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Smartphone-Based Monitoring Identifies the Importance of Farm Size and Soil Type for Coffee Tree Productivity at a Large Geographic Scale

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ABSTRACT

Smartphone-based monitoring has been increasingly applied to coffee crops for multiple tasks, such as predicting coffee tree productivity. However, its implementation remains limited to small-scale use, typically at the individual plant level. At larger scales, such as the farm level, its application is largely unexplored. Moreover, it is unclear whether the use of smartphone-based monitoring can help identifying key factors driving coffee tree productivity such as climate, soil, and management characteristics. To address these challenges, we investigate coffee tree productivity at the farm level and its key driving factors using smartphone-based monitoring and explainable artificial intelligence (xAI), and compare the results with those obtained from manual monitoring at the farm level. We used a multimodal data set composed of satellite data (soil and climate), smartphone-based monitoring (coffee tree productivity), and management characteristics (area, shade trees, and farm shape). The results showed that smartphone-based monitoring reached a of $R^2 = 0.84$ in predicting coffee tree productivity at the farm level. The xAI results revealed that both smartphone-based and manual monitoring approaches identified the coffee cultivation area (greater than 13 ha) and soil texture (sandy, clay loam) as the most important variables influencing coffee tree productivity at farm level. The analysis also indicated that shade trees do not significantly affect coffee tree productivity. These findings suggest that smartphone-based monitoring can serve as a reliable and scalable alternative to manual monitoring for evaluating coffee tree productivity at the farm level.

1 | Introduction

Coffee is one of the most traded commodities in the world. *Coffea arabica* is the most widely cultivated coffee species globally, accounting for approximately 60%–70% of total production, followed by *Coffea canephora* (commonly known as Robusta), which comprises about 30%–40% of global output (ICO 2024; Statista 2025). Coffee is particularly vulnerable to changes in temperature, rainfall, and extreme weather events (Lin 2007) and the production is highly susceptible to decline in the coming years due to its high sensitivity to climate variability (Bunn et al. 2015; Gay et al. 2006). The expansion of intensive coffee production aimed at maximising yields has led to soil degradation (Alam 2014), and a reduction in shaded coffee systems (Piato et al. 2020). Under these circumstances, understanding the variables of soil, climate patterns, and the presence of shade trees is crucial for improving the resilience of coffee crops to environmental stresses (Bosselmann et al. 2009; Jaramillo et al. 2013; Pham et al. 2019).

The key factors influencing coffee tree productivity, such as climate and soil, have also been widely studied. Temperature, rainfall, and altitude affect flowering and fruit development, while soil properties such as texture, pH, and organic matter impact water retention and nutrient availability (Bunn et al. 2015; Wintgens 2004). Large-scale coffee cultivation is often associated with higher productivity due to access to advanced technical advice and greater investment (Amrouk et al. 2025; Benami et al. 2021).

The benefits of growing coffee under shade have been widely studied, particularly for their role in mitigating the effects of climate change. Shade trees help modify the microclimate by reducing both temperature and water loss (Jaramillo et al. 2013; Pham et al. 2019). Additionally, shade trees can act as physical barriers, enhance the crop's physiological resistance, and support the conservation and activity of natural enemies against aerial pests (Ratnadass et al. 2012). In certain environments, shade trees may also contribute to improved coffee taste and enhance its quality (Vaast et al. 2006) and offer valuable ecosystem services such as carbon sequestration (Ehrenbergerová et al. 2016). Regarding farm shape, slope and elevation are strong indicators of land-use change or tree-cover loss (Harvey et al. 2021). However, in smallholder systems, the influence of management characteristics (area, shade trees, and farm shape), soil, and climate on coffee tree productivity is well recognised, but no previous studies have systematically examined the relative importance of these factors on coffee tree productivity across a large geographic scale.

A key reason is that collecting the information of coffee tree productivity under shade trees is challenging logistically. Traditional methods for assessing coffee productivity under shade are often time-consuming, costly, error-prone, and labour intensive, limiting scalability in time and space. For example, the use of unmanned aerial vehicles (UAVs) in shaded coffee systems is difficult due to limited visibility beneath the canopy and navigation challenges in dense vegetation. However, recent advancements in digital agriculture, such as smartphone-based monitoring collection and deep learning (Rivera-Palacio et al. 2024), offer promising alternatives. A recent study (Rivera-Palacio et al. 2024) demonstrated that the number of cherries as a proxy for tree productivity can be reliably estimated by photographing selected branches, using the (You Only Look Once) YOLO v8 (Jocher et al. 2023) model to detect and count coffee cherries, and then multiplying the counted number by the total number of the productive branches. This approach showed that smartphone-based monitoring is scalable at the local level and, with collaboration from local farmers, can also be applied across larger geographic areas. With this advancements, it is now possible to statistically analyse the relative influence of key factors on coffee tree productivity, while accounting for a large spatial heterogeneity. However, it remains unclear if the smartphone-based monitoring can provide the same conclusion on the key factors affecting coffee tree productivity when compared to manual monitoring at farm scale. Both approaches may produce errors in productivity estimation and therefore comparing these approaches is critical to deliver reliable conclusions.

