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Downscaling of SMAP Soil Moisture Satellite Via Multivariate Regression and Artificial Neural Network Methods

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ABSTRACT

Soil moisture is an important parameter in various applications such as climatology, meteorology, hydrology, and water resource management, so it is quintessential to have a product with high spatial resolution. Due to the fact that soil moisture data with high spatial resolution is not currently available, one of the goals of this article is to downscale the existing soil moisture products and improve their spatial resolution to 1 square kilometer. For this purpose, two methods have been used based on regression and neural network along with other available satellite data and products including different combinations of land surface temperature (LST), normalized difference vegetation index (NDVI), passive microwave sensor data including brightness temperature in different polarizations (TBH and TBV), digital elevation model (DEM) and short-wavelength infrared (SWIR) data from MODIS to downscale the 3 km SMAP satellite soil moisture products. The innovation of this study includes investigating the effect of window size on the accuracy of downscaling, the effect of interpolation type and the use of Sentinel-3 satellite. The evaluation results have shown that the soil moisture of Fars and Golestan provinces, respectively, have a correlation coefficient (R) of 0.82 to 0.93 and 0.72 to 0.77, the mean absolute percent error (MAPE) in both regression and neural network methods less than 21 to 30 and 42 to 46 percent, and the lowest root mean square error (RMSE) equal to 0.0448 and 0.0445 in the neural network method. Also, in the area of Fars province, the regression modeling results of the plain area are more satisfactory than those of the mountain area.

KEYWORDS

Downscaling
Neural Network
Regression
SMAP
Soil Moisture

1. Introduction

Achieving soil moisture is an important and challenging issue due to its wide applications. Remote sensing is used as an effective tool to estimate soil moisture in regional and global scales, especially for places where there is no basic knowledge. (Piles et al., 2014). Several approaches have hitherto been made to measure soil moisture either directly or indirectly using different remote sensing sensor in different electromagnetic wavelengths (Koley & Jeganathan, 2020).

However, the soil moisture measurements from remote sensing satellites are very low resolution, the main reason why we cannot use soil moisture products in a medium scale.

The relationship between soil moisture and temperature and vegetation has been known since the early 1990s. Optical and thermal satellite observations are usually used to increase the spatial resolution of microwave data. (Usually, the resolution of these satellites is several kilometres). Triple models are one of the most important models that are widely used in remote sensing to downscale the soil moisture product using data from optical and thermal satellites. This model uses the relationship between soil moisture, temperature, and vegetation (Kim & Hogue, 2012). In most of the conducted studies, this relationship is established by linear and non-linear model between soil moisture, Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) (Ru et al., 2016).

In 2017, Sadeghi et al. used the triangle model, which is the most popular remote sensing approach for surface soil moisture, and actually establishes a relationship between *soil moisture and land surface temperature, which is obtained through remote sensing optical observations. This method is called Thermal Optical TRAapezoid Model (TOTRAM) model, which uses the model within the land surface temperature-vegetation index (LST-VI) space in order to obtain soil moisture. The main weakness of this model; however, is that it is not suitable for satellites that do not have a thermal band (for example, Sentinel-2 satellite).*

To solve this problem, Sadeghi used the OPtical TRApezoid Model (OPTRAM) model, which is based on the linear relationship between soil moisture and shortwave infrared transformed reflectance (STR), and the parameterization is based on the pixels distributed within the short-wave infrared transformed reflectance-vegetation index (SRT-VI) space. In this study, data used is from Sentinel-2 and Landsat-8 satellite data. The predictions of OPTRAM and TOTRAM are comparable, the only difference between the models is that the observations in the OPTRAM model require observations in the frequency range of electromagnetic waves (Sadeghi et al., 2017). In 2018, Babaeian et al. used the global OPTRAM model for a long time (several decades), this study aimed to discover the history of soil moisture and agricultural drought in response to climate change in different regions (Babaeian et al., 2018).

In 2018, Cui et al. used the Leaf Area Index (LAI) from the GLASS satellite, the Microwave Polarization Difference Index (MPDI) obtained from the L-band brightness temperature of the SMAP satellite and the land surface temperature (LST) from the MODIS satellite to downscale the SMAP L3 product. Entering new data into the previous multiple linear regression model increased the accuracy of downscaling (Cui et al., 2018).

