



OPEN The compounding effects of agricultural expansion and snow drought on lake urmia's drying crisis

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Lake Urmia, one of the world's largest hypersaline lakes, has experienced severe drought in recent decades. This study investigates the combined impacts of agricultural expansion and climate variability on river inflows from 1985 to 2020. A hybrid framework incorporating statistical models and Convolutional Neural Networks was employed to estimate river discharge and disentangle the effects of hydroclimatic and anthropogenic drivers. Results indicate a persistent snow drought beginning in the late 1990s, concurrent with exceeding fourfold increase in irrigated lands. Scenario-based analysis, restoring key parameters to pre-1999 levels revealed that reverting agricultural water use was the dominant factor driving changes in river inflows, accounting for approximately 66% (95% CI: 56%–76%) of the total impact. In contrast, restoring precipitation and evaporation contributed 25% (95% CI: 18%–33%) and 9% (95% CI: 7%–12%), respectively, while restoring both simultaneously explained 34% (95% CI: 26%–43%) of the change. These results underscore the primary role of agricultural water demand amplified by declining snowpack and climatic shifts in altering basin hydrology. The findings highlight the urgent need for integrated water resource management, with a focus on climate adaptation, snowpack monitoring, and sustainable agricultural practices to address ongoing environmental degradation and ensure long-term water security.

Keywords Lake urmia, Snow dynamics, Agricultural water use, River inflows, Multiple linear regression, Response surface model, Convolutional neural network

Compounding effects of climate change and variability along with rapid urban and agricultural land development and unsustainable growth have resulted in major environmental challenges^{1,2}. As a consequence of these changes, some of the world's water bodies such as the Great Salt Lake in USA, Lake Urmia in Iran, the Dead Sea in the Middle East, Lake Tuz in Türkiye and the Aral Sea in Central Asia have experienced substantial declines in recent decades. These declines are primarily due to anthropogenic drought^{3,4} developed with notable contributions from climate change and variability^{5–8}, which have led these water bodies into the state of water bankruptcy⁹.

Lake Urmia, once one of the world's largest hypersaline lakes located in the northwestern Iran, has gradually lost its water body over the last three decades, with a large fraction of it transforming into a seasonal lake. Drought and a rapid increase in agricultural water withdrawal¹⁰ made possible through the construction of dams and increased groundwater extraction¹¹ are the primary causes of lake dryness¹². Studies have shown that the compounding effect of climate change and increased water demand intensifies drought and their

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socioeconomic impacts¹¹. While several studies have focused examined the detrimental effects of climate change on the lake's water levels¹³, the majority of recent studies have found indicate that local anthropogenic factors have a more significant impact on the lake's desiccation than climatic change^{10,14–18}. However, these studies have not adequately considered the role of snow dynamics in the region. The majority of the past studies focusing on the effects of climate change and human-induced activities on lakes have examined factors such as precipitation, temperature, evaporation, and agricultural development, without examining the significance of the snow component^{15,16,19–22}. Seasonal snow is a vital water resource, serving as a naturally distributed water reservoir in mountainous regions^{23,24}. Measuring and monitoring snow is essential for understanding climatic and hydrological cycles, developing water management policy and adaptation strategies, and ensuring the sustainable management of water resources^{25,26}.

There are only a few studies in the literature that investigate the impacts of snow changes on the Lake Urmia Basin (LUB). Nikraftar and Hasanlou (2015)²⁷ used Special Sensor Microwave/Imager (SSM/I) data along with Support Vector Regression (SVR) and a genetic algorithm to estimate snow depth on Sahand Mountain – a major source of snow in the lake's basin. Habibi et al. (2021)²⁸ applied Standard Precipitation Index (SPI), Standard Precipitation Evaporation Index (SPEI) and Standardized Snow Melt and Rain Index (SMRI) to understand drought dynamics in the LUB from 1981 to 2018. Their findings indicated that reduced snow cover has intensified drought in the region, particularly after 1995. In a recent study, Safari et al. (2023)²⁹ analyzed the variability of Snow Cover Area (SCA) in the LUB from 2000 to 2020. Although their findings indicated no significant long-term trends in SCA, they highlighted a strong association between SCA and the Standardized Evapotranspiration Deficit Index (SEDI), emphasizing SEDI's function in monitoring snow cover changes.

While these studies have aimed to comprehend the alterations in snow cover within the basin, they have overlooked the exploration of how snow drought and changes in Snow Water Equivalent (SWE) influence the water level fluctuations of Lake Urmia, separating the snow-effect from other climatic and anthropogenic factors. A snow drought refers to periods of abnormally low snowpack conditions and can be classified as either a dry snow drought, driven by reduced precipitation, or a warm snow drought, caused by higher temperatures leading to rain instead of snow or early snowmelt³⁰. Since the LUB is a mountainous region, a comprehensive study considering all factors such as SWE would be need to investigate and understand the dynamics of the water cycle in the region and the corresponding lake level changes. Snow-limited basins such as LUB rely on winter snowpack as a seasonal buffer that releases water in late spring, sustaining recharge and baseflow into the irrigation season. With warming, basins experience less snowfall, more rain, and earlier melt, which collectively advance runoff timing and weaken warm season flows a set of changes widely documented across snow dependent regions^{31–34}. These timing shifts undermine the long-standing supply demand synchrony assumed in water management and are a first order control on water availability for agriculture in spring- summer^{31–33}. Lake Urmia's water balance reflects the interaction of climate driven snow limitation and management driven demand: earlier snowmelt advances runoff and weakens warm season baseflows, while the irrigation calendar (winter wheat sown Sep–Nov, harvest mid-Apr–Jul; critical spring irrigations at stem-elongation/heading/grain-fill) concentrates demand in spring^{35,36}.

Lake Urmia's seasonal water balance reflects the interaction of a climate-driven shift toward a snow-limited regime less snowfall with earlier and slower melt that advances runoff and weakens late-spring/summer baseflows and management driven growth in AWU^{31,33,34,37–43}. This interaction narrows the overlap between supply and the spring irrigation calendar. Consistent with basin-wide evidence that both climate and human water use have materially contributed to lake's decline^{39–43}, we therefore treat their joint role as a first-order control on seasonal inflows and lake storage and test this mechanism with the trend diagnostics and scenario analysis that follow.

Geospatial snow measurements often have temporal and spatial limitations, particularly in high mountainous regions to overcome these challenges, remote sensing methods, such as satellite imagery are employed for monitoring snow cover and estimating SWE. These technologies offer a more comprehensive approach to tracking changes in snow cover and SWE over time. Currently, various types of SWE-related data are available globally, which can be classified into different categories, such as reanalysis, data assimilation and model simulation.

The primary objective of this research is to examine the effects of anthropogenic (agricultural expansion) and climatic (e.g., precipitation, evapotranspiration, snow impact on river inflows) factors on water level fluctuations of the Lake Urmia. A combination of in situ data, satellite data and reanalysis datasets are used to select the most accurate dataset for exploring the impacts of snow variations in the Lake Urmia. A key component of this research is the development of an efficient multi-model approach capable of accurately capturing the complex hydroclimatic dynamics of the LUB and estimating river inflows using statistical and Deep Learning (DL) methods.

Materials and methods

Study area

Lake Urmia (37°06'27"–38°15'16" N, 45°02'10"–45°49'38" E) with an average surface area of 5,000 km², is located between West Azerbaijan and East Azerbaijan provinces of Iran at an altitude of 1,275 m above sea level. This unique lake is a UNESCO Biosphere Reserve and an international wetland of great importance for its rich ecosystem, housing vital species in the food chain such as *Artemia* and providing a crucial habitat for migratory birds like flamingos. The LUB is encompassed by elevations ranging from 1222 m to 3,875 m and covers an area of approximately 52,000 km². Figure 1a indicates the elevation map of the basin produced using ASTER-GDEM (Global Digital Elevation Model) satellite imagery with a spatial resolution of 30 × 30 m (NASA, 2022). Areas with a slope of 0–4°, which are flat or nearly flat, cover the largest section with a 41% ratio and high infiltration occurs in these areas. Areas with a slope of 4–10°, constituting 25% of the landscape and consist of regions surrounding the flat or nearly flat areas with a slight slope. These sections are concentrated in the west and east

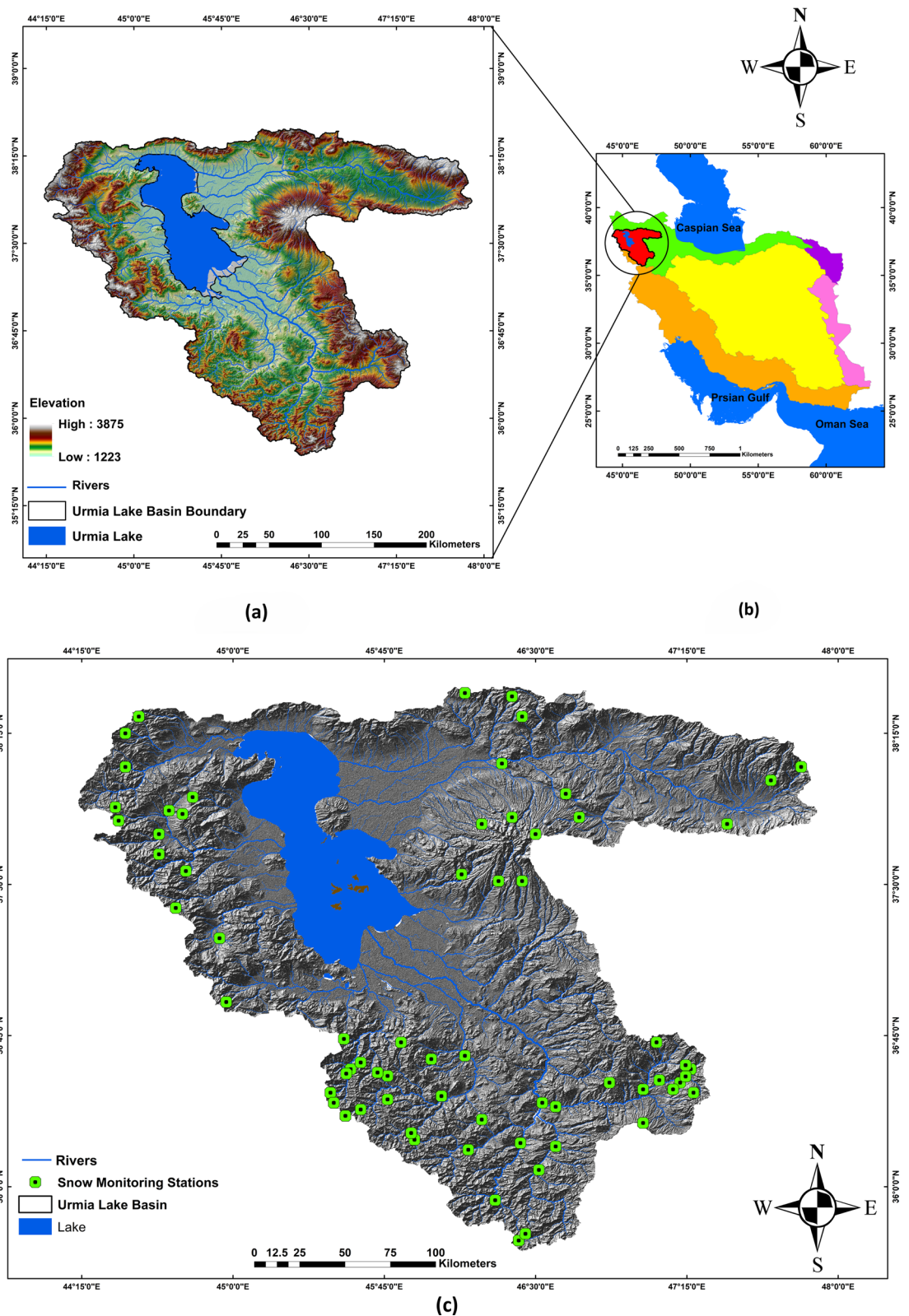


Fig. 1. (a) Digital Elevation Model (DEM) of the Lake Urmia Basin (LUB) (b) The location of the main water basins in Iran (c). The location map of snow measurement stations in the basin. These figures were produced using ArcMap 10.8 (ESRI, <https://www.esri.com/>).

of the basin, and the highest slope values are found near the Meydan and Mor Mountains on the Turkish border, reaching up to 78°⁴⁹. Approximately 7 million people inhabit this area, where Lake Urmia plays a significant role in the lives and economy of the local population and country as well¹⁵.

Figure 1b indicates the location of Lake Urmia and its basin in Iran. A causeway divides the lake into northern and southern portions and water can only flow beneath a 1,500-meter bridge built on the causeway^{44,45}. The region's climate is influenced by the surrounding mountains, with temperatures typically ranging from 0 °C to -20 °C in winter and up to 40 °C in summer⁴⁵. The average annual precipitation in the basin is about 350 mm¹². Direct precipitation and groundwater resources account for 25% of Lake Urmia's water inflow, with rivers supplying the remaining 75%^{46,47}. Several perennial and seasonal rivers feed into Lake Urmia, with Siminehrood and Zarrinehrood being the primary contributors, supplying nearly half of the lake's water⁴⁴. Reported evaporation from the lake surface ranges from 580 to 2,000 mm per year⁴⁷. As of February 2021, the lake's water surface elevation had dropped to 1,271.3 m, and salinity had exceeded 300 g/L¹².

In-situ data

In this study, the hydro-climatic and water storage data in the basin including precipitation (summation of rain, snow and ice), rain (liquid water), temperature, evaporation, river inflows, Agricultural Water Use (AWU) and water level fluctuations of the Lake Urmia were provided from the prior studies^{15,17}. These studies acquired data from several Iranian government organizations and previously processed the raw data. This study utilized runoff data from 16 rivers, comprising 10 main rivers and 6 minor rivers, as well as meteorological data (precipitation, temperature and evaporation) obtained from 36 synoptic stations in the basin and rain data from 110 rain measurement stations in the basin. This data was employed to gain insights into the climatic conditions within the study area. The agricultural development and irrigation demand in the basin were provided from the results of Alizade Govarchin Ghale et al., (2019)¹⁵ and Barhagh et al., (2021)¹⁷. The in-situ monthly snowfall data, measured between 2007 and 2013 in 81 locations, was obtained from the meteorological organization of Iran. Although access to more recent data was not possible, the 7 years of data were sufficient for the purpose of our study. Figure 1c indicates the location map of 81 ground-observed snow stations used in this study. The main parameters measured at these stations include snow density, snow depth and SWE. Snow measurement stations are typically situated in the higher elevation areas of the basin. The regions with the highest concentration of snow stations are, in order, the south, southwest, northwest, and east. Figure 2 indicates the monthly water level fluctuations of the Lake Urmia from 1985 to 2020. The ecological water level of the lake is 1274.10 m and the water level always change over time⁴⁵.

