

Original Research

Characterization of Drought Severity Using GRACE and TerraClimate Dataset in the Rift Valley Basin, Ethiopia

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Abstract

Characterizing drought severity using GRACE and TerraClimate datasets is globally important because it enables consistent, large-scale monitoring of both surface and subsurface water availability across data-scarce regions. This integrated perspective supports improved drought assessment, climate change impact analysis, and informed water-resource management worldwide. The Ethiopian Rift Valley has experienced recurrent hydrological drought hazards, posing serious threats to water availability, agricultural productivity, ecosystem stability, and the socio-economic well-being of local communities. The region's high spatial and temporal variability of rainfall has contributed to recurrent and severe drought episodes, emphasizing the need for reliable drought monitoring and assessment tools. This study utilizes GRACE (Gravity Recovery and Climate Experiment)-derived terrestrial water storage (TWS) data to develop a GRACE-based drought index (GRDI/WSDI) for the Rift Valley Basin from 2002 to 2016. GRACE data provide a unique integrated measure of hydrological components, including surface water, soil moisture, and groundwater, enabling the detection of droughts



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that conventional meteorological indices may not capture. The study also evaluates conventional drought indices, including SPI, SPEI, SRI, ESI, and EDDI, across multiple accumulation periods (3, 6, 9, 12, 18, 24, 36, and 48 months) to examine temporal drought characteristics such as severity, duration, and cumulative deficit. The GRACE-based analysis revealed extreme drought events in 2013 and 2014, with total drought indices of 10.3 and 15.9, respectively, indicating prolonged and severe water deficits. Additionally, significant drought periods were consistently identified during 2002-2003, 2007-2012, and 2014-2016 across multiple indices. Comparative analysis demonstrated strong agreement among SPI, SPEI, SRI, and ESI, while GRDI/WSDI uniquely captured large-scale water storage deficits, including groundwater depletion. The EDDI, which reflect atmospheric evaporative demand, displayed complementary drought signals, highlighting the importance of multiple indices for comprehensive drought assessment. The findings indicate that droughts in the Rift Valley Basin have become increasingly frequent, prolonged, and severe in recent decades, consistent with regional climate variability and global climate change trends. This study underscores the value of integrating satellite-based hydrological observations with conventional meteorological and remote sensing indices to improve drought monitoring, early warning systems, and water resources management. The results provide actionable insights for policymakers, water resource managers, and stakeholders to implement effective drought mitigation strategies, optimize water allocation, and enhance resilience to climate-induced water stress in one of Ethiopia's most vulnerable basins.

Keywords

GRACE; Terrestrial Water Storage (TWS); drought index; GRDI/WSDI; hydrological drought; Rift Valley Basin; water resource management; climate variability; drought monitoring

1. Introduction

Due to the combined effects of climate change and intensified anthropogenic activities, rapidly growing populations worldwide are increasingly exposed to water scarcity [1-3]. Recent studies indicate that hydrological droughts have significantly affected socio-economic systems, including agricultural productivity, water resource availability, and ecosystem functioning [4]. In Ethiopia, the impacts of climate variability and change are particularly pronounced, as the country has experienced recurrent climate-related hazards, including droughts, floods, and extreme rainfall events. These hazards are further exacerbated by human-induced factors, including land-use change, environmental degradation, population pressure, and socio-political instability [5, 6].

Ethiopia has endured several severe drought episodes in recent decades, including the worst drought recorded in the past 40 years, which resulted in widespread humanitarian crises, loss of livestock, reduced agricultural yields, and degradation of natural resources. Such extreme events have profound consequences for livelihoods, food security, and ecosystem resilience. Climate change is projected to increase both the frequency and intensity of these extreme hydrological events, thereby amplifying vulnerability, particularly among rural and pastoral communities [7]. The country's complex and highly variable topography further contributes to uneven spatial and

temporal rainfall distribution, thereby intensifying the persistence and severity of drought across regions.

Moreover, recent evidence suggests that droughts in Ethiopia have become more frequent, with some regions experiencing two or even three consecutive years of droughts [8, 9]. This increasing recurrence reduces recovery time for affected systems and undermines long-term socio-economic development. Consequently, a comprehensive understanding of drought characteristics—including frequency, duration, severity, and spatial extent—is essential for effective drought monitoring, risk assessment, and the development of sustainable adaptation and water-resource management strategies [10].

Characterizing drought at spatio-temporal scales remains challenging due to the complex interactions among multiple hydro-meteorological factors, including precipitation variability, evapotranspiration, soil moisture dynamics, and groundwater processes [11, 12]. Traditional drought indices, which are often based on single variables, may therefore fail to capture the integrated nature of drought conditions across different components of the hydrological cycle. In this context, satellite-based observations have emerged as valuable tools for overcoming data limitations, particularly in data-scarce regions.

The Gravity Recovery and Climate Experiment (GRACE) satellite mission provides unique insights into variations in terrestrial water storage (TWS), encompassing surface water, soil moisture, snow, and groundwater components [13-15]. GRACE-derived TWS anomalies have been widely applied to detect hydrological extremes and to develop drought indices that reflect integrated water storage deficits. Numerous studies have demonstrated the robustness and reliability of GRACE-based drought monitoring and evaluation, confirming its effectiveness across diverse climatic and hydrogeological settings [16-19]. Consequently, GRACE observations offer a powerful framework for improving drought characterization and assessment at regional to continental scales, particularly in regions where in situ hydrological data are limited or unavailable.

Despite extensive applications of conventional drought indices—such as the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and Palmer Drought Severity Index (PDSI)—these methods primarily rely on meteorological variables and often fail to capture subsurface hydrological processes, particularly groundwater dynamics and total basin-scale water storage changes. As a result, traditional indices may inadequately represent the cumulative and delayed impacts of drought, especially in regions characterized by complex hydroclimatic conditions and limited in situ observations [20, 21].

In contrast, drought indices derived from the Gravity Recovery and Climate Experiment (GRACE) satellite mission offer a fundamentally different and integrative perspective by directly measuring spatio-temporal variations in terrestrial water storage (TWS). GRACE-based indices inherently incorporate multiple components of the hydrological cycle, including surface water, soil moisture, and groundwater, thereby enabling the detection of both rapid-onset and long-term hydrological droughts. This capability is particularly valuable for identifying groundwater depletion and persistent water deficits that are often overlooked by precipitation-based indices [22-25].

Moreover, GRACE-derived drought indicators provide consistent, large-scale observations that transcend political boundaries and mitigate the limitations of sparse or unevenly distributed ground-based monitoring networks. Numerous studies have demonstrated that GRACE-based indices not only complement traditional drought metrics but also enhance drought early warning systems by capturing the integrated response of hydrological systems to climatic anomalies and

anthropogenic water use [12, 26, 27]. Consequently, the incorporation of GRACE-derived drought indices represents a significant advancement in drought monitoring and assessment, offering a robust and holistic framework for understanding drought dynamics under a changing climate.

Traditional methods for estimating drought, which focus on single factors like precipitation (meteorological), soil moisture (agricultural), and streamflow (hydrological), are insufficient for evaluating the total amount of water stored in a large river basin (terrestrial water storage) [24]. This is because these traditional methods do not capture the complex, interconnected processes of water storage, such as groundwater, snowpack, and vegetation [24]. Estimating terrestrial water storage requires a more comprehensive approach that considers all components of the water cycle, not just the more visible or commonly measured aspects [24]. Therefore, drought analysis is essential for understanding and managing water scarcity because it uses satellite data and indices to monitor conditions, support past research, and inform future planning.

Although classical drought indices and emerging holistic indicators have been widely applied at global and regional scales, their spatio-temporal dynamics, comparative performance, and inherent limitations at basin and sub-basin levels remain poorly understood [28-33]. This knowledge gap is particularly evident in data-scarce regions such as the Ethiopian Rift Valley Basin, where scale mismatch constrains the effective translation of global drought monitoring products into local water-resource management and early-warning applications. Numerous studies have examined droughts in the Rift Valley Lake Basin to characterize and measure drought indicators, using meteorological drought indices [10, 30]. Currently, no studies utilize GRACE-based water storage to estimate the drought index in the study region. The GRACE-based water storage shows the total volume of water in the region, including groundwater [13-15, 19, 34, 35]. Therefore, the work aims to evaluate the drought index using GRACE-based water storage change in the study region from 2002 to 2016. The specific objective of this study is to analyse the water storage deficit and the water storage deficit index based on the available GRACE dataset. To evaluate hydrological drought indices at different time periods. To evaluate drought severity, duration, and cumulative drought index, and compare it with the newly proposed GRACE drought index from 2002 to 2016 in the study region.

2. Materials and Methods

2.1 Description of the Study Area

The study was conducted in the southern Ethiopian Rift Valley lake basin, which is geographically situated between 36°-40° E and 4°-9° N (Figure 1) [36]. This region is a large, important basin in Ethiopia, extending south from the Afar depression to Kenya and encompassing the Abijata-Ziway, Abaya-Chamo, and Segen lake systems. It is part of the larger Ethiopian Rift Valley system.

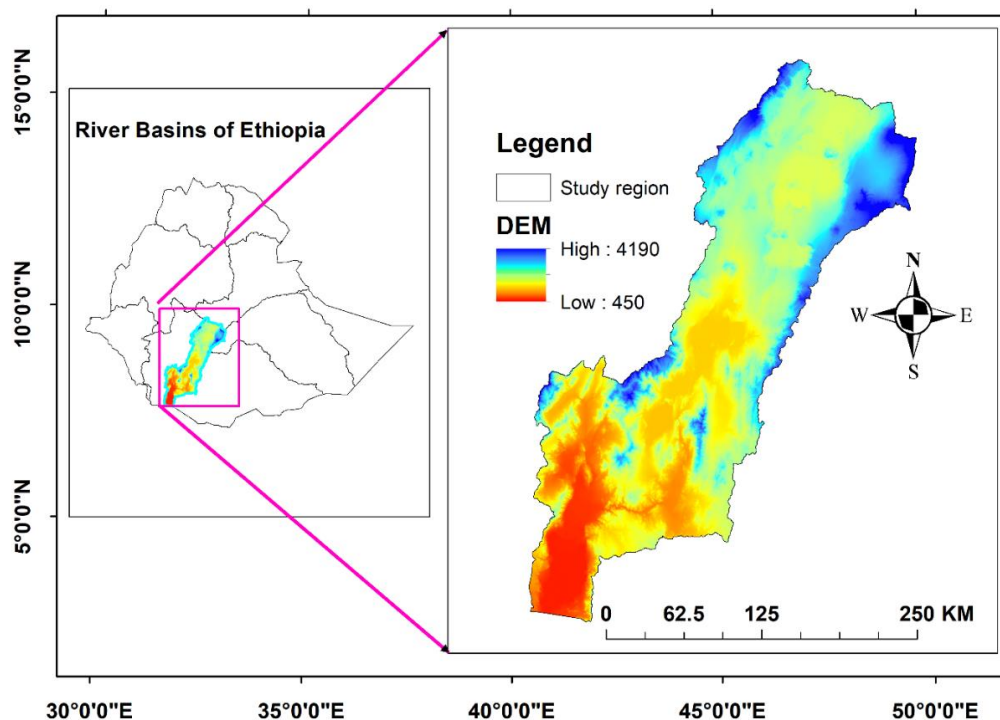


Figure 1 Location map of Rift Valley basin in Ethiopia with elevation model.

The Ethiopian Rift Valley Basin (ERVB) constitutes a major physiographic and hydrological system within the East African Rift System, extending from the central highlands of Ethiopia toward the Afar Depression. This geological structure creates a diverse landscape with varied elevations, a network of faults, volcanoes, and highlands that divide the country. The basin is characterized by complex topography, with high-altitude escarpments of 500-1700 meters and steep escarpments reaching 4181 meters on either side. This pronounced elevation gradient exerts strong control on climatic conditions, hydrological processes, and land-use patterns across the basin.

Hydrologically, the Rift Valley Basin is predominantly an endorheic (closed) drainage system, comprising a network of rivers, ephemeral streams, wetlands, and a chain of tectonically formed lakes, including Lakes Ziway, Langano, Abijata, Shala, Abaya, and Chamo. River flow within the basin is largely controlled by seasonal precipitation and exhibits strong interannual variability. Major rivers, such as the Meki, Katar, Bulbula, and Bilate, originate in the surrounding highlands and drain toward the rift floor, where they discharge into lakes rather than reaching the ocean. Groundwater plays a critical role in sustaining baseflow and lake levels, particularly during dry periods, and is closely linked to the region's complex volcanic geology and fault systems.

The basin provides ecosystem services, such as acting as a natural habitat for diverse birds, fish, and wildlife species. These services are vital for maintaining biodiversity and supporting life within the basin, which is a crucial concept in ecology. The Ethiopian Rift Valley is a biodiverse region with over 500 bird species and 33 fish species, and its ecosystems are significantly affected by land-use changes and climate dynamics. These changes, driven by human activities like agriculture and urbanization, impact the region's water resources and wildlife [37-39].

