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Detection of Carbon Content inside All Types of Soils using Image Processing Techniques

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ABSTRACT

Accurate estimation of soil carbon content is crucial for understanding ecosystem health, carbon cycling, and agricultural management. Traditional methods for measuring soil carbon content are labor-intensive and time-consuming, limiting their applicability in large-scale studies. In recent years, image processing techniques have gained significant attention as a non-destructive and efficient means of soil analysis. This paper proposes a novel approach that takes use of image processing techniques to detect and estimate the carbon content in all types of soils. Using technologies such as digital cameras or drones, the suggested method entails obtaining high-resolution photos of the soil. The images are then preprocessed to improve the contrast and remove any noise or odd forms. A re-entry charge is then added to the equation to avoid the requirement for a re-entry. The split soil regions are then examined more closely to identify features that correspond with carbon content, such as colour and texture. To establish a relationship between the extracted carbon content and soil carbon content, a calibration model is developed using a collection of reference soil samples with known carbon content. Machine learning techniques that can be employed in this situation include support vector machines and random forests. The calibration model is trained using the extracted features as inputs and the corresponding carbon content as output. Once trained, the model may be used to forecast the carbon content of new soil samples based on extracted features. The proposed method offers various advantages over traditional methods for determining the amount of carbon in soil. Because it does not harm the soil, you can collect readings on the same soil samples over time. It also produces quick findings, which saves time and money when processing samples. Furthermore, this approach is applicable to all soil types, removing the need for distinct approaches for different soil types.

INTRODUCTION

Soil carbon content plays a crucial role in various ecological and agricultural processes, such as nutrient cycling, soil fertility, and climate change mitigation. Accurate measurement and monitoring of soil carbon content are essential for understanding ecosystem dynamics and developing sustainable land management strategies. Traditional methods for quantifying soil carbon content involve laboratory-based techniques, which are time-consuming, labor-intensive, and often require destructive sampling. These limitations hinder large-scale studies and real-time monitoring of soil carbon dynamics. In recent years, image processing techniques have emerged as a promising alternative for non-destructive soil analysis. Image processing utilizes digital images of soil samples to extract relevant information and infer soil properties. This approach eliminates the need for physical sample processing, making it efficient and cost-effective for analyzing large numbers of soil samples. Additionally, image processing techniques can provide spatially explicit information about soil properties, allowing for detailed mapping and characterization of carbon content across landscapes. The objective of this study is to develop a methodology for detecting and quantifying carbon content inside all types of soils using image processing techniques. The proposed approach aims to overcome the limitations of traditional soil carbon analysis methods by providing a rapid, non-destructive, and scalable solution for soil carbon estimation.

Image segmentation methods are employed to separate the soil regions of interest from the backdrop. This phase separates the soil pixels from the rest of the image, making it easier to study specific areas and limiting the effect of non-soil objects. Following the segmentation of the soil regions, several image-based features, such as colour histograms, texture descriptors, or spectral indices, are extracted to capture the unique characteristics of soil content. To establish a relationship between the extracted features and soil features, a calibration model is built using a collection of reference soil samples with known carbon content. Machine learning algorithms like support vector machines or random forests can be employed to discover the intricate relationship between image features and carbon content. The calibration model is trained using the extracted features as inputs and the corresponding carbon content as output.

Based on the features of their derived images, the calibration model may subsequently be used to predict the carbon content of fresh soil samples. This prediction, which allows for rapid and non-destructive measurement of soil carbon content, enables large-scale studies, continual monitoring, and real-time decision-making. The use of image processing techniques to identify and measure the carbon content of various types of soils is one viable route for successful and non-destructive soil analysis. This approach has the potential to change soil carbon assessment by providing a rapid and scalable method for understanding soil dynamics and adopting sustainable land management practises. In the following parts, the methodology, experimental setup, and findings of this study's evaluation of the efficiency and dependability of this image processing-based approach are presented in detail.(Cao H et al,2019)

