Climate Variability and Trends in the Endorheic Lake Hayk Basin: Implications for Lake Hayk Water Level Changes in the Lake Basin, Ethiopia

Mezgebu Mewded (mezgebu24@gmail.com)
Ethiopian Institute of Water Resources, Addis Ababa University, Addis Ababa, Ethiopia
Adane Abebe
Arba Minch Water Technology Institute: Arba Minch University
Seifu Tilahun
Bahir Dar University Institute of Technology
Zeleke Agide
Ethiopian Institute of Water Resources, Addis Ababa University, Addis Ababa, Ethiopia

Research Article

Keywords: Climate variability/trends, Implications, Water level changes, Endorheic Lake Hayk basin

Posted Date: February 16th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1339334/v1

Climate variability and trends in the Endorheic Lake Hayk basin: Implications for Lake Hayk water level changes in the lake basin, Ethiopia

Mezgebu Mewded[1*], Adane Abebe[2], Seifu Tilahun[3], Zeleke Agide[1]

[1]Ethiopian Institute of Water Resources, Addis Ababa University, Addis Ababa, Ethiopia
[2]Water Technology Institute, Arba Minch University, Arba Minch, Ethiopia
[3]Faculty of Civil and Water Resources Engineering, Bahir Dar University, Bahir Dar, Ethiopia

* Corresponding author: mezgebu24@gmail.com

Abstract

Background: For sustainable climate hazard management, climate information at the local level is crucial for developing countries like Ethiopia, which has an exceptionally low adaptive capacity to changes in climate. As a result, rather than making local decisions based on findings from national-scale studies, the study area's research gap of local level climate variability and trend was investigated within the endorheic Lake Hayk basin for the historic series from 1986 to 2015 to scientifically show climate change/variability implications on Lake Hayk water level variations. To achieve the study objective, the precipitation, station and ERA5 reanalysis temperature and patchy lake level fused with remote sensed water extents were examined using various statistical approaches.

Results: The major findings revealed less variable (CV= 16.66%) and statistically nonsignificant declining trends (-33.94 mm/decade) in annual precipitation. Belg and Bega seasonal precipitation showed highly variable (CV = 43.94-47.46%) nonsignificant downward trends of 4.57 mm and 22 mm per decade respectively, whereas kiremt precipitation showed moderate variability (CV=23.80%) and increased nonsignificantly at a rate of 21.89 mm per decade. Annual and seasonal mean temperatures exhibited less variable but statistically significant rising trends ranging from +0.20 to +0.45°C each decade. The lake's water level showed less variable nonsignificant rising trends (70 mm to 120 mm per year) on annual and seasonal scales between 1999 and 2005. The lake's surface area has decreased from 2243.33 ha in 2005 to 2165.33 ha in 2011. During 2011-2015, it likewise demonstrated a high variable (CV > 30%) statistically significant dropping trend ranging from -250 mm to -340 mm per year on annual and seasonal periods.

Conclusions: The study discovered that the endorheic lake basin was dominated by variable and diminishing precipitation, as well as continuous warming trends, particularly in recent years. It is argued that this climatic state

was having a negative impact on Lake Hayk's substantially dropping water level, necessitating an immediate basin-based water management decision to save Lake Hayk from extinction.

Keywords: Climate variability/trends, Implications, Water level changes, Endorheic Lake Hayk basin

Background

Global studies indicated that variations of precipitation and temperature have been the crucial factors in the fluctuations of the water levels of lakes (Motiee and McBean 2009; Mekonnen et al. 2012; Kiani et al. 2017). Climate studies in Ethiopia by the national meteorological agency (NMA) and others indicated consistently increasing rates of changes in temperature and variable trends in precipitation at most parts and across the entire country (Conway 2000; Seleshi and Zanke 2004; Bewket and Conway 2007; NMA 2007; McSweeney et al. 2008; Ayalew et al. 2012; Alemayehu and Bewket 2017). This change pattern in climate of Ethiopia promoted reduced surface runoff, decreased overlake precipitation and increased evapotranspiration to reduce the water levels of lakes in the country (Kebede et al. 2006; Olana 2014; Gebeyehu 2017).

In Ethiopia, climate is largely influenced by seasonal shifts in atmospheric pressure systems controlling prevailing winds (NMA 2007) and the complex topography of the country (the elevation a.s.l. ranges from −120 to +4620 m) affecting the climate via its local heating and orographic effects (Figs. 1 and 2) (Camberlin 1997). Thus, Ethiopia receives seasonally varying precipitation in which most parts of it experience three precipitation seasons: kiremt or the long precipitation season (June–September), belg or the short precipitation season (March–May), and bega or the dry season (October–February) (NMA 2007). Seasonal precipitation failures of kiremt and belg due to El Nino/Southern Oscillation or ENSO to cause droughts have been common phenomena in the country (NMA 2007).

Fig.1 Ethiopia's topography and the location of the endorheic Lake Hayk basin

Fig.2 Mean annual ERA5 precipitation (left) and temperature (right) in Ethiopia (1986 –2015)

For developing countries like Ethiopia, where their adaptive capacity to changing climate is limited, climatic information at the local level is vital for sustainable climate hazard management on a specific lake. Due to its closed nature and location in one of Ethiopia's most drought-prone places (Conway 2000; Philip et al. 2018), the endorheic Lake Hayk basin is very sensitive and vulnerable to climate change. Previous studies on Lake Hayk revealed that the lake's water level has been continuously declining since the 1970s, posing a severe problem for the lake (Demlie et al. 2007; Yesuf et al. 2013). However, none of the studies have dealt with the issue in relation to climate variability and change. As a result, this study investigated the local level variability as well as trends in precipitation, temperature and lake level for the historic series from 1986 to 2015 on monthly, yearly and seasonal scales to scientifically show the implications of climate variability/change on Lake Hayk water level variations in the Endorheic Lake Hayk basin to aid in making local-level climate change oriented water management decisions to save Lake Hayk from extinction.

Materials and methods

Description of the study area

Ethiopia is situated in Eastern Africa, between 3° and 15° latitude and 33° and 48° longitude (Horn of Africa). The Lake Hayk basin is a naturally closed (endorheic) drainage that belongs to one of Ethiopia's most vulnerable zones to climate change and variability. Its areal extent is within 39.68°E to 39.81°E, 11.24°N to 11.39°N and its area coverage including the lake water surface area of 2156.76 ha was 8592.68 ha (Fig. 1). The Lake Hayk basin is under a subhumid tropical climate with bimodal precipitation regimes (kiremt and belg). The lake basin received a mean annual precipitation of 1192.31 mm; the mean annual surface temperature was 17.58°C.

Data sources

We assessed the hydro climate variability/trend in the Lake Hayk basin against the historical datasets of precipitation, mean temperature (Tmean), and the Lake Hayk's Water Level (LWL). We analyzed the precipitation and temperature data recorded at Hayk meteorological station (11.31˚N, 39.68˚E; 1984 m a.s.l.). The Ethiopian National Meteorological Agency has granted us mean monthly precipitation (1986–2015) and temperature (1994–2015) data for the lake basin. As well, the LWL data of Lake Hayk are measured using the water level measuring gauge situated on the southwest shore of Lake Hayk (Fig. 1). Ethiopia's Ministry of Water Resources, Irrigation and Electricity provided us with the lake average daily water level time series from 1986 to 2015. However, the LWL time series was full of badly missed data. Daily data with more than 10% missing values must not be included in the analysis (Seleshi and Zanke 2004). Full daily LWL data were available for the 1999–2005 and 2011–2015 periods. Therefore, we fused the water level observations from these periods with remote sensed water extents to bridge the gap between 2005 and 2011. We downloaded Landsat images for 2005, 2008, 2009, 2010, and 2011 without cloud (cloud cover ≤ 10%) from the archiving system of Earth Explorer (http://earthexplorer.usgs.gov/). We collected all Landsat data for months of the same dry season (bega) with the same but not always acquisition dates as the lake level measurement days to ensure accuracy of interpretation. In addition, we downloaded the reanalysis temperature of the same station for the 1986–2015 periods from the climate explorer (https://climexp.knmi.nl/) due to the availability of insufficient station data.

