_n x_n \qquad (5)$$

$$\tilde{A} = (\tilde{A}_0, \tilde{A}_1, \ldots, \tilde{A}_n) \qquad (6)$$

Where $\tilde{Y}$ is the fuzzy output, $x = [x_1, x_2, \ldots, x_{n1}]^T$ is the real valued input vector, $\tilde{A}$ is a set of fuzzy numbers.

Each number coefficient $\tilde{A}_i$ can be expressed as equation 7 in case of triangular membership functions of $\tilde{A}_i s$.

$$\tilde{A}_i = \left\{ a_i^L, a_i^C, a_i^U \right\} \qquad (7)$$

Where a_i^U is the upper limit, a_i^L is the lower limit and a_i^C is the point with the property $\mu_{\tilde{A}_i}(a_i^C) = 1$. The relations of equations 8 and 9 are derived based on the symmetry property of the fuzzy coefficient $\tilde{A}_i$.

$$a_i^C = \frac{a_i^L + a_i^U}{2} \qquad (8)$$

$$a_i^S = a_i^U - a_i^C = a_i^C - a_i^L \qquad (9)$$

Where a_i^C is the center, a_i^S is the spread of $\tilde{A}_i$. Therefore, the parameters for describing the symmetric fuzzy number coefficient $\tilde{A}_i$ can be defined such as a_i^C, a_i^S or a_i^L, a_i^U, as $\tilde{A}_i = \left\{ a_i^C, a_i^S \right\}$ or $\tilde{A}_i = \left\{ a_i^L, a_i^U \right\}$. The vector form of the fuzzy coefficient can be explained in terms of a_i^C and a_i^S as $\tilde{A} = \left\{ a^C, a^S \right\}$ where $a^C = [a_1^C, a_2^C, ..., a_n^C]^T$ and $a^S = [a_1^S, a_2^S, ..., a_n^S]^T$.

Determination the parameter $\tilde{A}_i$ with the fuzzy output set, $\left\{ y_j \right\}$ with a membership value greater than h, is the objective of the fuzzy regression method

$$\mu_{\tilde{Y}}(y_j) \geq h, \quad j = 1, ..., m \qquad (10)$$

The best-fitting model generation is the criteria in h selection.

The selection of confidence level parameter is based on the best-fitting model generation.

Therefore, minimization the spread of fuzzy output of all data was considered for finding the fuzzy coefficients, at the end the cost function was described such as equation 11.

$$Objective \ function \quad a_0^S + \sum_{i=1}^{n} a_i^S \sum_{j=1}^{m} |x_{ij}|$$

$$Subject \ to$$

$$(11)$$

$$a_0^C + \sum_{i=1}^{n} a_i^C x_{ij} - (1-h)\left[a_0^S + \sum_{i=1}^{n} a_i^S x_{ij} \right] \leq y_j$$

$$a_0^C + \sum_{i=1}^{n} a_i^C x_{ij} + (1-h)\left[a_0^S + \sum_{i=1}^{n} a_i^S x_{ij} \right] \geq y_j$$

Where y is a dependent parameter, x is an independent parameter, a_i^C is the center and a_i^S the spread of $\tilde{A}_i$ and h is the confidence level parameter.

If the triangular, is not symmetric, minimally three parameters are need. For example, $\tilde{A}_i$ can be described by the triplets $\left\{ a_i^L, a_i^P, a_i^U \right\}$ or by $\left\{ s_i^L, a_i^P, s_i^R \right\}$ where a_i^P is the point in which $\mu_{\tilde{A}_i}(a_i^P) = 1$, peak point, s_i^L is the left-side spread from the peak point a_i^P and s_i^R represents the right-side spread.

Another representation is also possible, if the spreads are normalized. Since $s_i^L = a_i^P - a_i^L$ and $s_i^R = a_i^U - a_i^P$. If s_i^L is chosen as the base, therefore s_i^R expressed as $s_i^R = k_i s_i^L$ where k_i are the skew factors (positive real number). The cost function in non-symmetric case can be expressed by following equations.

