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Research paper

Optimum Spectral Indices for Water Bodies Recognition Based on Genetic Algorithm and Sentinel-2 Satellite Images

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Abstract

Background and Objectives: Considering the drought and global warming, it is very important to monitor changes in water bodies for surface water management and preserve water resources in the natural ecosystem. For this purpose, using the appropriate spectral indices has high capabilities to distinguish surface water bodies from other land covers. This research has a special consideration to the effect of different types of land covers around water bodies. For this reason, two different water bodies, lake and wetland, have been used to evaluate the implementation results.
Methods: The main objective of this research is to evaluate the capabilities of the genetic algorithm in optimum selection of the spectral indices extracted from Sentinel-2 satellite image due to distinguish surface water bodies in two case studies: 1) the pure water behind the Karkheh dam and 2) the Shadegan wetland having water mixed with vegetation. In this regard, the set of optimal indices is obtained with the genetic algorithm followed by the support vector machine (SVM) classifier.
Results: The evaluation of the classification results based on the optimum selected spectral indices showed that the overall accuracy and Kappa coefficient of the recognized surface water bodies are 98.18 and 0.9827 in the Karkheh dam and 98.04 and 0.93 in Shadegan wetland, respectively. Evaluation of each of the spectral indices measured in both study areas was carried out using quantitative decision tree (DT) classifier. The best obtained DT classification results show the improvements in overall accuracy by 1.42% in the Karkheh Dam area and 1.56% in the Shadegan Wetland area based on the optimum selected indices by genetic algorithm followed by SVM classifier. Moreover, the obtained classification results are superior compared with Random Forest classifier using the optimized set of spectral features.
Conclusion: Applying the genetic algorithm on the spectral indices was able to obtain two optimal sets of effective indices that have the highest amount of accuracy in classifying water bodies from other land cover objects in the study areas. Considering the collective performance, genetic algorithm selects an optimal set of indices that can detect water bodies more accurately than any single index.

Introduction

Surface water bodies those are usually the sources of fresh water, have very important role in both human life and environmental protection [1]. The water supplies help to maintain biodiversity in water and wetland ecosystems. This is not only vital for ecosystems as a key component of the hydrological cycle, but also related to every aspect of human life such as drinking water, agriculture, electricity generation, transportation and industrial purposes. Changes in the characteristics of surface water bodies may lead to the occurrence of severe disasters such as floods, droughts and even the spread of water-related diseases, all of which have consequences for the safety of human life and property, [2], [3].

In order to reach the spatial distribution and expansion of geographic information, it is necessary to accurately recognize the surface water bodies based on satellite remote sensing data [4]-[8]. One of the most widely used remote sensing data analysis for detecting surface water bodies are the methods based on using spectral indices that identify water bodies based on water absorption bands in different wavelengths of the electromagnetic spectrum [9]-[16]. The results of surface water bodies recognition based on remote sensing data are important in various scientific fields, including research in the evaluation of existing and future climate models, agriculture, river dynamics, wetland studies, watershed analysis, flood mapping and environmental monitoring.

In a research conducted by Emami et al, four different water indices including the WRI (water ratio index), AWEI (automatic water extraction index), NDWI (normalized difference water index) and NDVI (normalized difference vegetation index) are used to reveal and evaluate the spatial-temporal changes in the water level of Uremia lake in the time period 2002 to 2016 and based on the Landsat satellite images [16]. The water ratio index is defined according to the spectral reflectance of water in the green and red bands in comparison with near-infrared and middle infrared regions. Values greater than one of this index are considered as water pixels. The automatic water extraction index is one of the indices that are mostly used for the extraction of water bodies in urban areas. This index is used to remove dark pixels and identify water surfaces with high accuracy in urban and mountain areas where the shadow problem prevents correct identification [16]. The normalized difference water index is sensitive to water changes. This index is calculated using near-infrared and short-wavelength infrared reflections. The range of changes of this index is between -1 and +1 and water has positive values [9], [17], [18]. The normalized difference vegetation index is defined by the amount of reflective energy in the red and near-infrared bands and has values between -1 and +1 [19]. In this index, water, snow and ice have negative values. One of the major errors affecting the values of this index is clouds and atmospheric pollution such as smoke, fog and dust, which increase or decrease the values of this index. Obviously, the absorption of infrared rays by water and its intense reflection by vegetation and soil provides an ideal combination of these bands for extracting water bodies. In 2018, Haung et al. investigated some water-related indices in the Poyang Lake region of China [20]. In this study, while examining different types of water indices, it was concluded that the improved normalized difference water index MNDWI is more reliable than the NDWI. Because, this index uses the SWIR spectral band and is less sensitive than NIR band to the density of sediments and other optically active components in water [20].