Land use and land cover (LULC) patterns within the basin have undergone substantial transformations over recent decades, driven primarily by population growth, agricultural expansion, urbanization, and infrastructure development. Rainfed and irrigated agriculture dominate the highland and mid-altitude areas, while pastoral and agro-pastoral systems prevail in the lowlands.

The expansion of irrigation schemes, particularly around rift lakes and along major rivers, has intensified pressure on both surface water and groundwater resources. Concurrently, deforestation, wetland degradation, and land conversion have altered hydrological response mechanisms, including infiltration rates, runoff generation, and evapotranspiration dynamics.

From a socio-environmental perspective, the Rift Valley Basin supports a large and rapidly growing population whose livelihoods are highly dependent on climate-sensitive sectors, including agriculture, fisheries, and livestock production. Water resources within the basin are increasingly contested due to competing demands from domestic, agricultural, industrial, and ecological users. Environmental challenges—including declining lake levels, groundwater depletion, soil erosion, and water quality deterioration—have been widely reported, raising concerns over long-term sustainability and ecosystem resilience.

Climatically, the basin exhibits marked spatial and temporal variability influenced by elevation, regional atmospheric circulation, and large-scale climate drivers such as the Intertropical Convergence Zone (ITCZ) and El Niño-Southern Oscillation (ENSO). Rainfall follows a bimodal to unimodal pattern by location, with the main rainy seasons typically occurring from June to September and secondary rains from February to May. The basin is highly vulnerable to climate extremes, particularly recurrent droughts and occasional floods, which have increased in frequency and intensity in recent decades. These climatic fluctuations, coupled with anthropogenic pressures, exacerbate hydrological variability and heighten the basin's susceptibility to water scarcity and drought-related impacts. The Ethiopian Rift Valley basin has three seasons based on rainfall: the main rainy season (Kiremt from June to September), the slight rainy season (Belg from February to May), and the dry season (Bega from October to January) that define the features of the region's climate and significantly impact its agriculture [36].

2.2 Data Collection

The necessary data (Table 1) used for the research were obtained from TerraClimate, which is available globally from 1958 at 0.5° [40-42]. The GRACE datasets from CSR (University of Texas/Center for Space Research), GFZ (GeoForschungsZentrum Potsdam), and JPL (NASA Jet Propulsion Laboratory) [13-15, 19, 34, 35, 43-45] and signal loss was removed to smoothed the dataset using a de-stripping filter, Gaussian smoothing, and glacier isostatic adjustment [45-48]. The data processing methodology employed in this study followed established procedures for Gravity Recovery and Climate Experiment (GRACE) data analysis, with particular emphasis on post-processing techniques designed to reduce noise and systematic errors. Specifically, Gaussian spatial smoothing and destripping methods were applied to mitigate correlated errors and north-south striping artifacts inherent in GRACE spherical harmonic solutions. These post-processing steps were implemented in accordance with the approaches outlined by Longuevergne et al. [43, 49], which have been widely adopted and validated in GRACE-based hydrological applications. The effectiveness of these techniques in enhancing signal-to-noise ratios and improving the reliability of terrestrial water storage anomaly estimates has been demonstrated across diverse climatic and hydrogeological settings [43, 50, 51]. The total water storage was evaluated by the following equation, which was supported by others.

$$TWS = S + SS + G + CW \quad (1)$$

where S, SS, G, and CW represent surface water, soil moisture, groundwater, and vegetation water, respectively.

Table 1 Remote sensing datasets used for this study.

Variables	Source and processing
GRACE-dataset	GRACE satellite (JPL, CSR, GFZ) at (1° × 1°)
Terra-Climate	Actual evapotranspiration (0.5° × 0.5°)
Actual evapotranspiration (AET)	Resample to (1° × 1°)
Terra-Climate	Precipitation (0.5° × 0.5°)
Precipitation (RF)	Resample to (1° × 1°)
Terra-Climate Actual Surface Runoff	Surface runoff (0.5° × 0.5°)
	Resample to (1° × 1°)

2.3 Methodology

The proposed methodology for evaluating drought indices in this study is based on GRACE data from 2002 to 2016 [43, 50] and Terra-Climate data from 1991 to the present [52, 53]. The drought indices used for this study were presented as follows.

2.3.1 Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) quantifies rainfall deficiencies on multiple time scales to detect and monitor drought. It does this by comparing a location's historical precipitation record to its current precipitation, creating a standardized value that indicates if conditions are wetter (positive SPI) or drier (negative SPI) than the median [53, 54]. The chosen timescale (e.g., 1, 6, or 12 months) determines whether the index captures short-term dryness or long-term drought and is frequently used and recognized worldwide [55].

Shorter-term SPI (1-6 months) is used for monitoring meteorological drought, as it reflects recent precipitation deficits, while longer-term SPI (12-24 months) acts as a proxy for agricultural and hydrological drought because it accounts for the cumulative effects on soil moisture and streamflow over a longer period [54, 56].

The Standardized Precipitation Index (SPI) requires only precipitation data and calculates drought by fitting that data to a gamma distribution to find the cumulative probability, which is then transformed to a standard normal distribution. This process compares the observed precipitation to its long-term average for a given period and location, providing a standardized measure of drought or wetness using equation (2) [57, 58]. The detailed method for evaluating SPI, including its normalization, was explained by different studies [25, 58, 59] and the cumulative deficit of precipitation (drought magnitude) (DM) was evaluated as follows [25].

$$DM = \sum_{i=1}^n SPI_{ij} \quad (2)$$

Equation (2) was multiplied by negative one to remove and rewritten as follows:

$$DM = \left(\sum_{i=1}^n SPI_{ij} \right) * (-1) \quad (3)$$

Drought magnitude divided by drought duration ($Dd(t)$) is called drought intensity (DI) and calculated as follows:

$$DI = \frac{DM}{Dd(t)} \quad (4)$$

2.3.2 Standardized Precipitation Evapotranspiration Index (SPEI)

The standardized Precipitation Evapotranspiration Index (SPEI) is a drought index that incorporates both precipitation and potential evapotranspiration (PET) and is therefore highly responsive to global warming, which increases atmospheric evaporative demand. Its ability to account for temperature-driven water loss makes it more effective than the SPI in characterizing drought severity, especially in arid and semi-arid regions. The SPEI is used to identify the onset, duration, and magnitude [59]. The SPEI analysis was carried out by different scholars using rainfall and potential evaporation data that were fitted with a log-logistic distribution [25, 60, 61], and its detailed analysis was supported by similar study [58], and its severity was associated with evaporative water demand [61].

2.3.3 Evaporative Stress Index (ESI)

Evaporative Stress Index (ESI) is computed as the ratio of actual evapotranspiration (ET_a) to potential evapotranspiration (ET_p) as shown in equation (5) [62-64]. This ratio indicates the degree of evaporative stress on an ecosystem, where a value closer to 1 means no stress and lower values indicate a higher level of drought stress [65].

$$ESI = \frac{ET_a}{ET_p} \quad (5)$$

Where ET_a is actual evapotranspiration, ET_p is potential evapotranspiration, which was calculated using the Hargreaves equation presented in equation (6) [65].

$$ET_p = 0.0135 * Rs(T_{mean} + 17.8) \quad (6)$$

Where Rs is solar radiation and T_{mean} is the average temperature of the study area in degree Celsius, ESI is sensitive to moisture stress, which indicates terrestrial water storage availability [66]. The ESI value ranges from -3.5 to 3.5 after normalization. A positive ESI value shows less or no drought occurrence, whereas the negative value indicates the occurrence of drought for a given location and period [67-69].

2.3.4 Evaporative Demand Drought Index (EDDI)

The Evaporative Demand Drought Index (EDDI) is a currently proposed drought index that relies on potential evapotranspiration (ET_p) [70]. EDDI is a drought monitoring tool that measures

anomalies in atmospheric evaporative demand (a measure of the atmosphere's "thirst" for water), which is a component of ET_p [69, 70]. EDDI uses a calculation based on atmospheric physics principles to assess the extent to which atmospheric demand is unusually high, which can lead to drought [67]. As in other drought index analyses, the calculated EDDI was normalized by surplus or deficit. A positive Evaporative Demand Drought Index (EDDI) value indicates drier-than-normal conditions with higher evaporative demand, whereas a negative value indicates wetter-than-normal conditions with lower evaporative demand [70]. For this study, the EDDI was evaluated at different time scales.

2.3.5 GRACE-Derived Based Drought Indices (WSDI)

The deficit in water storage is obtained by total monthly water storage minus long-term total water storage [12, 71, 72], which is expressed in equation (7).

$$WSD_{k,p} = TWS_{k,p} - \overline{TWSA}_{k,p} \quad (7)$$

Where $WSD_{k,p}$ shows scarcity of water, $TWS_{k,p}$ shows terrestrial water storage annuals; $\overline{TWSA}_{k,p}$ is the average of long-term water storage. A negative WSD indicates a water shortage, whereas a positive value indicates a water surplus [71]. Unlike other indices, WSDI provides a more holistic view by incorporating data from satellites like GRACE to show a more complete picture of water scarcity. This allows for a better characterization of the severity of drought, its duration, and spatial change, especially in areas with limited ground-based hydrological data, and is evaluated using equation (8).

$$WSDI_{k,p} = \frac{WSD_{k,p} - \mu}{\sigma} \quad (8)$$

Where $WSDI_{k,p}$ is WSDI time series for the P^{th} month in the year k ; μ is the mean of the WSD; and σ represents standard deviation of the WSD. The Water Storage Deficit (WSD) was standardized as the Water Storage Deficit Index (WSDI) to facilitate comparison with other standardized drought indices. This standardization involves a normalization process, typically using a mean-zero method, which allows for better characterization of drought severity and comparison with indices derived from meteorological data. The WSDI represents the relative monthly departure from the average situation, with negative values indicating drought conditions [71], and is presented in equation (9) below.

$$Sev(t) = Mm(t) * Dd(t) \quad (9)$$

Where $Sev(t)$ and $Mm(t)$ show the severity and the average WSD of drought events at period t , respectively, $Dd(t)$ indicates the number of consecutive months between the start and end of the drought events. This drought severity measure is the water storage deficit (WSD), whereas WSDI denotes the relative monthly water deficit for drought events.

2.3.6 Surface Runoff Drought Indices (SRI)

The surface runoff drought index is a multivariate hydrological drought index that shows the potential of rainfall runoff for evaluating drought in the river basin. It is calculated by fitting a

lognormal distribution function to the rainfall runoff [73]. It is similar to SPI and dimensionless. For this study, we used the Terra-Climate dataset to evaluate drought characteristics associated with rainfall-runoff.

2.4 Drought Severity Characterization

The following drought severity classes are used to describe the magnitude of drought events in the study region, as indicated in Table 2. These indices quantify drought into categories like mild, moderate, severe, and extreme, which can then be used for analysis and mitigation strategies in the region.

Table 2 Characteristics of drought intensity for EDDI, SPI, SPEI, ESI, and WSDI/GRDI.

Drought condition	EDDI	SPI, SPEI, ESI	WSDI/GRDI
Extreme drought	≥ 2.0	≤ -2	≤ -3
Severe drought	1.5 to 1.99	-1.99 to -1.5	-3 to -2
Moderate drought	1.0 to 1.49	-1.49 to -1.0	-2 to -1
Mild drought	0.5 to 0.99	-0.99 to -0.5	-0.99 to 0
Near Normal			
Normal	$-0.5 \leq 0 \leq 0.5$	$-0.5 \leq 0 \leq 0.5$	
Wild	-0.99 to -0.5	0.5 to 0.99	0.0 to 0.99
Moderate wet	-1.49 to -1.0	1.0 to 1.49	1 to 2
Very wet	-1.99 to -1.5	1.5 to 1.99	2 to 3
Extremely wet	≤ -2	≥ 2.0	≥ 3

Sources: [70, 74, 75].

2.5 Correlation Analysis

To estimate the consistency and similarity of GRACE and other drought indices, Pearson's correlation coefficient was used here, as shown in equation (10) below [76].

$$r(GR, GL) = \frac{\sum_{i=1}^n (GR_i - \overline{GR})(GL_i - \overline{GL})}{\sqrt{\sum_{i=1}^n (GR - \overline{GR})^2} \sqrt{\sum_{i=1}^n (GL - \overline{GL})^2}} \quad (10)$$

Where GR is the monthly terrestrial water storage estimated from GRACE, GL is the monthly hydroclimatic factor calculated from GRACE, and n is the number of months.

2.5.1 Evaluation of Methods of Model Performance

To calculate downscaled terrestrial water storage results, four statistical metrics were used MAE, NSE, R, and RME. The mathematical representation of MAE, NSE, R, and RME is shown in equations (11)-(14) below [76]. For RMSE and MAE, the values close to 0 indicate a perfect model, whereas in NSE and R, values closer to 1 indicate a perfect model [77].