Objective function $\quad (1+k_0)S_0^L + \sum_{i=1}^{n}\left[(1+k_i)S_i^L \sum_{j=1}^{m}|x_{ji}|\right]$

Subject to

$$(1-h)S_0^L + (1-h)\sum_{i=1} S_i^L|x_i| + \sum_i a_i^P x_i + a_0^P \le y_j \qquad (12)$$

$$(1-h)k_0 S_0^L + (1-h)\sum_{i=1} k_i S_i^L|x_i| - \sum_i a_i^P x_i - a_0^P \le -y_i$$

Where y is a dependent parameter, x is an independent parameter, h is the confidence level parameter, a_i^P is the point in which $\mu_{\tilde{A}_i}(a_i^P) = 1$, k is the skew factor, s_i^L is the left-side spread from the peak point a_i^P (Yen et al. 1999).

The sensitivity analysis must be conducted on two parameters of symmetric and non-symmetric membership function of fuzzy regression: confidence level parameter and skew factor.

The main objective of the research is the comparison of fuzzy regression performance using different vegetation indices for evapotranspiration estimation. In this regard, some criteria were used which their mathematical forms are brought in the following equations. The minimum values of criteria are related to the best performance of model.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - S_i)^2} \qquad (13)$$

$$RRMSE = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - S_i)^2}}{\overline{O}} \qquad (14)$$

$$MRE = \frac{\sum_{i=1}^{N}\left|\frac{O_i - S_i}{O_i}\right|}{n} \qquad (15)$$

$$MAE = \frac{\sum_{i=11}^{N}|O_i - S_i|}{n} \qquad (16)$$

Where O_i are observed data, S_i are simulated data, *RMSE* is root mean square error, *RRMSE* is relative root mean square error, *MRE* is mean relative error, and *MAE* is the mean absolute error.
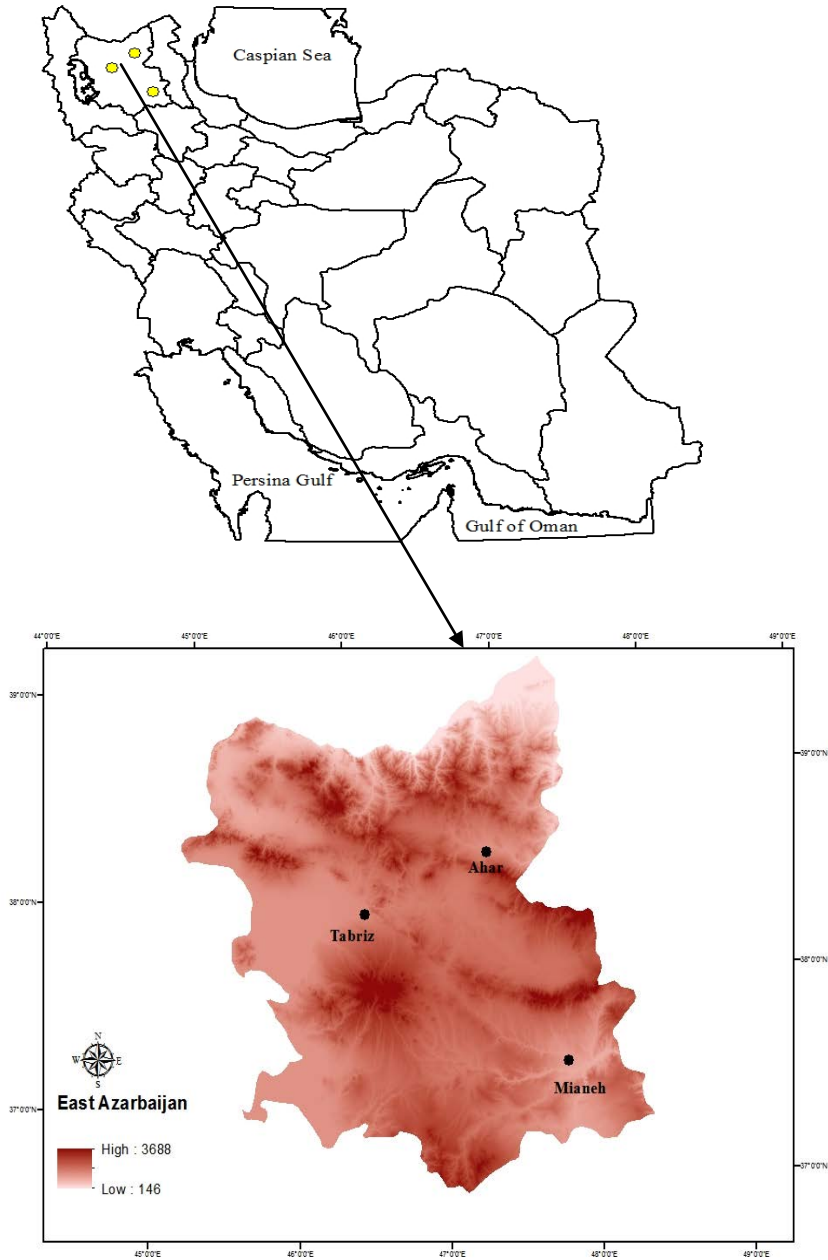

