COPULA-BASED CONSTRUCTION OF AN INTEGRATED DROUGHT INDEX IN THE BA RIVER BASIN, VIET NAM

Do Thi Ngoc Bich[1], Nguyen Tu Anh[1], Nguyen Thanh Long[1], Nguyen Hoang Bach[1], Khuong Van Hai[2]

[1]Water Resources Institute

[2]Viet Nam Academy for Water Resources

Received: 14/8/2025; Accepted: 5/9/2025

Abstract: *Drought is a complex natural hazard characterized by stochastic occurrence, wide-ranging impacts, and sequential propagation across the hydrological cycle. This study proposes a copula-based framework to construct an Integrated Drought Index (IDI) for the Ba River Basin, Viet Nam, combining meteorological (SPI), agricultural (SMI), and hydrological (SRI, SGI) drought dimensions. The VIC distributed hydrological model was developed and calibrated for 1980-2023, explicitly incorporating the operation of major reservoirs to better capture regulated flow regimes. Standardized drought indices were computed at monthly timescales, and a Clayton Copula was applied to model lower-tail dependence among them, enabling quantification of compound drought conditions. The resulting IDI was analyzed for four representative drought years (2015, 2016, 2019, 2020), which correspond to major El Nino episodes associated with severe rainfall deficits and socio-economic damages. Results show that the IDI effectively captures both the intensity and spatial extent of drought propagation, with 2016 emerging as the most extreme basin-wide drought, 2020 showing similarly widespread impacts, and 2015 and 2019 characterized by more localized drought hotspots. By integrating reservoir regulation, multi-source data, and copula-based dependence modeling, this study provided a more holistic representation of compound drought risk in a socio-hydrologically complex basin.*

Keywords: *VIC model, Integrated Drought Index (IDI), Clayton Copula, Ba River Basin.*

1. Introduction

Drought is widely recognized as one of the most devastating natural hazards, exerting profound impacts on ecosystems, agriculture, water resources, and socioeconomic development. Rather than being defined solely as a precipitation deficit, drought represents a multifaceted phenomenon with cascading effects throughout the hydrological cycle [1]. In general, three principal types of drought are distinguished: Meteorological, agricultural, and hydrological drought [2]. Meteorological drought is usually identified by sustained precipitation deficits, agricultural drought emerges as soil moisture becomes insufficient for crop needs, and hydrological drought develops later, manifested as reduced streamflow, reservoir storage, and groundwater recharge.

Traditional drought assessments have largely relied on single indicators that capture only one dimension of this process. For example, the Standardized Precipitation Index (SPI) reflects meteorological drought [3], whereas the Standardized Runoff Index (SRI) and the Standardized Groundwater Index (SGI) focus on hydrological drought [4]. While such indices are useful for monitoring specific components, they cannot fully capture the interconnected and evolving nature of drought. This limitation has motivated the development of integrated drought indices (IDI), which aim to combine diverse sources of information into a more comprehensive representation [5].

An effective IDI should do more than simply

Corresponding author: Do Thi Ngoc Bich
E-mail: bichdam555@gmail.com

aggregate existing indices; it must reflect the sequential propagation of drought. Typically, drought begins as a meteorological anomaly, spreads into the agricultural domain through soil moisture depletion, and eventually manifests in hydrological systems as declining streamflow and groundwater levels [6]. By integrating indicators such as SPI (precipitation), SMI (soil moisture), SRI (runoff), and SGI (groundwater), an IDI can provide insight into both the onset and evolution of drought conditions.

Developing such an index, however, requires careful consideration of interdependencies among hydro-meteorological variables. Precipitation, soil moisture, runoff, and groundwater are inherently linked, with feedbacks across different spatial and temporal scales. Consequently, integration cannot rely on simple linear averaging, as this may overlook nonlinearities and tail dependencies where extreme drought impacts occur. Methods such as Principal Component Analysis (PCA) have been applied to combine drought indicators, yet they often assume linear correlation structures, which may not adequately represent complex hydrological relationships [7].

Copula theory provides a promising alternative. By separating marginal distributions from their dependence structure, copulas enable flexible modeling of nonlinear associations and allow explicit representation of tail dependence, where co-occurring extremes are most critical [8], [9]. This makes copulas particularly suitable for constructing integrated drought indices, as they can capture both the diversity of individual indicators and the strength of their joint behavior. Among copula families, the Clayton copula is especially effective for modeling lower-tail dependence, which is essential for understanding the compounding impacts of severe droughts.

Building an IDI using the Clayton copula meets these requirements. By integrating SPI, SMI, SRI, and SGI into a unified framework, the approach accounts for nonlinear and asymmetric dependence among drought indicators while avoiding restrictive assumptions about their marginal distributions. This enhances the reliability of drought monitoring compared with traditional correlation-based methods. Moreover, the ability of copula-based models to characterize joint extremes strengthens their capacity to identify critical drought conditions and inform risk management.

Despite significant progress in drought monitoring worldwide, there remains a considerable gap in the development and application of integrated drought indices at the basin scale in Viet Nam. Most existing studies on the Ba River Basin have relied on single drought indicators such as SPI or SRI, which provide valuable information on specific drought types but fail to represent the multi-dimensional propagation and interactions among meteorological, agricultural, and hydrological droughts. Moreover, few attempts have been made to adopt advanced statistical tools such as copula functions to explicitly model nonlinear and asymmetric dependencies among drought indicators in this region. This limitation hinders comprehensive drought risk assessment and the design of effective water resources management strategies under a changing climate. To address these gaps, the present study aims to develop an Integrated Drought Index (IDI) for the Ba River Basin in Viet Nam using a copula-based framework. Specifically, the Clayton copula is employed to integrate four key drought indicators SPI, SMI, SRI, and SGI representing meteorological, agricultural, and hydrological droughts.

