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# The Relationship between Hydro-Agricultural Drought in the Corong River Basin: A Causal Time Series Regression Model

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## Abstract

This research explores the relationship between hydrological drought and agricultural drought in the Corong River Basin, focusing on the Gondang Reservoir Irrigation Area, Indonesia. By employing a Causal Time Series Regression Model, the study uncovers that agricultural drought twelve months prior has a significant impact on current agricultural drought and is influenced by current hydrological drought. Time series regression analysis reveals that 45.86% of agricultural drought is influenced by hydrological drought, with 54.14% influenced by other factors besides rainfall. Further research is needed to investigate these additional factors. These findings have practical implications, serving as a valuable index for assessing drought severity and planning mitigation actions, especially in the irrigation areas of interest. They emphasize the importance of effective irrigation management, appropriate cropping patterns, and a comprehensive understanding of the complex characteristics of drought in agricultural regions through comprehensive monitoring efforts in agricultural drought mitigation.



## Introduction

Drought is a recurring and extreme event that can disrupt agricultural production and lead to water scarcity [1]. The consequences of drought can result in various physical problems, such as crop failure [2,3], and it can also increase the likelihood of forest and land fires [4]. Several types of drought can be distinguished by the water deficit affecting different hydrological stages: meteorological drought, soil moisture or agricultural drought, and hydrological drought [5]. Meteorological drought occurs due to a deficiency (water deficit) as precipitation is less than evapotranspiration. Meanwhile, hydrological drought involves phenomena such as the decrease in water reserves (flow) in reservoirs, lakes, and groundwater due to the impact of drought caused by meteorological conditions in areas where forests are damaged [6]. Drought can be explained through specific characteristics known as drought characteristics. Hydrological drought characteristics include duration, timing, start and end dates, deficit, and the minimum flow of a river [5].

Hydrological drought is one of the types of drought closely related to surface and groundwater supply. This drought occurs when there is an imbalance between the available water supply and the water demand in a geographical area.

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Hydrological drought can significantly impact the environment, society, agriculture, and ecosystems [7]. Hydrological drought often requires careful monitoring, mitigation planning, and efficient water resource management to reduce its impacts. A good understanding of the factors influencing hydrological drought and effective water management systems are crucial in addressing this issue [8].

Many indices are used to define and describe hydrological drought, most of which are based on daily or monthly river flow data [9], and they can roughly be divided into threshold-based indices and standardized indices [10]. The recent drought period in the Central Chile has been defined as a "mega-drought." It has been extensively analyzed in terms of its impacts on hydroclimate and vegetation and its dynamic patterns [11]. In Indonesia, hydrological drought analysis has also been conducted in various regions. In the Keduang River Basin, hydrological drought with the Threshold Level Method was analyzed using flow rates Q50 (Normal discharge: the median of the flow rate distribution, indicating that 50% of the flow rate data is below the Q50 value) and Q80 (Reliable discharge: the 80th percentile of the flow rate distribution) as fixed thresholds to calculate drought deficits and durations [12]. Hydrological drought analysis was also carried out in the Bima Regency to determine deficits, drought durations, drought criteria based on deficits and surpluses following Oldeman's criteria, and the Threshold Level Method using Q50 and Q80 with the Flow Duration Curve (FDC) method to obtain hydrological drought characteristics [13].

Drought in agriculture is a complex global natural phenomenon that can cause significant economic losses, especially for developing countries, which often lack the resources and infrastructure to effectively mitigate its impact on agricultural production, leading to food insecurity and economic instability, compounded by the vulnerability of developing countries to extreme weather events and environmental changes that exacerbate the severity and frequency of drought, further worsening its impact on communities. [14,15]. Agricultural drought is closely related to water resilience and crop production [16,17]. Agricultural drought typically refers to a decrease in soil moisture that affects crop production or even leads to crop failures without explicitly referring to surface water resources [18]. With the increasing recognition of the importance of food security, many studies have been conducted to develop methodologies for monitoring agricultural drought. Over the past few decades, various methods have been developed to study agricultural drought based on rainfall, soil moisture, temperature, vegetation indices, and other indicators (Thornthwaite-Mather, Soil Water Deficit Index (SWDI) [19], Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI)) [20-22].

Advancements in remote sensing satellite technology have allowed researchers to use various types of remote sensing data, including multispectral, thermal infrared, or microwave data, to monitor drought on a large scale [23,24]. The Normalized Difference Vegetation Index (NDVI) calculated from remote sensing imagery is a widely used indicator for monitoring drought [25]. It separates vegetation from the background soil and provides valuable information about vegetation health [26,27]. However, NDVI alone may not be sufficient to identify vegetation drought because other factors, such as land cover changes and pest infestations, can cause similar anomalies. Rainfall and soil moisture data from microwave satellite sensors have also been used to monitor drought. Studies have shown that NDVI has a slow response to rainfall deficits [28,29]. In contrast, the Normalized Difference Water Index (NDWI) uses both near-infrared and infrared bands and is highly sensitive to rainfall [30]. The Normalized Difference Water Index (NDWI) is a tool used to measure the amount of water present in vegetation or soil [31]. It is used to detect water bodies and evaluate places experiencing water shortage stress [32]. NDWI is used to calculate the proportion of water contained in vegetation, which helps estimate the water within that vegetation cover and determine the level of saturation or water shortage stress that may affect the vegetation [33].

Furthermore, combining indices such as the Normalized Difference Drought Index (NDDI) enhances the analysis of drought behavior, distribution, and intensity [34]. The Normalized Difference Drought Detection Index (NDDI) is used to assess water deficiency in vegetation, particularly vegetation wilting due to drought or its impact on areas affected by forest fires [35]. NDDI allows for the evaluation of not only areas with severe drought but also areas with moderate and abnormal drought, helping to identify factors contributing to drought vulnerability in highland regions [36]. In Indonesia, NDDI has also been used for drought analysis. Drought analysis in agricultural land was conducted using the NDDI method based on NDVI and NDWI, with data collected in 2015 and 2019 in Ciampel Regency [37]. NDDI was also used to analyze extreme agricultural drought in Lampung, Indonesia [38]. In Lamongan Regency, identifying areas experiencing land drought was done using NDDI, utilizing Landsat 8 satellite imagery channels 4 (red), 5 (Near InfraRed/NIR), and 6 (Short et al./SWIR) [39,40]. From the explanations and previous research, it is evident that the Normalized Difference Drought Index (NDDI) is a superior drought index for several reasons. Firstly, NDDI measures the plant and soil water level, which is crucial for assessing drought severity. Secondly, NDDI provides a more accurate depiction of the impact of rainfall and crops compared to other indices. Additionally, NDDI effectively reduces noise from the atmosphere and vegetation, unlike indices such as NDVI or NDWI. Finally, NDDI relies entirely on satellite data, eliminating the need for additional weather data. These advantages make NDDI an excellent tool for accurately monitoring drought conditions and their impacts [41,42].

For effective and comprehensive drought preparedness in Indonesia, it is vital to grasp the connection between meteorological drought and agricultural drought. This is imperative since rainfall serves as the primary source of sustenance for agriculture, and there is a strong expected correlation between weather patterns and agricultural drought. The Corong River Basin, a tributary of the Bengawan Solo River Basin spanning an area of 815 km$^2$ and situated between the Lamongan and Gresik districts in East Java, Indonesia, possesses distinctive characteristics, particularly in its southern part, which markedly differs from conditions in other regions. The southern region experiences pronounced aridity during the dry season, significantly affecting the water supply to the Gondang Reservoir. This analysis holds paramount importance due to the Gondang Reservoir's pivotal role in housing six field reservoirs that cater to water supply in the Gondang irrigation area. Given its significance as a water supplier to the Gondang Reservoir, the Corong River Basin plays a substantial role. Monitoring drought in irrigation areas intertwines with agricultural drought, an indispensable aspect for overseeing and managing water availability in reservoirs and the water demands of rice fields [43]. Previous research has shown the importance of understanding the relationship between hydrological drought (HDI) and agricultural drought (NDDI) to effectively plan and manage agricultural water resources. This analysis aims to comprehend the relationship between hydrological drought (HDI) and agricultural drought (NDDI) in the Corong River Basin, particularly in the Gondang Reservoir Irrigation Area. Using a Causal Time Series Regression Model, we intend to identify the linkage between hydrological and agricultural drought and explore how one type of drought can influence the other. This analysis aims to provide in-depth insights into the dynamics of drought in this irrigation area, which can, in turn, be used to enhance water resource management, optimize agricultural production, and reduce the impact of drought on the local community.