Data analysis

The general methodology of the study is depicted schematically in Fig. 3.

Fig.3 A schematic illustration of the study's methodology

Evaluating the reanalysis temperature data

Reanalysis models, including NOAA-NCEP/NCAR, ERA5, and MERRA-2, are currently in use (Kalnay et al. 1996; Dee et al. 2011; Reinecker et al. 2011) and have been evaluated as part of this study. The R^2, *RMSE*, and statistical indices of relative bias (Alemseged and Tom 2015; Nkiaka et al. 2017) quantitatively evaluated the models in estimating temperature time series against ground station temperature data for the 1994 to 2015 time series on an annual and seasonal scales.

$$R^2 = \left[\left(\sum_{t=1}^{n} \left(T_r - \overline{T_r}\right)\left(T_s - \overline{T_s}\right) \right) \Big/ \left(\sqrt{\sum_{t=1}^{n} \left(T_r - \overline{T_r}\right) \sum_{t=1}^{n} \left(T_s - \overline{T_s}\right)} \right) \right]^2 \quad (1)$$

$$RMSE = \sqrt{\sum_{t=1}^{n} \left(T_r - T_s\right)^2 \Big/ n} \quad (2)$$

$$Bias = \left(\sum_{t=1}^{n} \left(T_r - T_s\right) \Big/ \sum_{t=1}^{n} T_s \right) x100\% \quad (3)$$

where Tr and Ts denote reanalysis and ground station temperature records respectively and n is the length of data. R^2 varies within $0 \leq R^2 \leq 1$; $R^2 = 0$ reveals no correlation and $R^2 = 1$ indicates perfect correlation between the reanalysis product and station temperature record. Bias detects a systematic error in temperature values. Zero bias indicates absence of systematic error, whereas negative/positive biases reveal respectively underestimation and overestimation of values (Alemseged and Tom 2015). The RMSE measures residual dispersion (estimation errors) around the best fitting line. RMSE near zero would be a better fit to the data.

Variability and trends analysis of hydro climate time series

Various statistical approaches were used to examine the variability/trend in the hydro climatic time series of the endorheic Lake Hayk basin from 1986 to 2015. The coefficient of variability (CV), the standardized rainfall anomaly (SRA) and the precipitation concentration index (PCI) were employed to study variability of the data. The Modified Mann Kendall (MK) trend test method and the Sen Slope estimator were applied to analyze the significance and magnitude of trend respectively using XLSTAT software. The CV value represents the level of variability in the dataset and is defined as the standard deviation (SD) to mean value (μ) ratio (Hare 2003).

$$CV = \left(SD/\mu\right)x100 \quad (4)$$

Hare (2003) characterizes variability as being less for CV values less than 20, moderate for CV values between 20 and 30 and high for CV greater than 30. PCI examines the heterogeneity of mean monthly precipitation data. For Pi is the ith month precipitation magnitude, Oliver (1980) defines PCI as follows:

$$PCI = \left[\left(\sum_{i=1}^{12} P_i^2 \right) \Big/ \left(\sum_{i=1}^{12} P_i \right)^2 \right] x100 \quad (5)$$

Precipitation concentration can be identified as low concentration (uniform distribution of precipitation) for PCI values lower than 10, high for values from 11 to 20 and very high for values above 21 (Oliver 1980). SRA offers insights on the occurrence and severity of drought periods. For P_t is annual precipitation at a year of interest t and P_m is the mean annual precipitation value during the study period, SRA can be estimated according to Agnew and Chappell (1999):

$$SRA = \left(P_t - P_m\right) / SD \quad (6)$$

Then, severity of drought can be categorized as extreme drought (SRA < −1.65), severe drought (−1.28 > SRA > −1.65), moderate drought (−0.84 > SRA > −1.28) and no drought (SRA > −0.84) (Agnew and Chappell 1999).

The modified Mann Kendall (MK) trend test was used to examine the monotonic trends of hydro climatic time series in the endorheic Lake Hayk basin from 1986 to 2015 at a significance level of 5% on a monthly, annual and seasonal basis. It was chosen because it is a rank-based (i.e., less affected by low-quality hydro climatic data-data with missing values and/or outliers) nonparametric (i.e., less sensitive to skewed datasets-applies for all distributions) method (Hirsch and Slack 1984). The MK tests the null hypothesis (H0) assuming no trend against the alternative hypothesis of monotonic trend (Ha) using either the S statistics (n < 10) or the standardized normal Z statistics (n ≥ 10) (Hirsch and Slack 1984; Yue et al. 2002). The MK test S statistic is calculated using the following equations (Eqs. 7 and 8) as:

$$S = \sum_{i=1}^{n=1} \sum_{j=i+1}^{n} \operatorname{sgn}\left(x_j - x_i\right) \tag{7}$$

$$\operatorname{sgn}\left(x_j - x_i\right) = \begin{cases} +1 & if\ \theta > 0 \\ 0 & if\ \theta = 0 \\ -1 & if\ \theta < 0 \end{cases} \tag{8}$$

where n is the data size and xi and xj are the data values at times i and j respectively, i = 1, 2,..., n-1 and j = i+1, i+2..., n. Every value in the chronologically ordered time series is compared to every value preceding it, yielding a total of n (n – 1) / 2 pairs of data. The total of all rises and falls result in the ultimate value of S (Yue et al. 2002). S values can be positive to show rising trends or negative to indicate falling trends.

When n ≥ 10, the S statistic is assumed to have a normal distribution, with the mean becoming zero and the variance computed using the following equation (Eq. 9) (Kendall 1975):

$$V(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{t=1}^{m} t_i\left(t_i - 1\right)\left(2t_i - 5\right)\right] \tag{9}$$

where V (S) is the variance of S statistics, m denotes the size of tied groups (groups with similar values) and ti represents the size of data points in the ith tied group. Then, the Z test statistics can be calculated from the known values of S and V(S) using the following equation (Eq. 10):

$$Z = \begin{cases} (s-1)/\sqrt{v\,(s)} & if\ \ S > 0 \\ 0 & if\ \ S = 0 \\ (s+1)/\sqrt{v\,(s)} & if\ \ S < 0 \end{cases} \tag{10}$$

The resulting Z values indicate the direction of a trend (values can be positive to show rising trends or negative to indicate falling trends). Furthermore, the Z statistic is used to measure significance of a trend. When testing for a trend (2 tailed) at significance α, H0 is rejected if $|Z|$ equals or exceeds its critical value $\left(|Z| \geq Z_{\alpha/2}\right)$. For instance, if the 5% significance level is used, H0 is rejected when $\left(|Z| \geq 1.96\right)$ or P ≤ 0.05, indicating that a trend exists (A time series has a trend when it is significantly correlated with time). The letter P symbolizes the probability of risk to reject/accept H0 while it is true.

Prior to trend testing, it is critical in time series analysis to examine autocorrelation or serial correlation, which is frequently overlooked in many trend detection studies. To account for the effect of autocorrelation, Hamed and Rao (1998) propose a modified Mann-Kendall test rather than the original MK test, which should be used only on datasets with no seasonality or significant autocorrelations. This is because the presence of significant autocorrelation in a dataset can alter the variance of the original MK test (the existence of positive autocorrelation will lower the actual value of V (S) and vice versa). Hence, when data exhibit autocorrelation, the modified MK test calculates the modified variance using the following equations (Eqs. 11 and 12):

$$V^*(S) = \frac{1}{18}\left[n\,(n-1)\,(2n+5)\right]\frac{n}{ns^*} \tag{11}$$

$$\frac{n}{ns^*} = 1 + \frac{2}{n\,(n-1)(n-2)}\sum_{i=1}^{p}(n-i)\,(n-i-1)\,(n-i-2)\;p_s(i) \tag{12}$$

where ns* is the effective number of data required to consider autocorrelation in the dataset, n/ns* is the data autocorrelation correction factor, $p_s(i)$ is the autocorrelation function between the ranks of the data for lag i, and p is the maximum lag time under consideration. As a result, this study used the XLSTAT MS Excel Add-in software, which is integrated with the Hamed and Rao (1998) modified MK trend test facility (at a significance level of 10%), to account for the autocorrelation effect.

