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Soil Property Prediction Under Data Scarcity Using a Tabular Foundation Model

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Abstract: Agriculture increasingly relies on data-driven insights to optimise management practices, improve crop yields, and promote sustainable resource use. While deep learning models have shown promise in spatial and image-based analytics, agricultural decision-making often depends on analysing structured, high-dimensional tabular datasets of point observations of soil, climate variables, crop records, and management histories. However, high-quality soil datasets are often scarce due to the high cost and logistical difficulty of sample collection, laboratory analysis, and multi-season monitoring, making it critical to use models that can learn effectively from limited, heterogeneous data.

In this study, we evaluate the performance of a specific type of foundation model, known as the Tabular Prior-Data Fitted Network (TabPFN). TabPFN is a pre-trained, adaptable architecture designed for structured data tasks. We use TabPFN for predictive modelling of a suite of agronomically important soil properties across 74 farms in Australia. TabPFN is benchmarked against conventional machine learning methods, including Random Forest, Extra Trees, Linear Regression, Multi-Layer Perceptron (MLP), and XGBoost, across multiple soil depth intervals and four target variables; Nitrogen (NO_3), Organic Carbon (OC), Electrical Conductivity (EC), and pH. The results show that TabPFN consistently outperforms traditional approaches in terms of prediction accuracy across all targets and sampling depths, while maintaining robust performance in the presence of feature sparsity and variable measurement noise.

These findings demonstrate the capability of tabular foundational models to leverage prior knowledge from large-scale tabular pre-training to deliver accurate, generalisable predictions in data-limited agricultural contexts. It underscores the potential of foundational models to advance predictive modelling for decision support in agriculture. This work underscores the transformative potential of foundational models in advancing the next generation of intelligent, data-driven agriculture.

Keywords: *Precision agriculture, Digital soil mapping, Tabular foundation models, TabPFN, Machine learning*

1 INTRODUCTION

Precision agriculture (PA) is transforming modern farming by integrating data-driven insights to optimise crop production, resource allocation, and environmental sustainability. With the proliferation of digital technologies, farms now generate vast amounts of structured data, at different spatial supports (point, polygon, raster) including soil measurements, weather observations, satellite indices, and crop phenotyping records. Predicting soil health and attributes is a long-standing challenge in environmental science, precision agriculture, and land management (Lehmann et al., 2020).

The past two decades have seen a surge in statistical and machine learning (ML) models for predicting soil attributes to improve management (Padarian et al., 2020). Techniques such as Linear Regression, Kriging, and Generalised Additive Models have been widely applied to interpolate soil properties using known point samples (McBratney et al., 2003; Hengl and et al., 2017). With the rise of geospatial data and remote sensing, ML algorithms like Random Forests, Support Vector Machines, and Gradient Boosting Machines have become popular due to their ability to model complex nonlinear relationships between predictors such as satellite indices, terrain attributes, and soil properties (Padarian et al., 2019; Zhang et al., 2022). Grundy and et al. (2015) developed the Soil and Landscape Grid of Australia (SLGA), which contains Australia's national soil attribute maps using decision-tree models with piecewise linear functions combined with residual kriging, leveraging measured soil data, spectroscopic estimates, and over 50 environmental covariates to produce spatially continuous soil attribute maps.

More recently, deep learning models have been explored for soil prediction tasks, particularly in cases where high-dimensional or multi-modal input data is available (Khanal et al., 2018). Fully Connected Networks (FCN), Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs) have been used to capture complex spatial patterns and interactions among soil-forming factors (Veres et al., 2015). However, these deep learning models traditionally performed best on unstructured data (images, time series), while the analysis of structured tabular data remains dominated by tree-based methods. Deep learning models often require large labelled datasets and are sensitive to data imbalance, missing values, and noise, which are inherent challenges in environmental datasets (Wadoux et al., 2020).

Foundational models (FM) are large, general-purpose models pretrained on diverse data that offer a promising solution. These FM's have revolutionised natural language processing and computer vision (Awais et al., 2025). Foundational models learn broad, transferable representations that can be fine-tuned on downstream tasks with limited supervision (Bommasani and et al., 2021). Despite their potential, foundational models have seen limited adoption in soil science and precision agriculture. This is partly due to the fragmentation of agricultural datasets, lack of large-scale benchmarks, and limited awareness within the soil and agronomic community (Yin et al., 2025; Li et al., 2023). Nonetheless, their ability to generalise across domains and adapt to new tasks with minimal fine-tuning makes them highly relevant for modern PA systems that aggregate multi-source, spatio-temporal, and heterogeneous data.

