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Intelligent Fuzzy-based Feature Selection for Soil Moisture Classification

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Abstract

Despite the capability of remote sensing to direct observation of soil moisture content, the radiances measured by sensors are usually affected by different soil and atmosphere parameters. Therefore, understanding the importance of selecting the optimal features for soil moisture recognition, the application of fuzzy logic to perform intelligent feature selection is a distinguished line of research. In the following, the selected features were used in two widely used classifiers (SVM (Support Vector Machine) and MLP (Multi-Layers Perceptron) artificial neural network) in order to soil moisture classification. These classifiers were found competitive with the best available machine learning algorithms. In other words, the main purpose of this model is to select the least number of features based on fuzzy logic aligning with increasing the accuracy of soil moisture classification. The proposed method was applied and validated using observations carried out for the Iran region. In order to compare the soil moisture classification accuracy using the features selected by fuzzy-based model, a different scenario was also considered. In the latter case, vegetation cover (NDVI), soil surface temperature (LST), and topography as selected features for soil moisture classification, were entered into the above-mentioned classifiers. The reason for choosing these three features among all the features is their significant effect on the amount of soil moisture. The results obtained were very encouraging and indicated about 8% improvement on soil moisture classification accuracy using the proposed feature selection method.

Key words: Remote Sensing, Soil Moisture Classification, Intelligent Feature Selection, Fuzzy Logic, SVM, Artificial Neural Network

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1. Introduction

Soil moisture information has been identified as one of the crucial data components for many aspects of global change studies and environmental applications (i.e. weather changes, flood, drought and runoff generation, soil evaporation and plant transpiration) ([7]; [38]). It serves as a determinant of the chemical, mechanical, and biological processes that occur in the soil ([21]; [23]; [29]). Due to increasing demand for global and spatially averaged surface soil moisture data, a number of studies have been carried out on soil moisture monitoring through remote sensing in wide areas ([6]; [28]; [33]; [31]). The derivation of such information increasingly relies on remote sensing technology due to its ability to acquire measurements of land surfaces at various spatial and temporal scales. On the other hand, one of the methods for information acquisition from the remotely sensed images is classification. Soil moisture classification is a foundation for many modern international soil classification systems. It is recognized at virtually all levels of soil Taxonomy. It has been conventional to recognize three soil moisture states or classes: saturated (wet), moist, and dry.

In the past decades, a variety of classification methods such as Support Vector Machine (SVM) using different kernels, artificial neural networks (ANNs), Fuzzy logic, maximum likelihood and etc. have been investigated and compared. According to many of these extensive studies, SVM and ANNs have been shown to be more accurate ([8]; [9]; [12]; [15]; [17]; [30]).

Regarding that machine learning techniques have become important tools in classification, in this study Support Vector Machine (SVM) and a Multi-Layer Perceptron (MLP) Neural Network have been used in order to soil moisture classification. In addition to the comparative performances of these classifiers, impacts of the configurations of SVM kernels on its performance and input features on classifiers were also evaluated.

Due to the amount of high-dimensional data captured by the sensors, machine learning methods have difficulty in dealing with the large number of input features ([10]). Therefore, in order to use machine learning methods effectively, pre-processing of the data is essential. Previous studies have shown, there is a large number of factors such as soil moisture, vegetation characteristics, surface roughness, temperature of the soil along with soil texture affecting the radiances observed from space ([22]). Therefore, selecting the appropriate features is essential in the classification of soil moisture. Feature selection is one of the most frequent and important techniques in data pre-processing ([4]; [32]; [35]). It is the process of detecting relevant features and removing irrelevant, redundant, or noisy data. This process improves predictive accuracy, and increases comprehensibility ([16]; [37]). Assessing the quality of the candidate's features is the main concern in the feature selection algorithms ([11]). Many methods have been developed to select features over the last decade. The review of the feature selection methods depict that a particular feature selection algorithm plays a vital role for accurate classification of soil moisture ([24]).

It is observed from the survey that the filter method is computationally more efficient and provides better generality than other methods. Wrapper and embedded approach should be used when there is a need to find optimal feature subset appropriate for a particular learning algorithm. Hybrid approach takes advantage by aggregating the merits of two or more techniques ([1]; [35]). Hence, further developments of feature selection approaches are required to be applied.

