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**Research and Full Length Article:**

## **Soil Moisture Estimation in Rangelands Using Remote Sensing (Case Study: Malayer, West of Iran)**

Hamid Nouri<sup>\*A</sup>, Muhammad Faramarzi<sup>B</sup>

<sup>A</sup>Assistant professor in climatology, Malayer University, Malayer, Iran, (Corresponding author) Email: hamidwatershed@yahoo.com

<sup>B</sup>M.Sc in Remote Sensing, University of Mohaghegh Ardebili, Ardebil, Iran

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**Abstract.** Soil moisture is generally regarded as the limiting factors in rangeland production. Although many studies have been conducted to estimate soil moisture in semiarid areas, there is little information on mountainous rangelands in west of Iran. The present study aims to investigate the soil moisture estimation in rangelands as compared to the other land uses over a mountainous area in central Zagros, Iran using remote sensing. The Surface Energy Balance Algorithm for Land was used to compute actual evapotranspiration (ET) and soil moisture by the means of Landsat8 images of March, April, May, June, July, August and September 2013 for diverse land uses in Malayer, Iran. SEBAL algorithm estimates the ET using net radiation flux, soil heat flux and sensible heat flux. The results showed that there was no significant difference between daily ET computed by SEBAL method and Penn man Monteith. Mean Bias Error (MBE) and Root Mean Square Error (RMSE) for daily and hourly ET were 0.15 and 0.39, respectively. The spatial regression was used to detect the relationship between soil moisture index (SMI) and Temperature dryness vegetation index (TDVI) as dependent variables and daily evapotranspiration (ET24) as independent variable. The results revealed that the correlation between SMI and ET24 was positively significant (0.78 to 0.49) and between TDVI and ET24 was negatively significant (-0.74 to -0.46) during the period of rangeland vegetation growth in this area (March to June). SMI in rangelands had the strongest correlation as compared to the other land uses. Thus, SEBAL model is a robust tool to calculate the soil moisture in rangelands by the means of remote sensing.

**Key words:** Soil moisture, SEBAL Algorithm, Rangeland, Land sat 8, Malayer

## Introduction

Soil moisture dynamics are the central components of the hydrological cycle (Legates *et al.*, 2011) and are mainly determined by the processes including infiltration, percolation, evaporation and root water uptake. Evapotranspiration (ET) is one of the most effective components of a catchment water balance in the arid and semiarid regions of the world. It is important to estimate ET and Soil Moisture Index (SMI) for water resources evaluation and irrigation monitoring. Actual evapotranspiration (ETa) is a key indicator in natural resources and agriculture management in diverse land use classes. Unfortunately, ET estimation under actual field conditions is still a very challenging task for scientists and water managers. The methods for estimating ET can generally be categorized into four groups including the water balance, Lysimeters, energy balance and empirical methods (Majnooni-Heris *et al.*, 2012). Most of these methods can only provide point estimates of ET which are not sufficient for system-level water management. Physically distributed hydrological models can compute ET values but require a lot of field data which are often unavailable in many basins in the world (Matinfar, 2012). ETa can be estimated from satellite remote sensing (Engman and Gurney, 1991; Kustas and Norman, 1996; Bastiaanssen *et al.*, 1998, 2002; Kustas *et al.*, 2003). Such methods provide a powerful tool to compute ETa from an individual pixel to an entire raster image. Emerging developments in the field of remote sensing make it possible to overcome information limitations on soil water status, the actual evaporative depletion and estimation of net groundwater use for agriculture (Scott *et al.*, 2003; Ahmad *et al.*, 2005). As surface energy balances and crop water stress are directly linked to agricultural water use, ETa variations in space and time are thought to be highly indicative