## Study Area

This study takes place in the Corong watershed, part of the Bengawan Solo watershed, covering 815,081 km$^2$. The Bengawan Solo River Basin is between 110°18' and 112° 45' east longitude and between 6° 49' and 8° 08' south latitude. The Corong Watershed is responsible for supplying water to the Gondang Reservoir. The Gondang Reservoir, currently under construction, is designed to supply water to 7 field reservoirs for ten months, covering an area of 6,233 hectares during the dry season. During the rainy season, water is obtained from rainfall. Besides meeting irrigation needs, the Gondang Reservoir is also intended for domestic use and is being developed for fish farming and tourism. The reservoir has motorboats, parks, and animal cages [44].

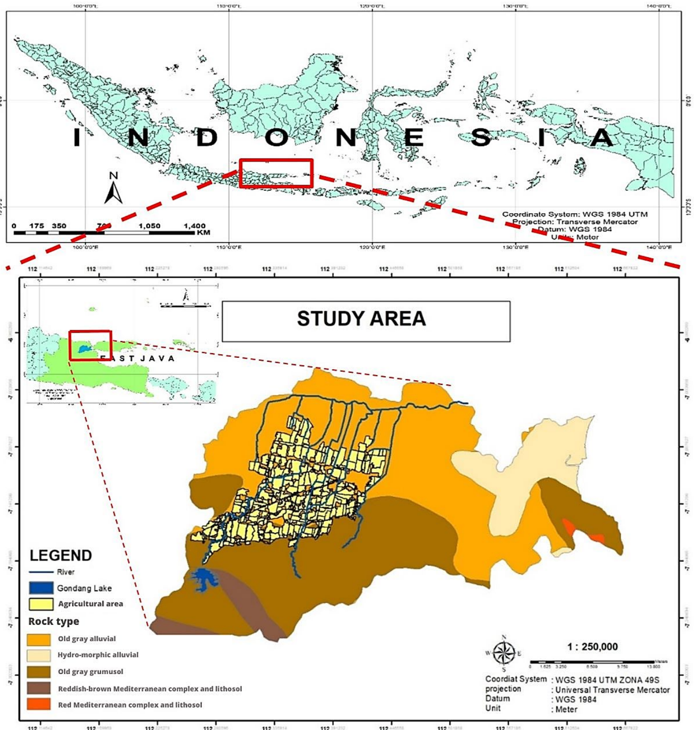


**Figure 1.** Corong River Basin Administration Map [40]

## Data Collection and Processing

The data utilized in this study comprises water discharge measurements from the Gondang Reservoir monitoring station located in the Corong River Basin, Indonesia, from 2016 to 2021. Additionally, discharge data from the Gondang Reservoir for the period 2016 to 2021 was sourced from the Bengawan Solo River Center, providing a comprehensive overview of water discharge trends and patterns during these years (https://sda.pu.go.id/balai/bbwsbengawansolo/portal/).

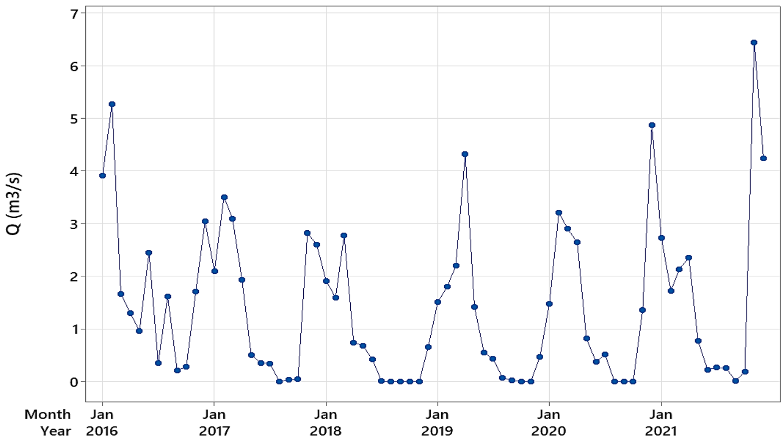


**Figure 2.** Corong River Basin Discharge Data (2016–2021)

Remote sensing image data analysis using Landsat 8 OLI/TIRS level 2 images, which have been geometrically and radiometrically corrected from 2017 to 2021, was conducted to identify drought using NDVI and NDWI, as well as to analyze NDDI. The data analysis steps include geometric correction to ensure the image coordinates match the original coordinates on the ground, which is not required for level 1 images that are already geometrically corrected; radiometric correction on the TOA Reflectance corrected images to fix reflectance values errors due to the sun's position; creation of NDVI and NDWI from radiometrically corrected images; and drought analysis using NDDI and the creation of spatial maps of NDVI, NDWI, and NDDI.

## Data Analysis

The determination of the dependable discharge uses the FDC (Flow Duration Curve) method, which represents the relationship between discharge and exceedance frequency by sorting semi-monthly data from highest to lowest values to obtain the exceedance frequency for each value (SNI 6738-2015). The steps include sorting discharge data, assigning ranking numbers, calculating exceedance frequency, reordering discharge values based on exceedance frequency, and plotting this data to form the FDC graph. Finally, the Q80 value, representing the discharge with an 80% exceedance frequency, is determined and used as a threshold to identify hydrological drought. Following these steps ensures the dependable discharge is accurately determined for further analysis in water resource management and drought mitigation.

The analysis of drought using the Normalized Difference Drought Index (NDDI), derived from the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI), involves several steps. First, satellite image data covering the study area, in this case, Landsat 8 imagery, is collected, eliminating the need for radiometric correction. Subsequently, NDVI and NDWI values are calculated. NDVI is computed using pixel values from the near-infrared (NIR) and red (RED) spectral bands, while NDWI is calculated using pixel values from the near-infrared (NIR) and short-wave infrared (SWIR) spectral bands. Following this, the NDDI value is determined by analyzing NDVI and NDWI. The NDDI map analysis is then utilized to identify areas affected by drought, with comparisons made across various time periods to discern changes and drought trends effectively.

Regression analysis is a statistical technique that establishes a relationship between the dependent variable and one or more independent variables. This analysis can assess the strength of the relationship between variables and make predictions about the relationship between two or more variables. It determines the relationship between Hydrological drought and agricultural drought. Hydrological drought uses the FDC-based HDI method with reservoir discharge parameters, while agricultural drought analysis uses the NDDI. Agricultural drought is highly influenced by hydrological drought, where agricultural drought occurs due to a decrease in water supply in reservoirs.

The causal model is a predictive technique that relies on understanding the connection between the predicted and influencing variables, which is unrelated to time. This means the model focuses more on cause-and-effect relationships without considering when the events or data occurred, unlike time series models which emphasize the time sequence for predictions [45]. In practical terms, this forecasting method involves regression and correlation techniques applicable to short- and long-term predictions. These methods utilize equations analyzed using the least squares technique to identify a function that elucidates the relationship between dependent and independent variables.

