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# Drought Level Analysis of Paddy Fields Using the NDDI Method Based on Sentinel-2A Imagery in South Polombangkeng District, Indonesia

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**ABSTRACT**

Drought is a significant climate-related hazard that severely impacts agricultural productivity, particularly in rainfed paddy fields. This study aimed to analyze the spatial distribution and severity of drought in paddy fields using the Normalized Difference Drought Index (NDDI) derived from Sentinel-2A satellite imagery. The research was conducted in South Polombangkeng District, Takalar Regency, South Sulawesi, Indonesia, during the dry season in October 2023. The NDDI was calculated by integrating the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI). The results indicated that 85.78% of the paddy fields experienced severe drought, while mild and moderate drought covered 9.30% and 4.92%, respectively. NDVI analysis revealed that 87.81% of the area had very low to low vegetation density, and NDWI confirmed extreme moisture deficiency, with 99.88% of the area under very severe drought conditions. The accuracy of the NDDI drought map, validated using the Area Under the Curve (AUC), was 0.62, indicating acceptable model performance. These findings provide critical spatial information for drought mitigation and water management in vulnerable agricultural regions. The study demonstrates the utility of Sentinel-2A and NDDI for localized drought assessment and supports evidence-based decision-making for sustainable farming practices in drought-prone areas.



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## 1. INTRODUCTION

Drought is a complex climatic phenomenon characterized by a prolonged deficiency of precipitation, leading to water shortages that adversely affect agriculture, ecosystems, and socioeconomic conditions (Wilhite, 2000). In the context of agriculture, drought directly impairs crop growth, reduces yields, and threatens regional food security, particularly in rainfed farming systems (FAO, 2017). Indonesia, as a tropical archipelago, experiences significant spatial and temporal climate variability, with certain regions such as South Sulawesi being highly susceptible to meteorological and agricultural drought during the dry season (Boer & Subbiah, 2005). The Meteorology, Climatology, and Geophysics Agency (BMKG) has repeatedly issued early warnings regarding drought risks in South Sulawesi, highlighting several regencies, including Takalar, as vulnerable areas (Dwi Herlambang, 2023). Within the Takalar Regency, the South Polombangkeng District is an important paddy-producing area where farmers rely heavily on seasonal rainfall and limited irrigation systems. In recent years, prolonged dry spells have raised concerns over water availability and crop failure, necessitating accurate and timely drought monitoring tools to support mitigation and adaptation efforts.

Remote sensing technology has emerged as a powerful tool for large-scale and repeatable drought assessments. Vegetation indices derived from satellite imagery, such as the Normalized Difference Vegetation Index (NDVI), are widely used to monitor vegetation health and density (Rouse Jr et al., 1974). Similarly, the Normalized Difference Water Index (NDWI) is effective in detecting surface water content and canopy moisture

(Gao, 1996). However, relying on a single index may not fully capture the multidimensional nature of agricultural droughts. To address this, the Normalized Difference Drought Index (NDDI) was developed by integrating NDVI and NDWI, providing a more robust indicator of vegetation water stress and drought severity (Gu et al., 2007).

Previous studies in Indonesia have applied NDDI for drought mapping in various regions, such as the Kendal Regency (Pramesto et al., 2019) and Jember Regency (Luqman et al., 2021). However, most of these studies have focused on general land drought assessments rather than specifically targeting paddy fields, which have unique hydrological and phenological characteristics. Moreover, there is a lack of high-resolution, spatially explicit drought studies in the South Polombangkeng District using recent Sentinel-2A imagery, which offers improved spatial and spectral resolution compared to earlier satellite systems. Sentinel-2A satellite imagery has been widely used for crop monitoring and yield estimation. Vegetation indices such as NDRE and EVI showed strong-to-very-strong correlations with rice and maize yields, underscoring their suitability for paddy-field drought assessment in this study (Hastina et al., 2023; Liku et al., 2024).

Consequently, this study sought to address this gap by employing the NDDI method, utilizing Sentinel-2A imagery, to evaluate the spatial distribution and severity of drought in paddy fields within the South Polombangkeng District. The specific objectives were as follows: (1) to generate NDVI, NDWI, and NDDI maps from Sentinel-2A data; (2) to classify drought severity levels; and (3) to validate the results using historical drought records from local disaster management agencies. These findings are anticipated to offer actionable insights for local agricultural planners, water resource managers, and farmers regarding the implementation of targeted drought-response strategies.