Thresholding is one of the most important methods in using spectral indices for water extraction. Based on the reflectance characteristics of water, the values of NDWI and MNDWI for water are usually greater than zero. Therefore, zero is often used to as threshold for extracting water from spectral index images. However, by fine-tuning the threshold values, better extraction results can usually be achieved [21].

In 2013, Fisher et al. investigated water indices extracted from SPOT-5 satellite images over the New South Wales region of Australia. These indices included three different types of normalized differences water index named $NDWI_{gao}$, $NDWI_{xu}$ and $NDWI_{McFeeters}$. In this research, by calculating the normalized differences between two bands and then applying a threshold, several different water indices are produced and their performance for the classification of water bodies in remote sensing images have been investigated. The $NDWI_{McFeeters}$ index consists of the combination of green and near-infrared bands, the $NDWI_{gao}$ index consists of the combination of near-infrared and short-wave infrared, and the $NDWI_{xu}$ index consists of the combination of green and short-wave infrared bands. The results of investigating the performance of these three indices in a coastal image containing abundant water areas showed that the $NDWI_{McFeeters}$ separates water and non-water effects well and has a strong negative value in vegetation, while the values of this index in water areas is greater than zero. Water values are higher in the $NDWI_{xu}$, although the vegetation response also has large values. The $NDWI_{gao}$ provides a very poor separation of water and non-water, and both vegetation and water have large positives [22].

Meta-heuristic methods such as genetic algorithm or SWARM intelligence algorithms are also successfully used in some research for optimum selection of features or image bands [23]-[25]. In the research conducted in this paper, instead of comparing the limited amount of spectral water indices, genetic algorithm is used for optimum selection from a large set of spectral indices. The main contributions of this research are as following:

- Evaluating the capabilities of genetic algorithm for optimum selection of water indices.
- Considering the impact of various land covers (especially vegetation) in water body recognition by

using two types of study areas with different characteristics.

- Discussing the relationships between the type of features selected by the genetic algorithm and the difference in land covers around each of the study areas.
- Comparing the efficiency results of each individual water index and optimum set of indices selected by genetic algorithm in water body recognition.

Materials and Method

One of the important issues related to the surface water bodies detection is the use of optimal indices in the detection and separation of water from other land covers. Karkheh dam with geographical location (21°29’32” N, 36°07’48” E) and Shadegan wetland with geographical location (58°38’30” N, 52°39’48”E) in Khuzestan province are two samples of surface water bodies those are considered as the study areas of this research. Karkheh dam is one of the largest dams in the world and is the largest dam in the Middle East, which was built on the Karkheh River in Andimshek city of Khuzestan province. The Karkheh River is the third largest river in Iran after the Karun and Dez rivers from the water supply point of view.

Shadegan international wetland is one of the large wetlands, which is located in the southwest of Iran and in the south of Shadegan city in Khuzestan province. The dams construction, not enough water supply of the wetland, the discharge of polluted effluents such as sugarcane fields, fish farming in Khuzestan, the passage of oil pipelines and the activity of 30 petrochemical units have included this unique wetland in the red list of international wetlands since 1993.

