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Soil Moisture Estimation Using Multitemporal Remote Sensing Data in Tabunio Watershed

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Abstract

Soil moisture, vegetation cover, and land surface temperature influence water energy balance, eco-hydrological processes, and water resources management. This research focused on the spatial and temporal variability of soil moisture, vegetation cover, land surface temperature, and Temperature Vegetation Dryness Index (TVDI) in Tabunio watershed. In this research, soil moisture and vegetation cover data were recorded and statistically evaluated from 2005 until 2020 using remote sensing data. Soil moisture, vegetation cover, and land surface temperature were significantly different over the research period. Increased vegetation cover had an inverse influence on land surface temperature and TVDI while directly affecting soil moisture. TVDI averages were 0 - 0.83. Decreased soil dryness in the period 2022 can increase water availability by controlling water resources. Proper watershed management can improve soil moisture and water availability. Vegetation cover protection and biological activities can be used to restore the watersheds. The approach combination of LST and NDVI to calculate TVDI is able to estimate the soil moisture as its estimation is extremely important for the evaluation of the overall ecological setting as well as the monitoring of the moisture content of wetland environments.

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Introduction

Research in the fields of climatology, ecology, hydrology, and agriculture all acknowledge that soil moisture is one of the most important elements. This parameter is extremely important for the exchange of energy and water that takes place at the soil-air interface (Baruti, 2004; Ansari and Deshmukh, 2017; Campos de Oliveira *et al.*, 2017). There is a large relationship between land surface temperature (LST) and the cover of vegetation (Amiri *et al.*, 2009; Solangi *et al.*, 2019; Guha and Govil, 2021;). Soil moisture also makes a significant contribution to the water-energy balance as well as ecological and hydrological processes. Activities that are performed to manage the watershed are the most likely to affect this parameter. Therefore, accurate measurement of the amount of moisture contained in the soil is of the utmost significance if one wishes to guarantee the efficacy of management measures (Doan and Luky, 2020). Three distinct methods are used to calculate the amount of moisture present in the soil that is utilizing meteorological data, using remote sensing data, and using field measurements. Even though taking measurements in the field is the most accurate method for determining the amount of moisture in the soil, this method is time-consuming and high-cost, particularly in more remote and hilly places (Borrelli and Schütt, 2014; Peng *et al.*, 2020). Alternatively, remote sensing methods can be utilized to monitor soil moisture and vegetation cover at high spatial and temporal resolutions at a reduced cost and in the shortest amount of time possible (Potic *et al.*, 2019; Wang *et al.*, 2020).

In recent decades, remote sensing techniques have been developed to estimate soil moisture (Moran *et al.*, 2004; Amani *et al.*, 2016; Mohamed *et al.*, 2020; Kazemzadeh *et al.*, 2021;). Radiation including near-infrared (NIR), visible light (VIS), thermal infrared (TIR), soil moisture ocean salinity (SMOS), short wave infrared (SWIR) reflectance, soil moisture active passive (SMAP), and microwave are used to retrieve soil moisture data from the topsoil. Integration of coarse spatial resolution microwave data with an optical/thermal infrared retrieval using a downscaling factor is the most extensively used satellite-based approach (Moran *et al.*, 2004; Mobasheri, 2016; Gao *et al.*, 2017; Amazirh *et al.*, 2018). The basic idea of thermal infrared observation is that soil moisture/water content affects surface heating processes. Most thermal infrared remote sensing of soil moisture content uses thermal inertia to distinguish surface thermal characteristics from the ambient temperature. Recently, quantitative indices have been used to study the spatiotemporal distribution of soil moisture characteristics (Vicente-Serrano *et al.*, 2004; Amazirh *et al.*, 2018). TVDI is frequently utilized due to its great precision and ease in monitoring soil moisture (Younis and Iqbal, 2015; Paddies, 2016; Peng *et al.*, 2020; Kazemzadeh *et al.*, 2021). TVDI is an optical/thermal remote sensing metric related to soil moisture fluctuation. It contains information on the senso r's visible to thermal infrared observations and can reflect soil moisture conditions. The TVDI data was extracted from LST and NDVI. Land Surface Temperature (LST), an excellent predictor of surface energy partitioning, is used to calculate vegetation and soil water stress. TVDI can accurately reflect soil moisture under diverse tree species, they found. Several studies have employed TVDI as a soil moisture indicator and shown good performance in different locations of the world (Peng *et al.*, 2020; Kazemzadeh *et al.*, 2021). The NDVI measures chlorophyll and vegetation cover. In dry locations, a lack of soil moisture raises both surface and leaf temperatures (due to stomata closure) (Hao *et al.*, 2012; Sidi Almouctar *et al.*, 2021; Guo *et al.*, 2022;).

