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Jean Paul Latyr Faye, Racine Ly, Khadim Dia, Babacar Ceesay, Mansour Dia, and Aïssatou Ndoye

Groundnut and Millet Crop Mapping in Senegal Using Satellite Remote Sensing and Machine Learning

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ABSTRACT

The growing global population poses a serious threat to food security, necessitating the adoption of innovative agricultural practices to meet the increasing demand for food in ways that mitigate the negative impacts of climate change. Timely, accurate, and efficient crop maps are essential for policymakers and decision-makers to make informed choices that improve production in local food systems. Recent advancements in machine learning and remote sensing techniques have significantly enhanced crop mapping capabilities. In this paper, we explore the application of machine learning techniques combined with remote sensing data to map groundnut and millet crops in the Groundnut Basin of Senegal. In 2023, we collected a ground-truth crop label dataset across the study area, on the crops present at specific sites. To generate the models to identify specific crops in the remotely sensed imagery for the study area, using a subset of 80 percent of the field data, we trained random forest, support vector machine, and artificial neural networks machine-learning techniques to generate models for using optical bands and calculated vegetation indices from the satellite imagery to predict the presence of specific crops. We then evaluated the performance of those models on the remaining 20 percent subset of the full field dataset—that is, 20 percent of the plots from which field data was collected in 2023. The evaluation showed that the random forest algorithm models achieved the highest accuracy on the test dataset, exceeding 83 percent. We applied the models using imagery from 2018 and 2023 for the Groundnut Basin to examine the dynamics of groundnut cultivation over this period. We highlight a significant decrease in land area dedicated to the crop. This analysis provides insights into recent changes in patterns of groundnut farming in Senegal and offers valuable information for regional policymaking to optimize groundnut cultivation practices.

Groundnut and Millet Crop Mapping in Senegal Using Satellite Remote Sensing and Machine Learning

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1. INTRODUCTION

Agriculture globally confronts a myriad of challenges stemming from the ever-increasing population. According to the U.S. Census Bureau, the world population is predicted to reach 10 billion by 2060 (Morse 2023). The current level of food produced will not be enough for the food security of this population (FAO 2017). Indeed, current yield levels must nearly double to meet global food security needs (Foley 2011). Continued food security is positively correlated with optimal water and soil management for agricultural production. However, conventional agricultural practices often fail in this regard, resulting in reduced water availability and insufficient soil nutrients, leading to increased soil degradation (Shannon et al. 2015). More sustainable agricultural practices offer more robust solutions to these challenges. However, such approaches require that public and private decision-makers, as well as research and development institutions, have access to detailed and timely agricultural data. In many African countries, access to reliable data remains a significant issue, making it particularly challenging to estimate the area planted to various crops accurately. This leads to poor estimations of crop production, undermining numerous governmental decisions based on the flawed information (You and Sun 2022).

In Africa, there is an urgent need for detailed agricultural crop maps at the national level. These crop maps are crucial for guiding sustainable resource allocation strategies that support food security, irrigation management, energy planning, and crop adaptation to climate change, among other needs (Blickensdörfer et al., 2022; Wang et al. 2022). The need for crop insurance also heightens the practical requirements for crop mapping in Africa. Consequently, having detailed crop variety statistics down to the plot level has become essential (Hudait and Patel 2022).

According to the FAO's definition of agricultural land (Latham et al. 2002), crop mapping involves identifying different crops (Meng et al. 2021), mapping crop associations (Zhou et al. 2019), whether groups or single crops of significant interest (Sabir and Kumar 2022), conducting crop phenological mapping (Gao and Zhang 2021), and conducting inter-annual crop rotation (Liu et al. 2021) and crop intensity (Pan et al. 2021) mapping. Among these components, crop association mapping is crucial for spatial quantitative estimation of crop production. Maps of crop associations enable the identification and spatial classification of agricultural production systems, which can be utilized for crop rotation planning.

Several techniques are used for crop mapping. Traditional techniques primarily rely on field survey missions. While these methods can be accurate, they face numerous challenges and disadvantages. Physically mapping a single crop parcel in a field can be a time-consuming process. Additionally, access to cropland to employ traditional plot mapping techniques is often challenging, as many farmers and landowners impose restrictions on field access, and plots may be located far from roads and difficult to reach. In general, traditional crop mapping techniques are often costly and inefficient (Saleem et al. 2021).

Remote sensing technologies have emerged as a promising alternative to traditional methods of crop mapping, with significant advancements

in their applications and increasing importance in agriculture over recent years (Weiss et al. 2020). The primary platform for imagery in crop mapping research using remote sensing techniques is satellites. Open access to Earth observation satellite data is now widespread. The satellite imagery commonly used for crop mapping includes Landsat 8 (Gilbertson et al. 2017), MODIS (Dell'Acqua et al. 2018), and Sentinel-2 (Mattupalli et al. 2018), with some limited use of hyperspectral imagery (Jahan and Awrangjeb 2017). The multispectral remote sensing imagery provided by these sensors has proven to be highly effective for crop mapping (Prins and van Niekerk 2020). The Sentinel-2 constellation of satellites provides the imagery that is the most suitable for crop type classification due to its high resolution, multispectral, and multi-temporal optical characteristics. Sentinel-2 satellites are equipped with 13-band multispectral sensors covering swath widths of 290 km at resolutions of 10, 20, and 60 meters, depending on the wavelength.

Satellite imagery data can be analyzed using machine learning techniques. When combined with ground truth and remote sensing data, machine learning techniques, such as supervised learning models, have demonstrated their ability to identify different crops in remotely sensed images accurately (Zhao et al. 2020). The number of publications on crop mapping using machine learning techniques to analyze remotely sensed images has increased continuously since 2014, and such analytical approaches are being used to examine issues related to population growth, food security, and climate change (Joshi et al. 2023). Most research on crop mapping using satellite imagery has been conducted in the United States and China (Machichi et al. 2023; Prins and van Niekerk 2020). Various non-parametric machine learning algorithms have been employed, including decision trees, random forests, neural networks, and support vector machines (Lary et al. 2016). Random forest and support vector machine methods were employed by Inglada et al. (2015) for a global study, while Valero et al. (2016) used random forest-derived classifiers to map crops across 12 sites around the world, and Immitzer et al. (2016) used decision tree and random forest techniques with Sentinel-2 data to produce crop classification maps for central Europe. The accuracy of the crop maps obtained using these machine-learning techniques with satellite imagery ranged from 50 to 80 percent, depending on the heterogeneity in the landscape at the field sites (Lary et al. 2016).

In Africa, however, there has been a notable lack of intensive research in this area. Given the significant contribution of agriculture to the continent's economy, there is a pressing need to enhance research efforts on crop mapping using machine learning techniques on remotely-sensed images to improve Africa's agricultural sector. This paper uses advanced machine learning techniques and remote sensing data to develop a model for crop mapping of groundnut and millet in the Senegalese Groundnut Basin. Our approach involves training machine learning models using ground-truth data collected in 2023 on features extracted from satellite images with a pixel size of 100 m^2. Applying the models to predict the spatial distribution of crops in satellite images from 2018 and 2023 from the Groundnut Basin demonstrates the precision of our model. It also reveals significant dynamics in cropland use within the study area.