The water of this international wetland is supplied from the rivers of Jarahi and Karun, as well as the tides of the Persian Gulf, which, despite the fact that its fresh water part is seasonal; the salt water of this wetland is permanent.

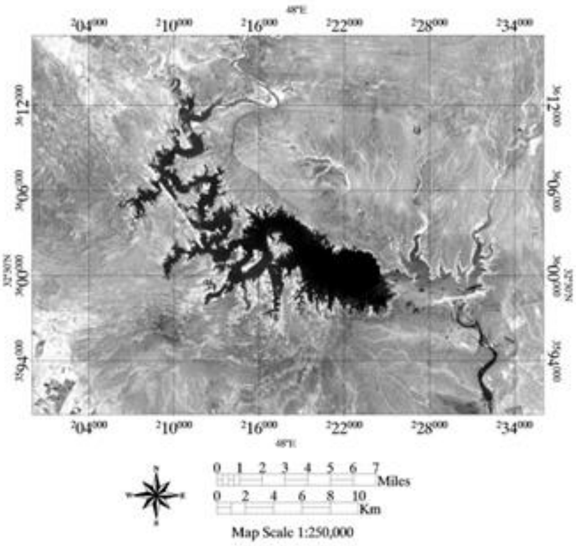
In this research, images those are taken by the medium spatial resolution Sentinel-2 satellite sensor have been used. The capabilities of this satellite sensor are the multi-spectral imaging using 13 spectral bands in the visible and infrared ranges. This satellite has regular global coverage and also covers the coastal waters and the entire Mediterranean Sea.

Two Sentinel-2 satellite images from the study areas of Karkheh Dam and Shadegan wetland on December 2020 were used in this study.

An attempt was made to use images with the right weather conditions, without dust or cloud covers. Sentinel-2 images from the study areas of this research are shown in Fig. 1.

As shown in Fig. 2, the proposed method in this research in the first stage consists of performing pre-processing (atmospheric correction, normalization and cropping) on Sentinel-2 satellite images obtained from the study areas.

(a)



(b)

Fig. 1: Sentinel-2 satellite image of a) Shadegan wetland, b) Karkheh Dam.

In the second stage, after measuring the large set of spectral indices related to the surface water bodies, the genetic algorithm followed by the support vector machine classifier is applied for determining the optimal set of spectral indices for surface water detection. In parallel, the decision tree classifier is performed in order to evaluate the capability of each spectral index and comparing it with the optimization results.

A. Spectral Water Indices

According to the research background, the names and definitions of the spectral indices used in the detection and classification of surface water bodies from remote sensing images are mentioned in this section and the mathematical formulas of these indices are also presented in Table 1 [26], [27].

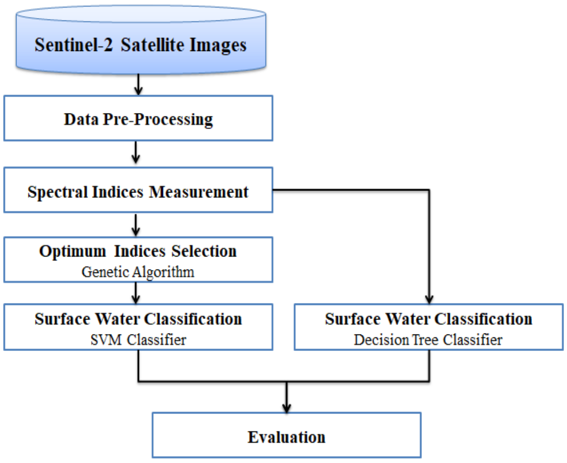


Fig. 2: Proposed method for surface water bodies classification.

