Article

Assessment and Impact of Soil Moisture Index in Agricultural Drought Estimation using Remote Sensing and GIS Techniques

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Received: date; Accepted: date; Published: date
Academic Editor: name

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Abstract: Soil moisture takes an important part in involving climate, vegetation and drought. This paper explains that how to calculate the soil moisture index and the role of soil moisture. The objective of this study is to assess the amount of moisture content in soil and soil moisture mapping by using remote sensing data, in the selected study area. We applied the remote sensing technique with the purpose of relies on the use of soil moisture index (SMI) which in its algorithm uses the data obtained from satellite sensors. The relation between land surface temperature (LST) and normalized difference vegetation index (NDVI) are based on experimental parameterization for Soil moisture index. Multispectral satellite data (visible, NIR and TIRS) were utilized for assessment of Land Surface Temperature (LST) and make vegetation indices map. GIS and image processing software utilized to determine the LST & NDVI. NDVI and LST are considered as essential data to obtain SMI calculation. The statistical regression analysis of NDVI and LST were shown in standardized regression coefficient. NDVI values are within range -1 to 1 where negative values present loss of vegetation or contaminated vegetation, whereas positive values explain that healthy and dense vegetation. LST values are the surface temperature in °C. SMI is categorized into classes from no drought to extreme drought to quantitatively assess drought. The final result is obtainable with the values range from 0 to 1, where values near 1 are the regions with a low amount of vegetation and surface temperature and present a higher level of soil moisture. The values near 0 are the areas with a high amount of vegetation and surface temperature and present the low level of soil moisture. The results indicate that this method can efficiently applied to estimation of soil moisture from multi-temporal Landsat images, which is valuable for monitoring agricultural drought and flood disasters assessment.

Keywords: Soil Moisture Index (SMI); LST, NDVI, Drought

PACS: J0101

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1. Introduction

Soil moisture is a key parameter which directy or indirectly influence the water cycle. Agriculture production of rabi crop in rainfed area mainly depends on it as well as irrigation practices decided based on it. Due to climate change and increasing trend of temperature has a significant impact on crop production (Leeuwen et al., 2015; Potic et al., 2017). It is linked to various hydrological phenomenon like drought, climate, and vegetation. The data collected for soil moisture analysis taken below the surface over the long term as well as at higher temporal and spatial resolutions data are valuable for assessing the extent and severity of drought quite accurately (Sridhar et al., 2007). Surface soil moisture is very sensitive which varies with space and time (Korres et al., 2013). Various study has done to assess the soil moisture. Two methods of soil moisture measurement which is based on spcaborne remote sensing like microwave part of electomanetic spectrum and thermal, infrared observation (Vicente-Serrano et al., 2004).

In situ measurements can provide accurate estimation of soil moisture, but they are both time consuming and expensive, and only represent a small area (few square decimeters). Nevertheless, a number of strategies can be adopted to upscale the spatially sparse ground-based observations (Crow et al., 2012; Cosh et al., 2016), which are invaluable for calibrating and validating land surface models and satellite-based soil moisture retrievals (Dorigo et al., 2011). 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 temporal and spatial scales since the 1970s (Schmugge et al., 1974; Zhang et al., 2018).

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 the residual soil moisture. The index values range from 0 to 1 with 0 indicating extreme dry condition and 1 indicating extreme wet condition (Chandrasekar et al., 2016).