This study presents a new Fuzzy-SVM and Fuzzy-ANN model, which applies fuzzy logic in combination with two different machine learning algorithms. In this mode, fuzzy logic is utilized for performing feature selection. The main goal of the model is to maximize the classification accuracy with the smallest possible number of features. In this method the number of selected features considered as inputs of a fuzzy number. Then, after defuzzification and using genetic algorithm, the optimal features can be determined. The purpose of this paper is to demonstrate the applicability of this feature selection algorithm to deriving optimum features in order to soil moisture classification. In this way, the performance of this method have been evaluated using two operational classifiers, i.e. SVM and ANN.

It is worth nothing that in some studies, after selecting the input features, fuzzy rules have been used to estimate soil moisture content ([25]; [19]). While in this study, as an innovation, fuzzy logic has been used to select the features required to classify soil moisture.

This paper is organized as follows: The study region and the data used are described in section 2. In sections 3 the proposed methods to feature selection and soil moisture classification are presented. Section 4 discusses about the potential capability of the feature selection model and soil moisture classification methods. Section 5 summarizes and concludes the paper.

2. Study area and dataset

2.1. Study region

During the Spring 2018, the experiment took place in a semiarid environment of IRAN (N 25°03′_39°47′, E 44°05′_63°18′). All analyses were conducted over this country. Iran has diverse topographic and climatic conditions. Unlike the northern and western, the topography of the central and southern regions of Iran is relatively flat. The average annual rainfall in some southern regions of

Iran does not exceed 4 mm. while for some western and northern regions is reported more than 600 mm. Geographic location of this region and ground sites are shown in Figure 1. The total number of sites used as samples is 40. Regarding the potential of the proposed algorithm, all sites with various soil moisture content have been selected for calibration and validation purposes. In the other word, due to evaluate the performance of proposed feature selection model and classification, in different soil moisture content, this vast area was selected.

2.2 Satellite dataset

The MODIS spectrometer with its 36 bands is operational on both Terra (10:30 A.M./10:30 P.M.) and Aqua (1:30 A.M./1:30 P.M.) spacecrafts. The MODIS data used in this study are the daily (ascending) MODIS/Aqua 1 km resolution acquired on 17 June 2018. Only day time MODIS data have been used in this study, because the ground soil moisture data have been collected around Noon and are more likely to be true at 1:30 pm than at 1:30 am.

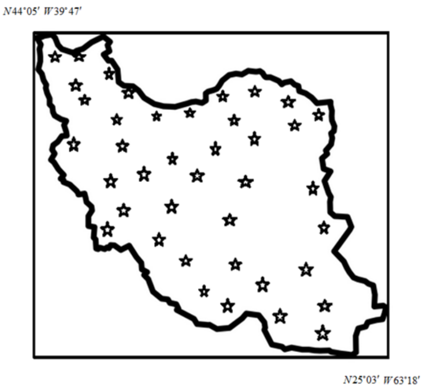


Figure 1. General location of the study region together with 40 ground sites in the IRAN

The useful characteristics of this sensor are mainly near real time data availability, 1 km spatial resolution, and overpass time compatibility required for soil moisture classification.

2.3 Ground truth datasets

The ground observed volumetric soil moisture (VSM), LST and height data sets collected on 15, 16, and 17 June 2018 have been used in this study. These data have been gathered in 40 sites all over IRAN. The VSM and LST measured in 0 to 6 cm and 0 to 1 cm depth, respectively.

3. Methodology

3.1. Fuzzy-based Feature selection

In general, methods for feature selection are divided into three categories, including filter, wrapper and embedded. According to Equation (1), a heuristic can be defined to determine the merit of a feature subset, includes k features ([13]).

$$Merits = \frac{k\overline{r_{cf}}}{\sqrt{k + k(k-1)\overline{r_{ff}}}} \tag{1}$$

Where $\overline{r_{cf}}$ is the mean correlation of feature-class and $\overline{r_{ff}}$ is the mean correlation of feature-feature. In equation (1), correlation is critical in determining the merit of a subset.

On the other hand, fuzzy logic generalization of standard logic, in which a concept can possess a degree of truth anywhere between 0.0 and 1.0. By the introducing of fuzzy logic, it was prepared to be useful in various field ([20]; [3]). It turns out that it is useful in machine learning and in this study, is used to feature selection. Considering the triangular membership function, fuzzy number is calculated based on Equation (2).

$$A(x) = \begin{cases} 0 & x \le a \;\; or \;\; x \ge b \\ \dfrac{x-a}{m-a} & a \le x \le m \\ \dfrac{b-x}{b-m} & m \le x \le b \end{cases} \tag{2}$$

In Equation (2), as shown in figure 2, a is lower boundary, b is upper boundary and m is middle boundary.