Tabular datasets in agriculture often suffer from issues such as high dimensionality, missing values, feature heterogeneity, and limited sample sizes. Standard deep neural networks, as well as tree-based methods, have historically underperformed on such limited data problems. This has spurred research into specialised architectures for tabular data. In the tabular domain, foundational models remain relatively underdeveloped; however, recent works have introduced architectures such as TabNet (Arik and Pfister, 2021*a*), SAINT (Somepalli and et al., 2021), FT-Transformer (Gorishniy and et al., 2021), and TabPFN (Hollmann and et al., 2023) that show strong performance across heterogeneous datasets. TabNet (Arik and Pfister, 2021*b*) incorporates attention-based learning to improve interpretability and feature sparsity. FT-Transformer (Gorishniy, Rubachev, Khrulkov and Babenko, 2021) adapts the Transformer architecture to handle mixed data types with feature-wise attention. TabPFN (Hess et al., 2023; Hollmann et al., 2025) creates a pre-trained transformer capable of few-shot learning on small tabular datasets with near-instant inference.

The use of foundational models for soil attribute prediction represents a novel direction that has the potential to unify disparate data sources and move beyond data- and site-specific training. By training on multi-site, multi-region data spanning a wide range of soil types and conditions, foundational tabular models could enable both fine-scale (within-farm) and broad-scale (state or national) prediction, while also supporting transfer learning to new, sparsely sampled regions. In this paper, we propose a foundational modelling approach to soil attribute prediction at the farm scale in Australia.

2 MATERIALS AND METHODS

2.1 Data

The dataset used in this study comprises soil survey measurements from 74 farms located across Australia's dryland cropping regions. Farms were sampled over the period 2023-2025. Sampling locations were selected using a stratified approach based on clustering of environmental covariates, ensuring that variation in spatial data layers and soil types was well represented. A similar approach to (Filippi et al., 2024) was used.

For each farm, 25 points were sampled, with soil cores collected in most cases at four standard depth intervals: 0–15 cm, 15–30 cm, 30–60 cm, and 60–100 cm. Some farms were sampled based on horizons; therefore, for consistency, these measurements were excluded from the dataset. This yielded a total of 6,851 samples across all depths. CSBP Laboratories conducted all laboratory analyses. Analyses included organic carbon (Walkley–Black; %), electrical conductivity (1:5; dS/m), pH (H_2O), and nitrate (NO_3; mg/kg). We use all these measurements as targets for our modelling.

We use a combination of remotely-sensed and terrain-derived covariates as the input feature set for training our models. Specifically, we include multispectral bands $(BE_{red}, BE_{green}, BE_{blue}, BE_{NIR}, BE_{SWIR1}, BE_{SWIR2})$ and terrain attributes $(Slope, Aspect, TWI, Sun\_Index, PM\_Silica, MrVBF)$. Multispectral bands were sourced from 25 m resolution mosaics of the Australian continent, representing barest earth conditions from a 30-year compilation of Landsat missions 5, 7 & 8 produced by Roberts et al. (2019). Terrain attributes have been sourced either directly from the Soil Landscape Grid of Australia (SLGA) and it's library of over 150 environmental covariates at 30–90 m resolution (Malone et al., 2025); or for the case of Sun_Index, determined from features of the SLGA following the methods of Wilson et al. (2003). These features were used consistently across all depths and target variables.

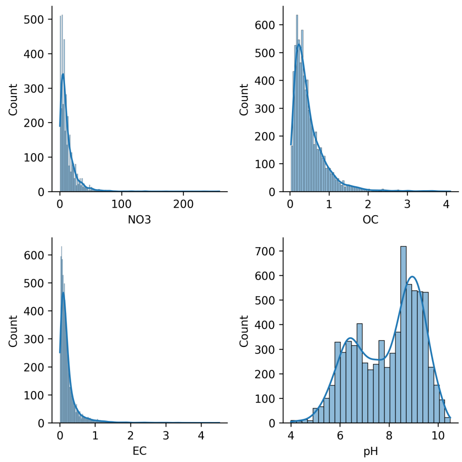

Figure 1. Distribution of target soil attributes in the dataset, Nitrogen (NO_3), organic carbon (OC), electrical conductivity (EC), and pH

Figure 1 shows the distributions of the target variables. Most variables (NO_3, OC, EC) display strong right-skewed distributions, indicating a predominance of low concentration values with occasional high outliers. pH, on the other hand, exhibits multimodal patterns, reflecting varying soil acidity and alkalinity levels across sites.