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (X_i - Y_i)^2}{N}} \quad (11)$$

$$NSE = 1 - \frac{\sum_{i=1}^N (Y_i - \bar{Y})^2}{\sum_{i=1}^N (X_i - \bar{X})^2} \quad (12)$$

$$R = \frac{\sum_{i=1}^N (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^N (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^N (Y_i - \bar{Y})^2}} \quad (13)$$

$$MAE = \frac{1}{N} \left(\sum_{i=1}^N |Y_i - X_i| \right) \quad (14)$$

where X_i and Y_i indicate control variables with the mean values of X and Y . The water storage was shown by X_i , and the prediction of the model is shown by Y_i . And N represents the total number of samples. The general methodology of the study is presented in Figure 2 below.

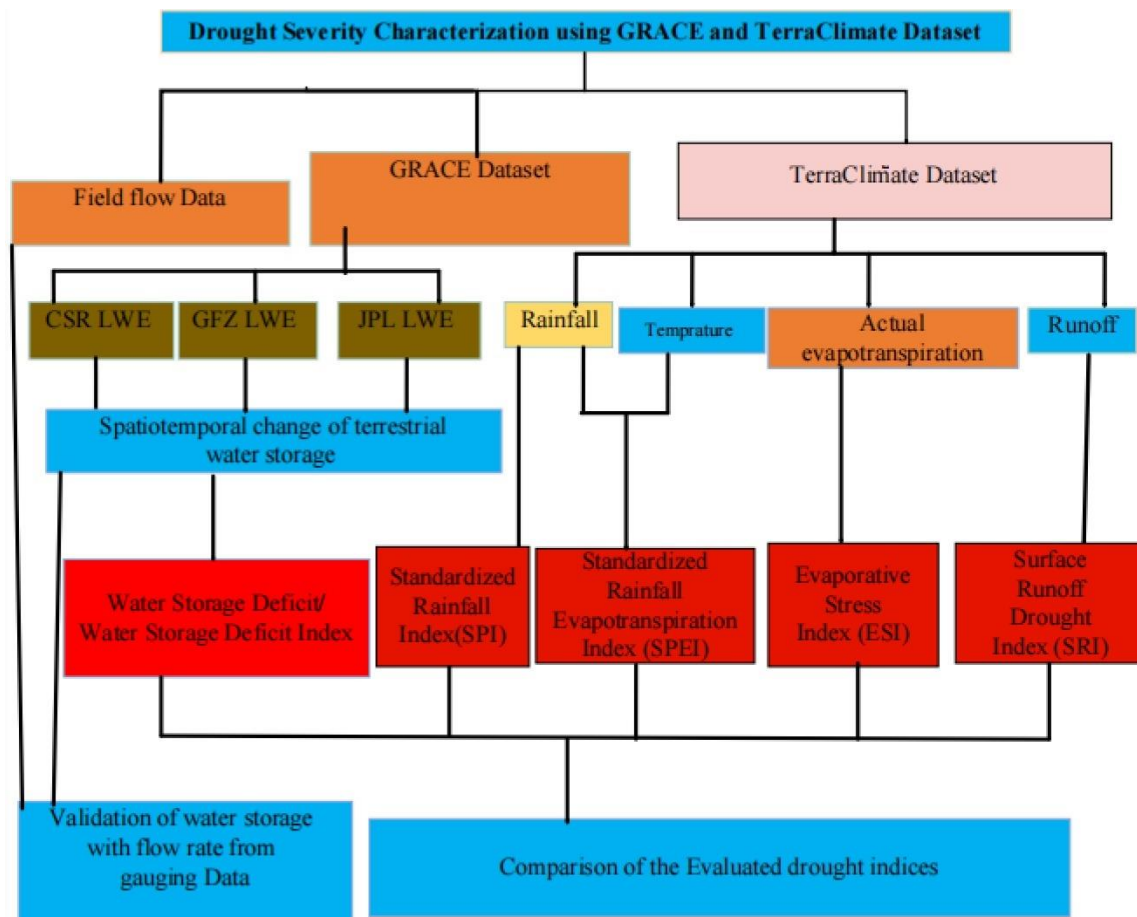


Figure 2 Flow chart for the evaluation of drought index in the region: where CSR - Centre for Space Research, GFZ - Centre for Space Research and JPL - Jet Propulsion Laboratory, LWE - liquid water equivalent.

3. Results and Discussion

3.1 Spatiotemporal Change and Trend of Seasonal and Annual Terrestrial Water Storage From GRACE

Figure 3 illustrates the interannual variability of terrestrial water storage (TWS) across the Rift Valley Basin, revealing pronounced temporal and spatial fluctuations over the study period. Overall, a declining trend in annual water storage is evident during the periods 2002-2006, 2007-2009, 2014-2016, and 2011. In contrast, increasing water storage trends were observed in 2007, 2010, and 2012-2014. Basin-wide negative water storage anomalies were particularly pronounced in 2004, 2005, and 2009, indicating widespread water mass deficits across the entire basin. The maximum terrestrial water storage anomaly was recorded in 2014, reaching 6.19 cm yr⁻¹, whereas the minimum value occurred in 2011, at 4.37 cm yr⁻¹.

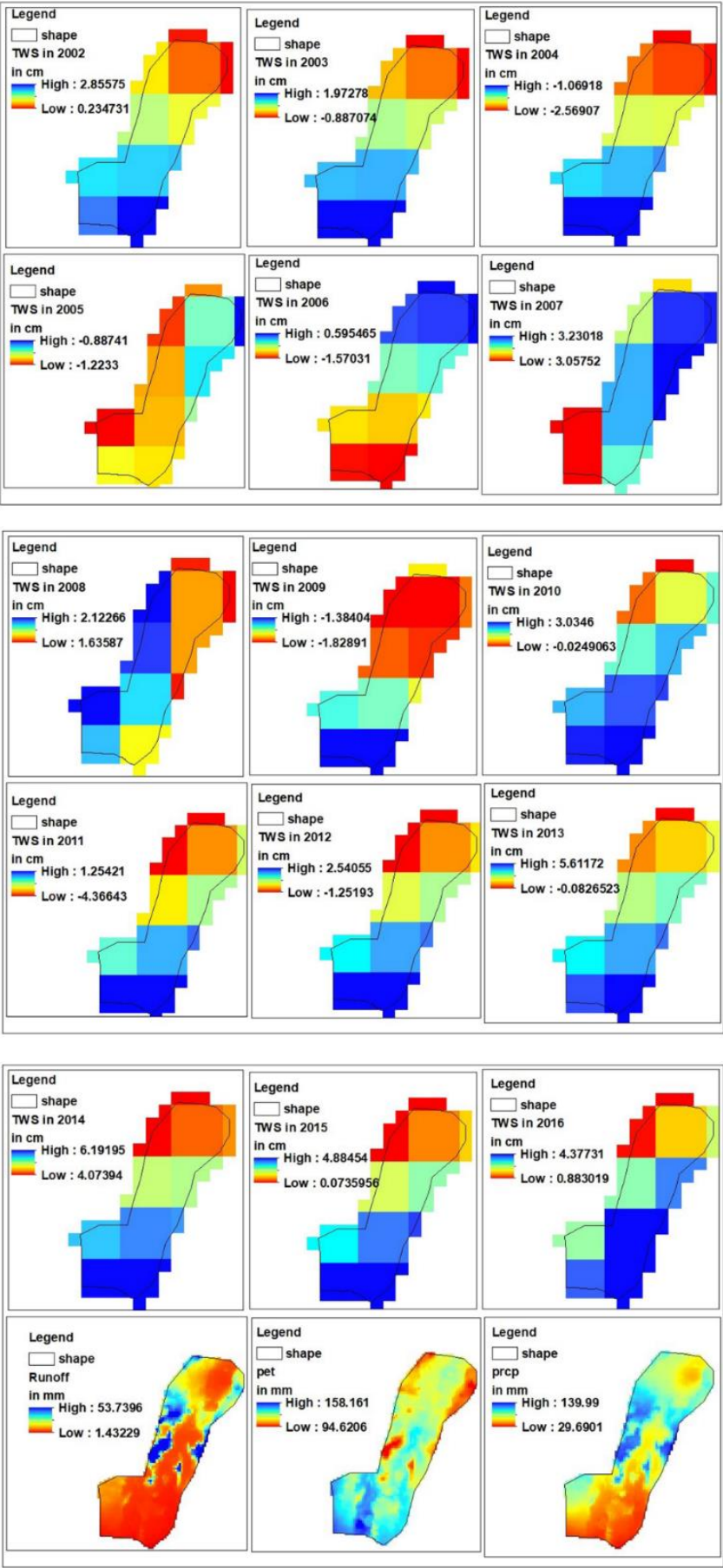


Figure 3 Annual and seasonal variation of the terrestrial water storage.

The spatio-temporal distribution of GRACE-derived TWS further highlights distinct regional patterns within the basin. Elevated water storage levels were predominantly observed in the southern parts of the Rift Valley Basin during the periods 2002-2004 and 2009-2016. In contrast, higher TWS anomalies in the northern region were detected primarily in 2006, while the central basin exhibited relatively high water storage during 2007 and 2008. Persistently low TWS values were observed in the northern portion of the basin throughout most of the GRACE observation period, except during 2006 and 2007, when the central Rift Valley experienced moderate to high terrestrial water storage. These spatial contrasts underscore the heterogeneous hydrological response of the basin to climatic variability and local hydrological controls.

3.1.1 Temporal Variation of GRACE-Based Terrestrial Water Storage for Rift Valley Basin

Figure 4 illustrates the temporal variability of terrestrial water storage (TWS) trends over the study period, highlighting alternating phases of water storage accumulation and depletion across the Rift Valley Basin. An increasing trend in TWS was observed during several periods, including a rise of approximately 7.81 cm yr^{-1} between 2002 and 2003, a substantial increase ranging from 5.0 to 46.24 cm between 2004 and 2007, an increase of 27.92 cm between 2009 and 2010, and sustained growth varying from 19.03 to 28.95 cm during the period 2011-2014.

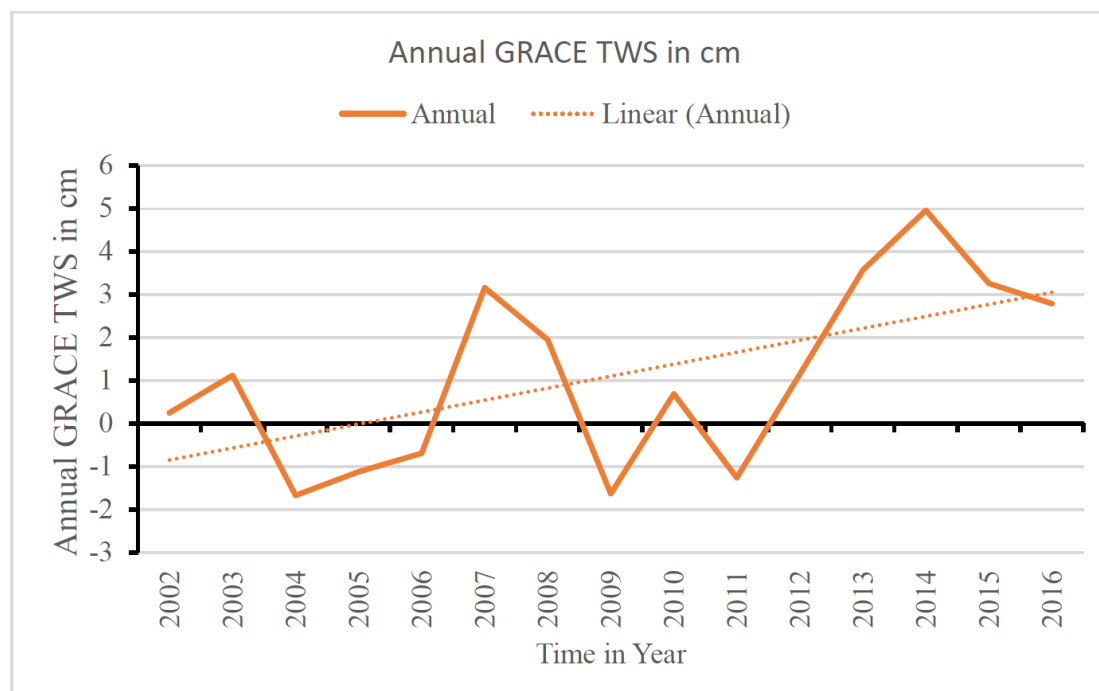


Figure 4 Annual GRACE terrestrial water storage for the rift valley river basin.