The SMAP satellite has produced soil moisture data with a resolution of 9 km through a combination of L-band radar and radiometer observations with a balance between accuracy and resolution. On July 7, 2015, the SMAP radar failed and soil moisture production with a resolution of 1 km was not possible. Therefore, the possibility of hydrological applications became impossible. In 2019, Hongtao et al. used a spatio-temporal fusion model based on a non-local filter called Spatio-Temporal Fusion Model (STFM) to downscale 36 km data to 9 km data with the help of past 9 km and 36 km products (Hongtao et al., 2019).

In addition to triple models from different researchers, other models such as machine learning algorithm and artificial intelligence have been used for downscaling of soil moisture (Liu et al., 2020).

In the research conducted by Portal, using important variable, the linear regression was employed to downscale the soil moisture. No comprehensive study has been carried out on the effectiveness of difference factor in downscaling soil moisture, for instance Digital Elevation Model (DEM) and Short-Wave Infrared (SWIR) are two most important factors for downscaling soil moisture but they do not use the regression method used by Portal et al. (2018).

Based on the lack of DEM and SWIR effectiveness results in previous studies that used LST and NDVI for downscaling, two methods including multivariate regression and artificial neural network are employed all over two difference case study Fars and Golestan in different climatic conditions. The main innovations of the parameters in multivariate regression are also examined. These include windows size, interpolation method and the performance of Sentinel-3.

In sections 2 and 3, case study and the frameworks of these methods are explained, respectively. In sections 4 and 5, results and conclusions are presented, respectively.

2. Case Study

Both downscaling methods were applied to two regions located in the north and south of Iran, Golestan province, whose climatic conditions are moderate and rainy, and Fars province, whose climatic conditions are cold, hot, and dry. Soil moisture results can provide important information for the management of water resources in various applications to governments. Therefore, it is substantial to have accurate and reliable soil moisture product.

3. Material and Method

3.1. Material

The auxiliary data used for downscaling is NDVI, LST, TBH, TBV, DEM and SWIR spectral band which are mainly provided by MODIS.

One of the goals of this research is to check the accuracy of Sentinel-3 products in the downscaling of soil moisture in comparison with MODIS products, therefore, at this stage, LST and NDVI have been extracted from Sentinel-3.

*Table **1**. Satellite images used in this study*

Data	Product	Spatial Resolution	Acquisition date
SMAP	SPL2SMAP-S	1-3 km	2021 (Jun. 8); 2021 (Oct. 9)
	L1C-TB	9 km	
MODIS	MYD11A1	1 km	
	MYD13A2		
	MYD021KM		
Sentinel-3	SL-2-LST	500 m	
	OL-1-EFR		
SRTM	DEM	30 m	

3.2. Method

In this paper, an attempt is made to downscale the SMAP soil moisture product using auxiliary data which are mostly produced by MODIS. The first method used for downscaling is an enhanced version of the regression method already proposed by Portal et al. (2018). The main difference lies in the input parameters used for the regression. In the method proposed by Portal, four different information layers *including NDVI, LST, TBV and TBH are originally used. One of the main innovations of the method used in this paper is to include two more data which may be directly related to the soil moisture, i.e., DEM and SWIR band of MODIS. Eq. (1) illustrates the relation used for the regression:*

$$SM = b_0 + b_1 LST + b_2 NDVI + b_3 T_{BH} + b_4 T_{BV} + b_5 DEM + b_6 SWIR \quad (1)$$

*Where b_i are the model parameters as coefficients which are to be estimated. The model parameters were estimated locally within a window with a specific size. One of the objectives of the present research is to investigate the effect of the estimation window size on the accuracy of the downscaled product. Moreover, this estimation is performed based on the information layers which are resampled on a grid with the pixel size of 3*3 km^2. After the estimation of the coefficients, they are interpolated on a new grid with the pixel size of 1*1 km^2. Evaluating the effect of different interpolation methods on the final results is another objective of the present article. The overall processing steps performed in the regression method is illustrated in Figure 1.*