- NDWI is the normalized difference water index for distinguishing water areas with little vegetation.
- MNDWI is the modified normalized difference water index.
- AWEIsh is automatic water extraction index shadow which is used for water extraction in urban areas.
- AWEInsh is automatic water extraction index no-shadow which is used more often in urban areas with fewer shadows.
- WRI is the water ratio index which is the ratio between total reflection of red and green bands to middle and near infrared bands.
- NDVI is the normalized difference vegetation index as the most widely used vegetation index, which is also used to identify water areas.
- NDMI is the normalized difference moisture index which is used to determine the soil moisture.
- NDPI is the normalized difference index of water ponds which is used to identify water areas in wetlands.
- TCW is wet index used to determine pixels with high humidity.
- WI2015 is the developed water index, which is one of the useful indices in determining water covers due to its high accuracy.
- NDSI is the normalized difference snow index which is used to identify snow covers from other water bodies.
- NDTI is the normalize difference turbidity index which is estimated using the spectral reflectance values of the water pixels to estimate the turbidity in water bodies.
- SWI is simple water index which expresses the simple relationship between blue and mid-infrared band reflections.

Table 1: Name and mathematical formulas of the utilized spectral indices in the paper

Index	Mathematical Formula	Index	Mathematical Formula
NDWI	(Green-NIR)/(Green+NIR)	TCW	0.1511NIR × BLUE - 0.7117 + 0.1973 × SWIR1 × GREEN - 0.4559 + 0.3283 × SWIR2 × RED
MNDWI	(Green-MIR)/(Green+MIR)	TCW2	0.0315×Bblue+0.1973×Bgreen+0.3279×Bred+0.3406×Bnir-0.7112×Bswir1-0.4572×Bswir2
AWEIsh	Blue+2.5×Green-1.5×(NIR+SWIR1)-0.25× SWIR2	NDWI (Blue)	(Blue-NIR)/(Blue+NIR)
AWEInsh	4×(Green-SWIR1)-(0.25×NIR+2.75×SWIR2)	NDWI (Red)	(Red-NIR)/(Red+NIR)
WRI	(Green+Red)/(NIR+SWIR1)	WI2015	1.7204 + 171(GREEN) + 3(RED) + 70(NIR) + 45(SWIR1) + 71(SWIR2)
MNDWI (Red)	(Red-MIR)/(Red+MIR)	GNDVI	(NIR-Green)/(NIR+Green)
MNDWI (Blue)	(Blue -MIR)/(Blue +MIR)	NDSI	(Green-SWIR)/(Green+SWIR)
NDVI	(NIR-Red)/(NIR+Red)	NDTI	(Red-Green)/(Red+Green)
NDMI	(NIR - SWIR)/(NIR + SWIR)	SWI	$1/\sqrt{(Blue - SWIR1)}$
NDPI	(SWIR - GREEN)/(SWIR + GREEN)		

B. Optimum Indices Selection

Feature selection methods have become an integral component of the machine learning processes for dealing with high-dimensional data. The selection of optimal features can be defined as the process of identifying relevant features that is able to obtain an optimal subset for well describing the problem and with minimal loss of efficiency [23]-[30]. Genetic algorithm uses Darwin's principles of natural selection to find the optimal way to predict or match the pattern. Genetic Algorithm is an evolutionary algorithm in which it is inspired by biology such as inheritance, mutation, natural selection and combination. Evolution starts from a completely random set of entities and is repeated in the next generations, and in each generation, the most appropriate solutions of the problem are selected.

The genetic algorithm was used in this research as the feature selection method in order to determine the optimal set of spectral indices for surface water bodies' detection and classification. As this algorithm works better for large set of features, in addition to the 19 spectral indices listed in Table 1, the spectral bands of Sentinel-2 satellite images were also used as features. Moreover, the support vector machine classifier was used as a cost function to evaluate the selected set of indices by the genetic algorithm for selecting the optimal set.

