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ASSESSING AND FORECASTING THE FUTURE OF WATER LEVELS DUE TO LAND-USE CHANGES ALONG THE COASTS

SUMMARY

Understanding the components of the water balance and predicting their future changes is essential for developing effective water resource management strategies. In recent years, the basin surrounding Lake Urmia has experienced significant growth in population, industrial activities, and agricultural expansion, all of which have had a considerable impact on the region's hydrological systems. This study examines the influence of land-use changes on the water levels of Lake Urmia. Land-use data for six specific years: 2001, 2005, 2010, 2015, 2020, and 2023 were analyzed. The analysis was conducted at three buffer zones located 10, 20 and 30 km from the lake's coastline, to assess how land-use dynamics at varying proximities influence the lake's water levels over time. The Pearson correlation test was applied to analyze the relationship between different land-use types and the lake's surface area over a 23-year period, using the NDWI index to assess water levels. Additionally, the ARIMA time series model was used to forecast the surface area of Lake Urmia from 2030. The study also investigated how land-use changes in 2023 influenced the lake's water area during the forecast period. The results showed that the highest concentrations of cropland, urban areas, and barren lands were located along the coastal strip (within the 10 km buffer). As the distance from the lake increased, the area of cropland decreased, while rangeland increased in the

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20-30 km buffers. Furthermore, an inverse relationship between cropland area and lake water levels was found. As population growth and the efficiency of water use for cropland increased, the water levels of Lake Urmia declined. This suggests that land-use changes and water management practices are key factors affecting the lake's water levels. The study also identified the adverse impacts of improper dam constructions upstream and a lack of water rights downstream on the lake's water levels. Future predictions using the ARIMA model (100) indicated an upward trend in the lake's water levels, driven by reduced drought, decreased unauthorized wells and cropland, and enhanced international and national cooperation on water rights. Sustainable water resource management can be achieved through the use of numerical models and remote sensing maps.

Keywords: Buffer Zones, Coastal strip, Remote Sensing Data, Water Balance.

INTRODUCTION

Predicting changes in water levels caused by climate change and human activities is an essential factor in the management and sustainable development of water resources (Coe *et al*. 2001; Xiang *et al*. 2013). Hydrological cycles and weather patterns are negatively impacted by these activities, and access to water sources is limited (Ahsan *et al*. 2023; Aslam *et al*. 2024). Due to changes in the water level and disturbance of the balance of water components such as precipitation or evaporation on the surface of the lake, exchange of underground water and incoming or outgoing river flows (Brennwald *et al.* 2004), it is predicted that the global temperature, the average temperature around the world, to increase to 40 degrees Celsius by the year 2100 which leads to changes in the hydrological cycle and aggravation of the water problem, especially changes in the water level becomes lakes (Hamdan 2023). Land-use and climate changes interact to reshape ecosystems, affecting agriculture, forestry, and fruit growing, while influencing biodiversity, soil health, and the complex interactions among natural resources (Spalevic *et al*, 2021). Land-use and climate changes have caused significant changes in Lake Urmia water area in recent years (Joshi *et al*. 2011). Changes in land-use and consequently the use of surface and ground water resources due to the increasing growth of the population, the need for housing and public infrastructure (Acharya *et al*. 2023), physical, climatic and socio-economic factors directly It affects the socio-economic status of the local people (Clark 1982; Jaiswal *et al*. 1999; Chilar 2000; Yuan *et al*. 2005; Joshi *et al*. 2011; Rawat *et al*. 2013).

Changes in land-use, without considering changes in environmental sustainability, increase the demand for land resources such as cropland, minerals, soil and water (Gibson and Power 2000; Lu *et al*. 2004; Zoran 2006; Santhiya *et al.* 2010). In the last two decades, almost 24% of the natural ecosystem has become inaccessible and has suffered a decrease in productivity (Kalensky *et al*. 2003; Meyer and Turne 2003), of which the share of human society can be said to be about 44% (Daily 1995). According to UNPD (2007), the population of coastal areas has doubled in the past 40 years and will continue to grow in the next 40 years. Due to the rapid population growth, there is a rise in the speed of entering natural areas, changes in natural land cover, and disturbances caused by the expansion of settlements and urban infrastructure (Mujabar and Chandrasekar 2013). Land cover change (LULC) can be considered a major driving force attributed to environmental change at all spatial and temporal scales (Gashaw *et al*. 2018). The parameters of the natural, economic, social, and cultural environments are altered, and people and wildlife are at risk because of these changes (Nicholls and Small, 2002; Yagoub and Kolan 2006; Kaliraj *et al*. 2014). Human interference with water resources has led to the most ecological disasters on humans in the 20th century (Sirjacobs *et al*. 2004). In the meantime, ecological environments have been defined for coastal areas, particularly the lake environment. Monitoring and evaluating these areas can be seen as an essential aspect of national development and natural resource management in this situation (Canal-Vergés *et al*., 2024). The monitoring of coastal areas and extracting water level changes at different intervals has been considered basic research for the past few decades.

Due to their dynamic nature, managing sensitive ecological environments like coastlines demands accurate information at various time intervals (Nayak. 2002; Zhang. 2011; Kaliraj and Chandrasekar 2012; Mujabar and Chandrasekar 2013). The development of the agricultural sector and the exploitation of water resources in its catchment area have caused a significant drop in Lake Urmia levels in recent years. But at what level these changes and especially the change in land-use took place, needs its own studies. In general, two methods: ground and remote sensing, can be utilized to investigate land-use changes (Zamorano *et al*., 2024). But in recent decades, with the development of hardware and software facilities for processing satellite images, as well as the ease of access to multispectral and hyperspectral images, the use of remote sensing techniques and advanced computing tools to produce land-use maps with accurate information and It has become more common (Wimberly *et al*. 2021; Pande 2022; Zhang and Li. 2022; Amraoui). In conventional methods, the land-use map was prepared using available information, maps, and field surveys. The output maps often become invalid over time, especially in a rapidly changing environment, making this process time-consuming and expensive (Nayak 2002; Wang *et al*. 2004& 2008; Rawat *et al.* 2013). But the use of satellite images provides users with a complete coverage in time and place (Misra *et al.* 2013). Due to the importance and necessity of investigating the role of land-use change on water levels, several studies have been conducted. Kaliraj and Chandrasekar (2012) stated that GIS and remote sensing using spatial data sets such as maps, aerial photographs and satellite images are suitable for preparing quantitative, qualitative and descriptive geographical databases of periodic changes in land-use characteristics. Liu *et al*. (2023) discussed the role of land-use on water resources under economic, environmental protection scenarios in Nanxi Lake, China. The findings showed that land-use has an effective role in water resources in three scenarios: more economic, less economic, and more conservation-focused. Pande *et al*. (2024) used a classification and regression tree (CART) model with Google Earth Engine (GEE) to assess winter land cover and the impact of change detection mapping on evapotranspiration parameters (crop water demand) in Maharashtra, India. This study's findings demonstrated the accuracy of these models in extracting land-use.

