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Article

Surface water change of a small lake in Central Asia and climatic factors: A dynamic linear model analysis

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Abstract: The area of lake surface water is shrinking rapidly in Central Asia. We explore anthropogenic and climate factors driving this trend in Shalkar Lake, located in the Aral Sea region in Kazakhstan, Central Asia. We employ the Landsat satellite archive to map interannual changes in surface water between 1986 and 2021. The high temporal resolution of our dataset allows us to analyze the water surface data to investigate the time series of surface water change, economic and agricultural activities, and climate drivers like precipitation, evaporation, and air temperature. Toward this end, we utilize dynamic linear models (DLM). Our findings suggest that the shrinking of Shalkar Lake does not exhibit a systemic trend that could be associated with climate factors. Our empirical analysis, adopted to address local conditions, reveals that water reduction in the area is related to human interventions, particularly agricultural activities during the research period. On the other hand, the retrospectively fitted values indicate a semi-regular periodicity despite anthropogenic factors. Our results demonstrate that climate factors still play an essential role and should not be disregarded. Additionally, considering long-term climate projections in environmental impact assessment is crucial. The projected increase in temperatures and the corresponding decline in lake size highlights the need for proactive measures in managing water resources under changing climatic conditions.

Keywords: surface water; dynamic linear model; Central Asia; climate factors

1. Introduction

Lakes are essential to the survival and growth of human settlements as well as for the stability of local ecology, especially in arid regions with fragile environments (Burchi and Mechlem, 2005; Klein et al., 2014; Micklin, 2007; Smith and Pavelsky, 2009; Wang et al., 2020). Across the Central Asia, many regions are undergoing rapid changes in the distribution and abundance of surface water (Chen et al., 2016a, 2016b, 2018; Conrad et al., 2016; Indoitu et al., 2015; Kozhoridze et al., 2012). Additionally, subarctic and arctic lakes are experiencing significant changes, impacting local hydrology and ecosystems (Bring et al., 2016; Prowse et al., 2011; Smith et al., 2005; Vincent et al., 2013). Previous studies show that the magnitude and direction of change vary according to anthropologic and climate factors (Berdimbetov et al., 2020; Jin et al., 2017).

Shalkar Lake is a terminal lake with no outlet located in the desert ecological catastrophe zone in the Aral Sea region of Central Asia. Shalkar Lake basin is located on the western borders of Shalkar town in Kazakhstan. The lake was split in half in 1937 with the help of a hydraulic structure. It is mainly fed by the Kaulzhyr River, which originated in the Mugodzhar mountains on the southeastern slope of Mount Airyuk and flows southeast for 142 km. The north-eastern freshwater half of the lake and the southwest saltwater half are thus separated. Water is released into the salty side of the lake through the outflow at the dam site during high water years. The Shalkar surface water area has shrunk from 25.5 km^2 in 1937 to 4.1 km^2 in 2021. The lake nearly dried up between 2013 and 2015, with water just remaining at the lowest point.

A combination of climate change and human activity is to account for the Central Asian lake's shrinkage (Chen et al., 2017; Micklin, 2010). Researchers predict that increasing temperatures will worsen the temporal and spatial distribution of water supplies and increase the frequency of extreme hydrological events (Chen et al., 2016a, 2016b; Hagg et al., 2013; Li et al., 2019; Zhang et al., 2016a, 2016b). According to White et al. (2014), a high-emission scenario that predicted rises in summer temperatures of up to 5 ℃ in the Amu Darya Basin by 2070–2099 would increase agricultural water consumption by 10.6% to 16%. Based on regional climate model simulations, Ozturk et al. (2017) revealed the future climate conditions of Central Asia. They found that the region's ecosystems and social systems will be more vulnerable due to an increase in surface air temperatures of between 3 ℃ and 7 ℃ and a decrease in precipitation. In the meantime, human activities have also been the primary causes of the Aral Sea's decrease, particularly the vast water withdrawal from transboundary rivers (Micklin, 2007). According to Chen et al. (2018), the imbalanced spatial distribution of land and water resources and excessive human activity are the main causes of the water resources crisis in the Aral Sea Basin.

Many academics have used remote sensing images in recent years as a result of the advancement and widespread use of remote sensing technology to study the driving forces behind both natural and human factors and to learn more about how lakes are changing dynamically (Hanrahan et al., 2009; Jin et al., 2017; Jing et al., 2018; Tan et al., 2017; Yang and Lu, 2014; Zhang et al., 2018). Remote sensing offers a robust tool for monitoring lake water quality, providing critical data on various parameters such as chlorophyll concentration, turbidity, and suspended sediment.

In the broader context of Central Asian lakes, satellite data has been instrumental in monitoring the environmental status of major water bodies. For instance, the Caspian Sea, the world's largest inland body of water, has been extensively studied using remote sensing techniques. Researchers have successfully applied satellite imagery to monitor changes in the Caspian Sea's water levels, pollution levels, and algal blooms. Mikhailov et al. (2018) and Lagutin et al. (2019) have demonstrated the utility of satellite data in tracking environmental changes and addressing water quality issues.

Similarly, the Aral Sea, another significant water body in Central Asia, has been the focus of numerous remote sensing studies. Satellite images have provided valuable insights into the dramatic shrinkage of the sea, the resulting ecological impacts, and the effectiveness of various restoration efforts. Pereira et al. (2015) and

Micklin (2016) have highlighted the potential of remote sensing in managing and mitigating the environmental challenges facing the Aral Sea.

Moreover, advancements in satellite technology, such as the launch of the Sentinel-2 and Landsat-8 satellites, have significantly enhanced the resolution and accuracy of water quality monitoring. These platforms offer higher temporal and spatial resolution, enabling more detailed and frequent observations of lake dynamics. Studies by Novoa et al. (2017) and Kuhn et al. (2019) utilizing data from these satellites have demonstrated their effectiveness in detecting and quantifying water quality parameters, further validating the importance of remote sensing in environmental monitoring.

The successful application of satellite data in monitoring water quality issues in lakes across Central Asia, including the Caspian and Aral Sea, provides a compelling precedent for its use in other lakes within the region. Integrating remote sensing technology into lake management practices offers a powerful approach to understanding and addressing the complex interplay of natural and anthropogenic factors affecting lake ecosystems. Furthermore, using the water balance approach, Lei et al. (2014) examined the dynamics of inland lakes in the Tibetan Plateau to investigate the impact of climate change on lake dynamics, suggesting that the significant increase in regional precipitation is the primary cause of lake growth. Li et al. (2017) used the grey relational analysis to assess the dynamic of Dalinor lakes based on Landsat imagery and looked at its interaction with climate variables and vegetation changes. Using the Least Squares Methods, Liu et al. (2019) studied the interannual and seasonal variations of the lakes in Central Asia from 2001 to 2016 and their driving factors. They discovered that the Plains lakes are primarily impacted by climate change, whereas the Alpine lakes are mainly impacted by human activities. Although many approaches are available to analyze time series data, researchers commonly use linear regression models to estimate time trends. However, time series data often deviate from the assumptions that justify using linear regression, in which case the obtained results may be biased and misleading. Furthermore, considering the usage of Google Earth Engine Satellite pictures available from 1986, the regression model might suffer from a relatively short time series. Alternatively, we analyze Shalkar's average water surface employing a dynamic state-space model (DLM) (Pole et al., 1994). Though conceptually comparable to linear regression, DLMs allow the modeling parameters to change over time systematically, thereby capturing the nonlinearity in the series (Zhang and Arhonditsis, 2008).

