Drought Assessment Using Remote Sensing and Geographic Information Systems (GIS) Techniques (Case Study: Klaten Regency, Indonesia)

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Abstract
Drought is a climate change phenomenon that is difficult to avoid, so disaster mitigation planning is needed to minimize the impact of damage. Drought potential mapping can take advantage of remote sensing data and analysis of spatial data using a Geographic Information System (GIS). Image extraction can produce Land Surface Temperature (LST) data, vegetation index obtained from the Normalized Difference Vegetation Index (NDVI) transformation, land use obtained from Object-Based Image Analysis (OBIA), and wetness index from the Normalized Difference Water Index (NDWI). This study integrates data between image extraction results and regional conditions such as rainfall, geology, soil types, and hydrogeology. Klaten Regency has the potential for very high-class drought covering an area of 101.53 ha. In Bayat district, the results of the identification of potential drought indicate very high levels of drought.

Keywords: Drought, Geographic Information System, Remote Sensing

1. Introduction

Indonesia is located on the equator, so there is a rainy and dry season throughout the year. In the dry season, drought often occurs in several areas due to the duration of the dry season being too long. Drought is a natural disaster that is difficult to predict but can be detrimental to human life. Indonesia often experiences meteorological drought in several areas. Meteorological drought variables are based on rainfall and temperature whose application can be determined on a local or regional scale depending on the availability of data and the spatial distribution of the earth station network (Rhee et al., 2010). The availability of data makes it difficult to predict drought in large areas. Drought is caused by an uneven distribution of rainfall over a long period in an area (Lei and Duan, 2011 and Jamil et al., 2013). Drought can also be interpreted as a lack of water supply compared to the need for water for human purposes.

Drought affects various sectors in society such as agriculture, ecosystem services, human health, recreation, and water resources and is the most detrimental natural disaster. Therefore, drought has the most damaging impact on various sectors compared to other natural disasters because it causes water scarcity, agricultural drought, and famine (Smith and Katz, 2013). Each region has different characteristics so it is difficult to determine the approach to identifying accurate drought characteristics (Hao et al., 2017). Difficulties in identifying droughts encourage researchers to develop related indicators of drought including the applications used, regional conditions, and data availability in the area. In general, researchers focus their research on drought in certain geographic areas that have the potential for drought (Zhang et al., 2017a). Drought mapping has temporal and spatial complexity, making it difficult to accurately determine and identify the start and end of the drought and drought duration (Wu et al., 2013). The potential for drought requires accurate spatial data in describing information about an area so that it can plan for handling drought disasters if at any time the disaster occurs.

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The phenomenon of drought often occurs in Indonesia every year during the dry season. One of the areas in Indonesia that often experiences drought is Klaten Regency, Central Java Province. The drought in Klaten Regency causes a lack of water supply for agricultural land so that agriculture in the region is threatened with crop failure. The drought in Klaten Regency occurs due to the long duration of dry season. Klaten Regency is a type of meteorological drought due to the lack of rainfall. The variability of rainfall is due to the various topographic conditions of Klaten Regency so that the difference in the amount of rainfall and its frequency. Rainfall in Klaten Regency has a different intensity every year and has a monsoon trend (Putri and Nurjani, 2018). The drought in Klaten Regency is also not only influenced by rainfall but also by topographic conditions and soil types in the region.

Droughts are generally natural disasters that occur slowly although sometimes they can occur quickly (Zhang et al., 2017b). At this time, the drought disaster causes a high vulnerability impact on human life systems and the environment (Van Loon et al., 2016).

Identification of potential drought can use field surveys, but it takes a long time and costs a lot. This causes the conventional method to be abandoned even though it obtains high accuracy results. Therefore, drought needs to be identified using appropriate methods for accurate temporal continuous mapping. Remote sensing data can provide data on the earth's surface temporally and the application of Geographic Information Systems (GIS) to analyze the potential for drought. Remote sensing has developed in mapping the earth's surface so that it allows observations and monitoring related to drought on a temporal and spatial scale better than conventional methods (Sur et al., 2015). GIS can provide convenience in performing spatial analysis such as analyzing the potential for drought in an area. This study identified drought using a combination of remote sensing methods and GIS. This method can carry out continuous and consistent monitoring as well as provide the availability of spatial data for drought analysis on a regional and global scale, especially in areas without or rarely available spatial data (Tang et al., 2009). Remote sensing has a role in monitoring effective water management in areas that have limited spatial data (Sheffield et al., 2018).