Soil moisture is often used to evaluate a watershed. Soil moisture interacts with various hydrological variables, including surface water, groundwater, and evaporation, and is affected by terrain, climate, soil texture, and vegetation cover. Soil moisture is vital to hydrological processes including the energy-water exchange cycle (Dong *et al.*, 2019; Bartels *et al.*, 2021; Kazemzadeh *et al.*, 2021). While remote sensing is considered an alternative approach for the estimation of the environmental factors at a watershed scale, the results need to be validated with ground-based measurement. The previous studies mainly focused on agricultural lands with a specific cultivated plant type (Bhan and Behera, 2014; Horrocks *et al.*, 2014) and there was not a comprehensive study on the effectiveness of watershed management practices in natural range lands in mountainous regions using satellite and ground-based measurements. As previous studies only used remote sensing techniques to estimate environmental factors and calculate indices within a given watershed, the change of soil moisture can be derived from spatio-temporal remote sensing data. It is noteworthy that the capabilities of remote sensing techniques in detecting change differences in the vegetation cover, soil moisture, and land surface temperature. This research focuses on the following objectives: (i) spatial and temporal variability of soil moisture, land surface temperature, TVDI, and vegetation cover under watershed; (ii) application of remote sensing technique to quantify the differences in soil moisture, land surface temperature, TVDI, and vegetation cover in Tabunio watershed. In Tabunio watershed, floods and droughts have been the outcome of the expanding area of crucial land, the high degree of erosion, and the shrinking water catchment area (Kadir *et al.*, 2017, 2022; Nurlina *et al.*, 2022). Due to this condition, there is a need for research to predict this and identify regions in the Tabunio watershed that are prone to environmental degradation so that they can be mitigated.

Materials and methods

Maximum cloud-free L1T (terrain corrected) total 4 scenes, Landsat 5, Landsat 7 ETM+, and Landsat 8-OLI images were collected from 2005 to 2020 from the United States Geological Survey (USGS) website https://earthexplorer.usgs.gov.