Extension principle is one of the basic ideas that induces the extension of non-fuzzy mathematical concepts into fuzzy ones. The Extension principle for a function $f: X \rightarrow Z$ indicates how the image of a fuzzy subset A of X should be computed when the function f is applied. It is expected that this image will be a fuzzy subset of Z. More details about the extension principle can be found in the report provided by de barros et al. (2017).

Now, considering the extension principle and integration of Equations (1) and (2), Equation (3) is obtained.

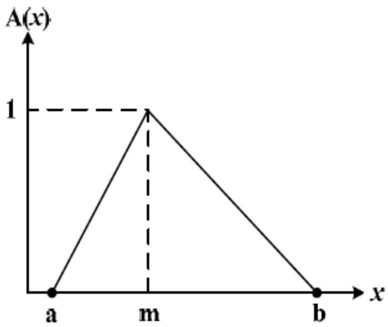


Figure 2. Triangular fuzzy number

$$\mu(M)=\begin{cases}0 & M\le M_1 \ or\ M\ge M_2\\ \dfrac{\dfrac{M^2(1-\overline{r_{ff}})}{\overline{r_{cf}}^{\,2}-M^2\overline{r_{ff}}}-\alpha}{m-\alpha} & M_1\le M\le M_3\\ \dfrac{\beta-\dfrac{M^2(1-\overline{r_{ff}})}{\overline{r_{cf}}^{\,2}-M^2\overline{r_{ff}}}}{\beta-m} & M_3\le M\le M_2\end{cases} \tag{3}$$

where M_1, M_2 and M_3 are merit values of subsets with lowest, highest and m number of features respectively and calculated using Equation (4) to (6).

$$M1=\overline{r_{cf}}\sqrt{\frac{\alpha}{1+(\alpha-1)\overline{r_{ff}}}} \tag{4}$$

$$M_2=\overline{r_{cf}}\sqrt{\frac{\beta}{1+(\beta-1)\overline{r_{ff}}}} \tag{5}$$

$$M_3=\overline{r_{cf}}\sqrt{\frac{m}{1+(m-1)\overline{r_{ff}}}} \tag{6}$$

Class-feature and feature-feature correlations are calculated using the training dataset. In this equation m controls the number of selected features, so that α and β are the least and the most features. Figure 3 shows the different forms of triangular membership function relative to different values of m.

Since M1 and M2 are fixed, in order to perform the defuzzification and determine the output, the value of M_3 considered as merit of each subset. Therefore, by changing the number of features, different merit values can be obtained.

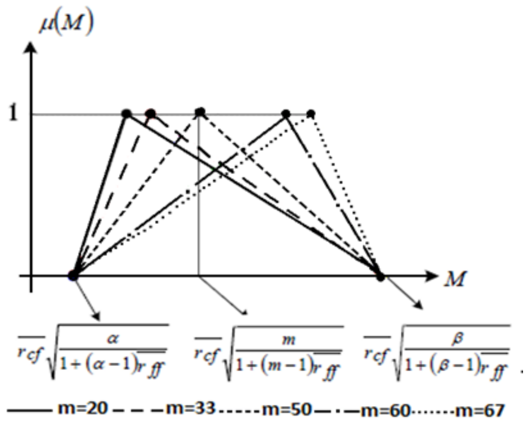


Figure 3. Triangular membership function with different values of m.

4. Implementation

The method of work is that, firstly α and β considered to be 1 and the highest number of features. In this way, by changing the number of features (controlled by m) there will be different values of merit. Then, the correlation matrix can be formed using these merit values. Eventually, using the genetic algorithm and defining a fitness function, an optimal subset of features can be selected. It is worth notice that in fitness function, the fewer features and higher merit result in more fitness value. Two scenarios have been considered for selecting the features. These features are used as input of mentioned classifiers. 1) Feature selection using the fuzzy-based proposed method. 2) Select the NDVI, LST and Height as features. Because vegetation characteristics, temperature of the soil and topography are the main factors affecting the soil moisture content especially in the soil-vegetation medium, these three features have been selected among others in the second scenario ([22]).