This study has two main objectives: (i) to evaluate the performance of smartphone-based monitoring of coffee tree productivity at the farm level using ground-truth data collected through manual monitoring, and (ii) To investigate whether smartphone-based monitoring identifies the same set of key factors as manual monitoring. We target the productivity of coffee trees at farm level of *C. arabica* in Colombia across nearly 400 smallholder farms. Specifically, we first calculate the average number of coffee cherries per tree on each farm. We then integrate this with additional predictor variables, including satellite data (soil and climate), management characteristics (area, shade trees, and farm shape). Finally, we apply tree-based machine learning models, namely random forests (RF) and gradient boosting, and use post-hoc explanation methods, specifically permutation importance and partial dependence plot to interpret model predictions. We compare the outputs from smartphone-based monitoring with those from manual monitoring, focusing particularly on identifying the most influential variables with special attention to the role of shade trees.

2 | Methodology

2.1 | Data Set

2.1.1 | Study Site and Survey Data

We conducted this study with 389 smallholder coffee farmers between March and November in 2022 in western Colombia. Our data collection took place in the municipality of Génova (Quindío) and in Cajibío, Morales, Timbío, Piendamó, Popayán, and El Tambo (Cauca). The study area spans from 2.35° to 4.33° N latitude and 75.75° to 76.81° W longitude covering diverse agroecological zones with varying coffee farming practices.

2.1.2 | Pre-Processing Data

We incorporated satellite-based climate data for the study areas using NASA's POWER (Prediction of World Energy Resource) (Stackhouse et al. 2018). This open-access data set, available online (NASA 2025), provides climate data with a spatial resolution of 0.5° latitude by 0.5° longitude. For farm-level features, we extracted daily data at each farm's coordinates and aggregated it into 30-day windows ending on the date of the image of tree. Temperature and relative humidity were averaged, and precipitation was summed.

For soil-related variables, we utilised data provided by the Instituto Geográfico Agustín Codazzi (IGAC), Colombia's national mapping. This data set includes a wide range of soil attributes, including electrical conductivity, texture, temperature, pH, rockiness, carbon content, aluminium saturation, sodium content, and soil loss (see Table 1 for details). Due to the absence of farm-level, polygons, we integrated the data at the municipal

TABLE 1 | Predictor variables used for explaining tree productivity.

Name	Description	Units
Climate	This is the weather perception for farmers.	There are three options: Warm, Cold, and Temperate
FarmArea	The area total of the farm	Hectares
FarmUseCoffee	This is the area where coffee is cultivated on the farm.	Hectares
CoffeeLand	The shape of the land is ideal for growing coffee	There are three options: with steep slopes, inclined and flat plane
TypesShadeTrees	The type of coffee trees surrounding of coffee cultivation	Categorical value
DistinctShadeTrees	Number of distinct shade trees in the surrounding coffee crop.	Numerica value
relative humidity	average relative humidity at 2 m above the ground in the month of taking picture	percentage (%)
temperature	Temperature at 2 m above the ground.	Celsius (°C)
pH	Indicates the acidity or alkalinity of the soil, affecting nutrient availability and microbial activity.	ranges from 0 to 14
precipitation	Precipitation during the month the picture was taken	millimetres (mm)
temperature soil	temperature mean in the month of taking picture	Celsius (°C)
electrical conductivity	measures how well the soil can conduct electricity	dS/m (deciSiemens per metre).
texture	Describes the proportion of sand, silt, and clay particles in the soil, which influences water retention and aeration.	Textural class (eg. Sandy loam, Loamy sand, Gravelly variants)
rockiness	Quantifies the amount of coarse rock greater than 0.045 mm diamater fragments present in the soil, impacting tillage and root penetration.	% surface coverage
carbon content	Measures the amount of organic carbon in the soil, which is essential for nutrient cycling and soil structure.	%
aluminum saturation	Indicates the degree to which aluminum occupies the soil's exchange sites, often related to soil acidity and toxicity.	cmol(+)/kg
soil loss	Describes the loss of topsoil due to water or wind, reducing fertility and crop productivity.	tons/ha/year or Mg/ha/year

level, which was obtained directly from [21]. The IGAC soil map (scale 1:100,000 and 2020 edition) was intersected with official municipal boundaries.