Figure 3 indicates the monthly variations of river inflows, precipitation, AWU and evaporation from 1985 to 2020, respectively. This figure presents considerable variability in the environmental parameters impacting Lake Urmia across different periods. The most significant inflows to the lake were documented in April and May of 1988, 1992 and 1993, with volumes ranging from 2,000 to 3,000 MCM, signaling times of substantial water abundance (Fig. 3a).

Conversely, the inflow reached its lowest levels during the hot season months of July and August, suggesting a marked decrease in water contributions from upstream sources during these times. Despite the observed fluctuations, the long-term analysis of precipitation data does not indicate any substantial changes, suggesting that factors other than rainfall may have a more pronounced effect on the lake's water level variability (Fig. 3b).

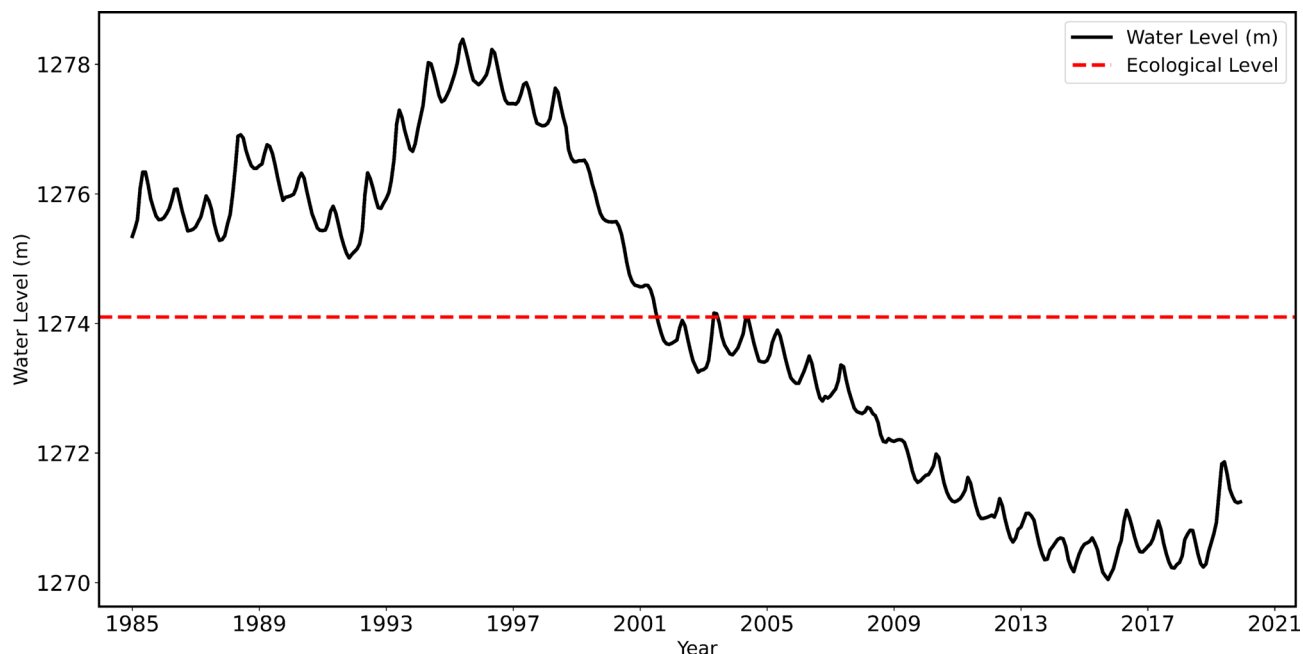


Fig. 2. Monthly water level fluctuations of Lake Urmia from 1985 to 2020.

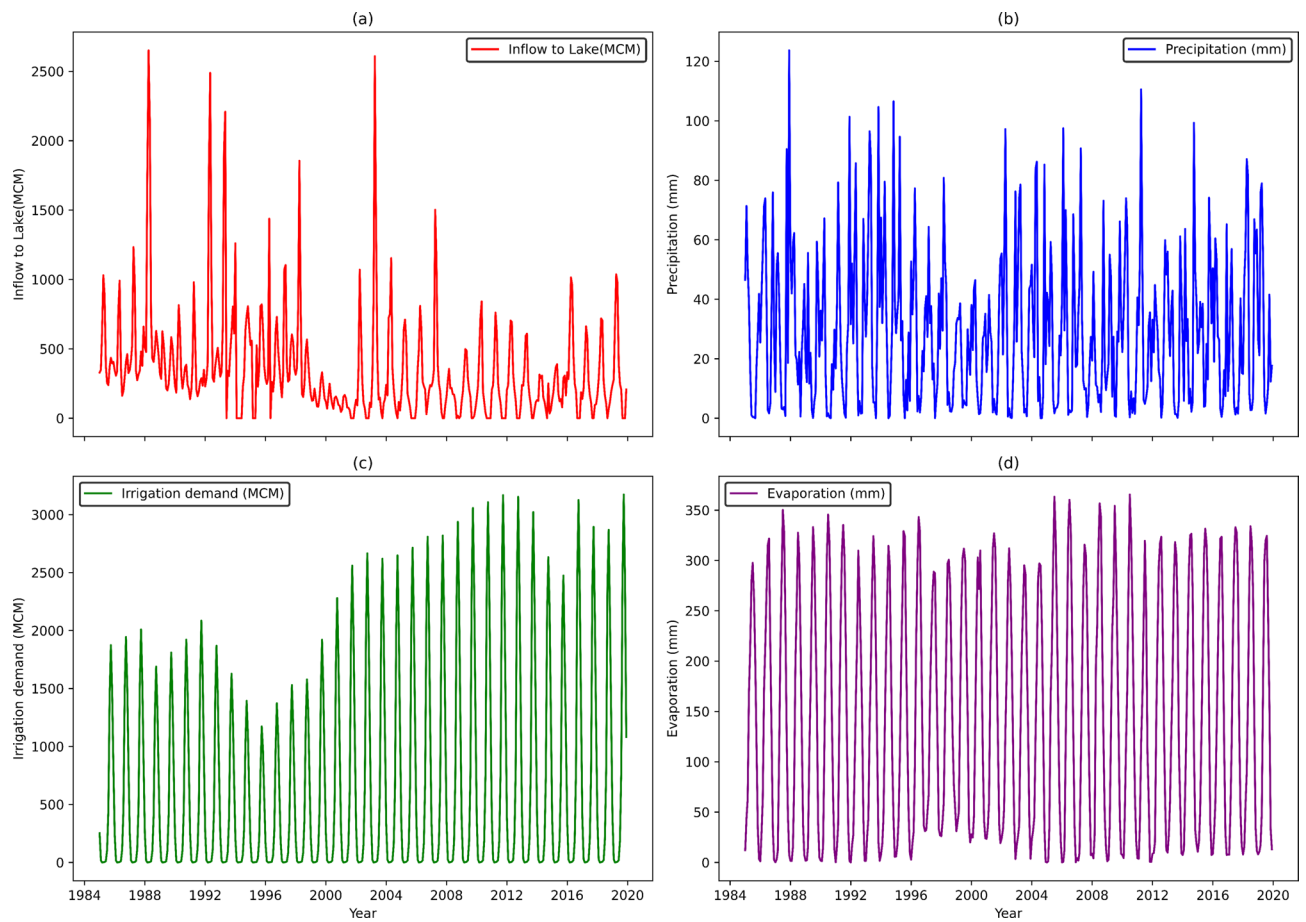


Fig. 3. (a) Monthly river inflows (b) Monthly precipitation (c) Monthly irrigation demand (d) Monthly evaporation in the Lake Urmia Basin from 1985 to 2020.

Based on the Fig. 3c, the demand for irrigation began to rise in the early 2000s, and peaked 2010 and 2011, reaching a record high of more than 10000 MCM per year. Long-term changes in evaporation patterns reflect those of precipitation, displaying no clear trend. However, evaporation declined from 1999 to 2005 before returning to levels observed prior to 1999.

Satellite data

In this study, different types of satellite data were used to investigate the snow dynamics in the LUB, with these products listed in Table 1.

AMSR-E

The Aqua satellite's Advanced Microwave Scanning Radiometer - Earth Observing System (AMSR-E) is a twelve-channel, six-frequency, dual-polarized microwave radiometer sensor. AMSR-E sensors allow for accurate prediction of snow characteristics and understanding the dynamics of snow cover⁴⁹.

AMSR-E provided a global-scale daily SWE dataset from June 19, 2002, to October 3, 2011⁵⁰. The pixel values of this data range from 0 to 255, with values from 0 to 240 representing SWE values in millimeters. Values of 252–253–254–255 indicate no snow or snow impossibility (252), glacier (253), water (254) and missing data (255), respectively. The real SWE values were divided by 2 for storage^{51,52}. Therefore, to use the data, each pixel value must be multiplied by 2. The algorithm developed by Chang et al., (1987)⁵³, known as the NASA algorithm, utilizes the brightness temperature degrees obtained from AMSR-E to generate SWE data. In this algorithm, snow density is assumed to be 300 kg/m³, and snow particle size is considered to be 0.3 mm. The Chang algorithm is shown in Eq. (1):

$$SWE = 4.8 \times (T_{b,18H} - T_{b,37H}) \text{ (mm)} \quad (1)$$

where, $T_{b,18H}$ and $T_{b,37H}$ represent the brightness temperatures at 18 and 37 GHz, respectively.

This algorithm has been developed over time (see Liang and Wang, 2020⁵⁴). For example, Foster et al., (1997)⁵⁵ demonstrated that algorithms developed without considering the presence of forested areas can lead to inaccurate estimates of SWE. They preferred to account for the influence of forested areas (denoted by the fraction “f”) and used this information to create a revised version of the NASA 96 algorithm. As forest scattering

Product	Details / Version	Variables used	Temporal coverage	Temporal resolution	Spatial coverage	Spatial resolution	Data source	Masks / QA filters	References
AMSR-E	Advanced Microwave Scanning Radiometer – Earth Obs. System, NSIDC standard product	SWE	2002–2011	Daily	Global	0.25° × 0.25° (~ 25 km)	NSIDC, Python	Water mask; valid flags; pixel codes excluded (252 = no snow, 253 = glacier, 254 = water, 255 = missing)	⁴⁹
MODIS	MOD10A1 Collection 6.1	SC	2000–present	Daily	Global	500 m	NSIDC, GEE	QA cloud mask; water mask; valid coverage ≥ 80%; NDSI ≥ 0.4 threshold	^{62,76}
GLDAS (Noah)	Global Land Data Assimilation System, v2.0 & v2.1	SWE	1985–2022	3-hourly	Global	0.25° × 0.25°	NASA/NOAH via GEE	Land mask; product QA applied	⁶⁹
ERA5-Land	ECMWF Reanalysis 5th Generation, v2 (C3S)	SWE, Precipitation, Temperature	1950–present	Hourly	Global	~ 9 km	Copernicus (C3S), GEE, R	Land/sea mask; Urmia Lake polygon excluded;	¹²⁵
PERSIANN-CDR	Precipitation Estimation using ANN, v1r1	Precipitation	1983–present	hourly	60°S–60°N	0.25° × 0.25°	GEE – CHRS Rainsphere	– (not applied)	⁶⁶
IMERG-GPM	Integrated Multi-satellite Retrievals for GPM, V06B	Precipitation	1998–present	Half-hourly	Global	0.1° × 0.1°	GEE	– (not applied)	¹²⁶

Table 1. Satellite data and reanalysis products employed to study snow dynamics in the LUB.

is closer in the 18 and 37 GHz channels, the brightness temperature difference mainly covers non-forested areas and is represented by the fraction (1-f). The revised algorithm is shown in Eq. (2):

$$SWE = \frac{4.8 \times (T_{b,18H} - T_{b,37H})}{(1 - f)} \text{ (mm)} \quad (2)$$

In this study, monthly AMSR-E SWE data for the years 2002–2011 were obtained from NSIDC in HDF-EOS2 format at Level 3, featuring a spatial resolution of 25 km × 25 km. It should be noted that using a fixed snow density can lead to incorrect results for different regions. Therefore, the algorithm was developed by incorporating the observed snow density measurements taken from ground-observed snow stations within the basin to obtain the SWE. To accomplish this task, the obtained SWE values were divided by the constant snow density value of 0.3, used in the Chang algorithm, and then multiplied by the actual snow density.

MOD10A1

The Moderate Resolution Imaging Spectroradiometer (MODIS) is a radiometric sensor with dual-sided scanning mirrors, developed by NASA. It was first integrated into the Terra satellite in 1999⁵⁶, followed by the Aqua satellite in 2002⁵⁷. MODIS can cover a wide area of the Earth's surface with its broad viewing angle and collects data in 36 spectral bands at various resolutions⁵⁸. This capability facilitates the production of various global-scale products, including snow cover. The high spatial resolution and wide scanning feature of MODIS have enabled cloud-differentiated snow cover data to be available since 2000⁵⁹. Snow and clouds, as captured by MODIS data, can be distinguished through their differing reflectance properties in the VIS and SWIR wavelengths. These differences are easily detected using the Normalized Difference Snow Index (NDSI). This index serves as a fundamental tool for distinguishing between snowy and non-snowy areas⁶⁰.

For the production of MODIS snow data, three processing levels are applied: L1B, L2, and L3. The L3 snow product is a geophysical product processed spatially and temporally, containing data for a specific region (grid) of the Earth. It is presented in a gridded map projection format as the grids of the global grid^{61,62}. The MOD10A1 snow product is generated from the global observations of MODIS sensors, combined algorithmically with the geographical matching of MOD10_L2 and MOD10_L2G products. The pixels produced through these algorithms contain the optimal NDSI, snow albedo and quality control data.

PERSIANN-CDR

PERSIANN⁶³ is an affective algorithm for reconstructing historical precipitation over the past three decades, utilizing infrared data as its primary source. The model is trained using National Centers for Environmental Prediction (NCEP) Stage IV hourly precipitation data and subsequently applied with fixed parameters. To minimize biases and ensure high-resolution consistency, Global Precipitation Climatology Project (GPCP) data are incorporated. The final product, known as Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record (PERSIANN-CDR), provides a 30-year record of daily precipitation data at 0.25° spatial resolution, covering the 60°N–60°S latitude range⁶⁴.

Global precipitation measurement (GPM)

The Global Precipitation Measurement (GPM) mission, a collaboration between NASA and JAXA, aims to provide accurate, global precipitation data through a constellation of advanced satellites. These satellites use sophisticated instruments such as the Dual-Frequency Precipitation Radar (DPR) and the GPM Microwave Imager (GMI) to capture both rainfall and snowfall across a broad range of latitudes. The Integrated Multi-

Satellite Retrievals for GPM (IMERG) algorithm processes and integrates data from various satellite sensors, offering high-resolution precipitation estimates at 0.1° spatial resolution and 30-minute temporal intervals^{65,66}.