for the adequacy and reliability of irrigation as well as the equity in water use. A number of studies have been made to estimate soil parameters using remote sensing to simulate soil moisture (Ragab, 1995; Walker *et al.*, 2001a and b). Ariapour and Nassaji Zavareh (2011) studied the estimation of daily evaporation using artificial neural networks in Broujerd, Iran. Their results showed the suitable capability and acceptable accuracy of artificial neural networks in estimating daily evaporation. Barkhordari and Semsar Yazdi (2015) studied the monthly water balance in an arid region using TM model and GIS in Pishkouh Watershed, Iran. They revealed that remote sensing and GIS are very helpful in finding out the periods of moisture deficit and moisture surplus for an entire basin. This study indicates that there is an annual deficit of 442.7 mm in the studied basin and an annual surplus of 26.4 mm. Several studies optimized soil parameters using soil moisture and soil temperature information (Enthekabi *et al.*, 1994; Gupta *et al.*, 1999; Hogue *et al.*, 2005; Liu *et al.*, 2005). Feddes *et al.* (1993a, b) used ET and surface soil moisture to derive effective soil hydraulic parameters of the root zone in a hypothetical watershed. Jhorar *et al.* (2002) also used ET to inversely identify the effective soil hydraulic parameters in a hypothetical soil profile. Ines and Mohanty (2008) used near-surface soil moisture from field measurements for quantifying the effective soil hydraulic parameters of the root zone. A number of studies had been made to estimate soil parameters using remote sensing to simulate soil moisture (Ragab, 1995; Walker *et al.*, 2001a, b). Several studies optimized soil parameters using soil moisture and soil temperature information (Enthekabi *et al.*, 1994; Gupta *et al.*, 1999; Hogue *et al.*, 2005; Liu *et al.*, 2005). Feddes *et al.* (1993a, 1993b) used ET and SMI to derive the effective soil hydraulic parameters of the

root zone in a hypothetical watershed. Ines and Mohanty (2008) used near-surface soil moisture from field measurements for quantifying the effective soil hydraulic parameters of the root zone.

Infiltration, runoff and sedimentation in rangeland are not similar to forest or other land uses and ecosystem hydrology. Thus, accuracy of hydrologic computations in rangelands is not like the other land uses probably. This study demonstrates the application of satellite remote sensing for soil moisture estimation in rangelands and other land uses of Malayer, Iran. The main purpose of this study was to compare the accuracy of soil moisture estimation of rangelands and diverse land uses using SEBAL computed by of the FAO Penman-

Monteith in comparison with Land sat 8 images in Malayer.

## Material and Methods

### Site information

Malayer area is 3208 km<sup>2</sup> including 16.9% of total Hamadan province area. Elevation ranged between 1617 to 3345 m indicating that the region is Mountainous area. Digital elevation model of the area is shown in Fig. 1. The mean annual precipitation ranges between 250 to 327 mm based on elevation gradient and extracted precipitation from all of the city stations and neighborhood stations (Nahavand, Toiserkan, Hamedan Airport, Nouzhe, Arak, Kangavar and Boroujerd) in a 17 year period (1995 to 2012). The average of 24 hourly potential ET was 7.58 mm in Malayer station.

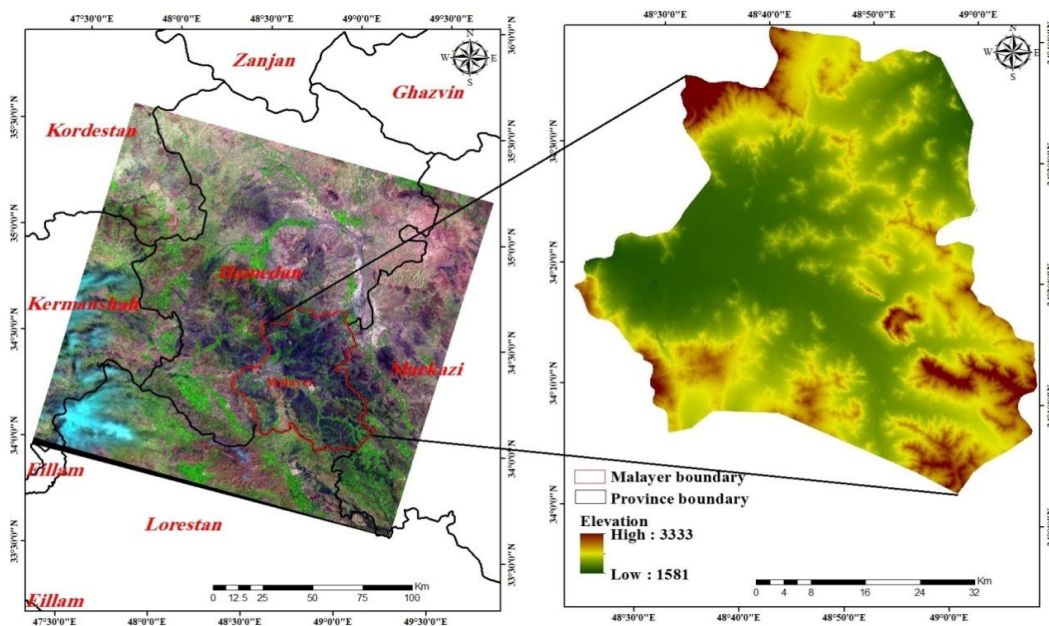


Fig. 1. Geographic Location of Malayer, Iran

### Image properties

New free Landsat8 images (OLI sensor) are one of the new features which have been selected for considering factors including temporal conditions, desirable quality and the lack of cloud cover spots. Although the selected images were Level-II and they did not need any geometric corrections, they were controlled with 80 Ground Control Points

(GCP) of GPS before using the images. Images did not need any atmospheric corrections according to record image time that was without any atmospheric turbulence and because of one-temporal interpretation (Song *et al.*, 2001). Table 1 presents the used image properties in different dates (seven months) in Malayer.