The current research on Shalkar Lake mainly focuses on the lake's water resource crisis, but the fact that the shrinking rate has slowed down in recent years is equally noteworthy. Thus, in our study, to explore the causes of changes in Shalkar and Kaulzhyr water surface change, we investigate surface water area data available from 1986 to 2021 (Model 1) and then the relationship between the water surface and potential climatic explanatory variables (Model 2). Considering up to a 3-year lag of explanatory variables, the model spans over 1988–2021. Model 1 provides the base to differentiate random from progressive patterns. In contrast, Model 2 explores whether the relationship with climatic and economic drivers may better explain the variability in the Shalkar water surface than simple trends evaluated by Model 1.

Additionally, to facilitate discussion, we analyze trends in the climatic variable over the period this data is available, applying the same approach used by Model 1. Our findings contribute to a decision-making process for managing and protecting Shalkar Lake and formulating water resources policies. It is also significant in improving water resource utilization efficiency and reforming the basin's crop planting structure.

2. Literature review

Our paper contributes to the following literature stream: the role of lakes in sustaining human settlements and maintaining ecological stability, particularly in arid and fragile environments. Prior research has highlighted the essential functions of lakes in providing water for drinking, agriculture, industry, and recreational activities, as well as supporting biodiversity (Burchi and Mechlem, 2005; Klein et al., 2014; Micklin, 2007; Smith and Pavelsky, 2009; Wang et al., 2020).

The literature documents significant changes in the distribution and volume of surface water across Central Asia, driven by both natural and anthropogenic factors. These studies emphasize the drastic reduction in lake sizes due to extensive water extraction for agriculture and the impacts of climate change (Chen et al., 2016a, 2016b, 2018; Conrad et al., 2016; Indoitu et al., 2015; Kozhoridze et al., 2012).

Climate change and human activities have markedly contributed to the shrinkage of Central Asian lakes. Rising temperatures and shifting precipitation patterns exacerbate water scarcity, while intensive agricultural water use further depletes lake volumes. Studies predict that increasing temperatures will intensify water distribution issues and the frequency of extreme hydrological events (Chen et al., 2017; Chen et al., 2016a, 2016b; Hagg et al., 2013; Li et al., 2019; Micklin, 2010; Zhang et al., 2016a, 2016b).

Our study aligns with existing research that underscores the utility of remote sensing technology in monitoring environmental changes in significant water bodies. Previous studies have successfully used satellite imagery to analyze changes in water levels, pollution, and algal blooms, demonstrating the effectiveness of remote sensing in environmental monitoring (Lagutin et al., 2019; Micklin, 2016; Mikhailov et al., 2018; Pereira et al., 2015). Advancements in satellite technology, such as Sentinel-2 and Landsat-8, have enhanced the precision and frequency of water quality monitoring (Novoa et al., 2017; Kuhn et al., 2019).

Like Central Asian lakes, subarctic and arctic lakes are undergoing significant transformations due to climate change, affecting local hydrology and ecosystems. This body of research highlights the necessity for comprehensive studies in these regions (Bring et al., 2016; Prowse et al., 2011; Smith et al., 2005; Vincent et al., 2013).

Our research on Shalkar Lake contributes to this literature by employing dynamic state-space models (DLMs) to capture non-linear trends and provide a detailed analysis of the factors driving the lake's shrinkage from 1986 to 2021. This approach allows for a nuanced understanding of how different factors interact over time, differentiating random fluctuations from progressive patterns in water surface changes.

The study supports findings emphasizing the significant role of human activities, mainly agricultural water extraction, in the shrinkage of lakes in Central Asia. It demonstrates the utility of remote sensing technology in providing high-resolution data crucial for environmental monitoring and management (Chen et al., 2017; Micklin, 2010).

Our study deviates from existing literature by utilizing dynamic modeling approaches that offer a more comprehensive analysis of the interactions between climatic and economic variables. By incorporating climatic and economic factors with up to three-year lags, this research presents deeper insights into the complex dynamics influencing Shalkar Lake.

In summary, our study enhances the understanding of Central Asia's multifaceted dynamics affecting lake ecosystems. It underscores the importance of integrated management strategies that consider human and environmental factors to ensure the sustainability of vital water resources. By employing advanced modeling techniques and high-resolution satellite data, this research provides valuable insights for developing effective conservation and management policies for lakes in arid regions.

3. Data and background

3.1. Study area

The water regime of the river Kauylzhyr and Shalkar Lake has yet to be extensively studied. Only in the period 1960–1963 the State Hydrological Institute (Gidrometeoizdat, Leningrad-GGI) of the USSR State Hydrometeorological Service opened a temporary gauging station on the Kauylzhyr River near the Kauylzhyr railway station. The GGI monograph (State Hydrological Institute, 1966) is one of the official documents on hydrology of the USSR State Hydrometeorological Service used in determining the calculated hydrological characteristics. It was carried out without hydrometric data for the Kauylzhyr River based on the calculations of the neighboring areas.

On the rivers of the southeastern part of the region, which includes the river Kauylzhyr, most of the annual runoff (80%–90%), and often its entire volume (temporary streams) occurs in the spring. In summer, the runoff stops due to the drying up of shallow rifts; its renewal occurs only in the next year's flood. On huge rivers (catchment areas above 5000 km^2), the flood lasts 40–55 days; on smaller rivers (catchment areas between 1000 and 3000 km^2), it lasts 15–30 days. The GGI expedition's observation station reveals how the Kauylzhyr River's discharge varied by season, with most passing in the spring (April to May).

The Kauylzhyr River, originating in the Mugodzhar Mountains, replenishes Lake Shalkar. Although the river's flow is primarily seasonal, the 1800 square kilometers that make up its basin are more than adequate for Shalkar to have an average amount of water. However, the riverbed was far narrower and covered in reeds compared to former times. Additionally, there has been a discernible decline in the river's water input during the past few years, and the most recent time Shalkar received a sizable inflow of water from Kauylzhyr occurred in the spring of 2015. Additionally, many springs became blocked, feeding the lake and river.

The lake, an open reservoir that receives annual replenishment from the Kauylzhyr River's flow, serves as a local recreation area and a source of domestic water for the city of Shalkar. It also serves as a watering hole for domestic animals, amateur fishing, a source of water for gardens and orchards, and a place for domestic animals to drink. The lands around Lake Shalkar are used by peasant farms, private entrepreneurs, and gardening groups (see **Figure 1**). However, their activities currently do not allow them to fully provide the city of Shalkar with agricultural products. At present, the population of the city of Shalkar is 28.6 thousand people. Currently, due to the lack of its flow (internal reservoir), Lake Shalkar is gradually degrading due to shallowing, deterioration of water quality, overgrowing of surface (reeds, sedge), and underwater (various algae) vegetation.