We also collected in situ data via a questionnaire completed by each farmer at the time of image acquisition. Respondents provided the following information: farm coordinates (latitude and longitude), the types of shade trees surrounding the coffee plots, local climate class (hot, temperate, or cold), and land-slope class (flat, sloped, or steep) (Table 1).

2.2 | You Only Look Once Version 8 (YOLO v8)

We applied a coffee cherry detection model developed by (Rivera-Palacio et al. 2024), which is based on the YOLO v8 architecture introduced by Ultralytics (Jocher et al. 2023). YOLO v8 is a real-time object detection algorithm that leverages a convolutional neural network (CNN) backbone and a decoupled head for classification and localisation tasks (Jocher et al. 2023). It features anchor-free detection and a mosaic augmentation strategy that improves generalisation across varied image conditions.

The model was fine-tuned using a custom data set of 436 images depicting coffee branches, each image containing up to 120 cherries. In total, the data set comprised 35,247 green cherries, 342 red cherries, and 105 black cherries. The data set was partitioned into training (80%, $n = 346$), validation (10%, $n = 43$), and test (10%, $n = 43$) subsets. This model achieved an average R^2 value of 0.7 on test data, with a good generalisability across regions. For the methodological and performance details, see (Rivera-Palacio et al. 2024).

2.3 | Smartphone-Based Monitoring

Smartphone-based monitoring refers to estimating coffee tree productivity by detecting coffee cherries by using YOLO v8 to detect coffee cherries in images of tree. We applied the approach proposed by Rivera-Palacio (Rivera-Palacio et al. 2024). At each farm, nine coffee trees were randomly selected. From each tree, three branches—one from the lower, one from middle, and one from upper sections—were photographed, one photograph per each section (i.e., three images per tree). The total number of productive branches on each selected tree was counted manually. The total number of cherries on each selected tree was then estimated by multiplying the average number of cherries per branch (calculated from the three photographed branches) by the total number of productive branches on that tree. Finally, we estimated the average number of coffee cherries per farm by taking the average across all nine trees.

2.4 | Manual Monitoring

Manual monitoring refers to estimating coffee tree productivity through visual inspection using hand-counting of coffee cherries in the field. The same nine trees and the same branches used in the smartphone-based monitoring were selected to ensure consistency and comparability between the approaches. The enumerators who took the photographs for smartphone-based monitoring also performed the manual counting. An average number of cherries per tree per farm was calculated in the same way as in the smartphone-based monitoring, except that that photographers performed visual inspection visual inspection was used instead of YOLO v8 for cherry detection.

2.5 | Interpretable Machine Learning Methods

We used xAI methods to understand the interactions between soil, climate, management characteristics and coffee tree productivity at the farm level. xAI focuses on the development of tools that increase the transparency and understanding of models (Carvalho et al. 2019).

In this study, we employed two machine learning algorithms, RF and Extreme Gradient Boosting (XGBoost), for regressing an average number of cherries per tree with the set of predictor variables (Table 1). RF is an ensemble learning algorithm using multiple decision trees trained on bootstrap samples and predictions are made via majority vote (classification) or averaging (regression) (Breiman 2001). At each split in a tree, RF selects a random subset of predictor variables—controlled by the hyperparameter (*mtry)*, which defines how many features are considered at each split. This mechanism reduces bias and variance (Goldstein et al. 2011) and makes RF well-suited for modelling nonlinear relationships between input features and the target variable.

XGBoost is another ensemble tree-based method that builds trees sequentially, where each new tree focuses on correcting the errors of the previous ones. It uses gradient boosting with regularisation to improve generalisation and model performance, making it efficient and highly accurate for structured data prediction tasks (Chen and Guestrin 2016). Two key hyperparameters in XGBoost are *n.trees*, which sets the total number of boosting iterations (i.e., trees to build), and *interaction.depth*, which defines the maximum depth of each tree—controlling the complexity of feature interactions the model can capture.

We trained the RF and XGBoost models using datasets randomly split into 80% training and 20% testing (total $n = 389$). A fivefold cross-validation was employed to identify the best hyperparameters for RF (*mtry* = 2) and XGBoost (*n.trees* = 500, *interaction.depth* = 3), based Root Mean Square Error (RMSE), using grid search algorithm implemented in caret (Kuhn 2011). The models were evaluated with R-squared (R^2) and RMSE.

