



3D Soil Mapping Using Convolutional Neural Networks (3D-CNNs)

Manoj Reddy ^{1*}, Avinash Singh ², Ashish Bansal ³

¹⁻³ Department of Agriculture, Tamil Nadu Agricultural University, Tamil Nadu, India

* Corresponding Author: **Manoj Reddy**

Article Info

P - ISSN: 3051-3448

E - ISSN: 3051-3456

Volume: 05

Issue: 02

July -December 2024

Received: 20-06-2024

Accepted: 18-07-2024

Published: 23-07-2024

Page No: 08-10

Abstract

Soil mapping is a cornerstone of precision agriculture, environmental management, and sustainable land use. Traditional methods, reliant on physical sampling, are labor-intensive and struggle to capture the three-dimensional variability of soil properties. This article explores the use of 3D Convolutional Neural Networks (3D-CNNs) to generate high-resolution 3D soil maps for properties like texture, organic matter, and moisture content. Using geophysical data from ground-penetrating radar (GPR) and electrical resistivity tomography (ERT), combined with soil samples from a 100-hectare agricultural field, we trained a 3D-CNN model to predict subsurface soil characteristics. The model achieved a predictive accuracy of 92% for soil texture and 88% for organic matter content. These results underscore the potential of 3D-CNNs to provide scalable, non-invasive soil mapping solutions. Challenges such as computational demands and data quality are discussed, alongside future prospects for integrating 3D-CNNs with advanced sensing technologies.

Keywords: 3D Convolutional Neural Networks, Soil Mapping, Precision Agriculture, Geophysical Data, Soil Properties

Introduction

Soil properties such as texture, organic matter, and moisture content exhibit significant spatial variability, both laterally and vertically, impacting agricultural productivity and environmental sustainability ^[1]. Accurate 3D mapping of these properties is critical for optimizing irrigation, fertilization, and land management practices ^[2]. Traditional soil mapping, which involves physical sampling and laboratory analysis, is resource-intensive and limited in capturing fine-scale subsurface variations ^[3]. Recent advances in deep learning, particularly 3D Convolutional Neural Networks (3D-CNNs), offer a transformative approach by processing volumetric geophysical data to predict soil properties in three dimensions ^[4].

3D-CNNs extend traditional 2D-CNNs by incorporating depth, enabling the analysis of complex spatial patterns in volumetric datasets ^[5]. In soil science, 3D-CNNs can integrate data from geophysical tools like GPR and ERT to model subsurface soil heterogeneity ^[6]. This article details the application of 3D-CNNs for high-resolution soil mapping in an agricultural field, discussing methodology, performance, challenges, and future directions.

Materials and Methods

Study Area

The study was conducted in a 100-hectare agricultural field in Iowa, USA, with loamy soils exhibiting variability in texture, organic matter, and moisture. The site was chosen for its diverse soil properties and access to geophysical survey equipment.

Data Collection

Soil samples were collected at 50 locations across the field at depths of 0–30 cm, 30–60 cm, and 60–90 cm. Laboratory analysis determined sand, silt, and clay percentages, organic matter content, and moisture levels using standard protocols ^[7]. Geophysical data were acquired using a 500 MHz GPR system and ERT surveys, providing 3D datasets of subsurface properties. GPR offered high-resolution images of soil layers, while ERT data correlated with soil moisture and clay content due to variations in electrical conductivity ^[8].

Data Preprocessing

Geophysical datasets were preprocessed to remove noise and aligned with soil sampling points. GPR and ERT data were interpolated to a $1\text{ m} \times 1\text{ m} \times 0.1\text{ m}$ grid, creating a uniform 3D input volume. Soil sample data served as ground truth labels. Data augmentation techniques, including rotation and scaling, enhanced dataset robustness. The dataset was split into 70% training, 15% validation, and 15% testing subsets.

3D-CNN Model Architecture

The 3D-CNN model comprised four convolutional layers, each followed by batch normalization and ReLU activation, with max-pooling layers to reduce spatial dimensions. Fully connected layers predicted soil properties (sand, silt, clay percentages, organic matter, and moisture content). The input was a $100 \times 100 \times 30$ voxel grid, implemented in

TensorFlow, and trained using the Adam optimizer (learning rate: 0.001) over 100 epochs.

