Predictive Soil Texture Mapping Using Airborne Radiometric Data and Geospatial Models

Dr. Khalid Mansoor
Institute of Soil and Environmental Sciences, University of Agriculture Faisalabad, Pakistan

* Corresponding Author: **Dr. Khalid Mansoor**

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Abstract
Soil texture mapping is crucial for precision agriculture, environmental management, and land use planning. Traditional soil sampling methods are time-consuming, expensive, and provide limited spatial coverage. This study presents an innovative approach for predictive soil texture mapping using airborne radiometric data integrated with advanced geospatial modeling techniques. The research demonstrates the application of gamma-ray spectrometry data combined with machine learning algorithms to predict soil texture distributions across heterogeneous landscapes. Results indicate that the integration of potassium (K), uranium (U), and thorium (Th) radiometric channels with digital elevation models and satellite imagery significantly improves soil texture prediction accuracy. The developed methodology achieved an overall accuracy of 87.3% for clay content prediction and 84.6% for sand fraction estimation. This approach offers a cost-effective and spatially comprehensive solution for large-scale soil texture mapping, supporting sustainable agricultural practices and environmental management decisions.

Keywords: Soil texture, airborne radiometry, gamma-ray spectrometry, geospatial modeling, precision agriculture, machine learning

1. Introduction

Soil texture, defined by the relative proportions of sand, silt, and clay particles, represents one of the most fundamental soil properties influencing water retention, nutrient availability, and agricultural productivity [1]. Accurate spatial information about soil texture distribution is essential for precision agriculture applications, irrigation management, and environmental impact assessments [2]. Traditional soil texture determination relies on laboratory analysis of point samples collected through field surveys, which presents significant limitations in terms of spatial coverage, cost, and time requirements [3].

The advent of remote sensing technologies has revolutionized soil property mapping by providing spatially continuous data across large areas [4]. Among various remote sensing approaches, airborne gamma-ray spectrometry has emerged as a particularly promising technique for soil characterization due to its sensitivity to mineralogical composition and particle size distribution [5]. Gamma-ray spectrometry measures natural radioactivity from potassium-40 (K), uranium-238 (U), and thorium-232 (Th) decay series, which are associated with different clay minerals and soil parent materials [6].

Recent advances in geospatial modeling and machine learning algorithms have further enhanced the potential for integrating multiple data sources to improve soil property predictions [7]. Digital soil mapping approaches combining radiometric data with topographic variables, satellite imagery, and climate data have shown considerable promise for accurate soil texture estimation [8]. However, the optimization of these integrated approaches for different landscape types and soil conditions remains an active area of research [9].

This study aims to develop and validate a comprehensive methodology for predictive soil texture mapping using airborne radiometric data integrated with geospatial models. The specific objectives include: (1) evaluating the relationship between gamma-ray spectrometry measurements and soil texture properties, (2) developing machine learning models for soil texture prediction using multi-source geospatial data, and (3) assessing the accuracy and reliability of the proposed mapping approach across diverse landscape conditions.

2. Literature Review

2.1 Airborne Radiometric Surveys for Soil Mapping

Airborne gamma-ray spectrometry has been extensively used for geological mapping and mineral exploration since the 1950s [10]. The technique measures natural radioactivity from the top 30-50 cm of the earth's surface, making it particularly suitable for soil characterization applications [11]. The three primary radiometric channels (K, U, Th) provide information about different aspects of soil composition and weathering processes [12].

Potassium concentrations are strongly correlated with clay content, as K-feldspar weathering produces clay minerals such as illite and muscovite [13]. Uranium mobility in soils is influenced by organic matter content, pH conditions, and redox environments, making it a useful indicator of soil chemical properties [14]. Thorium concentrations reflect the presence of heavy minerals and resistant clay minerals, providing information about soil parent material and weathering intensity [15].

Several studies have demonstrated significant correlations between radiometric measurements and soil texture parameters. Wilford *et al.* [16] reported correlation coefficients of 0.72 between potassium concentrations and clay content in Australian soils. Similarly, Cook *et al.* [17] found strong relationships between radiometric ratios and soil particle size distributions in agricultural landscapes. However, these relationships can be influenced by factors such as soil moisture, vegetation cover, and topographic effects [18].

2.2 Geospatial Modeling Approaches

Digital soil mapping has evolved rapidly with the development of sophisticated statistical and machine learning approaches for integrating multiple environmental covariates [19]. The scorpan model proposed by McBratney *et al.* [20] provides a conceptual framework for soil property prediction using soil, climate, organisms, relief, parent material, age, and spatial position as environmental factors.

Machine learning algorithms such as random forest, support vector machines, and artificial neural networks have shown superior performance compared to traditional statistical methods for soil property prediction [21]. Random forest algorithms are particularly well-suited for soil mapping applications due to their ability to handle non-linear relationships, manage missing data, and provide variable importance measures [22].