NEED OF THE STUDY

The study addresses numerous major demands in the field of soil analysis by focusing on the detection of carbon content inside all types of soils using image processing techniques. There is an increasing demand for reliable and non-destructive methods of determining the amount of carbon in soil. Traditional laboratory techniques for assessing soil carbon content are time-consuming and labor-intensive. The proposed image processing method provides a quick and scalable solution that does not require destructive sampling. This means that the same soil samples can be measured multiple times, making large-scale investigations easier. Comprehensive soil study necessitates the ability to determine the carbon content of various types of soils. Different soil types' carbon storage capacity can be influenced by variances in composition, texture, and organic matter content. Using a strategy like the one described above, it is feasible to gain a deeper understanding of the world's ecosystems.(Harlianto PA et al, 2017)

The study addresses the requirement for spatially explicit soil carbon information. Image processing techniques allow us to examine soil samples in a spatial context. This allows us to map and explain the carbon content of various environments. It should be noted that this information is only available in the United States. The proposed strategy is consistent with the goals of sustainable land management and mitigating climate change. Accurate measurement of soil carbon content is critical for determining the potential for carbon sequestration, assessing the efficacy of carbon offset schemes, and adopting land management techniques that enhance soil health and resilience. The study investigates the need for a quick, non-destructive, and scalable method of determining carbon content in various soils. It has the potential to improve soil analysis, learn more about how carbon travels, and assist farmers and environmentalists in making better decisions by utilising image processing techniques.

Literature Review

Patil, V. S et al (2021). Soil organic matter (SOM) and soil moisture content are two critical elements that influence soil health and the amount of food that can be grown on it. It is critical to accurately and efficiently measure these characteristics for successful soil management and sustainable farming practises. The purpose of this review is to examine the methods for determining soil organic matter and moisture content using traditional methods and image processing techniques. Traditional methods of measuring the amount of organic matter in soil are time-consuming and labor-intensive. These methods, which all take place in a lab, include soil sampling, chemical analysis, and gravimetric techniques. Similarly, traditional methods for estimating soil moisture content rely on physical measurements such as soil sample, drying, and weighing. Even though these methods are widely used and produce accurate findings, they have drawbacks such as low spatial resolution, high cost, and limited coverage. Remote sensing and digital image analysis are becoming more useful ways to learn about the characteristics of soil as image processing techniques advance. It is possible to obtain spectrum information from the Earth's surface using multispectral and hyperspectral photographs, as well as other remote sensing methods. This allows for a more indirect estimation of soil organic matter and moisture content. Techniques for processing images, such as machine learning methods and spectral indices, make it easier to extract usable information from remote sensing image data.

Li, S et al (2013). The bioaccumulation of multi-walled carbon nanotubes (MWCNTs) in organisms is a serious concern because MWCNTs are increasingly being employed in various industries and may have detrimental environmental implications. We need reliable and sensitive detection technologies to find out how organisms like earthworms, which are critical to soil ecosystems, take in and store MWCNTs. In this study, the bioaccumulation of MWCNTs in earthworms is assessed using a microwave-based detection technique. The microwave-based detection technique makes use of the particular electromagnetic capabilities of MWCNTs to selectively heat and induce thermal effects. The only way to tell if you're doing something correctly is to examine the consequences. The radiated thermal energy is then recorded using a thermal sensor, and the intensity of the signal is connected to the MWCNT concentration in the earthworms. A series of studies were conducted in a controlled laboratory setting using earthworms exposed to varying quantities of MWCNTs to validate the effectiveness of the microwave-based detection technique. The earthworms were collected with care, and their MWCNT content was determined using the suggested microwave-based detection technique. Additionally, complementary techniques such as transmission electron microscopy and Raman spectroscopy were employed to demonstrate the existence of MWCNTs in earthworm samples.

