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Modelling causality between agricultural and meteorological drought indices in the Corong River basin, East Java Indonesia

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Abstract: The Lamongan Regency is an area in East Java, Indonesia, which often experiences drought, especially in the south. The Corong River basin is located in the southern part of Lamongan, which supplies the irrigation area of the Gondang Reservoir. Drought monitoring in the Corong River basin is very important to ensure the sustainability of the agricultural regions. This study aims to analyse the causal relationship between meteorological and agricultural drought indices represented by standardised precipitation evapotranspiration index (*SPEI*) and standard normalisation difference vegetation index (*NDVI*), using time series regression. The correlation between *NDVI* and *SPEI* lag 4 has the largest correlation test results between *NDVI* and *SPEI* lag, which is 0.41. This suggests that the previous four months of meteorological drought impacted the current agricultural drought. A time series regression model strengthens the results, which show a causal relationship between *NDVI* and *SPEI* lag. According to the *NDVI*–*SPEI*-1 lag 4 time series model, *NDVI* was influenced by *NDVI* in the previous 12 periods, and *SPEI*-1 in the last four periods had a determinant coefficient value of 0.4. This shows that the causal model between *SPEI*-1 and *NDVI* shows a fairly strong relationship for drought management in agricultural areas (irrigated areas) and is considered a reliable and effective tool in determining the severity and duration of drought in the study area.

Keywords: drought, river basin, standard normalisation difference vegetation index *NDVI*, standardised precipitation evapotranspiration index *SPEI*, time series regression

INTRODUCTION

Drought is a recurring and unpredictable natural event occurring almost worldwide (Orimoloye *et al.*, 2022). Drought monitoring is very important to identify and examine the occurrence of drought, which always changes under different conditions and time scales (Chu *et al.*, 2021). In the last 20 decades, drought has affected nearly 1.4 bln people worldwide, with an increase of nearly 30% in frequency and duration. By 2050, nearly 216 mln people will migrate due to drought due to a lack of access to clean water and productive land. These significant changes result in hunger and economic loss and hinder progress towards the SDGs, especially Goals 2 and 6 (Vähänen, 2022).

The American Meteorological Society (AMS) categorises drought as having meteorological, agricultural, hydrological, and socioeconomic consequences (Mishra and Singh, 2010; Zargar *et al.*, 2011). Meteorological drought, the initial drought phenomenon, begins with reduced rainfall (Guttman, 1998). Reduced surface water and groundwater supply are one factors causing hydrological drought. The decrease in the water level in reservoirs, lakes and groundwater determines this drought. There is a lag between the decrease in rainfall and the level of rivers, lakes and groundwater (Chu, 2018). Drought in agriculture occurs when there is insufficient rainfall to support crop development. So, it is necessary to consider cropping patterns for sustainable agricultural output to overcome problems caused by changes and bad weather (drought) (Lesk, Rowhani and Ramankutty, 2016). In agricultural drought, the impact of the meteorological drought will also reduce evapotranspiration and soil moisture (Hobbins *et al*., 2016). As a result, governments and academics from various countries have turned their attention to research on agricultural drought.

Many studies have analysed the relationship between the effects of meteorological drought on agricultural drought. Recently, it became clear how important it is to distinguish between agricultural and meteorological droughts. The standard precipitation index (*SPI*), a meteorological drought indicator, is less responsive to climate change than agricultural drought as evaluated by the standard groundwater index, or standardised soil water index (*SSWI*) (Wang *et al*., 2011). The examining of the relationship between the vegetative condition index (*VCI*), derived from satellite data, and *SPI*, that the relationship between meteorological and agricultural drought indicators is strengthened by seasonal developments, indicating a time-varying relationship between the two variables (Dhakar, Sehgal and Pradhan, 2013). In Morocco, the relationship between meteorological drought and agricultural one is low, based on short-term (15 years) meteorological data and remotely sensed vegetation (Ezzine, Bouziane and Ouazar, 2014). The *SPI* index in meteorology and the standard precipitation evapotranspiration index (*SPEI*) in agricultural drought has a significant relationship (Hernandez and Uddameri, 2014). Using the *SPI* and *SPEI* indices for agricultural drought and Eastern Slovakia, *SPI* is more sensitive to water shortages and excesses in agricultural areas (Portela *et al*., 2017). In Zambia, the *SPEI* enable to foresee drought which is significantly longer and more severe than the one indicated by the *SPI*. Moreover, there is a difference between meteorological drought (*SPI*) and agricultural drought (*SPEI*) for effective planning and management of agricultural water resources (Tirivarombo, Osupile and Eliasson, 2018).

To assess the severity of the drought and to prevent significant losses and adverse effects from the disaster, drought monitoring was deployed. In addition to monitoring soil moisture, drought, temperature variability and precipitation, satellite measurements have been used to evaluate the consequences of drought on ecosystems, including vegetation growth and health (AghaKouchak, 2015; Nicolai-Shaw *et al*., 2017). The vegetation dryness index can show how little chlorophyll there is in plants experiencing drought. Vegetation-related drought indicators have been established, e.g. the normalised difference vegetation index (*NDVI*) (Wan, Wang and Li, 2004) and the vegetation health index (Kogan, 2002). Indicators derived from soil moisture and soil surface temperature (*LST*) are also used to track drought severity and duration (AghaKouchak, 2015; Liu *et al*., 2020). Variations of rainfall patterns in an area are attributable to the volatility of satellite-based environmental variables, such as *NDVI* and *LST* (Trenberth and Shea, 2005; Jia *et al*., 2011). The relationship between rainfall (*SPI*) and vegetation condition (vegetation health index) is very complex and strong, requiring a derivation approach with various time scales (Gidey *et al*., 2018; Spracklen *et al*., 2018). Subsequent research into a relationship with the highest correlation value between *NDVI* and *SPI* was obtained at nine months and six months with discounts of 43.5 and 40%, respectively. This shows that *NDVI* can be used to analyse agricultural drought (Mikaili and Rahimzadegan, 2022).

