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Urmia Lake Drying Process Modeling Based On Remotely Sensed Images and Artificial Neural Networks

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Abstract

Urmia Lake is about two decades, each year experiencing 40 cm of water level reduction. In this study, the Urmia Lake drought process is investigated by analyzing multi-temporal remote sensing images. The proposed technique is comprising the following three steps. In the first stage, Landsat 7 and 8 satellite images for 2012-2017 are investigated. In the second stage, each of the batch images is separated for each image of four areas of the blue zone, shallow water, soil and salt. In the third step, neural network trained for 2012-2016 as input and tested for 2017 as an output and a model has been developed for future changes in the next year (2018). The results showed that the trend of changes in Urmia Lake in the last 6 years from 2012 through 2014 witnessed a decrease in water and shallow water regions in July and in the last two years the amount of water and shallow regions has increased. In the following, modelling the process of changes using neural network for 2018 also indicated that in the next year we will see an increase in the water supply in the lake, which is not significant.

Keywords: Drying process, Modelling, Remote sensing, artificial neural networks, Urmia Lake

1. Introduction

In arid and semi-arid region, Iran does not have adequate water resources and is not desirable to the global average. Drought, climate fluctuations, lack of precipitation and disorder have faced the region more and more with all kinds of water and food problems. As a result, it has long been a remedy for water shortages in various sectors of agriculture, economics, industrial, drinking, harvesting from surface and subsurface waters. On the other hand, increasing the concentration of greenhouse gases, especially carbon dioxide, caused changes in precipitation and temperature and followed by changes in some components of the hydrology cycle in recent decades [10]. Urmia Lake is one of the most important aquatic ecosystems in Iran, which has a growing and increasing trend in climate conditions and socio-economic conditions and hydrology. Accordingly, the study and monitoring of lake water changes and its relation

with climate changes and regional hydrology are noteworthy [14].

Urmia Lake is located in northwestern Iran and in the region of Azerbaijan. The lake is divided into the last national divisions between East Azerbaijan and West Azerbaijan. This lake is the largest inland lake in Iran and the second in the world. It is highly saline. Urmia lake catchment area is 51800 km, which covers about 3 % of the total area of the country. There have been a drought and dam construction project during the past decade

and there are significant differences in lake water levels.

The drying process of Urmia Lake has begun over the past 20 years and has gone down more than 8 m this year. After recording the highest level for lake in 1995, the average level of lake level was reduced to 40 cm in two decades and in September of 2014, the lake's southern portion was almost completely dried. Due to the depth of the lake (the average depth of the lake is about 6 meters), the lake has lost a substantial amount of area and water volume during this period [6].

On July 24, 2015, the lake level was 1000 meters above sea level, 6 cm in comparison to the same year last year, and 6 cm in relation to the ecological level of Lake 380 cm. The unprecedented heat of air in the last few months has resulted in increased evaporation from the lake level and has also stepped up its decline.

In recent years, different data sources and various tools and models have been used in water resources domain. The availability of remote sensing (RS) images compared to limited ground-based observations made it as a cost-effective data source for water resources applications [4,5, 6,12,13,14,16,17].

The large-scale and high temporal coverage of water bodies by the RS images helps in understanding the evolution of hazards, which is critical for water managing resources [15].

As there are no restrictive assumptions such as linearity, normality, independence of residuals, etc. in Artificial Neural Network (ANN), it has been widely used in various applications especially in water resource domain [1,2,3,8,9]. In [2] an ANN model has been used to predict water level fluctuations of Lake Van (Turkey). The results showed that the ANN model is simpler and more reliable than the conventional methods such as autoregressive moving average with exogenous input (ARMAX) and autoregressive (AR) models.

Given the capabilities of ANN model and remote sensing data, in this study, the drying process of Urmia Lake is investigated via analyzing of multi-temporal remote sensing images and ANN model. In this regard, the main objective of this study is monitoring and modelling of water level changes and drying process of Urmia Lake in a period of time.