Remote sensing has made very rapid progress in providing continuous spatial data with good spatial resolution, and the sensor can record visible infrared, and near-infrared channels including thermal infrared (Hadi et al., 2012). The development of remote sensing is found in the detection of vegetation indices and land surface temperatures using multitemporal remote sensing methods such as Landsat or the Moderate Resolution Imaging Spectroradiometer (MODIS), these two satellites have often been used for drought estimation with various earth surface conditions (Asoka and Mishra, 2015). Therefore, this study analyzes the potential for drought disasters in Klaten Regency by integrating remote sensing and GIS. The data used in this study uses Landsat 8, Sentinel 2, and regional conditions such as rainfall, hydrogeology, soil type, slope, and geology data. This study extracted images to obtain land surface temperature (LST), the vegetation index was obtained from the Normalized Difference Vegetation Index (NDVI) transformation, land use was obtained from Object-Based Image Analysis (OBIA) and the wettability index was obtained from the Normalized Transformation Water Difference Index (NDWI). NDVI is an algorithm that can determine environmental conditions based on vegetation density (Bannari et al., 1995, Chen et al., 2012 and Rasmussen, 1998). The NDVI transformation is often used for drought identification with various sensors at global, continental, and regional scales (Nicolai-Shaw et al., 2017).

OBIA is an alternative to extracting land use using a pixel-based method with the basic unit of analysis as the image object, not individual pixels (Blaschke et al., 2008). OBIA is a remote sensing data processing by combining Geographic Information (GI) (Hossain and Chen, 2019). Meanwhile, the Normalized Difference Water Index (NDVI) Transformation is one of the algorithms used to determine the relationship between potential droughts in an area. The NDWI algorithm is used to detect the humidity of an area because NDWI is very sensitive to changes in leaf moisture content due to the SWIR spectrum dominating the effect of water absorption on green vegetation (Sánchez-Ruiz et al., 2014). Land Surface Temperature (LST) algorithm is used to determine the distribution of surface temperature in the research area to be used to analyze the potential for drought. This study integrates remote sensing data and regional condition data to obtain areas with the potential for drought using a geographic information system (GIS).

2. Methodology

This study identifies potential drought disasters in Klaten Regency which can be seen in Figure 1 using remote sensing data and shapefile data (.shp) in the form of environmental physical condition data. The flow of the process of carrying out this research is depicted in a flow chart which can be seen in Figure 2.

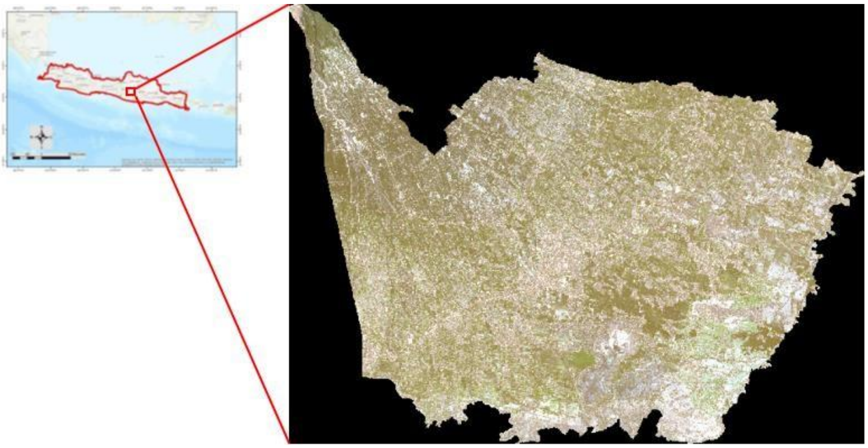

Figure 1: Study Area

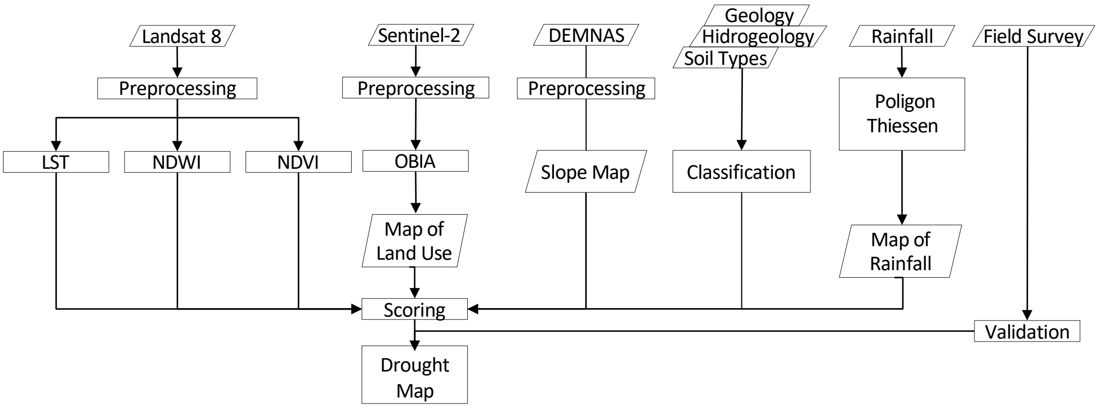

Figure 2: Flow Chart

Table 1: Research Data

Date Type	Date	Source
Landsat 8 OLI	13 September 2019	earthexplorer.usgs.gov
Sentinel 2 L1C	26 September 2019	the Copernicus Open Access Hub
DEMNAS	22 September 2020	tanahair.indonesia.go.id
Rainfall	2010 to 2019	Semarang Climatology Station
Hydrogeology	2020	BAPPEDA Klaten Regency
Soil Type	2020	BAPPEDA Klaten Regency
Geology	2020	BAPPEDA Klaten Regency