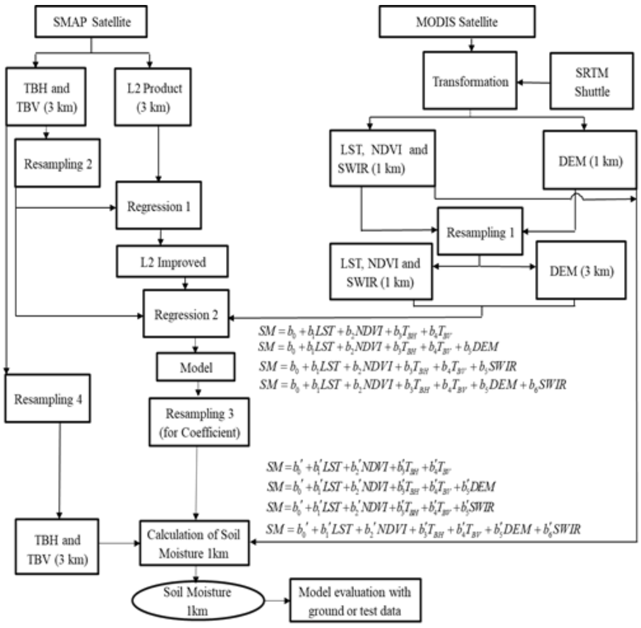


Figure 1. Different stages of downscaling using data from different satellites with multivariate regression method. b_0, b_1, b_2, b_3, b_4, b_5 and b_6 are the coefficients of the main regression model and b_0', b_1', b_2', b_3', b_4', b_5' and b_6' are the coefficient used to generate the downscaled map.

Another comparison method of this research is the use of neural network for downscaling of the SMAP soil moisture, which, according to previous research, has not been already used. Similar to the regression method, the types of input parameters of the model in the case of the neural network will also be examined in the accuracy of the results. Based on the neural network, the model forms a downscaling model globally for the entire region. The effect of different network architectures and structures on downscaling accuracy is also evaluated. The ANN method is shown in Figure 2.

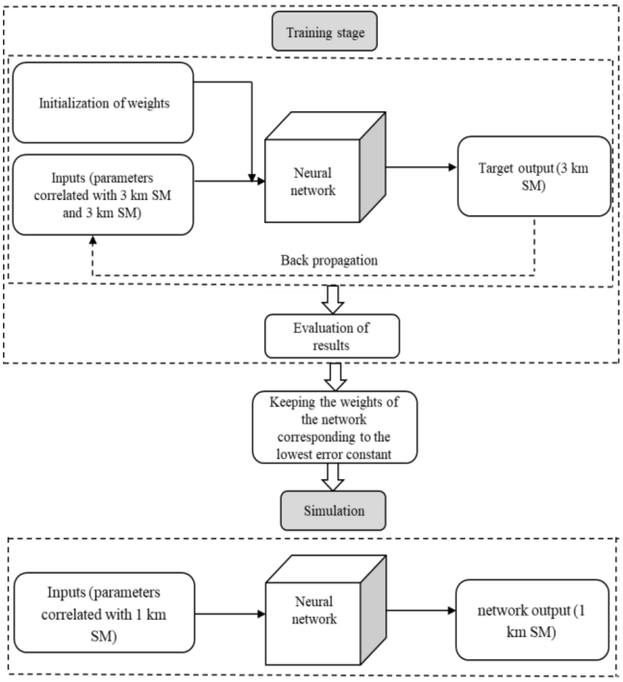


Figure 2. Different stages of downscaling using data from different satellites with ANN method

In order to investigate the effect of different input parameters including DEM and SWIR in the algorithm of regression and neural network methods, different combinations of input parameters were investigated.

According to Table 2, statistical parameters for evaluating the downscaled products include correlation coefficient (R), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Table 2. Statitistical metric used between downscaled soil moisture and 1 km SMAP soil moisture product which has already been downscaled using Sentinel-1

Metric	*Mathematical Definition*
R	$R = \frac{E\left[\left(SM_{obs} - E\left[SM_{obs}\right]\right)\left(SM_{down\_scaled} - E\left[SM_{down\_scaled}\right]\right)\right]}{\sigma_{down\_scaled}\sigma_{SMAP}}$
RMSE	$RMSE = \sqrt{E\left[\left(SM_{obs} - SM_{down\_scaled}\right)^2\right]}$
MAPE	$MAPE = E\left(\frac{abs\left(SM_{down\_scaled} - SM_{obs}\right)}{SM_{obs}}\right)$

4. Results

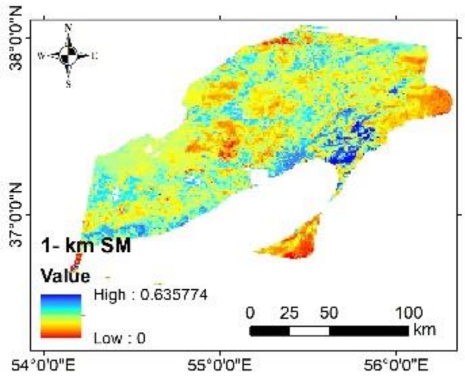
As mentioned in the previous section, both regression and neural network methods are used to downscale the SMAP soil moisture. In this section, the results of these two methods are discussed.

