Analysing the Impacts of Natural-Factor Variability on Lake Water Volume Using the Generalized Method of Moment

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Abstract

Natural-factor variability strongly influences the hydrological stability of large tropical lakes. As a major freshwater resource in East Africa, Lake Victoria has experienced notable water-volume fluctuations under changing climatic conditions. This study investigated the effects of precipitation, evapotranspiration (ET), El Niño–Southern Oscillation (ENSO), and normalized difference vegetation index (NDVI) on lake water volume using multi-source datasets and the generalized method of moments (GMM). The results show that precipitation is the dominant positive driver of water-volume variation, whereas ET has a negative effect through increased surface-water loss. Quantitatively, the GMM estimates indicate that precipitation has a positive coefficient of 1.291, while ET shows a negative coefficient of −0.137. In addition, NDVI exhibits clear seasonality and reaches a monthly maximum of 0.7293 in December 2015, reflecting the close linkage between hydrological fluctuations and vegetation conditions in the basin. Overall, this study clarifies the main hydroclimatic controls on Lake Victoria water-volume variability and provides empirical support for regional water-resource assessment and climate-adaptation planning.

1. Introduction

Freshwater lakes are critical components of the global hydrological cycle and regional socioecological systems. They function not only as water-storage units, but also as integrators of catchment processes, regulators of local climate, and sentinels of environmental change. Because lake fluctuations respond rapidly to climatic forcing, land-surface processes, and human intervention, long-term lake monitoring has become increasingly important in the context of climate change and sustainable water-resource management (Williamson et al., 2009; Pekel et al., 2016). Lake water volume is a more direct indicator of water-resource availability than lake area alone, because it reflects the combined effects of shoreline migration, lake-level change, and basin morphology (Donchyts et al., 2016; An et al., 2022). Recent advances in remote sensing, including satellite altimetry, multispectral imagery, and large-scale geospatial products, have substantially improved the capacity to monitor inland-water dynamics over long periods and broad spatial extents, especially in regions where in situ observations are sparse or discontinuous (Cretaux et al., 2005; Becker et al., 2010).

Lake water-volume variation is regulated by the combined effects of hydroclimatic forcing and basin-scale environmental processes. Precipitation contributes directly to water input, evapotranspiration represents a major pathway of water loss, and large-scale climate oscillations such as ENSO can alter regional rainfall regimes and thereby affect lake storage. Vegetation dynamics, commonly characterized by NDVI, are also closely linked to hydrological conditions because they reflect moisture availability, evapotranspiration intensity, and land-atmosphere interactions within the basin (Senay et al., 2020; Huete et al., 2002). NDVI has therefore been widely used to characterize ecological responses to changing hydroclimatic conditions (Pettorelli et al., 2005). However, existing studies often emphasize individual drivers or single processes, whereas the interactions among precipitation, evaporation-related processes, climate oscillations, vegetation response, and lake water storage remain insufficiently quantified (An et al., 2022; Moran, 1950). These relationships are frequently nonlinear, temporally lagged, and statistically endogenous, which may reduce the explanatory power of conventional regression models under coupled environmental conditions (Hansen, 1982; Sargan, 1958). This issue is particularly important when climatic and environmental variables are mutually dependent over time (Arellano and Bond, 1991).

Lake Victoria provides a representative case for investigating such interactions. As the largest lake in Africa and one of the most socioeconomically important inland-water systems in the world, it supports fisheries, transportation, domestic water supply, agriculture, hydropower, and regional livelihoods across multiple riparian countries. Meanwhile, its water storage exhibits pronounced seasonal and interannual variability under the combined influence of rainfall, evaporation, inflow processes, and large-scale atmosphere-ocean variability (Awange et al., 2013; Vanderkelen et al., 2018). Previous studies have shown that Lake Victoria is highly sensitive to hydroclimatic anomalies and regional climate variability (Khaki et al., 2019; Khaki et al., 2021). Earlier hydrological analyses also documented the importance of precipitation and basin processes in shaping lake-level and storage changes (Birkett et al., 1999; Mistry and Conway, 2003). Regional climate studies have further highlighted the role of coupled atmospheric processes in controlling rainfall variability over the lake basin (Anyah et al., 2006). Recent satellite-based reconstructions demonstrate that major fluctuations in Lake Victoria water level and storage can be effectively captured from space (Yu et al., 2023).