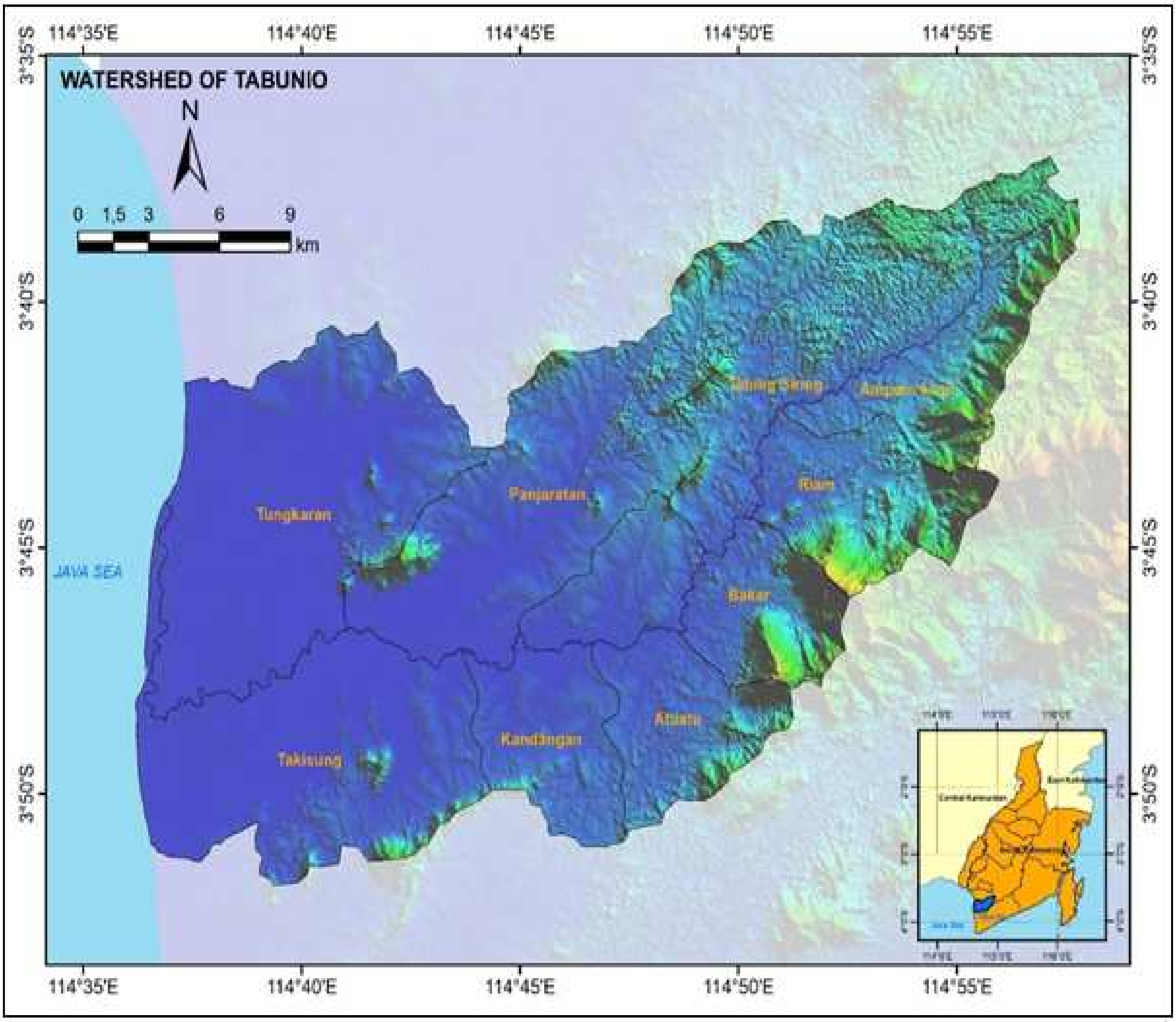

Fig. 1. Research location map of Tabunio Watershed.

The research was carried out in the Tabunio Watershed, which is situated in the Tanah Laut Regency. It covers an area of 62,558.56 hectares and can be found physically located at 3°37'2.72"-3°51' 51.43" South Latitude and 114°36' 12.02"-114°57'47.62" East Longitude. In terms of administration, the Tabunio watershed encompasses a total of 44 villages, in addition to 4 sub-districts and 10 sub-watersheds (ecologically). The study that is currently being done for the Tabunio watershed is displayed on a map, which may be found in Fig. 1. NDVI is founded on the premise that healthy vegetation visibly reflects in the near-infrared section of the electromagnetic spectrum, with green leaves reflecting 20% or less in the 0.5 to 0.7 m range (green to red) and 60% in the 0.7 to 1.3 m range (near-infrared). Sobrino *et al.* (2004) based the vegetative index on the expression.

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \quad (1)$$

where ρ_{NIR} and ρ_{Red} represent the reflectance of Landsat images in near-infrared and red bands respectively.

