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Rising temperatures and sinking hopes: An in-depth analysis of the interplay between climate change, land use patterns, and the desiccation of a global biosphere reserve

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ABSTRACT

Global ecosystems and communities are significantly impacted by climate change and extreme events. The rapid desiccation of massive wetlands, which are essential for controlling water cycles, and biodiversity, preventing floods, and supplying essential ecosystem services, is one of the most upsetting effects. The once-largest lake in the Middle East, Lake Urmia, had a significant impact on ecology, economy, and human life contributing to climate regulation, species preservation, habitat conservation, tourism and recreation, and a wide range of other ecosystem services. The Ramsar Convention classified the lake as a Wetland of International Importance, and UNESCO designated it as a Biosphere Reserve. The ecological, agricultural, and societal challenges caused by rising temperatures, improper water resource management and overuse, enhanced salinity, and declining water levels have made Lake Urmia an acute symbol of environmental vulnerability. Using Landsat imagery, this study begins a thorough analysis of changes in the Lake Urmia basin from 1990 to 2020. The endeavor aims to develop effective conservation and restoration strategies by identifying the multiple reasons that led to its vulnerable situation. The study attempts to identify the role of precipitation, temperature trends, agricultural development, population growth, water consumption, evapotranspiration, and atmospheric salt and aerosol concentrations in the desiccation of the lake. This study presents a comprehensive knowledge of the complex interplay between climate change, human activity, and water management and may have implications for the holistic recovery of the lake. The findings have the potential to improve prognostic models and inform targeted mitigation strategies for not only Lake Urmia but also for other globally threatened wetlands.

1. Introduction

Climate change and extreme events are global phenomena that have a significant impact on people and ecosystems all over the world, with the drying up of the planet's large wetlands being one of the most concerning consequences (Abou, 2022; An et al., 2020; Hidalgo and Rezapouraghdam, 2023; Scott and Huff, 1996). These are aquatic ecosystems that play an important role in water cycle

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regulation, biodiversity, and flood mitigation. Because of increased greenhouse gas emissions, global temperatures are rising, causing weather patterns to shift and wetlands to become endangered (Alizadeh et al., 2016; Barideh and Nasimi, 2022; Scott and Huff, 1996). They are also important carbon sinks because they store large amounts of carbon in soil and aquatic plants as organic matter. Climate change is causing a series of changes in these ecosystems that endanger their health and functionality, potentially affecting people's quality of life. One of the most obvious impacts of climate change on wetlands is rising temperatures (Abou, 2022; Barideh and Nasimi, 2022; Delju et al., 2013; Scott and Huff, 1996). Warmer temperatures cause water to evaporate faster, resulting in lower water levels. Thus, the study conducted on Toshka lakes (Egypt) between 2001 and 2019 reported that Land User/Land Cover (LULC) changes were a driver of the increase in Land Surface Temperatures (LST) and as a result decreased water surface by 1517 km^2 (Abou, 2022). This has an adverse effect on the people who reside in these places as well as tourism because wetlands are frequently recognized as tourist attractions due to their high ecological and environmental importance. It also has an adverse effect on the fauna and flora that depend on these ecosystems for existence. Furthermore, climate change is changing precipitation patterns, which may lead to longer droughts in some areas. Reduced rainfall reduces water availability in wetlands and can cause desiccation of previously permanently flooded areas, such as the Aral Sea (Fathian et al., 2016; Karbalaee et al., 2022). This has an effect on the local residents' way of life in addition to the biodiversity. The once-largest lake in the Middle East, Lake Urmia (Iran), is a crucial illustration of how climatic change and other human stresses are causing it to dry up. The lake significantly influenced nature, the economy, and human life, helping to regulate the climate, preserve species, conserve habitats, promote tourism and recreation, and provide a wide range of other ecosystem services. However, its water's size and volume have drastically shrunk over the past few decades (Parsinejad et al., 2022). Rising temperatures caused by climate change have increased water evaporation, resulting in lower water levels and higher lake salinity, which has had a negative impact on aquatic life, agricultural areas, and neighboring populations (Barideh and Nasimi, 2022; Mojtahedi et al., 2022). Poor water resource management, as well as excessive water extraction for agriculture and population supply, have all contributed significantly to Lake Urmia's drying up. Desiccation has had serious environmental, economic, and social ramifications. It has caused salinization of nearby agricultural land, which has a negative impact on agriculture and the local economy. Furthermore, the loss of aquatic habitats has resulted in a decline in biodiversity. According to the United Nations Environment Programme (UNEP) (UNEP, 2012, in addition to supporting numerous species of reptiles, amphibians, and mammals, the lake itself is home to a rare species of brine shrimp called Artemia urmiana. The only link between the lake's primary algal production and the variety of migratory bird populations that consume these shrimps is its population of brine shrimp. Many migratory bird species including pelicans and flamingos find a very important seasonal habitat at this lake. Due to the brine shrimp's critical role in the ecosystem, their extinction would likely result in the dwindling of many migratory bird populations in Lake Urmia and have an impact on the sustainability of the entire ecosystem. On the other hand, the lake's desiccation has forced tourism and recreation activities to stop in this unique destination too.

Numerous investigations have been conducted in recent decades and within the scientific community regarding the lake's drying process and its causes. Many studies (Hamzekhani et al., 2016; Shadkam et al., 2016) confirmed decreases in water surface of 40–86% between 1966 and 2011, while a recent study by Barideh and Nasimi (2022) reported an 80% decrease. Climate change and anthropogenic or human interference are two of the reasons attributed to this desiccation process. The former includes rainfall and temperatures, while the latter consists of agricultural expansion, increased evapotranspiration, growing populations, urban areas, and higher salinity and aerosol concentrations in the air (Alizadeh et al., 2016; Barideh and Nasimi, 2022; Chaudhari et al., 2018; Delju et al., 2013; Farokhnia et al., 2018; Fathian et al., 2016; Foroumandi et al., 2022; Janalipour et al., 2022; Karbalaye Ghorbanpour et al., 2021 Mojtahedi et al., 2022; Parsinejad et al., 2022). Previous studies reported that rainfall had remained constant in recent decades and thus it was not a motivating factor for the lake's drying up (Foroumandi et al., 2022; Karbalaye Ghorbanpour et al., 2021). In terms of temperature increase, the studies (Alizadeh et al., 2016; Barideh and Nasimi, 2022; Farokhnia et al., 2018) report an increase of 0.05 °C per year, which represents an increase of 0.50 °C per decade. In contrast, and with regard to the increase in agricultural areas, Barideh and Nasimi (2022) reported a 174% increase between 2000 and 2020, and Farokhnia et al. (2018) found an increase of 200%–400% between 1988 and 2007. This growth in agricultural areas has resulted in an increase in areas destined for urban areas and in the population to house the immigrant population in search of work. In this regard, Chaudhari et al. (2018) reported a 180% increase between 1980 and 2010, while Kanani et al. (2020) reported an 88.9% increase between 1970 and 2014. Between 1980 and 2010, the increase in agricultural areas and population resulted in an estimated 300% increase in water demand (Chaudhari et al., 2018). The increase in temperatures together with the decrease in the level of the lake and the rise in the areas destined for agriculture has generated an increase in evapotranspiration of 38% between the years 1990 and 2011 (Mojtahedi et al., 2022). This has further reduced the volume of reservoir water and has led to an increase in salinity and aerosol concentrations in the environment (Janalipour et al., 2022; Mojtahedi et al., 2022; Nadizadeh et al., 2018). The drawback of all these works is that they analyze the possible causes that have caused the decrease in the water level in the lake individually, relating the effect produced either with the increase in temperatures, with changes in land use, the increase in population, or evapotranspiration. On the contrary, and here is where the novelty or the GAP of this research is found, a global analysis of the basin is proposed, analysing not only each cause individually but also jointly in order to know the relationship between the different causes and which ones indirectly cause others. In this way, the study will allow in an exhaustive way not only the causes but also the relationships between them, allowing us to obtain an accurate diagnosis of the drying process and to be able to implement more effective protection measures not only for the lake but also for the population.

In recent years, and among the different methodologies used to determine changes on the planet's surface that present excellent results, there is Remote Sensing. Thus, there are numerous studies that use high-resolution satellite images that allow the analysis and identification of changes in different land covers (Abou, 2018, 2021; Hidalgo and Arco, 2022; Otukei and Blaschke, 2010), the study of vegetation and buildability indices in urban areas and studies (Du, 2020; Fang and Tian, 2020) on LST and the Urban Surface Heat

Island (SUHI) phenomenon (Abou, 2023; Fathian et al., 2016; Hidalgo and Arco, 2021). Its use in this type of study such as the one presented here is widely justified.