### Hydrological Drought Index (HDI)

The Hydrological Drought Index (HDI) is a tool that measures the level of drought based on the availability of water in hydrological systems, starting from an extended period without rainfall, causing a reduction in soil moisture, until water discharge falls below the established drought threshold [46]. The drought index is a primary tool for detecting, monitoring, and assessing drought events. Drought is a multidisciplinary phenomenon that lacks a universally accepted definition worldwide. Similarly, there is no universally applicable drought index [47]. The hydrological drought index is a single value that represents the severity of drought in terms of the duration of the longest drought and the most significant number of drought occurrences, each with specific return periods. To calculate the hydrological drought index value, use the following formula [48]:

$$\mathrm{HDI} = \frac{\text{Deficit}}{\text{Reliable dischargeQ80}} \tag{1}$$

with HDI is Hydrological drought index, $Q_d$ is Discharge deficit/surplus ($m^3/s$), and $Q_{80}$ = Reliable discharge or normal water level ($m^3/s$)

Drought Criteria with HDI Values:
Drought criteria are determined based on the hydrological drought index values, with the following thresholds [49]:
• Dry Criteria (K) between 0.000 < HDI < 0.0155
• Very Dry Criteria (SK) between -0.0006 < HDI < 0.00
• Extremely Dry Criteria (ASK) below HDI < -0.0006 These criteria are only considered when drought occurs. If the HDI value is above the specified threshold, it is classified as a wet month.

### The Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is the most used vegetation index for global greening. In green plants, chlorophyll substantially absorbs the blue spectrum (0.4-0.5 m) and the red spectrum (0.6-0.7 m) while reflecting the green spectrum (0.5-0.6 m). As a result, we see healthy plants as green. Between 0.7 and 1.3 m, the Near Infrared (NIR) band of healthy plants has a high reflectivity. The internal leaf structure of the plat prim formula is below [50].

$$NDVI = \frac{(\rho NIR - \rho Red)}{(\rho NIR + \rho Red)} \tag{2}$$

In this research analysis, Landsat 8 data was used to obtain NDVI values using the formula:

$$NDVI = \frac{(\text{Band 5 – Band 4})}{(\text{Band 5 + Band 4})} \tag{3}$$

NDVI is a classic index that measures vegetation growth and density and ranges from -1.0 to 1.0. Negative values indicate clouds or water, while positive values indicate bare soil (values close to zero) and dense green vegetation (values equal to or greater than 0.4). NDVI is widely used to evaluate key vegetation parameters primarily influenced by climate conditions, human activities, and anthropogenic causes.

Generally, the following results were obtained: NDVI values ranging from -1 to 0 represent bodies of water. NDVI values ranging from -0.1 to 0.1 represent barren rock, sand, or snow. NDVI values ranging from 0.2 to 0.5 represent shrubs, grasslands, or mature plants. NDVI values ranging from 0.6 to 1.0 represent dense vegetation or tropical rainforests [51].

### The Normalized Difference Water Index (NDWI)

The Normalized Difference Water Index (NDWI) is used to analyze water bodies using remote sensing bands of Near Infrared and Green. This index exploits the fact that liquid water reflects more light in the Blue spectrum (0.4-0.5

μm) compared to Green and Red spectra. Clear water appears blue due to its reflection in the visible blue region, while murky water has higher reflectance in the visible spectrum and minimal reflection in the Near Infrared (NIR) band. Introduced by Gao in 1996, NDWI enhances the detection of water-related features in landscapes by utilizing the Near Infrared (NIR) and Shortwave Infrared (SWIR) bands [52].

$$NDWI = \frac{(\rho NIR - \rho SWIR)}{(\rho NIR + \rho SWIR)} \tag{4}$$

For Landsat 8 data,

$$NDWI = \frac{(\text{Band 5} - \text{Band 6})}{(\text{Band 5} + \text{Band 6})} \tag{5}$$

This research uses the NDWI transformation to explore its correlation with the likelihood of drought. The study posits that the object is drier when the spectral value of the moisture index transformation for an object is low, as indicated by the red-colored spatial data index. Conversely, the object is wetter or more humid when the spectral value is high, as noted in the blue-colored spatial index.

### *The Normalized Difference Drought Index (NDDI)*

The NDDI (Normalized Difference Drought Index) transformation is employed to assess drought conditions in agricultural land. Previous research has established a connection between vegetation and moisture indexes. This study hypothesizes that high drought index values will manifest when both the vegetation and moisture indexes decline. In such cases, drought conditions are likely to occur on agricultural land.

NDDI serves as a drought index to identify drought conditions in agricultural areas. NDDI combines vegetation data from NDVI and water data from NDWI to provide a more comprehensive assessment of agricultural drought conditions than relying solely on vegetation indices [53]. The equation for calculating the NDDI value is as follows [54]:

$$NDDI = \frac{NDVI - NDWI}{NDVI + NDWI} \tag{6}$$

NDVI represents the Normalized Difference Vegetation Index, while NDWI represents the Normalized Difference Wetness Index. The NDDI value, ranging from -1 to 1, indicates drought conditions, with higher values indicating more severe drought [54]. To evaluate the severity of drought, the occurrence of drought for each pixel was assessed by considering the NDDI classes [55,56] that were wet and exceeded 0.5. These classes correspond to wet (NDDI<0.5 Moderate Wet (NDDI 0.5–0.7), Dry (NDDI 0.7–1.0), and Strong Dry (NDDI>1.0).

### *Image Processing*

The image processing of Landsat-8 OLI/TIRS surface reflectance data involves several steps. First, the entire multispectral band is scaled by dividing it by 10,000. Next, a data composite is performed to compute the average spectral values of the image using a median composite technique. The composite result is then cropped to match the study area's location and processed to calculate the NDVI and NDWI indices. Following that, the NNDI index is calculated. The estimated results are subjected to a threshold analysis of drought-affected areas. The threshold results are further examined for spectral changes and mapped to depict the drought-affected areas.

## Results and Discussion

### *Flow Duration Curve (FDC)*

The Flow Duration Curve (FDC) is a tool used in hydrology to analyze river flow characteristics or other water channels. The FDC presents the relationship between discharge (the volume of water flowing per unit of time) and exceedance frequency (how often a certain discharge is exceeded during the observation period). The FDC has several fundamental values, such as Q50 and Q80. Q50, or the 50th percentile discharge, is the discharge value that is exceeded 50% of the time and is often used as an indication of median discharge. This provides a general overview of water flow under average conditions. Meanwhile, Q80, or the 80th percentile discharge, is the discharge value that is exceeded 80% of the time and is frequently used in drought analysis and water resource planning. Q80 serves as an indicator of relatively common low flow, assisting in planning for water availability during dry periods [48].

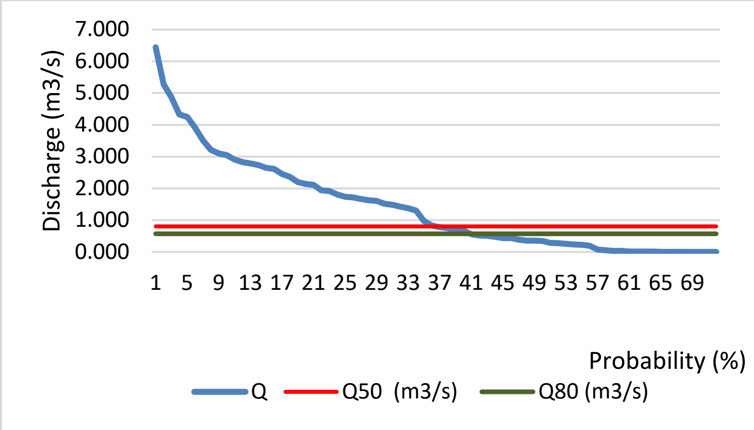


**Figure 3.** Flow Duration Curve of Gondang Reservoir Monitoring Station, Corong River Basin

Based on Figure 3, the duration and deficit of hydrological drought can be determined by identifying daily, semi-monthly, or monthly discharge that falls below the Q80 threshold [55] Duration refers to the length of days from the beginning to the end of the drought, while deficit volume is the difference between the discharge and the threshold throughout the drought duration. According to Oldeman, drought criteria are based on discharge values as follows [56].