2. Data and Methods

2.1. Study area

The Ba River Basin has an elongated and narrow shape with a total area of about 13,417 km². It lies mainly within three provinces Gia Lai, Dak Lak, and Phu Yen covering one city, two towns, and 19 districts. The Ba River originates from Ngoc Ro Mountain (1,549 m) in the Truong Son Range. From its headwaters to An Khe, the river flows Northwest-Southeast, then shifts North-South, and after the Hinh River confluence turns west-east before discharging into the East Sea at the Da Rang estuary in Tuy Hoa City, Phu Yen Province. The basin receives an average annual rainfall of around 1,760 mm.

Due to the influence of the eastern Truong Son rainfall regime, the wet season lasts from May to December, contributing 78-82% of annual rainfall, while the dry season contributes only 18-22%. Maximum rainfall usually occurs in August, whereas the driest months are January to February. Despite its relatively large size, the basin has one of the sparsest rainfall and water level monitoring networks in Viet Nam. There are five major reservoirs in the basin: An Khe-Ka Nak, Ayun Ha, Krong H'nang, Song Hinh, and Song Ba Ha which are vital for hydropower generation, irrigation, and water management (Figure 1).

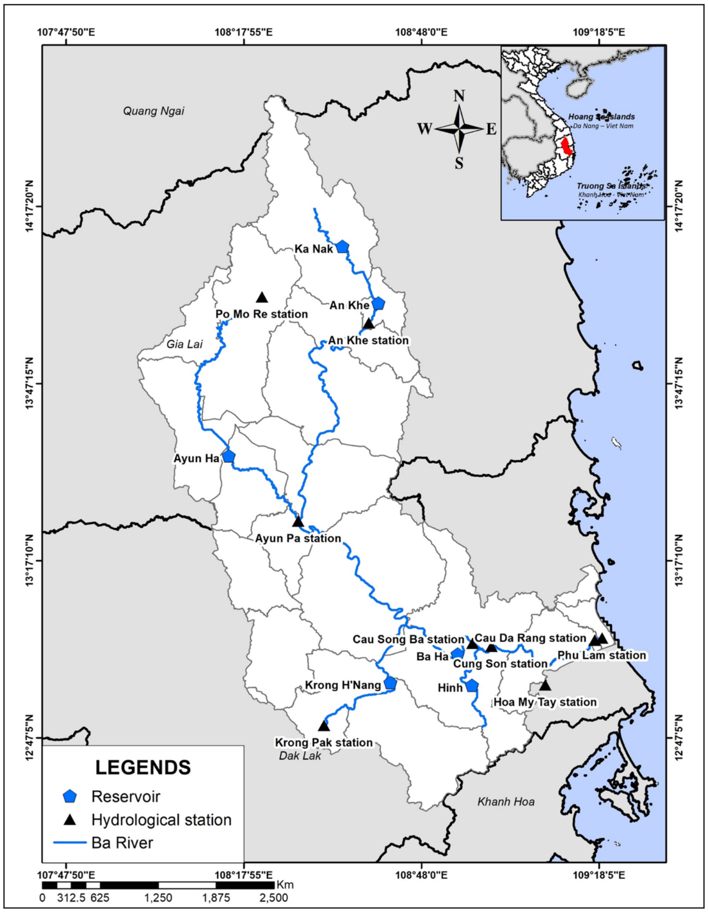


Figure 1. Location, rivers, reservoirs and gauging stations in the Ba Basin, Viet Nam

2.2. Data

This study employs gauged streamflow records for the period 1980-2023 were obtained from the Viet Nam Meteorological and Hydrological Administration (VMHA), providing long-term observations of river discharge. Precipitation data for the same period were taken from the Viet Nam Gridded Precipitation (VnGP) dataset [10], which has been specifically developed and validated for hydrometeorological applications in Viet Nam.

To capture atmospheric variables, we used the ERA5 global reanalysis dataset (1980-2023) produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) [11]. This dataset provides gridded information on wind speed, evapotranspiration, and mean, minimum, and maximum temperatures, which are essential inputs for drought monitoring and hydrological modeling.

Topographic information was derived from the Advanced Land Observing Satellite (ALOS) World 3D dataset (AW3D30), which offers a Digital Elevation Model (DEM) with approximately 30-meter resolution, produced by the Japan Aerospace Exploration Agency (JAXA) Earth Observation Research Center (EORC) in 2012 [12]. Soil characteristics were obtained from the FAO-UNESCO Soil Map of the World (SMW) [13], which provides spatially distributed information on soil types and properties. In addition, land use and land cover patterns were derived from the Land Cover CCI Product (ESA Version 2.0, 2017) [14].

2.3. Methods

2.3.1. VIC model

In this study, the Variable Infiltration Capacity (VIC) model [15] is applied to simulate hydrological processes in the Ba River Basin. The VIC model was selected for several reasons. First, it is a fully distributed, physically based model that explicitly represents the spatial heterogeneity of meteorological and surface inputs. Second, as a land surface hydrological model, it quantitatively represents the exchange of water, energy, and momentum fluxes between the land surface and the atmosphere. Third, the model structure allows the inclusion of human influences, such as reservoir operations and land use/land cover changes, which are critical for basin-scale applications.