Against this background, this study investigates the impacts of natural-factor variability on Lake Victoria water-volume change by integrating multi-source remote-sensing and climate datasets within a generalized method of moments framework. Monthly precipitation from GSOD, actual ET from the SSEBop product, the multivariate ENSO index, and MODIS NDVI are analyzed together with a previously constructed monthly water-volume series derived from multi-mission altimetry and multispectral imagery for 2000–2020 (Senay et al., 2020; Yu et al., 2023). The analysis first examines the temporal variability and pairwise relationships among precipitation, ET, ENSO, vegetation condition, and lake-volume change, and then evaluates their combined effects under potentially endogenous multi-factor conditions using moment-based estimation. The objective is to

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identify the dominant natural drivers of Lake Victoria water-volume variability and to clarify how climate factors and vegetation dynamics interact within the lake-basin system, thereby providing a more rigorous basis for hydrological interpretation, ecological assessment, and regional water-resource management.

2. Study Area and Materials

2.1 Study Area

The Lake Victoria Basin is located in equatorial East Africa and occupies a key position in the upper Nile system. The basin extends approximately from 31°39′E to 34°53′E and from 0°20′N to 3°00′S, crossing the equator and connecting lacustrine, riverine, and upland catchment environments. Lake Victoria is mainly shared by Uganda, Kenya, and Tanzania, while the broader drainage system also involves Rwanda and Burundi. The lake surface lies at about 1,135 m above sea level, and its northern outlet at Jinja forms the headwater connection to the White Nile. In this study, Lake Victoria is considered primarily from the perspective of hydrological sensitivity. Because the lake is broad and relatively shallow, variations in rainfall, evaporation, and tributary inflow can be rapidly reflected in measurable changes in storage and water volume (Becker et al., 2010; Awange et al., 2013). Previous studies have also shown that the lake responds clearly to hydroclimatic variability at seasonal and interannual scales (Vanderkelen et al., 2018). The geographical setting of the Lake Victoria Basin is shown in Figure 1.

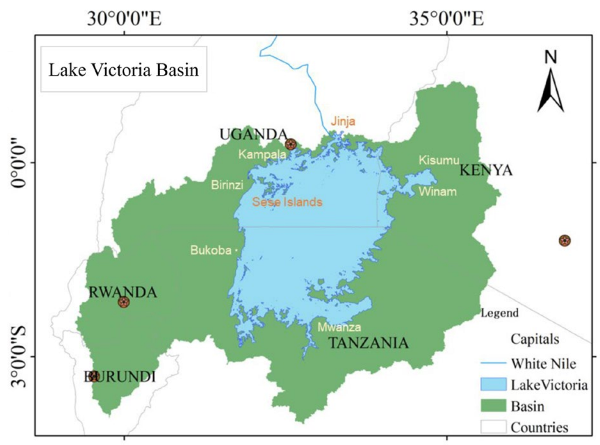


Figure 1. Geographic setting of the Lake Victoria Basin.

The basin also represents a coupled natural–human system with strong regional importance. Major urban centers such as Kampala, Kisumu, Mwanza, Jinja, and Bukoba are distributed around the lakeshore or within the wider basin, and the lake supports domestic water supply, inland navigation, fisheries, agriculture, and energy-related activities. As a result, hydrological fluctuations are closely linked to livelihoods, infrastructure exposure, and regional production systems. For this reason, Lake Victoria has frequently been used as a representative lake for examining climate variability, hydrological extremes, and basin-scale storage anomalies in East Africa (Birkett et al., 1999; Mistry and Conway, 2003). More recent studies have further highlighted its importance for understanding regional hydrological response under changing climatic conditions (Khaki et al., 2021).

From the perspective of research design, the Lake Victoria Basin is well suited for investigating natural-factor variability for three reasons. First, the basin is climatically dynamic, with rainfall variability influenced by both large-scale atmospheric forcing and local lake–atmosphere interactions. Second, its hydrological response can be observed using multiple remote-sensing products, including water-level, water-area, ET, and vegetation indicators, which makes cross-variable analysis feasible. Third, the basin combines strong environmental sensitivity with clear socioeconomic implications, allowing hydrological interpretation to be linked to practical water-resource concerns. Accordingly, the basin is treated not simply as a geographic background, but as a representative case in which natural variability, storage response, and regional exposure can be examined within an integrated framework (Anyah et al., 2006; Khaki et al., 2019).

2.2 Research Data

This study integrates multi-source hydroclimatic, vegetation, and lake-storage datasets to characterize the main natural controls on water-volume variability in the Lake Victoria Basin. Rather than relying on a single observational stream, the data design combines direct lake-storage information with basin-scale atmospheric and land-surface indicators so that short-term hydrological forcing and broader climate teleconnections can be evaluated within a unified analytical framework. The research data include lake water volume, precipitation, evapotranspiration, ENSO-related indices, and vegetation greenness represented by NDVI.