### *The Calculation of Deficit and Drought Duration Q50 at Gondang Water Gauge Station*

The computation of Q50 and Q80 thresholds in the CORONG River basin involves determining the Normal discharge (Q50) and Reliable discharge (Q80). Given Indonesia's dual-season climate, the standard discharge is utilized to calculate the Hydrological Drought Index (HDI), while the dependable discharge aids in assessing the severity of drought by employing the Weibull formula to estimate probabilities. The deficit calculation for the Gondang water gauge station in the Corong watershed is carried out by subtracting the discharge with the threshold over six years (2016-2021). The duration of the drought can also be determined from the length of the deficit that occurs.

$$P(X \geq x) = \frac{m}{n+1} x100\% \tag{7}$$

with: P (X≥ x) is the probability of occurrence of variable X (discharge) equal to or greater x $m^3/s$, m is data rangking; n = amount of data; and X = discharge data series; x is mainstay discharge if the probability corresponds to its designation, e.g., P (X≥ Q80%) = 0.8.

Example calculation:

$P(X \geq x) = \frac{1}{72+1} x100\% = 1.369$

$P(X \geq x) = \frac{2}{72+1} x100\% = 2.739$

From Figure 3, the results of the analysis, Q50 = 0.802 $m^3/s$ and Q80 = 0.043 $m^3/s$ for more details can be seen in the Figure 4.

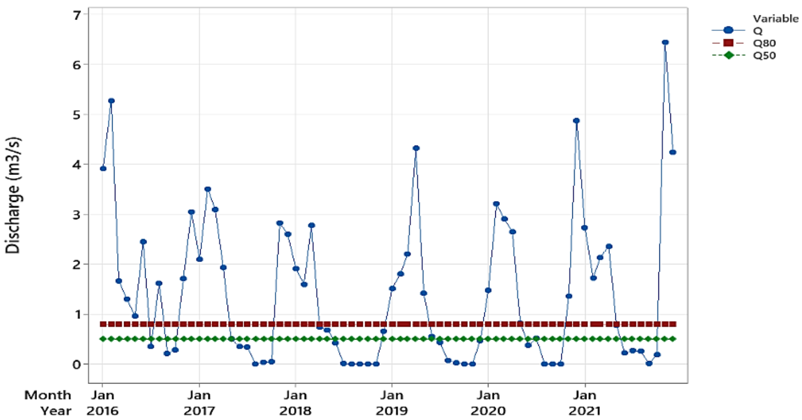


**Figure 4**. Threshold Discharge Data Q50 and Q80 Corong River Basin (2016–2021)

**Table 1.** The Deficit and Duration of Drought Q50 at Gondang Water Gauge Station, Corong Watershed

| Years | Total Deficit ($m^3/s$) | Max Deficit ($m^3/s$) | Duration (Month) |
|---|---|---|---|
| 2016 | -1.5460 | -0.5822 | 3 |
| 2017 | -3.5032 | -0.7924 | 6 |
| 2018 | -4.6745 | -0.8020 | 8 |
| 2019 | -4.0340 | -0.7280 | 7 |
| 2020 | -3.0966 | -0.7983 | 5 |
| 2021 | -3.0632 | -0.7875 | 6 |

Based on Figure 4 and Table 1, The analysis of flow deficits at the Gondang Water Gauge Station shows a trend of increasing deficits from 2016 to 2018, peaking in 2018 at -4.6745 $m^3/s$ and lasting for eight months. Although deficits decreased in 2019 and 2020, they remained high, indicating ongoing drought conditions. In 2021, the deficit decreased to -3.0632 $m^3/s$, but there was still a significant flow shortage. This data highlights the need for better water resource management to address drought conditions in the Corong River basin.

### *The Hydrological Drought Index (HDI)*

The categories used to determine the Hydrological Drought Index (HDI) are listed in the table below. Based on the analysis results of the hydrological drought index (HDI) at the water forecast post of the Corong River basin over six years, the data is summarized in the graph in Figure 5 and Table 1.

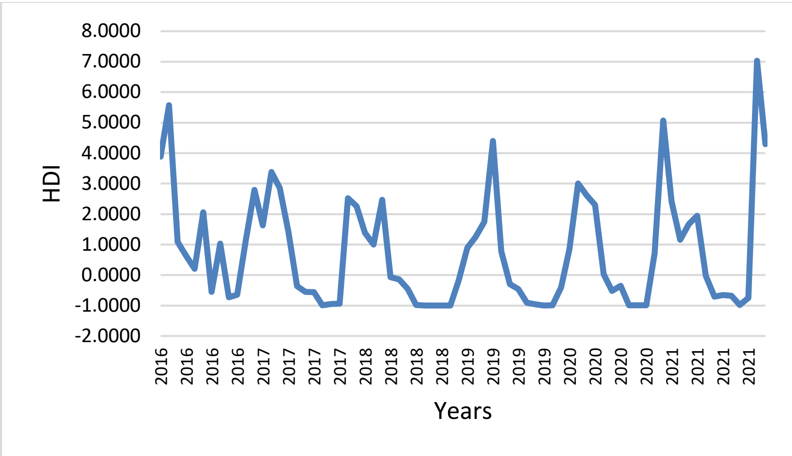


**Figure 5.** Hydrological Drought Index

**Table 2.** HDI Recapitulation of the Corong River Basin

| Year | Moon | HDI | Category HDI IWAY |
|---|---|---|---|
| 2016 | September | -0.726 | Strong |
| 2017 | August | -0.988 | Very Strong |
| 2018 | September | -1.000 | Very Strong |
| 2019 | September | -0.961 | Very Strong |
| 2020 | September | -0.995 | Very Strong |
| 2021 | September | -0.982 | Very Strong |

### *The Normalized Difference Vegetation Index (NDVI)*

The Normalized Difference Vegetation Index (NDVI) measures vegetation density in a region by analyzing digital brightness. The waves of light reflected by plant leaves, which impact digital brightness values, are measured by the Landsat satellite. NDVI is computed using mathematical equations and can be processed using ArcGIS software to obtain NDVI readings from Landsat 8 satellite data. Decreasing NDVI values indicate potential drought in the area, whereas increasing NDVI values indicate higher vegetation density.

From Figure 6, Landsat 8 data processing outcomes reveal a dominance of green color, depicting the vegetation density levels in the Corong River basin. NDVI in this area tends to be dominated by medium and dense vegetation densities from 2017 to 2021, with a minimum NDVI value of 0.21 in November 2021 and a maximum value of 0.732 in February 2021. This suggests that the Corong River basin has relatively healthy and dense vegetation during this period.

