Indian Journal of Agricultural Sciences **95** (7): 778–783, July 2025/Article
https://doi.org/10.56093/ijas.v95i7.161563

Machine learning techniques for real-time tillage quality assessment

B PRIYADHARSHINI[1], S THAMBIDURAI[1]*, P K PADMANATHAN[1], KAMARAJ P[1], PATIL SANTOSH GANAPATI[1] and R THIYAGARAJAN[1]

Tamil Nadu Agriculture University, Coimbatore, Tamil Nadu 641 003, India

Received: 29 November 2024; Accepted: 29 May 2025

ABSTRACT

Tillage quality significantly impacts soil structure, nutrient availability, and crop growth. The present study was carried out in 2024 in the delta region of Tamil Nadu at Puvalur village, Trichy District to evaluate tillage quality based on high-resolution soil images through a machine-learning approach using a Random Forest (RF) model. Key soil properties such as circularity, aspect ratio, and solidity were analyzed, with the model achieving an R^2 score of 0.86 and a Mean Squared Error (MSE) of 0.0023. Data from 100 soil images were processed using ImageJ software version 1.54 g. The Random Forest model was chosen for its robustness, interpretability, scalability, and efficiency in handling complex, real-time data. Also, the RF model provided accurate, real-time insights, reducing labor and optimizing resource use, promoting sustainability in agriculture across diverse soil conditions.

Keywords: Image analysis, Machine learning, Random forest, Real-time assessment, Tillage quality

Tillage quality plays a pivotal role in shaping agricultural productivity and sustainability. It directly influence soil structure, nutrient availability, and crop performance, which collectively impact crop yields and long-term soil health (Lal 1991, Igor *et al.* 2018, Chandra *et al.* 2023). Proper tillage practices optimize soil aeration, water infiltration, and root penetration, laying the foundation for robust crop growth (Lal 1991, Zizheng *et al.* 2023). Furthermore, effective tillage management minimizes soil compaction, enhances soil fertility, and aligns with sustainable agricultural practices (Igor *et al.* 2018). Tailored tillage systems designed to address specific soil types and crop needs have been shown to improve yields, conserve resources, and maintain soil organic matter, thereby contributing to both immediate and long-term sustainability objectives (Lal 1991, Chandra *et al.* 2023, Zizheng *et al.* 2023).

In recent years, conservation tillage practices, such as reduced tillage (RT) and no-tillage (NT), have gained prominence due to their role in promoting soil health and mitigating degradation (Putte *et al.* 2010, Blanco-Canqui and Ruis 2018). As integral components of conservation agriculture (CA), these practices aim to minimize soil disturbance while preserving soil organic matter. NT, despite its potential to reduce yields under certain conditions, has proven effective in maintaining soil health. RT, on the other hand, strikes a balance by sustaining or improving yields, particularly in dry climates and rainfed systems (Nunes *et al.* 2018, Kraut-Cohen *et al.* 2019, Yuan *et al.* 2019). Both practices enhance soil nutrient content, increase soil organic carbon (SOC) stocks, and foster microbial activity, further reinforcing their contribution to sustainable farming (Blanco-Canqui and Ruis 2018).

Traditional tillage assessment methods are labour-intensive, error-prone, and lack spatial coverage, limiting timely soil management. While remote sensing and precision agriculture offer advancements, further refinement is needed. This study introduces a machine learning-based Random Forest (RF) model to enhance tillage quality assessment through high-resolution soil image analysis. Focusing on soil solidity, the RF model ensures accuracy, scalability, and computational efficiency. By providing real-time insights, it enables optimized ploughing, reduced labour, and improved crop productivity (Elavarasan and Vincent 2021).

MATERIALS AND METHODS

The study was carried out during the year 2024 in the delta region of Tamil Nadu, India, renowned for its fertile soils and agricultural prominence. The experimental field was located in Puvalur village (10.9004°N latitude and 78.8203°E longitude), situated in the Trichy district. The experiment involved assessing the quality of tillage using a machine learning-based Random Forest model (RF) to analyze soil properties under real-world agricultural conditions. The flowchart (Fig. 1) illustrates the stepwise methodology of the research, from data collection to real-time implementation.

