



A geospatial approach in monitoring the variations on surface soil moisture and vegetation water content: a case study of Palakkad District, Kerala, India

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Received: 2 February 2022 / Accepted: 17 September 2022 / Published online: 11 October 2022
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Abstract

Soil moisture and vegetation water content play an important role in studies involving vegetation, drought, and climate change. The present paper gives details of how to calculate the Soil Moisture Index (SMI), Normalized Difference Moisture Index (NDMI), and Normalized Difference Water Index (NDWI) using Landsat 7 ETM+ and Landsat 8 OLI (Operational Land Imager) and Thermal Infrared Sensor (TIRS) data and how spatially and temporally it has been changed over Palakkad District, Kerala. The present study develops an image processing method using band 3 (Green), band 4 (Red), band 5 (NIR), band 6 (SWIR 1), and band 10 (TIR) of Landsat 8 and band 2 (Green), band 3 (Red), band 4 (NIR), band 5 (SWIR) and band 6 (TIR) of Landsat 7 data for determining the different spectral indices. The relationship between Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) are based on experimental parameterization for soil moisture index. Both LST and NDVI are considered indispensable data to obtain SMI calculation. The statistical analysis of NDVI and LST was exposed in the standardized regression coefficient. The study found a weak negative correlation between NDVI and LST in both 2001 ($R^2 = 0.37$) and 2021 ($R^2 = 0.16$). As the LST increases, the vegetative cover reduces due to the record of high temperatures in the study area. The SMI result for 2021 shows that the majority of the study area experienced extreme anomalies when compared to the 2001 result. Second, a significant negative correlation existed between SMI and LST ($R^2 = 0.664$ in 2001 and $R^2 = 1$ in 2021), which indicates that the surface soil moisture reduces with LST. The normalized difference moisture index (NDMI) value ranges from -0.71 to 0.75 in 2001 and -0.33 to 0.40 in 2021. In 2001 and 2021, the normalized difference water index (NDWI) ranges from -0.47 to 0.64 and -0.531 to 0.154 , respectively. Therefore, the current study gives a clear understanding of considerable variations in soil moisture and vegetation water content in the Palakkad District during the study period.

Keywords Land surface temperature (LST) · Normalized difference moisture index (NDMI) · Normalized difference vegetation index (NDVI) · Normalized difference water index (NDWI) · Soil moisture index (SMI)

Introduction

One of the most significant natural resources that must be carefully conserved for healthy ecosystems is soil (Subodh Chandra Pal et al. 2022). Ecosystem services of land are greatly affected by agricultural activities for soil cultivation

which changes the topographical condition, soil compaction and texture (Subodh Chandra Pal et al. 2021). The partitioning of precipitation into evapotranspiration and runoff is hampered by soil moisture, which is a substantial component of terrestrial water storage (Seneviratne et al. 2010). When moisture availability starts to decline, the normal growth and function of plants are disrupted and crop yields are started to reduce. Crop output declines as a result of significant land degradation caused by surface soil wetness and associated erosion (Rabin Chakraborty et al. 2022). Whenever water infiltrates into the soil, the pore spaces fill with water. When all the pores are filled with water, the water moves through the soil by gravity and capillary forces. Therefore, capillary water is the most important thing for agriculture, because it

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is held by soil particles against the force of gravity (Scherer Thomas et al. 1996).

Estimating soil moisture content (SMC) is crucial in many disciplines, such as meteorology, hydrology, and agriculture. (Alexakis et al. 2017). For evaluating the extent and severity of drought, spatiotemporal data, as well as data for soil moisture analysis taken below the surface, are very helpful. Concerning the benefits and drawbacks of almost all currently available SMI measurement techniques, many critical review articles have recently been published (Susha et al. 2014; Babaeian et al. 2019; Bogena et al. 2015; Ochsner et al. 2013). While point-based measurements typically have limited spatial representativeness (a maximum of a few square meters), traditional techniques have relatively high accuracy (Petropoulos et al. 2013; Babaeian et al. 2019). In general, SM is more likely to show significant spatiotemporal fluctuation, particularly in heterogeneous locations, where topography, soil texture, vegetation cover, climatic pattern, and other pertinent factors strongly influence the spatiotemporal distribution of SMI. Most of the currently available remotely sensed SM is referred to as skin or surface SM (e.g., only a few millimeters for the optical and thermal band) or near-surface SM (e.g., a few centimeters for microwave sensors at X-, C-, or L-frequency). This is because it follows the principle of sensing depths for electromagnetic radiation with different wavelengths (Babaeian et al. 2019). For ease of use, the remotely sensed SM is referred to as surface soil moisture (SSM) moving forward in this work. In situ measurements can provide an accurate assessment of soil moisture, but they are time-consuming and expensive and they can only represent a small area. Due to certain limitations of in situ observation of soil moisture globally, satellite-based SMI provides relatively large spatial variability, and repetitive coverage of measurements of the earth's surface on a global and regional basis (Owen et al. 1998; Malik & Shukla 2018). Satellite remote sensing has developed into a formidable tool for tracking the spatial–temporal fluctuations in regional soil moisture and providing quantitative estimates (Zhang & Zhou 2016). Surface soil moisture monitoring is currently available in multiple spectrum ranges: microwave, thermal band, shortwave band, and red–infrared band (Gao Zhongling et al. 2013). Microwave remote sensing techniques have been used to obtain surface soil moisture, commonly referred to as the water content of the uppermost soil layer, at various spatial–temporal scales since the 1970s. Over the years satellite image-based SMI has become an important criteria for studying agriculture production, climate change, vegetation monitoring studies (Kour Retinder et al. 2016; LN Wanderley et al. 2019; Kumar et al. 2020).

Apart from SMI estimation, the thermal infrared region of electromagnetic spectrum has potential to estimate more indices, which can easily give a quick estimation. Previous

studies in the current research area have mainly examined how paddy and vegetation degradation affect soil water retention rather than analyzing vegetation water content and soil moisture dynamics and how they respond to agriculture. It has been determined that there is a significant study gap in this area, and current research has looked at and investigated this area to get the desired outcome using optical–thermal sensors. The soil moisture index (SMI) is defined as the proportion of the difference between the current soil moisture and the permanent wilting point to the field capacity and residual soil moisture. The index value ranges from 0 to 1, with 0 indicating extreme dry conditions and 1 indicating extreme wet conditions (Cosh Michael et al. 2016).

Numerous aspects of the environment and living things can be impacted by the quality of vegetation and its spatial distribution. In this regard, monitoring and evaluating the status of vegetation water content is one of the crucial components of determining environmental health and reducing global warming. This type of investigation will enable us to detect changes in vegetation state more precisely and with greater spatial detail (Sadhan Malik et al. 2020). To effectively monitor and manage vegetation health, we need to have a good comprehension of the spatial–temporal dynamics of vegetation state. The NDWI is the most suitable for water body mapping as it has strong absorption in nature and low radiation in the range from visible to infrared wavelength (Fatima haque et al. 2020). The NDMI describes a crop's water stress level and it is calculated as the ratio between the difference and sum of the refracted radiations in the Near Infrared (NIR and Short Wave Infrared (SWIR), i.e., (NIR-SWIR)/(NIR + SWIR). The rich terrestrial biodiversity, the maintenance of human existence, the provision of resources, and the maintenance of current environmental issues are all fundamentally supported by natural vegetation/forests. In addition, the presence of forests mitigates the effects of global warming, improves groundwater quality, and serves as a carbon sink to maintain the equilibrium of atmospheric carbon dioxide (Asish Saha et al. 2021).

Here conducted a study of Palakkad District, Kerala, India, analyzing:

- i. Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) determine the indispensable data to obtain SMI calculation.
- ii. Spatio-temporal changes of NDMI and NDWI conclude the water index effects.