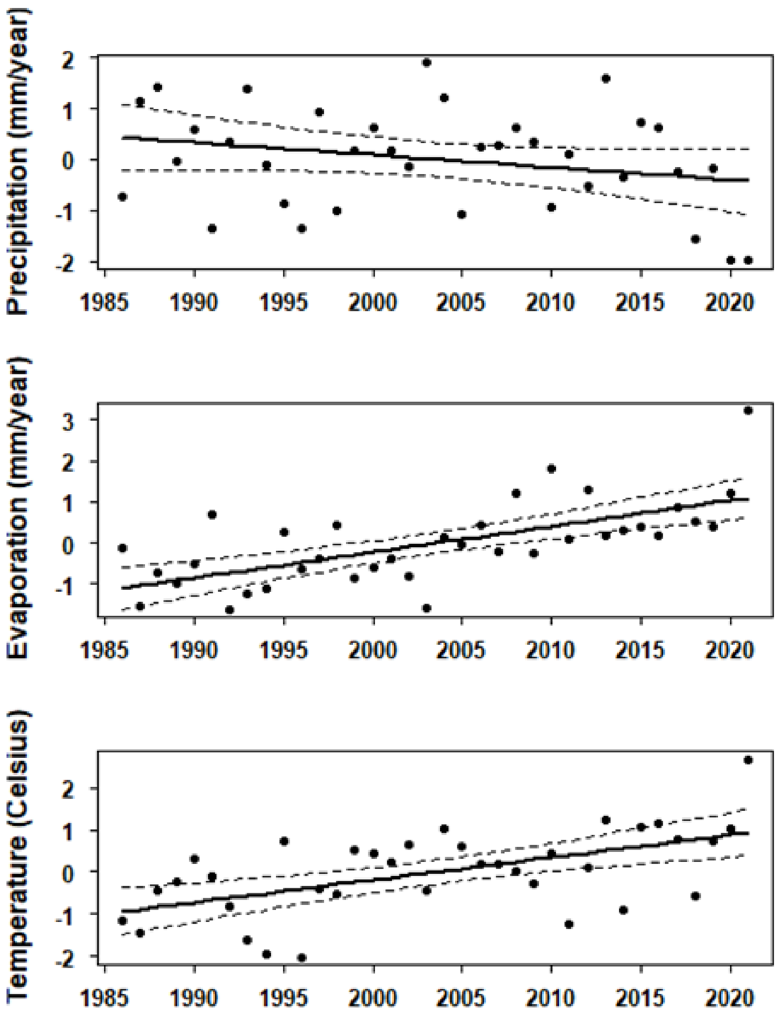

Figure 1. (a) Lake Superior precipitation (mm/year) = constant trend (δT = 0.9) fitted values (bold, black); **(b)** Lake Superior Evaporation (mm/year) = constant trend (δT = 0.9) fitted values (bold, black); **(c)** Lake Superior Temperature (℃) = constant trend (δT = 0.9) fitted values (bold, black). Dotted lines are 90% credible intervals for fitted values (solid, bold lines).

Lake Shalkar is ice-covered during the cold seasons. The lake's maximum depth is approximately 7 m, with a mean depth of about 3 m. It has a cold monomictic mixing regime. The lake's surface area is around 10 square km, with a volume of roughly 30 million cubic meters.

The city of Shalkar is situated on an elevated plain that gently descends from the northwest to the southeast and is bordered by the Chagray plateau's ledges in the southwest and the southern spurs of Mugalzhar in the west. The terrain is relatively calm, hilly-ridged, and has relative altitudes between 1m and 5m. Lake basins indent the terrain significantly. The eastern portion of the region, where the Bolshiye Barsuki sands are created, is the most fractured and shows how blowout basins and sandy mounds alternate there. The city of Shalkar is close to the Lake Shalkar basin, which borders it from the west (**Figure 2**). The area has a continental climate. The yearly temperature amplitude is 40.4 ℃. The typical annual air temperature is 5.5 ℃, whereas the average July high is 25 ℃, and the usual January low is 15.4 ℃. The average annual relative humidity is 62%. In summer it is 42%. In the daytime (13 hours) it drops to 28%–29%. According to the amount of precipitation, the region is classified as slightly wet −171 mm per year. The number of days with snow cover is 108, and the depth of snow cover, according to long-term data, is 16 cm.

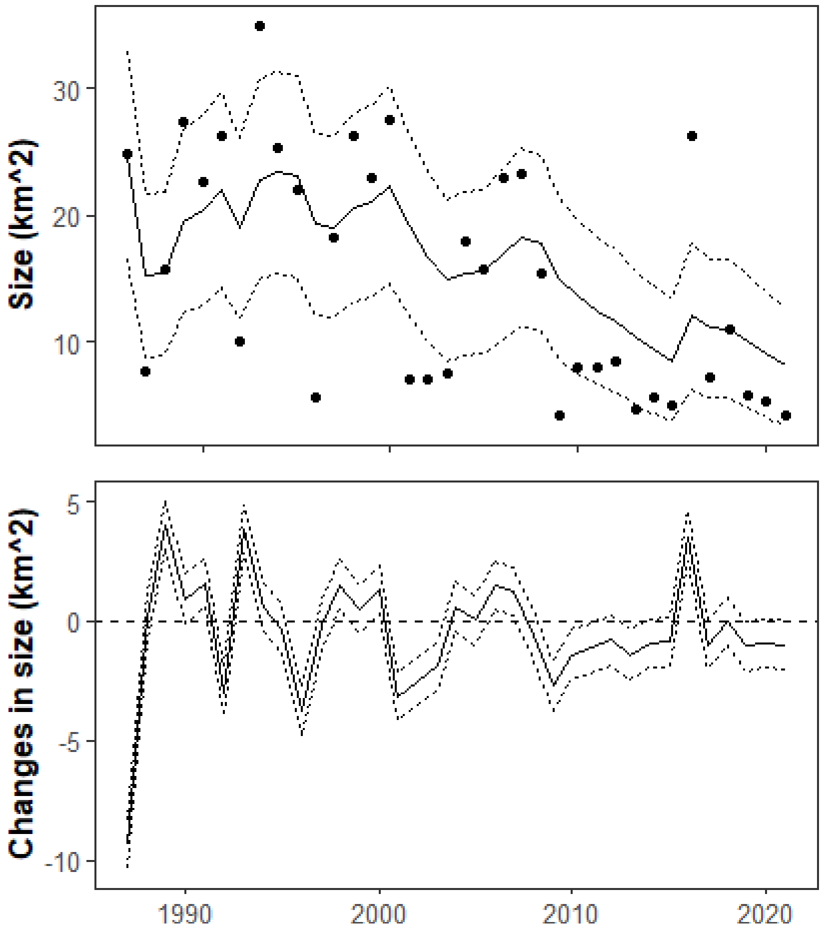

Figure 2. (a) Fitted values (solid, bold black line) and 90% credible intervals for the Superior DLM with the linear trend and δ = 0.80 (default value); **(b)** The retrospective growth parameter represents the rate of change in the water surface series in **Table 1**.