Lake water volume is the core response variable and is adopted from the reconstructed Lake Victoria storage dataset developed by Yu et al. (2023), which integrates multi-mission altimetry and multispectral observations to generate a temporally continuous monthly record. Precipitation describes direct atmospheric water input to the basin and was compiled from the GSOD station archive around Lake Victoria. ET was derived from the SSEBop product to capture surface-water loss and seasonal energy-water constraints across the basin (Senay et al., 2020). Vegetation conditions were represented by monthly MODIS NDVI data extracted within a 100-km buffer around the lake (Huete et al., 2002). ENSO variability was characterized mainly by the Multivariate ENSO Index (MEI) to reflect large-scale climate forcing (Wolter and Timlin, 2011). The datasets used in this study are summarized in Table 1.

Source	Time	Temporal Resolution	Use
Water volume (Yu et al., 2023)	2000-2020	Monthly	Lake storage analysis
Precipitation (GSOD)	2000-2020	Monthly	Meteorological forcing
ET (SSEBop)	2003-2020	Monthly	Water-loss analysis
ENSO (MEI)	2000-2020	Monthly	Climate teleconnection
NDVI (MODIS)	2000-2020	Monthly	Vegetation response analysis

Table 1. Research data list.

3. Methodology

3.1 Bivariate Analysis

To obtain an initial understanding of the relationships among hydroclimatic factors, vegetation conditions, and lake-water variation, this study first applied bivariate correlation analysis. Let X_t and Y_t denote two monthly variables observed at time t. Their Pearson correlation coefficient is defined as

$$r_{XY} = \frac{\sum_{t=1}^{n} (X_t - \bar{X})(Y_t - \bar{Y})}{\sqrt{\sum_{t=1}^{n} (X_t - \bar{X})^2}\sqrt{\sum_{t=1}^{n} (Y_t - \bar{Y})^2}}, \quad (1)$$

where $\bar{X}$ and $\bar{Y}$ are the sample means of X_t and Y_t, and n is the number of observations. Positive values of r_{XY} indicate that the two variables tend to increase together, whereas negative values indicate an inverse relationship.

In this study, correlation analysis was used as a diagnostic step rather than a final attribution tool. This is because the monthly series of precipitation, evapotranspiration, ENSO, vegetation condition, and lake-water variation may share seasonal structure, delayed responses, and mutual dependence. Therefore, the correlation matrix is used to identify the sign and strength of pairwise association and to support the subsequent multivariate modeling.

3.2 Ordinary Least Squares

To evaluate the joint effects of multiple variables, this study next employed ordinary least squares (OLS) regression. The general linear model can be written as

$$y = X\beta + \varepsilon, \quad (2)$$

where y is the dependent-variable vector, X is the matrix of explanatory variables, β is the vector of regression coefficients to be estimated, and ε is the disturbance term.

The OLS estimator is obtained by minimizing the residual sum of squares:

$$\hat{\beta}_{OLS} = \arg\min_{\beta} (y - X\beta)^{'} (y - X\beta), \quad (3)$$

which yields the closed-form solution

$$\hat{\beta}_{OLS} = (X^{'}X)^{-1}X^{'}y. \quad (4)$$

OLS provides an interpretable benchmark for identifying the direction and average magnitude of variable associations. However, in hydroclimatic systems the strict exogeneity assumption may be violated, because precipitation, evapotranspiration, vegetation dynamics, and lake-water storage are linked through the same environmental processes. Under such conditions, OLS coefficients remain informative as baseline estimates, but may be biased or inconsistent if endogeneity, heteroskedasticity, or serial dependence is present.

3.3 Generalized Method of Moment

To address the limitations of conventional regression under endogenous multi-factor conditions, this study adopted moment-based estimation. Suppose that a valid instrument matrix Z exists such that the instruments are correlated with the explanatory variables but orthogonal to the disturbance term. The population moment condition can then be written as

$$E(Z'u) = 0, \quad (5)$$

where $u = y - X\beta$ is the structural error term. The corresponding sample moment function is

$$g_n(\beta) = \frac{1}{n} Z'(y - X\beta). \quad (6)$$

In the exactly identified case, the method-of-moments (MM) estimator is

$$\hat{\beta}_{MM} = (Z'X)^{-1}Z'y. \quad (7)$$

The GMM extends this idea by allowing more moment conditions than parameters and by assigning a weighting matrix to the sample moments. The GMM estimator is defined as

$$\hat{\beta}_{GMM} = \arg\min_{\beta} [g_n(\beta)'Wg_n(\beta)], \quad (8)$$

where W is a positive semi-definite weighting matrix. In the linear case, the estimator can be expressed as

$$\hat{\beta}_{GMM} = (X'ZWZ'X)^{-1}X'ZWZ'y. \quad (9)$$

When the model is overidentified, the validity of the moment conditions can be evaluated by the Hansen--Sargan J statistic:

$$J = n\, g_n(\hat{\beta}_{GMM})'\hat{S}^{-1}g_n(\hat{\beta}_{GMM}), \quad (10)$$

where $\hat{S}$ is a consistent estimate of the covariance matrix of the sample moments. In addition, AR(1) and AR(2) tests are used to examine first- and second-order serial correlation in the transformed residuals. A statistically insignificant AR(2) result, together with a non-rejected J test, indicates that the instrument set and moment conditions are acceptable.