The approach presented in the current paper does not require in-situ measurements of soil moisture and vegetation parameters and it is only based on remote

sensing data. Instead of providing absolute soil moisture values, it gives an index ranging from low to high soil moisture. These maps will aid in our early planning and damage prevention. The research area's current vegetation water content and surface soil moisture can be determined with outstanding accuracy using remote sensing techniques (Subodh Chandra Pal et al. 2018). Therefore, given this circumstance, determining the status of the vegetation has become crucial and urgent work for all of us, and this has been our main goal for our study area. To achieve our goals, we have chosen key vegetation indices from Landsat 8 data sets, such as the Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), and Normalized Difference Water Index (NDWI), to reflect the vegetation status from various perspectives (Sadhan Malik et al. 2020). In this context, the present study incorporates an organized integration of GIS and Remote Sensing data to provide a fast and cost-effective means of soil moisture index assessment, normalized difference moisture index, and normalized difference water index. Based on physical and meteorological characteristics, this study seeks to propose an operational and practical approach for monitoring surface soil moisture and vegetation water content in tropical climate locales in the Midland and Highland areas of Palakkad District. The current study is crucial for the study area, because it allows for the quantification of irrigation needs before a crop exhibits signs of stress. Understanding soil moisture enables efficient irrigation, providing the water as and when required, and reducing the careless use of water when irrigation is not needed in the study area. To regulate the movement of water and heat energy between the land surface and the atmosphere through evaporation and plant transpiration, soil moisture and vegetation water content are the crucial factors in the study region. The current study is also crucial for the early diagnosis of vegetation stress, the assessment of drought, the planning of irrigation systems, and the estimation of crop production in crops.

The present research has studied SMI using NDVI and LST and Petropoulos et al. (2009) classified the LST/NDVI association as having a linear relationship with the SMI. The Triangle method is a technique Zeng et al. (2004) suggested to recover SMI based on the integration of LST and NDVI. These techniques are sometimes referred to as optical, thermal infrared remote sensing, since LST is calculated from thermal emission and NDVI is computed based on surface reflection of red and the near-infrared regions of the electromagnetic spectrum (Amato et al. 2015; Hammam and Mohamed 2018; Rahimzadeh-Bajgiran et al. 2013). The main focus of this research is to evaluate SMI and spatio-temporal changes of NDMI and NDWI which concludes the water index effects

in Palakkad District under irrigated soil conditions using thermal infrared remote sensing.

Description of study area

Palakkad District is one of the 14 Districts and is located right in the middle of the South Indian state of Kerala, India. The District to be found in the realm of tropical climate lies between $10^{\circ} 21' N$ to $11^{\circ} 14' N$ latitude to $76^{\circ} 02' E$ to $76^{\circ} 54' E$ longitude. (Department of town and country planning- Government of Kerala, 2011). It is the largest district in Kerala since 2006 and Palakkad city is the District Headquarters. The District is bounded on the Northwest by the Malappuram District, on the Southwest by the Thrissur District, on the Northeast by Nilgiris District, and the east by the Coimbatore District of Tamil Nadu state. The district is often called the Gateway to Kerala due to the presence of the Palakkad Gap in the Western Ghats. Palakkad is the major paddy-growing area of Kerala and it is nicknamed the "Granary of Kerala" it is the land of Palmyra and paddy field. The District covers an area of 4480 sq. km and it is 11.05% of the state's area which makes it the largest district of Kerala State. Out of the total area, about 1360 sq. km of the land is covered by forests and Palakkad is one among the five Districts in Kerala not having a sea coastal area.

According to the District Census handbook-2011, the physiography of the Palakkad district is categorized into two major natural divisions, namely, Midland and Highland based on their physical features. The Midland region consists of valleys and plains. The eastern region of the district has high mountains, extensive ravines, and dense forest cover. The Western Ghat ranges dominate the District and the entire area lies either in the midland (less than 80 m) or in the highland (above 80 m). The majority of the District area falls in the midland region, except the Nelliampathy-Parambikulam area in the Chittur taluk in the South and Attappadi Malampuzha in the north, which are hilly and fall in the highland region with an elevation of > 250 m (District Census Hand Book 2011). Since the altitude of the District varies from 15 m in the west to 2500 m in the northeast and south, the highland region is further categorized into mountain land, which includes high mountains, long spurs dense forests, and tangled jungles. The important peaks above an altitude of 1440 m are Anginda (2383 m), Karimala (1998 m), Nellikotta or Padagiri (1585 m), and Karimal Gopuram (1440 m). Besides all these mountains, the plain areas are scattered with several hills. Palakkad district is categorized into four natural regions based on topography, geology, climate, soils, and natural vegetation. These are Pattambi an undulating plain, Palakkad-Mannarkkad, the forested hills, Palakkad gap, and Chittur forested hills. The climate is more pleasant for most parts of the year, except in the summer months. The District is blessed with

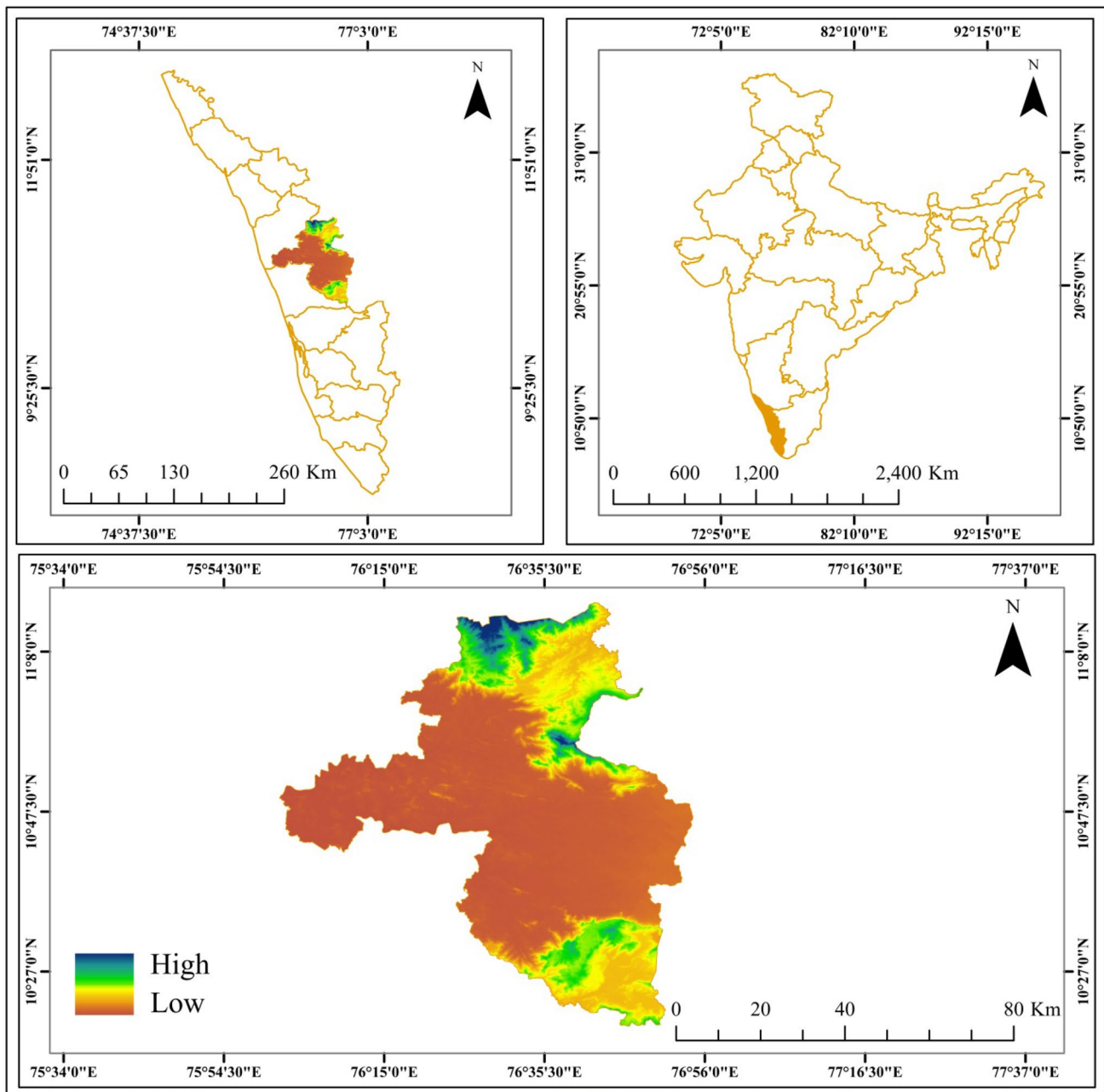


Fig. 1 Location map of the study

several small and medium rivers, which are tributaries of the Bharathapuzha River. Even though there are considerable changes in the land use and cropping pattern have been observed in the district for the last 5 years and also the over-dependence on groundwater for domestic, irrigation and industrial activities in the district has led to water scarcity, especially along the eastern parts of the district (Fig. 1).