C. Evaluation by Decision Tree Classifier

The results of applying the SVM classifier on the optimal indices obtained from the genetic algorithm for detecting surface water bodies are compared with the results of applying the decision tree (DT) classifier for each individual spectral index in Table 1 in order to validate the optimization. The decision tree classifier places each pixel in a class by performing multi-stage classification using a series of binary decisions. The result of these successive decisions is a set of object classes. In this research, DT classifier has been used to classify pixels of each spectral index images into water or non-water land cover classes.

Results and Discussion

The pre-processing performed on satellite images in this research includes atmospheric corrections, normalization and cropping of images. QUick Atmospheric Correction (QUAC) algorithm is used for atmospheric correction of satellite images in ENVI software. This algorithm is suitable for correcting images with lack of the atmospheric and terrestrial samples. In this method, correction is done only by using several spectral bands and their wavelengths, and the image is corrected without providing additional information. Compared to other methods such as FLAASH, which are heavily affected by sensors' noise, the QUAC algorithm performs the correction process without affecting by the sensors' noise, and it also has very high speed.

The next pre-processing step is normalization in which, all data are placed between zero and one to have the same impact in performing measurements. Considering that the spectral indices are measured based on satellite images, the data should be normalized so that they are in the same range and very large or small values do not have a negative impact on the indices. After applying the pre-processing on the images those are taken from both study areas of Karkheh Dam and Shadegan wetland, all spectral indices are measured based on the formulas in Table 1. Then, the genetic algorithm is applied to determine the optimal set of these spectral indices. In order to improve the efficiency of the genetic algorithm, in addition to 19 indices in Table 1, 10 spectral bands of Sentinel-2 images were also added to the collection as individual spectral indices. These 10 spectral bands composed of three visible bands (B2, B3, B4), five NIR bands (B5, B6, B7, B8 and B8a) and two SWIR bands (B11 and B12).

The parameters setting of the Genetic algorithm are as follows: size of population=40, keeping rate=0.7, mutation probabilities=0.2 and maximum number of iterations=300. Table 2 shows the optimum set of spectral indices selected by the genetic algorithm based on SVM classification in each of the study areas of Karkheh Dam and Shadegan Wetland.

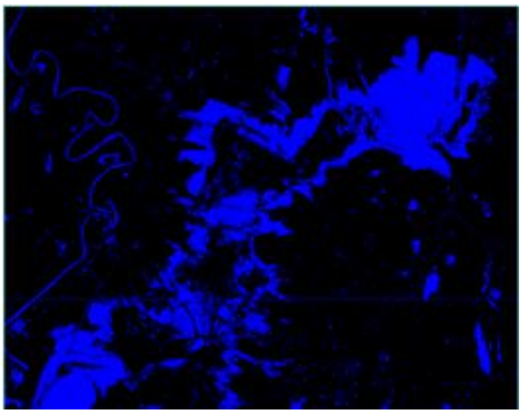
Table 2: Optimum spectral indices selected by genetic algorithm followed by SVM classifier

Study Area	Optimum Set of Indices			
Karkheh Dam	NDPI	MNDWI (Red)	AWEInsh	Band RedEdge3
Shadegan Wetland	NDPI	MNDWI	AWEIsh	SWI

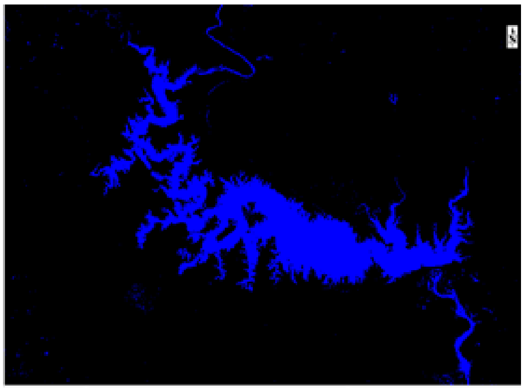
Fig. 3 shows the results of applying the SVM classifier using the optimum spectral indices selected by the genetic algorithm in both study areas.