Garbout, A et al (2012) Understanding the dynamic interactions between plants and soil is critical for optimising agricultural practises, increasing crop output, and increasing environmental sustainability. Traditional methods of studying the interactions between soil and plants frequently involve destructive sampling or indirect readings, making it difficult to obtain real-time, three-dimensional (3D) data. This paper introduces the use of positron emission tomography/computed tomography (PET/CT) scans for 3D visualisation and quantification of real-time soil / plant interactions. The beginner's guide to the World Wide Web, the world's most advanced technology, is a terrific place to start. The PET imaging component visualises and tracks plant movement inside the soil and neighbouring soil by utilising a radiotracer, such as 11C or 18F, which plants absorb and emit as positrons. The CT imaging component provides simultaneous high-resolution 3D images of the soil and root architecture. It is common routine to gather and evaluate data using a computerised system, such as the Internet of Things (IoT) or the Internet of Things (IoT).

Surya, S. G. et al (2020) Accurate and timely soil moisture measurement is critical for optimal irrigation control, water saving, and healthy crop growth. This study demonstrates how to build and test an in-field integrated capacitive sensor for immediately detecting and measuring soil moisture. The suggested capacitive sensor employs the capacitance principle to identify and measure variations in the dielectric constant of the soil produced by changes in moisture content. The sensor is made up of two electrodes that are housed in a sturdy housing that allows it to be easily inserted into the soil. An integrated electrical circuitry system processes the capacitance measurements and provides real-time moisture readings. Field studies were carried out in various soil types and crop-growing situations to validate the performance of the integrated capacitive sensor. The sensor was positioned at various depths in the soil profile, and measurements were recorded at various periods to demonstrate how soil moisture changes over time. To determine the accuracy of the sensor data, standard gravimetric measurements and commercially available soil moisture sensors were used. According to the findings, the integrated capacitive soil moisture sensor delivered quick and precise soil moisture measurements. The sensor exhibited a good association with gravimetric measurements and was just as accurate as commercially available sensors. Installing the sensor in the field allowed for real-time moisture monitoring of the soil. This enabled us to make timely judgements about irrigation and water management.

Sources of Remote Sensing Data

Remote sensing data can be obtained from various sources, including:

Satellite Imagery: Satellite-based remote sensing platforms capture images of the Earth's surface using sensors onboard satellites. Examples of satellite imagery sources include:

a. NASA Earth Observing System (EOS): Satellites such as Landsat, Terra, and Aqua provide multispectral and hyperspectral data for a wide range of applications.

b. European Space Agency (ESA) Sentinel Missions: Sentinel-2, Sentinel-3, and other Sentinel satellites provide high-resolution and multi-temporal data for environmental monitoring and land management.

c. Commercial Satellite Providers: Companies like DigitalGlobe (now Maxar), Planet, and Airbus offer high-resolution satellite imagery for various applications, including mapping, urban planning, and agriculture.

Aerial Imagery: Aerial photography involves capturing images using cameras mounted on aircraft. Aerial imagery can provide higher spatial resolution than satellite imagery. Sources include:

a. National and Regional Mapping Agencies: Government agencies often conduct aerial surveys and make the imagery available for public use.

b. Remote Sensing Service Providers: Companies specializing in aerial photography and remote sensing offer services and datasets acquired from aerial platforms.

Unmanned Aerial Vehicles (UAVs): Also known as drones, UAVs equipped with remote sensing sensors can capture imagery and data at relatively low altitudes. This allows for high-resolution and flexible data acquisition. Sources include:

a. Research Institutions: Universities and research organizations conduct UAV-based remote sensing studies and make their data available.

b. Commercial Drone Service Providers: Companies offer UAV-based remote sensing services, including data acquisition and processing.

LiDAR (Light Detection and Ranging): LiDAR technology uses laser pulses to measure distances and create 3D models of the Earth's surface. LiDAR data sources include:

a. Government Agencies: National mapping agencies and forestry departments often collect LiDAR data for terrain modeling, forest inventories, and floodplain mapping.

b. Commercial LiDAR Providers: Companies specialize in capturing and processing LiDAR data for various applications, such as urban planning and infrastructure development.