Physiography and land use/land cover

The development of a particular type of land use in the district has been influenced by moderate rainfall, thick soil cover, and irrigation facilities. The major portion of the district comes under arable land, which comprises both irrigated and un-irrigated land. Rice, pulses, vegetables, and banana are the major crops in the district (Department of mining and geology, 2016). The northern and southern side of the district comprises the high hills of Western Ghats

(Mountain land) constitute forest land. A significant area of the forest land has been converted to plantations, especially on the northeastern side of Palakkad District. The eastern side of the Palakkad district area is underlain by thick laterite, which is best suitable for open wells. Followed by the area underlain by thin laterite toward the west of Palakkad district. The northern and southern side of the district is fully covered by hilly/mountainous area, which is considered tropical evergreen forest land. The foothills, which are highly undulating linear stretched areas, located between mountainous and thin laterite zones are suitable for practicing agriculture. The eastern side of the Palakkad district comprises a midland land area and also the area falls under the Bharathapuzha river basin is concentrated agricultural land (Fig. 2).

Materials and methods

The calculation of soil moisture index is mainly based on the LST and vegetation indices of the study area. In the present study, the Landsat 8 satellite imagery with a spatial resolution of 30 m was downloaded from the United States Geological Survey (USGS) Earth Explorer website. As one scene cannot cover the entire study area, a total of two satellite images were used having different rows and paths (Table 1). The satellite images are reprojected to a

Universal Transverse Mercator (UTM) coordinate system, (datum WGS84, zone 43 N).

The study area satellite image has been downloaded from USGS earth explorer.com for which the details are given in Table 1. The red and near-infrared (NIR) bands are used for the NDVI calculation, thermal infrared (TIR) bands for the LST calculation, NIR and SWIR 1 bands are used for NDMI, and Green and NIR bands are used for the estimation of NDWI. The methodology adopted in the study is given in Fig. 3.

Soil moisture index

Soil moisture plays an important in agricultural monitoring, drought, and flood forecasting. Soil moisture observations can give a warning of near future drought or flood conditions before other more standard indicators are triggered. The algorithm applied to the calculation of SMI is based on NDVI and LST operations, which are calculated using a multispectral Landsat satellite image for each pixel. In Michigan Tech Research Institute, (2009) presents SMI values from 0 to 1, where higher values close to 1 represent higher soil moisture levels. Parida et al. (2008) classify SMI values greater than 0.3 as no drought or favorable soil moisture conditions, whereas SMI values less than 0.3 were classified into three classes of drought, namely, slight, moderate, and

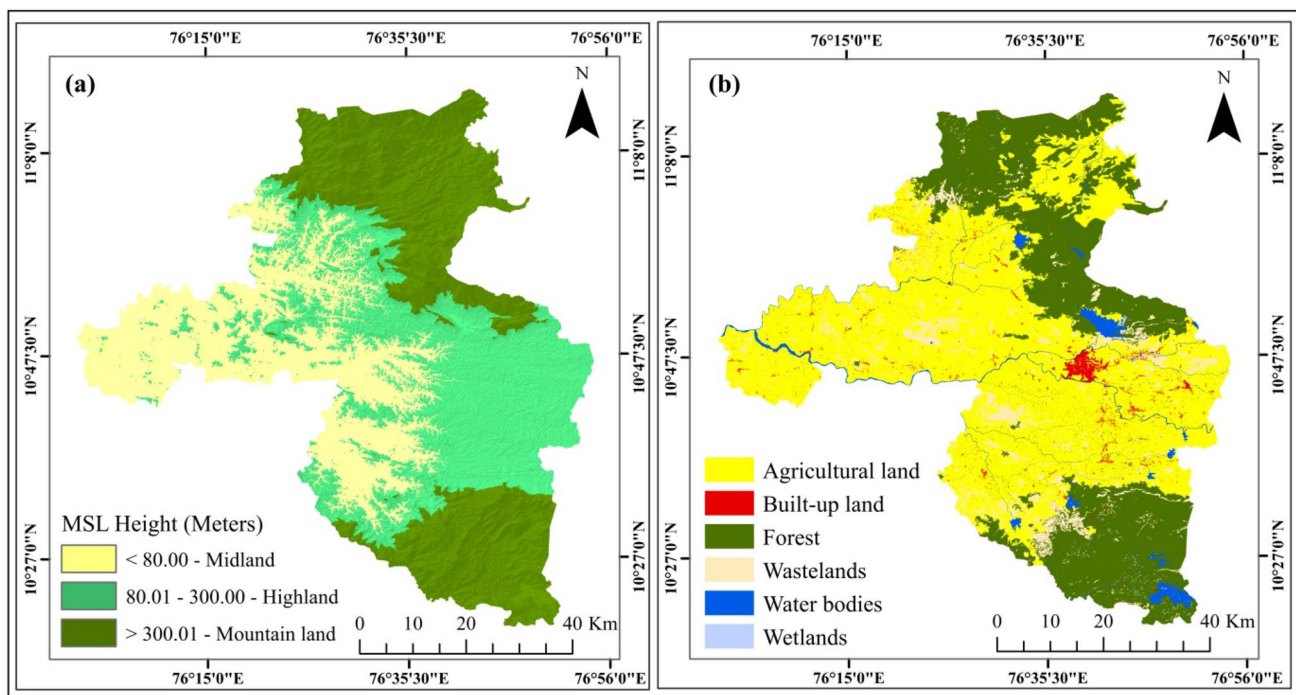


Fig. 2 Physiography a and LULC b of Palakkad district

Table 1 Landsat data used

S. no.	Data	Date	Path/ Row	UTM Zone	Band				
					For NDVI	For LST	For SMI	For NDMI	For NDWI
1	LE07_L1TP_14 4052_2001030 3_20200917_ 02_T1	3/3/2021	144/52	43	NIR & RED	TIR	NDVI & LST	NIR & SWIR 1	GREEN & NIR
2	LE07_L1TP_14 4053_2001030 3_20200917_ 02_T1	3/3/2021	144/53	43	NIR & RED	TIR	NDVI & LST	NIR & SWIR 1	GREEN & NIR
3	LC08_L1TP_14 4052_2021030 2_20210311_ 02_T1	2/3/2021	144/52	43	NIR & RED	TIRS 1 & TIRS 2	NDVI & LST	NIR & SWIR 1	GREEN & NIR
4	LC08_L1TP_14 4053_2021030 2_20210311_ 02_T1	2/3/2021	144/53	43	NIR & RED	TIRS 1 & TIRS 2	NDVI & LST	NIR & SWIR 1	GREEN & NIR