The remainder of this paper is structured as follows: Section 2 describes our materials and methods, including the region of interest, field data collection for ground truthing, satellite image processing, and the selection of satellite spectral signatures and features. Section 3 presents the crop mapping results and assesses their validity and usefulness. Finally, Section 4 discusses how such research might be applied and extended to inform efforts to develop and expand agricultural production across Africa, thereby better ensuring food security for all.

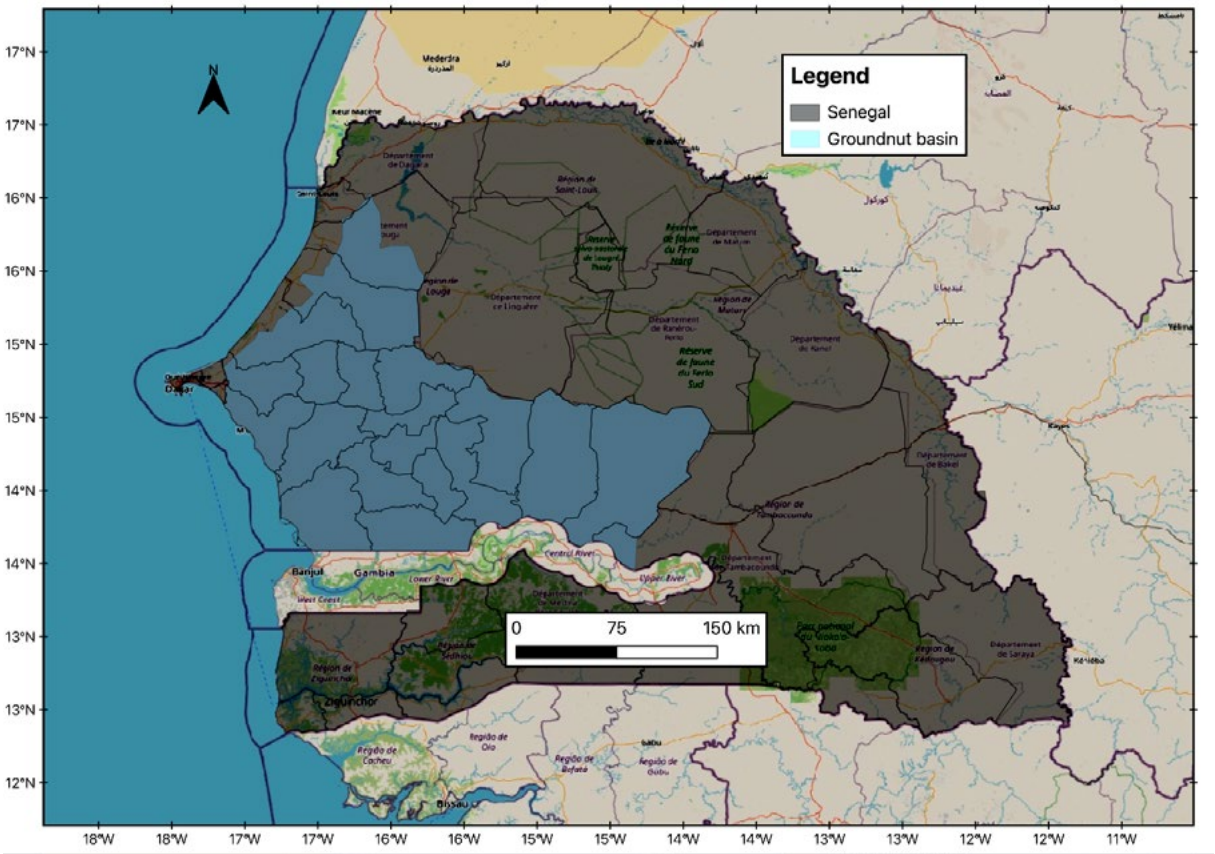
2. MATERIALS AND METHODS

In this section, we describe the region of interest for our research, the field data collected for ground truthing the satellite imagery, the satellite data analyzed, and how the machine learning model was constructed for the study.

2.1 Region and crops of interest

The crop mapping study was conducted in the Groundnut Basin of Senegal, an important agroecological zone known for both its agricultural significance and economic contribution (Ndiaye et al. 2016). The Basin spans parts of Kaolack, Fatick, Diourbel, and Kaffrine administrative regions in central Senegal, as shown in Figure 2.1. The region benefits from favorable climatic and soil conditions that support the rainfed cultivation of various crops, including groundnut, millet, sorghum, and cowpea (Faye et al. 2018). Smallholder farmers grow these crops either as sole crops or as intercrops, most commonly with millet. The climate in the Groundnut Basin is classified as Sudano-Sahelian, characterized by a rainy season from July to October and a long dry season for the rest of the year. Annual rainfall in the region averages between 400 mm and 650 mm.

Figure 2.1: Senegal – map highlighting the Groundnut Basin.



Source: Authors' construction.

The study focuses on developing crop maps for groundnut and millet grown in the Groundnut Basin. The two are the main crops cultivated in the area. Millet is primarily grown for consumption by the producing household, whereas groundnuts are both consumed and sold.

Groundnut is typically sown between late June and early July and harvested between September and October. Most rural households in Senegal depend on groundnut for both subsistence and income generation (World Bank 2017). Historically, the groundnut subsector has

driven agro-industrial development in Senegal, serving as a critical input for the production of edible oil and animal feed. As a nitrogen-fixing legume, groundnut also contributes to soil fertility maintenance. While in the 1960s, groundnut played a central role in the national economy, the groundnut value chain in Senegal has since faced numerous challenges. These include declining yields. For example, from 2009 to 2024, Senegalese groundnut productivity was estimated at 900 kg/ha, compared to 1,500 kg/ha in Nigeria, 3,000 kg/ha in China, and 6,900 kg/ha in Israel (World Bank 2017). The main factors contributing to this decline have been identified to be traditional farming practices, increased cultivation on marginal lands, inefficiencies in seed and fertilizer distribution, low-yielding seed varieties, uncontrolled outbreaks of pests and diseases, and, more recently, the impacts of climate change.

Millet is a staple crop in the Groundnut Basin region, primarily grown for consumption. It plays a crucial role in the diets of local communities, providing essential nutrition and contributing to food security. Millet is usually sown with the first rains between late May and early July and harvested between September and October.

2.2 Field data collection

Data was collected in the field on plots with specific crop types grown in them, including groundnut, millet, maize, and other crops. This was done in the Groundnut Basin over the 2023 agricultural season. Since only a single round of data collection was conducted, the phenological stage of the crops was not recorded. The locations of these crops are illustrated in Figure 2.2. This study particularly emphasizes groundnut and millet.