Figure 2 shows the flow of research carried out to identify drought in Klaten Regency. Meanwhile, the research data can be seen in Table 1 and Figure 3. Landsat 8 data were processed to obtain LST, NDWI, and NDVI values. Then, Citra Sentinel 2 produces a land use map from the results of OBIA processing. Slope Map obtained from DEMNAS. Regional condition data such as geology, hydrogeology, soil type, and map of rainfall data are classified for drought analysis. All data were scored to identify the drought disaster in Klaten Regency.

The field survey is used to validate the results of drought identification and land use maps. Research data using Sentinel 2 L1C recording on September 26, 2019 in the dry season. Data collection in the dry season aims to determine the effect of the vegetation index on the potential for drought. The dry season causes plants to become dry and rice fields become unproductive. Vegetation growth is influenced by monsoon rainfall so that the health status of vegetation is closely related to rainfall (Ramadan et al., 2021).

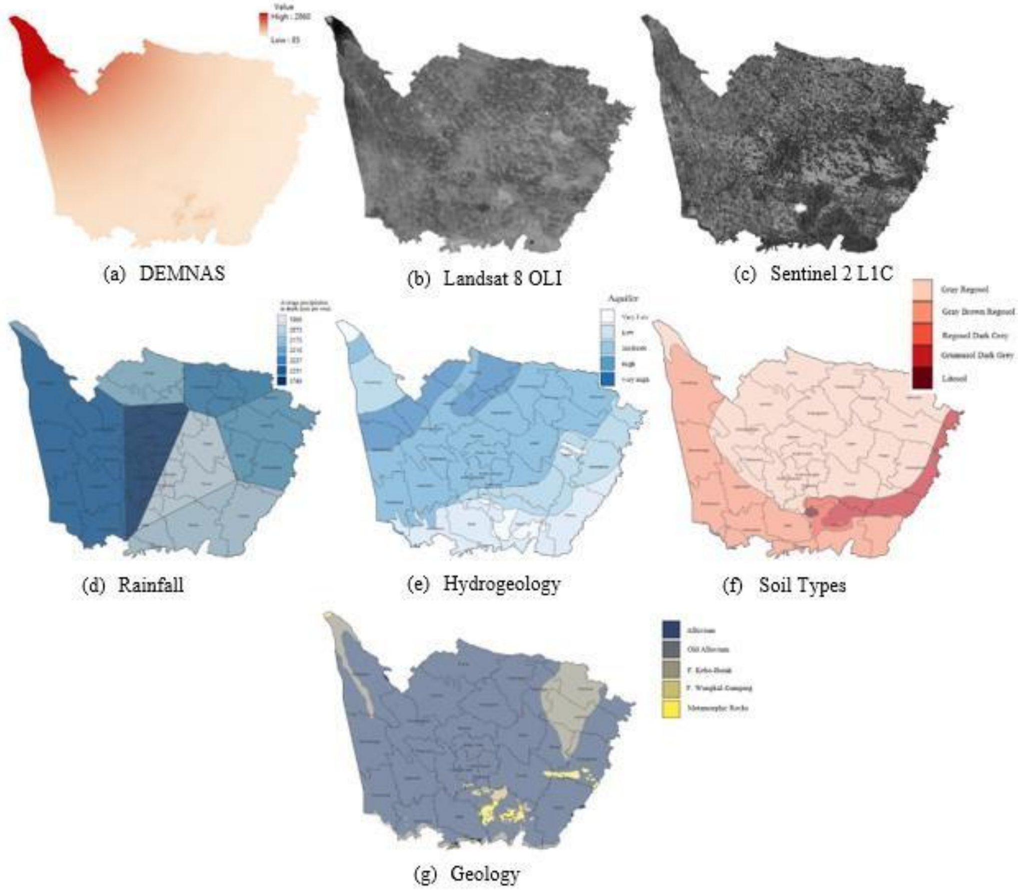

Figure 3: Research Data

2.1 Object-Based Image Analysis (OBIA)

The OBIA algorithm extracts satellite image data into an object based on its spectral, spatial, and texture characteristics (Hay and Castilla, 2008). OBIA produces satellite image classification by grouping homogeneous pixels based on the identification of the similarity of spectral values in the formation of an object delineation by utilizing elements such as spectral, texture, and spatial. OBIA has advantages compared to traditional pixel-based classification methods (eg maximum likelihood classifier) because this technique performs grouping of the same neighboring pixels into a delineation object using specified parameters (Hulet et al., 2014). OBIA also identifies objects based on the pattern recognition process (Lei and Duan, 2011). OBIA utilizes a bottom-up approach by first detecting the spectral values for each pixel that are homogeneous in the formation of small objects, then combining them into large objects according to their actual shape. The OBIA algorithm extracts satellite image data based on image. segmentation, the process divides the entire image area into several non-overlapping polygonal object shapes according to homogeneity or heterogeneity criteria, and each object has the same internal feature shape including spectrum, spatial, texture, shape, etc. (Dilpreet and Yadwinder, 2014).

2.2 Normalized Difference Vegetation Index (NDVI)

Multispectral satellite imagery data is extracted to obtain the vegetation density of an area easily and quickly (Pirotti et al., 2014). Vegetation density is extracted from satellite imagery based on estimates of photosynthetic activity in a vegetated area by combining the Red(R) and Near-Infrared (NIR) bands which can show the presence of chlorophyll (Spadoni et al., 2020). The two bands are used as vegetation index parameters because the results of the band size are influenced by chlorophyll absorption, are sensitive to vegetation biomass, and can distinguish between vegetated land, open land, and water. The results of NDVI processing get a comparison of the ratio values.

If the value is low then it can be classified as land without vegetation such as waters, settlements, vacant land, and open land, whereas if the value is high then it is classified as land with dense vegetation (Andana, 2015). NDVI can show the vegetation density of an area from high vegetation density to low vegetation density. The spectral reflectance sensitivity of the Red (R) and Near-Infrared (NIR) bands is influenced by the cellular structure of the leaves and the chlorophyll pigment (Tucker, 1979). The NDVI algorithm equation can be seen in Equation 1.