2.2 Methods

We evaluate a single type of tabular foundation model, the Tabular Prior-Data Fitted Network (TabPFN) (Hess et al., 2023; Hollmann et al., 2025). TabPFN is a pre-trained transformer-based architecture designed for tabular data, which leverages Bayesian inference to achieve strong generalisation under limited data availability. Its pre-training on a broad distribution of synthetic and real-world datasets enables rapid adaptation to heterogeneous agricultural data with varying feature availability. We select TabPFN due to its relative simplicity in application. The full implementation of the model is available in (Hollmann et al., 2025). To assess relative performance, we benchmark TabPFN against five conventional machine learning methods widely used in agricultural modelling: Random Forest (RF), Extra Trees (ET), Linear Regression (LR), Multi-Layer Perceptron (MLP), and Extreme Gradient Boosting (XGBoost).

Model evaluation was conducted across four standard soil depth intervals: 0—15 cm 15—30 cm 30—60 cm and 60—100 cm along with an aggregated overall dataset that averaged the depth-wise measurements to a single site average. For this study, data from all farms were consolidated into a single dataset to develop global models representing the full Australian dataset. Farm-specific or region-specific models were not considered within the scope of this work. For each depth interval, the dataset was randomly partitioned into training (70 %) and testing (30 %) subsets to facilitate model development and evaluation. The data was standardised using `StandardScaler` prior to model fitting and inverse-transformed for evaluation. We test the robustness of each model by conducting 10 repeated experiments, each with a uniquely seeded, randomly selected train and test dataset. We present the mean and standard deviation of the model performance on the testing dataset across those 10 experimental runs. Model performance is quantified using the coefficient of determination (R^2), Root Mean Squared Error (RMSE), and Lins Concordance Correlation Coefficient (LCCC).

All experiments were conducted in an Anaconda environment running Python 3 on a Windows 11 Enterprise workstation equipped with an Intel® Xenon® w5-2465X with 32 CPUs, 64 GB RAM, and an NVIDIA® RTX 5000 Ada Generation GPU for accelerated training. Models were initially run with default parameters, followed by a manual hyperparameter tuning based on prior model configurations to maximise performance.

3 RESULTS

Table 1. Model prediction performance (RMSE and LCCC; mean ± std) across soil attributes trained on the aggregated all-depth dataset.

	EC				NO_3				OC				pH			
Model	RMSE		LCCC		RMSE		LCCC		RMSE		LCCC		RMSE		LCCC	
Linear Regression	0.054	±0.009	0.128	±0.020	104.013	±13.945	0.236	±0.038	0.062	±0.006	0.548	±0.018	0.789	±0.052	0.572	±0.018
MLP	0.062	±0.006	0.376	±0.025	131.572	±15.409	0.389	±0.016	0.060	±0.007	0.682	±0.030	0.664	±0.063	0.724	±0.026
Random Forest	0.045	±0.009	0.366	±0.060	101.639	±14.471	0.332	±0.045	0.044	±0.005	0.720	±0.024	0.536	±0.040	0.733	±0.016
Extra Trees	0.041	±0.007	0.443	±0.046	95.306	±12.680	0.380	±0.040	0.041	±0.005	0.739	±0.022	0.507	±0.050	0.747	±0.019
XGBoost	0.047	±0.009	0.358	±0.047	104.995	±14.771	0.336	±0.046	0.045	±0.005	0.721	±0.022	0.548	±0.040	0.739	±0.013
TabPFN	0.037	±0.009	0.505	±0.062	86.521	±13.140	0.420	±0.038	0.033	±0.004	0.798	±0.017	0.379	±0.040	0.831	±0.018

Table 2. Model training and prediction time (seconds) across soil attributes trained on the aggregated all-depth dataset.

