 https://doi.org/10.1051/e3sconf/202560503041

Spatial and temporal monitoring of drought hazards in Opak Watershed

Sapta Suhardono [1], *Iva Yenis* Septiariva [2], *Sovia* Wijayanti [1], *Naila Maulida* Ibriza[1], *I Wayan Koko* Suryawan [3*]

[1]Department of Environmental Sciences, Faculty of Mathematics and Natural Sciences, Universitas Sebelas Maret, Indonesia
[2] Department of Civil Engineering, Faculty of Engineering, Universitas Sebelas Maret, Indonesia
[3]Department of Environmental Engineering, Faculty of Infrastructure Planning, Universitas Pertamina, Jakarta Selatan 12220, Indonesia

Abstract. The Opak Watershed in Yogyakarta Province has been under persistent drought threat. This study monitored drought conditions spatially and temporally using Sentinel-2 satellite imagery and rainfall data. The Standardized Precipitation Index (SPI) was employed for drought assessment based on rainfall, while the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Moisture Index (NDMI) evaluated drought via satellite images. A Pearson correlation analysis revealed significant relationships: SPI and NDVI (r = 0.527), SPI and NDMI (r = 0.704), and NDVI and NDMI (r = 0.921). The findings provide a comprehensive understanding of drought patterns and trends, revealing critical insights into the development of drought conditions over time and across various locations within the Opak Watershed.

1 Introduction

Drought is a natural hazard that is occasionally confused with aridity, which is the result of a region experiencing low levels of rainfall. Drought is characterized by the prolonged absence of rainfall in a specific location over a defined duration [1]. Droughts are prevalent across various climatic and can be categorized into several types: (1) meteorological drought, characterized by prolonged periods of below-average precipitation; (2) hydrological drought, occurring when surface and groundwater levels decline; (3) agricultural drought, resulting from insufficient soil moisture leading to crop losses; and (4) socioeconomic drought, associated with water scarcity impacting economic activities [2]. Drought poses a serious threat to the sustainability of ecosystems, agriculture, and human life in various parts of the world [3].

In Indonesia, the drought has had a substantial impact, particularly in places that are susceptible to climate change and erratic rainfall patterns. Opak Watershed, situated in the Special Region of Yogyakarta Province, is currently encountering significant difficulties associated with drought. Monitoring and analyzing drought spatially and temporally was

* Corresponding author: i.suryawan@universitaspertamina.ac.id

crucial in efforts to mitigate and adapt to the impacts of drought in the Opak Watershed. This study aimed to provide a deeper understanding of drought patterns in the area through an approach that integrated rainfall data and satellite imagery. By utilizing rainfall data, this research calculated the Standardized Precipitation Index (SPI), which is a commonly used method to measure drought severity based on rainfall anomalies.

Additionally, this study leveraged satellite imagery to generate the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Moisture Index (NDMI), which provided insights into vegetation conditions and drought severity spatially. By combining these two approaches, this research will produce a more comprehensive mapping of drought, both in terms of temporal and spatial scales. The information obtained from this study is expected to serve as a basis for developing more effective mitigation strategies and provide guidance for decision-making in water resource management in Opak Watershed. Thus, the findings of this study will not only contribute to drought management in Opak Watershed but also provide valuable insights into drought mitigation efforts more broadly.

2 Methods

In this study, ArcGIS was employed to process spatial data, including the boundaries of the Opak Watershed, which were utilized for drought mapping. Rainfall data was essential for calculating the Standardized Precipitation Index (SPI) to analyze drought patterns. The sampling process involved selecting representative rainfall stations throughout the watershed to ensure comprehensive coverage of spatial variability.

Pearson correlation analysis was utilized to explore the relationships among SPI, NDVI, and NDMI, justifying its use due to its effectiveness in measuring the linear correlation between continuous variables. Variables were defined as follows: SPI represented the standard measure of precipitation deficits; NDVI indicated vegetation health and cover; and NDMI assessed moisture content in vegetation. By employing these tools and methodologies, the study aimed to generate accurate drought mapping and enhance the understanding of drought dynamics in the Opak Watershed.