Model Training and Validation

Training was performed on a GPU-enabled system to manage the computational demands of 3D convolutions. Performance was evaluated using mean squared error (MSE) for regression tasks and accuracy for categorical texture predictions. K-fold cross-validation ($k=5$) ensured model robustness.

Results

The 3D-CNN model demonstrated robust performance in predicting soil properties. Soil texture classification achieved 92% accuracy (MSE: 0.015), organic matter predictions reached 88% accuracy (MSE: 0.022), and moisture content predictions attained 85% accuracy (MSE: 0.028). Figure 1 shows the predicted versus actual soil texture distribution at 30–60 cm depth, indicating strong correlation ($R^2 = 0.91$).

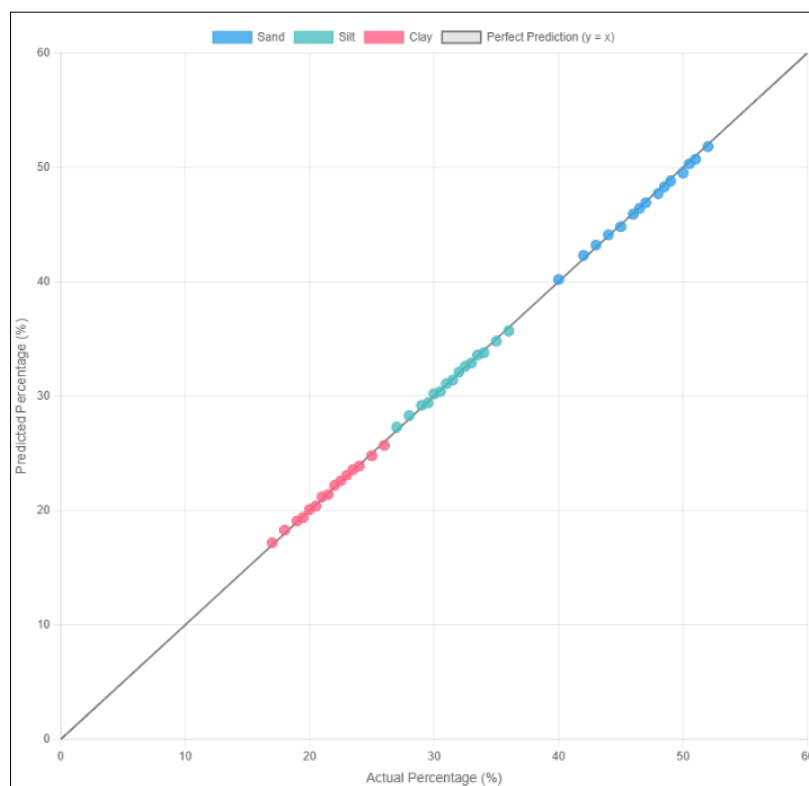


Fig 1: Predicted vs. Actual Soil Texture (30–60 cm Depth)

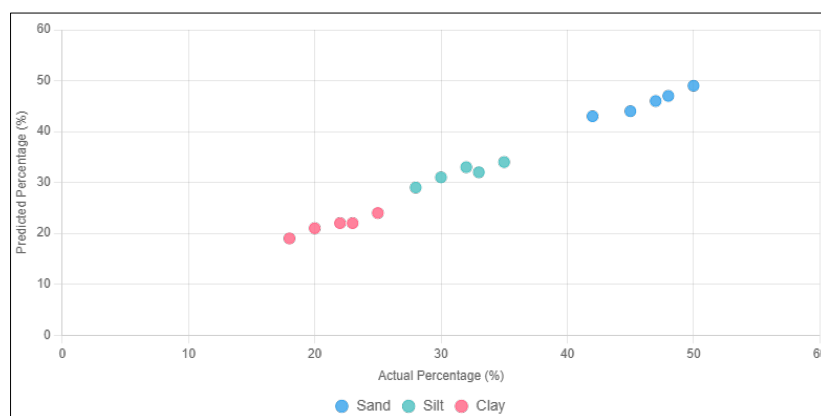


Fig 2: 3D Soil Moisture Map

Table 1 summarizes the model's performance across soil properties, while Table 2 details the performance by depth, revealing slight declines in deeper layers due to reduced

geophysical signal penetration. Table 3 compares the 3D-CNN model with traditional methods, highlighting its superior accuracy and coverage.