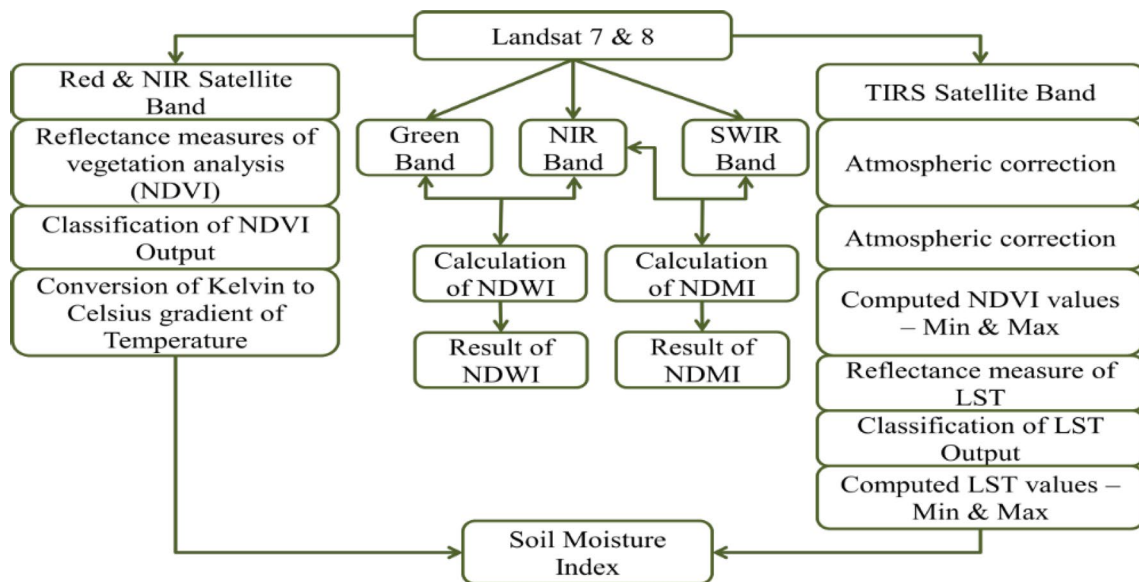


Fig. 3 Flow diagram of methodology

severe drought. In the existing work, continuous SMI data ranging between 0 and 1 describe the level of soil moisture. Therefore, the Michigan Tech Research Institute (2009) method was used to present the mode of SMI in the study area. The soil moisture index is based on parameterization of the relationship between LST and NDVI and it has been calculated using the equation:

$$SMI = (LST_{max} - LST) / (LST_{max} - LST_{min})$$

where LST_{max} and LST_{min} are the maximum and minimum surface temperature and it is derived from Landsat 8 image.

Land surface temperature using landsat 8 satellite

Land surface temperature is the temperature of the surface which can be measured when the land surface is in direct contact with the measuring instruments. In general, it can be defined as the skin temperature of the land surface (Reddy and Manikiam 2017). Calculating land surface temperature from remote sensing images is very much needed, since it is an important factor controlling most of the physical, chemical, and biological processes of the Earth (Becker and Li 1990). Landsat 8 image carries two individual sensors to

capture the thermal waves, and these bands are band 10 and band 11. The formulas given below are used to find out the surface temperature from the Landsat 8 images, which were obtained from the Landsat User’s Guide (<http://landsat.usgs.gov/landsat8>, 2016) (Tables 2, 3).

Calculation of TOA (top of atmospheric) spectral radiance Using the radiance rescaling factor, thermal infrared digital numbers are converted to TOA spectral radiance (Latif 2014). ML and AL information have been taken from the Metadata file (Landsat8 (L8) Data Users Handbook 2019).

$$L\lambda = ML * Q_{cal} + AL$$

where: $L\lambda$ = TOA spectral radiance (watts / (m²*sr*μm)), ML = Radiance multiplicative Band (No), AL = Radiance Add Band (No), Q_{cal} = Quantized and calibrated standard product pixel values (DN).

Top of atmosphere (TOA) brightness temperature conversion Spectral radiance data can be converted to top of atmosphere brightness temperature using the thermal constant values in the Metadata file (Avdan, Ugur, and Gordana Jovanovska, 2016).

Conversion of Kelvin to Celsius:

$$T \text{ Celsius} = (TKelvin - 273.15)0^{\circ}\text{Celsius} = 273.15 \text{ Kelvin}$$

$$BT = K_2 / \ln(K_1 / L\lambda + 1) - 273.15$$

Table 2 Pre-calibrated constants for Landsat

Landsat 8	
Radiance multiplicative Band 10	0.0003342
Radiance Add Band 10	0.1
Q_{cal}	Corresponds to Band 10
K_1 Constant Band 10	774.8853
K_2 Constant Band 10	1321.0789
Landsat 7	
Radiance multiplicative Band 6	0.067087
Radiance Add Band 6	-0.06709
Q_{cal}	Corresponds to Band 6
K_1 Constant Band 6	666.09
K_2 Constant Band 6	1282.71

Table 3 Temperature variations based on physiography—2001 and 2021

Physiography division	Temperature in °C (2001)			Temperature in °C (2021)		
	Minimum	Maximum	Mean	Minimum	Maximum	Mean
Midland	17.36	43.81	28.04	26.16	40.27	30.75
Highland	11.51	41.78	28.32	24.89	41.06	30.49
Mountain land	7.84	40.3	21.6	15.66	38.03	26.02

where: $L\lambda$ = TOA spectral radiance (watts/(m²*sr*μm)), K_1 = K_1 Constant Band (No), K_2 = K_2 Constant Band (No).

Normalized differential vegetation index (NDVI) The Normalized Differential Vegetation Index (NDVI) is a standardized vegetation index calculated using Near Infra-red (Band 5) and Red (Band 4) bands. The calculation of NDVI is much more important for LST estimation. The proportion of vegetation (PV) is highly related to NDVI and emissivity (E) is highly related to the PV (Cihlar et al. 1991):

$$NDVI = (NIR - RED) / (NIR + RED)$$

where: RED = DN values from the RED band, NIR = DN values from the Near-Infrared band.

Land surface emissivity (LSE) Land Surface emissivity (LSE) is the average emissivity of an element on the surface of the Earth calculated from NDVI values. The minimum and maximum values of the NDVI image can be displayed directly in the image and also it can be available from the properties of the raster image (Vanhellemont 2020; Rozenstein et al. 2014):

$$PV = \left[\frac{(NDVI - NDVI_{min})}{(NDVI_{max} + NDVI_{min})} \right]^2$$

where: PV = Proportion of Vegetation, NDVI = DN values from NDVI image, $NDVI_{min}$ = Minimum DN values from NDVI image, $NDVI_{max}$ = Maximum DN values from NDVI image

$$\text{Calculate Emissivity (E)} = 0.004 * PV + 0.986$$

where: E = Land Surface Emissivity, PV = Proportion of Vegetation.

Apply the formula in the raster calculator in Arc GIS software, the value of 0.986 corresponds to a correction value of the equation.

Calculate land surface temperature (LST) The Land Surface Temperature (LST) is the radiative temperature which calculated using the Top of atmosphere brightness temperature, Wavelength of emitted radiance, Land Surface Emissivity (Sruthi and Aslam 2015; Orhan Osman et al. 2014)

$$LST = (BT/1) + W * (BT/C2) * \ln(E)$$

where: BT=Top of atmosphere brightness temperature (°C), C2 = 14,388 μm K, W = Wavelength of emitted radiance, E=Land Surface Emissivity.

The final step is the determination of empirical parameters by the linear regression method. To do so, Arc GIS software is used to process the data for the same pixel from two raster sets, LST and NDVI, and represent the distribution of the data in a scatter plot (Sun and Kafatos 2007; Deng Lei et al. 2018). Linear regression values range from 0 at the warm edge to 1 cold edge. The pixels close to the warm edge are drier relative to the cold edge, which is wet (maximum evaporation-unlimited water access). The scatter plot position of a pixel defines its moisture condition.

Calculation of normalized difference moisture index (NDMI)

The NDMI is mainly used to determine vegetation water content and it is a remote sensing-based indicator sensitive to the change in the water content of leaves Gao, B. C. 1996. NDMI describes the crop's water stress level and it is calculated as a ratio between the NIR and SWIR values. The interpretation of the exact value of the NDMI makes it possible to recognize the farm or field areas with water stress problems. The NDMI was calculated using the following equation:

$$NDMI = (NIR - SWIR 1) / (NIR + SWIR 1)$$

where: NIR = Near Infrared, SWIR = Short Wave Infrared.