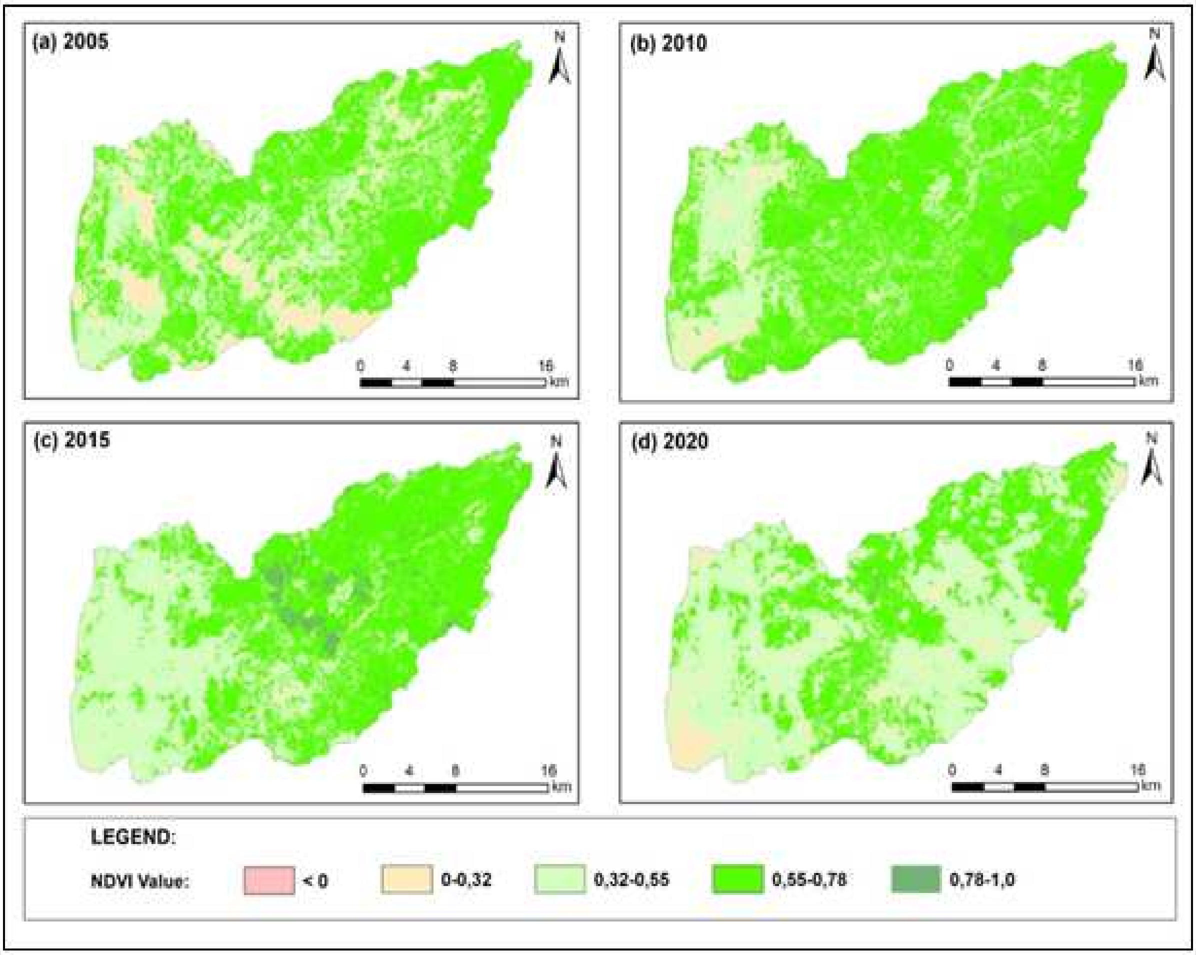

Fig. 2. Spatial distribution of NDVI in Tabunio Watershed 2005 – 2020.

Landsat TM is responsible for collecting the data that is used to calculate LST. The values of the LST are calculated by applying a procedure that may be broken down into three distinct stages. To begin, the digital numbers are transformed to surface radiance by employing sensor-specific calibration standard values. The picture pixels that make up the digital numbers are then used. The radiance measurements are then translated to an analogous temperature range for dark things as the second step of the process. The third phase involves determining both the emissivity-corrected temperature and the type of land cover that is significant to the calculation. Both of these steps take place in the same phase.

