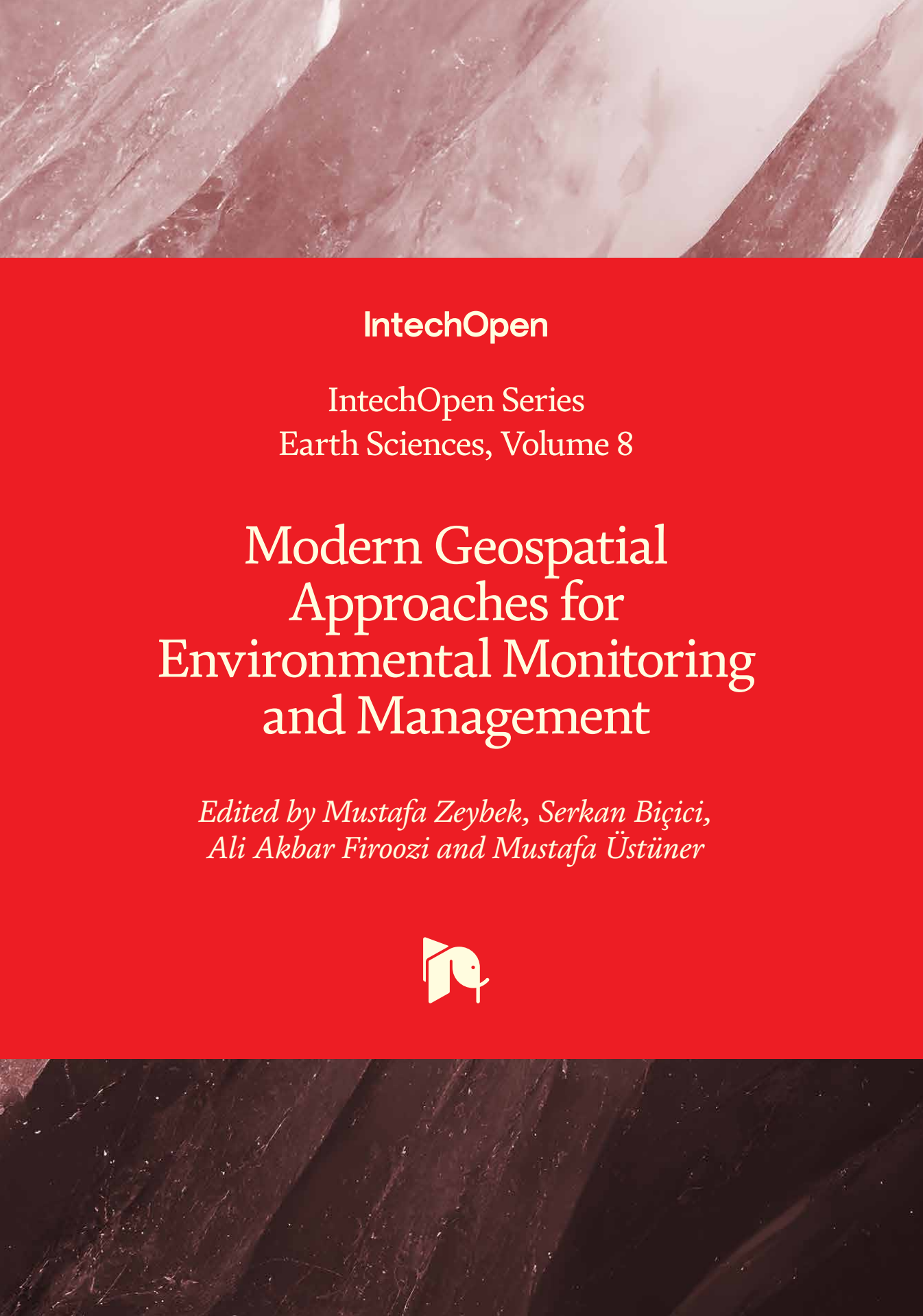




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Earth Sciences, Volume 8

Modern Geospatial Approaches for Environmental Monitoring and Management

*Edited by Mustafa Zeybek, Serkan Biçici,
Ali Akbar Firoozi and Mustafa Üstüner*



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Aims and Scope of the Series

The world of Earth Sciences, considering the interactions within the geosphere and between the geosphere–biosphere, is a place in which a large number of scientists find and have found over time their own relationship or sector of application precisely because it is absolutely transversal to many disciplines and subdisciplines, which do not necessarily fall within the Geosciences. The objective of this book series is to welcome original scientific contributions both in consolidated contexts and in new frontiers of research, as well as review papers included in the various disciplines of Earth Sciences, but above all, those that show a modern and transversal vision of applications and impacts on the community in a particular historical context, which, following the COVID-19 pandemic, has shifted global attention to sectors that were previously more neglected. In particular, those of mining research and fossil and renewable energy sources, environmental geology and the sustainable use of natural resources and impacts on the built environment, land consumption, geoarchaeology, forensic geology, geotourism/geoheritage, georisks and climate and environmental changes, considered at different scales, up to new applications of geostatistical and geospatial analysis, GIS and artificial intelligence for the definition of forecasting models and scenarios in various sectors of basic and applied research.

Meet the Series Editor



Dr. Maurizio Lazzari has a Ph.D. in Earth Science and is a researcher at the Italian National Research Council, Institute of Cultural Heritage Sciences. Since 2001, Dr. Lazzari has been a Professor of Pedology at the University of Basilicata (Italy) and a geoarchaeologist at the University of Salento (Italy). His research activities are focused on natural and anthropic hazards and risk factors, aimed at safeguarding and conserving settlements and the historical-monumental heritage of the Mediterranean, with particular attention to landslide processes, susceptibility maps, monitoring, and modelling. Since 2004, he has been working as a scientific coordinator for several national research projects studying landslides and triggering factors, natural and anthropogenic risks, geological and geomorphological mapping, soil erosion, preservation of historical and archaeological sites, enhancement of degraded areas, geo-touristic use, and the protection of the landscapes. He is the author of about 150 scientific publications in national and international journals, monographs, book chapters, and conference proceedings concerning applied geology, geomorphology, dynamics of artificial reservoirs, soil erosion, landslides, geoarchaeology, hydrogeological instability, natural hazards, monitoring, cultural landscape, UNESCO Heritage, geoarchaeology, and geo-tourism.

Meet the Volume Editors



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Serkan Biçici is currently working as an Assistant Professor in the Department of Geomatics Engineering at Artvin Çoruh University, Turkey. He received both his M. Sc. and Ph.D. degrees in Civil Engineering from The Ohio State University, USA. His research interests span a wide range of topics within transportation engineering, including transportation planning, traditional travel demand modeling, and statistical modeling techniques for transportation data. In recent years, his research has increasingly focused on remote sensing applications in transportation, particularly on developing methods for extracting road surface characteristics and road infrastructure information from 3D geospatial data. He is actively involved in interdisciplinary studies that integrate transportation engineering with geospatial technologies to improve data-driven decision-making in infrastructure planning and management.



Mustafa Üstüner is an assistant professor at the Department of Climate Science and Meteorological Engineering at Samsun University. Dr. Üstüner obtained his Ph.D. from the Department of Geomatic Engineering at Yildiz Technical University and was a visiting researcher in the Geo-Spatial Analytics Lab at the University of South Florida, USA, and in the Department of Earth Observation at the Institute of Geography, Friedrich-Schiller-University of Jena, Germany. His main research interests include Polarimetric Synthetic Aperture Radar (PolSAR) Remote Sensing, Applied Machine Learning and particularly Hyperspectral Data Analysis. Recently, he has been working on dimensionality reduction and classification of hyperspectral images. He has been serving as an associate editor for the European Journal of Remote Sensing and as one of the co-editors for the Turkish Journal of Remote Sensing. He received the award for Top Reviewers for Geosciences - September 2018 from Publons.



Dr. Ali Akbar Firoozi is a distinguished Civil Engineer with over 16 years of academic and professional experience in geotechnical and structural engineering. He has authored over 60 peer-reviewed journal articles, four books, and contributed to ten book chapters. He is known for integrating AI and nanotechnology into sustainable infrastructure. As an Associate Professor at the University of Botswana, he supervises postgraduate research and leads pioneering projects in soil stabilization and smart construction. Internationally recognized, he has delivered over 40 conference presentations and serves on the editorial boards and review panels of top journals. His work bridges innovative research with real-world engineering applications.

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Preface

Geoinformatics, as an interdisciplinary field, has undergone rapid development with the integration of new technologies, including remote sensing, spatial analysis, machine learning, and geostatistics. These advancements have not only expanded the scope of geospatial applications but also provided robust solutions to complex challenges in fields such as environmental monitoring, natural resource management, urban planning, and infrastructure development.

This book, *Modern Geospatial Approaches for Environmental Monitoring and Management*, brings together the latest developments and practical applications in the field of geoinformatics. It presents various case studies and methodological frameworks that demonstrate the power of geospatial technologies in solving real-world problems. From coastal sediment modeling to soil erosion assessment, urban carbon estimation to plant health monitoring, each chapter demonstrates how data-driven geospatial methods are transforming decision-making and sustainability efforts.

Designed for researchers, practitioners, and graduate students, this book highlights the integration of cutting-edge technologies, including UAV photogrammetry, TLS LiDAR, AI, and GIS, across various thematic areas. The chapters were prepared through collaboration among experts in geosciences, engineering, computer science, and environmental studies, offering a multidisciplinary perspective.

We hope this compilation will serve as a valuable reference source and inspire further research into innovative geoinformatics solutions for today's complex spatial challenges.

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Section 1

Remote Sensing Applications
in Vegetation and Carbon
Monitoring

Quantifying Aboveground Carbon Stock at Species Level Using TLS LiDAR and UAV Photogrammetry for Urban Trees

Rezaul Roni, Shah Nurul Hasnat Sadi and Abdullah Al Mamun

Abstract

Urbanization is increasing the depletion of natural carbon sinks and the intensification of urban heat islands, creating urban vegetation critical for carbon sequestration and climate regulation. In this study, a fusion approach was applied that combined Terrestrial Laser Scanning (TLS) Light Detection and Ranging (LiDAR) with high-resolution Unmanned Aerial Vehicle (UAV) imagery to estimate the aboveground carbon stock of individual trees along Manik Mia Avenue, Dhaka, Bangladesh. UAV imageries and dense point cloud data from TLS LiDAR were collected and georeferenced using Real-Time Kinematic (RTK) GPS. After screening and contouring the models to filter the aboveground vegetation, it was possible to segment individual trees, measure tree height and diameter at breast height (DBH), and calculate aboveground carbon stock through species-specific allometric equations. The results indicate a strong correlation between field-measured and point cloud-derived height ($r^2 = 0.94$, RMSE = 0.49) and DBH ($r^2 = 0.88$). While species-specific carbon stock estimation achieved a high correlation ($r^2 = 0.80$), species with aerial roots posed challenges in DBH measurement, resulting in a low correlation ($r^2 = 0.26$) when assessed separately. Limitations include insufficient scanning angles in TLS, variability in point cloud density, and constraints of non-invasive techniques. Future research could integrate multispectral data and geometric shape fitting to address species-specific challenges and enhance precision, contributing to urban carbon management and Sustainable Development Goals (SDGs) 11 and 15, which are related to sustainable cities and forest management.

Keywords: LiDAR, photogrammetry, tree carbon stock, urban vegetation, SDG

1. Introduction

While accounting for only about 3% of the Earth's land surface, urban areas contribute to nearly 70% of global energy-related carbon emissions, yet 55% of the world's total population resided in urban areas in 2018, and the percentage is projected to increase to 68% by the year 2050 [1–3]. In Bangladesh, rapid urbanization fueled

by accelerated population growth, industrialization, and insufficient urban planning has led to a significant decrease in urban vegetation cover, with Dhaka's green space declining from 56% in 1989 to only 8% vegetation cover in 2020, with only 2% of it being healthy vegetation, which is significantly below the recommended 20% for sustainable urban ecosystems [4, 5]. Dhaka, the capital of Bangladesh, has undergone rapid urbanization, leading to a dramatic reduction in green spaces and becoming one of the most densely populated cities globally.

Urban street trees play an essential role in alleviating the adverse effects of carbon emission in urban areas by carbon sequestration and improving air quality [6]. Studies suggest that urban forests can contribute up to 20% of total carbon sequestration in urban region, where street trees account for approximately 10–15% of the total aboveground biomass (AGB) and carbon stock in urban settings [7, 8]. Therefore, understanding the contribution of street trees to carbon sequestration is crucial for urban ecosystem management and planning. Regardless of their environmental significance, the carbon stock of urban street trees in regions like Dhaka remains very poorly estimated [9]. Existing research often concentrates on large green spaces, such as parks and urban forests, while neglecting the dispersed street trees that remain understudied [10]. This knowledge gap is particularly concerning, given the role of street trees in sequestering carbon amidst densely built environments. The lack of knowledge is especially concerning, given the importance of street trees in sequestering carbon amidst packed built environments [11]. Additionally, traditional methods for quantifying carbon stock with ground-based measurements are labor and time-intensive, destructive, and prone to inaccuracies [12, 13]. Advanced geoinformatics techniques can provide highly precise means of aboveground carbon quantification by integrating remote sensing non-invasive methods using Terrestrial Laser Scanning (TLS) and UAV-based photogrammetry [14–16].

Remote sensing has revolutionized urban forestry by enabling the acquisition of detailed three-dimensional (3D) data on tree structure. LiDAR uses laser pulses and calculates the time taken by a pulse to return to the active sensor to produce X, Y, and Z coordinates for each point and generate a precise 3D point cloud. These point clouds have been extensively applied for measuring the tree height, DBH, and volume of tree canopy and trunk [17, 18]. Particularly, TLS LiDAR has shown to be highly effective in capturing fine-scale structural information of individual trees, achieving as low as 1 cm accuracy for DBH measurements [19, 20]. However, the TLS-derived point cloud fails to capture the accurate structure of the canopy crown of trees, as the scanning procedure is taken from the ground-based station level (**Figure 1**). UAV-based LiDAR, on the other hand, offers broader spatial coverage but its accuracy in delineating tree structure below the canopy, such as trunk and branches can be impacted in areas with high canopy density due to occlusions and shadowing effects [22]. Another cost-effective method of generating point clouds relies on UAV photogrammetry, which is capable of only providing accurate structure of the crown of a tree canopy from overlapping aerial images [18, 23].

The fusion of TLS LiDAR and UAV photogrammetry offers a novel solution by combining TLS-derived point clouds containing precise structure of the trunk, branch, and leaf of a tree and UAV photogrammetry-derived accurate structure of the crown of a tree canopy. Studies have shown that this hybrid approach of combining TLS LiDAR data with UAV photogrammetry can greatly increase the accuracy of carbon stock estimation by up to 15% compared to single-platform methods [1, 24–27]. For example, Balestra et al. [7] demonstrated that integrating terrestrial laser scanning data with UAV photogrammetry could improve carbon stock estimation accuracy

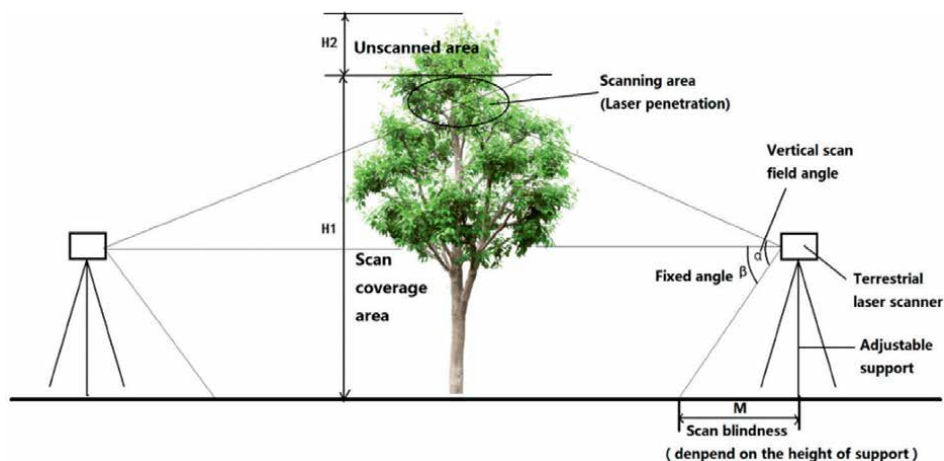


Figure 1.
 Unscanned area of a tree by TLS scanner (Source: [21]).

carbon stocks in urban areas, achieving an accuracy improvement of 20% over traditional methods [28]. However, difficulties remain in rectifying and combining datasets generated by these two platforms due to discrepancies in scale, resolution, and point density [8, 29]. Furthermore, species-level classification, which is critical for applying species-specific allometric equations, is frequently overlooked in existing hybrid approaches, leading to generalized results that fail to account for interspecies variability [24]. Forests densely packed with similar tree structures, shapes, and characteristics further restrict the classification of tree species.

Point cloud data generated from TLS and UAV photogrammetry present multiple technical difficulties. Noise, occlusions, and gaps in data coverage often require advanced preprocessing and filtering steps to extract meaningful structural information [30]. For example, insufficient scans from different angles could result in generating incomplete or partial structures of trees. While TLS is highly effective at capturing detailed data on tree trunks and lower canopy structures but often fails to adequately map the upper canopy and crown due to occlusion effects caused by overlapping branches and leaves (**Figure 1**), UAV photogrammetry-derived point cloud excels at capturing upper canopy-level details by stitching overlapping aerial images but it struggles to resolve lower canopy components, such as trunks and large branches [31–33]. The integration of TLS and UAV photogrammetry overcomes these individual constraints by combining the strengths of both systems, where TLS provides precise measurements of the trunk and lower canopy and UAV photogrammetry provides detailed data on the canopy crown structure [18]. The fusion of these datasets enhances the accuracy of key structural attributes, such as DBH, tree height, and canopy volume [34]. The necessity for integrated, species-specific methodology is especially integral in urban forestry, where tree species and structures differ greatly. Urban environments often present additional complexities, such as irregular tree spacing, dense construction, and mixed vegetation types, which further complicate data acquisition and processing [32]. Machine learning algorithms have been developed to classify tree species and extract biomass attributes from fused point cloud data and achieving up to 85% classification accuracies in controlled environments [10]. However, the application of these algorithms to urban street trees remains understudied, particularly in the context of species-level carbon stock estimation.

The overall aim of this study is to quantify the aboveground carbon stock of urban street trees using a fusion approach of combining TLS and UAV-based photogrammetry in Dhaka, Bangladesh. This study attempts to address the drawbacks associated with single-platform approaches and traditional ground-based methods, by utilizing the advantages of these complementary remote sensing techniques. The present study specifically focuses on developing a robust methodology for combining TLS-derived and UAV photogrammetry-derived point clouds to extract structural attributes, such as tree height and DBH, and apply species-specific allometric equations to estimate the aboveground biomass and carbon stock. Finally, this study assesses the accuracy and viability of the proposed methodology in an urban environment.

2. Study area and data

2.1 Study area

The study focuses on Manik Mia Avenue, a prominent road in Dhaka, Bangladesh (**Figure 2**). The study area extends over a total length of approximately 925 meters and an average width of 65 meters. The avenue connects two major points in Dhaka: the Mirpur Road junction on one side ($90^{\circ}22'27.843''$ E, $23^{\circ}45'29.682''$ N) and Khamar Bari Mor on the other ($90^{\circ}23'0.436''$ E, $23^{\circ}45'31.252''$ N). This road features a two-way carriageway, each spanning 24 meters in width and separated by a central median approximately 3 meters wide. The topography of the area is relatively uniform, with elevation variations ranging between 7.4 and 8.4 meters. The gradual incline from one end of the road to the other represents a height difference of only 1 meter, ensuring minimal topographical interference in data collection and analysis. These topographical insights were gathered by generating longitudinal sections and cross-sections of the study area.

2.2 Remote sensing data

2.2.1 TLS LiDAR data

The TLS LiDAR data were acquired in March of 2022 by a Teledyne Optech Polaris Laser Scanner (Teledyne Technologies, California, USA) that emitted laser pulses at a frequency of 500 kHz and a wavelength of 1550 nm. About 18 scans were successfully conducted in the study area to acquire 46,312,535 three-dimensional points with an average point cloud density of 1000 points/m². The scanner was mounted on a pickup truck to lessen the complexity of moving the scanner from one scanning position angle to another.

2.2.2 Photogrammetry data

UAV-based photogrammetry data were acquired in March of 2022 by a DJI Phantom-4 PRO (Da-Jiang Innovations, Shenzhen, Guangdong, China). The UAV was equipped with a built-in 13.2 × 8.8 mm complementary metal oxide semiconductor red green blue (CMOS) RGB sensor with a 20-megapixel 16-bit resolution and a focal length of 8.6 mm. The flight mission was planned using Pix4D Capture (Pix4D, Prilly, Switzerland) and flown on autopilot using DJI GO-4 Application. The UAV was flown at an average altitude of 78 meters, capturing raw images at a 3:2 aspect ratio with 5472 × 3648 resolution. The camera angle maintained a nadir view of 90°, as well

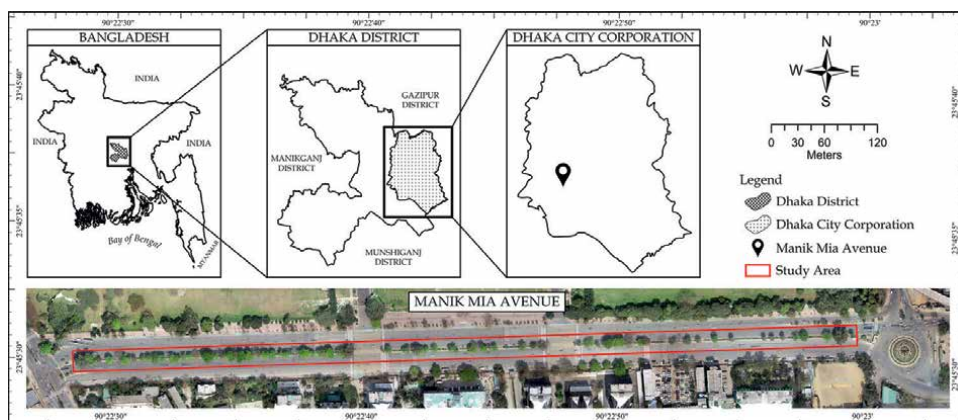


Figure 2.
 Location of the study site.

as a front overlap of 80% and a side overlap of 70% during the imagery capture procedure to ensure comprehensive coverage and accurate reconstruction of tree crowns. A total of 369 images were captured to cover the study area.

2.3 Ground truthing data

2.3.1 Ground control points and GPS data

A CHC 8i GNSS RTK (Huace Navigation Technology, Shanghai, China) was used to collect ground control points (GCPs) with centimeter-level accuracy for the accurate rectification of both the TLS LiDAR and UAV imagery data [35, 36]. A total of 16 LiDAR reflective GCP markers were used along with this equipment to produce ground truthing data for precise georeferencing.

2.3.2 Field survey

A field survey was conducted in March of 2022, a day after the UAV photogrammetry data collection. Survey maps were produced from the photogrammetry-derived orthophoto. A total of 121 trees present in the study area were measured for tree height (H) and DBH. Each tree was also classified by its species and the following six unique species were identified: *Terminalia catappa*, *Albizia procera*, *Phoenix dactylifera*, *Bombax ceiba*, *Ficus benghalensis*, and *Azadirachta indica*. The tree heights were measured using a digital clinometer and the angles were noted in degrees from a constant distance of around 25 meters and a base height of 1.5 meters. Next, a trigonometric formula was applied, where the value of the degrees in $\tan\theta$ was multiplied by 25 to measure tree heights. Tree DBHs were measured using a tape measure at a height of around 1.3 meters from the base of each tree.

3. Methods

The processes of carbon stock estimation at species using fusion of TLS LiDAR and UAV-derived photogrammetry are segmented into four major steps that include:

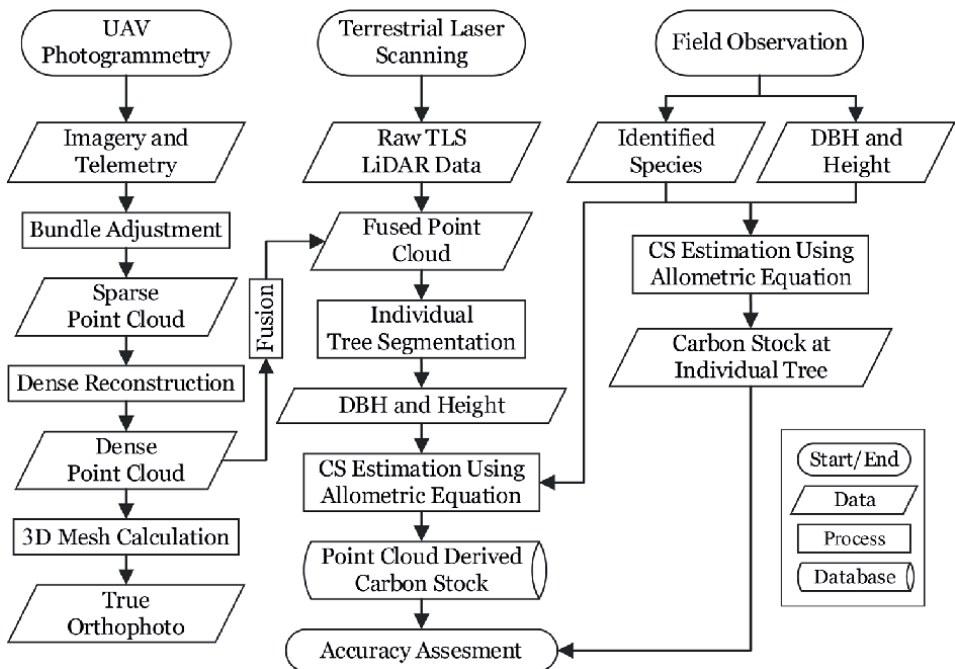


Figure 3.
The flowchart of tree-level carbon stock estimation from fusion of TLS LiDAR and photogrammetry.

(1) data processing; (2) individual tree segmentation and feature extraction; (3) tree-level carbon stock estimation; and (4) accuracy assessment (**Figure 3**).

3.1 Data processing

In this study, the raw point cloud derived from TLS LiDAR was first georeferenced using the ground truthing data collected from the RTK module. Then, it was classified using the TerraSolid and TerraScan (TerraSolid Corporation, Jyväskylä, Finland) software on Bentley MicroStation (Bentley Systems, Dublin, Ireland). This classification process uses an adaptive triangulated irregular network (TIN) algorithm adapted from the method developed by Axelsson et al. [37], where routine classification fragmented the point cloud into two distinct classes: (1) ground return (GR) and (2) high vegetation return (HVR). However, the high vegetation return consisted of noise from shrubs planted in between trees and other source. So, a tree detection classifier by TerraScan was performed, which showed a high success rate of extracting only trees from the point cloud in many studies [38–40]. After some manual adjustment and noise removal, the output filtered down the point cloud to 20,058,018 points containing only the trees scanned by TLS LiDAR. This extracted point cloud of vegetation is shown in green color in **Figure 4**.

The process of preparing the photogrammetry data started with importing a total of 369 images into the 3Dsurvey software (3Dsurvey, Ljubljana, Slovenia). These images were captured with UAV—high-precision camera ensuring a consistent same overlap and a minimal distortion of pairing images. Following that, the telemetry data from the aerial images were imported in EXIF (exchangeable image file) data format, a metadata standard containing crucial flight parameters, such as altitude,

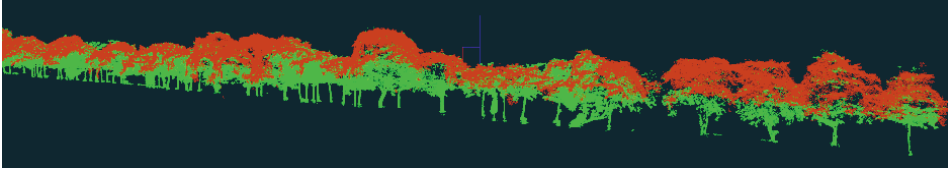


Figure 4.
 TLS- and photogrammetry-derived point clouds. (TLS-derived = Green color; photogrammetry-derived = Red color).

latitude, longitude, camera orientation, focal length, and sensor calibration specifics. These parameters were automatically recognized by the 3Dsurvey, ensuring accurate initial georeferencing aligned with the UAV model specifications used in this study. After verifying the correct images, these parameters were imported without any error, the Bundle Adjustment process was initiated to develop a sparse point cloud from automatic tie points (ATPs), which proved to be highly effective in connecting aerial images [40]. Further rectification was done utilizing the Orientation tool by importing the ground truthing data. The GCPs were stored in a text file format, using whitespaces as a delimiter. This direct georeferencing along with manual adjustments improves spatial-referencing accuracy of each GCP, as demonstrated by Zeybek et al. [41]. Completing this step provides us with Estimated Errors (meters) in X, Y, and Z coordinates for each GCP. In this study, the average Estimated Error was 0.003 meter, which is adequate for the scale of the current study area [42]. This procedure improves the formulation of the sparse point cloud [43]. Next, Dense Reconstruction was applied on the dataset that generated the UAV-derived dense point cloud of the study area (**Figure 5**). The final exported LAS files contained a total of 50,467,108 points.