Reanalysis and land data assimilation system data

In this study, we utilized both space-based snow products and the ERA5 and GLDAS datasets to investigate snow changes in the Lake Urmia Basin. We conducted an accuracy assessment to compare all datasets against ground-observed data, enabling us to identify the most reliable dataset for our analysis.

The European Centre for Medium-Range Weather Forecasts (ECMWF) developed ERA5 reanalysis data, which are among the leading programs that provide global-scale data⁶⁷. This dataset offers 8 different snow parameters, including snow albedo, snow cover, snow depth, snowfall, snow layer temperature, snowmelt, snow density and SWE⁶⁸. The dataset covers the time period from January 1950 to the present with spatial resolutions of 9 km × 9 km on both hourly and monthly timescales.

Land Data Assimilation Systems (LDAS) provide global-scale climatic and hydrological data by running numerical models in addition to ground and satellite observations⁶⁹. Four different Land Surface Models (LSMs) are used in the production of GLDAS data: NOAH, Catchment (CLSM), Community Land Model (CLM), and Variable Infiltration Capacity (VIC). Surface conditions and flux products simulated by these models, including soil moisture, surface temperature, evaporation and SWE are made accessible through the NASA Goddard Earth Sciences Data and Information Services Center (GES DISC). The 0.25-degree resolution products exclusively contain data from the NOAH model⁷⁰. In the production of SWE data within the GLDAS/NOAH model, snow cover data obtained from the MODIS sensor on NASA's Terra satellite is used with the update technique described by Rodell and Houser (2004)⁶⁹. The modeled SWE data is updated by comparing it with MODIS snow cover data. If MODIS snow cover percentage is greater than 40% where there is no snow in the model, 10 mm of SWE is added to the pixels⁶⁹. For GLDAS SWE data, 3-hourly outputs of the NOAH model with a spatial resolution of 0.25° were used in this study.

Table 2 provide the uncertainty budget of datasets used in this study. Uncertainty budgets are essential in hydro-climate studies because they quantify the confidence and limitations of ground-based, satellite, and reanalysis data, which are critical for detecting climate trends, comparing datasets, validating models, and informing policy decisions. Each data type carries its own sources of uncertainty such as instrument errors, processing methods, or model assumptions and accounting for these ensures that climate analyses are scientifically credible, statistically robust, and properly interpreted. Without understanding these uncertainties, we risk drawing misleading conclusions or making poorly informed decisions about climate change.

Data preprocessing

In the first step of data processing, satellite data and reanalysis data were filtered and masked based on the boundaries of the Lake Urmia Basin. The satellite data, referenced to the Earth's surface, were projected using the Universal Transverse Mercator (UTM) coordinate system, with the WGS 84 Datum and the 38th zone applied to the study area.

To spatially interpolate the point-based SWE measurements across the basin, Co-Kriging⁸² and Inverse Distance Weighted (IDW) interpolation methods were employed^{84,85}. In the Co-Kriging method, elevation was incorporated as a secondary variable to improve estimation accuracy. The predictive performance of both interpolation techniques was evaluated through cross-validation⁸⁶. In each iteration, 25% of the snow measurement stations were excluded, and the interpolated values were compared with the actual measurements at these omitted stations. This process enabled the identification of the most accurate interpolation method for generating basin-wide SWE distributions. The interpolated SWE results were compared with SWE estimates derived from AMSR-E, Improved AMSR-E, GLDAS, and ERA5 products, and the dataset that showed the best agreement with SWE measurements was selected.

For the generation of ERA5 SWE maps, monthly output data were used. ERA5 SWE raster data, with a spatial resolution of 9 km × 9 km, were downloaded in NetCDF format from the Copernicus Climate Change Service (C3S, 2023). Similarly, for GLDAS, monthly outputs from the GLDAS NOAH Land Surface Model L4 were employed. These SWE data, with a spatial resolution of 25 km × 25 km, were obtained in NetCDF format from GES DISC⁸⁷, covering the period from 1985 to 2023.

Component	Dataset / Step	Main uncertainty sources	Typical magnitude / evidence	References
Measurement (in-situ)	Snow tubes / pits (SWE)	Sampler & observer bias; core loss; density estimation; representativeness	Bias typically ~ 5–15% depending on snow state; large-diameter tubes can deviate by ~ 7–10% vs. pit reference; repeat sampling reduces variance	71–74
Measurement (remote)	MODIS Snow Cover (SCE/FSC)	Cloud contamination; forest & topographic effects; 500 m pixel; thin snow detectability	Overall accuracy ~ 0.88–0.93 under clear-sky; FSC MAE < 0.10; degraded accuracy with cloud/terrain; gap-filled methods improve to ~ 0.91–0.98	75,76
Reanalysis bias	ERA5-Land (SWE/SC/SD)	Land-surface physics; orography/elevation mismatch; rain–snow partition; sparse assimilation	Regional SWE overestimation, often 150–200% in spring; improved hydrologic use with local bias correction; in this study: $r=0.88$, RMSE = 9.13 mm, mKGE = 0.74	77–80
Reanalysis bias (other)	GLDAS SWE; passive microwave (AMSR-E/2)	Fixed density assumptions; microwave penetration limits; forest effects	GLDAS underestimates SWE peaks (up to ~ 35% in mountains); stand-alone PMW SWE has low correlations and higher RMSE; new ANN/dynamic density algorithms reduce bias	81
Interpolation	Station → gridded SWE/SD (IDW, OK, KED/co-kriging)	Sparse station density; elevation gradients; variogram choice	Cross-validation errors commonly 10–30%; elevation-aware kriging/KED outperforms IDW and reduces bias	82

Table 2. Uncertainty budget table of datasets used in the study.

Snow drought analysis

In this study, the snow mass was initially calculated for each year to evaluate snow drought in the basin. The snow mass was derived from ERA5-SWE data for the period from 1985 to 2023. The annual snow mass was computed using the Eq. (3)⁸⁹:

$$Snow\ Mass_{year} = \sum_{i=1}^{Day-1} (\Delta SWE_i) \quad (3)$$

Here, i represents the months of the hydrological year, and ΔSWE_i refers to the change in SWE for each month. If ΔSWE_i is negative, it is not included in the accumulation.

To classify snow drought intensity, snow accumulation values are compared with the historical climate distribution. Snow drought occurs when the total snow accumulation for a year falls below the 25th percentile of the historical climate data^{89–91}. The severity of snow drought is classified into four categories based on the snow accumulation percentile thresholds: 1- Light Snow Drought: 50th – 25th percentile, 2- Medium Snow Drought: 25th – 15th percentile, 3- Heavy Snow Drought: 15th – 5th percentile and 4- Extreme Snow Drought: below the 5th percentile.

Statistical indices and models

The accuracy of satellite data and global products based on observational data was evaluated using several performance metrics, including the modified Kling-Gupta Efficiency (KGE)^{92,93}, R-squared^{94,95}, and Root Mean Square Error (RMSE)⁹⁶. All data preprocessing procedures and statistical analyses were conducted using the R and Python programming environments, utilizing packages such as HydroGOF⁹⁷, CDT (Climate Data Tools)⁹⁸, Statsmodels, SciPy, and scikit-learn^{99,100}. For the deep learning model implementation, the Keras library within the TensorFlow framework¹⁰¹ was employed.

Other effective statistical and deep learning methods employed in this study include the Mann-Kendall trend analysis, Welch's t-test, regression analysis, Multiple Linear Regression (MLR), Response Surface Model (RSM), and Convolutional Neural Networks (CNNs). These methods have been widely applied in previous studies to analyze hydrological processes^{102–105}. Figure 4 indicates the methodology and data processing steps used in this study.

Kling-Gupta efficiency (KGE)

The modified Kling Gupta Efficiency (KGE) performance metric has been employed to assess the accuracy of satellite data and global products based on observational data. KGE combines the correlation coefficient (r), bias (β) and variability component^{92,93}. The Kling-Gupta Efficiency Index is a measure recommended for evaluating model performance in hydrological modeling and similar simulation fields. This index assesses the accuracy of a model's outputs through three main components: correlation, bias and variability^{106,107}. KGE aims to provide a comprehensive analysis of model performance by balancing these three components. The index is formulated by calculating the Euclidean distance of these components as shown in Eqs. (4, 5):

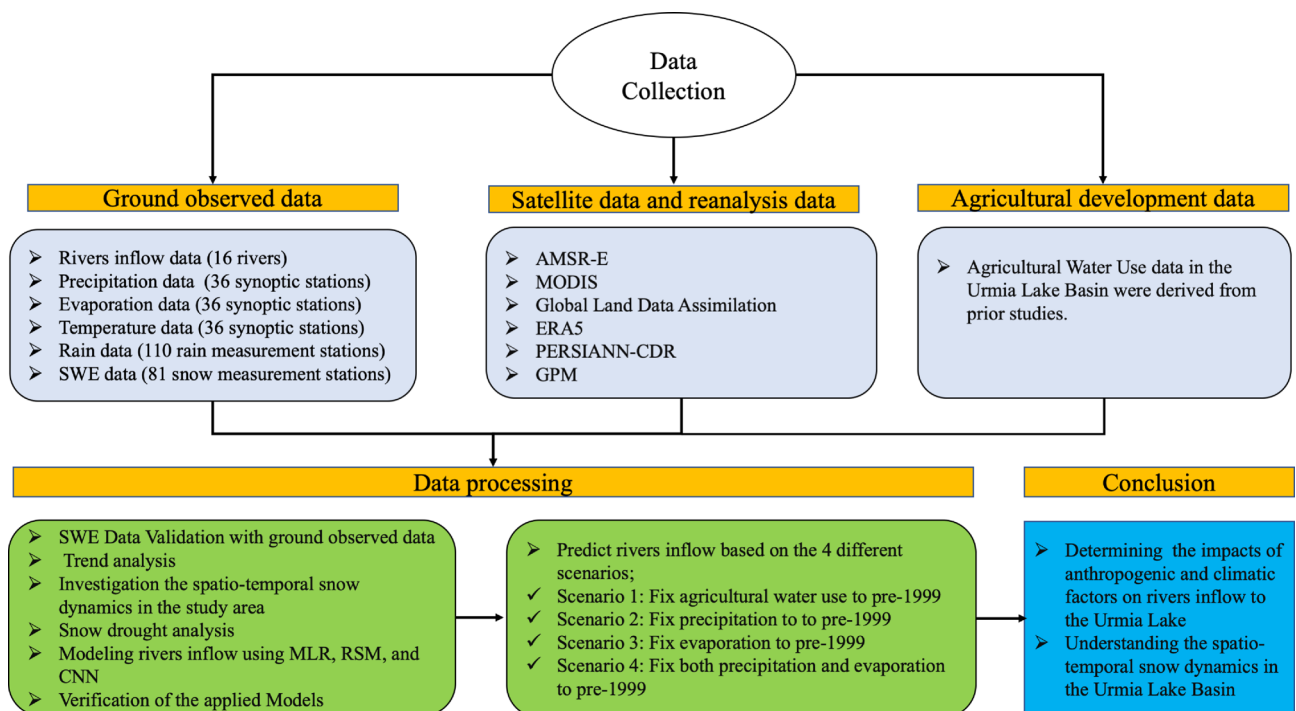


Fig. 4. The methodology and data processing steps used in this study.

$$KGE = 1 - ED, -\infty < KGE \leq 1 \quad (4)$$

$$ED = \sqrt{[S_r \cdot (r - 1)]^2 + [S_\alpha \cdot (\alpha - 1)]^2 + [S_\beta \cdot (\beta - 1)]^2} \quad (5)$$

Here, ED is the Euclidean distance; r is the linear correlation coefficient between observed (O_i) and simulated (P_i) values; Variability Ratio (α), is the ratio of the standard deviation of simulated values to the observed values (σ_p/σ_o); Bias Ratio (β), is the ratio of the means of simulated and observed values (μ_p/μ_o or $\bar{P}/\bar{O}$). S_r , S_α and S_β are scaling factors used to rescale the criterion space before calculating ED , adjusting the impact of each component on KGE . Typically, they are equally weighted, i.e., $s_r = s_\alpha = s_\beta = 1$.

Ideally, the value should be close to 1, indicating that the simulated and observed data have similar variability. The value should also ideally be 1, indicating that the simulated and observed values are of similar magnitude.

Trend analysis and significance tests

In this study, the Mann-Kendall test¹⁰⁸ was used to evaluate trends in SWE, precipitation, water level, evaporation, and other hydro-meteorological parameters.

The Mann-Kendall test, a non-parametric method recommended by the World Meteorological Organization, detects monotonic trends in time series data and is suitable for non-normally distributed datasets common in hydrology and meteorology^{109–111}. The MK test computes a statistic, S , which indicates whether data values increase or decrease over time, with positive or negative S suggesting rising or falling trends, respectively. The standardized statistic, ZS , tests the null hypothesis of no trend. A trend is significant at the 95% ($\alpha = 0.05$) or 99% ($\alpha = 0.01$) confidence levels if $|ZS|$ exceeds 1.96 or 2.576, respectively.

In addition, Welch's T-Test¹¹² was employed to assess the statistical significance of differences in monthly SWE averages across different periods, as well as to evaluate whether changes in river inflows under various scenarios were statistically significant. This test, appropriate for comparing means between groups with unequal variances and sample sizes, was utilized not only to detect notable changes in SWE but also to identify monthly shifts in snowfall patterns.

Regression-Based statistical models

The first-order polynomial-based RSM, often referred to as MLR, is utilized to illustrate the linear interconnection between the response variable and its predictors. The equation typically integrates intercept and slope parameters, correlating each predictor to the response in a linear fashion. In MLR analysis, the general formula of the regression equation that determines the relationship between variables is shown in Eq. (6):

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + \varepsilon \quad (6)$$

In the MLR model, precipitation (mm), agricultural water usage (MCM) and evaporation (mm) were used as input variables (X_1 , X_2 and X_3) and river inflows (MCM) was used as the output layer (y). β_0 and β_i are model constants and ε is the residuals.

The relationships between variables were determined by calculating correlation coefficients and results were obtained using the Least Squares Method. The statistical significance of the obtained results was tested using the F-test. Nonetheless, for a MLR model to be effective, it is crucial that the input variables demonstrate a significant linear correlation with the output variables^{113,114}. This requirement can sometimes result in inadequate model fitting, particularly in the context of hydrological forecasting. To overcome this shortcoming and to better capture the complexity of the system, a second-order polynomial RSM was implemented in addition to the MLR model, aiming to examine the intricate interactions among key hydrological factors in the Lake Urmia Basin. The application of RSM in hydrological studies has demonstrated promising results in previous research^{102,105}, supporting its potential for modeling such complex relationships.

