A Field-Ready Image-Based Method for Soil Texture Assessment in Urban Landscapes

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Abstract: This study explores a field-deployable soil texture classification method based on mobile images. Soil texture is one of the fundamental elements of a successful landscape project. It impacts plants' root growth, drainage, moisture balance, and the overall resilience of an ecosystem, making it a core metric of planting success, stormwater function, and long-term sustainability. Conventional texture analysis, however, relies on laboratory equipment and sampling procedures that are time-consuming and costly. This study explores a Soil Texture Recognition Platform (STRP) based on mobile phone images to quickly identify texture types on real soil surfaces without laboratory processing. It employs Convolutional Neural Network, texture feature extraction, and supervised learning model training. Through a comparison experiment based on manual and platform-based evaluation, the researcher assesses and further improves this STRP's effectiveness and accuracy. This research provides the landscape architecture field with a low-cost, reproducible, and rapid method for soil texture testing, contributing to evidence-based design and smart landscapes.

Keywords: Urban soil texture assessment, image-based analysis, machine learning, smart landscapes

1 Introduction

Soil texture is one of the primary factors that impacts plant survival, root development, water infiltration and retention, and long-term stability (BRADY & WEIL 2008). In urban settings, soil texture conditions decide irrigation efficiency, stormwater performance, soil compaction risk, and maintenance costs (CRAUL 1992, PHILLIPS et al. 2019). Although soil has significant ecological and engineering value in the field of landscape architecture, texture assessment has not become a routine step in actual design and management. Instead, many decisions rely on professional experience, rather than consistent and repeatable field-based data. On-site designers and researchers commonly use the Soil Texture-by-Feel Method (FRANZMEIER & OWENS 2008) and Soil Sedimentation Test (PALTSEVA 2024) to analyze soil texture. However, both methods have certain limitations. The soil texture-by-feel method is inherently subjective and requires training to achieve reliable results, and its accuracy can vary from one practitioner to another. Although these two methods can provide reasonably accurate results, they are labor-intensive, time-consuming, and impractical for large-scale or frequent field tests.

Urban soils are complex and heterogeneous, with soil composition varying substantially across different features, such as planting areas, lawns, pedestrian walkways, and stormwater facilities. These spatial differences affect plant growth, irrigation efficiency, and soil remediation priorities, necessitating more extensive and frequent on-site assessments to guide design and maintenance decisions (HERNANDEZ et al. 2017). Also, with growing interest in urban agriculture (HODGSON et al. 2011), the need for more detailed and spatially resolved urban soil information has increased accordingly. Historically, the United States Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) did not tradition-

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ally map urban soils (Ohm et. al. 2024), leaving significant knowledge gaps in densely developed areas. At the same time, a growing body of research and professional literature underscores the importance of urban soil practices (Rakshit et al. 2022, Rate, 2022), and the USDA has also addressed this topic through its Urban Soil Primer (Scheyer & Hipple 2005).

On the one hand, there is a growing demand for high-resolution soil data covering large areas; on the other hand, such data is severely scarce, which is one of the greatest challenges (Grunwald et al. 2011). Obviously, the two methods commonly used by landscape architecture professionals, because of their labor demands and the disturbance caused to the site, make it difficult to obtain soil information at a meaningful spatial resolution or to update it on a regular basis. The landscape architecture field needs a rapid, low-cost, and reproducible method to support rapid on-site soil texture assessment. With advancements in imaging technologies, utilizing visual cues on the soil surface as indicators of texture characteristics has increasing potential. This study explores high spatial resolution soil texture analysis methods and tools based on mobile phone images that can be directly applied to the field for rapid estimation of soil texture in urban environments to support future urban landscape design and workflows. At the same time, it also contributes to making up for the lack of high spatial resolution soil data in urban environments.

2 Materials and Methods

Figure 1 illustrates the study's three main stages, including: 1) Building a Soil Texture Recognition Platform (STRP); 2) field soil sample collection and texture identification; 3) model retraining and evaluation.