We used post hoc methods, namely variable importance and a partial dependence plots. The permutation-based is a measure to rank the importance of predictor variables (Ryo 2022). It evaluates each variable's contribution by measuring the change in model error after randomly shuffling its values (Breiman 2001). Predictors that, when permuted, result in a greater decrease in model accuracy are considered more influential (Molnar et al. 2020). The partial dependence plot visualises the association between one or more predictor variables and the target variable, while holding the effects of all other variables constant (Ryo 2022; Molnar et al. 2020). We used R software v 4.4.1, and the libraries: caret v 6.0.94 (Kuhn 2011), vip v 0.4.1 (Greenwell et al. 2020), and pdp v 0.8.2 (Greenwell BM 2017). The R script is available at the GitHub repository with Zenodo doi: (https://doi.org/10.5281/zenodo.16938956).

3 | Results

3.1 | Performance of the Smartphone-Based Monitoring at the Farm Level

We evaluated the performance of the smartphone-based monitoring in predicting coffee tree productivity at the farm level, using manual monitoring as the ground-truth data reference. Smartphone-based monitoring demonstrated strong predictive performance, achieving an $R^2 = 0.84$ and RMSE = 367, suggesting strong agreement between manual and smartphone-based monitoring.

The smartphone-based monitoring consistently estimated a higher number of cherries than the manual monitoring, with a mean count of 590.62 cherries per tree, compared to 465 cherries for manual monitoring (Table 2). Additionally, it showed high discrepancy in the number of cherries between the approaches when the count exceeded 2600 cherries per tree (Figure 1B). For instance, the maximum number is 4763 for smartphone-based monitoring, while that is about 2600 for manual monitoring (Table 2).

3.2 | Comparison of Monitoring Approaches Using xAI

We compared the outputs of RF and XGBoost models between smartphone-based and manual monitoring approaches. RF outperformed XGBoost for both approaches (Figure A1: Appendix). With RF, the smartphone-based monitoring achieved predictive accuracy comparable to that of manual monitoring in estimating coffee tree productivity. Specifically, the model trained with manual monitoring data yielded a moderate performance ($R^2 = 0.25$; RMSE = 236.2), while that

TABLE 2 | The statistics of smartphone monitoring against the manual monitoring.

Metric	Smartphone monitoring (average cherries per tree per farm)	Manual monitoring (average cherries per tree per farm)
Mean	590.62	465
SD	689.11	422.06
Median	420.67	370.26
Min	8.85	9.33
Max	4763.14	2597.86
Number of farms	389	

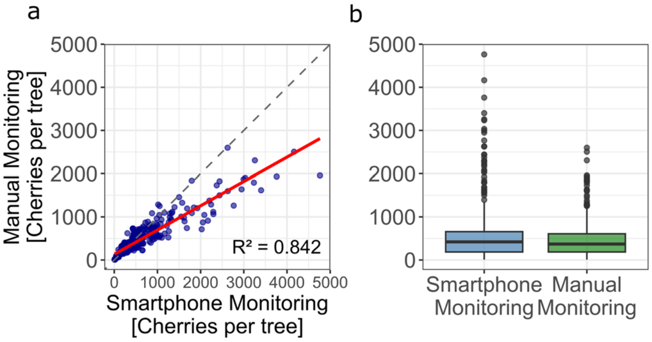

FIGURE 1 | (a) The scatter plot shows average number of total cherries per tree per farm, estimated based on the manual coffee monitoring against the smartphone monitoring ($n = 389$). (b) The box-plots show the distribution of an average number of total cherries per tree per farm both smartphone-based monitoring data and manual monitoring.

with smartphone-based data achieved a lower performance (0.17; 323).

In terms of variable importance, the RF for both manual and smartphone monitoring commonly selected the area allocated to coffee cultivation on the farm (*FarmUseCoffee*) as the most important predictor. This was followed by total farm area (*FarmArea*) for smartphone monitoring (Figure 2a) and the farmer's perception of climate (*Climate*) (Figure 2b). for manual coffee monitoring. Additional influential variables included satellite-based, texture of soil (*texture*) for both approaches. However, variables related to shade trees, *DistinctShadetrees* and *TypesShadeTrees*, did not show high importance for coffee tree productivity.