$$NDVI = \frac{(NIR - R)}{(NIR + R)}$$

Equation 1

Equation 1 can be described where NIR is the reflectance value of the near-infrared band, and R is the reflectance value of the red band. The results of processing NDVI index obtained values with a range between -1 and +1, in this case, the increasing value will affect the results of vegetative density. NDVI can provide information on the thermal trends of vegetation areas, land use types, and determination of vegetation types (Yang et al., 2019 and Zeng et al., 2020).

2.3 Normalized Difference Water Index (NDWI)

NDWI is an algorithm used to estimate soil moisture and canopy moisture content (Sánchez-Ruiz et al., 2014). NDWI is built based on the assumption of spectral values in satellite images to obtain a wetness index. The results of the NDWI can be classified that the lower the value, the drier the area is, and conversely, the higher the value, the wetter the area. NDWI is a popular index for determining drought based on vegetation moisture. In this case, researchers have used NDWI in identifying humidity and dryness in an area with satellite image data (Gao, 1996). The application of NDWI utilizes a combination of band channels between Near-Infrared (NIR) and Short-Wave Infrared (Gao, 1996). In this case, NIR reflectance shows the internal structure of dry leaves without moisture content, while SWIR reflectance shows the effect of changes in vegetation moisture content and spongy mesophyll structure on the vegetation canopy. The estimation of vegetation moisture content using a combination of NIR and SWIR in increasing the accuracy of the results because these two bands can eliminate variations due to leaf internal structure and leaf dry matter content (Ceccato et al., 2001). The NDWI algorithm can be seen in Equation 2.

$$NDWI = \frac{(R_{NIR} - R_{SWIR})}{(R_{NIR} + R_{SWIR})}$$

Equation 2

Where R_{NIR} is the reflection of the NIR band, while R_{SWIR} is the reflectance of the SWIR band on Landsat 8. NDWI in determining the wetness index is influenced by leaf moisture content, vegetation type, and land cover (Gao, 1996). The results of the NDWI value with high vegetation water content can be indicated by the acquisition of a high value, while low vegetation water content and low vegetation cover mean that it has a low NDWI value.

2.4 Land Surface Temperature (LST)

Remote sensing satellite images can be extracted to obtain ground surface temperature data by utilizing the thermal infrared (TIR) channel. LST from sensing data processing is much more applicable and preferable to measuring ground stations in large-scale areas (NourEldeen et al., 2020). Land surface temperature (LST) can be used as the main parameter of environmental and urban dynamics studies to determine the effect of surface energy balance and energy exchange that can have an impact on the comfort of urban residents (Abdelmalik, 2020). LST can also be one of the parameters for determining drought disasters. LST is obtained from the average ground surface temperature for each pixel in the satellite image. Ground surface heat emission can be captured by satellite image data by utilizing thermal infrared wavelengths. The built area is influenced by the distribution of the building and the surface temperature reaches 40◦C based on the results of satellite imagery LST processing (Yang et al., 2021). Therefore, Land Surface Temperature data can be used to determine meteorological and hydroclimatic prediction models at regional and local scales (Dash et al., 2002).

