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Geospatial mapping of soil organic carbon in Sirsi Forest division of Uttara Kannada District using remote sensing techniques

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Abstract
The amount of soil organic carbon (SOC) varies with time and space and essential for plant growth and productivity. The study was aimed for Digital Soil Mapping (DSM) of soil organic carbon stock in sirsi forest division using appropriate remote sensing techniques which is labour and time efficient and identifying patterns, trends and potential factors influencing variations in the soil organic carbon. A 30 soil samples were collected from different forest types in two depths (0-30, 0 – 30 – 60 cm) using stratified random sampling method. Estimated and geospatially mapped soil organic carbon stock among different depths (0-30, 30-60 and 0-60 cm) by using Random Forest (RF) algorithm model in R studio software with correlating to the different environmental and spectral indices which are derived Sentinel 2A satellite data using Google Earth Engine (GEE). The RF model predicted SOC stock (0-30 cm) ranging from 59.45 Mgha^{-1} to 76.59 Mgha^{-1}, with an average of 68.02 Mgha^{-1}.In 30 to 60 cm the SOC stock was ranging from 53.4 Mgha^{-1} to 71.87 Mgha^{-1}, with an average of 62.63 Mgha^{-1}.The total SOC stock from 0 to 60 cm is ranging from 114.75 Mgha^{-1} to 145.89 Mgha^{-1}, with an average of 130.3 Mgha^{-1}.The SOC stock prediction map for 0-30cm, 30-60 cm and 0-60 cm soil depth indicated higher SOC content in the western parts as compared to the eastern parts, because of dense and abundant vegetation with favorable climatic conditions in western parts of the study area.

Keywords: Soil organic carbon (SOC), digital soil mapping (DSM), random forest (RF) google earth engine (GEE) and r studio software

1. Introduction

Soil Organic Carbon (SOC) is a critical component of soil organic matter and a key indicator of soil health, integral to various ecological processes such as soil fertility, water retention and nutrient cycling (Lal, 2004). SOC plays a significant role in global carbon cycling and climate change mitigation, as it serves as a dynamic reservoir that can absorb or release carbon dioxide (CO_2) depending on management practices [1, 2]. In forested ecosystems, SOC stocks are substantial due to continuous organic material input and minimal disturbance, making soils the largest and most stable carbon pool in forests [3]. Factors influencing SOC accumulation include climatic conditions, soil properties and vegetation type, with cooler and wetter regions generally exhibiting higher SOC levels due to slower decomposition rates [4, 5]. Understanding SOC dynamics is essential for effective carbon sequestration and climate change mitigation [6, 7].

Topography significantly influences Soil Organic Carbon (SOC) distribution by affecting water movement, erosion and deposition, with slope, aspect and elevation being key factors [8, 9]. Accurate SOC assessment is vital for effective land resource management, environmental monitoring and climate change mitigation. Traditional methods such as the Walkley-Black wet oxidation and dry combustion are commonly used for SOC measurement. The Walkley-Black method is cost-effective but may underestimate SOC in high organic matter soils, whereas dry combustion offers greater accuracy but is labour-intensive and requires specialized equipment [10, 11].

Recent advancements include digital soil mapping (DSM) techniques, which use remote sensing data, Geographic Information Systems (GIS) and machine learning algorithms to estimate SOC across large areas. DSM approaches utilize environmental covariates like topography, climate and vegetation indices to model SOC distribution [12].

Geostatistical methods and machine learning algorithms, such as Random Forest (RF), Support Vector Machines (SVM) and Artificial Neural Networks (ANN), enhance SOC predictions by capturing complex, non-linear relationships [13]. Remote sensing technologies, including satellite imagery from Landsat, Sentinel-2 and MODIS, provide spatially continuous data on vegetation cover, soil moisture and land use changes, with vegetation indices like NDVI and NDMI reflecting SOC levels [14, 15, 16, 17, 18]. The integration of these techniques, particularly the RF model, has shown promise in improving SOC prediction accuracy and reliability compared to traditional methods [19].

2. Methodology

To map Soil Organic Carbon (SOC) stock in various forest types within Uttara Kannada district, Sentinel-2 and Shuttle Radar Topography Mission (SRTM) data were employed, utilizing machine learning algorithms for predictive modeling. Sentinel-2, part of the European Space Agency's Copernicus program, provides high-resolution optical imagery, while SRTM offers elevation data essential for terrain analysis.