Forecasting tools can be used to simulate changes in lake water levels based on available measured data, enabling the prediction of potential responses under various scenarios, including land-use changes and management decisions for valuable water resources. Predicting water level fluctuations in lakes can be achieved using time series forecasting methods, which define random trends or variables. The Autoregressive Integrated Moving Average (ARIMA) model is one of the most commonly used approaches. In this model, the autoregression and moving average components account for systematic effects and the internal changes in the endogenous variable, respectively (Ediger *et al.* 2007). More research has been conducted on the spatial configuration of land-uses to better comprehend the relationship between land-use patterns and water characteristics in watersheds. The inclusion of advanced statistical analysis and spatial analysis techniques has significantly advanced these studies (Bu *et al.* 2014). The aim of this study is to assess the impact of land-use changes on the future water levels of Lake Urmia. The presentation seeks to offer valuable management models for water resource managers and stakeholders in the watershed, assisting them in stabilizing the lake's water ecosystem. Moreover, the study investigates innovative strategies for sustainable land-use practices in the surrounding areas, ensuring that land use is optimized for productive purposes while minimizing negative impacts on the water body. By integrating advanced predictive modelling and real-time monitoring through remote sensing, the study provides a comprehensive framework that incorporates environmental, social, and economic factors into the management of Lake Urmia's water resources.

MATERIAL AND METHODS

Description of study area. Lake Urmia, situated in northwest Iran, is a significant catchment area with a basin spanning 51,876 km^2. It lies across three provinces: West Azerbaijan, East Azerbaijan, and Kurdistan, encompassing 46%, 43%, and 11% of the basin area, respectively. As the largest lake in Iran, Lake Urmia represents a vital and unique water ecosystem, holding immense importance not only for Iran but also on a global scale. The ecological system of Lake Urmia exemplifies a closed watershed, where all runoff from the basin's rivers converges into the lake. Additionally, the lake and its catchment area form an integral part of a dynamic ecosystem. The defined boundary of the Urmia Lake catchment has served as a clear framework for managing factors that influence the lake and the critical habitats within the basin. The catchment area of Lake Urmia includes the northern part of the Zagros Mountains, the southern slopes of Sabalan Mountain, and the northern, western, and southern slopes of Sahand Mountain. Approximately 65% of the catchment area, equivalent to 33,469 km^2, is covered by mountainous regions, while 24% (12,564 km^2) consists of plains and foothills, and 10% (5,320 km^2) is occupied by the lake itself. Figure 1 depicts the location of the Lake Urmia basin and the land use in the region as well as across Iran.

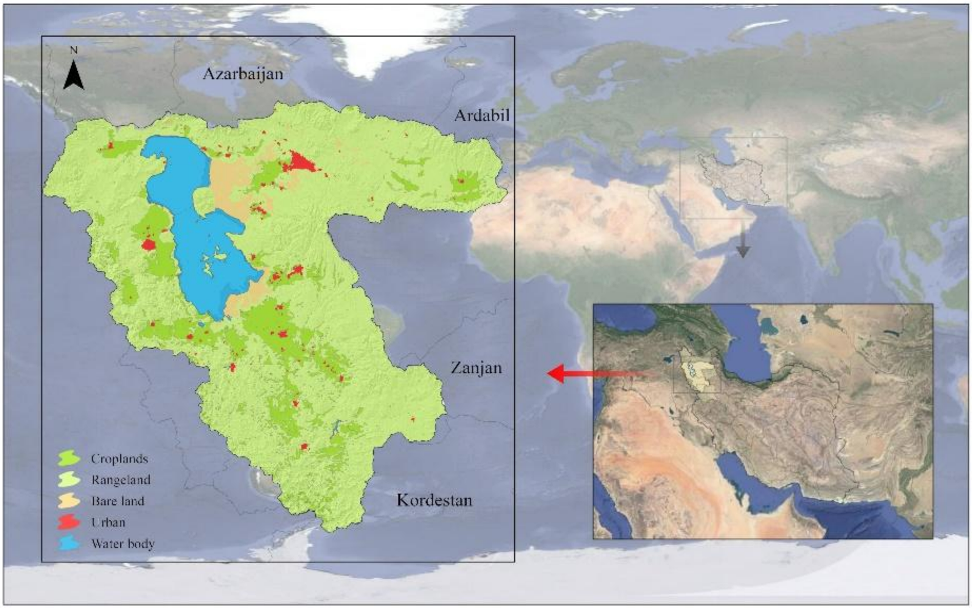

Figure 1. Location of Urmia basin and land-use in the region and Iran

Dataset collection

In this study, data from the ETM+ sensors on Landsat 7 and 5 (2001–2012) and the Operational Land Imager (OLI) on Landsat 8 (2012–2023) were utilized to analyze changes in land-use and the water level of Lake Urmia. Satellite imagery was obtained from the USGS Earth Explorer website (Table 1), provided by the United States Geological Survey. The images used featured minimal atmospheric errors and a cloud cover of less than 10%. Changes in the surface area of Lake Urmia were identified through the application of the biophysical parameter NDWI.

Table 1: Specifications of satellite images used in the study area

Year	Study area	Satellite	Sensor	Clouds	Path & row
2001 to 2012	UROMIA	Landsat -5	ETM+	0.00	147.42
2001 to 2012	UROMIA	Landsat -7	ETM+	0.00	147.42
2013 to 2023	UROMIA	Landsat -8	OLI-TIRS	0.00	147.42

Normalized Difference Water Index

The Normalized Difference Water Index (NDWI) is designed to enhance the detection of water bodies by maximizing the reflectance of water using green wavelengths and minimizing the low near-infrared (NIR) reflectance typical of water features. Additionally, it highlights the high NIR reflectance associated with vegetation and soil. The NDWI method for delineating open water features is expressed in Eq. (1) (Taloor *et al*, 2021):

$$\text{NDWI} = (\text{Grean} - \text{NIR})/(\text{Grean} + \text{NIR}) \quad (1)$$

The earth engine software was used to extract changes in Lake Urmia level for a period of 23 years by coding the NDWI index.

Extraction of land-use changes

Four land-use types with common characteristics, excluding lake use, were identified for the entire catchment area of Lake Urmia using coding in Google Earth Engine[2]. The land-use types were classified into five categories: cropland, rangeland, urban areas, and bare land. To examine the impact of each land-use type on Lake Urmia, the effects of land-use changes on the water level were assessed using sub-watersheds in ArcMap software.