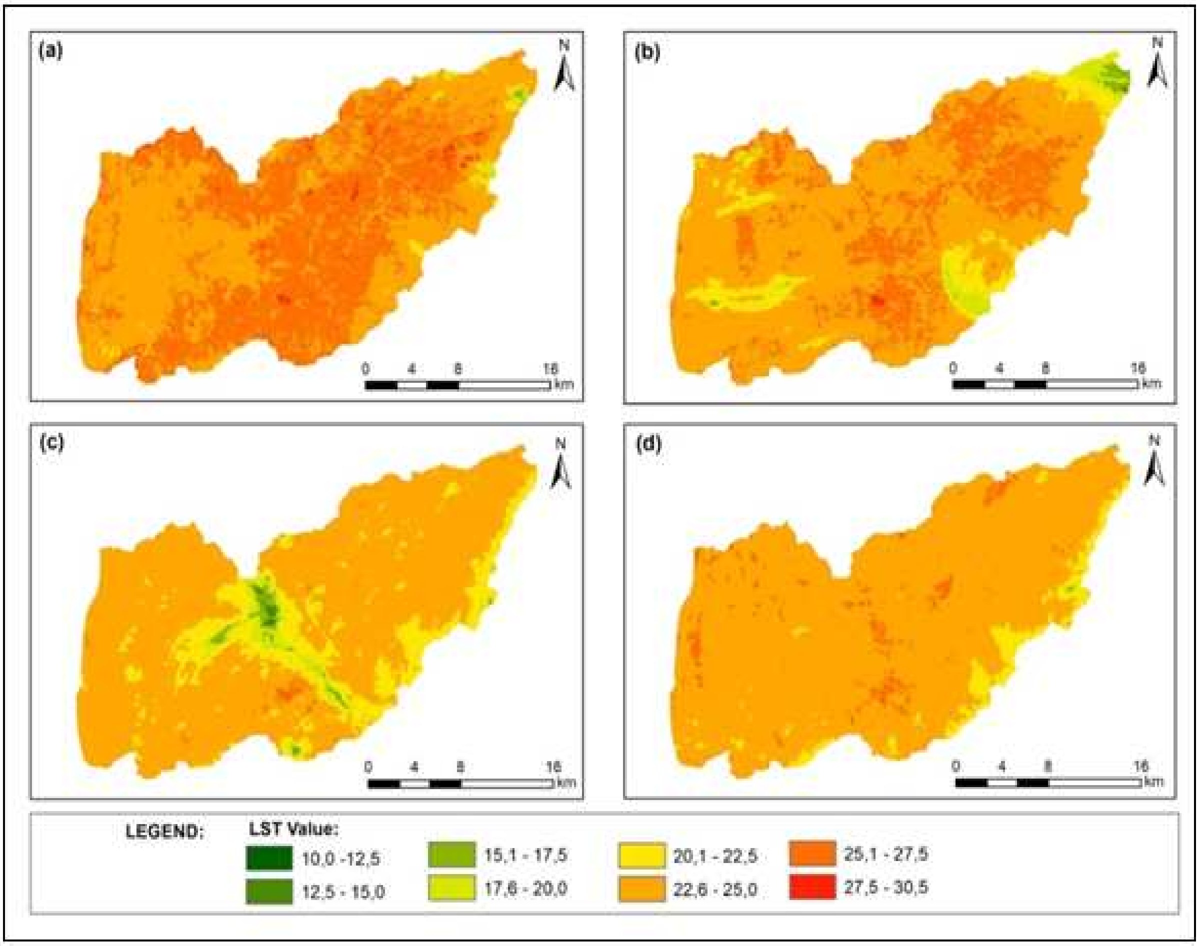

Fig. 3. Spatial distribution of Land Surface Temperature (LST) in Tabunio Watershed 2005 – 2020.

The method that was just detailed was utilized on both of the sensors that were mentioned earlier. A calculation was performed using the Landsat-5 TM satellite to determine the temperature of the region's surface by making use of the TIR band 6 data. The transformation from digital numbers, to radiance LTM

LTM = 0.124+0.00563*DN (2)

The radiance to equivalent blackbody temperature TTM Surface at the satellite using

$TTM_{Surface} = [K2 / (K1 - \ln LTM)] - 273$

For Landsat TM, K1 = 4.127 and K2 = 1274, respectively, the coefficients K1 and K2 are dependent on the range of blackbody temperatures. Calculating the non-uniform emissivity of the land surface requires an extra correction for spectral emissivity (ε). The emissivity-corrected land surface temperature (Ts) was finally computed as follows (Fu & Weng, 2016).