Additionally, a 3D mesh was calculated from the point cloud data to form triangulation between the point clouds, which contributed to the generation of the true orthophoto of the study area. This orthophoto was utilized to create survey maps for the fieldwork. The resolution was set to be 2 cm/pixel as the ground sampling distance (GSD) of the aerial images was calculated to be around 2.187 cm/pixel, ensuring efficiency and prevention of data loss. The GSD (Eq. (1)) was calculated by multiplying the flight altitude (cm) with sensor width (cm) and dividing the value by the multiplication of focal length (cm) and image width (cm).

$$GSD = \frac{H \times SW}{F \times ImW} \quad (1)$$

GSD = ground sampling distance in cm/pixel.

H = flight height in cm.

SW = sensor width in cm.

F = focal length in cm.

ImW = image width in pixels.

The exported LAS file was then imported into TerraScan for classification as the algorithm used by TerraScan performs more efficiently than 3Dsurvey [44]. The photogrammetry data were classified into three classes: routine: (1) ground return (GR), (2) low vegetation return (LVR), and (3) high vegetation return (HVR). From here, the HVR points were clipped to the area of interest of the study and exported. This



Figure 5.
Dense point cloud from photogrammetry.

delivered a point cloud of total of 1,960,405 points representing the upper canopy crown of trees, ready to be fused with the TLS LiDAR data. This UAV-derived point cloud of the trees is shown in red color in **Figure 4**. Finally, the point clouds from both TLS LiDAR and photogrammetry were again imported into 3Dsurvey and the datasets were merged and exported as a new fused LAS dataset, using the merge tool. The combined point cloud is displayed with a height profile in **Figure 6**.

3.2 Tree segmentation and feature extraction

To detect and segment individual trees, the point cloud was imported into CloudCompare software (Telecom ParisTech and EDF R&D, Dublin, Ireland). First, spatial subsampling at 0.1 m was performed to reduce any noise present. Then, a cloth simulation filter was put to use to filter any ground returns as they intercept the tree segmentation process [45]. Next, the compute geometric feature tool was utilized and the connected component tool was used, where the octree level was set to 11 and the minimum points per component were 10,000. Finally, individual trees were segmented and displayed with bounding boxes (**Figure 7**).

For the quantification of carbon stock present in the trees along the study area, tree height and DBH attributes were extracted at the scale of individual trees. These structural features have been widely used and proven to be effective for the estimation of AGB and carbon stock [34, 46, 47]. Tree heights were measured using a programming script compiled by the author (Appendices (1)), written in Python Language (Python Software Foundation, Delaware, USA) in the Google Colab cloud

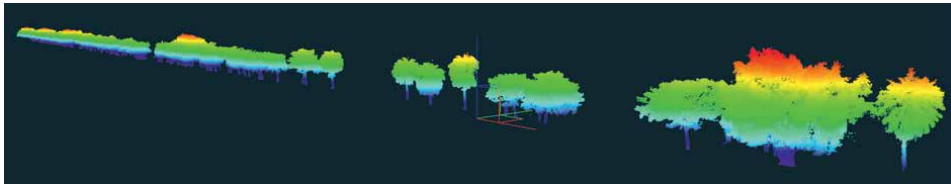


Figure 6.
Processed combined point cloud of trees with height profile.



Figure 7.
Segmented trees in CloudCompare.

platform (Google Colaboratory, California, USA), which is hosted Jupyter Notebook service (Project Jupyter, New York, USA). This script utilizes Python libraries, such as: laspy, numpy, pandas, and os. The script calculated the distance between the highest and lowest Z value in the point cloud of individual trees (Eq. (2)). DBH was measured by taking multiple diameters at an average height of 1.25–1.35 meters from the base and finding the mean DBH for each tree (Eq. (3)).

$$H = \max(z_i) - \min(z_i) \quad (2)$$

$$DBH = \frac{\sum D}{n} \quad (3)$$

Here, z_i represents the height of the i th point in the point cloud, D refers to the diameters measured, and n is the number of samples for diameters.

3.3 Carbon stock estimation

This study estimated the carbon stock at individual tree level using allometric equations for biomass estimation and carbon coefficient. After an in-depth literature review, allometric equations were found for only two out of the six species present in the study area as shown in **Table 1**. However, a generalized equation developed by Alamgir and Al Amin (2008) for other species along with equations for *Albizia procera* and *Bombax ceiba* was found [48]. This generalized equation was utilized for the other species, as the study focuses on demonstrating the accuracy of combining TLS LiDAR and UAV photogrammetry for carbon stock estimation.

Here, Y is the aboveground biomass in tree biomass, measured in ton. And BA represents the basal area of trees, which is measured from DBH (Eq. (4)). And lastly, carbon stock of these trees was estimated by multiplying the aboveground biomass with carbon coefficient (Eq. (5)). In the absence of species-specific carbon coefficient, a default carbon fraction of 0.5 was used, which is recommended by the Intergovernmental Panel on Climate Change (IPCC) and several other studies [49, 50].

$$BA = 0.00007854 \times DBH^2 \quad (4)$$

$$CS = AGB \times CC \quad (5)$$

Lastly, a programming script compiled by the author, written in Python Language in Google Colab Notebook, was put to use in Google (Appendices (2)). Here, Python's

Species	Formula	Reference
<i>Albizia procera</i>	$Y = -0.421075 + 24.809910(BA)$	[48]
<i>Bombax ceiba</i>	$Y = -0.255484 + 15.542905(BA)$	
Other species	$Y = -0.118030 + 17.749190(BA)$	

Table 1.
 List of allometric equations.

Pandas library is mainly used for the script. This script is integrated with allometric equations and iterates through the column containing the scientific names of the species in a CSV (comma-separated values) file to output AGB and carbon stock of individual tree based on species.

3.4 Accuracy assessment

For assessing the accuracy of extracted structural features of trees and the performance of the carbon stock estimation model, the following four accuracy assessment measures were used: The coefficient of determination (r^2) (Eq. (6)), mean absolute error (MAE) (Eq. (7)), root mean square error (RMSE) (Eq. (8)), and percentage RMSE (PRMSE) (Eq. (9)). The PRMSE is RMSE expressed as a percentage of the mean value. These metrics have been widely used for the accuracy assessment of predictive models [51]. In these equations, n is the number of samples, y_i and $\hat{y}_i$ are the true and predicted values of the i th sample, and $\bar{y}$ is the average true value of all samples. These metrics were calculated in the Google Colab cloud platform using Python scripts compiled by the author (Appendices (3)). Here, libraries, such as pandas and numpy, are used for preparing the data, regression analysis metrics are imported from sklearn.metrics, and matplotlib is used to plot and visualize the findings.

$$r^2 = \frac{\sum_{i=1}^n \left(\hat{y}_i - \bar{y} \right)^2}{\sum_{i=1}^n \left(y_i - \bar{y} \right)^2} \quad (6)$$

$$MAE = \frac{1}{n} \left[\sum_{i=1}^n abs \left(\hat{y}_i - y_i \right) \right] \quad (7)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\hat{y}_i - y_i \right)^2} \quad (8)$$

$$PRMSE = \left(\frac{RMSE}{\bar{y}} \right) \times 100\% \quad (9)$$

4. Result and discussion

4.1 Tree height

This study extracted tree height attributes from the point cloud and compared these values with the field survey measured values as shown in **Table 2**. Then the above-mentioned accuracy assessment metrics were calculated from it. A high coefficient of determination ($r^2 = 0.944$) was found between the tree heights measured

Tree height (meters)	Point cloud (trees)	Field survey (trees)
4.19–6.63	11	10
6.63–8.53	22	21
8.53–10.7	65	60
10.7–12.87	16	22
12.87–15.04	7	8
Total =	121	121

Table 2.
Tree height summary.

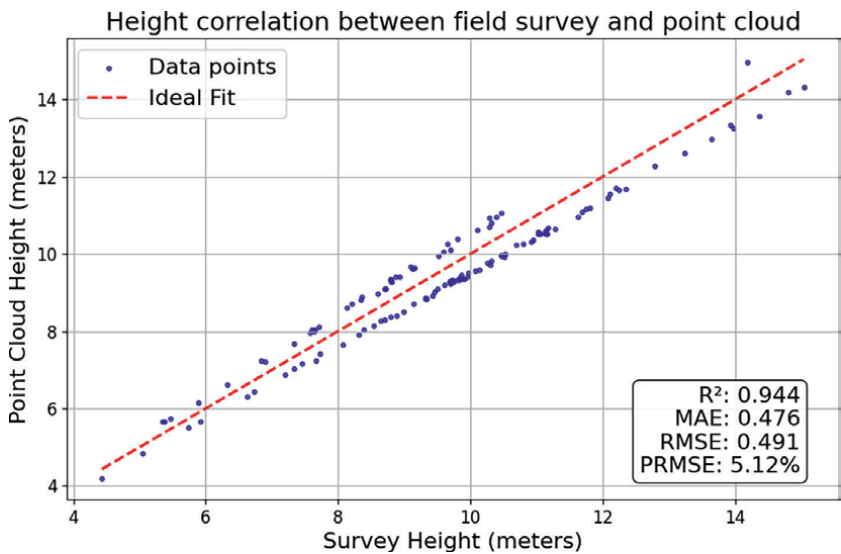


Figure 8.
Tree height correlation.

in the field survey and point cloud extracted heights (**Figure 8**). The low MAE of 0.476 meters and RMSE of 0.491 meters suggest that the fusion of TLS and photogrammetry point cloud methodology is highly effective in estimating tree height. Additionally, the PRMSE of 5.12% underscores the precision of this approach, making it a reliable tool for non-invasive tree height assessment.

This high level of accuracy reflects the combined strengths of TLS LiDAR and UAV photogrammetry in capturing structural details. TLS excels in resolving lower canopy features like the trunk of trees, while UAV-derived photogrammetry provides detailed upper canopy structure. Together, these techniques mitigate occlusion effects, ensuring a comprehensive representation of tree structure. Similar studies have reported the suitability of hybrid approaches in accurately capturing canopy and trunk details for height measurements in complex environments [7, 21]. The results are consistent across all six species analyzed, indicating that height estimation using point clouds is unaffected by interspecies variability. These findings reaffirm the suitability of the hybrid TLS-UAV fusion approach for urban forestry applications.

4.2 Tree DBH

A variance in field-measured tree DBH and point cloud-derived DBH is noticed in **Table 3**. The high coefficient of determination ($r^2 = 0.789$) (**Figure 9**) demonstrated that, DBH measured from the point cloud had a good level correlation with field data, but lower accuracy than other structural features, i.e., tree height (**Figure 8**). The error metrics were found to be low, with MAE of 4.819 cm and RMSE of 7.018 cm, considering the mean DBH was 36.18 cm. The PRMSE of 19.88% indicates a nominal error rate from the mean values, consistent with findings by Shimizu et al. [16] in similar urban forestry applications.

Discovering the variations between point cloud-derived and field-measured values, this study looked into species-specific DBH regression metrics. While the point cloud data showed a high degree of accuracy for most species (**Figure 10**), the DBH values for *Ficus benghalensis* were notably inflated as seen in **Figure 11**. The coefficient of determination was very low ($r^2 = 0.381$) compared to the coefficient of other species ($r^2 = 0.792$). The MAE and RMSE for *Ficus benghalensis* were 21.854 and

Tree DBH (cm)	Point cloud (Trees)	Field survey (Trees)
14–47.8	106	103
47.9–81.6	7	13
81.7–115.4	4	3
115.4–149.2	2	1
149.3–183	2	1
Total =	121	121

Table 3.
Tree DBH summary.

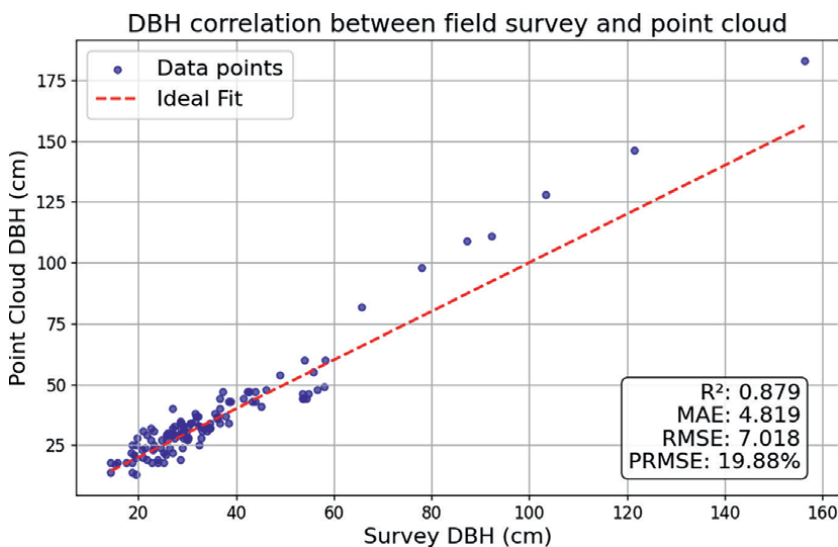


Figure 9.
DBH correlation.

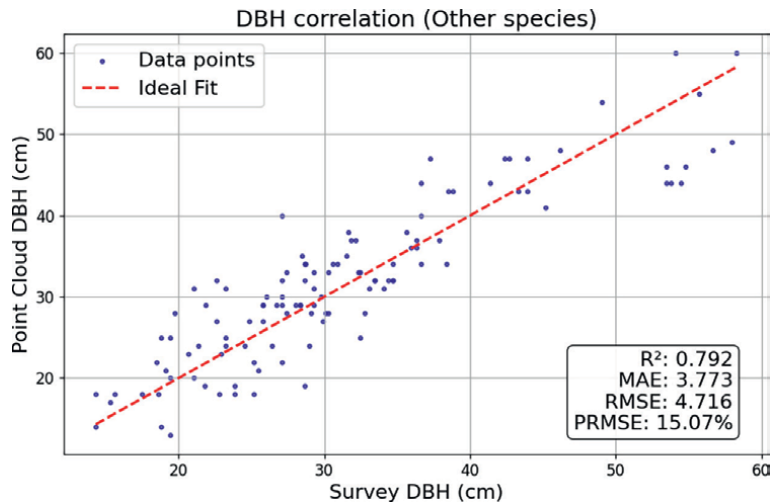


Figure 10.
DBH correlation: other species.

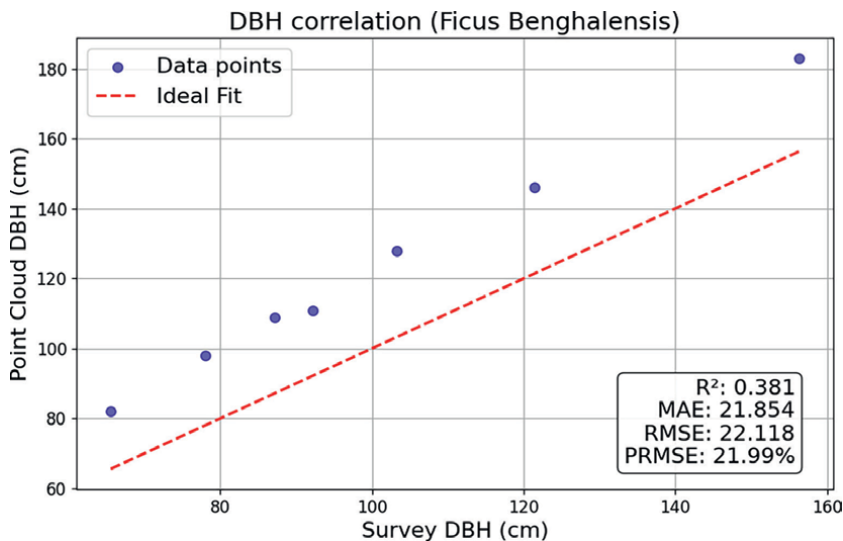


Figure 11.
DBH correlation: *Ficus benghalensis*.

22.118 cm, respectively, which are comparatively very much higher than the MAE of only 3.773 cm and RMSE of 4.716 cm for other species. Additionally, DBH measured for *Ficus benghalensis* had a high PRMSE of 21.99% compared to the PRMSE of 15.07% of other species.

This discrepancy arises from the unique growth habit of this species, which develops aerial roots that descend from the canopy to the ground, merging with the trunk, both of which pose challenges in point cloud analysis, as highlighted in Rodríguez-Puerta et al. [22]. Additionally, excessive tree bark was observed in field measurements. This excessive tree bark along with aerial roots was excluded the possibility to capture the true trunk DBH. However, in the point cloud data, these bark and roots

were indistinguishable from the trunk, leading to exaggerated DBH estimates. This species-specific anomaly impacted the overall DBH correlation and accuracy metrics. When *Ficus benghalensis* was excluded, the point cloud measurements showed much closer alignment with field data for the other species. These findings highlight the importance of species-specific considerations in remote sensing applications.

4.3 Tree carbon stock

Carbon stock measured from both, field and LiDAR-derived structural features, shows that most of the trees in the study area stayed within the minimum range of up to 4703 kg, while only 6 trees exceeded that range as shown in **Table 4**. These six trees turned out to be six out of seven *Ficus benghalensis* trees found in the study area. The combined coefficient of determination of all trees was low ($r^2 = 0.773$), with a very high MAE of 384.99 kg and RMSE of 952.29 cm, resulting in an extreme PRMSE of 83.85% (**Figure 12**). This significant variance was influenced by the discrepancies in DBH measurements as observed in **Table 3** and **Figure 9**.

Tree carbon stock (kg)	Point cloud (Trees)	Field survey (Trees)
58–4703	115	116
4703–9348	3	3
9348–13,993	1	1
13,993–18,638	1	1
18,638–23,284	1	0
Total =	121	121

Table 4.
Tree CS summary.

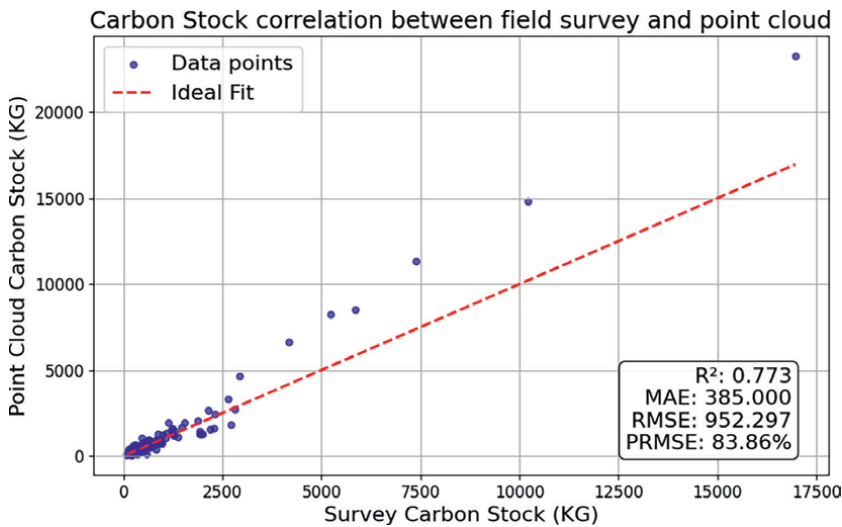


Figure 12.
Carbon stock correlation.

Diving into species-specific regression metrics of measured carbon stocks. This study found that, for most species, the carbon stock values showed strong agreement between point cloud-derived and field-measured data with a high coefficient of determination ($r^2 = 0.804$) as seen in **Figure 13**. However, for *Ficus benghalensis*, the very low coefficient of determination ($r^2 = 0.257$) suggests that the inflated DBH measurements propagated to the carbon stock calculations, leading to overestimations (**Figure 14**). Similar findings have been reported in studies where species-specific traits influenced the accuracy of biomass estimation [28, 34]. As DBH is a critical input in allometric equations used for biomass and carbon stock estimation,

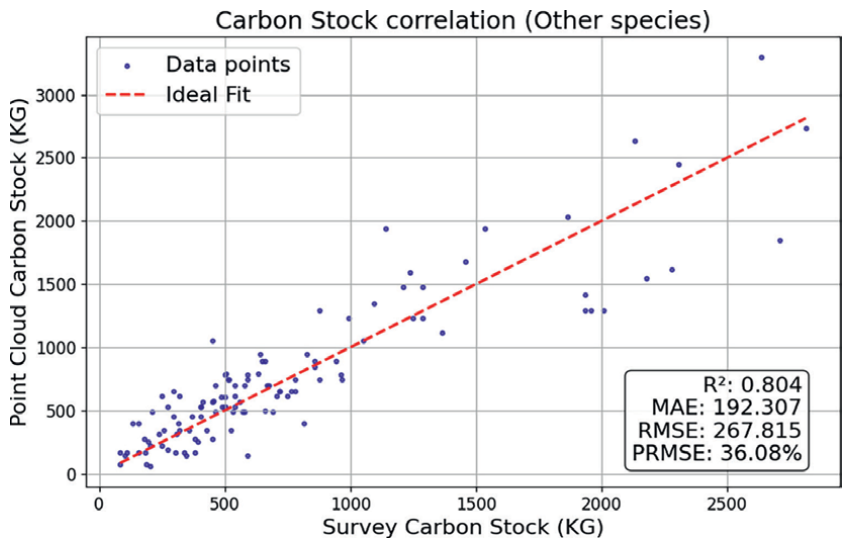


Figure 13.
CS correlation: other species.

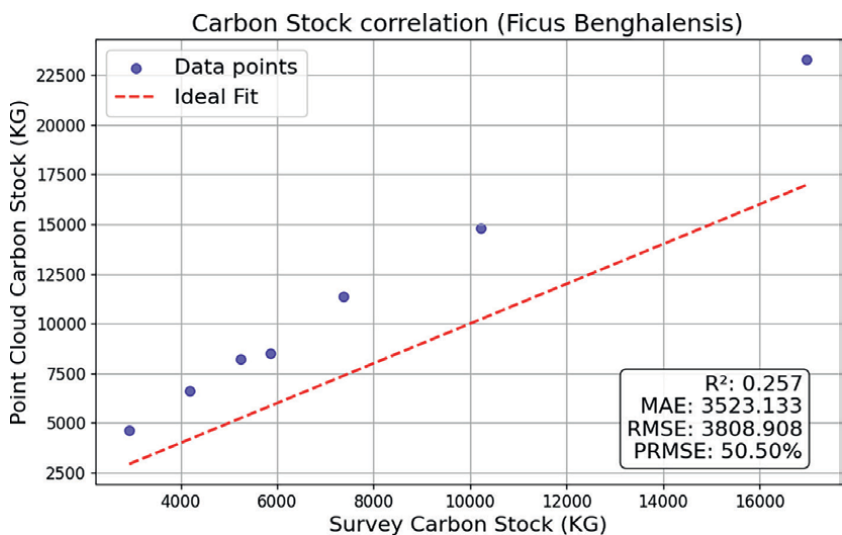


Figure 14.
CS correlation: *Ficus benghalensis*.

inaccuracies in DBH directly affected the reliability of carbon stock assessments. When *Ficus benghalensis* was excluded, the MAE and RMSE were calculated to be 192.3 kg and 267.81 kg, respectively. And when the metrics were calculated only for *Ficus benghalensis*, the MAE and RMSE, the values hiked up to an extreme 3523.13 kg and 3808.908 kg, respectively. This difference is noticed clearly by their PRMSE, one being in the range of acceptability with 36.08% and the other being utmost 50.50%. These findings suggest that, while TLS and UAV-derived point clouds are proven to have significant success in carbon stock estimation, some species may stand as challenging in this methodology.

Despite these challenges, the hybrid TLS-UAV fusion approach offers a promising methodology for non-invasive carbon stock estimation. The ability to accurately measure tree height and DBH for most species underscores its potential for urban forestry management. The carbon stock estimation, on the other hand, showed notable potentiality but is faced with challenges for specific species, i.e., *Ficus benghalensis*. Future studies and methods could mitigate this issue, such as increasing the number of scanning angles to accurately delineate aerial roots and loose barks and eliminate them manually or using machine learning algorithms.

5. Conclusion

This study explored the potential of combining TLS LiDAR and UAV photogrammetry to estimate aboveground carbon stock at the species level for urban street trees in Dhaka, Bangladesh. Structural attributes, including tree height and DBH, were extracted from the fused point cloud data, and their accuracy was evaluated against field measurements. The findings demonstrated that TLS and UAV-derived features alone could provide reasonable estimates of structural attributes, with high coefficients of determination for tree height ($r^2 = 0.94$) and DBH ($r^2 = 0.88$).

As expected, integrating TLS and UAV photogrammetry improved the accuracy of aboveground carbon stock estimation, with an enhanced precision for most species. The fusion method mitigated individual platform limitations, such as TLS's reduced effectiveness in capturing upper canopy structures and UAV photogrammetry's challenges in resolving trunks and lower branches. The improvement in accuracy can be attributed to the complementarity of TLS-derived structural precision and UAV photogrammetry's canopy-level detail. These results underscore that aboveground carbon stock estimation is not solely dependent on structural attributes but also on species-specific biomass conversion factors, which can be refined through multispectral imaging, advanced species classification techniques, and applying species-specific allometric equations. Therefore, the fusion of TLS and UAV data remains a robust methodology for accurately estimating urban tree-level carbon stock.

This study offers a valuable framework for researchers and urban planners to obtain precise carbon stock estimates. Future research should focus on developing species-specific allometric equations for species with aerial roots and enhancing this approach by incorporating multispectral imagery and machine learning for species identification and feature extraction, applying it to diverse urban environments, and exploring its scalability across larger areas. Additionally, the integration of multitemporal remote sensing data could enable dynamic monitoring of urban forest carbon sequestration, contributing to climate change mitigation efforts.

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Conflict of interest

The authors declare no conflict of interest.

Appendices

1. LiDAR_article_tree_heights_calculation.ipynb <https://colab.research.google.com/drive/14XAJ4vBhlcCUcDHmtYZO503JyvT2YFfs?usp=sharing>
2. LiDAR_article_allometric_calculation.ipynb https://colab.research.google.com/drive/1EyX8m32ji-x_QVStiZMiBeqrECBsYHWA?usp=sharing
3. LiDAR_article_metrics_calculation.ipynb <https://colab.research.google.com/drive/1z3k9i3Hflv6Jgknz-alWoIn5XXvzG1bI?usp=sharing>

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Section 2

Spatial Modeling and Resource Management

Comparative Modeling of Coastal Clay Layer Depths Using Spatial Interpolation Techniques versus Conventional Methods: A Case Study in Chonburi Province, Thailand

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Abstract

This research focuses on visualizing the depth of clay layers along the coastline of Chonburi, Thailand. Utilizing a GNSS receiver, 36 points were recorded, and trenches measuring $0.30 \times 1.00 \times 0.60$ m were excavated to gauge clay depth. The collected data were depicted using traditional profile and cross-sectional techniques. Spatial interpolation methods such as Inverse Distance Weighting (IDW), Natural Neighbor, Spline, and Kriging were employed to model the clay layer depths. These models were then compared to presentations. Cross-validation was used to evaluate the performance of IDW and Kriging, with RMSE of 8.241 and 7.478 cm. Kriging offered a more precise representation of the clay layer depth. Kriging has demonstrated success in modeling clay layer depth variations, capturing the trend of increasing depth away from the shoreline. This method accounts for spatial correlation between data, providing a representation of subsurface conditions and proving valuable for geospatial analysis. This continuous representation facilitates better visualization and analysis of clay layer distribution patterns, supporting informed decision-making in coastal management. Spatial interpolation can extrapolate clay layer depth values to unmeasured locations, enhancing the overall understanding of coastal environments. Kriging present an efficient and effective approach to studying coastal ecosystems, ensuring a better understanding of dynamic coastal sedimentation processes.