**Table1.** Image properties used to study soil moisture in Malayer

Band	Resolution (m)	Date	Sensor	Image
11	30	Mar to Sep 2013	OLI, TIRS	Landsat8

### SEBAL Algorithm

Meteorological data including maximum and minimum temperature, relative humidity, sunshine and wind speeds were extracted from Malayer synoptic station (Iran Meteorological Organization). Zonal statistic method (Fotheringham *et al.*, 2002) was used to investigate the relationship between the amount of actual ET and land use in Malayer. In present research, the SEBAL was used to compute ETa from satellite imagery having visible, near infrared and thermal infrared bands (Bastiaanssen *et al.*, 1998; Bastiaanssen, 2000). SEBAL computes a complete radiation and energy balance along with the resistances for momentum, heat and water vapour transport for each pixel. SEBAL is a well-tested and widely used method to compute ETa (Bastiaanssen *et al.*, 1998, 2002; Farah, 2001; Tasumi *et al.*, 2003). ETa from remote sensing was estimated from LANDSAT images using SEBAL (Bastiaanssen *et al.*, 1998). Various applications have demonstrated the ability of SEBAL to accurately estimate daily ET. The SEBAL is an image-processing model comprised of 25 computational steps that calculate the actual (ETa) and potential evapotranspiration rates (ETp) as well as other energy exchanges between land and atmosphere. SEBAL requires visible, near-infrared and thermal infrared satellite imageries together with routine weather data to estimate the sensible heat

flux (Mutiga *et al.*, 2010). SEBAL computes a complete radiation and energy balance along with the resistances for momentum, heat and water vapor transport for every individual pixel. The resistances are a function of state conditions such as soil water potential (and thus soil moisture), wind speed, air temperature and changes from day to day. Satellite radiances will be converted first into land surface characteristics such as surface albedo, leaf area index, vegetation index and surface temperature. These land surface characteristics can be derived from different types of satellites. First, an instantaneous ET was computed, and subsequently scaled up to 24 hours and longer periods. The primary basis for the SEBAL model is the surface energy. The instantaneous ETa flux is calculated for each cell of the remote sensing image as a 'residual' of the surface energy budget (Equation 1):

$$ET = R_n - G - H \quad (1)$$

Where:

ET = the latent heat flux ( $W/m^2$ ),

$R_n$  = the net radiation flux at the surface ( $W/m^2$ ),

G = the soil heat flux ( $W/m^2$ ),

H = the sensible heat flux to the air ( $W/m^2$ ).

Soil heat flux ( $G_o$ ): After calculating the net radiation, the empirical equation developed by (Bastiaanssen *et al.* 2002) was applied to calculate the soil heat flux ( $G_o$ ):

$$\frac{G}{R_n} = \frac{T_s}{\alpha} (0.0038\alpha + 0.0074\alpha^2)(1 - 0.98NDVI^4) \quad (2)$$

Where:

$T_s$  = the surface temperature ( $^{\circ}C$ ),

$\alpha$  = the surface albedo

NDVI = the Normalized Difference Vegetation Index.

Sensible heat flux: The sensible heat flux is estimated using the bulk aerodynamic resistance model and a procedure that assumes a linear relationship between  $T_s$  calculated at "hot" and "cold" pixels (extreme pixels) and air temperature

difference ( $dT$ ). The cold and hot pixels are selected from a well-irrigated crop surface and bare agricultural field, respectively. Sensible heat flux is assumed to be zero for the cold pixels and equals to “ $Rn - G_o$ ” for hot pixels. Then,  $H$  for each pixel was calculated from:

$$H = \frac{\rho \cdot C_p \cdot dT}{r_{ah}} \quad (3)$$

Where:

$\rho_a$  = the air density ( $\text{kg/m}^3$ )  
 $C_p$  = the air-specific heat ( $1004 \text{ J/kg/K}$ )  
 $dT$  (K) = the temperature difference,  
 $r_{ah}$  = the aerodynamic resistance to heat transport (s/m) (Tasumi et al, 2003).