Figure 1: Location of used synoptic stations

Case study

East Azarbaijan Province was the region chosen as the study area. The province covers an area of approximately 47830 km^2 which was in the semi-arid climatic region based on De Martonne climate classification. According to the climate change and the effect of that on the agricultural activities, water requirement and etc., evapotranspiration estimation is the major issue in the Province. In this regard, synoptic stations must be selected for evapotranspiration using the FAO Penman-Monteith method which is proposed by The FAO as the standard method (Raki et al., 2013) . The synoptic stations are Tabriz, Ahar and Mianeh stations with different vegetation cover. NDVI and land surface temperature are derived from MODIS data because of the sensor's moderate spectral spatial resolution. Figure 1 shows the location of synoptic stations in the East Azarbaijan Province.

RESULTS AND DISCUSSION

Evapotranspiration is affected by vegetation indices and land surface temperature. In this study, improvement the evapotranspiration estimates was related to the vegetation indices. Due to the high efficiency of FAO Penman-Monteith method, it was used for evapotranspiration calculation. This method has been chosen as the standard method for estimating evapotranspiration (Serban et al., 2010). The images were sampled every 10 days in each month, June and July, 2007- 2014 which 16 and 8 data are presented the calibration and validation periods, respectively. The climatological parameters which are used for evapotranspiration estimates using FAO Penman-Monteith were: mean air temperature, maximum air temperature, minimum temperature, wind speed at 2 m above the ground, relative humidity.

Table 1. Variation of confidence level, center and spread.

Confidence level parameter	Tabriz-July		Ahar-July	
	spread	Center	spread	Center
0.1	1.51	3.94	0.036	4.49
0.2	1.7	3.94	0.04	4.49
0.3	1.94	3.94	0.046	4.49
0.4	2.26	3.94	0.054	4.49
0.5	2.72	3.94	0.065	4.49
0.6	3.4	3.94	0.081	4.49
0.7	4.53	3.94	0.1	4.49
0.8	6.8	3.94	0.16	4.49
0.9	13.6	3.94	0.32	4.49

The fuzzy linear regression is an alternative modeling tool which is employed instead of classical regression for evapotranspiration modeling using NDVI and land surface temperature. Independent variables of fuzzy regression which are NDVI and land surface temperature derived from satellite images.

Coefficient estimation of fuzzy regression model is the first step in the modeling process. The variation of confidence level, center and spread of fuzzy number are brought in Table 1. The variation of confidence level had no effect on the center of fuzzy number but the increasing the confidence level parameter led to increasing spread of fuzzy number. Yen et al. (1999) indicated the spread increasing of fuzzy number coefficient with increasing the confidence level parameter.

The results indicated the negligible variation of fuzzy regression performance against the confidence level parameter. Therefore in the non symmetric fuzzy regression, the sensitivity analysis must be taken on the skew factor. The results of skew factor sensitivity analysis are listed in Table 2.

Table 2. Skew factor sensitivity analysis.

K_0	K_1	K_2	RMSE
1.1	1.25	1.4	5.2
1.4	1.6	1.9	5.73
1.9	2.3	2.6	6.1
2.7	2.9	3.2	6.47
1	1	1	5.15
1.25	1	1	5.47
1.4	1	1	5.73
1.9	1	1	6.1
2.6	1	1	6.46

According to table 2, $K_0 = K_1 = K_2 = 1$ has the minimum error, therefore the selected skew factor are applied for the next modeling process. The variation of skew factor versus spread peak point variation in non symmetric fuzzy regression is listed in Table 3.