Sen's slope estimator computes the linear annual rate and direction of change (Sen 1968). It is a nonparametric approach for dealing with skewed datasets and outlier effects. The linear model f (t) is defined by the equations (Eqs. 13 and 14) (Sen 1968) as follows:

$$f(t) = Qt + \beta \tag{13}$$

$$Q = Median \quad (X_i - X_j)/(i-j), \quad \forall j < i \tag{14}$$

where Q is the slope, β is a constant and X_i and X_j are data values at times i and j (i > j).

Lake Hayk water level response to climate change/variability

Due to the endorheic (closed) nature of the Lake Hayk basin, the main underlying hydrological processes are surface runoff and evapotranspiration, with precipitation and temperature being the most prominent climatic factors. Under such conditions, water level is the primary response variable that serves as an indicator to better reflect the climate change/variability effects on lake storage. In addition, it can easily be measured at observation stations and the changes in lake water levels can be monitored easily, accurately and continuously (Tan et al. 2017). Nevertheless, in cases of the patchy lake level data that lakes such as Lake Hayk do have, the remote sensed water extents from Landsat images would allow us to extend their water level time series (McFeeters 1996; Xu 2006).

The Modified Normalized Difference Water Index (MNDWI) can efficiently extract open waters from Landsat images by easily suppressing signals from various environmental noises (such as vegetation and built-up areas) compared to its predecessor, the Normalized Difference Water Index (NDWI) using Shortwave Infrared

(SWIR) rather than Near Infrared (NIR) used in the NDWI (Xu 2006). The formula used for the MNDWI calculation is:

$$MNDWI = (Green - SWIR)/(Green + SWIR) \tag{15}$$

For Landsat 7 TM and ETM+, MNDWI becomes:

$$MNDWI = (band2 - band5)/(band2 + band5) \tag{16}$$

The index values are from −1 to +1. The zero threshold value was used to segment the MNDWI results into water and nonwater features; a feature is water if MNDWI > 0 and it is nonwater if MNDWI ≤ 0 (Xu 2006). The optimal MNDWI threshold can also be obtained by manual thresholding where the gray image histogram of MNDWI shows specific location of water threshold for that acquisition date.

As a result, to bridge the time gap between 2005 and 2011, water level observations from 1999–2005 and 2011–2015 were fused with remote sensed water areas derived from MNDWI analysis. The cloud free (cloud cover ≤ 10%) Landsat 7 TM and ETM+ data of the years 2005, 2008, 2009, 2010 and 2011 were used to extract open water feature of Lake Hayk using manual thresholds for MNDWI in delineating water and nonwater features in the environment of ArcGIS 10.1.

The MNDWI model area results were evaluated by correlating them with station water level observations of the Lake Hayk by using the Pearson's coefficient (parametric) and Kendall's tau (nonparametric) correlation coefficients at 0.01 significance level using SPSS 20 software. For *n* sample sizes of X and Y variables, the Pearson coefficient (*r*) can be computed as:

$$r = \sum_{i=1}^{n}\left[\left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)\right] \Bigg/ \left(\sqrt{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2 \sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2}\right) \tag{17}$$

This can be confirmed by the nonparametric Kendall's correlation coefficient. The Kendall's correlation helps to minimize the effects of extreme values and/or the effects of violations of the normality and linearity assumptions (Kendall 1938). The Kendall's correlation coefficient, tau is calculated based on signs as:

$$\tau = \frac{2}{n(n-1)} \sum_{i<j} sign\left[\left(x_i - x_j\right)\left(y_i - y_j\right)\right] \tag{18}$$

In both cases, the correlation coefficients are within −1 and +1. Correlation values close to ±1 indicate strong relationships. For result interpretation, the hypothesis for a 2-tailed test of the correlation at a given significant level is defined as: H0: *r*, tau = 0 versus Ha: *r*, tau ≠ 0.

Results and discussion

Performance evaluation of the reanalysis temperature data

The small RMSE and bias values obtained for the ERA5 reanalysis indicated that it functioned better than the MERRA-2 and NCEP/NCAR reanalysis products. Similarly, the R^2 criteria showed that the correlation between ERA5 and ground station temperature data appeared to be very strong. Therefore, the ERA5 product represented the temperature time series of the Lake Hayk basin (Table 1).

Table 1 Evaluating reanalysis temperature estimates in the lake basin (1994–2015)

Time scale		Reanalysis	R^2	RMSE	Bias (%)
Annual		ERA5	0.965	0.070	−0.233
		MERRA-2	0.108	0.482	−1.260
		NCEP/NCAR	0.274	0.182	0.255
Seasonal	Kiremt	ERA5	0.957	0.092	−0.479
		MERRA-2	0.223	0.577	−4.003
		NCEP/NCAR	0.024	0.258	−5.297
	Belg	ERA5	0.970	0.128	−0.376
		MERRA-2	0.049	0.652	3.237
		NCEP/NCAR	0.214	0.583	3.046
	Bega	ERA5	0.958	0.099	−0.083
		MERRA-2	0.133	0.565	−1.763
		NCEP/NCAR	0.229	0.321	3.179

Precipitation variability and trends

Table 2 depicts the variability/trend in precipitation in the Lake Hayk basin for the time series 1986–2015 computed using the MK and Sen's methods. The average annual precipitation was 1192.31 mm. The highest annual precipitation (1835.30 mm) was recorded in 2010 and the lowest (827.10 mm) in 2015 that respectively stood out as the wettest and the driest years over the study period. Kiremt (June to September) or the principal rainy season contributed about 63.15% of the entire yearly rain. About 50% of kiremt precipitation occurred in July and August, while June and September contributed 2.93% and 10.37% respectively. This statistic was a clear indicator of high precipitation concentrations during the kiremt season in the lake basin. The short rainy or belg season (March to May) also contributed to a significant amount of precipitation (about 22.93% of total yearly precipitation). Bewket and Conway (2007) and Ayalew et al. (2012) also indicated that 55–85% and 8–24% of the annual mean precipitation of the Amhara national regional state (the region where the Lake Hayk basin is found) was due to the kiremt and belg seasons respectively.

Precipitation variability expressed in CV terms showed notable precipitation variability on a monthly scale varying from 31.70% in August to 133.68% in December. On the other hand, the Lake Hayk basin was characterized by less variable annual mean precipitation (CV = 16.66%) and moderate to high variable seasonal precipitation according to variability classification of Hare (2003). Seasonally, the belg (CV = 43.94%) and bega (CV = 47.46%) seasonal precipitations were almost 2-fold more variable than kiremt (CV = 23.80%) seasonal precipitation. Similar findings were reported by (Ayalew et al. 2012; Alemayehu and Bewket 2017). With respect to the precipitation trend, each month (excluding February, September and November) showed statistically nonsignificant trends. February and September showed a significant decreasing trend; November alone changed positively. Likewise, the annual and belg seasons showed nonsignificant decreasing trend, whereas the kiremt season exhibited nonsignificant increasing change. This is in line with Bewket and Conway (2007) and Ayalew et al. (2012) that indicated nonsignificant precipitation trends in several locations in Ethiopia.

Table 2 Variability and trend tests of precipitation (1986–2015)

Time period	Min (mm)	Max (mm)	Mean (mm)	Contribution (%)	SD	CV (%)	P values (2 tailed)	Sen's slope
Jan	0.00	119.10	27.90	2.34	32.28	115.68	0.943	0.000
Feb	0.00	192.50	50.08	4.20	57.74	115.28	0.005*	−2.716
Mar	0.00	259.70	103.92	8.72	60.52	58.24	0.521	−1.082
Apr	2.20	246.10	94.93	7.96	59.95	63.15	0.498	−1.150
May	1.00	219.72	74.50	6.25	66.38	89.11	0.887	0.418
Jun	0.00	143.20	34.89	2.93	33.80	96.87	0.411	0.509
Jul	40.00	544.90	298.14	25.01	112.00	37.57	0.134	3.150
Aug	97.60	617.60	296.27	24.85	93.92	31.70	0.521	1.250
Sep	44.40	237.20	123.68	10.37	51.35	41.52	0.006*	−2.727
Oct	0.00	161.50	41.17	3.45	37.76	91.72	0.232	0.636
Nov	0.00	133.80	26.09	2.19	34.25	131.30	0.029*	0.264
Dec	0.00	77.40	20.74	1.74	27.73	133.68	0.621	0.000
Kiremt	411.30	1218.60	752.98	63.15	179.24	23.80	0.544	2.189
Belg	63.90	515.11	273.35	22.93	120.11	43.94	0.915	−0.457
Bega	24.00	339.90	165.98	13.92	78.77	47.46	0.06	−2.200
Annual	827.10	1835.30	1192.31	100.00	198.69	16.66	0.372	−3.394

* Statistically significant ($P \leq 0.05$)

The other variability measurement index called the PCI indicated a high to very high concentration of monthly precipitation in the lake basin (Table 3). Similarly, Alemayehu and Bewket (2017) reported high precipitation concentration in the highland areas of central Ethiopia.