For effective, comprehensive drought planning in Indonesia, it is important to understand the relationship between meteorological drought and agricultural drought. It is necessary since rain is the main source of water in agriculture, and there is a high correlation between weather patterns and agricultural drought. The Corong River basin is a sub-river basin of the Bengawan Solo River basin. It has an area of 815 km^2 and is located between Lamongan and Gresik districts in East Java, Indonesia. The characteristics of this river basin, especially its southern part, are very different from conditions in other areas. The southern region tends to be very dry during the dry season, which affects water supply to the Gondang Reservoir. It is important to analyse it because the Gondang Reservoir has six field reservoirs to supply water in the Gondang irrigation area. Being a supplier to the Gondang Reservoir, the Corong River Basin plays a very important role. The monitoring of drought in irrigation areas is closely related to agricultural drought, which is very important for monitoring and regulating water availability in reservoirs and water demand in paddy fields (Yasa *et al*., 2018).

Previous studies show that it is important to examine the relationship between meteorological drought and agricultural drought to plan and manage agricultural water resources effectively. This research needs to be done because plants do not immediately react to drought caused by the shortage of rainfall. Agricultural and meteorological droughts occur at different times, so each condition and region needs to be analysed to detect and mitigate agricultural drought. Although heavily dependent on agriculture, similar studies have yet to be conducted in Indonesia, particularly in the East Java River basin. Therefore, this study aims to determine the causal relationship between meteorological drought and agricultural drought and the time gap between the two in the Corong River basin and to examine the highest correlation between meteorological drought (*SPEI*-1, *SPEI*-3, *SPEI*-6, *SPEI*-9, *SPEI*-12 and *SPEI*-24 to agricultural drought (*NDVI*). Thus, we determine the lag from the beginning of the drought (rainfall) and its impact on agriculture (vegetation). Two types of drought indicators are used: meteorological drought (*SPEI*) based on rainfall, temperature, and agricultural drought determined by using remote sensing based on the standardized normalized difference vegetation index (*NDVI*) to calculate vegetation density in the Corong River basin. Thus, *SPEI* and *NDVI* can be used as appropriate indices to estimate and determine drought severity and mitigate agricultural drought disasters, especially in irrigated areas.

STUDY MATERIALS AND METHODS

STUDY AREA

The research area is located in the Corong River basin which includes the Gondang Irrigation Area, Lamongan Regency, Indonesia. It is one of the largest sub-river basins in the

Bengawan Solo River basin, with an area of 815,081 km^2. The Corong River basin supplies water to the Gondang Reservoir. The Corong River basin is located at coordinates 7°52'–7°28' S and 125°23'–121°36' E, which flows through three sub-districts, namely Sugio District, Lamongan District, and Karangbinangun District (Fig. 1). The Corong River flows from the Gondang Reservoir which is in the Sugio District. Then it flows downstream to the Karangbinangun District. The Gondang Reservoir supplies water to seven field reservoirs for ten months, covering 6,233 ha during the dry season (Nuf'a, Limantara and Soetopo, 2016; Himawan, Susanto and Purwanta, 2021).

DATA COLLECTION AND PROCESSING

In the Corong River basin, there are three important rain stations: Gondang, Karangbinangun, and Lamongan. The required meteorological data include rainfall and temperature. The 2001–2021 rainfall data were obtained from the Bengawan Solo River Center (BBWS-Bengawan Solo, no date). Meanwhile, temperature data for the same period were obtained from the Meteorology, Climatology and Geophysics Agency (Ind. Badan Meteorologi Klimatologi dan Geofisika – BMKG) at Perak II Station (BMKG, no date). These data were then analysed to assess their impact on the Thiessen polygon method within the 2001–2021 timeframe. In addition, the Meteorology, Climatology, and Geophysics Agency of the Republic of Indonesia provided the researchers with minimum and maximum temperatures from the Tanjung Perak Station in Surabaya in 2001–2021. This information is presented in Figure 2.

The geographic location of the rain stations and data periods used are as follows: Waduk Gondang Station located at –7.20108337 latitude and 112.271833 longitude, data from 2001 to 2021. Lamongan Station situated at –7.12058337 latitude and 112.417516 longitude, data from 2001 to 2021. Karangbinangun Station positioned at –7.01286004 latitude and 112.505036 longitude, and data from 2001 to 2021. Lastly, Balongpanggang Station located at –7.27025004 latitude and 112.414033 longitude, data from 2010 to 2021.

DATA ANALYSIS

SPEI

The standardized precipitation evapotranspiration index (*SPEI*) was used to measure the rainfall deficit for multiple timescales by moving the time average. This period reflected the impact of drought on different water resources. The *SPEI* is an extension of the standardized precipitation index (*SPI*). However, the analysis includes a temperature change (Vicente-Serrano, Beguería and López-Moreno, 2010; Lweendo *et al.*, 2017). The *SPEI* succeeds in providing a complete measure of climate variability in a region since it is simple, multitemporal in nature, and statistical in the interpretation of the *SPI*. The *SPEI* gives a drastically different