Table 1. Results of model 1 search—1986–2021 (no explanatory variables).

	MSE	MAD	Log10Lik	AIC	BIC
C (def)	89.691	7.453	100.580	205.160	208.327
C (0.85)	21.328	2.079	52.474	108.947	112.114
C (0.80)	17.517	1.264	25.705	55.411	58.578
Linear (def)	52.649	0.697	108.358	220.716	223.883
Linear (0.85)	7.575	-0.480	60.787	125.574	128.741
Linear (0.80)	7.780	-0.498	64.857	133.715	136.882

Source: Authors' calculations. MSE = mean squared error, MAD = median absolute deviation, Log10lik = log base 10 of the likelihood, AIC = Akaike information criterion, BIC = Bayesian information criterion.

The disappearance of water in Shalkar Lake and the Kualinger River concerns the local population. It is also an impetus for the migration of the local population to big cities. In the opinion of the population and environmental activists, one of the factors determining the current state of the lake is the activity of crushed stone factories. Dust rising from crushed stone plants leads to the degradation of the soil cover, getting into the water in large quantities and clogging the natural paths for streams. Thus, due to the development of crushed stone in the Mugodzhar mountains, the source of the Kauylzhyr River does not receive enough water, negatively affecting Lake Shalkar.

3.2. Ecological and human impact of shrinking lake in Central Asia

Lake Shalkar, like many lakes in Central Asia, is vital for maintaining the ecological balance of its region. It serves as a natural reservoir, supporting diverse flora and fauna and providing critical habitats for migratory birds and endemic species. Over 200 species of birds, including pelicans, herons, and ducks, rely on Lake Shalkar for nesting and feeding, making it crucial for biodiversity conservation. Additionally, the lake influences local climate patterns by regulating temperature and humidity levels, essential for sustaining the delicate ecosystems of the surrounding areas.

Beyond its ecological significance, Shalkar Lake is vital for human activities in the Aktobe region. It is a primary water source for domestic, agricultural, and industrial use. Shalkar City, home to 28,600 people, depends on the lake for drinking water and household use. The agricultural sector, including peasant farms and gardening groups, relies on the lake for irrigation to cultivate crops such as wheat, barley, and vegetables. Livestock farming, which is significant in the region, depends on the lake for water for cattle and sheep. Fishing activities employ around 200 families and rely on the lake, providing species such as carp, perch, and pike.

Moreover, Lake Shalkar is a popular recreational area, attracting tourists who want to swim, boat, and birdwatch. Local businesses, including guesthouses, restaurants, and tour operators, benefit from tourism, contributing to the region's socio-economic development. The lake's aesthetic and recreational value make it essential for promoting local tourism and fostering economic growth.

However, the shrinking of Lake Shalkar poses significant threats to local communities and ecosystems. Reduced water levels have led to a 30% decrease in the lake's surface area over the past decade, impacting water quality with increased salinity and pollution levels. This decline threatens the health of both human populations and aquatic life. Reduced water availability affects agricultural productivity, leading to lower crop yields and threatening food security in the Aktobe region. Livestock dependent on the lake for water may suffer from dehydration and malnutrition, exacerbating economic challenges faced by rural communities.

The loss of recreational areas and reduced aesthetic value can diminish tourism, leading to a decline in income for businesses dependent on this sector. Tourism revenue, contributing approximately $500,000 annually to the local economy, could significantly decrease, impacting livelihoods. Ecologically, Lake Shalkar's shrinking disrupts various species' habitats, leading to a decline in biodiversity. The reduction in water volume affects the breeding and feeding grounds of fish and other aquatic organisms, impacting the entire food web. Migratory birds that rely on the lake for resting and feeding during their long journeys may need more resources, leading to population declines. Additionally, the encroachment of vegetation, such as reeds and algae, in shallower areas can alter the ecological balance, promoting invasive species and reducing the ecosystem's overall health.

Lake Shalkar's importance to the ecosystems and human activities of the Aktobe region in Kazakhstan cannot be overstated. The potential impacts of its shrinking on local communities and ecosystems are profound, affecting biodiversity, water quality, agricultural productivity, and economic stability. Understanding these dynamics is essential for developing effective conservation and management strategies to protect this vital water body and ensure the sustainability of the region it supports. Addressing the causes of the lake's shrinkage, such as improving water management practices and mitigating climate change effects, is crucial for the long-term preservation of Lake Shalkar and the well-being of the communities that depend on it.

3.3. Data

Since 1972, the joint U.S. Geological Survey/NASA Landsat series of Earth Observation satellites have continuously acquired images of the Earth's land surface, providing uninterrupted data to help land managers and policymakers make informed decisions about natural resources and the environment. Landsat is a part of the USGS National Land Imaging (NLI) Program. We use this rich data source, particularly from Landsat Collection 1, which includes Landsat-5, Landsat-7, and Landsat-8, to quantify trends in surface water from 1986 to 2021 (Dwyer, 2019). For further details on the dataset, see the USGS Landsat Missions webpage.

Landsat Collection Tiers are the inventory structure for Level-1 data productions and are based on data quality and level of processing. We used Tier 1 Top-of-Atmosphere (TOA) scenes (n = 35), which are geometrically and radiometrically calibrated for use in time-series analysis (Dwyer, 2019). Scenes impacted by the Landsat-7 scan line corrector failure beginning in 1995 were also excluded from our analysis. To ensure snow-free conditions and consistency in seasonal water surface and atmospheric constituents across the time series, we filtered data to include only scenes from May and August. We preferentially selected scenes within a two-month window representing summer conditions between June 15 and August 15, and 40% of scenes fell within this period. We masked pixels impacted by clouds and cloud shadows in each image using the Quality Assessment Band. After removing clouds and cloud shadows, each scene was visually inspected and discarded if smoke or clouds remained in the study area. All Landsat image pre-processing steps were performed in Google Earth Engine. We applied a method developed by Olthof et al. (2015) to map surface water using data from the Landsat satellite image archive. Olthof et al. (2015) show that this method outperforms binary classifications of land and water and linear un-mixing techniques. To apply this method, we defined pure land and water thresholds using mean threshold values from a random subset of 12 scenes used in this analysis. We also checked for linear trends in threshold values over time and detected no significant trend. We applied a pure water threshold of 0.023 and a pure land threshold of 0.25 to all images in the study area. This method quantifies the proportion of a pixel covered by water (sub-pixel water fraction) by interpolating between thresholds in the shortwave infrared reflectance band (SWIR1), representing pixels containing pure land and pure water. Average annual precipitation, evaporation, and temperature (1986–2021) were obtained from the meteorological stations for the Shalkar basin.

4. Methodology

Dynamic Linear Models (DLMs) were chosen for their ability to address the retrospective analysis of time series data, offering insights into the historical states and changes in the process under study. The flexibility and adaptability of DLMs in handling time-varying parameters make them suitable for capturing the dynamics of complex processes, such as surface water levels influenced by climatic and economic factors. Retrospective analyses utilizing DLMs, also known as smoothing or filtering, help address the question, “Where has the process under study been?” or “What occurred?” (Pole et al., 1994; West and Harrison, 1989).