Table 3 Precipitation concentration indices (1986–2015)

Index	Category	Frequency of occurrence (Number of years)
< 10	Low concentration (uniform distribution of rainfall)	0
11–20	High concentration	22
≥ 21	Very high concentration	8
Mean PCI (1986-2015) = 18.30 (High concentration of rainfall)		

Furthermore, the interannual precipitation fluctuations based on the SRA criterion indicated values of precipitation anomalies varied from −1.84 in 2015 (driest year) to +3.24 in 2010 (wettest year) (Fig. 4). This signified that the annual precipitations during the driest and the wettest years have been 1.84 and 3.24× the SD below and above the long term (1986 to 2015) mean respectively. Very low values of precipitation anomalies corresponded to severe drought periods. The year 2015 could be placed in the extreme drought category (SRA < 1. 65). Philip et al. (2018) also showed 2015 was a strong El Niño driven worst drought year in recent decades occurred in large parts of Ethiopia including Lake Hayk basin. Moreover, similar seasonal and annual precipitation anomaly patterns were observed, nevertheless some dry years in kiremt appeared wet in belg and vice versa.

Fig.4 Standardized rainfall anomalies (1986–2015)

Temperature variability and trends

Table 4 depicts the results of the variability/trend analysis of temperature time series (1986-2015) computed using MK and Sen's methods. The highest and lowest mean monthly temperature values were 22.06°C in April and 13.91°C in December respectively. Likewise, the highest seasonal mean temperature was observed in belg and the lowest was in bega season. The annual Tmean value ranged from 16.65°C (minimum) in 1989 to 18.54°C (maximum) in 2015. Its annual mean value over the study period was 17.58°C. The monthly, annual and seasonal CV values indicated that Tmean was in a less variability category. The standardized anomalies of Tmean revealed that most of the 2000s were warmer than Tmean's long run average (Fig. 5). 2015 was the ever-hottest year during the study period in the lake basin.

Table 4 Variability and trend tests of mean temperature (1986–2015)

Time period	Min (°C)	Max (°C)	Mean (°C)	SD	CV (%)	P values (2 tailed)	Sen's slope
Jan	14.13	17.18	15.81	0.71	4.49	0.153	0.024
Feb	15.41	18.32	17.17	0.86	5.01	0.108	0.031
Mar	16.59	20.25	18.22	0.94	5.16	0.008*	0.059
Apr	16.90	22.06	18.93	1.05	5.55	0.038*	0.049
May	17.53	21.82	19.68	1.26	6.40	0.284	0.035
Jun	17.69	21.58	19.75	1.19	6.03	0.544	0.021
Jul	16.83	19.50	18.22	0.56	3.07	0.643	0.007
Aug	17.10	18.81	17.97	0.43	2.39	0.002*	0.029
Sep	16.58	18.07	17.31	0.40	2.31	0.001*	0.030
Oct	15.56	18.18	16.65	0.57	3.42	0.032*	0.028
Nov	14.14	17.48	15.96	0.87	5.45	0.164	0.030
Dec	13.91	16.96	15.31	0.91	5.94	0.721	−0.011
Kiremt	17.56	19.19	18.31	0.43	2.34	0.042*	0.020
Belg	17.13	20.86	18.94	0.91	4.82	0.020*	0.045
Bega	15.35	17.37	16.18	0.50	3.08	0.046*	0.022
Annual	16.65	18.54	17.58	0.43	2.45	0.004*	0.026

*Statistically significant ($P \leq 0.05$)

Concerning trends of Tmean, statistically significant upward trends were detected in March, April and August through October; the rest months, excluding December (December showed a nonsignificant decreasing trend) indicated nonsignificant increasing trends. The monthly mean temperature varied from +0.07 to +0.60°C per decade over the 12 months of the year. The most rapid increase occurred in March and April at rates of +0.60 and +0.50°C per decade respectively. The months between August and November experienced almost similar rate of increase (about 0.30°C every 10 years). The annual and seasonal Tmean time series showed statistically significant upward trends. The seasonal Tmean varied from +0.20 to +0.45°C per decade; the highest rate was recorded during the belg season. The annual Tmean has been changed at a linear rate of +0.26°C per decade. Similarly, McSweeney et al. (2008) showed an increase of 0.28°C per decade in the average annual temperature in Ethiopia for the period 1960-2006. This warming trend has tended to accelerate the lake water evaporation in the endorheic Lake Hayk basin that could have negative implications on the water level changes of Lake Hayk in the lake basin.

Fig.5 Mean annual and seasonal Tmean standardized anomalies (1986–2015)

Lake Hayk water level response to climate change/variability

Lake water level change during 1999–2005

As shown in Table 5, the monthly CV values ranged from 15.81% in June to 39.26% in December, with the majority of the months falling into the moderate to high variability category. However, there was less variability in the annual and seasonal LWL data. The MK trend test results demonstrated a nonsignificant positive trend in LWL data over monthly, yearly and seasonal periods.

Table 5 Variability and trends of mean water level of Lake Hayk (1999–2005)

Time period	Minimum (m)	Maximum (m)	Mean (m)	SD	CV (%)	P values (2 tailed)	Sen's slope
Jan	0.22	0.84	0.63	0.22	34.79	0.260	0.03
Feb	0.31	0.65	0.51	0.13	24.76	0.260	0.02
Mar	0.75	2.85	1.87	0.70	37.34	0.260	0.32
Apr	1.55	2.56	2.07	0.40	19.16	0.260	0.09
May	0.26	1.22	0.90	0.34	37.45	0.260	0.04
Jun	0.71	1.17	0.98	0.16	15.81	0.260	0.06
Jul	1.74	3.99	2.83	0.71	24.99	0.260	0.19
Aug	1.81	3.93	2.91	0.67	22.98	0.452	0.20
Sep	1.66	2.74	2.29	0.37	15.93	0.707	0.12
Oct	0.98	2.05	1.54	0.43	27.75	0.970	0.05
Nov	1.08	1.90	1.45	0.37	25.34	0.970	0.05
Dec	0.30	1.61	1.20	0.47	39.26	0.970	0.05
Kiremt	1.48	2.75	2.25	0.41	18.03	0.452	0.12
Belg	1.21	1.99	1.61	0.31	19.37	0.260	0.11
Bega	1.14	1.82	1.52	0.24	15.49	0.452	0.07
Annual	1.15	1.90	1.60	0.25	15.63	0.452	0.09

Changes in precipitation and temperature are the most important climatic elements influencing lake level variations in endorheic lake basins (Tan et al. 2017). Increases in annual precipitation result in increased overlake precipitation and surface runoff into the lake, whereas increases in annual temperature result in increased lake water evaporation loss. During the period 1999-2005, both precipitation and temperature were characterized by substantial inter-annual variability, alternating every year or two years, with annual precipitation and temperature data exhibiting positive and negative anomalies in approximately half of the total years (Figs. 4 and 5). It was discovered that the impacts of precipitation in increasing LWL were less compensated negatively by the effects of rising temperatures, resulting in a statistically nonsignificant upward trend in Lake Hayk's water level (Table 5 and Fig. 6).