In contrast, pronounced declines in terrestrial water storage were recorded during other intervals, with a decrease of approximately 31.34 cm yr^{-1} between 2003 and 2004, reductions ranging from 14.51 to 42.98 cm between 2007 and 2009, a decline of 23.44 cm between 2010 and 2011, and decreases varying from 6.3 to 17.4 cm yr^{-1} during the period 2014-2016. These alternating phases of increasing and decreasing TWS reflect the strong interannual variability of basin-scale water storage, driven by climatic fluctuations and hydrological processes influencing surface and subsurface water components.

Figure 5 illustrates the seasonal time series of terrestrial water storage (TWS) in the Rift Valley River Basin, revealing distinct seasonal and interannual variability throughout the study period. The spring season is characterized by persistent water deficits from 2002 to 2014, with the lowest TWS anomaly recorded in 2011, reaching -7.66 cm yr^{-1} . In contrast, the summer season exhibited the highest terrestrial water storage, with a maximum of 22.1 cm yr^{-1} in 2016, indicating substantial water accumulation during peak rainfall periods.

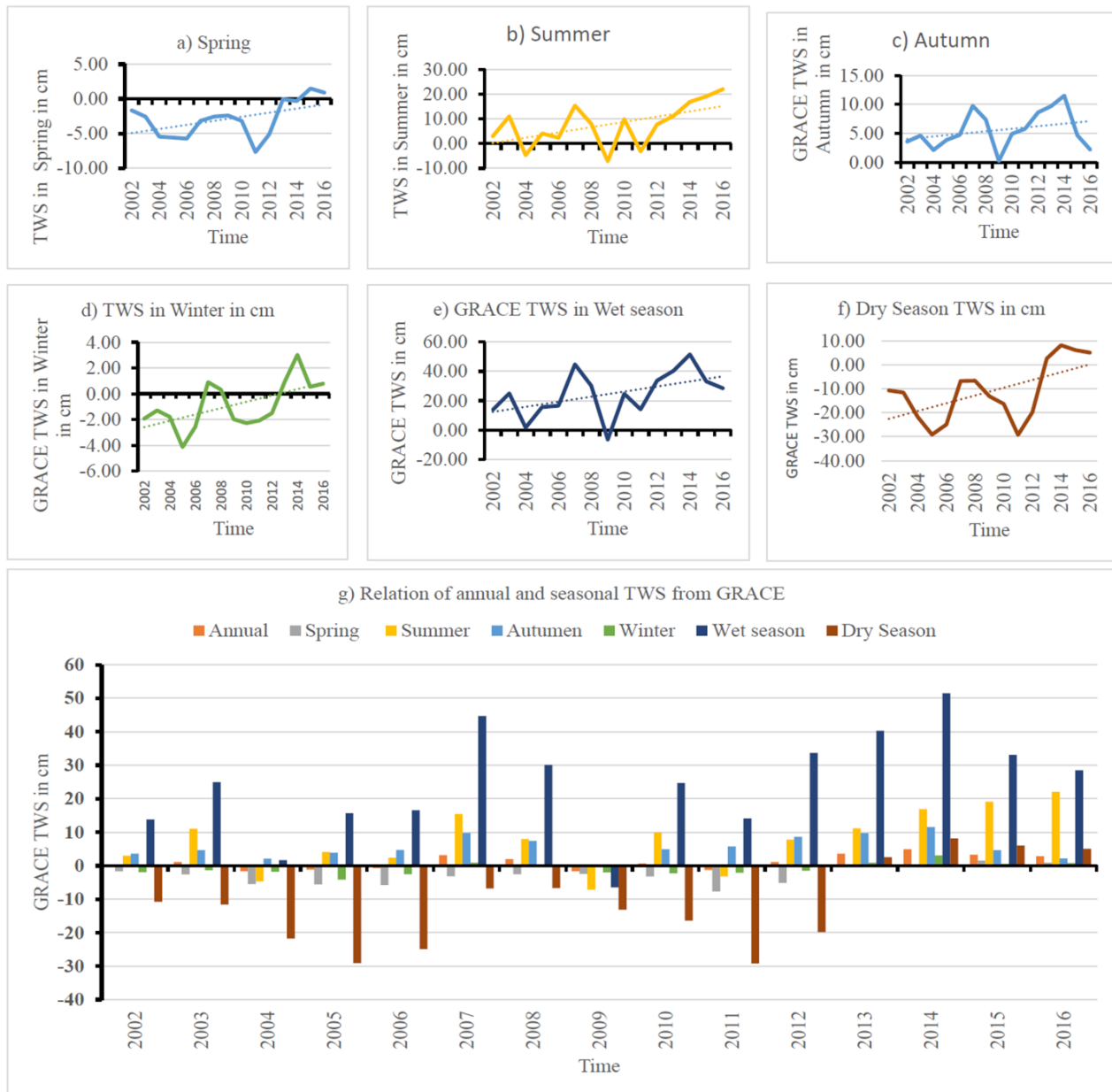


Figure 5 Seasonal and annual GRACE-based terrestrial water storage for the Rift Valley Basin.

As shown in Figure 5, positive terrestrial water storage anomalies were generally observed during the wet season in most years of the study period, reflecting seasonal recharge. However, notable exceptions occurred in 2004 and 2009, when the basin experienced markedly reduced water storage even during the wet season, indicating severe hydrological stress. During the dry season,

persistent water deficits were evident from 2002 to 2007 and from 2009 to 2013, while near-neutral or marginal water storage conditions were observed during 2007-2009 and 2013-2016.

As a result, the observed seasonal variability and long-term patterns of terrestrial water storage in the Rift Valley Basin are consistent with findings from previous studies conducted in the East African Rift System and parts of the Niger Basin, which report increasing trends in regional water storage attributed to climate variability and long-term climatic changes [78-80]. These results further support the robustness of GRACE-derived TWS observations in capturing large-scale hydrological responses to changing climate conditions.

3.1.2 Trend Analysis Using R-Studio and Forecasting of GRACE-Based Terrestrial Water Storage

The temporal variability of GRACE-derived terrestrial water storage (TWS) for the Rift Valley River Basin was analyzed using RStudio through a structured time-series analysis framework. Initially, the GRACE dataset was preprocessed by addressing missing observations using appropriate gap-filling techniques to ensure temporal continuity. The statistical properties of the dataset were then examined, including stationarity and univariate behavior, to assess its suitability for time-series modeling. The temporal index of the dataset was aligned with the sampling frequency of the original GRACE observations, and the univariate TWS data were subsequently transformed into a time-series format.

Trend estimation and time-series decomposition techniques were applied to separate the observed TWS series into its constituent components: trend, seasonal, and random (irregular). This decomposition facilitated seasonal adjustment and enabled a clearer interpretation of underlying hydrological signals. The resulting decomposed time-series components—observed, trend, seasonal, and residual—are presented in Figure S1. The seasonal component reveals pronounced oscillations in terrestrial water storage, reflecting recurring seasonal recharge and depletion cycles in the Rift Valley Basin. The trend component indicates alternating periods of increasing and decreasing water storage, with an overall upward trend over the study period. The observed component represents the original GRACE-derived TWS data, while the residual component captures stochastic variations not explained by the trend or seasonal patterns.

Based on the trend and seasonality assessment, the non-stationarity of the time series was addressed using an autoregressive integrated moving average (ARIMA) model. Non-stationarity was mitigated through differencing and stabilization procedures, ensuring constant mean and variance in the time series. Seasonal effects were removed by subtracting the estimated seasonal component from the original series, and additional differencing was applied where necessary to achieve stationarity. The final model selected for the GRACE TWS time series was an ARIMA (1, 0, 0) (1, 1, 0) model with drift, which effectively captured both the short-term autocorrelation structure and seasonal dependence of the data [12] presented in Table 3 for the forecasting of terrestrial water storage in the rift valley river basin.

Table 3 Coefficients for the evaluated ARIMA for the Rift Valley River Basin.

	Coefficients		
	ar1	Sar1	Drift
s.e	0.752	-0.4	0.009
	0.051	0.073	0.04
Log likelihood	AIC	AICC	BIC
	748.83	749.08	761.33
	-370.42	Sigma2	4.819

Once the dataset was fully prepared and all modeling assumptions were satisfied, the R forecast package was employed to generate a 25-year projection of the GRACE-derived terrestrial water storage time series. The resulting forecasts are presented in Figure S2. In the forecast visualization, the central estimate is represented by a blue line, while uncertainty bounds are illustrated by shaded prediction intervals, with the dark shaded region indicating the 80% confidence interval and the lighter shaded region representing the 95% confidence interval.

Model performance was quantitatively evaluated using Equations (11)-(14). The assessment yielded a correlation coefficient (R) of 0.89 and a Nash-Sutcliffe Efficiency (NSE) of 0.85, indicating strong agreement between simulated and observed values. Error-based metrics further demonstrated satisfactory model accuracy, with a mean absolute error (MAE) of 14.68 cm and a root mean square error (RMSE) of 37.6 cm. The objective of this performance evaluation was to assess the model's ability to reproduce observed terrestrial water storage dynamics with minimal error. Overall, the results indicate that the model exhibits robust predictive capability and effectively captures the temporal variability of terrestrial water storage in the study area.

3.2 GRACE-Derived Drought Index (WSD) Estimation for Rift Valley Basin

The GRACE-based water storage deficit (WSD), estimated using Equation (7), is illustrated in Figure 5 and reveals persistent deficits across much of the study period. The most pronounced deficit occurred in July 2011, reaching -8.36 cm, followed by significant deficits in June 2004 (-7.72 cm) and July 2005 (-7.59 cm). In contrast, episodic water storage surpluses were observed during certain months, reflecting periods of enhanced recharge and favorable hydrometeorological conditions. Overall, the Rift Valley Basin is characterized by prolonged and severe terrestrial water storage deficits, indicative of sustained hydrological stress.

The combined effects of recurrent droughts, climate change-induced increases in evaporative demand, and anthropogenic pressures such as unsustainable water resource management practices, groundwater overexploitation, land-use change, and deforestation likely drive these persistent deficits. The spatial concentration of water storage deficits in specific sub-basins further amplifies their ecological and socio-economic impacts, posing significant challenges to ecosystem sustainability, agricultural productivity, and regional water security.

Figure 6 also illustrates the relationship among water storage deficit (WSD), the water storage deficit index (WSDI), and precipitation. A strong direct relationship is evident between WSD and WSDI, confirming the consistency of the deficit-based drought characterization approach. In contrast, precipitation exhibits an inverse relationship with WSD, underscoring the dominant influence of rainfall variability on terrestrial water storage dynamics. The correlation coefficient

between cumulative precipitation and cumulative water storage deficit is 0.96, indicating that precipitation is a primary driver of GRACE-observed terrestrial water storage variations in the Rift Valley River Basin.

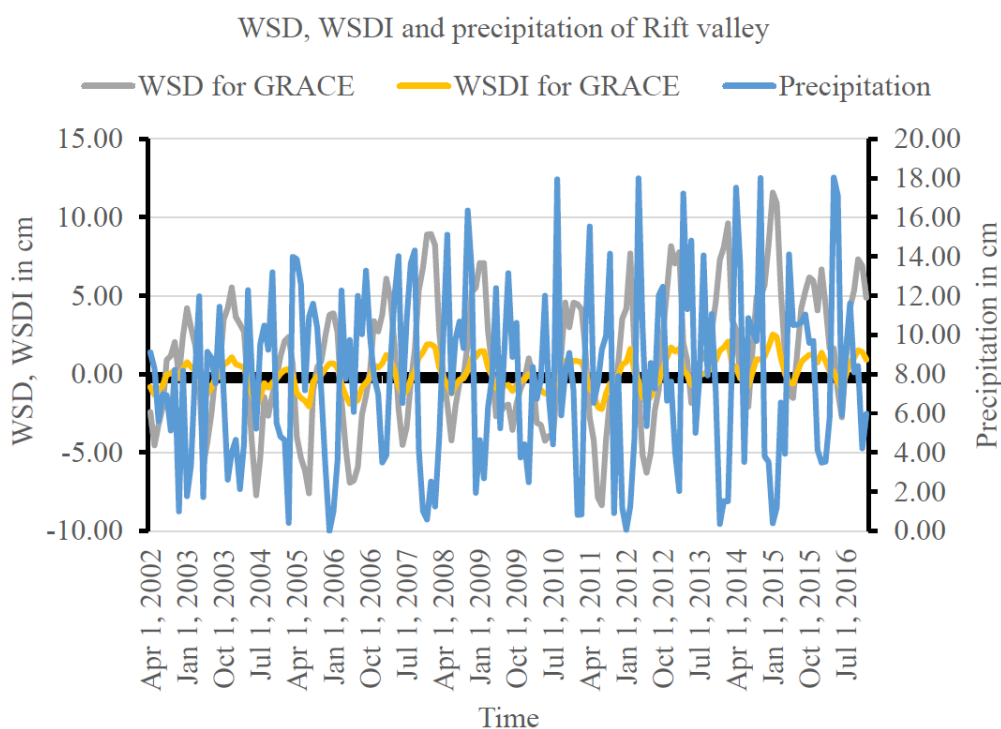


Figure 6 The relationship between WSD, WSDI, and precipitation in the Rift Valley basin.