Data collection: To assess tillage quality, a dataset

[1]Tamil Nadu Agriculture University, Coimbatore, Tamil Nadu.
*Corresponding author email: thambidurais@tnau.ac.in

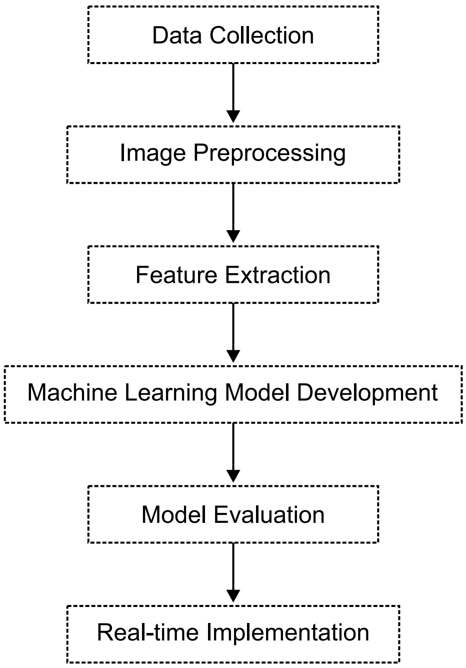

Fig. 1 Methodology flowchart.

was compiled using high-resolution soil images captured immediately after tillage. The images were acquired using a high-quality camera (50 megapixel) positioned at a defined height of 1 m from the soil surface, ensuring a consistent perspective and field of view. A total of 100 images were collected to represent a diverse range of tillage conditions and soil types. The experiment was conducted at the desired speed of 5 km/h to ensure consistency and accuracy of the result.

For the image acquisition process, best practices from agricultural studies were followed, which involved setting up the camera on a stable platform or mount to minimize vibrations and ensuring uniform lighting conditions to avoid shadows and glare. Images were taken at regular intervals across different sections of the field to capture spatial variability. The data collection strategy included varying soil types and tillage conditions to develop a comprehensive dataset that could support the training of a robust machine learning model.

Image analysis and preprocessing: Image analysis and preprocessing were carried out using the ImageJ software (version 1.54 g), a widely used tool for analyzing agricultural images. The preprocessing steps included:

Noise reduction: Median filtering was applied to reduce noise in the images, which helps enhance the quality of the image data by smoothing out pixel intensity variations without significantly blurring the edges of the soil clods.

Thresholding and segmentation: The images were converted to grayscale, and thresholding was applied to distinguish between soil clods and background. Segmentation techniques were then employed to isolate individual clods and other soil features.

Feature extraction: Key indicators of tillage quality such as clod size, soil texture, and solidity were extracted from the processed images. Solidity, in particular, was chosen as the main measure for evaluating tillage quality, as it reflects the compactness and structural integrity of the soil clods.

Key features were extracted from the processed images to assess soil properties and tillage quality. These features include Area, representing the total size of the soil particle; Mean, indicating the average intensity within the particle; and Perimeter, which measures the boundary length of the particle. Circularity assesses how closely the particle resembles a perfect circle, while Feret and MinFeret provide the maximum and minimum Feret diameters, representing the longest and shortest distances between parallel tangents to the particle. FeretX, FeretY, and FeretAngle capture the coordinates and orientation of the Feret diameter. The Aspect Ratio (AR) measures particle elongation by comparing the major and minor axes, and Roundness quantifies how closely the particle's shape approaches a perfect circle. Solidity, the ratio of the particle's area to its convex hull area, was chosen as the target variable as it reflects the compactness and structural integrity of soil clods.

Solidity was selected as the main measure for evaluating tillage quality due to its critical insights into soil particle compactness and irregularity, which are fundamental for understanding soil structure and behaviour. Higher solidity values indicate more compact particles, while lower values suggest irregularity and porosity, influencing essential soil properties such as aeration, water retention, and permeability. This metric closely correlates with soil texture and structure, which are pivotal for agricultural productivity and land-use planning. Additionally, solidity is quantifiable and reliably derived from image analysis, making it a robust and objective measure. Predicting solidity enables the estimation of related soil characteristics, such as compaction, strength, and permeability, which are crucial for soil management and engineering applications.