2.1 The Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) method is used to assess meteorological drought. SPI utilizes rainfall data to determine the level of drought in a specific region. Calculation using the SPI method [4], with the equation as follows in Equation 1.

$$Z_{ij} = \frac{X_{ij} - \overline{X_j}}{\sigma_j} \quad (1)$$

Where Z_{ij} is drought index for month i of year j; X_{ij} is monthly rainfall for month i of year and X_j is average rainfall for year j and σj: Standard deviation for year j.

2.2 Spectral Transformation

We utilized GEE to efficiently acquire data for the calculation of NDVI and NDMI. GEE has been used in many studies, such as for monitoring land use changes [5] or monitoring air quality [6]. Sentinel-2 comprises 13 spectral bands with diverse spatial resolutions, spanning from 10 to 60 meters, delivering high-resolution multispectral data [7]. NDVI was computed using the subsequent formula, yielding values from -1 to 1, with negative values signifying the presence of water:

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$$NDVI = \frac{NIR-RED}{NIR+RED} \tag{2}$$

NDMI was calculated using the formula:

$$NDMI = \frac{NIR-SWIR}{NIR+SWIR} \tag{3}$$

The indices were computed using the radiance or reflectance from the red channel at around 0.66 µm and the near-infrared (NIR) channel at approximately 0.86 µm [8]. The NDMI (Normalized Difference Moisture Index) is an index that utilizes the near-infrared (NIR) and shortwave infrared (SWIR) bands to represent moisture content. Researchers employ NDMI to assess alterations in leaf water content. The SWIR band is responsive to variations in vegetation water content and the spongy mesophyll architecture of plant canopies. The NIR band is unaffected by water content; rather, it is influenced by the interior structure of leaves and the content of dry matter. NDMI values span from -1 to 1, where negative values may signify water stress.

3 Results and Discussion

3.1 Monthly rainfall graph

The given rainfall data provided precise information on monthly precipitation levels at four distinct locations: Bedukan, Beji Ngawen, Siluk, and Tanjung Tirto.

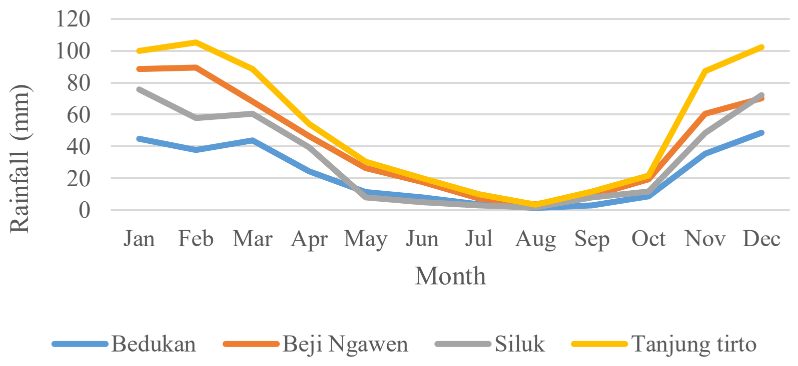

Fig 1. The average monthly rainfall 2011 – 2020 at each station.

The data analysis uncovered substantial fluctuations in precipitation throughout the year. Months such as May, June, July, August, and September generally received minimal precipitation in all areas, frequently measuring less than 15 millimeters. In contrast, months such as January, February, November, and December had a higher amount of rainfall. Some specific localities, such as Tanjung Tirto, experienced peak rainfall during December, reaching 102.3424 millimeters as seen in Figure 1. These variations indicated strong seasonal patterns in rainfall, which could have significant impacts on the environment and livelihoods in these areas. For instance, heavy rainy seasons might affected agriculture and water availability. From the provided data, it could be observed that the Bedukan Station tends to experience the highest rainfall in January, December, and November, with the highest peak reaching 102.3424 mm in December. Meanwhile, the Beji Ngawen Station showed a different pattern, with the highest rainfall occurring in February at 105.248 millimeters. Siluk demonstrated its highest pattern in January and December, albeit within a lower range compared to other stations. The Tanjung Tirto Station exhibited a relatively uniform monthly rainfall pattern throughout the year, without significant peaks in specific months, although its overall figures were highest in February. Thus, these patterns depicted unique variations in monthly rainfall at each station, with significant differences in intensity and peak rainfall months.