DLMs have a notable advantage over ARIMA models in handling non-stationary processes through time-varying parameters, eliminating the need for differencing to achieve stationarity (Box and Jenkins, 1970). This makes DLMs more straightforward and interpretable. They also excel in modeling structural changes and regime shifts, which ARIMA models struggle with due to increased complexity (Hyndman and Athanasopoulos, 2018; West and Harrison, 1997).

Moreover, DLMs use Bayesian updating for parameter estimation, allowing for sequential updates and real-time adaptability (Petris et al., 2009). In contrast, ARIMA models often require re-estimation with new data, which can be computationally intensive (Brockwell and Davis, 2002).

DLMs offer superior interpretability to machine learning models, providing insights into underlying components and their contributions (Pole et al., 1994). Machine learning models, though powerful, often lack transparency (Molnar, 2020).

DLMs also perform well with smaller datasets by incorporating prior information, which is beneficial in data-scarce environments (Shumway and Stoffer, 2017). Conversely, machine learning models generally need large datasets to be effective (Goodfellow et al., 2016).

Lastly, DLMs reduce the risk of overfitting through parameter regularization via prior distributions, leading to more robust models (Gelman et al., 2013). Machine learning models are more prone to overfitting, especially with complex data structures and limited data (Hastieet al., 2009).

4.1. Bayesian framework in DLMs

At any given time, *t*, the posterior distribution of model parameters (θ) is updated using Bayes' theorem by combining prior information with the likelihood of current observations. This approach allows for continuously updating and refining the model as new data becomes available, effectively handling non-stationary time series data.

$$\rho(\theta_t|D_{t-1}, y_t) = \frac{\rho(Y_t = y_t|\theta_t)\rho(\theta_t|D_{t-k})}{\rho(Y_t = y_t)} \tag{1}$$

where θ_t is the state (parameter) vector, D_{t+k} is the state of knowledge after t informs our knowledge on θ_t, where k is some positive constant. The posterior distribution $\rho(\theta_t|D_{t-1}, y_t)$ combines the observation likelihood $\rho(Y_t = y_t|\theta_t)$with the prior distribution $\rho(\theta_t|D_{t-k})$ reflecting the updated state of knowledge.

Quantitative model evaluation criteria, such as the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC), are needed to determine how well various models capture data dynamics. Several criteria are available for model comparison and selection; many have a similar basis, with the key difference being the severity of the penalty for model complexity. We compute the Akaike Information Criterion (AIC,1973; Akaike, 1973) and the Bayesian Information Criterion (BIC,1978; Schwarz, 1978) to choose between competing models and discount factors for a given model structure. Models with lower values fit better than those with higher values because AIC and BIC are deviance-based metrics (a generalization of the variance or sum of squares).

Model 1

For each time series under consideration, we looked at the constant and linear trend component parameters. The pattern with time is similar to a random walk in the constant trend model, which has one trend parameter at a time *t* that is a discounted version of the trend parameter at the preceding time period (*t*–1). Note that a parameter referred to as a "constant" can fluctuate over time and is comparable to a constant (or intercept) in a linear regression. A constant and an annual rate of change, discounted versions of the constant and rate at time *t*–1, are the two parameters at time *t* in the linear trend model. It is known as a linear trend model because, given a fixed time increment, the annual rate of change may be understood as a linear slope between succeeding time periods. However, this linear component is subject to vary over time. AIC or BIC differences between the linear trend and constant trend DLM indicate whether there has been a systematic change as opposed to a random progression through time.

Although surface water is the main subject of our analysis, we also utilized DLMs to compare whether a constant or linear trend model effectively captured the economic and climatic drivers. For each economic and climatic driver, we give retrospective analysis for the model that best fits the data.

Model 2

For the surface water analysis, we estimated economic and environmental factors with up to three annual lags in addition to two specifications of the trend component. For environmental factors, we considered yearly precipitation, evaporation, and temperature, while for economic factors, agricultural land in square kilometers directly connected to the lake and crash stone mining in tonnes of millions.

Precipitation is the major water source for Shalkar surface water bodies. More precipitation leads to more water bodies and a larger water body area. The volume of surface waters can be reduced by global increases in air temperature and the corresponding increases in water temperature. In addition to other effects like faster wind speed, lower air vapor concentration, lower air pressure, wider surface area, etc., higher temperature promotes evaporation. The need for more water in agriculture may also rise with rising temperatures. Therefore, a higher temperature may result in fewer and smaller bodies of water. Data on precipitation, temperature, and evaporation of Shalkar Lake and the area were obtained from the National Hydrometeorological Services "Kazhydromet". Surface subsidence and/or fractures brought on by crash stone production in the lake area result in surface water leakage. Mine drainage pollutes the lake water. The average distance between 14 crash stone firms and the lake, according to spatial analysis of the distribution of lakes about crash stone production zones, was just 15.72 km. The amount of crushed stone production has increased steadily since 1994 from 17 million tons to 1.2 billion in 2021, according to internal statistical bulletins that were requested for the purpose of this research from the mayor's office of Shalkar City (Akimat of the Shalkar City).

The hydraulic relationship between surface water and groundwater is not close. The Lake Shalkar is an open reservoir that receives yearly resupply from the river's flow. The river Kauylzhyr is utilized as a recreational area for the locals and a source of household water for the city of Shalkar. It is also used to water livestock, water gardens and orchards, and for amateur fishing. Peasant farms, independent business owners, and gardening clubs use the areas near Lake Shalkar to cultivate fruits and berries, potatoes, melons, and other crops. According to the internal statistical bulletins of the mayor's office of Shalkar City, the agricultural land in square kilometers directly connected to the lake has been relatively stable since the 90s.

The assumption that the size of the water surface integrates antecedent conditions across time justifies the examination of the lagged candidate variable. Using up to three annual lags is entirely empirical and based on exploratory analysis. To make it easier to depict the data, all potential explanatory factors were changed by focusing on their mean values.

In addition to forecasts for the Model 1 and Model 2 specifications that best fit the data, we depict the retrospectively fitted values. Models are chosen based on their performance; for each model we evaluated, we computed the cumulative log-likelihood, median absolute deviation, and mean squared error. We calculated DLMs using truncated environmental data (1988–2021) and economic data (1991–2021), providing up to three annual lags for each potential explanatory variable, such that model comparison using log-likelihoods would be based on the same amount of data for Model 2.

4.2. Evaluating the long-term impact of climate change on lake size

Furthermore, we conducted an additional assessment of the long-term impact of climate change, specifically focusing on temperature increases, using the following methodology. This robust approach analyzes the potential effects of climate change on lake size by leveraging historical data, standardization, dynamic regression modeling, and time series forecasting. We obtained meaningful and interpretable model coefficients by centering the year variables and standardizing the data. Additionally, the interaction term effectively captures the dynamic relationship between temperature and lake size over time, providing a comprehensive understanding of the long-term effects of rising temperatures.