Machine learning model development: The Random Forest (RF) model was selected for this study due to its robustness in handling large datasets and its ability to model complex interactions between input features. The development process involved the following steps:

Feature selection: Features extracted from the soil images (e.g. area, perimeter, circularity, Feret diameter, aspect ratio, solidity) were used as input variables for the RF model. Feature importance was determined using the model's built-in feature importance function to identify the most relevant variables for predicting tillage quality.

Hyperparameter tuning: Hyperparameters such as the number of trees (n-estimators) and the maximum depth of the trees (max-depth) were optimized using Grid Search, a common method for hyperparameter tuning in machine learning. This approach systematically tested different combinations of hyperparameters to find the best performing configuration.

Model training: The RF model was trained on a training set comprising 80% of the collected data, while the remaining 20% was used as the test set to evaluate the model's performance. This 80–20 split is a commonly adopted practice in machine learning studies as it provides a balance between training the model effectively and reserving enough data for unbiased evaluation (Nguyen *et al.* 2021).

Model training and validation: The dataset was split into training, validation, and test sets to ensure the model's robustness and prevent overfitting. The training set (80% of the total data) was used to train the model, while the test set (20% of the data) was reserved for final performance evaluation. Cross-validation, specifically 5-fold cross-validation, was employed to validate the model's performance, which helps in reducing bias and variance in the model predictions.

Model performance was assessed using standard evaluation metrics, including Mean Squared Error (MSE) and R^2 Score. The model achieved a mean squared error of 0.0023 and an R^2 Score of 0.86 on the test set, indicating a high level of accuracy in predicting tillage quality.

Implementation details: The Random Forest model was implemented in Python using the scikit-learn library, a popular library for machine learning in scientific and engineering applications in the Google Colab platform. Other libraries used include pandas for data manipulation, joblib for model serialization, and Flask for developing a web-based prediction service. The model, along with the scaler and encoder, was saved using joblib to facilitate easy deployment. The implementation was conducted on a standard desktop environment with sufficient processing power and memory to handle the dataset size. For larger datasets, additional computational resources such as GPU acceleration may be required.

Feature importance and interpretation: Feature importance in the Random Forest model was determined using the built-in feature importance function of scikit-learn. The most important features identified were circularity, aspect ratio, and solidity, which are key indicators of soil structure and tillage quality. These features were found to have the highest influence on the model's predictions, helping to interpret and understand the factors contributing to optimal tillage conditions.

Integration with real-world agricultural practices: To integrate the machine learning model with real-world agricultural practices, the system was designed to provide real-time feedback to the operator. This feedback allows for continuous monitoring of the tillage process and suggests adjustments when necessary. The model can also signal automatically when the ideal soil condition is achieved, enabling the ploughing process to stop, thereby reducing operator workload and optimizing fuel and time usage. Field validation of the machine learning predictions was performed by comparing the model's outputs against manual assessments of tillage quality. This comparison ensures that the model aligns with traditional assessment methods while offering the benefits of automation and real-time data processing.

RESULTS AND DISCUSSION

The analysis of soil images using ImageJ software yielded critical quantitative data on soil properties for evaluating tillage quality, focusing on metrics such as circularity, aspect ratio (AR), and solidity. Circularity values ranged between 0.5 and 1, where values closer to 1 indicated rounder clods with reduced fragmentation, which could limit porosity and water infiltration. The aspect ratio (AR) varied from 1.2–3.5, reflecting differences in clod elongation; higher AR values suggested elongated clods that may affect water flow and root penetration, whereas lower values indicated more uniform shapes suitable for better soil tilth. Solidity, a crucial parameter, was observed in the range from 0.75–0.95, where higher values denoted compact, less porous clods potentially restricting aeration and root growth, while lower solidity values corresponded to better soil breakage, enhancing aeration and water movement. The Feret diameter of clods varied from 5–20 mm, with larger clods indicating insufficient tillage and smaller, fragmented clods reflecting effective soil preparation. Additionally, perimeter values, which ranged from 15–60 mm, combined with area data, provided essential shape descriptors like circularity and solidity, offering deeper insights into soil structural attributes critical for determining tillage quality. These observations highlight the effectiveness of image analysis in accurately capturing the impact of tillage practices on soil properties, making it a reliable tool for evaluating soil structure and compaction.