The ecological, economic, and societal significance of Lake Urmia's drying is of utmost importance on a local as well as a global scale. It bridges significant knowledge gaps, guides management and policy decisions, and advances knowledge of environmental issues in the face of climate change. International discussions on coping with climate change, managing water resources, and preserving wetlands are insights that can be gained from studying Lake Urmia's drying process. This study aims to analyze and investigate the changes that the Lake Urmia basin experienced between 1990 and 2020 using Landsat images. Identifying the causes of the lake's desiccation can provide us with important implications for developing effective restoration and preservation strategies that will lead to the area's sustainable development. Due to its significance on the local and global ecological, economic, and social scales, the study of Lake Urmia's drying is essential. It closes significant knowledge gaps, supports management and policy choices, and advances awareness of the environmental problems brought on by climate change. The following issues are raised by this study: 1) How have rainfall, temperatures, agricultural development, population growth, water supply demand, evapotranspiration, and salt and aerosol concentrations in the atmosphere changed between 1990 and 2020? 2) Is there a correlation between these factors, and if so, which one affects the lake's drying process more or less? 3) Will the results of this study be helpful in creating a thorough lake recovery plan?

The results obtained in this study are of great importance not only at a local level (Lake Urmia) but also at an international level since the causes and effects of the drying reported here can be extrapolated to other wetlands around the world. The causes reported here will help us understand the exact reasons for the drying of the lake, including the impact of climate change, anthropogenic and human factors, water management and the relationship between these variables. A better understanding of the causes and their interrelations could lead to more effective mitigation strategies in the short and long term, as well as to the development of more precise models in future research that allow for a more accurate and adequate prediction of the future evolution of the lake, its environment and the degree of impact on population and tourism. The results of this study could have broader implications since our results can be applied to other wetlands around the world in order to avoid the mistakes made in Lake Urmia. On the other hand, it is of great importance to national government administrations and provides useful information for formulating policies that can slow down the rate at which land use and land cover, water use, and lake desiccation are changing in the region. Government administrations should give top priority to land use management strategies that reduce urbanization, and water use and improve environmental conservation. In addition, local decision makers should promote sustainable tourism planning and management, especially for travelers staying abroad.

2. Materials and methods

2.1. Study area

The area under study is the Lake Urmia basin located in northwestern Iran (Fig. 1). Lake Urmia used to be a popular tourist destination that supported the livelihood of countless people. Bathers would submerge themselves in the salty water and cover their bodies in the lake's mythical black mud when it was a popular destination for tourism several years ago. The recreation facilities are all now in ruins. The port towns are now sparsely populated settlements that young people left for neighboring cities. According to the UNEP (UNEP, 2012) in its prime, this lake was both a vital resting place for migrating birds like flamingos and pelicans as well as the largest natural habitat for the saline-adapted Artemia brine shrimp. More than just an environmental disaster and the loss of a vital economic source, the lake was a social identity and cultural icon for individuals who can still picture what this place once was

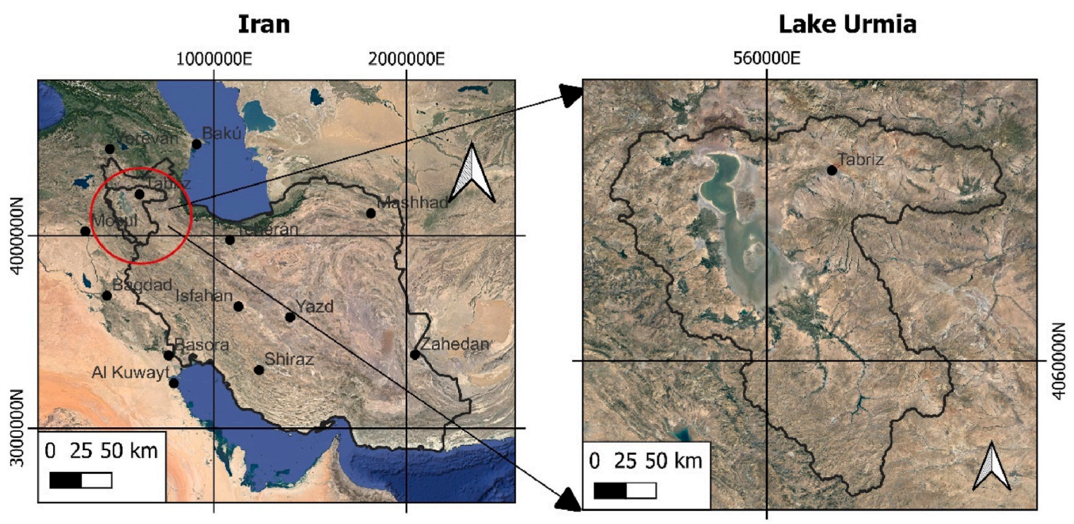

Fig. 1. Study area, lake Urmia, Iran.

(Daryani, 2020). Environmental and human health are impacted by Lake Urmia's decline. The lake, its islands, and the nearby wetlands are recognized as a national park, a Ramsar site, and the United Nations Educational, Scientific and Cultural Organization (UNESCO) Biosphere Reserve because they include vital habitats (UNESCO, 1976). The region serves as a stopover for migratory species as well as a breeding destination for waterbirds. There were 200 recognized species of migratory birds that used Lake Urmia as a critical seasonal habitat, including pelicans, egrets, ducks, and flamingos. Millions of people reside within a 500 km radius of the lake, which is an important agricultural zone for the majority (UNEP, 2012). Low lake levels, however, stress brine shrimp populations and other sources of food for larger animals because the remaining water becomes more salinized. A diminishing lake also raises the chance that winds will pick up dust from the exposed lakebed, lowering the quality of the air. Recent research has connected the local population's respiratory health issues with Lake Urmia's low water levels (Feizizadeh et al., 2023). It is debatable how much of the effect that climate, water use, and dams have on Lake Urmia's water level (Schulz et al., 2020). The importance of Lake Urmia in maintaining livelihoods and regional economies is highlighted by the substantial human presence, which emphasizes the need to comprehend and reduce its desiccation.

Until 2010, it was considered one of the world's largest saline lakes, with a maximum area of 4995 km^2. The lake basin's Universal Transverse Mercator (UTM) coordinates are 37.5^o North and 45.5^o East, and it covers an area of 52700 Km^2 with average elevations ranging from 1280 to 4880 m above sea level. This lake is connected by 13 rivers, including the two largest, the Zarrineh and the Simineh, which originate in the mountains and provide nearly half of the lake's flow (Parsinejad et al., 2022). The basin is home to 6.4 million people, the majority of whom live in the cities of Tabriz and Urmia. The basin has a humid-hot continental climate (Dsa), according to the Köppen-Geiger which translates into very cold winters and dry summers. The average rainfall in the basin is between 350 and 400 mm/year, and previous studies have calculated evapotranspiration to be between 580 and 2000 mm/year (Parsinejad et al., 2022). The transformation of different land uses for agriculture, as well as the construction of more than 40 small reservoirs and locks for irrigation, has caused the lake level to drop from 1278 to 1270 m in the last 40 years, resulting in an 80% increase in the dry surface and a high salinity of both water and land in the basin. Fig. 2 shows the significant decline in the evolution of the surface area occupied by water between 1990 and 2020.

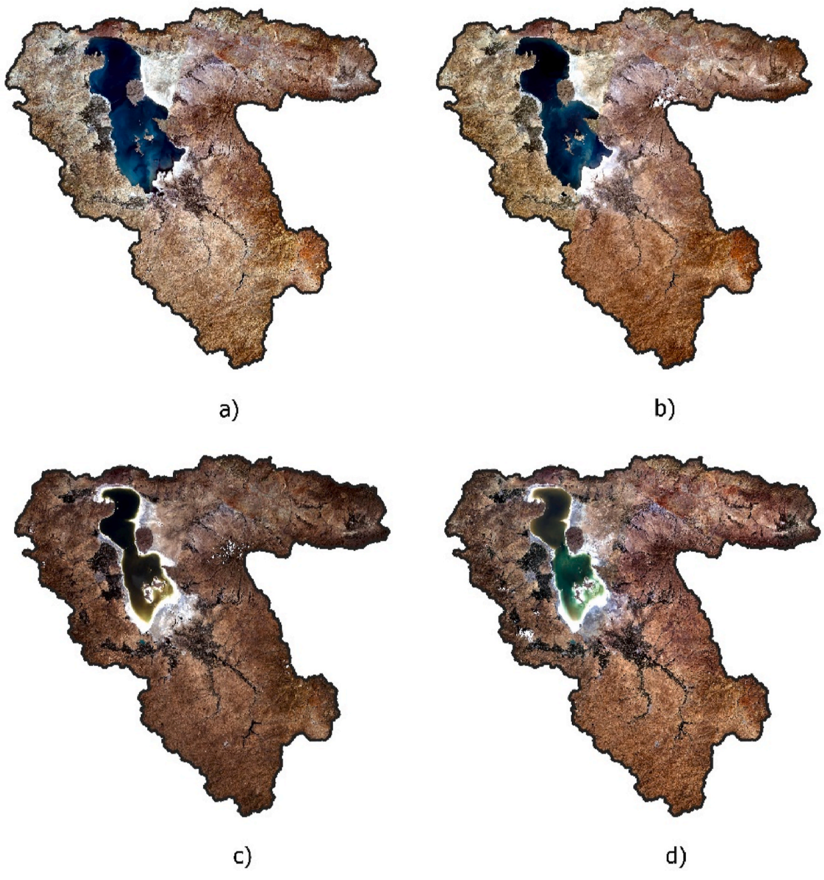

Fig. 2. Evolution of Lake Urmia between 1990 (a), 2000 (b), 2010 (c) y 2020 (d). True color satellite images, bands 4-3-2. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