Keywords: chonburi, coastal clay layer, coastal engineering, coastal geomorphology, coastal soil, environment engineering, geospatial analysis, inverse distance weighting, ordinary kriging, spatial interpolation

1. Introduction

The emergence of Thailand’s coastline traces back to approximately 10,000 years, attributed to shifts in sea levels leading to sedimentary deposition. Over time, this coastline has evolved into significant morphological characteristic signifying coastal alterations [1].

The coastal regions of the Gulf of Thailand host a delicate balance of ecological systems, where land meets sea in a dynamic interplay of geological processes. Among the critical factors shaping these coastal landscapes, sedimentation stands as a fundamental force, influencing shoreline stability, habitat formation, and land-use dynamics. In this context, understanding the sedimentary rates of coastal soils becomes paramount for assessing environmental changes and implementing sustainable coastal management strategies.

In the province of Chonburi, situated along the eastern coast of Thailand as depicted in **Figure 1**, the intricate relationship between land and sea unfolds with particular significance. Chonburi, renowned for its vibrant coastal communities and thriving economic activities, also grapples with the challenges posed by coastal erosion, sediment deposition, and land subsidence. Against this backdrop, investigating the sedimentary rates of coastal soils emerges as a pertinent endeavor, offering insights into the evolving coastal landscape and its implications for both natural and human systems. Chonburi Province boasts a coastline stretching roughly 157

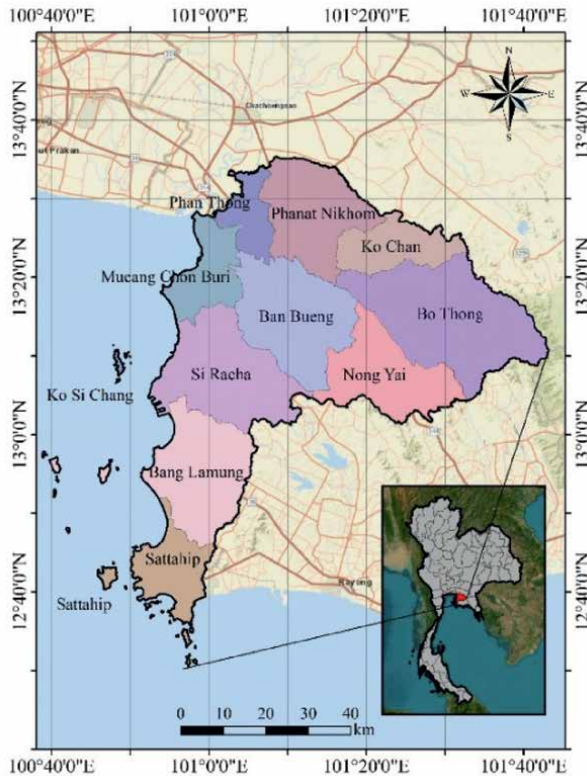


Figure 1.
Chonburi Province, Thailand.

kilometers, extending toward Rayong Province [2]. Situated on the continental shelf, this coast exhibits a gradual incline. Predominantly characterized by sandy beaches, its formation dates back to a sea-level decline during the Holocene period, around 4000–5000 years ago.

Understanding the depth and distribution of clay layers along coastlines is of paramount importance due to its multifaceted implications for coastal management, infrastructure development, environmental conservation, and climate change adaptation. Studying clay layer depth along coastlines is crucial for several reasons as follows:

- *Coastal erosion and stability:* Understanding the depth and distribution of clay layers can provide insights into the stability of coastal landforms. Clay layers often play a role in stabilizing coastlines by resisting erosion and providing structural support to coastal features such as cliffs and bluffs. Knowledge of clay layer depth helps in assessing the vulnerability of coastal areas to erosion and landslides [3–5].
- *Groundwater management:* Clay layers can act as barriers to groundwater flow, influencing aquifer recharge rates and groundwater quality. Studying clay layer depth helps in identifying areas where groundwater resources may be confined or protected from contamination. This information is crucial for sustainable groundwater management along coastlines, especially in areas with high population density and intensive agricultural activities [6, 7].
- *Coastal infrastructure development:* Clay layers affect the feasibility and cost-effectiveness of coastal infrastructure projects, such as harbors, ports, and coastal defense structures. Knowledge of clay layer depth allows engineers to design foundations and structures that can withstand coastal erosion, wave action, and other environmental factors. Understanding the spatial distribution of clay layers is essential for selecting suitable locations for infrastructure development and minimizing risks associated with construction [8, 9].
- *Environmental management:* Clay layers influence the ecological dynamics of coastal ecosystems by regulating sediment transport, nutrient cycling, and habitat availability. Changes in clay layer depth can affect the distribution and abundance of coastal flora and fauna, including wetland habitats and marine biodiversity. Studying clay layer depth helps in assessing the impact of human activities, such as dredging, land reclamation, and coastal development on coastal ecosystems and guiding conservation efforts [10, 11].
- *Climate change adaptation:* Coastal areas are particularly vulnerable to the impacts of climate change, including sea-level rise, storm surges, and coastal flooding. Understanding the depth and distribution of clay layers is essential for assessing the resilience of coastal landscapes and identifying adaptation strategies to mitigate the risks associated with climate change. Clay layers may play a role in natural coastal defense mechanisms, and their study can inform coastal management strategies aimed at enhancing resilience and reducing vulnerability to climate-related hazards [12].

This study aims to investigate the spatial distribution of clay layer depth in Chonburi, Thailand, by employing various spatial interpolation techniques, such as

Inverse Distance Weighting (IDW), Natural Neighbor, Spline, and Ordinary Kriging. The performances of the spatial interpolation techniques were evaluated to identify the most suitable model for estimating clay layer depth along the coastline. The visualization of these interpolation surfaces was compared with conventional profiles and cross-sections commonly used for representing clay layer depth.

2. Study area

Chonburi Province, situated in the eastern region of Thailand, holds significant geographical and ecological importance, making it an ideal study area for examining sedimentary rates along the Gulf of Thailand coast. Its location along the eastern seaboard of the Gulf of Thailand, between latitudes 12°30'N and 13°36'N and longitudes 100°40'E to 101°45'E as depicted in **Figure 1**, exposes it to various environmental factors influencing sediment deposition.

The province's coastline stretches approximately 157 kilometers, extending toward Rayong Province, and features predominantly sandy beaches with a gentle slope. This coastal morphology, shaped by sea-level fluctuations over millennia, offers a unique opportunity to investigate sedimentary processes and rates in a dynamic coastal environment [2].

Chonburi Province's proximity to Bangkok, located just 79 kilometers away [13], facilitates accessibility for research purposes while presenting contrasts between urbanized and natural coastal settings. Moreover, its administrative division into 11 districts [14] provides a comprehensive spatial framework for sampling and analysis.

Chonburi, located in Thailand's eastern region along the Gulf of Thailand, experiences significant coastal dynamics due to its geography, human activities, and natural processes. Here are some key aspects:

- **Coastal erosion and deposition:** Chonburi's coastline is subject to erosion and deposition processes. Erosion occurs when waves and currents remove sediment from the shore, often exacerbated by human activities such as coastal development, which can disrupt natural sediment transport. Deposition occurs when sediment settles on the coastline, influenced by factors like wave energy and sediment supply.
- **Natural factors:** Chonburi's coastal dynamics are influenced by natural factors, such as tides, storms, and sea-level variations. Tropical storms and monsoons can bring intense waves and rainfall, affecting erosion rates and sediment transport. Sea-level rise due to climate change also poses a long-term challenge to coastal stability.
- **Human activities:** Rapid urbanization and tourism development in Chonburi have altered the coastal landscape. Construction of ports, resorts, and residential areas often involves coastal modification, which can disrupt natural sediment flows and increase erosion in some areas while promoting deposition in others.
- **Ecological impact:** Coastal dynamics in Chonburi affect marine and coastal ecosystems. Changes in sedimentation patterns can impact habitats for marine life, while erosion can threaten mangrove forests and other coastal vegetation that provide crucial ecosystem services, such as shoreline protection and habitat for biodiversity.

- **Management and mitigation:** To manage coastal dynamics, Chonburi employs various strategies, such as beach nourishment (adding sediment to eroded beaches), seawalls, and mangrove restoration. These efforts aim to stabilize shorelines, protect infrastructure, and preserve natural habitats.
- **Socioeconomic implications:** Coastal dynamics also have socioeconomic implications for Chonburi. Tourism, fishing, and port activities are vital to the local economy but can be vulnerable to coastal hazards. Sustainable coastal management practices are increasingly important to balance development with environmental and societal needs.

Overall, understanding and managing coastal dynamics in Chonburi involves a multidisciplinary approach that considers both natural processes and human activities to ensure the long-term sustainability of the region's coastal resources.

Chonburi, located in Thailand's eastern region along the Gulf of Thailand, boasts diverse and significant ecological features, despite its heavily urbanized and industrialized landscape. The following are some notable ecological aspects of Chonburi:

- **Mangrove forests:** Chonburi is home to several mangrove forests, particularly in areas like Bang Phra and Khao Sam Muk. Mangroves provide crucial habitats for various marine species, protect coastlines from erosion, and serve as nurseries for fish and other aquatic organisms.
- **Marine biodiversity:** The coastal waters off Chonburi support a rich diversity of marine life, including coral reefs, seagrass beds, and numerous fish species. These ecosystems contribute to local fisheries and tourism activities.
- **Natural reserves:** Chonburi includes natural reserves and protected areas like Khao Kheow-Khao Chomphu Wildlife Sanctuary and Khao Sam Muk-Muang Pattaya. These reserves help conserve biodiversity, including endangered species such as gibbons and various reptiles.
- **Environmental challenges:** Despite its ecological richness, Chonburi faces environmental challenges, such as habitat loss due to urbanization and industrialization, pollution from urban runoff and industrial discharge, and coastal erosion. Efforts are ongoing to balance development with conservation through sustainable practices and conservation initiatives.
- **Community conservation efforts:** Local communities and organizations in Chonburi actively participate in conservation efforts, including mangrove restoration projects, beach cleanups, and education programs aimed at raising awareness about environmental issues and biodiversity conservation.

In summary, while Chonburi's rapid development has posed challenges to its ecological health, efforts to protect and conserve its diverse ecosystems are crucial for sustaining the region's natural heritage and supporting both local livelihoods and tourism.

Coastal erosion has long been a persistent issue in Chonburi Province, attributed to both natural phenomena and human activities. The erosion rate has been reported at 1–5 meters per year. Naturally occurring erosion is primarily driven by seasonal

waves during the southwest monsoon from May to August. Anthropogenically induced erosion results from an unbalanced sediment budget and the construction of man-made coastal structures, such as piers, seawalls, revetments, and reclamations. The interaction between coastal erosion and clay layers is critical in shaping the stability and resilience of coastal environments. Clay layers, due to their composition and properties, play a significant role in coastal sediment dynamics. They often act as barriers that reduce the infiltration and drainage of water, which can help stabilize shorelines by minimizing the loss of underlying sediment and mitigating the erosive impact of wave energy. This natural protection is especially valuable in coastal areas where erosion poses a threat to infrastructure, habitats, and communities. However, despite their protective qualities, clay layers can themselves be vulnerable to erosion under certain conditions. When the overlying sediment or vegetation cover is disturbed or removed—whether due to natural processes like storm surges or human activities such as coastal development or dredging—the exposed clay becomes susceptible to erosion by wave action. This can lead to the destabilization of the coastline and exacerbate erosion rates in affected areas.

Therefore, Chonburi was selected as the study area due to its strategic location in the Gulf of Thailand and its diverse coastal environments, ranging from sandy beaches to mangrove forests. By focusing on Chonburi Province as a case study, researchers can delve into the sedimentary dynamics of coastal soil in the Gulf of Thailand, shedding light on crucial processes shaping the region's coastal landscapes and informing sustainable coastal management strategies.

3. Methodology

3.1 Data collection

The data were collected on January 18, 2023 along the Chonburi coastline involved field surveys, during which sediment samples were gathered from multiple locations utilizing standard sampling techniques. Trenches measuring $0.30 \times 1.00 \times 0.60$ m ($W \times L \times H$) were dug along the coastline. The depth of clay layer was determined from the ground surface of the coast using measurement tape. The coordinates of trenches were meticulously recorded with a handheld global navigation satellite system (GNSS) receiver (Trimble Geo-XT), ensuring submeter accuracy [15]. These boreholes were segmented into 12 sections, organized along 3 lines running parallel to the coastline (Lines A, B, and C), as depicted in **Figure 2**.

The study utilized a spatial interpolation technique to create a model of the clay layer beneath the sand layer along the beach within the designated area. These interpolations were then compared with the conventional method of soil profile presentation, which involved the use of cross-sections and profile plots.

The data collection strategy focused on 36 specific points along the coastline for several reasons. First, limiting the points helps mitigate the influence of tidal changes, which can significantly alter coastal conditions and measurements. By selecting specific points, researchers can better control for these variations and obtain more consistent data. Second, choosing non-urban and less tourist-impacted areas for data collection reduces potential interference from human activities during the data collection.

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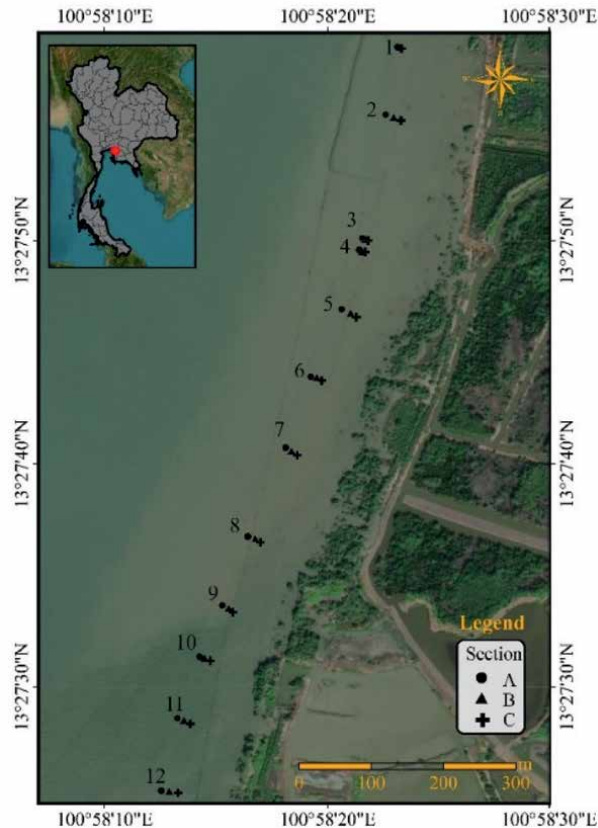


Figure 2.
Locations of observation trenches.

spots often have complex dynamics influenced by human infrastructure, activities, and interventions (such as seawalls or beach grooming) that can obscure natural coastal processes.

According to **Figure 3**, it is evident that urban development is spread along the Chonburi coastline. Data collection within these urban areas could be adversely affected by human activities. Therefore, by conducting data collection in less developed and less frequented coastal areas, researchers aim to capture more pristine and representative environmental conditions. This approach enhances the reliability and accuracy of the data gathered, supporting more robust scientific analysis and conclusions about coastal processes and changes.

3.2 Spatial interpolation techniques

Spatial interpolation is a method used to estimate unknown values of a variable at unsampled locations within a study area based on known values from sampled locations. In scientific reports, spatial interpolation techniques are commonly employed in fields, such as geography, environmental science, geology, and remote sensing, to create continuous surfaces of variables like elevation, temperature, soil properties, or pollutant concentrations. Spatial interpolation in Geographic Information Systems (GIS) refers to the process of estimating the values of unknown points within

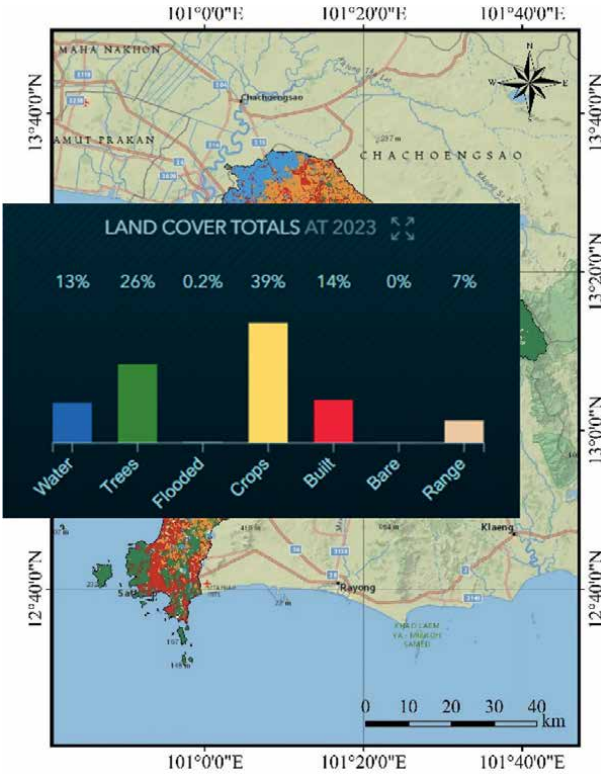


Figure 3.
Land use land cover (LULC) of Chonburi.

a defined geographic area based on known values sampled at specific locations. It's commonly used to predict or generate continuous surfaces or datasets from discrete data points. This is particularly useful when working with spatial data, such as elevation, temperature, soil properties, pollution levels, or any other continuous phenomenon that varies across space.

The basic principle of spatial interpolation involves using mathematical algorithms to infer values at points where direct measurements are not available [16]. These algorithms consider the spatial relationships and patterns observed in the sampled data to make educated guesses about values in between those points.

There are various interpolation methods available in GIS, each with its own strengths, weaknesses, and suitability for different types of data and spatial patterns. The interpolation techniques that are commonly used in GIS include:

- Inverse Distance Weighting (IDW): Assigns values to unsampled locations based on the inverse of the distance to known points, giving closer points more influence.
- Kriging: A statistical method that estimates values by accounting for spatial autocorrelation, utilizing variogram models to characterize spatial dependence.
- Splines: Fits a smooth curve through known points, balancing goodness of fit with smoothness.

- **Natural Neighbor:** Estimates values at unsampled locations based on the Voronoi diagram or Delaunay triangulation of known sample points.
- **Radial Basis Functions:** Uses functions centered on known points to interpolate values.

The selection of the appropriate interpolation method depends on factors, such as data distribution, spatial variability, and the underlying process being modeled. Validation and assessment of interpolation results are critical to ensure the accuracy and reliability of the interpolated surfaces.

In summary, spatial interpolation is a method used to estimate unknown values of a variable at unsampled locations within a defined geographic area based on known values from sampled locations. The basic concept revolves around the idea of predicting values at points where direct measurements are not available by leveraging the spatial relationships and patterns observed in the sampled data. In essence, spatial interpolation bridges the gap between discrete data points by creating smooth, continuous surfaces that depict the spatial distribution of variables, thereby enhancing our understanding of spatial relationships and patterns in the natural and built environment.

3.2.1 Inverse distance weighting (IDW)

Inverse Distance Weighting (IDW) is a spatial interpolation technique used to estimate values at unsampled locations based on the values of nearby observed data points. It is based on the assumption that points closer to the location of interest have a greater influence on the estimated value than points farther away [17]. The IDW method works by calculating a weighted average of the observed data points, with the weights being inversely proportional to the distance between the unsampled location and the observed data points [18]. Specifically, the IDW estimator is given by Eq. (1) [19].

$$X_p = \frac{\sum_{i=1}^n \left(\frac{X_i}{d_i^p} \right)}{\sum_{i=1}^n \left(\frac{1}{d_i^p} \right)} \quad (1)$$

where: X_p is the predicted value at location P .

n is the number of X_p surrounding points considered in the calculation.

X_i is the measured value at i th point.

D is the distance between X_p and X_i .

P is the power function governs the influence of distance on the weights.

The power parameter p determines how quickly the weights diminish with increasing distance. A higher value of p assigns more significance to the closest data points, while a lower value allows more data points to influence the estimation, even if they are farther away [20].

Inverse Distance Weighting (IDW) is a deterministic interpolation method, meaning that the estimated values are entirely determined by the observed data points and the specified parameters (e.g., power parameter, search radius). It is widely used in various fields, such as environmental sciences, geology, and geography, due to its simplicity and computational efficiency. However, IDW does not account for spatial

autocorrelation or anisotropy in the data, which can be better addressed by geostatistical methods like kriging [21].

3.2.2 Natural neighbor

Natural Neighbor spatial interpolation is a method used to interpolate values for unsampled locations based on the values of nearby observed data points. It is a geometric interpolation technique that is particularly well suited for applications where the data are irregularly spaced or clustered. The Natural Neighbor interpolation method is based on the concept of Voronoi tessellation, which partitions the plane into a set of polygons (known as Voronoi cells or Thiessen polygons) around each observed data point. Each polygon contains the region of space that is closer to its associated data point than to any other data point [22]. The Natural Neighbor interpolation method works by constructing a Voronoi tessellation from the observed data points and then assigning weights to each data point based on the proportional area of overlap between the Voronoi cell at the unsampled location and the Voronoi cells of the surrounding data points. The estimated value at an unsampled location is calculated as a weighted average of the observed values at the surrounding data points, with the weights being determined by the proportional area of overlap between the Voronoi cells [23].

The Natural Neighbor interpolation method offers several advantages for spatial interpolation. It produces a smooth and continuous interpolated surface without abrupt changes or discontinuities. The method is locally driven, ensuring that the interpolated value at any given location is influenced solely by nearby observed data points. This local influence helps preserve localized features and patterns present in the data, such as ridges, valleys, and terrain characteristics. Furthermore, the Natural Neighbor approach constrains the interpolated values within the range of the observed data, preventing unrealistic extrapolation beyond the data extent [24]. These properties make Natural Neighbor interpolation a suitable choice for applications involving irregularly spaced or clustered data, where the preservation of local patterns and the avoidance of unrealistic extrapolation are desirable. Natural Neighbor interpolation is widely used in various fields, including cartography, geophysics, hydrology, and environmental modeling, particularly when dealing with irregularly spaced or clustered data [25].

3.2.3 Spline

Spline spatial interpolation is a technique used to estimate values at unsampled locations based on a mathematical function that fits a smooth curve (or surface) through the observed data points. It is a form of piecewise polynomial interpolation, where the study area is divided into smaller subregions, and individual polynomial functions are used to represent the data within each subregion [26].

In spline interpolation, the polynomial functions are constrained to pass through the observed data points while maintaining a certain degree of smoothness at the boundaries between adjacent subregions. This smoothness is achieved by enforcing continuity conditions on the function and its derivatives at the boundaries, resulting in a continuous and differentiable surface [27]. There are different types of spline interpolation methods, including:

- **Regularized Spline:** This method minimizes the curvature of the interpolated surface, resulting in a smooth and gradually varying surface. It is suitable for interpolating data with a gradual trend [28].

- **Tension Spline:** This method allows for control over the tension or stiffness of the interpolated surface, enabling the surface to either conform more closely to the data points or produce a smoother surface [28].
- **Thin Plate Spline:** This method minimizes the total bending energy of the interpolated surface, resulting in a smooth and natural-looking surface that passes through the data points exactly [29].

Spline interpolation methods are widely used in various fields, including geospatial analysis, computer graphics, and engineering design, due to their ability to produce smooth and visually appealing surfaces. However, it's important to note that spline interpolation can be sensitive to outliers or noise in the data, as the interpolated surface will pass through all observed data points exactly [30].

When compared to other spatial interpolation techniques, such as kriging or inverse distance weighting, spline interpolation is generally considered more computationally intensive, especially for large datasets or high-dimensional problems. Nevertheless, it remains a valuable tool for applications that require smooth and visually appealing representations of spatial data [31].

3.2.4 Kriging

Kriging is a geostatistical interpolation technique that is widely used in various fields such as geology, environmental sciences, mining, and spatial analysis. It is a method for estimating values at unsampled locations based on values observed at nearby locations, taking into account the spatial correlation and variability of the data.

The fundamental principle behind kriging is based on the assumption that spatial data are not random but exhibit spatial autocorrelation, which means that points closer together in space tend to have more similar values than points farther apart. Kriging uses this spatial autocorrelation to estimate values at unsampled locations by considering the values and relative locations of the surrounding known data points [32].

Kriging is a powerful geostatistical interpolation method that estimates values at unsampled locations by exploiting the spatial autocorrelation present in the data. It operates on the principle that points closer together in space tend to have more similar values than those farther apart. The technique involves modeling the spatial dependence structure of the data using a variogram, which quantifies the average squared difference between pairs of data points at various distances [33].

The key steps in kriging include exploratory data analysis, variogram modeling, and kriging interpolation. During interpolation, kriging uses a weighted linear combination of surrounding known data points to estimate the value at an unsampled location, with weights determined based on the variogram model and spatial configuration of the data [34].

Kriging has several advantages over other interpolation techniques, such as its ability to provide estimates of uncertainty (kriging variance) and its flexibility in handling different data configurations and spatial patterns. However, it also has limitations, including the assumption of stationarity (constant mean and variance) and the computational complexity for large datasets [35]. Kriging is widely used in various applications, including mapping mineral resources, environmental monitoring,

soil characterization, precision agriculture, and spatial prediction of meteorological variables, among others [36].

Despite its strengths, kriging assumes stationarity (constant mean and variance) and can be computationally intensive for large datasets. Variants like ordinary kriging, universal kriging, and indicator kriging address specific data scenarios, making kriging a versatile and powerful spatial interpolation tool in the geoscientist's toolkit [37].

3.2.5 Comparisons of the performance of spatial interpolation techniques

Comparisons of the performance of spatial interpolation techniques play a crucial role in various fields, such as environmental science, geostatistics, and Geographic Information Systems (GIS). These techniques are essential for estimating values at unsampled locations based on known data points, enabling informed decision-making in resource management, urban planning, and environmental monitoring. Evaluating their performance involves assessing factors like accuracy, computational efficiency, and suitability for different spatial datasets and conditions.

Spatial interpolation	Advantages	Disadvantages
IDW	• Simplicity, easy to understand and implement • Lower computational time and faster processing • Generates smooth surfaces	• Susceptibility to outliers. • Sensitivity to the choice of parameters. • Tendency to produce oversmoothed surfaces. • Difficulty in handling complex spatial relationships.
Natural neighbor	• Preserves sharp boundaries and local details in data. • Handles irregularly spaced data points effectively. • Provides smooth transitions between neighboring data points.	• Computationally demanding, especially for large datasets. • Sensitivity to outliers in data. • Can be complex to implement and understand compared to simpler methods like IDW.
Spline	• Produces smooth and continuous curves. • Can accurately represent complex relationships in data. • Provides flexibility in choosing the degree of smoothness.	• Computationally intensive, especially for large datasets. • Requires careful selection of parameters to avoid overfitting. • May not extrapolate well beyond the range of observed data points.
Ordinary kriging	• Provides optimal predictions by accounting for spatial autocorrelation. • Offers quantification of prediction uncertainty through variogram analysis. • Handles complex spatial patterns and irregularly spaced data effectively.	• Requires knowledge of variogram parameters, which can be challenging to estimate. • Computationally intensive and may be slow for large datasets. • Assumes stationarity of the underlying spatial process, which may not always hold true.

Table 1.
Performances of spatial interpolations.

Determining the optimal spatial interpolation technique depends on various factors, including the nature of the data, spatial context, accuracy requirements, and computational considerations. Each method has distinct strengths and weaknesses tailored to different data characteristics and analysis goals, as presented in **Table 1**. Different techniques excel in specific applications based on empirical testing and validation against known data or ground truth. The choice of the most suitable technique hinges on aligning these strengths with the specific needs and constraints of the project or study at hand.

4. Results and discussions

4.1 Clay layer cross-sections

The data from all 36 boreholes collected in the field were presented as cross-sections (sections 1 to 12). The depth of the clay layer beneath the soil layer along the beach at each section is illustrated in **Figure 4**.

Figure 4 illustrates the cross-sectional profiles of the clay layer depth perpendicular to the coastline in Chonburi Province, Thailand, across 12 different sections. Each section is measured at various distances from a starting point from point A (left trench) to point C (right trench) at each section in **Figure 2**.

The figure shows variations in clay layer depths, which typically indicate where clay soil begins or where a significant layer of clay is present near the coast. The depths range from -10 to -30 cm, with an average depth of around -20 cm. The variations of clay layer depth at each cross-sectional profile are presented in **Table 2**.