Modelling time series

Time series modelling was employed to forecast future changes in the water environment for the seven-year period from 2023 to 2030, with the lake's area and changes being extracted. A time series model is a stochastic model that uses N observations from an infinite population, generated by a random process. Time series models can be categorized into autoregressive, moving average, and composite models. Some processes not only satisfy autocorrelation conditions but also exhibit moving average characteristics. In these cases, a combination of autoregressive and moving average models, along with cumulative moving average autoregressive models, is employed. Determining or identifying the model is the first step in modelling, which is based on the characteristics of a series of observations. The characteristics of the model can be revealed by analyzing changes in statistical parameters, such as mean, standard deviation, and skewness, in the initial step (Ishfaque *et al*. 2023).

Autoregressive integrated moving average (ARIMA)

In this model, appropriate time series models are fitted to the data by using ACF[3] autocorrelation and PACF[4] partial autocorrelation functions, and by using the behaviour of these two functions, the stationary and seasonal properties of the data are investigated. The most frequently used model has been the ARIMA model (Dong *et al*. 2024). ARIMA models can be classified in two ways: non-seasonal ARIMA (p,d,q) or multiplicative seasonal ARIMA (P,D,Q) × (p,d,q). Autoregressive parameters representing non-seasonal and seasonal moving averages can be found in these relationships, with q and p representing non-seasonal and seasonal moving averages. The other two parameters, i.e. d and D, are differential parameters for stationary time series. The differential operator used for dynamic time series are B) $\Delta = 1 - B$ is the backward jump operator) and $\Delta d = (1 - B)\, d$ is for seasonal differentiation. This form of non-seasonal ARIMA models is written in the form of Eq. (2):

[2] https://code.earthengine.google.com/
[3] Autocorrelation Function
[4] Partial Autocorrelation Function

$$\Phi(B)Z_t = \Phi(B)(1-B)Z_t = \theta(B)a_t \quad (2)$$

where Zt is the observed series, Φ(B) is the rank of polynomial p and θ(B) is the rank of polynomial q. For seasonal time series which are often cyclical, seasonal differentiation is used, where we will have the multiplicative seasonal model in Eq. (3):

$$\varphi_p(B)\Phi_p(B^s)\Delta^d\Delta_s^D(z_t-\overline{Z}) = \theta_q(B)\Theta_Q(B^s)a_t \quad (3)$$

where θ q and Φp are the seasonal polynomials of Q and P, respectively. The rank of multiplicative seasonal ARIMA models is in the form of (P, D, Q) × (p, d, q).

Parameter estimation

After specifying the model, the parameters should be estimated effectively. For autoregressive and moving average calculations, the parameters must satisfy two conditions: stationarity and reversibility. Additionally, the parameters should be examined for significance, which relates to the error values of the estimates and the calculation of t-values. If θ is a point estimate of the desired parameter S_θ is the estimation error, the value of t will be in the form of Eq. (4):

$$t = \frac{\theta}{s_\theta} \quad (4)$$

If the null hypothesis is equal to or more than α=0.05, considering the probability of error, then the parameter will be significant and will remain in the model.

Goodness of fit test

The accuracy of models is checked by checking the goodness of fit tests with tools (Mansour *et al.* 2020). The models fitted to the data were checked by examining the residuals of the model for the normality of the autocorrelation. To perform this test, SPSS and Minitab software were utilized to assess both the normality and homogeneity of the dataset (Abdi 2023). In addition to these tests, T-statistics and P-values were employed to analyze the significance of the relationship between the observed and predicted data. The T-statistics help determine if the differences between observed and predicted values are statistically significant, while the P-value indicates the probability that the results are due to chance. Finally, the Bayesian Information Criterion (BIC) was used to assess the fit of the models and identify the one that most appropriately balances model complexity and goodness of fit. This combination of statistical tools ensures a robust evaluation of the model's performance and reliability (Ebrahim *et al*. 2024).

Examining the appropriateness of the model

Two complementary methods are employed to make the model suitable (Yaseen *et al.* 2018). The first method analysis of the residuals of the fitted model (the randomness or non-correlation of the residuals is proved), and analysis of models that have more parameters. If several suitable models are identified, Akay criteria are used. In the analysis of the residuals of the fitted model, the assumption of normality of the residuals, the assumption of constant variance of the residuals, the assumption of independence of the residuals, the graph of the residuals against time, and Pratt-Manto test were used for each model. The assumption of normality of the residuals is accepted if the points are located almost along a straight line and have a uniform distribution. As a standard method to test the hypothesis of non-correlation of the residuals, Pratt-Manto test was used, which is based on the modified Box-Pearson statistic. Pratt-Manto test is based on Eq. (5) (Eslamian *et al.* 2024).

$$Q(LBQ) - n(n+2)\sum_{h=1}^{k}(n-h)^{-1}\rho_h^2 \tag{5}$$

where, n: the number of observations, Q: the test statistic, which is modified LBQ Ljungbox[5]. Under the hypothesis H_0, it has approximately Kido distribution[6]. If the value of the Q statistic is greater than the corresponding value in the Kido table, the hypothesis H_0 is rejected, that is, the data are correlated. Also, the value of the correction index should be greater than the value of α.

RESULTS AND DISCUSSION

Extraction of land-use changes

Considering the size of Lake Urmia and the influence of the surrounding environment, as well as the various land-uses in the area, this study also considers the proximity of these land-uses to the lake. Land-use data were extracted for six key time periods: 2001, 2005, 2010, 2015, 2020, and 2023. Based on the results shown in Figure 2, the analysis of land-use changes from 2001 to 2023 reveals significant shifts in the surrounding environment of Lake Urmia. Cropland has shown a steady increase from 26.77% in 2001 to 32.80% in 2023, reflecting the growing demand for agricultural production, likely driven by population growth and economic needs. This rise in cropland is indicative of intensifying agricultural activities in the region, which may place additional pressure on water resources, especially considering the reliance on irrigation for crop cultivation. Conversely, rangeland has decreased from 64.86% in 2001 to 55.40% in 2023, pointing to a conversion of pastureland to other land uses, such as cropland or urban development. This reduction in rangelands could have adverse effects on biodiversity and the natural ecosystem, as well as contribute to soil degradation. Bare land, which initially increased from 5.37% in 2001 to 9.11% in 2015, has significantly decreased to just 1.35% in 2023.