Adding DEM and SWIR into the initial input parameters already mentioned do not always significantly improve the downscaling results. This conclusion is achieved while examining the downscaling approached on other areas whose results are not presented in this article. We came to the conclusion that it is not possible to make a general rule for choosing the input parameters for downscaling. The performance of downscaling and its relationship with the input parameters are highly influenced by the climatic and topography conditions of the study area.

The downscaling results are compared to the soil moisture product which has been already downscaled using Sentinel-1 SAR data. This product which is used as an assessment criterion is one of the standard products of SMAP. The main goal of re-downscaling of 3km product is to evaluate how much the optical and passive microwave remote sensing has potential for downscaling similarly to the SAR data whose backscattering coefficient is directly related to the soil dielectric constant or soil moisture. The evaluation shows that the correlation coefficient in Golestan and Fars provinces for the regression method is 93% and 77%, respectively, while this coefficient for the neural network method in Golestan and Fars provinces is estimated at 87% and 42%, respectively. Also, the best RMSE of Golestan and Fars province is estimated as 0.0436 and 0.0440, respectively, and belongs to the regression method. The lowest MAPE is related to the regression method in Golestan province, which is calculated as 21%.

Also, the evaluation shows that the correlation coefficient in Fars provinces for the regression method with MODIS data is 73% but with Sentinel-3 data is 77%.

Regarding the evaluation quantities, the downscaling results are comparable to similar studies. It is expected that the results would be more satisfactory in plains when compared to the mountainous areas. However, in the Golestan province, despite the presence of topography, the results of downscaling in plain and mountains were almost similar which is probably due to the high percentage of moisture in the soil over the whole area. The downscaling results are presented in Figure 3,4 (c and d). As observed, the small-scale variations of soil moisture are satisfactorily modeled by the regression. The reason is that the model parameters are locally estimated in this method. On the other hand, the neural network method is only able to model the main spatial trends of the soil moisture. However, the results of both methods are more smoothed than the original 1 km soil moisture that is depicted in Figure 3 and 4 (b).



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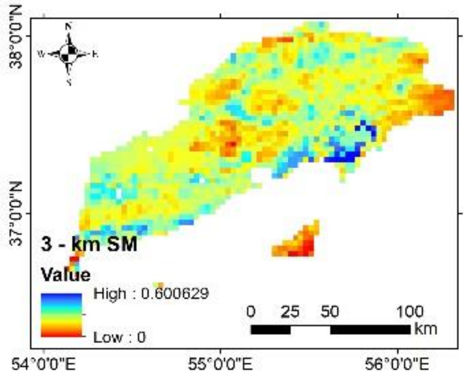

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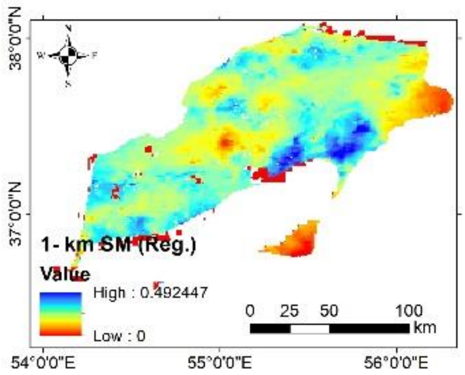

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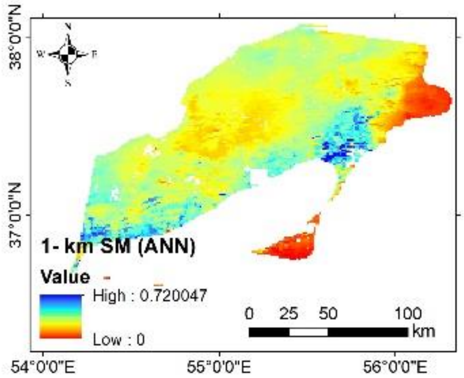
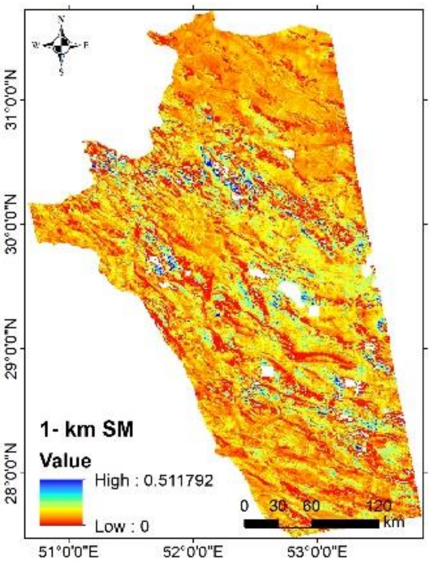


