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EXPLORING SPATIAL AND TEMPORAL VARIATIONS OF AGRICULTURAL DROUGHT IN RORAYA WATERSHED USING NORMALIZED DIFFERENCE DROUGHT INDEX (NDDI)

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ABSTRACT

Agricultural drought is a critical concern for food security, particularly in regions with significant climatic variability such as the Roraya Watershed in Southeast Sulawesi. This watershed is vulnerable due to its reliance on rain-fed agriculture and distinctive karst topography. This research aims to describe and map drought-prone areas within the Roraya Watershed using the Normalized Difference Drought Index (NDDI) from 2019 to 2023 comprehensively. The findings indicate a consistent presence of severe drought conditions across the watershed, which led to prolonged dry spells and decreased rainfall. Our results reveal that the Roraya Watershed's agricultural areas are predominantly experiencing severe drought, with NDDI values ranging from 0.25 to 1. Despite some annual variations, the overall trend shows an increasing severity of drought conditions. This research highlights the necessity for targeted interventions and supports the development of effective drought mitigation strategies to enhance the resilience of agricultural systems in drought-prone regions.

A. INTRODUCTION

Agricultural drought poses a significant threat to the sustainability of food production systems, especially in regions with pronounced climatic variability. In the context of the Roraya Watershed in Southeast Sulawesi, an area identified as having a high risk of agricultural drought by the Indonesian Disaster Risk (InaRisk) assessment, understanding and mitigating drought impacts is critical. This watershed, characterized by its reliance on rain-fed agriculture, is highly vulnerable to variations in precipitation and temperature, which can lead to severe agricultural drought conditions. Limestone rock types in Southeast Sulawesi or the study location (high porosity leading to rapid drainage, water easily absorbed into the ground; karst topography) exacerbates this vulnerability (Hasria, et. al., 2023). The implications of such droughts are profound, affecting not only crop yields and food security but also the

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socioeconomic stability of farming communities dependent on agriculture for their livelihoods (Yang et al., 2019; Zhang et al., 2020).

One of the key indicators for assessing agricultural drought is the Normalized Difference Drought Index (NDDI). The NDDI is derived from remote sensing data and provides a quantitative measure of vegetation stress due to water scarcity. It combines information from the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI), thereby offering a robust means of identifying and monitoring drought conditions over large spatial and temporal scales (Zargar et al., 2019). The integration of NDVI, which reflects vegetation health, and NDWI, which indicates moisture content, allows for a more nuanced detection of drought stress, making NDDI a valuable tool for agricultural drought assessment (Wang et al., 2021; Zhang et al., 2020).

The primary objective of this research was to delineate and map areas within the Roraya Watershed susceptible to agricultural drought using NDDI values. By leveraging satellite imagery and NDDI calculations, we aim to produce a comprehensive spatial representation of drought-prone areas, which can serve as a valuable tool for local farmers, policymakers, and disaster management authorities. This spatial analysis will facilitate targeted interventions and resource allocation to mitigate drought impacts. Additionally, this study seeks to quantify the total area affected by agricultural drought from 2019 to 2023, providing critical insights into the temporal dynamics and severity of drought conditions within the watershed. Understanding these temporal patterns is crucial for developing adaptive management strategies and improving resilience to future drought events (Vicente-Serrano et al., 2019).

This research area is located in Roraya Watershed, where the watershed is located within three districts: Kolaka Timur Regency, Konawe Selatan Regency, and Bombana Regency. The largest part of the Roraya Watershed covers the South Konawe Regency, while the Bombana Regency area is the smallest part of the Roraya Watershed. In general, the three districts within the Roraya Watershed have similar characteristics in terms of rainfall, soil type, and landforms that support the agricultural sector. Based on data from the Sulawesi IV Watershed Agency (Balai Wilayah Sungai Sulawesi IV) (2016), the average discharge of the Roraya River over five years (2011-2015) was 15.31 m^3/s. When converted to daily units, the river's daily discharge of 1,322,784 m^3/day. The average monthly discharge variations of the Roraya River are influenced by rainfall, land cover, and soil properties (Singh, 1992). Rainfall across the entire DAS Roraya affects the magnitude of surface runoff and the amount of water that infiltrates into the soil (La Baco et al., 2017).