We further investigated the effects of *FarmUseCoffee* and *textura* because they were ranked in the top 3 as important variables (Figure 2b) and showed a modest positive correlation with coffee tree productivity (smartphone: $r = 0.3$, manual $r = 0.21$) (Figure A2: Appendix). Partial dependence plots were depicted to diagnose how the associations between *FarmUseCoffee* and coffee tree productivity were modelled by each of two approaches (Figure 3a) and Figure 3b). Both approaches suggest a positive relationship with coffee tree productivity. The curve shape for the smartphone-based monitoring appears to be very similar to that for the manual monitoring one with an upward shift of approximately 60 units.

In terms of *textura* (Figure 4a) and (Figure 4b), both approaches showed similar effects on coffee tree productivity across all soil textures. Both approaches suggested a highest coffee prediction when the texture of soil is *sandy clay loam*. The highest coffee tree productivity was observed when the field area exceeded 13 ha (Figure 3a; smartphone-based monitoring: 550 coffee cherries, manual monitoring: 440 coffee cherries).

Two-dimensional partial dependence plots were generated to visually confirm the joint effects of *texture* and *FarmUseCoffee* (Figures 4 and 5). Both smartphone-based coffee monitoring and manual coffee monitoring suggest that relative coffee tree productivity is dependent on both *texture* and *FarmUseCoffee*. The observed patterns show a clear division around a *FarmUseCoffee* value of 13 ha (red vertical line in Figure 4) and soil *texture* of *sandy clay loam*, indicating their significant contribution to coffee tree productivity.

4 | Discussion

We evaluated the performance of smartphone-based monitoring at the farm level. Our results show that it achieved an $R^2 = 0.84$ when validated against ground-truth data collected via manual monitoring. We also found that both smartphone-based and manual monitoring identified the same key factors for coffee productivity at the farm level: the area cultivated with coffee (*FarmUseCoffee*) and soil texture (*Texture*) where the texture *sandy clay loam* is important at areas greater than 13 ha.

The overestimation of total cherries at the farm level using smartphone monitoring is significant. Our previous study (Rivera-Palacio et al. 2024) also detected that overestimation also occurs when estimating an average number of cherries per tree (but not averaged across trees in the same farm), which is consistent with our results. Therefore, the approach has a systematic bias. However, overestimation does not affect to find key factors driving coffee tree productivity. Our findings revealed similar results between manual monitoring and smartphone monitoring regarding the most important variables: two of the top three most important variables (*FarmUseCoffee* and *texture*) remained the same across both approaches, and the partial dependence plots showed similar patterns in *FarmUseCoffee*. Nevertheless, this overestimation can be critical when high-precision accuracy is required, as it may introduce bias into the predictions.

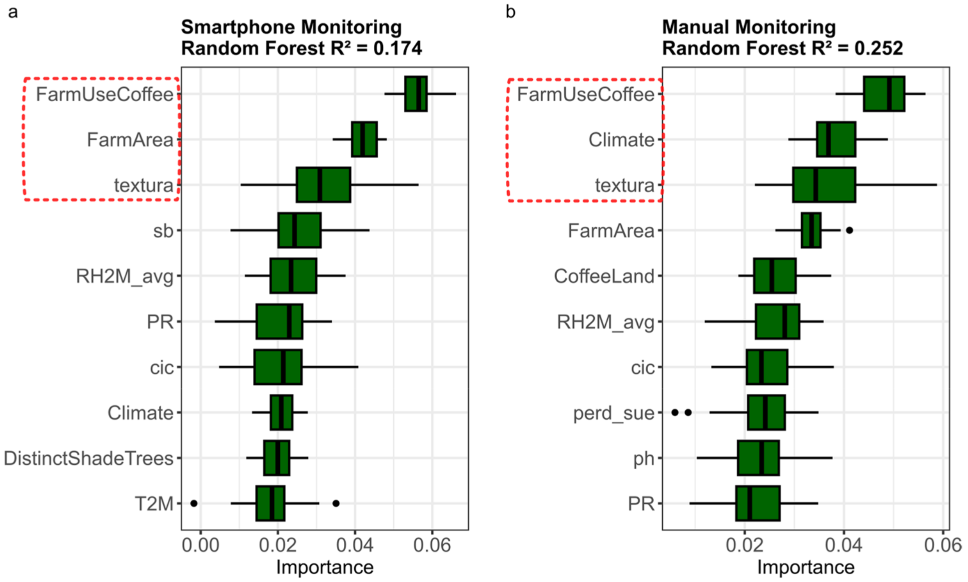

FIGURE 2 | Permutation-based variable importance plots: (a) Random Forest for smartphone monitoring, (b) Random Forest for manual monitoring. *FarmUseCoffee* refers to the area (ha) cultivated with coffee. *FarmArea* is the total area of the farm (ha). *Climate* represents the farmer's perception of the climate. For the detailed description of the variables, see Table 1.