The data on crop plots was collected through field surveys and the use of drones. During the field surveys, numerous crop plots were mapped, and the specific crop types grown in them were documented. As shown in Figure 2.2, some plots featured intercrops, with multiple crops grown together in the same field at the same time. In addition to the survey data, drone technology was employed to capture high-resolution images of the fields. These images were then processed to provide detailed information on crop distribution. This combination of ground-based surveys and drone imagery provided a comprehensive and accurate dataset on 325 crop plots in the study area.

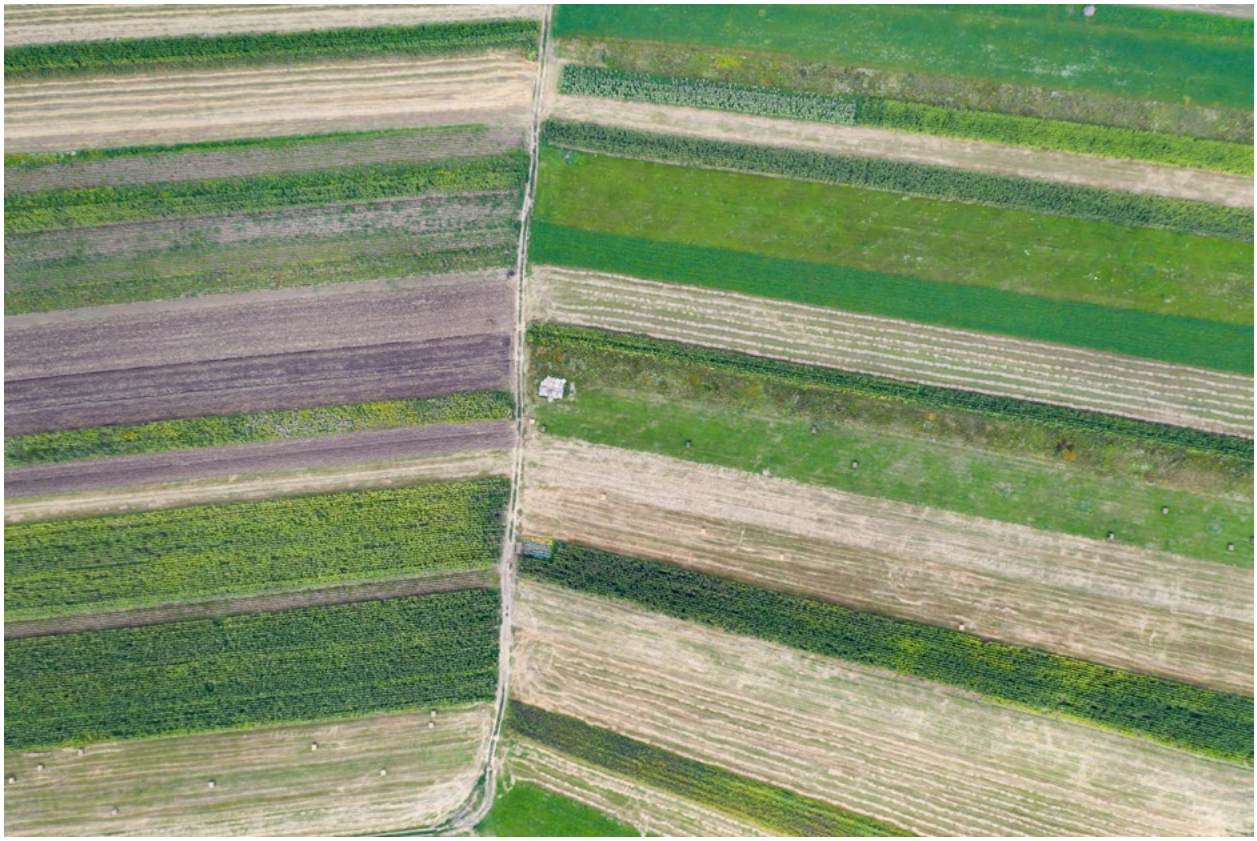
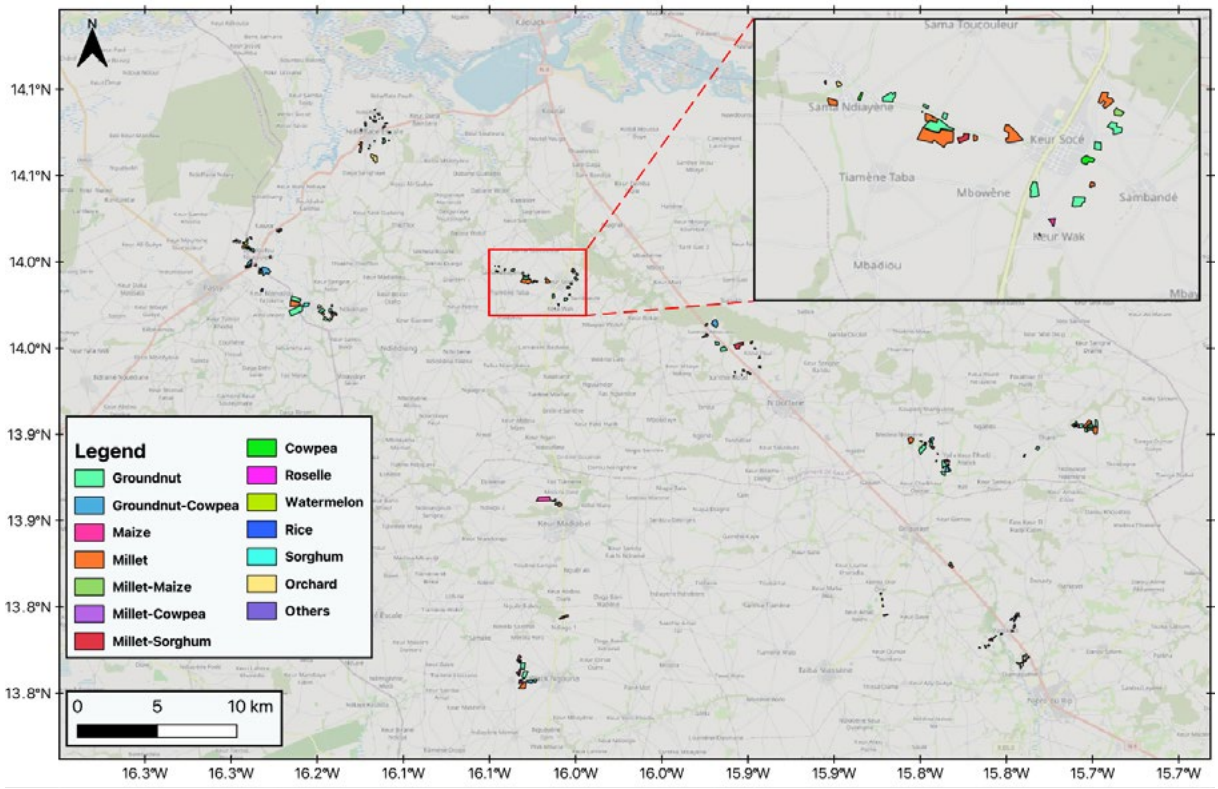