3.4 Empirical Model Specification

Due to the potential endogeneity, heteroskedasticity, and serial correlation among hydroclimatic variables, multiple linear regression may lead to biased and unstable estimates. Therefore, this study employed the GMM to estimate the parameters of Lake Victoria water-volume change and vegetation dynamics. ΔV_t and $NDVI_t$ were respectively set as dependent variables. For water-volume change, ET_t, $ENSO_t$, and $Precipitation_t$ were selected as explanatory variables because they represent the main climatic controls on lake storage. For vegetation dynamics, ΔV_t, $ENSO_t$, and $Precipitation_t$ were selected as explanatory variables because vegetation conditions are affected by both hydrological variation and climatic forcing. The two linear models are expressed as follows:

$$NDVI_t = \beta_0 + \beta_1\Delta V_t + \beta_2 ENSO_t + \beta_3 Precipitation_t + e_{it} \quad (11)$$

$$\Delta V_t = \beta_0 + \beta_1 ET_t + \beta_2 ENSO_t + \beta_3 Precipitation_t + e_{it} \quad (12)$$

4. Results and Discussion

4.1 Precipitation Variability and Lake-Water Volume response

Figure 2 shows the monthly co-variation between precipitation and ΔV. The precipitation series preserves the bimodal seasonal regime that characterizes much of the Lake Victoria Basin, with peaks during the long and short rainy seasons. This seasonal structure is consistent with regional rainfall climatology reported for East Africa and for the lake basin itself (Nicholson, 2017; Cattani et al., 2018). In the plotted series, months with above-average rainfall are commonly followed by positive ΔV anomalies, while drier months are associated with reduced or negative storage change. The correspondence is especially evident during 2006–2007, 2018–2019, and 2020, when enhanced precipitation coincides with clear increases in lake storage. These years fall within periods of anomalous rainfall identified in East African records and are consistent with the known sensitivity of Lake Victoria to rainfall forcing (Kizza et al., 2012; Akurut et al., 2014).

The relationship is not strictly synchronous at every month because lake storage integrates several processes, including direct rainfall on the lake, delayed tributary inflow, basin wetness, and the damping effect of a large lake surface. Even so, precipitation remains the most immediate input term in the water-balance system. The pattern in Figure 2 therefore supports the regression outcome in which precipitation has the largest positive coefficient in the ΔV equation. In hydrological terms, this means that rainfall anomalies are transferred efficiently into storage anomalies when catchment and lake-surface conditions are favorable. The observed association also agrees with earlier basin studies showing that rainfall over the lake and surrounding catchment is the main driver of level and storage fluctuations because Lake Victoria receives a large share of its effective inflow directly from atmospheric input (Kizza et al., 2012; Akurut et al., 2014).

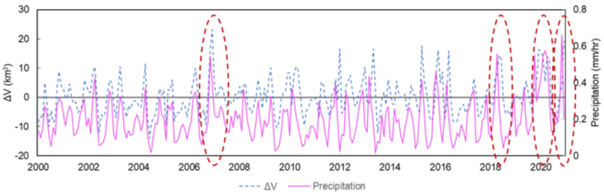
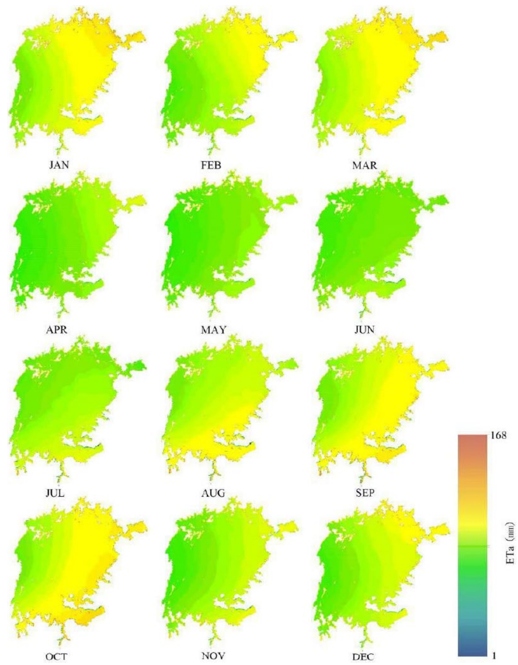
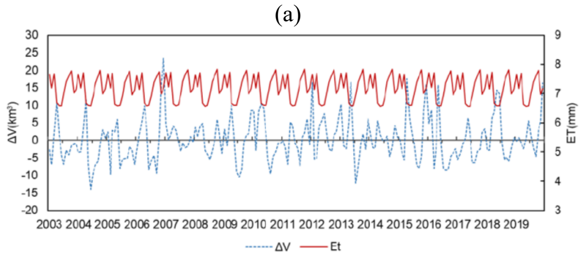