Fig.6 Mean annual water level and level variations of Lake Hayk (1999–2005)

Changes in lake water extent (2005-2011)

The MNDWI extracted Landsat images of the Lake Hayk basin from 2005 to 2011 were classified into two categories: water and non-water features. The MNDWI model's performance was assessed by comparing the obtained water areas to the observed lake water levels using the Pearson and Mann Kendall correlation coefficients (Table 6). The Pearson and Mann Kendall correlation coefficients had p values less than 0.01 (0.000 outputs in MK as rounded to a usual three decimal places), indicating a highly significant relationship between the two variables. As a result, H0 was rejected, implying that the LWL and the lake area are correlated. Pearson (r = 0.975) and Kendall (tau = 0.983) correlation coefficients confirmed that the lake water surface area values estimated from MNDWI represented the Lake Hayk basin and were suitable for water area change detection analysis.

Table 6 Correlating water level to surface area of Lake Hayk (2005–2011)

			LWL (mm)	Area (ha)
Pearson correlation (Parametric)	LWL (mm)	Correlation coefficient	1	0.975*
		Sig. (2 tailed)		0.005
	Area (ha)	Correlation coefficient	0.975*	1
		Sig. (2 tailed)	0.005	
Kendall's tau (Nonparametric)	LWL (mm)	Correlation coefficient	1	0.983*
		Sig. (2 tailed)		0.000
	Area (ha)	Correlation coefficient	0.983*	1
		Sig. (2 tailed)	0.000	

* Correlation is significant at the 0.01 significant levels (2 tailed)

The validated lake areas were then used to detect changes in water extent of Lake Hayk during 2005-2011 (Table 7 and Fig. 7). Water surface area of Lake Hayk was 2241.33 ha on 19 December 2005 and went down to 2158.58 ha on 26 January 2008. It then began to rise to 2268.83 ha on 25 December 2010, before falling to 2165 ha on 10 January 2011. The lake's water area decreased and increased most in 2008 and 2010 respectively, with area changes fluctuating within the 110.25 ha range between 2005 and 2011. As a result, the lake areas in 2008 and 2010 could be the prominent symptoms of the exacerbation of drought and flood climate hazards in the lake basin respectively. This pattern of change in the LWL data could be related to the patterns of precipitation and temperature changes. The mean annual precipitation has most of the time shown negative anomalies (except in 2005 and 2010, which showed positive anomalies), with the largest negative anomaly (-1.33) recorded in 2008 and the maximum positive anomaly (3.24) recorded in 2010 (Fig.4), contributing to the 2008 drought and the 2010 flood events respectively.

Table 7 Lake Hayk water area variations (2005–2011)

Date of acquisition	Satellite	Type of imagery/sensor	Path/row	Spatial resolution (m)	LWL (mm)	Water area (ha)
19 Dec 2005	Landsat 7	ETM+	168/052	30	1780	2243.33
26 Jan 2008	Landsat 7	ETM+	168/052	30	470	2158.58
06 Dec 2009	Landsat 7	TM	168/052	30	980	2173.33
25 Dec 2010	Landsat 7	TM	168/052	30	2640	2268.83
10 Jan 2011	Landsat 7	TM	168/052	30	660	2165.33

Fig.7 MNDWI maps of the Lake Hayk basin (2005–2011)

Lake Hayk water level changes (2011–2015)

As shown in Table 8, the mean monthly LWL ranged from 330 mm in February to 1910 mm in August. Seasonal values ranged from 580 mm in bega to 2090 mm in kiremt, while annual values varied from 1337.5 mm in 2011 to 570 mm in 2015. On monthly, annual, and seasonal scales, the LWL in the lake basin showed high variability. The MK test revealed statistically significant downward trends on monthly, annual and seasonal scales. The kiremt season had the greatest seasonal drop (-340 mm/year), while the bega season had the least (-250 mm/year). From 2011 to 2015, the mean annual rate of fall in LWL was 280 mm/year.

Unlike the preceding two periods (1999-2005 and 2005-2011), there were no discernible inter-annual fluctuations in precipitation and temperature data between 2011 and 2015 (Figs. 4 and 5). The consistent reduction in precipitation, along with rising temperature, resulted in less surface runoff into the lake, reduced overlake precipitation and increased lake water evaporation. As a result, a statistically significant declining trend in Lake Hayk's water level was identified (Table 8 and Fig.8). Similarly, WMO (2016) reported that the 2011–2015 was the hottest period and 2015 was the warmest year since modern observations started in the late 1800s. Philip et al. (2018) also confirmed that 2015 was an El Niño driven worst drought year in most parts of Ethiopia including the Lake Hayk basin, causing the worst decline in the water level of Lake Hayk during that time.

Table 8 Variability and trends in mean water level of Lake Hayk (2011–2015)

Time period	Minimum (m)	Maximum (m)	Mean (m)	SD	CV (%)	P values (2 tailed)	Sen's slope
Jan	0.16	0.72	0.44	0.22	48.92	0.046*	−0.13
Feb	0.04	0.56	0.33	0.20	60.45	0.046*	−0.12
Mar	0.68	1.89	1.22	0.50	40.57	0.046*	−0.32
Apr	0.02	2.19	1.26	0.83	65.76	0.027*	−0.49
May	0.49	1.58	0.92	0.43	46.86	0.027*	−0.15
Jun	0.15	1.01	0.61	0.33	54.35	0.046*	−0.21
Jul	0.51	2.46	1.51	0.76	50.00	0.027*	−0.47
Aug	1.20	2.56	1.91	0.56	29.08	0.027*	−0.37
Sep	0.52	2.35	1.45	0.71	48.99	0.027*	−0.44
Oct	0.15	1.76	1.04	0.62	59.18	0.046*	−0.39
Nov	0.62	1.63	1.06	0.42	39.34	0.046*	−0.27
Dec	0.19	1.38	0.83	0.46	55.43	0.046*	−0.29
Kiremt	0.85	2.09	1.37	0.52	38.02	0.027*	−0.34
Belg	0.76	1.71	1.13	0.41	36.28	0.027*	−0.27
Bega	0.58	1.58	1.04	0.40	38.39	0.027*	−0.25
Annual	0.57	1.34	1.05	0.43	41.04	0.027*	−0.28

*Statistically significant ($P \leq 0.05$)

Fig.8 Mean annual water level and level variations of Lake Hayk (2011–2015)

The findings of this study were supported by findings from global and local studies. Globally (Motiee and McBean 2009; Mekonnen et al. 2012; Kiani et al. 2017) and on a local level in Ethiopia (Kebede et al. 2006; Olana 2014; Gebeyehu 2017) reported that the regional variability and declining trends in precipitation and increased evapotranspiration via consistently warming trends caused significant changes in the water levels of lakes utmost for their disappearance.

Conclusions

The study found that the Endorheic Lake Hayk basin experienced variable and declining precipitation, as well as a consistent warming trend. Concurrently, Lake Hayk's water level varied in response to changes in precipitation and temperature. In recent times, the Lake Hayk water level has been negatively impacted by declining precipitation coupled with continually rising temperature. This suggests that climate change/variability in the lake basin has direct implications for Lake Hayk's water level changes, necessitating immediate climate change oriented water management strategies for Lake Hayk to save it from demise.

Acknowledgements

We are thankful to the Ethiopian National Meteorological Agency and the Ministry of Water Resources of Ethiopia for providing monthly climate and water level data respectively.

Authors' contributions

Mr. Mezgebu Mewded, Dr. Adane Abebe, Dr. Seifu Tilahun and Dr. Zeleke Agide conceived and planned the idea of the study. Mr. Mezgebu Mewded collected the data. All authors carried out the analysis and contributed to the interpretation of the results. Mr. Mezgebu Mewded wrote the manuscript in consultation with Dr. Adane Abebe, Dr. Seifu Tilahun and Dr. Zeleke Agide. All authors read and approved the final manuscript.

Funding

This study was not funded by any grants.