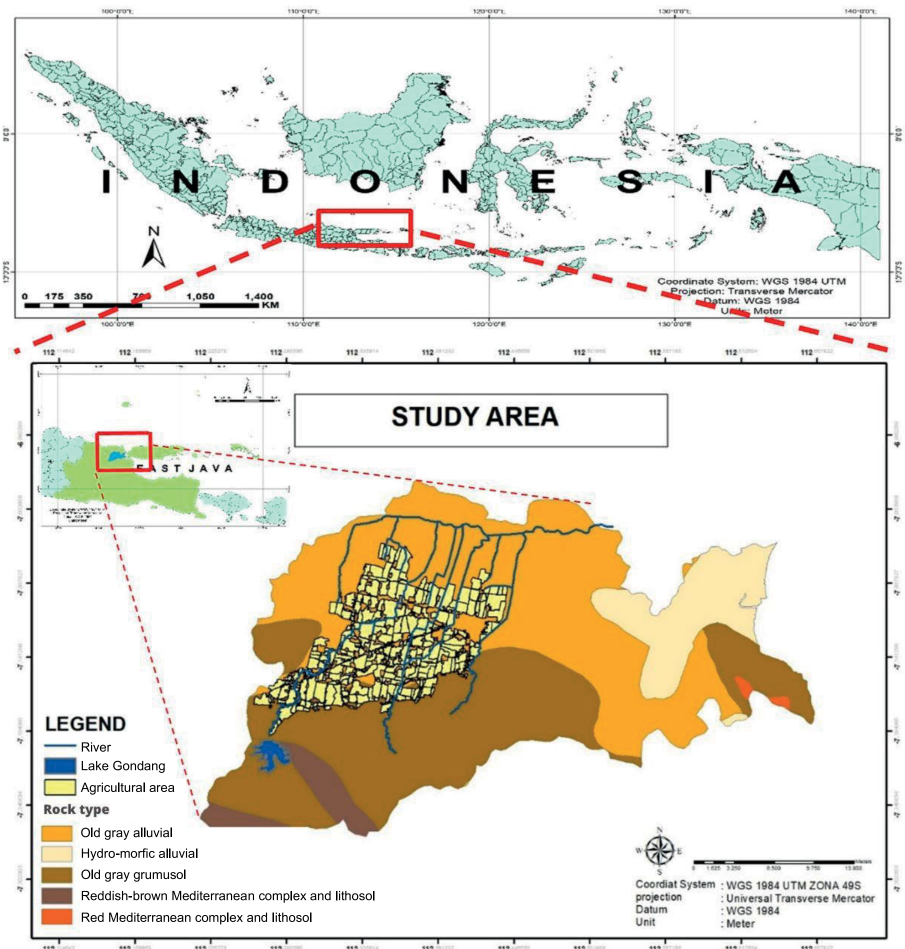

Fig. 1. Corong River basin administration map; source: own study

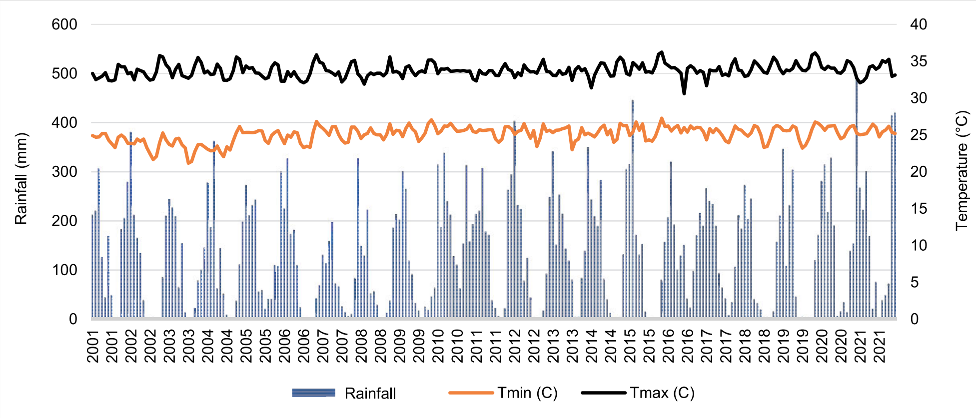

Fig. 2. Average annual rainfall and maximum and minimum temperature of the Corong River basin (2001–2021); source: own elaboration

drought index than the *SPI*, confirmed by the index value changing when potential evapotranspiration (*PET*) is considered. Then, the *SPEI* was suggested as an alternative to the *SPI* for computing climate water balance accumulation anomalies that took into account potential evapotranspiration (Stagge *et al.*, 2014).

Rstudio carried out the *SPEI* analysis with the SPEI package (R Core Team, 2021). The required data was rainfall and *PET*. *PET* data were obtained using maximum and minimum temperature data calculated through Rstudio. The *SPEI* calculated multiple timescales, meaning it processed many different types of drought due to the temporal flexibility in evaluating rainfall conditions concerning water supply (Tirivarombo, Osupile and Eliasson, 2018).

While the Thornthwaite technique requires temperature data as input, the Hargreaves model is more straightforward but still requires temperature data as input; the Hargreaves model is more specific but requires two meteorological parameters: temperature (mean, maximum, and minimum) and incident radiation. Despite the necessity for fewer data, Thornthwaite developed a way of enhancing the *PET* in locations other than the original application site. Thornthwaite developed a method of strengthening the *PET* in places other than the original application site despite the need for fewer data.

$$SPEI_i = P_i - PET_i \tag{1}$$

where: $SPEI_i$ = standardized precipitation-evapotranspiration index calculation for time *i*, P_i = observed precipitation (rainfall) for time *i*, PET_i = potential evapotranspiration for time *i*.

The *PET* can be modelled using several equations (e.g. Thornthwaite equation, Penman–Monteith equation, Hargreaves equation, etc.). Compared to the Thornthwaite technique, the Hargreaves model is more straightforward but requires two meteorological parameters: temperature (average, maximum, and lowest) and radiation effect (Hargreaves and Samani, 1985; Tukimat, Harun and Shahid, 2012). The Thornthwaite approach, despite requiring fewer data, can overestimate the *PET* at locations other than where the procedure was first used (Tukimat, Harun and Shahid, 2012). Due to the limited amount of data available for this investigation, the *PET* was calculated using the Thornthwaite method.

$$PET = 1.6K\left(\frac{10T}{I}\right)^m \tag{2}$$

where: *PET* = monthly potential evapotranspiration, *T* = mean temperature, *I* = heat index calculated as the total of 12 monthly index values, *m* = coefficient that depends on the heat index, *K* = factor of correction calculated as a function of the month and latitude.

Based on this concept, the *SPEI* was computed at 1-, 3-, 6-, 9-, 12-, and 24-month time scales using the SPEI package in R-statistical software (Beguería and Vicente-Serrano, 2017).

NDVI

Imagery from Landsat 8 OLI Two sensors, the Operational Land Imager and the Thermal Infrared Sensor, are carried by the Landsat 8 spacecraft (TIRS). Whereas the OLI image sensor (Operational Land Imager) has a spatial resolution of 30 m and has 1 near-infrared channel as well as 7 visible reflective channels that may cover the wavelengths reflected by objects on the earth's surface. Additionally, the thermal infrared sensor (TIRS) can measure and record the earth's surface temperature. Landsat imaging aims to gather data on natural alterations to improve forecasts of climate, weather, and natural calamities.