Table 3. Skew factor variation versus spread peak point variation-July.

K_0	Tabriz		Mianeh	
	spread	center	spread	center
1	2.39	3.6	2.97	7.51
1.1	2.28	3.66	2.82	7.58
1.25	2.13	3.73	2.64	7.68
1.4	1.99	3.73	2.47	7.76
1.9	1.65	3.8	2.04	7.97
2.6	1.33	3.97	1.65	8.17
2.7	1.29	4.15	1.6	8.19

The left-side spread decreases with the increase of skew factor and the peak point is increased. In the research of Yen et al. (1999), the increasing of skew factor in the case of non-symmetric membership functions led to decreasing of the spread S_0^L and increasing of the center, a_0^P. The variation of skew factor and coefficient of fuzzy regression are presented in Table 4.

Table 4. Variation of skew factor and coefficient of fuzzy regression.

Skew factor			Mianeh-June			Ahar-July		
K_0	K_1	K_2	C_0	C_1	C_2	C_0	C_1	C_2
1.1	1.25	1.4	5.69	1.37	0.007	3.94	4.79	0.015
1.4	1.6	1.9	5.8	1.37	0.007	4.1	4.79	0.015
1.9	2.3	2.6	5.92	1.37	0.007	4.3	4.79	0.015
2.7	2.9	3.2	6	1.37	0.007	4.5	4.79	0.015
1	1	1	5.65	1.37	0.007	3.88	4.79	0.015
1.25	1	1	5.75	1.37	0.007	4.03	4.79	0.015
1.4	1	1	5.8	1.37	0.007	4.1	4.79	0.015
1.9	1	1	5.92	1.37	0.007	4.3	4.79	0.015
2.6	1	1	6.04	1.37	0.007	4.48	4.79	0.015

The peak point of constant parameter changes with the skew factor variations but skew factor variations cannot change the peak point of other coefficients. The model performance for evaporation estimation using NDVI and land surface temperature is listed in Table 5.

Table 5. Performance of fuzzy regression in regard to evapotraspiration estimation.

Station	Month	RMSE		RRMSE		MAE		MRE	
		Symmetric	Non symmetric	Symmetric	Non symmetric	Symmetric	Non symmetric	Symmetric	Non symmetric
Tabriz	June	0.86	0.88	0.13	0.14	0.61	0.63	0.11	0.11
	July	0.68	0.65	0.093	0.089	0.52	0.52	0.074	0.074
Mianeh	June	0.82	0.87	0.12	0.12	0.63	0.65	0.09	0.092
	July	0.54	0.54	0.093	0.094	0.45	0.45	0.084	0.084
Ahar	June	1.21	1.11	0.23	0.21	1.05	0.87	0.23	0.2
	July	0.94	0.78	0.13	0.1	0.76	0.67	0.11	0.099

Based on Table 5, there is not major difference between symmetric and non symmetric fuzzy regression but in general, the decreasing of error in non symmetric case is more than symmetric (Parviz and Paymai, 2017), for example the error decreasing of Ahar from symmetric to non symmetric case are: RMSE of July=17%, RRMSE of June= 8.69%, MAE of June= 27.61%, and MRE of June=13%. In the research of Shayannejad et al. (2008) for daily potential evapotranspiration estimation, fuzzy regression had minimum error in comparison to the used methods such as Penman-Monteith, ANN.

The representation of green vegetation cover is basis on high and low reflectance of near infrared and red reflectance, respectively. The difference between values of reflectance in each band can be illustrated with the scatterplot of image cell values using near infer red and red brightness.

In our study, the improvement of evapotranspiration estimates is focused on the vegetation indices which SAVI were used in this case. Therefore, fuzzy regression performance was evaluated in June in all stations. L is one of the most important parameters to determine SAVI which soil line is used in this regard.