The developed statistical models aim to give a clear insight into the mechanism in the background of inflow to the lake with high prediction accuracy. The formulation of the second-order polynomial model is presented in Eq. (7):

$$Y = \beta_0 + \sum_{i=1}^n \beta_i x_i + \sum_{i=0, i < j}^n \beta_{ij} x_i x_j + \sum_{i=1}^n \beta_{ii} x_i^2 + \epsilon \quad (7)$$

Here, a second-order polynomial model was developed, incorporating key variables such as River Inflows to Lake (I), Precipitation (P), Agricultural Water Usage (AWU) and Evaporation (E), was developed in this study. This model is capable of capturing both linear and nonlinear relationships between these variables, thereby enhancing the understanding of their combined impact on the lake's water balance. The core idea of RSM lies in performing a small number of well-defined experiments, which enable the definition of quadratic relationships and interactions among the investigated factors and the observed responses.

The model validation was conducted by partitioning the dataset into training and testing sets in varying ratios of 80–20 and 70–30, respectively to test its robustness across different scenarios. At the final step the best model was selected based on the results of accuracy assessment to explore the interactions between precipitation, evaporation, agricultural water usage and their influence on the river inflow and lake's water level as well.

Layer (type)	Output shape	Key parameters
Input	(sequence_length = 3, features = 3)	–
Conv1D	(3, 8)	filters = 8, kernel_size = 3, padding = "same", activation = ReLU
Flatten	(24)	–
Dense	(8)	units = 8, activation = ReLU
Dropout	(8)	rate = 0.05
Output (Dense)	(1)	activation = Linear (regression)

Table 3. CNN architecture.

Item	Value
Sequence length	3 (sliding window)
Input features	Precipitation, Evaporation, Irrigation
Target	Inflow
Train/Test split	0.8 / 0.2 (chronological)
Validation split	0.10 (within training)
Batch size	32
Epochs	30 (no early stopping)
Optimizer	Adam (LR = 0.01)
Loss function	MSE
Random seed	120
Scaling	Standardization (zero mean, unit variance; fitted on training only)

Table 4. CNN hyperparameters.

Convolutional neural networks (CNNs)

CNNs¹¹⁵, initially developed for processing visual data, have also been effectively applied for modeling one-dimensional (1D) data types, such as time series and tabular numerical datasets¹¹⁶. This capability provides significant advantages in the analysis of geospatial datasets, including satellite imagery and Digital Elevation Models (DEM), thereby facilitating the processing of remote sensing data. Additionally, the ability of CNNs to learn from time series data has proven to be a powerful approach for modeling hydrological processes (see Tripathy and Mishra, 2024¹⁰⁴).

In this study, a CNNs model was employed to predict river inflows based on precipitation, evaporation, and agricultural water usage data. The input features were normalized using the MinMaxScaler to ensure numerical stability and to improve model performance. The model was implemented using the TensorFlow and Keras libraries, while scikit-learn was utilized for data preprocessing and performance evaluation. The model architecture has been explained in the Table 3.

A comprehensive hyperparameter tuning process was conducted, evaluating 10,000 distinct hyperparameter combinations, alongside modifications to model architecture and variations in training methodologies, to systematically optimize model performance. The model hyperparameters has been explained in Table 4.

The architecture of the CNN model consisted of an input layer, a 1D convolutional layer (Conv1D), a Flatten layer, one fully connected (Dense) layer, a Dropout layer, and an output layer. The Rectified Linear Unit (ReLU) activation function was used in both the convolutional and dense layers due to its ability to mitigate the vanishing gradient problem and enhance model training efficiency.

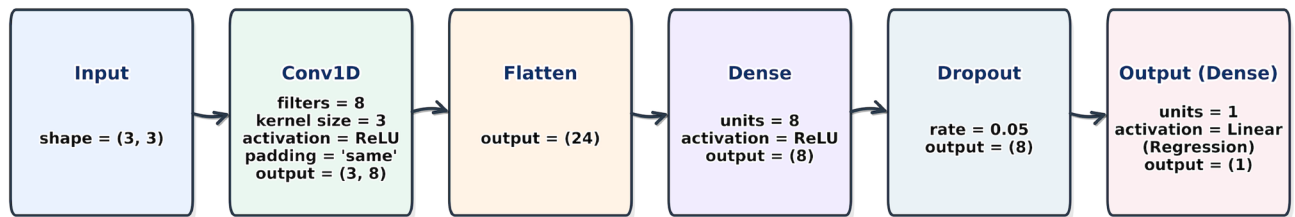
The explored hyperparameters included: Learning rates, Epochs, Number of filters in the Conv1D layer, Kernel sizes, Number of neurons in the dense layer, Sequence lengths (input time steps), Dropout rates, Batch sizes and Random seeds.

The optimization algorithm used was the Adam optimizer, which was chosen for its adaptive learning rate properties and computational efficiency. The model was compiled with Mean Squared Error (MSE) as the loss function. To ensure reproducibility, all experiments were conducted with a fixed random seed for NumPy and TensorFlow. The dataset was split into training and testing sets using a time series approach, where 80% of the data was used for training, and the remaining 20% was used for testing. A 10% validation split was applied to the training set during model fitting. A detailed explanation of the CNN architecture, including annotated layer sizes, is provided in Fig. 5.

Results

Performance analysis of snow products

The SWE results derived from AMSR-E, Improved-AMSR-E, ERA5, and GLDAS were compared with in-situ SWE measurements for the period of 2007–2013, at both monthly and annual scales. Moreover, observed data from 4 stations in the basin were used for further verification purposes. Figure 6; Table 5 indicate the overall performance and correlation coefficients of ERA5, GLDAS, AMSR-E and Improved-AMSR-E.



Note: Shapes follow the Keras model with padding = 'same'.

Fig. 5. CNN architecture with annotated layer sizes.

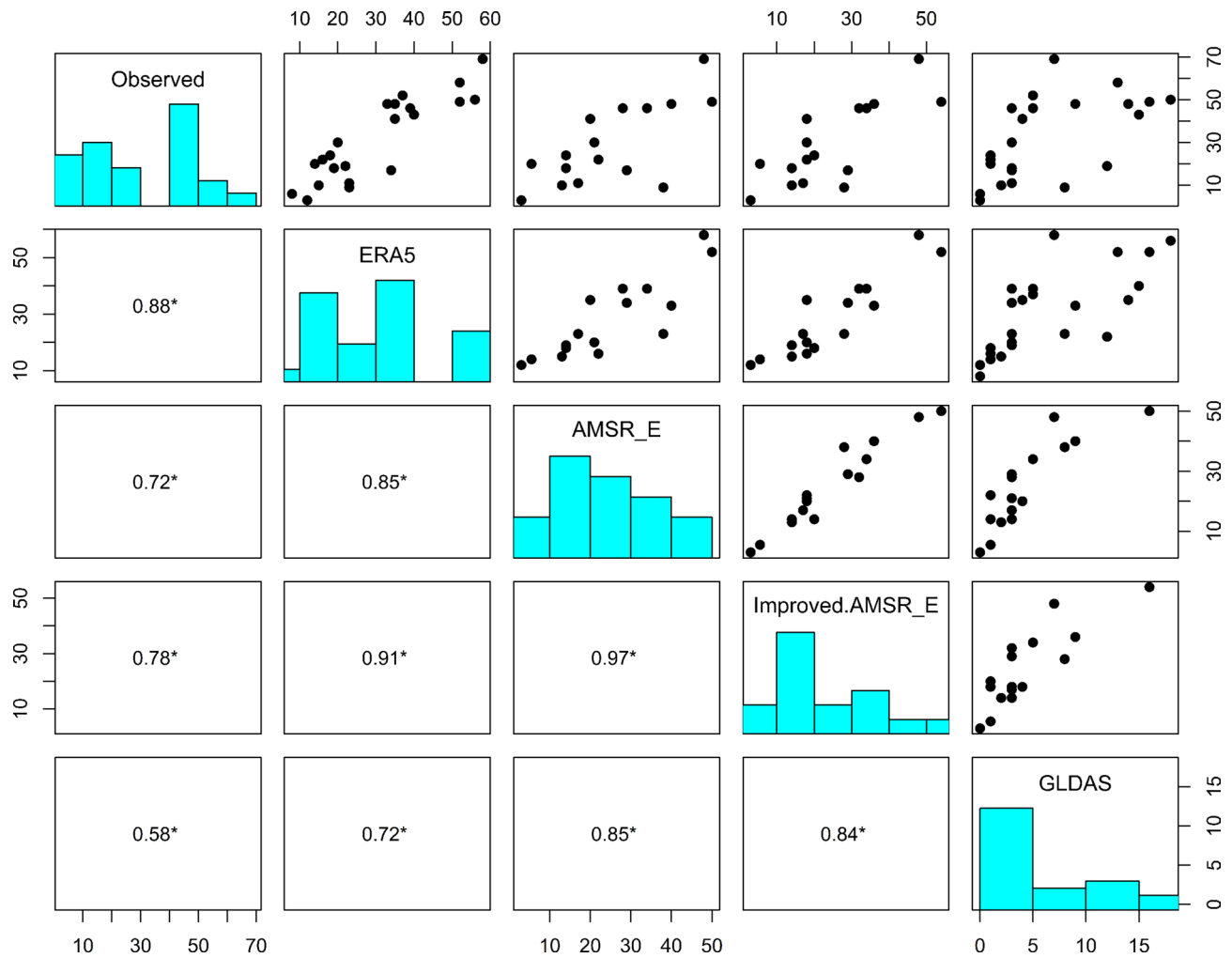


Fig. 6. The relationship between the Snow Water Equivalent (SWE) values derived from ERA5, GLDAS, AMSR-E and Improved-AMSR-E with in-situ SWE values of the LUB.

The correlation matrix in Fig. 6 depicts the relationships between all datasets. The correlation coefficients between observed data and ERA5, Improved-AMSR-E, AMSR-E and GLDAS were estimated as 0.88, 0.78, 0.72 and 0.58, respectively. According to the results, the derived SWE values from Improved-AMSR-E and ERA5 data exhibited better performance compared to other datasets. In addition to the correlation coefficients, Table 5 displays the results for all evaluation metrics used in this study.

According to this table, ERA5 and Improved-AMSR-E achieve the highest KGE values of 0.74 and 0.63, respectively. The RMSE values of ERA5 and Improved-AMSR-E were calculated 9.13 and 12.30, respectively. Based on the findings of this study, the ERA5 data demonstrate significantly better alignment with observed data compared to other datasets. Additionally, the Improved AMSR-E algorithm exhibits improved correspondence

Metric	ERA5	AMSR-E	Improved-AMSR-E	GLDAS
mKGE	0.74	0.60	0.63	-0.14
RMSE	9.13	13.31	12.30	30.40
Correlation	0.88	0.71	0.78	0.58
Bias Ratio	0.94	0.85	0.84	0.19
Variability Ratio	0.77	0.75	0.75	0.29
R ²	0.78	0.51	0.60	0.34

Table 5. The calculated statistical parameters to check the performance of derived SWE values from ERA5, GLDAS, AMSR-E and Improved-AMSR-E with in-situ SWE values of the lake urmia Basin.

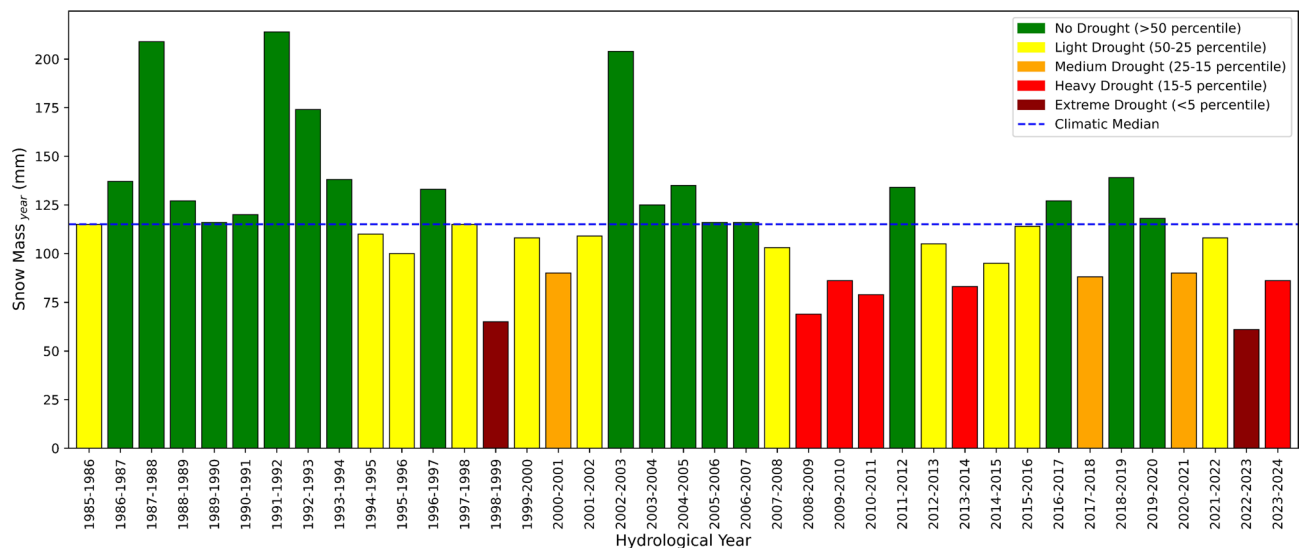


Fig. 7. Snow drought condition for each hydrological year from 1985 to 2023.

with observed data over the raw AMSR-E data. This enhancement was achieved by integrating observed monthly snow density values measured in the basin into the data retrieval algorithm. Consequently, for the timeframe of 1985 to 2023, ERA5 SWE data has been employed in this study and its relationship to other hydroclimatic data was investigated.

Spatio-Temporal analysis of snow dynamics

To investigate the impacts of climate change and snow drought in the basin, a matched sample T-test was conducted using ERA5 SWE results for two separate periods, spanning November, December, January, February, March, and April. The first period lasts from 1985 to 1998, while the second runs from 1999 to 2023. The time periods were selected based on the snow drought analysis shown in Fig. 7, as well as drought assessments from previous studies^{3,15}.

The snow drought results in the Fig. 7 revealed no drought or only light drought conditions in the basin before 1999. However, after 1999, drought began to significantly impact changes in snow mass. The T-test is used to determine whether the mean differences between the two groups are statistically significant. The results of T-test revealed that the difference between the two selected periods in terms of SWE were significant. The results indicated consistently lower SWE during the second period (1999–2023). The mean monthly average SWE were 42.3 mm and 23.9 mm for the period 1985–1998 and 1999–2023, respectively (Fig. 8).

The mean annual SWE were 253.59 mm and 143.31 mm (43.49%) for the period of 1985–1998 and 1999–2023, respectively. The declines in monthly averages were 30.61%, 37.35%, 33.78%, 34.87%, 54.41%, and 57.62% for November, December, January, February, March, and April, respectively. In the initial period, the peak of the snow season, marked by the highest SWE, transpired in March. Conversely, during the second period, a noticeable shift occurred, with the highest SWE now occurring a month earlier, in February. This shift suggests a dual change in both the volume and seasonal timing of snowfall, which may reflect the intensifying impacts of climate change, as also indicated in Figs. 7 and 8.