This *NDVI* is used to compare the amount of chlorophyll in vegetation, which is generated from multispectral data as a normalised value (Lillesand, Kiefer and Chipman, 1997).

$$NDVI = \frac{\rho\text{NIR} - \rho\text{RED}}{\rho\text{NIR} + \rho\text{RED}} \tag{3}$$

where: ρ = reflectance values, NIR = Near-Infrared (band 5), RED = Red band (band 4).

Relationship between *SPEI* and *NDVI*

The calculation results for agricultural drought (*NDVI*) and meteorological drought (*SPEI*) were correlated using the Pearson correlation to investigate the relationship between *SPEI* and *NDVI* due to a single data (Schober, Boer and Schwarte, 2018). The formula and interpretation of the correlation coefficient values used by the authors are presented in Equation (4).

$$r_{XY} = \frac{n\sum XY - (\sum X)(\sum Y)}{\sqrt{\left[n\sum(X^2) - (\sum X)^2\right]\cdot\left[n\sum(Y^2) - (\sum Y)^2\right]}} \tag{4}$$

where: r_{XY} = correlation between variable *X* and *Y*, *n* = number of data points, *X* = first variable (*SPEI*), *Y* = second variable (*NDVI*).

This study uses correlation analysis (*r*) and regression analysis to examine the influence and relationship between the two. The correlation analysis aims to assess the degree of similarity between variable (*X*), which contains the meteorological drought index (*SPEI*) value, and variable (*Y*), which includes the agricultural vegetation drought index (*NDVI*) value. Conversely, regression analysis aims to assess the scope of the impact caused by changes in each unit variable (*X*).

RESULT AND DISCUSSION

ANALYSIS OF STANDARDIZED PRECIPITATION EVAPOTRANSPIRATION INDEX (*SPEI*) WITH RSTUDIO

Rstudio carried out the standardized precipitation evapotranspiration index (*SPEI*) analysis with the SPEI package (RCore, 2021). It required data on rainfall and potential evapotranspiration (*PET*). The *PET* data were obtained using maximum and minimum temperature data calculated through Rstudio. The *SPEI* can be calculated for multiple timescales, meaning it can process many different types of drought due to the temporal flexibility in evaluating rainfall conditions concerning water supply (Vicente-Serrano, Beguería and López-Moreno, 2010). The *SPEI* can be designed to measure the rainfall deficit for multiple timescales by moving the time average. Such a period reflects the impact of drought on different water resources. In agricultural drought, meteorological conditions and soil moisture respond to precipitation anomalies over a relatively short period (1–6 months), while rivers, reservoirs, and groundwater respond to long-term rainfall anomalies (6–24 months and longer). The *SPEI* for this research is calculated at 1, 3, 6, 9, 12, and 24 months; rainfall data (2001–2020) from the Bengawan Solo Regional Center is used in this analysis. Maximum and minimum temperature data are obtained from BMKG (Ind. Badan Meteorologi Klimatologi dan Geofisika) Tanjung Perak.

METEOROLOGY DROUGHT (*SPEI*)

The standardized precipitation evapotranspiration index (*SPEI*) can be calculated for multiple timescales, which means it can process different types of drought due to its temporal flexibility in evaluating rainfall conditions related to water supply (Vicente-Serrano, Beguería and López-Moreno, 2010). The *SPEI* can be designed to measure the rainfall deficit for several time scales by moving the time average. This period reflects the impact of drought on different water resources. In the context of agricultural drought, meteorological conditions and soil moisture respond to rainfall anomalies in a relatively short time (1–6 months), while rivers, reservoirs, and groundwater respond to long-term rainfall anomalies (6–24 months and longer). The *SPEI* for this study was calculated at 1, 3, 6, 12, and 24 months.

The *SPEI* results in Figure 3 show substantial fluctuation during 1-month; this does not apply to 3-, 6-, and 12-month