3.2 The amount of Annual Rainfall for each Station Recording

Firstly, it was evident that each location exhibits distinct annual fluctuations in rainfall. For instance, Beji Ngawen demonstrated a relatively stable pattern with moderate increased from 2011 to 2016, followed by larger fluctuations between 2017 and 2020 as shown in Figure 3. On the other hand, Tanjung Tirto displayed more dramatic variations, with significant spikes from 2015 to 2017, followed by substantial declines in 2018 and 2019 before rebounding in 2020. Comparative analysis between locations can also provided insights into spatial variations in rainfall. For example, in 2016, Tanjung Tirto experienced much higher rainfall than other locations, while Bedukan and Siluk exhibited more similar patterns. In other years, these changing patterns may differ, reflecting the complex interactions among local and regional factors influencing rainfall patterns. From this, it could be concluded that analyzing rainfall data can offer valuable insights into climate dynamics at each location during the analyzed period. However, to gain a deeper understanding of these patterns, other factors such as topography, global climate change, and local weather variability that can influence this rainfall data need to be considered [9].

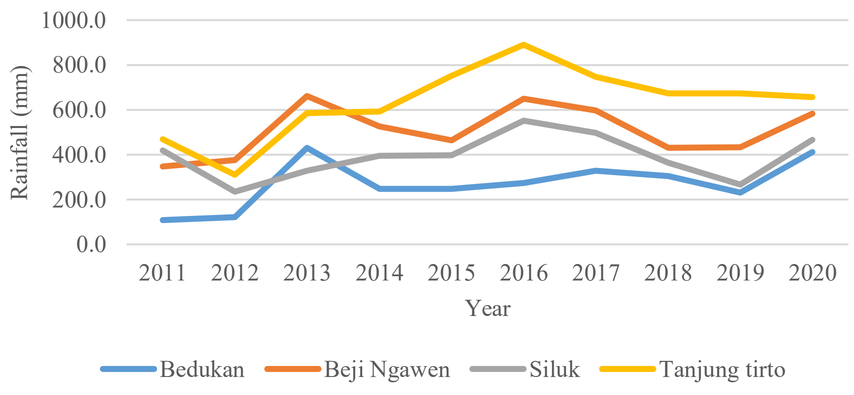

Fig 2. The annual rainfall amount at each station.

In Figure 2, it showed the annual rainfall amounts (in millimeters) in Opak Watershed from 2011 to 2020, indicating annual variations in rainfall amounts in the Opak Watershed during the observed period. In 2013 and 2016, there were significant spikes in rainfall, where rainfall reached its highest peak during that period. Meanwhile, in 2012, 2018, and 2019, the amount of rainfall tended to be lower compared to other years. Analyzing these trends can provide insights into local climate fluctuations during this period. The significant spikes in rainfall in 2013 and 2016 may be linked to extreme weather events or unusual natural patterns, while the declines in certain years may depict natural variability in the rainfall cycle. Based on the Pearson correlation analysis, the relationship between rainfall and ENSO shows a very weak negative correlation and is not statistically significant ($r = -0.1$; $p = 0.138$), indicating that ENSO does not have a clear influence on rainfall in this dataset. In contrast, the relationship between rainfall and IOD shows a weak to moderate negative correlation that is statistically significant (r = -0.241; p = 0.004), suggesting that an increase in IOD tends to be followed by a decrease in rainfall, with a statistically significant impact.