To analyze the fluctuations in clay layer depth, one can visualize the data through cross-sectional representations akin to those used in road construction. Furthermore, the cross-sectional profiles can be tabulated, as demonstrated in **Table 2**. However, interpreting the clay depth information from either **Figure 4** or **Table 2** can prove challenging. Consequently, users relying on these visualization methods may encounter difficulty in interpretation, necessitating a considerable degree of imagination. These challenges represent inherent drawbacks of conventional cross-sectional data presentation techniques.

The cross-section in **Figure 4** illustrates clay layer depth that is perpendicular to profile view, offering insights into the thickness and continuity of clay layers across different locations. By examining clay depths in cross-sections, variations in clay depth can be visualized.

4.2 Clay layer profiles

Building on the insights from the preceding section, it becomes apparent that relying solely on cross-sections is insufficient for adequately representing the variability in clay layer depth. Therefore, it is imperative to complement these cross-sections with additional plots depicting the clay layer depth as profiles. In this context, the term “profile” aligns with its meaning in road construction, illustrating elevations or depths along the longitudinal axis of a road project [38]. The profile view in this study presents a horizontal perspective of the soil profile (along the coastline), showcasing the horizontal extent and continuity of clay layers. This view allows for the

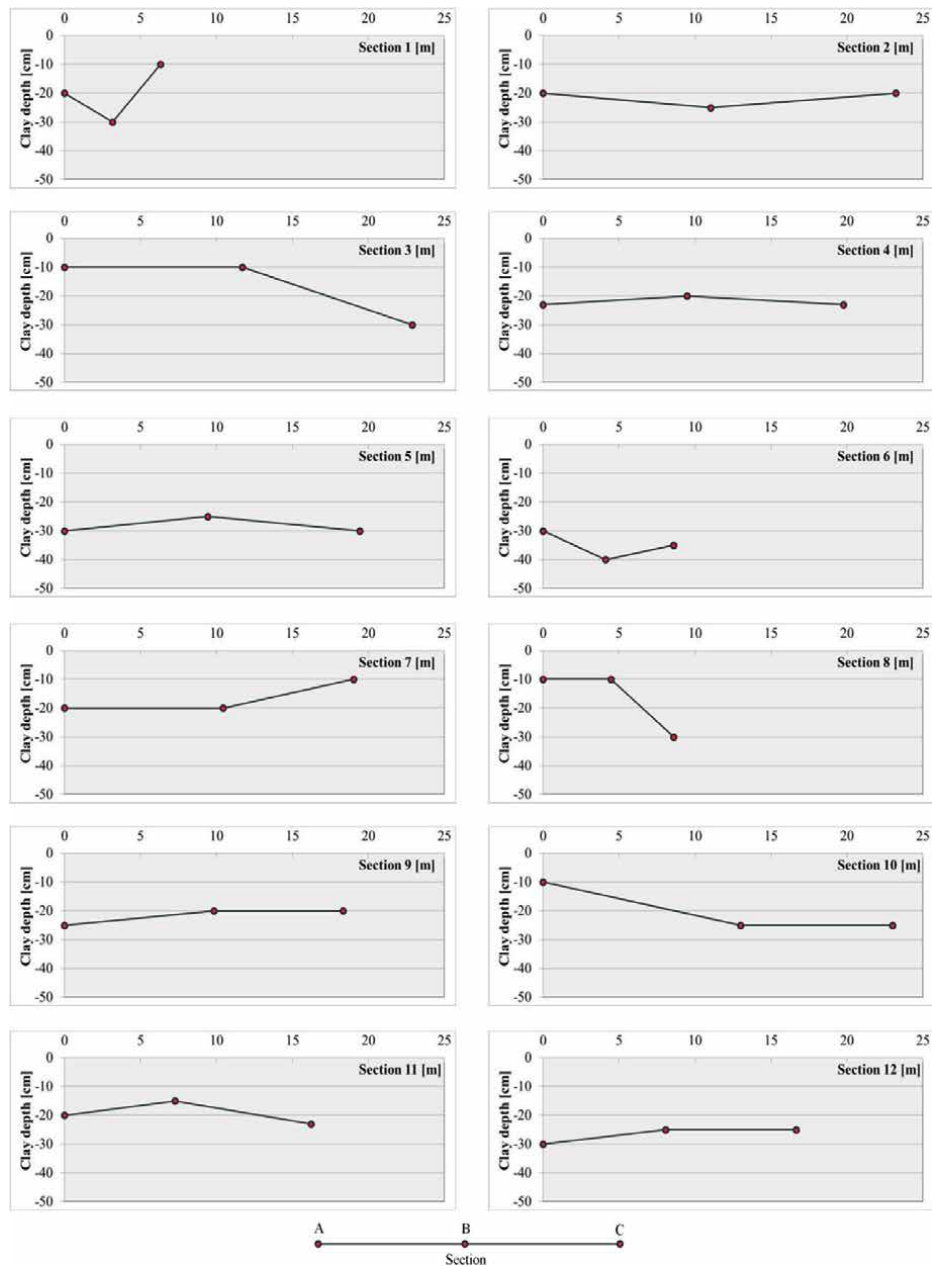


Figure 4.
Cross-section of clay depth at stations 1 to 12.

assessment of how clay layers vary across the landscape and their relationship with environmental factors.

Thus, in this study, the profile represents the clay layer depth along the coastline, specifically along points A, B, and C, as delineated in **Figure 2**. The profiles of clay layer depth along the coastlines (Lines A, B, and C) are illustrated in **Figure 5**.

Figure 5 depicts variations in the depth of the clay layer along different distances, showing both increases and decreases in depth across the measured profiles.

Cross-section number	Clay layer depth explanation
1	The depth begins at around –30 cm and fluctuates, reaching –10 cm at 5 meters before decreasing to around –25 cm at 10 meters and ending at approximately –15 cm at 20 meters.
2	The depth remains relatively constant, starting at about –25 cm at 0 meters and maintaining the same depth with slight fluctuations up to 20 meters.
3	A consistent decrease in depth from around –20 cm at 0 meters to about –40 cm at 20 meters.
4	Fairly constant depth with minor fluctuations, starting at approximately –25 cm at 0 meters and ending at a similar depth at 20 meters.
5	The depth begins at –25 cm, increases slightly to –20 cm at 5 meters, and then remains constant, ending at approximately –20 cm at 20 meters.
6	Starts at about –25 cm at 0 meters, increases slightly at 5 meters, decreases back to around –25 cm at 10 meters, and remains relatively constant until 20 meters
7	Begins at about –25 cm at 0 meters and maintains a relatively constant depth with slight fluctuations, ending at around –25 cm at 20 meters.
8	The depth starts at about –10 cm at 0 meters and consistently decreases to about –45 cm at 20 meters.
9	Starts at about –25 cm at 0 meters, shows a slight increase, and remains relatively constant, ending at around –25 cm at 20 meters.
10	Starting at about –10 cm at 0 meters and ending at about –35 cm at 20 meters.
11	Exhibits similar patterns of decreasing depth, with Section 10. Starts at about –25 cm at 0 meters, shows a slight increase, then decreases again, ending at approximately –25 cm at 20 meters.
12	Starts at about –20 cm at 0 meters and remains relatively constant with slight fluctuations, ending at around –20 cm at 20 meters

***Remark: The starting point at 0 meters is designated as point A.

Table 2.
The depth variation of the clay layer at each cross-section.

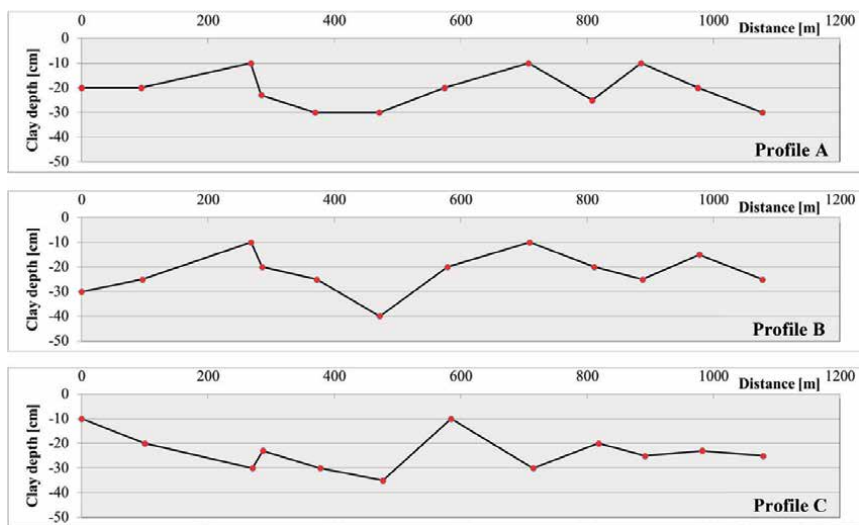


Figure 5.
Profiles of clay layer along the coastline.

The variations in depth could indicate differences in sediment deposition or erosion processes along the coastline.

4.2.1 Profile A

The clay depth along the studied beach area varies significantly, ranging from approximately -10 to -40 cm. Initially, at the starting point of the measurement line (0 meters), the clay depth is around -20 cm. As the measurement progresses, there is a slight decrease in depth, reaching around -10 cm between 200 and 400 meters. However, beyond 400 meters, the depth begins to increase steadily, peaking at about -30 cm at 600 meters. From 600 to 1000 meters, the depth fluctuates slightly between -20 and -40 cm, indicating a relatively consistent pattern of sedimentation along this stretch of the coastline. This variation in clay depth provides valuable insights into the sedimentary processes and environmental dynamics of the coastal area under study.

4.2.2 Profile B

The clay depth fluctuates between approximately -20 and -40 cm, suggesting varying sedimentation patterns along the coastline. At the beginning of the measurement line (0 meters), the clay depth starts relatively deep, around -30 cm, indicating significant sediment accumulation. As the measurement progresses, there's a slight increase in depth to around -20 cm at 200 meters, followed by a decrease to approximately -35 cm at 400 meters, possibly reflecting changes in sediment deposition and erosion dynamics. Subsequently, there's a steady increase in depth to about -20 cm at 600 meters, suggesting renewed sedimentation processes. However, this trend is interrupted by a decrease to approximately -40 cm at 800 meters before showing a slight fluctuation, eventually stabilizing around -30 cm at 1000 meters. This complex pattern of clay depth variations underscores the dynamic nature of coastal sedimentation processes and highlights the importance of detailed spatial analysis in understanding such phenomena.

4.2.3 Profile C

The clay depth along Profile C exhibits a considerable range, spanning from approximately -10 to -45 cm, indicating diverse sedimentation patterns along the coastline. Initially, at the starting point of the measurement line (0 meters), the clay depth is relatively shallow, around -10 cm, suggesting minimal sediment accumulation. However, as the measurement progresses, there's a steady decrease in depth, reaching approximately -40 cm by 200 meters, implying increased sediment deposition. Subsequently, there's a slight increase in depth to about -30 cm at 400 meters, possibly indicating localized sedimentary dynamics. This is followed by another decrease and subsequent increase, resulting in the depth fluctuating between -20 and -40 cm until 1000 meters, suggesting a complex interplay of sedimentation and erosion processes along the coastline. This variability underscores the dynamic nature of coastal environments and emphasizes the importance of detailed spatial analysis for comprehensive understanding and management of coastal ecosystems.

Profiles A, B, and C along the studied beach area reveal significant variations in clay depth, ranging from approximately -10 to -45 cm, indicating diverse sedimentation patterns. Profile A begins with a depth of around -20 cm at 0 meters, decreasing slightly to -10 cm between 200 and 400 meters before steadily increasing

to -30 cm at 600 meters. The depth fluctuates between -20 and -40 cm from 600 to 1000 meters, suggesting consistent sedimentation. Profile B starts deeper at -30 cm, fluctuating between -20 and -40 cm, with notable increases and decreases along the measurement line. Profile C spans from -10 to -45 cm, with depths decreasing steadily from -10 cm at 0 meters to approximately -40 cm at 200 meters, followed by fluctuations between -20 and -40 cm until 1000 meters. These variations underscore the dynamic nature of coastal sedimentation processes, highlighting the need for detailed spatial analysis for comprehensive understanding of the clay sedimentation at the study area.

4.3 Spatial interpolation surface

Spatial interpolation techniques, including Inverse Distance Weighting (IDW), Spline, Natural Neighbor, and Kriging [39], are invaluable tools in estimating the depth of the clay layer across a geographical area. In the context of clay layer depth estimation, spatial interpolation serves as a crucial method for generating continuous surfaces from discrete measurement points, providing insights into the spatial distribution and variability of clay deposits. By applying these interpolation methods, we can extrapolate clay depth values to unmeasured locations, facilitating a comprehensive understanding of sedimentary processes, geological characteristics, and environmental dynamics along the coastline. This comparative analysis of interpolation techniques allows us to identify the most suitable approach for accurately representing the clay layer depth, thereby aiding in informed decision-making for coastal management. The data presented in **Figures 3** and **4** were used as input in the interpolations.

Figure 6(a) illustrates that the clay layer depth exhibits spatial variability across the mapped area. The depth of the clay layer is represented by different color gradients, ranging from dark brown (indicating the deepest clay layers) to light yellow (indicating shallower clay layers). The deepest accumulation observed near row 6, ranging from -40 to -37 cm, suggesting localized clay deposition or geological features. Conversely, shallower depths are found near the northern and southern edges, ranging from -13 to -10 cm. The transition from deeper to shallower layers occurs gradually, with intermediate depths dominating the midregions, reflecting the gradual change in clay depth. IDW interpolation emphasizes this gradual transition, presenting a smooth and continuous surface that captures the spatial distribution of clay depth based on sampled points, with row 6 displaying the deepest value indicative of a distinct geological feature. Other points, such as 1, 2, and 12, exhibit shallower depths, highlighting geological variability or differences in depositional environments. It is evident that IDW generates bull's-eye patterns around the measured points [40].

Figure 6(b) depicts the results of a Natural Neighbor interpolation of clay layer depth along the coastline, with depth measurements taken at 12 points marked on the map. The deepest clay layers, ranging from -40 to -37 cm, are concentrated around row 6 as in **Figure 6(a)**, as indicated by the dark brown color. This suggests that the clay layer in this region is significantly thicker compared to other areas. Adjacent to this zone, slightly shallower depths are observed, represented by a medium brown shade extending toward points 5 and 7. This gradation implies a gradual thinning of the clay layer as one moves away from the central region of the study area. Moving further from the central zone at row 6, the clay depth continues to decrease, indicated by the lighter brown and yellow shades. For instance, near rows 2 and 7, the depth

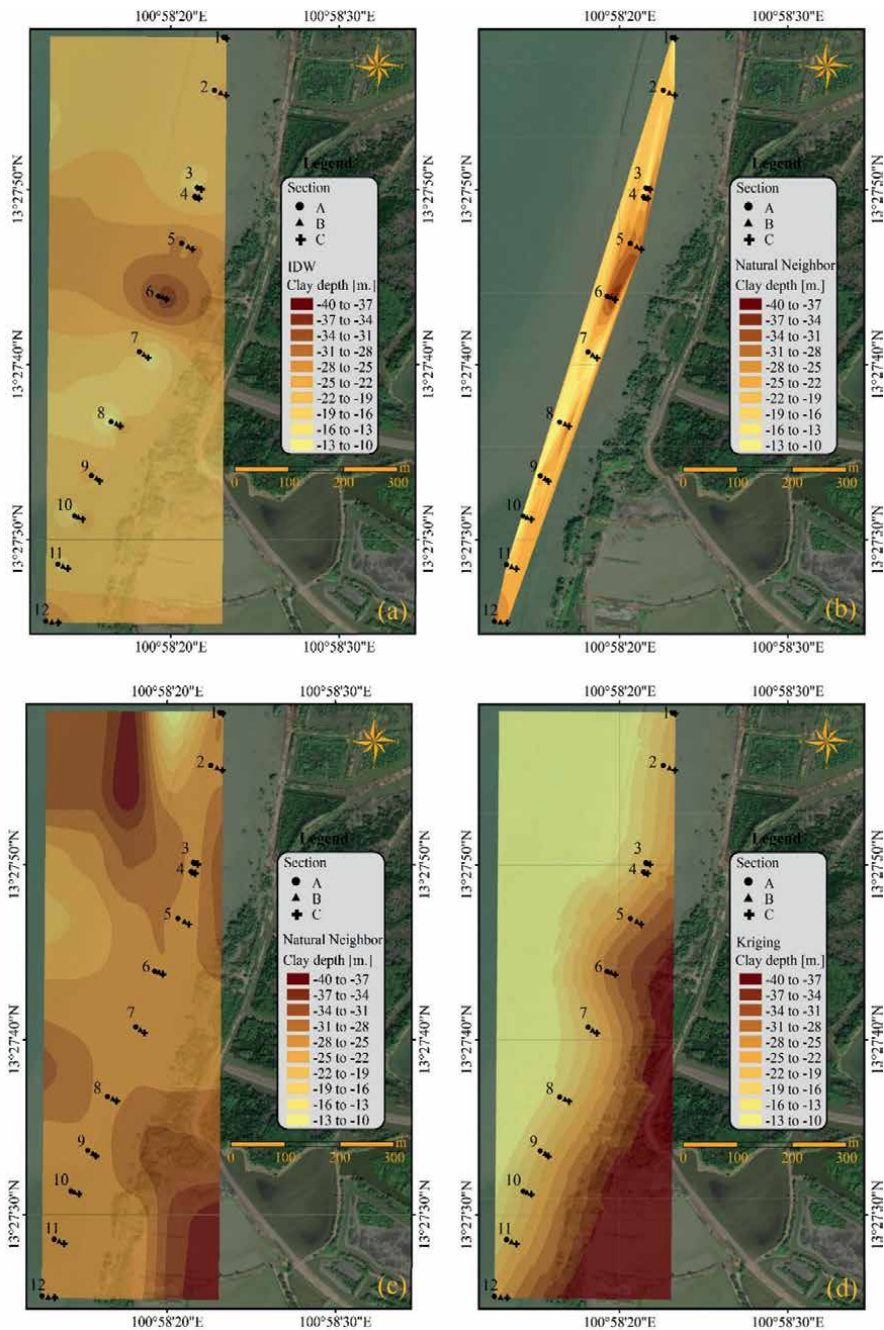


Figure 6.
Depth of clay layer derived from different spatial interpolation techniques (a) IDW, (b) Natural Neighbor, (c) Spline, and (d) Ordinary Kriging.

ranges from -16 to -13 cm and -28 to -25 cm, respectively. This pattern continues with further shallowing, with depths of -22 to -19 cm near rows 9 and 10, and even shallower depths (-16 to -13 cm and -13 to -10 cm) near rows 11 and 12 at the southern end of the section. The interpolation suggests a clear spatial trend in the clay

layer depth, with the thickest accumulation around the central part of the study area at row 6, and gradually decreasing toward both the northern and southern ends. The method's use of Natural Neighbor interpolation ensures a smooth and continuous representation of clay layer depths, making it a reliable tool for such spatial analyses. The significance of Natural Neighbor spatial interpolation lies in the fact that the boundary of the interpolation surface does not extend beyond the data points (the feature boundary is preserved). Consequently, the interpolated surface in **Figure 6(b)** does not exhibit a rectangular shape like the other interpolation surfaces. Furthermore, the interpolated Natural Neighbor values consistently fall within the range defined by the highest and lowest values of the data points, ensuring that they never exceed the maximum or dip below the minimum measured values [24].

Figure 6(c) illustrates the results of a Spline interpolation of clay layer depth along the coastline. The Spline interpolation technique creates a smooth surface that passes through the measured points. The figure shows a pronounced variation in clay layer depths, with the deepest zones concentrated in the upper left and lower right corners of the interpolated surface, while the shallowest zone is observed at the north of the study area. Additionally, the clay layer depth is constant at every measured point (rows 1 to 12). This result reveals that the Spline interpolation technique is not appropriate for this type of geological data. Spline interpolation tends to create overly smooth surfaces that may not accurately reflect the actual variations and discontinuities present in the subsurface clay layers. This smoothing effect can lead to unrealistic representations of depth, as it forces the interpolated surface to pass through all measured points, potentially exaggerating or underestimating the actual clay thickness in some areas. The Spline interpolation appears to generate clay layer depth surface that does not align with the expected geological formations based on field observations. For example, the abrupt changes in depth at the upper left and lower right corners of the interpolated surface might not be as pronounced in reality, and the smooth transitions between different depth zones may overlook significant geological features. Therefore, while Spline interpolation can be useful for certain types of spatial data, it is not suitable for accurately representing the complex and variable nature of clay layer depths in this context [41].

Figure 6(d) presents the results of Ordinary Kriging interpolation for clay layer depth along a coastline, with depth measurements taken at 36 points. Ordinary Kriging is a geostatistical method that provides an optimal interpolation by considering both the spatial autocorrelation of the data and the inherent variability in the measurements. The Kriging interpolation reveals a clear spatial trend where the clay layer depth increases as one moves further away from the coastline. This trend is evident from the color gradation on the map. Near the coastline, along Profile A, the clay depth is relatively shallow, indicated by the light yellow and light brown colors, representing depths between -19 and -16 cm. As we move inland, the clay layer depth gradually increases. Profiles B and C show moderate depths, with the color transitioning to medium brown shades, representing depths from -22 to -19 cm and -25 to -22 cm. The deepest regions are found further inland, where the dark brown and reddish-brown colors indicate depths ranging from -34 to -31 meters and -40 to -37 meters. This pattern clearly aligns with the geological expectation that the clay layer depth increases as the distance from the beach increases.

In summary, the interpolation surfaces depicted in **Figure 6** effectively represent the variations in clay layer depth within the study area. These surfaces provide clear interpretations of the clay layer depth information generated by different spatial

interpolation techniques (**Figure 6(a)-(d)**). However, these surfaces show different characteristic of the surface within the same study area. Therefore, further investigation into the accuracy of each technique is necessary to determine the most suitable interpolation method for representing clay layer depth in this study.

4.4 Validation of the results

To evaluate the efficacy of spatial interpolations, cross-validation was employed to calculate the root mean square error (RMSE) for each technique. RMSE is a metric used to assess the accuracy of a predictive model or an interpolation technique by quantifying the difference between predicted values and actual observed values. RMSE provides a measure of the average magnitude of the errors between predicted values and actual observations. A lower RMSE indicates that the model or interpolation technique is more accurate, as it means the predicted values are closer to the observed values on average. RMSE is a valuable metric for evaluating predictive accuracy, providing a quantitative measure of how well-predicted values match observed values. It used to assess the reliability and effectiveness of models or interpolation techniques in representing and predicting real-world phenomena.

Root mean square error (RMSE) is often used in conjunction with other metrics and validation techniques to assess the overall performance of a model or interpolation method. It provides a single numerical value to summarize the accuracy but should be considered alongside other factors like bias, precision, and visual inspection of model predictions. The interpretation of RMSE may vary depending on the specific application and domain. What constitutes an acceptable RMSE can depend on the field of study, the precision requirements of the analysis, and the consequences of prediction errors.

Generally, error assessments for deterministic interpolation methods, such as IDW, Natural Neighbor, and Spline, pose challenges within ArcMap software, particularly with Spline interpolation where the surface may pass through observation points. However, the RMSE of IDW can be determined using the Geostatistical Analyst tool. Hence, in this study the assessment of spatial interpolations focused solely on IDW and Ordinary Kriging. The RMSE values obtained were 8.241 cm for IDW and 7.478 cm for Ordinary Kriging. Consequently, it can be inferred that Ordinary Kriging offers a more precise representation of clay layer depth compared to other spatial interpolation techniques. This finding is consistent with those of previous studies demonstrating that this spatial interpolation technique performs well in surficial coastal sediment, elevation, and gravity modeling [42, 43].

5. Conclusion

Spatial interpolation techniques offer several advantages over conventional techniques such as profiles and cross-sections for representing clay layer depth along coastlines. First, spatial interpolation provides a continuous surface representation of clay layer depth, allowing for a more comprehensive understanding of spatial variability compared to discrete point measurements obtained from profiles or cross-sections. This continuous representation enables better visualization and analysis of clay layer distribution patterns, facilitating informed decision-making in coastal management and planning. Additionally, spatial interpolation techniques can extrapolate clay layer depth values to unmeasured locations, providing a more complete

picture of the coastal environment. Such continuous models enhance visualization, facilitate analysis, and support informed decision-making in coastal management and planning. Ordinary Kriging, in particular, proved successful in modeling the variation in clay layer depth, highlighting the trend of increasing depth with distance from the shoreline. This method accurately captures the spatial structure of the clay layer, reflecting subsurface conditions realistically and reliably. Unlike other methods, Kriging considers the spatial correlation between data points, providing a nuanced and accurate representation of subsurface conditions. Overall, spatial interpolation techniques, especially Ordinary Kriging, present an efficient and effective approach to studying and managing coastal ecosystems, ensuring a better understanding of the dynamic coastal sedimentation processes.

The appropriateness of using Ordinary Kriging for this interpolation is underscored by its ability to capture the spatial structure of the clay layer depth accurately. Unlike other interpolation methods, Kriging accounts for the spatial correlation between data points, resulting in a more realistic and reliable representation of the subsurface conditions. This technique effectively reflects the gradual deepening of the clay layer as one moves away from the coast, providing insights that are consistent with field observations. This method is particularly suitable for this type of geological data as it provides a nuanced and accurate representation of the subsurface conditions, making it a valuable tool for geospatial analysis in environmental and engineering studies. Overall, spatial interpolation techniques offer a more efficient and effective approach to representing clay layer depth along coastlines, enhancing our ability to study and manage coastal ecosystems.

In coastal engineering and management, understanding the presence and characteristics of clay layers is crucial. Engineers and planners must consider these factors when designing and implementing coastal protection measures, such as seawalls, revetments, and beach nourishment projects. By accounting for the role of clay layers in coastal dynamics, it becomes possible to develop strategies that enhance coastal resilience while balancing the needs of natural ecosystems and human development. Effective management of clay layers and their interaction with coastal erosion is essential for sustainable coastal development and the preservation of coastal habitats and communities.

Therefore, the selection of the appropriate spatial interpolation technique plays a crucial role for accurately representing clay layer depths. Accurate representation of clay layer depths can guide decisions in coastal environmental management, providing stakeholders with valuable information for sustainable land-use planning and resource management strategies. Understanding clay layer depths from these perspectives enhances our ability to predict soil behavior and effectively address challenges related to soil quality, erosion control, and infrastructure development.

6. Limitations

The limitations of the clay layer depth visualization utilizing spatial interpolation techniques in this study are as follows:

- **Sampling density and coverage:** The study is limited by the number of observation points [36], which might not fully capture the variability in clay layer depth across the entire coastline of Chonburi Province. More extensive sampling could provide a more detailed and accurate spatial representation.

- **Interpolation technique limitations:** While Ordinary Kriging showed better accuracy compared to other methods, it assumes stationarity and isotropy, which might not always hold true for coastal environments. These assumptions can lead to inaccuracies in areas with non-stationary or anisotropic conditions.
- **Environmental and temporal variability:** The study only captures a snapshot in time, and coastal environments are dynamic. Seasonal variations, climatic changes, and human activities can influence sediment deposition and clay layer depth, which were not accounted for in this study.
- **Equipment and measurement errors:** The accuracy of GNSS receivers and the manual measurement of trench depths can introduce errors. Small inaccuracies in data collection can propagate through the interpolation process, affecting the final models.
- **Limited comparison with other regions:** The findings are specific to Chonburi Province, and the applicability of these results to other coastal regions remains untested. Different coastal environments may exhibit different sedimentation patterns and require tailored interpolation methods.

7. Future works

Based on the limitations highlighted in the previous section, the following recommendations are proposed for future work to enhance the reliability of this study:

- **Increasing sampling density:** Future studies should aim to increase the number of observation points to improve the resolution and accuracy of spatial models. High-density sampling could provide better insights into local variations in clay layer depth.
- **Longitudinal studies:** Conducting longitudinal studies that monitor changes in clay layer depth over time would help in understanding the temporal dynamics of sedimentation processes and the impact of environmental changes and human activities.
- **Incorporating additional variables:** Future research could incorporate other relevant variables, such as soil type, vegetation cover, and hydrodynamic factors, to improve the accuracy and robustness of the spatial interpolation models.
- **Advanced interpolation techniques:** Exploring advanced geostatistical methods and machine learning algorithms that can handle non-stationary and anisotropic conditions might provide more accurate and flexible modeling options for coastal sedimentation studies.
- **Comparative studies:** Conducting comparative studies in different coastal regions would help in validating the findings and methodologies. This could also provide insights into the generalizability and adaptability of the interpolation techniques used.