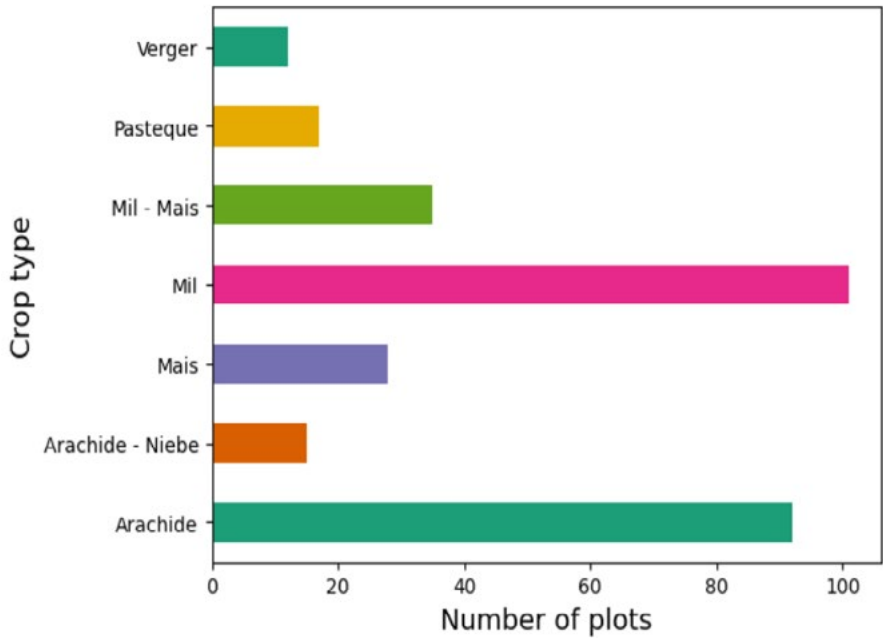
Figure 2.2: Plots from which field data was collected in 2023 in the Kaolack region in the south-central part of the Groundnut Basin, with corresponding crop types.



Source: Authors' construction.
Note: The inset map provides a zoomed-in view to better illustrate the polygons and their distribution.

Figure 2.3 displays the count of plots by crop type. This figure highlights millet and groundnut as the primary crops cultivated in the study area. For clarity, crop types with plot counts of fewer than ten, such as roselle and sorghum, were excluded from the analysis.

Figure 2.3: Crop type count, by plot.



Source: Authors' analysis.
Note: Arachide="groundnut"; Mais="maize"; Mil="millet"; Niebe="cowpea"; Pasteque="watermelon"; Verger="orchard".

2.3 Satellite data

Due to the generally open access to analysis of the imagery they gather, earth observation satellites are the primary source of imagery used in crop mapping research involving remote sensing. Satellite images can be classified based on their spatial resolution: low, medium, or high. Spatial resolution refers to the area covered by the individual pixels in a satellite image, which influences the level of detail captured and the potential of the imagery for use in crop mapping and geospatial analysis applications. For agricultural applications in the Sahel, characterized by a heterogeneous agricultural landscape composed of small crop plots, a spatial resolution of 10 meters, corresponding to pixel sizes of 100 square meters or finer, is required for effective crop mapping (Leroux et al. 2014). The detail provided at this level of resolution allows for the identification and differentiation of various crop types within the Groundnut Basin's fragmented and diverse crop plot patterns.

The identification and differentiation of land cover from remotely sensed images is based on spectral signatures in the pixels of an image. These signatures capture the unique electromagnetic radiation patterns associated with different crop types. The signatures are derived from the reflectance or emission of light across various electromagnetic spectrum bands, including near-infrared (NIR) and the visible spectrum. The ability of spectral band sensors to distinguish between crop types is primarily due to the reflectance values unique to each crop.

The satellite images used for the crop mapping research in the Groundnut Basin were collected from the Sentinel-2 satellite at level 2A. These images provide top-of-canopy reflectance values with a cloud mask. In processing the images, we only retained those with cloud cover of less than 25 percent. Sentinel-2, a part of the European Sentinel satellite constellation, features optical sensors capable of capturing Earth's features across 13 spectral bands. With a revisit time ranging from 2 to 5 days, Sentinel-2 provides high temporal resolution, which is crucial for monitoring dynamic changes on the ground. Sentinel 2 has bands of 10, 20, and 60-meter spatial resolution. All bands of 10 m spatial resolution—that is, bands 2 (Blue), 3 (Green), 4 (Red), and 8 (NIR)—were used in the analysis for this paper (Table 2.1).

Table 2.1: Optical bands used in the study, with wavelength ranges.

Optical band	Wavelength range, nanometers
Blue	458 – 523
Green	573 – 608
Red	650 – 680
Near Infrared	785 – 900

Source: SentinelHub (2025).

The Groundnut Basin was divided into small squares to process the satellite imagery using Google Earth Engine. A time series of images for each square was collected from June 01, 2023, to October 31, 2024, with a time step of one month. Images from several weeks before sowing and several weeks after harvest were included to capture comprehensive information over the entire growing season.

In addition to the Blue, Green, Red, and NIR optical bands given in Table 2.1, several vegetation indices were calculated from the satellite imagery to be included in the machine-learning model. A key index widely used in land cover and crop mapping with satellite imagery is the Normalized Difference Vegetation Index (NDVI). This index is useful for characterizing crop dynamics and generally correlates well with crop growth parameters, such as leaf area index and chlorophyll concentrations. However, NDVI may not fully capture certain phenological phases and variations in leaf pigments, water content, and residue cover, especially in regions with complex crop cultivation patterns. To address these limitations, several other spectral

indices were constructed. All the indices used in this study are presented in Table 2.2. All these indices were calculated from the Sentinel-2 optical bands, which have a spatial resolution of 10 meters.