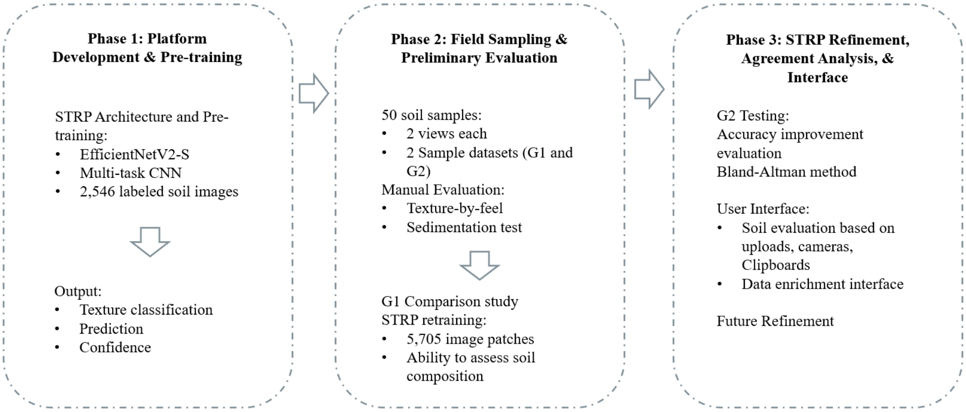


Fig. 1: Conceptual diagram of the research

This STRP is built upon a multi-task learning Convolutional Neural Network, which is specialized algorithms primarily used for image recognition. It can perform soil texture classification and particle composition prediction simultaneously. The employment of EfficientNetV2-S ensures the balance between accuracy and computational efficiency. Three main components of this STRP include: 1) a feature extraction model that processes input images into high-dimensional feature representations, (2) a classification head that predicts soil texture classes, and (3) a regression head that predicts continuous percentages of sand, silt, and clay particles. This multi-task learning approach enables the model to leverage both categorical and compositional information during training, improving overall prediction accuracy.

The researcher first conducted the pre-training phase. The model was initially pre-trained on a curated dataset of 2, 546 soil texture images (852 clay, 859 loam, and 835 sand) to learn general features distinguishing different soil textures. This pre-training phase helps the model develop robust feature representations before fine-tuning on field-collected samples.

All images imported into the STRP are initially pre-processed to ensure a consistent image format. The image preprocessing workflow includes white balance correction using a detected reference card (or the gray-world assumption when a reference card is unavailable), contrast enhancement based on Contrast Limited Adaptive Histogram Equalization, resizing to a uniform resolution of 500 x 500 pixels, and normalization using ImageNet statistical parameters. Pre-training employed standard data augmentation techniques (random flips, rotations, color jittering, and cropping) to improve generalization and robustness to field variability.

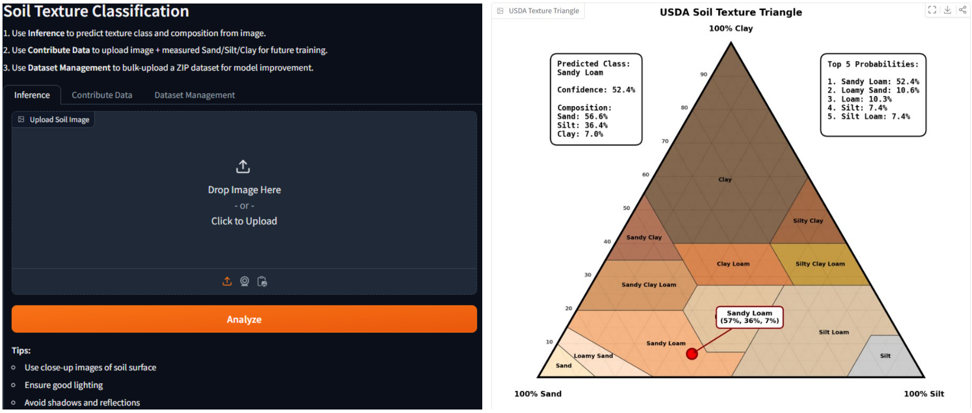
The research team identified a total of 50 soil sampling points (Figure 2) on the University of Georgia campus and in surrounding areas based on four common urban soil scenarios: (1) tree lawns, (2) planting beds, (3) pedestrian sidewalk edges, and (4) retention ponds. Field data collections were conducted between September 15th and November 15th in 2025. This is the seasonal change and leaf drop period in the Atlanta-Athens metropolitan area with variable soil conditions. At each sampling point, the researcher gently cleaned the surface debris, such as leaves or mulch fragments, without disturbing the surface soil structure. The researcher used 4 field marking flags to create a 0.6m x 0.6m (2ft x 2ft) sampling boundary and puts a Tri-color reference card at one corner for the purpose of white balance correction. Two photos were taken by the smartphone: one top view (90°) of the site at approximately 2ft above the surface and one oblique photo (45°) about 3ft above the surface. A portable GPS was deployed to record the location.