2.1 SRTM Data: The SRTM digital elevation model (DEM) with 30 m spatial resolution was pre-processed using Google Earth Engine (GEE). Key terrain attributes, including elevation, slope and aspect, were derived from this DEM. These attributes are crucial for understanding terrain effects on SOC distribution [8, 9].

2.2 Sentinel-2 Data: Harmonized Sentinel-2 MSI Level-2A data was used, which includes 13 spectral bands spanning visible to shortwave infrared wavelengths. Bands 1, 9 and 10 were excluded due to their limited relevance for terrestrial studies. The Sentinel-2 bands utilized with a focus on those most applicable for SOC modeling.

2.3 Preprocessing: The SRTM data was normalized and terrain attributes were calculated in GEE. For Sentinel-2 data, preprocessing involved normalization of pixel values to a 0-1 range using the "normalize" function. Cloud masking was applied with the "maskS2clouds" function and image collections were filtered by date (2024-01-01 to 2024-03-31) and cloud coverage (<50%). Median computation was performed to reduce outlier effects and the resultant image was clipped to the study area (Sirsi Forest Division).

2.4 Predictor Variables: Various vegetation indices and terrain attributes were computed to serve as predictor variables:

- **Slope and Aspect:** Derived from SRTM data using GEE functions "ee.Terrain.slope()" and "ee.Terrain.aspect()".
- **NDVI (Normalized Difference Vegetation Index):** Calculated as (NIR - RED) / (NIR + RED), with bands 5 (NIR) and 4 (RED) from Sentinel-2.
- **EVI (Enhanced Vegetation Index):** Computed as 2.5 * ((NIR - RED) / (NIR + 6 * RED - 7.5 * BLUE + L)), utilizing bands 8 (NIR), 4 (RED) and 2 (BLUE).
- **SAVI (Soil-Adjusted Vegetation Index):** Calculated using ((NIR - RED) / (NIR + RED + L)) * (1 + L), with a soil adjustment factor (L) set to 0.5.
- **NDMI (Normalized Difference Moisture Index):** Computed as (NIR - SWIR) / (NIR + SWIR), using bands 8 (NIR) and 11 (SWIR).
- **GNDVI (Green Normalized Difference Vegetation Index):** Determined as (NIR - GREEN) / (NIR + GREEN), with bands 8 (NIR) and 3 (GREEN).
- **LSWI (Land Surface Water Index):** Calculated as (NIR - SWIR) / (NIR + SWIR), using bands 8A (NIR) and 11 (SWIR).
- **BSI (Bare Soil Index):** Computed using ((SWIR + RED) - (NIR + BLUE)) / ((SWIR + RED) + (NIR + BLUE)), with bands 11 (SWIR), 4 (RED) and 2 (BLUE).

2.5 Combined Data Extraction: All image layers, including SRTM data, terrain attributes, Sentinel-2 bands and indices, were merged into a single image. This image was reprojected to EPSG:4326 and exported for further analysis in R.

2.6 Machine Learning for SOC Prediction

Raster values were extracted at field point locations using the "extrac t()" function, merging these with field data. The dataset was split into training (70%) and testing (30%) sets using 'createDataPartition()'. Predictors included Sentinel-2 bands and vegetation indices, with SOC as the response variable.

The Random Forest (RF) machine learning algorithm was used for SOC prediction. Random Forest was chosen for its ability to handle complex interactions between predictors and SOC. RF operates by building multiple decision trees from bootstrap samples of the data and averaging their predictions, thus managing complex relationships and improving prediction accuracy [20, 21]. This approach ensures a comprehensive and robust analysis of SOC distribution across different forest types using advanced remote sensing and machine learning techniques.