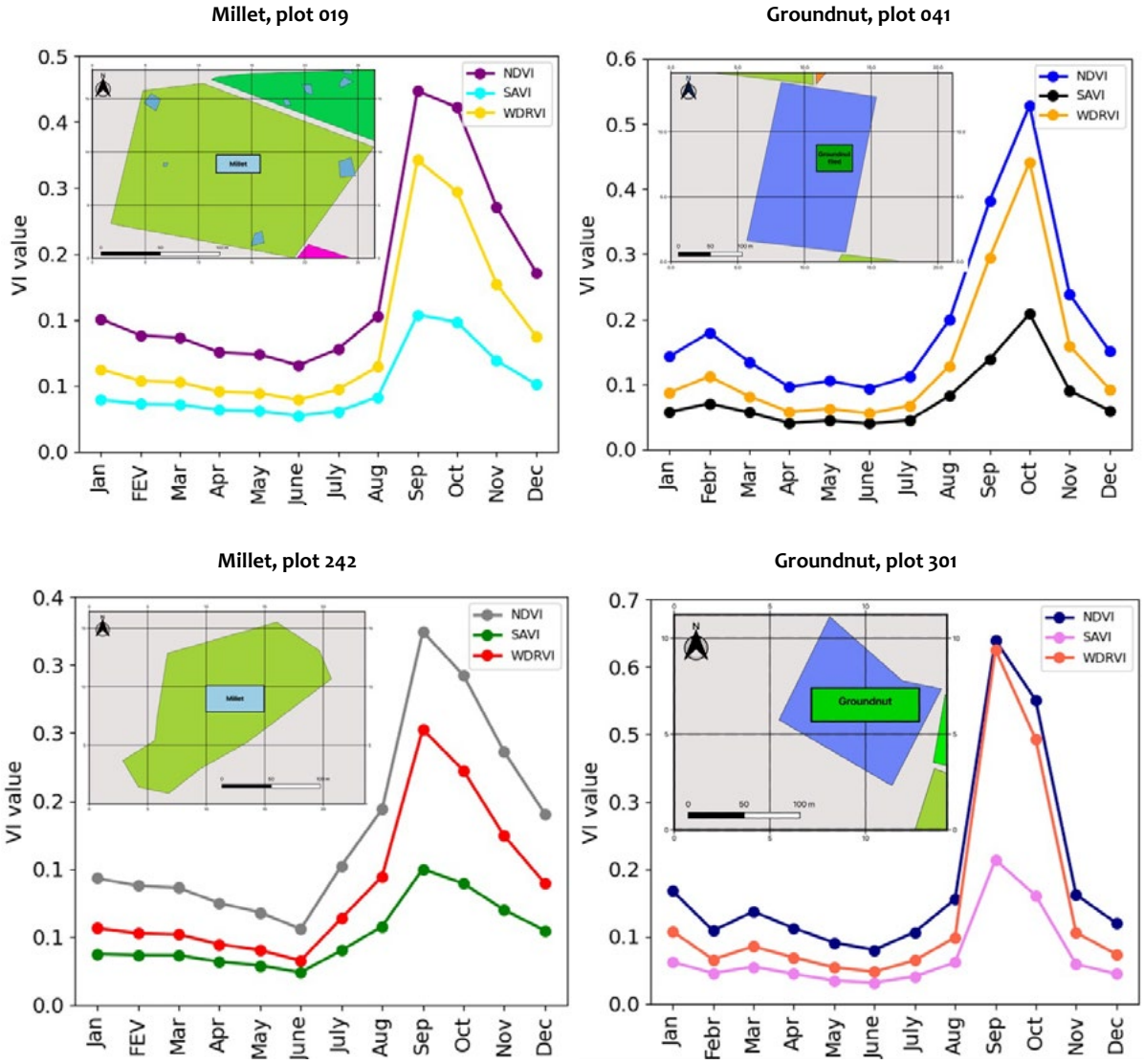
Table 2.2: Vegetation indices used in the study.

Abbreviation	Vegetation Index Name	Formula
NDVI	Normalized Difference Vegetation Index	(NIR – Red) / (NIR + Red)
SNDVI	Standardized Normalized Difference Vegetation Index	(NIR – Red) / (NIR + Red + 0.16)
WDRVI	Wide Dynamic Range Vegetation Index	(0.2 NIR – Red) / (Red + 0.2 NIR)
SAVI	Soil-Adjusted Vegetation Index	[(NIR – Red) / (NIR + Red + 0.5)] * 1.5
PSRI	Plant Senescence Reflectance Index	(Red – Blue) / NIR

Source: Authors' compilation; Jiao et al. (2024); Gitelson (2004); Huete (1988); Ren et al. (2016).
Note: In addition to these vegetation indices, the study also includes the optical bands Blue, Green, Red, and Near-Infrared (NIR).

To create crop maps for groundnut and millet over the study site, we extracted from the satellite imagery for each of the 325 plots in our field data, the optical bands and vegetation indices at 30-day intervals from June 01, 2023, to October 31, 2023. This approach provides a detailed spectral signature for each crop type and captures the whole dynamics of the crops in the plots throughout the growing season. As a result, the generated training dataset is a time series. In Figure 2.4, the evolution in time of the vegetation indices NDVI, SAVI, and WDRVI for two randomly selected millet plots in our field data set and two groundnut plots are shown.

Figure 2.4: Evolution over the 2023 growing season of three vegetation indices—NDVI, SAVI, and WDRVI—for two millet plots (left) and two groundnut plots (right).



Source: Authors' analysis and construction.

Note: The Inset map displays the plot location. NDVI = "Normalized Difference Vegetation Index"; SAVI ="Soil-Adjusted Vegetation Index"; WDRVI = "Wide Dynamic Range Vegetation Index"

2.4 Machine learning model construction

Machine learning techniques have recently garnered attention in crop mapping. Unlike parametric modeling, machine learning techniques offer the advantage of learning from and predicting cultivated crop distributions without requiring any prior assumptions about the model. This flexibility allows for more accurate and adaptable analysis of agricultural data. In this study, we evaluated random forest, support vector machine, and artificial neural network machine-learning techniques, all of which have been previously utilized for crop mapping (He et al. 2022; Yan et al. 2021). These techniques were chosen for their effectiveness in handling complex datasets and their ability to capture intricate crop distribution patterns.

Many machine learning techniques directly predict the class label of the target crop. In contrast to these, we adopt a probabilistic crop mapping approach, which estimates the likelihood that a given pixel corresponds to a specific crop type, rather than assigning a single fixed label. This method offers several

advantages for regions like Africa, where fields are often small, irregularly shaped, and contain a mixture of crops. Such approaches also aid decision-makers, as they provide flexibility in precision based on the level of informational detail required for specific planning needs.

3. RESULTS

We trained various machine learning models using the optical bands and calculated vegetation indices with three techniques: random forest, support vector machine, and artificial neural networks. We evaluated the models developed on a test dataset that consisted of a 20 percent subset of the full dataset—that is, 20 percent of the plots from which field data was collected in 2023.

Evaluation of the resultant models showed that the random forest algorithm achieved the highest accuracy on our test dataset, with an accuracy of over 83 percent (Table 3.1). In contrast, the accuracies of the neural network and the support vector machine did not exceed 60 percent. Therefore, we concentrate only on the results from the random forest classifier. We used the random forest model to predict crop types in pixels of the satellite imagery from the Groundnut Basin analyzed for this study.

Table 3.1: Evaluation of random forest model for millet and groundnut crop classes, percent.