(d)

Figure 3. (a) 3 km SMAP soil moisture product, (b) 1 km SMAP soil moisture product which has already been downscaled using Sentinel-1, (c) 1 km SMAP soil moisture product downscaled using regression method



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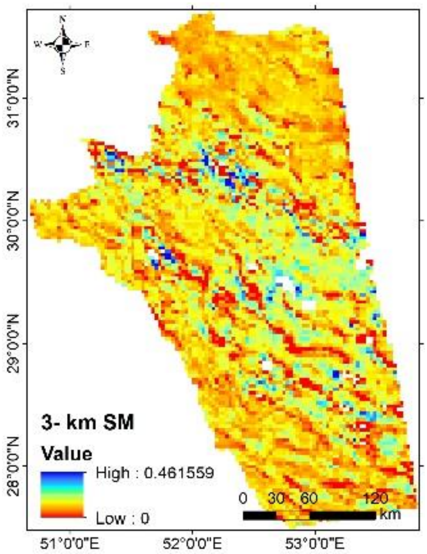

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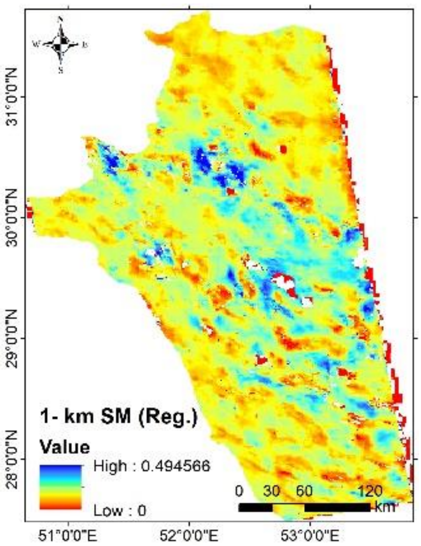

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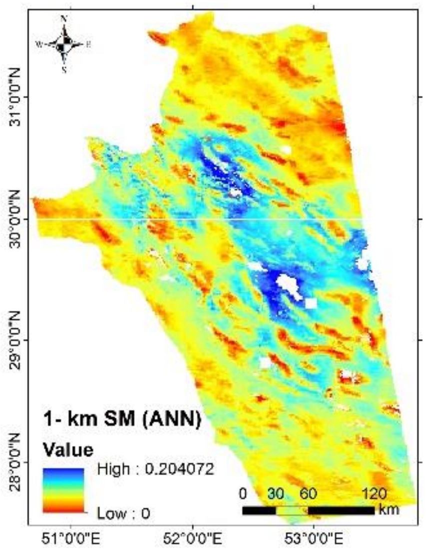


(d)

Figure 4. (a) 3 km SMAP soil moisture product, (b) 1 km SMAP soil moisture product which has already been downscaled using Sentinel-1, (c) 1 km SMAP soil moisture product downscaled using regression method and (d) 1 km SMAP soil moisture product downscaled using neural network method

In this article, the effect of different data from different types of satellites, such as the effect of microwave waves in determining SM or the effect of waves from passive sensors and their related products in downscaling methods, is investigated. Due to the fact that each satellite has its own unique products, the corresponding parameter of the regression model will be different and as a result, the method used and the accuracy will be different. The products used are various products from different satellites that have the highest correlation with SM data. Among these products, SWIR, DEM or the combination of these two products are mentioned.

Adding DEM and SWIR in two regions according to the chosen method (regression or neural network) and also the satellite used brings different accuracy, so that in some of the areas of adding named products to the main products improved the results but, in some areas, it did not improve the results. The results are presented in each area in Tables 3, 4, 5, 6 and 7.

Table 3. Statistical metrics for the comparison of downscaled SM maps against concurrent in 1 km SMAP SM product which has already been downscaled using Sentinel-1 with Regression method for the 2021/10/09 in the Golestan province

	Regression Method (Linear Interpolation)		
Input Features	**R**	**RMSE (cm^3/cm^3)**	**MAPE (%)**
LST, NDVI, TBH, TBV	0.83	0.069	30.09
LST, NDVI, TBH, TBV, SWIR	0.83	0.069	30.03
LST, NDVI, TBH, TBV, DEM	0.82	0.07	30.10
LST, NDVI, TBH, TBV, SWIR, DEM	0.82	0.07	30.00

Table ۴. Statistical metrics for the comparison of downscaled SM maps against concurrent in ۱ km SMAP SM product which has already been downscaled using Sentinel-۱ with ANN method for the ۲۰۲۱/۱۰/۰۹ in the Golestan province