The basin boasts a functional rice field area of 4,105 hectares (BPS Provinsi Sulawesi Tenggara, 2016). Abundant annual rainfall ensures adequate water supply for various agricultural activities. Fertile soils, including Latosols, Podzols, and Andosols, provide a supportive environment for the growth of food crops and plantations. The main agricultural commodities cultivated in the region include rice, maize, cocoa, oil palm, and cloves. Lowland areas are extensively utilized for paddy fields and gardens producing rice and maize, while hills and mountains are dominated by cocoa and oil palm plantations. In addition, the inland fisheries sector is also growing and can support food security and the community's economy. Despite the thriving agricultural sector in Roraya Watershed, the region has also faced challenges in the form of seasonal droughts that impact water production and availability. To address these challenges, the government and local communities have implemented various mitigation strategies, including the construction of reservoirs, dams, and the development of more efficient irrigation systems.

This research addresses the following key questions: Which areas within the Roraya Watershed exhibit the highest potential for agricultural drought based on NDDI values? How has the extent of agricultural drought-affected areas changed from 2019 to 2023? By answering these questions, we aim to enhance the understanding of agricultural drought patterns in the Roraya Watershed and support the development of targeted interventions to mitigate the adverse impacts of drought on agriculture. This study not only contributes to the scientific knowledge base but also provides practical guidance for managing agricultural resources in drought-prone regions. The integration of NDDI in drought monitoring offers a scientifically robust and operationally feasible approach to drought management, aligning with global efforts to enhance food security and agricultural sustainability in the face of climate change (Trenberth et al., 2014).

B. METHOD

This research investigates the distribution of agricultural drought in the Roraya Watershed from 2019 to 2023. The data for this study was Sentinel 2A imagery from the Google Earth Engine platform. This data, Sentinel-2A, has a surface reflectance correction level, which is the bottom of atmospheric correction with a spatial resolution of 10 meters in RGB and NIR bands. This resolution is appropriate for the watershed area studied. Image preprocessing included filtering for watershed areas, time range, and cloud masking. Image preprocessing included filtering for watershed areas, time range, and cloud masking. Image data processing was limited to the study area using the Roraya Watershed boundary shapefile. The watershed boundary shapefile was obtained from the Ministry of Environment and Forestry. The image data used amounted to 5 (five) according to the range of years studied. The recording time was determined based on the best appearance of the agricultural area each year. The filtering process uses a percentage of pixels with 20% cloud cover. In this cloud masking process, the QA60 band is also used, which is a bitmask band with cloud mask information. The results of this filtering will provide the best image in the specified annual time span.

The input data for NDVI and NDWI calculation is Sentinel 2A imagery from 2019 to 2023, pre-processed with surface reflectance correction. The results of index transformation will serve as an input for calculating the Normalized Difference Drought Index (NDDI) using the formula from Gu et al (2007). In this study, The calculation processes of NDVI, NDWI, and NDDI are done by Google Earth Engine. Before calculating the NDDI using NDVI and NDWI, the range of NDVI and NDWI should be converted into 8 bits (0 - 255) due to the NDDI value that should have a range from -1 to 1. The value of NDDI is used to assess agricultural drought severity in the Roraya Watershed, classifying it into five classes: non-drought, mild drought, moderate drought, severe drought, and extreme drought. The resulting NDDI index transformation consists of NDDI index values within the entire watershed area. Therefore, land cover classification is necessary to determine NDDI values for identifying agricultural drought in the Roraya Watershed.