Radar Imagery: Radar sensors use microwave signals to measure properties of the Earth's surface. Radar data sources include:

a. Synthetic Aperture Radar (SAR) Satellites: SAR satellites, such as those from the ESA Sentinel-1 mission, provide radar imagery for applications like land cover mapping, disaster monitoring, and agriculture.

b. Government Agencies: Some national agencies acquire and provide radar imagery, especially for defense and security applications.

Open Data Platforms: Several open data initiatives and platforms make remote sensing data freely available for public use. Examples include:

a. NASA Earth Observing System Data and Information System (EOSDIS): Offers access to various satellite imagery and data products.

b. ESA Earth Observation Data: Provides access to data from the Sentinel missions and other ESA satellites.

c. USGS EarthExplorer: Enables searching and downloading satellite imagery and aerial photography datasets.

These are just a few examples of remote sensing data sources. The availability and accessibility of data may vary depending on the specific region, application, and data provider.

Algorithm

As described in the "Dataset collection" section, the dataset used in this study comprises of RGB images of soils. Figure 1 depicts the many procedures taken to process the images. Each RGB image is first converted into HSV and CIELab* colour modes. Second, the three colour modes each have their own set of bands. Third, 1,364 features are extracted from various sources. The fourth stage is to identify the most significant features and create feature descriptions using feature selection methods. Fifth, SVM and other machine learning models are trained using feature descriptors. Sixth, using the trained models, the test image set is evaluated to determine how effectively the soil type can be detected. Finally, the results are examined and compared to two other recent soil categorization studies to determine how well the proposed model works. More information on these stages can be found in the sections that follow.

Step 1: Image Acquisition

Step 2: Preprocessing

Step 3: Image Segmentation

Step 4: Feature Extraction

Step 5: Calibration and Training

Step 6: Carbon Content Estimation

Step 7: Validation and Accuracy Assessment

Artificial Neural Network (ANN)

Artificial Neural Network (ANN)-based soil classification models have been found to be beneficial for evaluating and categorising various types of soil. Using a combination of input features and target labels, these models learn the underlying patterns and produce accurate predictions about soil types. The majority of ANNs consist of an input layer, one or more secret layers, and an output layer. The input layer receives soil data such as pH, organic matter content, texture, moisture, and nutrient levels as input features. These are the first features that the neural network considers while determining what to perform. The hidden layers, which are made up of neurons that are linked together, are critical for determining complicated relationships in the input data. Each neuron receives weighted inputs from the layer below it, generates an output using an activation function, and transfers it to the layer above it. The activation function introduces non-linearities, allowing the ANN to learn non-linear relationships between input features and target labels. The output layer displays the final sorting results. The number of soil groups in this layer is the same as the number of nerve cells. The activation function employed in the output layer is determined by the classification task. In multi-class classification, the softmax function is frequently used to generate probability distributions across classes. The ANN modifies the weights and biases of its neurons throughout the training phase using a technique known as backpropagation. This technique estimates the gradient of the loss function with regard to the network's parameters and updates it accordingly to minimise the discrepancy between expected outputs and actual labels. To ensure the model's accuracy and generalizability, a wide and representative dataset is required for training. The dataset's soil samples should represent a wide range of soil types and environmental conditions. Preprocessing procedures such as data normalisation and feature reduction can also be employed to increase the ANN's performance.