3. Results And Discussion

3.1 Object-Based Image Analysis (OBIA)

Classification of land use in this study using the OBIA method. In the first stage, the scale parameter is determined in advance to determine the large or small delineation of objects in the image. The value is determined based on the smallest object that can be delineated in the visually visible image. The delineation of the segmented object is strongly influenced by the value of the scale parameter. If the given value is large, the object delineation result will also be large. In this case, the determination of the value must also consider the smallest size of the object to be classified.

Inaccuracy in determining the value will result in the accuracy of land use classification. In this case, the value of the scale parameter is also greatly influenced by the resolution of the image used, so that the application of this value between satellite images can be different. The parameter value of this research scale uses a value of 60 with agricultural land class can be detected as the smallest object. The results of the segmentation are classified into land use classes that have been determined by selecting the training area in each class. The number of samples is determined proportionally in each class. The determination of the training area sample is influenced by the operator's knowledge of visually identifying the image so that it can affect the accuracy of the classification results. This study resulted in a land use classification of 5 classes including built-up land, open land, forest, agricultural land, and shrubs which can be seen in Table 2.

Land use using the OBIA method resulted in 5 classification classes. Based on the classification results, the land use of Klaten Regency is dominated by agricultural land with an area of 35,022 Ha or 50% of the total area. This shows that the majority of the population of Klaten Regency earns as farmers. Klaten Regency is also dominated by built-up land classes with an area of 19,961 Ha or 28% of the total area. This indicates that the central area of Klaten Regency is a developing area with a high population density and is the center of government activities. The land use of the region also shows that the further away from the center of the region, the more dominated by the agricultural class. The method used to test the accuracy of the results of land use classification using a confusion matrix. Field survey data collection is carried out proportionally according to the area of each class. Field survey data in this study amounted to 200 points. Field survey data is used to determine the level of suitability of land use classification results based on actual objects in the field. The results of the confusion matrix calculation obtain an overall accuracy of 81%. The biggest misclassification in the Open Land class is caused by the slight difference between the Open Land class and the Shrubs class. These are difficult to distinguish because they have almost the same range of values. The results of land use classification using the OBIA method need to be tested for accuracy so that the accuracy of the classification results can be used for various purposes. The accuracy assessment uses field survey data as validation data for the classification results to determine the level of truth. Test the accuracy of the classification results using a confusion matrix calculation to see the accuracy of the classification results from satellite imagery. Accuracy assessment is carried out by utilizing 200 data from field surveys. The field survey data are spread across all sub-districts in the Klaten regency. The results of land use classification obtained an accuracy rate of 81%. The classification results show some errors in the classification of objects in the form of forests and shrubs that are mutually shrubs. This is because the pixel value between forest and bush has almost the same value.

3.2 Normalized Difference Vegetation Index (NDVI)

This study produces a range of values between -0.01 to 0.899 using the NDVI algorithm, the acquisition of this value range is because the study area is mostly land so the range of values is relatively high. The higher NDVI value indicates the greenness of the vegetation (chlorophyll level) in plants, while the lower NDVI value indicates the lower greenness of the vegetation (chlorophyll level). Therefore, the NDVI value can be used as a parameter to see the vegetation density and drought level of an area. The smaller the NDVI value, the sparser the vegetation density in the area and the greater the potential for drought, while the greater the NDVI value, the higher the vegetation density and the smaller the drought potential. The results of NDVI values are classified into several classes as shown in Table 3. The number of classes on the NDVI results is divided into 5 classes. Determination of the class range based on the results of the field survey and the visual appearance of the image. Non-vegetation class has a range of values < 0. The very high vegetation density class has a range of 0.675 to 0.899. The NDVI results represent the chlorophyll of vegetation with the highest NDVI value in the land cover class in the form of forest. Spectral reflectance is affected by dense vegetation coverage.