2. Study Area & Data used

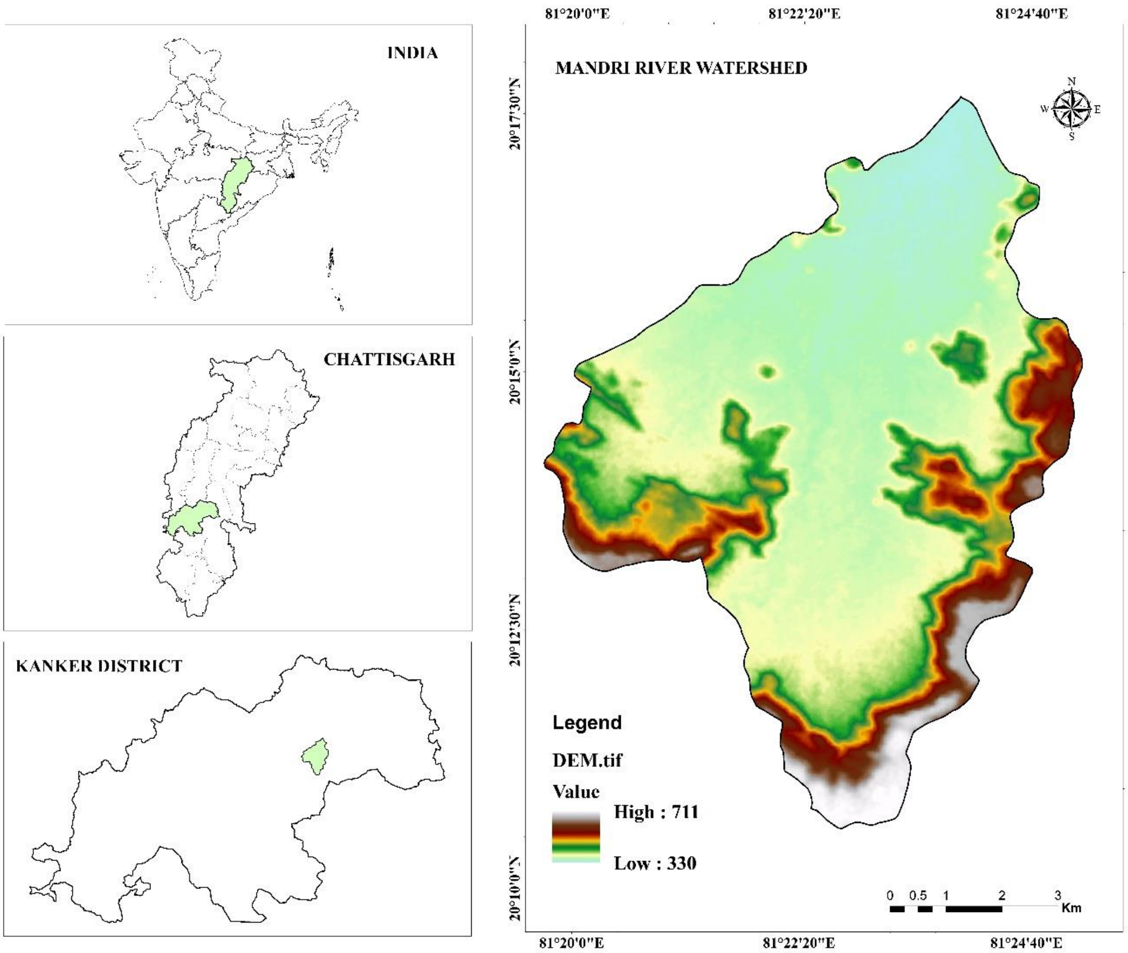

Figure 1. Study area map of Mandri river watershed in Chattisgarh

The study area is Mandri river watershed which is falls in the Middle Mahanadi basin. This watershed lies in the district Kanker of Chattisgarh, India. Mandri nadi is the major stream flowing through the area.It is located between 20.1990° N latitude and 81.0755° E longitude, having a total geographical area of 6670.3 ha. The topography of the watershed is undulating. The watershed has a maximum elevation of 711m above mean sea level and minimum elevation of 330m above msl. On an average the region experiences an annual rainfall of around 1300 mm approximately 90% of which falls during the period from mid June to mid october. The average annual rainfall has fluctuated greatly over the last ten years. Agriculture is the major activity for employment. Majority of the rainfall occurs in the Kharif season thereby making it a rainfed region.The overall drainage pattern of the watershed is dendritic. The figure 1 (right side image) shows digital elevation of the watershed.

Soil moisture index was mainly based on land surface temperature and vegetation indices of the study area. In the present work, the spatial resolution of the used band is 30m of Landsat 8 satellite imagery were downloaded using USGS Earth Explorer website. 6th December 2017 dated satellite imagery were downloaded. Essential bands from the satellite images for the calculation are Red and Near Infrared (NIR) for the NDVI calculation and Thermal Infrared (TIR) bands for the LST calculation.