3. Results and Discussion

3.1 Correlation of SOC Stock and predictive variables

Understanding the associations between SOC stock with each predictive covariate is crucial for assessing the contribution of each variable in the model. Figure 1. Represents the results of Pearson's correlation analysis, revealed that the relationships between SOC stock and the predictive variables. The results showed that the SOC stock is positively correlated with slope (0.12), B2 (0.04), B3 (0.07), B4 (0.14), B6 (0.03), B7 (0.04), B8 (0.35), B8A (0.003), NDVI (0.14), EVI (0.07), SAVI (0.05), NDMI (0.11), GNDVI (0.11) and LSWI (0.13), but negatively correlated with elevation (-0.13), aspect (-0.3), B5 (-0.02), B11 (-0.17), B12 (-0.16), and BSI (-0.13). These results indicate positive correlations among SOC stock and spectral bands, environmental covariates and spectral indices such as B2, B3, B6, B7, B8 and B8A. Similar results were reported by Duarte *et al*. 2022 [22] showed soil organic carbon stock was positively correlated with B_{blue}, B_{green} and $B_{red.}$ Badgley *et al*. 2017 [23] reported B8 band (NIR) was positively correlated because of its importance in vegetation modelling.

The geographic distribution of various predictive variables used in mapping SOC stock, including elevation, slope, aspect, NDVI, EVI, SAVI were represented in Figure 2, GNDVI, NDMI, LSWI and BSI were represented in Figure 3. The elevation in the study area ranges from 230 to 675 meters, while the slope varies from 0.00° to 44.59°. Aspect is represented on a scale of 1:1. NDVI values ranges from 0.4 to 88, reflecting significant variability in vegetation cover across the region. EVI values range between 0.12 and 1. Other predictive variables have the following ranges: SAVI (0.13 to 0.79), NDMI (-0.31 to 0.52), GNDVI (0.31 to 0.8), BSI (-0.46 to 0.29) and LSWI (-0.23 to 0.5) in the study area, with these results and several studies have been indicated NDVI [24, 25], EVI and SAVI are positively correlated [6, 7] many studies have been depicted that soil organic carbon stock decreased with elevation [35].