2.2. Methodology

Fig. 3 depicts the steps taken in the methodology. The following indices were determined using images from Landsat 5 (1990), Landsat 7 (2000 and 2010), and Landsat 8 (2020): Normalized Difference Vegetation Index (NDVI), Proportion Vegetation (PV), Normalized Difference Built Index (NDBI), Bare Soil Index (BSI), Normalized Difference Water Index (NDWI), Normalized Difference Moisture Index (NDMI), and soil salinity. The LULC drawings were created using the Support Vector Machine (SVM) methodology from Landsat imagery. A precision matrix was used to determine the accuracy of land cover (Campbell, 1996; Hidalgo and Arco, 2022; Yoo et al., 2019). The LST for the indicated years has been calculated using the Landsat thermal band. The provisional Landsat Evapotranspiration (Eta) science product from collection 2 (C2) level 3 (L3), which represents the combined level of daily evaporation and transpiration for each pixel in a Landsat scene, was used to calculate the actual Eta for the Landsat satellites. The aerosol concentrations were then obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite using the MOD04_L2 product. Finally, the basin's average annual rainfall has been calculated using the Tropical Rainfall Measuring Mission (TRMM) model. Following that, all data was statistically analyzed using the Data Panel and the Mann-Kendall test. This methodology allows for the analysis of the evolution and trends of various variables in time studies (Foroumandi et al., 2022; Shamloo et al., 2022). All of the graphic documentation was created with the open-source software QGIS, and the various statistical analyses were completed with the specialized software STATA.

2.3. Landsat imagery

Landsat images 5 (year 1990), 7 (years 2000 and 2010), and 8 (year 2020) were obtained The National Aeronautics and Space Administration (NASA). The Landsat imagery used in this study is shown in Table 1. With Landsat 8, only band 10 was used to calculate LST. The Dark Object Subtraction (DOS) algorithm was used through the Semi-Automatic Classification Plugin (SCP) in the QGIS to proceed with the atmospheric correction of all bands (Chavez, 1988; Congedo, 2016; García and Díaz, 2021). The dataset was collected for the month of June of each indicated year because the climate in Iran is typically sunny and cloudy (<5%). As a result, it allows for

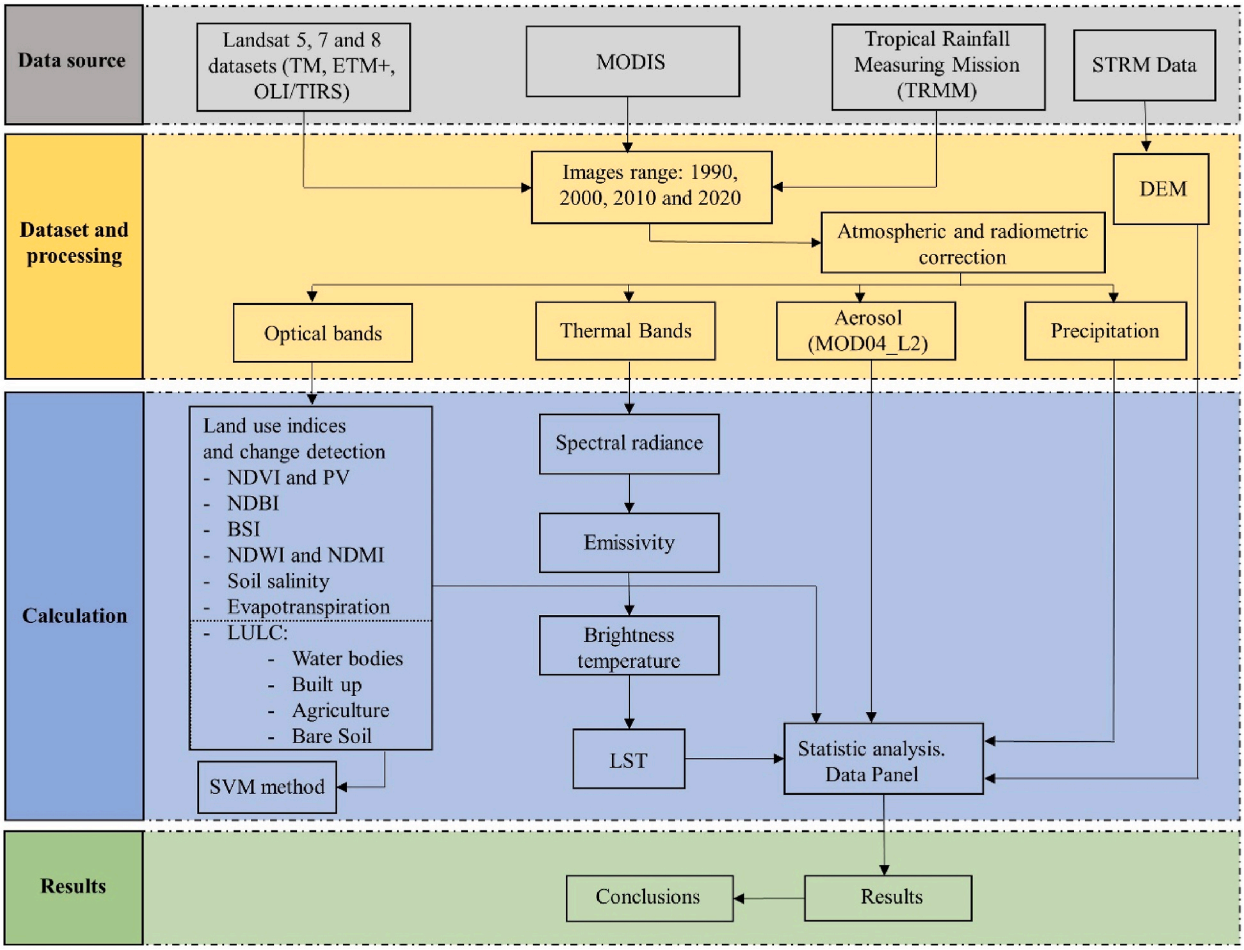

Fig. 3. Methodology.

Table 1
Landsat and MODIS imagery used in the study.

Name product	Date (yyyymmdd)	UTC Time (hhmm)	Cloudiness (%)	Spatial Resolution (m)
LT05_L2SP_168034_19900625_19900625_02_T1	19900625	08:37	1.37	30
LE07_L2SP_168034_20000628_20000628_02_T1	20000628	08:35	2.45	30
LE07_L2SP_168034_20100624_20100624_02_T1	20100624	08:45	1.28	30
LC08_L2SP_168034_20200627_20200627_02_T1	20200627	08:29	0.86	30
MOD04_L2.061	19900626	08:45	2.10	10000
MOD04_L2.061	20000627	08:43	1.39	10000
MOD04_L2.061	20100625	08:39	1.01	10000
MOD04_L2.061	20200627	08:49	0.86	10000

better differentiation of soil uses and typologies.

2.4. *MODIS images*

The MODIS is a satellite instrument that monitors the Earth's surface and is installed on the Terra (EOS AM-1) and Aqua (EOS PM-1) satellites. It has a strip width of 2330 km and orbits the planet once every 1, or 2 days. MODIS has 36 spectral bands that collect data at 250, 500, and 1000 m spatial resolutions. The MODIS products used in this study were obtained from the United States Geological Survey (USGS) and, like the Landsat images, were corrected using the DOS algorithm. They were later georeferenced with the ETRS89/UTM Zone 38N projection system. The MODIS images used in this study are shown in Table 1.