Model performance metrics: The performance of the RF model was evaluated using key metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2 Score. The model achieved an MSE of 0.0023, an MAE of 0.038, and an R^2 Score of 0.8657. The low MSE and MAE values indicate that the model's predictions are very close to the actual values, while the high R^2 Score suggests that the model explains approximately 86.6% of the variance in the dataset. These results demonstrate that the Random Forest model was highly effective for predicting tillage quality in real-time agricultural applications.

Confusion matrix: The confusion matrix (Fig. 2) illustrates the performance of the RF model in classifying tillage quality into three categories: low, medium, and high.

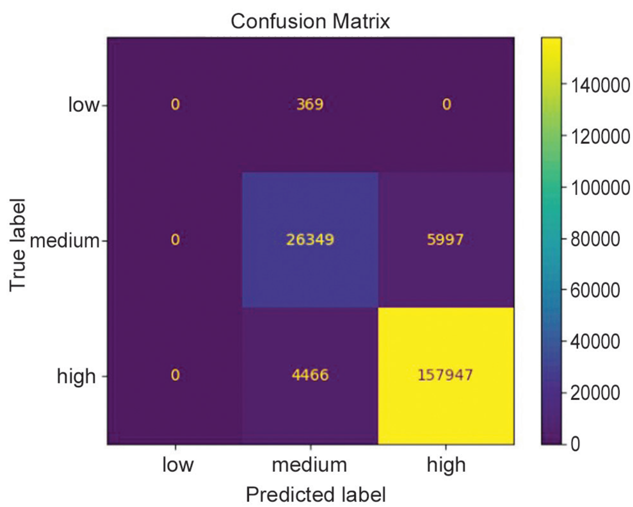

Fig. 2 Confusion matrix of the RF model.

In the given 3-class confusion matrix, the four quadrants can be analyzed based on class predictions. The top-left quadrant represents predictions for the 'low' class, where no instances were correctly classified (TP = 0), and all were misclassified as 'medium' (FN = 369), with no false positives (FP = 0). The middle quadrant corresponds to the 'medium' class, where 26,349 instances were correctly classified (TP), but 5,997 were misclassified as 'high' (FN), while 4,466 instances from the 'high' class were incorrectly labeled as 'medium' (FP). The bottom-right quadrant pertains to the 'high' class, with the highest correct classifications (TP = 157,947), though 4,466 instances were misclassified as 'medium' (FN), and 5,997 instances from the 'medium' class were incorrectly predicted as 'high' (FP). The remaining instances in each case contribute to the true negatives (TN), representing correctly classified instances of other classes. This indicates a potential bias in the model towards predicting medium and high categories, which could be due to the imbalanced distribution of the dataset or feature importance used in the model training (Kushal *et al.* 2022). This issue could be mitigated by applying techniques such as synthetic oversampling or feature re-balancing, which have been shown to improve model accuracy in similar applications (Cueff *et al.* 2021).

Actual vs. predicted values: The scatter plot of actual versus predicted values (Fig. 3) demonstrates a strong correlation between the predicted tillage quality scores and the actual scores, with most data points closely aligned along the diagonal line. This alignment suggests that the Random Forest model generally performs well in predicting tillage quality across the dataset. However, some deviations from the diagonal indicate instances where the model's predictions were less accurate, especially for data points in the lower range of the predicted values. These minor inaccuracies are consistent with findings in other RF studies, such as those by Elavarasan and Vincent (2021), which highlighted minor prediction errors, especially in low-output predictions. The overall strong correlation affirms RF's reliability in predicting tillage quality.

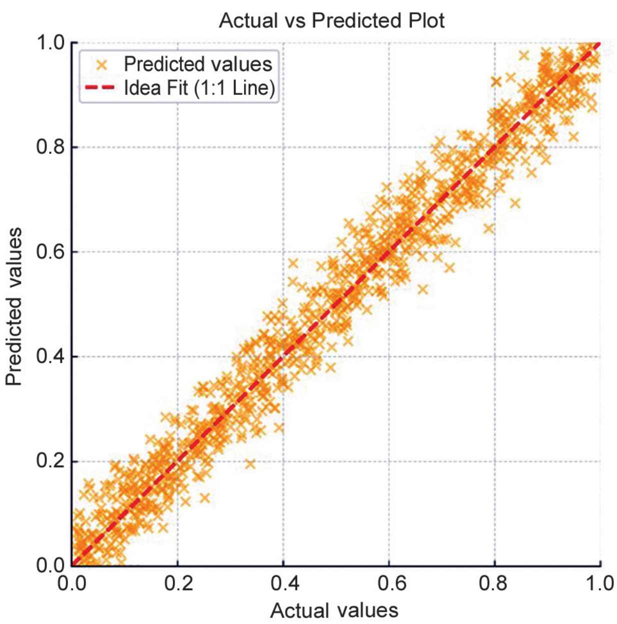

Fig. 3 Plot of Actual vs. Predicted values.