An Exponential Smoothing model was employed to analyze the historical trend of standardized maximum temperatures and forecast future temperatures over the next decade.

$$\hat{T}_{t=1} = \alpha Y_t + (1-\alpha)\hat{T}_t,,$$

where $\hat{T}_{t+1}$is the forecasted temperature, Y_t is the observed temperature at time t, and a is the smoothing parameter.

Hypothetical scenarios based on the projected temperature increases were created to assess potential future impacts on the lake's size.

A regression model was fitted to both historical and forecasted data, incorporating an interaction term between time and temperature to capture dynamic effects. The regression model used was:

$$y_t = \beta_0 + \beta_1 x_t + \beta_2 time_t + \beta_3 (x_t\ time_t) + \varepsilon_t$$

where y_t is the standardized size of the lake at time t, and x_t is the standardized maximum temperature, $time_t$, represents the centered year variable, and ε_t is the error term.

4.3. Comparative analysis of climatic and anthropogenic factors on lake surface area

To evaluate the contributions of climatic and anthropogenic factors to changes in the surface area of Shalkar Lake, we standardized the dataset to ensure comparability across variables and facilitate the interpretation of model coefficients. Lagged variables were created to capture the potential delayed effects of both climatic and anthropogenic factors.

Three regression models were constructed: the Climate Model, which includes climatic factors (evaporation, temperature, and precipitation); the Anthropogenic Model, which includes the anthropogenic factor (agricultural activities); and the Combined Model, which includes both climatic and anthropogenic factors. These models were evaluated using the Akaike Information Criterion (AIC) and the

Bayesian Information Criterion (BIC), which penalize models for complexity while rewarding them for goodness-of-fit. Lower values of AIC and BIC indicate better-fitting models.

5. Results

5.1. Physical meaning of model parameters

The model parameters, particularly the constant trend component and its discount factor (δ), provide insights into the dynamics of lake surface water changes. The constant trend component, included in the best-fitting model for the 1986–2021 period, indicates that the series' movement over time has been more random than systemic (**Table 1**). This suggests that lake surface water changes do not follow a consistent upward or downward trend but exhibit fluctuations that various external factors may influence.

The discount factor (δ), with a value of 0.80, reflects the rate at which past observations influence current estimates. A low discount factor indicates that recent observations are given more weight, allowing the model to adapt quickly to changes. This adaption is crucial for capturing the impact of sudden events, such as human interventions, on the lake surface area. The relatively low discount factor suggests that human activities, which can cause rapid and significant changes in the lake area, dominate the observed fluctuations.

Including the constant trend component with a low discount factor indicates that lake changes are more influenced by irregular, possibly human-induced activities rather than long-term climatic trends. This aligns with observations of periodic but irregular cycles in the data. The retrospectively fitted values showing semi-regular periodicity highlight the influence of human activities, such as water extraction for agriculture, urban development, or infrastructure projects. These activities can lead to abrupt changes in water levels, which are captured by the model's ability to adapt quickly to local conditions. Although climatic factors like precipitation, evaporation, and temperature are modeled, their impacts appear more gradual and less dominant than anthropogenic ones. Climatic changes typically lead to slower, more systemic trends in lake levels, which the model does not identify as the primary drivers within the observed period. The general decline in the time series is particularly visible in 2009 when the mean of the constant trend turned negative for the most period.

5.2. Differentiating and quantifying anthropogenic and climate change impacts

The study indicates that anthropogenic activities have a more significant impact on lake area than climate change. The analysis incorporated explanatory variables related to human and climatic factors to differentiate and quantify their contributions. The results showed a stronger fit for models that included anthropogenic factors, particularly agriculture, over those with only climatic trends.

Table 2. Results of model 2 search—1985–2021 using explanatory variables.

	MSE	MAD	Log10Lik	AIC	BIC
C + stevap 1	1.054	0.830	33.113	70.227	73.394
C + stevap 1, 2	1.073	0.834	33.460	70.920	74.087
C + stevap 1, 2, 3	1.094	0.839	33.663	71.325	74.492
C + stprec 1	0.999	0.821	33.383	70.765	73.932
C + stprec 1, 2	0.999	0.821	33.383	70.765	73.932
C + stprec 1, 2	0.976	0.800	33.932	71.864	75.031
C + sttemp 1	1.971	0.965	33.184	70.369	73.535
C + sttemp 1,2	1.976	0.966	33.531	71.062	74.229
C + sttemp 1, 2, 3	1.978	0.966	33.734	71.467	74.634
C + mining (log) 1	1.1079	0.8631	29.502	63.004	65.807
C + mining (log) 1, 2	1.106	0.811	36.974	77.948	80.750
C + mining (log) 1, 2, 3	1.276	0.903	43.605	91.209	94.012
C + starg, 1	1.2735	0.7025	22.3250	48.6500	51.7607
C + starg, 1, 2	1.2715	0.7020	22.6716	49.3431	52.4538
C + starg, 1, 2, 3	1.2695	0.7014	22.8743	49.7486	52.8593
C (0.85) + stagr, 1	0.402	0.300	−11.676	−19.352	−16.241
C (0.85) + stagr, 1, 2	0.401	0.300	−11.329	−18.659	−15.548
C (0.85) + stagr, 1, 2, 3	0.405	0.301	−11.127	−18.253	−15.143
C (0.80) + stagr,1	0.376	0.275	−14.838	−25.677	−22.566 Model 1
C (0.80) + stagr, 1, 2	0.375	0.274	−14.492	−24.984	−21.873
C (0.80) + stagr, 1, 2, 3	0.374	0.274	−14.289	−24.578	−21.468

Anthropogenic activities, particularly agriculture, highlight the role of water extraction for irrigation, which can drastically reduce lake levels. Increased water usage for domestic and industrial purposes can also contribute to fluctuations in lake area, as can infrastructure projects such as dams, reservoirs, and water diversion projects that directly impact water availability and distribution. Climatic factors like changes in rainfall affect lake water's inflow and outflow. However, the gradual nature of these changes makes them less pronounced in the short-term analysis. Rising temperatures increase evaporation rates, potentially reducing lake levels over time, though this effect is gradual and may be overshadowed by more immediate human activities. Long-term trends in temperature can influence evaporation rates and precipitation patterns, indirectly affecting lake levels.

The comparison of model fits (**Table 2)** shows that models incorporating anthropogenic factors, particularly agriculture, provide a better explanation of lake changes than those including only climatic predictors. This suggests that human activities have a more significant and immediate impact on lake areas than climate change within the study period. Models with agricultural predictors had lower MSE and AIC values, indicating a better fit and higher explanatory power. While still relevant, Climatic models showed higher MSE and AIC values, reflecting their lesser immediate impact compared to human activities. The strong performance of anthropogenic models suggests that human activities are the primary drivers of lake area changes in the short to medium term. Climate change impacts, while present, contribute more to long-term trends and may require longer observation periods to become the dominant factor.

Overall, the model parameters provide valuable insights into lake surface water changes' dynamics, emphasizing anthropogenic activities' dominant role over climatic factors in the observed period. Differentiating and quantifying these impacts highlights the need for integrated water management strategies that consider human and environmental influences.