## MATERIALS AND METHODS

### 2.1 Materials

The materials used in this study are as follows:

1. Sentinel-2A Level-2A MSI imagery acquired on October 6, 2023, downloaded from the Copernicus Open Access Hub.
2. Administrative boundary map of the Takalar Regency (RBI map, scale 1:50,000) obtained from the Indonesian Geospatial Portal.
3. Historical drought data for 2023 were provided by the Regional Disaster Management Agency (BPBD) of the Takalar Regency.

### 2.2 Research Procedure

The research procedure consisted of data preparation, index calculation, classification, and validation.

#### 2.2.1 Data Preparation and Preprocessing

Sentinel-2A imagery was preprocessed through layer stacking of bands 2, 3, 4, 8, and 11. The image was clipped to the study area (South Polombangkeng District) using administrative boundaries.

#### 2.2.2. NDVI Calculation

The Normalized Difference Vegetation Index (NDVI) was calculated using the following formula:

$$NDVI = \frac{B8-B4}{B8+B4} \quad (1)$$

NDVI values ranged from -1 to 1, with higher values indicating denser and healthier vegetation. The vegetation density was classified into five levels based on Marlina (2022) (Table 1).

Table 1. NDVI classification for vegetation density

| Class | NDVI Value Range | Density Level |
|---|---|---|
| 1 | -1 – 0.12 | Non-Vegetated Land |
| 2 | 0.12 – 0.22 | Very Low Vegetation |
| 3 | 0.22 – 0.42 | Low Vegetation |
| 4 | 0.42 – 0.72 | Moderate Vegetation |
| 5 | 0 .72 - 1 | High Vegetation |

#### 2.2.3. NDWI Calculation

The Normalized Difference Water Index (NDWI) was calculated using:

$$NDWI = \frac{B8-B11}{B8+B11} \quad (2)$$

NDWI values indicate surface moisture, with higher values representing greater water content. Drought levels based on NDWI were classified according to Cahyono et al. (2023), as shown in Table 2.

Table 2. NDWI-based drought classification

| No. | Classification Drought | NDWI Value |
|---|---|---|
| 1 | Very Severe Drought | NDWI < 0.2 |
| 2 | Severe Drought | 0.2 – 0.35 |
| 3 | Moderate Drought | 0.35 – 0.45 |
| 4 | Light Drought | 0.45 – 0.55 |
| 5 | Normal | NDWI > 0.55 |

**2.2.4. NDDI Calculation**

The Normalized Difference Drought Index (NDDI) was derived from NDVI and NDWI using

$$NDDI = \frac{NDVI - NDWI}{NDVI + NDWI} \quad (3)$$

Higher NDDI values indicate more severe drought conditions. Drought severity was classified into three levels based on the classification used in this study (Table 3).

Table 3. Drought classification based on NDDI

| Class | Drought Level | NDDI Range |
|---|---|---|
| 1 | Mild drought | <= 0.30 |
| 2 | Moderate Drought | 0.31 - 0.65 |
| 3 | Severe Drought | > 0.65 |

**2.2.5. Accuracy Validation**

The accuracy of the NDDI drought map was validated using the Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC), with reference data from BPBD Takalar Regency.

**3. RESULTS AND DISCUSSION**

**3.1 NDVI Analysis**

The NDVI map of paddy fields in the South Polombangkeng District (Figure 1) shows a dominance of very low to low vegetation density. The percentage distribution of vegetation levels was as follows: non-vegetated land (10.80%), very low vegetation (66.59%), low vegetation (21.22%), and moderate vegetation (1.39%). Notably, no areas were classified as having high vegetation (NDVI > 0.72), indicating limited vegetation vigor during the observation period in October 2023.