The VIC framework typically consists of three main components. The rainfall-runoff module forms the core of the system, simulating the interactions among climate forcings, land surface characteristics, and hydrological responses. It uses meteorological drivers together with physiographic properties to produce gridded estimates of surface runoff and baseflow. These outputs are then aggregated by the routing module to estimate streamflow at specified basin outlets. Additionally, a calibration component is incorporated to improve the accuracy of both runoff generation and routing. While the MOEA module is often employed for this purpose, in the present study the SCE-UA (Shuffled Complex Evolution-University of Arizona) optimization algorithm is adopted instead of the NSGA multi-objective genetic algorithm to achieve efficient parameter estimation and calibration. In this study, the Ba River Basin was discretized into a VIC model grid with three soil layers at a spatial resolution of 0.04°, resulting in 1,683 grid cells (51 × 33), of which 752 cells fall within the basin boundary.

In routing module, reservoir operation was explicitly incorporated through two parameter groups: (1) Reservoir location and (2) Reservoir characteristics together with the operation rule curves. Reservoir locations were integrated into the model using GIS-based spatial referencing, ensuring accurate representation of their position within the river network. Reservoir physical parameters (e.g., storage capacity, release structures) and operating rules (e.g., flood control, irrigation, hydropower priorities) were then embedded to govern inflow-outflow relationships.

2.3.1. Development of IDI

Monthly time series of precipitation, soil moisture, surface runoff, and baseflow were extracted from the VIC simulations for each grid cell. These outputs were then aggregated to the district scale using area-weighted averaging to generate consistent datasets for drought index computation.

Four univariate drought indices were derived: SPI (Standardized Precipitation Index), SMI (Soil Moisture Index), SRI (Standardized Runoff Index), and SGI (Standardized Groundwater Index). Each index was calculated at multiple accumulation timescales to capture the response dynamics of different hydrological components: 1-3-6-12 months for SPI, SRI, and SGI, and 1-6 months for SMI.

To integrate these indicators, we adopted the copula-based approach proposed by Shah and Mishra (2019) [5]. As drought propagates sequentially through the hydrological cycle from meteorological deficits (SPI) to soil moisture depletion (SMI), reduced runoff (SRI), and groundwater decline (SGI) lagged correlations were first assessed. Pearson correlation analysis was conducted to identify the most representative timescales for each index, ensuring that the selected combinations reflect the strongest interdependencies across drought types.

The joint dependence structure among SPI, SMI, SRI, and SGI was modeled using the Clayton Copula, which is particularly effective in capturing lower-tail dependence representing simultaneous extreme deficits across variables. In this framework, the standardized indices were first transformed into cumulative probabilities through the standard normal cumulative distribution function. These probabilities were then combined using the Clayton Copula:

$$C\ (u_1, u_2, u_3, u_4, \theta) = \left(u_1{}^{-\theta} + u_2{}^{-\theta} + u_3{}^{-\theta} + u_4{}^{-\theta} - d + 1\right)^{\frac{-1}{\theta}} \quad (1)$$

Where, u_i denotes the marginal cumulative probability of each drought index, $d=4$ is the number of variables, and $\vartheta>0$ is the dependence parameter estimated by maximum likelihood.

The resulting joint cumulative distribution function (Joint CDF) quantifies the probability of concurrent drought conditions. A lower Joint CDF indicates a higher likelihood of simultaneous severe deficits, while higher values imply wetter conditions. To enhance interpretability, Joint CDF values were converted back into a standard normal score using the inverse normal function, yielding the Integrated Drought Index (IDI):

$$IDI= \phi^{-1}\ (JointCDF) \quad (2)$$

The IDI time series thus provides a comprehensive measure of drought, integrating meteorological, agricultural, and hydrological dimensions. Negative IDI values indicate drought, positive values indicate wet conditions, and values near zero correspond to near-normal states.

The research method schematic of this study is depicted in Figure 2.

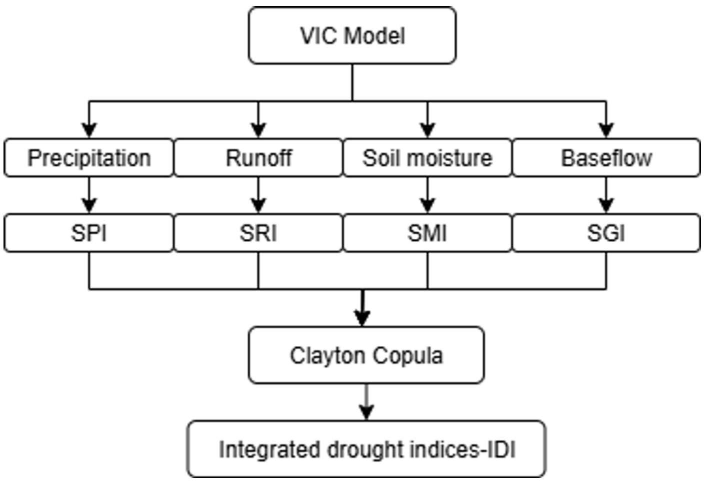


Figure 2. Research method schematic

3. Results and discussion

3.1. Calibration and validation of the VIC model

3.1.1. Calibration period (1995-2001)

The VIC model was first calibrated for the pre-dam period (1995-2001) at An Khe and Cung Son stations. Six soil parameters (bin, Ds, Dmax, Ws, D2, D3) were optimized to reproduce the observed streamflow. The performance of the model was evaluated using the statistical indicators NSE, RMSE, Pbias, and R^2. The results indicate that the model achieved satisfactory performance at both stations, with NSE values of 0.80 at An Khe and 0.84 at Cung Son, and high coefficients of determination (R^2>0.90). The calibration statistics are presented in Table 1, while the simulated and observed hydrographs during the calibration period are illustrated in Figure 3.