$$T_s = \frac{T_B}{1+\left(\lambda x \frac{T_B}{\rho}\right)\ln \varepsilon}$$

Where λ is the wavelength of emitted radiance. The peak response of λ and the average of the limiting wavelengths (λ=11.5 µm) were used, ρ=h×c/σ (1.438×10^{-2} mK), σ=Stefan Boltzmann's constant (5.67×10^{-8} Wm^{-2} K^{-4}=1.38×10^{-23}J/K), h=Planck's constant (6.626×10^{-34}Jsec), c=velocity of light (2.998×10^{8} m/sec), and ε is spectral emissivity.

Temperature Vegetation Dryness Index (TVDI) (3)

The TVDI is a direct reflection of the severity of the drought, and research has shown that boosting the TVDI can help minimize the amount of soil degradation (Sardiana *et al.*, 2017). To determine the land surface temperature (LST) of the research area, the normalized difference vegetation index (NDVI) was combined with historical temperature and relative humidity data using a mono window technique (Younis and Iqbal, 2015; Muro *et al.*, 2018;).

In this study, the temperature vegetation drought index (TVDI) (Eqs.5-7) was used to calculate TVDI. This methodology was chosen since it is based on the TS-NDVI principle.

$$TVDI = \frac{Ts - Ts_{min}}{Ts_{maks} - Ts_{min}}$$

$$Ts_{maks} = a_1 + b_1 * NDVI$$

$$Ts_{min} = a_2 + b_2 * NDVI$$

Where Ts, Ts_{min}, dan Ts_{max}, represent the land surface temperature of a pixel (K), the S_{maks} S_{min} highest and lowest surface temperature corresponding to NDVI(K), respectively a_1, b_1, a_2 dan b_2 are the coefficients for dry and wet edge (5) equations.