The land cover classification was performed using the Maximum Likelihood algorithm. This supervised classification algorithm is widely employed for land cover classification tasks. Maximum Likelihood quantitatively evaluates the variance and covariance of spectral responses when classifying unknown pixels (Lillesand and Kiefer, 1994). In this study, the land cover classes to be classified were divided into five categories: water, buildings, soil, agriculture, and non-agricultural vegetation. The classification results were then masked to obtain only biotic land cover objects (agriculture, non-agricultural vegetation), water, and soil. Building land cover objects were excluded from drought calculations as the factors influencing drought are primarily biotic factors and water.

An agricultural drought assessment in the Roraya Watershed was conducted by calculating the area of agricultural land affected by drought. The calculations were performed for each built-up area masked image using the calculate geometry feature in ArcGIS software. The results of these calculations will show the differences in the extent of agricultural land affected by drought in the Roraya Watershed over a five-year period. The results of these differences will be analyzed in relation to the factors that cause them, including regional characteristics and climatic conditions at the time of image recording.

C. RESULT AND DISCUSSION

C.1. RESULT

Based on the result of the NDVI calculation, the range of NDVI values in the Roraya Watershed in 2019 was -0.598216 to 0.923805, in 2020 it ranged from -0.70929 to 0.945304, in 2021 it ranged from -0.63655 to 0.938031, in 2022 it ranged from -0.299947 to 0.714808, and in 2023 it ranged from -0.269297 to 0.708324. The NDVI for 2019 and 2020 has a similar and wide range of values. This is due to the higher variation in water content and more diverse weather conditions. In 2021, the range of NDVI values narrowed compared to 2019 and 2020. However, the range of values still showed wide variations. In 2022 and 2023, the NDVI values in the Roraya Watershed narrowed from the range of values in previous years. Likewise, the maximum NDVI value in 2023 was the lowest among the previous years.

Based on the spatial and temporal variation of NDWI values in the Roraya Watershed. In 2019, NDWI values ranged from -0.846934 to 0.694118. In 2020, NDWI values ranged from -0.860359 to 0.774618, in 2021 ranged from -0.859087 to 0.722553, in 2022 ranged from -0.654675 to 0.342979, and in 2023 ranged from -0.634726 to 0.30511. In 2019 and 2020, the NDWI values gave the same range. This wide range indicates a high variation in water content. In 2021, the NDWI values in the Roraya Watershed showed a narrower range than in 2019 and 2020 so it can be assumed that the variation in water content in that year was smaller. Meanwhile, the NDWI values in 2022 and 2023 were narrower than the previous years so the variation in water content was smaller.