Calculation of normalized difference water index (NDWI)

The NDWI is known to be powerfully related to the plant water content. It is a new method that has been developed to delineate open water features and enhance their existence in satellite imagery. NDWI makes use of reflected near-infrared radiation and visible green to enhance the presence of such features and in most cases, it can enhance the water information very effectively. The NDWI is used to calculate the following equation (McFeeters 1996).

$$NDWI = (GREEN - NIR) / (GREEN + NIR)$$

Results

Derivation of NDVI and LST for SMI

Normalized Difference Vegetation Index is the most popular vegetation index and is calculated on a per-pixel basis

as the normalized difference between the red and near-infrared bands from an image. Whereas NDVI seems sensitive to differences in Canopy Cover in sparse canopies it loses sensitivity in moderate and dense canopies. NDVI normally ranges from -1 to +1 (Chander et al. 2009). The vegetation is very closely related to LST, it is because the vegetation dense areas lower the surface temperature by evapotranspiration. Landsat 8 is the most favorable satellite data for the calculation of LST which is having two thermal bands (Lambin et al. 1996).

In 2001 the study result shows that the values varied from -0.52 to 0.62, whereas it has shifted from a minimum of -0.11 to a maximum of 0.59 in 2021. The negative value indicates the absence of vegetation or poor vegetative cover, whereas the positive value shows the dense and good vegetative cover in the study area. The LST values are the temperature of the surface which is measured at °C. The correlation coefficient is a statistical measure of the relationship between the relative moves of two variables (NDVI and LST). There are numerous correlation coefficient methods; the one that is most commonly used is the Pearson correlation (*r*). This measures the strength and direction of linear courting between NDVI and LST variables. A correlation of -1 indicates an idea of a bad correlation, whereas a correlation of 1 indicates a high-quality correlation. A correlation of 0 indicates no linear courting between NDVI and LST. Here, NDVI and LST calculations are based on necessary data and compared with scatter plots of NDVI and LST to obtain SMI computation (Fig. 4).

As per the study undertaken, the following conclusions are drawn: The LST values are within the range of < 15 °C to > 40 °C and it is divided into seven classes, as mentioned in Fig. 5. In 2001, the area falling below 20 °C has observed in the north and eastern side of Palakkad District, especially in the mountain land, whereas it has shifted to the range of 20 °C to 25 °C in 2021. The area falls between the range of 15 °C to 25 °C dominant in the northern part of the District and it has reduced the spatial extend and shifted to the class range of 25.01 °C to 35.00 °C. The temperature falls below 25 °C areas in the high land are completely shifted to the range of 25 °C to 35 °C. Similarly, the trend has been visible in > 35 °C areas of Palakkad District. The LST of high land and mid-land areas in Palakkad District has increased in recent days and it has been reflected in the above map.

The scatter plot between the pixels with NDVI values with corresponding LST values are shown in Fig. 6.

In 2001 the NDVI value ranged from -0.52 to 0.62, which gradually reduced to between -0.11 to 0.59 in 2021. Therefore, it can be said that the Vegetation index had a decreasing trend in Palakkad District. The correlation results in a negative correlation between NDVI and LST. As the LST increases the Vegetation reduces due to the record of

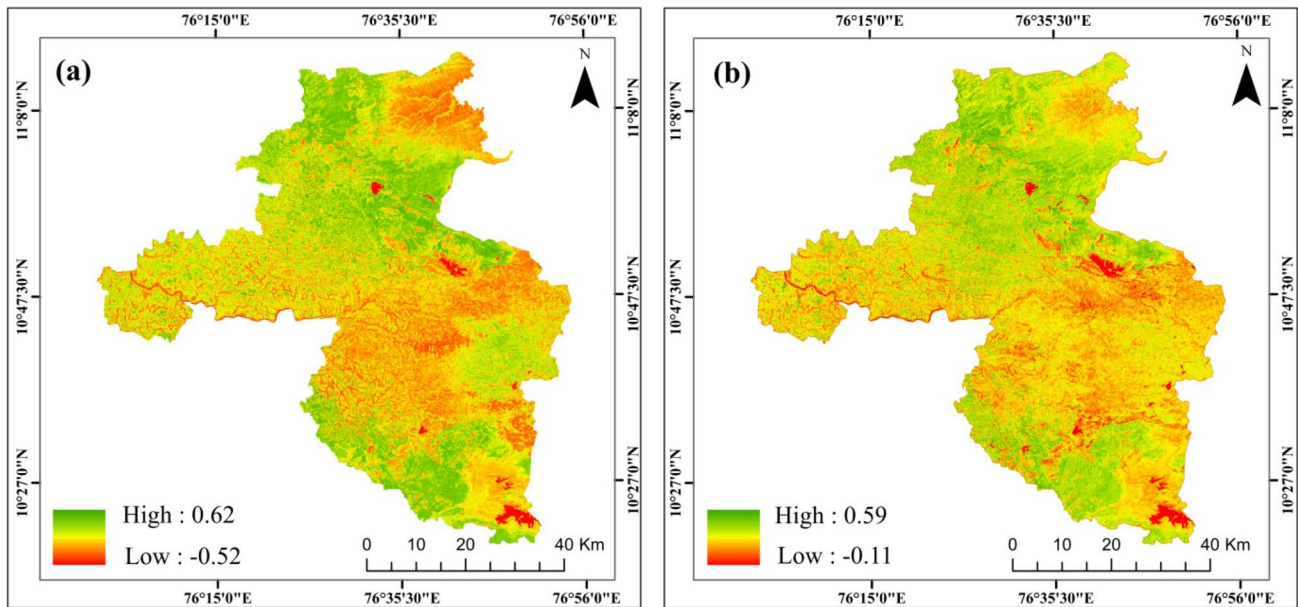


Fig. 4 Normalized difference vegetation index 2001 (a) and 2021 (b)

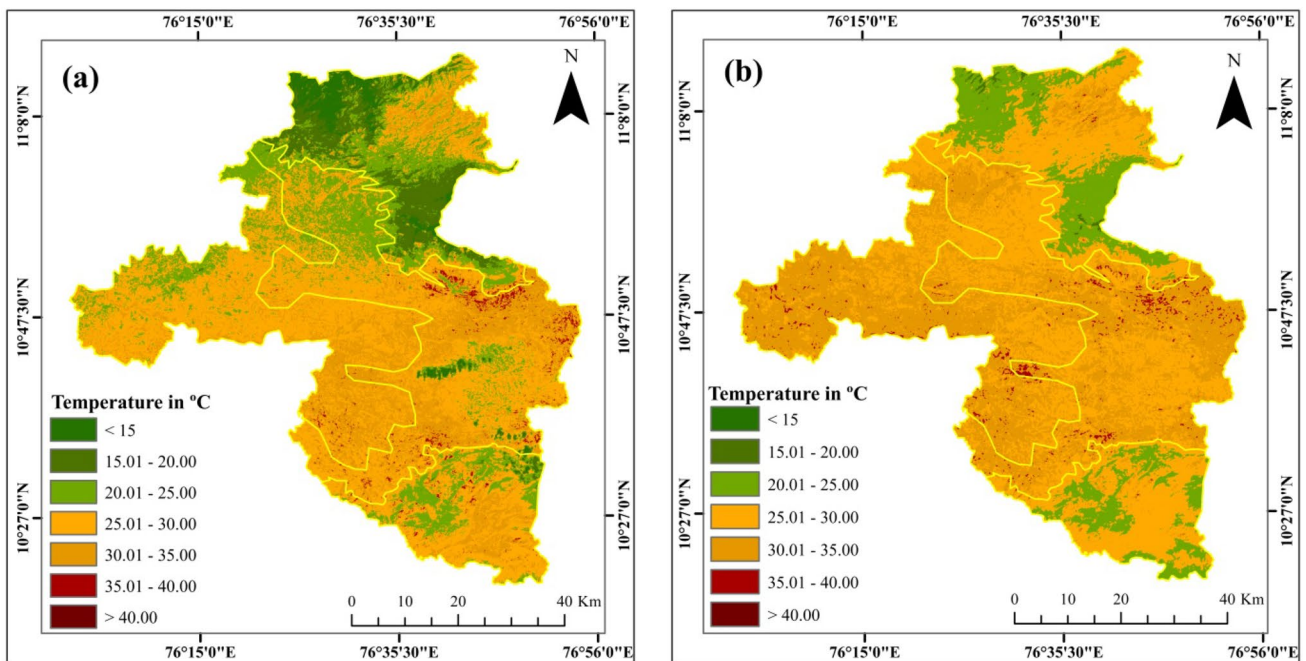


Fig. 5 Land surface temperature 2001 (a) and 2021 (b)