Availability of data and materials

The climate and hydrology data that support the findings of this study are available in the National Meteorological Agency and the Ethiopian Water Resources, Irrigation, and Electricity ministry repositories. Access to these data can be allowed based on reasonable requests submitted to the respective organizations.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

References

Agnew CT, Chappell A (1999) Drought in the Sahel. Geo Journal 48(4): 2993-3011

Alemayehu A, Bewket W (2017) Local spatiotemporal variability and trends in precipitation and temperature in the central highlands of Ethiopia. Geografiska Annaler: Series A, Physical Geography 99(2): 85-101

Alemseged TH, Tom R (2015) Evaluation of regional climate model simulations of precipitation over the Upper Blue Nile basin. Atmospheric Research 161: 57-64

Ayalew D, Tesfaye K, Mamo G, Yitaferu B, Bayu W (2012) Variability of rainfall and its current trend in Amhara region, Ethiopia. African Journal of Agricultural Research 7(10): 1475-1486

Bewket W, Conway D (2007) A note on the temporal and spatial variability of precipitation in the drought-prone Amhara region of Ethiopia. International Journal of Climatology: A Journal of the Royal Meteorological Society 27(11): 1467-1477

Camberlin P (1997) Precipitation anomalies in the source region of the Nile and their connection with the Indian summer monsoon. Journal of Climate 10: 1380-1392

Conway D (2000) Some aspects of climate variability in the north east Ethiopian highlands-Wollo and Tigray. SINET: Ethiopian Journal of Science 23(2): 139-161

Dee DP, Uppala SM, Simmons AJ, Berrisford P, Poli P, Kobayashi S, et al. (2011) The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. Quarterly Journal of the Royal Meteorological Society 137(656): 553-597

Demlie M, Ayenew T, Wohnlich S (2007) Comprehensive hydrological and hydrogeological study of topographically closed lakes in highland Ethiopia: the case of Hayq and Ardibo. Journal of Hydrology 339(3-4): 145-158

Gebeyehu E (2017) Impact of climate change on Lake Chamo water balance, Ethiopia. International Journal of Water Resources and Environmental Engineering 9(4): 86-95

Hamed KH, Rao AR (1998) A modified Mann-Kendall trend test for auto correlated data. Journal of Hydrology 204(1-4): 182-196

Hare W (2003) Assessment of knowledge on impacts of climate change- Contribution to the specification of Art. 2 of the UNFCCC: Impacts on ecosystems, food production, water and socio-economic systems. WBGU, Berlin

Hirsch RM, Slack JR (1984) A nonparametric trend test for seasonal data with serial dependence. Water Resources Research 20(6):727-732

Kalnay E, Kanamitsu M, Kistler R, Collins W, Deaven D, Gandin L, et al. (1996) The NCEP/NCAR 40-year reanalysis project. Bulletin of the American Meteorological Society 77(3): 437-471

Kebede S, Travi Y, Alemayehu T, Marc V (2006) Water balance of Lake Tana and its sensitivity to fluctuations in precipitation, Blue Nile basin, Ethiopia. Journal of Hydrology 316(1-4): 233-247

Kendall MG (1938) A new measure of rank correlation. Biometrika 30(1/2): 81-93

Kendall MG (1975) Kendall rank correlation methods. Charles Griffin, London

Kiani T, Ramesht MH, Maleki A, Safakish F (2017) Analyzing the impacts of climate change on water level fluctuations of Tashk and Bakhtegan lakes and its role in environmental sustainability. Open Journal of Ecology 7: 158-178

McFeeters SK (1996) The use of normalized difference water index (NDWI) in the delineation of open water features. International Journal of Remote Sensing 17: 1425-1432

McSweeney C, New M, Lizcano G (2008) United Nation Development Programme (UNDP) climate change country profiles: Ethiopia. UNDP, New York

Mekonnen MM, Hoekstra AY, Becht R (2012) Mitigating the water footprint of export cut flowers from the lake Naivasha basin, Kenya. Water Resources Management 26(13): 3725-3742

Motiee H, McBean E (2009) An assessment of long-term trends in hydrologic components and implications for water levels in lake Superior. Hydrology Research 40(6): 564-579

Nkiaka E, Nawaz NR, Lovett JC (2017) Evaluating global reanalysis precipitation datasets with rain gauge measurements in the Sudano-Sahel region: Case study of the Logone catchment, Lake Chad basin. Meteorological Applications 24(1): 9-18

NMA (National Meteorological Agency) of Ethiopia (2007) Climate change national adaptation program of action

(NAPA) of Ethiopia. NMA, Addis Ababa

Olana KY (2014) Assessment of climate change impacts on highland lake of eastern Ethiopia. International Journal of Scientific and Engineering Research 5(6): 1-12

Oliver JE (1980) Monthly precipitation distribution: A comparative index. The Professional Geographer 32: 300-309

Philip S, Kew SF, Van Oldenborgh GJ, Otto F, O'keefe S, Haustein K, et al. (2018) Attribution analysis of the Ethiopian drought of 2015. Journal of Climate 31(6): 2465-2486

Rienecker MM, Suarez MJ, Gelaro R, Todling R, Bacmeister J, Liu E, et al. (2011) MERRA: NASA's modern-era retrospective analysis for research and applications. Journal of Climate 24(14): 3624-3648

Seleshi Y, Zanke U (2004) Recent changes in rainfall and rainy days in Ethiopia. International Journal of Climatology: A Journal of the Royal Meteorological Society 24(8): 973-983

Sen PK (1968) Estimates of the regression coefficient based on Kendall's tau. Journal of the American Statistical Association 63(324): 1379-1389

Tan C, Ma M, Kuang H (2017) Spatial-temporal characteristics and climatic responses of water level fluctuations of global major lakes from 2002 to 2010. Remote Sensing 9(2): 1-15

WMO (World Meteorological Organization) (2016) Hotter, drier, wetter: face the future. Bulletin 65(1): 64

Xu H (2006) Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. International Journal of Remote Sensing 27(14): 3025-3033

Yesuf HM, Alamirew T, Melesse AM, Assen M (2013) Bathymetric study of Lake Hayq, Ethiopia. Lakes and Reservoirs: Research and Management 18(2): 155-165

Yue S, Pilon P, Cavadias G (2002) Power of the Mann-Kendall and Spearman's rho tests for detecting monotonic trends in hydrological series. Journal of Hydrology 259: 254-271

Figures

Figure 1

Ethiopia's topography and the location of the endorheic Lake Hayk basin

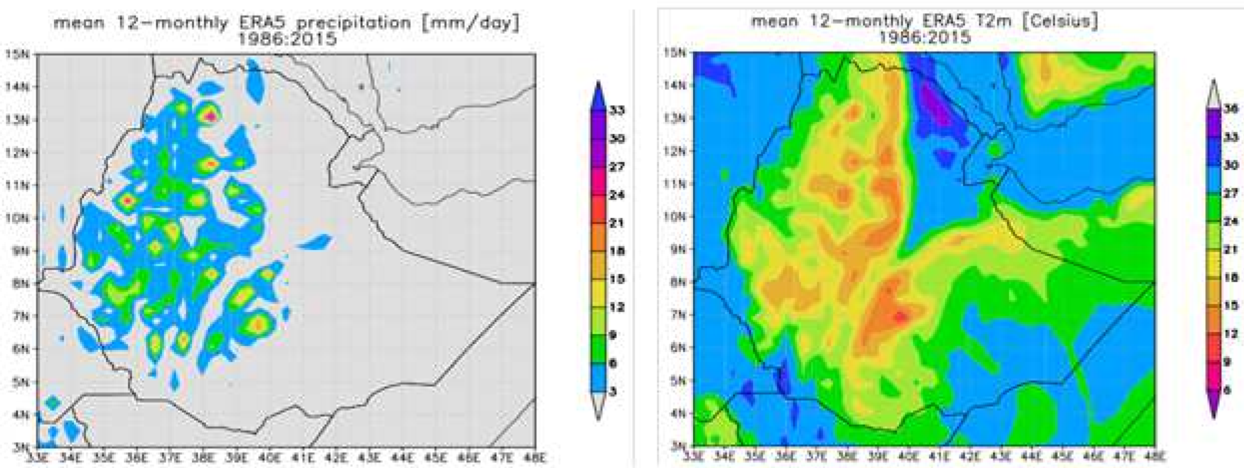

Figure 2

Mean annual ERA5 precipitation (left) and temperature (right) in Ethiopia (1986 –2015)