Residual analysis of the relationships shown in Figure 6 indicates that, although precipitation explains a substantial portion of the variability in WSD and WSDI, systematic deviations remain. The residuals are generally centered around zero, suggesting no strong overall bias; however, their dispersion increases during extreme wet and dry periods, indicating heteroscedasticity and reduced model performance under hydroclimatic extremes. Periods with large negative residuals correspond to times when WSD and WSDI indicate more severe drought conditions than precipitation alone would suggest, highlighting the influence of subsurface water storage dynamics and delayed hydrological responses. Overall, the residual patterns confirm that precipitation is a key driver of drought variability in the Rift Valley basin. Still, GRACE-derived water storage information captured by WSD and WSDI provides additional, non-redundant insight into hydrological drought conditions.

In addition, drought conditions were evaluated using the Water Storage Deficit Index (WSDI) across multiple accumulation time scales of 3, 6, 9, 12, 18, 24, 36, and 48 months, with the results presented in Figure 7. Drought severity for the six-month time scale was quantified using Equation (8), and the corresponding results are provided in Table S1. Based on the water storage deficit (WSD) analysis, 15 drought events were identified in the Rift Valley River Basin during the study period. The most prolonged drought episodes persisted for eight consecutive months, occurring from April to November 2004 and from May to December 2009, with cumulative water storage deficits of -24.06 cm and -15.77 cm, respectively. Detailed statistics for each drought event—including duration (consecutive months), average deficit (cm), total deficit (cm), peak deficit (cm), and the timing of peak deficit—are comprehensively documented in Table S1.

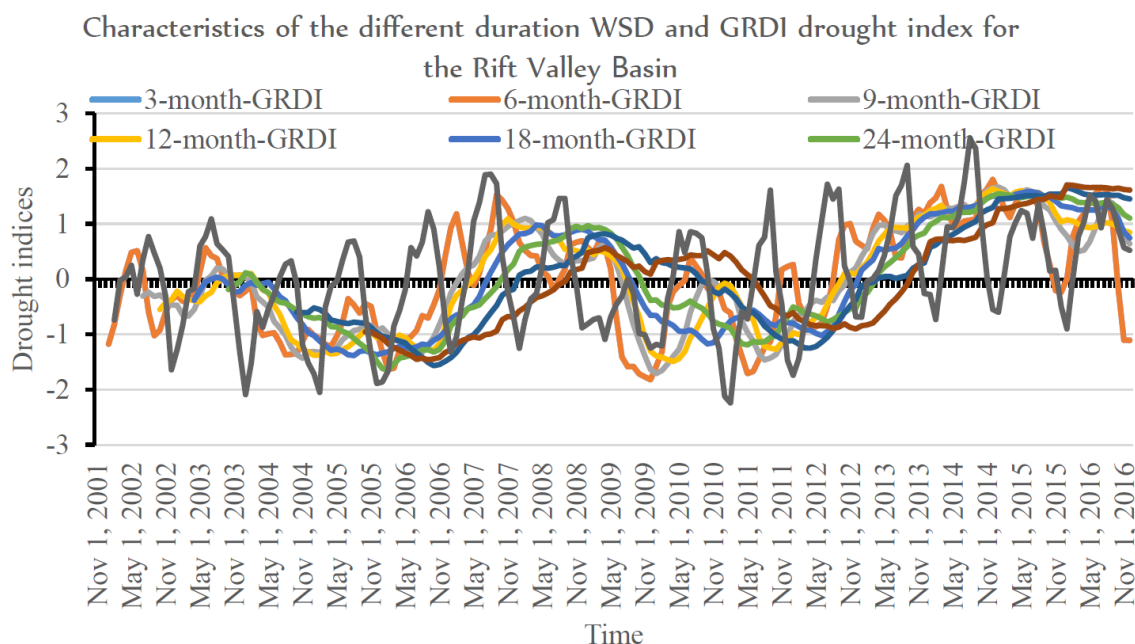


Figure 7 Characteristics of the different duration WSD and GRDI drought index for the Rift Valley Basin: 3-month-WSDI(GRDI), 6-month-GRDI, 9-month-GRDI, 12-month-GRDI, 18-month-GRDI, 24-month-GRDI, 36-month-GRDI, 48-month-GRDI, GRDI for GRACE.

The GRACE-based GRDI/WSDI analysis further evidences the severity and persistence of droughts in the Rift Valley Basin. As shown in Table S1, 13 major drought events were detected between 2002 and 2016 using the newly proposed GRACE-based drought index. The longest drought duration extended for 12 consecutive months during 2013 and 2014, with peak drought index values of 1.18 and 1.80, respectively, observed in December. The most severe cumulative drought conditions were also recorded in 2013 and 2014, with total drought values of 10.31 and 15.9, respectively, indicating unprecedented water storage depletion during these periods.

Because GRACE-derived terrestrial water storage represents the integrated sum of all components of the hydrological water balance, its variability provides a robust and comprehensive measure of total water scarcity in both time and space. This integrative characteristic makes GRACE-based indices particularly effective for drought identification and severity assessment in regions with limited hydrological observations. The newly developed WSDI/GRDI successfully captured extreme drought conditions during 2013 and 2014, consistent with findings from previous drought assessments in Ethiopia [81, 82].

Trend analysis conducted in RStudio further revealed statistically significant increases and decreases, as well as pronounced seasonal variability, in terrestrial water storage across the Rift Valley Basin. These findings are consistent with results reported for other major basins and lake systems in the region, including the Blue Nile Basin, Lake Tana, and Lake Victoria [13-15, 78, 79]. Moreover, GRACE-derived terrestrial water storage demonstrated a strong ability to accurately detect changes in drought severity across time periods. Similar drought conditions during 2013 and 2014 have been reported in other Ethiopian river basins, further corroborating the robustness of the proposed GRACE-based drought assessment framework [83]. Overall, the GRDI/WSDI exhibited both upward and downward trends across the Rift Valley Basin, reflecting heterogeneous drought dynamics and spatially variable hydrological responses.

3.3 Estimation of Potential Evapotranspiration Using R-Studio

The potential evapotranspiration (PET) of the study area was estimated using the Hargreaves method in R-Studio, incorporating key climatic inputs including precipitation, minimum and maximum temperatures, and the latitude of the study region. The resulting PET estimates are presented in Figure 7. As shown in Figure 8, PET values for the period 1991-2021 ranged from 91.80 to 174.65 mm, exhibiting clear seasonal variability throughout the study period, reflecting the influence of climatic seasonality on atmospheric water demand.

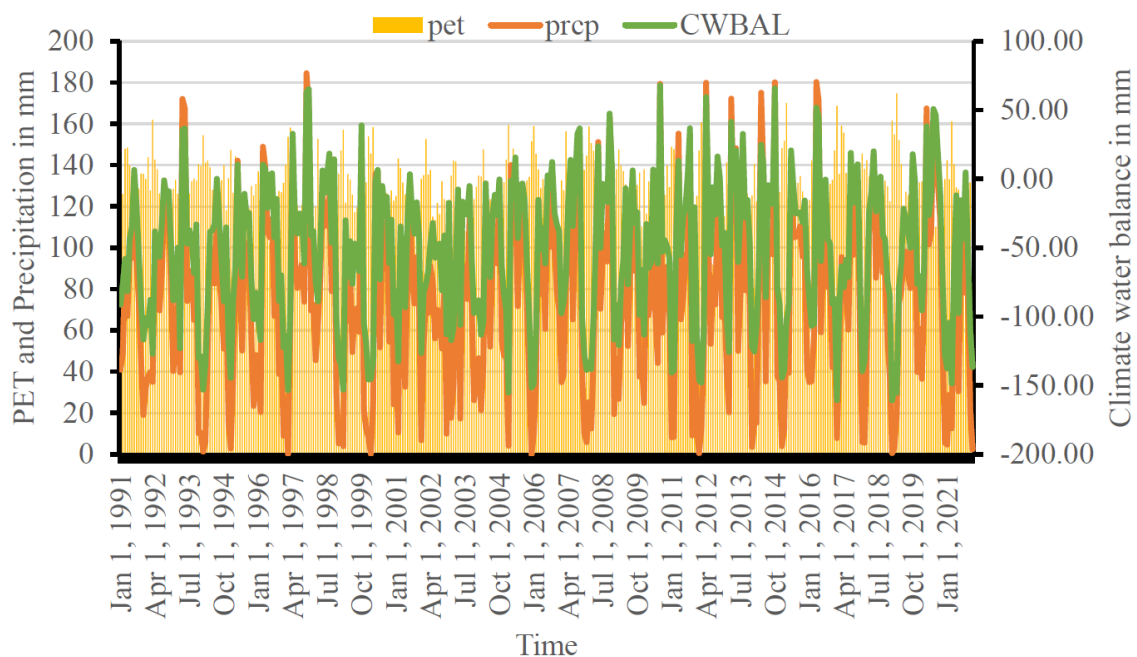


Figure 8 Relationship between estimated potential evapotranspiration (PET), estimated climatic water balance and precipitation (CWBAL), precipitation (prcp).

Following PET estimation, the climatic water balance (CWBAL) of the study area was computed by integrating observed precipitation with estimated PET values, and the results are also presented in Figure 8. The analysis demonstrates a direct relationship between CWBAL and precipitation, whereby higher rainfall contributes to a positive water balance, and an inverse relationship with PET, indicating that periods of elevated potential evapotranspiration correspond to reduced water availability. These findings highlight the critical role of climatic factors in controlling water availability and provide essential context for understanding hydrological variability and drought risk in the Rift Valley River Basin.

3.4 SPEI Drought Indices for Different Durations for the Rift Valley Basin

Figure 9 illustrates the characteristics of the Standardized Precipitation Evapotranspiration Index (SPEI) evaluated across multiple accumulation periods, including 3-, 6-, 9-, 12-, 18-, 24-, 36-, and 48-month drought durations. The most severe drought for an 18-month accumulation period was recorded in March 2000, with a SPEI value of -2.61. Between 2002 and 2019, the most pronounced drought conditions were observed at the six-month accumulation scale, indicating the sensitivity of short- to medium-term water deficits to climatic variability. The severity of these drought events is

closely associated with increased evaporative water demand driven by elevated evapotranspiration, a pattern corroborated by previous studies [59, 61].

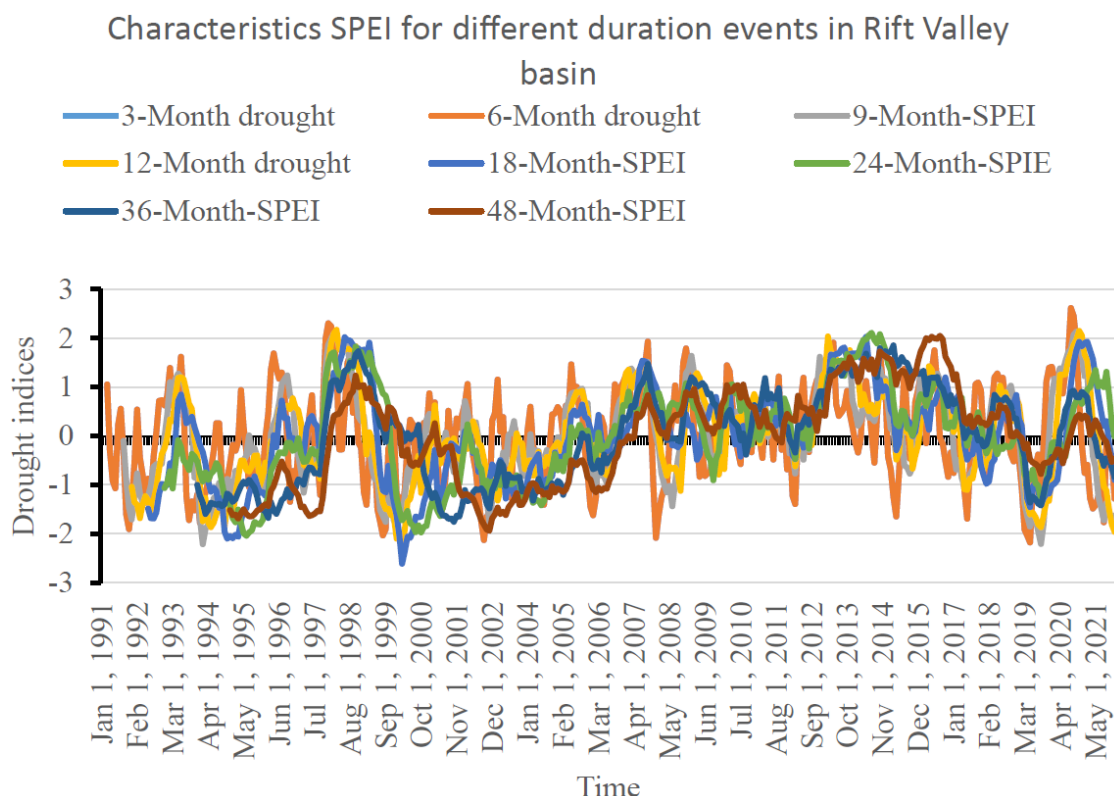


Figure 9 Characteristics SPEI for different duration events in the Rift Valley basin (3-, 6-, 9-, 12-, 18-, 24-, 36- and 48-month) SPEI drought indices.