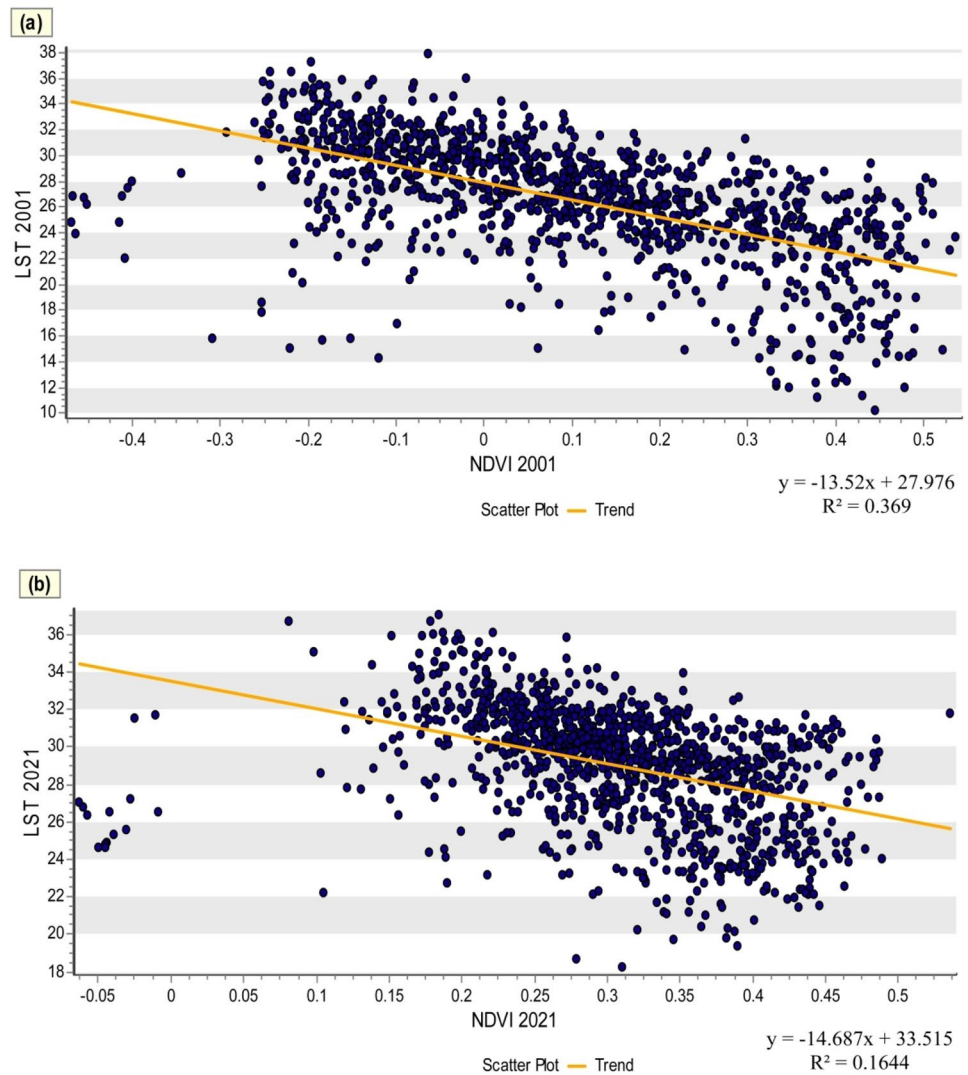
high temperatures in the study area, which shows an increasing trend in future scenarios.

The SMI result is available with the value ranging from 0 to 1. The values are close to 1 are the region with a low amount of vegetation and surface temperature and a higher level of soil moisture presented there. The values near 0 are

the areas with a significant amount of vegetation and surface temperature and present a low level of soil moisture (Fig. 7).

The final result of the SMI map indicates that the soil moisture was in the range of 0 to 1 as classified in four color gradients. The study area, as shown in Fig. 7 (red and yellow color), has a value close to 0, which was highly affected

Fig. 6 Correlation between LST and NDVI 2001 (a) and 2021 (b)



by the water deficit. The values near 1 (green and light yellow) are forest cover which has moisture as compared to the rest of the land cover. The output result concluded that the majority of the area which falls under high land and mid-land areas were close to 0, which indicates a moisture deficit in the off-season throughout the study area. As per the SMI index, 1 represents a higher presence of water/moisture, and 0 indicates minimum moisture content, such as in dry areas. The area close to the values of 0 SMI has increased from 2001 to 2021, especially in high land and mid-land areas of Palakkad District. Figure 8 shows the average SMI values on different Land cover types. The SMI value on all LULC types has a decreasing trend, which indicates the rapid expansion of impervious surface, agricultural land conversion, and vegetative stress, which gives rise to high surface temperatures. The SMI values were very less over Built-up land, whereas the other LULC types have comparatively high surface soil moisture.

A significant negative correlation existed between SMI with LST in both 2001 and 2021, which indicates that the vegetation, water, and surface soil moisture reduced with LST. There is a strong negative spatial correlation between SMI and LST in 2021 ($R^2=1$), while in 2001, comparatively weak negative spatial correlation with LST ($R^2=0.664$). When the level of LST is increasing, the values of SMI are getting decreased as well as suggesting that the water content in vegetation also got declined (Fig. 9).

Derivation of NDMI and NDWI

In the present study, the NDMI result ranges from -0.71 to 0.45 and -0.331 to 0.404 in 2001 and 2021, respectively. The result can be depicted in the map (Fig. 10). In 2021 the foothill areas, which are undulating linear stretched areas, located between mountainous and thin laterite zones have a high content of moisture as compared to other areas. A water