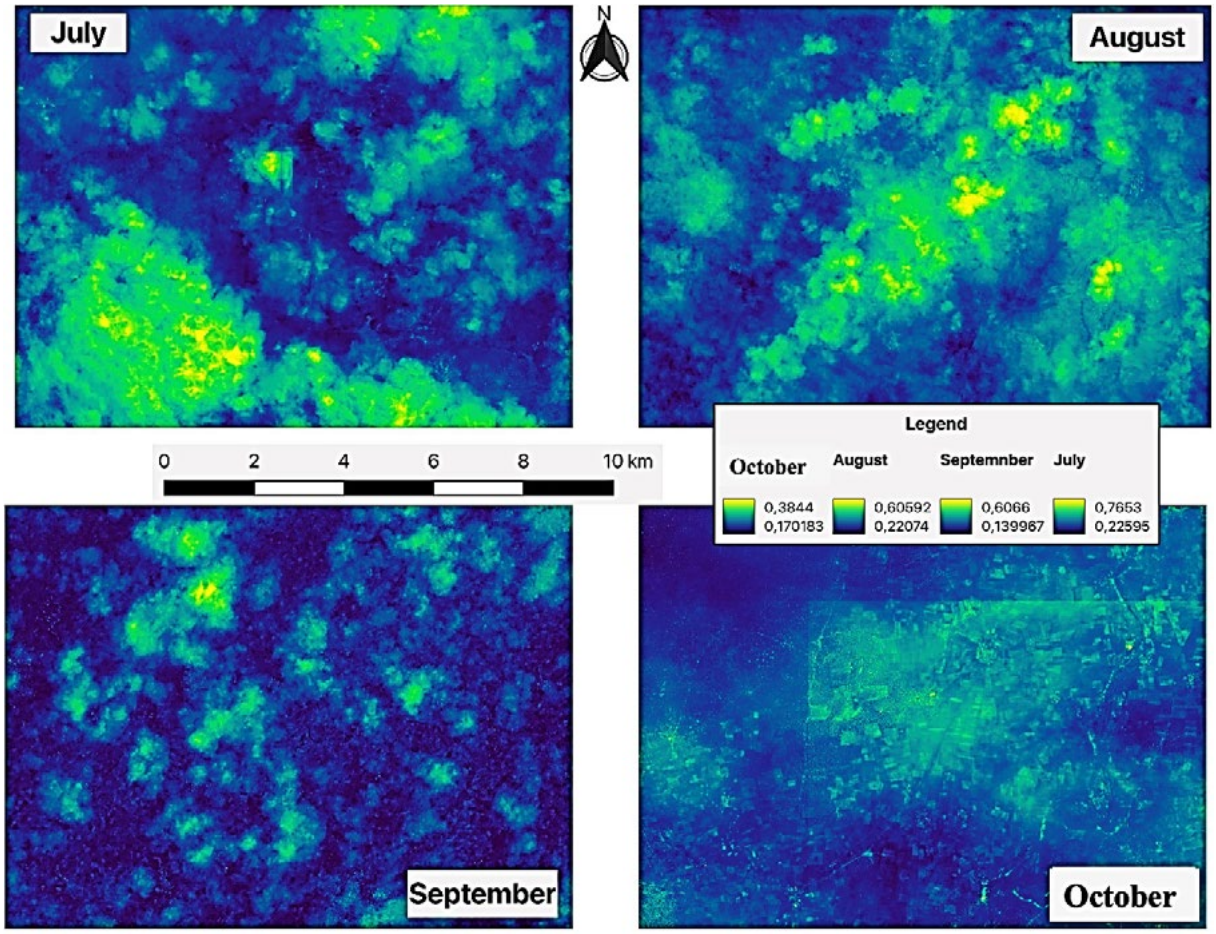
	Millet	Groundnut	Accuracy	Macro average	Weighted average
Precision	85.7	78.5	83.3	83.4	83.4
Recall	90.9	68.0	83.3	79.7	83.3
F1-score	88.2	61.1	83.3	80.6	82.6

Source: Authors' analysis.

The random forest algorithm employs an ensemble of decision trees for better generalization and is relatively robust against overfitting. In addition, it utilizes an extra trees algorithm, which introduces an element of randomness to each decision tree split, thereby reducing bias and variance (Wang et al. 2019). Thus, the random forest approach is particularly well-suited to the task of crop mapping.

To predict the locations of millet and groundnut production, we collected satellite images covering the Groundnut Basin. Due to the limitations of Google Earth Engine in processing large images, the region was divided into smaller polygons for the analysis. For each pixel in those images, values for the four optical bands (Table 2.1) and the calculated vegetation indices (Table 2.2) were compiled. Figure 3.1 shows some of the images used in the analysis of the distribution of crop production in the Groundnut Basin for July, August, September, and October 2023. The different colors across the images indicate differences in the intensity of the reflected signal from crops or other land cover captured by the satellite sensors.

Figure 3.1: Samples of satellite images from the Groundnut Basin of Senegal used in the analysis of the distribution of crop production.