Table 1. The NSE, R^2, RMSE, BIAS index stations in the calibration period 1995-2001

Hydrological station	NSE	RMSE	Pbias	R^2
An Khe	0.80	26.27	32.46	0.95
Cung Son	0.84	155.33	29.71	0.93

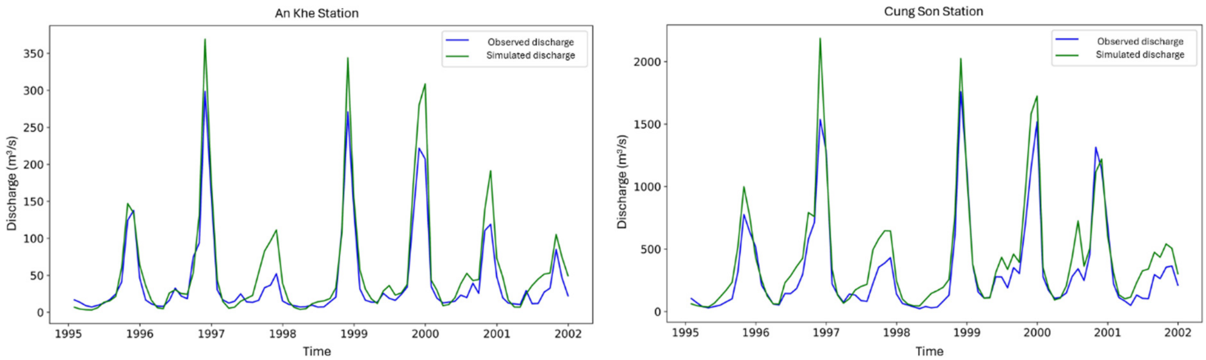


Figure 3. The simulated and observed monthly discharge at An Khe and Cung Son stations in the calibration period 1995-2001

3.1.2. Validation period (2002-2008)

Model validation was carried out for the subsequent period (2002-2008), prior to the operation of large reservoirs in the basin. Using the calibrated parameters, the VIC model was applied to both An Khe and Cung Son stations. The results (see Table 2) show that model performance remained acceptable, with NSE of 0.77 at An Khe and 0.76 at Cung Son, and R^2 values of 0.96 for both stations. These results confirm the model's robustness in reproducing observed monthly streamflow. The comparison between observed and simulated discharge for the validation period is illustrated in Figure 4, demonstrating good agreement in both magnitude and seasonal variation.

Table 2. The NSE, R^2, RMSE, BIAS index stations in the validation period 2002-2008

Hydrological station	NSE	RMSE	Pbias	R^2
An Khe	0.77	23.93	35.19	0.96
Cung Son	0.76	110.68	32.08	0.96

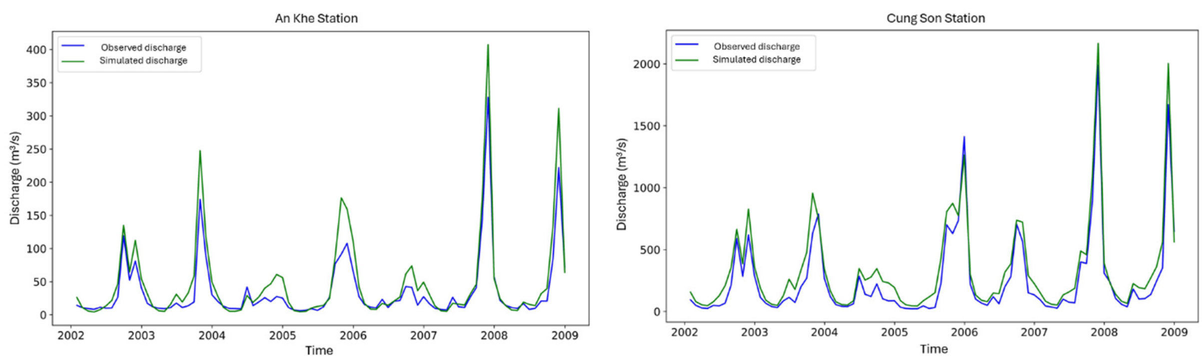


Figure 4. The simulated and observed monthly discharge at An Khe and Cung Son stations in the validation period 2002-2008

3.1.3. Validation for the post-dam period (2009-2022)

The calibrated parameters were further applied to the post-dam period (2009-2022), when major reservoirs became operational across the Ba River basin. The performance statistics (Table 3) show a reduction in model efficiency, with NSE values declining to 0.64 at An Khe and 0.60 at Cung Son, and increased RMSE and Pbias values. This degradation reflects the impact of human interventions. Nevertheless, the model was still able to reproduce the general discharge patterns, as shown in Figure 5.

Table 3. The NSE, R^2, RMSE, BIAS index stations in the validation period 2009-2022

Hydrological station	NSE	RMSE	Pbias	R^2
An Khe	0.64	21.30	40.82	0.72
Cung Son	0.60	206.51	42.04	0.71

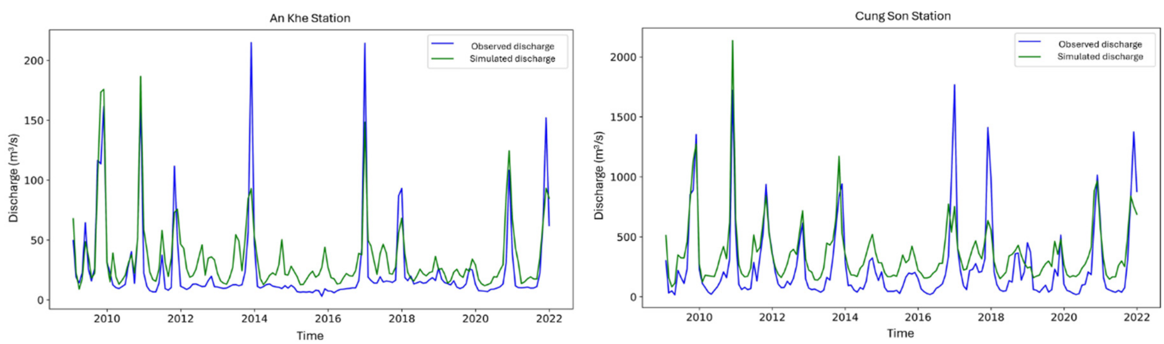


Figure 5. The simulated and observed monthly discharge at An Khe and Cung Son stations in the validation period 2009-2022