Figure 2. Comparison of monthly precipitation and water-volume change.



(a)



(b)

Figure 3. (a) Spatial distribution of monthly mean evapotranspiration for each year; (b) Comparison between water-volume change and evapotranspiration trends, and the periodic pattern of evapotranspiration.

4.2 Spatiotemporal Characteristics of ET and Δ*V*

ET shows a different temporal role from precipitation. Figure 3(a) presents the spatial distribution of monthly mean ET, while Figure 3(b) compares ET with ΔV through time. The spatial maps indicate that ET remains persistently high over the lake surface and exhibits a repeated east–west gradient across months. This pattern is consistent with the strong energy control on evaporation over large tropical lakes and with regional studies showing that ET is a continuous component of the basin water balance rather than an episodic forcing term (Onyutha et al., 2020; Akurut et al., 2014).

In the time series comparison, ET varies more smoothly than precipitation and ΔV. High ET months do not necessarily produce immediate negative storage anomalies, but they reduce the fraction of water input that is retained as measurable storage. For this reason, ET operates as a continuous loss term within the lake-basin system. The negative sign of the ET coefficient in the regression results is therefore physically consistent with the temporal pattern in Figure 3(b). When precipitation is moderate rather than extreme, high ET can limit the magnitude of storage recovery. This interpretation also agrees with regional analyses of precipitation–evapotranspiration balance in East Africa, which show that shifts in atmospheric demand can substantially affect hydrological availability even where seasonal rainfall remains the main water source (Onyutha et al., 2020).

4.3 ENSO-Related Variability in Relation to Δ*V*

Figure 4 compares ENSO-related variability with lake-water change. In contrast to precipitation, the ENSO signal is expressed mainly at the interannual scale. The time series indicates that some positive ΔV phases occurred during or after positive ENSO conditions, whereas other storage anomalies show weaker alignment. This pattern is consistent with the role of ENSO as a large-scale climatic control that influences East African rainfall through circulation anomalies rather than through direct hydrological forcing at the monthly scale.

The plotted lag structure further indicates that the response of lake storage to ENSO is delayed relative to the climate index. Such delay is expected because the teleconnection first modifies rainfall and moisture transport, after which the lake responds through rainfall over the water surface, tributary inflow, and cumulative basin wetness. This mechanism has been reported in broader East African studies and in vegetation-focused work that links ENSO phases with shifts in moisture availability and ecological response (Ndomeni et al., 2018; Kalisa et al., 2019). In the present results, ENSO does not dominate month-to-month storage variation, but it remains relevant for explaining why some wet or dry sequences depart from the average seasonal cycle.

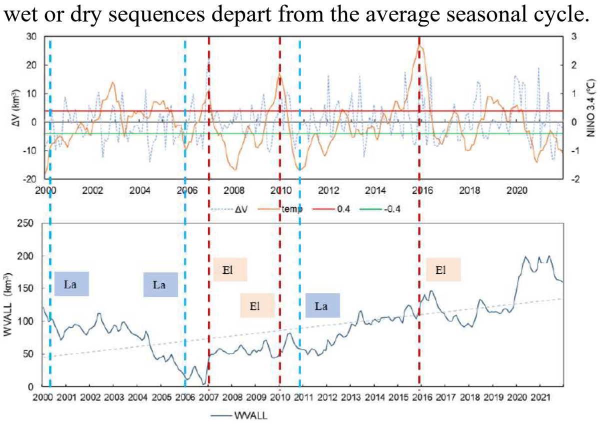
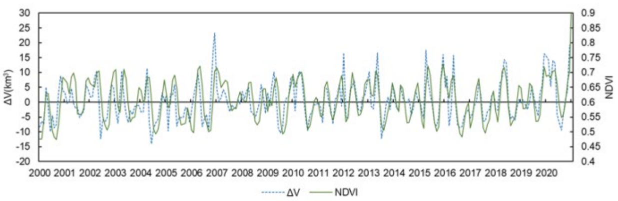


Figure 4. Comparison between ENSO and water-volume change for each year.