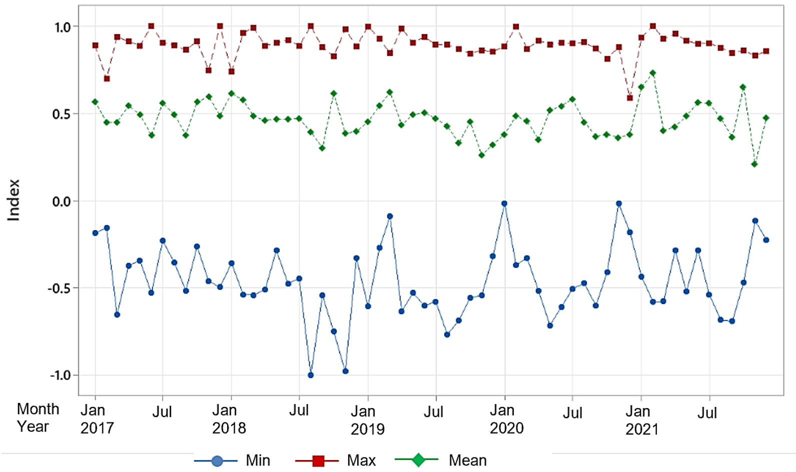


**Figure 6.** The Normalized Difference Vegetation Index (NDVI) Values of the Corong River Basin in 2017–2021

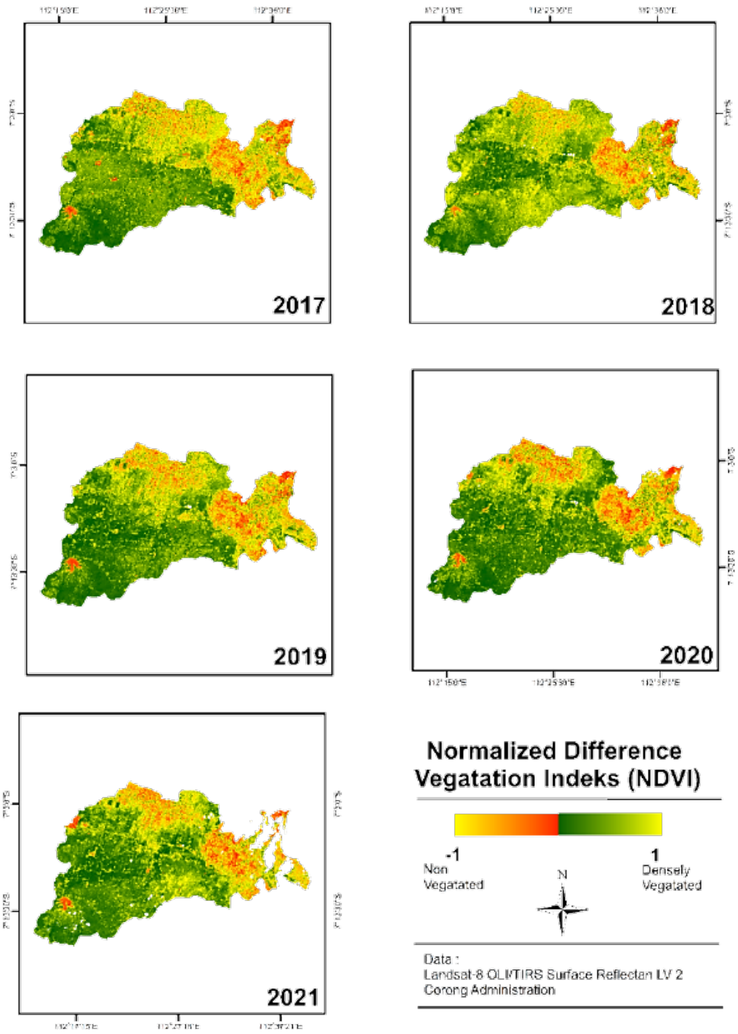


**Figure 7.** NDVI Distribution (2017-2021) in the Corong River Basin

## *The Normalized Difference Water Index (NDWI)*

NDWI is used to assess the reflection of water content in the soil and on the surface of plants. NDWI (Normalized Difference Water Index) is an index used to detect water content by utilizing remote sensing data. The NDWI value ranges from -1 to +1, where higher values indicate higher water content in plants, and lower values indicate lower water content in vegetation. During water absorption periods, the NDWI value tends to decrease because vegetation absorbs water from the soil. Therefore, NDWI is often used to determine the degree of wetness or dryness of an area. When rainfall increases, the NDWI value also tends to increase due to the rise in water content in the soil and plants.

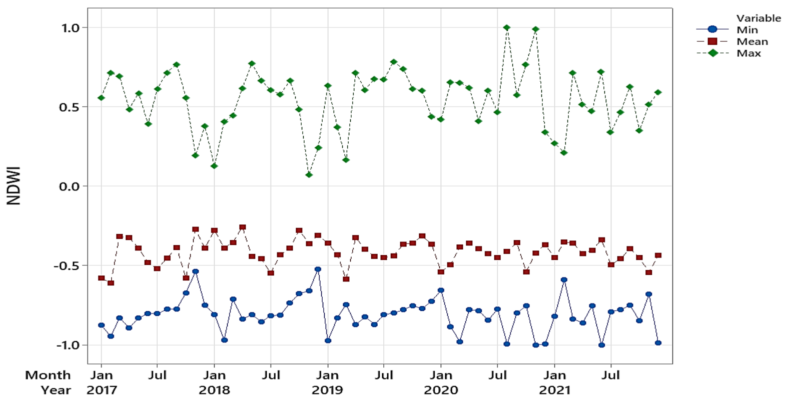


**Figure 8.** The Normalized Difference Water Index (NDWI) Values of the Corong River Basin in 2017–2021

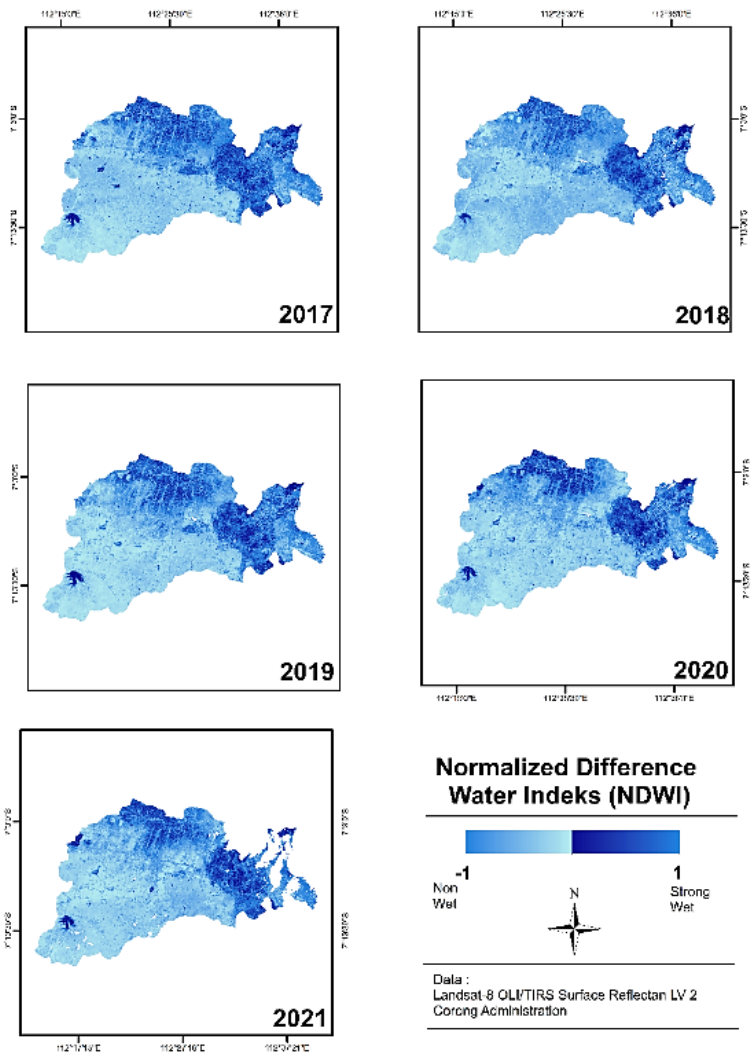


**Figure 9.** NDWI Distribution (2017-2021) in the Corong River Basin

Figure 8 shows the NDWI data for the Corong River Basin, with values ranging from -0.608 to -0.256 and an annual average of -0.506. These values generally indicate low moisture levels, tending towards dryness. The northern area is relatively wetter, while the central to southern areas are drier. This pattern aligns with previous research, especially around the Gondang reservoir.