- Integration with coastal management practices: Future work should focus on integrating these spatial interpolation models with practical coastal management strategies. This could involve developing user-friendly tools for policymakers and practitioners to make informed decisions based on the spatial distribution of clay layers.

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Geospatial Management of Customers for Water Companies

Ferim Gashi, Amir Rexha and Adelina Nura Rexha

Abstract

Today, institutions typically manage consumer data through databases presented in tabular or graphical formats. However, these formats often miss a crucial component that is essential in the modern age: the geographic location of the consumer. This information is extremely valuable for managing and improving various processes related to consumers and the services they receive. A powerful opportunity that can bring significant benefits to consumer data management is the integration of Geographic Information Systems (GIS). GIS enables the collection, analysis, and visualization of geographic data in real-time, providing a more advanced and accurate approach to managing information about consumers. For example, water supply companies can leverage GIS to optimize a range of processes closely tied to consumer management and the services provided. The use of GIS can greatly improve how areas affected by drought are identified and analyzed. This helps in planning water supply, ensuring that specific areas have sufficient water during drought periods. Moreover, GIS can streamline the billing process for consumers. Integrating geographic information makes it easier to identify specific consumers and areas, enabling the creation of more accurate and efficient invoices. At the same time, GIS assists in monitoring the water network to detect and locate leaks, improving resource management and reducing water losses. Another key aspect is spatial-based reporting and analysis. With GIS, companies can create reports and analyses based on the geographic locations of consumers, providing a deeper understanding of consumer behavior and demands in different areas.

Keywords: costumers, GIS, location, management, analysis

1. Introduction

Information has become a valuable and often expensive resource in today's society. The rapid rise in the creation and expansion of IS departments within organizations lends credence to the importance that is attached to providing managers with timely and useful information to enable them to better perform their duties through more effective decision making. To make clear the role of information within the operations of organizations, we must define exactly what is meant by the term. Information is data that has been converted, or operationalized, into a meaningful and useful context. Once such a context has been agreed upon, the information is of considerable value to specific organizational members, who use this information to arrive at better

(i.e., more effective or more efficient) decisions [1]. Spatial data form the backbone of many science and engineering investigations and applications. For example, spatial data are fundamental to construction and engineering, social sciences and life sciences, art and visualization, and many more fields. In spatial data, the geometry component captures the concept of shape, presence, movement, and similarity about things in space [2]. Geographical information has two separate components: spatial and thematic. The spatial component contains the position, referred to a given reference system, and it answers the question where. The thematic component answers the question of what and it defines the characteristics of the phenomenon or feature that occurs at the location indicated by the spatial component [3]. Geospatial management of customers for water companies refers to the strategic use of geographic information systems (GIS) and spatial data to enhance the management, service delivery, and operations of water utilities. This approach allows water companies to visualize, analyze, and optimize the distribution and management of water resources to their customer base by mapping essential infrastructure, such as pipelines, meters, and treatment plants, alongside customer locations. By leveraging advanced geospatial technologies, water companies can gain deeper insights into the geography of their service areas, improving both operational efficiency and customer satisfaction.

2. Purpose and methods

The purpose of this work is to highlight the importance of applying GIS (Geographic Information Systems) in consumer data management through the visualization of records. The primary goal is to enhance the speed of information retrieval and support the company in making more informed and effective decisions. In summary, this work aims to demonstrate how GIS can streamline data management, improve decision-making processes, and provide valuable insights for the company.

The methods used for this paper are as follows: Analysis method: This involves the systematic examination of data to identify patterns, trends, and insights. It helps in understanding the relationships between different variables and drawing meaningful conclusions [4, 5]. To achieve and facilitate the analysis and enable efficient distribution, demand forecasting, customer service optimization, and resource management, methods such as Geospatial Data Analysis have been used [6]. Through this, the spatial distribution of consumers around key infrastructure such as treatment plants, reservoirs, and pipelines has been analyzed. Additionally, through Clustering and Hotspot Analysis, we have identified areas with unusual water usage patterns and identified areas with high customer density that may require more water supply or service improvements [7, 8]. Meanwhile, by analyzing the pipe network using the Voronoi method, we have assessed the water availability within the respective service areas based on water consumption over specific periods by consumers [9]. We have also analyzed water usage patterns (e.g., high, medium, and low) through segmentation analysis. Comparison method: This method is used to compare different datasets, approaches, or scenarios to evaluate their effectiveness or identify the best solution [10, 11]. The application of this method has been carried out in cases of comparisons for active and passive consumers (**Figure 1**), as well as domestic and non-domestic consumers (**Figure 2**). It has also been applied in the comparison of the age of water meters (**Figure 3**) and consumer consumption within the context of DMA-zones for



Figure 1.
Active and passive customer.

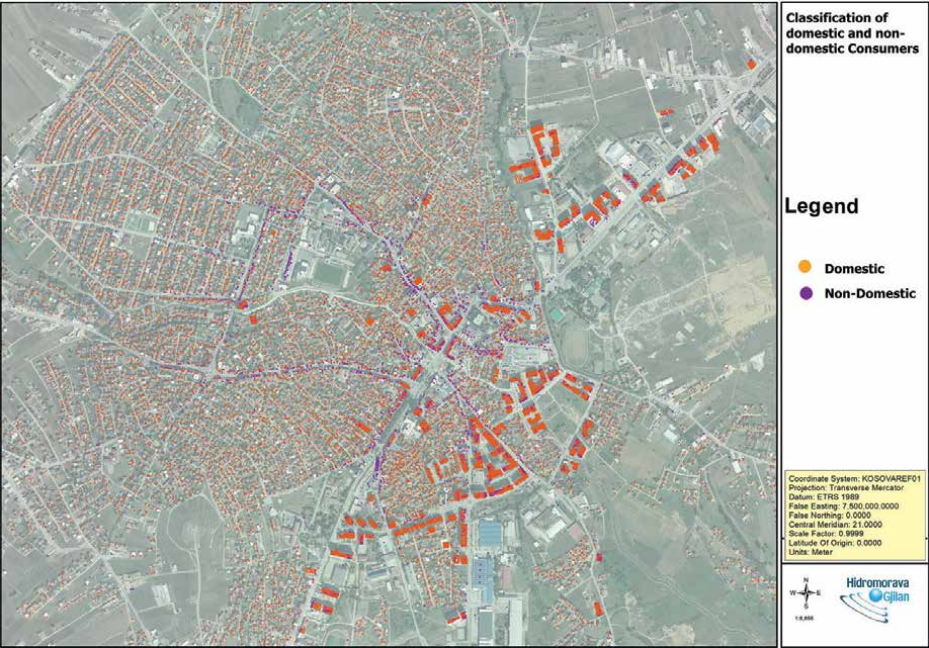


Figure 2.
Classification of customers.



Figure 3.
Lifespan of water meters.

the years 2018 and 2020 (**Figures 4 and 5**). In water utility management, comparative methods assist in evaluating infrastructure performance, consumer behavior, and resource allocation [12]. Cartographic method: This method focuses on the creation and interpretation of maps. It is essential for visualizing spatial data and understanding geographic patterns, which is a key aspect of GIS applications [13, 14]. During the development of this work, we used several cartographic methods, such as Mapping Consumer Distribution, which helped us map the locations of consumers according to different categories. Additionally, through the cartographic method, Geospatial Analysis of Water Consumption was performed, analyzing areas with higher demand for water over different time periods [15]. The application of the cartographic method is quite beneficial as it enables decision-making regarding the identification of issues, and by developing models, we can achieve sustainable planning. Furthermore, spatial modeling and predictive cartographic techniques allow for better decision-making regarding the identification of issues, and by developing models, we can achieve sustainable planning for future water supply needs [16]. Visualization method: This method involves presenting data in graphical or visual formats (e.g., charts, graphs, and maps) to make complex information easier to understand and interpret [17, 18]. It enhances the speed and clarity of decision-making. Throughout the development of this work, several visualization methods were used for specific cases, such as the graph showing the increase in the number of consumers from 2010 to 2024 (**Figure 6**), the graph for water consumption (**Figure 7**), as well as maps for visualizing readings (**Figures 1–5, 8–10**). Through the application of this method, the information has become easier to understand and more accessible, enabling faster analysis and presenting information in a more engaging way for others.

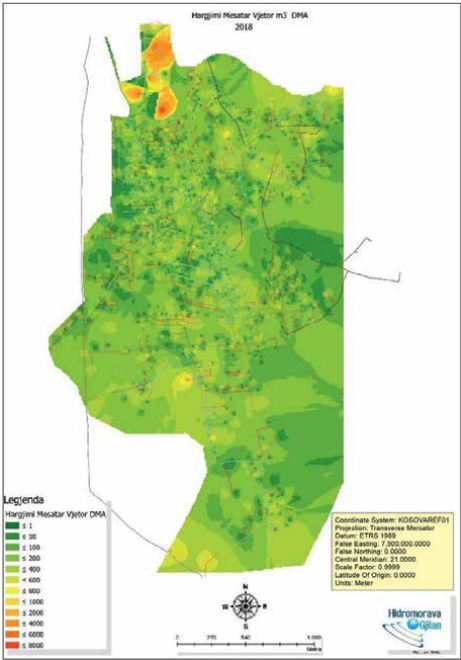


Figure 4.
Average annual consumption 2018.

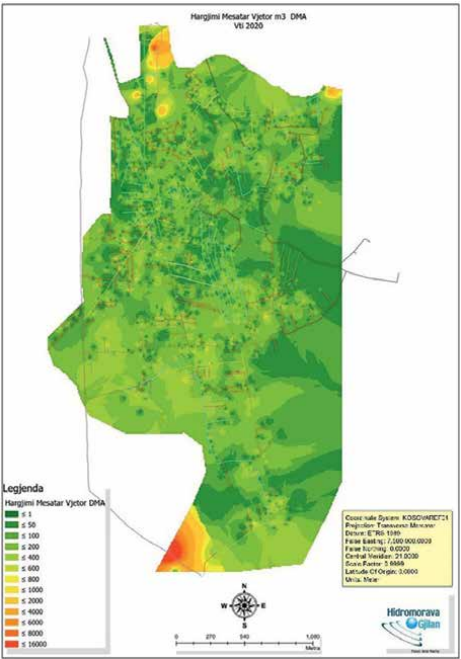


Figure 5.
Average annual consumption 2020.

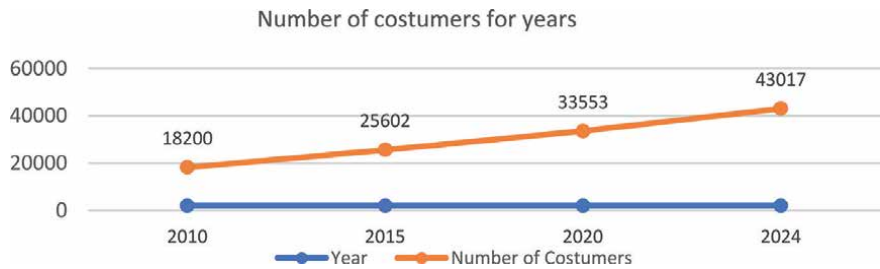


Figure 6.
Number of customers for year.

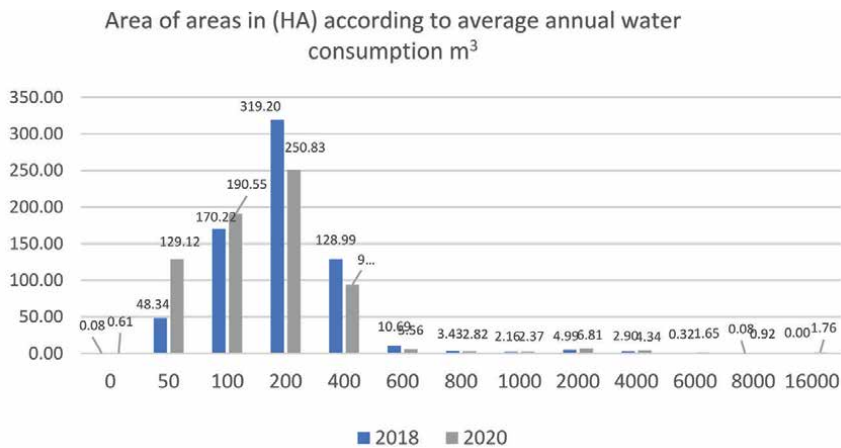


Figure 7.
Area of areas in HA.



Figure 8.
Connecting the billing system to GIS.

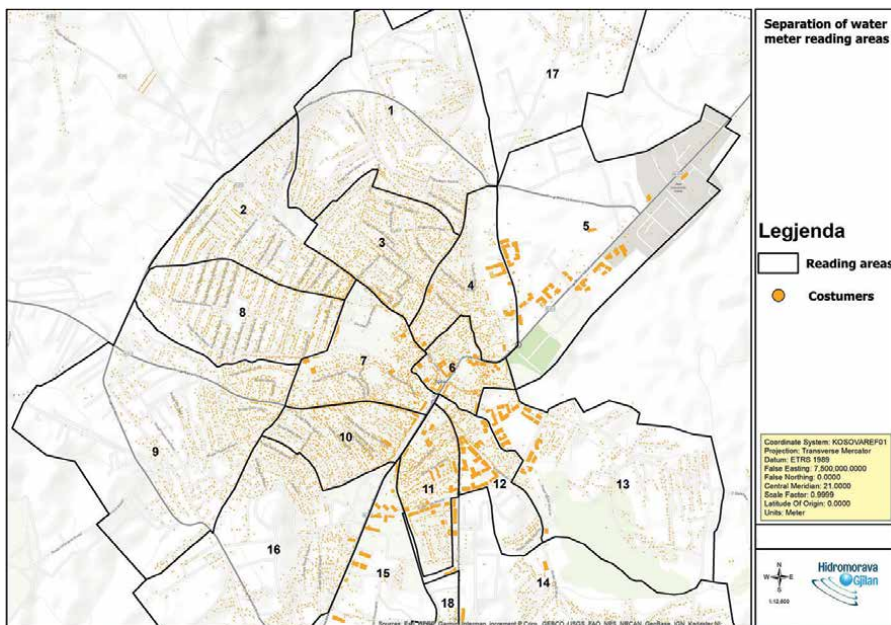


Figure 9.
Separation of water meter reading areas.

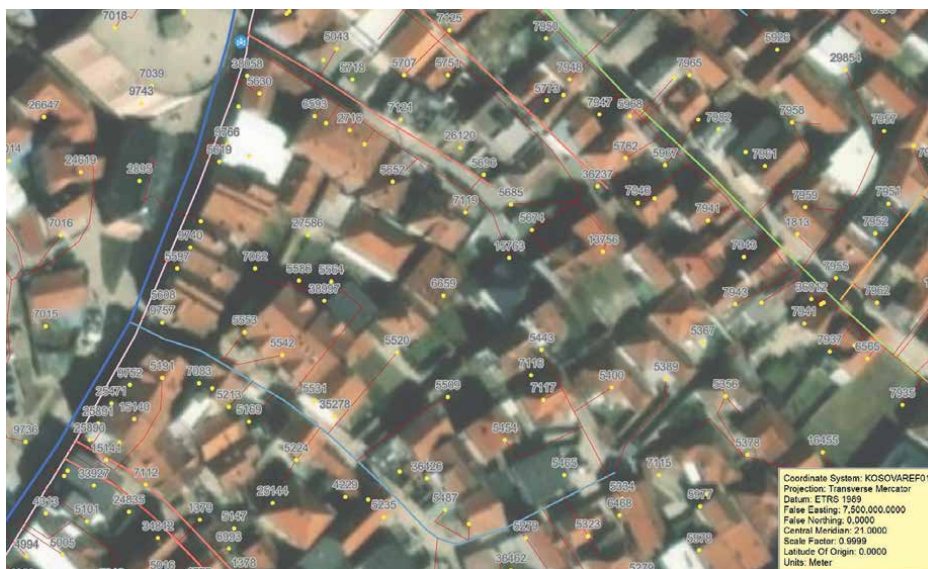


Figure 10.
Localization of consumer connections.

3. Case study

The company in which the customer management model has been developed through the GIS system is the Regional Water Company “Hidromorava” J.S.C., a regional public company engaged in the collection, treatment, and supply of water

for the Anamorava region in the Republic of Kosovo. In the early stages of the company's operation, customer management through databases without the spatial component was easier due to the relatively small number of customers. However, with the expansion of the service area, managing customers has become almost impossible, as it requires determining their spatial location. This process is most efficiently and quickly achieved through the application of GIS, which enables the integration between the graphical and tabular database.

4. Consumer management through GIS

Most geographic information applications are fed with geographical data produced in a different context than the application itself. These geographical data long were paper maps and are now often digital data [19]. Considering that companies engaged in the collection, treatment, and supply of drinking water are generally organized into two main pillars—the financial sector and the technical (operational) sector—the application of Geographic Information Systems (GIS) can be implemented equally in both areas. Through GIS, not only can analyses and visualizations be performed using GIS desktop applications, but continuous and real-time monitoring can also be achieved through WebGIS applications. These applications are available both as paid software packages and as open-source solutions. GIS management functions include customer support, operations, data management, and application development and support [20].

The application of GIS in the financial-commercial sector within water supply companies can be implemented as follows:

1. Connecting the billing system and GIS.
2. Zoning of consumers.
3. Categorization of consumers (domestic/non-domestic).
4. Localization of consumers – active and passive.
5. Localization of consumers in debt, etc.

4.1 Connecting the billing system and GIS

The integration of a billing system with a Geographic Information System (GIS) is a powerful solution for organizations managing geographically distributed services, such as companies responsible for supplying drinking water. By applying GIS, service providers can link each customer account to an exact geographic location, ensuring that bills are sent to the correct address. In the map presented below, an example of the connection between GIS and the billing system is shown.

Additionally, it helps in identifying discrepancies in billing data and enables real-time monitoring of consumption and automatic bill generation. The integration of GIS with billing systems brings significant benefits, increasing accuracy, preventing revenue losses, and optimizing asset management. This integration helps companies make more informed decisions and provide better services to their customers.

4.2 Zoning of consumers

It represents a crucial element in the operation of water supply companies, as it significantly optimizes the work of meter readers. Through zoning, both the surface area of the zone and the number of consumers that need to be visited within a specific period can be precisely determined. By creating zones using the GIS system, a clearer overview of consumers and the number of meter readers (worker) has been achieved. Before zoning, the average number of consumers per meter reader was approximately 2000 (households and businesses). However, after implementing zoning, this number has been nearly halved, with each meter reader now responsible for around 1000 consumers. This zoning can be seen on the map with number (Figure 9).

4.3 Categorization of consumers (domestic/non-domestic)

By categorizing consumers into domestic/non-domestic (businesses, institutions), we can obtain a clear spatial distribution of consumers. Additionally, this categorization allows for the analysis of consumption differences between consumer types, payments, tariffs, and other relevant factors. In the map below, we can see the status of the classification of domestic and non-domestic consumers, which means that non-residential consumers (businesses, institutions) are concentrated along the main roads.

4.4 Localization of consumers: Active and passive

Geographic analysis links locations with the information associated with them and presents the results in the form of a map. Often, this provides such a new perspective that trends and patterns, previously unseen, become apparent [21]. In the map below, we have reflected how visualization of active and passive consumers helps water utility companies analyze the trend of new consumers as well as those who no longer wish to receive water services. It allows them to investigate the causes and reasons why consumers become passive and identify the areas where this trend is increasing.

In addition to its application in the financial sector, GIS is also used in the technical operations of water supply companies as follows:

1. Localization of consumer connections.
2. Determining the age of water meters.
3. Defining consumption zones etc.

4.5 Localization of consumer connections

Customer connection localization refers to the accurate identification, mapping, and management of customer service points within a Geographic Information System (GIS). This process is essential for utility service providers to optimize resource distribution, reduce losses, and enhance customer satisfaction. By utilizing advanced GIS technologies, automation, and real-time data synchronization, service providers can gain a comprehensive view of customer connections, enabling proactive decision-making and more efficient service delivery. GIS provides a visual representation of all connections, meters, and service points, making it easier to monitor infrastructure

and customers. Service providers can track service history for each connection, predict maintenance needs, and detect unauthorized connections in the water supply network by comparing registered connections with physical ones. Additionally, this management approach directly impacts planned maintenance or unexpected service interruptions. The localization of customer connections through GIS and smart technologies is revolutionizing the way utility companies operate.

The map presented above (**Figure 1**) provides us with a model of the connections of consumers and the localization of the status of connections in a water supply company.

4.6 Determining the age of water meters

Monitoring the lifespan of water meters is a crucial element in ensuring accurate reading and efficient billing. With the application of GIS, companies can maintain a detailed database of the exact location of water meters, installation date, expected service life, and maintenance history. This advanced management approach enables proactive planning for meter replacements, reducing inaccuracies in water measurement and preventing technical and commercial losses. Furthermore, GIS allows for the visualization of clusters of aging meters, making it easier to prioritize areas for improvements and maintenance.

4.7 Defining consumption zones

Is of particular importance, as these analyses allow us to identify water consumption trends across different areas and consumer categories over various time periods. By utilizing GIS, companies can monitor water movement patterns, detect seasonal variations, and optimize resource distribution to improve overall efficiency in water supply management.

This diagram presents a structured workflow for integrating billing and GIS data to analyze and visualize water consumption trends over time using interpolation techniques, as shown in **Figure 11**. The Billing Data block represents the database that stores information on water consumption and billing for individual customers, including Customer ID, annual consumption, and water usage trends. This dataset is essential as it provides the actual consumption values needed for spatial analysis.

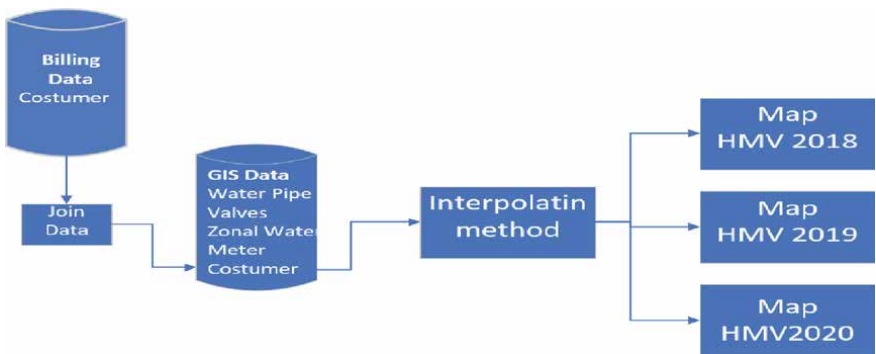


Figure 11.
Data analysis structure.

In the Join Data section, billing data is linked with GIS datasets to establish spatial relationships through the Customer ID. The water consumption data for each customer is associated with their geographical location, enabling spatial analysis.

Within the GIS Data, key spatial layers have been analyzed to understand water distribution and consumption patterns, which include the following: water pipes – the pipeline network distributing water across different zones, valves – infrastructure components controlling water flow and pressure in the pipeline network, zonal water meters – devices measuring water consumption in specific zones rather than for individual customers, customers – geolocated points representing the physical locations of consumers (houses, businesses, institutions, etc.).

After integrating these elements, interpolation was applied. Interpolation is used because water consumption data is typically available only at specific points (customer locations), and the goal is to predict values for unmeasured areas.

Once interpolation was applied, thematic maps were created for different years, illustrating spatial water consumption patterns. These maps allow year-to-year comparisons and help identify trends such as areas with increasing or decreasing water consumption, potential leaks or inefficiencies in the distribution network, and seasonal or long-term trends in water demand.

By integrating GIS and billing data, this method provides a powerful approach for analyzing and efficiently managing water consumption.

Based on the collected data on annual average consumption for each consumer within the DMA zone in Gjilan and its analysis using GIS (**Figures 4** and **5**), we observe that the variability of zones with annual average water consumption over these periods is more pronounced mainly in certain areas: commercial center zones, public and private educational institution zones (kindergartens and primary schools), and industrial zones.

5. Conclusions

In conclusion, the geospatial management of customers for water companies stands as a pivotal development in the modernization of water utilities, offering a comprehensive and innovative approach to managing the complexities of water distribution and service delivery. By harnessing the power of Geographic Information Systems (GIS) and spatial data, water companies are able to visualize, analyze, and manage their infrastructure and customer base with unprecedented precision. This not only enables effective management of critical assets such as pipelines, treatment plants, and water meters but also allows utilities to optimize resource allocation, predict water demand, and improve overall operational efficiency. Through GIS, utilities can better understand and anticipate fluctuations in water demand across different regions, helping them to allocate resources more effectively, improve pressure management, and reduce waste. In addition, the ability to pinpoint areas where issues such as leaks, disruptions, or inefficiencies occur enables faster responses to problems, reducing service downtime and minimizing customer inconvenience. Geospatial management also promotes equity and sustainability in water service delivery. By mapping customer locations and consumption patterns, water companies can ensure a more balanced distribution of water resources, prioritizing underserved or high-demand areas. In sum, the geospatial management of customers for water companies not only enhances the operational effectiveness and responsiveness of utilities but also fosters sustainable practices that contribute to the overall well-being

of communities. It is a cornerstone of the evolving water sector, where technological innovation and data-driven strategies will continue to shape the future of water distribution, management, and conservation for generations to come. Through continued investment in these technologies, water companies can ensure that they are well-equipped to meet the growing challenges of an increasingly complex and interconnected world.

Conflict of interest

The authors declare no conflict of interest.

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Section 3

Soil Erosion Monitoring Using Integrated Technologies

Integrating Remote Sensing, GIS, and AI Technologies in Soil Erosion Studies

Salman A.H. Selmy, Dmitry E. Kucher and Ali R.A. Moursy

Abstract

Soils are one of the most valuable non-renewable natural resources, and conserving them is critical for agricultural development and ecological sustainability because they provide numerous ecosystem services. Soil erosion, a complex process caused by natural forces such as rainfall and wind, poses significant challenges to ecosystems, agriculture, infrastructure, and water quality, necessitating advanced monitoring and modeling techniques. It has become a global issue, threatening ecological systems and food security as a result of climatic changes and human activities. Traditional soil erosion field measurement methods have limitations in spatial and temporal coverage. The integration of new techniques such as remote sensing (RS), geographic information systems (GIS), and artificial intelligence (AI) has revolutionized our approach to understanding and managing soil erosion. RS technologies are widely applicable to soil erosion investigations due to their high efficiency, time savings, and comprehensiveness. In recent years, advancements in RS sensor technology and techniques have resulted in fine spatial-resolution images and increased the accuracy of soil erosion detection for spatial mapping purposes. Satellite imagery provides critical data on land cover and soil properties, whereas digital elevation models (DEMs) provide detailed elevation information required to assess slope and flow accumulation, which are important factors in erosion modeling. GIS enhances soil erosion analysis by integrating multiple spatial datasets, making it easier to identify erosion hot spots and utilizing models like the Revised Universal Soil Loss Equation (RUSLE) to estimate soil loss and guide land management decisions. Furthermore, AI techniques, particularly machine learning (ML) and deep learning (DL), significantly improve the accuracy of erosion predictions by analyzing historical data and extracting relevant features from RS imagery. These techniques use convolutional neural networks (CNNs) and data augmentation, as well as integrating spatial data from GIS to identify erosion hot spots and risk factors. Additionally, innovative methods, including biodegradable materials, hydroseeding, and autonomous vehicles for precision agriculture, are being developed to prevent and mitigate soil erosion effectively. Although specific case studies demonstrate the successful implementation of this integrated framework in a variety of landscapes, ongoing challenges such as data availability and model validation must be addressed. Ultimately, the collaboration of

RS, GIS, and AI not only enhances our understanding of soil erosion but also paves the way for innovative and effective erosion control strategies, underscoring the importance of continued research in this vital area. This chapter addresses the basic concerns related to the application of RS technology in soil erosion: concepts, data acquisition, tools, data types, data quality, data management, data visualization, and challenges to provide an overview of this technology type and its role in soil erosion.