Fig. 2:
Spatial distribution of the 50 soil sampling sites in the study area. The soil texture base map presented in the figure is based on data from the USDA Soil Survey Map (UNITED STATES DEPARTMENT OF AGRICULTURE (n. d.)).

These 50 soil samples were manually analyzed for soil texture using the Soil Texture-by-Feel Method and the Soil Sedimentation Test. This process served two purposes: (1) to conduct cross-comparative experiments for preliminary evaluation of the STRP's accuracy, and (2) to assign texture labels to the samples for inclusion in the STRP training process, thereby improving its classification performance. Images of the 50 samples were divided into two groups (G1 and G2), 25 samples (50 images) each group.

The 50 images in G1 were first used to evaluate the accuracy of the STRP's predictions after pre-training through the comparison study based on the STRP outputs and manual assessments. After that, these images were processed through the platform's image processing pipeline, generating a total of 5,705 image patches with a resolution of 500 × 500 pixels. These images have soil texture labels and quantitative component proportions derived from the Soil Sedimentation Test. They were imported into the system to further train the STRP. This process not only improved the model's classification performance but also enabled the prediction of soil component proportions (sand, silt, and clay) from soil images. The remaining 50 images in G2 were reserved as an independent test set and used exclusively for the final evaluation of the STRP's predictive accuracy and generalization performance.

The STRP is implemented as a server-based web platform, providing an intuitive interface for soil texture analysis. This web interface provides two primary functions: 1) Rapid soil texture evaluation (Figure 3), which outputs texture classes with confidence scores, predicted percentages of texture components, and a visualization of the prediction on the soil texture triangle diagram; 2) Allowing users to upload soil images with verified texture labels to expand the dataset and increase training volume, thereby improving overall model performance.



Soil Texture Classification

1. Use **Inference** to predict texture class and composition from image.
2. Use **Contribute Data** to upload image + measured Sand/Silt/Clay for future training.
3. Use **Dataset Management** to bulk-upload a ZIP dataset for model improvement.

Tips:

- Use close-up images of soil surface
- Ensure good lighting
- Avoid shadows and reflections

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Predicted Class:
Sandy Loam

Confidence: 52.4%

Composition:
Sand: 56.6%
Silt: 36.4%
Clay: 7.0%
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Top 5 Probabilities:

1. Sandy Loam: 52.4%
2. Loamy Sand: 10.6%
3. Loam: 10.3%
4. Silt: 7.4%
5. Silt Loam: 7.4%
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Fig. 3: The user interface of the rapid soil texture evaluation function (left) and an example of the STRP outputs on the user interface (right)

3 Results

Table 1 presents an example of the STRP's analytical results for a soil image in G1 after the pre-training stage. All prediction results are originally stored as a single row in a CSV file; for clarity and readability, the result format in Table 1. has been manually reorganized. For each prediction, the system analyzes the input image and outputs the five most probable soil texture classes along with their corresponding confidence scores. The system ranks the predicted texture classes from the highest to the lowest probability (Top-1 to Top-5). The class with the highest confidence is selected as the final predicted texture and is reported to the user together with its associated confidence value. The top five predicted texture classes and their confidence scores are reported to reflect the uncertainty present at this early stage of model development. This design allows users to view both the most probable prediction and several plausible alternatives. More importantly, it allows the researcher to obtain more informative details for evaluating the STRP's performance than a single deterministic label.

Table 1: Example of STRP analytical output after pre-training stage

Image Name	**Sample ID**	**Predicted Class (Top-1 Class)**	**Confidence (Top-1 Prob.)**
007_2.png	14	Sandy Loam	0.6851760745
Top-2 Class	**Top-3 Class**	**Top-4 Class**	**Top-5 Class**
Loamy Sand	Silt Loam	Loam	Sand
Top-2 Prob.	**Top-3 Prob.**	**Top-4 Prob.**	**Top-5 Prob.**
0.2066360861	0.03786857054	0.01919812523	0.0101066893

The validation results of the 50 images in G1 indicate that, after the pre-training stage, the STRP achieved a Top-1 classification accuracy of 78%, with 39 predictions matching the manual assessments. For the remaining 11 misclassified samples, the correct soil texture labels were consistently ranked as the Top-2 predictions. When considering the top two ranked predictions, the correct texture label was included in all cases. All errors occurred between sandy loam and its neighbouring texture classes. Specifically, six samples were misclassified as loam and five as loamy sand.