2. Materials, Method, and Results

Remote sensing images can be acquired from different spectral bands, including optical, thermal, and microwave ranges of electromagnetic spectrum. In this study, optical Landsat satellite images have been prepared from the United States Geological Survey (USGS) to monitor and model the drying process of Urmia Lake. The multi-temporal Landsat TM satellite imageries of Urmia Lake (during 2012-2017) are shown in Figure 1.

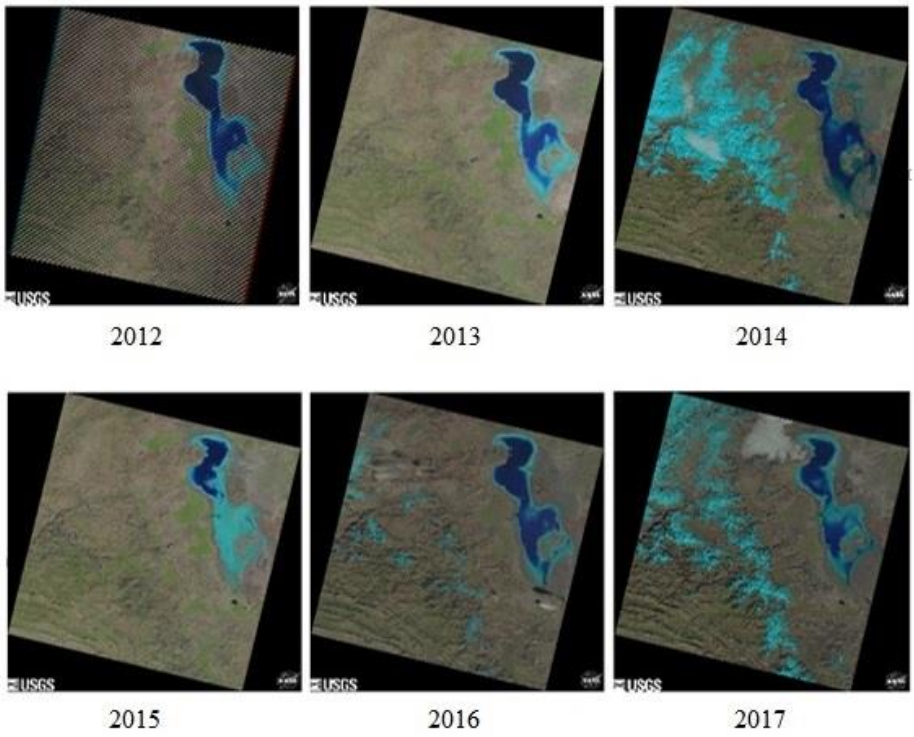

Fig.1 Landsat TM satellite imageries of Urmia Lake during 2012– 2017

2.1 Spectral library

A standard spectral library containing pure samples, broad coating of materials, very high precision, and degradation of samples and describing spectrum quality. Some pixels need to be introduced as a single pixel so that the neural network is classified as a pixel. In this study we have divided the studied area into four classes of water zone, shallow region, salt and soil. Each class had to introduce a set of pixels per class.

2.2 Classification using artificial neural network (ANN)

Each neural network consists of a node (node) and weighted link connections. The main task of each node in the neural network is that it receives input from its neighbor node to compute an output (other nodes output) and calculated output to other nodes. In fact, nodes are related to different layers in the neural network. In the neural network, there are several layers such as input, hidden and output layers. After receiving input and processing, the output layer show the results in the output. Neural networks are two basic steps of training and recalling processing, which starts with the import of satellite images and the spectral library of that neural network [4,11]. For classification of images, images of neural network have been used. To extract the trend of lake change, the lake has a number of pixels of low water and shallow water and is included in the Table 1.

Table1. Number of pixels of low water and shallow water in different years

Year	2012	2013	2014	2015	2016	2017
Water	2,839,077	1,239,003	826,014	413,024	842,521	770,934
Shallow water	7,641,345	2,009,116	1,255,697	917,625	1,506,836	2,028,434

The trend of lake change changes over the last six years has shown that from 2012 to 2015, we have witnessed a reduction in water and shallow water regions. But in 2016 and 2017, the amount of water has increased.