Figure 9 provides a spatial representation of NDWI values from 2017 to 2021, ranging from -0.256 to -0.608. The northern region has higher NDWI values, indicating wetter conditions compared to the southern region. Information on moisture patterns and drought vulnerability is crucial, especially for water resources and agricultural management. The results of the drought distribution using NDWI for the period 2017-2021 show that the minimum value occurred in February 2021, and the maximum value occurred in April 2020.

### *The Normalized Difference Drought Index (NDDI)*

The NDDI (Normalized Difference Drought Index) transformation is used to assess drought conditions on agricultural land. NDDI combines data from NDVI and NDWI, providing a more precise range of values with differences of up to 5%. NDVI measures chlorophyll and mesophyll content in vegetation, while NDWI measures moisture content. In NDDI, higher values indicate drier areas.

The study assumes a high drought index occurs when both the vegetation and wetness indices decrease, leading to agricultural drought. Drought damage is categorized from mild to severe. Mild damage reduces irrigation water supply without causing crop failure. Severe drought causes significant crop and yield losses. Extreme drought (puso) results in total crop failure and substantial losses for farmers.

NDDI can be classified into three categories: no drought (NDDI value less than 0.1), moderate drought (NDDI value ranging from 0.1 to 0.3), and severe drought (NDDI value greater than 0.3).

**Table 3.** The Classification of NDDI

| Years | Month | NDDI | Drought Classification |
|---|---|---|---|
| 2017 | 1 | 10,539 | Dry |
| | 2 | 6,74 | Dry |
| | 3 | 10,974 | Dry |
| | 4 | 10,681 | Dry |
| | 5 | 9,562 | Dry |
| | 6 | 9,316 | Dry |
| | 7 | 11,175 | Dry |
| | 8 | 5,827 | Dry |
| | 9 | -4,895 | Wet |
| | 10 | 10,539 | Dry |
| | 11 | 14,889 | Dry |
| | 12 | 12,156 | Dry |
| 2018 | 1 | 14,885 | Dry |
| | 2 | 15,016 | Dry |
| | 3 | 10,83 | Dry |
| | 4 | 10,02 | Dry |
| | 5 | 9,133 | Dry |
| | 6 | 3,788 | Dry |
| | 7 | 3,456 | Dry |
| | 8 | -1,848 | Wet |
| | 9 | -7,373 | Wet |
| | 10 | 14,885 | Dry |
| | 11 | -5,992 | Wet |
| | 12 | 5,003 | Dry |
| 2019 | 1 | 9,255 | Dry |
| | 2 | 10,598 | Dry |
| | 3 | 13,212 | Dry |
| | 4 | 9,113 | Dry |
| | 5 | 9,992 | Dry |
| | 6 | 6,272 | Dry |
| | 7 | 2,776 | Dry |
| | 8 | -1,575 | Wet |
| | 9 | -7,545 | Wet |
| | 10 | 9,255 | Dry |
| | 11 | -8,524 | Wet |
| | 12 | -10,152 | Wet |
| 2020 | 1 | 7,627 | Dry |
| | 2 | 8,968 | Dry |
| | 3 | 9,019 | Dry |
| | 4 | 6,96 | Dry |
| | 5 | 13,614 | Dry |
| | 6 | 11,068 | Dry |
| | 7 | 8,404 | Dry |
| | 8 | 1,133 | Dry |
| | 9 | -6,034 | Wet |
| | 10 | 7,627 | Dry |
| | 11 | -3,628 | Wet |
| | 12 | 12,023 | Dry |
| 2021 | 1 | 17,412 | Dry |
| | 2 | 11,257 | Dry |
| | 3 | 6,485 | Dry |
| | 4 | 8,468 | Dry |
| | 5 | 10,473 | Dry |
| | 6 | 10,078 | Dry |
| | 7 | 7,719 | Dry |
| | 8 | 1,621 | Dry |
| | 9 | -5,061 | Wet |
| | 10 | -2,73 | Wet |
| | 11 | -3,88 | Wet |
| | 12 | 10,671 | Dry |

Table 3 explains the classification of NDDI (Normalized Difference Drought Index) values for agricultural drought in the Corong River Basin during the period from 2017 to 2021, covering a range of values varying from -10.152 to 17.412. Specifically, it can be observed that dry conditions occurred almost every year during this period, with the peak of dryness reached in January 2021, when the NDDI value reached its highest point. Throughout this period, the Corong River Basin frequently experienced drought conditions. The peak level of dryness in January 2021 signifies years of extreme dryness or severely limited water resources in the area.

From Figure 10, the Corong River Basin experienced dry conditions almost every year, with the peak of dryness occurring in January 2021, marked by the highest NDDI value. The peak level of dryness in January 2021 depicts years of extreme dryness or severely limited water resources in the area. A spatial representation or visualization map can be observed depicting the NDDI (Normalized Difference Drought Index) values for agricultural drought during 2017-2021 in the Corong River Basin. This map illustrates the level of agricultural drought using a color scale. In this map, red indicates areas experiencing higher levels of drought, while green areas signify wetter conditions or no drought.

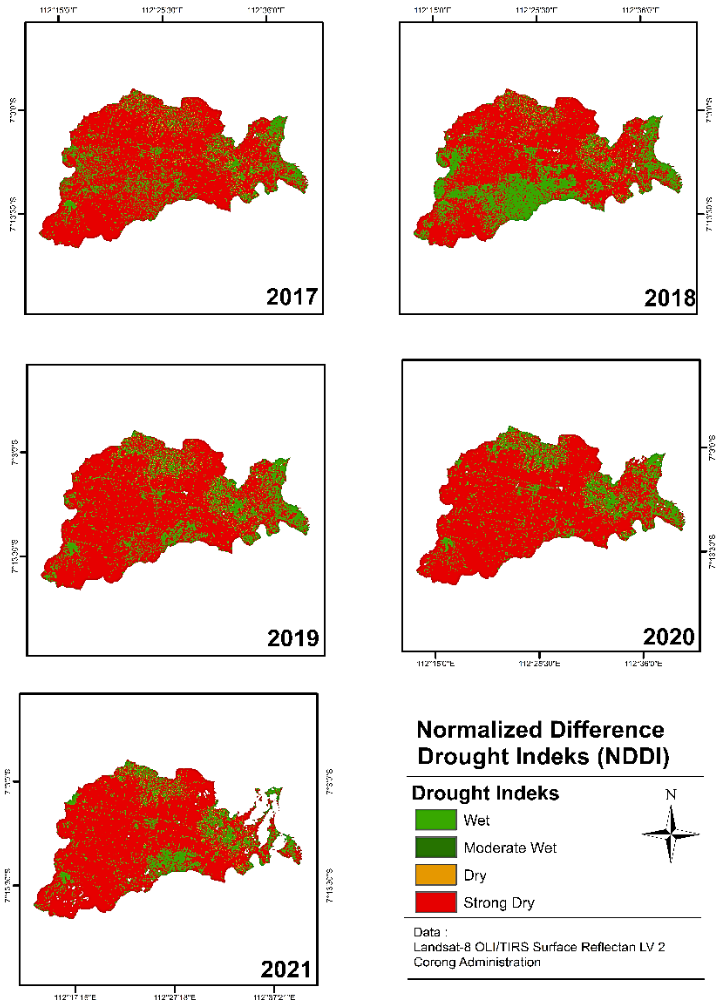


**Figure 10.** Spatial NDDI Drought Index

### *The Relationship Between Hydro-Agricultural Drought (HDI and NDDI)*

The characteristics of drought in this study are determined by linking the hydrological drought index using HDI and agricultural drought using NDDI to describe drought in the Corong River Basin.