Table 2: Land use classification

Land Use	Area (Ha)	Percentage (%)
Built-up Land	19,961	28
Open Land	7,038	10
Forest	2,474	4
Agricultural Land	35,022	50
Shrubs	5,528	8

Table 3: NDVI Results

No	Class	Description	Area (Ha)
1	< 0	No Vegetation	3.55
2	0 – 0.225	Low Vegetation Density	4,965.98
3	0.225 – 0.450	Medium Vegetation Density	28,053.89
4	0.450 – 0.675	High Vegetation Density	23,992.67
5	> 0.675	Very High Vegetation Density	12,952.25

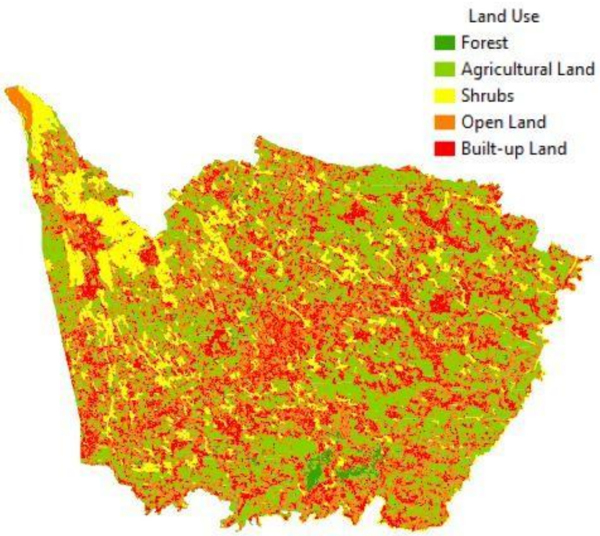

Figure 4: Land Use maps in Klaten Regency

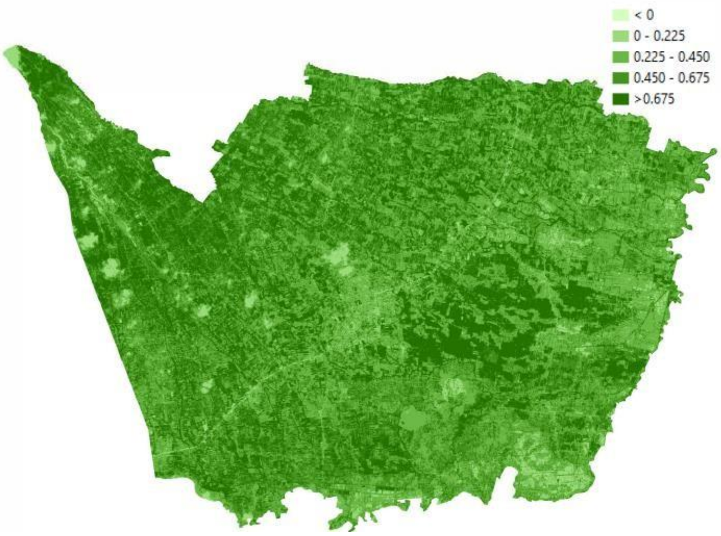

Figure 5: Normalized Difference Vegetation Index (NDVI) maps in Klaten Regency

Table 3 and Figure 5 show the results of NDVI processing in the Klaten Regency. These results indicate that the vegetation density in the study area is mostly in the medium to high vegetation density category. The NDVI results can show that most of the Klaten Regency area is an agricultural land area that is by the land use classification. The category of low vegetation density is found in the city center. The city center has a low vegetation density due to a lot of build-up land in the area. Low vegetation density is also found in the southern area because it is located at the foot of the low hills, namely the Jiwo Hills. The plain is composed of Quaternary deposits. The rock unit consists of alternating sandstone and siltstone and limestone lenses. This causes the area to have low-density vegetation found in Bayat district.

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3.3 Normalized Difference Water Index (NDWI)

Normalized Difference Water Index transformation was used to determine its relationship with the potential for drought. The NDWI value can be assumed that the lower the NDWI value of an object, the drier the object is, on the contrary, the higher the spectral value of the NDWI result of an object, the wetter the object. This study produces NDWI values with a range of values from -0.4 to 0.762. This research data was recorded in September so that most areas in the Regency have NDWI values with a low range of values. These results are caused by September which is included in the dry season so the object in the research area shows that most of the area is dry.

Based on Table 4, shows that the Klaten Regency area is mostly dominated by very low wettability classes with an area of 30,298.17 ha, most of which are in the Bayat district. Wetness index with very high wetness category is mostly identified in swamp areas in Klaten Regency because the area is waterlogged. A very low wetness index can indicate that the area has the potential for drought.

3.4 Land Surface Temperature (LST)

The results of image processing obtain LST with a value range of 21° to 46° Celsius. LST in this study was divided into 5 classes including 21°-26°, 26°-31°, 31°-36°, 36°-41°, and >41° Celsius. The Klaten Regency area mostly has LST with a range of 21°-26° located on the slopes of Mount Merapi which has relatively cool air compared to other areas. The area which has relatively high ground surface temperature is in Bayat district. Bayat sub-district has a high ground surface temperature which causes the area to be prone to drought.