For L calculation process, the shape of soil line must be calculated which Figure 2 shows the scatter plot of near infrared and red reflectance.
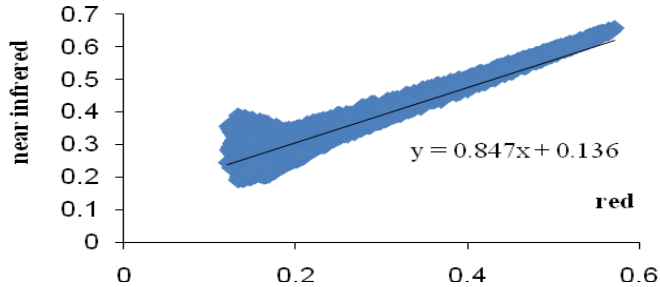

Figure 2: Scatterplot of near infrared versus red reflectance.

The range of L is zero to 1 for dense and low vegetation cover, respectively. The variation of NDVI and L in the studied stations and some days are shown in Fig. 3. For 2007-159, the maximum and minimum of NDVI happened in Ahar and Tabriz stations, respectively. In this regard, the minimum and maximum of L happened in Ahar and Tabriz stations. Therefore, the maximum case of NDVI is related to the minimum case of L. This trend is preserved in the other days such as 200-158, 2009-155 and 2014-158. At the end, Figure 3 satisfied the variation of L against the vegetation cover, because NDVI is related to the vegetation cover.
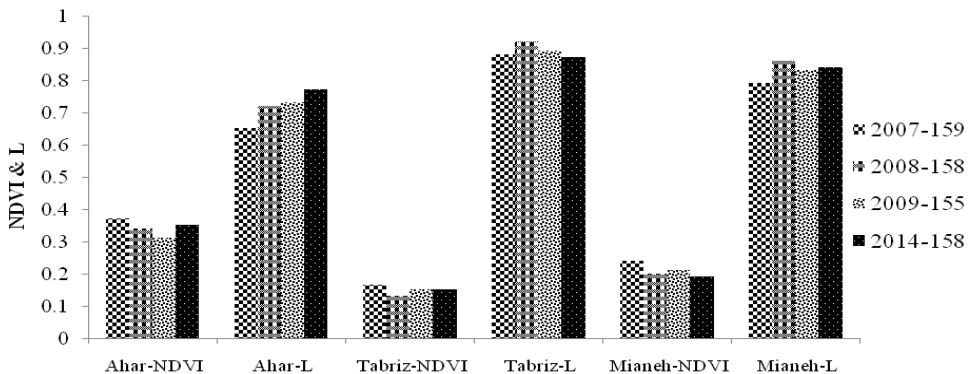

Figure 3: Diurnal variation of NDVI and L in some stations.

Comparison between observed and estimated evpotranspiration (using SAVI) in three stations showed the 7.85% and 5.51% underestimation in Mianeh and Ahar stations and 6.53% overestimation in Tabriz station.

The evpotranspiration estimates using SAVI and NDVI are compared and the results of comparison are shown in Figure 4.
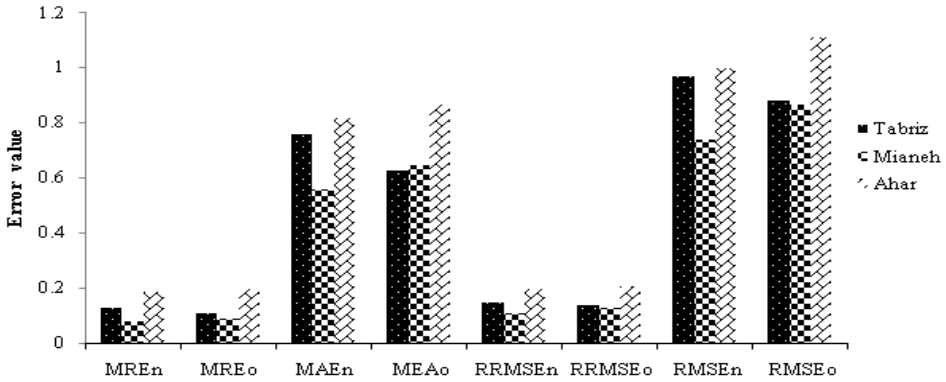
Figure 4: Comparison of fuzzy regression performance in two cases: NDVI(o), SAVI (n).