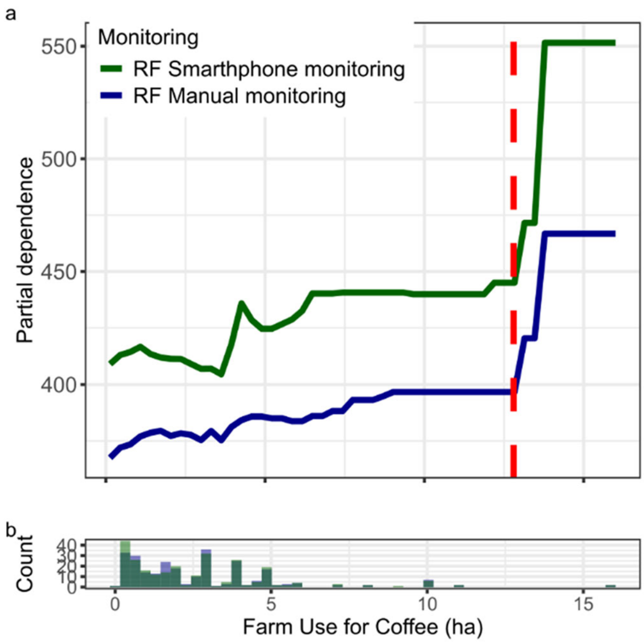

FIGURE 3 | (a) Partial dependence plots for *FarmCoffeeUse* (area (ha) of the farm cultivated with coffee). (b) Data distribution of *FarmCoffeeUse*.

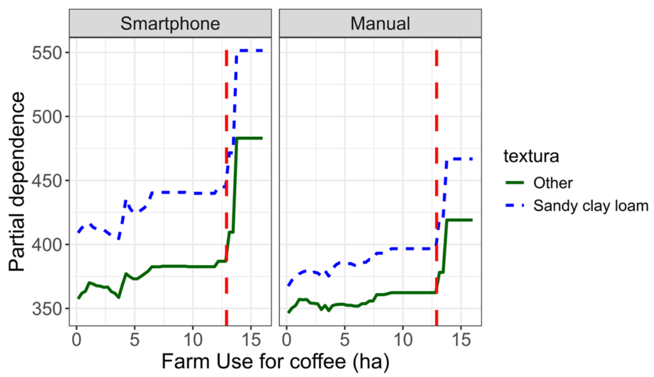

FIGURE 4 | Partial dependence plot of *FarmUseCoffee* conditional on soil type (sandy clay loam vs. other). Smartphone monitoring (left panel); Manual monitoring (right). The red vertical line marks a coffee area of 13 ha, where a significant increase in coffee productivity is observed. This suggests that relative coffee tree productivity is higher when the soil is sandy clay loam, independent of the planted area.

The permutation-based variable importance and partial dependence plots for smartphone monitoring and manual monitoring showed similar patterns in the influence of shade trees, climate, soil, and land shape on coffee tree productivity. Our analysis revealed that coffee tree productivity is positively correlated with soil texture, *sandy, clay, and loam* soils and coffee area plantation greater than 13 hectares. These soil textures allow for water retention, good drainage, and proper aeration, which are essential for healthy coffee plant growth (Wintgens 2004). These physical properties also enhance the retention of potassium and sulfur, two nutrients that are closely associated with crop yield (Kouadio et al. 2018).

Larger farm areas are associated with higher coffee tree productivity, presumably due to greater access to capital for investing in cultivation and better access to financial services (Benami et al. 2021; Ayele et al. 2021; Thurston et al. 2013). Most studies have focused on the general importance of soil (Wintgens 2004; Kouadio et al. 2018). However, they do not compare multiple factors together, such as coffee tree productivity, climate, shade trees, shape of land, and size of the cultivation area. In particular, there is a lack of evidence on whether certain soil textures interact with larger farm areas to influence coffee tree productivity. Here, we show that such an interaction exists.