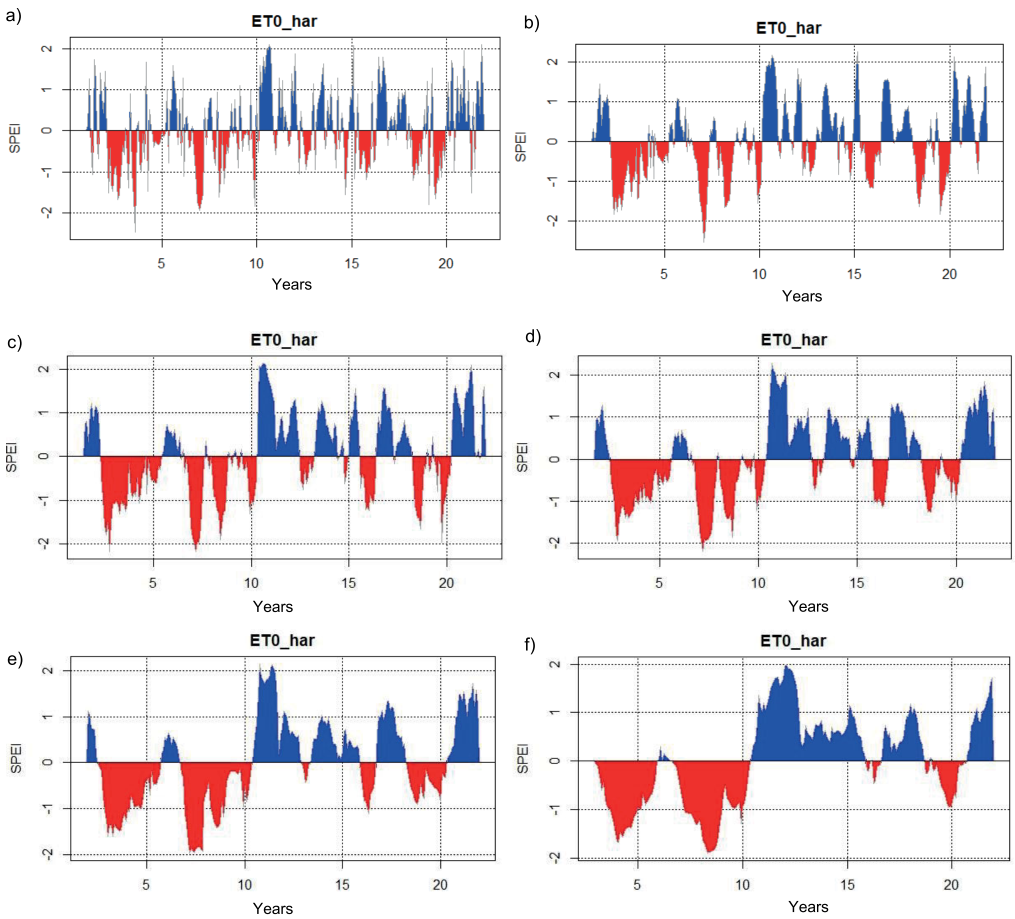

Fig. 3. The temporal distribution of *SPEI* time scales from 2001 to 2021; a) *SPEI*-1; b) *SPEI*-3; c) *SPEI*-6; d) *SPEI*-9; e) *SPEI*-12; f) *SPEI*-24; *ETO*_har = evapotranspiration reference (Hargreaves); source: own study

grades. A negative index corresponds to a rainfall deficit, which can cause drought. According to the *SPEI* 1-month, the maximum drought index value occurred in February 2019 (–1.833) (Fig. 3a), whereas the 3-month *SPEI* value shows the lowest index value for June 2018 (–1.754) (Fig. 3b). The 6-month *SPEI* value shows the lowest index value for June 2018 (–1.981) (Fig. 3c). The 9-month *SPEI* value shows the lowest index value for September 2018 (–1.999) (Fig. 3d), while the 12-month *SPEI* value shows the lowest index value for September 2018 (–1.6758) (Fig. 3e), and the 24-month *SPEI* value shows the lowest index value for November 2019 (–1.8048) (Fig. 3f).

AGRICULTURAL DROUGHT (*NDVI*)

The normalized difference vegetation index (*NDVI*) is based on the analyses of digital brightness to calculate the density of vegetation in a given area. The waves that the digital recording device receives impact the digital brightness value, the satellite Landsat in this instance. Sunlight waves are made up of several waves that reach plant leaf surfaces. Some are absorbed and used for photosynthesis, while others are reflected. The reflected wave is used to gauge the vegetation density in a region. Healthy vegetation absorbs large amounts of visible (infrared) light and reflects large amounts of near-infrared light. Equation (3) can mathematically calculate the *NDVI*, and the ArcGIS can be used to process satellite data to acquire *NDVI* readings. Landsat 8 data were obtained and each image had a unique processing method (Fig. S1). The likelihood of drought in the area increases with decreasing *NDVI* values but decreases with increasing *NDVI* values. *NDVI* processing is divided into 5 classes, namely land with no vegetation, very low density, low density, medium density, and high density vegetation (Hartoyo *et al*., 2021).

As a result, in Figure 4 green dominates as regards the land use based on the outcomes of data processing from Landsat 8 which reflects the degree of vegetation density in the river basin. With a minimum value of 0.21 in November 2021 with medium vegetation density and a maximum value of 0.732 in February 2021 with dense vegetation density, the *NDVI* value in the Corong River basin tended to be dominated by medium density and dense vegetation from 2017 to 2021.

THE RELATIONSHIP BETWEEN METEOROLOGICAL AND AGRICULTURAL DROUGHTS

The characteristics of drought in this study are determined by linking the meteorological drought index using the *SPEI* and agricultural drought using the *NDVI* to characterise drought in the Corong River basin. The characteristics can later be applied to the drought analysis in the Gondang irrigation area. Regression and correlation analyses were used to better understand the relationship between meteorological and agricultural drought. This study uses the *SPEI* drought index from four rainfall gauges in the study area based on rainfall and temperature parameters between 2001 and 2021, while the *NDVI* vegetation analysis is performed using Landsat 8 satellite data from 2017 to 2021. The analysis of the linear relationship between *SPEI* and *NDVI* was carried out with several types of timeframe, *SPEI* 1-month, *SPEI* 3-months, *SPEI* 6-months, *SPEI* 9-months, *SPEI* 12-months, and *SPEI* 24-months against *NDVI*. 2017–2021 *NDVI* and *SPEI* data are used because they adjust the available *NDVI* data. The *NDVI* processing uses Landsat 8 satellite imagery, while the data in the previous range have very poor resolution.

REGRESSION ANALYSIS

A statistical technique called the regression analysis establishes a link 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. This analysis determines the relationship between meteorological drought and agricultural drought. The meteorological drought uses the *SPEI* method with parameters for rain and potential evapotranspiration. The agricultural drought analysis uses the *NDVI* method.

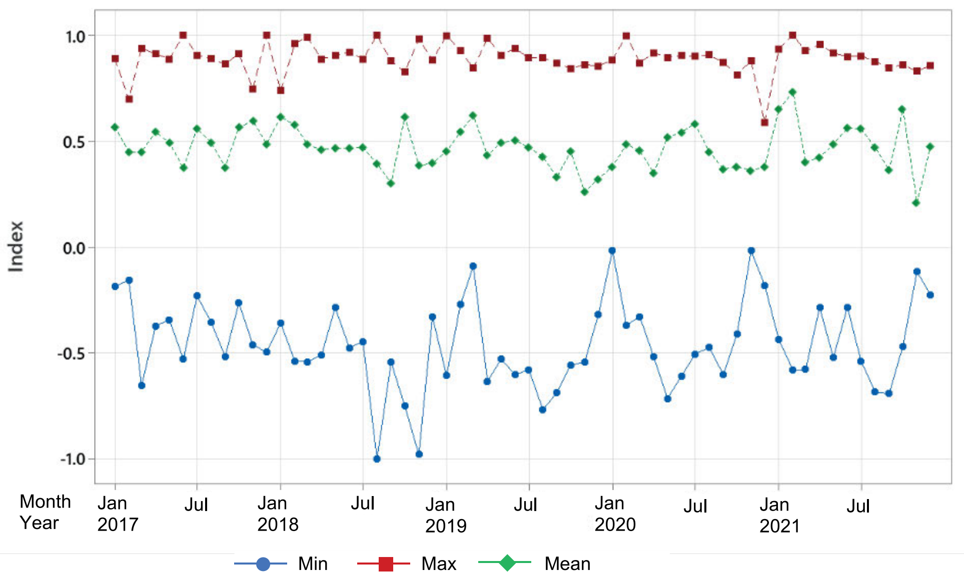

Fig. 4. The average normalized difference vegetation index (*NDVI*) values of the Corong River basin in 2017–2021; source: own study