SPEI operates similarly to the Standardized Precipitation Index (SPI), but it incorporates temperature to calculate the climatic water balance, accounting for both precipitation and potential evapotranspiration [25, 59-61]. In addition to drought severity, key metrics, including drought duration, cumulative deficit, and peak deficit, were evaluated for the six-month accumulation period and are presented in Table S2. A total of 30 drought events were detected using SPEI from 1991 to 2021, with the longest event persisting for 12 consecutive months in 2021, reaching a peak deficit of -1.76 in August. These findings are consistent with previous studies conducted in various Ethiopian river basins, which also reported severe and prolonged drought episodes during the same periods [65, 67].

3.5 Evaporative Demand Drought Index (EDDI)

Figure 10 illustrates the characteristics of the newly proposed Evaporative Demand Drought Index (EDDI), which is based solely on potential evapotranspiration within the study area. The EDDI was evaluated across multiple accumulation periods, including 3-, 6-, 9-, 12-, 18-, 24-, 36-, and 48-month drought durations. Key drought metrics—duration, average deficit, total deficit, and peak intensity—were computed for the six-month accumulation period and are presented in Table S3. The longest drought events persisted for 11 months in 1992 and 2021, with peak EDDI values of 1.50 in July 1992 and 1.06 in May 2021, respectively. A total of 29 drought events were detected

over the study period, with the most extreme event occurring in April 2019, reaching a peak EDDI value of 2.28. Detailed characteristics of all EDDI-based drought events are provided in Table S3.

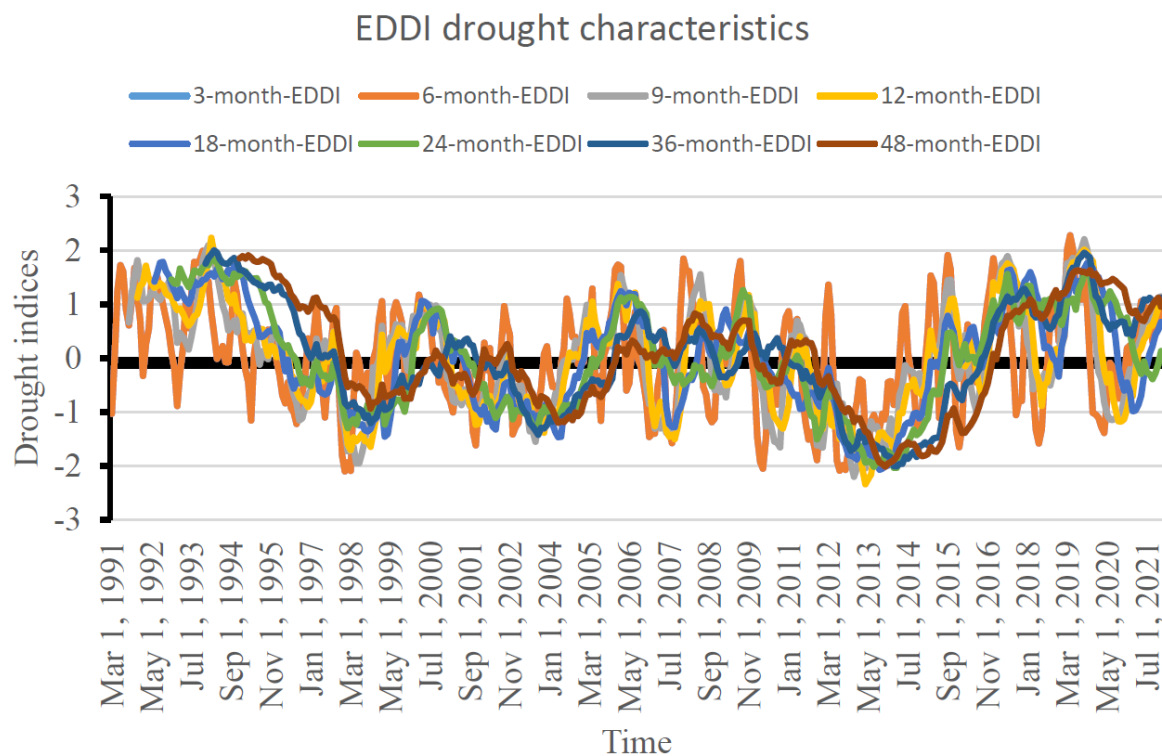


Figure 10 Characteristics of EDDI drought index for different durations in the Rift Valley basin: 3-, 6-, 9-, 12-, 18-, 24-, 36-, and 48-month-EDDI.

The EDDI quantifies the atmospheric drying potential and its associated stress on vegetation and land surface water availability. Positive EDDI values indicate increased atmospheric water demand and associated drought stress, whereas negative values reflect periods of sufficient water availability. By capturing the influence of elevated temperatures and reduced precipitation on evaporative demand, EDDI provides an effective measure of drought conditions driven by atmospheric water deficits. These results are consistent with previous studies demonstrating the utility of EDDI for identifying drought severity and timing in regions susceptible to climate-induced water stress [67-69].

3.6 Characteristics of Standardized Precipitation Index (SPI)

Figure 11 presents the Standardized Precipitation Index (SPI), evaluated using Equation (2), at 36- and 48-month accumulation periods. Table S4 provides detailed statistics on drought duration, average severity, total severity, and peak severity for the six-month accumulation period. Over the study period, 31 drought events were identified using SPI, with the longest drought episodes lasting 11 consecutive months in 1999 and 2021, corresponding to cumulative drought severity values of -12.96 and -11.95, respectively.

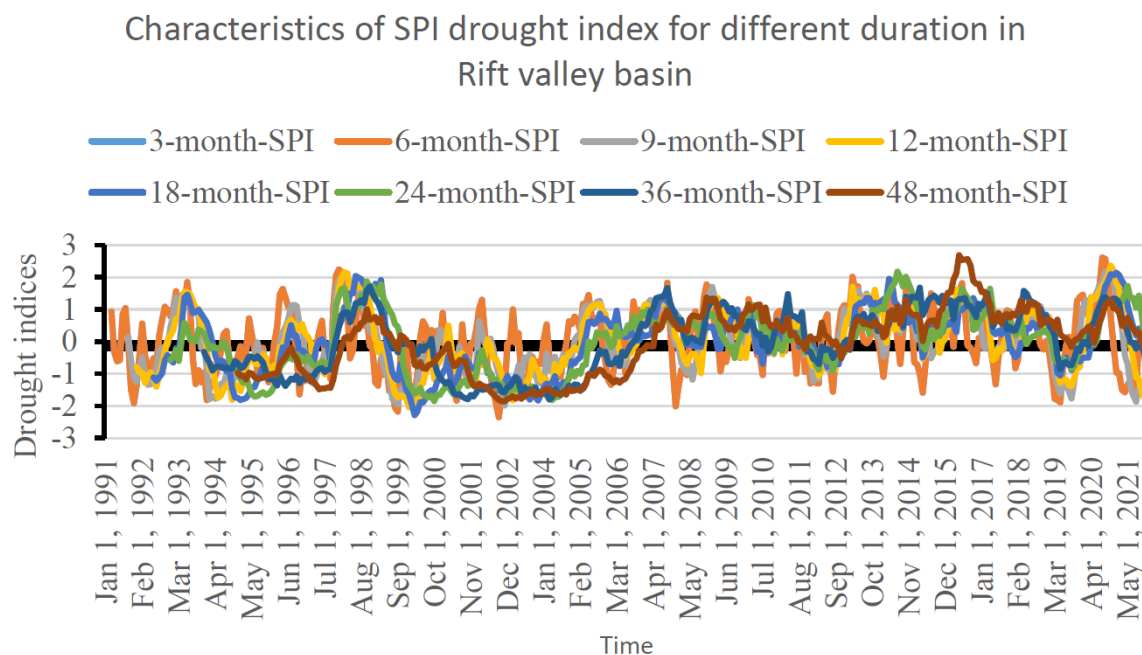


Figure 11 Characteristics of SPI drought index for different durations in the Rift Valley basin: 3-, 6-, 9-, 12-, 18-, 24-, 36-, and 48-month-SPI.

The SPI values exhibit frequent fluctuations above and below the zero line, reflecting the index's sensitivity to monthly precipitation variability. Positive SPI values indicate wetter-than-average conditions, whereas negative values reflect dry periods. This temporal variability of SPI aligns closely with other studies conducted in Ethiopian river basins and similar hydrological settings, confirming its effectiveness in capturing both short-term and long-term drought dynamics [83-85].

3.7 Characteristics of Evaporative Stress Index (ESI) in Rift Valley Basin

Figure 12a illustrates the Evaporative Stress Index (ESI), a remote sensing-based drought indicator estimated using Equation (5), with values ranging from 0 to 1 for the study area throughout the observation period. The ESI reflects soil moisture stress and provides insight into the availability of terrestrial water storage within the river basin. Higher positive values indicate that atmospheric evaporative demand is largely met, corresponding to sufficient vegetation and soil moisture. In contrast, lower values signify that the land surface meets little or none of the atmospheric evapotranspiration demand. These interpretations are consistent with previous studies [67, 68].

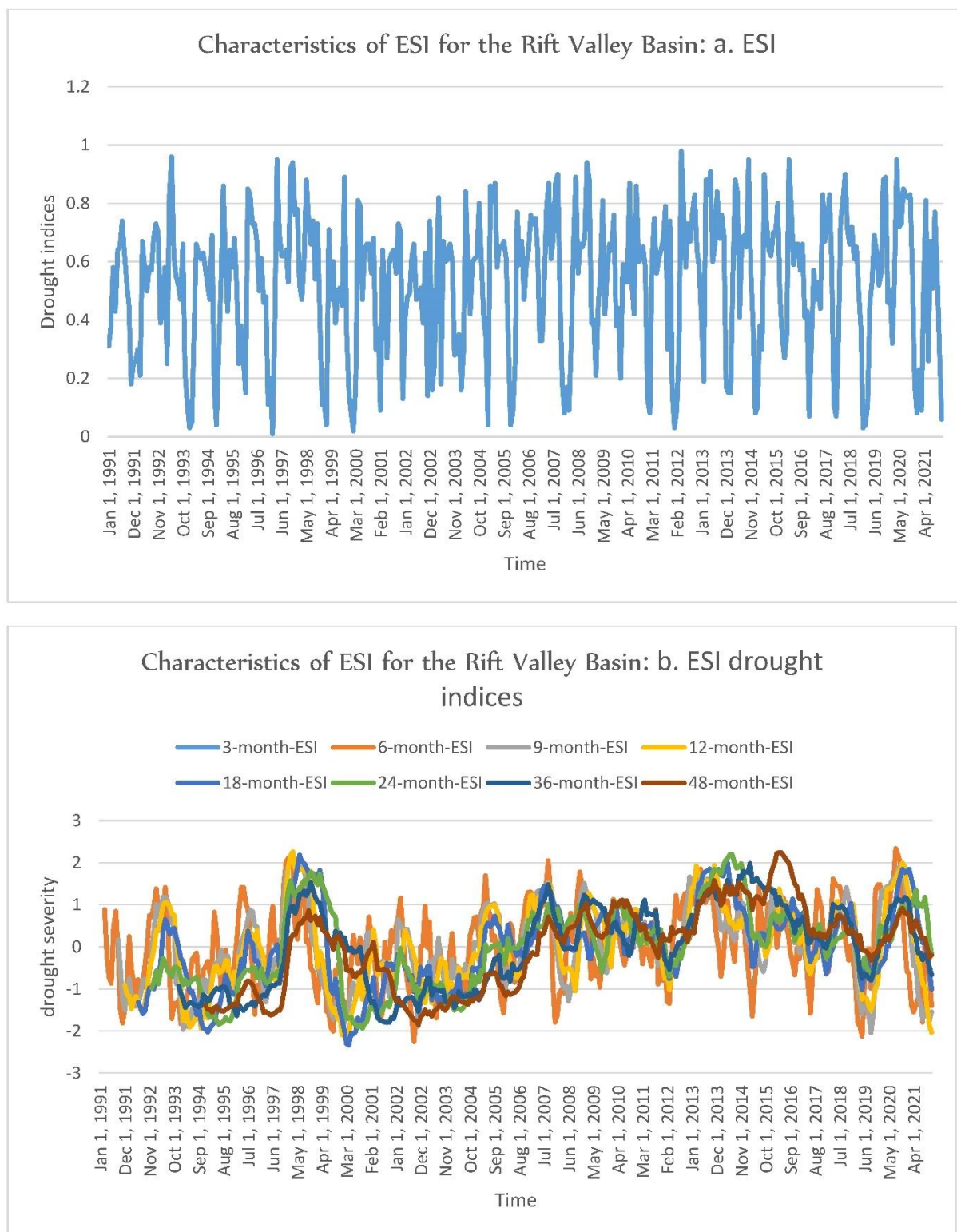


Figure 12 Characteristics of ESI for the Rift Valley Basin: a. ESI drought index before normalization; b. ESI drought index after normalization at different duration events: 3-, 6-, 9-, 12-, 18-, 24-, 36-, and 48-month-ESI.