Regarding prediction confidence, the average confidence score across all 50 samples was approximately 0.60. For the 39 correctly classified images, the mean confidence was 0.62. In contrast, the 11 misclassified images exhibited a lower average confidence of 0.54 for the incorrect Top-1 predictions, while the confidence assigned to the true classes was notably lower, with a mean value of 0.26. The descriptive statistics of these confidence distributions are summarized in Table 2.

Following retraining with the 5,705 samples with corrected texture labels created from G1, the STRP was capable of producing extended outputs for each new soil image, including predicted percentages of sand, silt, and clay in addition to the information listed in Table 1. The testing results of the 50 samples in G2 using the refined STRP indicate that 44 images were correctly classified in terms of soil texture, while 6 were misclassified, resulting in an overall accuracy of 88%. Similarly, for the six misclassified samples, the correct texture labels consistently appeared as the second most probable class in the prediction outputs. Table 3 summarizes the prediction confidence of the refined STRP evaluated using the 50 images in G2. Compared with the initial testing results reported in Table 2, the refined STRP exhibited higher overall confidence in its predictions. In addition, the ratio between the standard deviation and the mean, the coefficient of variation, indicates that the stability of the STRP also improved, with the CV decreasing from 28.61% to 21.39%.

Table 2: Descriptive statistics of prediction confidence for samples in G1

N	Class Name	Minimum	Maximum	Mean	Std. Deviation
50	Predicted Class Confidence (Top-1 Class Prob.)	0.3178	0.9540	0.6036	0.1727
39	Predicted Class Confidence (Top-1 Class Prob.)	0.3178	0.9540	0.6211	0.1764
11	Predicted Class Confidence (Top-1 Prob.)	0.3830	0.8865	0.5416	0.1508
11	Top-2 Prob.	0.0584	0.3678	0.2628	0.1038

Table 3: Prediction confidence of the refined STRP evaluated on samples in G2

N	Class Name	Minimum	Maximum	Mean	Std. Deviation
50	Predicted Class Confidence (Top-1 Class Prob.)	0.5125	0.9737	0.7068	0.1512
44	Predicted Class Confidence (Top-1 Class Prob.)	0.5125	0.9737	0.7163	0.1310
6	Predicted Class Confidence (Top-1 Prob.)	0.4917	0.7538	0.6153	0.1424
6	Top-2 Prob.	0.1538	0.2367	0.1774	0.0833

As a pilot evaluation, agreement between the STRP-predicted soil component proportions and the sedimentation-based measurements was examined using Bland-Altman analysis (DOĞAN 2018). The objective was not to establish definitive quantitative equivalence, but to explore initial agreement patterns and identify systematic limitations. For sand and silt contents, the differences between the two methods showed moderate dispersion. According to the results of difference descriptive statistics (Table 4), the mean bias was +5.65% for sand and −2.49% for silt. Approximately 93% of the observations fell within the 95% Limits of Agreement (LoA). These results suggest a moderate level of agreement between the two methods at this preliminary stage (Figure 4). In contrast, the agreement for clay content was notably lower, characterized by larger dispersion of differences and wider limits of agreement. Although most clay observations were located within the 95% limits of agreement and the absolute differences appeared small, the relative errors were substantially larger due to the small magnitude of clay content. Thus, the overall agreement remained limited. This indicates that, compared with sand and silt, the current STRP still exhibits considerable uncertainty in predicting clay proportions.