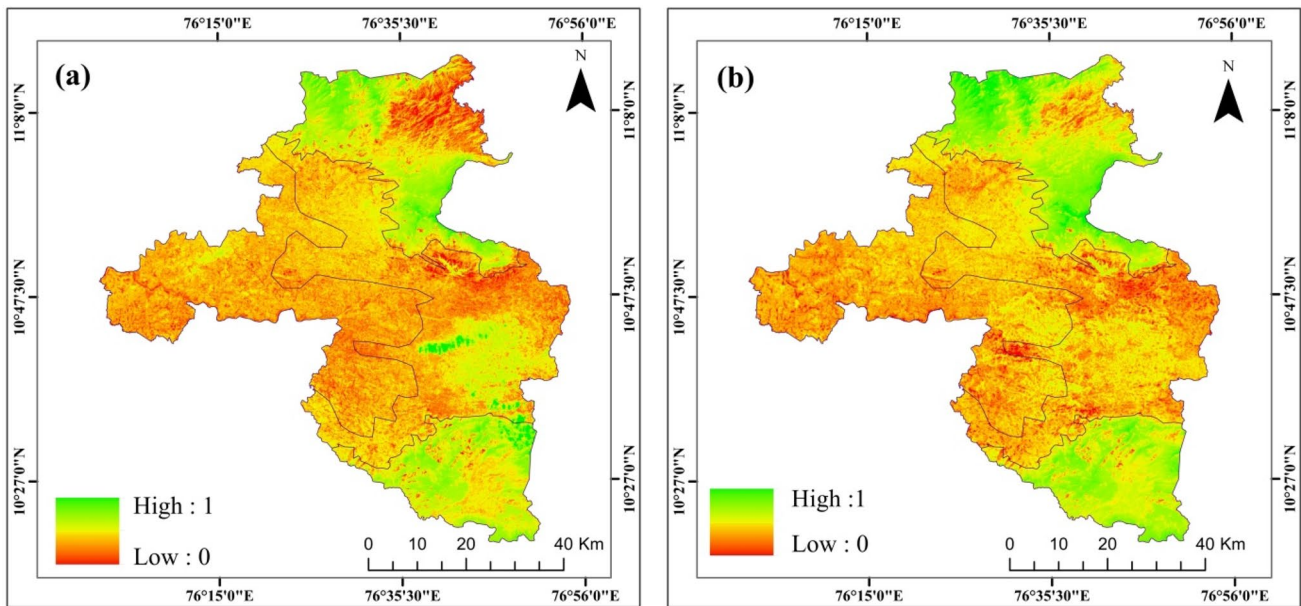
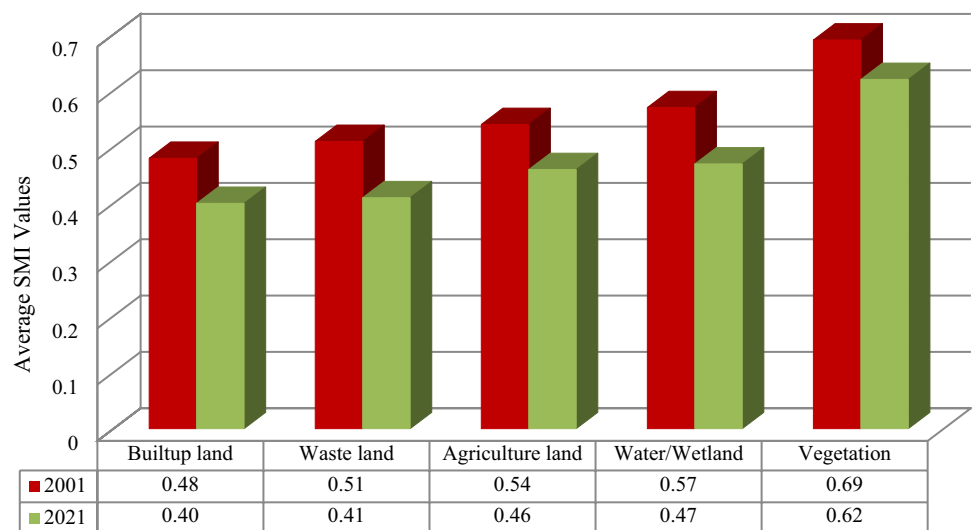


Fig. 7 Soil moisture index 2001 (a) and 2021 (b)

Fig. 8 Variation of average SMI over land use land cover types



body location also shows high moisture content as compared to plains. The barren land shows the lowest content of moisture, as there is very less existence of vegetation and water bodies. The variations in the NDMI values of Palakkad District in both 2001 and 2021 can be seen in Fig. 10.

The NDWI has been calculated for identifying the water index and in the present study, the value ranges from - 0.47 to 0.64 and -0.53 to 0.15 in 2001 and 2021, respectively. The areas where water bodies and rivers show high values of NDWI when compared to the area where water bodies and rivers do not exist. In the current study, the high-altitude areas have high NDWI than the agriculture and built-up areas, which are normally situated in the

plain area. The output result indicated that the majority of mountain land, high land, and midland regions in 2021 fall under a low index value as compared to 2001. The blue and green shade represents high water index values and the majority of them are shifted to low water index in 2021. Therefore, the present study gives us to understand that, the District is going to face a serious threat in near future (Fig. 11).

Limitations

Cloudy/hazy weather, dense vegetation, forest cover, and water bodies are all factors that limit soil moisture resultant.

Fig. 9 Correlation between LST and SMI 2001 (a) and 2021 (b)

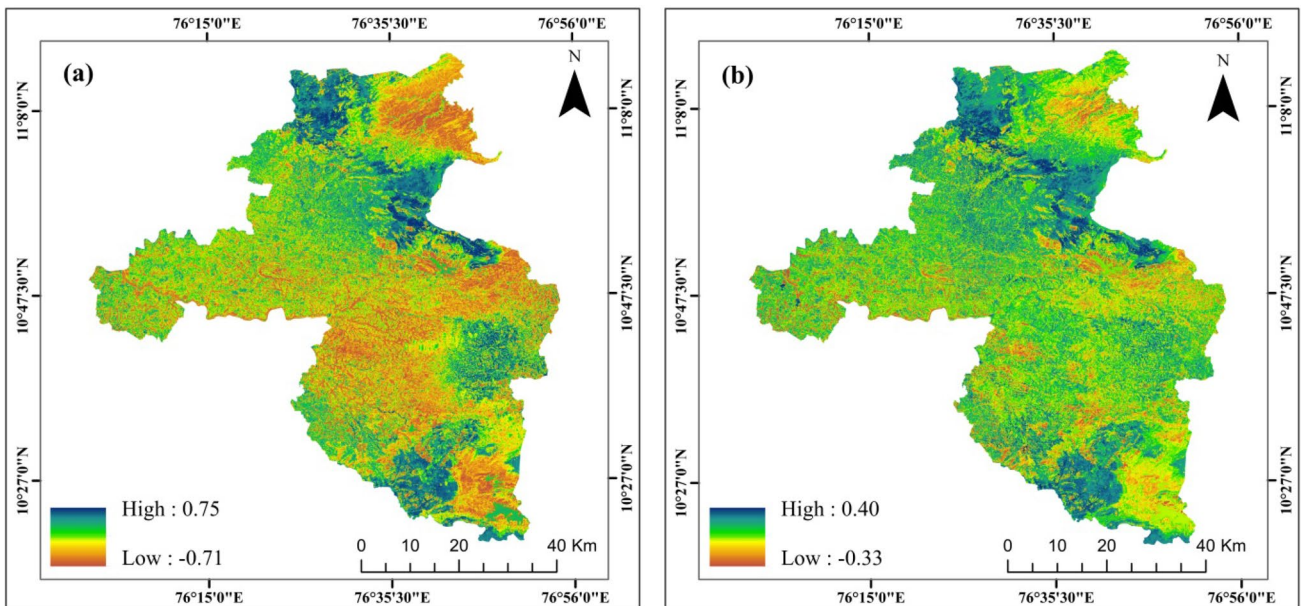
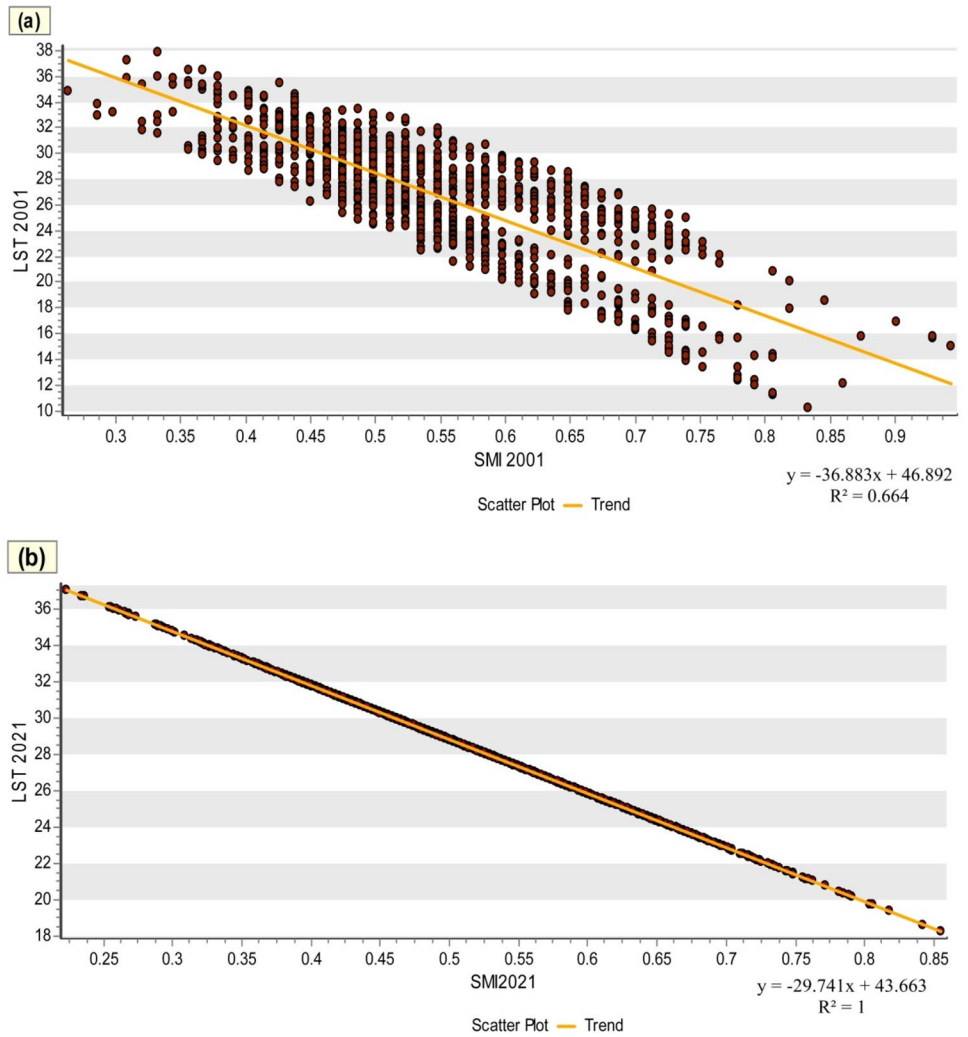