In general, water absorbs the electromagnetic spectrum, and the reflection from the surface water bodies is insignificant compared to other land covers. The highest reflection from water bodies occurs in the blue band range, and the water's reflection reaches zero in the middle IR range of the electromagnetic spectrum. However, plants have the most absorption in the red band and the most reflection in the near infrared band.

According to the aforementioned interpretation of the spectral behavior of water and vegetation cover, the presence of Red, Red Edge, NIR and MIR bands in the formulas of the optimum indices selected by the genetic algorithm in the Karkheh dam area, which has relatively pure water, can be reasonable.



(a)



(b)

Fig. 3: SVM classification results using optimum indices in a) Shadegan wetland, b) Karkheh Dam.

These indices are able to detect and remove vegetation, soil and other land covers to identify pure surface water bodies.

But in the Shadegan wetland study area, surface water bodies are mixed with vegetation. Thus, the optimum selected indices by the genetic algorithm in this area have the blue band in their formulas, which has the highest reflection from the surface water.

As mentioned in the description of spectral indices, the AWEIsh index is suitable for use in areas with shadow effects. Considering that Shadegan wetland study area has water mixed with vegetation, the AWEIsh index has a better performance in this area due to its ability to detect water bodies from plants' shadows.

To evaluate the performance of the genetic algorithm in selecting the optimal set of spectral indices, the result of applying the SVM classifier on the optimal indices are compared with the results of applying the decision tree classifier on each individual index. Table 3 shows the overall accuracy and Kappa coefficient of the obtained results from applying decision tree classifier on each of the spectral indices in both study areas.

As it is depicted in Table 3, the highest accuracy of the decision tree classifier has been obtained in the Karkheh dam study area using the AWEInsh, NDWI and TCW2 spectral indices and in the Shadegan wetland study area using the AWEIsh, NDWI and GNDVI spectral indices.

The most obtained DT classification accuracy is 96.76% (by AWEInsh) in Karkheh dam and 96.48% (by AWEIsh) in Shadegan wetland, respectively. However, the SVM classifier based on the optimal set of selected indices (see Table 2) by the genetic algorithm has a higher overall accuracies and Kappa coefficients in both study areas.

For visual evaluation, the results of applying the DT classifier on each of the AWEInsh, NDWI and TCW2 spectral indices in the Karkheh Dam area (Fig. 4) and the AWEIsh, NDWI and GNDVI spectral indices in the Shadegan Wetland area (Fig. 5) have been compared with some other spectral indices.

In Fig. 6, the accuracy of the SVM classification results based on the optimal indices of the genetic algorithm is compared with the results of applying the decision tree classifier using AWEInsh in the Karkheh dam area and AWEIsh in the Shadegan wetland area.

Table 3: DT classification results of the individual spectral indices

Spectral Index	Study Areas			
	Karkheh Dam		Shadegan Wetland	
	Overall Accuracy (%)	Kappa	Overall Accuracy (%)	Kappa
WRI	90.51	0.87	93.60	0.87
WI2015	91.90	0.89	93.18	0.82
TCW2	**96.12**	**0.95**	84.26	0.56
TCW	91.24	0.88	91.47	0.72
SWI	94.27	0.89	95.77	0.91
NDWI	**96.72**	**0.95**	**96.26**	**0.91**
NDWI (RED)	89.04	0.76	93.61	0.79
NDWI (Blue)	92.66	0.88	93.66	0.85
NDVI	89.04	0.76	92.61	0.79
NDTI	92.60	0.89	87.68	0.95
NDSI	92.93	0.89	91.57	0.87
NDPI	95.70	0.92	95.57	0.85
NDMI	69.77	0.27	72.77	0.35
MNDWI	95.93	0.93	94.57	0.86
MNDWI (RED)	92.39	0.84	95.47	0.89
MNDWI (Blue)	93.33	0.90	95.14	0.89
GNDVI	90.88	0.82	**96.32**	**0.91**
AWEIsh	92.05	0.84	**96.48**	**0,90**
AWEInsh	**96.76**	**0.95**	82.31	0.52