5.3. Climatic trends

Trend analysis of environmental data is crucial for understanding long-term changes and making informed decisions. To evaluate the performance of different trend models for the variable's precipitation, evaporation, and temperature with specified trend parameters (tau = 0.90, tau = 0.85, tau = 0.80), we compared constant trend models, linear trend models, and quadratic trend models using AIC and BIC **(Table 3).**

Table 3. The model performance comparison.

Model	**Variable**	**AIC (0.90)**	**BIC (0.90)**	**AIC (0.85)**	**BIC (0.85)**	**AIC (0.80)**	**BIC (0.80)**
Constant	Evaporation	20.81	23.98	10.43	13.59	0.92	4.09
Linear	Evaporation	−53.50	−48.75	−61.67	−56.92	−61.25	−56.50
Quadratic	Evaporation	−51.78	−45.44	−59.70	−53.37	−60.12	−53.78
Constant	Temperature	12.19	15.36	10.60	13.77	14.39	17.56
Linear	Temperature	−69.41	−64.66	−60.28	−55.53	−63.15	−58.40
Quadratic	Temperature	−67.44	−61.11	−58.87	−52.54	−61.64	−55.31
Constant	Precipitation	21.03	24.20	12.70	15.86	16.30	19.47
Linear	Precipitation	−76.46	−71.71	−52.64	−47.89	−51.93	−47.18
Quadratic	Precipitation	−76.22	−69.88	−51.06	−44.72	−53.73	−47.39

For evaporation, the linear trend model shows the lowest AIC and BIC values across all tau values, indicating it provides the best fit for evaporation data. Similarly, the linear trend model for temperature consistently has the lowest AIC and BIC values, making it the best model for temperature data across all tau values. For precipitation, the linear trend model is the best fit for tau = 0.90 and tau = 0.85. For tau = 0.80, the quadratic model shows the lowest AIC value, but the linear model remains competitive. The results suggest that the linear trend model is the most appropriate for evaluating trends in the environmental variables studied. The linear trend model with tau = 0.90 shows superior performance.

The Mann-Kendall trend test results indicate a significant positive trend in standardized evaporation and temperature, with Kendall's tau values of 0.508 and 0.371, respectively. The corresponding p-values of 0.000014 and 0.001505 suggest these trends are statistically significant. Sen's slope estimator confirms these findings, indicating positive slopes of 0.060180 for evaporation and 0.052195 for temperature, with confidence intervals not encompassing zero. Conversely, precipitation shows weak negative trends with Kendall's tau values of −0.166 and identical *p*-values of 0.16045, which are not statistically significant. Sen's slope estimates further corroborate the absence of significant trends in these variables (**Table 4**).

Table 4. Kendall's tau and sen's slope analysis.

	Kendall's Tau	***P*-value (Mann-Kendall)**	**Sen's slope**	***P*-value (Sen's Slope)**	**95% confidence interval (Sen's Slope)**
Precipitation (0.90)	−0.1660	0.1605	−0.0065	0.1604	[−0.01597, 0.00417]
Evaporation (0.90)	0.5080	0.0000	0.0602	0.0000	[0.03899, 0.08019]
Temperature (0.90)	0.3710	0.0015	0.0522	0.0015	[0.02381, 0.07935]

Based on the analysis, we found that linear trend models perform the best for the evaporation and air temperature series (1986–2021) (**Figure 1**). The fitted values are a smoothed, retrospective estimate of the mean as it drifts through time, and the inference is that evaporation and air temperature cannot be inferred from a random walk.

In 2014, we noticed a significant change in the random walk for evaporation, marking a transition from a relatively stable period to a phase where the mean began to decrease. This shift aligns with a long-term trend of rising air temperatures, although precipitation has only recently started trending downward. Despite these changes, linking these environmental variations directly to changes in lake surface water size is challenging. The period when the lake's surface water began declining at an increasing rate started in 2009, complicating the connection (**Figure 2**).

Given these observations, it is prudent to explore the potential long-term impact of rising temperatures on the lake's size for several reasons. The sustained upward trend in temperature suggests significant long-term changes that could affect the lake size. The increase in evaporation, often correlated with higher temperatures, indicates a potential mechanism through which temperature can affect lake size by increasing water loss. Understanding the impact of rising temperatures on natural water bodies is crucial in the context of climate change, as it informs water resource management and conservation strategies.

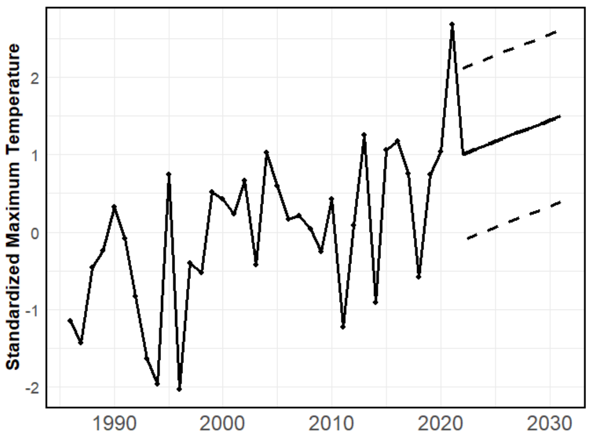

Figure 3. Observed and forecasted standardized maximum temperature with confidence intervals.

The Exponential Smoothing model projected a consistent upward trend in standardized maximum temperatures over the next ten years. The forecasted temperatures for the period 2022–2031 indicated a significant increase, which was used as the basis for further analysis (**Figure 3**).

The dynamic regression model included the historical relationship between the lake size and temperature, with an interaction term for time. The model's coefficients were then applied to the forecasted temperature data to predict future lake sizes.

The fitted regression model on historical data yielded the following results:

$$size\ of\ lake_t = 0.0106 + 0.1629\ tempreture_t - 0.0603\ time_t - 0.0087(tepreture_t\ time_t) + \epsilon_t$$

The fitted regression model on historical data yielded the following results:

$$R^2 = 0.325$$

$$\rho(temperature) = 0.3652$$

$$\rho(time) = 0.0010$$

$$\rho(interaction) = 0.5089$$

Using the projected temperatures, the model predicted a declining trend in the standardized size of the lake (**Figure 4**).

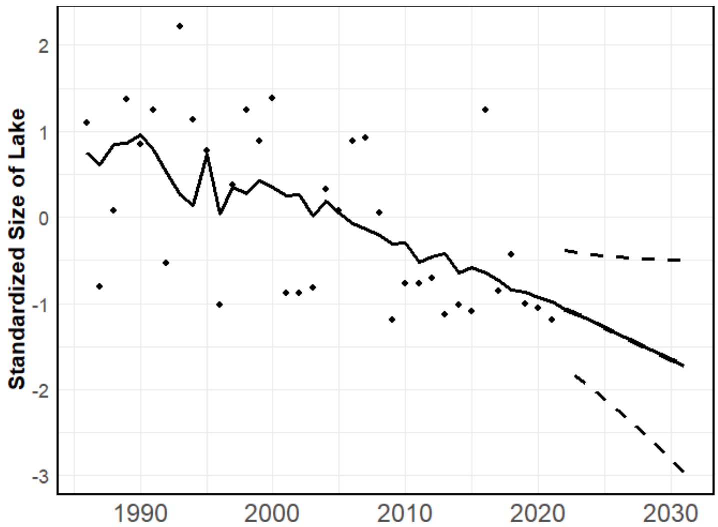

Figure 4. Historical and forecasted standardized size of lake with confidence intervals.