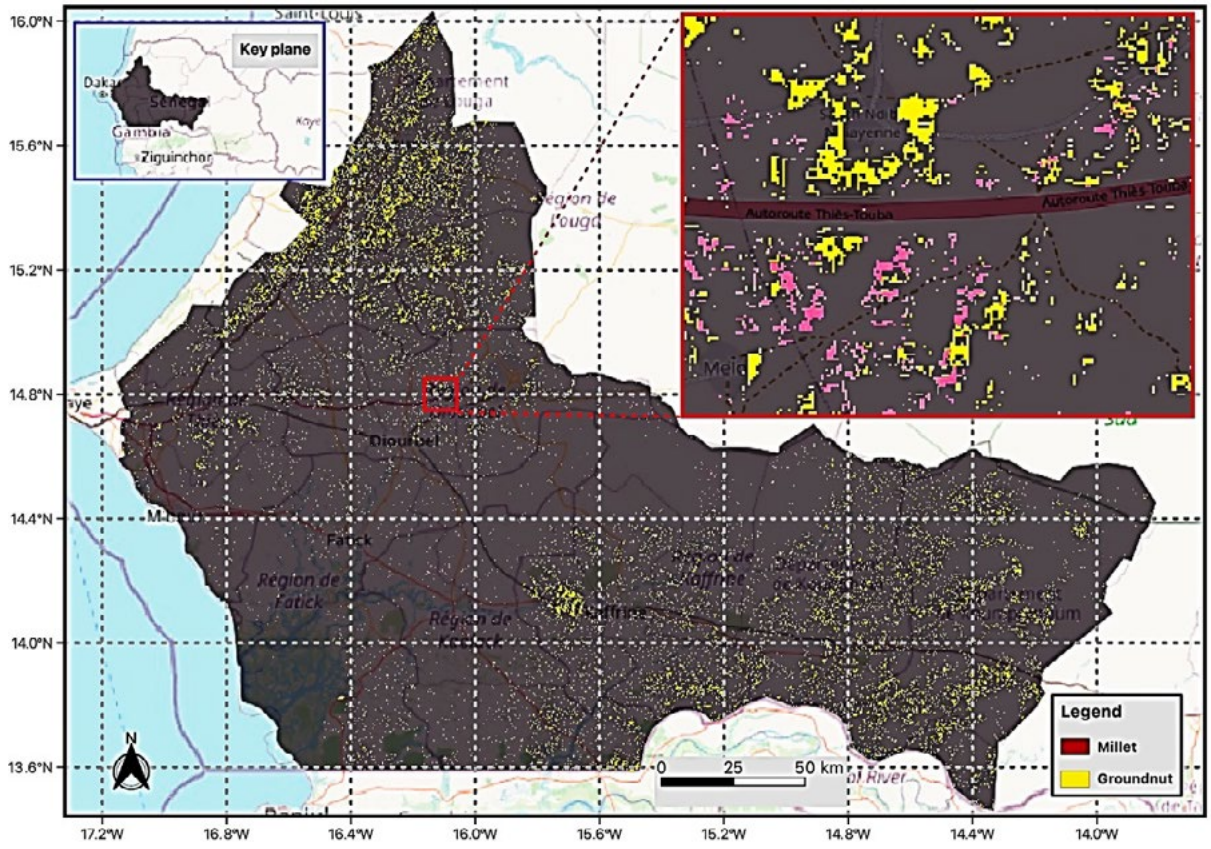


Source: Authors' construction.
Note: The different colors across the images indicate differences in the intensity of the reflected signal from crops or other land cover captured by the satellite sensors.

3.1 Mixed crop mapping

We first investigate crop mapping for the two major crops, millet and groundnut. Figure 3.2 presents the results of our satellite imagery analysis for 2023, highlighting that the cultivation of groundnut and millet is more heavily concentrated in the northern region of the Groundnut Basin. This distribution suggests a regional suitability for these crops in that part of the Basin. As each pixel represents an area of 100 square meters, we determined the extent of land classified as millet and groundnut—millet is cultivated on just over 16,000 hectares. In contrast, groundnut occupies a larger area of over 24,200 hectares. These findings highlight the role of groundnut as a major cash crop in the region, generating income for many smallholder farmers and contributing to the livelihoods of local communities.

Figure 3.2: Groundnut Basin of Senegal – map illustrating the spatial distribution of millet (red) and groundnut (yellow) with probabilities exceeding 50 percent for 2023.



Source: Authors' construction.
Note: The top left inset map indicates the area of interest within Senegal, while the top right inset map highlights the distribution of millet and groundnut within a small area of the Groundnut Basin.

Millet, although cultivated on a smaller scale than groundnut, remains an essential staple food crop. It is crucial for sustaining the dietary needs of the local population. The dual significance of these crops—groundnut as an economic driver and millet as a food security staple—illustrates the importance of a balanced agricultural system in supporting economic growth and the dietary needs of local communities.

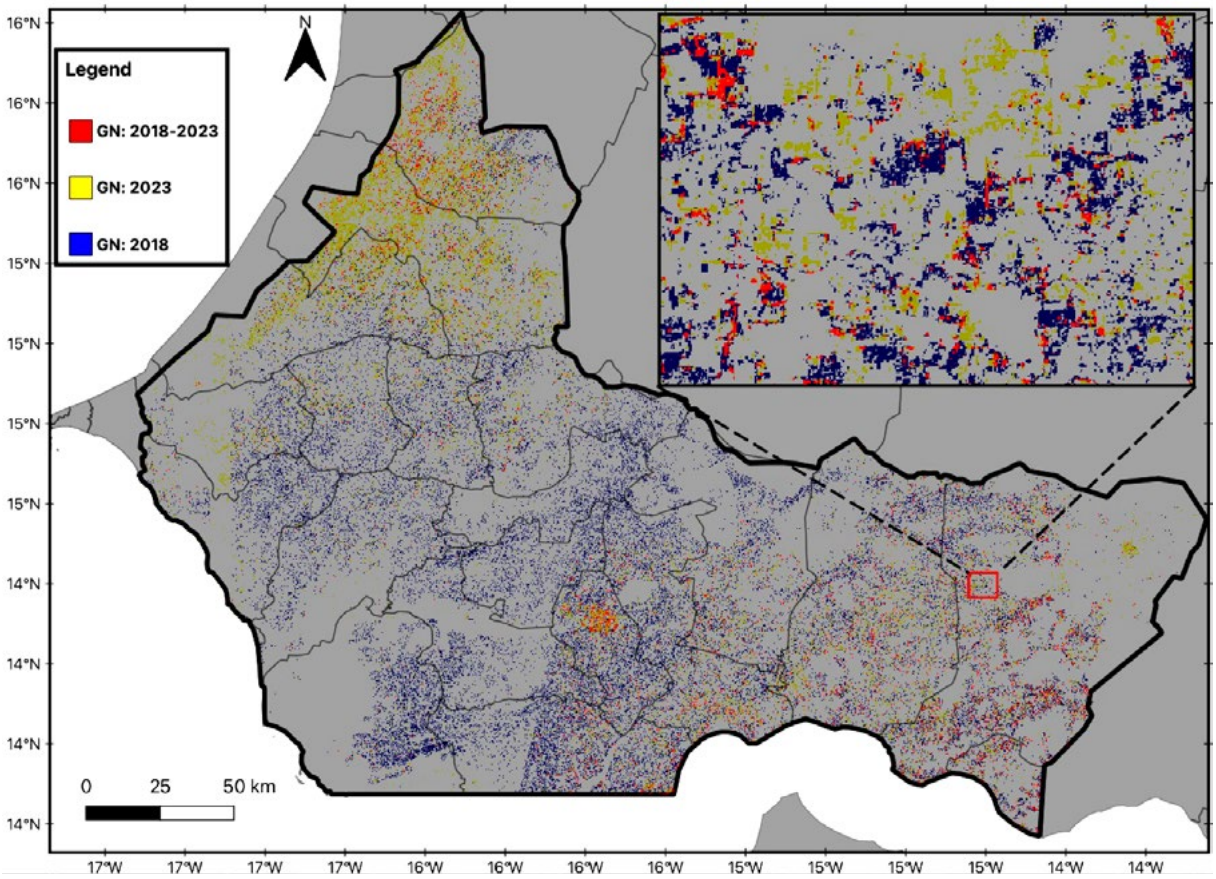
3.2 Spatial dynamics in groundnut cultivation in the Groundnut Basin

To better understand changes in groundnut cultivation within the Groundnut Basin, we use satellite imagery from 2018 and 2023. Our approach involved using a model optimized to accurately identify groundnut fields in satellite imagery. This model was trained using field data collected in 2023. The model was then applied to satellite imagery collected in 2018 to predict the extent of groundnut cultivation in the same year. As the model was trained on data collected in 2023, given the potential for increased error when applying the model to data from five years prior, we focused only on pixels in both the 2018 and 2023 satellite imagery that were predicted to be groundnut with very high probabilities of greater than 65 percent.