Table 4: Descriptive statistics and agreement analysis of soil texture fractions

Soil Fraction	Method	Mean	Std. Deviation	Mean Bias	95% LoA	% within LoA
Sand	Manual	55.83	20.04	5.65	[-21.31, 32.61]	93.20%
	STRP	61.48	17.70			
Silt	Manual	39.77	20.61	-2.49	[-30.67, 25.68]	93.20%
	STRP	37.28	17.45			
Clay	Manual	4.40	2.45	-3.16	[-8.17, 1.85]	100%
	STRP	1.24	1.54			

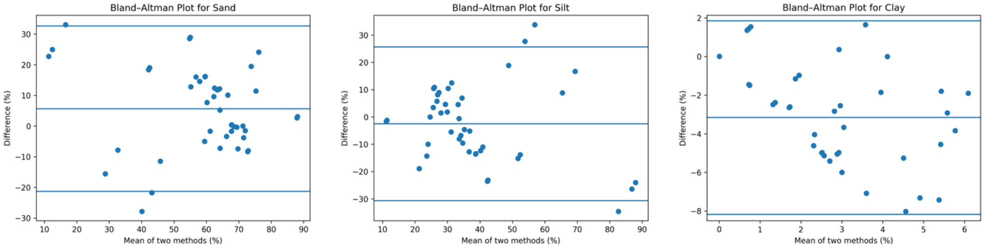

Fig. 4: Results of Bland-Altman analyses

In the web-based interface, users can upload soil images via local files, a camera, or the clipboard. After submission, the system generates the analytical outputs shown in Figure 3 within approximately 5 seconds. Users may also switch to an alternative interface to upload images together with manually annotated component proportions. These images are stored on the server and undergo both automated and manual validation before being incorporated into the STRP training dataset.

4 Discussion and Conclusion

This study explores a rapid, image-based soil texture recognition method, the STRP, and conducts a two-stage experimental evaluation of its performance in soil texture and composition prediction. The results indicate that the STRP is capable of providing soil texture information with practical reference value without requiring laboratory conditions, offering a new technical pathway to support rapid decision-making in urban landscape design and management.

At the soil texture classification level, the STRP achieved a Top-1 accuracy of 78% in the pre-training stage, which increased to 88% on the independent G2 test set after model refinement. In addition, across both experimental stages, the true soil texture class of every misclassified sample consistently appeared within the Top-2 prediction results. This finding suggests that although uncertainty remains when distinguishing between closely related texture classes, the STRP outputs are reliable at the candidate-range level. From an application perspective, this “Top-2 full coverage” characteristic is particularly valuable for field-based assessments, as it allows users to rapidly narrow down plausible texture categories under uncertain outdoor conditions.

Prediction confidence analysis further reveals changes in model performance over the training process. After retraining, the STRP exhibited a higher average confidence on the G2 dataset, accompanied by a clear reduction in the coefficient of variation. This indicates an improvement in output stability. These results suggest that incorporating field-collected data with manual verification into the retraining process not only enhances classification accuracy but also reduces prediction variability across samples, providing a foundation for further model improvement.

Bland-Altman analysis of agreement between STRP-predicted soil component proportions and sedimentation-based measurements indicates a moderate level of agreement under the current experimental conditions. This does not directly imply that the STRP can replace laboratory-based compositional analysis, but rather that it provides reference-level quantitative information at the scale of overall trends and magnitudes. Agreement was notably weaker for clay content. One possible explanation is that although the USDA soil survey map (Figure 2) suggests a certain proportion of clay within the study area, manual assessments revealed that most samples were dominated by sandy loam with very low clay content. In urban environments, soils are often disturbed by construction activities, grading, fill materials, and other engineering processes, which can substantially alter fine-particle distributions. As a result, the STRP may not have been sufficiently trained on clay-rich samples under field-representative conditions. This limitation also reflects the broader challenge of image-based feature representations in capturing fine-scale soil structure, particularly for clay fractions. Addressing this issue may require expanding the training dataset, incorporating multi-scale image features, or integrating complementary sensing information. In addition, the current field dataset is limited in both sample size and geographic coverage. Larger and more diverse datasets encompassing a wider range of soil textures will be necessary to improve the model’s ability to represent complex urban soil conditions. Future work may also explore integrating the STRP with GIS or digital twin platforms to support higher-resolution urban soil modeling.

Overall, this study contributes a new paradigm for landscape architecture by combining artificial intelligence with in-situ sensing approaches. The current STRP demonstrates the ability to extract meaningful soil texture and compositional information from complex urban environments with a reasonable level of accuracy and stability. It shows potential to support research relates to urban soil diagnosis, stormwater management, planting design, and irrigation planning. As a pilot study, the objective of this research is not to achieve perfect agreement with high-precision laboratory measurements, but rather to demonstrate the feasibility and practical value of a high-frequency, low-cost, non-destructive, and scalable approach. Thus, another primary contribution is exploring the applicability and limitations of image-driven methods for urban soil assessment.

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