This decline suggests that efforts to rehabilitate and convert previously unused or degraded lands into productive areas have been successful, potentially improving land-use efficiency. Lastly, urban areas have expanded dramatically

[5] Box Logang

[6] Ķ Distribution

from 3.00% in 2001 to 10.45% in 2023, highlighting the rapid urbanization of the region.

This urban growth is likely driven by population increase and economic development, placing additional pressure on natural resources, including water. The changes in land-use patterns over this period underline the complex relationship between agricultural, urban, and environmental pressures in the region, with significant implications for water resource management in the future.

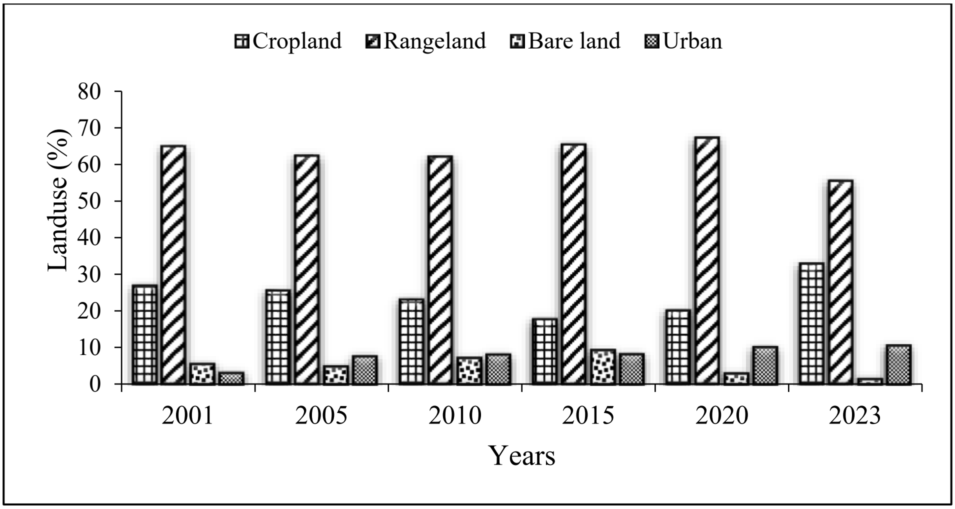

Figure 2. Land-use changes in the studied years

In this study, to thoroughly investigate the effects of land-use changes on the water levels of Lake Urmia, three buffers were established at varying distances of 10, 20, and 30 km from the lake's shoreline (Figure 3). These buffer zones were chosen to capture the influence of human activities and land-use changes at different proximities to the lake, providing a comprehensive view of how urbanization, cropland expansion, and other land-use changes affect the lake's hydrological conditions.

By analyzing the land-use changes within these buffers, the study aimed to assess the relationship between proximity to the lake and the extent of land-use impacts on water resources. The results from these buffers helped identify trends in land-use patterns and their potential contribution to fluctuations in the lake's water levels, offering valuable insights for future management and conservation efforts.

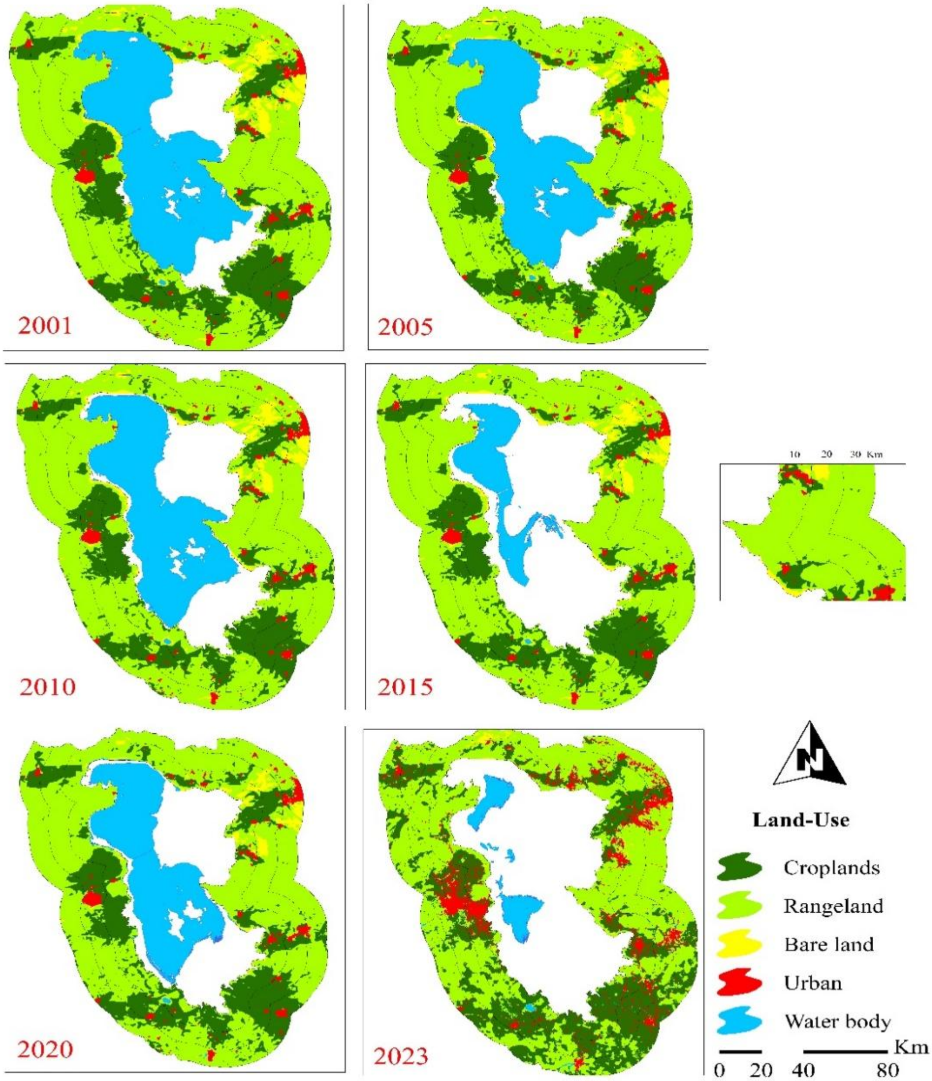

Figure 3. Land-use changes at distances of 10, 20 and 30 km around Lake

Extraction of water levels based on NDWI index

The NDWI index was applied to extract the lake area over a span of 23 years, distinguishing land-use changes based on selected intervals. To model and predict the area of the blue zone for the next seven years (2023-2030), ARIMA time series modelling was employed (Figure 4). The results indicate a consistent decrease in the area of Lake Urmia from 2001 to 2015, with this downward trend continuing and accelerating in the years following 2015.