Keywords: soil erosion, geospatial data, remote sensing, GIS, sustainable development, soil conservation, artificial intelligence (AI), machine learning (ML), deep learning (DL), soil loss

1. Introduction

Climate change, population growth, changes in land use and cover, soil erosion, and other issues are raising global concerns, as expressed by Ebi et al. [1]. Soil erosion is a natural process that is triggered by human activities and natural forces and poses a significant threat to the environment, land management, agricultural production, and sustainability [2]. Moreover, soil erosion as a natural phenomenon refers to the natural removal of the soil's surface layer due to natural forces [3]. Furthermore, there are many causes of soil erosion as described by Bao et al. [4], including water erosion (i.e., rainfall and runoff), wind erosion (i.e., strong winds), gravity erosion (i.e., soil movement induced by steep slopes), and ice erosion (i.e., glaciers and frost). These soil erosion types result in the loss of fertile soils, reduced crop yields, pollution sedimentation, increased floods, and climate change impacts [5]. Therefore, a comprehensive understanding of soil erosion monitoring is critical for future decision-making [6]. Given the shortcomings of traditional methods for identifying, analyzing, and interpreting the soil erosion phenomenon, there is an essential need for new, rapid, accurate, eco-friendly, and non-destructive approaches for achieving these tasks.

On the other hand, the remote sensing (RS) technique is a rapid, powerful, non-laborious, cost-effective, and eco-friendly tool for identifying, characterizing, and evaluating soil erosion at different geographical scales [7]. Additionally, several types of remote sensors like satellite platforms (e.g., optical, radar, and LiDAR), unmanned aerial vehicles (UAVs), and airplane-captured images provide spatial and spectral information for the Earth's surface and its phenomena such as land use and land cover (LULC), topography, soil, vegetation, etc. [8]. Furthermore, ground-based sensors, such as field and laboratory spectral instruments (e.g., analytical spectral device 'ASD', Fourier transform infrared 'FTIR', etc.) across various spectral ranges (e.g., visible 'vis'; near-infrared 'NIR'; shortwave infrared 'SWIR'; mid-infrared 'MIR'; etc.), are frequently employed in soil studies for soil fertility and mineralogical estimation [9]. Remotely sensed data can be multispectral (a limited number of broad bands) as demonstrated by Qi et al. [10] or hyperspectral (an extensive number of narrow bands) as illustrated in the research by Abd-Elazem et al. [9], in the form of absorbance, reflectance, or radiance. Land managers, policymakers, stakeholder groups, and researchers can use these datasets to estimate soil erosion levels, categorize different areas (vulnerable and non-vulnerable), and implement successive soil erosion mitigation plans [11].

Geographic information systems (GIS) and RS both employ various statistical and mathematical models to detect, categorize, and map the spatial variability of

soil erosion [12]. Senanayake et al. [13] pointed out that the RS and GIS techniques are important for understanding and monitoring soil erosion. Artificial intelligence (AI) is rapidly expanding in the field of research, with applications including characterizing, estimating, and predicting soil erosion levels [14]. Furthermore, machine learning (ML) and deep learning (DL) models and algorithms are critical for accurately estimating soil erosion using RS and GIS datasets. Popular algorithms for estimating and predicting soil erosion include random forests (RF), conventional neural networks (CNNs), and artificial neural networks (ANNs) [15]. According to Phinzi and Szabó [16], soil erosion studies use multivariate regression models such as partial least square regression (PLSR), multivariate adaptive regression splines (MARS), support vector regression, and others. The AI models and algorithms have varying degrees of accuracy in forecasting and mapping soil erosion; for instance, the RF model had the highest accuracy for predicting and mapping the soil erosion status compared to other ML models. Although RS, GIS, and AI are valuable approaches for advancing soil erosion studies through improved mapping and predictive capabilities, addressing challenges related to data integration, model accuracy, and cost is essential for maximizing their effectiveness in sustainable land management practices. Therefore, future research will focus on overcoming these limitations in order to improve the reliability and applicability of these technologies in a variety of settings.

Thus based on the previous brief introduction, the integration of RS, GIS, and AI is regarded as a highly effective technique for detecting, characterizing, estimating, predicting, monitoring, and mapping soil erosion at various scales. In this chapter, we demonstrate how RS technology integrates with AI, GIS, and other related methods to detect, quantify, monitor, predict, and map soil erosion. We also discuss the significance of these techniques and their applications in soil erosion research.

2. Remote sensing (RS): Importance and applications

The RS technology is considered an effective approach for remotely detecting, characterizing, and monitoring a wide range of physical objects and phenomena using reflectance or emittance spectrum data [17]. Furthermore, RS techniques are invaluable tools for monitoring and assessing environmental changes, including soil erosion, in a variety of settings. Thus, modern technologies, such as RS techniques, can help to identify and map erosion processes in a GIS environment, allowing for more accurate soil loss estimates. Aerial photography, satellite imagery, synthetic aperture radar (SAR), and light detection and ranging (LIDAR) are examples of the RS techniques that can be used to detect, predict, monitor, and map soil erosion. These techniques provide detailed images of the Earth's surface, meteorological data, and distance measurements [18].

The RS technology is crucial for monitoring land resources and tracking environmental changes over time [19]. It assesses the sustainable utilization of environmental resources like soil, forests, water, minerals, etc., as well as natural hazards by identifying areas vulnerable to disasters such as floods, landslides, earthquakes, and fires [20]. Furthermore, the RS techniques are used in urban planning and contribute to the development of infrastructure, cities, and transportation [21]. The RS is crucial in the agriculture and food sectors as it aids in identifying and monitoring crop health, as well as estimating and predicting various parameters related to soil, moisture, and vegetation [22]. In addition to these important aspects, RS is used to study climate

change and its effects, including rising sea levels, soil degradation, drought, changes in vegetation, and glacial retreat [23].

The RS technologies are employed in a variety of applications, including assessing environmental pollutants (chemical, physical, thermal, radiological, biological, etc.), detecting deforestation, and mitigating environmental disasters [24, 25]. Furthermore, these technologies are used for urban mapping, development, and planning, as well as recognizing LULCC at different scales [26]. Additionally, RS technologies are utilized to monitor crop growth, health, and yields, along with assessing and forecasting many aspects of precision agriculture activities, including irrigation, fertilization, and pest control [27, 28]. These RS technologies can also be used to discover and monitor other domains, such as preserving the cultural heritage of ancient cities [29]. Moreover, the RS technologies are considered effective tools for monitoring climatic changes (temperature, ice melting, and rising sea level) and tracking, identifying, and quantifying the availability and quality of the different water resources [30]. Besides these applications, RS techniques can be used on mineral deposit identification, monitoring migration patterns, and habitats in conserving wildlife [31].

3. Applications of remote sensing in agriculture

Remote sensing (RS) in agriculture enhances precision, efficiency, and sustainability by enabling real-time decision-making, optimizing resource use, and reducing environmental impact. As technology advances, its role in agriculture will grow. The RS technology has numerous applications in the agricultural sector and soil research. It delivers precise, timely, and important information at high spatial and spectral resolutions about crops, soils, water, watersheds, desertification, drought, agroforestry, rangelands, erosion, and climatic variations and their effects on the agriculture industry. The RS plays a crucial role in crop production by providing geospatial data on crop types and area estimates. It also helps evaluate yield potential, assess ecosystem health, and manage pests, diseases, and weeds effectively. This is accomplished by analyzing spectral reflectance, modeling, and applying vegetation indices derived from remotely sensed data. It can predict and estimate crop biomass and yield by applying various vegetation indices to the RS data [32, 33]. For instance, vegetation indices such as the normalized difference vegetation index (NDVI) can be used to assess crop health. Additionally, this index, along with others, can be valuable for monitoring crop health and development throughout the different growth stages during phenological studies. This monitoring can provide important insights for managing cultivation, harvesting, and overall crop development [34, 35]. As a result, the information and data generated by RS technologies can be used to inform future crop management decisions, such as fertilizer application [36] and water application [37]. Furthermore, RS techniques can use satellite imagery to estimate, predict, and map crop acreage and types on various geographic scales [38, 39]. **Figure 1** demonstrates the applications of RS in crop monitoring.

Another important application of RS in agriculture is the detection and mapping of LULC changes caused by natural phenomena and human activities [40, 41]. Furthermore, the RS technique is utilized for monitoring vegetation cover [42] under various types of stress, both biotic and abiotic. It enables the early detection of symptoms associated with these stresses on growing plants [43, 44]. RS can be used to study soil systems, including soil characteristics,

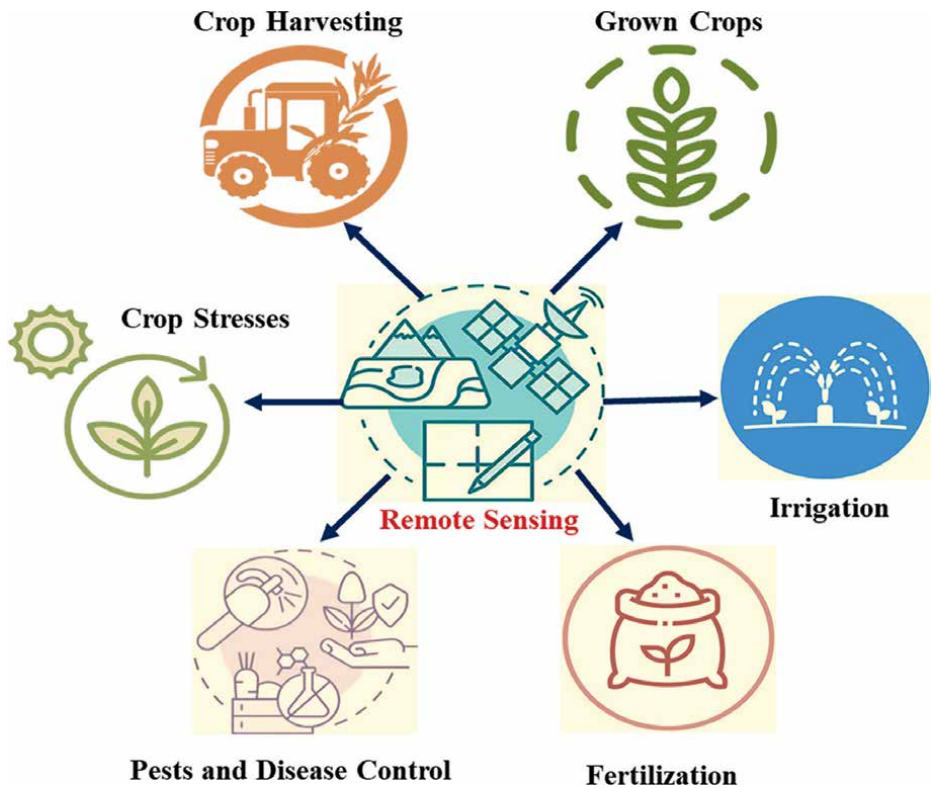


Figure 1.
Remote sensing applications for crop monitoring.

types, spatial variability, degradation, moisture, erosion, fertility, allocation, etc. It was employed to identify, characterize, estimate, and predict various soil parameters, including soil moisture [45], fertility [46], minerals [47], and soil erosion [48]. This approach provides valuable insights that contribute to achieving sustainability in agriculture. Therefore, the data, information, and maps generated using RS technologies can be used to allocate resources, generate a precise database, and make informed decisions. AI algorithms and ML models enhance the analysis of soil erosion data by identifying complex patterns and relationships within high-resolution RS data. They enable predictive modeling that forecasts erosion risks under various scenarios. Additionally, techniques such as explainable AI can improve interpretability by quantifying the influence of individual factors on predictions, leading to more informed land management decisions.

The RS technology has the potential to significantly improve soil erosion detection and mapping in the future. Mapping erosion hot spots will become more precise due to advanced satellite imagery, allowing for accurate identification of vulnerable areas that require immediate conservation efforts. Additionally, quantifying soil erosion rates using RS will provide critical data for developing effective management strategies, enabling researchers to track changes over time and assess the impact of various conservation practices. Furthermore, predictive modeling capabilities will improve, allowing for proactive measures against potential erosion events through the integration of real-time data on environmental factors such as rainfall and land use changes.

4. Soil erosion: Causes, types, and effects

Soil erosion is a natural phenomenon that occurs by displacing or removing a top soil layer (productive part of soil), which has different causes, types, and effects [49]. Water, wind, ice (glaciers), snow, plants, animals, and human activities are all examples of erosive agents that cause soil erosion. Human activities that contribute to soil erosion include agricultural practices (e.g., tillage, monocropping, farming on steep slopes, pesticide and chemical fertilizer use, row cropping, surface irrigation, etc.), deforestation, overgrazing, and road construction. The main erosive agents that cause soil erosion are water (precipitation, flooding, and surface runoff) and wind erosion, which can transport loose soil over long distances [50]. Furthermore, ice erosion occurs in icy regions, where frost and glacier action displace the surface soil layer [51]. Gravity can also cause soil erosion because soil particles are displaced by gravitational forces on steep slopes [25].

There are many types of soil erosion, as illustrated in **Figure 2**. These erosion types encompass water, wind, glacial, thermal, chemical, and saltwater erosion. The two most common types of soil erosion are water erosion and wind erosion. Water erosion takes many forms, including sheet, rill, gully, bank, splash, and tunnel erosion (**Figure 2**). Sheet erosion occurs when thin soil layers are uniformly removed, whereas rill erosion occurs when concentrated flow forms small channels [52]. Splash erosion happens when raindrops hit the soil strongly enough to break apart soil particles, causing them to splash and disperse. Tunnel erosion is a type of water erosion that occurs below ground when water creates hidden channels, transporting soil with its flow. Gully erosion is another type of soil erosion, whereas it occurs in croplands where channels with more depth can be developed [53]. Jarrah et al. [54] discussed another type: wind erosion, in which strong winds transport soil particles from one location to another. Each form or type of soil erosion has diverse impacts on the ecosystem and requires certain conservation practices. For instance, gully erosion and rill erosion differ significantly in their ecological impacts and management challenges. Gully erosion creates large, deep channels that lead to habitat destruction, biodiversity loss, and severe soil degradation, requiring complex and costly management strategies for rehabilitation. In contrast, rill erosion involves smaller channels that can be managed more easily through preventive practices like contour plowing and cover cropping, allowing for timely interventions that can prevent the development of more severe gully erosion.

Soil erosion diminishes the quantity and quality of soil ecosystems and arable land while also decreasing biodiversity at all levels: above, within, and beneath the topsoil. It also leads to environmental disasters, such as clogged waterways, air and water

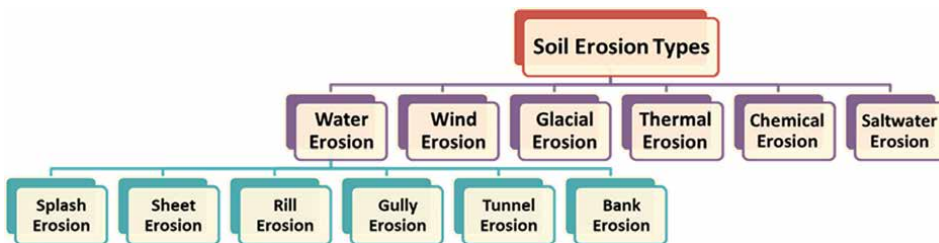


Figure 2.
Types of soil erosion.

pollution, desertification, and the destruction of infrastructure and ecosystems. Soil erosion negatively affects soil productivity, leading to decreased soil fertility, loss of arable land, and reductions in agricultural outputs and crop yields [55]. Furthermore, water pollution is caused by soil erosion, which contaminates water bodies with soil-laden water [56]. Moreover, Rashmi et al. [57] pointed out that soil erosion causes sediment buildup, which disrupts the waterflow. Besides these effects, soil erosion reduces vegetation, carbon sequestration, and relative climatic changes [58]. Therefore, soil erosion has significant implications for food security, land management, and global sustainability [59].

5. The role of remote sensing in soil erosion studies

Understanding the role of RS in detecting and monitoring soil erosion is critical for interpreting the significant spectral bands in remotely sensed data associated with erosion [60]. The relationship between RS and soil erosion is shown in **Figure 3**. The detection of soil erosion relies on various physical parameters related to RS, including electromagnetic radiation (EMR), sensors, and spectral bands [61]. Additionally, the detection of soil erosion relies on the types of platforms and sensors used. Optical, radar, and LIDAR platforms, along with their sensors, are examples of the RS technologies utilized in studying soil erosion [62]. The acquired data from these sensors includes the spectral signatures of the soil surface, which are utilized to calculate various spectral indices. These indices include the NDVI, normalized difference moisture index (NDMI), normalized difference water index (NDWI), modified normalized

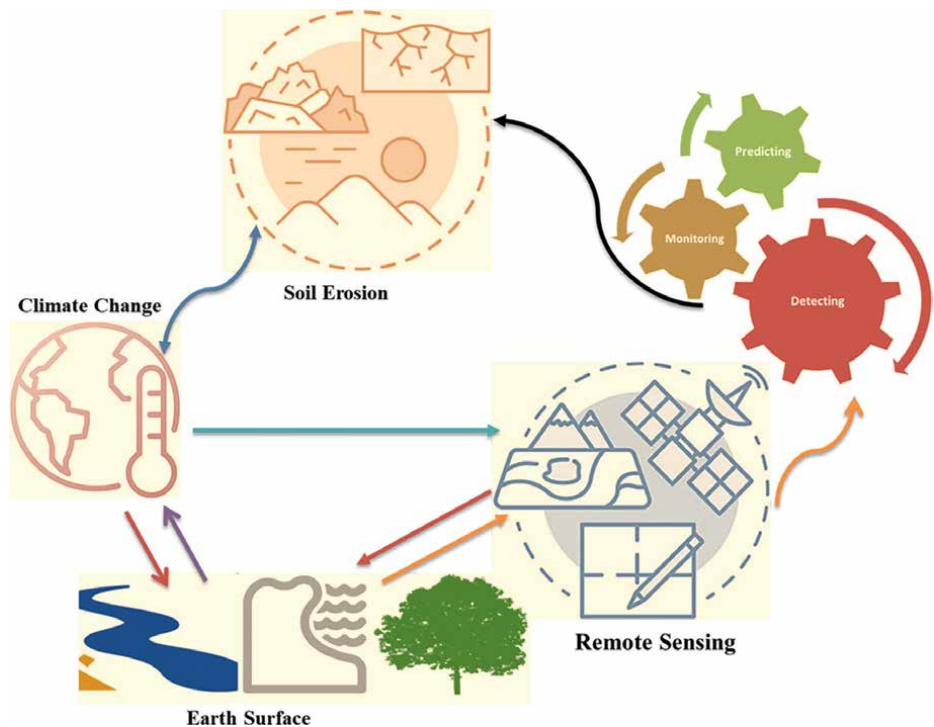


Figure 3.
Relation between RS, climate change, and soil erosion.

difference water index (MNDWI), soil-adjusted vegetation index (SAVI), water ratio index (WRI), and automated water extraction index (AWEI). These indices serve as indicators for soil erosion [63, 64].

The RS technologies can detect and monitor soil erosion patterns and vulnerable areas using aerial and satellite imagery [65]. It can also help to mitigate soil erosion and its effects on soil quality and health [66]. Furthermore, RS technologies utilizing multispectral and hyperspectral imagery can detect, identify, and characterize soil erosion [67]. These sensors (multispectral and hyperspectral) capture various facets of soil erosion, including LULC, spatial variability in topography, elevation, and slope [68]. Additionally, LiDAR sensing is employed to assess vegetation, surface structure, and terrain elevation [69]. Furthermore, the radar imager can penetrate cloud cover and provide comprehensive meteorological information, indicating regions impacted by these climatic conditions and their relationship to soil erosion [70]. Integration of various RS techniques can help with the quantitative estimation of soil erosion transport trajectories, river network density, and terrain slope [71]. Further, combining RS-acquired data with high-quality and resolution spatiotemporal data produces very accurate outputs [72]. When using remotely sensed data to identify soil erosion, some factors can be extracted, such as soil erosion spectral feature recognition, gully erosion, and vegetation coverage estimation [73]. Various platforms, including different sensors, collect a range of spectral data types, such as time-series data [74]. These time-series data are utilized for analyzing the soil erosion dynamics, soil erosion rates, transportation sediments, and the different patterns of deposition. Furthermore, these datasets can be employed to estimate or predict soil erosion dynamics over time [75]. Overall, the integration of ground measurements, RS techniques, and statistical or mathematical models constitutes an efficacious approach for gaining significant insights about soil erosion status. **Figure 3** shows the relation between RS, climate change, and soil erosion.

6. Integration of RS, GIS, and AI for soil erosion research

The combination of AI, RS, and GIS can enhance effective and timely decision-making. Furthermore, it provides valuable opportunities for the monitoring and management of natural resources across varying temporal, spectral, and spatial resolutions. This integration is critical in detecting, characterizing, monitoring, and predicting soil erosion. The RS technologies, which include platforms like satellites, aircraft, drones, and robotics, along with various attached sensors such as multispectral and hyperspectral imagers, instruments, and cameras, are invaluable for gathering detailed spectral, spatial, and temporal information about objects and phenomena on the Earth's surface. As illustrated in **Figure 4**, this integration can be utilized to examine Earth's surface objects and phenomena, including vegetation cover [42], LULC changes [1], soil erosion [13], and more. The GIS technique is responsible for receiving, analyzing, visualizing, and storing spatial data and related attribute data, such as soil erosion datasets. In addition, the GIS technique can effectively map the spatial variation patterns of soil erosion and identify areas at risk. It also allows for the assessment of the spatial variability of factors influencing soil erosion, such as vegetation cover, land use, soil characteristics, runoff, and slope. [76]. Furthermore, integrating RS and GIS is advantageous for monitoring and predicting future soil erosion patterns. As a result, integrating RS and GIS is extremely useful for detecting, characterizing, mapping, monitoring, and predicting soil erosion [77].

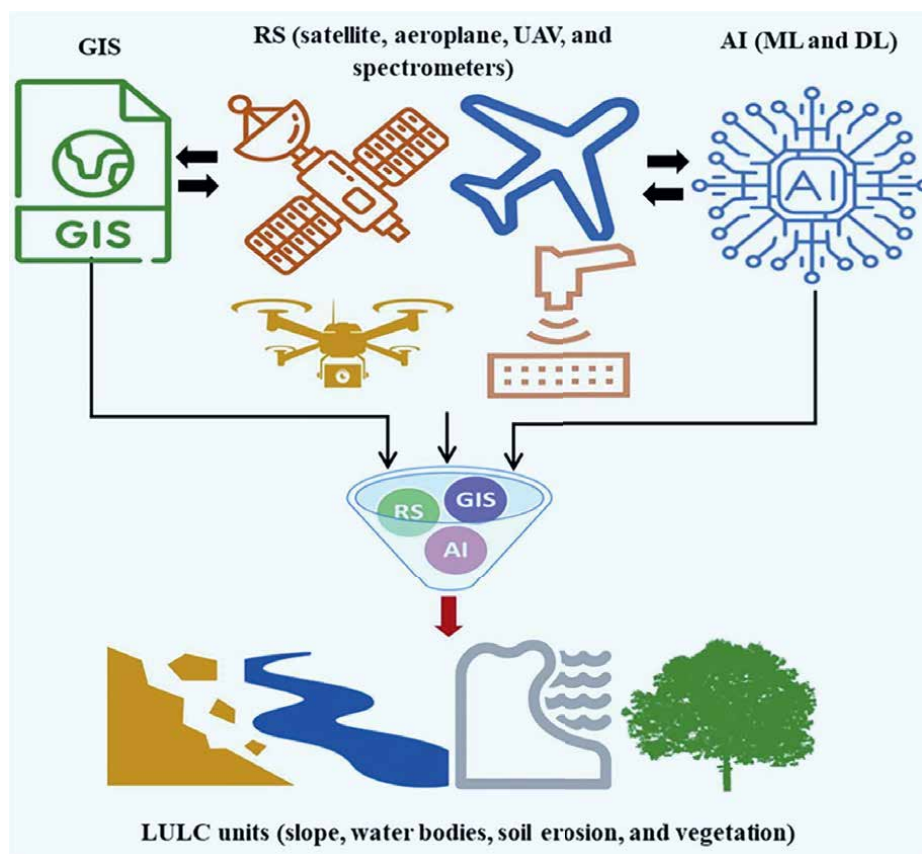


Figure 4.
Integration of RS, GIS, and AI for detecting various LULC units, including soil erosion.

Techniques in AI, including ML and DL, are being utilized to enhance the detection, characterization, prediction, and understanding of soil erosion [78]. The AI algorithms can process and classify hyperspectral and multispectral satellite images to identify various LULC units, including vegetation cover, bare soils, water bodies, urban areas, and others [79]. AI approaches can also be used to detect LULCC by analyzing historical satellite images (time series) for quantifying soil erosion. Furthermore, AI is employed to create prediction models for quantifying soil erosion as well as other land parameters such as vegetation, slope, moisture, and soil properties. In addition to these applications, AI is used to select soil erosion features and parameters using various spectral indices derived from data obtained by satellites and other platforms or instruments [80].

7. Advantages and disadvantages of incorporating RS and AI in soil erosion research

There are benefits and challenges to integrating RS and AI in soil erosion detection, as well as using each separately. The merits can include the importance of integration and its applications, whereas the drawbacks can be the challenges and

limitations of these techniques. The benefits of RS and AI in detecting and modeling soil erosion include their ability to cover large-scale areas and provide detailed spatial information, which is beneficial for mapping and monitoring extensive regions [7]. The advanced techniques, including RS and AI, are eco-friendly and non-destructive to ecosystems. They also eliminate the need for physical efforts like traditional ground surveying and sampling, which can harm ecosystems [81]. The RS technology provides spatiotemporal information that can be employed to monitor soil erosion over time by repeating measurements with historical RS data and using AI for calculations and modeling [82]. Both hyperspectral and multispectral RS data can capture multiple soil parameters and be used to calculate soil erosion [9]. The utilization of RS and AI technologies facilitates rapid data collection, processing, modeling, and detection of soil erosion, owing to the efficiency of these techniques [12].

Every technology has advantages and disadvantages, including the RS and AI techniques. One significant limitation of these techniques is the lack of available data, as building training and calibrating models in the AI environment requires a substantial amount of soil erosion data. A high-quality training dataset is mandatory to develop an accurate model, as well as data homogeneity and uniformity for detecting soil erosion [83]. Over the past three decades, researchers have tried to build a global model for estimating and predicting soil erosion, but this remains a challenge. This challenge arises from the necessity for the model to be accurate, robust, interpretable, and to encompass all soil erosion variables worldwide [61]. Another drawback is the heterogeneity of the collected remotely sensed data, which includes data on climate, LULC, vegetation, soil minerals, etc. This diversity in datasets (heterogeneity) makes building an AI model complex, challenging, and potentially inaccurate [49]. Therefore, extracting spectral information relevant to soil erosion solely through the unmixing process is extremely difficult. The varied resolutions and scales of data obtained from different RS sources present significant challenges in mapping local or regional areas using both coarse and fine remotely sensed data [84]. Additionally, the validation process of RS data requires precise validation points that can be tested using the AI model. However, these ground validations for soil erosion are often labor-intensive, costly, time-consuming, and frequently inaccurate. Overall, the integration of RS and AI approaches necessitates careful handling, particularly when dealing with data from various sources [9].

The ML models can effectively detect, analyze, map, and predict soil erosion by integrating the RS data with ground data. Gradient boosting, support vector machines (SVM), and CNN are examples of ML models that have been utilized to predict erosion susceptibility by processing a variety of inputs such as slope, vegetation indices, and rainfall. In studies, gradient boosting has shown high predictive power for soil erosion mapping, while CNNs have improved accuracy in identifying erosion intensity using high-resolution UAV imagery, demonstrating the potential of ML in enhancing soil management practices.

8. Challenges and future directions

Several challenges exist in integrating the three components of soil erosion detection: RS, GIS, and AI. One of the challenges in data integration is the need for various data processing and transformations that require time and effort [85]. Another challenge is data scale and resolution, which differ depending on area scale (local, regional, or global) and spatial resolution accuracy (fine or coarse) [86]. The most

significant challenge, in our opinion, is the difficulty of developing and improving soil erosion management techniques through interdisciplinary collaboration among researchers, policymakers, authorities, and organizations. Therefore, in the future, more efforts are necessary to establish a standardized protocol or approach for the integration of RS, GIS, and AI in soil erosion modeling. This integration standardization must be validated with highly accurate estimation models to be trusted and guaranteed for use in soil erosion modeling.