**Table 4.** *Pearson Correlation*

| | | NDDI | HDI |
|---|---|---|---|
| NDDI | *Pearson Correlation* | 1 | 0,349** |
| | *Sig. (2-tailed)* | | 0,006 |
| HDI | *Pearson Correlation* | 0,349** | 1 |
| | *Sig. (2-tailed)* | 0,006 | |

The analysis results show a significant positive relationship between Agricultural Drought (NDDI) and Hydrological Drought (HDI) with a Pearson correlation coefficient of 0.349 and a p-value of 0.006, indicating that an increase in NDDI is generally associated with an increase in HDI (Table 4). However, this relationship may not fully capture the complexity of the interaction between the two variables. To gain a deeper understanding of the relationship structure and nonlinear dependencies between NDDI and HDI, the use of Copula methods can provide a more accurate and informative analysis.

### *Partial Autocorrelation Function (PACF)*

Partial correlation is a statistical concept used to measure the relationship between two variables while considering the effects of control variables. The partial autocorrelation function (PACF) in time series analysis helps identify relationships between variables by eliminating the influence of intervening variables. For example, in regression, partial correlation refers to the relationship between the dependent variable and one specific independent variable while accounting for the influence of other independent variables. By following the definition of partial correlation above, the PACF for time series data, the partial autocorrelation between yt and yt−k is the correlation between yt and yt−k after adjusting for or taking into account the values of $y_{t-1}, y_{t-2}, \ldots, y_{t-k+1}$.

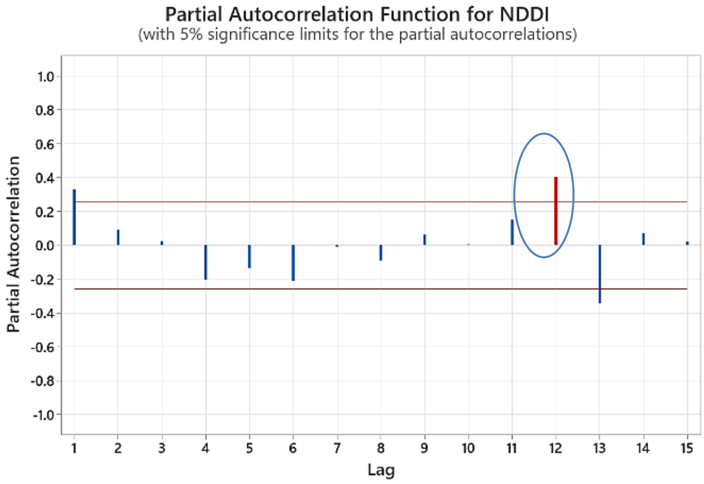


**Figure 11.** Normalized Difference Drought Index (NDDI) Graph for Partial Autocorrelation Function (PACF) (with 5% Significance Limits for The Partial Autocorrelations)

The analysis of the PACF graph, shows a strong dependency at lag 12 (Figure 11). It can be inferred that there is a significant monthly seasonal pattern in NDDI. This indicates that NDDI observations in a particular month have a strong relationship with observations that occurred 12 months earlier. Understanding this pattern is crucial as it allows for a better understanding of how long the influence of previous droughts may last and how significant their impact is on the current drought. Therefore, the use of PACF aids in understanding and modeling seasonal changes in NDDI data, as well as improving accuracy in forecasting future droughts.

### *Cross-Correlation (HDI-NDDI)*

Cross-correlation is a widely used method in time series data analysis. This technique predicts a system's relationship between data series X (input) and data Y (output). To perform cross-correlation analysis, both series must be sampled at the same time interval and assumed to remain stationary in mean and variance [57].

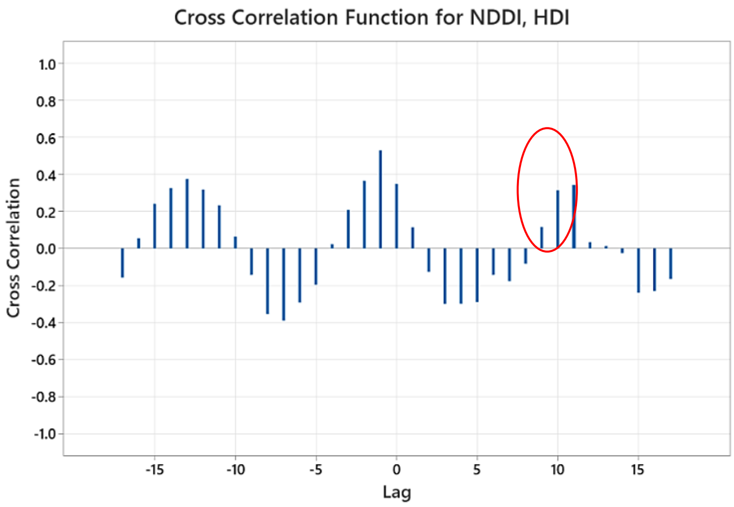


**Figure 12.** Cross-Correlation between NDDI_HDI

The results of the cross-correlation analysis between the hydrological drought index (HDI) and the agricultural drought index (NDDI) indicate significant interrelations at various time points (Figure 12). It was found that the hydrological drought conditions from one month prior significantly impacted the current agricultural drought (lag -1), while hydrological and agricultural droughts often co-occurred or had nearly immediate effects on each other (t).

Additionally, the influence of hydrological drought over a longer term, precisely ten months prior, also affects current agricultural drought conditions (lag 10), albeit with a longer delay. These findings underscore the importance of considering these factors in drought planning and management to achieve more effective mitigation strategies.

### *The Coefficient of Determination and the Linear Relationship between NDDI and HDI*

The coefficient of determination measures the fit of a regression line, indicating the proportion of variance in the dependent variable (Y) explained by the independent variable (X), expressed as a percentage.