According to Sandholt *et al.* (2002), temperature dryness vegetation index (TDVI) was used to retrieve surface soil moisture from Land sat data.

$$TDVI = \frac{T_s - T_s(\min)}{T_s(\max) - T_s(\min)} = 1 - \frac{W - W(\min)}{W(\max) - W(\min)} \quad (4)$$

Where:

TDVI=temperature dryness vegetation index

$T_s$  =the observed surface temperature at a given pixel.

$T_s(\max)$  = temperature of the dry edge (the upper straight line in the triangle).

$T_s(\min)$  = the temperature of the wet edge (lower horizontal line of the triangle).

This index could be easily derived with the satellite information using bands 3 and 4 in the case of ETM+ (Land sat). NDVI varies between -1 and 1 (Sandholt *et al.*, 2002).

A simplified representation of TVDI is presented in Fig. 2. The linear combination of NDVI-LST normally shows a strong negative relationship and could form a triangle shape if the study area is large enough to provide a wide range of NDVI and LST conditions (Gillies *et al.*, 1997).

The dry and wet edges were calculated from the NDVI-LST space regression with small intervals of NDVI. ( $T_s - F_v$ )

indicator shows maximum temperature and vegetation cover under the stress. ( $T_{sw} - T_{vw}$ ) reveals minimum temperature and vegetation cover under the saturated water (Fig.2).

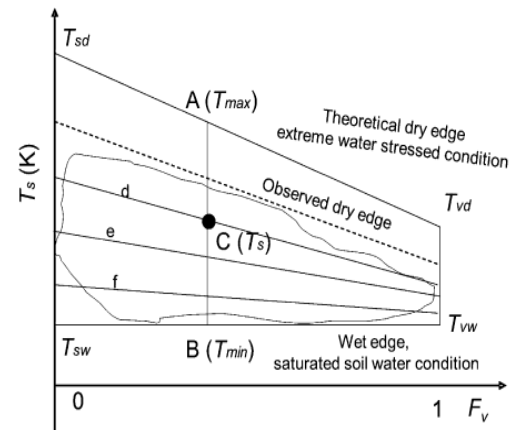


Fig. 2. Relationship between of ( $T_s$ ) and ( $T_v$ )

For the soil moisture index (SMI), the following method was used (Mutiga *et al.*, 2010)

$$SMI = \frac{T_s(\max) - T_s}{T_s(\max) - T_s(\min)} \quad (5)$$

Where:

$T_s(\max) = a_1 \cdot NDVI + b_1$

$T_s(\min) = a_2 \cdot NDVI + b_2$

SMI= soil moisture index

The coefficients of (a) and (b) were computed from the relationships between  $T_s(\min)$  and NDVI,  $T_s(\max)$  and NDVI (Fig.3).

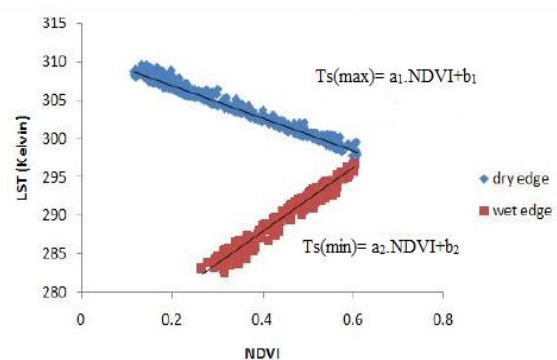


Fig. 3. Relationship between  $T_s(\min)$  and NDVI,  $T_s(\max)$  and NDVI

### Statistical analyses

The testing process involved generating the estimated values from the proposed model. The estimated values were

compared with actual values through error analysis. Two statistical parameters, namely Mean Bias Error (MBE) and Root Mean Square Error (RMSE) were used in evaluating the performance of the models. Hourly and 24 hour values of ET obtained via FAO-Penman-Monteith method using hourly data of Malayer meteorological station were used to validate SEBAL model. The values of RMSE and MBE present the amount of model error (Dashtaki *et al.*, 2010; Mutiga *et al.*, 2010).

Spatial regression analysis was used to detect the relationship between SMI and TDVI as dependent variables and daily

evapotranspiration (ET24) as independent variable. Correlations between SMI and ET24 and between TDVI and ET24 during 7 months in different land uses were also estimated.

### Results and Discussion

The NDVI, Ts and ET24 maps were drawn (Fig.4). The results show that there were indirect relationships between NDVI and Ts and indirect relationships between NDVI and ET24 maps. Thus, SEBAL algorithm displays the relationships of The NDVI, Ts and ET24 maps.