2.5. *TRMM*

The TRMM mission was launched as a result of a collaboration between the NASA and the Japanese Aerospace Exploration Agency (JAXA) with the goal of monitoring precipitation in various parts of the world. It generates precipitation time series using a variety of methodologies. Data with 0.25^{o} x 0.25^{o} latitudinal and longitudinal resolution are available. There have been numerous studies that have used this methodology to analyze and study rainfall in various parts of the world (Foroumandi et al., 2022; Keikhosravi-Kiany et al., 2022). For our research, multisatellite precipitation data with average monthly values (3B43, hereinafter TRMM 3B43) were used.

2.6. *Landsat spectral indices*

Table 2 lists the various spectral indices calculated with Landsat.

Table 2
Landsat spectral indices.

Index	Equation	Number	Reference
NDVI	$NDVI = \frac{NIR - Red}{NIR + Red}$	(1)	García and Díaz (2023)
PV	$PV = \left[\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right]^2$	(2)	Yu et al. (2014)
BSI	$BSI = \frac{(SWIR_1 + Red_2) - (NIR + Blue)}{(SWIR_1 + Red_2) + (NIR + Blue)}$	(3)	Sultana and Satyanarayana (2020)
NDBI	$NDBI = \frac{SWIR_1 - NIR}{SWIR_1 + NIR}$	(4)	Zha et al. (2003)
NDWI	$NDWI = \frac{Green - NIR}{Green + NIR}$	(5)	Zha et al. (2003)
NDMI	$NDMI = \frac{NIR - SWIR_1}{NIR + SWIR_1}$	(6)	Ghosh et al. (2020)
Soil Salinity	$IndSal = \frac{NIR - SWIR_2}{NIR + SWIR_2}$	(7)	Lamz and González (2013)
Spectral radiance	$L_\lambda = M_L \times Q_{Cal} + A_L$	(8)	Kafer et al. (2019)
Brightness temperature (°C)	$T = \frac{K_2}{\log\left(\frac{K_1}{L_\lambda} + 1\right)} - 273.15$	(9)	Weng et al. (2004)
Land Surface Emissivity	$\varepsilon = 0.004 \times \mathrm{Pv} + 0.986$	(10)	Sharma et al. (2021)
LST (°C)	$LST = \frac{T}{\left(1 + \left(\lambda \frac{T}{C_2}\right) x \log(\varepsilon)\right)}$	(11)	Weng et al. (2004)
	$C_2 = \frac{h\, x\, c}{s},$	(12)	Weng et al. (2004)

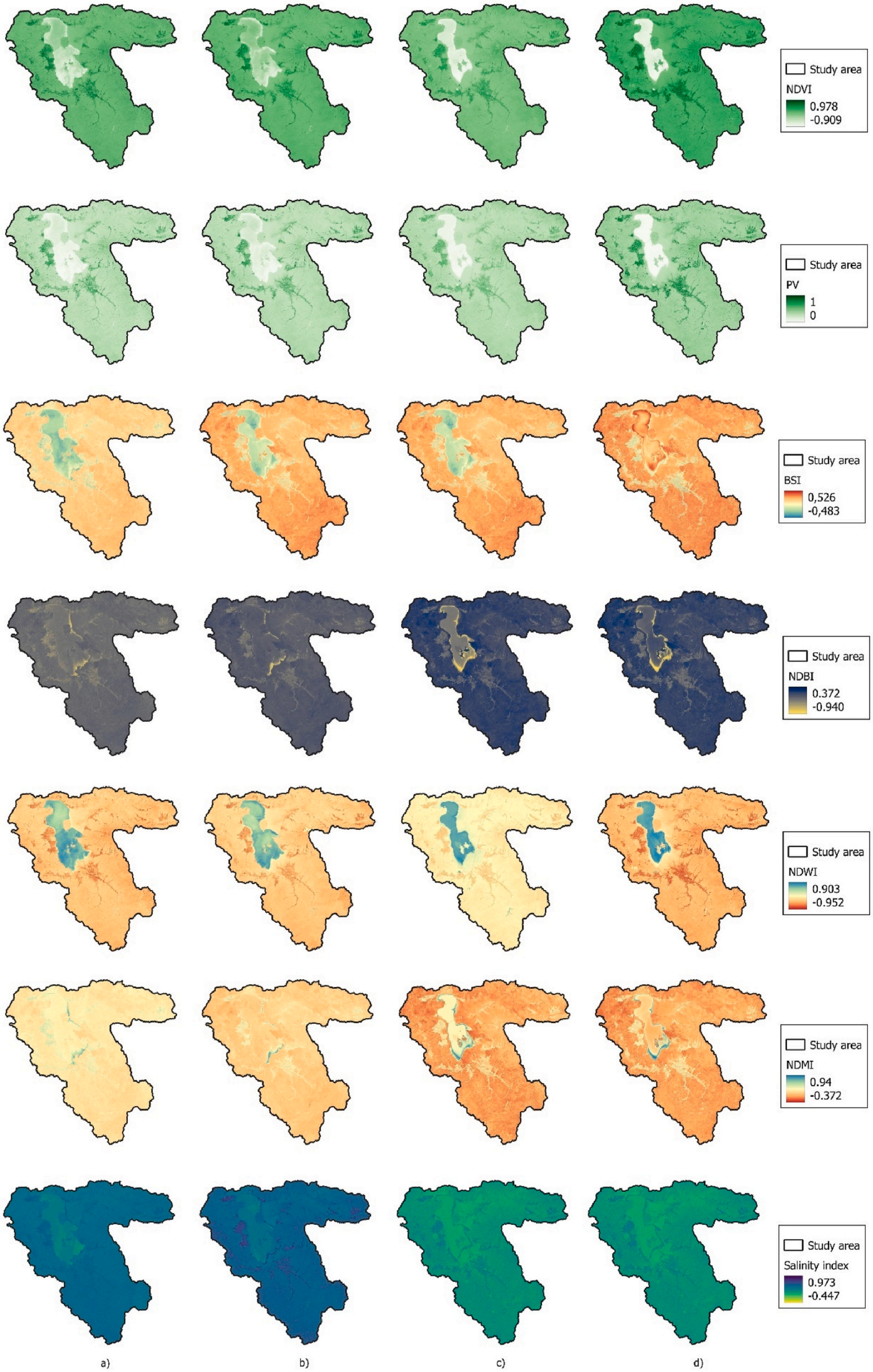

Fig. 4. Evolution of the NDVI, PV, BSI, NDBI, NDWI and soil salinity index between 1990 (a), 2000 (b), 2020 (c) and 2020 (d) obtained by remote sensing according to bands and equations (1)–(7).

2.7. LULC

LULC maps were created using Landsat images and a red, green, and blue band (RGB) plane. After that, the LULC drawings were obtained using the SVM and QGIS software. In numerous studies, this system has been used and reported with excellent results (Otukei and Blaschke, 2010; Shafri and Ramle, 2009) because it enables precise classification of various land uses (Amindin et al., 2021). Four types of soil or cover have been identified for this work: bodies of water, urbanized, agriculture, and bare soil. Following that, the accuracy of the coverage was determined using a precision matrix in order to know the degree of precision obtained and by downloading Sentinel 2 images from the year 2022.

2.8. Digital Elevation Model (DEM)

The Shuttle Radar Survey Mission (SRTM) operated by the NASA provides Digital Elevation Model (DEM) maps in high spatial resolution (Karbalaye Ghorbanpour et al., 2021; Schneider et al., 2010) from anywhere on the planet. DEM data for the Lake Urmia basin with a spatial resolution of 90 m were downloaded from https://srtm.csi.cgiar.org/. According to the findings, the basin has an altitude range of 3862 to 1 m, with an average altitude of 1740 m.

2.9. Lake level

Lake Urmia had depths ranging from 6 to 16 m, with the deepest point located at an altitude of 1267.1 m above sea level. The water level in the years studied was as follows: 1990: 1276 m; 2000: 1273 m; 2010: 1271 m; and 2020: 1271.8 m. The highest water level was reported in 1995 at 1278 m, while the lowest level was reported in 2014 at 1270.8 m. Beginning this year, the water level has been gradually rising as a result of the Iranian government's policies to preserve the lake as an element of the area's ecological, tourism, and supply sustenance (Parsinejad et al., 2022).

2.10. Strategy of analysis

For our statistical analysis, we used two complementary methods: the Mann-Kendall Trend Test and the Data Panel. Both methods are appropriate for studying cross-sectional data in time series in order to confirm the existence of a trend and the factors that influence it. The MK test is commonly used in hydrological and climate change research (Foroumandi et al., 2022; Shamloo et al., 2022). High positive and low negative values indicate statistically significant increasing and decreasing trends, respectively. The trend's significance is determined by the p value. Equation (13) is used to calculate it:

Table 3
Statistics of spectral indices calculated with Landsat.