The values of error are decreased in case of using SAVI for evapotranspiration estimation in Ahar and Mianeh stations but any improvement were not observed in evapotarspiration estimation of Tabriz. The value of RMSE decreasing is 14.29% and 9.9% in case of Mianeh and Ahar, respectively. The value of MRE decreasing is 13.84% and 5.74% in case of Mianeh and Ahar, respectively. The evapotranspiration improvement was observed in case of using other indices instead of NDVI such Zhang et al. (2009), Chang and Sun (2013) and Helman et al. (2015) which their comparison was related to NDVI and EVI indices.

The amount of error decreasing in Mianeh is higher than Ahar station. The reason of that may be related to the vegetation cover. The average NDVI of Ahar and Mianeh stations are 0.32 and 0.18. Therefore, the region with minimum NDVI corrected better than maximum NDVI and this matter shows the impact of vegetation index improvement for evapotranspiration estimates. The variation of L and estimated evapotranspiration are compared in Figure 5.
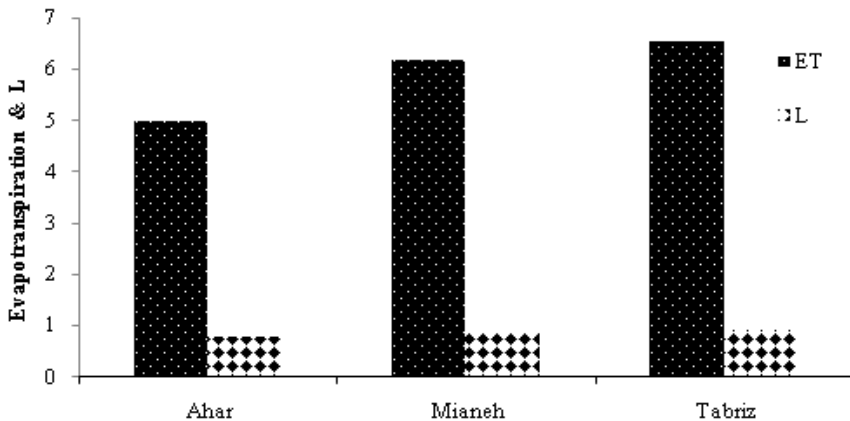

Figure 5: Variation of L and estimated evapotrasnpiration.

Results showed that increasing of L causes increasing of estimated evapotranspiration which are consisting of other results (Hassanpour et al., 2011). The spatial variation of indices showed the importance of spatial distribution studies (Moradi et al., 2015; Milos and Bensa, 2014).

The reason of error decreasing and increasing in the studied stations can be related to the vegetation cover. The main vegetation cover in Maineh and Ahar stations are rain fed areas and irrigated farming lands as agriculture and garden, whereas most parts of Tabriz station is related to urban areas. According to the vegetation cover of stations, it can be said that in the areas with low vegetation in Maineh and Ahar station, using SAVI led to correction the spectral bands, but in the Tabriz station, SAVI has not better results and several advanced vegetating indices which are from SAVI family such as Transformed Soil Adjusted Index (TSAVI) must be used.

CONCLUSIONS

Accurate evapotranspiration is one of the major issues in the many fields such as water resources and land management, land surface and vegetation processes, and agricultural activities. The aim of this study is the component of evapotranspiration improvement with emphasis on vegetation index. Using SAVI index in most stations had minimum error because of reducing the impact of background soil surface. The vegetation cover is important factor in the evapotranspiration improvement determination. This shows that if land use map is not available in areas with low vegetation, L parameter would be important. Therefore, for evapotranspiration improvement, the precise and accurate vegetation index must be developed with emphasis on the correction of spectral and thermal bands. The land surface temperature, vegetation index and evapotranspiration modeling conducted with linear fuzzy regression which the efficiency of fuzzy regression was proved in many studies for modeling. The decreasing of error in non symmetric case is more than symmetric. The coefficient determination of fuzzy regression and skew factor are affected the evapotranspiration estimation. The evapotranspiration improvement is affected by type of modeling and the determination the precise components of modeling. Therefore, the suggestion of the research can be divided in two parts: 1- using the other improved satellite indices in order to model the behavior of spectral data 2- improving the regression methods such as using the support vector regression.

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