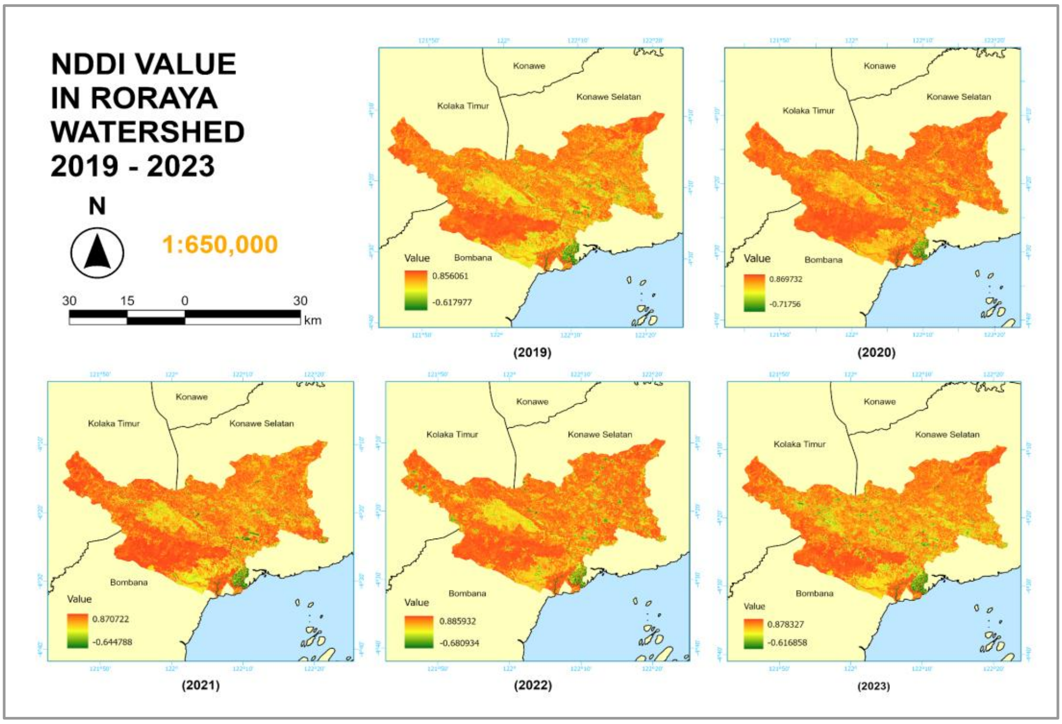

Figure 1. NDDI Value in Roraya Watershed 2019 – 2023
(Source : Research Processing Result, 2024)

Normalized Difference Drought Index (NDDI) is an index used to detect and monitor drought, especially agricultural drought, using remote sensing imagery. It identifies drought in an area by combining two indices, namely NDVI and NDWI. Figure 1 shows the changes in NDDI values in the Roraya Watershed from 2019 to 2023. In order, the range of NDDI values in 2019 to 2023 are as follows, -0.6179977 to 0.856061, -0.71756 to 0.869732, -0.644788 to 0.870722, -0.680934 to 0.885932, and -0.616858 to 0.878327.

Land cover classification in the Roraya Watershed was performed using Maximum Likelihood supervised digital classification. This classification resulted in 5 land cover classes, namely water, buildings, non-agricultural vegetation, agriculture, and soil. Based on the classification result, land cover changes within 5 years show very significant differences visually.

Table 1. Agricultural Area in Roraya Watershed 2019 – 2023.

Year	Agricultural Area (ha)
2019	49198.20
2020	67985.57
2021	46050.71
2022	56984.01
2023	53112.67

(Source : Research Processing Result, 2024)