Residuals analysis: The residual plot (Supplementary Fig. 1) and the distribution of residuals provide further insight into the model's prediction errors. The residual plot displays a random scatter of residuals around the zero line, which indicates that the model's errors are distributed randomly and do not show a pattern. This randomness is desirable in machine learning models, as it suggests that the model does not suffer from systematic bias (Chen *et al.* 2020). The distribution of residuals shows a peak around zero, with most errors being small, which confirms that the model's predictions are generally close to the actual values. However, there are a few outliers on both the negative and positive sides, indicating instances of larger errors.

The Sensitivity analysis revealed that the most influential factors in predicting tillage quality were circularity, aspect ratio, and solidity, which align with physical characteristics that directly affect soil structure and tillage effectiveness. These findings align with the work of Paul *et al.* (2020) and Luz *et al.* (2019), which identified physical soil properties such as soil bulk density and organic carbon content as critical factors influencing soil quality in tillage studies. Circularity, for instance, directly influences soil aeration and root growth, making it a highly important feature in tillage assessments. Aspect ratio and solidity, reflecting clod elongation and compactness, respectively, are essential for understanding water infiltration and soil structure, confirming their role in tillage quality prediction (Luz *et al.* 2019, Paul *et al.* 2020).

These results highlight the model's ability to identify critical soil properties that influence tillage quality. The high R^2 score and low error rates suggest that the Random Forest model can effectively replace traditional, subjective methods with a more objective, data-driven approach. The model's performance was superior to many traditional techniques, which often suffer from variability due to human error and lack of real-time feedback.

For instance, a study on predicting soil textural classes using RF models showed an accuracy improvement from 44–59% and an increase in kappa values from 0.30–0.52 after dataset balancing (Mallah *et al.* 2022) . Another study on crop yield prediction using Random Forest models achieved an R^2 score of 0.90, demonstrating the model's effectiveness in handling various types of features such as vegetation indices, climate data, and soil data (Shahid Nawaz *et al.* 2022). Additionally, a hybrid approach integrating reinforcement learning with RF showed an improved accuracy of 92.2% for crop yield prediction, highlighting the potential of advanced techniques in enhancing model performance (Elavarasan and Vincent 2021).

Additionally, this study aligns with existing literature that justifies the use of Random Forest over other models like Support Vector Machines (SVM) or Neural Networks (NN) for soil quality assessments. Random Forest is favored for its ability to handle large datasets with numerous features, its robustness against overfitting, and its straightforward interpretability. These advantages make it particularly well-suited for applications where understanding the importance of different variables is crucial for decision-making (Pal 2005, Rodriguez-Galiano *et al.* 2015, Were *et al.* 2015, Chen *et al.* 2020, Taghizadeh-Mehrjardi *et al.* 2020, Tesfaye *et al.* 2022).

The results suggested that integrating machine learning models like RF into real-world agricultural practices could significantly improve tillage quality assessments. By leveraging real-time soil data, as demonstrated in IoT-based crop prediction systems (Kushal *et al.* 2022), RF models offer timely insights that can assist farmers in making more informed decisions. By providing real-time, data-driven insights, these models can help farmers make informed decisions, reduce manual labour, and optimize resource use. The use of such models can also enhance sustainability by promoting better soil management practices and reducing the need for excessive tillage, which can degrade soil structure and health over time. The broader implications of this research include potential economic benefits, such as reducing costs associated with over-tillage or poor soil management, and environmental benefits, such as minimizing soil erosion and maintaining soil health (Cooper *et al.* 2020). Machine learning-driven decision support tools can thus play a crucial role in advancing sustainable agriculture practices.