The results indicate a potential long-term impact of rising temperatures on the lake size, even though the direct relationship was not statistically significant in the historical data. The significant time trend suggests other underlying lake sizes over the observed period. The predicted decline in lake size aligns with the hypothesis that climate change, manifested through increasing temperatures, could adversely affect natural water bodies over time.

All in all, our results demonstrate the importance of considering long-term climate projections in environmental impact assessments. The projected increase in temperatures and the corresponding predicted decline in lake size highlight the need for proactive measures in managing water resources under changing climatic conditions.

Table 5. Comparative analysis of climatic and anthropogenic factors.

Model	df	AIC	BIC
Climate Model	5	105.153	112.929
Anthropogenic Model	3	71.561	76.227
Combined Model	6	74.435	83.767

Note: The Climate Model includes climatic factors such as evaporation, temperature, and precipitation, aiming to capture their impact on the lake's surface area. The Anthropogenic Model focuses solely on the impact of agricultural activities on the lake's surface area. The Combined Model incorporates both climatic and anthropogenic factors to analyze their combined impact comprehensively. All models were calibrated using standardized data for comparability.

Furthermore, our comparative analysis of climatic and anthropogenic factors on the Lake Surface Area was conducted to determine the relative contributions of climatic and anthropogenic factors to changes in the surface area of Shalkar Lake (**Table 5**). The analysis highlights the dominant role of anthropogenic activities in influencing the surface area of Shalkar Lake. The superior performance of the Anthropogenic Model in terms of AIC and BIC values underscores the significant and immediate effects of human activities on the lake's size. The relatively good performance of the Combined Model suggests that climatic factors should not be completely disregarded; however, their impact appears to be secondary to that of anthropogenic factors within the study period. This finding is consistent with existing literature that emphasizes the substantial influence of human activities on water bodies in Central Asia.

6. Discussion and conclusion

The shrinkage of the Central Asian lakes has attracted the attention of numerous scholars who have analyzed the changes in them from various perspectives, and most of them concluded that the lakes in Central Asia had shrunk dramatically (Jin et al., 2017; Stanev et al., 2004; Shi et al., 2014). In the current study, we calculated Shalkar Lake's abrupt retreat and attempted to identify its reasons.

Our results indicate strong evidence favoring the presence of a random walk-over of the systemic trend in the gradual shrinking of Shalkar Lake that can be observed over recent decades. We found that the better fitting models are those that adapt more readily to local conditions, perhaps reflecting human interventions occurring over the investigated period. We concluded that the impact of human activities on the lake is more significant than climate change, even though the annual air temperature and annual evaporation have increased in the region over time. On the other hand, although there are anthropogenic influences, the retrospectively fitted values suggest a semi-regular periodicity. We present evidence that the water surface in Shalkar and Kaulzhyr has generally been dropping.

Our study highlights the importance of considering long-term climate projections in environmental impact assessments. The projected increase in temperatures and the corresponding predicted decline in lake size underscores the need for proactive measures in managing water resources under changing climatic conditions. In this context, the study's results indicate a potential long-term impact of rising temperatures on lake size, even though the direct relationship was not statistically significant in the historical data. The significant time trend observed suggests that other underlying factors influence lake size over the observed period. The predicted decline in lake size aligns with the hypothesis that climate change, manifested through increasing temperatures, could adversely affect natural water bodies over time.

Furthermore, our comparative analysis confirms that anthropogenic factors are the primary drivers of changes in the surface area of Shalkar Lake. While climatic factors are relevant, they are less significant during the observed period. These insights highlight the need for integrated water management strategies that prioritize controlling and mitigating human impacts while considering long-term climatic trends.

Our findings are consistent with previous research on lakes in Central Asia that suggests a minimal influence of climate change (Michlin, 2007; Wang et.al, 2020). While this is happening, human actions have also been the primary causes of the decline, such as the large water withdrawal from transboundary rivers in places like the Aral Sea (Micklin, 2007). According to Chen et al. (2018), the imbalanced spatial distribution of land and water resources and excessive human activity are the main causes of the water resources crisis in the Aral Sea Basin. Like the findings of Yang et al (2020) and Michlin (2014) on the Aral Sea, we found that irrigated water withdrawal is the dominant factor influencing the long-term variations of Shalkar Lake. Alleviating the water and ecological crisis of Shalkar Lake is not only a duty but also an obligation for the region and country in the basin.

The present study has certain limitations that need to be acknowledged. One primary limitation is the reliance on a relatively short-term dataset (1986–2021) for analyzing Shalkar Lake's surface water changes. While this timeframe provides valuable insights, extending the dataset further back in time would offer a more comprehensive view of historical trends and variability, thus enhancing the robustness of the findings. Additionally, the study focused on a limited set of climatic and economic variables. Although significant, other environmental variables such as soil moisture, groundwater levels, and land use changes also play crucial roles in lake dynamics and were not included in the current models.

Our analysis employed dynamic state-space models (DLMs) to capture non-linear trends. While effective, these models could be expanded to include more complex hydrologic models that account for additional physical processes governing lake hydrology. For example, incorporating models considering groundwater-surface water interactions or using high-resolution climate projections could provide a more detailed understanding of the lake's hydrologic processes.

Utilizing high-resolution climate projections from advanced climate models, such as those from the Coupled Model Intercomparison Project (CMIP6), would provide more detailed future climate scenarios. This would help in assessing the potential impacts of climate change on lake hydrology with greater precision (Eyring et al., 2016). Including a broader range of environmental variables, such as soil moisture, groundwater levels, and vegetation cover, would offer a more holistic understanding of the factors influencing lake dynamics. Remote sensing technologies and field observations could be used to gather this data (Rodell et al., 2004). By addressing these areas, future research can provide a more comprehensive understanding of the complex dynamics affecting lake ecosystems in Central Asia and inform the development of effective conservation and management policies.

Future research should extend the dataset further back in time and incorporate additional environmental variables to enhance the robustness of the findings. This extension could involve utilizing paleoclimatic data or historical records. Incorporating more complex hydrologic models that account for additional physical processes, such as groundwater-surface water interactions, soil moisture dynamics, and detailed land use changes, would improve the accuracy of predictions. Using more complex models that account for interactions between climatic and anthropogenic factors could provide deeper insights into the dynamics affecting lake ecosystems in Central Asia.

On the other hand, Magnuson (1990) noted that it can be difficult to identify cause-and-effect interactions in ecosystems. The ongoing gathering of long-term surface water and meteorological data, although a challenging process, is an investment that offers stakeholders in the small Western regions of Kazakhstan a platform for identifying and comprehending phenomena that are very important to them.

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