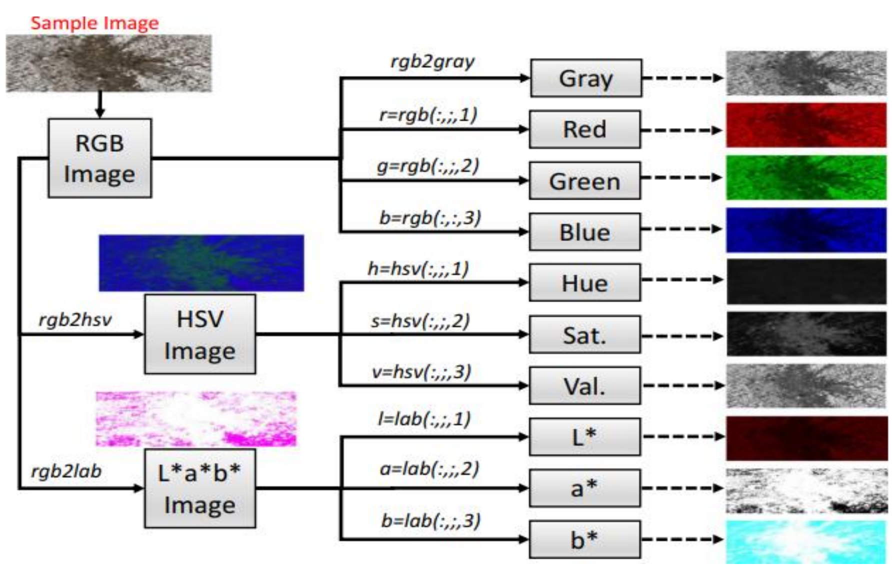

Figure 1 Images of different partitioned channels from a sample RGB image using Matlab functions

The mathematical equations for this soil classification model can be written as follows:

Input layer:

X = [X1, X2]

Hidden layer:

H1 = f1(X1 * W11 + X2 * W21 + b1)

H2 = f1(X1 * W12 + X2 * W22 + b1)

Output layer:

Y1 = f2(H1 * W31 + H2 * W41 + b2)

Y2 = f2(H1 * W32 + H2 * W42 + b2)

Y3 = f2(H1 * W33 + H2 * W43 + b2)

Here:

X1 and X2 are the input features.

H1 and H2 are the outputs of the hidden layer neurons.

Y1, Y2, and Y3 are the predicted probabilities of the soil classes.

W11, W21, W12, W22, W31, W41, W32, W42, W33, and W43 are the weight parameters.

b1 and b2 are the bias parameters. f1 and f2 are the activation functions (typically sigmoid or ReLU for hidden layer, and softmax for output layer in classification problems).

During the training process, you would use a loss function (such as cross-entropy) to measure the difference between the predicted probabilities and the true labels. Backpropagation is then used to update the weights and biases to minimize this loss. The specific learning algorithm, optimization technique, and hyperparameters would depend on the implementation framework or library you're using (e.g., TensorFlow, PyTorch).

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Result and Discussion

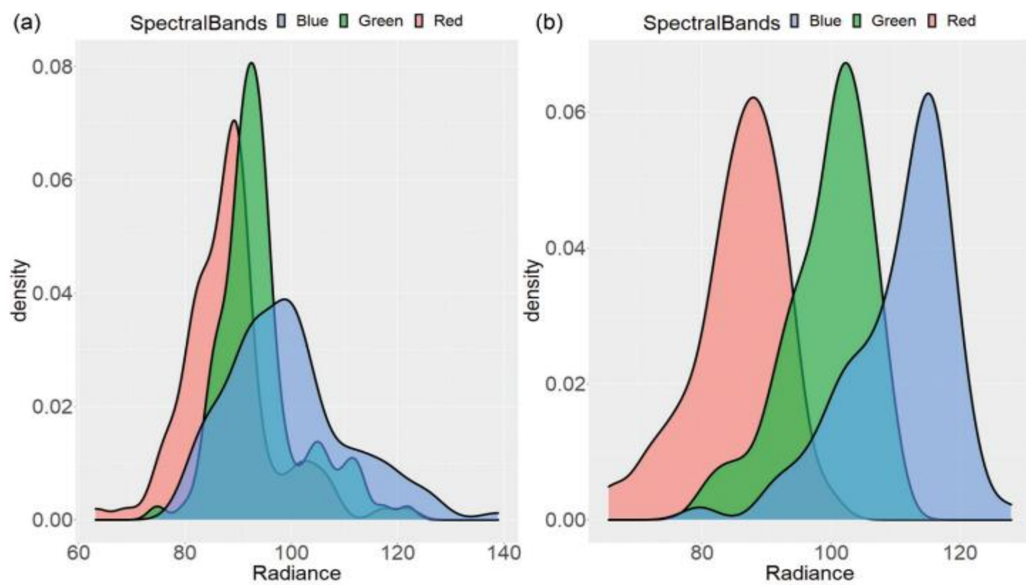

Figure 2. Histograms in the grayscale, RGB channels of (a) Oxisol and (b) Inceptisol digital images.