2.3 Neural network modeling

In the neural network, if we know the trend of the last five years of the lake surface, and the process of converting the input indicators into the output, then we can predict the next year/years. For this purpose, we introduced the classification of 2012 through 2016 images as the input of the neural network and introduced 2017 image as an output so that the network should be trained. The type of training is that by introducing values related to pixels in the region from the desired region in the images of 2012 to 2106 as inputs and the introduction of pixels in the same region in 2017 as an output of the neural network, they are trained as an output of the neural network. The purpose of the vector is that every pixel in an image is connected to the same pixel in the image and is trained by the analysis of changes. In Figure 2, the summary of this trend is illustrated.

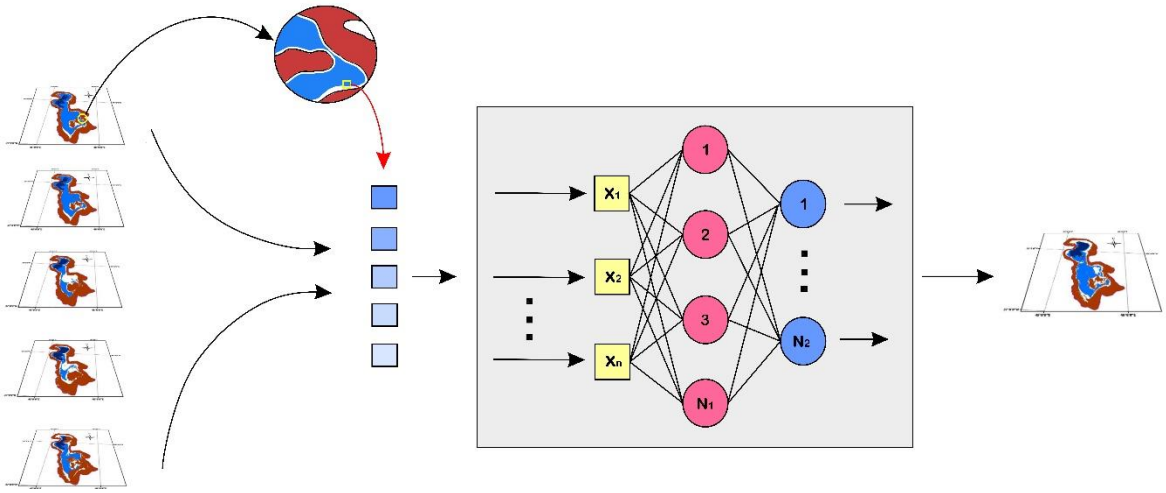

Fig. 2 Summary of neural network modelling

In this study, 20 percent of the data were used to test the neural network training rate and 20 percent for the evaluation of final results. Methods for training the neural network and the summary of the training process are shown in Figure 3.

