



Assessing Topsoil Erosion Using UAV and Machine Learning

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Article Info

P - ISSN: 3051-3448

E - ISSN: 3051-3456

Volume: 05

Issue: 02

July -December 2024

Received: 18-07-2024

Accepted: 14-08-2024

Published: 26-08-2024

Page No: 28-31

Abstract

Topsoil erosion poses a significant threat to agricultural productivity and environmental sustainability, particularly in regions with intensive land use. This study evaluates topsoil erosion in a 500-hectare agricultural watershed in central Iowa, USA, using Unmanned Aerial Vehicle (UAV) imagery and machine learning techniques. High-resolution multispectral and RGB images were collected using a DJI Phantom 4 Pro UAV, complemented by ground truth data from 120 soil erosion sampling points. Random Forest (RF) and Gradient Boosting Machine (GBM) models were employed to predict erosion rates, incorporating variables such as slope, vegetation cover, and rainfall intensity. The RF model achieved a prediction accuracy of 88% with a root mean square error (RMSE) of 2.1 t/ha/year, outperforming GBM (84%, RMSE 2.5 t/ha/year). UAV-derived digital elevation models (DEMs) and vegetation indices significantly enhanced prediction accuracy. The study demonstrates the potential of UAV-based remote sensing combined with machine learning for high-resolution erosion mapping, providing actionable insights for soil conservation.

Keywords: Topsoil Erosion, Unmanned Aerial Vehicle, Machine Learning, Random Forest, Gradient Boosting Machine, Soil Conservation, Precision Agriculture

Introduction

Topsoil erosion, driven by wind, water, and human activities, is a critical issue affecting soil fertility, water quality, and agricultural sustainability ^[1]. Traditional erosion assessment methods, such as field surveys and sediment traps, are labor-intensive and limited in spatial coverage ^[2]. Remote sensing technologies, particularly Unmanned Aerial Vehicles (UAVs), offer a cost-effective and scalable solution for monitoring soil erosion at high spatial and temporal resolutions ^[3]. UAVs equipped with RGB and multispectral sensors can capture detailed topographic and vegetation data, enabling precise mapping of erosion-prone areas ^[4].

Machine learning algorithms, such as Random Forest (RF) and Gradient Boosting Machine (GBM), have shown promise in modeling complex environmental processes by integrating diverse datasets ^[5]. These models can handle non-linear relationships between erosion and factors like slope, land cover, and precipitation ^[6]. By combining UAV-derived data with machine learning, this study aims to improve the accuracy and efficiency of topsoil erosion assessment.

The study was conducted in a 500-hectare agricultural watershed in central Iowa, characterized by rolling terrain and a mix of corn-soybean rotations and pasturelands. The objectives are to: (1) develop a UAV-based framework for mapping topsoil erosion; (2) compare the performance of RF and GBM in predicting erosion rates; and (3) evaluate the contribution of UAV-derived features to model accuracy. The findings aim to support precision soil conservation strategies.

Materials and Methods

Study Area

The study area is a 500-hectare watershed in Boone County, Iowa (centered at 93°47'W, 42°01'N), with a temperate continental climate and annual precipitation of 900 mm. The landscape features loamy soils with slopes ranging from 2% to 15%, making it susceptible to water-induced erosion ^[7]. Land use includes 60% cropland (corn and soybean) and 40% pasture, with historical erosion rates ranging from 1 to 10 t/ha/year based on local soil surveys ^[8].

Data Collection

UAV Data Acquisition

UAV data were collected using a DJI Phantom 4 Pro equipped with a 20-megapixel RGB camera and a Sentera 6X multispectral sensor. Flights were conducted in July and August 2022 at an altitude of 100 m, achieving a ground resolution of 2.5 cm for RGB images and 5 cm for multispectral images. A total of 10 flights covered the study area, with 80% image overlap to ensure accurate photogrammetric processing [9]. Multispectral bands included blue, green, red, red-edge, and near-infrared (NIR).