3.2. Evaluation of IDI

From the monthly time series of precipitation, runoff, soil moisture, and baseflow (1980-2023), four standardized drought indices (SPI, SRI, SMI, and SGI) were derived for each district within the Ba River basin. Based on correlation analysis, the study identified an optimal set of indices to be used as inputs for the Copula model:

SPI-6: Standardized Precipitation Index with a 6-month accumulation period.

SRI-6: Standardized Runoff Index with a 6-month accumulation period.

SMI-3: Soil Moisture Index with a 3-month accumulation period.

SGI-3: Standardized Groundwater Index with a 3-month accumulation period.

Notably, both SMI and SGI were incorporated with a one-month lag relative to SPI and SRI. The selection of this combination followed the principle of maximizing cross-correlation among indices, thereby ensuring that the Copula framework could effectively integrate drought signals across different hydrological components. Correlation analysis revealed that the strongest interdependencies occurred at specific accumulation periods, which did not necessarily coincide across indices. Identifying this optimal configuration was therefore essential for selecting inputs to the Copula model. By capturing highly correlated signals, the Copula model can more accurately represent the dependence structure among indices, ultimately yielding a composite drought index (IDI) that is both statistically robust and physically meaningful.

The computation of the four univariate drought indices (SPI-6, SRI-6, SMI-3, SGI-3) together with the composite IDI provides a comprehensive view of drought evolution in the Ba River Basin. The analysis in this study focuses on assessing integrated drought during the dry season in 2015, 2016, 2019, 2020. These periods were selected because they coincide with strong El Nino events that caused substantial rainfall deficits and elevated temperatures across Viet Nam. Historical records confirm that these episodes led to widespread water shortages, agricultural losses, and hydrological stress within the Ba River Basin. The results for the most severe drought months across four major drought episodes show that IDI effectively captures both the intensity and spatial extent of drought impacts at the district scale (Figure 6-8).

In 2015, the meteorological drought index (SPI-6) indicated rainfall deficits mainly in the upstream areas such as K'Bang and some midstream districts. The soil moisture index (SMI-3) also reflected soil water shortages in these regions, although the extent of drought impacts had not yet spread across the basin. The runoff (SRI-6) and groundwater (SGI-3) indices showed only moderate hydrological impacts in the downstream areas. The integrated drought index (IDI) suggested localized severe drought in upstream and midstream areas, but without a wide spatial extent. This pattern is consistent with reported damages in Gia Lai Province, where drought in 2015 affected more than 12,803 ha of crops with estimated losses of VND 176.68 billion; particularly in the 2014-2015 winter-spring crop, more than 9,845 ha were damaged with a total loss of about VND 141.2 billion [16].

By 2016, drought became the most severe and widespread event in the entire study period. SPI-6 maps highlighted basin-wide rainfall deficits, while SMI-3 showed extensive soil moisture depletion, especially in midstream and downstream areas. SRI-6 and SGI-3 emphasized severe shortages in streamflow and groundwater, with many districts recording persistently negative anomalies. The IDI indicated extreme drought conditions (IDI < -2) covering the upstream, midstream, and downstream sub-basins. This coincides with a strong El Nino year, which is consistent with observed meteorological records and reported socio-economic damages: In Gia Lai, drought affected 22,849 ha of crops, including rice, maize, coffee, and pepper, with total losses estimated at VND 372.8 billion. This confirms that 2016 was both the most intense and socio-economically damaging drought on record [17].

In 2019, meteorological drought (SPI-6) was more localized, with deficits concentrated in the eastern and Southeastern districts such as Krông Pa and Ia Pa. SMI-3 indicated soil moisture decline extending into several midstream areas, while SRI-6 and SGI-3 reflected delayed impacts on runoff and groundwater, particularly downstream. Compared with 2016, the extent of extreme drought was smaller and mainly clustered in specific districts. The IDI clearly captured this pattern, showing severe drought conditions in a few localized hotspots rather than across the whole basin. Reported damages were also relatively limited, with 1,335.5 ha of crops affected and estimated losses of VND 16.6 billion, confirming that the 2019 drought was regionally confined [18].

In 2020, drought severity and spatial coverage approached that of 2016, although with slightly lower extremes. SPI-6 indicated widespread rainfall deficits, while SMI-3 revealed severe soil moisture depletion across midstream and downstream areas. SRI-6 and SGI-3 further highlighted critical streamflow and groundwater shortages, especially in districts such as Mang Yang, K'Bang, An Khe. The IDI maps showed extensive areas experiencing severe to extreme drought, with a spatial footprint much larger than in 2015 and 2019, and only slightly less severe than in 2016. This is consistent with field reports from Gia Lai, where drought affected approximately 9,116 ha of crops with total estimated damages of VND 188 billion, largely concentrated in coffee, pepper, and rice cultivation [19].