Based on Table 5, shows that the distribution of LST in the Klaten Regency is dominated by the 26°-31° Celsius class. This shows the normal class temperature that occurs in the area because the land use in the area is in the form of agricultural land and built-up land. Several areas in Klaten Regency have LST values of 41°-46° Celsius and > 46° Celsius. Land Surface Temperature class with a high category in an area can trigger the potential for drought if it occurs for a long period.

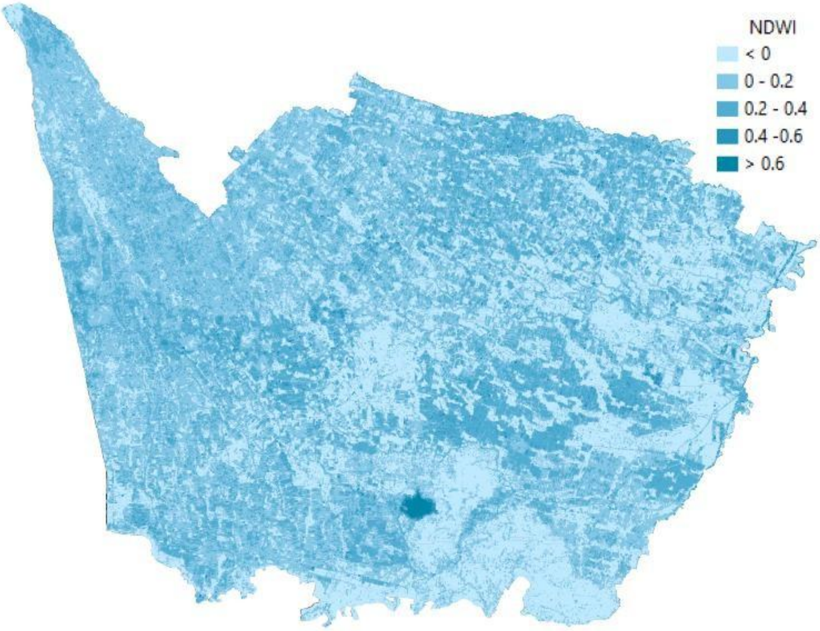

Figure 6: NDWI Results maps in Klaten Regency

Table 4: NDWI results

No	Class	Description	Area (Ha)
1	< 0	Very low wetness	30,298.17
2	0 – 0.2	Low wetness	28,627.63
3	0.2 – 0.4	Moderate wetness	10,744.96
4	0.4 – 0.6	High wetness	205.57
5	> 0.6	Very high wetness	92.67

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Table 5: Classification of Land Surface Temperature Klaten Regency

No	Class LST (Celcius)	Area (Ha)
1	21°-26°	1,800.09
2	26°-31°	35,375.40
3	31°-36°	31,279.05
4	41°-46°	1,498.05
5	>46°	9.45

Figure 7: Land Surface Temperature Klaten Regency

3.5 Drought Potential

The results of processing satellite image data produce land use data, NDWI, NDVI, LST, and regional conditions such as rainfall, hydrogeology, soil type, slope, and geology in order to obtain the potential for drought disasters in Klaten Regency. LST and NDVI provide importance in detecting potential drought disasters for large and medium scale areas (Wijayanti et al., 2021). Rainfall data were obtained from seven rain stations including Cokrotulung, Bawak, Karangnongko, Tegal Duwur, Karangdowo, Ngupit, and Ketandan. Data processing uses the Thiessen polygon method to determine the magnitude of the influence of rain stations on rainfall in each sub-district for 10 years from 2010 to 2019. The results of rainfall processing are obtained in the annual rainfall range of 1.966-2.746 mm which is classified into class 3. Data Land use in Figure 4 is classified and assessed based on objects that have the potential to cause drought in the order of built-up land, open land, shrubs, agricultural land, and forest. Forests and agricultural land are in the last order and the score is small because they do not have an impact on drought. The vegetation index as a result of NDVI processing is given a score based on the value of -0.01-0.2 to 0.5-0.899 from the No Vegetation class which is given the highest score because it has an impact on drought and the lowest score is in the Very High Vegetation Density class in Figure 5. Parameters Wetness index from NDWI processing was used to determine the level of potential drought with a value range of -0.4-0 to 0.4 - 0.762. The higher the NDWI value, the lower the vulnerability to drought and vice versa. The NDWI value is divided into 5 classes with the same value and the scoring value is given based on Figure 6. The land surface temperature (LST) parameter in Figure 7 is given a score of 1 to 5 based on the temperature value range between 21° to > 46°C. The potential for drought can also be determined from the hydrogeology parameters in Klaten Regency. Groundwater conditions can describe the amount of water below the ground so that hydrogeology data are classified and scored based on the condition of the amount of water that has high productivity to rare groundwater. Topographic conditions are also a factor causing drought, so the steeper the slope, the higher the risk of drought.

