DOWNSCALING OF SOIL MOISTURE PRODUCT OF SMAP

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ABSTRACT:

Soil moisture as a variable parameter of the Earth's surface plays a very important role in many applications such as meteorology, climatology, water resources management and hydrology. Therefore, access to soil surface moisture product with high spatial resolution is very important. Due to the lack of access to soil moisture information with high spatial resolution, the main goal in this article is to downscale the existing soil moisture products and improve their spatial resolution into 1 square kilometer. For this purpose, two methods based on regression and neural network have been used for downscaling the 3 km soil moisture products of SMAP satellite. To this end, other available satellite data and products including various combinations of land surface temperature (LST), normalized difference vegetation index (NDVI), brightness temperature in different polarizations of (TBH and TBV) passive microwave sensor data, digital elevation model (DEM) and short-wavelength infrared (SWIR) data of MODIS and Sentinel 3 have been used. In this study, two regions in the north and south of Iran, Golestan and Fars provinces, have been examined, due to the lack of ground measurements of soil moisture, the SMAP product with the resolution of 1 km which has been already downscaled by exploiting the Sentinel-1 radar data, was used to evaluate the results. The evaluation results in Golestan and Fars provinces showed the correlation coefficient of 0.82 to 0.93 and 0.72 to 0.77, respectively, and the average percentage of absolute error in both regression and neural network methods was less than 21 to 30 and 42 to 46 percent.

1. INTRODUCTION

1.1 General Instructions

Achieving soil moisture is an important and challenging issue due to its wide applications. Remote sensing is used as a practical concept 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 been made to measure soil moisture directly or indirectly using different spatial techniques in different electromagnetic wavelengths. (Koley & Jeganathan, 2020).
Since the early 1990s, the relationship between soil moisture and temperature and vegetation has been known. Optical and thermal satellite observations are usually used to increase the spatial resolution of microwave data. (Usually the resolution of these satellites is several kilometers). 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. In most of the conducted studies, this relationship is established by linear and non-linear relationship between soil moisture, Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI). In the research conducted by Portal et al., 2018, in a 35 square km grid in Spain, the correlation coefficient value of the investigated method with ground data ranges from 0.31 to 0.86, and in a 60 square km grid in Australia, the correlation coefficient value lies within the range of 0.63 to 0.92 (Portal et al., 2018). In the article of Sadeghi et al., in different scenarios, the estimated soil moisture is compared to the field soil moisture measured. The correlation coefficient value in the OPTRAM method is between 0.54 and 0.90 and in the TOTRAM method between 0.69 and 0.94 (Sadeghi et al., 2017). In the research carried out by Babaeian et al., the soil moisture obtained by remote sensing is compared to the field soil moisture measured. The correlation coefficient value in the OPTRAM method is calculated in the range of 0.10 to 0.70 (Babaeian et al., 2018).
In this paper, the downscaling results of two different methods including regression and neural network are compared in order to find out how they are trustworthy. In Section 2, the frameworks of these methods are explained. In section 3 and 4, results and conclusions are presented, respectively.

1.2 Data sets and 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.
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, LST and NDVI at this stage has been extracted from Sentinel 3.

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2. METHODOLOGY

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 is 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. Digital Elevation Model (DEM) and Short Wave Infrared (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 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 Fig. 1.
Another innovation 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. The model based on the neural network forms a downscaling model globally for the entire region. The effect of different network architectures and structures on downscaling accuracy is also evaluated.
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. 1, Statistical parameters for evaluating the downscaled products include correlation coefficient (R), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

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

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

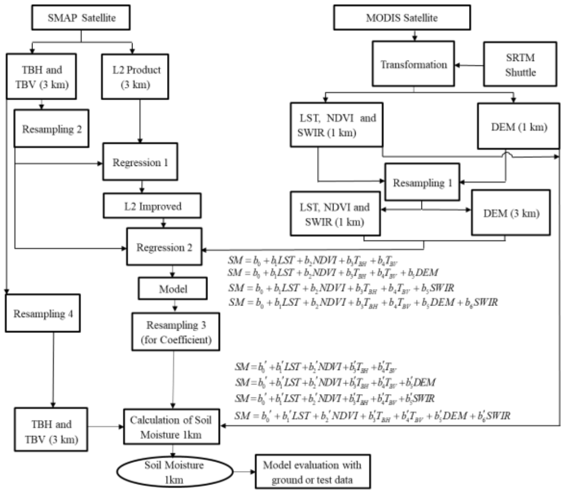
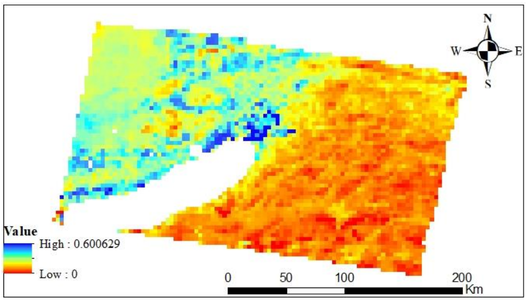


Figure 1. Different stages of downscaling using data from different satellites.