To facilitate comparative analysis, ESI values were normalized to a range of -3 to 3, as shown in Figure 12b. Positive normalized values indicate minimal or no drought, whereas negative values indicate drought at a given location and time, consistent with prior research [69, 70, 86]. Table S5

provides detailed metrics for the six-month drought accumulation period, including drought duration, average severity, total severity, and peak severity. Using this analysis, a total of 29 drought events were identified from 1991 to 2021. The longest event in 1999 persisted for 12 consecutive months, with a peak ESI value of -2.01 and a cumulative drought index of -12.1, highlighting the intensity and persistence of severe drought conditions in the basin.

3.8 Surface Runoff Drought Indices (SRI)

Figure 13 presents the Standardized Runoff Index (SRI) evaluated across multiple accumulation periods, including 3-, 6-, 9-, 12-, 18-, 24-, 36-, and 48-month durations, using R-Studio. As shown in Figure 13, the most severe drought for the six-month accumulation period occurred in January 1994, with a peak SRI value of -2.66. Over the study period from 1991 to 2021, a total of 30 drought events were identified using SRI. The longest drought event in 2021 persisted for 12 consecutive months, with a cumulative severity of -12.37, indicating extreme hydrological stress within the basin.

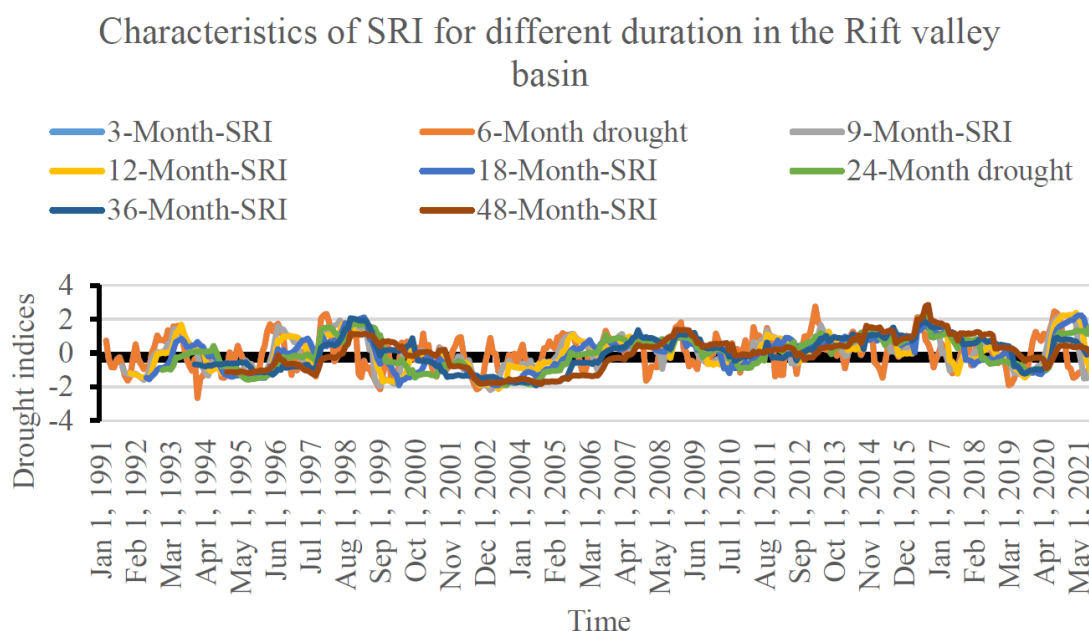


Figure 13 Characteristics of SRI for different durations in the Rift valley basin: 3-, 6-, 9-, 12-, 18-, 24-, 36-, and 48-month-SRI.

Detailed characteristics of each drought event, including duration, average severity, total severity, and peak intensity, are provided in Table S6. The timing and magnitude of major SRI deficits closely correspond to documented drought episodes reported in other studies, confirming the robustness of SRI in capturing hydrological drought conditions in the Rift Valley Basin [87].

3.9 Correlation between the SPI, ESI, SPEI, SRI, EDDI, and GRDI Drought Indices

To investigate the interrelationships among the drought indices—SPI, ESI, SPEI, SRI, EDDI, and GRDI, a correlation analysis was conducted using Pearson’s correlation coefficient at a significance level $P < 0.05$, with the results presented in Figure S3. Assessing the relationships between these indices allows for the identification of drought indicators that are strongly interrelated, providing insight into the coherence and redundancy of different drought metrics. Such analyses are essential

for evaluating the relative contribution of independent indices and for understanding their interactions in representing hydrometeorological drought conditions.

As shown in Figure S3, SPI, ESI, SRI, and SPEI exhibited strong positive correlations, indicating their similar sensitivity to precipitation-driven drought variability. In contrast, the GRDI showed little to no correlation with the other indices, reflecting its unique sensitivity to integrated terrestrial water storage as captured by GRACE. The EDDI displayed a negative correlation with the other drought indices, consistent with its focus on atmospheric evaporative demand rather than water availability.

Following the correlation analysis, cross-correlation was performed to further examine temporal relationships and the variability of drought events across indices, with results presented in Figure S4. The cross-correlation coefficients highlight the close agreement among precipitation- and hydrology-based indices, with values of 0.96 between ESI and SPEI, 0.95 between SPI and SPEI, 0.92 between SPI and ESI, 0.90 between SPI and SRI, 0.89 between SPEI and SRI, and 0.82 between ESI and SRI. Conversely, SPEI and EDDI, as well as ESI and EDDI, exhibited negative correlations of -0.66 and -0.61, respectively, underscoring the distinct nature of EDDI as an atmospheric demand-based drought metric. These results emphasize the complementary information provided by GRACE-based and evapotranspiration-driven drought indices relative to conventional precipitation-based metrics.

3.10 Comparison of Different Drought Characteristics (SPI, ESI, SPEI, SRI, GRACE-WSDI/GRDI, and EDDI)

Assessing multiple drought indices is critical for understanding climate variability and for developing effective strategies for sustainable water resources management. In the Rift Valley Basin, temporal and spatial variability of precipitation has led to significant socio-economic impacts, with recurrent droughts adversely affecting agriculture, water availability, and livelihoods. The highly variable rainfall in Ethiopia, both temporally and spatially, is reflected in peaks observed across the evaluated drought indices, including GRACE-based GRDI/WSDI, SPI, ESI, SPEI, EDDI, and SRI.

For this study, drought indices were analyzed at accumulation periods of 3, 6, 9, 12, 18, 24, 36, and 48 months, as illustrated in Figures 7, 9, 11, 12b, and 13. Longer accumulation periods (≥ 6 months) primarily capture hydrological droughts, which are crucial for water resource planning and management [74, 88]. For the six-month accumulation period, drought duration, average severity, total severity, and peak values were evaluated for each index and are provided in Table S1-Table S6. Figure 14 shows the time series of the six-month SPI, ESI, GRDI, EDDI, SPEI, and SRI for the Rift Valley Basin over the study period. All indices exhibited both upward and downward trends, following broadly similar temporal patterns.

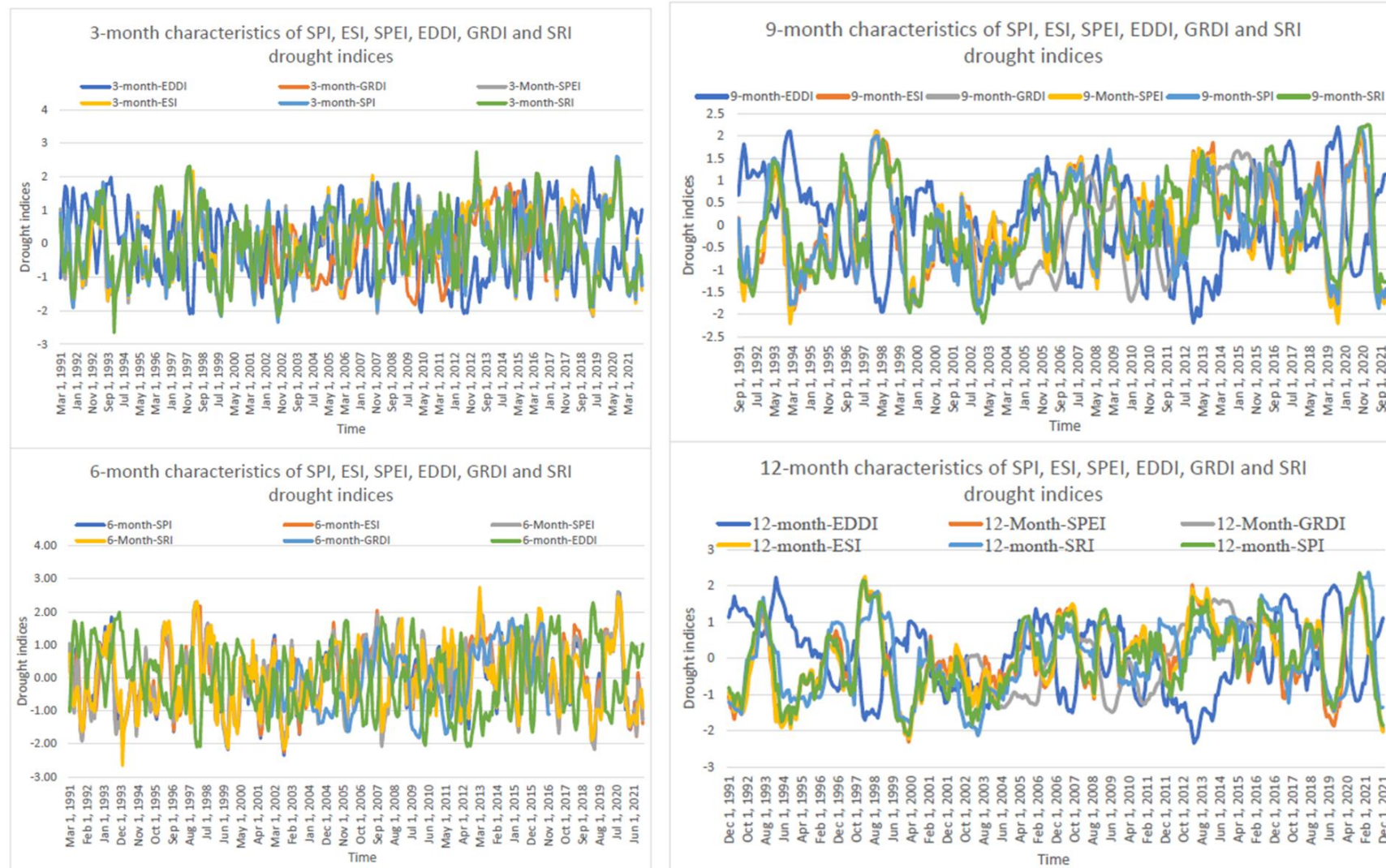


Figure 14 Characteristics of drought index of the SPI, ESI, SPEI, SRI, EDDI, and GRDI at 3-, 6-, 9-, 12-months from 1991 to 2021, for GRDI from 2002 to 2016 in the Rift Valley basin.

For six-month droughts, 31, 29, 30, 30, and 29 drought events were identified for SPI, ESI, SPEI, SRI, and EDDI, respectively, during 1991-2021. In contrast, the GRACE-based GRDI/WSDI detected 13 drought events during 2002-2016, reflecting the temporal coverage of the GRACE dataset. The time series analysis highlights that droughts have become increasingly frequent and prolonged in recent years across the Rift Valley Basin.- Under equivalent accumulation periods, SPI, ESI, SPEI, and SRI exhibit similar behavior, where negative values indicate drought and positive values indicate wet conditions. Conversely, for EDDI and GRDI, positive values correspond to drought conditions, whereas negative values indicate wet conditions.