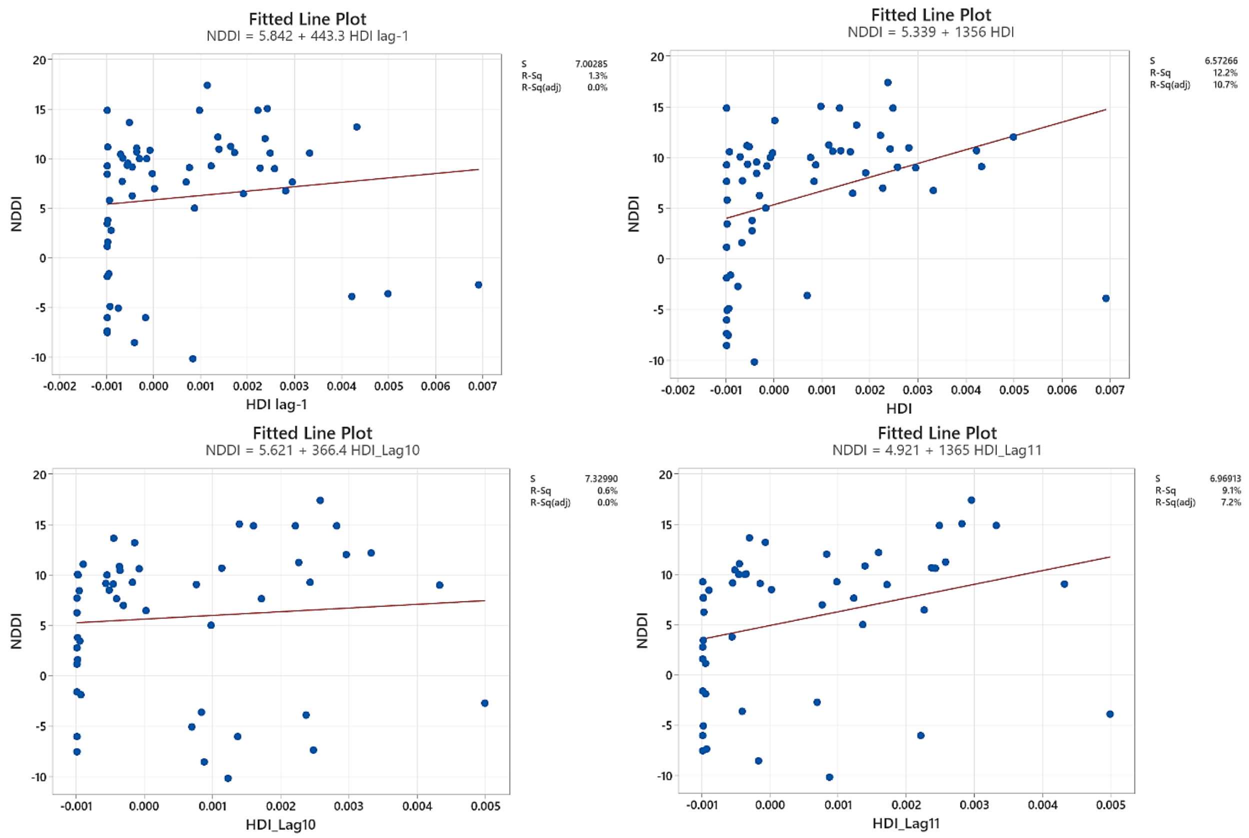


**Figure 13.** The Coefficient of Determination NDDI and HDI

Figure 13 displays the linear regression equation between NDDI and HDI. Linear regression is utilized to evaluate the influence of hydrological drought (HDI) on agricultural drought (NDDI), yielding low coefficient of determination ($R^2$) values. There is a time delay in observing their effects. The analysis reveals low $R^2$ values at various lags: 1.30% for lag -1, 12.16% for lag 0, 0.64% for lag 10, and 9.11% for lag 11. These results indicate that linear regression is not sufficiently effective in explaining the relationship between HDI and NDDI at the tested time delays. Additionally, the low $R^2$ values suggest that most of the variation in NDDI cannot be explained by variation in HDI at the examined lags. Therefore, further research is needed to understand the more complex relationship between hydrological drought and agricultural drought.

**Table 5.** Pearson Correlation for the Relationship between NDDI and HDI

| | NDDI | NDDI_Lag12 | HDI_lag-1 | HDI | HDI_Lag10 |
|---|---|---|---|---|---|
| NDDI_Lag12 | 0.595 | | | | |
| HDI_Lag-1 | 0.114 | 0.015 | | | |
| HDI | 0.340 | 0.006 | 0.545 | | |
| HDI_Lag10 | 0.075 | -0.002 | 0.638 | 0.392 | |
| HDI_Lag11 | 0.290 | 0.280 | 0.524 | 0.624 | 0.613 |

In applying the linear relationship between NDDI and HDI, the Pearson correlation coefficient is used to examine how closely the linear relationship between the two variables holds at different time intervals. The Pearson correlation coefficient measures the strength and direction of the linear relationship between two variables, ranging from -1 to +1. A value of +1 indicates a perfect positive linear relationship, -1 indicates a perfect negative linear relationship, while 0 indicates no linear relationship. Therefore, the Pearson correlation coefficient aids in evaluating the extent to which changes in one variable are associated with changes in the other variable, which is crucial in understanding the dynamics between NDDI and HDI in analyzing the relationship between hydrological drought and agricultural drought.

The results of the Pearson correlation between hydrological drought (HDI) and agricultural drought (NDDI) show that NDDI with NDDI_lag12 has a correlation of 0.595, NDDI with HDI has a correlation of 0.340, NDDI with HDI lag -1 has a correlation of 0.114, NDDI with HDI lag 10 has a correlation of 0.075, and NDDI with HDI lag 11 has a correlation of 0.290 (Table 5). The moderate correlation between NDDI and NDDI lag 12 indicates that agricultural drought conditions tend to be quite strongly related to the conditions from a year ago, possibly due to the influence of annual cycles or seasonal patterns. The weak correlation between NDDI and HDI lag 0 indicates a weak linear relationship between agricultural drought and hydrological drought at the same time, which may suggest that other factors also affect agricultural drought. The very weak correlation with other HDI lags indicates that hydrological drought in those periods did not significantly impact the current agricultural drought. Based on these results, a regression model incorporating NDDI lag 12 as the primary predictor variable and HDI as an additional variable can be used to evaluate the simultaneous influence of hydrological and agricultural drought.

### Causal Time-Series Regression

Based on the PACF, cross-correlation, and Pearson correlation analyses, it is evident that agricultural drought is influenced by previous agricultural drought conditions, hydrological drought, and other variables. To gain a more accurate understanding of the impact of HDI on NDDI, a causal time-series regression model is required. This model allows for analyzing causal relationships between variables while accounting for autocorrelation in the data. Linear regression, commonly used in time-series analysis, can be applied to determine this relationship. Next, using Causal Regression Time Series analysis, we will connect NDDI and HDI based on the data shown in Figures 11 and 12. Figure 11 indicates that current agricultural drought ($NDDI_t$) is influenced by agricultural drought 12 months prior ($NDDI_{t-12}$). Meanwhile, Figure 12 shows two possibilities: $HDI_t$ may be influenced by hydrological drought 10 months prior ($HDI_{t-10}$) or 11 months prior ($HDI_{t-11}$). The Causal Regression Time Series model will be developed and presented in Table 6 to provide a better estimate of the relationship between HDI and NDDI.

**Table 6.** Causal Regression Time Series

| Model | Regression Time Series | $R^2$ (%) | MAPE | Durbin-Watson |
|---|---|---|---|---|
| 1 | $NDDI_t = 0.97 + 0.614\ NDDI_{t-12} + 1313\ HDI_t$ | **45.64%** | 0.621 | 1.354 |
| 2 | $NDDI_t = 1.57 + 0.616\ NDDI_{t-12} + 118\ HDI_{t-10}$ | 35.50% | 0.636 | 1.220 |
| 3 | $NDDI_t = 1.59 + 0.581\ NDDI_{t-12} + 562\ HDI_{t-11}$ | 36.85% | 0.635 | 1.239 |

Based on the analysis, Model 1 is the best model for describing the causal relationship between NDDI and HDI. Model 1 explains 45.64% of the variability in NDDI and has the lowest MAPE of 0.621, indicating superior predictive performance compared to Models 2 and 3 (Tabel 7). Additionally, Model 1 shows the least amount of positive autocorrelation in the residuals with a Durbin-Watson statistic of 1.354. This model demonstrates that NDDI is significantly influenced by its values from 12 periods earlier and the current year's HDI, capturing both the temporal and contemporaneous effects more effectively than the other models.

The analysis results above indicate that the coefficients of determination ($R^2$) in the evaluated models are still low. The reason for the low $R^2$ values is the presence of a time lag between the influence of hydrological drought and agriculture. This phenomenon has been explained in research conducted by Ezzine, Bouziane, and Ouazar [58] and Zuo et al. [59], which suggests that when there is no rainfall, plants can still use the water reserves in the soil. According to Maina [60], this time lag occurs because plants have energy reserves that allow them to develop even during droughts. The intensity and duration of hydrological drought affect the water reserves in reservoirs or rivers. When rainfall is low and prolonged, water availability decreases, causing plants' water consumption needs to remain unmet. This leads to agricultural drought as a result of hydrological drought. These findings are consistent with research stating that during a drought period, it is sometimes the longest duration that is the strongest, depicting drought as a process that occurs over a certain period [40,61,62].

## Conclusions

The analysis shows that agricultural drought (NDDI) has a moderate relationship with agricultural drought 12 months prior, highlighting the impact of conditions from a year ago, while the best causal time-series regression model explains 45.64% of the variability in NDDI by combining NDDI_lag12 and current HDI. Although this model demonstrates strong predictive performance, the low $R^2$ value indicates a time lag in the impact of hydrological drought on agricultural drought. Therefore, further studies are needed to gain a deeper understanding of drought characteristics and to enhance monitoring techniques.

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