Agricultural drought is related to meteorological drought, where the occurrence of agricultural drought results from meteorological drought. The analysis results show that meteorological droughts and agricultural droughts, in general, do not start at the same time, but there is a time lag. The time lag occurs because the soil water content does not decrease directly when there is a rainfall deficit. The research examined the time lag between meteorological and agricultural droughts based on the *SPEI* value relationship to the *NDVI* value with the linear regression time series and based on the correlation coefficient between the *NDVI* and a monthly scale *SPEI*-1, *SPEI*-3, *SPEI*-6, *SPEI*-9, *SPEI*-12, *SPEI*-24 in the Corong River basin.

THE ANALYSIS OF THE PARTIAL AUTOCORRELATION FUNCTION (PACF)

Partial correlations are conditional correlations between two variables, assuming that we know and account for the values of some other variables. The partial autocorrelation function (PACF) is a function that shows the magnitude of the partial correlation between observations at the time t with previous observations. The ACF and PACF functions identify models from time series data. As an illustration, let us consider a regression where independent variables are $x1$, $x2$, and $x3$, and the dependent variable is y. The correlation between y and $x3$ that considers how y and $x3$ connect to $x1$ and $x2$ is known as the partial correlation. By following the definition of partial correlation above, the PACF for time series data, the partial autocorrelation between y_t and y_{t-k} is the correlation between y_t and y_{t-k} after adjusting for or taking into account the values of $y_{t-1}, y_{t-2}, \ldots, y_{t-k+1}$.

Figure 5 with the PACF graph reveals a meaningful PACF value at lag 12 that is almost equal to the limit value; this illustrates a seasonal periodisation of monthly (s = 12) intervals. Then, to determine the optimal association between *NDVI* lag 12 and the *SPEI*, we must do a cross-correlation between each type of *SPEI* and *NDVI* lag 12.

CROSS-CORRELATION (*NDVI–SPEI*)

Cross-correlation is a widely used method in the time series data analysis. The technique predicts a relationship between data series X (input) and data Y (output) in a system. To perform the cross-correlation analysis, both series must be sampled in the same time interval and assumed to be stationary in mean and variance (Metcalfe and Cowpertwait, 2009).

In the serial data analysis, cross-correlation is used as a common technique. This technique can predict how a data set and y (output) in a system relate. The optimum relationship between *SPEI*-1 and *NDVI* occurs at *SPEI*-1 lag 4, as shown in Figure S2a. For *SPEI*-3 and *NDVI*, the best relationship is seen in *SPEI*-3 lag 2 (Fig. S2c). An association occurs at *SPEI* lag 1. Figure S2d shows the *SPEI*-9 cross-correlation with *NDVI* and it is the best relationship at *SPEI*-9 lag 2. In Figure S2e we can see the *SPEI*-12 cross-correlation with *NDVI*, and the best relationship is demonstrated in *SPEI*-12 lag 3. Figure S2f shows the cross-correlation between *SPEI*-24 and *NDVI*, with *SPEI*-24 corresponding to the best relationship.

COEFFICIENT OF DETERMINATION

The coefficient of determination is a measure of the line fit. Regression of the data is used to examine the influence of X (*SPEI*) on Y (*NDVI*) and express it in percentage figures.

Figure S3 shows a linear regression equation *SPEI* to *NDVI* and *SPEI* lag to *NDVI*. The linear regression relationship used to determine the effect of meteorological drought (*SPEI*) on agricultural drought (*NDVI*) results in a very small coefficient of determination (R^2). There is a time-out to see the influence of the two. Based on the *SPEI*-1 linear regression analysis for *NDVI*, the R^2 value obtained is 1.5%. The *SPEI*-1 effects are lagged according to the cross-correlation results between *SPEI* and *NDVI*, and the *SPEI*-1 lag 4 value is connected to the *NDVI*, and the R^2 value increases to 16.7%. We do this step on *SPEI*-3,

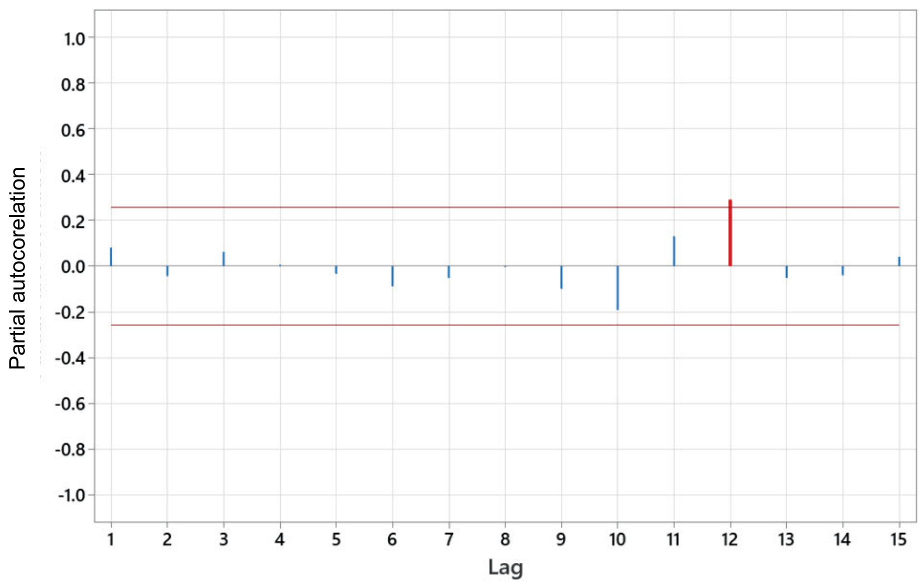

Fig. 5. Normalized difference vegetation index (*NDVI*) graph for partial autocorrelation function (PACF) (with 5% significance limits for the partial autocorrelations); source: own study

SPEI-6, *SPEI*-9, *SPEI*-12 and *SPEI*-24. The result is that the value of R^2 has increased.