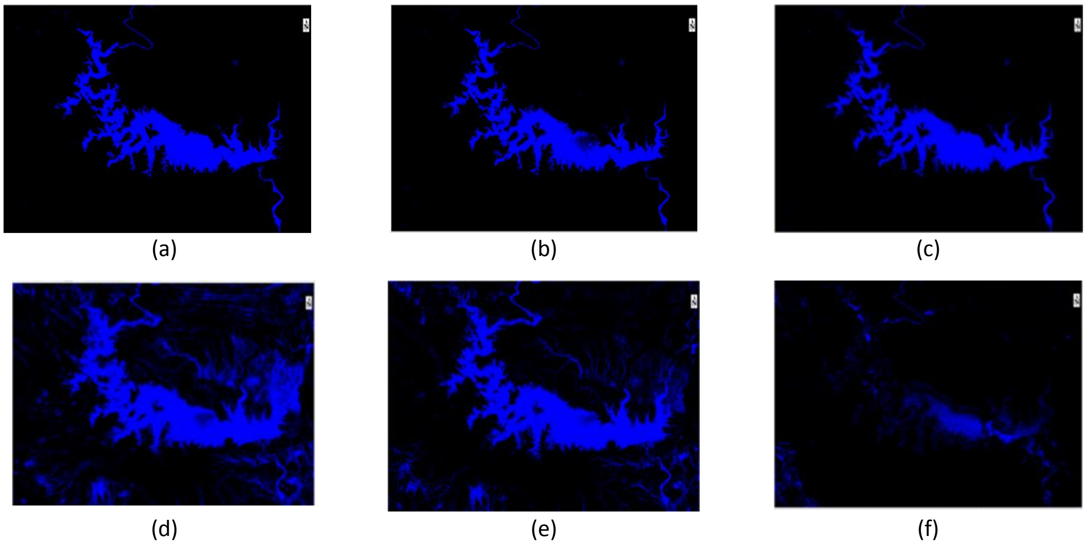


Fig. 4: Visual evaluation between the best decision tree classification results of Karkheh Dam by a) AWEInsh, b) NDWI and c) TCW2 indices compared with d) GNDVI, e) AWEIsh and f) NDMI.