Comparative analysis of GRDI with SPI, ESI, SPEI, SRI, and EDDI (Table S1-Table S6) demonstrates that major drought events were consistently observed during 2002-2003, 2007-2012, and 2014-2016. Variations among indices are expected due to differences in their constructs and input variables, as shown in Figure 13. These differences emphasize the value of GRDI in providing additional insights for identifying extreme droughts in the Rift Valley Basin, thereby supporting sustainable water resource management. The SPI values fluctuate frequently around the zero line, reflecting monthly rainfall variability [84, 85].

Findings from SPI, ESI, SPEI, and SRI are consistent with previous studies in Ethiopia [87, 88]. The GRDI successfully captured major drought events during 2002-2016, aligning with prior regional assessments [81-83]. Previous studies indicate that ENSO is a primary driver of severe droughts in Ethiopia [89-92], consistent with the patterns observed in the Rift Valley Basin. Following established recommendations that multiple indices are required to characterize drought accurately [66, 88, 93], this study employed a combination of widely used indices (SPI, SPEI, ESI) alongside the newly proposed WSDI/GRDI and EDDI to provide a more comprehensive description of drought events.

Historical severe and prolonged droughts in Ethiopia—including those in 1991, 1994-1995, 1999, 2002-2003, and 2019—align closely with the results of this study [81, 82, 88, 94]. Using SPI, ESI, SPEI, and EDDI, the identified drought years are 1991-2001, 2002-2006, 2008-2009, 2011-2012, 2015-2016, and 2017-2021. Globally, evidence indicates that climate change has intensified the frequency, duration, and severity of droughts in recent decades [95-98]. Overall, the evaluation of drought indices, their severity, and duration in this study is consistent with documented drought events in Ethiopia, reinforcing the reliability of the multi-index approach for drought monitoring and water resources management [99-103].

3.11 Discussion

This study utilized GRACE-derived terrestrial water storage (TWS) data to develop a GRACE-based drought index (GRDI/WSDI) for the Rift Valley Basin from 2002 to 2016. The analysis incorporated temporal assessment of drought severity, duration, and total deficit. For comparison, other widely used drought indices, including SPI, SPEI, SRI, ESI, and EDDI, were evaluated over multiple accumulation periods (3, 6, 9, 12, 18, 24, 36, and 48 months). Correlation and cross-correlation analyses were performed to investigate relationships among these indices, and time-series decomposition methods were applied to assess trends, seasonality, and variability. Based on GRACE data from 2002 to 2016, the terrestrial water storage in the Rift Valley Basin reveals pronounced temporal and spatial fluctuations over the study period. Overall, a declining trend in annual water storage is evident during the periods 2002-2006, 2007-2009, 2014-2016, and 2011. In contrast,

increasing water storage trends were observed in 2007, 2010, and 2012-2014. These spatial contrasts underscore the heterogeneous hydrological response of the basin to climatic variability and local hydrological controls and are consistent with similar studies [104].

The seasonal component exhibits pronounced oscillations in terrestrial water storage, reflecting recurring recharge-depletion cycles in the Rift Valley Basin. The estimated trend indicates alternating periods of increasing and decreasing water storage, with an overall upward trend over the study period. The observed component represents the original GRACE-derived TWS data, while the residual component captures stochastic variations not explained by the trend or seasonal patterns. The evaluated correlation coefficient (R) was 0.89, and the Nash-Sutcliffe Efficiency (NSE) was 0.85, indicating strong agreement between simulated and observed values. Error-based metrics further demonstrated satisfactory model accuracy, with a mean absolute error (MAE) of 14.68 cm and a root mean square error (RMSE) of 37.6 cm.

The GRACE-based water storage deficit (WSD) was evaluated. Based on the evaluation results, the most pronounced deficit occurred in July 2011, at -8.36 cm, followed by significant deficits in June 2004 (-7.72 cm) and July 2005 (-7.59 cm). In contrast, episodic water storage surpluses were observed during certain months, reflecting periods of enhanced recharge and favorable hydrometeorological conditions. The water storage deficit index (WSDI) was evaluated, and a strong direct relationship was observed between WSD and WSDI, confirming the consistency of the deficit-based drought characterization approach. In contrast, precipitation exhibits an inverse relationship with WSD, underscoring the dominant influence of rainfall variability on terrestrial water storage dynamics. Based on the water storage deficit (WSD) analysis, a total of 15 drought events were identified within the Rift Valley River Basin during the study period. The most severe cumulative drought conditions were recorded in 2013 and 2014, with total drought values of 10.31 and 15.9, respectively, indicating unprecedented water storage depletion during these periods. As a result, the newly developed WSDI/GRDI successfully captured extreme drought conditions during 2013 and 2014, consistent with findings from previous drought assessments in Ethiopia [87, 88]. Based on the analysis, the GRDI/WSDI exhibited both upward and downward trends across the Rift Valley Basin, reflecting heterogeneous drought dynamics and spatially variable hydrological responses. A total of 30 drought events were detected using SPEI from 1991 to 2021, with the longest event persisting for 12 consecutive months in 2021, reaching a peak deficit of -1.76 in August. These findings are consistent with previous studies conducted in various Ethiopian river basins, which also reported severe and prolonged drought episodes during the same periods [65, 67]. Detailed characteristics of all EDDI-based drought events are provided in Table S3. Over the study period, 31 drought events were identified using SPI, with the longest drought episodes lasting 11 consecutive months in 1999 and 2021, corresponding to cumulative drought severity values of -12.96 and -11.95, respectively. This temporal variability of SPI aligns closely with other studies conducted in Ethiopian river basins and similar hydrological settings, confirming its effectiveness in capturing both short-term and long-term drought dynamics [83-85]. Over the study period from 1991 to 2021, a total of 30 drought events were identified using SRI. The longest drought event in 2021 persisted for 12 consecutive months, with a cumulative severity of -12.37, indicating extreme hydrological stress within the basin. The cross-correlation coefficients highlight the close agreement among precipitation- and hydrology-based indices, with values of 0.96 between ESI and SPEI, 0.95 between SPI and SPEI, 0.92 between SPI and ESI, 0.90 between SPI and SRI, 0.89 between SPEI and SRI, and 0.82 between ESI and SRI. Conversely, SPEI and EDDI, as well as ESI and EDDI, exhibited negative correlations of -0.66

and -0.61, respectively, underscoring the distinct nature of EDDI as an atmospheric demand-based drought metric. Findings from SPI, ESI, SPEI, and SRI are consistent with previous studies in Ethiopia [81, 82]. The GRDI successfully captured major drought events during 2002-2016, aligning with prior regional assessments [81-83]. Previous studies indicate that ENSO is a primary driver of severe droughts in Ethiopia [89-92], consistent with the patterns observed in the Rift Valley Basin. Following established recommendations that multiple indices are required to characterize drought [66, 88, 93] accurately, this study employed a combination of widely used indices (SPI, SPEI, ESI) alongside the newly proposed WSDI/GRDI and EDDI to provide a more comprehensive description of drought events.

The results demonstrate that GRACE-derived Water Storage Deficit (WSD) and the Water Storage Deficit Index (WSDI) effectively capture the temporal evolution and severity of hydrological drought in the Ethiopian Rift Valley Basin, with a clear but non-linear relationship to precipitation variability. The divergence observed during extreme events indicates that subsurface water storage responds more slowly than rainfall, emphasizing the importance of incorporating GRACE-based indicators to complement conventional precipitation-based drought assessments. Similar findings have been reported in other regional and global studies, in which GRACE data have been shown to outperform precipitation-only indices in identifying prolonged and groundwater-driven drought conditions, particularly in data-scarce and semi-arid regions. The comparative analysis of this study shows that the performance of the GRACE-based drought index (GRDI) is consistent with results reported in other data-scarce and semi-arid regions. For instance, studies in the Murray-Darling Basin (Australia) found that GRACE-derived terrestrial water storage anomalies provided more accurate assessments of prolonged drought and groundwater depletion than precipitation-based indices alone, particularly during multi-year dry spells [73]. Similarly, research in the Colorado River Basin (USA) demonstrated that GRACE water storage trends improved the detection of hydrological drought onset and severity relative to conventional drought indicators, especially where groundwater plays a major role in sustaining basin water balance [105]. In India's drought-prone regions, GRACE TWS deficits showed strong agreement with soil moisture and crop yield anomalies, outperforming meteorological indices in capturing deep-storage changes under intense agricultural water use [106, 107]. Likewise, in the Lower Limpopo Basin (Southern Africa), GRACE-derived storage anomalies were more closely aligned with streamflow reductions and agricultural impacts than SPI and SPEI, emphasizing the utility of integrated water storage data for basin-scale drought monitoring [108].

Despite these strengths, the study has several limitations. The relatively coarse spatial resolution of GRACE data may mask localized drought conditions within the Rift Valley Basin, and uncertainties in signal leakage and scaling factors can affect the magnitude of estimated water storage changes. In addition, TerraClimate precipitation data, although widely used, are subject to biases related to sparse ground observations in parts of Ethiopia. Future work that integrates in situ hydrological data and higher-resolution satellite products would further improve drought characterization and validation.

This study directly supports the United Nations Sustainable Development Goals, particularly SDG 6 (Clean Water and Sanitation), by providing improved tools for monitoring water availability and hydrological drought in vulnerable regions. By enhancing drought early warning and supporting informed water-resource planning, the findings also contribute indirectly to SDG 2 (Zero Hunger) and SDG 13 (Climate Action) through improved agricultural system resilience and climate-risk management.

4. Conclusions

This study assessed the spatiotemporal variability of terrestrial water storage (TWS) derived from GRACE to develop and apply a novel GRACE-based drought index (GRDI) over the Ethiopian Rift Valley Lake Basin. Drought conditions during 2002-2016 were characterized using GRDI and compared with conventional drought indices (SPI, SPEI, SRI, ESI, and EDDI) computed for 1991-2022. By integrating GRACE-derived TWS, the analysis captured both surface and subsurface water storage dynamics, providing a more comprehensive representation of drought in this data-scarce region.

GRACE TWS anomalies revealed strong seasonal and interannual variability, with negative anomalies indicating water loss during dry periods and positive anomalies reflecting wet-season recharge. Significant declines in water storage were detected during 2004-2007, 2009-2010, and 2011-2012, consistent with documented drought episodes and confirming the effectiveness of GRACE in identifying basin-scale hydrological stress.

The GRDI successfully quantified drought severity, duration, and cumulative deficits across the basin. The most severe event occurred in 2014, with a peak deficit of 1.80, a cumulative deficit of 15.9, and a duration of 12 months. Compared with conventional indices, GRDI and water storage deficit metrics more effectively captured integrated hydrological drought severity, particularly groundwater-related depletion.

Correlation analysis showed strong agreement among precipitation- and evapotranspiration-based indices, while EDDI exhibited negative correlations due to its sensitivity to atmospheric evaporative demand. These results highlight the complementary strengths of multiple drought indicators and the added value of GRACE-based indices.

Overall, the GRDI provides a robust and transferable framework for drought monitoring and assessment, offering valuable insights for water resource management, drought preparedness, and climate adaptation in the Ethiopian Rift Valley Lake Basin and other data-limited regions.

4.1 Recommendation

Anthropogenic factors, including irrigation expansion and increasing groundwater abstraction, likely intensify drought severity and persistence in the basin. Future studies should integrate human water-use data with GRACE observations to better quantify these impacts.

Author Contributions

The author did all the research work for this study.

Competing Interests

The author has declared that no competing interests exist.

Data Availability Statement

The dataset utilized for the estimation drought severity during this study are available from the corresponding author on reasonable request. Additionally, some of the datasets are as follow: Teera-Climate Dataset: <https://developers.google.com/earth->

[engine/datasets/catalog/IDAHO EPSCOR TERRACLIMATE#citations](https://engine/datasets/catalog/IDAHO_EPSCOR_TERRACLIMATE#citations). GRACE Dataset:
[https://developers.google.com/earth-engine/datasets/catalog/NASA GRACE MASS GRIDS LAND](https://developers.google.com/earth-engine/datasets/catalog/NASA_GRACE_MASS_GRIDS_LAND).

Additional Materials

The following additional materials are uploaded at the page of this paper.

1. Figure S1: Time series plot for the estimated terrestrial water storage using R-studio.
2. Figure S2: Time series of the observed and forecasted terrestrial water storage for the Rift Valley Basin.
3. Table S1: Characteristics of the 6-month GRDI drought index for the Rift Valley Basin.
4. Table S2: Characteristics of the 6-month drought index for the SPEI drought index.
5. Table S3: Characteristics of the 6-month (EDDI) drought index for the Rift Valley Basin.
6. Table S4: Characteristics of 6-month SPI drought events in the Rift Valley Basin.
7. Table S5: Characteristics of the 6-month ESI drought index in the Rift Valley Basin.
8. Table S6: Characteristics of 6-month SRI drought index in Rift Valley Basin.
9. Figure S3: Correlation of drought indices for the Rift Valley River Basin.
10. Figure S4: Cross correlation between different drought indices in Rift Valley Basin.

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