Overall, 2016 was the most extreme drought in terms of severity, extent, and socio-economic damages, followed by 2020 with a similarly large spatial footprint, particularly in the midstream and downstream regions. The 2015 and 2019 events were less severe, with 2015 mainly affecting upstream districts and 2019 characterized by localized drought in the Southeastern basin. The combination of model-based assessments (DHI, IDI) with reported damage statistics demonstrates why these four years were selected as representative case studies: They illustrate different forms of drought propagation and intensity while capturing distinct socio-economic impacts within the Ba River Basin.

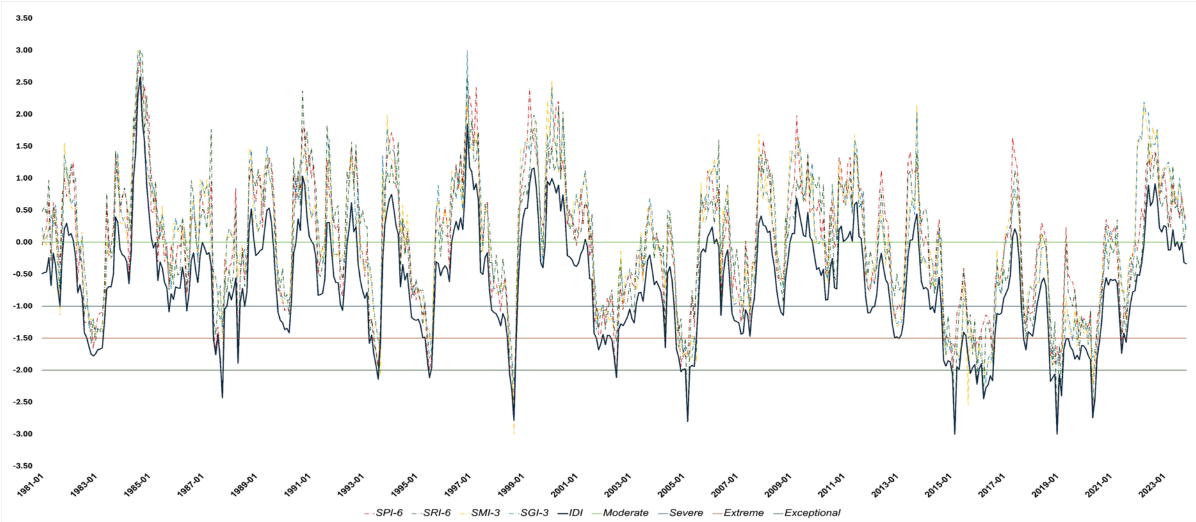
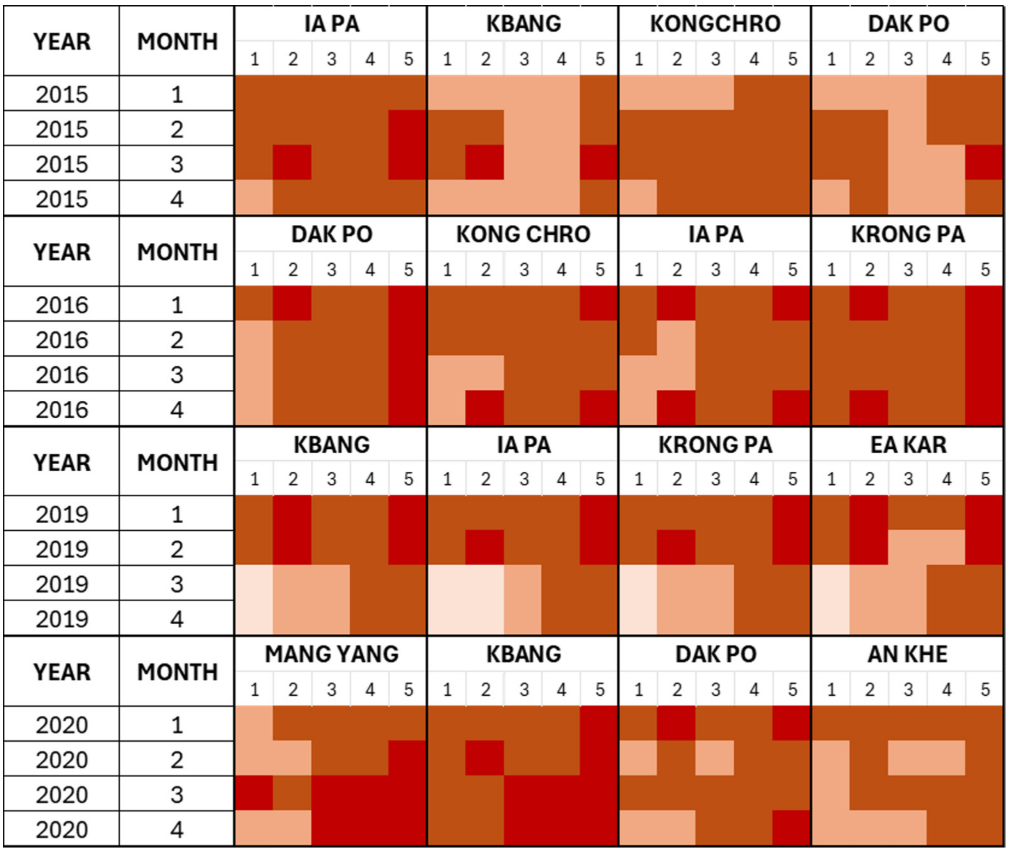


Figure 6. Evolution of Drought Based on SPI-6, SRI-6, SMI-3, SGI-3, and IDI in Ia Pa District (1980-2023)



> 0	< 0	< -1	< -1.5	< -2
Normal	Moderate Drought	Severe Drought	Extreme Drought	Exceptional Drought