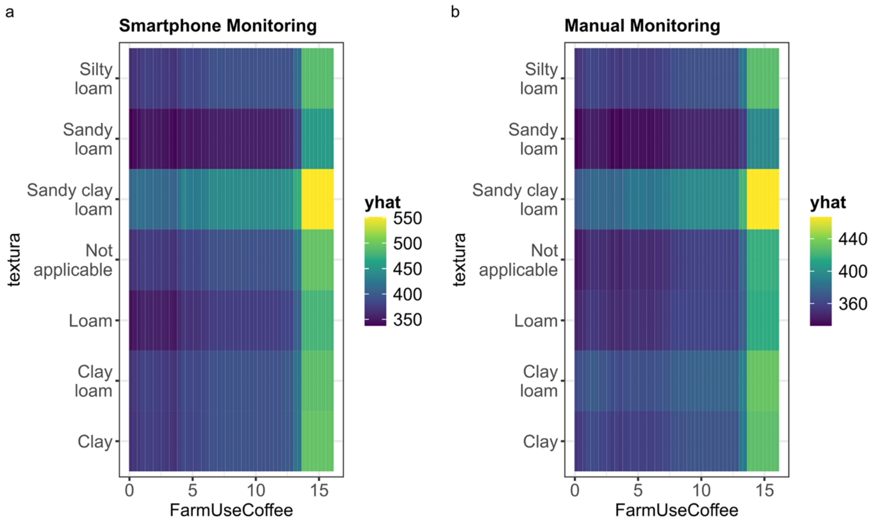

FIGURE 5 | Partial dependence plot (2D) showing the interaction between farm use of coffee and soil type. (a) Smartphone monitoring. (b) Manual Monitoring.

Unexpectedly, the importance of shade trees was not detected in this study. Previous studies and recommended practices commonly suggest the positive effect to mitigate the effects of climate change (Jaramillo et al. 2013), to reduce temperature and water loss trough the microclimate (Pham et al. 2019), and protect the crops as physical barrier (Ratnadass et al. 2012). A potential reason for the lack of importance of shade trees in this study is that the concept of 'shade tree' may still be unclear to farmers, who often confuse shade trees with intercrop species. As a result, the classification in our data may be inconsistent or ambiguous. In addition, the shade-tree variable was limited, recorded only as the predominant type, with no multi-season data on density, canopy cover, spatial arrangement, or canopy height, thereby limiting the ability to capture functional effects.

The main limitations of this study related to constraints in the temporal data and the lack of variety in tree selection on farms. Data were collected during only one season (2022), which means that temporal variability was not captured. Additionally, the random selection of tree on farms introduced bias, as it depended on the enumerator. New methods for selecting trees are therefore necessary for future research to provide a more precise overview of the influence of trees, for example along diagonals or transects (Hedley and Buckland 2004). Finally, the study focused only on *C. arabica* and Colombia varieties, so evaluation across additional species and a broader geographical area is required.

5 | Conclusion

This study demonstrated that smartphone-based monitoring is a promising tool for assessing coffee tree productivity at the farm level. Despite a systematic overestimation of total cherries, the approach achieved strong agreement with manual monitoring ($R^2 = 0.84$) and consistently identified the same key factors driving productivity, namely the area cultivated with coffee and soil texture. In particular, sandy clay loam soils and larger farm areas (greater than 13 ha) were found to be positively associated with higher yields. Although the importance of shade trees was not detected, this may reflect data limitations and ambiguities in farmer classification rather than their true functional role. The study also highlighted key methodological limitations, including the lack of temporal data, restricted climate variables, and limited species coverage.

Overall, smartphone-based monitoring offers a scalable and cost-effective alternative to manual monitoring for identifying major drivers of coffee productivity. Future research should focus on improving sampling strategies, expanding temporal and climatic datasets, and validating the approach across different coffee species and geographical regions.

Author Contributions

Juan C. Rivera-Palacio: conceptualisation, data curation, formal analysis, methodology, validation, visualisation, and writing – original draft. **Christian Bunn:** conceptualisation, funding acquisition, project administration, supervision, writing – review and editing. **Masahiro Ryo:** conceptualisation, funding acquisition, project administration, supervision, writing – review and editing.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data and code are open source and freely available for download in the GitHub repository with the Zenodo. https://doi.org/10.5281/zenodo.16938956.