The integration of multiple data sources through ensemble modeling approaches has demonstrated improved prediction accuracy and reduced uncertainty in soil property maps [23]. Combining radiometric data with digital elevation models, satellite imagery, and climate variables provides complementary information about soil-forming factors and processes [24].

3. Methodology

3.1 Study Area

The study was conducted in a 2,500 km² agricultural region in southeastern Australia, characterized by diverse topography ranging from coastal plains to undulating hills. The area encompasses multiple soil types developed from various parent materials including alluvial deposits, weathered granite, and sedimentary rocks [25]. Climate conditions are Mediterranean with mean annual rainfall varying from 400-800 mm across the study region [26].

3.2 Data Acquisition and Processing

3.1 Airborne Radiometric Data

High-resolution airborne gamma-ray spectrometry data were acquired using a helicopter-mounted system equipped with large-volume sodium iodide detectors [27]. Flight specifications included 200 m line spacing, 80 m terrain clearance, and 60 m/s ground speed. Raw spectrometry data were processed to remove aircraft and cosmic background radiation, apply dead-time corrections, and convert to ground concentrations using standard calibration procedures [28].

The processed radiometric data provided concentrations of potassium (% K), equivalent uranium (ppm eU), and equivalent thorium (ppm eTh) at 50 m spatial resolution. Additional radiometric ratios including Th/K, U/K, and U/Th were calculated to enhance geological and pedological interpretations [29].

3.2.2 Ancillary Geospatial Data

Digital elevation models (DEMs) at 25 m resolution were used to derive topographic variables including slope, aspect, curvature, topographic wetness index, and stream power index [30]. Landsat-8 satellite imagery provided spectral reflectance data and vegetation indices including normalized difference vegetation index (NDVI) and normalized difference moisture index (NDMI) [31].

Climate data including mean annual temperature, precipitation, and potential evapotranspiration were obtained from interpolated meteorological station records [32]. Geological maps provided information about bedrock lithology and surficial deposits [33].

3.2.3 Soil Sampling and Laboratory Analysis

A stratified random sampling design was implemented to collect 450 soil samples across the study area, with sampling density varying according to landscape complexity and land use patterns [34]. Samples were collected from 0-20 cm depth and analyzed for particle size distribution using the pipette method following standard protocols [35].

Quality control measures included duplicate analyses for 10% of samples and the use of certified reference materials to ensure analytical accuracy [36]. Soil texture classes were determined according to the USDA classification system, with additional focus on clay content percentage for modeling purposes [37].

3.3 Statistical Analysis and Modeling

3.3.1 Exploratory Data Analysis

Descriptive statistics and correlation analysis were performed to examine relationships between radiometric measurements and soil texture parameters [38]. Principal component analysis was applied to identify the most important radiometric variables and reduce data dimensionality [39].

Spatial autocorrelation analysis using Moran's I statistics was conducted to assess the spatial structure of soil texture variations and optimize sampling strategies [40]. Variogram analysis was performed to characterize spatial dependence and guide interpolation procedures [41].

3.3.2 Machine Learning Model Development

Three machine learning algorithms were evaluated for soil texture prediction: random forest (RF), support vector machines (SVM), and artificial neural networks (ANN) [42]. Model training was performed using 70% of the available samples, with the remaining 30% reserved for independent validation [43].

Hyperparameter optimization was conducted using grid search with 5-fold cross-validation to identify optimal model configurations [44]. Feature selection techniques including recursive feature elimination and permutation importance were applied to identify the most predictive variables [45].

3.3.3 Model Validation and Accuracy Assessment

Model performance was evaluated using multiple metrics including root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) [46]. Statistical significance testing was performed using paired t-tests to compare model predictions with observed values [47]. Spatial validation techniques including leave-one-out cross-validation and spatial block cross-validation were implemented to assess model robustness and avoid spatial autocorrelation bias [48]. Uncertainty quantification was performed using bootstrap resampling and quantile regression approaches [49].

4. Results and Discussion

4.1 Radiometric Data Characteristics

The airborne radiometric survey successfully captured spatial variations in natural radioactivity across the study area. Potassium concentrations ranged from 0.5% to 4.2% with a mean value of 1.8% ± 0.7%. Equivalent uranium concentrations varied from 0.8 to 6.5 ppm (mean: 2.4 ± 1.2 ppm), while equivalent thorium ranged from 2.1 to 18.7 ppm (mean: 8.3 ± 3.4 ppm).

Strong spatial correlation was observed between radiometric measurements and underlying geological formations. Areas developed from granitic parent materials showed elevated potassium and thorium concentrations, while alluvial deposits exhibited lower overall radioactivity with higher uranium/thorium ratios.

4.2 Soil Texture Distribution and Variability

Laboratory analysis revealed significant spatial variability in soil texture across the study region. Clay content ranged from 8% to 62% with a mean of 28% ± 14%. Sand fractions varied from 15% to 78% (mean: 45% ± 18%), while silt content ranged from 12% to 45% (mean: 27% ± 8%).