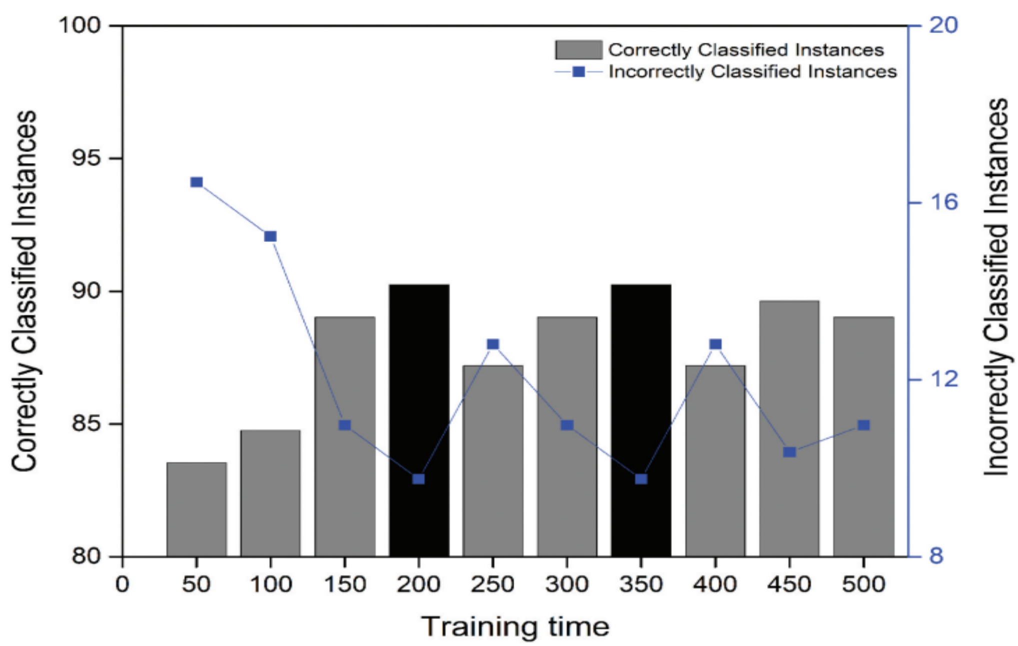

Figure 3. Soil classification versus training time by ANN.