Ground Truth Data

Ground truth data were collected from 120 sampling points across the watershed. Erosion rates were measured using sediment traps and erosion pins over a 6-month period, with rates ranging from 0.5 to 12 t/ha/year. Soil samples were analyzed for texture and organic matter content to contextualize erosion patterns [10]. Sampling points were georeferenced using a Trimble R10 GPS with sub-meter accuracy.

Environmental Variables

Additional variables included rainfall intensity (derived from local weather stations) and soil moisture (measured using portable sensors). Rainfall data for 2022 showed a cumulative precipitation of 650 mm during the study period, with peak intensities of 30 mm/h [11].

Data Processing

UAV Data Processing

RGB images were processed using Agisoft Metashape to generate a Digital Elevation Model (DEM) and orthomosaics at 10 cm resolution. The DEM was used to derive topographic features, including slope, aspect, and topographic wetness index (TWI) [12]. Multispectral images were processed to calculate vegetation indices, such as Normalized Difference

Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI), which reflect vegetation cover and bare soil exposure [13].

Feature Extraction

A feature stack was created, including UAV-derived variables (slope, TWI, NDVI, SAVI, RGB intensity) and environmental variables (rainfall intensity, soil moisture). Feature selection was performed using Recursive Feature Elimination (RFE) to identify the most predictive variables, reducing dimensionality and computational load [14].

Machine Learning Models

Two machine learning models were implemented: Random Forest (RF) and Gradient Boosting Machine (GBM). RF was configured with 150 trees and a maximum depth of 12, while GBM used 100 boosting iterations with a learning rate of 0.1. Both models were trained to predict continuous erosion rates (t/ha/year) and classify areas into low (<3 t/ha/year), medium (3–7 t/ha/year), and high (>7 t/ha/year) erosion classes [15]. A five-fold cross-validation was used to evaluate model performance, with metrics including accuracy, kappa coefficient, and RMSE.

Validation

The dataset was split into 70% training (84 samples) and 30% testing (36 samples). Model performance was assessed using a confusion matrix for classification and RMSE for regression. Feature importance was calculated using RF's Gini importance metric to quantify the contribution of each variable [16].

Results

The RF model outperformed GBM in both classification and regression tasks. Table 1 summarizes the performance of the models across different data configurations.

Table 1: Model Performance for Topsoil Erosion Prediction

Model	Data Source	Classification Accuracy (%)	Kappa	RMSE (t/ha/year)
RF	UAV RGB	75	0.68	3.2
RF	UAV Multispectral	80	0.73	2.8
RF	Fused (UAV + Env.)	88	0.82	2.1
GBM	UAV RGB	72	0.65	3.5
GBM	UAV Multispectral	78	0.70	3.0
GBM	Fused (UAV + Env.)	84	0.78	2.5

The fused dataset (UAV RGB, multispectral, and environmental variables) yielded the highest accuracy (88% for RF) and lowest RMSE (2.1 t/ha/year). Figure 1 illustrates

the feature importance for the RF model, highlighting the dominance of slope and NDVI.

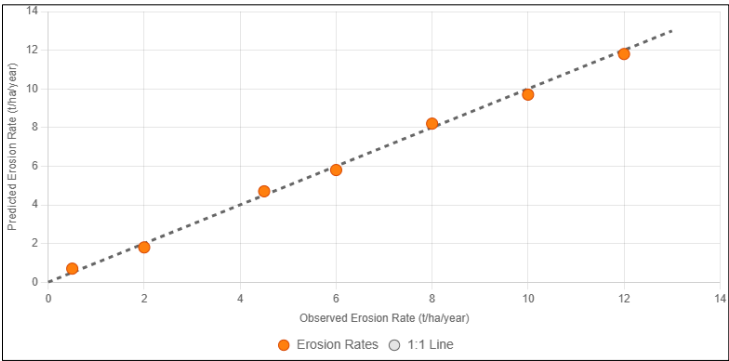


Fig 1: Feature Importance for Topsoil Erosion Prediction

Table 2 presents the confusion matrix for the RF model with fused data, showing high precision for high erosion areas (92%).