4.1. Classification

The training speeds of the applied classifiers were affected by many factors, including numbers of training samples and input variables, noise level in the training data set, as well as algorithm parameter setting. This is especially the case for the SVM and ANN. Many studies have demonstrated that the training speed of ANN depends on network structure, momentum rate, learning rate and converging criteria ([26]). The training of the SVM was affected by training data size, kernel parameter setting and class separate ability. Furthermore, polynomial kernels, especially high-order kernels, took far more time to train than RBF kernels. In this study, among 40 observed ground soil moisture sites, 27 sites have been selected as control points, have been used for training, and the rest have been used as check points, have been used for accuracy assessment. Regarding the potential of the proposed algorithm, all sites with various vegetation densities and soil moisture content, have been selected for training and validation purposes. Due to the impact of training sample size and selection method on better performance of classifiers ([12]), these point have been respected in training samples selection. Because the SVM originally separate the binary classes with the maximized margin criterion, the multi class classification problems are commonly decomposed into a serious of binary problems such that the standard SVM can be directly applied. Two representative ensemble schemes are one versus rest and one versus one approaches ([36]; [18]). Here, the scheme of one versus one has been used. For further clarification, the flowchart of the steps taken in this study is presented in Figure 4.

4.2. Results and discussion

In order to obtain an estimate of overall accuracy of the soil moisture classifications according to the two scenarios, it is necessary to use check points which have been excluded from the training procedure. SVM uses kernel functions to map non-linear decision boundaries in the original data space into linear ones in a high-dimensional space. Results from different experiment showed that kernel type and kernel parameter affect the shape of the decision boundaries as located by the SVM and thus influence the performance of the SVM ([12]). Due to directly interpretable, overall accuracy was selected as the primary criterion in this assessment ([14]; [34]). The overall accuracies of classification using 10 selected features are shown in figure 5. Table 1 provides the different values of overall accuracy based on the number of selected features. Several patterns can be observed from figure 5 to 7 and table 1, as follows:

-Because, the SVM is designed to locate an optimal separating hyperplane, it was more accurate than ANN and it gave significantly higher accuracy.

- For polynomial kernels, when the input data have very few features, higher order polynomial kernels were demanded. While the number of input features were sufficient, further increases in polynomial order had little impact on accuracy.

- For RBF kernels the accuracy increased slightly when c increased. However, previous studies have revealed that misclassification error is a function of c ([12]).

- A comparison between figure 6 and figure 7 reveals that the performance of the RBF kernel is less affected by c than that of the polynomial kernel by *p*.

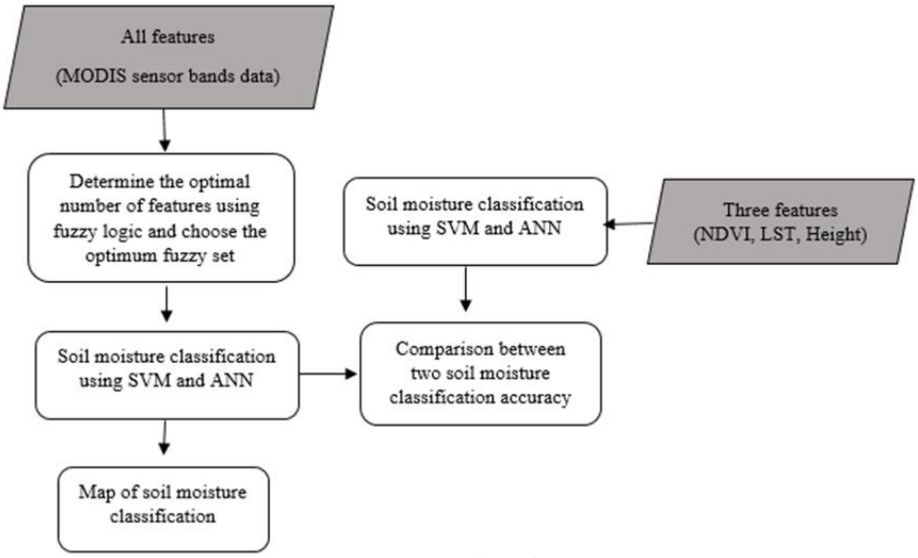


Figure 4. The graphical presentation of the of the steps taken in this study

Confusion Matrix of Artificial Neural Network

class	Wet	Semi-wet	Dry	accuracy
Wet	2 15.4%	0 0.0%	0 0.0%	100% 0.0%
Semi-wet	1 7.7%	4 30.75%	0 0.0%	80% 20%
Dry	0 0.0%	1 7.7%	5 38.45 %	83.3% 16.7%
Accuracy Error	66.7% 33.3%	80% 20%	100% 0.0%	84.6% 15.4%