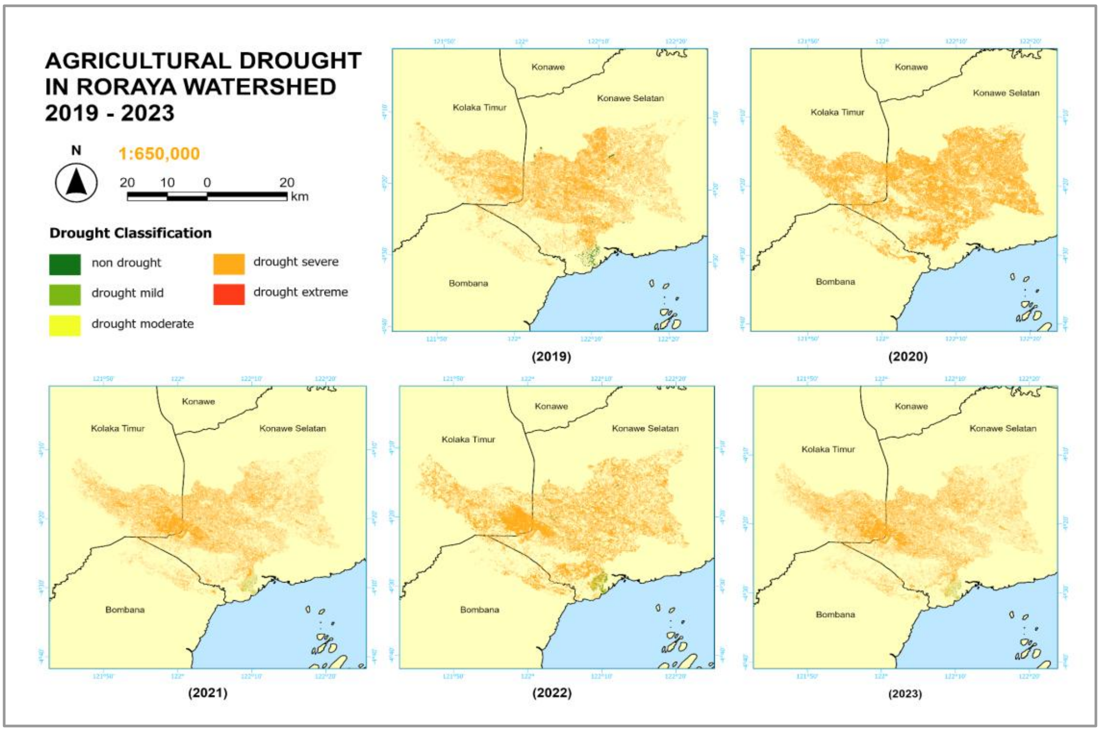

Figure 2. Agricultural Drought in Roraya Watershed 2019 – 2023
(Source : Research Processing Result, 2024)

The drought index values are categorized into five classes: Non-Drought, Drought Mild, Drought Moderate, Drought Severe, and Drought Extreme. In the context of agricultural land cover, the NDDI classes range from Non-Drought to drought-severe, with a predominance of the Drought Severe class across all years. Across all years, the Drought Severe class is the most prevalent on agricultural land, indicating a persistent risk of severe drought conditions in these areas.

Table 2. Agricultural Drought Area Roraya Watershed 2019 – 2023.

Year	Agricultural Drought Area (ha)				
	Non Drought	Drought Mild	Drought Moderate	Drought Severe	Drought Extreme
2019	31.46	61.19	108.90	48996.66	0
2020	0	0	0.13	67985.44	0
2021	168.80	226.82	210.80	45444.30	0
2022	477.75	430.42	458.50	55617.41	0
2023	58.82	499.01	916.70	51638.14	0

(Source : Research Processing Result, 2024)

This can be caused by the characteristics of the study area which has geomorphological characteristics in the form of karst topography.

C.2. DISCUSSION

Changes in the range of values in each year indicate changes in vegetation and environmental conditions, including drought. Severe drought will cause a drastic decrease in vegetation index values as the health of the vegetation also declines. Insufficient water availability in the dry season will cause drought. During drought, vegetation does not have enough water to carry out the process of photosynthesis and growth. This causes the vegetation condition to decline. The decline in vegetation condition is characterized by decreasing NDVI values over time. The El Nino phenomenon in Indonesia in 2023 affects changes in weather patterns, namely a decrease in rainfall which results in a long drought. This is also assumed to be the cause of drought in 2023.

Based on the maximum value, the NDWI values decreased from 2019 to 2023. The range of values and lower maximum values indicate a decrease in water content in the region, especially in vegetation and soil. The El Nino phenomenon in 2023 which has an impact on reduced rainfall in Indonesia is one of the causes of indications of drought in the Roraya Watershed area in 2023. Visually (Figure 5), 2019 showed that most areas of the Roraya Watershed were dry. NDWI has a high sensitivity in indicating agricultural drought because NDWI describes plant water stress (Jayawardhana & Chathurange, 2020). Meanwhile, the severity of drought is indicated by the NDDI drought index which combines NDVI with NDWI. Some areas with low NDDI values are visualized in green indicating wet areas (water bodies). In 2020, the dry areas expanded with more orange to red color and less green color (wet areas). In 2021, the maximum NDDI value is higher than in 2020 and the minimum NDDI value is lower than in 2020. However, the dominance of more drought areas indicates that there are indications that the drought is still severe. In 2022, the maximum NDDI value increased, indicating a more severe drought.

Based on the map, land cover changes within 5 years show very significant differences visually. Changes in agricultural land cover over time are presented in Table 2, where the actual agricultural land area shows a downward trend. However, many misclassifications between non-agricultural and agricultural vegetation land cover caused the agricultural land area to increase in several years. The possibility of massive forest clearing could lead to a decrease in non-agricultural vegetation land cover and an increase in agricultural land. The weakness of the digital classification method is the appearance of salt and pepper, as well as the indistinguishability between non-agricultural and agricultural vegetation (misclassified).