Fig. 10 Normalized difference moisture index 2001 (a) and 2021 (b)

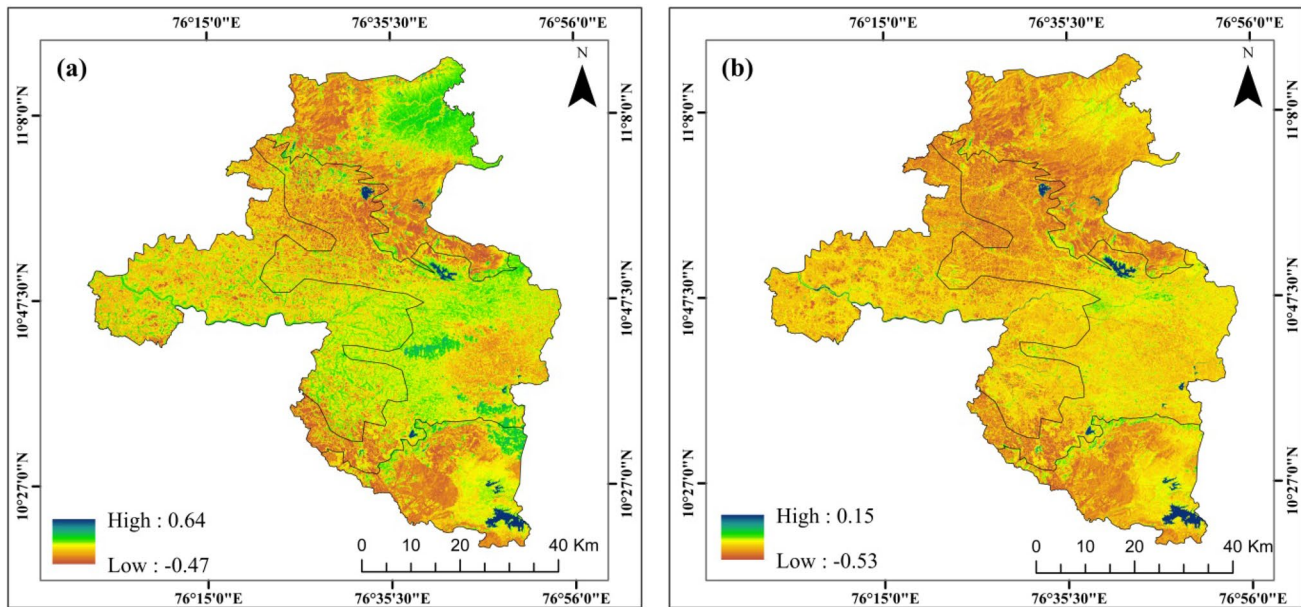


Fig. 11 Normalized difference water index 2001 (a) and 2021 (b)

In terms of the soil–moisture estimation depth, currently used methods have been relatively successful in measuring the moisture at a depth of 5 cm from the top soil surface for bare soil or soil with less vegetation. Estimating soil moisture at the root zone level, which is 10 cm or more below the soil surface, can be considered another challenge. Therefore, current study methods have not been successful in estimating soil moisture from deep soil layers, such as at the root-zone soil layers. Based on the active remote sensing methods, estimating soil moisture on bare soil or soil with less vegetation gives more accurate results, as compared to using the methods on a mixture of land-cover soil. Moreover, the estimation process becomes more challenging when the vegetation cover is dense.

Discussion

The sensitivity study revealed that the SWIR, and particularly the spectral regions near the main absorption bands, are quite effective at detecting changes in soil moisture. By limiting the impact of differing albedo values and generalising the vegetation properties across different species, the normalised difference technique has already demonstrated success in the context of vegetation indices (Haubrock, S.N., et al.). To make the SMI more applicable across the board, such as for agricultural areas, more in-depth analysis of vegetation is required. Alluvial soils are generally found in very small areas in the district, mainly along the

banks of the Bharathapuzha River valley portions (middle area) and are more suitable for intensive types of cropping. Laterite soils are the most predominant soil type in the midland areas of the district (Shaji et al. 2007). It is largely concentrated in the midland and partially in highland areas, especially Ottapalam, Alathur, Chittur, and Palakkad Taluks. Lateritic soil has attracted the attention of earth scientists all over the world because of its importance in agriculture (Ollier and Galloway 1990; Aleva 1994). The forest soil mainly occurs along the eastern part of the district, and the area is hilly and mountainous with steep slopes and escarpments. These areas are mainly comes under tropical evergreen forest.

A time series of retrieved vegetation water content and soil moisture maps is being researched from 2001 to 2021 and will be the focus of future research papers. Future efforts could concentrate on enhancing the retrieval algorithm in the soil moisture estimation process and employing remotely sensed time series images with high resolution in both time and space to produce a more accurate map. The final result indicates the surface soil moisture index values are low in the midland and highland areas of the Palakkad District. The area covered by low moisture content in Palakkad District has tremendously increased in 2021 as compared to 2001. The results of NDVI, NDMI, and NDWI give a clear idea about the spatiotemporal variations of vegetation water content in the district and also an indication that the district is facing a serious threat in terms of surface soil moisture and vegetation water content in the near future.

Conclusions

The current study was undertaken in Palakkad District, Kerala, of which the majority of the area is dominated by agricultural land. The results conclude that the midland and highland areas are dry conditions and the remaining forest cover has normal moisture conditions, which comes under mountain land. To increase agriculture productivity, it has to focus on reforestation to increase precipitation as well as moisture conditions. The majority of the study area has a lack of moisture in the soil, especially in highland and midland areas. This data can be used as an excellent indicator of the soil moisture condition and also it can support the Multi-Criteria Decision Making strategy for resolving the problems of emerging environmental stresses. The effective use of this technology for determining the normalized difference water index, moisture index, and vegetation index has immensely enhanced the capability of human beings to further explore remote sensing data for quick and accurate results. The application of robust geospatial technology with freely available data such as Landsat has the potential to be effective in monitoring soil moisture and vegetation water content in Palakkad District.

The study result can be utilized as a predictor of natural disasters, such as floods and droughts, as well as environmental changes, such as dust storms and erosion. The methods described in this study can also be used to create a regional geospatial database, which can subsequently be utilized to support numerous researches in India on agricultural water use, identify the moisture level of soil, greenhouse gas emissions estimations, and food security. It is expected that the current study will be very helpful to climatologists, environmentalists, and hydrologists in further studies as well as in sustainable planning and management of various natural resources. Other missions, such as Soil Moisture Active Passive (SMAP), could benefit from the resulted soil moisture estimation. Moreover, the information regarding natural resources and their changes is very much important for managing sustainable development policies.

Declarations

Conflict of interest The authors are not having any conflict of interest with the previous studies.

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