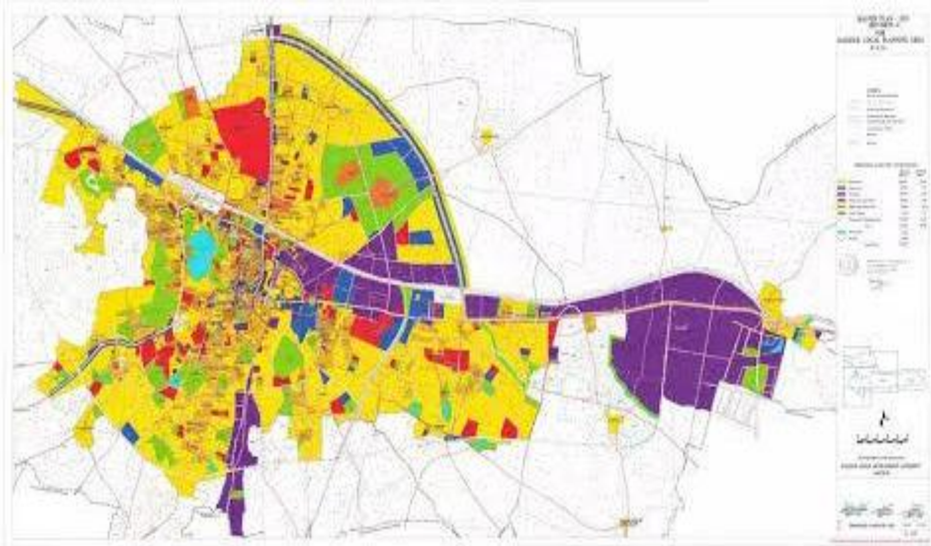

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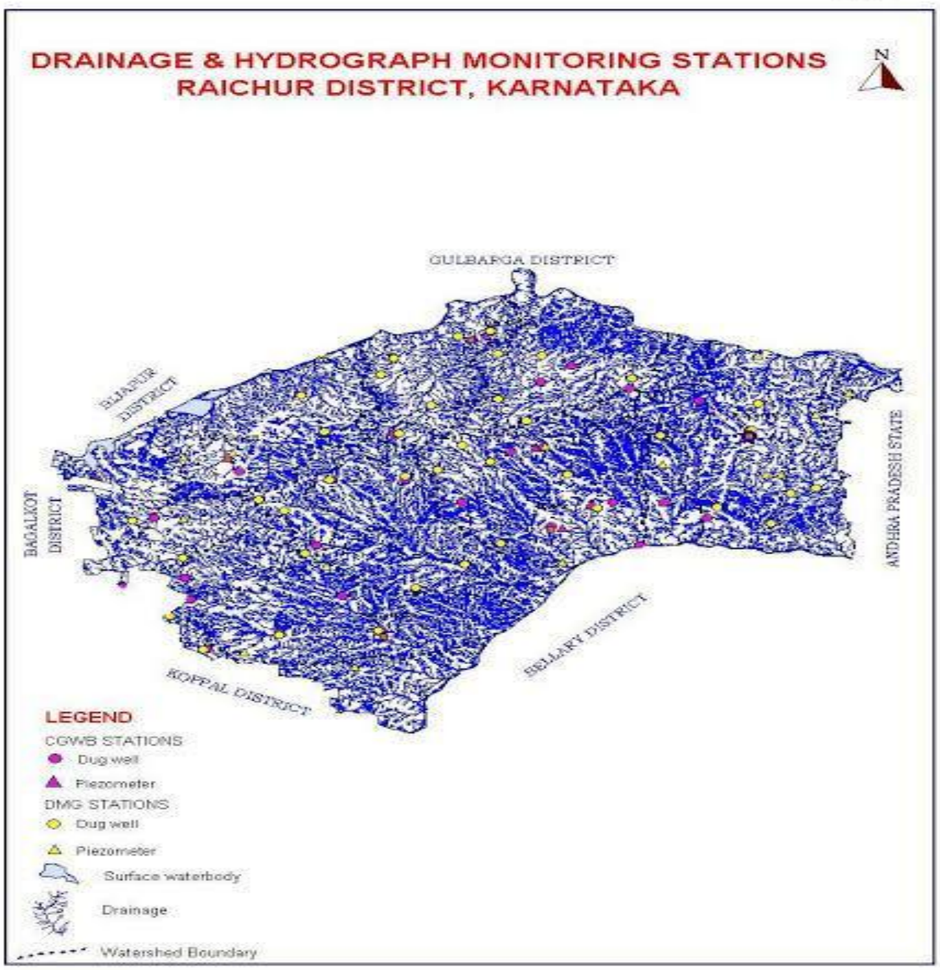
Fig. 2