3. 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 into 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, and 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 researches. 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 Fig. 2,3 (c and d) and Fig. 4 (a and b). As observed, the small-scale variations of soil

moisture are better 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 Fig. 2 and 3 (b).



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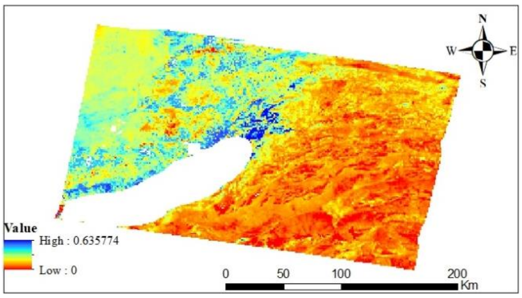

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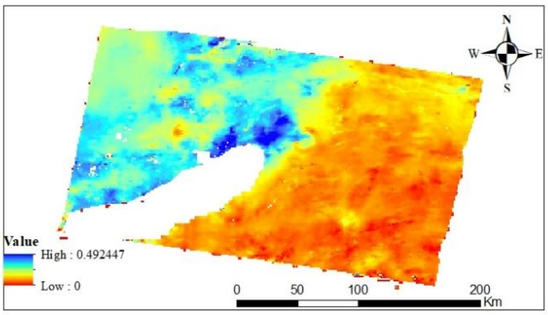
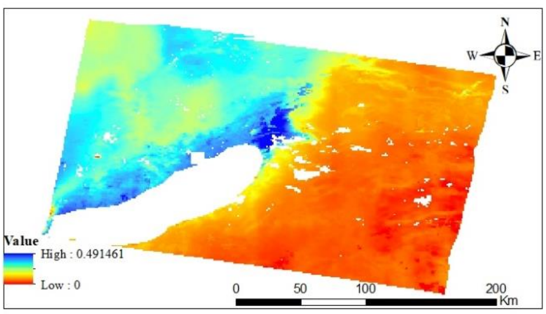
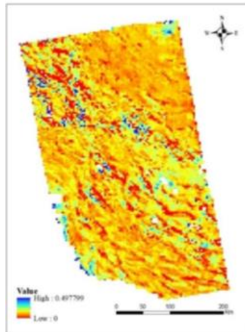


(c)

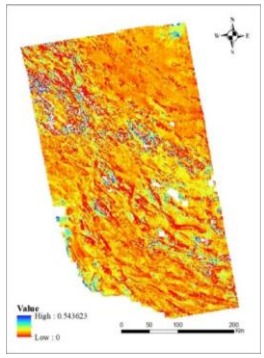


(d)

Figure 2. (a) 3 km SMAP soil moisture product, (b) 1 km SMAP soil moisture product which has been already 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



(a)



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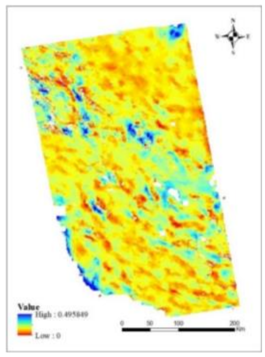