The *NDVI–SPEI*-1 lag 4 coefficient of determination (R^2) is 16.7%, meaning that the variation that occurs in agricultural drought (*NDVI*) is caused by meteorological drought (*SPEI*-1 lag 4). In contrast, the remaining 83.3% of variables are caused by other variables that are not analysed. *SPEI*-1 lag 4 shows that the *SPEI*-1 monthly lag takes four months to affect the *NDVI*. For the *NDVI–SPEI*-3 lag 2 relationship, the R^2 value is 9.8% with a lag time of 2 months. The *NDVI–SPEI*-6 lag 1 relationship obtains an R^2 value of 6.8% with an interval of 1 month. R^2 of *NDVI–SPEI*-9 lag 2 is 5.8% with a lag time of 2 months. In *NDVI–SPEI*-12 lag 3, R^2 is 3.5% with a 3-month lag time, while *NDVI–SPEI*-24's R^2 value is 6% without any lag time.

This small R^2 value becomes part of the next analysis covering other variables that affect drought in agriculture (*NDVI*); the influence of the previous *NDVI* also affected it.

THE LINEAR RELATIONSHIP BETWEEN *NDVI* AND *SPEI*

Many studies have focused on the relationship between two or more variables. Correlation is a measure of the linear relationship between variables. While examining the linear relationship between *NDVI* and *SPEI*, Pearson's correlation coefficient was used to determine the linear relationship between *NDVI* and *SPEI* at different times. Pearson's correlation coefficient was used to test the linear relationship between *NDVI* and *SPEI*.

The result is shown in Table 1 and 2. The *SPEI*'s correlation with the *NDVI* is negative in *SPEI*-1 while the others are positive or in the same direction. *SPEI* lag correlation values with *NDVI* are all positive or unidirectional. This positive and one-way correlation means that if a meteorological drought occurs, it impacts agricultural drought in the Corong River basin. The highest correlation was in *SPEI*-1 lag 4 (0.408), and the lowest in *SPEI*-12 lag 1 (0.186). The p-value < 0.05 indicates a real and significant relationship between *SPEI*-1 lag 4, *SPEI*-3 lag 2, and *SPEI*-6 lag 1. Meanwhile, for *SPEI*-9 lag 2, *SPEI*-12 lag 1, and *SPEI*-24, the p-value is > 0.05. This is insignificant. *SPEI*-1 correlation results in a lag of higher value than the *SPEI* without lag. This shows that the meteorological drought in the Corong River basin does not directly affect the vegetation condition at that time. There is a lag time of 4 months until the meteorological drought affects the state of vegetation in the Gondang irrigation area, which in this case translates into agricultural drought. These results are consistent with Touhami *et al*. (2022) who state that *SPEI* and *NDVI* have a good relationship in terms of drought duration, repetition time, and severity.

CAUSAL TIME-SERIES REGRESSION

The analysis of PACF, cross-correlation, and Pearson correlation shows that agricultural drought is influenced by previous agricultural drought, meteorological drought, and other variables. This could be the subject of next research. So to obtain a relationship that further expresses the effect of the *SPEI* on the *NDVI*, it is necessary to use the causal time series regression method.

The time series regression analysis is us used under the condition that the response variable (Y) is autocorrelated,

Table 1. Pearson correlations between standardized precipitation evapotranspiration index (*SPEI*) and standardized normalized difference vegetation index (*NDVI*)

Meteorological drought	Agricultural drought	Correlation	95% *CI* for ρ	p-value
SPEI-1	*NDVI*	–0.121	(–0.363, 0.137)	0.359
SPEI-3	*NDVI*	0.107	(–0.151, 0.352)	0.415
SPEI-6	*NDVI*	0.186	(–0.071, 0.420)	0.154
SPEI-9	*NDVI*	0.178	(–0.079, 0.414)	0.173
SPEI-12	*NDVI*	0.169	(–0.089, 0.405)	0.198
SPEI-24	*NDVI*	0.245	(–0.009, 0.470)	0.059

Explanations: *CI* = confidence interval, ρ = Pearson correlation coefficient, p = level of statistical significance in an analysis.
Source: own study.

Table 2. Pearson correlations *SPEI* lag-*NDVI*-*NDVI* lag

Meteorological drought	Agricultural drought	Correlation	95% *CI* for ρ	p-value
*NDVI*_lag 12	*NDVI*	0.407	(0.138, 0.619)	0.004
SPEI-1_lag 4	*NDVI*	0.408	(0.163, 0.606)	0.002
SPEI-3_lag 2	*NDVI*	0.313	(0.059, 0.528)	0.017
SPEI-6_lag 1	*NDVI*	0.261	(0.005, 0.485)	0.046
SPEI-9_lag 2	*NDVI*	0.241	(–0.019, 0.470)	0.069
SPEI-12_lag 1	*NDVI*	0.186	(–0.074, 0.422)	0.158
SPEI-24_lag 0	*NDVI*	0.245	(–0.009, 0.470)	0.059

Explanations: *NDVI* = standardized normalized difference vegetation index, *NDVI* lag = *NDVI* time lag, *SPEI* = standardized precipitation evapotranspiration index, other symbols as in Tab. 1; Source: own study.

allowing for the construction of a functional causal relationship between the two variables. The linear regression is the only relationship type ever used in the time series data analysis. Except for calculating estimated values of a parameter, which cannot always be utilized as a reference, the ordinary linear regression analysis may be applied to the time series regression analysis as a whole.