Data fusion and integration must be improved for AI future directions, particularly when RS data is acquired from multiple sources (e.g., satellite images, airplane images, drones, and filled-laboratory ground-based spectrometers), as detailed by Pott et al. [87]. A more promising future for AI lies in integrating hyperspectral and multispectral environmental data to develop powerful models and a thorough understanding for estimating LULC changes, soil properties, and soil erosion. In the future, advanced AI algorithms could be integrated with high-resolution remotely sensed data to estimate soil erosion. Among these AI algorithms, multivariate regressions and ML algorithms are two AI methods that can be improved to predict soil erosion more accurately. Furthermore, the convolutional neural network (CNN) is an AI algorithm that can handle complex datasets of RS and ground validation observations, enabling precise spatial and temporal detection of soil erosion [88]. Moreover, transferring AI learning has the potential to improve RS and AI techniques for detecting soil erosion and developing models for estimating erosion in different regions and geographic scales.

High-resolution sensors and data from advanced RS technologies can assist in detecting and mapping soil erosion at high spatial and temporal resolutions. Further, the development of small satellites, nano-satellites, and constellations is useful for frequent monitoring of the land surface as well as soil erosion at smaller scales [89]. The combination of the RS and AI technologies, employing high-resolution data and precise algorithms, will aid in the automatic detection of LULC changes, particularly soil erosion features such as landslides and gullies, as well as the quantitative analysis of their patterns. The most advanced soil spectroscopic technique, which is based on the integration of RS and AI technologies, is the real-time detection approach. The real-time detection approach can be used directly in the field to alert decision-makers to specific risks, allowing for timely action [90]. Pucino et al. [91] discussed how involving scientists and researchers from local communities in these technologies can improve the calibration and training datasets used in the development of AI soil erosion estimation models. Initiating and developing mobile applications for detecting, characterizing, classifying, and mapping spatial and temporal land features can contribute to building the global database [92].

For accurate erosion detection, soil erosion must be included in the ecosystem services evaluation and sustainable land management practices. Besides these important factors, quantifying the soil loss effects on agricultural activities, water availability, quality, and biodiversity can also be included. Furthermore, soil erosion studies using the RS and AI must include additional data layers, such as climate change scenarios and the LULCC, because these changes can affect soil erosion rates. Strategies for mitigating soil loss and erosion can be developed and implemented after accurately identifying the causes and influencing factors [1]. The integration of RS and AI in soil erosion research offers significant advantages over traditional methods, particularly in terms of accuracy, efficiency, and scalability. For instance, ML models such as GBSVM and CNN have demonstrated improvements in predictive accuracy by up to 25.57% compared to conventional models like the RUSLE. These AI-powered

techniques can analyze big datasets derived from high-resolution data-acquisition UAV and satellite images, enabling real-time monitoring and mapping of erosion patterns over vast areas that would otherwise be difficult and time-consuming with traditional field surveys. However, challenges remain, including the need for extensive training datasets and the complexity of model interpretations, which may impede adoption in real-world land management scenarios.

The integration of RS, GIS, and AI in soil erosion studies presents significant advancements; however, it also faces challenges related to data availability and model validation. Reliable data is crucial for effective soil erosion modeling. High-quality RS data, such as fine-resolution satellite images, may not be available to everyone due to accessibility and expense constraints. Furthermore, historical data may not be accessible or sufficiently comprehensive to inform models accurately. The spatial resolution of RS data can affect the accuracy of erosion assessments. Coarse-resolution data may overlook localized erosion hot spots, while fine-resolution data can be expensive and difficult to obtain over large areas. Temporal resolution is also critical; infrequent data collection can miss significant changes in land use or environmental conditions that influence soil erosion. Soil erosion studies often require integrating diverse datasets from various sources, including soil properties, land cover, topography, and climatic conditions. Discrepancies in data formats, scales, and collection methods can complicate integration efforts, leading to potential inaccuracies in modeling outcomes. Soil erosion is influenced by a multitude of factors, including topography, vegetation cover, soil type, and climatic conditions. The complexity of these interactions makes it challenging to develop models that accurately represent real-world conditions. Simplified models may fail to capture critical dynamics, leading to erroneous predictions. Validating models requires extensive field measurements for calibration and testing against observed erosion rates. However, obtaining sufficient ground-truth data can be resource-intensive and time-consuming. In many regions, especially in developing countries, there may be a lack of baseline data for effective model calibration. Models developed for specific regions may not perform well when applied to different geographical areas due to variations in local conditions. This necessitates extensive validation efforts across diverse landscapes to ensure the robustness and applicability of the models. Quantifying the uncertainty associated with model predictions is essential for effective decision-making in soil erosion management. However, assessing uncertainty can be complex due to the interplay of various factors influencing erosion processes and the variability inherent in both input data and model parameters.

9. Conclusion

This chapter presents integrated approaches to soil erosion detection that incorporate RS, GIS, and AI to improve soil erosion monitoring accuracy and efficiency. It highlights advancements in data acquisition, innovative erosion control strategies, and practical applications through case studies while addressing challenges like data availability and model validation. This comprehensive overview underscores the importance of continued research in leveraging technology for sustainable agricultural practices and ecological conservation. The key issues with employing these techniques in soil erosion investigations are data availability and quality, as reliable datasets are often limited, making accurate modeling challenging. Additionally, model validation remains a significant issue, as many existing models struggle to

accurately select optimal erosion parameters and weights during practical applications. Moreover, the integration of diverse data sources can be complex, requiring advanced techniques to effectively combine and analyze the information from RS, GIS, and AI for comprehensive erosion assessments.

Future directions and prospects for using RS, GIS, and AI in soil erosion studies focus on enhancing data integration and predictive modeling. Advances in RS technologies, including multi-platform and high-resolution imagery, will increase the spatial and temporal accuracy of erosion assessments. Furthermore, the advanced GIS techniques would facilitate comprehensive analysis by integrating diverse datasets. Additionally, the developed AI approaches, particularly those based on machine learning and deep learning techniques, are expected to improve erosion prediction models by identifying key parameters that influence soil erosion, allowing for more effective management strategies and real-time monitoring of erosion risks under changing environmental conditions. Therefore, advances in AI algorithms, improved sensor technologies, and innovative data integration methodologies will all have a significant impact on the future of soil erosion research. Enhanced machine learning and deep learning techniques will refine predictive modeling, while higher-resolution remote sensing data will provide more accurate assessments of erosion dynamics. Moreover, integrated frameworks combining RS, GIS, and AI will facilitate comprehensive analyses, enabling more effective management strategies and sustainable land use practices. Integrating RS, GIS, and AI can improve soil conservation practices and land management strategies by identifying erosion hot spots and assessing risks. This approach can guide policymakers in developing effective soil conservation programs and promoting sustainable agricultural development.

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Introduction to Soil Erosion: Scope, Significance, and Framework

Ali Akbar Firoozi and Ali Asghar Firoozi

Abstract

This chapter provides a comprehensive exploration of soil erosion, a critical environmental issue that poses significant challenges to global stability and sustainability. It delves into the causes, mechanisms, and impacts of soil erosion across various ecological and socio-economic contexts. By categorizing erosion into water, wind, and chemical types, the chapter highlights the diverse nature of erosion processes and their profound effects on agricultural productivity, biodiversity, and water management. Integrative strategies for managing soil erosion are discussed, emphasizing the importance of interdisciplinary approaches that combine geotechnical engineering, environmental science, agronomy, and policy-making. This chapter sets the stage for understanding soil erosion not just as an environmental issue but as a multi-dimensional challenge that intersects with global food security, climate stability, and human development. The need for robust policy frameworks, community engagement, and global cooperation is articulated as essential for the effective and sustainable management of soil resources. Through a blend of theoretical insights and practical applications, this chapter aims to equip readers with the knowledge and tools necessary to address soil erosion in a holistic and impactful manner.

Keywords: soil erosion, environmental sustainability, agricultural productivity, interdisciplinary strategies, soil conservation, global cooperation

1. Introduction

Soil erosion represents one of the most significant environmental challenges of our time, manifesting in the displacement of the uppermost layer of soil. This process not only alters the physical landscape but also undermines the ecological and agricultural foundations essential for sustaining human civilizations. The phenomenon of soil erosion is primarily categorized into three types: water, wind, and chemical erosion, each playing a pivotal role in land degradation and the consequent reduction of agricultural productivity across the globe [1, 2].

Water erosion, the most prevalent form, occurs when rainfall or irrigation exceeds the soil's absorption capacity, leading to runoff that sweeps away the fertile top layer. This type of erosion is particularly detrimental in areas with poor vegetation cover or inadequate land management practices. Wind erosion, on the other hand, is more common in arid and semi-arid regions where loose, dry soils are easily lifted and transported by strong winds. Chemical erosion, though less discussed, involves the

removal of soil components through chemical reactions, often exacerbated by acid rain and industrial pollutants, leading to soil structure breakdown and nutrient depletion [3, 4].

Historically, soil erosion has played a critical role in shaping the geographical and cultural landscapes of various regions. It has been a decisive factor in the rise and fall of empires, as agricultural productivity directly influenced the economic and social stability of civilizations. For example, the decline of the Mesopotamian Civilization is partly attributed to severe soil erosion, which rendered once-fertile lands barren and led to socio-economic downfall [5, 6]. In contemporary times, the challenges posed by soil erosion are magnified by increased human activities such as deforestation, urban development, and intensive agricultural practices, coupled with climatic changes that intensify weather patterns, thereby increasing the incidence and severity of erosion [7, 8].

The study of soil erosion transcends academic interest, addressing critical global issues such as food security, water management, and biodiversity conservation. The degradation of soil through erosion directly threatens agricultural production by reducing land fertility and the availability of arable land. Moreover, it impacts water quality and availability through sedimentation of water bodies and pollution, which can disrupt aquatic ecosystems and diminish freshwater resources. The ecological consequences are profound, affecting biodiversity through the loss of habitat and altering natural habitats, which can lead to the extinction of species and reduced ecological resilience [9, 10].

Recognizing and understanding these impacts is crucial for the development of effective mitigation strategies aimed at managing soil erosion. These strategies must be multifaceted, involving not only direct interventions to reduce erosion but also broader land management practices that enhance the sustainability of environments under threat. Through sustainable practices, such as improved agricultural techniques, reforestation, and the use of erosion control technologies, we can significantly diminish the adverse effects of soil erosion, thereby ensuring a more stable and productive environmental future.

2. Global significance of soil erosion

Soil erosion stands as a formidable global environmental threat, critically impacting agricultural productivity and food security across the planet. According to estimates from the Food and Agriculture Organization (FAO), approximately 75 billion tons of soil are lost each year to erosion. This staggering volume of loss translates into a reduction of the earth's productive capacity by 1–2% annually, a significant figure that poses serious concerns, especially for developing countries where agriculture constitutes a vital economic and subsistence activity [11, 12]. The situation is further complicated by the increasing demands placed on agricultural systems by a rapidly growing global population. This scenario highlights the critical need for a robust and comprehensive understanding of soil erosion processes, alongside proactive interventions to mitigate their effects.

Table 1 provides a comprehensive breakdown of annual soil loss by continent, measured in billions of tons and represented as a percentage of the global total. Key contributing factors specific to each region highlight the diverse causes of soil erosion, underscoring the need for tailored mitigation strategies [13, 14].

The consequences of soil erosion extend far beyond the mere loss of topsoil. One of the most significant indirect effects is the sedimentation of rivers and lakes, which

Continent	Annual soil loss (billion tons)	Percentage of global total	Key contributing factors
Asia	20	26.67%	Deforestation, intensive agriculture
Africa	15	20%	Overgrazing, poor agricultural practices
North America	10	13.33%	Industrial agriculture, urban sprawl
South America	12	16%	Deforestation, illegal mining
Europe	8	10.67%	Industrial activities, agricultural runoff
Australia	10	13.33%	Land clearing, natural variability in rainfall

Table 1.
Annual global soil loss.

severely impacts aquatic ecosystems. The accumulation of sediments in waterways not only degrades water quality but also affects the health and diversity of aquatic life by altering habitats and obstructing natural flows. Furthermore, sedimentation can increase the risk of flooding, particularly in low-lying areas, by reducing the capacity of rivers and streams to channel water effectively during heavy rains [15, 16].

Additionally, soil erosion contributes to a broader environmental degradation by causing the loss of soil organic matter and essential nutrients. This depletion of soil fertility can lead to diminished agricultural yields and increase the need for chemical fertilizers, which in turn can exacerbate soil degradation and pollution. The loss of organic matter also has implications for biodiversity; as soil quality degrades, the habitats support a diverse range of flora and fauna deteriorate, leading to a decline in biodiversity and the disruption of local ecosystems [17, 18].

Moreover, the disruption of carbon cycles through the loss of soil organic carbon is a critical factor in global climate change. Soil plays a key role in carbon sequestration, and erosion reduces this capacity, thereby enhancing atmospheric carbon dioxide levels and contributing to global warming. This complex interaction between soil erosion and climate change exemplifies the interconnected nature of environmental systems and underscores the need for an integrated approach to managing soil erosion that considers both its immediate and long-term impacts on the environment and human societies [19, 20].

Impact area	Specific effects	Long-term consequences
Aquatic ecosystems	Sedimentation, altered water flow	Reduced biodiversity, changes in aquatic habitat structure
Agricultural productivity	Reduced soil fertility, lower crop yields	Increased reliance on fertilizers, decreased land value
Biodiversity	Habitat loss, altered species distribution	Loss of species, reduced genetic diversity
Hydrological cycles	Increased runoff, reduced infiltration	Altered water availability, increased flooding risk
Carbon cycle	Loss of soil organic carbon	Enhanced atmospheric CO ₂ levels, exacerbated global warming

Table 2.
Impact of soil erosion on ecosystems.

The global perspective on soil erosion reveals its deep interconnectedness with critical environmental and socio-economic issues, highlighting the necessity for a multi-disciplinary approach in its study and management. Addressing soil erosion effectively requires collaboration across fields such as geology, agronomy, climatology, and environmental policy to develop scientifically sound, economically viable, and socially acceptable strategies. These strategies must not only aim to reduce soil loss but also enhance the resilience of landscapes and communities against the adverse effects of erosion, thereby contributing to the sustainability of ecosystems worldwide. **Table 2** outlines the significant environmental impacts of soil erosion across various ecosystems and agricultural systems. It details specific effects such as sedimentation in aquatic environments and reduced soil fertility in agricultural lands, along with the long-term consequences these changes pose to biodiversity, hydrological cycles, and global climate [21, 22].

3. Theoretical framework

Understanding the dynamics of soil erosion requires a thorough grasp of the physical and chemical processes that drive this complex environmental phenomenon. Soil erosion is shaped by an intricate interplay of climatic factors, soil properties, topography, and vegetation cover, influencing how soil particles are detached, transported, and eventually deposited. **Table 3** organizes and presents the various factors influencing soil erosion, categorized into climatic conditions, soil properties, topography, and human activities. It details how each factor impacts erosion processes, providing a foundational understanding that supports further discussion on mitigation and management strategies [23, 24].

3.1 Physical processes

The physical processes of soil erosion are primarily concerned with the movement of soil particles, driven by the forces of water and wind. These processes are

Factor category	Specific factor	Impact on erosion processes
Climatic conditions	Rainfall intensity	Increases surface runoff and soil detachment
	Wind speed	Enhances soil particle displacement, especially in dry areas
Soil properties	Texture (clay, sand, silt)	Affects soil's susceptibility to erosion; sandy soils are easily eroded, while clay resists but can crack and erode severely
	Structure	Well-structured soils resist erosion better than compacted or degraded soils
Topography	Slope	Steeper slopes increase the speed and volume of runoff, enhancing erosion
Human activities	Land use (deforestation, urbanization)	Reduces vegetative cover, increasing erosion risk
	Agricultural Practices (tillage type, crop rotation)	Certain practices can either protect against or exacerbate erosion

Table 3.
Factors influencing soil erosion.

fundamentally divided into three stages: detachment, transport, and deposition, each playing a critical role in the cycle of erosion.

Detachment is the initial stage where soil particles are dislodged from their original position. This occurs when raindrops impact bare soil with sufficient force to break the bonds holding the particles in place, or when wind velocities are high enough to lift particles from the soil surface. The intensity of this process depends greatly on the kinetic energy of the raindrops or the speed of the wind, making it a critical factor in the erosion process [25].

Following detachment, the transport stage involves the movement of these dislodged soil particles. This movement can occur *via* water flow across the soil surface during rainfall events, or through air as wind carries the particles away. The degree of transport is significantly influenced by several factors including the soil's texture and structural integrity, its moisture content, and the speed and pattern of the water flow or wind. This stage is critical as it determines the extent and direction of soil erosion, shaping the landscape and affecting land usability [26].

The final stage, deposition, occurs when the forces of water or wind carrying the soil particles lose energy and the particles settle in new locations. This results in the formation of sediment layers, which can occur in areas where water velocity decreases, such as in the bends of rivers or lakes, or where wind speed diminishes. Deposition can lead to significant changes in topography and soil fertility, often depositing rich soil materials in some areas while depleting others, thereby creating a new set of environmental conditions for ecosystems and human activities [27].

Understanding these physical processes is essential for developing effective soil conservation strategies, as it allows for targeted interventions at each stage of soil erosion. By mitigating the impact at any point in this cycle, whether reducing the energy of raindrops, altering the flow of water, or managing windbreaks, the overall process of soil erosion can be effectively managed to sustain the land's productivity and ecological balance.

3.2 Chemical processes

Chemical processes play a significant role in soil erosion, influencing the soil's stability and fertility through various mechanisms. These processes often occur in conjunction with human activities that alter the natural landscape and disrupt ecological balance.

One of the primary chemical mechanisms involved in soil erosion is the alteration of soil pH. Changes in pH levels can lead to the breakdown of soil structure, making it more susceptible to erosion. This pH change can be a result of various factors, including the deposition of acidic or basic substances through atmospheric deposition or agricultural inputs. As the soil structure deteriorates, its ability to hold together against erosive forces such as water and wind diminishes, increasing the likelihood of erosion [28].

Salinization is another critical chemical process that affects soil stability. This condition often arises from irrigation practices where water used contains high levels of salts. The accumulation of salts in the soil can severely impair its fertility, leading to a reduction in plant growth and an increase in soil erosion risks. The salts can cause soil particles to disperse, weakening the soil's structure and making it more prone to erosion by water and wind [29].

The leaching of essential nutrients such as nitrogen and phosphorus is also a significant concern associated with chemical soil erosion. This process not only

Erosion type	Process	Description	Consequences
Physical	Detachment	Soil particles are dislodged by water impact or wind.	This leads to the loss of topsoil and alters the land surface.
	Transport	Soil particles are moved by water flow or wind.	This can result in deposition far from the original location, altering landscapes.
	Deposition	Transported soil particles settle when water or wind loses energy.	This leads to sediment build-up, can create new landforms, or obstruct waterways.
Chemical	pH changes	Soil acidity or alkalinity alters, weakening soil structure.	Increases susceptibility to erosion and affects nutrient availability.
	Salinization	Accumulation of salts in the soil due to improper irrigation practices.	Reduces soil fertility and can lead to crop failure.
	Nutrient leaching	Essential soil nutrients are washed away.	Depletes soil fertility and can pollute water bodies with nutrients.

Table 4.
Comparison of physical and chemical erosion processes.

depletes the soil of its fertility, crucial for plant growth but also contributes to water quality issues. As nutrients are washed away from the soil, they can enter bodies of water, leading to eutrophication—a process that can cause excessive growth of algae and subsequently harm aquatic ecosystems [30].

These chemical processes are frequently exacerbated by human actions such as unsuitable agricultural practices, deforestation, and improper land use planning. Such activities strip the land of its natural vegetation and disrupt the soil’s ability to naturally regenerate, thereby enhancing the conditions for both physical erosion and chemical erosion. By understanding and addressing these chemical processes within the context of human environmental impact, strategies can be developed to mitigate soil erosion and preserve both soil health and overall environmental quality.

Table 4 provides a side-by-side comparison of physical and chemical erosion processes, delineating the mechanisms by which each type of erosion occurs and their respective consequences. This comparison highlights how both physical and chemical factors contribute to the overall process of soil erosion, affecting ecosystem stability and land usability [31, 32].

3.3 Role of human activity

The influence of human activity on soil erosion cannot be overstated. Land use changes—such as agricultural expansion, urban development, and deforestation—significantly alter the natural landscape and its ability to resist erosion. For instance, the removal of vegetation for agriculture or urban development decreases the soil’s organic matter content and its ability to absorb water, directly increasing erosion risk. **Table 5** outlines the impact of various human activities on soil erosion, detailing how actions such as deforestation, urban development, and certain agricultural practices directly contribute to soil degradation. This summary emphasizes the need for sustainable land use practices to mitigate these adverse effects and promote soil conservation [33, 34].

Human activity	Direct impact on soil erosion	Consequences
Deforestation	Removal of tree cover increases surface runoff and erosion	This leads to loss of soil stability, and biodiversity and increases sediment in waterways
Urban development	Sealing of soil surfaces accelerates runoff	Enhances flood risk, reduces natural infiltration
Agricultural expansion	Over-tillage and monocropping deplete soil structure	Increases susceptibility to erosion, reduces soil fertility
Overgrazing	Removal of vegetation exposes soil to erosion	This leads to compacted soil enhances runoff and erosion
Improper irrigation	Increases water logging and salinization	This leads to soil structure breakdown, enhances erosion

Table 5.
Impact of human activities on soil erosion.

3.4 Socio-economic factors

Additionally, socio-economic factors play a crucial role in shaping land use patterns. Economic pressures to maximize agricultural yields can lead to practices that intensify soil erosion, such as overgrazing, the use of heavy machinery, and the cultivation of highly erodible lands. Understanding these socio-economic drivers is vital for developing sustainable land management practices that balance environmental health with human needs [35, 36].

3.5 Integration in erosion studies

Integrating these physical and chemical understandings with human dimensions is essential for developing predictive models and effective conservation techniques. Such integration allows for a holistic approach to managing soil erosion, ensuring that strategies are not only scientifically sound but also socio-economically viable [37]. This comprehensive approach is crucial for crafting policies and practices that mitigate soil erosion while supporting sustainable development goals.

4. Objectives of soil erosion

The pressing environmental issue of soil erosion serves as the focal point, which aims to unravel the complex dynamics of erosion through a comprehensive and scholarly lens. The primary objective of this volume is to elucidate the multifaceted nature of soil erosion, exploring its various causes and manifestations, ranging from water-induced erosion to wind and chemical erosion processes, by dissecting the mechanisms behind each type and examining their profound impacts on ecosystems and human societies. **Table 6** provides a categorized summary of the different types of soil erosion discussed in the book, highlighting their mechanisms, key characteristics, and typical impact areas. This table serves as a quick reference for understanding the diverse mechanisms and effects of soil erosion across various environments [38, 39].

Types of erosion	Mechanisms	Key characteristics	Typical impact areas
Water-induced	Detachment by raindrop impact, runoff	Causes gullying, sheet, and rill erosion	Agricultural lands, riverbanks
Wind	Particle detachment and transport by wind	Most effective in dry, loose soils	Arid regions, exposed farmlands
Chemical	Soil structure breakdown by chemical change	Salinization, acidification	Irrigated agricultural lands
Thermal	Cracking due to temperature changes	This leads to increased vulnerability to other erosion types	Areas with extreme temperature variations
Biological	Soil disturbance by organisms	May increase porosity and susceptibility to erosion	Forest floors, agricultural fields

Table 6.
Overview of soil erosion types and mechanisms.

4.1 Holistic understanding and interdisciplinary approach

A significant emphasis on soil erosion is fostering a holistic understanding of soil erosion. This involves integrating diverse perspectives from fields such as geotechnical engineering, environmental science, and agronomy. Such an interdisciplinary approach allows for a more robust exploration of how soil erosion interacts with and impacts various environmental systems and human activities. This comprehensive viewpoint is critical, as it equips readers with the knowledge needed to grasp the complexity of soil erosion beyond its mere physical consequences [40, 41].

4.2 Practical applications for soil conservation

The section on practical applications for soil conservation expands upon the theoretical discussions earlier in the chapter by providing actionable strategies and innovative solutions for managing and preventing soil erosion. This is crucial for stakeholders such as farmers, policymakers, and environmental managers, who play integral roles in implementing these strategies within their respective domains [42].

One effective method discussed is terracing, which involves creating stepped levels on sloped land to significantly reduce runoff velocity and soil erosion. This technique is particularly useful in hilly or mountainous agricultural areas and has been employed with notable success in various regions, including the rice terraces in Asia and the ancient Incan terraces in Peru [43].

Another traditional approach is contour plowing, which entails plowing along the natural contours of the land. This method helps conserve rainwater and reduce soil erosion on sloped agricultural fields. It has been widely adopted across Europe and North America due to its simplicity and effectiveness [44].

Riparian buffers, which involve planting vegetation along waterways, are highlighted as a critical method for preventing soil erosion in areas adjacent to rivers and streams. Successful implementations can be seen in Oregon, USA, where streamside vegetation buffers have been established [45].

The use of geotextiles, synthetic fabrics designed to stabilize soil, is discussed as a modern technological solution applicable to construction sites and areas prone to

erosion. These materials are integral to projects such as erosion control in highway embankments [46].

Bioengineering techniques, which utilize living plants to stabilize soil, are effective in preventing erosion on riverbank slopes. An example of this is the use of willow spilling on riverbanks in the UK, which demonstrates how bioengineering can blend ecological considerations with effective erosion control [47].

No-till farming, which reduces or eliminates tillage to maintain soil structure, is another significant practice covered in the section. This method is particularly prevalent in intensive agricultural lands and has been embraced as part of conservation agriculture in Brazil [48].

Managed grazing, which involves rotating grazing areas to prevent overgrazing, is presented as an essential strategy for maintaining pasture health and preventing soil degradation. This technique has been successfully implemented in the holistic management practices in New Zealand [49].

Lastly, afforestation and reforestation are discussed as crucial for restoring forest cover and reducing erosion in deforested and vulnerable regions. China's reforestation efforts in the Loess Plateau are cited as a key example of how large-scale tree planting can be used to combat soil erosion effectively.

Conservation technique	Description	Applicability	Examples of implementation
Terracing	Creating stepped levels on slopes to reduce runoff velocity	Hilly or mountainous agricultural lands	Rice terraces in Asia, Incan terraces in Peru
Contour plowing	Plowing along land contours to conserve rainwater	Sloped agricultural fields	Used widely in Europe and North America
Cover crops	Planting crops to cover the soil between main crops	Agricultural lands during off-season	Winter rye in the US Midwest
Riparian buffers	Planting vegetation along waterways to prevent erosion	Areas adjacent to rivers and streams	Streamside vegetation buffers in Oregon, USA
Geotextiles	Using synthetic fabrics to stabilize soil	Construction sites, eroded areas	Erosion control in highway embankments
Bioengineering techniques	Utilizing living plants to stabilize soil	Riverbanks slopes prone to erosion	Willow spilling on riverbanks in the UK
No-till farming	Reducing or eliminating tillage to maintain soil structure	Intensive agricultural lands	Conservation agriculture in Brazil
Managed grazing	Rotating grazing areas to prevent overgrazing	Pastures, rangelands	Holistic management in New Zealand
Afforestation/ reforestation	Planting trees to restore forest cover and reduce erosion	Deforested areas, vulnerable regions	Reforestation projects in China's Loess Plateau
Rainwater harvesting systems	Capturing and storing rainwater to reduce surface runoff	Urban and agricultural areas	Rain barrels and cisterns in urban California

Table 7.
Practical applications and solutions for soil conservation.

Furthermore, the integration of rainwater harvesting systems in urban and agricultural areas helps reduce surface runoff and control soil erosion. Examples from urban California, where rain barrels and cisterns are extensively used, illustrate the effectiveness of these systems in managing water resources sustainably.

Table 7 outlines various practical applications and innovative solutions for soil conservation as discussed in the book. It describes each conservation technique, details its applicability to different environments, and provides real-world examples of how these methods have been successfully implemented to mitigate soil erosion [50, 51].

4.3 Inspiration for action and alignment with sustainability goals

Ultimately, the overarching goal of this book is to inspire action toward more sustainable soil management practices. This aspiration is aligned with global sustainability goals, emphasizing the critical need for responsible land use and soil conservation strategies that mitigate environmental impact while enhancing the productivity and resilience of landscapes. By providing a foundation of knowledge and a suite of potential solutions, the book aims to motivate a wide range of readers—from academic researchers to practitioners and policymakers—to implement practices that contribute to the sustainability and health of the Earth’s soil resources [52, 53].