Indices	Variable	1990	2000	2010	2020
NDVI	Max	0.986	0.917	0.917	0.999
	Min	−0.857	−0.997	−0.707	−0.969
	Mean	0.181	0.149	0.178	0.268
	SD	0.178	0.145	0.170	0.206
PV	Max	1.000	1.000	0.981	1.000
	Min	0.001	0.001	0.011	0.001
	Mean	0.280	0.288	0.311	0.369
	SD	0.110	0.101	0.091	0.139
BSI	Max	0.655	0.582	0.667	0.574
	Min	−0.753	−0.647	−0.579	−0.687
	Mean	0.121	0.115	0.086	0.065
	SD	0.133	0.122	0.082	0.110
NDBI	Max	0.849	0.998	0.637	0.858
	Min	−0.919	−0.928	−0.889	−0.966
	Mean	0.048	0.051	0.083	0.108
	SD	0.105	0.095	0.132	0.141
NDWI	Max	0.927	0.998	0.665	0.969
	Min	−0.993	−0.978	−0.968	−0.999
	Mean	0.292	0.218	0.134	0.182
	SD	0.271	0.237	0.178	0.292
NDMI	Max	0.929	0.928	0.889	0.966
	Min	−0.849	−0.997	−0.636	−0.858
	Mean	0.048	0.054	0.073	0.096
	SD	0.105	0.095	0.133	0.141
Soil salinity	Max	0.948	0.599	0.964	0.987
	Min	−0.925	−0.785	−0.834	−0.918
	Mean	0.074	0.094	0.114	0.126
	SD	0.078	0.057	0.056	0.061

Max: Maximun; Min: Minimun; Mean: Mean; SD: Standard deviation.

$$S = \sum_{K=1}^{n-1} \sum_{j=K+1}^{n} sgn(X_j - X_k), \tag{13}$$

where sgn (x) is: 1 if X > 0; 0 if X = 0 y −1 if X > 0.

The Data Panel is frequently cited in the literature because it employs multiple regression models (Fang and Tian, 2020; Hidalgo García and Arco Díaz, 2021) that allow for the inclusion of more data than traditional methods. According to equation (14), the following phases are followed (Chen et al., 2011):

$$Y_{it} = \beta X_{it} + (\alpha_i + \mu_{it}) \tag{14}$$

where μ_{it} is the model error, t = time, i = individual, α_i represents the individual effects, β is an independent variable and X_{it} are explanatory variables.

3. Results

3.1. Landsat spectral indices

The spatiotemporal analysis of the spectral indices obtained with Landsat: NDVI, PV, BSI, NDBI, NDWI, NDMI and soil salinity of the area under study can be visualized in Fig. 4. Table 3 shows the basic values for each of the analyzed indices.

It can be seen how the NDVI and PV indices related to vegetation have presented an increase in the average values between 1990 and 2020 of 32.46% and 24.12%, respectively. Thus, the lowest average value of both indices (0.181 and 0.280) is reported in 1990 while the highest value (0.268 and 0.369) is reported in 2020. The values of the NDVI and PV indices indicate that vegetation and areas destined for agriculture have experienced significant growth between 1990 and 2020. This claim is supported by the changes observed in the BSI and NDMI indices. The first index allows to determine the variations that may have occurred in the soil while the second allows to obtain the levels of humidity in the vegetation. Thus, the BSI index has shown an average increase of 86.15% between 1990 and 2000. The highest average value (0.121) occurs in 1990 while the lowest average value is reported in 2020 (0.065) representing a reduction of 86.15%. The NDMI index has experienced an average growth of 50% and presents the highest value (0.096) in the year 2020 while the lowest average value is reported in the year 1990 (0.048). Therefore, a significant increase in the areas destined for agriculture is corroborated by the evolution experienced in the NDVI and PV indices that is compatible with the evolution denoted in the BSI index that corroborates changes in the soil surface together with an increase in vegetation moisture reported by the increase in the NDMI index.

Between 1990 and 2020, the average value of the NDBI index for building and construction increased by 125%. Thus, the lowest average value of the index (0.048) is reported in 1990 while the highest value (0.108) is reported in 2020. This variation in the index indicates that urban areas have grown significantly as a result of population growth. With respect to the NDWI index that allows us to determine the amount of water in an area, indicate that it has experienced an average decrease of 62.34%. The highest mean value (0.292) is reported in the year 1990 while the lowest mean value (0.182) is reported in the year 2020. This index variation indicates a significant decrease in the amount of water in the basin under consideration between 1990 and 2020.

Finally, the salinity index, which determines the amount of salts in a soil, shows an average increase of 170.21%. The lowest mean value (0.074) is reported in the year 1990 while the highest mean value (0.126) is reported in the year 2020. This variation of the index indicates a significant increase in the number of salts that the analyzed surface has compatible with the significant decrease in the amount of water reported by the NDWI index.

3.2. LULC analysis

The spatiotemporal analysis of the evolution of the LULC between 1990 and 2020 can be seen in Fig. 5 while the variability between the different years is located in Table 4.

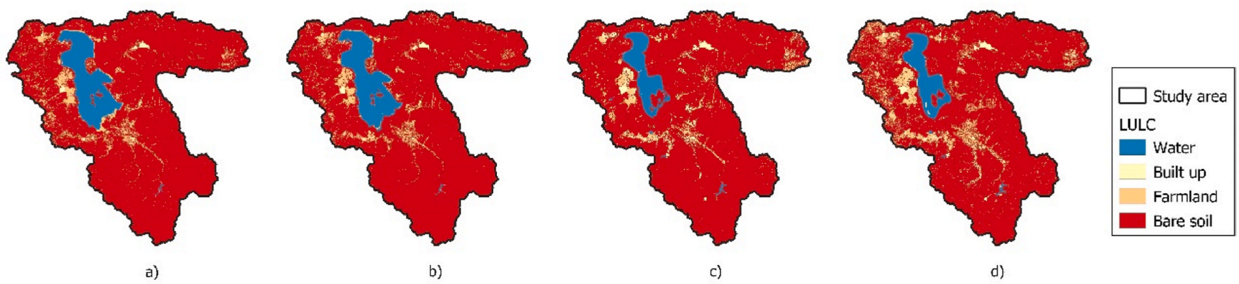

Fig. 5. Evolution of LULC between 1990 (a), 2000 (b), 2010 (c) and 2020 (d) obtained by remote sensing using QGIS software and SVM classification.

Table 4
Change in land use by year.

LULC (Ha)	1990	2000	2010	2020	Variability (%) (1990–2020)
Water bodies	4847	4509	1890	1734	−64.22
Built up	209	223	1089	1214	481.65
Farmland	3336	3800	5234	4956	148.55
Bare soil	45627	45428	45486	46115	1.10

The coverage identified as water presents the highest average value with 4847 Ha (Hectares) in 1990 while the lowest average value of 1734 Ha occurs in 2020. These values establish an average decrease between 1990 and 2020 of −64.22%. On the contrary, the hedges of Built up and farmland present a lower average value in 1990 with values of 209 Ha and 3336 Ha, respectively, while the highest average value has been obtained in 2020 with values of 1214 Ha and 4956 Ha, respectively. These values represent an average increase of 481.65 and 148.55%, for Built up and farmland coverages, respectively. With respect to bare soil cover, it has remained constant between the different years analyzed with an average increase of 1.10%. These results are consistent with those obtained in the previous point for the various indices studied.

The results of the precision matrices, obtained using Landsat 8 images to verify the LULC maps for the years 1990, 2000, 2010, and 2020, are reflected in Tables 5–8. The precision values of the matrices for each of the years described are 78.8%, 83.8%, 86.3%, and 85%, respectively. The Kappa values for each of the years described are 0.768, 0.823, 0.853, and 0.835, respectively. However, for the purposes of the investigation, after the automatic classification, a subsequent manual correction was made of the points that did not coincide with the LULC maps obtained in order to increase the precision obtained.

3.3. Spatiotemporal evaluation of LST

Fig. 6 and Table 9 show the evolution of LST values between the years 1990 and 2020 in the Lake Urmia basin. In general, it can be observed how the highest values of LST are located in the Bare soil and Built-up coverage areas of the LULC planes in contrast to the wetter and farmland coverage areas that present lower LST values. Therefore, the lowest temperatures occur in areas with higher values in the NDVI, PV, and NDMI indices and lower NDBI values. On the contrary, the highest temperatures are found in areas with lower NDVI, PV, and NDMI index values and higher NDBI index values.