Table 3 shows a causal relationship between *NDVI* and *SPEI* lag. According to the *NDVI–SPEI* 1 lag 4 model, which is a time series model, a given *NDVI* is influenced by the *NDVI* in the previous 12 periods and *SPEI*-1 in the last four periods by 39.55%. For *NDVI* and *SPEI*-3 in lag 2, the meteorological drought of *SPEI*-3 in the previous two periods is also influenced by the *NDVI* agricultural drought in the previous twelve periods by 31.92%. For *NDVI-SPEI*-6 in Lag 1, *NDVI* is affected by *NDVI* in the previous 12 periods, and for *SPEI*-6 in the last period, the R^2 value is 27.20. In *NDVI-SPEI*-9 in lag 2, the relevant *NDVI* is influenced by the *NDVI* in the previous 12 periods, and *SPEI*-9 in the last two periods has an R^2 value of 29.20%. *NDVI–SPEI*-12 in lag 3, this *NDVI* is influenced by the *NDVI* in the previous 12 periods and *SPEI*-12 in the last three periods, and R^2 has the value of 27.08%. For *NDVI–SPEI*-24 in lag 0, *NDVI* in the previous 12 periods and *SPEI*-24 in the same period have the same impact on the *NDVI*; the R^2 value is 24.77%. Based on the results above, the best model to determine the relationship between meteorological drought and agricultural drought is the *NDVI–SPEI* lag four models with the highest R^2 value found in a causal relationship of 39.55% and a correlation value of $r = 0.408$; the latter is quite strong. This model is also significant because it has a $p < 0.05$.

Figure S4 shows the $NDVI_t$ graph, which closely resembles the actual *NDVI*, based on the time series plots of *NDVI* and $NDVI_t$. The four categories, namely *NDVI*, $NDVI_t$, and the residual, exhibit a remarkably similar pattern. The $NDVI_t$ model is presented in Table 3. $NDVI\text{-}1_t$ represents a causal time series regression model between *NDVI* lagged by 12 and *SPEI*-1 lagged by 4. Next, the same applies to $NDVI\text{-}3_t$ through $NDVI\text{-}24_t$.

Table 3. Causal regression time series

Regression time series	R^2 (%)
$NDVI\text{-}1_t = 0.1956 + 0.594\ NDVI_{t\text{-}12} + 0.0554\ SPEI\text{-}1_{t\text{-}4}$	39.55
$NDVI\text{-}3_t = 0.2021 + 0.583\ NDVI_{t\text{-}12} + 0.0441\ SPEI\text{-}3_{t\text{-}2}$	31.92
$NDVI\text{-}6_t = 0.2068 + 0.571\ NDVI_{t\text{-}12} + 0.0354\ SPEI\text{-}6_{t\text{-}1}$	27.79
$NDVI\text{-}9_t = 0.1733 + 0.650\ NDVI_{t\text{-}12} + 0.0443\ SPEI\text{-}9_{t\text{-}2}$	29.20
$NDVI\text{-}12_t = 0.1896 + 0.616\ NDVI_{t\text{-}12} + 0.0371\ SPEI\text{-}12_{t\text{-}3}$	27.08
$NDVI\text{-}24_t = 0.2186 + 0.545\ NDVI_{t\text{-}12} + 0.0284\ SPEI\text{-}24_t$	24.77

Explanations: R^2 = coefficient of determination, $NDVI\text{-}1_t$ = normalized difference vegetation index at time *t*, $NDVI_{t\text{-}12}$ = normalized difference vegetation index at time t = 12, $SPEI_t$ = standardized precipitation evapotranspiration index at time *t*.
Source: own study.

DISCUSSION

Agricultural drought connects many aspects of meteorological (or hydrological) drought that affect agriculture through precipitation deficits, discrepancies between actual and prospective evapotranspiration, soil water deficits, decreased groundwater or reservoir levels, etc. The amount of water a plant needs depends on the weather, biological qualities of a plant, its growth stage, and the physical and biological characteristics of soil (Prabhu, 2021).

According to the results of the analysis above, the coefficient of determination (R^2) is still low. It is because meteorological drought does not directly affect agriculture, as there is a pause in drought. This is described in a study by Ezzine, Bouziane and Ouazar (2014) and Zuo *et al.* (2019) that if there is a rainfall deficit, plants can still use water reserves accumulated in soil, and according to Maina (2018), this lag time occurs because plants still have energy reserves in their bodies. The intensity and duration of meteorological drought certainly affect vegetation and water availability. If the intensity of rainfall is small and lasts for a long time, the availability of water will also be depleted, and the demand for water in plants can no longer be met. This is when agricultural drought occurs as a result of meteorological drought. This is in line with the research according to which one period of drought, sometimes the longest only, becomes the strongest. Such drought is a process that lasts for a certain period (Adhyani, June and Sopaheluwakan, 2017). Benedict and Jaelani (2021) state that the five-month shift has the highest correlation coefficient and it is considered the best shift model. This means that the current rainfall affects the vegetation *NDVI* in the next five months; this supports the research above (Benedict and Jaelani, 2021).

CONCLUSION

The highest correlation test results apply to the relationship between *NDVI* and *SPEI* lag 4 (0.41); this indicates that the meteorological drought of the previous four months has affected the current agricultural drought. The time series regression model reinforces the analysis, and it shows a causal relationship between *NDVI* and *SPEI* lag. According to the *NDVI–SPEI*-1 lag 4 time series model, the relevant *NDVI* is influenced by the *NDVI* in the previous 12 periods and *SPEI*-1 in the last four periods by 0.4. This shows that the causal relationship between *SPEI*-1 and *NDVI* can be used as an effective index to assess the severity and duration of drought and apply mitigation measures, especially in irrigated areas. This helps to prepare for future droughts. The longer the *SPEI* time scale, the number of drought events decreases, but the drought severity increases. We must protect water catchment areas from agricultural drought by managing a comprehensive irrigation system, building an effective water distribution system, and determining wise cropping patterns. We also need to provide a thorough analysis of variables that affect agricultural drought, especially those representing components of the water balance, such as ground water and ground humidity. We should also increasingly often use advanced remote sensing techniques. Long-term studies are needed to further examine drought characteristics, especially in agricultural areas, with more comprehensive drought monitoring.

SUPPLEMENTARY MATERIAL

Supplementary material to this article can be found online at https://www.jwld.pl/files/Supplementary_material_Affandy.pdf

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CONFLICT OF INTEREST

No potential conflict of interest was reported by the author(s).

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