1	2	3	4	5
SPI-6	SRI-6	SMI-3	SGI-3	IDI

Figure 7. The district-level drought indices for the Ba River Basin during the dry season in 2015, 2016, 2019, 2020

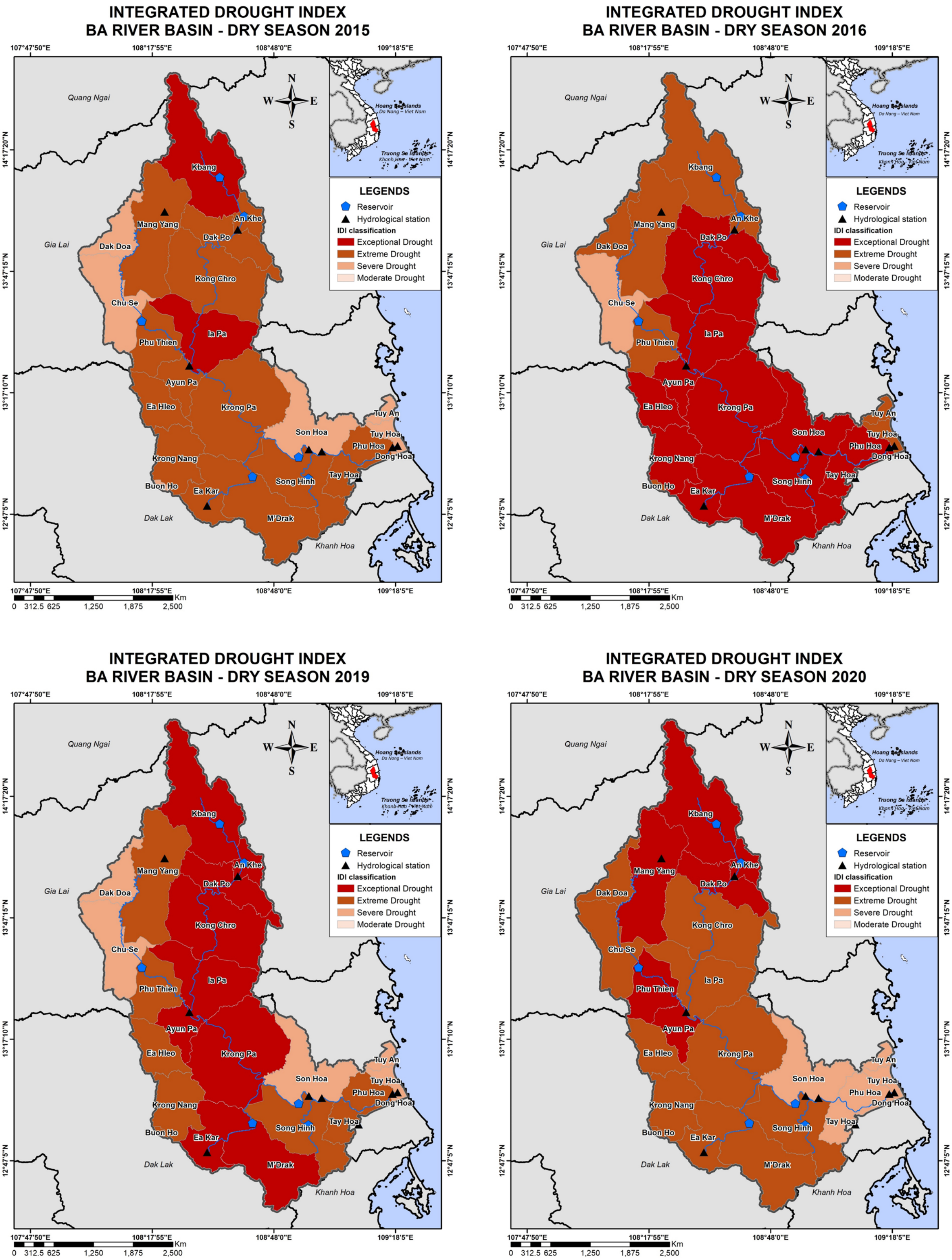


Figure 8. Spatial distribution of the IDI across districts of the Ba River Basin during the dry season in 2015, 2016, 2019, 2020

4. Conclusion

This study conducted a comprehensive assessment of drought and water security in the Ba River Basin by integrating a distributed hydrological model, multiple univariate drought indices, a copula-based integrated drought index (IDI), and risk-vulnerability analysis tools. The VIC model was developed and calibrated to simulate streamflow, soil moisture, surface runoff, and baseflow for 1980-2023. A key advance lies in explicitly incorporating reservoir operations, thus addressing a common limitation of earlier studies that often neglected the significant role of dams in shaping dry-season flows and downstream water availability.

On this modeling foundation, four univariate drought indices (SPI, SMI, SRI, SGI) were calculated and combined through a Clayton Copula to construct the IDI. Unlike single indices, the IDI effectively captured the sequential propagation of drought-from meteorological deficits (precipitation) through agricultural impacts (soil moisture decline) to hydrological stress (reduced runoff and groundwater). Case analyses of the 2015, 2016, 2019, and 2020 droughts confirmed that the IDI reflects both the intensity and spatial distribution of compound drought impacts. In particular, 2016 emerged as the most extreme drought in terms of basin-wide severity and socio-economic losses, followed by 2020, whereas 2015 and 2019 were characterized by more localized drought hotspots.

Nevertheless, several limitations remain. First, the VIC model could not fully account for water abstractions due to data scarcity, which lowered calibration-validation performance in the reservoir-influenced period. Second, aggregation from gridded outputs to district-level indicators may introduce smoothing errors. Third, while the Clayton Copula is well suited to lower-tail dependence, it has limited capacity to capture complex nonlinear and dual-tail dependencies; future studies should explore more flexible structures such as empirical or vine copulas.