Figure 9a illustrates the inverse relationship between SWE and temperature changes in the basin. After 1999, temperature has risen, while SWE has declined during the same period. The mean temperature has increased about 1 Celsius in the basin after 1999. While the minimum mean temperature was observed in 1992 with a value of 9.5 Celsius, the maximum one has observed in 2010 with a value of about 13.5 Celsius. Previous studies show that snow and SWE are sensitive to different levels of warming^{117–119}. For this reason, snow droughts are

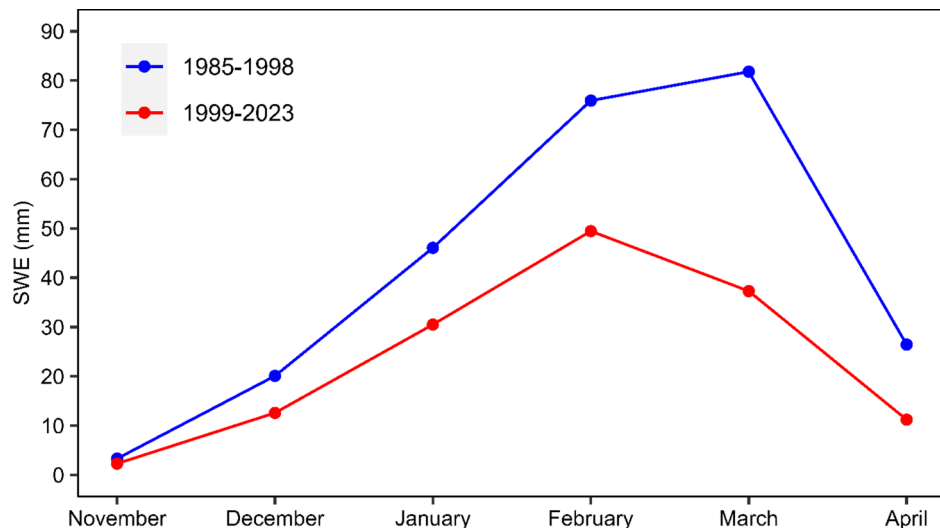


Fig. 8. The monthly mean SWE during 1985–1998 and 1999–2023.

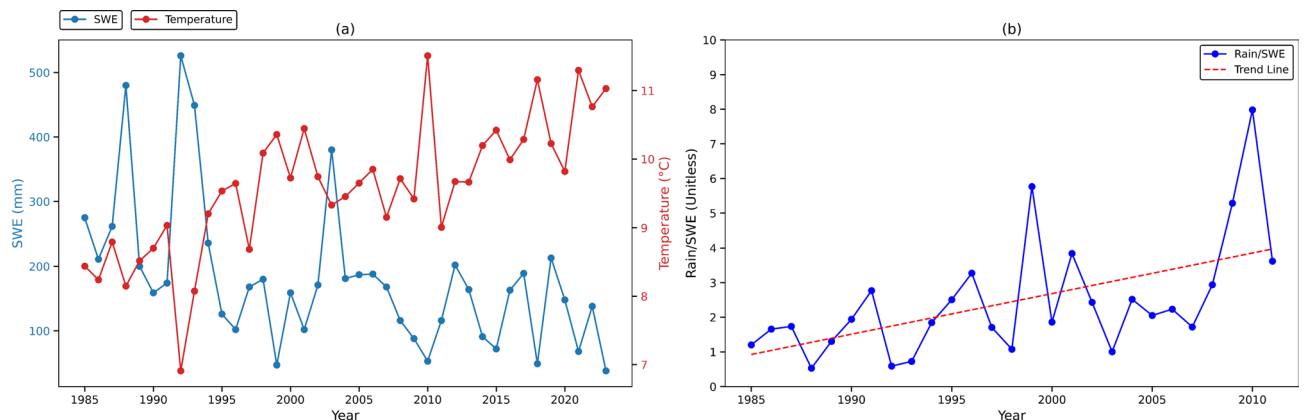


Fig. 9. (a) Annual SWE and annual mean temperature changes in the study area from 1985 to 2019 (b) Rain over SWE ratio in the study area.

projected to become increasingly frequent⁹⁰ due to warming winters, with increasing impacts on the environment. However, lower snow does not necessarily lead to lower available water as the rain-snow ratio may increase over time¹²⁰. Considering the decline in snow and that the overall precipitation has not changed significantly in Lake Urmia (Fig. 3), it is reasonable to conclude that rain-snow ratio has increased in the Lake Urmia Basin. The advance of peak SWE reflects warmer mid-winter conditions that push precipitation toward rain near the rain-snow transition ($\sim 0\text{--}2^\circ\text{C}$), increasing rain-on-snow occurrence, and trigger earlier melt onset that proceeds at lower melt rates in shallower packs mechanisms widely observed in warming, snow-limited basins. Rain data from 110 stations within the basin, spanning from 1985 to 2011, were analyzed to examine changes in the rain-to-SWE ratio across the study area (Fig. 9b). The results showed a noticeable increase in the rain-SWE ratio, particularly after 1999. This increase suggests a shift towards decreasing SWE and increasing rain over time.

To clarify the correlation structure, we added a qualitative path diagram (Fig. 10). It shows that precipitation (P) affects inflow (Q) primarily through snow storage and melt ($P \rightarrow \text{SWE} \rightarrow Q$), with a weaker direct rain-runoff path ($P \rightarrow Q$). Temperature (T) modulates the partitioning of precipitation into rain or snow and controls the timing/rate of melt, while anthropogenic water use (AWU) reduces Q via withdrawals. Pairwise correlations therefore reflect only part of the system: for example, the correlation between P and Q may appear weak when SWE mediates most of the effect. This framework highlights that the dominant pathway in this basin is $P \rightarrow \text{SWE} \rightarrow Q$, while the direct $P \rightarrow Q$ pathway is secondary and seasonally episodic^{31,121}.

Figure 11a displays the spatio-temporal changes in ERA5 SWE across the Lake Urmia Basin from 1985 to 2023. The first two maps depict average SWE distributions for the periods 1985–1998 and 1999–2023, respectively. The third map shows the difference in SWE between these two periods. Figure 11b shows the spatio-temporal changes in ERA5 temperature across the same region and timeframe. The first two maps present the average temperature distributions for the periods 1985–1998 and 1999–2023, respectively. The third map emphasizes the difference in temperature between these two periods. This figure reveals a strong correlation between temperature changes

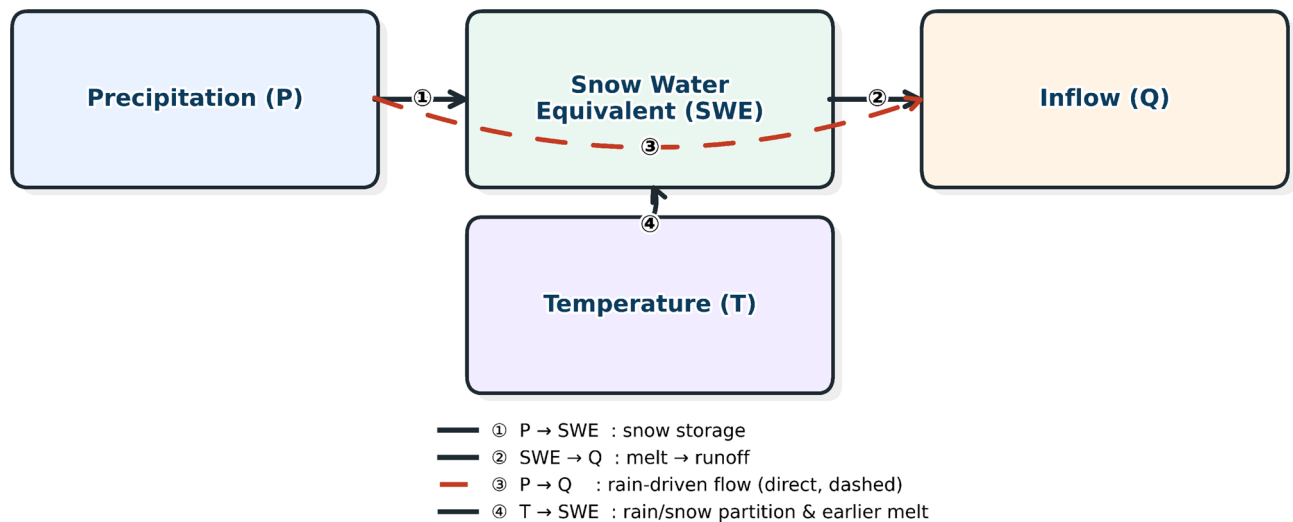


Fig. 10. Conceptual path diagram of the relationships between precipitation, temperature, SWE, and river Inflows.

and variations in SWE. An inverse spatio-temporal relationship between temperature and SWE is evident across different regions of the basin.

This figure highlights also the spatial variation in SWE reduction within the Lake Urmia Basin over two periods. The largest decreases, 20–30 mm, occur in the mountainous western region, followed by smaller declines in the southwestern and southeastern areas (15–20 mm). The eastern sector sees consistent reductions, while low-lying areas experience minimal changes (0–5 mm). These patterns suggest significant shifts in hydrological accumulation across different topographies. These changes are affecting regional water availability and could significantly impact the area's hydrological dynamics.

In addition to the SWE changes in the basin, the SCA results derived from MODIS satellite images were used to better interpret snow dynamics in the study area. Figure 12 presents the time series of the monthly average SCA, offering insights into seasonal variations in snow cover. Additionally, it depicts average snow cover levels across different months of the year and provides a comparative analysis with the findings of SWE. Panel (a) shows the Normalized Difference Snow Index (NDSI) time series from 2000 to 2023, revealing no significant changes in snow cover area (note: this dataset reflects snow cover, not depth or volume).

The years 2000, 2010, and 2015 had the lowest snow cover, corresponding to declines in SWE. Panel (b) highlights seasonal NDSI variability, with peak snow cover in winter and minimal cover in summer, indicating the snowmelt season. Snow cover is most consistent in winter, while spring and autumn are transitional. Panel (c) illustrates SCA trends, showing a decline from April to October, minimal cover in summer, and a sharp increase from November to March, aligning with seasonal snow accumulation and melt cycles. Panel (d) contrasts monthly SCA and SWE, revealing that while snow cover peaks in January, SWE does not. This suggests that the SCA may not correlate with maximum water content, possibly due to lighter snowfall or colder temperatures. In contrast, higher SWE in March and April, with lower snow cover, likely indicates denser snow or the start of the melt season, leading to higher water content. These seasonal variations are important for accurate water availability predictions and assessing the impact of climate change on snow dynamics and hydrological responses. So, it is necessary to investigate all available snow parameters to understand the snow dynamics in the basin and its impacts on river inflows. Focusing on just one parameter such as SCA may lead to unreal and mistake results.

Trend analyses

To gain a better understanding of the meteorological parameters, annual precipitation changes in the basin were derived from different sources including; ERA5, PERSINN-CDR, GPM and synoptic stations in the basin (Fig. 13). The time series analysis of all precipitation datasets showed consistent variations without any significant trends. However, a notable decline in values was observed across all datasets between 1998 and 2001, corresponding to a period of severe drought in the basin.

Kendall Tau and corresponding Z-score and P values were calculated for all hydroclimatic parameters and AWU in the period of 1985–2020. The results of calculated S_{MK} (Mann-Kendall test statistics), Z_{MK} (Test statistics), and P_{MK} (Probability value)¹²² are listed in Table 6. The statistical analyses revealed a statistically significant trend (at 0.05 significance levels) in the volume of water entering the lake (river inflows), SWE, AWU. However, there were no statistically significant trends in precipitation and evaporation. None of the precipitation datasets analyzed showed a significant trend.

This indicates that although SWE has decreased over the study period, the increase in rain has not led to significant changes in precipitation levels. The trends lines for these parameters were presented in Fig. 14. This figure illustrates the significant trends in the factors affecting the lake water budget. Panel (a) indicates significant decrease trend in river inflows. Panel (b) illustrates the annual SWE derived from the ERA5

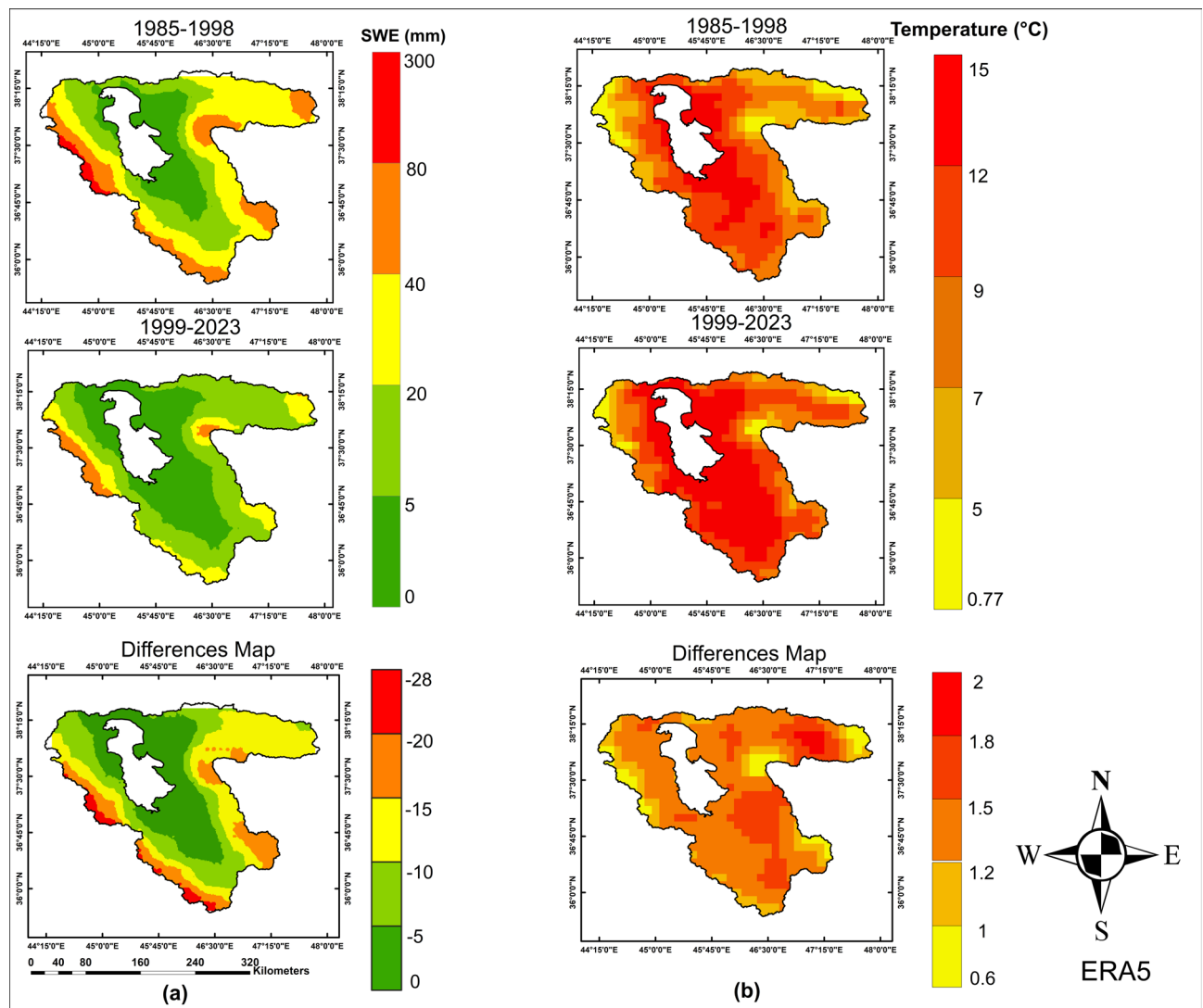


Fig. 11. Spatio-temporal changes in (a) SWE and (b) temperature in the Lake Urmia Basin. For each variable, the top panel shows the average for 1985–1998, the middle panel shows the average for 1999–2023, and the bottom panel shows the difference between the two periods. This figure was produced using a combination of the Google Earth Engine (GEE) JavaScript API (<https://earthengine.google.com/>) for data processing and generation of difference maps, followed by cartographic rendering and visualization in ArcMap 10.8 (ESRI, <https://www.esri.com/>).