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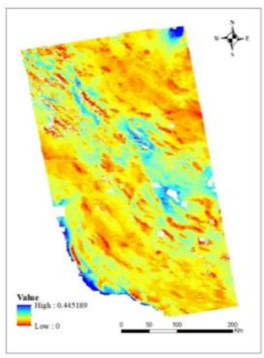
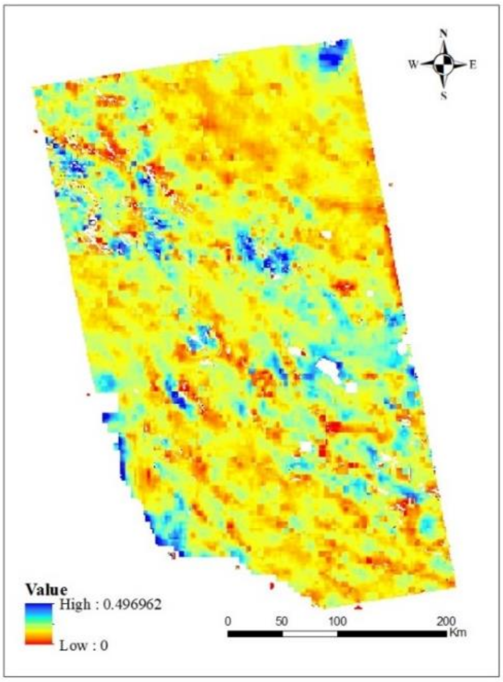
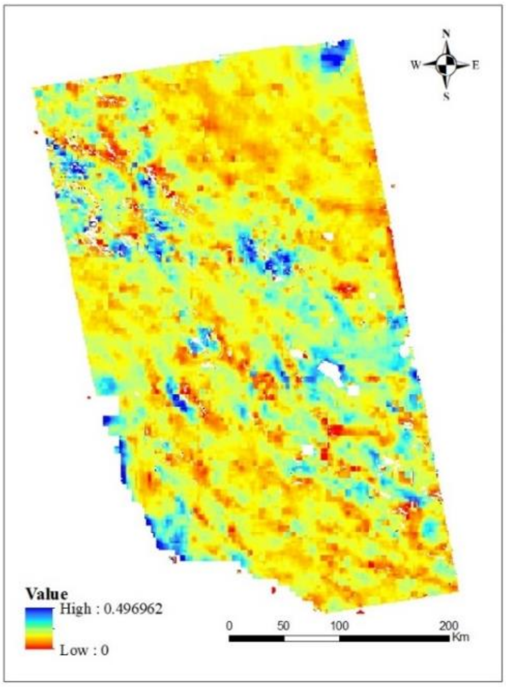


(d)

Figure 3. (a) 3 km SMAP soil moisture product, (b) 1 km SMAP soil moisture product which has been already 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



(a)



(b)

Figure 4. (a) 1 km SMAP soil moisture product downscaled using regression method with Sentinel 3 data and (b) 1 km SMAP soil moisture product downscaled using neural network method with Sentinel 3 data

Based on the MAPE map in Fig. 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, and 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 Fig. 6 (a), (b). Also, the minimum and maximum value of root mean square 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 Fig. 7 (a), (b).

Fig. 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. 2, 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.

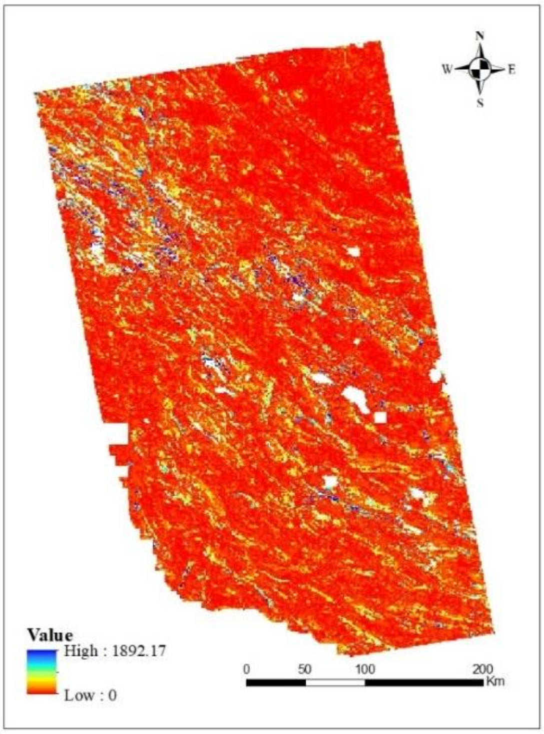
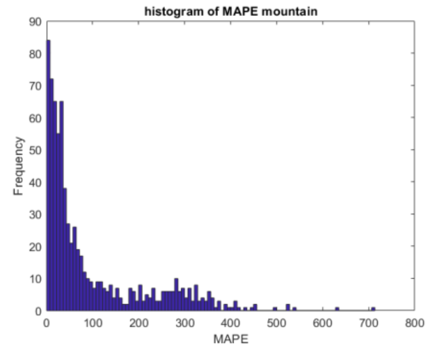
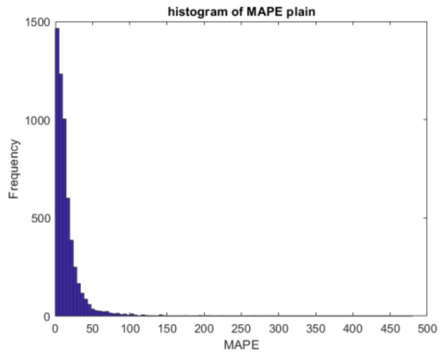


Figure 5. Diagram of the mean absolute percent error (MAPE) in the whole Fars province.