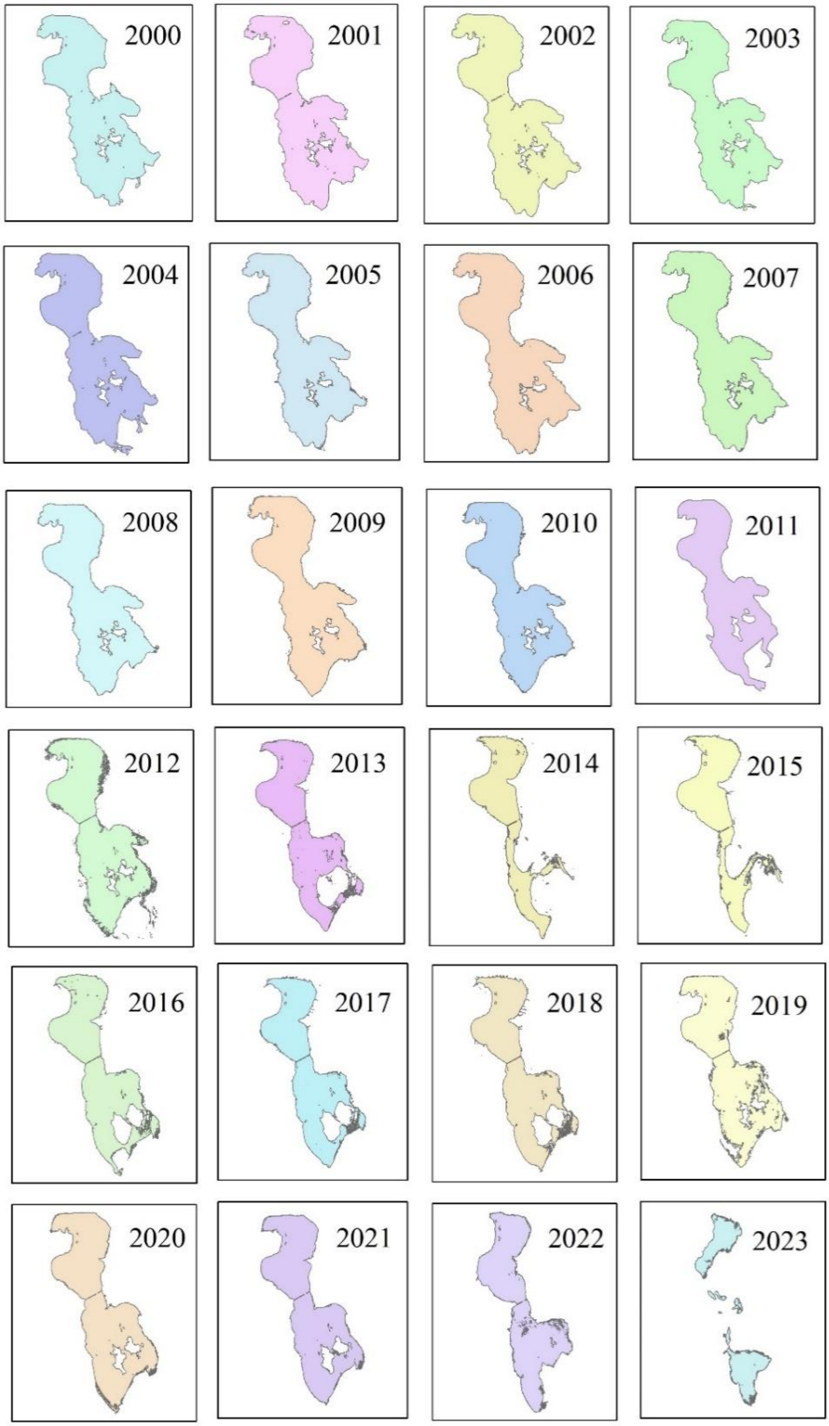

Figure 4. Changes in the area of Lake Urmia in a period of 23 years

Impact of Land-Use Changes on Lake Urmia's Water Area

The distance from Lake Urmia was used to extract the effects of land-use changes. ARIMA time series modelling was used to predict land-use changes in the future water levels of Lake Urmia, which predicted the area of Lake Urmia for seven years after 2023. Table 2 analyzed the impact of land-use changes in 2023 on Lake Urmia water area.

Table 2. Correlation of land-use changes on the surface of Lake Urmia based on Pearson correlation

Land-use	**Lake area (Km^2)**	**Distance**	**Cropland**	**Rangeland**	**Bare land**	**Urban**
2001	2001-2005	Buffer 10	0.56	0.36	0.82	-0.16
		Buffer 20	0.34	0.73	-0.57	-0.57
		Buffer 30	-0.59	0.93*	-0.08	-0.03
2005	2005-2010	Buffer 10	-0.09	-0.85	0.46	0.58
		Buffer 20	-0.28	0.72	-0.68	0.38
		Buffer 30	-0.46	0.10	-0.54	-0.48
2010	2011-2015	Buffer 10	-0.16	0.74	0.32	0.54
		Buffer 20	-0.28	0.62	-0.54	0.37
		Buffer 30	-0.31	-0.01	-0.66	-0.32
2015	2016-2020	Buffer 10	-0.29	-0.69	-0.68	-0.75
		Buffer 20	-0.07	0.90*	0.59	-0.41
		Buffer 30	0.79	-0.27	-0.53	0.52
2020	2020-2023	Buffer 10	-0.18	0.95	0.20	0.40
		Buffer 20	-0.33	0.66	-0.71	0.23
		Buffer 30	-0.34	0.14	-0.33	-0.40
2023	2023-2030	Buffer 10	-0.41	-0.37	0.20	0.65
		Buffer 20	-0.46	0.12	-0.29	-0.41
		Buffer 30	0.25	-0.13	0.09	0.51

* 95% significance level and ** 99% significance level

Based on the results from Table 2, the correlation between land-use changes and the surface area of Lake Urmia shows varying patterns across different periods and buffer zones. In general, cropland and urbanization, particularly in the 10 km buffer zone, were associated with a decrease in the lake's surface area, while rangeland expansion in the 30 km buffer zone tended to positively influence the lake's surface area. Between 2001 and 2005, cropland showed a positive correlation with lake area in the 10 km buffer zone, while rangeland had a strong positive correlation in the 30 km zone. However, from 2005 to 2010, the 10 km buffer zone showed a negative correlation with both cropland and rangeland, indicating that these land-use changes were associated with a decrease in lake surface area. From 2010 to 2015, urbanization in the 10 km buffer zone showed a moderate positive correlation with lake area, suggesting a slight increase in surface area due to urban growth. However, bare land and rangeland showed negative correlations in the 20 km and 30 km zones during this period. In the 2015-2020 period, urbanization in the 10 km buffer zone strongly correlated with a decrease in lake area, while rangeland expansion in the 20 km buffer zone had a positive impact. In the 2020-2023 period, rangeland showed a strong positive correlation with lake area in the 10 km buffer zone, while bare land in the 20 km zone showed a negative correlation. Urbanization in the 10 km zone continued to impact the lake negatively. Looking ahead to 2023-2030, urbanization in the 10 km buffer zone is expected to continue influencing the lake's surface area negatively, while rangeland expansion further from the lake may still have a positive effect on its water levels. Overall, the findings suggest that land-use changes, particularly in the immediate vicinity of the lake, have a significant impact on its surface area, highlighting the need for strategic land-use management to preserve Lake Urmia's water resources.