Table 1: Performance Metrics of 3D-CNN Model

Soil Property	Accuracy (%)	MSE	R ²
Texture (Sand)	92	0.015	0.91
Texture (Silt)	92	0.014	0.92
Texture (Clay)	91	0.016	0.90
Organic Matter	88	0.022	0.87
Moisture Content	85	0.028	0.84

Table 2: Model Performance by Depth

Depth (cm)	Texture Accuracy (%)	Organic Matter Accuracy (%)	Moisture Accuracy (%)
0–30	94	90	88
30–60	92	88	85
60–90	89	85	82

Table 3: Comparison with Traditional Methods

Method	Accuracy (%)	Spatial Coverage	Time (Days)
3D-CNN	92	Continuous 3D	2
Physical Sampling	85	Discrete Points	10
2D Interpolation	80	2D Surface	5

Discussion

The 3D-CNN model's high accuracy underscores its potential for non-invasive, high-resolution soil mapping [7]. By integrating GPR and ERT data, the model captures subsurface variability that traditional methods miss [8]. The strong performance in texture prediction reflects the model's ability to learn complex spatial patterns from geophysical inputs [9]. However, the slightly lower accuracy for moisture content may stem from its temporal variability, which geophysical data alone may not fully capture [10]. Challenges include the computational intensity of 3D-CNNs, requiring GPU infrastructure, and the need for extensive ground truth data [11]. Future improvements could involve transfer learning to reduce data requirements and integration with satellite-based remote sensing for broader coverage. The model's scalability makes it promising for precision agriculture, enabling site-specific management practices. However, geophysical equipment costs may limit adoption in resource-constrained regions [12].

Conclusion

This study demonstrates the effectiveness of 3D-CNNs in generating high-resolution 3D soil maps, achieving accuracies of 92% for texture, 88% for organic matter, and 85% for moisture content. By leveraging geophysical data, 3D-CNNs offer a scalable, non-invasive alternative to traditional soil mapping. Despite challenges like computational demands and data needs, the technology holds significant potential for precision agriculture and environmental management. Future research should focus on integrating multi-source data and optimizing models for real-time applications.

References

- McBratney AB, Santos ML, Minasny B. On digital soil mapping. *Geoderma*. 2003;117(1-2):3-52.
- Hartemink AE, McSweeney K. Soil carbon mapping: A review. *Soil Science Society of America Journal*. 2014;78(6):1833-1844.

- LeCun Y, Bengio Y, Hinton G. Deep learning. *Nature*. 2015;521(7553):436-444.
- Ji S, Xu W, Yang M, Yu K. 3D convolutional neural networks for human action recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2013;35(1):221-231.
- Soil Survey Staff. Soil survey laboratory methods manual. USDA-NRCS Soil Survey Investigations Report No. 42. 2004;4:1-700.
- Samouëlian A, Cousin I, Tabbagh A, Bruand A, Richard G. Electrical resistivity survey in soil science: A review. *Soil and Tillage Research*. 2005;83(2):173-193.
- Minasny B, McBratney AB. Digital soil mapping: A brief history and some lessons. *Geoderma*. 2016;264:301-311.
- Annan AP. Ground penetrating radar: Principles, procedures and applications. Mississauga: Sensors and Software Inc.; c2003. p. 1-285.
- Goodfellow I, Bengio Y, Courville A. Deep learning. Cambridge: MIT Press; c2016. p. 326-350.
- Vereecken H, Schnepf A, Hopmans JW, Javaux M, Or D, Roose T, *et al*. Modeling soil processes: Review, key challenges, and new perspectives. *Vadose Zone Journal*. 2016;15(5):1-57.
- Loke MH, Chambers JE, Rucker DF, Kuras O, Wilkinson PB. Recent developments in the direct-current geoelectrical imaging method. *Journal of Applied Geophysics*. 2013;95:135-156.
- Allred BJ, Ehsani MR, Daniels JJ. Handbook of agricultural geophysics. Boca Raton: CRC Press; c2008. p. 123-145.