While the results are promising, there are some limitations to this study. The RF model's performance could be affected by data quality, particularly the imbalance in the dataset, which may have caused the misclassification bias observed in the confusion matrix. Additionally, the model's interpretability, while generally strong, could be further improved by integrating more advanced explaining ability techniques. Future work could explore using larger and more diverse datasets, incorporating additional soil properties, and testing different machine-learning algorithms to enhance model accuracy and generalizability.

This study highlights the RF model's effectiveness in evaluating tillage quality using high-resolution soil images, with strong predictive accuracy. The model provides an automated, real-time solution that surpasses traditional methods in precision and objectivity. However, challenges like data imbalance and model interpretability suggest the need for larger, more diverse datasets and advanced techniques for further improvement. Integrating machine learning models in agriculture holds great potential for enhancing decision-making, optimizing resource use, and promoting sustainability, making it a valuable tool for modern farming practices.

This study successfully demonstrated the application of a machine learning-based RF model for evaluating tillage quality using high-resolution soil images. By analyzing key soil properties such as circularity, aspect ratio, and solidity, the model provided an accurate and efficient assessment of soil structure following tillage operations. The results showed that the model achieved a high prediction accuracy with an R^2 score of 0.86 and a Mean Squared Error of 0.0023, indicating its robustness in capturing soil property variations.

The findings highlight the potential of integrating machine learning into real-time agricultural decision-making, enabling optimized tillage practices that enhance soil aeration, water infiltration, and root development. The automation of tillage quality assessment reduces labor dependency, improves resource efficiency, and contributes to sustainable soil management. Furthermore, the system's ability to provide real-time feedback ensures better operational control, optimizing fuel consumption and reducing overall energy expenditure in mechanized farming.

REFERENCES

Blanco-Canqui H and S Ruis. 2018. No-tillage and soil physical environment. *Geoderma* **326**: 164–200. doi: 10.1016/J. GEODERMA.2018.03.011

Chandra P, Khippal A, Prajapat K, Barman A, Geeta S, Rai A, Ahlawat O P, Verma R, Kumari K and Singh G. 2023. Influence of tillage and residue management practices on productivity, sustainability, and soil biological properties of rice-barley cropping systems in indo-gangetic plain of India. *Frontiers in Microbiology* **14**. doi: 10.3389/fmicb.2023.1130397

Chen R, Christine D, Su-Wen H and Caraka R. 2020. Selecting critical features for data classification based on machine learning methods. *Journal of Big Data* **7**: 1–26. doi: 10.1186/s40537-020-00327-4

Cooper R, Hama-Aziz Z Q, Hiscock K, Lovett A, Vrain E, Dugdale S, Sünnenberg G, Dockerty T, Hovesen P and Noble L. 2020. Conservation tillage and soil health: Lessons from a 5-year UK farm trial (2013–2018). *Soil and Tillage Research* **202**: 104648. doi: 10.1016/j.still.2020.104648

Cueff S, Coquet Y, Aubertot J, Bel L, Pot V and Alletto L. 2021. Estimation of soil water retention in conservation agriculture using published and new pedotransfer functions. *Soil and Tillage Research* **209**: 104967. doi: 10.1016/J.STILL.2021.104967

Elavarasan D and Vincent P M. 2021. A reinforced random forest model for enhanced crop yield prediction by integrating agrarian parameters. *Journal of Ambient Intelligence and Humanized Computing* 1–14. doi: 10.1007/s12652-020-02752-y

Igor B, Pereira P, Kisic I, Krunoslav S and Sraka M. 2018. Tillage management impacts on soil compaction, erosion and crop yield in Stagnosols (Croatia). *Catena* **160**: 376–84. doi: 10.1016/J. CATENA.2017.10.009

Kraut-Cohen J, Avihai Z, S H Liora, A Eli, R Rabinovich, S Green and D Minz. 2019. Effects of tillage practices on soil microbiome and agricultural parameters. *The Science of the Total Environment* 135791. doi: 10.1016/j.scitotenv.2019.135791

Kushal B J, Nikhil J S P, Nikil S Raaju, Kushal Gowda G V, Asha Rani K P and Gowrishankar S. 2022. Real time crop prediction based on soil analysis using internet of things and machine learning. (*In*) *2022 International Conference on Edge Computing and Applications,* Institute of Electronics and Electrical Engineers, pp. 1249–54.