5. Importance of integrated approaches

The challenge of soil erosion, with its complex interactions between environmental processes and human activities, requires integrated approaches that encompass scientific, technological, social, and policy dimensions. This section discusses the necessity for such holistic strategies in understanding and mitigating soil erosion effectively. **Table 8** provides an overview of the multidimensional framework that integrates scientific, technological, social, and policy aspects in addressing soil erosion. It illustrates how these components come together to form a holistic strategy,

Aspect	Description	Examples of integration	Impact
Scientific	Utilization of empirical data and theories to understand erosion mechanisms	Use of soil physics in predicting erosion patterns	Enhances accuracy in erosion assessment and mitigation planning
Technological	Application of advanced tools and techniques for erosion analysis and control	Implementation of GIS and remote sensing for erosion monitoring	Improves the precision and scope of erosion management efforts
Social	Inclusion of community perspectives and local knowledge in erosion control strategies	Community-based participatory approaches in soil conservation	Ensures that erosion control measures are culturally acceptable and sustainable
Policy	Development of policies that support effective and sustainable erosion management	Enacting land use regulations that limit erosion-prone activities	Provides a regulatory framework that promotes long-term soil conservation

Table 8.
Framework of integrated approaches in soil erosion management.

with descriptions, examples of integration, and their respective impacts on managing soil erosion effectively [54, 55].

5.1 Scientific integration

Addressing the challenges posed by soil erosion requires a rigorous and integrated scientific approach, leveraging insights from multiple disciplines. This chapter emphasizes scientific integration as a core principle, ensuring that the research and strategies presented are both comprehensive and innovative. This integration is crucial for developing effective, long-term solutions to manage and mitigate soil erosion.

5.1.1 Multidisciplinary research

Multidisciplinary research is crucial for tackling the intricate challenge of soil erosion, which spans various scientific fields, each contributing unique insights into the issue. This approach merges specialized knowledge from geotechnical engineering, environmental science, agronomy, and climatology, offering a comprehensive understanding of soil dynamics and erosion processes [56].

Geotechnical engineering delves into the physical and mechanical properties of soils, which are pivotal for assessing soil stability and understanding the impacts of different erosion processes. This discipline's focus on the behavior of soils under various stress conditions provides essential data for analyzing and predicting erosion patterns and potential mitigation techniques [57].

Environmental science expands the scope by examining how soil erosion impacts ecosystems and water quality. This field's broad perspective is vital in understanding the broader ecological consequences of erosion, such as habitat degradation, changes in hydrological systems, and the resultant effects on biodiversity and water pollution [58].

Agronomy assesses the effects of soil erosion on agricultural productivity and explores how different farming practices influence erosion rates. This discipline is particularly concerned with the interactions between agricultural activities and soil conservation, offering strategies to enhance crop production while minimizing adverse environmental impacts [59].

Climatology contributes critical information on how climate variables such as rainfall intensity and wind patterns affect erosion rates. Insights from climatology are essential for predicting future erosion trends and developing adaptive management strategies that can cope with the variability and extremes of weather patterns [60].

By synthesizing these diverse perspectives, multidisciplinary research facilitates a richer understanding of soil erosion, enabling the development of more effective and sustainable soil conservation techniques. For instance, integrating climatic data with agronomic practices allows for the creation of farming methods that effectively reduce soil degradation while maintaining or increasing agricultural productivity. This holistic approach not only addresses the technical aspects of soil conservation but also considers the ecological, agricultural, and climatic dimensions, ensuring a sustainable and integrated solution to soil erosion.

Table 9 details the diverse contributions of various scientific disciplines to soil erosion management, highlighting how each field aids in understanding and mitigating erosion. The table includes specific examples of how these disciplines are applied in practical erosion management strategies, demonstrating the interdisciplinary nature of effective soil conservation [61, 62].

Discipline	Contributions	Examples of erosion management applications
Geotechnical engineering	Analyzes physical and mechanical properties of soils	Design of soil stabilization structures such as retaining walls and terraces
Environmental science	Studies the impact of erosion on ecosystems	Development of conservation strategies that protect water quality and habitat
Agronomy	Examines soil erosion effects on agriculture	Implementation of soil conservation practices such as contour farming and crop rotation
Climatology	Provides data on how weather patterns affect erosion	Forecasting erosion risk and adapting agricultural practices to climate variability
Social sciences	Investigate socio-economic impacts and policy implications	Community engagement programs and policy formulation for sustainable land use

Table 9.
Contributions of various disciplines to soil erosion management.

5.1.2 Innovation in measurement and modeling

In the quest to better understand and manage soil erosion, the role of innovation in measurement and modeling is indispensable. This section highlights the cutting-edge techniques and technologies that are transforming the way researchers and practitioners assess and predict soil erosion processes. The adoption of advanced measurement tools such as remote sensing, Light Detection and Ranging (LiDAR), and geographic information systems (GIS) technologies has enabled specialists to gather detailed, high-resolution data on landforms, soil types, and erosion patterns across extensive areas with unparalleled accuracy [63].

These technological advancements extend beyond data collection to the realm of sophisticated modeling software, which facilitates the simulation of various erosion scenarios. By incorporating a wide range of variables and conditions, these models predict future changes and impacts with improved accuracy. This capability is crucial for enhancing the precision of erosion assessments and significantly augments the effectiveness of planning and implementing erosion control measures [64].

The integration of these innovative methodologies into current practices offers deeper insights and more reliable forecasts, enabling a more strategic and effective management of soil resources. Enhanced simulation models, which consider both environmental and human factors, are instrumental in providing accurate predictions of erosion under different scenarios. These models prove invaluable not only for forecasting but also for planning and executing soil conservation measures. They allow researchers and policymakers to assess the potential effectiveness of various strategies under anticipated climatic and land-use changes, ensuring that interventions are both proactive and well-informed [65].

Moreover, the utilization of remote sensing and GIS technologies has revolutionized the monitoring and analysis of soil erosion over large and sometimes inaccessible areas. These technologies deliver critical high-resolution data that aid in mapping erosion risk areas, assessing changes in land cover, and monitoring the success of conservation practices already in place. By providing precise measurements of erosion rates and patterns, these innovations support targeted interventions, and the continual refinement of management practices based on up-to-date, real-time data. This ongoing improvement is essential for the sustainable management of soil resources,

ensuring that conservation efforts are both effective and adaptable to changing environmental conditions [66].

Table 10 outlines advanced measurement and modeling techniques used in soil erosion studies, detailing their specific applications and the outcomes they achieve. This table exemplifies how modern technologies such as remote sensing, GIS, LiDAR, and nanotechnology play pivotal roles in enhancing the accuracy and effectiveness of soil erosion assessment and management [67, 68].

5.1.3 Goal of scientific integration

The goal of integrating these scientific disciplines and innovative methodologies is to develop a more dynamic and responsive approach to soil erosion management. By understanding the interactions between various factors that contribute to erosion, and by employing advanced technologies for measurement and prediction, the strategies developed are both proactive and adaptive. This scientific integration not only enhances the theoretical understanding of soil erosion but also translates into practical applications that can be implemented across different geographical and environmental contexts [69].

5.2 Technological advancements

In the battle against soil erosion, technological advancements play a pivotal role, particularly through the application of nanotechnology and the utilization of geographic information systems (GIS) and remote sensing. These technologies not only enhance our understanding of erosion dynamics but also offer practical tools for implementing effective mitigation strategies.

5.2.1 Application of nanotechnology

The application of nanotechnology in soil management and erosion control represents a significant advancement in the field, introducing innovative solutions that address erosion at a molecular level. This section delves into how nanotechnology offers transformative approaches to enhancing soil stability, improving water retention, and mitigating erosion risks with unprecedented precision and efficiency. By manipulating materials at the nanoscale, scientists can significantly alter the physical and chemical properties of soil, providing targeted interventions that stabilize soil and promote sustainable land management [70].

Technology	Application	Outcome
Remote sensing	Monitoring large-scale land cover and erosion changes	Provides comprehensive data on erosion patterns and hotspots
Geographic information systems (GIS)	Integration and analysis of spatial data related to erosion	Facilitates precise mapping and risk assessment of erosion-prone areas
Light detection and ranging (LiDAR)	High-resolution mapping of landforms to assess erosion risks	Delivers detailed topographical data essential for accurate erosion models
Nanotechnology	Development of soil stabilizers at the molecular level	Enhances soil resistance to erosion by improving soil structure and cohesion

Table 10.
Innovative measurement and modeling techniques.

Nanotechnology, with its capacity to manipulate materials at the molecular level, provides groundbreaking solutions for soil stabilization and erosion control. The introduction of nanostructured materials into the soil can dramatically change its mechanical properties. For example, nanoparticles such as nano-silica or nano-clay can be incorporated into the soil to enhance particle cohesion, thus reducing susceptibility to erosion caused by water and wind. These nano-enhancements work at the smallest scales to create bonds between soil particles, effectively increasing the soil's resistance to erosive forces and thereby stabilizing landscapes that are prone to degradation [71].

Moreover, the application of hydrophobic nano-coatings to soil particles plays a crucial role in enhancing water retention, which is particularly vital in arid regions where water scarcity exacerbates erosion. These nano-coatings modify the surface properties of soil particles, allowing them to retain more moisture and thereby reducing the need for frequent watering. Additionally, the incorporation of biochar nanoparticles improves soil structure and increases its organic matter content. This not only enhances the soil's capacity to absorb and retain water but also reduces surface runoff, further limiting erosion risks [72].

Nanotechnology also contributes to more sustainable agricultural practices by reducing the reliance on chemical soil enhancers, which can lead to soil salinization and further degradation. The controlled release of nutrients through nanocarriers is another innovative feature of nanotechnology in soil management. These carriers ensure that plants receive a steady supply of nutrients over time, minimizing the risk of nutrient runoff which is often associated with the conventional fertilizers. This targeted nutrient delivery system not only boosts plant health and yield but also contributes to the overall sustainability of agricultural ecosystems by preventing the over-application of fertilizers and preserving the natural soil structure [73].

These multifaceted applications of nanotechnology not only bolster the physical stability of soil but also enhance the ecological sustainability of land management practices, marking a significant step forward in combating soil erosion effectively.

5.2.2 GIS and remote sensing

The integration of geographic information systems (GIS) and remote sensing technologies has indeed revolutionized the field of soil erosion management, providing a robust suite of tools for monitoring, analyzing, and effectively responding to erosion across varied landscapes. This section underscores the pivotal roles that GIS and remote sensing play in advancing our comprehension and management of soil erosion, significantly transforming data collection, analysis processes, and the strategic deployment of conservation resources [74].

GIS and remote sensing technologies have fundamentally transformed the capabilities for monitoring and analyzing soil erosion over extensive geographic areas. These tools facilitate the systematic collection of data regarding land use, vegetation cover, and topography—all critical factors in assessing erosion risk. By providing detailed and accurate geographical data, GIS enables a nuanced understanding of how different factors contribute to erosion in various environments. This capability is crucial for developing targeted, effective strategies to combat soil erosion [75].

Moreover, GIS and remote sensing are invaluable in evaluating the effectiveness of erosion control measures implemented across diverse landscapes. These technologies provide the means to observe changes over time, allowing researchers and policymakers to assess the impact of specific conservation efforts. By enabling the visualization of erosion trends and the dynamic adjustment of conservation strategies, these

tools ensure that interventions are not only effective but also optimally allocated and implemented. This real-time feedback loop is essential for adapting strategies in response to evolving environmental conditions and erosion patterns [76].

Additionally, the precise mapping capabilities of GIS are instrumental in identifying areas that are prone to erosion, which are critical for strategic planning and resource allocation. This targeted approach ensures that conservation resources are focused where they are most needed, thereby enhancing the efficiency and overall effectiveness of soil conservation programs. By pinpointing high-risk areas, GIS aids in prioritizing interventions and optimizing the use of limited resources, ensuring that soil management efforts are both practical and impactful [77].

Through these advanced technological applications, GIS and remote sensing not only enhance our understanding of soil erosion but also significantly improve the management and conservation of soil resources. This strategic integration of technology in soil erosion management facilitates a more informed, responsive, and effective approach to preserving vital land resources.

5.2.3 Integrating technological advancements

The integration of nanotechnology and GIS/remote sensing technologies into soil erosion management represents a significant advancement in how we understand, monitor, and combat this environmental challenge. These technologies not only provide new solutions but also enhance the precision and effectiveness of existing strategies. By harnessing these technological innovations, stakeholders are better equipped to implement proactive and adaptive management practices that respond to the dynamic nature of soil erosion [78].

5.3 Social and economic considerations

Effective management of soil erosion extends beyond scientific and technological solutions, requiring significant social engagement and economic considerations. Integrating these elements into soil conservation strategies is crucial for achieving long-term sustainability and effectiveness. This section of the book delves into the vital roles that community engagement, education, and economic incentives play in the broader context of soil erosion management.

Table 11 highlights the socio-economic benefits of employing integrated approaches to soil erosion management, detailing how community engagement, economic incentives, and impactful policies contribute to sustainable soil management practices. This table provides examples of how these benefits are realized in different contexts, demonstrating the practical advantages of a comprehensive erosion management strategy [79, 80].

5.3.1 Community engagement and education

Community engagement and education are indispensable components of effective soil erosion management. This section emphasizes the critical importance of involving local communities in efforts to combat soil erosion, using educational initiatives to empower residents, and fostering long-term sustainability through their active participation. By integrating community insights and energy into erosion control strategies, these efforts help to devise solutions that are both effective and appropriately tailored to local conditions [81].

Benefit	Description	Examples
Community engagement	Empowers local communities to participate in soil conservation, enhancing local knowledge and ownership	Community-led projects in Nepal's hill farms, where locals implement terracing and water management
Economic incentives	Provides financial rewards for sustainable practices, making it economically viable to adopt soil conservation measures	Subsidies for no-till farming in the United States, which reduce soil disturbance and erosion
Policy impact	Strong policies and regulations help ensure long-term sustainability and adherence to best practices in soil management	European Union's CAP (Common Agricultural Policy), which includes directives to manage soil quality and reduce erosion

Table 11.
Economic and social benefits of integrated soil erosion management.

The involvement of local communities is crucial to the success of soil erosion management efforts. Residents who live in close contact with their environment often bear the brunt of soil erosion and possess an intimate understanding of local ecological dynamics. Their participation in the planning and implementation of soil conservation measures not only fosters greater acceptance and adherence to these practices but also leverages their local knowledge. This collaboration enables the development of solutions that are finely tuned to the specific environmental and cultural conditions of the area, enhancing the effectiveness and sustainability of conservation efforts [82].

Education is a powerful tool in empowering communities to address soil erosion. Through educational programs that elucidate the causes and impacts of soil erosion, communities can shift their perceptions and behaviors toward more sustainable practices. These programs are vital in illustrating the direct connection between individual actions and soil health, promoting land use practices that community members can adopt in their daily activities to aid in soil conservation. By increasing community knowledge and awareness, these educational initiatives lay the groundwork for robust, community-led conservation efforts that resonate more deeply with local needs and values [83].

Sustainability in soil erosion management is significantly enhanced through continuous community engagement. When communities are actively involved not just in implementing but also in monitoring and refining erosion control measures, they develop a vested interest in the success and longevity of these practices. Community members who observe and report on the outcomes of conservation strategies become powerful advocates for sustained action, helping to ensure that these practices are maintained over the long term. This ongoing engagement helps to create a cycle of feedback and improvement, making soil conservation efforts more dynamic and responsive to changing environmental and community needs [84].

5.3.2 Economic incentives

Economic incentives are pivotal in promoting sustainable land management practices that effectively combat soil erosion. This section delves into the various financial strategies used to encourage the adoption of conservation practices, the role of penalties in deterring detrimental land use, and the broader economic benefits of investing in soil conservation [85].

Economic incentives serve as powerful tools for encouraging the adoption of sustainable land management practices that minimize soil erosion. Providing subsidies for erosion control measures, such as the construction of terraces or the planting of cover crops, can significantly reduce the financial barriers to implementing these practices. Such financial support not only assists in immediate soil conservation efforts but also enhances the overall economic viability of agricultural practices in erosion-prone areas. By reducing the cost of adopting these methods, subsidies make it economically feasible for farmers to invest in long-term soil health, which is essential for sustainable agriculture [86].

Conversely, penalties and regulations for practices that exacerbate soil erosion act as deterrents, nudging land users toward more sustainable practices. Regulations that impose penalties for unsustainable land use activities, such as overgrazing or deforestation, encourage a shift toward conservation-oriented practices. However, these penalties should be well-balanced with educational support to ensure that land users are not only aware of these regulations but also have the means and knowledge to comply with them. This balance helps to foster a more cooperative approach to conservation, where land users are partners rather than adversaries in the efforts to protect soil resources [87].

The economic benefits of investing in soil conservation extend far beyond immediate environmental impacts. Healthier soils lead to higher agricultural productivity and a reduced need for chemical inputs, which can lower costs and increase profits for farmers. Over time, enhanced soil health can lead to more sustainable agricultural outputs and greater economic stability for communities dependent on agriculture. By highlighting these long-term economic benefits, stakeholders can motivate land users to invest in soil conservation measures. Demonstrating the financial gains from such investments not only promotes wider adoption of these practices but also aligns economic incentives with environmental sustainability, creating a win-win scenario for both land users and the broader community. This strategic alignment makes economic sense and fosters a stronger commitment to combating soil erosion through sustainable land management practices [88].

5.3.3 Integrating social and economic strategies

The integration of social and economic strategies into soil erosion management ensures that conservation efforts are both effective and rooted in the realities of local communities. By aligning scientific and technological approaches with social engagement and economic incentives, soil conservation becomes a shared responsibility, supported by a community that understands its value and is motivated to sustain its efforts [89].

5.4 Policy integration

Effective soil erosion management is not just about implementing ground-level interventions; it also involves crafting and integrating robust policy frameworks. These policies play a crucial role in guiding and sustaining efforts to control soil erosion by aligning them with the broader land management and environmental objectives. This book emphasizes the importance of both comprehensive land management policies and global cooperation in addressing the pervasive challenge of soil erosion [90].

5.4.1 Comprehensive land management policies

The effectiveness of soil erosion control is heavily dependent on the establishment of comprehensive land management policies. These policies need to be robust, encompassing not only the prevention and control of soil erosion but also the mitigation and restoration of already degraded lands. This section examines the critical components of developing such frameworks, their alignment with broader environmental goals, and the necessity of tailoring these policies to meet regional needs [91].

Effective soil erosion control requires the establishment of robust policy frameworks that integrate soil conservation into broader land management strategies. These policies should be comprehensive, addressing everything from prevention and control to mitigation and restoration. They must also take into account the specific needs and circumstances of different regions, considering local environmental conditions, land use patterns, and socio-economic factors. Developing such frameworks involves a meticulous process of policy design that incorporates scientific research, stakeholder input, and a clear understanding of regional characteristics to ensure that policies are both effective and sustainable [92].

Moreover, these policies must align with national and international environmental goals, such as those outlined in the sustainable development goals (SDGs). This alignment ensures that soil erosion management policies not only contribute to the preservation of soil health but also support broader objectives such as enhancing water quality, preserving biodiversity, and mitigating the impacts of climate change. By integrating soil conservation efforts with these wider environmental goals, policies can create synergies that amplify their effectiveness and facilitate the achievement of multiple objectives simultaneously [93].

Lastly, these policies must be tailored to meet the specific needs and circumstances of different regions. This customization requires a deep understanding of the unique challenges faced by each area—be it climate, topography, or socio-economic conditions—and adapting policies accordingly. Flexible policies that can be adjusted to local conditions are more likely to be successful because they are relevant and practical to those who implement them. Such region-specific policies ensure that soil erosion control measures are not only applicable but also embraced by local communities, enhancing their effectiveness and sustainability. This approach fosters a more responsive and effective policy environment that can adeptly handle the complexities of soil erosion in varied geographical and cultural landscapes [94].

5.4.2 Global cooperation

Soil erosion is a pervasive issue with transboundary impacts that affect biodiversity, climate stability, and global food security. This section explores the necessity for global cooperation in addressing soil erosion, emphasizing the importance of sharing knowledge, harmonizing policies, and exchanging best practices across nations [95].

Soil erosion is a global issue that touches all corners of the world, with far-reaching effects on biodiversity, climate change, and global food security. As such, it demands a coordinated international response. Global cooperation is crucial for sharing knowledge, resources, and technologies that can significantly enhance the effectiveness of efforts to combat soil erosion. This collective approach allows countries to pool their resources and knowledge, leading to more efficient and impactful strategies that leverage global expertise and technology [96].

International cooperation also facilitates the harmonization of policies across borders. This is especially critical in regions where water bodies, ecosystems, and climatic conditions do not adhere to national boundaries. Harmonizing policies across these boundaries ensures a unified approach to managing soil erosion, maximizing the effectiveness of interventions, and preventing unilateral actions that could have detrimental cross-border implications. By aligning strategies and regulatory frameworks, countries can address soil erosion more holistically and effectively, ensuring that efforts in one country are complemented rather than undermined by actions in another [97].

Moreover, through global networks and partnerships, countries can share best practices and innovations in soil erosion control. This exchange is invaluable as it not only enhances existing strategies but also promotes innovation by exposing countries to a variety of approaches and technologies that they might not have considered independently. Sharing successful strategies and cutting-edge technologies enables a dynamic exchange of ideas, fostering continual improvement and adaptation of soil erosion control measures globally. This collaborative environment encourages the diffusion of innovative solutions and best practices, which can be adapted to local conditions around the world, thereby enhancing the global response to the challenge of soil erosion [98].

5.4.3 Integrating policies for sustainable outcomes

The integration of comprehensive land management policies with global cooperation creates a robust framework for tackling soil erosion. Such integration ensures that soil conservation efforts are not isolated but are part of a global effort to create sustainable, resilient landscapes capable of supporting current and future generations [99].

This policy integration is vital not only for managing soil erosion but also for ensuring that the solutions implemented are sustainable and that they contribute to the overall health of the planet's ecosystems.

5.5 Goal of integrated approaches

The overarching goal of adopting integrated approaches to soil erosion management is to foster synergies among diverse fields of knowledge and different sectors of society. This holistic strategy is crucial for tackling the multifaceted challenge of soil erosion, ensuring that efforts are not only effective in the short term but also sustainable over the long haul [100].

5.5.1 Creating synergies

Creating synergies through interdisciplinary collaboration and leveraging technological innovations are crucial for enhancing the effectiveness of soil erosion management strategies. This approach not only broadens the scope of potential solutions but also deepens the impact of interventions by integrating diverse expertise and cutting-edge technologies [101].

Interdisciplinary collaboration is foundational in creating integrated approaches that bring together experts from various fields such as geotechnical engineering, environmental science, agronomy, policy-making, and social sciences. This collaborative effort enriches the understanding of soil erosion by incorporating diverse perspectives and expertise, which leads to more comprehensive and effective management

strategies. For example, by combining technical insights of geotechnical engineering with ecological knowledge from environmental science, teams can develop erosion control methods that are not only effective but also ecologically sensitive. Such collaborations ensure that solutions are both scientifically sound and environmentally sustainable, enhancing their acceptance and implementation across different sectors [102].

Moreover, leveraging technology and innovation plays a pivotal role in these integrated approaches. The incorporation of advanced technologies such as remote sensing, geographic information systems (GIS), and nanotechnology transforms soil erosion management into a more precise and efficient endeavor. These technologies enable detailed monitoring of erosion patterns and the effectiveness of mitigation strategies, providing vital data that allows for timely adjustments and informed decision-making. Remote sensing and GIS offer high-resolution imagery and data analysis capabilities that help in accurately assessing erosion risks and impacts over large areas, while nanotechnology offers solutions at the molecular level that can enhance soil stability and water retention. By harnessing these technologies, soil erosion management not only becomes more effective but also more adaptive to changing conditions and new challenges, ensuring long-term sustainability and resilience [103].

5.5.2 Engaging society

Engaging society is essential for the success and sustainability of soil erosion management efforts. This section explores how integrating community involvement and robust policy frameworks into soil conservation strategies can not only enhance their effectiveness but also ensure their long-term viability.

Community involvement and education are pivotal for successful soil erosion management. Active participation from local communities is crucial, as their engagement can significantly bolster the support and sustainability of conservation efforts. By implementing educational programs that elucidate the causes, consequences, and solutions to soil erosion, communities are empowered to actively participate in soil conservation efforts. These programs are designed to raise awareness and understanding, motivating community members to take proactive steps in preserving their environment. Education serves as a cornerstone for building community capacity to respond to and manage soil erosion effectively, ensuring that conservation efforts are not only understood but also valued by those most affected by them [104].

Additionally, effective policies are integral to guiding and sustaining soil erosion management. Integrated approaches call for the development of comprehensive land management policies that align with both national and international environmental goals. These policies should encompass a wide range of activities from prevention and mitigation to restoration of degraded lands. By providing a strong policy framework, governments and organizations can facilitate the implementation of practical and effective soil conservation measures. These policies act as a backbone for all conservation activities, ensuring that they are carried out in a systematic and coordinated manner that reflects both local needs and broader environmental objectives. The integration of robust policy frameworks supports the long-term sustainability of soil erosion efforts, making it possible to maintain and enhance soil health across generations [105].

5.5.3 Addressing root causes and providing long-term solutions

Addressing soil erosion effectively requires tackling the root causes, not just managing the symptoms, to develop sustainable and adaptable solutions. This section

dives into strategies for identifying and mitigating the foundational issues leading to soil erosion, emphasizes the importance of adaptability in solutions, and underscores the overarching goal of sustainability in soil management practices [106].

Targeting the root causes of soil erosion is crucial for effective management. Integrated approaches focus on preventative measures rather than merely reacting to erosion events. This might involve changing agricultural practices that contribute to soil degradation, such as shifting from traditional plowing to no-till farming to maintain soil structure and reduce disruption. Additionally, protecting areas prone to erosion with vegetative barriers like tree lines or grassed waterways can significantly mitigate erosion by stabilizing the soil and reducing runoff velocity. Redesigning landscapes to enhance water absorption and decrease runoff, through terracing or constructing retention basins, also plays a vital role in addressing the root causes of soil erosion [107].

Adaptability and environmental soundness are the key aspects of the solutions developed through integrated approaches. The strategies for managing soil erosion need to be flexible enough to adapt to different environmental conditions and societal needs. This adaptability ensures that soil erosion management strategies remain effective under changing climatic conditions, varying land use patterns, and advancements in technology. For example, the use of advanced modeling tools can help predict how alterations in land use or climate variables could impact erosion, allowing for preemptive adjustments to management practices [108].

Ultimately, the goal is to promote sustainability in soil management practices. Sustainable practices aim to enhance soil health, support biodiversity, and contribute to the resilience of ecosystems. By focusing on methods that not only prevent erosion but also enhance the environmental quality, these practices ensure that soil management contributes positively to the broader ecological and economic health of the community. Sustainable soil management practices are designed to be long-lasting, providing benefits that extend beyond immediate erosion control to foster healthier ecosystems and communities.

6. Conclusion

The exploration of soil erosion within this chapter underscores its multifaceted nature and its profound implications for environmental stability and sustainability. By delving deep into the mechanisms and impacts of soil erosion, we reveal how this pervasive issue extends beyond mere land degradation to influence global food security, biodiversity conservation, and climate resilience. The discussion has highlighted the critical role of water, wind, and chemical erosion in reshaping landscapes and affecting ecosystems across the globe. This comprehensive approach not only enriches our understanding of soil erosion but also emphasizes the necessity of a coordinated response that integrates scientific research, technological innovation, and community involvement.

The strategies for managing soil erosion discussed herein advocate for a holistic approach that addresses the root causes and not just the symptoms. Through interdisciplinary collaboration, we can harness diverse expertise and perspectives, from geotechnical engineering to environmental science, to develop more effective and sustainable erosion control methods. This collaborative approach ensures that solutions are scientifically sound and environmentally sensitive, offering a blueprint for future efforts in soil conservation.

Furthermore, the necessity of robust policy frameworks cannot be overstated. Effective policies are instrumental in guiding and sustaining efforts against soil erosion, aligning these initiatives with broader land management and environmental objectives. As we have seen, global cooperation and policy harmonization play crucial roles in this endeavor, facilitating a unified strategy that transcends national boundaries and local contexts.

In conclusion, this chapter calls for a renewed focus on soil erosion as a pressing environmental challenge. It advocates for an integrated approach that not only seeks to mitigate erosion but also enhances the resilience of landscapes and communities against its impacts. By fostering an understanding of soil erosion's underlying causes and promoting innovative solutions, we can inspire concerted action toward sustainable land management practices. The path forward requires collaboration across disciplines, sectors, and borders to forge strategies that are as adaptable and dynamic as the landscapes they aim to protect. In doing so, we can safeguard our soil resources for future generations while supporting the ecological and socio-economic foundations of our global community.

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