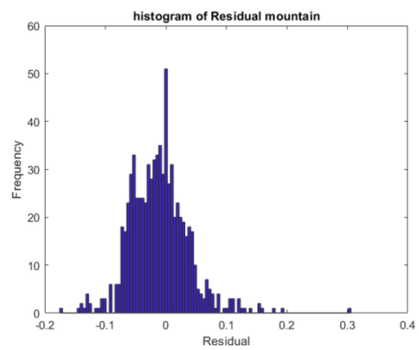


(a)

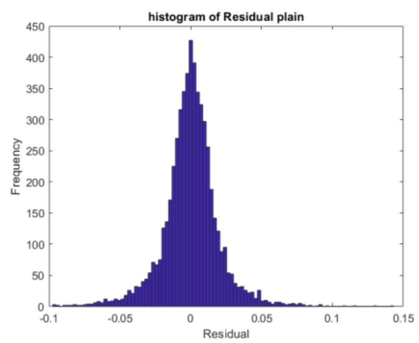


(b)

Figure 6. Mean absolute percent error (MAPE) histogram of the regression method in Fars province (a) mountain area, (b) plain area.

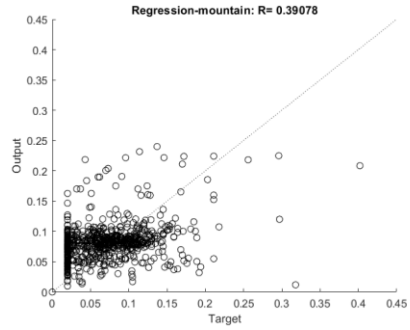


(a)

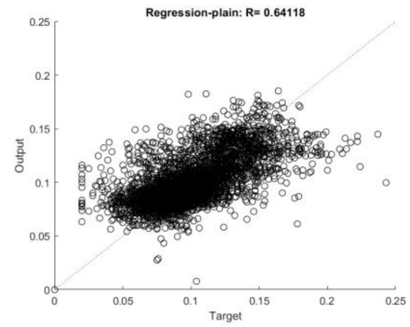


(b)

Figure 7. Residual error histogram of the regression method in Fars province (a) mountain area, (b) plain area.



(a)



(b)

Figure 8. Diagram of regression method 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)

Table 2. The percentage of presence of pixels based on the absolute average percentage of error in Fars province (a) mountain area, (b) plain area

The effect of increasing the estimation window size is shown in Fig. 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.

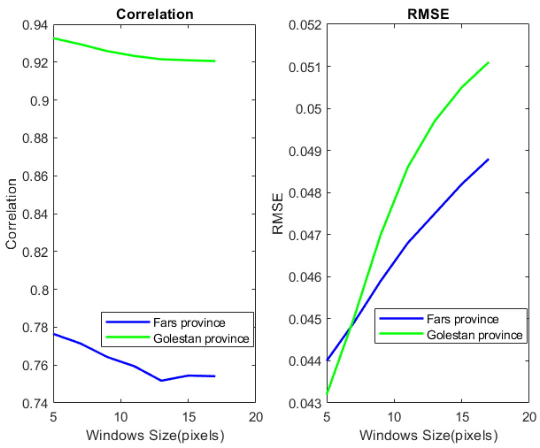


Figure 9. Effect of increasing the estimation window size on the downscaling results.

4. CONCLUSION

By comparing the performance of two downscaling methods, it was found that the regression-based model, due to its nature of local estimation, has the ability to 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 researches. This is an indication of the high performance of the proposed downscaling methods.
The results are different in two climates. The results in different climates showed that the data of Fars province with a predominant cold and dry climate, the regression modeling results in the plains were better than the mountains, and the data of the Golestan province with a predominant moderate and rainy climate, despite the presence of altitudes, the results of the plains and mountains were better in both 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. 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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