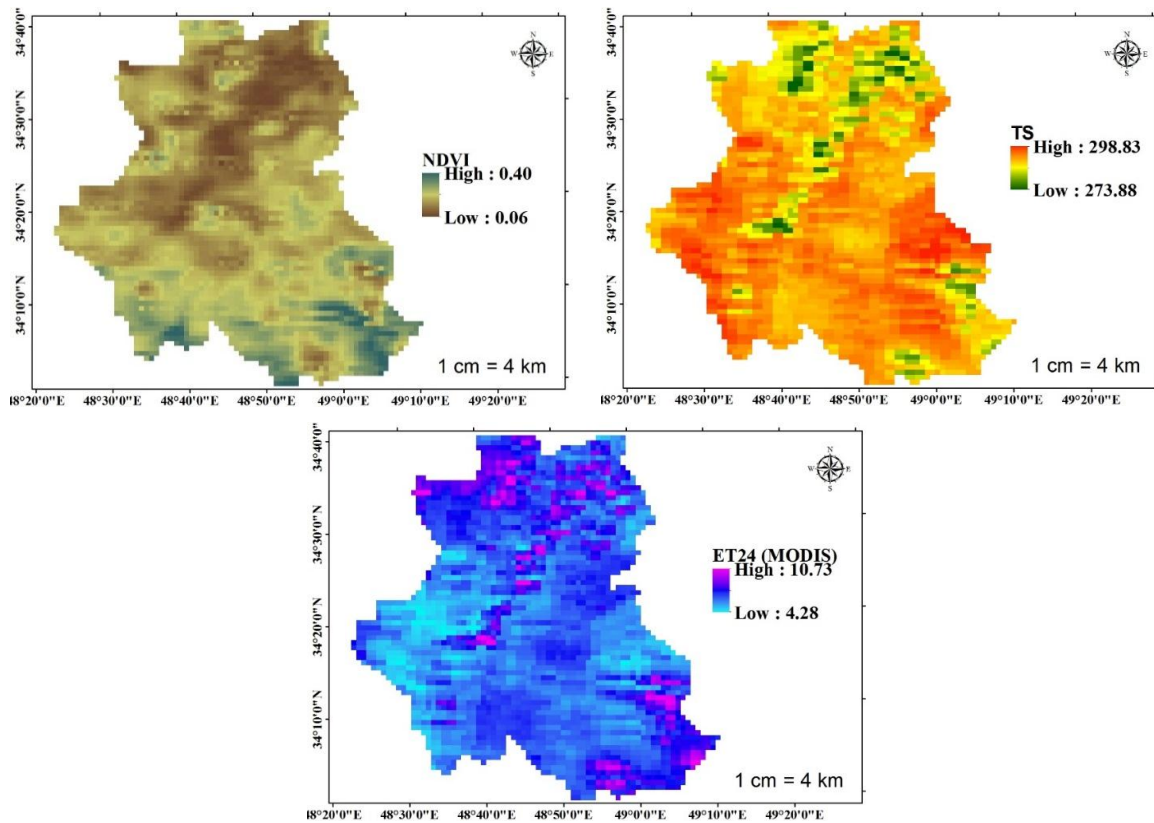


Fig. 4. The NDVI, Ts and ET24 maps in Malayer

The reference evapotranspiration (Etr) and ET\_SEBAL were computed as 6.86 and 6.89 mm per hour, respectively. The results showed that the estimated daily average of ET was 0.43. There was no difference between FAO Penman-Monteith method and SEBAL; therefore, the accuracy of SEBAL algorithm can be acceptable. The land use map was

provided by the object oriented approach with 88% accuracy coefficient.

Error matrix of land use classification is shown in Table 2. The most widely promoted classification accuracy is in the form of error matrix which can be used to derive a series of descriptive and analytical statistics. The highest error has been observed in the irrigated farming. The total error value in rangeland is 458.

Overall accuracy, producer accuracy, user accuracy and Kappa statistics are generally reported and these terms have

been explained in detail in many studies. Total accuracy of land uses was 0.88 and kappa coefficient is 0.85.

**Table 2.** Error matrix of land use classification

Land uses	water	Saline lands	Residential areas	Dryland farming	Rangeland	Mountainous areas	Irrigated farming	Total	Precision producer	Precession of user
Water	40	0	0	0	0	0	0	40	1	1
Saline lands	0	184	3	0	1	0	3	191	0.92	0.96
Residential areas	0.5	2	453	5	9	0	6	476	0.94	0.95
Dry land farming	0.5	1	4	548	23	0	12	588	0.93	0.93
Rangeland	1.5	5	8	31	421	0	73	540	0.91	0.77
Mountainous area	1	0	31	12	42	500	6	593	0.85	0.83
Irrigated farming	1.5	6	5	2	4	0	986	1005	0.91	0.91
Total	45	198	473	586	458	500	1080	2840		

ETr statistic amounts in different land uses are described in Table 3. The minimum and maximum amounts of ETr are the irrigated farming and residential.