The lowest mean LST value was 34.85 °C in 1990 while the highest value was 36.95 °C in 2020. LST spatial statistics for the Lake Urmia basin show a continuous increase of 2.10 °C (0.53 °C/decade) from 1990 to 2020, representing a 106.30% increase. The maximum values, on the other hand, show greater increases in the trend, with values of 6.85°C (1.71°C/decade). On the contrary, minimum temperatures are rising at a rate of 2.12 °C (0.53°C/decade).

3.4. Spatiotemporal evaluation of aerosols

Fig. 7 shows the spatiotemporal analysis of aerosols between 1990 and 2020 in the studied area obtained with MODIS. Table 10 presents the basic statistical measures of each variable.

The lowest mean aerosol value was 0.170 μm in the year 1990 while the highest value was 0.265 μm in the year 2020. Aerosol spatial statistics from the Lake Urmia basin show a continuous increase of 0.095 μm (0.024 μm/decade) from 1990 to 2020, representing a 173.52% increase. As a result, a significant increase in aerosol levels has been reported in the Lake Urmia basin. This circumstance could be influenced by two factors: 1) As the lake's water level drops, the wind has an easier time moving the salt particles and depositing them in the adjacent territories. 2) The expansion of cropland implies a greater use of pesticides for pest control. Both circumstances are revealed by the results obtained in the previous points where the evolution of the indices and LULC was examined.

3.5. Spatiotemporal evaluation of Eta

Fig. 8 depicts the spatiotemporal analysis of Eta in the studied area using the Landsat satellite between 1990 and 2020. Table 11 shows the central tendency and dispersion measures for this variable.

The lowest mean Eta value was 61 mm/m^2 in 1990 while the highest mean value was 102 mm/m^2 in 2020. Spatial Eta statistics

Table 5
LULC Precision Matrix year 1990.

	1	2	3	4	UA (%)
1	16	3	1	0	20
2	1	16	2	1	20
3	0	2	15	3	20
4	0	0	4	16	20
PA (%)	17	20	22	20	80

Table 6
LULC Precision Matrix year 2000.

	1	2	3	4	UA (%)
1	17	2	1	0	20
2	1	17	1	1	20
3	0	2	16	2	20
4	0	0	3	17	20
PA (%)	18	21	21	20	80

Table 7
LULC Precision Matrix year 2010.

	1	2	3	4	UA (%)
1	17	1	1	1	20
2	0	17	2	1	20
3	0	0	17	3	20
4	0	1	1	18	20
PA (%)	17	19	21	23	80

Table 8
LULC Precision Matrix year 2000.

	1	2	3	4	UA (%)
1	18	2	0	0	20
2	0	18	1	1	20
3	0	2	15	3	20
4	0	0	3	17	20
PA (%)	18	22	19	21	80

Note: 1: Water bodies. 2: Built up. 3: Farmland. 4: Bares soil. PA: Exactitud productor. UA: Exactitud usuario.

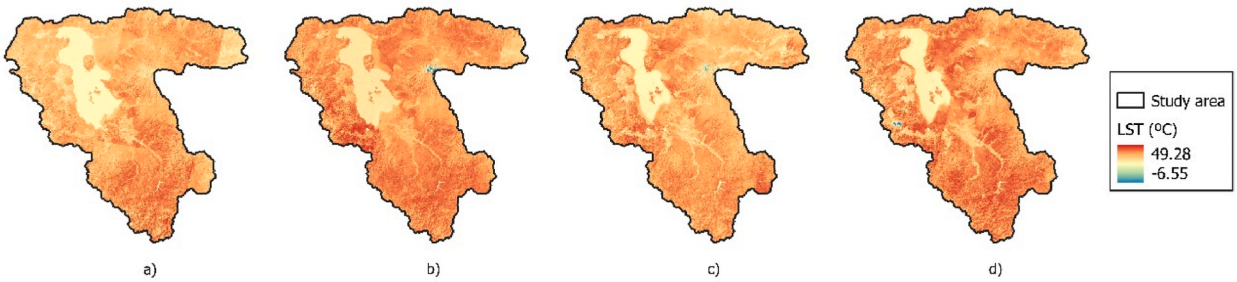

Fig. 6. Evolution of the LST between 1990 (a), 2000 (b), 2020 (c) and 2020 (d) obtained with Landsat.

Table 9
LST dispersion measures.

Year	Max	Min	Mean	SD
1990	56.97	−6.85	34.85	5.97
2000	59.95	−4.34	35.50	5.79
2010	61.98	−5.72	36.52	5.24
2020	63.82	−4.73	36.95	5.66

Min: Minimum; Mean: Mean; Max: Maximum; SD: Standard deviation.

from the Lake Urmia basin show a continuous increase during the period 1990–2020 of 0.095 μm (0.024 μm/decade) representing an increase of 173.52%. These results are compatible with those reported by the LST and the various indices, so that, the higher the temperature, the greater the evaporation and the greater the vegetation, the greater the Eta. In this way, and as a result of the increase in LST and vegetation area, Eta has increased significantly.

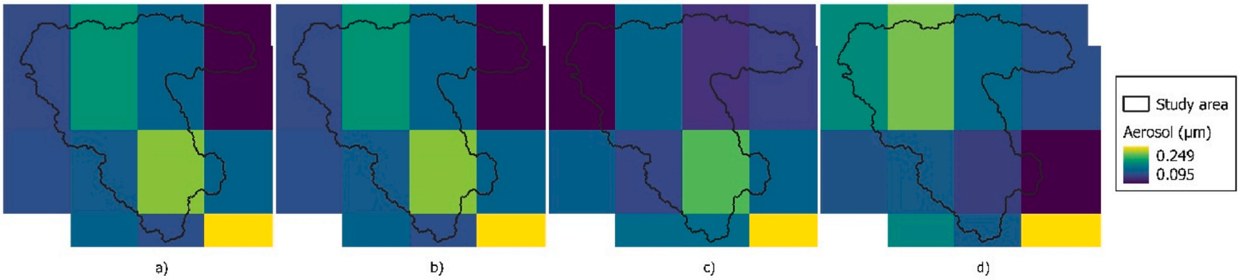

Fig. 7. Evolution of aerosols between 1990 (a), 2000 (b), 2020 (c) and 2020 (d) obtained with MODIS.

Table 10
Aerosol dispersion measurements.

Year	Max	Min	Mean	SD
1990	0.204	0.142	0.170	0.025
2000	0.235	0.163	0.195	0.028
2010	0.375	0.160	0.258	0.077
2020	0.393	0.126	0.265	0.081

Min: Minimum; Mean: Mean; Max: Maximum; SD: Standard deviation.

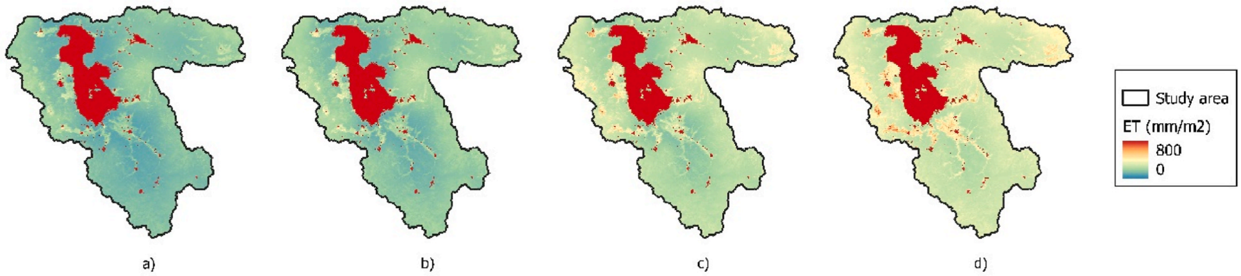

Fig. 8. Evolution of Eta between 1990 (a), 2000 (b), 2020 (c) and 2020 (d) obtained with Landsat.

Table 11
Eta dispersion measures.

Year	Max	Min	Mean	SD
1990	406	9	61	124
2000	478	11	71	146
2010	655	15	98	200
2020	685	20	102	199

Min: Minimum; Mean: Mean; Max: Maximum; SD: Standard deviation.