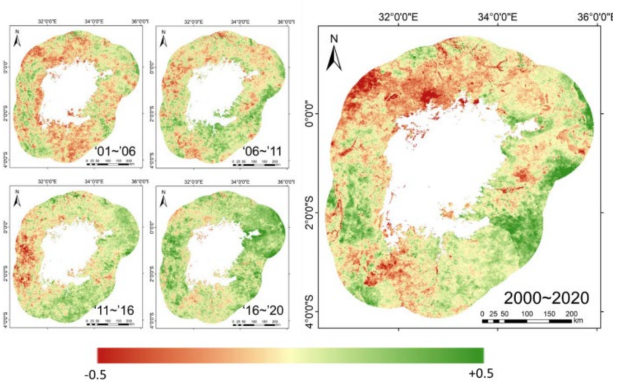
4.4 Vegetation Dynamics and Lake-storage Response

The NDVI series indicates a clear seasonal rhythm in the 100-km buffer surrounding the lake in Figure 5(a). NDVI generally rises during wetter periods and declines during drier intervals, which reflects the dependence of vegetation activity on moisture availability in East African landscapes. This seasonal behavior agrees with long-standing evidence that NDVI over East Africa responds to rainfall anomalies with varying lag and strength according to land cover and regional hydroclimatic setting (Nicholson et al., 1990; Davenport and Nicholson, 1993). In the present study, NDVI also shows an overall correspondence with ΔV, which indicates that vegetation conditions around the lake are associated not only with precipitation but also with the hydrological status of the lake-basin system.

The relationship between NDVI and climatic forcing is not spatially uniform. Previous regional analyses have shown that vegetation response differs across humid, subhumid, and semiarid zones, and that the precipitation–NDVI link changes with vegetation type and water limitation (Chamaillé-Jammes and Fritz, 2009; Hawinkel et al., 2016). Studies over East Africa and the Horn of Africa also indicate that NDVI is generally more sensitive to precipitation than to temperature in moisture-limited environments, while lagged or buffered responses emerge in areas with stronger hydrological memory (Ghebrezgabher et al., 2020; Kalisa et al., 2019). The NDVI results in this study fit that pattern: the basin-scale vegetation signal follows seasonal hydroclimatic variability, but its month-to-month behavior reflects both direct climatic forcing and the persistence of moisture conditions connected with lake storage.



(a)



(b)

Figure 5. (a) Seasonal variation of NDVI and lake-water volume change; (b) Spatial evolution of NDVI within the Lake Victoria buffer zone over different periods

4.5 GMM Results and Integrated Interpretation

Table 2 summarizes the GMM estimates for the ΔV equation, and Table 3 reports the estimates for the NDVI equation. The correlation results indicate that ΔV is positively related to precipitation and NDVI and negatively related to ET. The OLS results preserve the same sign pattern, with precipitation showing a positive and statistically significant coefficient and ET showing a negative coefficient in the water-volume model. In the NDVI model, both precipitation and ΔV are positively associated with vegetation activity, while the effect of ET is weaker after other variables are included. These sign patterns are consistent with the observed time series and with the wider East African literature on rainfall control of lake storage and vegetation change (Kizza et al., 2012; Hawinkel et al., 2016).

The GMM estimates provide the final parameter set used for interpretation. In the ΔV equation, precipitation has a positive coefficient of 1.291 and ET has a negative coefficient of -0.137, while ENSO retains a smaller positive coefficient of 0.090. These results indicate that rainfall remains the dominant short-term driver of storage increase, whereas ET acts as a compensating loss term and ENSO contributes as a background climate control. The diagnostic statistics are acceptable: the AR(1) and AR(2) tests do not indicate problematic higher-order serial correlation, and the Hansen J statistic is within the acceptable range for the selected moment conditions. In the NDVI equation, precipitation remains significant and positive, and the coefficient associated with hydrological conditions is also positive, indicating that vegetation activity increases under wetter climatic and hydrological states. This result is consistent with studies showing that vegetation greenness in East Africa is coupled to rainfall variability and moisture storage rather than to instantaneous rainfall alone (Nicholson et al., 1990; Hawinkel et al., 2016).

The regression results therefore support a two-step interpretation. First, precipitation, ET, and ENSO shape ΔV through the lake water balance, with precipitation exerting the largest positive influence. Second, NDVI responds to both climatic forcing and hydrological state, which means that vegetation dynamics in the buffer zone can be interpreted as an ecological response to the same climate variability that controls lake storage. This structure is also consistent with regional rainfall data evaluations and climate–vegetation studies across eastern Africa, which report strong but lagged linkages among precipitation, surface moisture, and vegetation indices (Asadullah et al., 2008; Cattani et al., 2018).