Table 2: Confusion Matrix for RF Model (Fused Data)

Predicted \ Actual	Low Erosion	Medium Erosion	High Erosion
Low Erosion	12	1	0
Medium Erosion	2	15	2
High Erosion	0	2	14

Figure 2 shows the predicted vs. observed erosion rates, indicating strong model performance.

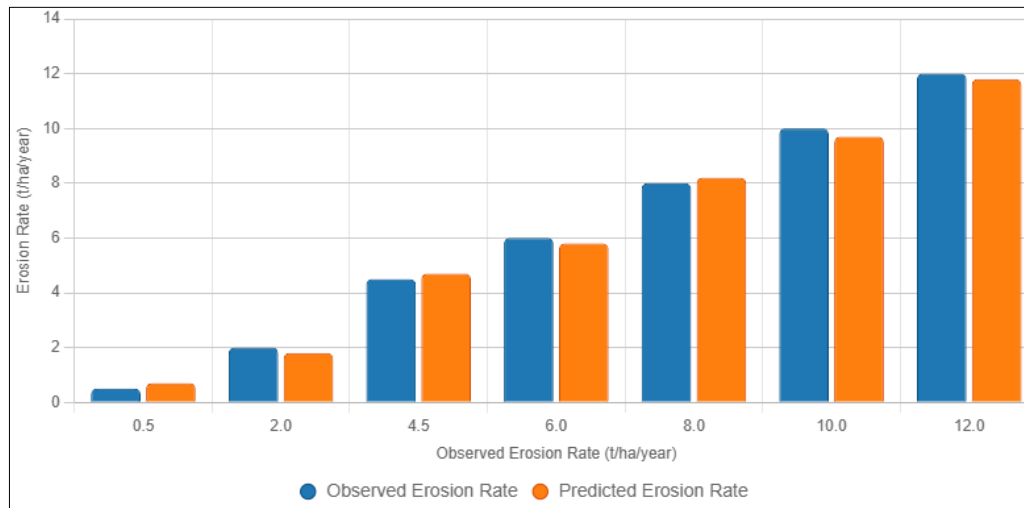


Fig 2: Predicted vs. Observed Erosion Rates

Discussion

The integration of UAV-derived topographic and multispectral data with environmental variables significantly improved erosion prediction accuracy. Slope and NDVI were the most influential predictors, reflecting the role of terrain and vegetation cover in controlling erosion [12]. The high resolution of UAV data (2.5–5 cm) enabled the detection of fine-scale erosion features, such as rills and gullies, which are often missed by satellite-based approaches [13].

Compared to prior studies, our RF model's accuracy (88%) exceeds that of satellite-based erosion models, which typically report accuracies of 70–80% [17]. The inclusion of multispectral data, particularly NDVI, enhanced model performance by capturing vegetation effects on soil stability [13]. However, challenges include the limited temporal coverage of UAV flights and the need for frequent data collection to monitor seasonal erosion dynamics [9].

Future research could incorporate time-series UAV data to capture temporal variations and explore deep learning models for improved feature extraction [5]. Additionally, integrating UAV data with satellite imagery could extend the spatial scale of erosion assessments while maintaining high resolution.

Conclusion

This study demonstrates the effectiveness of combining UAV-based remote sensing with machine learning for assessing topsoil erosion. The RF model, leveraging fused UAV and environmental data, achieved an accuracy of 88% and an RMSE of 2.1 t/ha/year, offering a robust tool for high-resolution erosion mapping. These findings support precision soil conservation by identifying erosion hotspots for targeted interventions. Future work should focus on scaling the approach and incorporating temporal data to enhance erosion monitoring.

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