3. Methodology

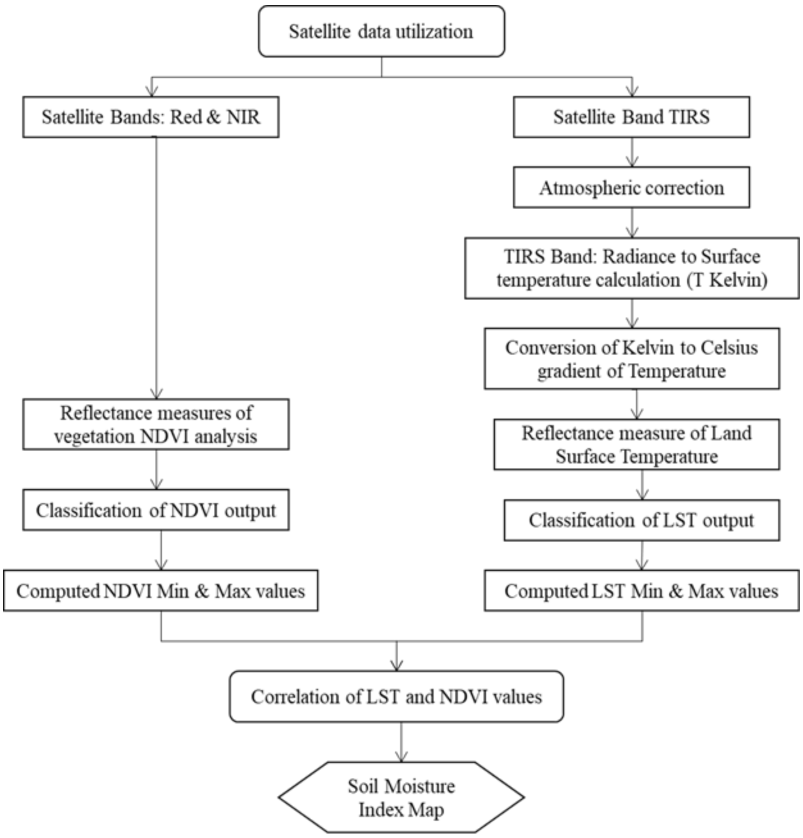

Figure 2. Methodology flowchart of SMI calculations

Soil moisture index is based on empirical parameterization of the relationship between land surface temperature (LST) and normalized difference vegetation index (NDVI) and calculated using following Eq. 1 (Zeng et al., 2004; Parida et al., 2008; Wang et al., 2009; Potic at al., 2017):

$$SMI = (LST_{max} - LST)/(LST_{max} - LST_{\min}) \quad (1)$$

Where, LST_{max} and $LST_{\min}$ are the maximum and minimum surface temperature for a given NDVI and LST is Land Surface Temperature, the surface temperature of a pixel for a given NDVI derived using remote sensing data. LST_{max} and $LST_{\min}$ are calculated using following Eq. 2 and 3, respectively (Zhan et al., 2004; Parida et al., 2008; Potic at al., 2017):

$$LST_{max} = a_1 * NDVI + b_1 \quad (2)$$

$LST_{min} = a_2 * NDVI + b_2$ (3)

where a_1, a_2, b_1 and b_2 are the empirical parameters obtained by the linear regression (a present slope and b present intercept) defining both warm and cold edges of the data. First step in SMI calculation is the conversion of digital number (DN) to spectral radiance (L W/m^2/sr/μm) using following Eq. 4 (Lwin et al., 2010; Potic at al., 2017):

L = LST_{min} + ((($LST_{max} - LST_{min}$) / ($QCAL_{max} - QCAL_{min}$)) * (DN – $QCAL_{min}$)) (4)

Where, LST_{min} and LST_{max} are spectral radiance calibration constants (Table 1), $QCAL_{max}$ and $QCAL_{min}$ are the highest and lowest quantized calibration pixel values (Table 2) and DN is the Digital Number.

Table 1. Spectral radiance (Lmin and Lmax) values for thermal bands of Landsat imagery (source: NASA (2013), USGS (2015))

Landsat 5 (Band 6)		Landsat 8 (Band 10 & 11)	
Radiance maximum	Radiance minimum	Radiance maximum	Radiance minimum
1.238	15.303	0.1003	22.0018

Table 2. Quantized calibration pixel (Qmin and Qmax) values for thermal bands of Landsat imagery (source: NASA (2013), USGS (2015))

Landsat 5 (Band 6)		Landsat 8 (Band 10 & 11)	
Radiance maximum	Radiance minimum	Radiance maximum	Radiance minimum
1	255	1	65535

Two inputs must be calculated (LST and NDVI) to be able to calculate LST_{max} and LST_{min}. LST (K) is calculated using Landsat 5 and Landsat 8 Thermal bands using Eq. 5 (Weng et al., 2004):

LST = T_b / [1 + (λ * T_b / C_2) * ln (ε)] (5)

where: T_b (Eq. 6) is At-Satellite Brightness Temperature, λ is wavelength of emitted radiance, C_2 = 1.4388*10^{-2} m K and it is presented with Eq. 7 and ε – emissivity (typically 0.95).

T_b = (K_2 / (ln (K_1 * ε / L + 1))) (6)

where K_1 – sensor dependent calibration constant 1 and K_2 – sensor dependent calibration constant 2 (Table 3), ε – emissivity (typically 0.95) and L – spectral radiance (Lwin et al., 2010).