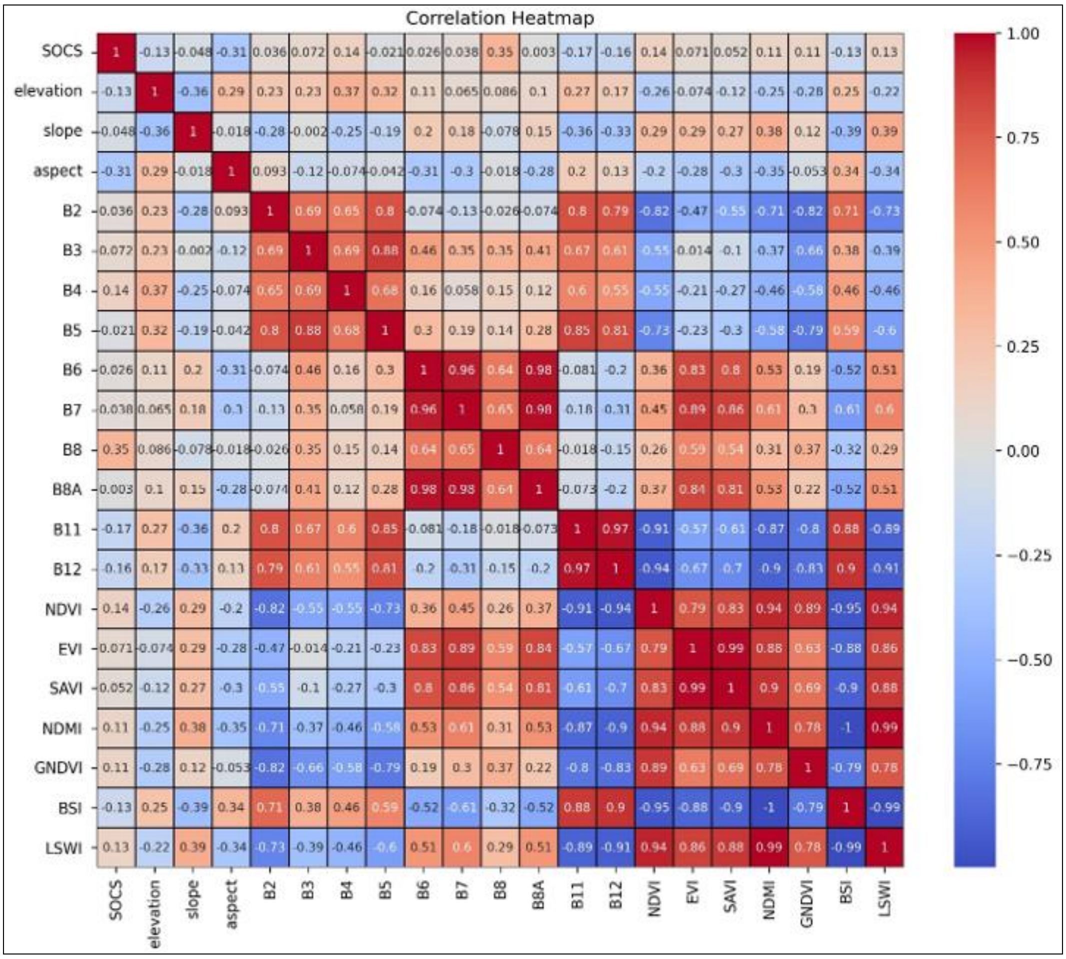

Fig 1: Pearson`s correlation coefficient analysis of observed SOC stocks and Environmental covariates and spectral indices

3.2 Importance of predictive variables for SOC stock mapping using random forest modelling

3.2.1 Percentage Increase in Mean Squared Error (%IncMSE)

How much the prediction error increases when particular variable is excluded from the model was represented in Figure 4. Using random forest modelling. B11, B12, BSI, NDVI have the highest %IncMSE, which indicates the variables are crucial for the model accuracy. B8A, B7, B6, B8 and B2 have the lowest IncMSE, which indicate they contribute less to the model prediction accuracy.

3.2.2 Increase in Node Purity (IncNodPurity)

The total decrease in node impurity from splitting on a variable, averaged over all trees were depicted in Figure 4. B11, NDVI and LSWI highest IncNodPurity, indicating they significantly improve the homogeneity of the nodes when used for splits. B3, B2 and B8A have the lowest IncNodePurity, indicate they are less critical for making splits.

The ranking of variable importance for predicting soil organic carbon (SOC) stocks was depicted in Figure 4. Using the Random Forest (RF) model which scaled from 0 to 150. Among the predictors, the Normalized Difference Vegetation Index (NDVI) is identified as the most influential, showed an importance value of 100. This finding highlights that SOC stocks are strongly influenced by variations in vegetation cover. The levels of SOC are closely associated with the density of natural vegetation and the remaining plant residues after harvesting, as supported by previous studies [17, 18, 27]. Other significant predictors with importance values above 75 include the Sentinel-2 Band 11, Land Surface Water Index (LSWI), Band 12 (B12), Bare Soil Index (BSI), Normalized Difference Moisture Index (NDMI), Band 7 and Enhanced vegetation index (EVI). Furthermore, the Soil-Aspect, Band 6, Band 4, Adjusted Vegetation Index (SAVI), Band 8, elevation, slope, Band 5, Gross Normalized difference vegetation index (GNDVI), Band 8A, Band2 and Band 3are also notable predictors, each with importance values exceeding 50.

The application of the Normalized Difference Vegetation Index (NDVI) has been instrumental in highlighting the role of biomass and vegetation cover in predicting soil organic carbon (SOC) stocks [28]. Previous studies have demonstrated that SOC levels can be effectively estimated by considering vegetation presence alone [23, 29]. Thus, NDVI serves as a reliable proxy for assessing SOC content. Furthermore, incorporating the Bare Soil Index (BSI) in the analysis underscores the relevance of examining bare soil conditions, which is particularly important in areas with highly fragmented secondary forests [22]. Additionally, topographic variables such as elevation and slope have been consistently found to be strongly associated with variations in soil organic carbon (SOC) in studies by Boettinger *et al*. (2010) and Hinge *et al*. (2018) [8, 9].