	ANN method		
Input Features	**R**	**RMSE (cm^3/cm^3)**	**MAPE (%)**
LST, NDVI, TBH, TBV	0.88	0.045	24.05
LST, NDVI, TBH, TBV, SWIR	0.89	0.046	24.33
LST, NDVI, TBH, TBV, DEM	0.89	0.045	23.55
LST, NDVI, TBH, TBV, SWIR, DEM	0.88	0.045	23.90

Table 5. Statistical metrics for the comparison of downscaled SM maps against concurrent in 1 km SMAP SM product, which has been already, downscaled using Sentinel-1 with Regression method for the 2021/06/08 in the Fars province

	Regression Method (Linear Interpolation)		
Input Features	**R**	**RMSE (cm^3/cm^3)**	**MAPE (%)**
LST, NDVI, TBH, TBV	0.74	0.047	42.71
LST, NDVI, TBH, TBV, SWIR	0.73	0.048	42.92
LST, NDVI, TBH, TBV, DEM	0.73	0.048	42.64
LST, NDVI, TBH, TBV, SWIR, DEM	0.73	0.048	42.65

Table 6. Statistical metrics for the comparison of downscaled SM maps against concurrent in 1 km SMAP SM product, which has already been downscaled using Sentinel-1 with ANN method for the 2021/06/08 in the Fars province

	ANN method		
Input Features	**R**	**RMSE (cm^3/cm^3)**	**MAPE (%)**
LST, NDVI, TBH, TBV	0.35	0.046	46.21
LST, NDVI, TBH, TBV, SWIR	0.35	0.046	45.32
LST, NDVI, TBH, TBV, DEM	0.39	0.045	45.51
LST, NDVI, TBH, TBV, SWIR, DEM	0.42	0.045	44.24

Table 7. Statistical metrics for the comparison of downscaled SM maps against concurrent in 1 km SMAP SM product which has already been downscaled using Sentinel-1 with Regression method using features extracted from Sentinel-3 data for the 2021/06/08 in the Fars province

	Regression Method (Linear Interpolation)		
Input Features	**R**	**RMSE (cm^3/cm^3)**	**MAPE (%)**
LST, NDVI, TBH, TBV	0.77	0.044	43.58
LST, NDVI, TBH, TBV, SWIR	0.76	0.044	43.50
LST, NDVI, TBH, TBV, DEM	0.77	0.044	43.80
LST, NDVI, TBH, TBV, SWIR, DEM	0.76	0.045	42.73

Based on the MAPE map in Figure 5, it can be seen that the MAPE value is systematically lower in some areas and higher in others. With a closer examination, we find that the value of MAPE is lower in the plain and in areas where the area is flat and without topography, and higher in mountainous areas. In other words, the downscaled soil moisture product in flat and plain areas is more accurate compared to mountainous areas.

The linear regression method in the plain area of Fars province has far better results than the mountain area. One of the reasons can be that the humidity changes in the plains have more spatial correlation and less diversity due to the lack of topography, so it can be modeled with the help of a simple regression model. On the other hand, in mountainous areas, due to the spatial variation of the soil moisture product, the regression method will not be able to model these spatial changes. Therefore, the result of downscaling will not be accurate enough.

In the plain, most of the pixels in the area have an error of less than 50%, while in the mountain region; this value reaches 200% in Figure 6 (a), (b). Also, the minimum and maximum value of Residual error in the plain is approximately -0.05 and +0.05, while this quantity is *approximately -0.1 and +0.1 in the mountains in Figure 7(a), (b).*

Figure 8(a), (b), shows the regression diagram in the plains and mountains, where the correlation coefficient in the plains is much higher than the correlation coefficient in the mountains.

According to Table 8, the percentage of pixels presence is displayed based on the average error for the plains and mountains. Then, based on the average percentage of error, the plain and mountain areas are also classified into three classes 1, 2 and 3. According to the table, unlike the mountain region, most of the pixels in the plain area of Fars province (approximately 95%) fall into the three mentioned classes. Therefore, these high percentages of the presence of pixels in the three classes of the plain region compared to the mountains show the very appropriate performance of the regression method in the plain area of Fars province.