reanalysis in millimeters (mm) over the study period. There is a good match between the river inflows and SWE changes. According to these figures, the period from 1985 to 1995, consistently shows elevated runoff and SWE values. Particularly noteworthy are years such as 1988, 1992, and 1993, characterized by peak inflow and snow accumulation, with basin-wide averages reaching up to 9 BCM of river inflows and 500 mm of SWE. Post-1999, there is a notable shift in SWE observations, predominantly reflecting a trend toward reduced values. The results show decreased SWE levels ranging from 50 to 200 mm, which could potentially signal the onset of snow drought conditions during this period. Occasionally, years such as 2003, 2012, 2017, and 2019 experienced a resurgence of higher SWE values. However, the overall trend indicates a decline in SWE, particularly evident from the early 2000s onward. Panels (c) and (d) show the trends in AWU and the lake's water level, respectively. While the lake level has declined from 1278 to 1270 m above sea level, irrigation demand has increased from 4 BCM to 11 BCM over the same period. Panel (e) and (f) show the trends in precipitation and evaporation. Although there have been no significant changes in overall precipitation and evaporation, rainfall in the basin has increased over the study period. As a result, to better understand the impacts of each parameter on changes in river inflows to the lake, statistical models were employed in the next phase to estimate river inflows and assess the influence of each parameter.

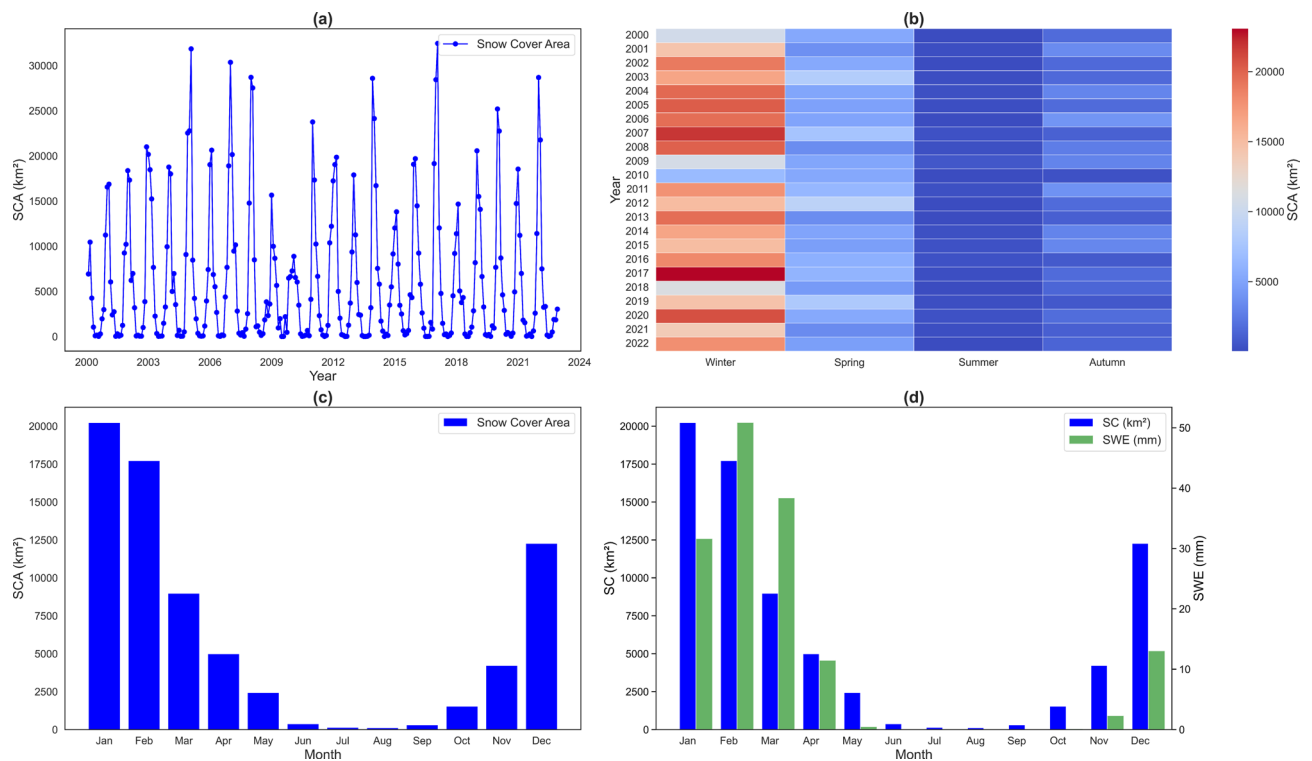


Fig. 12. (a) Monthly average SCA changes from 2000 to 2023, (b) Seasonal fluctuations in snow cover, (c) The average snow cover levels across different months of year, (d) Monthly SCA and SWE changes in the Lake Urmia Basin in the period of 2000–2023.

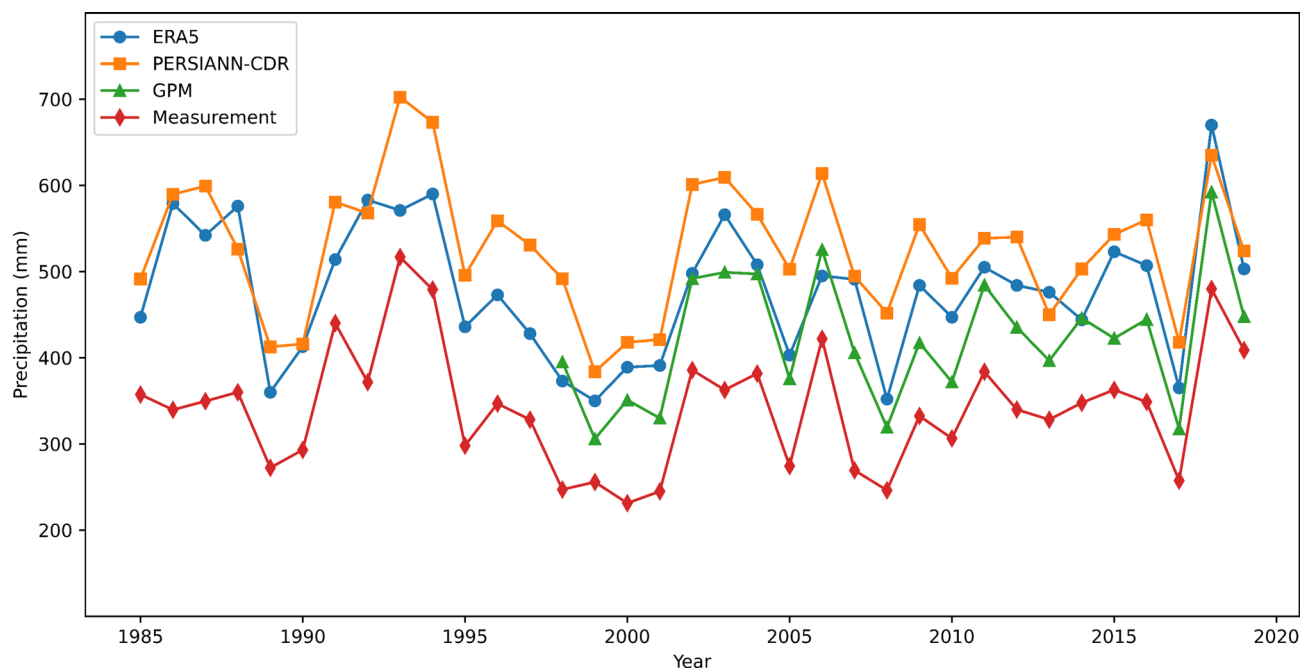


Fig. 13. The precipitation variability in the Lake Urmia Basin derived from different datasets.

Parameter	SWE ERA5	Inflow to Lake	Precipitation	Agricultural Water Use	Evaporation	Rain
S_{MK}	- 245	- 227	- 16	357	118	82
Z_{MK}	- 3	- 3.21	- 0.21	5.05	1.66	1.69
P_{MK}	0.002	0.001	0.83	4.288e-07	0.097	0.091
VarS	6323	4958	4957	4958	4957	2300
τ	- 0.35	- 0.38	0.03	0.6	0.2	0.23

Table 6. Consolidated Mann-Kendall trend test results for selected hydroclimatic parameters.

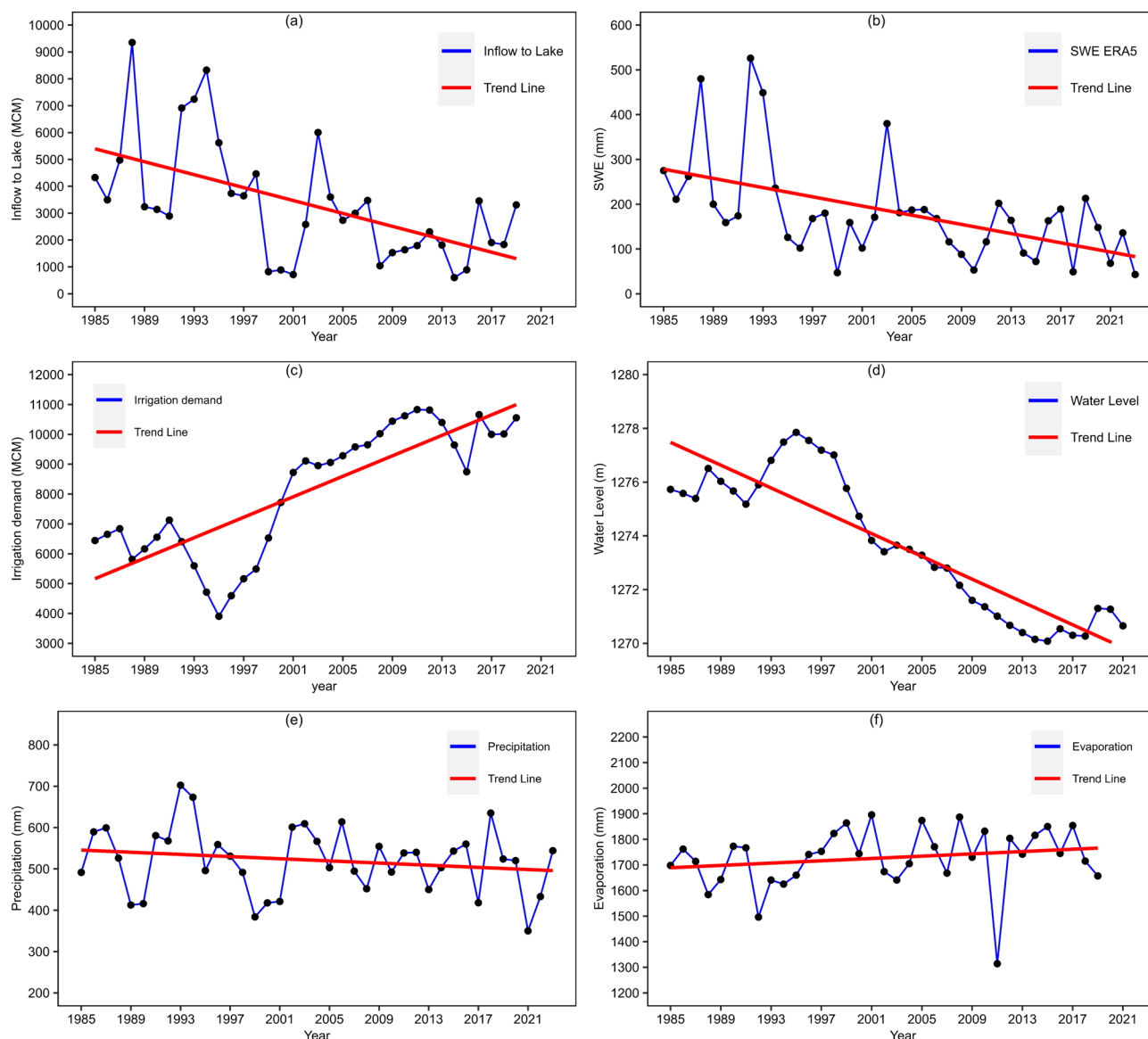


Fig. 14. The trend lines of (a) river inflows to lake (b) SWE (c) agricultural water use (d) lake water level (e) Precipitation (f) Evaporation.

Modeling of hydrological processes

A bivariate simple linear regression model was used to examine the relationship between river inflows and parameters including precipitation, AWU, and evaporation. As shown in the supplementary material, evaporation in the basin is directly linked to temperature changes, so evaporation data were incorporated into the model to predict river inflows, alongside the other parameters. Temperature data for the basin are provided in the supplementary section, with Supplementary Fig. S1 illustrating both temperature trends and the relationship between evaporation and temperature in the study area. The correlation matrix of the selected variables is

examined in Fig. 15. Based on the results of this study, while precipitation (total amount of snow and rain) has positive effects on river inflows, AWU and evaporation (temperature) have negative effects on river inflows. The results reveal a predominant positive correlation between river inflows and snow dynamics, evidenced by a correlation coefficient of 0.81, while displaying a negative correlation with AWU, denoted by a coefficient of -0.60. Moreover, the dependency of river inflows on precipitation changes is indicated by a correlation coefficient of 0.51. The relationship between lake water level fluctuations and other parameters shows a strong dependence on AWU, river inflows, and SWE, with correlation coefficients of -0.95, 0.63, and 0.42, respectively.