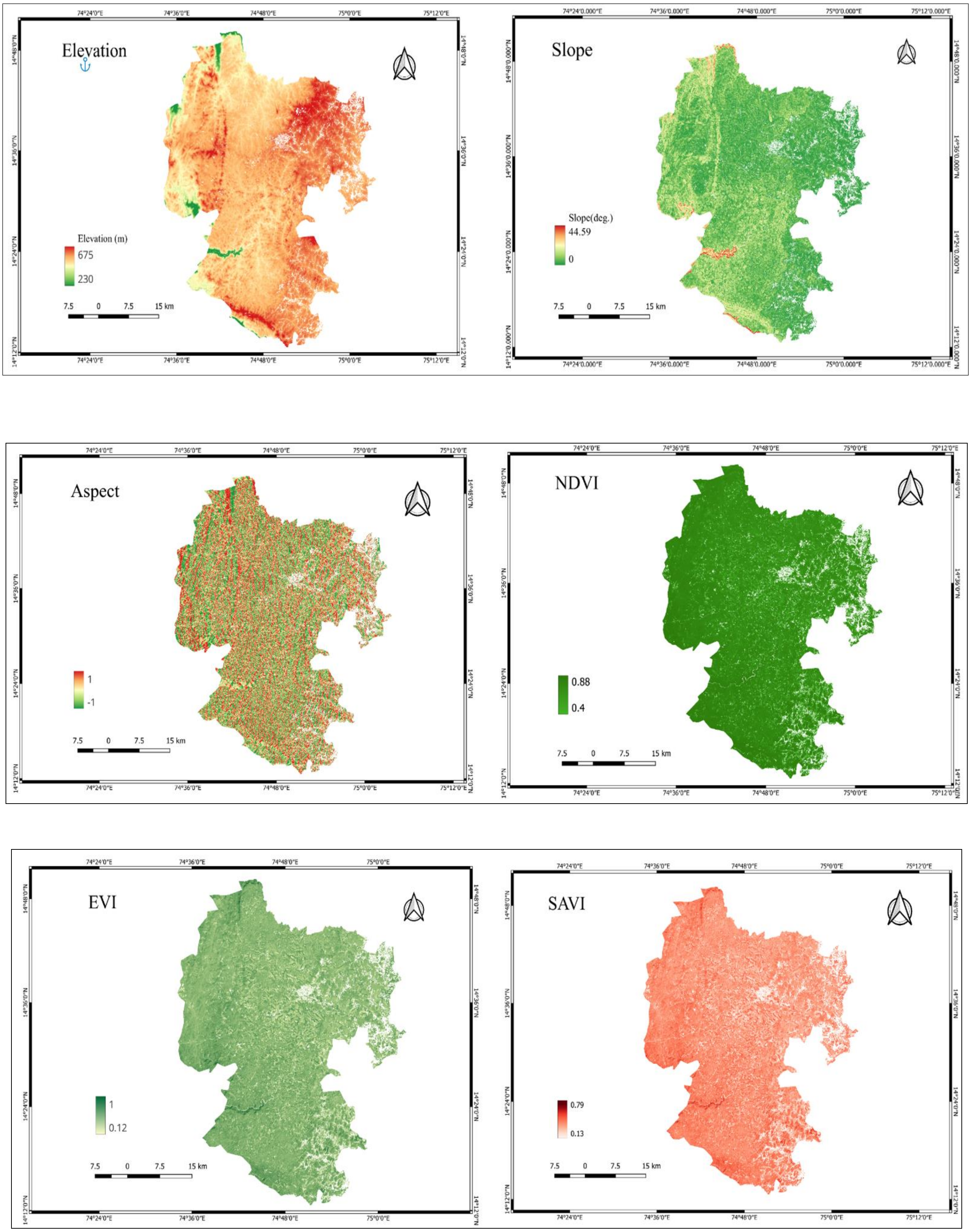

Fig 2: Predictive variables Elevation, Slope Aspect, NDVI, EVI, SAVI used in random forest modelling