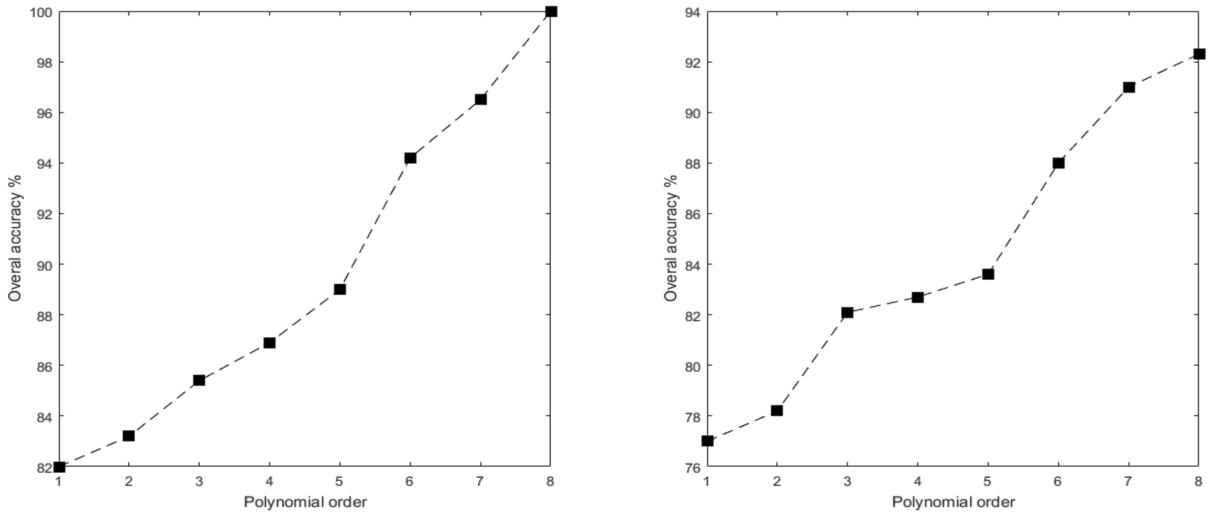
Confusion Matrix of SVM (RBF kernel)

class	Wet	Semi-wet	Dry	accuracy
Wet	2 15.4%	0 0.0%	0 0.0%	100% 0.0%
Semi-wet	0 0.0%	5 38.45%	0 0.0%	100% 0.0%
Dry	0 0.0%	1 7.7%	5 38.45%	83.3% 16.7%
Accuracy Error	100% 0.0%	83.3% 16.7%	100% 0.0%	92.3% 7.7%

Confusion Matrix of SVM (Polynomial kernel)

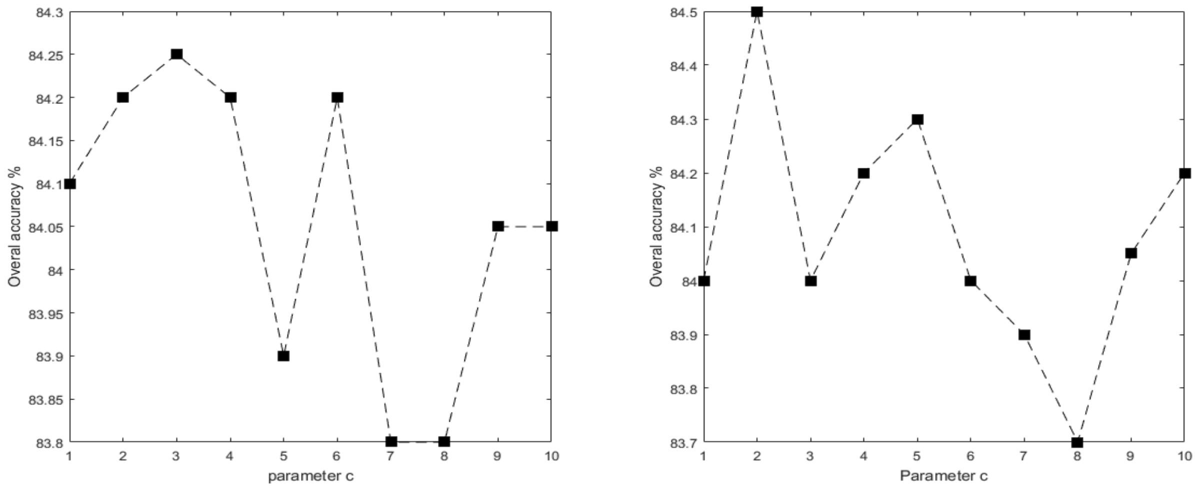
class	Wet	Semi-wet	Dry	accuracy
Wet	2 15.4%	0 0.0%	0 0.0%	100% 0.0%
Semi-wet	0 0.0%	5 38.45%	0 0.0%	100% 0.0%
Dry	0 0.0%	0 0.0%	6 46.15%	100% 0.0%
Accuracy Error	100% 0.0%	100% 0.0%	100% 0.0%	100% 0.0%