C_2 = h ∗ c / s (7)

Where, (Weng et al., 2004) h is Planck's constant = 6.626∗10^{-34}J s, c is velocity of light = 2.998∗10^8 m/s and s is Boltzmann constant = 1.38 ∗ 10^{-23}J/K.

Table 3. Landsat 5 & 8 TIRS Thermal constant (source: Lwin (2010), NASA (2013), USGS (2015))

Landsat 5 (Band 6)		Landsat 8 (Band 10 & 11)	
Radiance maximum	Radiance minimum	Radiance maximum	Radiance minimum
1	255	1	65535

The ratio of the reflectivity differences for the NIR and the Red band to their sum (NDVI) is calculated using following Eq. 8 (Rouse et al. 1974; Potic at al., 2017):

NDVI = (NIR – Red) / (NIR + Red) (8)

The final step in the data collecting is the determination of empirical parameters by linear regression. To do so, statistical software was developed being able to process the data for the same pixel from two raster sets, LST and NDVI, and present the distribution of the data in the scatter plot. Linear regression values range from 0 at the "warm edge'' to 1 at the ''cold edge''. Pixels close to the warm edge are drier relative to the cold edge which is wetter (maximum evapotranspiration - unlimited water access). The scatter plot position of a pixel defines its moisture condition. The parameters are implemented in the Equations 2 and 3.

4. Results and Discussion

LST (figure 4) and NDVI (figure 3) are calculated based on essential data to obtain SMI calculation. NDVI values varies in range of -1 to 1 where negative values existent absence of vegetation or poor vegetative cover, while positive values shows the dense and good vegetative cover. LST values are the temperature of surface which is measured in °C. The result is accessible with the values range within 0 to 1, where values close to 1 are the regions with a less amount of vegetation and surface temperature which indicated that surface have low infiltration and present a higher amount of soil moisture. The values close to 0 are the areas with a major amount of vegetation and surface temperature and present the low level of soil moisture and increases the infiltration capacity of the to soil surface.