Forecasting the area of Lake Urmia

Figure 5 illustrates the trend graph depicting changes in the water level of Lake Urmia over a 20-year period. The analysis began by examining the dataset for mean stationary and non-stationarity. To address the presence of a non-stationary mean (trend) in the non-seasonal and annual data, first-order differencing was applied. This step effectively removed the underlying trend, ensuring the dataset was stationary and suitable for further analysis (Figure 5).

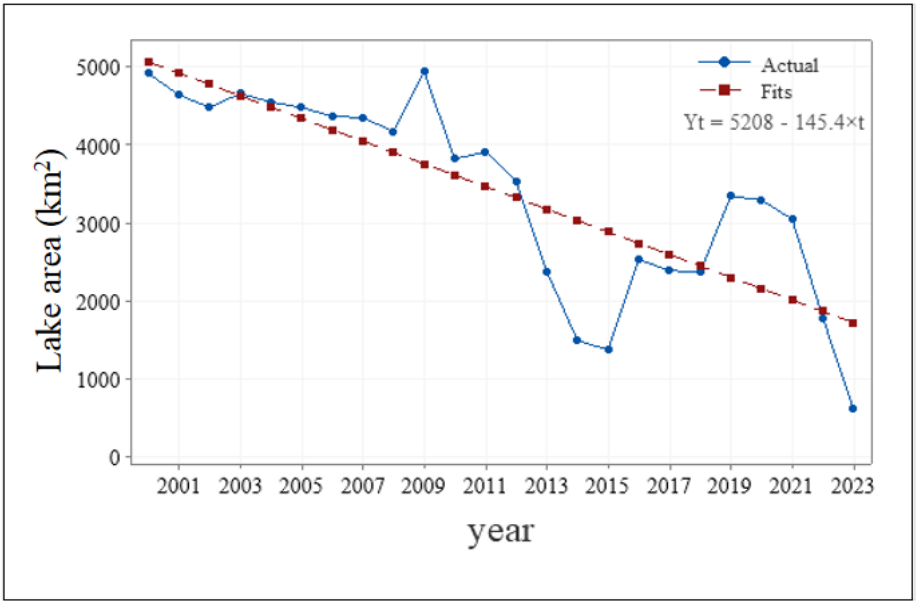

Figure 5. Annual trend of changes in the area of Lake Urmia

Next, the non-seasonal and annual data were differenced once at the first order to remove the non-stationary mean (trend). The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots for Lake Urmia, before and after differencing, are shown in Figure 6. These plots allow for the extraction of appropriate coefficients for p and q.

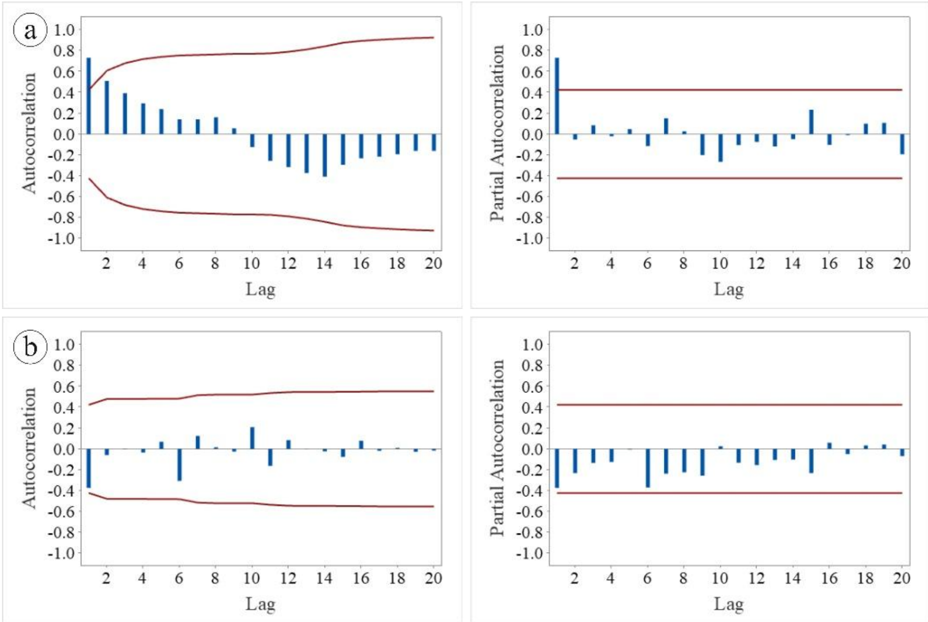

Figure 6. ACF autocorrelation analysis and PACF partial autocorrelation before (a) and after differencing (b)

The ACF and PACF diagrams were employed to evaluate and fit four predictive models for Lake Urmia (Table 3). This table outlines key statistical metrics for each model, including MA (Moving Average), AR (Autoregression), BIC (Bayesian Information Criterion), and RMSE (Root Mean Square Error). Based on the results presented in Table 3, the table presents the results of fitting several ARIMA models to the stationary annual data series of Lake Urmia's area. Among these models, the ARIMA (1,0,0) model, which includes the autoregressive term (AR1), stands out as the best fitting model. It shows statistical significance for the AR1 parameter with a p-value of 0.00, and the T-statistic of 7.53 suggests a strong influence of past values on the current value. The BIC value for this model is the lowest at 13.52, indicating a better balance between model complexity and fit. Its RMSE is also relatively low at 757.60, suggesting good prediction accuracy. The ARIMA (1,1,0) model, with an AR1 term, shows a weaker relationship with a p-value of 0.48, indicating that the past values have less influence on the current value. However, it still performs relatively well with a BIC of 13.19 and RMSE of 640.61, which are quite close to the ARIMA (1,0,0) model, but it doesn't provide a better fit. The ARIMA (0,0,1) model, which includes the moving average term (MA1), has a higher RMSE of 889.71 and is less effective in capturing the patterns in the data. Models such as ARIMA (1,1,1) and ARIMA (1,0,1), which combine both autoregressive and moving average terms, do not outperform the ARIMA (1,0,0) model. Specifically, the ARIMA (1,1,1) model has a p-value of 0.22 for AR1 and 0.24 for MA1, showing a relatively weak relationship between the parameters and the series, while the ARIMA (1,0,1) model has a better fit for AR1 but does not significantly improve the model's performance. In conclusion, the ARIMA (1,0,0) model provides the most accurate forecast for Lake Urmia's area, as indicated by its low BIC and RMSE, along with the statistical significance of its autoregressive term.