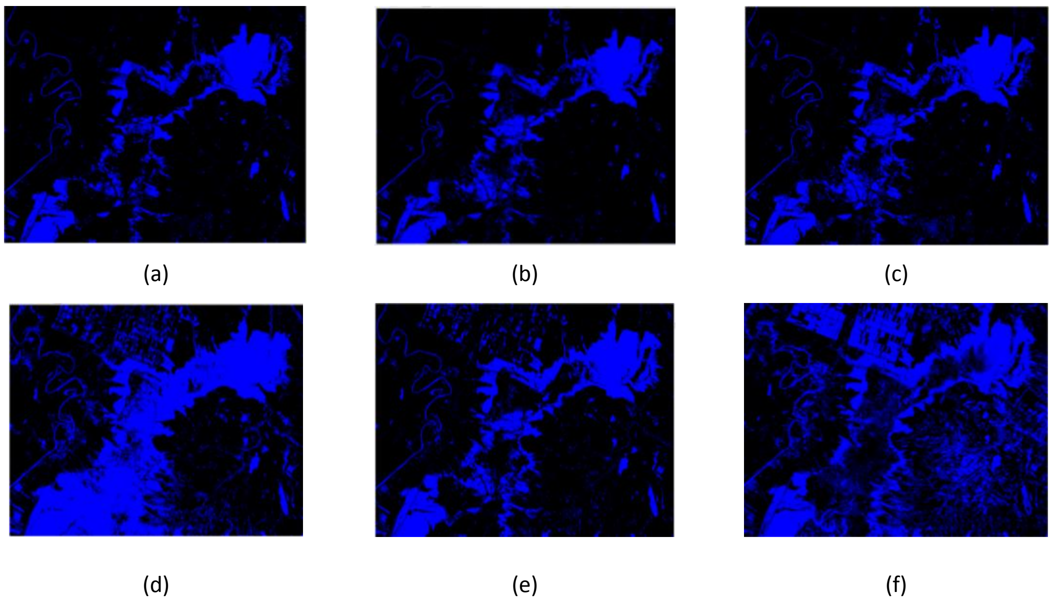


Fig. 5: Visual evaluation between the best decision tree classification results of Shadegan by a) AWEIsh, b) NDWI and c) GNDVI indices compared with d) AWEInsh, e) TCW and f) NDMI.

As it can be seen in Fig. 6, use of the optimal set of spectral indices selected by the genetic algorithm has been able to improve the classification accuracy of surface water bodies from other land covers.

Moreover, the obtained classification accuracies are compared with Random Forest classifier (Fig. 6). The comparison shows that random Forest classifier also has the overall accuracy 97.35 for Karkheh Dam and 97.14 for Shadegan wetland based on the optimum spectral indices by genetic algorithm in both study areas.

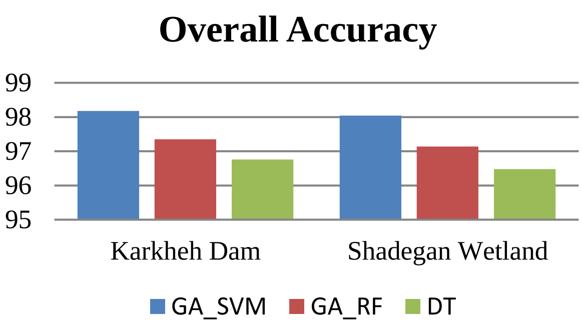


Fig. 6: Comparing the classification accuracies.

Conclusion

The main objective of this research is to evaluate the capabilities of the genetic algorithm to select an optimal set of spectral indices in order to classify surface water bodies from other land cover objects. For this purpose, after measuring the number of 19 conventional spectral indices in the detection of water bodies, each of these indices were classified into two classes of water and non-water objects using the decision tree classifier.

The evaluation of each of the spectral indices measured in both study areas of Karkheh Dam and Shadegan Wetland was carried out using quantitative decision tree classification criteria. Based on the differences in the nature of the two study areas (pure water of Karkheh Dam and water mixed with vegetation in Shadegan wetland), the number of three different indices in each area had the highest values of classification accuracy.

Applying the genetic algorithm on the spectral indices was able to obtain two optimal sets of effective indices that have the highest amount of accuracy in classifying water bodies from other land cover objects in each of the study areas. The evaluation of the obtained classification results of Sentinel-2 satellite images taken from the study areas showed that the use of optimum indices selected by the genetic algorithm could improve the overall classification accuracy by 1.42% in the Karkheh Dam area and 1.56% in the Shadegan Wetland area.

In addition to increasing the classification accuracy of the surface water bodies, considering the effects of the type of land cover objects on the efficiency of spectral indices, the use of genetic algorithm can significantly reduce the computational cost of comparing the results of a wide set of spectral indices. Moreover, considering the collective performance, genetic algorithm selects an optimal set of indices that can detect water bodies more accurately than any single index.

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Author Contributions

Hamzeh Karim Tabahfar has the following rolls in this manuscript: Data capturing, Formal analysis; Methodology implementation. Fatemeh Tabib Mahmoudi as the corresponding author has the following responsibilities: Supervision; Results' validation; Visualization; Writing - original draft; Writing - review & editing.

Conflict of Interest

The author declares that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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Abbreviations

GA	Genetic Algorithm
DT	Decision Tree
NDWI	Normalized Difference Water Index
SVM	Support Vector Machine

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