Based on these findings, three recommendations are made for the future studies. Improving water use datasets is essential for enhancing VIC reliability under reservoir regulation. Incorporating spatial downscaling, remote sensing, and high-resolution climate products would help reduce aggregation biases. Finally, adopting advanced copula families could better represent multivariate dependence and extremes, thereby strengthening compound drought risk assessments.

Author contributions: *Conceptualization, Methodology, Formal analysis, Validation, Writing - Original Draft: Do Thi Ngoc Bich; Calculation, Data processing and Visualization: Nguyen Thanh Long, Nguyen Hoang Bach; Model setup and simulation: Khuong Van Hai; Supervision and Writing - Review & Editing: Nguyen Tu Anh.*

Acknowledgments: *This research is funded by the Viet Nam Ministry of Natural Resources and Environment under the research study: "Assessment of drought risk to ensure water security in river basins. A case study of the Ba River basin", code number TNMT.2024.02.06.*

Declaration: *The authors hereby declare that this article is their own research work, has not beenpreviously published, is not copied or plagiarized; there is no conflict of interest among the authors.*

References

1. D. Wilhite, (2000), *"Drought as a Natural Hazard: Concepts and Definitions", Drought A Glob. Assess.,* vol. 1, pp. 3-18.
2. A. K. Mishra and V. P. Singh (2010), *"A review of drought concepts," J. Hydrol.,* vol. 391, no. 1, pp. 202-216, doi: https://doi.org/10.1016/j.jhydrol.2010.07.012.
3. T. Mckee, N. Doesken, and J. Kleist (1993), *"The relationship of drought frequency and duration to time scales," in Proc. 8th Conf. on Applied Climatology,* vol 17, pp. 179-183.
4. S. Shukla and A. W. Wood (2008), *"Use of a standardized runoff index for characterizing hydrologic*

drought," Geophys. Res. Lett., vol. 35, no. 2, doi: https://doi.org/10.1029/2007GL032487.

5. D. Shah and V. Mishra (2020), *"Integrated Drought Index (IDI) for Drought Monitoring and Assessment in India," Water Resour. Res.,* vol. 56, no. 2, p. e2019WR026284, Feb. 2020, doi: https://doi.org/10.1029/2019WR026284.
6. S. I. Seneviratne et al. (2010), *"Investigating soil moisture-climate interactions in a changing climate: A review," Earth-Science Rev.,* vol. 99, no. 3, pp. 125-161, doi: https://doi.org/10.1016/j.earscirev.2010.02.004.
7. J. A. Keyantash and J. A. Dracup (2004), *"An aggregate drought index: Assessing drought severity based on fluctuations in the hydrologic cycle and surface water storage," Water Resour. Res.,* vol. 40, no. 9, Sep. doi: https://doi.org/10.1029/2003WR002610.
8. R. B. Nelsen, Ed. (2006), *"Methods of Constructing Copulas - An Introduction to Copulas",* New York, NY: Springer New York, pp. 51-108.
9. G. Christian and F. Anne-Catherine (2007), *"Everything You Always Wanted to Know about Copula Modeling but Were Afraid to Ask," J. Hydrol. Eng.,* 12(4), 347-368, doi: 10.1061/(ASCE)1084-0699(2007)12:4(347).
10. T. Nguyen-Xuan et al. (2016), *"The Viet Nam Gridded Precipitation (VnGP) Dataset: Construction and Validation", SOLA,* 12, 291-296, 2016, doi: 10.2151/SOLA.2016-057.
11. H. Hersbach et al. (2023), *ERA5 monthly averaged data on single levels from 1940 to present*, Copernicus Climate Change Service (C3S) Climate Data Store (CDS). https://doi.org/10.24381/cds.f17050d7.
12. JAXA EORC (2023), *ALOS Global Digital Surface Model 'ALOS World 3D - 30m' (AW3D30) Version 4.0*. https://www.eorc.jaxa.jp/ALOS/en/aw3d30/data/index.htm.
13. G. Fischer et al. (2008), *Global Agro-ecological Zones Assessment for Agriculture (GAEZ 2008)*, IIASA, Laxenburg, Austria and FAO, Rome, Italy.
14. ESA (2017), *Land Cover CCI Product User Guide Version 2. Tech. Rep*. maps.elie.ucl.ac.be/CCI/viewer/download/ESACCI-LC-Ph2-PUGv2_2.0.pdf.
15. X. Liang et al. (1994), *"A simple hydrologically based model of land surface water and energy fluxes for general circulation models", J. Geophys. Res. Atmos.,* 99(D7), 14415-14428, Jul. 1994, doi: 10.1029/94JD00483.
16. Steering Committee for Natural Disaster Prevention and Control Search and Rescue of Gia Lai Provice (2015), *Summary report on natural disaster prevention and search and rescue in Gia Lai Province in 2015* (in Vietnamese).
17. Steering Committee for Natural Disaster Prevention and Control Search and Rescue of Gia Lai Provice (2016), *Summary report on natural disaster prevention and search and rescue in Gia Lai Province in 2016* (in Vietnamese).
18. Steering Committee for Natural Disaster Prevention and Control Search and Rescue of Gia Lai Provice, (2019), *Summary report on natural disaster prevention and search and rescue in Gia Lai Province in 2019* (in Vietnamese).
19. Steering Committee for Natural Disaster Prevention and Control Search and Rescue of Gia Lai Provice (2020), *Summary report on natural disaster prevention and search and rescue in Gia Lai Province in 2020* (in Vietnamese).