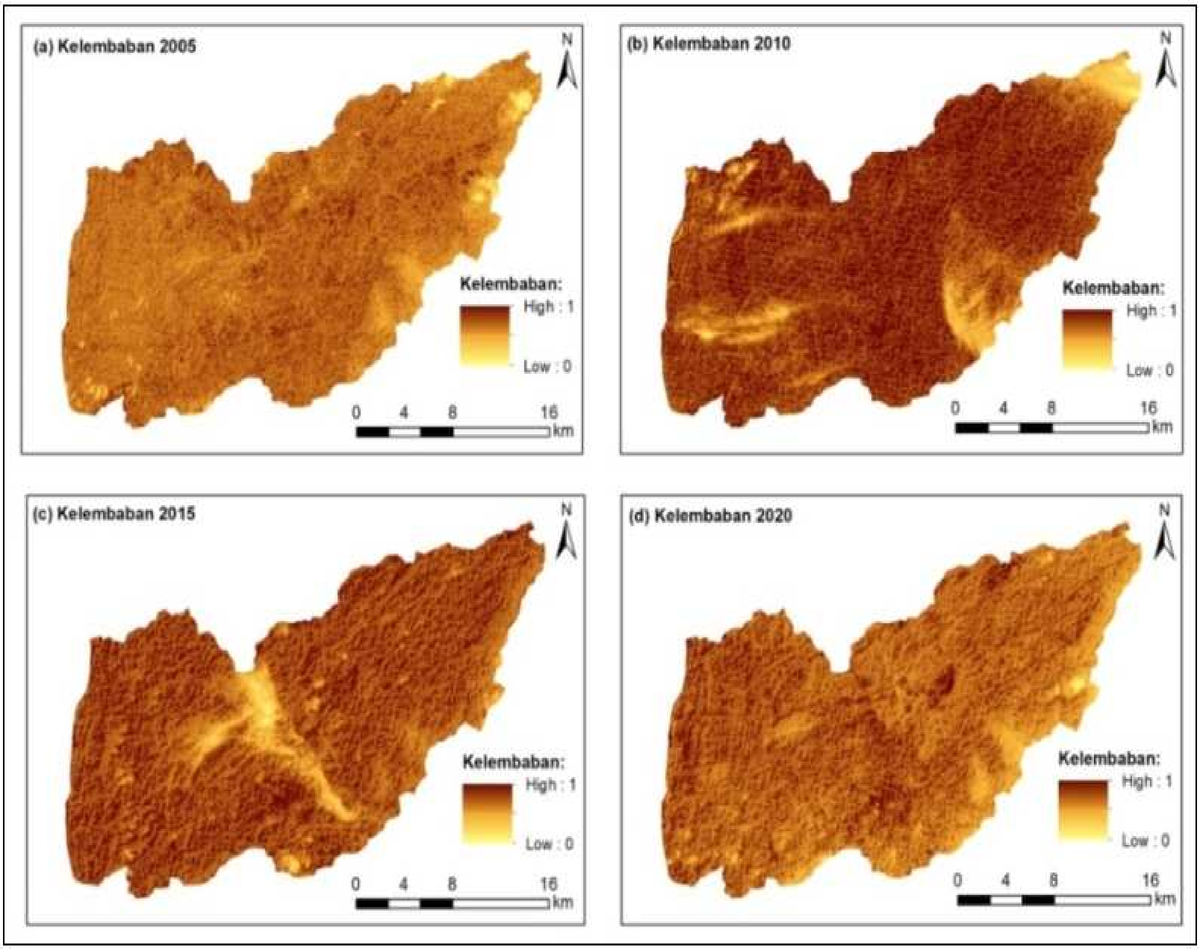

Fig. 4. Spatial distribution of soil moisture in Tabunio Watershed 2005 – 2020.

Result and discussion

The normalized difference vegetation index, also known as the NDVI, is a measurement of the intensity of vegetation that enables the distinguishing of different kinds of plants and non-vegetated surfaces. A low NDVI value of approximately 0.3 was achieved as a result of the large reduction in the vegetative cover that took place in the center of the watershed in 2005. (Fig. 2). This NDVI value typically rises as one walks away from the city center toward the city's periphery, which is an indication that the value is a reaction to the decreasing land use intensity. Since 2005, considerable shifts had taken place, as a result of which the spatial breadth of green areas had been significantly diminished as a direct effect of the increasing urbanization that was taking place throughout the city (Fig. 2). Furthermore, the considerable reduction has occurred in the geographical extent of vegetative land cover in the year 2020.

Table 1. LST variation (°C) in Tabunio Watershed from 2005 to 2020.

Year	Min (°C)	Max (°C)
2005	16	31
2010	14	29
2015	12	28
2020	17	28

The examination of the ecological environment is greatly aided by the variations in the Normalized Difference Vegetation Index (NDVI), which reflects the worldwide land surface vegetation coverage (Shao *et al*., 2016; Guo *et al*., 2022; Ridwan *et al*., 2022;).

The values of the NDVI for the area under investigation range from 0.00244 to 0.80481. The mountainous region has terrain that is predominantly grassland and forest, and both of these types of land have high NDVI values. The activities of humans have an impact on some of these regions. The most common categories of land use are impervious, bare land, and water bodies, all of which have low levels of vegetation coverage (Hosseini & Saradjian, 2011) conducted research on four distinct soil water content estimation models: NDVI LST, enhanced vegetation index (EVI) LST, NDVI LST NDWI, and EVI LST NDWI. Statistical analysis demonstrated that the accuracy of the soil moisture estimation increased when the EVI was replaced with the NDVI in the model.

From Fig. 3, the LST experienced a dramatic drop as one moved from the plains to the hilly zones. The former is impacted by both the lower altitude and the higher temperatures that were produced by human activity. In this regard, a higher altitude may be an important factor for reducing LST, which, when combined with the reduced human activities in the mountainous areas and higher vegetation coverage, resulted in a relatively lower LST. In this regard, a higher altitude may also be an important factor in reducing LST. As a direct result of the dense cloud cover, anomalous inversion patterns were seen. As a direct consequence of this, the temperatures in these regions are lower than 5 degrees Celsius. The majority of the land is used for plantation areas, and there is a significant amount of vegetation cover. Temperatures more than 20 degrees Celsius can be seen in some of the places because of the influence of human activities or the direction or gradient of the slope. The land surface temperatures (LST) are typically in the range of 15–29 degrees Celsius which are composed primarily of Plantation areas. The main urban center is located in the middle of the plains and is composed primarily of land suitable for construction; the LST values there range from 28 to 30 degrees Celsius (Table 1).