The results support the use of MLR, RSM, and CNN models to predict river inflows based on AWU and climatic parameters. For the statistical models, significance was assessed via the F-test. The MLR model yielded an F-statistic of 35.78 (4 and 30 degrees of freedom) with a p-value of 1.389×10^{-11} and the RSM model produced an F-statistic of 11.71 with a p-value of 9.90×10^{-7} both surpassing the critical F-value of 3.20. These results confirm the statistical significance of MLR and RSM, indicating that the independent variables effectively explain the variability in river inflows.

Table 7 demonstrates the performance of the MLR, RSM, and CNN models in estimating river inflows under two training and testing data percentages. Specifically, 80% and 70% of the data were utilized for model training, while the remaining 20% and 30% were used for testing. The table presents a comprehensive array of statistical measures for all three models across the calibration and verification phases.

Among the evaluated models, the CNN model consistently outperformed MLR and RSM in both training and testing phases, demonstrating lower RMSE and higher R^2 and KGE scores, which indicates its stable and superior predictive performance. In the 80% training scenario, the CNNs model achieved R^2 and KGE values of approximately 0.9 in both calibration and verification phases, with notably lower RMSE values (745 MCM and 347 MCM for calibration and verification, respectively) compared to MLR and RSM. In contrast, RSM exhibited higher RMSE values (964 and 993 for calibration and verification, respectively) and lower KGE scores (0.74 in verification), while MLR demonstrated poor calibration performance ($R^2 = 0.61$, KGE = 0.69) despite strong verification results ($R^2 = 0.96$, KGE = 0.97). The MLR model's suboptimal calibration performance

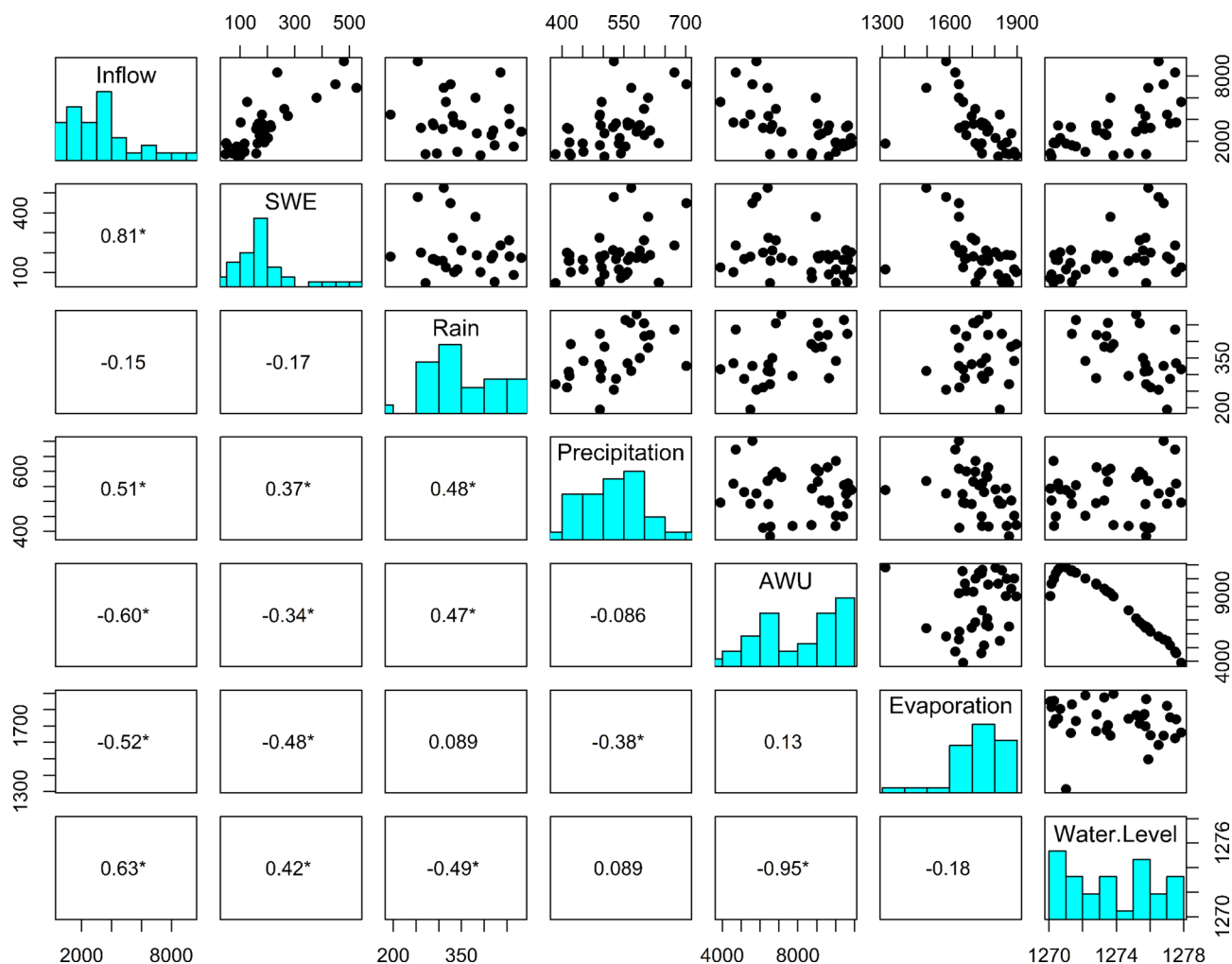


Fig. 15. Correlation matrix between hydroclimatic variables and AWU.

Train size	Models	Calibration	KGE	RMSE (mcm)	Verification	KGE	RMSE (mcm)
		R ²			R ²		
80	CNN	0.89	0.92	745	0.88	0.90	347
	RSM	0.80	0.84	964	0.92	0.74	993
	MLR	0.61	0.69	1334	0.96	0.97	445
70	CNN	0.86	0.86	885	0.43	0.73	645
	RSM	0.84	0.87	884	0.90	0.32	1762
	MLR	0.63	0.71	1327	0.74	0.86	1084

Table 7. Performance in predicting yearly river inflows to the lake Urmia.

suggests limited reliability, despite its robust verification outcomes. Similarly, the RSM model’s elevated RMSE and reduced KGE values, particularly in verification, indicate diminished predictive accuracy.

In the 70% training scenario, the CNNs model maintained strong calibration metrics ($R^2 = 0.86$, $KGE = 0.86$, $RMSE = 885$), although its verification performance was less stable ($R^2 = 0.43$, $KGE = 0.73$), likely due to the reduced training dataset. Conversely, RSM’s verification KGE declined sharply to 0.32, accompanied by a high RMSE of 1,762, while MLR exhibited moderate performance ($R^2 = 0.74$, $KGE = 0.86$, $RMSE = 1,084$). The CNN model’s consistent performance in the 80% training scenario, characterized by R^2 and KGE values near 0.9 and substantially lower RMSE, underscores its reliability and superiority.

The apparent drop in validation R^2 when moving from an 80%–20% to a 70%–30% split arises from two related factors. Sample size effect; With a 30% validation set, the training set becomes smaller, reducing the effective information available for parameter optimization. As CNNs typically require relatively large training samples to capture spatio-temporal patterns, this reduction naturally leads to lower predictive skill. Interannual variability of inflows; Our dataset (1985–2020) contains strong interannual variability, including several extreme drought years. When a larger fraction of years is allocated to validation, there is a greater likelihood that such extreme years are included in the validation subset, disproportionately lowering performance metrics despite identical architecture and hyperparameters. We confirm that the CNN architecture and hyperparameters (filters, kernel sizes, sequence length, batch size, optimizer) were kept identical between these two configurations, with the only change being the relative proportion of training and validation samples. Overall, the performance drops under a 70%–30% split reflects the trade-off between training size and validation representativeness in a limited dataset, driven primarily by the uneven distribution of extreme years rather than by CNN instability. Consequently, the CNN model was selected for developing predictive scenarios due to its enhanced accuracy and consistency.

The performance of the CNN model with varying hyperparameters was further evaluated and visualized using a Taylor diagram. Figure 16 illustrates the comparative performance of these CNN configurations in predicting river inflows.

The diagram reveals a strong correlation between observed and predicted values, with a correlation coefficient (r) of 0.94 for the best-performing configuration. The KGE values, represented by the color gradient, range from 0.50 to 0.90, indicating satisfactory to high model efficiency across configurations. The RMSE values vary between 400 mcm and 800 mcm, with the majority of configurations clustering around lower RMSE values, suggesting good predictive accuracy. Additionally, the standard deviation of the predicted inflows aligns closely with the observed data, ranging from 0.66 to 1.31, with most configurations positioned near the reference point of 1.0. These results highlight the robustness of the CNN model, particularly for configurations achieving KGE values above 0.80 and RMSE below 500 mcm, further supporting its selection for predictive scenario development. Figure 17 panels (a) and (b) illustrate the relationship between the observed and predicted annual river inflows using the optimized CNN model based on selected predictors, including AWU, precipitation, and evaporation. Panels (c) and (d) present the corresponding results for monthly river inflows predictions. The outcomes confirm the CNN model’s robust predictive capability and its effectiveness in capturing the hydrological response patterns at both annual and monthly temporal scales.

In the last step, different scenarios have been developed based on the model’s outputs to investigate the impacts of each scenario on the potential changes in the river inflows.

To evaluate the relative influence of Agricultural Water Use (AWU), precipitation, and evaporation on river inflow variability over the study period, we normalized the contribution of each factor so that their combined total equals 100%. This allows for a direct comparison of the relative importance of each factor. These normalized percentages do not change the actual effect of each factor, but they help in comparing their relative contribution to river inflow change. The fact that AWU initially showed increased inflow by > 100% (109%) implies it has a dominant effect. While precipitation and evaporation indicated 42% and 15% increase in inflow, respectively. For normalization we converted each percentage to a proportion of the total. The results attributed the relative contributions of different factors to river inflow changes by normalizing their effects against a total impact of 166%. AWU emerged as the dominant factor, accounting for approximately 66% of the total impact, with an associated uncertainty of $\pm 10\%$ (95% CI: 56% to 76%). Precipitation changes contributed $25\% \pm 8\%$ (95% CI: 18% to 33%), while evaporation accounted for $9\% \pm 3\%$ (95% CI: 7% to 12%). When combined, the hydroclimatic factors (precipitation and evaporation) explained $34\% \pm 8\%$ (95% CI: 26% to 43%) of the total impact. These findings reinforce the conclusion that anthropogenic drivers, particularly agricultural water demand, have had a significantly greater influence on river inflow reductions than climate variability alone. Figure 18 shows the results of 4 different scenarios on the river inflows feeding the Lake Urmia.

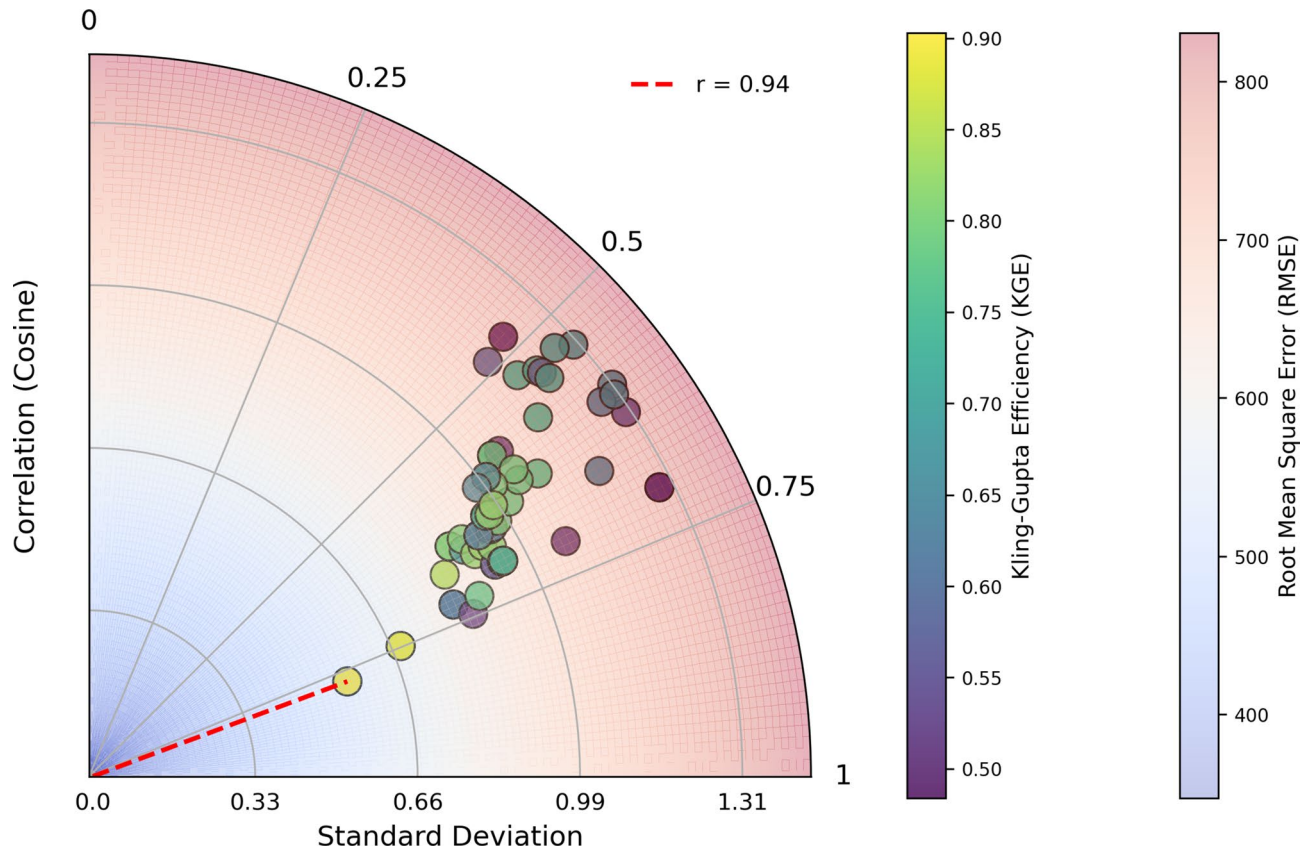


Fig. 16. Taylor diagram showing CNN model performance with varying hyperparameters for river inflows prediction. This figure was created by the first authors using the Python programming language (v3.12.3; <https://www.python.org/>) within a Jupyter Notebook environment (<https://jupyter.org/>), and visualized using the Matplotlib library (v3.7.1).

The results of scenario-based analysis were explained in Table 8 by considering 95 CI. Based on the results of this study, agricultural development in the basin is the predominant factor, though its contribution to river inflows varies across years. While climatic factors especially snow drought were the predominant influence during severe drought years, such as 1999–2001 and 2008, agricultural factors had a greater impact on river inflows in the remaining years, with a more significant difference compared to climatic factors. Overall, it can be concluded that unsustainable agricultural development and the lack of proper water resource management have led to a significant decrease in inflows to the lake, with climate change accelerating both the speed and intensity of this process.