Table 3. Fitting random models for the annual stationary data series of Lake Urmia area

Model	Parameter	P-value	T	BIC	RMSE
ARIMA (0,0,1)	MA1	0.00	-5.97	13.84	889.71
ARIMA (1,0,0)	AR1	0.00	7.53	13.52	757.60
ARIMA (1,1,0)	AR1	0.48	0.70	13.19	640.61
ARIMA (1,1,1)	AR1	0.22	-1.26	13.37	654.08
	MA1	0.24	-1.19		
ARIMA (1,0,1)	AR1	0.01	5.07	13.63	750.08
	MA1	0.29	-1.07		
ARIMA (0,1,1)	MA1	0.45	-0.76	13.19	640.08

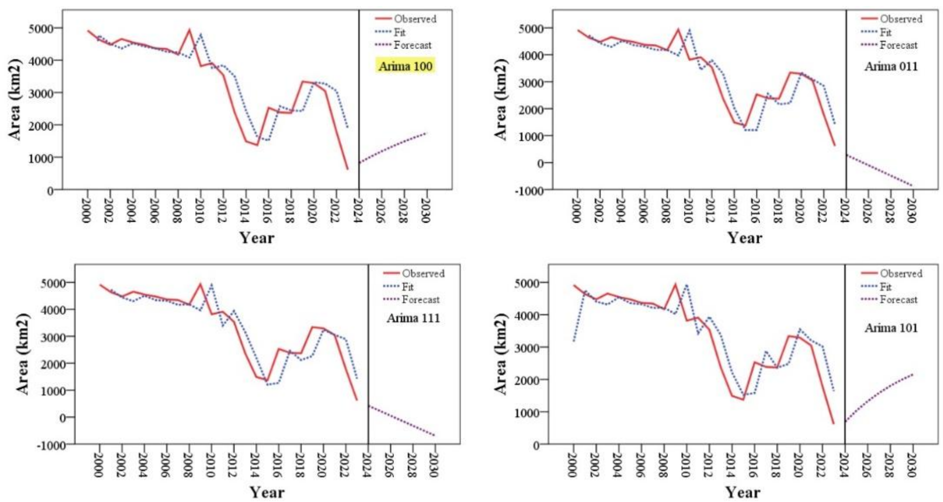

Figure 7. Plot of predicted and observed values for the static data of the annual area of Lake Urmia based on the fitted models

The area of Lake Urmia from 2000 to 2030 was predicted using a model fitted to the annual area data. Figure 8 visually presents a comparison between the observed and predicted values. This graph highlights the accuracy of the model's forecasts, showcasing the differences between the actual recorded data and the predicted values.

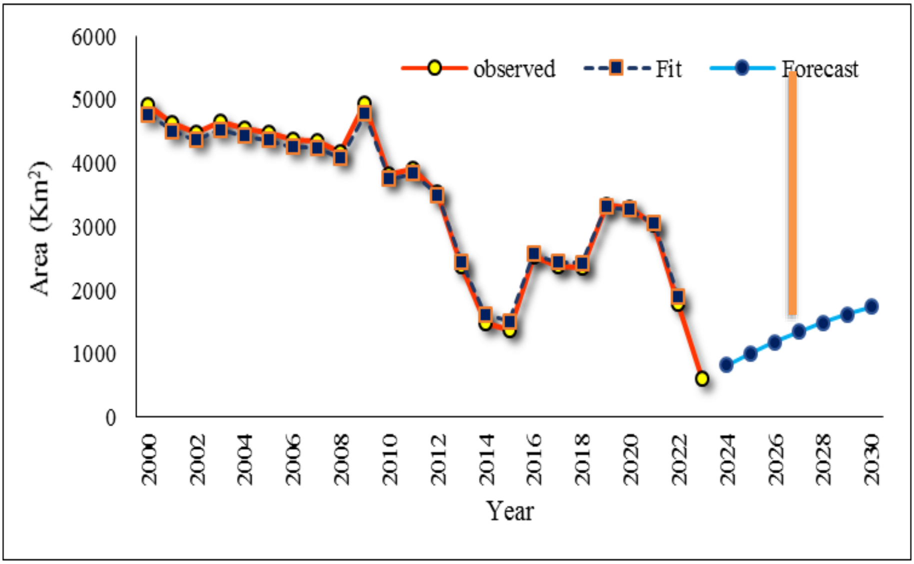

Figure 8. Plot of predicted and observed values for the stationary data of the annual area of Lake Urmia based on the (1,0,0) ARIMA model

According to Figure 8, the area of Lake Urmia is increasing in the coming years with the release of water from upstream dams and the improvement of climatic conditions in the region, and this upward trend is occurring at a gentle slope. Based on Table (2), in examining the land-use changes in 2023 on the projected area of Lake Urmia, the results indicate that there is an inverse relationship between the area of the lake and cropland and horticultural use. The highest level of water stress in the lake during all the years studied is caused by cropland and croplands surrounding the lake. If ignored, the return to a stable state will be slow.

The overall findings of this study indicate that a comprehensive framework arises from the intricate relationship between human activities and changes in natural ecosystems, highlighting the deep interconnection between humanity and the Earth. This framework operates on the principle of interdependence, where a change in one component triggers cascading effects throughout interconnected systems. Lake Urmia, recognized as one of the most sensitive and vital ecosystems in Iran, serves as a prime example of this dynamic. Over the years, the lake has undergone profound changes driven by both climate change and human interventions.

Extensive dam constructions upstream, unauthorized well drilling around the lake, agricultural expansion, and the development of orchards have significantly reduced the lake's water levels. These activities have not only disrupted the lake's hydrology but also led to the degradation of its natural environment, pushing this critical habitat toward potential extinction in recent years. Human-induced changes in land use often cause significant damage to natural environments, even before the full impacts of climate change are realized.