	EC				NO_3				OC				pH			
Model	Training Time		Prediction Time		Training Time		Prediction Time		Training Time		Prediction Time		Training Time		Prediction Time	
Linear Regression	0.002	±0.000	0.001	±0.000	0.002	±0.001	0.001	±0.000	0.002	±0.001	0.001	±0.000	0.002	±0.000	0.001	±0.000
MLP	6.333	±2.283	0.002	±0.001	4.397	±1.247	0.001	±0.000	5.026	±1.355	0.002	±0.000	5.465	±1.410	0.002	±0.000
Random Forest	1.033	±0.067	0.015	±0.008	1.200	±0.165	0.014	±0.003	1.008	±0.057	0.012	±0.000	0.940	±0.066	0.013	±0.002
Extra Trees	0.373	±0.033	0.017	±0.009	0.454	±0.086	0.018	±0.007	0.386	±0.056	0.018	±0.009	0.377	±0.049	0.019	±0.009
XGBoost	0.120	±0.013	0.001	±0.000	0.133	±0.039	0.001	±0.000	0.122	±0.013	0.001	±0.000	0.119	±0.007	0.001	±0.000
TabPFN	0.316	±0.011	0.671	±0.054	0.322	±0.012	0.695	±0.082	0.319	±0.006	0.653	±0.063	0.312	±0.003	0.614	±0.036

Table 1 summarises the predictive performance of all models on the four soil attributes on the depth-averaged dataset. TabPFN achieved the lowest RMSE and highest LCCC across all the targets, indicating superior predictive accuracy compared to the other approaches. Notably, on NO_3, TabPFN outperformed all other models, achieving substantial performance gains relative to ensemble-based methods.

Among the tree-based ensemble methods, XGBoost consistently outperformed Extra Trees and Random Forest in predicting most properties, except for NO_3, where Random Forests was second best only to TabPFN. The MLP achieved a competitive RMSE for NO_3, but its performance was less consistent across targets and generally underperformed relative to XGBoost and TabPFN. Linear Regression had the poorest performance for most soil properties, reflecting its limited capacity to capture the complex non-linear relationships inherent in soil property datasets. However, Linear Regression performed better than tree-based methods for predicting organic carbon. We also observe that the prediction time of the TabPFN model is consistently higher than that of all the other models (Table 2). The training time is comparable; however, it is slower to train than Linear Regression and XGBoost.

When model performance was assessed for each depth profile and each soil property, as given in Figure 2, TabPFN again emerged as the top-performing model, achieving the highest mean $LCCC$ while having the