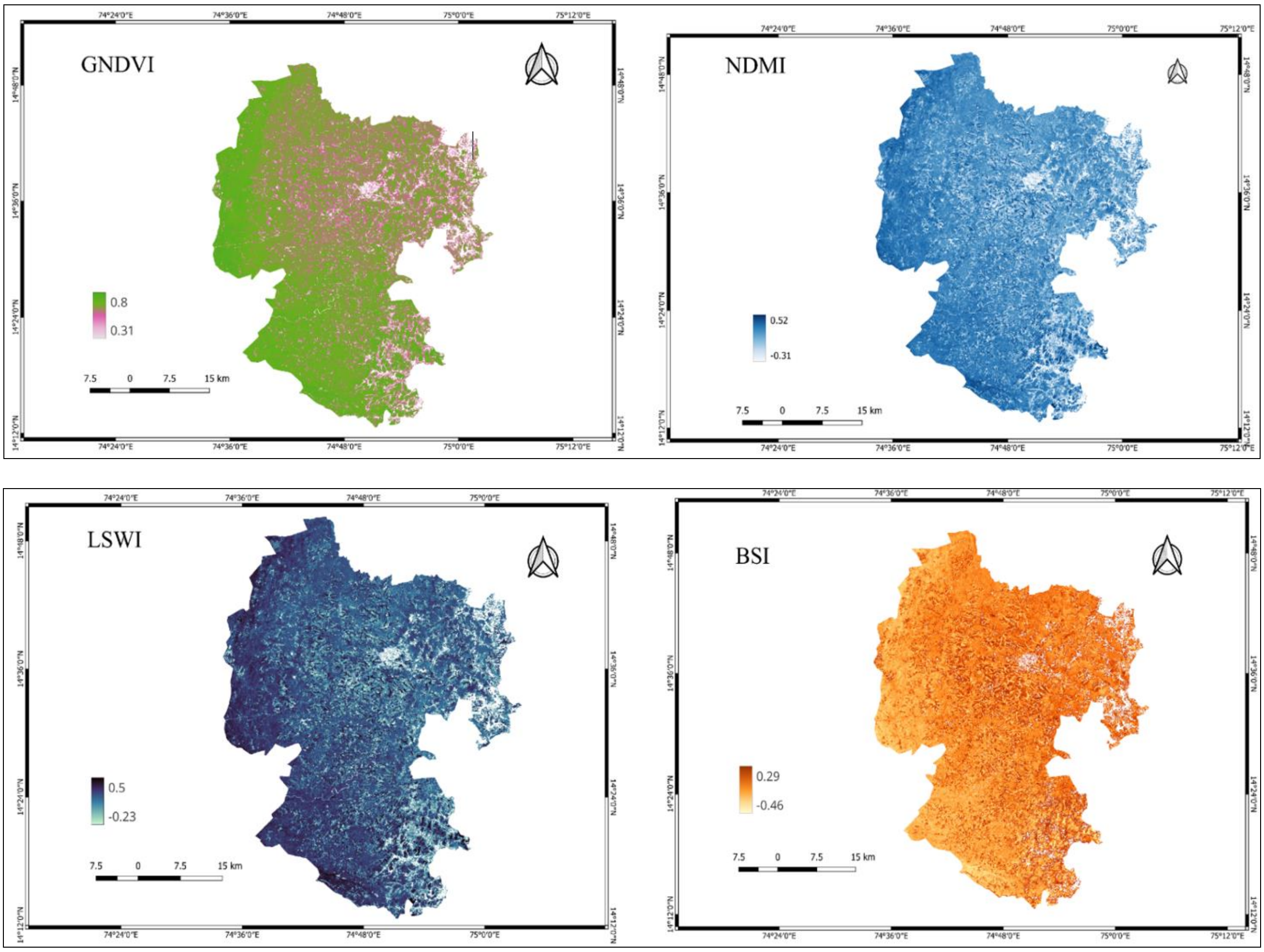

Fig 3: Predictive variables GNDVI, NDMI, LSWI and BSI used in random forest modelling