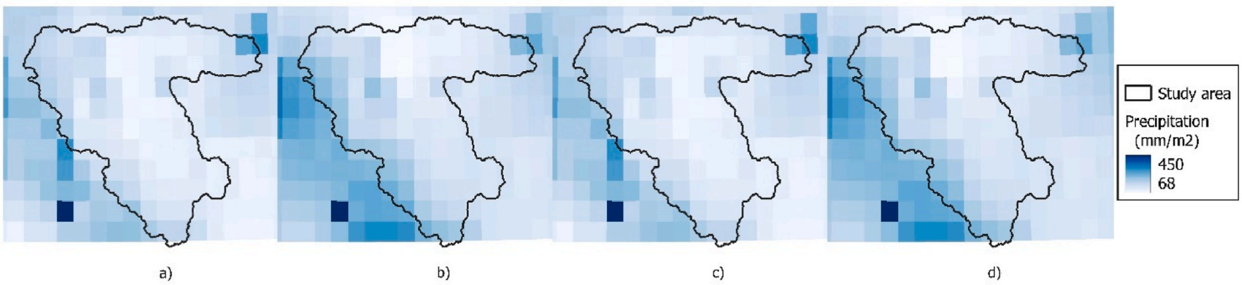

Fig. 9. Evolution of rainfall between 1990 (a), 2000 (b), 2020 (c) and 2020 (d) obtained with TRMM.

3.6. Spatiotemporal evaluation of precipitation

Fig. 9 shows the spatiotemporal analysis of rainfall between 1990 and 2020 of the studied area obtained using the TRMM 3B43 model. Table 12 presents the measures of central tendency and dispersion of this variable.

The lowest mean value of aerosol precipitation was 360 mm/m^2 in 2000, while the highest mean value was 390 mm/m^2 in 2020. Spatial precipitation statistics for the Urmia Lake basin show a slight increase between the years 1990 and 2020.

3.7. Statistical analysis

3.7.1. Mann-Kendall trend test

Between 1990 and 2020, the possible growth or decrease trends of the various variables studied in the Lake Urmia basin were investigated.

The Mann-Kendall test was used for this, and the results are shown in Table 13. The test results showed that the variables PV, NDBI, NDWI, NDMI, Salinity, Aerosols, ET, and precipitation increased or showed a positive trend (above 99%) between 1990 and 2020. The variables LST and NDVI have also increased, but with statistical relationships of 99% and 95%, respectively. The BSI variable, on the other hand, has shown a negative or decreasing trend with a statistical relationship of 99%. These findings support the analytical data presented in the preceding sections.

3.7.2. Data panel

Firstly, Pearson correlation coefficients have been calculated to determine the relationship between the investigated variables (Table 14). It can be seen how the lake level variable has a strong negative correlation with the NDWI variable (−0.927), as well as a negative correlation with PV (−0.332), salinity (−0.283) and aerosols (−0.279). Finally, it has a weak and negative correlation with the variables LST (−0.155) and NDBI (−0.199), but positive with the BSI (0.126). The Table shows how these correlations have a significance of less than 5% (statistically significant above 99%), so we reject the null hypothesis and confirm the correlation between the variables outlined.

The results of the statistical analysis using the Data Panel technique (Table 15) report a statistically significant and negative relationship above 99% between the lake level and the NDVI, PV, NDWI, Salinity, LULC, and aerosols variables. The results also present a negative link of 99% between the lake level with the variables ET, NDBI, and LST and a positive association with the variable precipitation. Finally, it shows a negative relationship of 95% with the NDMI variable and a positive link with the BSI variable. The obtained values of R^2, F, and Prob > chi^2 provide a good agreement between the dependent and the independent variables used with a level of adjustment greater than 99% of significance (Prob > chi^2 = 0.000). For all this, it is statistically confirmed that the lake level is influenced by the investigated variables with a significance of at least 99%. In this way, the control or mitigation actions in the lake drying process must be focused on the control of these variables.

4. Discussion

In order to implement effective conservation strategies that can be extrapolated to other wetlands around the world, it is necessary to know the reasons behind the decrease in the water level of lakes such as Urmia. In this way, other wetlands facing similar challenges could benefit from the results of this research. This study reports how various factors (human activities and climate change) have had significant effects on the variation in the water level of the lake. In general, there has been a significant increase in built-up coverage between 1990 and 2020. This could be motivated by the region's significant urbanization as a result of population growth or immigration. To accommodate this population, new urban areas had to be developed. As evidenced by the reported rise in the NDBI index related to construction. These findings are consistent with those reported by other similar studies, which reported an increase in urban areas of 180% between 1980 and 2010 or 88.9% between 1970 and 2014 in the same basin using simulations (Chaudhari et al., 2018; Kanani et al., 2020). However, there has been a large increase in the covering designated for farmland, indicating a significant expansion of the area set aside for farming and growing crops. The BSI, NDMI, and PV indices, which measure vegetation and its state of conservation, have all increased significantly, as have the NDVI and NDMI as well. Our research demonstrates that as a result, the vegetation and crops in the area have grown in area, vigor, and health. These results are in line with those of other researchers who found large increases in farmland of 200–400% between 1988 and 2007 (Alizadeh et al., 2016; Farokhnia et al., 2018; Safarrad et al., 2021). We could refer to the authors' studies from more recent times (Roushangar et al., 2023), which showed a 48% growth between 1987 and 2013, and Barideh and Nasimi (2022), which showed a 174% increase between 2000 and 2020, to get more up-to-date data.

Table 12
Rainfall dispersion measures.

Year	Max	Min	Mean	SD
1990	441	378	380	6.12
2000	412	312	360	10.65
2010	432	363	370	6.68
2020	443	367	390	7.43

Min: Minimum; Mean: Mean; Max: Maximum; SD: Standard deviation.

Table 13
Mann-Kendall trend test.

	Kendall Score	Prob > [Z]
NDVI	6233	*0.016**
PV	30261	*0.000****
BSI	−8908	*0.001***
NDBI	9335	*0.000****
NDWI	12249	*0.000****
NDMI	9335	*0.000****
Salinity	16196	*0.000****
Aerosoles	8890	*0.000****
ET	35139	*0.000****
Precipitation	20000	*0.000****
LST	8947	*0.001***

***$p < 0.001$ **$p < 0.01$ and *$p < 0.05$.

Large amounts of water are now required to ensure irrigation and supply within the basin due to the expansion in arable land and vegetation in the Lake Urmia region, as well as the increase in population. In keeping with this, Chaudhari et al. (2018) revealed in their study a 300% rise in water usage. The area occupied by the lake is therefore thought to have decreased between 1990 and 2020 by 3113 Km2, or 64.22 percent, as a result of the rise in water demand, according to our findings. This is corroborated by a sharp decline in the water content-measuring NDWI index as well as a decline in the LULC coverage of water bodies. These findings are consistent with the previous studies (Chaudhari et al., 2018; Shadkam et al., 2016), which reported lake surface decreases ranging from 40 to 86% between 1966 and 2011, as well as the most recent remote sensing studies, which reported reductions of between 39 and 45% (Kanani et al., 2020) and 80% (Barideh and Nasimi, 2022), validating our findings.

The reduction of the lake's surface has resulted in a 173.52% increase in the expansion of salinized lands around it. This is significant because the wind easily moves the salt particles found in salinized lands and quickly distributes them in the adjacent lands (urban and rural). This finding was corroborated in our study by images of aerosols obtained by MODIS between the studied years. However, this should not be the only situation that allows for an increase in aerosol concentrations in an area, as an increase in arable land implies a greater use of pesticides for pest control (Janalipour et al., 2022; Mojtahedi et al., 2022). Numerous recent studies have found that both salinity and agricultural pesticides reduce people's quality of life (Lamz Piedra and González Cepero, 2013). These findings are consistent with previous research (Nadizadeh et al., 2018; Shadkam et al., 2016), which found a 34-fold increase in saline lands around the lake between 1976 and 2015. Salinity causes significant soil degradation and is primarily caused by overexploitation of water resources for agricultural purposes in arid and semi-arid areas (Lamz Piedra and González Cepero, 2013). Aerosol concentration is a major concern because it affects not only vegetation but also public health, regional climate, and visibility. According to the MODIS study (Effati et al., 2019), dust emissions increase as wind speed increases and soil moisture decreases. The study of biomonitoring to examine metal and sodium levels around the lake (Hemmati et al., 2021), on the other hand, reported arsenic and sodium hotspots related to aerosol emissions and nearby wastewater as a result of population growth. In the coming years, this situation will pose a significant problem for agriculture because it causes an effect known as anthropic salinity, which significantly reduces plant production and increases water consumption for irrigation (Lamz Piedra and González Cepero, 2013).