Discussion

The absence of adequate snowpack storage or deviations in the timing of snowmelt from the different reservoirs can pose challenges for water resource management^{31,90}. Snow droughts are categorized as either dry or warm, depending on whether they result from insufficient cold-season precipitation (dry) or a failure in snow accumulation despite nearly normal precipitation¹²³. This failure is typically attributed to elevated temperatures, leading to precipitation falling as rain rather than snow, or an exceptionally premature snowmelt (warm) leading to an overall snow amount for the time of the year^{31,90}. Most previous studies did not investigate the effect of snow drought on Lake Urmia and/or primarily concentrated on the influences of precipitation, temperature, and evaporation as climatic factors affecting water level fluctuations in the Lake Urmia, neglecting the significance of snow changes. In mountainous regions such as northwestern Iran, characterized by towering peaks like Sahand Mountain, snow functions as a crucial natural reservoir and a vital component of the water cycle.

This study focused on the intricate interplay of human-related and climatic factors, with a special emphasis on snow dynamics, influencing the rivers that contribute essential inflows to the Lake Urmia. The results highlight the negative impacts of snow drought in conjunction with anthropogenic activities (e.g., agricultural water withdrawal) in the Lake Urmia Basin. The drying up of Lake Urmia can be primarily attributed to the evolution of agriculture and ensuing economic development. This process, intertwined with snow drought and climate variations, especially post 1990s, stand out as critical factors in the lake's diminishing water levels.

We show that despite enduring snow drought, agricultural expansion has thrived over the past four decades, with irrigated lands expanding over fourfold¹⁵. Increasing water discharge for agricultural irrigation resulted in a significant reduction in runoff flow, particularly between 1999 and 2002, when the region also began

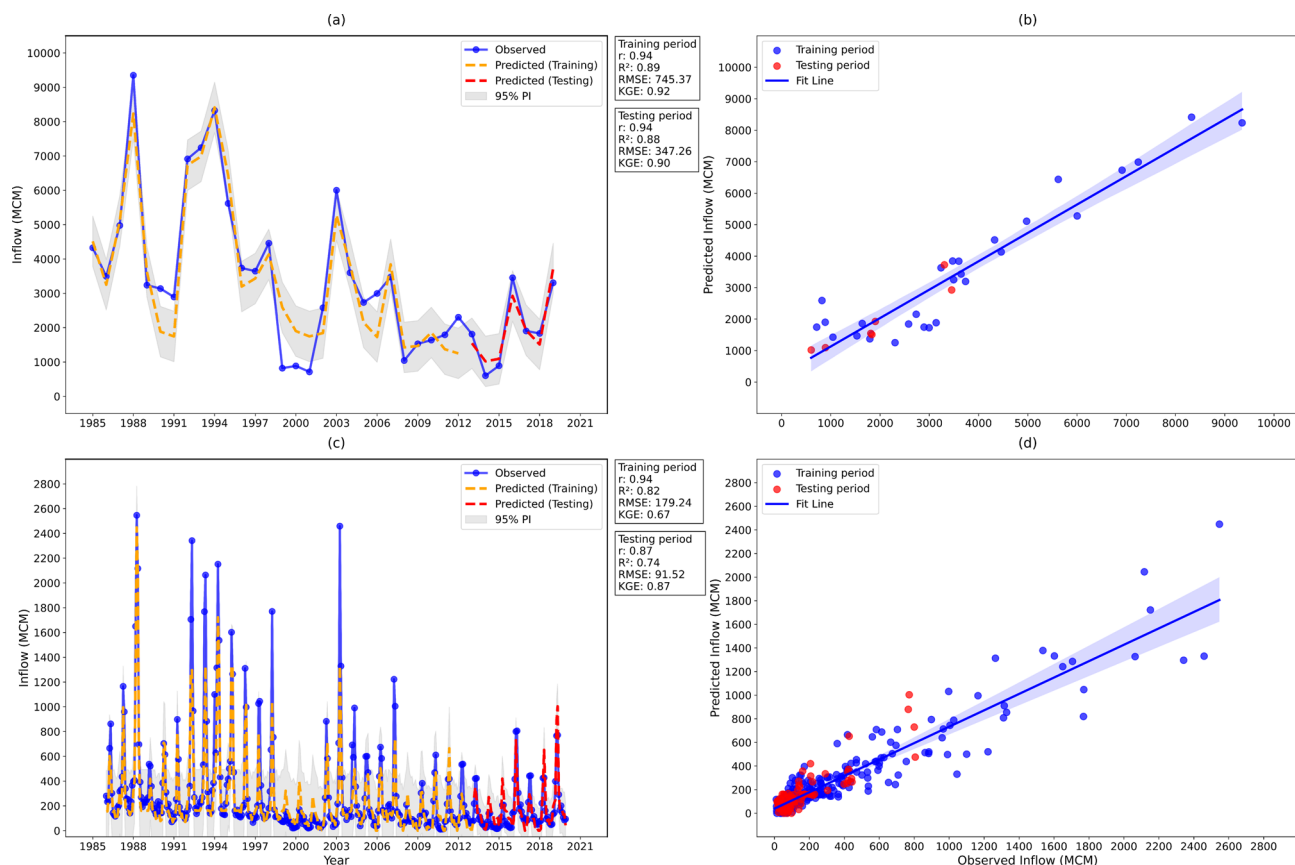


Fig. 17. (a) Time series plot of observed and predicted annual river inflows (b) Scatter plot of observed vs. predicted annual river inflows (c) Time series plot of observed and predicted monthly river inflows (d) Scatter plot of observed vs. predicted monthly river inflows.

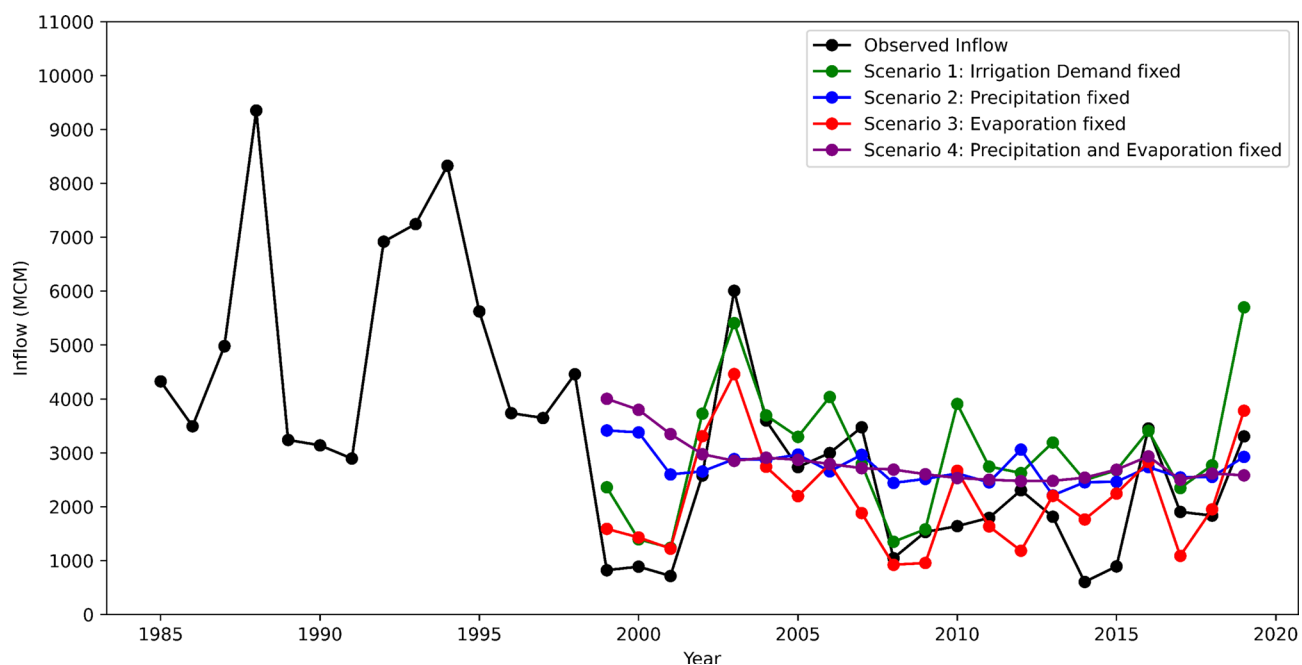


Fig. 18. The results of all applied scenarios to predict the river inflows in the period of 1999–2020 based on the values of pre-1999.

Scenario	Impact on river inflows (%)	95% CI lower	95% CI upper
AWU fixed	66	56	76
Precipitation fixed	25	18	33
Evaporation fixed	9	7	12
Precipitation + Evaporation fixed	34	26	43

Table 8. Summary of the impacts of different scenarios on river inflow.

experiencing a snow drought. After 1999, the basin experienced snow drought, causing the annual runoff into the lake to reach its lowest level during the study period. Despite this, agricultural water withdrawals continued to rise during the same time^{10,15}.

Based on the findings of this study, the root cause of water challenges in the Lake Urmia Basin lies in the inadequate management of water supply and demand, compounded by insufficient preparedness for drought and climate variability. While agricultural expansion and irrigation withdrawals have been the dominant drivers of water scarcity under typical conditions, the analysis reveals that during extreme drought years particularly those associated with snow drought climatic factors can overwhelm even the most efficient management interventions. In such instances, reduced snowpack and early snowmelt significantly diminish inflows, limiting the effectiveness of policy and infrastructure responses.

A shift from snow-dominated to rain-dominated winter precipitation significantly alters the hydrologic regime and challenges existing water management strategies. A rain-heavier winter regime disrupts the timing and reliability of water supply. It requires a fundamental rethinking of reservoir operations, irrigation scheduling, and environmental water management. Proactive adaptation measures such as dynamic reservoir rule curves, updated cropping calendars, and improved forecasting will be critical to sustaining water availability under these shifting climatic conditions. Given that snow plays a critical role in the region's hydrological balance, as it does in many mountainous basins worldwide, restoration and future development policies must be strategically designed with a nuanced understanding of the basin's natural coping capacity, projected climatic shifts, and the ecological sustainability of implemented measures. Crucially, water policies should distinguish between normal and extreme hydrological years and incorporate contingency planning to address scenarios in which natural constraints severely limit water availability.

According to a report by the Iran Water Resources Management Organization, approximately 10.3 billion cubic meters of additional water is needed to restore the lake to its ecological level of 1,274.1 meters¹²⁴. Achieving this target will require significant improvements in agricultural practices, including the adoption of efficient irrigation techniques and precision farming that tailors irrigation and crop management to local conditions. Without sustainable water management systems and effective water policies in place, especially in the context of a changing climate, restoring the lake will be extremely challenging. Additionally, water and environmental policies must be aligned with local realities, supported by a strong and independent judiciary to enforce regulations, and efforts to minimize corruption and illegal water withdrawals within the basin must be intensified.

Conclusion

The primary objectives of this research were to examine the impact of snow drought on river inflows in the Lake Urmia Basin over the last decades. Furthermore, a comprehensive examination was conducted to delineate the compounding impacts of anthropogenic (i.e., agricultural development) and climatic factors on the lake. This encompassed an analysis of agricultural water use, precipitation, evaporation and snow. Notably, this study went beyond previous research efforts by leveraging in situ data, satellite data, and reanalysis datasets to select the most accurate dataset for investigating the effects of snow variations on the lake. A crucial facet of this research was the development of efficient statistical models, namely Multiple Linear Regression (MLR) model, Response Surface Model (RSM), and Convolutional Neural Networks (CNNs) designed to adeptly capture the intricate hydroclimatic dynamics of the Lake Urmia Basin.

The MLR, RSM, and CNN models demonstrated robust performance in predicting river inflows to the Lake Urmia Basin. The effectiveness of these modeling techniques underscores their reliability in capturing and forecasting the intricate dynamics of inflow. Notably, the CNN model outperformed both MLR and RSM, achieving R² and KGE values of approximately 0.9 in both calibration and verification phases, with significantly lower RMSE values (745 MCM and 347 MCM for calibration and verification, respectively) compared to RSM and MLR. The RSM model exhibited strong explanatory power during both calibration and verification phases, while the MLR model showed weaker calibration performance (R² = 0.61, KGE = 0.69) despite robust verification results (R² = 0.96, KGE = 0.97). The CNN model's consistent and superior performance, particularly in the 80% training scenario, established it as the most reliable approach for predicting river inflows.

Various scenarios were developed based on the model's outputs to assess their impact on river inflows to Lake Urmia. The first scenario, which maintains AWU at pre-1999 levels, shows a 66% increase in average river inflows. The second scenario, where precipitation is kept at pre-1999 levels, leads to a 25% increase in average inflows. In the third scenario, maintaining evaporation at pre-1999 levels results in a 9% increase in average inflows. Finally, the fourth scenario, which holds both precipitation and evaporation at pre-1999 levels, results in a 34% increase in average inflows.

Based on the results of this study, agricultural development in the basin is identified as the predominant factor influencing river inflows, although its impact varies across different years. While climatic factors, particularly

snow drought, were the main drivers during severe drought years such as 1999–2001 and 2008, agricultural factors had a greater influence on river inflows in the intervening years, with a more pronounced difference compared to climatic factors. Overall, it can be concluded that unsustainable agricultural development and inadequate water resource and demand management have caused a significant reduction in inflows to the lake, with climate change further accelerating both the speed and intensity of this decline.

Based on the findings of this study, three key priorities emerge:

- Reduce irrigation demand and leakage losses, as these represent the most impactful and immediate management levers under current conditions.
- Strengthen snowpack monitoring and seasonal forecasting to improve preparedness for shifting winter conditions and earlier melt patterns.
- Revise water allocation rules to account for increasingly rain-dominated winters and earlier runoff peaks, ensuring timely and equitable supply for both agricultural and environmental needs.

In addition to management challenges, this study highlights that snow droughts among various climatic factors have played a particularly significant role in disrupting the basin's hydrological balance. These droughts have triggered a cascade of environmental, economic, and social consequences. To mitigate their impact and ensure long-term water security, a combination of effective water management, climate adaptation strategies, and sustainable agricultural practices is essential.

Data availability

The datasets used in this study are available from the primary corresponding author, Yusuf Aydin (Yusuf Alizade Govarchin Ghale) (alizade@itu.edu.tr) upon reasonable request.

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A S, Y A: Supervision, Conceptualization, Methodology, Programming, Data Analysis, Statistical Modeling and Deep Learning, Visualization, Data Acquisition, Validation and Writing-Original Draft. G D S, E N, B V, and N B: Methodology, Data Acquisition, Editing and Statistical analysis. A U, K M and A A: Methodology, Terminology, Revision, Editing, Validation and Conceptualization. All authors read and commented the final version of the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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