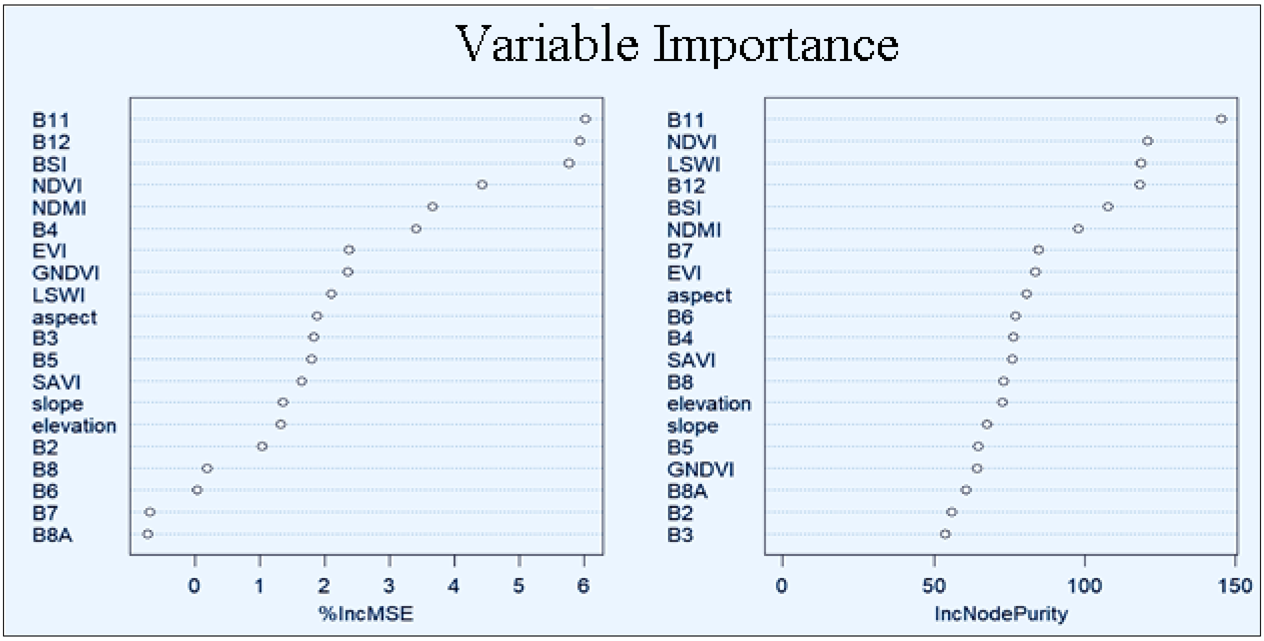

Fig 4: Variable Importance

3.3 Predictive mapping of soil organic carbon stock

The predicted soil organic carbon (SOC) stock maps in different soil depths 0-30, 30-60, 0-60 cm are generated using RF models were depicted in Figures 5, 6 and 7 respectively. The RF model predicted SOC stock (0-30 cm) in Figure 5. ranging from 59.45 Mgha^{-1} to 76.59 Mgha^{-1}, with an average of 68.02 Mgha^{-1}. RF model predicted SOC stock (30-60 cm) in Figure 6 ranging from 53.4 Mgha^{-1} to 71.87 Mgha^{-1}, with an average of 62.63 Mgha^{-1}, with an average of 96.627 Mgha^{-1} and SOC stock (0-60 cm) in Figure 7 predicted using RF model are ranging from 114.75 Mgha^{-1} to 145.89 Mgha^{-1}, with an average of 130.3 Mgha^{-1}. The predicted SOC stock map Figures 5, 6 and 7 revealed higher

SOC stock in the western region as compared to the eastern region of the study area. SOC stock was highest in evergreen forests, followed by semi-evergreen and moist deciduous forest.

The accurate estimation of soil organic carbon and its stock is crucial because it indicates the soil's ability to capture atmospheric carbon and function effectively as a carbon sink. This information is essential for various applications, including land resource monitoring, land evaluation and environmental modelling, as it provides insights into the carbon sequestration potential of soils. Utilizing digital soil mapping (DSM) techniques improves the accuracy and robustness of SOC estimates by integrating multiple data sources and environmental variables. These techniques generate high-quality spatial data that are invaluable for ongoing assessments of SOC dynamics and for advancing research in environmental and soil sciences [30].

The study used machine learning algorithm, specifically Random Forest (RF) [31, 32] to estimate soil organic carbon (SOC) stocks in forested areas of the Sirsi forest division. Areas classified as non-forest were excluded from the SOC stock analysis and are showed as uncoloured regions on the maps. According to the RF algorithm, the SOC stock from 0-30 cm, 30-60 cm and 0-60 cm within the study area varied between 59.45 $Mgha^{-1}$ to 76.59 $Mgha^{-1}$, 53.4 $Mgha^{-1}$to 71.87 $Mgha^{-1}$ and 114.75 $Mgha^{-1}$ to 130.3 $Mgha^{-1}$ respectively and these maps were represented in the Fig 5, 6 and 7. Mitran *et al*. (2018) [6] carried out a study in the semi-arid zone of South India to examine the spatial distribution of total soil organic carbon stocks up to a certain depth of 30 cm. They found that the Western Ghats region in Karnataka, which is characterized by high rainfall, elevated terrain, dense vegetation and limited human activity, had substantially higher total carbon stocks, ranging between 8 and 14 kg m^{-2}. These findings are consistent with the results reported by Lo Seen *et al*. (2010) [33] which highlighted the impact of favourable climatic and ecological conditions on carbon sequestration in similar landscapes.