Trends in average temperatures between 1990 and 2020 have reported a continuous increase of 0.53 °C per decade, representing an average increase of 106.30%. However, these increases in LST have been greater in bare soil and built up hedges than in hedges identified as toilet bodies or farmland. These results are in line with the growth values justified by climate change and reported in previous studies on Lake Urmia (Alizadeh et al., 2016; Barideh and Nasimi, 2022; Delju et al., 2013; Farokhnia et al., 2018) where they establish an average growth rate of 0.05 °C per year. It has been demonstrated that the average LST in rural areas is higher than in urban areas. This is due to the fact that solar radiation is higher in rural areas than in urban areas during the early hours of the morning. This is because of the shadows raised by buildings and trees, the heterogeneous system of impermeable walls and high thermal absorption, as well as the cooling rates experienced by areas with vegetation and the warming rates experienced by areas with scarce vegetation and bare soils. The shadows cast by the city's buildings and trees prevent solar radiation from heating the impermeable walls of urban areas, causing high doses of heat to be released and altering the LST of the area (García and Díaz, 2023; Li and Meng, 2018). In turn, numerous studies using satellite imagery have demonstrated that vegetation has a cooling effect in urban areas (Du et al., 2020; Hidalgo García, 2023) ranging between 1 and 3 °C and warming in areas with a shortage of vegetation and/or bare soils. These effects occur not only by influencing the processes of shade and evapotranspiration but also on the rates of cooling and heating by convection and transpiration that would alter the LST of the areas. On the other hand, our study has reported that rainfall has increased slightly between 1990 and 2020. These results are in line with those reported previously (Fathian et al., 2016; Karbalaee et al., 2022; Pooralihossein and Delavar, 2020) but differ from those obtained by others (Alizadeh et al., 2016) who report a slight decrease. The reason for these differences could be justified by the method of determining precipitation and is that the latter have used computer simulations while the former have used satellite data through observations. However, it is important to indicate that the reported reduction is −0.9 mm/year not being an important or noteworthy value globally within the extensive Lake Urmia basin. In contrast, (Shamloo et al. (2022) reported a significant precipitation deficit between 2001 and 2005, which resulted in a significant decrease in lake level. However, because our study covers ten-year intervals from 1990 to 2020, this drought was not included in the results. A significant increase in evapotranspiration has been reported with an average growth between 1990 and 2020 of 173.52%.

Table 14
Pearson correlation coefficient and its significance between the lake level and the rest of the investigated variables.

	Lake Level	NDVI	PV	BSI	NDBI	NDWI	NDMI	Salinity	LULC	Aerosol	ET	Precipitation	LST
Lake Level	1.000												
NDVI	−0.048	1.000											
PV	−0.332***	0.923***	1.000										
BSI	0.126	0.148	0.015	1.000									
NDBI	−0.199***	0.084	−0.088	0.737***	1.000								
NDWI	−0.927***	−0.694	−0.593	−0.483***	−0.285	1.000							
NDMI	−0.199***	−0.084	0.088	−0.737	−1.000	0.285***	1.000						
Salinity	−0.283***	0.566***	0.657***	0.054***	−0.229***	−0.388***	0.229***	1.000					
LULC	−0.040	0.483***	0.364***	0.509***	0.366***	−0.733***	−0.366	0.274	1.000				
Aerosol	−0.279***	−0.255***	−0.163***	−0.228***	−0.195***	0.279***	0.195***	0.025***	−0.064***	1.000			
ET	−0.097	−0.605	0.474***	−0.509***	−0.456***	0.179***	0.456***	−0.260***	−0.636***	0.191***	1.000		
Precipitation	0.095***	0.189***	0.267***	0.100***	0.026***	0.129***	−0.026***	0.241**	−0.079***	−0.306***	0.034***	1.000	
LST	−0.155***	0.304***	0.229***	0.609***	0.458***	−0.392***	−0.458***	0.226***	0.566***	0.130**	−0.484***	0.110***	1.000

Significance level: **$p < 0.01$, ***$p < 0.001$.

Table 15
Results Data Panel between lake level and the rest of the investigated variables.

	β	ρ	sd
NDVI	−19.358	*0.000****	1.1350
PV	−9.1487	*0.000****	0.4856
BSI	2.3344	*0.017**	0.9743
NDBI	−0.7783	*0.006***	0.2806
NDWI	−4.8464	*0.000****	0.4856
NDMI	−1.4841	*0.033**	0.6951
Salinity	−7.9724	*0.000****	1.5920
LULC	−0.5034	*0.000****	0.1041
Aerosol	−10.232	*0.000****	1.3894
ET	−0.0001	*0.007***	0.0004
Precipitation	0.0193	*0.005***	0.0069
LST	−0.0559	*0.002***	0.0182
	$R^2 = 0.42$	F = 1476	Prob > $chi^2 = 0.000$

β: Coefficient; Robust standard errors: $^*p < 0.05$, $^{**}p < 0.01$ and $^{***}p < 0.001$; sd, Standard deviation; F: Statistical; R^2: Linear regression coefficient.

This increase implies an increase of between 61 and 102 mm/m2 that would be compatible with the reported increase in temperatures. Plants dissipate much of the heat generated by solar radiation as temperatures rise, which increases evapotranspiration. Therefore, the higher the temperature, the higher the % of evapotranspiration. Our findings outperform those of the authors (Mojtahedi et al., 2022), who reported a 38% increase in evapotranspiration between 2008 and 2015. This circumstance could be explained by the fact that that investigation examined the period of drought experienced between 2001 and 2005, during which the basin had less water, reducing evapotranspiration significantly. Our results are in line with those reported by the authors (Barideh and Nasimi, 2022) with an increase in evapotranspiration reported between 2009 and 2020 of 4.88 * 109 m^3 throughout the basin. In this way, as the lake level drops, cultivated areas expand, and thus salinity and aerosol concentrations rise, affecting a larger proportion of the population.

Therefore, the fluctuations and generalized decrease in water level that Lake Urmia has experienced throughout the years analyzed are related to the variables investigated in this study. These have played a crucial role in the lowering of the lake level and in its drying process. Therefore, proper management of water levels should be essential for ecological restoration and sustainable development for future generations. For all this, and in order to recover the lake, strict control by public administrations of agricultural, urban, and tourist areas that require high quantities of water for irrigation and supply is established. In this line of control are the studies carried out on Lake Baiyangan (Lei and Wu, 2009) or the study carried out on the Three Gorges Dam (China) (Zhang et al., 2012). On the other hand, it is not enough to just control the zones but it is necessary to establish control policies on the current water consumption required by those zones. To do this, it is necessary to establish a control plan that allows consumption to be reduced. More efficient facilities and population awareness programs. Along these lines are the studies carried out and already cited on Lake Baiyangan (Lei and Wu, 2009) or the one carried out by the authors Gardner and Finlayson (2018) on the rational use of global consumption.

5. Conclusions

The study of the drying process of the world's large wetlands has become an important field of research in recent decades. All of this is motivated by the need to understand what factors influence these areas of critical importance to life and to develop mitigation and restitution measures for the coming decades that will allow their preservation for future generations. Based on the findings, it is possible to conclude that Lake Urmia's environmental deterioration in recent decades has been caused by an increase in temperature in the area caused by global warming and anthropogenic factors. Among the latter is the rapid expansion of agricultural activities, as well as the increase in population and tourism in the area, which has put significant strain on the area's limited water resources. Given that rainfall has remained stable, the high demand for water has resulted in a process of desiccation of the lake, which has resulted in an increase in the concentration of aerosols and salinity of the exposed bed, potentially affecting not only the health of the population but also agricultural production and tourism activities.

Consequently, and as specific mitigation strategies, it is necessary for the public administrations of the region or country to establish measures that allow controlling the uncontrolled growth of areas intended for agricultural activities, urban areas, and tourist areas. These are responsible for the increase in temperatures due to the changes produced in the LULC and the drying process of the lake due to the high demand for water for irrigation and supply. Therefore, better management of water resources by public administrations would restore the ecological level of the lake and establish a sustainable balance between nature and the quality of life of the inhabitants of the area.

Limitations to the study

As limitations to the present study, the following issues must be taken into account. 1. Although the Landsat images used have a moderate resolution of 30 m, it may not be sufficient to capture small details that may occur mainly on the lake's shoreline. 2. Although Landsat offers regular temporal coverage, there may be key events that affect the lake's drying that are not captured by Landsat. 3. Finally, although the 1990–2022 period covers a wide range, it may not capture long-term trends or cyclical fluctuations that could have occurred before 1990 and that have not been taken into account in this research. 4. Finally, it is necessary to note that the use of 1 image per year may not be enough to consider possible intra-annual fluctuations due to rain and drought conditions, not obtaining completely accurate results due to these conditions. For all these reasons, it is recommended to carry out new studies that increase the time scale of the study by using several images per year in different periods, expanding the interval of years studied and using higher resolution satellite images.

CRediT authorship contribution statement

Hamed Rezapouraghdam: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **David Hidalgo-Garcia:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Osman M. Karatepe:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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