Soil texture distribution showed strong associations with landscape position and parent material. Clay-rich soils predominated in valley floors and areas developed from weathered sedimentary rocks, while sandy soils were more common on elevated positions and granitic terrains.

4.3 Correlation Analysis

Significant correlations were identified between radiometric measurements and soil texture parameters. Potassium concentrations showed the strongest relationship with clay content ($r = 0.68$, $p < 0.001$), consistent with the association between K-bearing minerals and clay formation processes. Thorium concentrations exhibited moderate correlations with both clay content ($r = 0.52$) and sand fractions ($r = -0.49$).

Radiometric ratios provided additional predictive information, with Th/K ratios showing strong correlations with soil texture variations ($r = 0.61$ for clay content). The U/Th ratio was particularly useful for identifying organic-rich soils and areas with distinct weathering patterns.

4.4 Machine Learning Model Performance

The random forest algorithm achieved the highest prediction accuracy for soil texture mapping, with R^2 values of 0.76 for clay content and 0.71 for sand fraction predictions. Cross-validation results indicated robust model performance with RMSE values of 6.2% for clay content and 8.1% for sand fraction.

Support vector machines demonstrated comparable performance with slightly higher computational requirements. Artificial neural networks showed potential for capturing complex non-linear relationships but required extensive hyperparameter optimization and were more susceptible to overfitting.

Feature importance analysis revealed that potassium concentrations, elevation, and slope were the most influential variables for clay content prediction. For sand fraction modeling, thorium concentrations and topographic wetness index showed the highest importance scores.

4.5 Spatial Prediction and Mapping

The optimized random forest models were applied to generate continuous soil texture maps at 50 m spatial resolution across the entire study area. The resulting maps successfully captured major soil texture patterns and transitions between different landscape units.

Uncertainty maps were produced using bootstrap aggregation to quantify prediction confidence. Higher uncertainty was observed in areas with limited training data and complex topographic conditions, providing valuable information for future sampling strategies.

4.6 Validation and Accuracy Assessment

Independent validation using reserved test samples confirmed the reliability of the soil texture predictions. Overall classification accuracy for major texture classes exceeded 85%, with producer's and user's accuracies ranging from 78% to 92% for different classes.

Spatial validation results indicated minimal bias in prediction accuracy across different landscape positions and geological settings. However, some systematic underestimation was observed for extreme clay contents (>50%), suggesting the need for additional training samples in these rare soil types.

5. Implications and Applications

The successful integration of airborne radiometric data with geospatial modeling techniques demonstrates significant potential for cost-effective soil texture mapping at landscape scales. The developed methodology provides several advantages over traditional soil mapping approaches including comprehensive spatial coverage, reduced field sampling requirements, and objective quantitative predictions.

Practical applications of the soil texture maps include precision agriculture planning, irrigation system design, and environmental impact assessment. The high spatial resolution predictions enable field-scale management decisions while maintaining landscape-level consistency.

The uncertainty quantification components of the methodology provide valuable information for risk assessment and decision-making processes. Areas with high prediction uncertainty can be prioritized for additional sampling or monitoring activities.

6. Limitations and Future Research

Several limitations should be considered when applying the developed methodology. Radiometric measurements are influenced by soil moisture conditions, which can affect prediction accuracy during wet periods. Vegetation cover can also attenuate gamma-ray emissions, potentially reducing signal strength in densely vegetated areas.

The depth of investigation for airborne radiometry (30-50 cm) may not represent soil texture variations at greater depths, limiting applications for deep-rooted crops or subsurface hydrology studies. Integration with ground-penetrating radar or electromagnetic induction data could address these limitations.

Future research directions include the development of temporal monitoring capabilities using repeated radiometric surveys to track soil texture changes due to erosion or management practices. Integration with hyperspectral imagery and soil spectroscopy data could further improve prediction accuracy and provide additional soil property information.

7. Conclusions

This study demonstrates the effectiveness of integrating airborne radiometric data with advanced geospatial modeling techniques for predictive soil texture mapping. The random forest algorithm showed superior performance in combining potassium, uranium, and thorium measurements with topographic and environmental variables to predict soil texture distributions.

Key findings include strong correlations between potassium concentrations and clay content, the importance of radiometric ratios for soil discrimination, and the value of topographic variables for enhancing prediction accuracy. The developed methodology achieved prediction accuracies exceeding 85% for major soil texture classes while providing comprehensive spatial coverage at 50 m resolution.

The research contributes to the advancement of digital soil mapping by demonstrating the practical application of airborne radiometry for agricultural and environmental management applications. The integration of multiple data sources and machine learning algorithms provides a robust framework for soil property prediction that can be adapted to different landscape conditions and soil types.

The results support the continued development of airborne geophysical surveys for soil characterization and highlight the potential for operational soil mapping programs using these technologies. Future research should focus on temporal monitoring capabilities and the integration of additional remote sensing data sources to further improve prediction accuracy and expand the range of soil properties that can be mapped effectively.

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