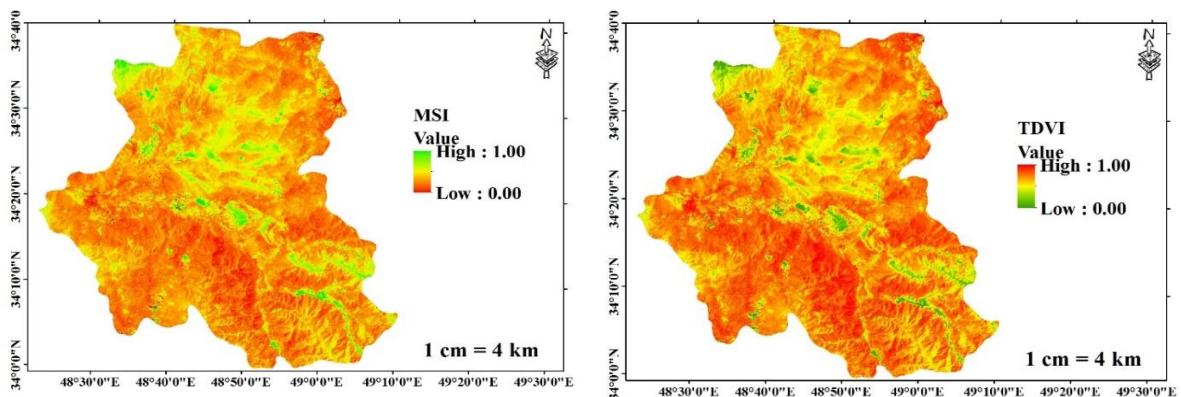
The largest standard deviation of ETr is rangeland and the lowest STD is water bodies.

**Table 3.** ETr statistics amounts in different land uses

Land uses	Reference Evapotranspiration (ETr) (mm/day)			
	MIN	MAX	MEAN	STD
Residential areas	5.00	7.42	6.79	0.44
Irrigated farming	4.28	10.60	6.72	0.92
Mountainous areas	4.99	10.60	6.81	0.94
Water bodies	7.44	8.50	7.45	0.005
Dry land farming	4.99	10.60	6.80	0.92
Saline areas	4.86	10.48	6.34	0.93
Rangelands	4.72	10.3	6.75	0.97

SMI and TDVI average maps calculated in Malayer have been shown in Fig. 5. SMI map is against TDVI map. Wherever pixel value of SMI is low, pixel value of

TDVI is high and vice versa. TDVI and SMI maps have some values against the values of humidity. SMI and TDVI values are between 0 and 1.



**Fig. 5.** MSI (left) and TDVI (right) average maps calculated in Malayer.

Relationships between TDVI and ET24 and also SMI and ET24 in Malayer have been indicated in Fig. 6. Correlation

between TDVI and ET24 (left map in Fig 6) is negative for different land uses and between SMI and ET24 (right map in Fig

6), it is positive for different land uses. Thus, TDVI and SMI can be calculated through these equations and ET<sub>24</sub>

variable in different land uses, especially rangelands.