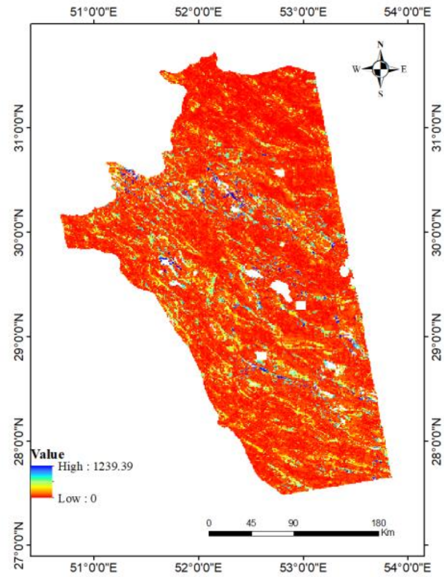
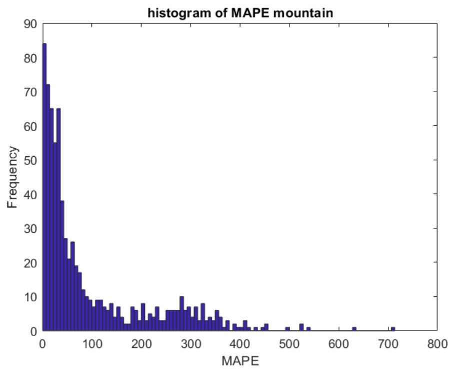


Figure 5. Diagram of the mean absolute percent error (MAPE) in the whole Fars province.



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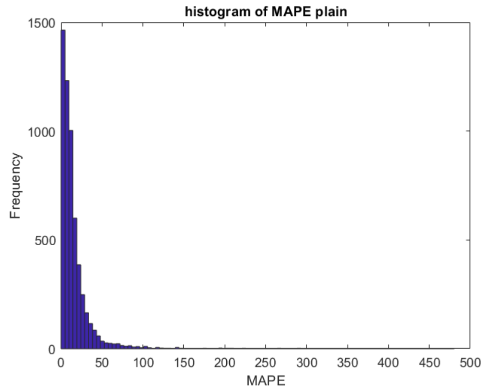
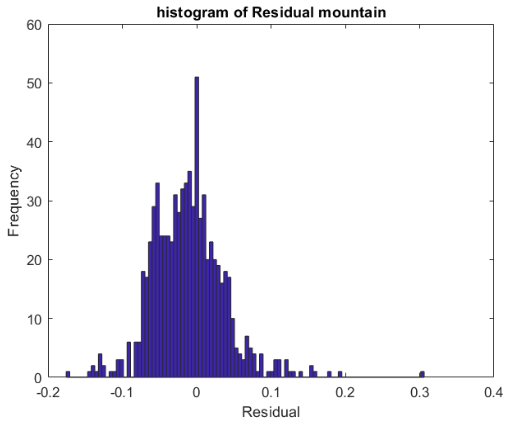


(b)

Figure ۶. Mean absolute percent error (MAPE) histogram of the regression method in Fars province (a) mountain area, (b) plain area.



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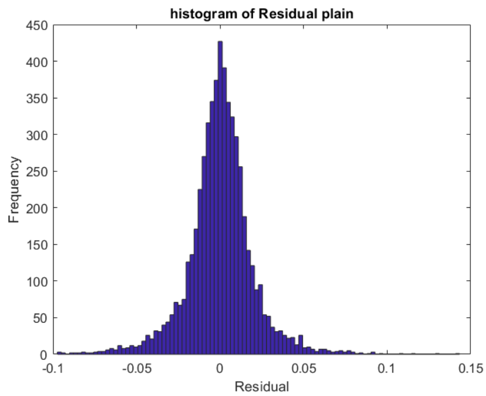
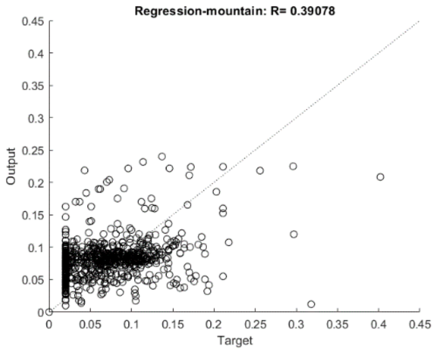


(b)

Figure ۷. Residual error histogram of the regression method in Fars province (a) mountain area, (b) plain area.



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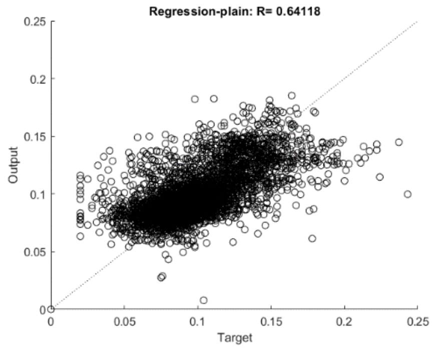

(b)

Figure 8. Diagram of regression method in Fars province (a) mountain area, (b) plain area.