Table 6: Classification of potential drought in Klaten Regency

No	Class	Area (ha)
1	Very Low	2,425.39
2	Low	45,606.31
3	Moderate	19,678.26
4	High	1,988.84
5	Very High	101.53

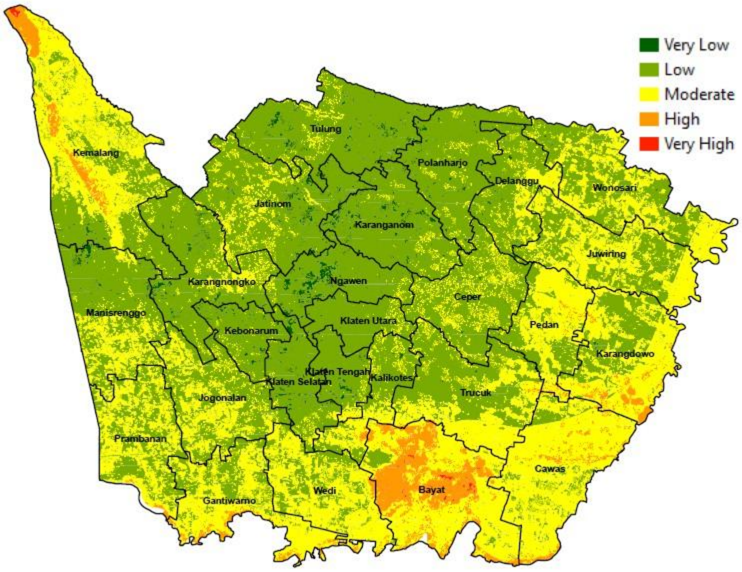

Figure 8: Map of potential drought in Klaten Regency

Therefore, the slope data are classified in the range of 0-8%, 5-15%, 15-25%, 25-45%, and >45%. Klaten Regency has a diversity of geology structures that can provide different potential impacts on each type of drought. Geology structures are classified based on their types that can affect the potential for drought in Klaten Regency. Geology structure affects surface water flow. Soil type greatly affects drought because it affects the ability of the soil to hold water below the surface. The ability of the soil is represented by the condition of soil moisture in storing water so that it can indicate the level of drought based on the availability of groundwater. Klaten Regency consists of soil types in the form of gray regosol, gray brown regosol, regosol dark grey, grumusol dark grey, and litosol which are classified based on the ability of the soil to hold water below the surface. All parameters are done by adding up the scores for each predetermined class. The scoring values for all parameters are added up to obtain a range of values between 15 to 38. The results of the range of potential drought values are classified based on the level of drought which can be seen in Table 6 by dividing into 5 classes with the same range value for each class.

The scores for each parameter were summed so that the scores ranged from 15 to 38. The scores were divided into 5 classes with the same distribution. Figure 8 shows the identification of drought in Klaten Regency. The majority of the Klaten Regency area does not have the potential for drought, but there are some areas that have been identified as drought. Based on the results of the processing, several sub-districts have the potential for drought including the districts of Kemalang, Manisrenggo, Jatinom, Prambanan, Trucuk, Bayat, Pedan, and Karangdowo. The results of the classification show that Bayat district has very high, high, and moderate drought classes, indicating that the area has a high potential for drought in the dry season. The Bayat district area has the potential to experience drought due to the type of soil in the form of littoral soil. This type of soil is a type of soil that is difficult for plants to grow because of its low nutrient content. Hydrogeology data shows Bayat district is an area where groundwater is scarce. This causes Bayat district to have a high potential for drought. Bayat district has an annual rainfall volume with a relatively moderate category of 2,073 mm/year obtained from Bawak station.

Even so, if there is a dry season, Bayat district has the potential to experience drought. In addition, land surface temperature also plays a role in determining the potential for drought where Bayat district has a higher surface temperature than other districts. The results of the transformation of the NDVI and NDWI algorithms show that Bayat district has a low vegetation density and level of wetness.

4. Conclusions

The results of the identification of potential droughts in Klaten Regency are areas that may experience droughts such as Kemalang, Manisrenggo, Jatinom, Prambanan, Trucuk, Bayat, Pedan, and Karangdowo sub-districts. The results of the classification show that Klaten Regency has a very high level of drought covering an area of 1,988.84 ha and a very high area of 101.53 ha and a moderate area of 19,678.26 ha. Klaten Regency shows that the southern region may experience the highest drought, which is located in Bayat Sub-district. Based on the processing of satellite image data using NDVI, NDWI, LST, it is known that the sub-district has a low vegetation density, a low wettability index, and a land surface temperature in the range of 41°- 46° Celsius and >46° Celsius. Bayat district is located at the foot of the Jiwo Hills with a steep slope, the rocks consist of sandstone and limestone lenses. Some of these things have caused Bayat district to become one of the sub-districts with a very high potential for drought.

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