Dependent: ΔV	
explanatory variable	β(P-value)
ENSO	0.090(0.0914*)
ET	-0.137(0.059*)
Precipitation	1.291(0.000***)
AR(1)=0.0156	AR(2)=0.17
J=3.588	PWald=0.000

Table 2. GMM parameter estimates for monthly lake-water volume change.

Dependent: NDVI	
explanatory variable	β(P-value)
ENSO	1.203(0.019**)
ET	-0.087(0.541)
Precipitation	2.9(0.001***)
AR(1)=-0.309	AR(2)=0.314
J=5.122	PWald=0.000

Table 3. GMM parameter estimates for NDVI in the 100-km buffer zone.

5. Conclusion

This study examined the impacts of natural-factor variability on Lake Victoria water volume by integrating hydroclimatic indicators with econometric estimation methods. The results show that precipitation is the dominant factor controlling water-volume variation, while evapotranspiration exerts a negative effect through enhanced surface-water loss. ENSO affects lake water volume mainly by modulating regional rainfall and hydroclimatic conditions, although its influence is less direct and less stable than that of precipitation. In addition, NDVI is significantly associated with water-volume change, indicating that vegetation conditions within the basin respond sensitively to hydrological fluctuations and reflect broader land–water interactions. From the comparison of statistical approaches, bivariate analysis and OLS are effective for identifying general relationships, whereas moment-based estimators, particularly GMM, provide more reliable inference when endogeneity and temporal dependence are present.

This study provides an empirical framework for understanding the hydroclimatic sensitivity of Lake Victoria under changing natural conditions and offers useful evidence for regional water-resource assessment and lake management. However, several limitations should be noted. The analysis is constrained by the temporal consistency and spatial resolution of remote-sensing and climatic datasets, and some hydroclimatic processes may not be fully captured by the selected variables. In addition, the indirect influence of large-scale climate signals on lake dynamics may involve more complex lagged and nonlinear mechanisms than those represented in the present models. Future work should incorporate higher-resolution multi-source observations, longer time series, and more comprehensive process-based or coupled modeling strategies to improve the explanation of lake-volume variability and strengthen predictive capability under climate uncertainty.

References

Akurut, M., Willems, P., and Niwagaba, C. B. (2014). Potential impacts of climate change on precipitation over Lake Victoria, East Africa, in the 21st century. *Water*, *6*(9), 2634–2659.

An, C., Zhang, F., Chan, N. W., Johnson, V. C., & Shi, J. (2022). A review on the research progress of lake water volume estimation methods. *Journal of Environmental Management*, *314*, 115057.

Anyah, R. O., Semazzi, F. H. M., & Xie, L. (2006). Simulated physical mechanisms associated with climate variability over Lake Victoria Basin in East Africa. *Monthly Weather Review*, *134*(12), 3588-3609.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277-297.

Asadullah, A., McIntyre, N., and Kigobe, M. (2008). Evaluation of five satellite products for estimation of rainfall over Uganda. *Hydrological Sciences Journal*, *53*(6), 1137–1150.

Awange, J. L., Anyah, R., Agola, N., Forootan, E., & Omondi, P. (2013). Potential impacts of climate and environmental change on the stored water of Lake Victoria Basin and economic implications. *Water Resources Research*, *49*(12), 8160-8173.

Becker, M., Llovel, W., Cazenave, A., Güntner, A., & Crétaux, J.-F. (2010). Recent hydrological behavior of the East African great lakes region inferred from GRACE, satellite altimetry and rainfall observations. *Comptes Rendus Geoscience*, *342*(3), 223-233

Birkett, C. M., Murtugudde, R., & Allan, J. A. (1999). Indian Ocean climate event brings floods to East Africa's lakes and the Sudd Marsh. *Geophysical Research Letters*, *26*(8), 1031-1034.

Cattani, E., Merino, A., Guijarro, J. A., and Levizzani, V. (2018). East Africa rainfall trends and variability 1983–2015 using three long-term satellite products. *Remote Sensing*, *10*(6), 931.

Chamaillé-Jammes, S., and Fritz, H. (2009). Precipitation–NDVI relationships in eastern and southern African savannas vary along a precipitation gradient. *International Journal of Remote Sensing*, *30*(13), 3409–3422.

Cretaux, J.-F., Kouraev, A., Bergé-Nguyen, M., & Cazenave, A. (2005). Satellite altimetry for monitoring lake level changes. *In Transboundary Water Resources: Strategies for Regional Security and Ecological Stability* (pp. 141-146).