Figure 5. Overall accuracies of classifications using 10 selected features



(a) (b)

Figure 6. Performance of polynomial kernels as a function of polynomial order. (a) 10 features extracted using proposed feature selection method, (b) 3 proven features



(a) (b)

Figure 7. Performance of RBF kernels as a function of parameter c. (a) 10 features extracted using proposed feature selection method, (b) 3 proven features.

Table 1: Different values of overall accuracy based on the number of selected features.

Overall accuracy (%)			Number of features (m)
SVM (RBF kernel)	SVM (Polynomial kernel)	Neural Network (MLP)	
84.6	100	84.6	5
92.3	100	84.6	10
92.3	100	76.9	15
92.3	92.3	76.6	20
84.6	76.9	76.9	25

According to the second scenario, the same two classifiers have been applied while the three proven features i.e. NDVI and LST and Height have been used. The overall accuracies of classification using second scenario are shown in figure 8. In this case, the overall accuracies of the SVM with RBF kernel were slightly lower than those of ANN. The lower accuracies of SVM with RBF kernel than ANN on three features are probably due to the inability of the SVM to transform non-linear class boundaries in the original space into linear ones in a high-dimensional space ([2]). In order to quantitative measurement of relative stability, the variations of the overall accuracies of the classifiers have been shown in figure 9.

This figure reveals that the stabilities of the algorithms differed greatly and were affected by number of input variables. In general, the overall accuracies of the algorithms were more stable when 10 features were used.

The SVM with polynomial kernel gave more stable overall accuracies than the others, especially when trained using with 10 variables. But when trained using three features, it gave overall accuracies in a wider range in both RBF and Polynomial kernels. The proposed method for feature selection has provided new insights into the fuzzy logic application in addition to the reliable, and acceptable soil moisture classification accuracies. It should be noted that there are some differences between satellite-derived parameters with the ground observations that should be considered in accuracy assessment.

The main differences are follows: 1) difference in the nature of observation (i.e. the ground data are point measurements whereas the satellite derived soil parameters are spatial average over the ground pixel) and 2) difference in depth measurement. First, the sensing depth of ground observation soil moisture data is ~6 cm, whereas for the MODIS thermal infrared band is ~1 mm. Note that the thermal regime of 0–5 cm and of 0–1 mm (skin) are likely to be quite different ([27]).

Confusion Matrix of Artificial Neural Network

class	Wet	Semi-wet	Dry	accuracy
Wet	2 15.4%	0 0.0%	0 0.0%	100% 0.0%
Semi-wet	1 7.7%	4 30.75%	0 0.0%	80% 20%
Dry	0 0.0%	1 7.7%	5 38.45 %	83.3% 16.7%
Accuracy Error	66.7% 33.3%	80% 20%	100% 0.0%	84.6% 15.4%

Confusion Matrix of SVM (RBF kernel)

class	Wet	Semi-wet	Dry	accuracy
Wet	2 15.4%	0 0.0%	1 7.7%	66.7% 33.3%
Semi-wet	0 0.0%	4 30.75%	1 7.7%	80% 20%
Dry	0 0.0%	1 7.7%	4 30.75%	80% 20%
Accuracy Error	100% 0.0%	80% 20%	66.7% 33.3%	76.9% 23.1%