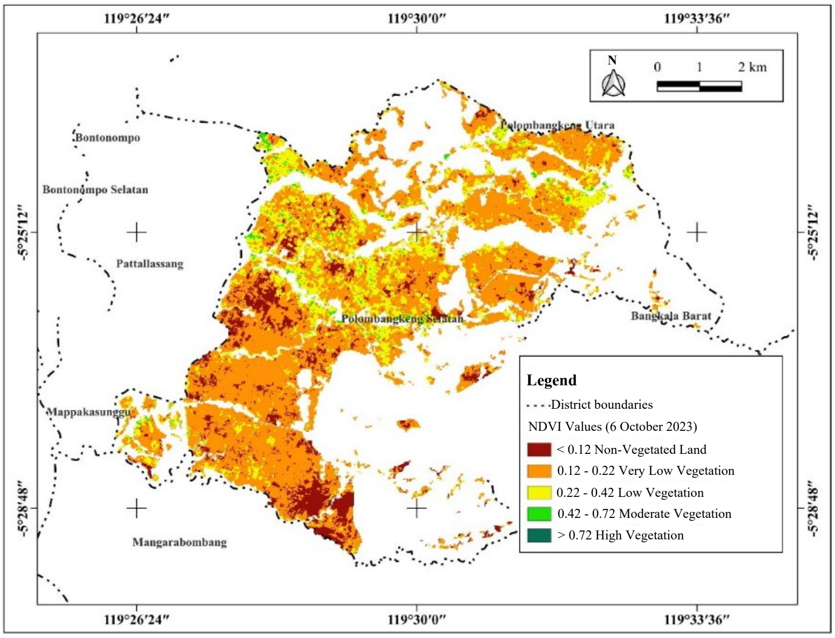


Figure 1. NDVI Results of Rice Fields in Subdistrict South Polombangkeng.

The low NDVI values suggest that paddy fields were experiencing stress, likely due to water shortages during the dry season. This is consistent with regional climate patterns, where October marks the peak of the dry season in South Sulawesi.

### 3.2 NDWI Analysis

The NDWI results (Figure 2) indicate extremely dry conditions across the study area. The majority of the region (99.88%) was classified under very severe drought (NDWI < 0.2), with only a small portion (0.12%) experiencing severe drought (NDWI 0.2–0.35). None of the areas fell into the moderate, mild, or normal categories.

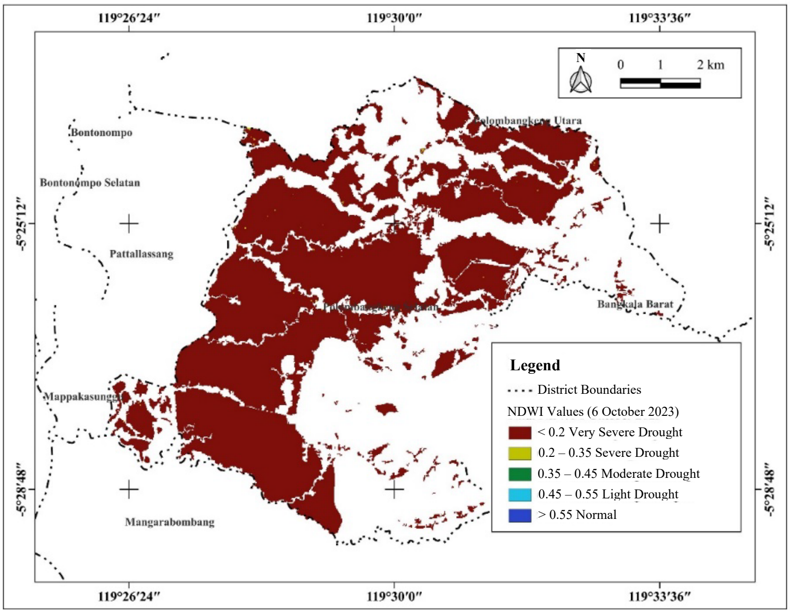


Figure 2. NDWI Results of Rice Fields in Subdistrict South Polombangkeng.

The notably low NDWI values suggest a significant decrease in both vegetation and soil moisture, indicating that the region was undergoing considerable water stress when the images were captured. NDWI is recognized for its sharp decline during droughts and its high sensitivity to reductions in canopy water content (Chou et al., 2022; Soni et al., 2023; Viswambharan et al., 2022). Consequently, the very low NDWI detected here accurately represents a severe moisture shortage, aligning with the NDVI-derived evidence of vegetation stress.

### 3.3 NDDI Analysis

The NDDI map (Figure 3) reveals widespread drought severity across paddy fields. The distribution of drought levels was as follows: mild drought (9.30%), moderate drought (4.92%), and severe drought (85.78%). The severe drought category (NDDI ≥ 0.65) dominated this region, indicating critical water stress conditions.