Based on Table 3, in 2019, the agricultural area in the Roraya Watershed was 49,198.20 hectares. The drought map for this year indicates a moderate spread of drought conditions, with areas classified under mild and moderate drought categories. The prevalence of severe and extreme drought conditions was minimal. This year likely experienced relatively stable climatic conditions, characterized by average rainfall and temperatures, which contributed to moderate NDDI values. The literature supports that such conditions typically result in moderate drought stress, allowing vegetation to maintain a certain level of health despite reduced water availability (Dai, 2011).

By 2020, the agricultural area expanded significantly to 67,985.57 hectares. This increase in agricultural land correlates with a notable expansion of drought-affected areas, with a higher incidence of severe and extreme drought conditions. The strain on water resources due to the increased agricultural area, coupled with potentially below-average rainfall and higher temperatures, likely exacerbated drought conditions, as indicated by higher NDDI values. According to Trenberth et al. (2014), such climatic anomalies can lead to significant drought stress, especially in regions with increased anthropogenic water demand.

The agricultural area decreased to 46,050.72 hectares in 2021, which coincided with a reduction in the extent of drought conditions. The maps for this year show fewer areas under severe drought compared to 2020. This reduction in agricultural area likely relieved some pressure on water resources. Additionally, more favorable climatic conditions, such as better rainfall distribution, may have contributed to the observed decrease in NDDI values. This aligns with findings by Dai (2011), which suggest that reduced agricultural intensity and improved rainfall can mitigate drought severity.

The year 2022 saw an increase in the agricultural area to 55,617 hectares, which corresponded with a resurgence of severe and extreme drought areas. This increase in agricultural land likely heightened the pressure on water resources, leading to higher NDDI values. Unfavorable climatic conditions, such as reduced rainfall or higher temperatures, might have compounded this effect. The literature suggests that such increases in agricultural intensity, coupled with adverse climatic conditions, can significantly exacerbate drought severity (Dai, 2011; Trenberth et al., 2014). Extreme climate events can result in damage to agricultural land, leading to reduced harvest areas or decreased productivity (Surmaini & Faqih, 2016).

In 2023, the agricultural area further decreased to 53,112.67 hectares. Correspondingly, the drought conditions were less severe, with a marked reduction in areas affected by extreme drought. The sharp reduction in agricultural areas likely played a significant role in alleviating drought conditions by reducing water demand. Favorable climatic conditions, including increased rainfall or lower temperatures, also likely contributed to this trend. Trenberth et al. (2014) highlight that such climatic factors can significantly impact drought severity and distribution, underscoring the importance of both land use and climate in drought dynamics.

The data suggests a dynamic interplay between climatic factors and land use changes in influencing agricultural drought conditions in the Roraya Watershed. Years with increased agricultural areas tend to show more severe drought conditions, likely due to higher water demand and reduced water availability for irrigation. Conversely, reductions in agricultural areas generally correlate with less severe drought conditions, indicating a release of pressure on water resources. Climatic events, such as El Niño and La Niña, also play a crucial role, with El Niño typically leading to warmer temperatures and reduced rainfall, exacerbating drought conditions, while La Niña can bring increased rainfall and cooler temperatures, potentially alleviating drought (Trenberth et al., 2014). Indonesia's location in the tropical monsoon climate makes it vulnerable to El Niño climate anomalies that can trigger drought (Rahman el al., 2017). These climatic variations, coupled with land use changes, create a complex pattern affecting the severity and distribution of drought.

D. CONCLUSION

Based on the results of this study, several things can be concluded, including:

1. Agricultural areas in the Roraya Watershed are dominated by severe drought levels with a range of NDDI values of 0.25 to 1. This causes the entire agricultural area in the Roraya Watershed to have a very high potential for drought, which is supported by its topographic characteristics which contain a lot of limestone.
2. Changes in the agricultural areas that experienced drought did not show significant changes. This is because the results of the NDDI analysis show an increase in drought from year to year, but in each year, the dominant level of drought remains severe in all agricultural areas.

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