Davenport, M. L., and Nicholson, S. E. (1993). On the relation between rainfall and the normalized difference vegetation index for diverse vegetation types in East Africa. *International Journal of Remote Sensing*, *14*(12), 2369–2389.

Donchyts, G., Baart, F., Winsemius, H., Gorelick, N., Kwadijk, J., & van de Giesen, N. (2016). Earth's surface water change over the past 30 years. *Nature Climate Change*, *6*, 810-813.

Ghebrezgabher, M. G., Yang, T., Yang, X., and Sereke, T. E. (2020). Assessment of NDVI variations in responses to climate change in the Horn of Africa. *Egyptian Journal of Remote Sensing and Space Science*, *23*(3), 249–261.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, *50*(4), 1029-1054.

Hawinkel, P., Thiery, W., Lhermitte, S., Swinnen, E., Verbist, B., Van Orshoven, J., and Muys, B. (2016). Vegetation response to precipitation variability in East Africa controlled by biogeographical factors. *Journal of Geophysical Research: Biogeosciences*, *121*(9), 2422–2444.

Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*, *83*(1-2), 195-213.

Kalisa, W., Igbawua, T., Henchiri, M., Ali, A., Zhang, S., Mzuri, O. R., Ujoh, F., Namugize, J. N., and Zhang, J. (2019). *Assessment of climate impact on vegetation dynamics over East Africa from 1982 to 2015. Scientific Reports*, *9*, 16865.

Khaki, M., Awange, J., & Forootan, E. (2021). The 2019-2020 rise in Lake Victoria monitored from space. *Sensors*, *21*(13), 4304.

Khaki, M., Awange, J., Forootan, E., Kuhn, M., van Dijk, A. I. J. M., Schumacher, M., & Sharifi, M. A. (2019). Improved remotely sensed satellite products for studying Lake Victoria's water storage changes. *Science of the Total Environment*, *652*, 915-926.

Kizza, M., Westerberg, I., Rodhe, A., and Ntale, H. K. (2012). Estimating areal rainfall over Lake Victoria and its basin using ground-based and satellite data. *Journal of Hydrology*, 464–465, 401–411.

Mistry, V. V., & Conway, D. (2003). Remote forcing of East African rainfall and relationships with fluctuations in levels of Lake Victoria. *International Journal of Climatology*, *23*(1), 67-89.

Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika*, *37*(1-2), 17-23.

Nicholson, S. E. (2017). Climate and climatic variability of rainfall over eastern Africa. *Reviews of Geophysics*, *55*(3), 590–635.

Nicholson, S. E., Davenport, M. L., and Malo, A. R. (1990). A comparison of the vegetation response to rainfall in the Sahel and East Africa, using normalized difference vegetation index from NOAA AVHRR. *Climatic Change*, *17*, 209–241.

Onyutha, C., Acayo, G., and Nyende, J. (2020). Analyses of precipitation and evapotranspiration changes across the Lake Kyoga Basin in East Africa. *Water*, *12*(4), 1134.

Pekel, J.-F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes. *Nature*, *540*(7633), 418-422.

Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J.-M., Tucker, C. J., & Stenseth, N. C. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in Ecology & Evolution*, *20*(9), 503-510.

Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. *Econometrica*, *26*(3), 393-415.

Senay, G. B., Kagone, S., & Velpuri, N. M. (2020). Operational global actual evapotranspiration: Development, evaluation, and dissemination. *Sensors*, *20*(7), 1915.

Vanderkelen, I., van Lipzig, N. P. M., & Thiery, W. (2018). Modelling the water balance of Lake Victoria (East Africa) - Part 1: Observational analysis. *Hydrology and Earth System Sciences*, *22*, 5509-5525.

Williamson, C. E., Saros, J. E., Vincent, W. F., & Smol, J. P. (2009). Lakes and reservoirs as sentinels, integrators, and regulators of climate change. *Limnology and Oceanography*, *54*(6 part 2), 2273-2282.

Wolter, K., & Timlin, M. S. (2011). El Niño/Southern Oscillation behaviour since 1871 as diagnosed in an extended multivariate ENSO index (MEI.ext). *International Journal of Climatology*, *31*(7), 1074-1087.

Yu, J., Rong, Y., Lin, Y., Li, X., Gao, C., Zhang, T., Zhou, X., Cai, J., & Sneeuw, N. (2023). Spatiotemporal dynamic impacts of Lake Victoria water volume variations on sustainable economic development. *International Journal of Applied Earth Observation and Geoinformation*, *123*, 103475

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