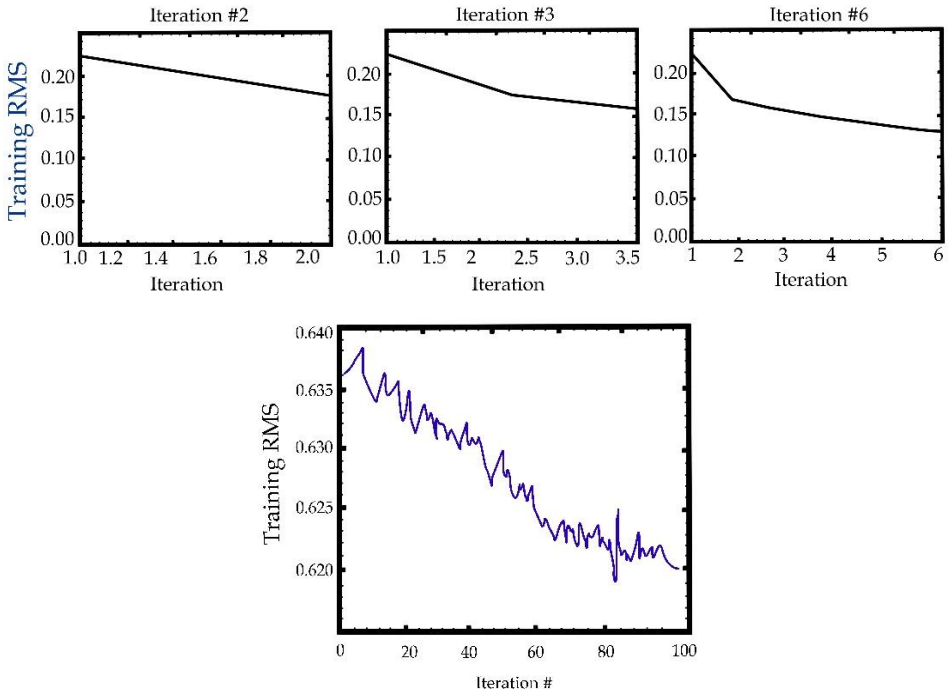

Fig. 3 Training the neural network in each iteration

After training the neural network with the last five years trend, the lake water level has been predicted for 2018. In order to estimate the 2018 map, we introduced the 2017 map as the input of the neural network. In Figure 4, error histogram is shown .

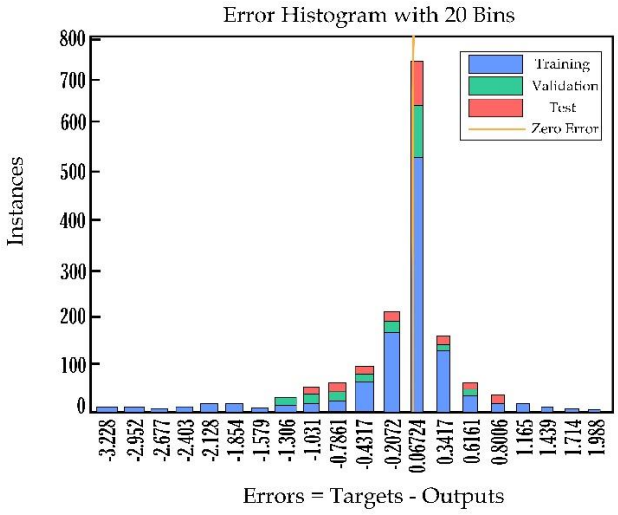

Fig. 4 Error Histogram

3. Conclusions

Due to the studies and researches that have been done during this study, the results showed that there have been a lot of research on lake drought prediction with integration of remote sensing and spatial information system. The results of the study showed that the trend of changes in Urmia Lake in the last 6 years from 2012 through 2014 witnessed a decrease in water and shallow water regions in July. In the last two years, the level of water and shallow regions has increased. In the following, the process of changes using the neural network for the 2018 s also revealed that there will be a rise in the lake's water supply in this year, which is not a significant increase. The rise in water in this period is quite logical and predictable, considering the plans to increase the lake's water.Although the recent decade of drought is a major factor in the growth of Urmia Lake has been considered, but the harvesting on the one hand and waste has caused the crisis too much. A detailed examination of the drought factors is

required to complete the Urmia Lake and the systematic management of the use of existing water resources. Because of the ecosystem changes, the emergence of various diseases, the destruction of salt and forests, the effects of salt on humans, salt storms and the creation of salty dunes and affecting future generations is one of the thousands of consequences of the drying of lake. Interfering parameters in modeling the drought process for the next few years, the study of the water level of the lake in a continuous manner, fusion of drought prevention strategies with a single model for annual and monthly forecasting of lake water and quality control of the relevant model can be considered in future research.

Declarations and ethics statements

- **Ethical approval:** "Not applicable"
- **Informed consent from participants:** "Not applicable"
- **Data availability:** "The datasets and material are available from the corresponding author on reasonable request".
- **Clinical trial registration:** "Not applicable"
- **Consent to publish statement:** "Not applicable"
- **Competing interests:** "The authors declare that they have no competing interests
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