The temperature of the land's surface in 2005 showed a range of values between 16 and 31 degrees Celsius, according to the regional distribution of the data (Fig. 3a). The average temperature was a comfortable 25.3 degrees Celsius. On the other hand, for the year 2010, the average temperature of the land surface across the region ranges from 14 to 29 degrees Celsius (Fig. 3b). A significant rise was observed in 2015 when the LST value ranged from 12 to 28 degrees Celsius. This was the year that the range began (Fig. 3c). The average temperature of the land surface of the region is expected to range between 17 and 28 degrees Celsius in the year 2020 (Fig. 3d).

Table 2 and Fig.4 shows spatial distribution of soil moisture in Tabunio Watershed and the change in soil moisture. In general, the year 2005 is slightly moist and decreased drastically in 2010 then in 2015 soil moisture began to increase and continue to increase in 2020. This can occur in line with the plantation expansion of oil palm which continues to increase in the study area.

The results of the TVDI indicated the highest soil moisture dryness in general, which is consistent with the LST values. These results indicated that the soil dryness index, which was calculated based on the Vegetation cover index and LST using the remote sensing technique, was spatially and temporally different at the 0.01 significance level. In this context, the effects of increased plant cover on other significant elements such as soil moisture and land surface temperature are still unknown, which raises an issue. It is possible to conclude that the increased vegetation cover in the Tabunio watershed led to a lower temperature at the land surface. This indicates that regions that have a smaller cover of vegetation are experiencing a greater temperature at the land's surface, and vice versa. This result is consistent with the findings of the research that was carried out.

Table 2. The change of soil moisture from 2005 – 2020 in Tabunio Watershed.

Soil Moisture value	Soil Moisture Classes	Year			
		2005	2010	2015	2020
< 0,2	Very wet	314,29	452,72	275,59	70,02
0,2 – 0,4	Moist	571,79	2.106,45	1.869,47	502,76
0,4 – 0,6	Slightly moist	33.358,55	12.486,78	16.521,84	19.624,99
0,6 – 0,8	Slightly dry	28.196,92	47.358,43	43.818,94	41.599,53
>0,8	Dry	117,00	154,18	72,72	761,25

According to the value of LST and NDVI, the temperature of the surface area is lower when there is a greater amount of vegetation that covers the surface. Additionally, it is possible to conclude that the vegetation cover has a moderating and cooling effect on the surface temperature of an area (Jackson *et al.*, 2004; Zeng *et al.*, 2004; Younis and Iqbal, 2015).

A deeper comprehension of the connection between soil moisture and LST could not only contribute to the overall representation of LST in existing hydrological and climate prediction models, in addition to the development and improvement of SM techniques for retrieval or microwave-optical disaggregation, relating to evapotranspiration and the state of vegetation (Pablos *et al.*, 2016).

Activities that are performed to manage watersheds can affect the moisture content of the soil, which is an important variable in eco-hydrological processes. This variable plays an essential part in the exchange of energy and water at the soil-air interface. Field measurements and remote sensing techniques were utilized to analyze the temporal and geographical variability of soil moisture, vegetation cover, TVDI, and LST. These variables were studied in the context of watershed management operations.

The derived vegetation cover index (NDVI), land surface temperature (LST), and total vegetation depth index (TVDI) were proven to be helpful indices for quantifying the effect of watershed management measures when using the remote sensing technique.

Conclusion

In conclusion, the variation in soil moisture was connected with the variation in TVDI within the study area. The LST and NDVI values were acquired and then used to calculate TVDI values. TVDI was then used for the assessment of surface soil moisture using remotely sensed data, as well as for the establishment of the results using field-measured soil moisture data.

The triangulation of TVDI, LST and NDVI approach is able to estimate the soil moisture as its approximation is extremely important for the evaluation of the overall ecological setting as well as the monitoring of the moisture content of wetland environments.

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