Table 1. Correlation between rainfall and regional climate

Correlations	Pearson Correlation	Sig. (1-tailed)
Rainfall and ENSO	-0.1	0.138
Rainfall and IOD	-0.241**	0.004

3.3 Standard Precipitation Index

The Standardized Precipitation Index (SPI) graph presented was a dataset depicting the drought or excess water index for each month over several years. SPI was used to assess how extreme rainfall conditions are compared to normal conditions over a period of time. The interpretation of SPI values indicated that positive values indicate excess water (rainfall above average), while negative values signify drought (rainfall below average) [10]. Trends and patterns in rainfall over several years can be observed from this SPI data as shown in Figure 3. Analysis of drought trends based on the Standardized Precipitation Index (SPI) table showed significant variations during the observed period. In 2011, a tendency towards drought is evident starting from the middle of the year, with SPI values becoming increasingly negative towards the end of the year. This trend continued into 2012, where certain months exhibited more extreme drought conditions. Subsequently, there was a shift in early 2013 with a significant increase in SPI values, indicating excess water. However, drought conditions returned in 2014 and 2015 with predominantly negative SPI values, especially in some months of those years. Some months stand out with extreme SPI values, such as January 2017 and January 2018, which have very high SPI values, indicating significant excess water. Additionally, December 2015 and November 2017 also showed notable excess water.

In 2016, there was a positive change with an increase in SPI values, indicating continued excess water conditions into 2017. However, by late 2017 and throughout 2018, there is a return to drought conditions with low SPI values, indicating decreased rainfall. Then, in 2019, drought conditions persist with negative SPI values in most months, although there are some specific months with increased excess water. Finally, in 2020, significant variability is observed with several months showing excess water, especially at the beginning of the year, but drought conditions recur towards the end of the year. There was significant fluctuation in annual variability, with some years exhibiting consistent drought patterns in several consecutive months. This analysis provided a more comprehensive picture of changes in rainfall conditions over time and how this affects the drought or excess water index [11].

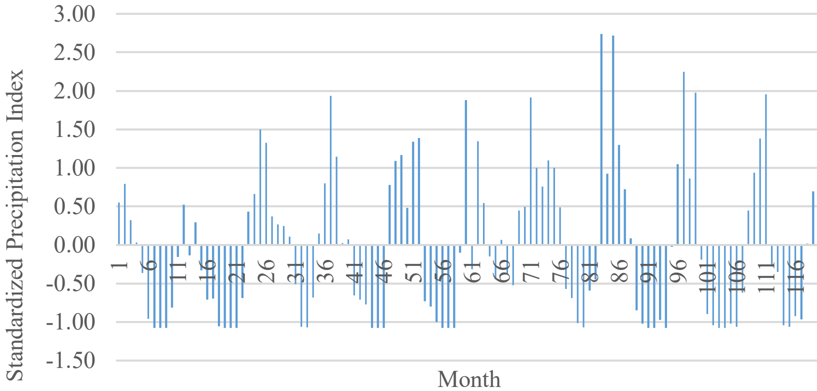

Fig 3. Standardized precipitation index

3.4 NDVI and NDMI

Drought in the Opak River Basin can be assessed by NDVI (Normalized Difference Vegetation Index) data, which reflect the state of vegetation in the region. NDVI values between 0.9415 and -0.5849 indicate that regions with elevated positive values near 0.9415 are characterized by dense and robust vegetation, implying these areas presumably possess enough water resources. Regions exhibiting negative values nearing -0.5849 signify places with sparse vegetation or potential land degradation, possibly indicative of severe drought conditions. Suboptimal vegetation conditions can intensify the effects of drought in the Opak River Basin, particularly when coupled with less precipitation or alterations in climatic patterns. This analysis is essential for comprehending the prevalence and severity of drought and its effects on the ecology in the Opak River Basin.