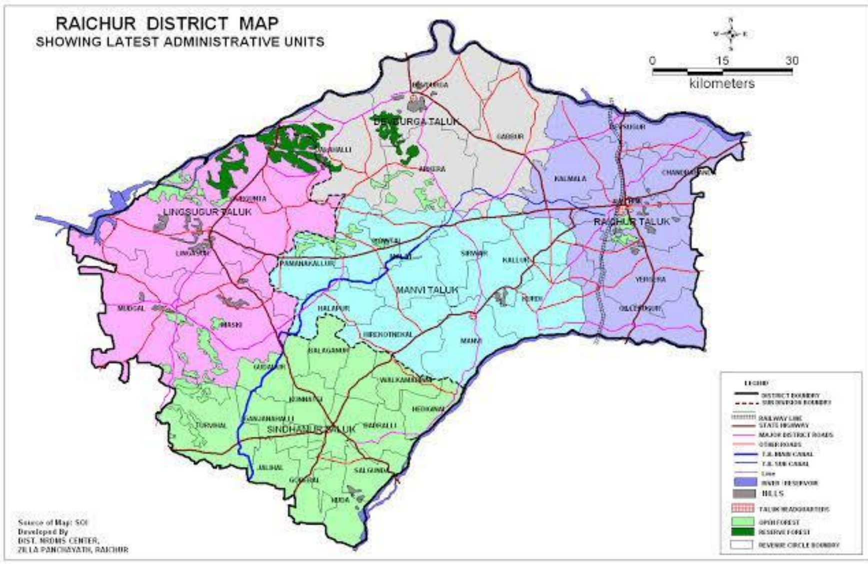


Figure 4 Geographical localization of study areas.

PROBLEM STATEMENT

Accurate soil carbon content measurement and tracking are critical for understanding ecosystem dynamics, agricultural production, and climate change mitigation. The time and effort necessary for traditional methods of assessing soil carbon content, which involve labor-intensive laboratory experiments, limit the scalability and effectiveness of soil investigations. Furthermore, because these methods frequently entail destructive sampling, the same soil samples cannot be measured more than once throughout time. The fact that many organisations now provide carbon offsets demonstrates the need for a quick, dependable, and economical approach to quantify your company's carbon footprint. Such a technology would allow for large-scale soil analysis, real-time tracking of carbon movement, and informed decisions on how to manage property in an environmentally friendly manner. Existing image processing methods could be employed to solve this problem. It is possible to create models that illustrate a relationship between image features and soil carbon content by using high-resolution images of soil and removing essential elements such as colour and texture. The challenge is to develop accurate and dependable image processing algorithms and calibration models capable of capturing the complicated link between picture features and soil carbon content over a wide range of soil types and environmental circumstances.

The issue statement is to develop a reliable and accurate method for finding and measuring the carbon content of all types of soils using image processing techniques. This methodology should solve the constraints of standard soil carbon measurement methods by providing a non-destructive, efficient, and scalable method for estimating soil carbon in various environmental and agricultural applications.

Conclusion

To summarise, utilising image processing techniques to detect and quantify carbon content in all types of soil offers numerous advantages and has the potential to improve soil analysis. This work proposed a novel approach that uses image processing algorithms and machine learning models to accurately assess soil carbon content in a non-destructive and effective manner. The findings of this study reveal that image processing techniques can detect crucial soil features linked to carbon content. Image enhancement and noise removal are two preprocessing procedures that can improve image quality and increase the reliability of feature extraction. The image segmentation algorithms perform a fantastic job of isolating the soil areas of concern, allowing for targeted analysis while reducing the effect of non-soil items. By extracting key aspects such as colour and texture qualities, the proposed approach creates a relationship between image characteristics and soil carbon content. Using machine learning methods, the calibration model efficiently learns this relationship from reference soil samples with known carbon content. This model predicts the carbon content of new soil samples based on extracted image attributes. The advantages of this image-processing-based approach are obvious. It provides a non-destructive analysis technique that preserves the original shape of soil samples to enable for repeated readings and longitudinal research. Because image processing techniques are effective and scalable, large quantities of soil samples may be evaluated fast. This approach also works for all types of soil, so you don't have to employ separate methods depending on the composition or texture of your soil. The successful application of image processing techniques to estimate soil carbon content has far-reaching ramifications. It enables a large-scale study of carbon stocks and dynamics in ecology, which helps us understand more about how ecosystems work and how they respond to environmental changes. It can be used in agriculture to improve soil management practises and determine how well carbon sequestration technologies operate.

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