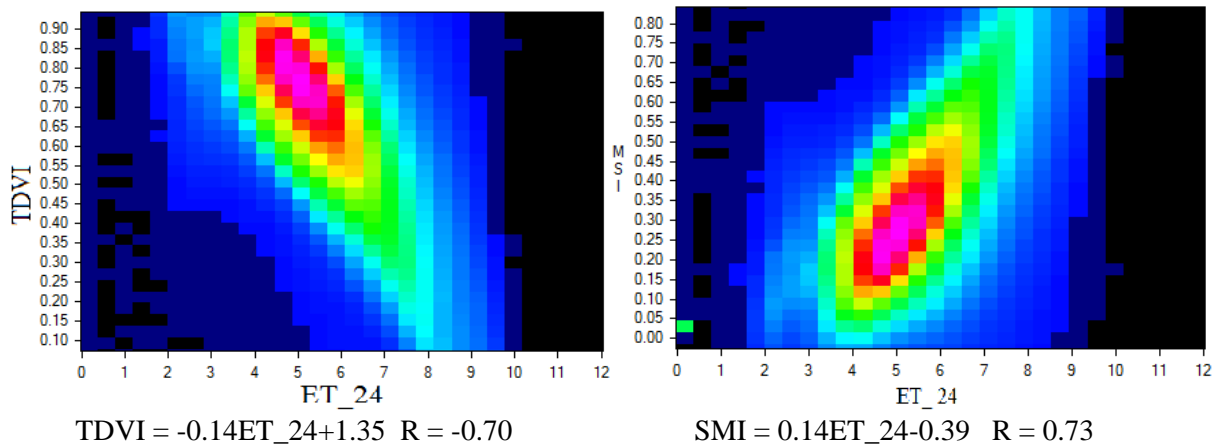


Fig. 6. Relationships between TDVI and ET<sub>24</sub> (left) and SMI and ET<sub>24</sub> (right) in Malayer.

Spatial regression analysis was used to detect the relationship between SMI and TDVI as dependent variables and daily evapotranspiration (ET<sub>24</sub>) as independent variable. Correlations between SMI and ET<sub>24</sub> and between TDVI and ET<sub>24</sub> during 7 months in different land uses have been shown in Table 4. The results revealed that SMI and ET<sub>24</sub> had a positive correlation ranged from 0.78 to 0.14 for rangelands and from 0.67 to 0.23 for the

other land uses. Soil Moisture indicators (SMI) in rangelands had a bit higher correlation than the other land uses from March to June. The results revealed that TDVI and ET<sub>24</sub> had a negative correlation ranged from -0.74 to -0.70 for rangelands and from -0.66 to -0.27 for the other land uses. MSI in rangelands had a bit higher correlation than the other land uses from March to June.

Table 4. Correlations between SMI and Daily evapotranspiration (ET<sub>24</sub>), TDVI and daily evapotranspiration during 7 months in different land uses

Date	Rangeland		Other land uses	
	ET <sub>24</sub> vs. TDVI	ET <sub>24</sub> vs. SMI	ET <sub>24</sub> vs. TDVI	ET <sub>24</sub> vs. SMI
March	-0.74 *	0.78 *	-0.66 *	0.67 *
April	-0.71*	0.75*	-0.69 *	0.68 *
May	-0.62 *	0.64 *	-0.60 *	0.60*
June	-0.46	0.49	-0.54	0.52
July	-0.36	0.41	-0.46	0.45
August	-0.21	0.30	-0.32	0.35
September	-0.70	0.14	-0.27	0.23

\*=correlation between two parameters is significant at 0.05 probability level.

According to the obtained results in the area, soil moisture could clearly detect using landsat8 and SEBAL algorithm. Soil moisture indicator estimation in rangeland is better than the other land uses in Malayer. The estimation of these indicators was emphasized by many researchers in different climatic conditions (Enthekabi *et al.*, 1994; Gupta

*et al.*, 1999; Hogue *et al.*, 2005; Liu *et al.*, 2005). Different relationships were caused by diverse species and soil in the region. So, the ecologic conditions of vegetation cover and species affect soil moisture values. This result is in accordance with other researches in connection with the effect of different species and phenology times on



temperature, ET and water budget in different land uses (Mutiga *et al.*, 2010; Kustas *et al.*, 2003). During this investigation, changes in soil moisture estimation in the land uses were due to several reasons including irrigation, ET, temperature, sensible and latent heat, soil type, soil texture, vegetation cover and different species (Bastiaanssen *et al.*, 1998, 2002; Kustas *et al.*, 2003). In spite of that, most of researches in this respect do not put emphasis on rangeland rather than other land uses and vegetation forms, but in the area, rangeland had more effects on soil moisture and water budget in comparison with the other plant forms and land uses; this result is confirmed by some researchers (Fotheringham *et al.*, 2002; Scott *et al.*, 2003; Ahmad *et al.*, 2005).

### Conclusions

Soil moisture is a key factor in semiarid catchment water balance. It is important to achieve information on mountainous rangelands where vegetation growth is very dependent on the moisture availability. The present study aims to investigate the soil humidity indices in rangelands in comparison with the other land uses over a mountainous area in central Zagros using remote sensing. In this study, the SEBAL was used to compute the actual ET and soil moisture by the means of Landsat8 images of March to October 2013 for diverse land uses in Malayer, Iran. The SEBAL method developed by Bastiaanssen *et al.* (1998) is a direct application of the residual method, combining an empirical and physical parameterization. The input data include local meteorological data (mainly wind velocity), and remote sensing data (radiance and LST). From these data, the net radiation ( $R_n$ ), NDVI, albedo ( $\alpha$ ), roughness height ( $z_0$ ) and soil heat flux ( $G$ ) were estimated. The sensible heat flux is estimated by contrasting two sites (one site of wet soil or with vegetation without water stress,