Table 8. The percentage of presence of pixels based on the mean absolute percent error (MAPE) in Fars province (a) mountain area, (b) plain area

Class	***MAPE (%)***	***Percentage of pixels (%)***
1	*<10*	*12.08*
2	*<20*	*24.83*
3	*<50*	*51.27*

(a)

Class	***MAPE (%)***	***Percentage of pixels (%)***
1	*<10*	*49.29*
2	*<20*	*77.69*
3	*<50*	*95.18*

(b)

The effect of increasing the estimation window size is shown in Figure 9. We came to the conclusion that, in general, increasing the size of the estimation window in the regression approach decreases the accuracy of downscaling of soil moisture. The reason for the decrease in accuracy due to the increase in the window size is the decrease in the efficiency of the regression method in modeling the soil moisture of heterogeneous data. Moreover, the comparison between the results of cubic and linear interpolation methods show that the cubic interpolation improves the downscaling results.

The neural network with different architectures is also applied for downscaling the SMAP soil moisture. As a result, we observed that increasing the dimension of the neural network does not highly affect the results. Therefore, we chose the simplest type of architecture.

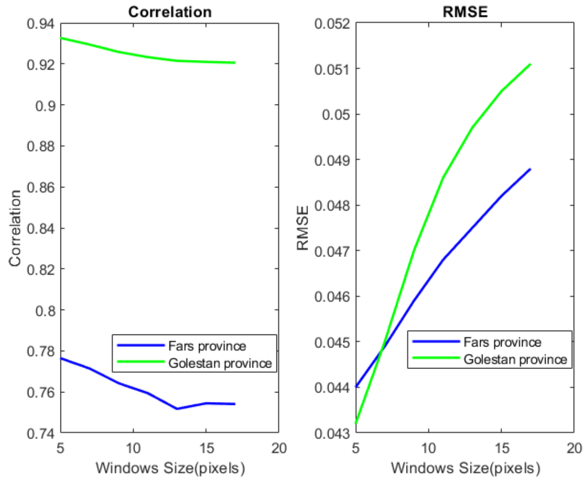

Figure 9. Effect of increasing the estimation window size on the downscaling results.

5. Conclusion

In this article, two different methods based on multivariate regression and artificial neural network were used for downscaling soil moisture. The effect of different variable in downscaling is investigated. The main contribution of this research is to incorporate DEM and SWIR in multi regression method.

By comparing the performance of two downscaling methods, it was found that the regression-based model, due to its nature of local estimation, could estimate the local and small-scale soil moisture effects, while the neural network-based method is only able to model the general spatial trend of the soil moisture. Moreover, the results were not considerably improved by adding the DEM and SWIR spectral band. However, regarding the assessment quantities, the downscaling results are comparable to the similar studies. This is an indication of the high performance of the proposed downscaling methods.

The results of the downscaling evaluation show a correlation coefficient of about 0.72 to 0.93, which is comparable to the research done by other researchers. For example, in the research conducted by Portal et al., the value of the correlation coefficient of the investigated method in a 35 square kilometre network in Spain, in the range of 0.31 to 0.86 and in a 60 square kilometre network in Australia, in the range of 0.63 to 0.92 has been calculated (Portal et al., 2018). In the OPTRAM and TOTRAM method proposed by Sadeghi et al., the value of the correlation coefficient between 0.54 to 0.90 and 0.69 to 0.94 was obtained, respectively (Sadeghi et al., 2017). Also, in the OPTRAM method by Babaeian et al., correlation coefficient was calculated in the range of 0.10 to 0.70 (Babaeian et al., 2018). The validation results of the downscaling product by

Fang et al., show relatively good accuracy with an average correlation coefficient of 0.73 (Fang et al., 2020).

The results are achieved over the study areas with different climatic conditions. The result in different climate showed the data of the Fars province with the predominant cold and dry climate, the regression modeling results in the plains were more satisfactory than those of the mountains. However, the results achieved in the Golestan province with a predominant moderate and rainy climate, despite the presence of altitudes, the results over plains and mountains were the same and both are satisfactory, because in this area, in addition to high humidity, there are no large spatial changes in soil moisture.

The effect of Sentinel-3 satellite on Fars province was investigated too. The results showed the high accuracy of Sentinel-3 in extracting LST and NDVI, which has caused more accuracy in downscaling and improved results.

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