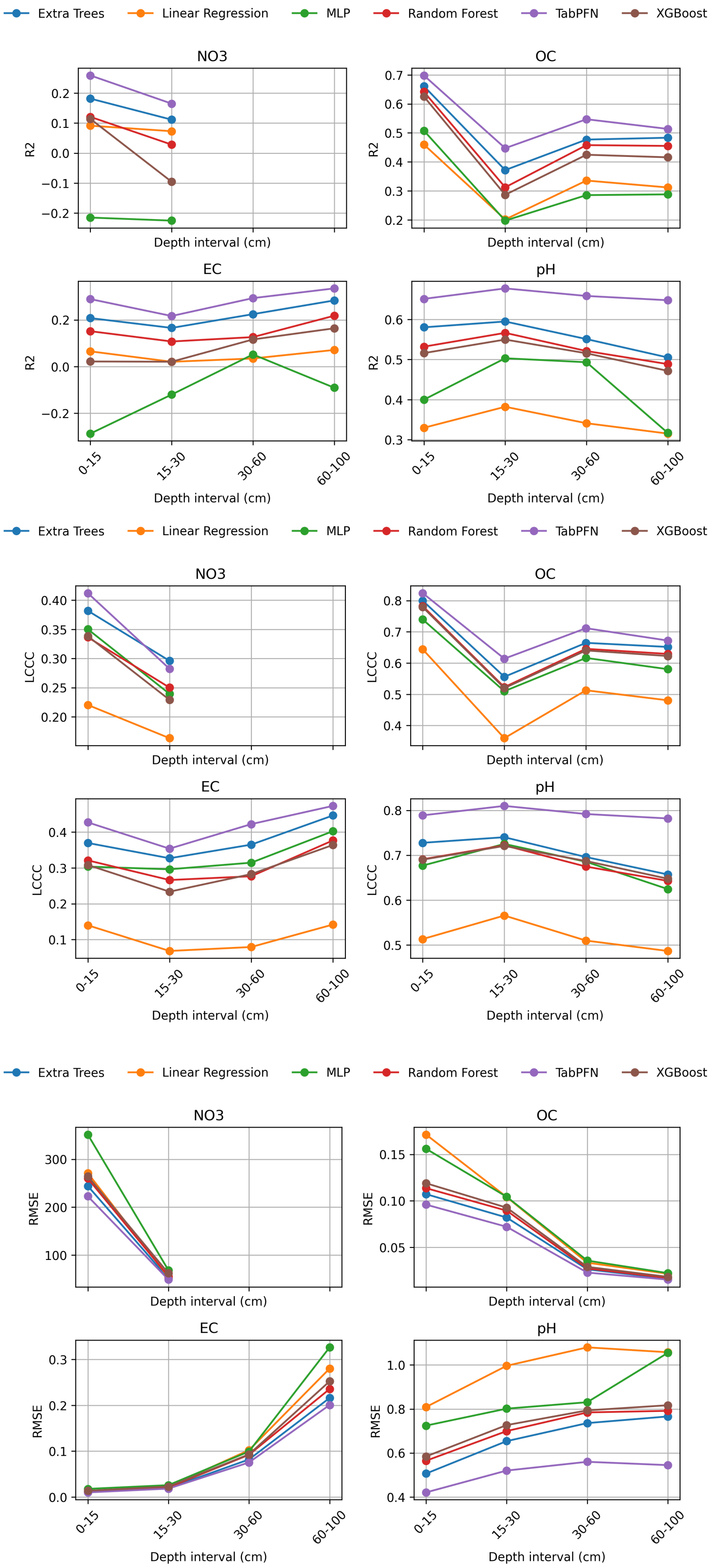

Figure 2. **Model performance in predicting soil attributes across the four depth intervals of the testing dataset using Random Forest, Extra Trees, Linear Regression, MLP, XGBoost, and TabPFN. The plots show the mean R^2, $LCCC$, and $RMSE$ values across 10 experimental runs on the test dataset for each model and target variable across every depth horizon.**

lowest average RMSE across targets. This result reinforces the advantage of transformer-based tabular models in capturing multi-dimensional relationships from diverse environmental covariates, even without depth-specific optimisation. Tree-based models, particularly Extra Trees, showed a different trend. Extra Trees had better performance across all depths of the soil, while XGBoost and Random Forest maintained moderate but consistent performance. Linear Regression was again the worst-performing model without any exceptions.

4 Discussion

The results demonstrate that TabPFN offers clear benefits for soil property prediction with continuous input covariates. Ensemble methods such as XGBoost and Extra Trees provide a good baseline and are less computationally demanding, making them suitable for rapid deployment when computational resources are limited. However, the magnitude of improvement delivered by TabPFN, particularly for nutrient variables with high spatial variability such as NO_3, suggests that advanced foundation models can significantly enhance the accuracy of digital soil mapping workflows. We find that targets with stronger nonlinearity or heavy-tailed distributions such as NO_3 benefit significantly from TabPFN's capacity to model heterogeneous regimes, yielding clear margins over tree ensembles and linear baselines. Furthermore, the consistently small standard deviations suggest that improvements are not due to favourable random splits but to systematic modelling advantages.

For pH, EC, and OC, TabPFN exceeds the best-performing baselines, despite already having low error floors, implying limited room for further absolute improvement; percentage gains are still notable. Given its dominance in both pooled and stratified evaluations, TabPFN is a strong default for operational mapping across depths. Where computational budget or model simplicity is paramount, Extra Trees and XGBoost remain reasonable alternatives, but they are less reliable for nitrate.

Despite its strong performance, this study has several limitations. First, while TabPFN benefits from pre-training, the model was not fine-tuned on domain-specific agricultural data beyond the available training set. This may limit its ability to fully capture region-specific or management-specific soil dynamics. Additionally, the analysis was restricted to a set of conventional baselines; future work could expand comparisons to include other foundation models and hybrid approaches that integrate spatial and temporal dependencies. Addressing these limitations will further strengthen the applicability of TabPFN for operational decision support in agriculture.

5 Conclusion

This study demonstrates the potential of applying tabular foundation models to advance predictive soil analytics for agriculture as well as general spatial soil resource assessment. By benchmarking TabPFN against five widely used machine learning approaches across four depth intervals and an aggregated dataset, we show that TabPFN delivers consistent performance gains, with improvements ranging from 20% to 60% in RMSE over conventional methods. TabPFN's robustness to sparse, heterogeneous data makes it particularly valuable for agricultural contexts, where laboratory analyses are expensive, sampling is logistically constrained, and available datasets are fragmented across locations and seasons. However, we note that these findings are limited to only four soil attributes and within the scope of 74 farms. Further investigation is necessary to assess the robustness of the Foundational Models in agricultural contexts and how they compare to locally tailored models such as the SLGA for Australia. Future work will explore integrating spatial dependencies, multi-task learning across soil properties, and fine-tuning foundation models with domain-specific agricultural datasets. This could further enhance predictive accuracy and generalisation, enabling more effective decision support tools for farm management and sustainability planning.

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