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Appendix

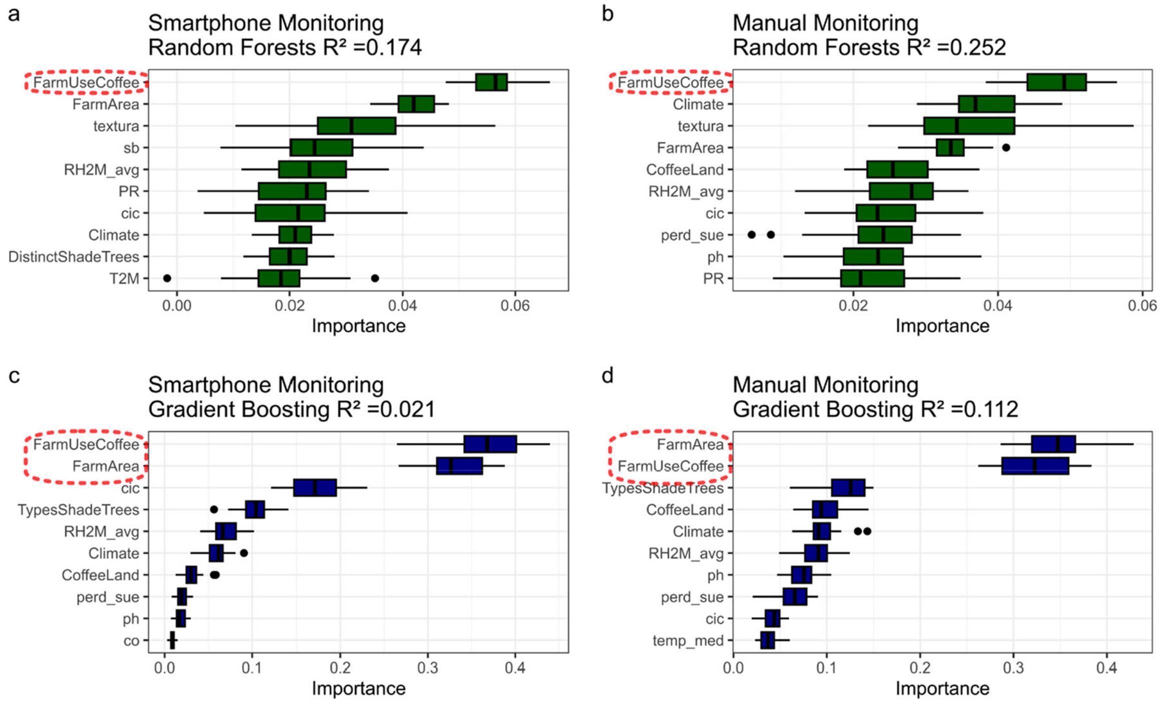

FIGURE A1 | The performance of gradient boosting and random forest.

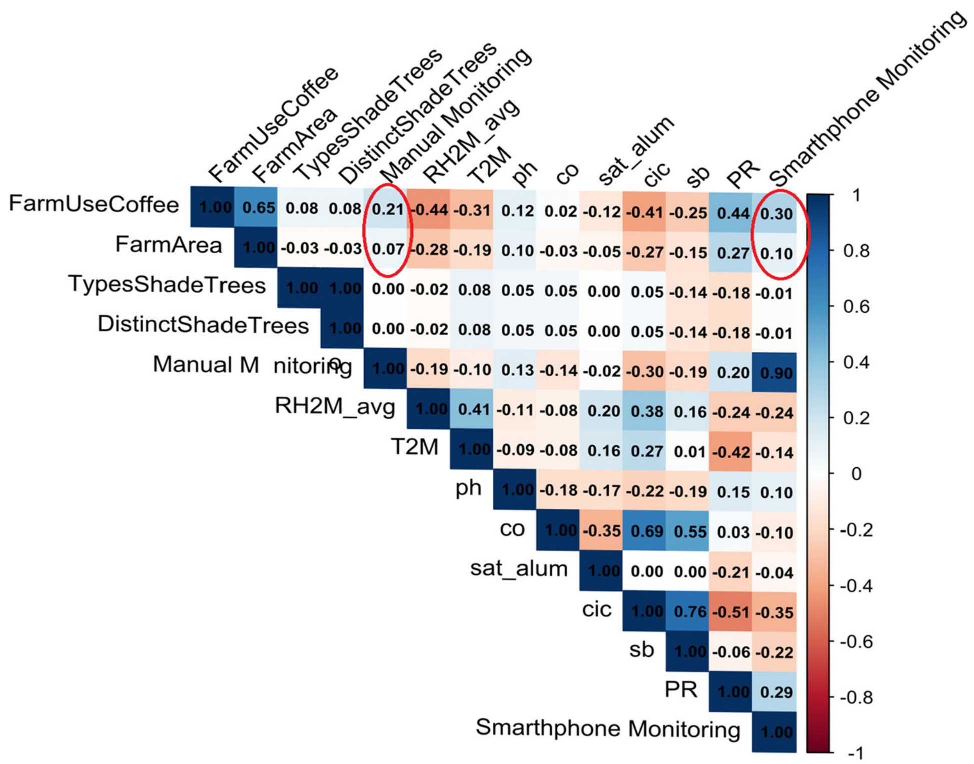

FIGURE A2 | Correlation matrix between the variables, where colour intensity indicates the magnitude of the correlation.