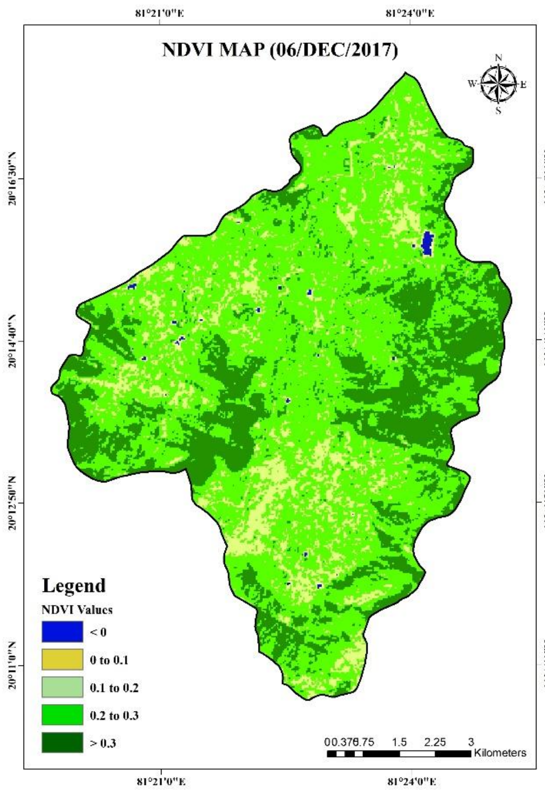

Figure 3. NDVI map

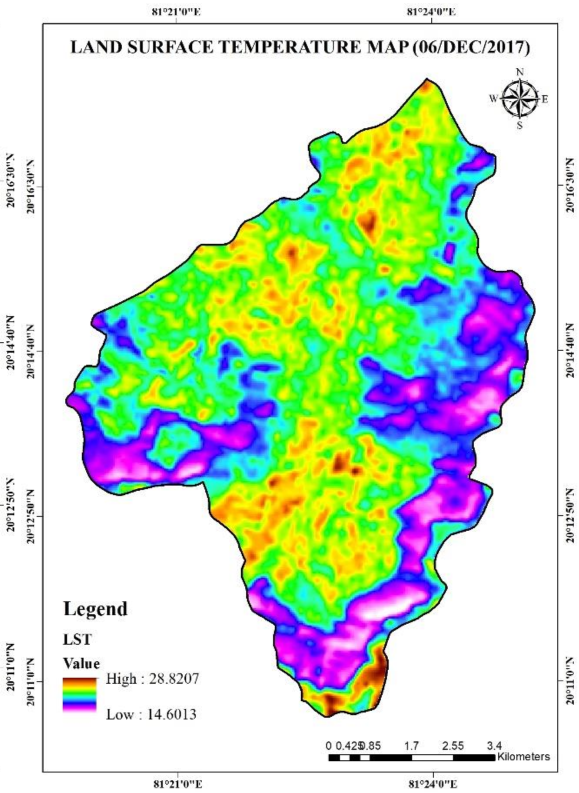

Figure 4. LST map

As per the research done the following research are concluded:
NDVI value is showing within the range of -1 to +1 and its divided in between five classes as mention in figure 3. LST value is varies at minimum of 14.60°C to maximum of 28.82°C. The scatter ploted between the pixels with NDVI values with corresponding LST values.

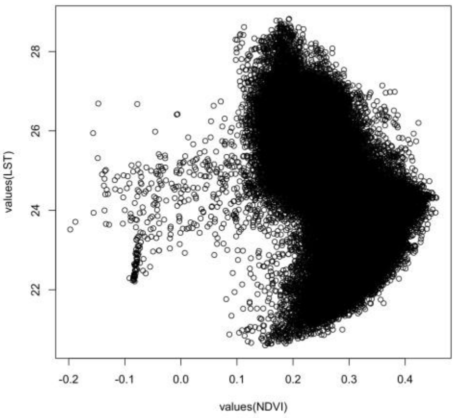

Figure 5. Scatterplots for corresponding areas of interest

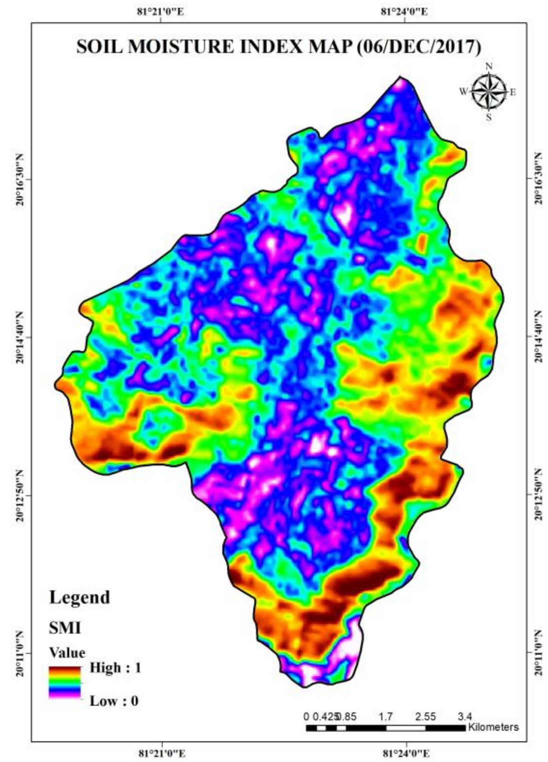

Figure 6. Soil moisture index map of study area

Soil moisture index map of December 2017 is represent in results which indicated soil moisture index in rage of 0 to 1 as classified in four colour ramp. Most of the study area as shows in figure 6 (violet and blue colour) have in the value closed to zero, which were highly affected by water deficit. The values near by 1 (red and yellow) are forest cover which have moisture as compare to rest of the land cover. The result concluded that more than 50 percent area showing closed to zero, that purely indicate moisture deficit in off season throughout the study area. As per the index 1 represent the higher amount of water or moisture presence and zero shows minimum moisture content such as dry areas.

5. Conclusions

Soil moisture have important in agricultural watershed for crop production. The study is done in Mandri river watershed of Kanker distict in Chhattisgarh, which is highly dominated to agriculture land which have around 39% of total area. The number of irrigation depends on soil moisture. Results concluded that around 50% area have sever drought condition and rest of the forest cover have normal moisture condition. to increase the agriculture productivity we have to main focus on forest plantation to increase precipitation as well as moisture condition.

Acknowledgments: Thanks to National Institute of Hydrology, Roorkee for providing feedback on the results of this research. The author would also like to thank the editors for inviting this present contribution.

Author Contributions: AS: contributed to all sections. MP: contributed to all sections. VCG: contributed to introduction and discussion sections. DSR: contributed to results and discussion sections. The author read and approved the final manuscript.

Conflicts of Interest: The authors declare that they have no competing interests

Abbreviations

The following abbreviations are used in this manuscript:

SMI: Soil Moisture Index
NDVI: Normalized Difference Vegetation Index
LST: Land Surface Temperature
NIR: Near Infrared
TIR: Thermal Infrared
USGS: United States Geological Survey

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