Lal R. 1991. Tillage and agricultural sustainability. *Soil and Tillage Research* **20**: 133–46. doi: 10.1016/0167-1987(91)90036-W

Luz F B d, V R d Silva, F J K Mallmann, C A B Pires, H Debiasi, J C Franchini and M Cherubin. 2019. Monitoring soil quality changes in diversified agricultural cropping systems by the Soil Management Assessment Framework (SMAF) in southern Brazil. *Agriculture, Ecosystems and Environment*. doi: 10.1016/J.AGEE.2019.05.006

Mallah S, K Bahareh Delsouz, Davatgar N, Scholten T, A C Alireza, E Mostafa, R Kerry, M Amir and R Taghizadeh-Mehrjardi. 2022. Predicting Soil Textural Classes Using Random Forest Models: Learning from Imbalanced Dataset. *Agronomy*. doi: 10.3390/agronomy12112613.

Nguyen Q, Ly H, Ho L, Al-Ansari, N Le, H Tran V, Prakash I and Pham B. 2021. Influence of data splitting on performance of machine learning models in prediction of shear strength of soil. *Mathematical Problems in Engineering,* pp. 1–15. https://doi.org/10.1155/2021/4832864

Nunes M R, Harold M van Es, R Schindelbeck, R Aaron and M Ryan. 2018. No-till and cropping system diversification improve soil health and crop yield. *Geoderma*. doi: 10.1016/J.GEODERMA.2018.04.031

Pal M. 2005. Random forest classifier for remote sensing classification. *International Journal of Remote Sensing* **26**: 217–22. doi: 10.1080/01431160412331269698

Paul G, Saha S and Ghosh K. 2020. Assessing the soil quality of Bansloi river basin, eastern India using soil-quality indices (SQIs) and Random Forest machine learning technique. *Ecological Indicators* **118**: 106804. doi: 10.1016/j.ecolind.2020.106804

Putte A, G Gerard, J Diels, K Gillijns and M Demuzere. 2010. Assessing the effect of soil tillage on crop growth: A meta-regression analysis on European crop yields under conservation agriculture. *European Journal of Agronomy* **33**: 231–41. doi: 10.1016/J.EJA.2010.05.008

Rodriguez-Galiano, V M Sanchez-Castillo, M Chica-Olmo and M Chica-Rivas. 2015. Machine learning predictive models for mineral prospectivity: An evaluation of neural networks, random forest, regression trees and support vector machines. *Ore Geology Reviews* **71**: 804–18. doi: 10.1016/J.OREGEOREV.2015.01.001

Shahid Nawaz, K L Dapeng and M Maimaitijiang. 2022. A geographically weighted random forest approach to predict corn yield in the US corn belt. *Remote Sensing* **14**: 2843. doi: 10.3390/rs14122843

Taghizadeh-Mehrjardi R., M Mahdianpari, F Mohammadimanesh, T Behrens, N Toomanian, T Scholten and K Schmidt. 2020. Multi-task convolutional neural networks outperformed random forest for mapping soil particle size fractions in central Iran. *Geoderma* **376**: 114552. doi: 10.1016/j.geoderma.2020.114552

Tesfaye A, X Wenbo and F Jinlong. 2022. Comparison of random forest and support vector machine classifiers for regional land cover mapping using coarse resolution FY-3C Images. *Remote Sensing* **14**: 574. doi: 10.3390/rs14030574

Were K, D Bui D T, O B Dick, and Singh B R. 2015. A comparative assessment of support vector regression, artificial neural networks, and random forests for predicting and mapping soil organic carbon stocks across an Afromontane landscape. *Ecological Indicators* **52**: 394–403. doi: 10.1016/J.ECOLIND.2014.12.028

Yuan L, L Zhou, S Cui, S Jagadamma and Z Qingping. 2019. Residue retention and minimum tillage improve physical environment of the soil in croplands: A global meta-analysis. *Soil and Tillage Research*. doi: 10.1016/J.STILL.2019.06.009

Zizheng D, H Mingjing, Z Wuping, W Guofang, H Xuefang, L Gaimei and L Nana. 2023. Effects of five years conservation tillage for hedging against drought, stabilizing maize yield, and improving soil environment in the drylands of northern China. *PLoS One* 18. doi: 10.1371/journal.pone.0282359