Confusion Matrix of SVM (Polynomial kernel)

class	Wet	Semi-wet	Dry	accuracy
Wet	2 15.4%	0 0.0%	0 0.0%	100% 0.0%
Semi-wet	0 0.0%	5 38.45%	1 7.7%	83.3% 16.7%
Dry	0 0.0%	0 0.0%	5 38.45%	100% 0.0%
Accuracy Error	100% 0.0%	100% 0.0%	83.3% 16.7%	92.3% 7.7%

Figure 8. Overall accuracies of classification using second scenario based on three features

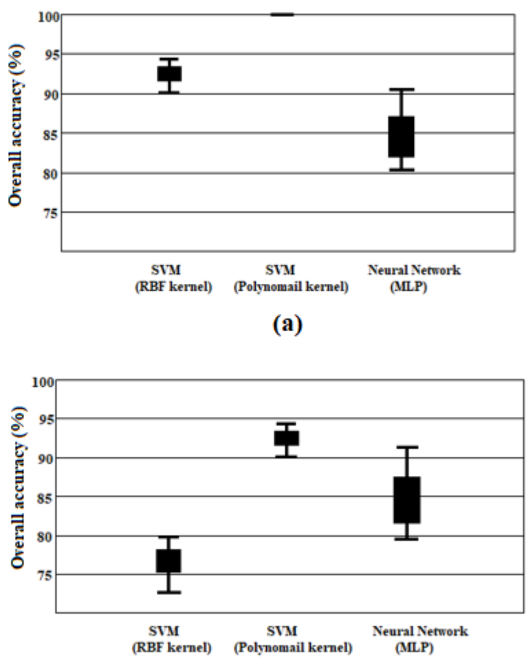


Figure 9. Boxplots of the overall accuracies of classifications developed using ten sets of training samples randomly selected (a). 10 features. (b) three features

in order to better understanding the results, the map of soil moisture classification based on SVM with polynomial kernel is presented in figure 10.

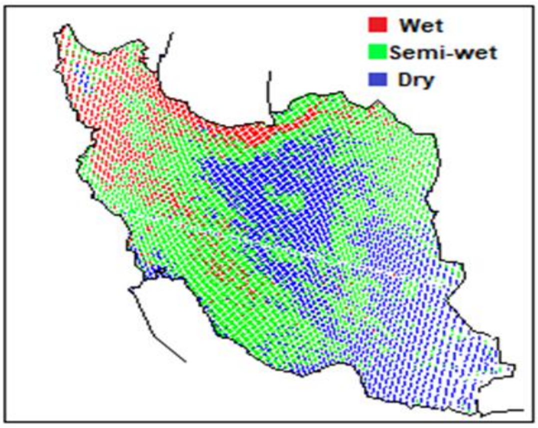


Figure 10. Soil moisture map based on the SVM (Polynomial Kernel) model June 17, 2018

5. Conclusion

In this study a method for feature selection based on correlation, using the extension principle, was proposed. Monitoring the number of selected features is one of the most important advantages of this method.

After selecting the optimal features, SVM and MLP neural network classifiers have been used to classify the soil moisture content. Furthermore, as a second scenario, the same two classifiers were applied while the proven features (NDVI, LST, Height) were used. Doing this step is in order to demonstrate the capability of the proposed feature selection method.

As it was expected, the first scenario presents better accuracy in soil moisture classification using SVM with RBF and polynomial kernels. Because, the SVM is designed to locate an optimal separating hyperplane, it was more accurate than ANN and it gave significantly higher accuracy.

On the other hand, while the same two classifiers have been applied according to the second scenario, the overall accuracies of the classification using SVM with RBF kernel were the lowest. This can be due to the inability of the SVM to transform non-linear class boundaries in the original space into linear ones in a high-dimensional space.

In all, a large and fruitful effort has been performed on various feature selection and classifier systems during the last years. Concisely, an intelligent method of feature selection, instead of selection based on the physical concepts and theories, was investigated in this study. Furthermore, intelligent methods were used to classify soil moisture, while in most of the previous studies, the content of soil moisture has been estimated by theoretical models.

According to the results, the proposed feature selection method achieved about 8 percent improvement on soil moisture classification accuracy using the proposed feature selection method.

Hence, superior performance of intelligent fuzzy-based feature selection is in its meaningful improvement on soil moisture classification accuracy in comparison with the second scenario

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