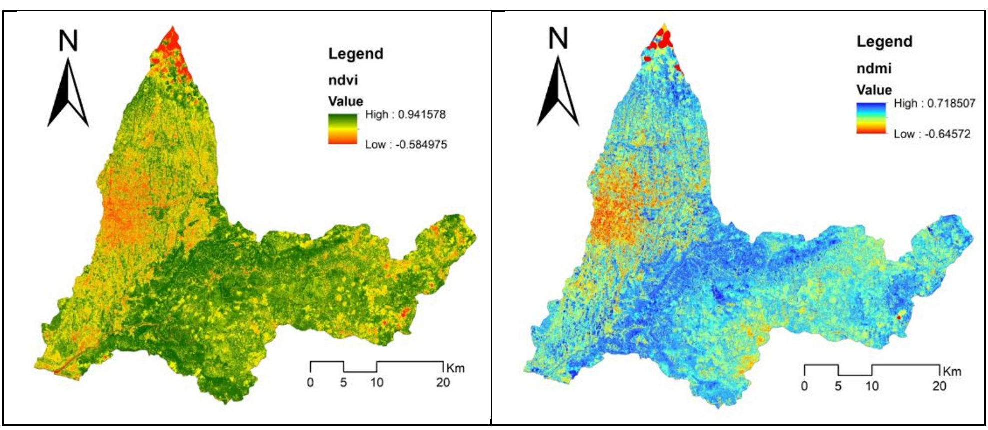

Fig 4. NDVI and NDMI

Drought in the Opak River Basin can be assessed using NDMI (Normalized Difference Moisture Index) measurements, which indicate soil moisture content. NDMI values between 0.785 to -0.6457 offer a summary of soil moisture conditions in the region. Regions exhibiting positive NDMI values near 0.785 signify soil with elevated moisture levels, indicating comparatively humid conditions and a low likelihood of drought. Conversely, places with negative values nearing -0.6457 signify extremely arid soil, suggesting these areas are under stress from insufficient water, indicative of drought conditions. This condition indicates that several regions within the Opak River Basin are facing considerable moisture deficits, potentially affecting ecosystem vitality, agricultural yields, and water accessibility for adjacent communities.

3.5 Correlation SPI, NDVI, and NDMI

The Table 1, illustrates the correlations among three environmental indices: Standardized Precipitation Index (SPI), Normalized Difference Vegetation Index (NDVI), and Normalized Difference Moisture Index (NDMI). A substantial positive correlation exists between SPI and NDVI, evidenced by a Pearson value of 0.527 (p = 0.004), signifying that increases in SPI correspond with increases in NDVI. This result is similar to previous studies indicating that NDVI and SPI have a positive correlation [12]. The link between SPI and NDMI is robust, evidenced by a Pearson value of 0.704 (p = 0), indicating that increased rainfall correlates with elevated leaf moisture levels. Furthermore, a strong association exists between NDVI and NDMI, evidenced by a Pearson value of 0.921 (p = 0), signifying that enhancements in chlorophyll vegetation are intricately associated with increases in moisture. This result aligns with previous research, which found a close relationship between NDVI and NDMI, confirming the link between photosynthetic activity and plant water content [13]. These results demonstrate substantial correlations among precipitation, vegetation, and humidity within the examined environment.

Table 2. Correlation between parameters

Correlations	Pearson Correlation	Sig. (1-tailed)
SPI and NDVI	0.527**	0.004
SPI and NDMI	0.704**	0
NDVI and NDMI	0.921**	0

4 Conclusions

This study highlights the need of employing rainfall data to evaluate drought risk over time using the Standardized Precipitation Index (SPI). An SPI number below zero signifies the presence of drought during a certain month. To improve this assessment, spatial analysis may be performed utilizing satellite data processed into the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Moisture Index (NDMI). These databases enable a thorough analysis of drought patterns within a watershed, both geographically and temporally.

The findings intend to offer significant insights for stakeholders, especially government agencies, acting as a dependable information source for planning. This data can inform the creation of efficient mitigation and adaptation methods in drought-prone regions, thus reducing adverse effects. To enhance the research's relevance, it is imperative to provide explicit policy suggestions for decision-makers and delineate avenues for future research, such the incorporation of supplementary environmental variables or the creation of predictive models for drought forecasting.

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