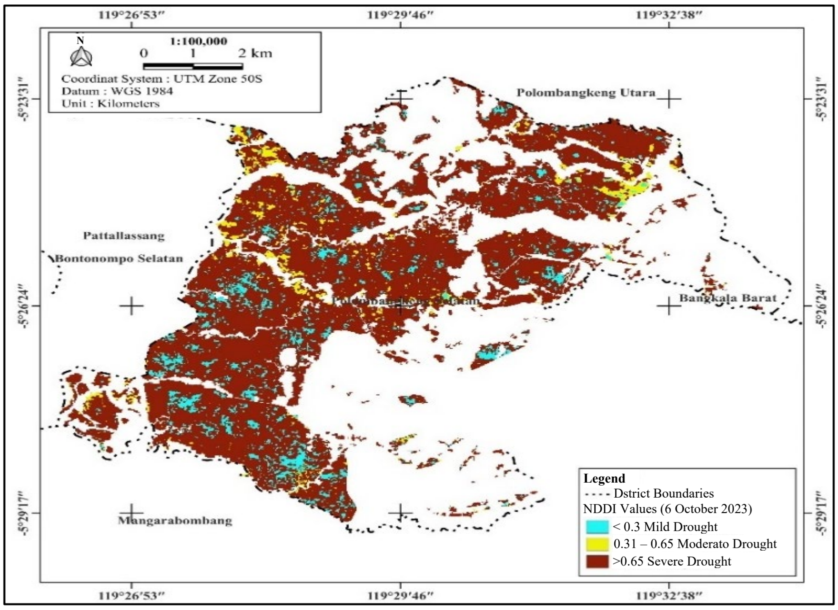

Figure 3. NDDI Map of Sub-district Rice Fields in South Polombangkeng.

The high prevalence of severe drought (NDDI ≥ 0.65) suggests that the combined effect of low vegetation vigor (NDVI) and extreme dryness (NDWI) is pronounced. This integrated index provides a more robust picture of agricultural drought than NDVI or NDWI alone. The NDDI-based drought intensity quantification methodology has been used in tropical/subtropical studies and compared with official monitors (Salas-Martínez et al., 2023); therefore, the NDDI approach in this study is in line with recent practices.

**3.4 Validation of NDDI Model Accuracy**

The accuracy of NDDI drought classification was evaluated using ROC-AUC analysis. The AUC value obtained was 0.62 (Figure 4), indicating that the model performs better than random chance. According to Fawcett (2006), an AUC value above 0.5 suggests acceptable discriminative ability, though there is room for improvement.

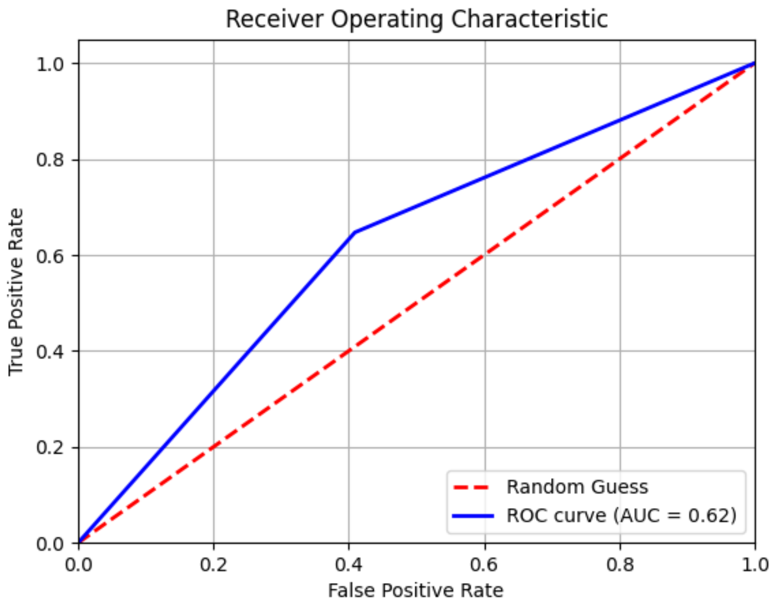

Figure 4. ROC curve for NDDI drought classification accuracy.

While the AUC of 0.62 is acceptable, it also indicates limitations, possibly due to the coarse resolution of Sentinel-2A bands used for NDWI (band 11 at 20 m) or the need for additional drought indicators, such as land surface temperature (LST) or soil moisture data. where LST (MODIS) is widely used for drought monitoring, and L-band soil moisture (SMAP) has been shown to improve drought monitoring skills when combined with vegetation indices or surface water models (Mladenova et al., 2020; Phan & Kappas, 2018; Velpuri et al., 2016).

## 4. CONCLUSION

Based on the analysis conducted using Sentinel-2A imagery and the NDDI method, this study concludes the following conclusions were drawn.

1. Severe drought dominated paddy fields in South Polombangkeng District in October 2023, with 85.78% of the area classified as severe drought (NDDI ≥ 0.65), followed by mild drought (9.30%) and moderate drought (4.92%).
2. The NDVI results indicated poor vegetation health, with very low to low vegetation density covering 87.81% of the area, reflecting water stress during the dry season.
3. NDWI confirmed extreme moisture deficiency, as 99.88% of the area experienced very severe drought (NDWI < 0.2), highlighting critical water scarcity.
4. The NDDI model demonstrated acceptable accuracy with an AUC value of 0.62, indicating moderate predictive capability suitable for regional drought monitoring, although further refinement is recommended for higher precision.

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