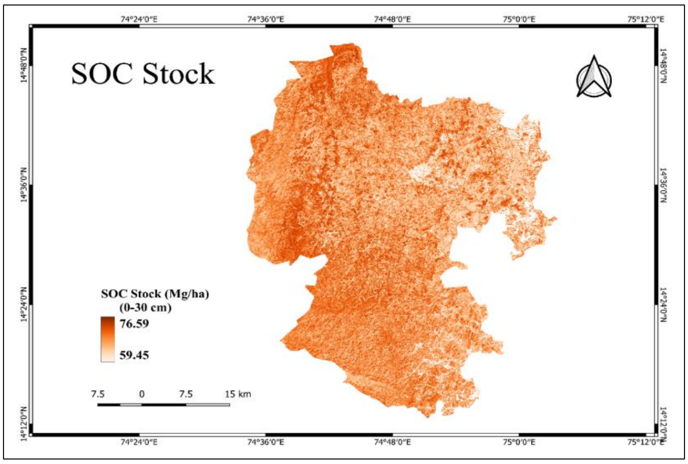

Fig 5: Predicted Soil Organic Carbon Stock of 0-30 cm soil depth

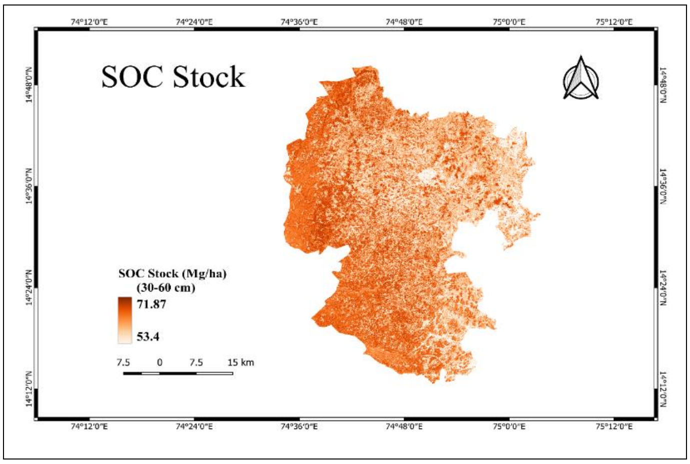

Fig 6: Fig 5: Predicted Soil Organic Carbon Stock of 30-60 cm soil depth

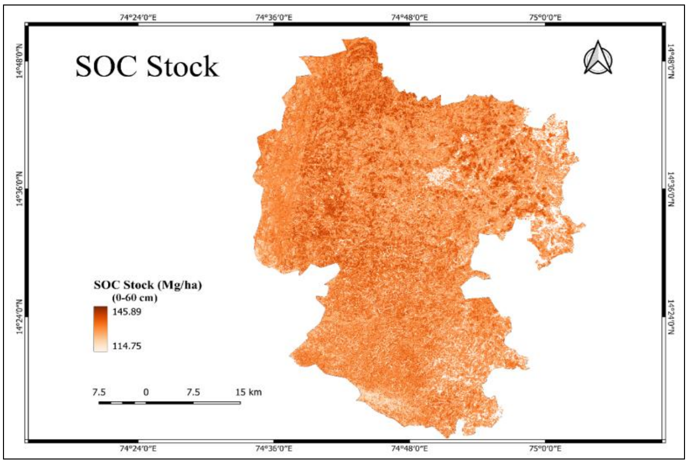

Fig 7: Predicted Soil Organic Carbon Stock of 0-60 cm soil depth

4. Conclusion

This study provides variation and amount of soil organic carbon stock among different depths in sirsi forest division. Through geospatial mapping of SOC stock contributes to the growing body of knowledge on digital soil mapping and remote sensing for SOC assessment, demonstrating its potential to aid in sustainable land management and climate change mitigation efforts. The methodologies and insights presented here can serve as a foundation for future research and policy-making focused on soil carbon management in forested and other terrestrial ecosystems.

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6. Competing interests

Authors have declared that no competing interests exist

7. Authors' Contributions

This work was carried out in collaboration among all authors.

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