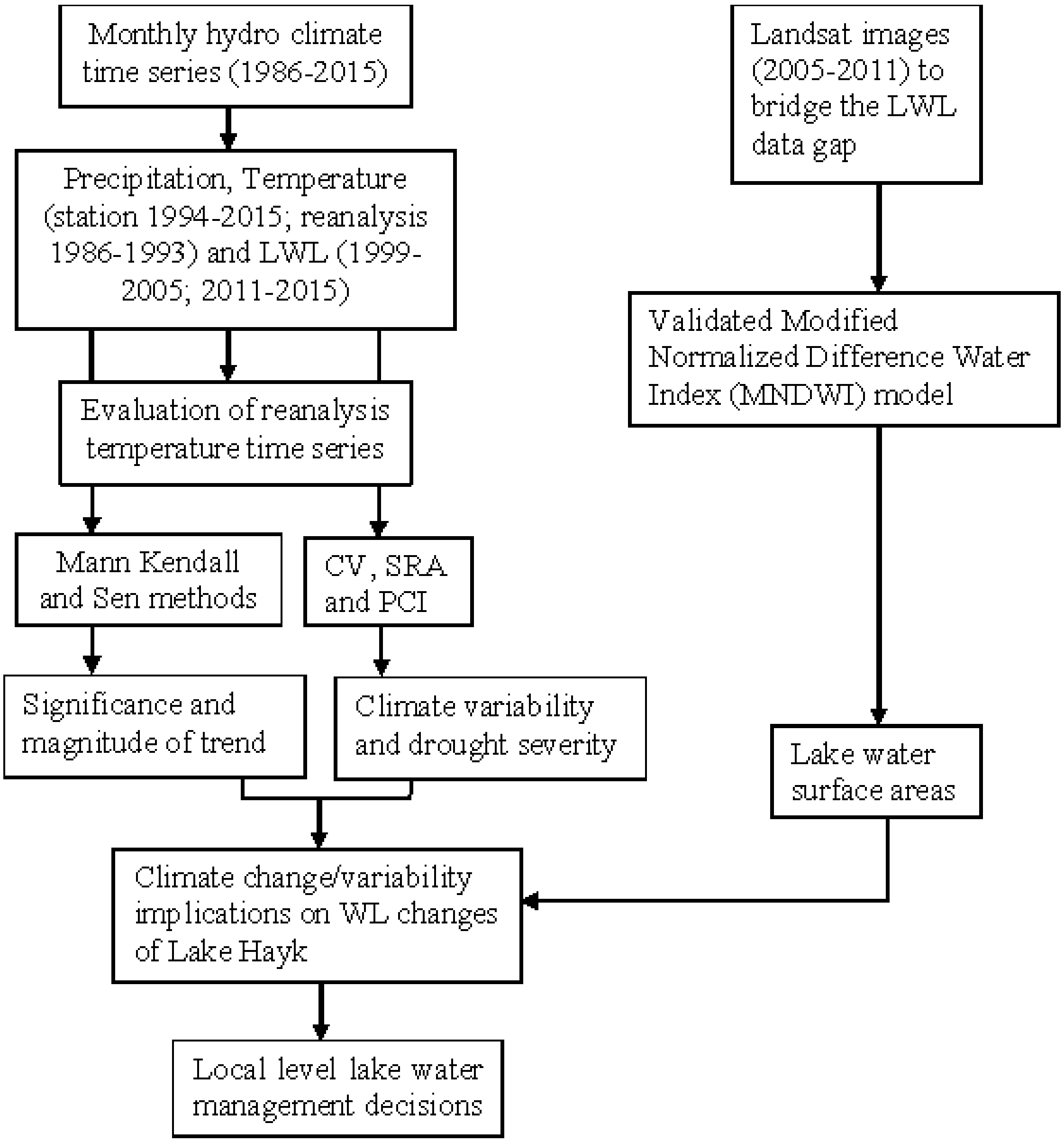

Figure 3

A schematic illustration of the study's methodology

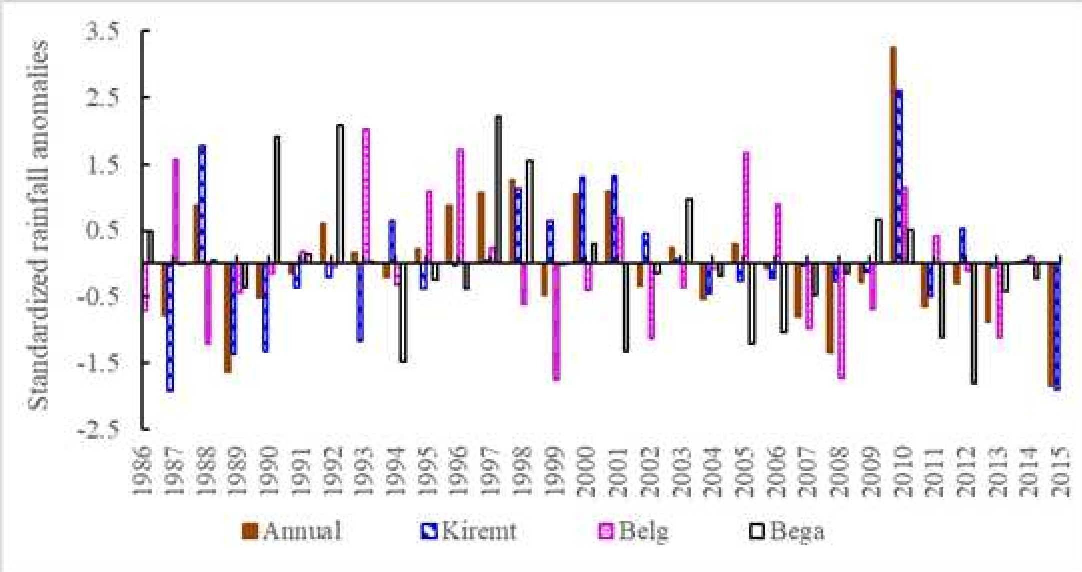

Figure 4

Standardized rainfall anomalies (1986–2015)

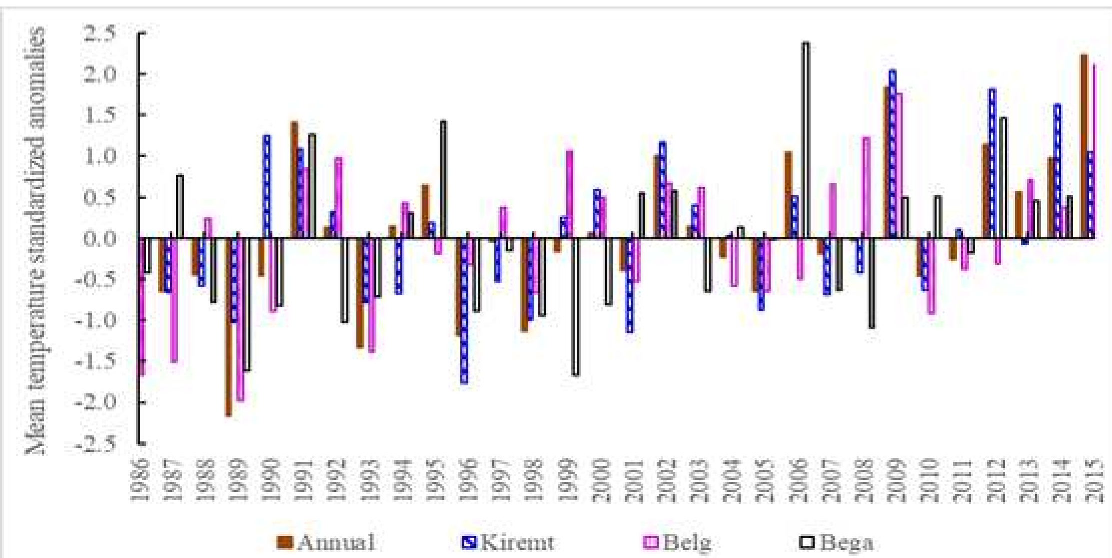

Figure 5

Mean annual and seasonal Tmean standardized anomalies (1986–2015)