This study examined land-use changes around Lake Urmia across six distinct time periods using Landsat satellite imagery. Land-use types were categorized within three buffer zones—10, 20, and 30 km from the lake—allowing for an analysis of how different land uses and their proximities affected the lake's water levels. The results indicated that the most substantial expansion of croplands and urban areas occurred during the 2001–2005 period, particularly in regions closest to the lake. Despite some urban and cropland development, the relatively slow pace of these changes in the study area suggests that climate change remains the primary driver of fluctuations in the lake's water levels. This finding underscores the interconnected effects of human activity and climate variability on sensitive ecosystems like Lake Urmia.

The natural cover in the region has boosted permeability levels and improved groundwater aquifers, but it has also decreased the amount of runoff in the area. These results agree with the findings of Germinal *et al*. (2019) and Guzha *et al*. (2019). In 2005-2010 and 2010-2015, with the beginning of population growth and increased human intervention and conversion of rangeland to cropland, increased evaporation and transpiration, successive droughts, and unprincipled dam construction have caused a decrease in lake levels, the expansion of saline lands, and the elimination of plant species. Humans have increased the exploitation of the lake to reach maximum production, which has resulted in a decrease in its water efficiency. The results of this study align with the findings of Qing *et al*. (2024), which indicate that increased human interventions have contributed to changes in the ecosystem health index of Poyang Lake. Specifically, human activities such as dam construction, over-extraction of water, and land-use changes have played a significant role in the lake's declining health and ecological imbalance. The study highlights the connection between human-induced alterations and the environmental status of the lake, reinforcing the need for sustainable management practices to mitigate further degradation. In the study area, surface runoff has increased and groundwater resources have decreased due to the increase in cropland. Alamdari *et al*. (2022) indicated that as human activities continue to interfere with land use and land cover, the impact of these changes on runoff depth also increases.

The climate changes in the Lake Urmia basin from 2015 to 2020 were significantly influenced by the growth of urbanization and expansion in the cropland sector. This period marked a critical phase for the lake, as urban and cropland development around the basin contributed to an increase in water demand, leading to further depletion of the lake’s water resources. The development of cropland in particular has been linked to increased water consumption and reduced natural water flow into the lake, exacerbating the overall trend of shrinking water levels. Studies show that land-use changes, such as urbanization and cropland expansion, are key contributors to the declining water levels of the lake (Xie *et al*. 2017; Mekuria *et al*. 2023; Jing *et al*. 2024).

By late 2015, Lake Urmia was experiencing severe negative conditions. This period of decline was particularly concerning due to the combined effects of climate change and anthropogenic pressures, including over-extraction of water for irrigation and dam construction upstream. As noted by Huang *et al*. (2022), these changes have accelerated the environmental crisis in Central Asia, further exacerbating the challenges faced by the region's lakes. These comparative studies highlight the crucial role of addressing both climate change and land-use management to mitigate the decline in lake levels (Shirmohammadi *et al*. 2020; Gunacti *et al*. 2023; Kalfas *et al.* 2024). By evaluating the impacts of various factors, these studies stress the need for comprehensive strategies that tackle environmental changes and human activities, ultimately ensuring the long-term sustainability of lake ecosystems. The findings align with broader research suggesting that effective management practices are essential for reversing the detrimental effects observed in critical water bodies worldwide. The Lake Urmia basin has experienced an increase in barren lands due to several factors, including frequent droughts, population growth, and the expansion of cultivated areas. These changes have contributed significantly to the declining water levels of the lake. The combination of these human and environmental factors has exacerbated the ongoing ecological challenges faced by Lake Urmia. As a result, sustainable land-use and water management strategies are crucial for mitigating further degradation. Only in the years after 2015 has the region witnessed an increase in vegetation cover due to management measures taken to preserve the lake. Based on the findings of this study, it is clear that land-use changes, particularly in cropland and urban areas around Lake Urmia, have played a significant role in influencing the water levels of the lake.

The analysis revealed that the areas closer to the lake, specifically within a 10 km buffer, showed higher levels of cropland expansion and urbanization. These activities were found to be inversely related to the water levels of the lake. As cropland areas increased, accompanied by rising population numbers and enhanced water use efficiency, the lake's water levels continued to decline. In addition, the construction of dams upstream, coupled with insufficient water distribution rights downstream, further aggravated the situation, accelerating the loss of water from the lake. However, the results from the ARIMA time series model suggest that there may be hope for recovery in the future. The model predicts an increase in the lake’s water levels, driven by the improvement of several key factors. These include the alleviation of drought conditions, the reduction in the number of unauthorized wells, and the overall better management of water resources through international and national agreements. These outcomes highlight the importance of effective water management and the need for coordinated efforts across various levels of governance. This study underscores the necessity of adopting sustainable water management practices, which are critical for the long-term conservation and restoration of Lake Urmia. The integration of numerical models and remote sensing tools provides valuable insights into monitoring and managing the lake's water resources. Furthermore, the research stresses the importance of land-use management strategies, ensuring fair water rights allocation, and adopting ecosystem-centred policies as key elements in safeguarding the future sustainability of the lake and its surrounding environment. Ensuring a balanced approach to land use and water resources will be essential for reversing the negative trends observed in recent decades and restoring the health of Lake Urmia.

CONCLUSION

This study examines the impacts of land-use changes and human activities on the water levels of Lake Urmia. Human activities, such as dam construction, unauthorized well drilling, agricultural expansion, and the development of orchards, have significantly reduced the lake's water levels. These changes, combined with the effects of climate change, have disrupted the lake's hydrology and led to the depletion of its water resources. The analysis of land-use changes indicated that the most significant expansion of croplands and urban areas occurred in the 2001–2005 period, particularly near the lake. However, the relatively slow pace of these changes suggests that climate change remains the primary driver of fluctuations in the lake's water levels. Additionally, the growth of croplands and the increased evaporation and water consumption during the 2015–2020 period have exacerbated the depletion of the lake's water. The construction of dams upstream and inadequate water distribution rights downstream further aggravated the situation, accelerating the loss of water from the lake. The results from the ARIMA time series model suggest that there may be hope for recovery in the future. The model predicts an increase in the lake's water levels, provided that key factors such as alleviating drought conditions, reducing the number of unauthorized wells, and improving water management through international and national agreements are addressed.

This study emphasizes the critical need for sustainable water management practices and effective land-use management strategies to ensure the long-term conservation and restoration of Lake Urmia. By integrating numerical models and remote sensing tools, valuable insights into monitoring and managing the lake's water resources are provided. Moreover, the research stresses the importance of ensuring fair water rights allocation and adopting ecosystem-cantered policies to safeguard the future sustainability of the lake and its surrounding environment. A balanced approach to land use and water resources will be essential for reversing the negative trends observed in recent decades and restoring the health of Lake Urmia.

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