and another site of dry soil).  $ET_a$  is derived as the residual term of surface energy balance. The results showed that there was no difference between daily ET, computed SEBAL and Penman Monteith significantly. RSME and MBE indices for the daily and hourly ET were 0.14 and 0.37, respectively. The results showed that the estimated daily average of ET had 0.43 percent difference between FAO Penman-Monteith method and SEBAL; therefore, the accuracy of SEBAL algorithm can be acceptable. The land use map was provided by the object oriented approach with 88% accuracy and kappa coefficient. The minimum and maximum amounts of  $ET_R$  were the irrigated farming and residential one. The higher and lower standard deviations (SD) of  $ET_R$  were obtained in rangeland and water bodies, respectively. The spatial regression for detecting the relationship between both SMI and TDVI as independent and  $ET_{24}$  as dependent variable showed that MSI and  $ET_{24}$  had a significantly positive correlation higher than 0.60 and TDVI and  $ET_{24}$  had a negative correlation higher than -0.60 during the growth period (March to June). MSI in rangelands had a bit higher correlation than the other land uses. It was concluded that SEBAL model is a robust tool to calculate the ET and soil moisture by the means of remote sensing.

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## ارزیابی تخمین رطوبت خاک در مراتع با استفاده از سنجش از دور (مطالعه موردی: مراتع کوهستانی ملایر)

حمید نوری<sup>الف</sup>، محمد فرامرزی<sup>ب</sup>

<sup>الف</sup> استادیار آب و هواشناسی، دانشگاه ملایر، ایران (نگارنده مسئول)، پست الکترونیک: hamidwatershed@yahoo.com  
<sup>ب</sup> محمد فرامرزی، کارشناس ارشد سنجش از دور، دانشگاه محقق اردبیلی، ایران

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**چکیده.** رطوبت خاک و آب از عوامل محدود کننده تولید در مراتع هستند. اگرچه مطالعات زیادی برای تخمین رطوبت خاک در مناطق نیمه خشک انجام شده است، اما اطلاعات اندکی در مراتع مناطق کوهستانی غرب ایران وجود دارد. در این مطالعه تخمین رطوبت خاک در مراتع و سایر کاربری‌های اراضی در مناطق کوهستانی زاگرس مرکزی با استفاده از سنجش از دور باهم مقایسه شدند. برای محاسبه تبخیر و تعرق واقعی و رطوبت خاک در ملایر از الگوریتم سبال و تصاویر لندست ۸ در ماه‌های اسفند، فروردین، اردیبهشت، خرداد، تیر، مرداد و شهریور در سال ۲۰۱۳ استفاده و با روش پنمن مانیتیت مقایسه شد. روش سبال با به کار بردن تابش خالص، گرمای خاک و گرمای محسوس، تبخیر و تعرق را برآورد می نماید. نتایج نشان داد که تفاوت معنی‌داری بین تبخیر و تعرق محاسبه شده به روش پنمن مانیتیت و الگوریتم سبال وجود ندارد. شاخص‌های جذر میانگین مربعات خطا (RMSE) و میانگین اریب خطا (MBE) برای تبخیر و تعرق روزانه و ساعتی به ترتیب ۰/۱۵ و ۰/۳۹ محاسبه شد. برای تحلیل رابطه بین شاخص‌های رطوبت خاک (SMI) و دما خشکی پوشش گیاهی (TDVI) به عنوان متغیر وابسته با تبخیر و تعرق روزانه به عنوان متغیر مستقل از رگرسیون فضایی استفاده شد. نتایج نشان داد که در طول ماه‌های رشد و نمو گیاهان مرتعی (اسفند تا خرداد)، همبستگی بین شاخص رطوبت خاک و تبخیر و تعرق روزانه بین ۰/۴۹- لغایت ۰/۷۸ و همبستگی بین شاخص دما خشکی پوشش گیاهی و تبخیر و تعرق روزانه بین ۰/۴۶- لغایت ۰/۷۴- بود شاخص رطوبتی خاک در مراتع همبستگی قوی‌تری نسبت به دیگر کاربری‌های اراضی در منطقه از خود نشان داد. مدل سبال یک ابزار قدرتمند برای محاسبه رطوبت خاک با استفاده از سنجش از دور در مراتع پیشنهاد گردید.

**کلمات کلیدی:** رطوبت خاک، الگوریتم سبال، مرتع، لندست ۸، ملایر