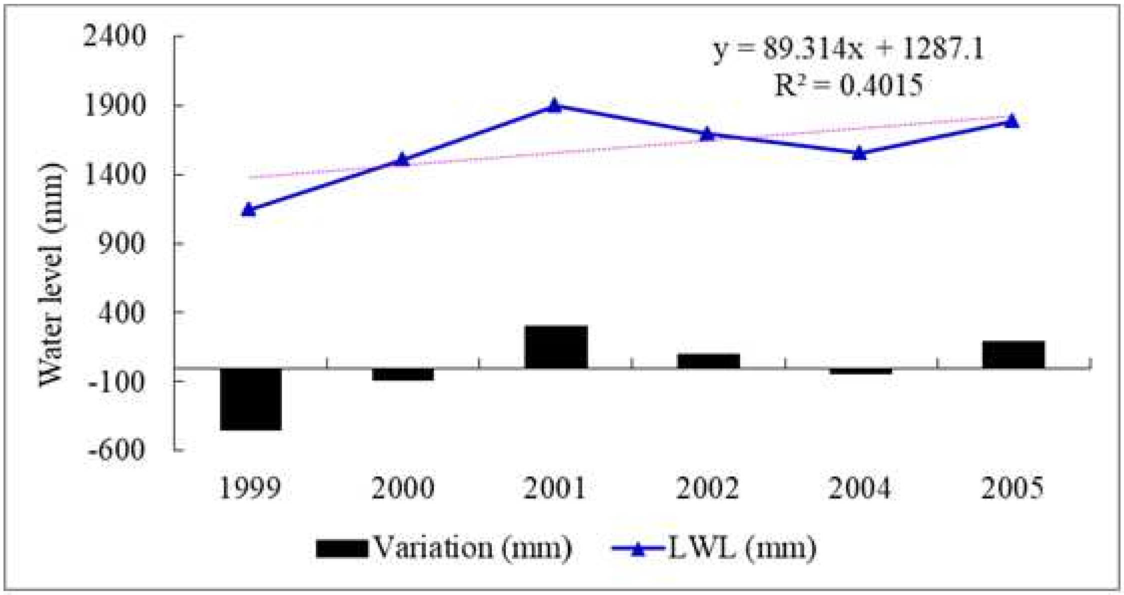

Figure 6

Mean annual water level and level variations of Lake Hayk (1999–2005)

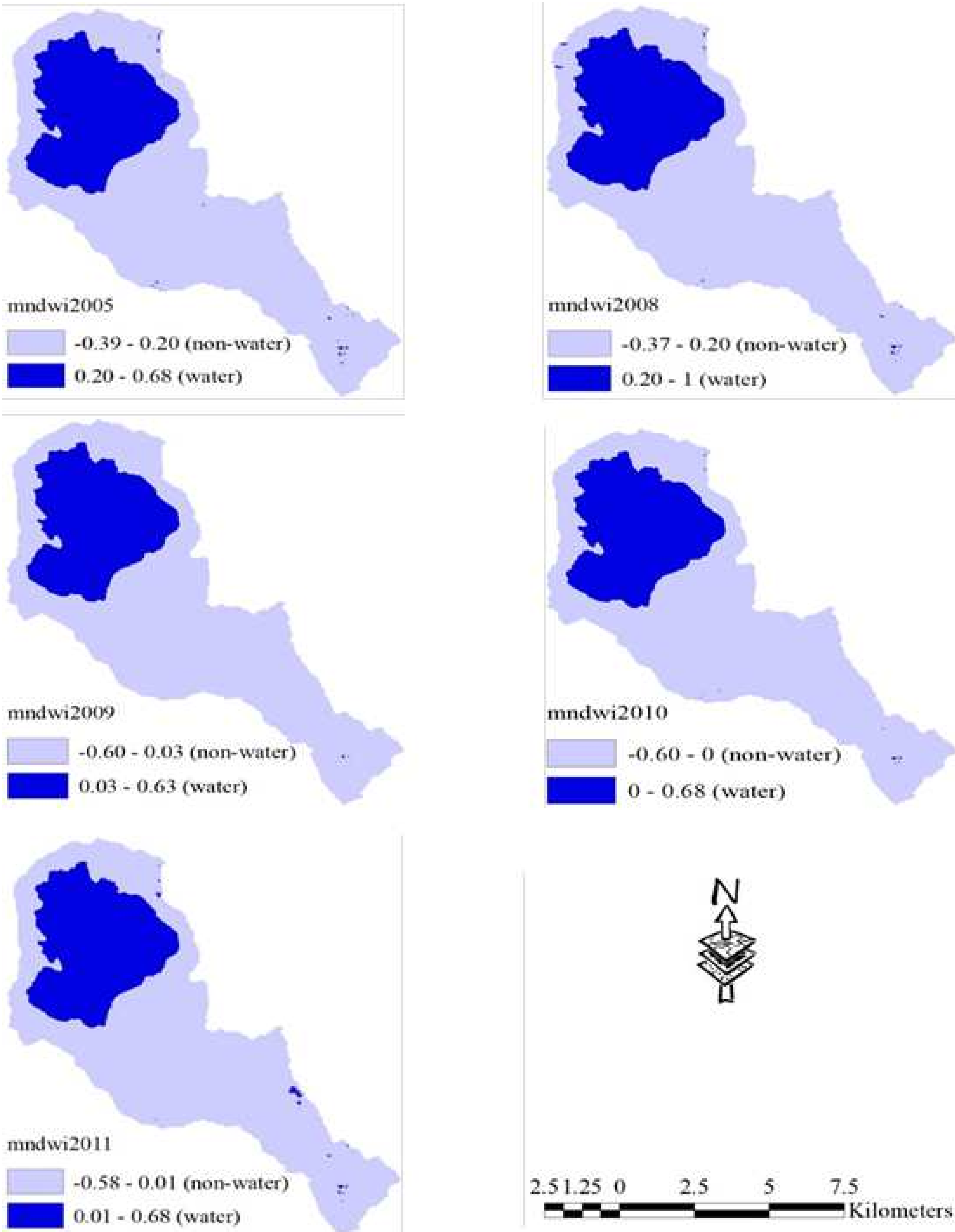

Figure 7

MNDWI maps of the Lake Hayk basin (2005–2011)

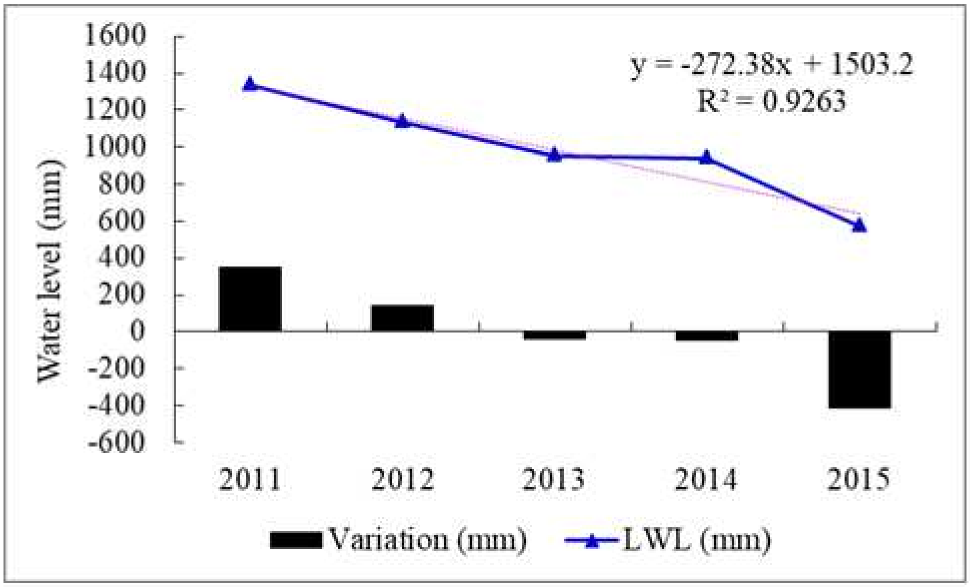

Figure 8

Mean annual water level and level variations of Lake Hayk (2011–2015)