By comparing the predictions of groundnut cultivation across the 2018 and 2023 images, we were able to analyze shifts in groundnut cropping over the five-year period and gain insights into the changes that occurred within this time frame. The results are shown in Figure 3.3, with areas in which groundnut was cultivated only in 2018 shown in blue and those areas in which groundnut was cultivated only in 2023 in yellow. The pixel areas where groundnuts were cultivated in both years are represented in red. Table 3.2 shows the total area in the Groundnut Basin cultivated with groundnut as predicted by the model for these two years. In 2018, over 536,600 hectares were cultivated with groundnut. However, by 2023,

this area decreased to under 495,000 hectares—a reduction of 7.79 percent. The land taken out of groundnut production was either abandoned or repurposed. Several factors may explain the decline in cropland dedicated to groundnut, including the migration of farmers to urban areas for employment, shifts to alternative crops, other socio-economic changes, and climate change.

Figure 3.3: Groundnut Basin of Senegal – distribution of groundnut production in 2018 and 2023, yellow indicates groundnut in 2023, blue in 2018, red in both years.



Source: Authors' construction.
Note: Groundnut probability values of 65 percent or greater from the satellite imagery interpretation were used to designate pixels as planted with groundnut. The inset offers a zoomed view of the area near Diourbel.

Table 3.2: Predicted total cultivated area of groundnut in the Groundnut Basin for 2018 and 2023 based on the interpretation of satellite images from the two years.

Cultivated area, ha	2018	2023	Difference, %
	536 642	494,843	-7.79

Source: Authors' analysis.

This situation is exacerbated by the limited availability of resources to implement effective soil restoration and climate adaptation strategies. As a result, large tracts of land once productive for groundnut farming have either been abandoned or repurposed for other uses. The declining productivity in the region threatens farmers' livelihoods and impacts the region's overall agricultural output and the food security of its residents. Addressing this issue will require adopting precise cultivation practices that utilize new technologies to support climate-resilient agriculture. These advancements will help local farmers adapt to the challenging environmental conditions and improve the sustainability of their farming practices.

3.3 Precision location of crop distribution: probabilistic strategy

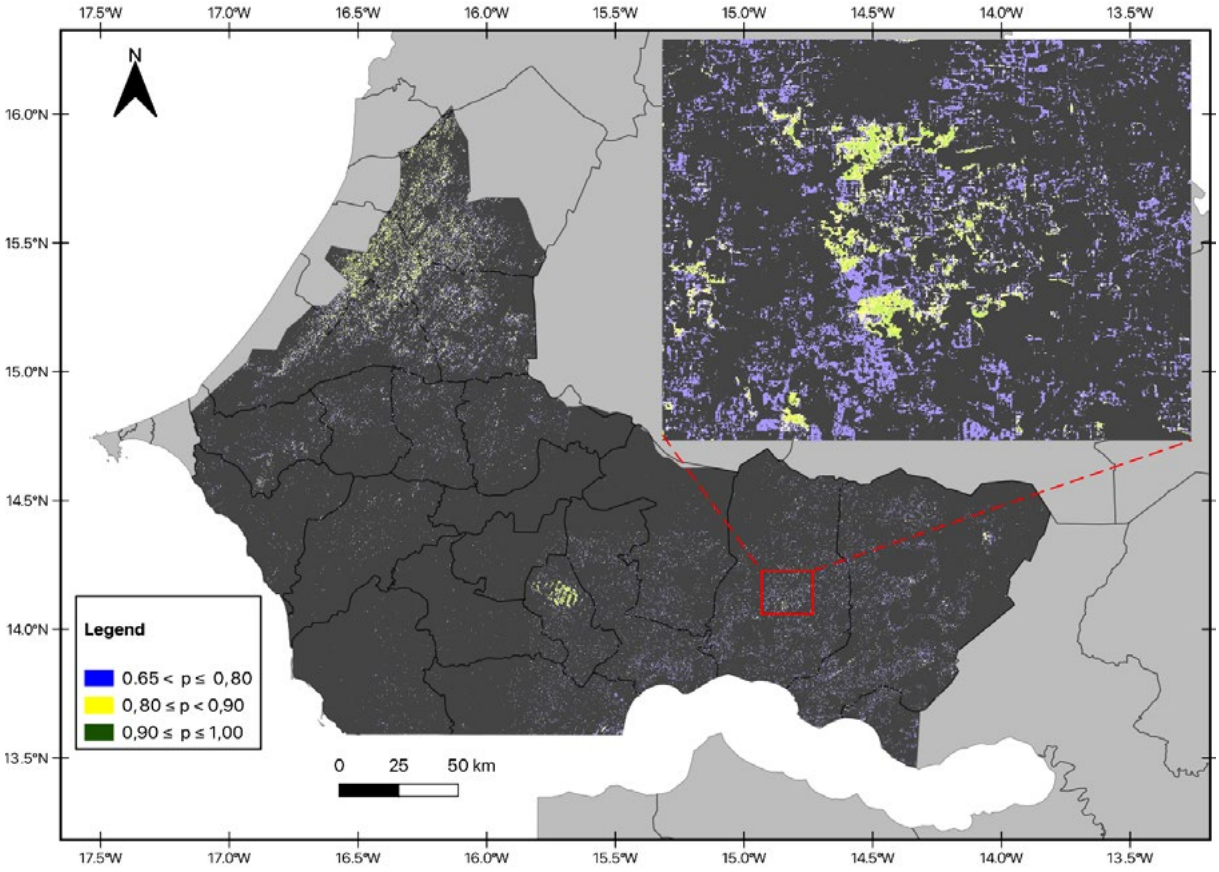
In crop classification using machine learning with satellite imagery, there are two approaches to categorizing crops. The first involves directly outputting the crop class to which a pixel belongs. In contrast, the second approach provides the probability of the pixel being in a possible crop class. These two methods are connected through the argmax function, which assesses the probability values for all of the various crop classes considered for each pixel and finds the maximum probability value, returning the crop class value with the highest probability.

However, relying solely on crop class predictions based on the highest probability may not be sufficient for accurate crop mapping. This limitation arises because satellite imagery may not always have sufficient resolution to accurately identify crop types based solely on their spectral signatures. Consequently, machine learning models may struggle to differentiate between similar crops using only the simple highest probability.

To improve the accuracy of crop mapping, it is advantageous to utilize the probabilities directly rather than converting them into discrete class labels immediately. By focusing on the probabilities and retaining those with higher levels of precision, the model can offer more nuanced insights into crop classification. This approach enables a more refined assessment, allowing uncertain or ambiguous classifications to be flagged for further review or combined with additional data sources. Such methods enhance the reliability of machine learning outputs and contribute to more precise and useful crop distribution maps.

Figure 3.4 maps the results of the satellite imagery analysis for the Groundnut Basin, showing the probability that each pixel is classified as being planted with groundnut. Blue pixels represent groundnut probabilities exceeding 80 percent, yellow pixels indicate a probability between 70 and 80 percent, while grey pixels have probabilities of being planted to groundnut of less than 70 percent. The map shows a higher concentration of pixels with a high degree of confidence of being planted to groundnut in the northern part of the Groundnut Basin.

Figure 3.4: Groundnut Basin of Senegal—distribution of groundnut cultivation for different probability scales.



Source: Authors' construction.
Note: The inset map provides a zoomed view of the area near Koungheul. = "probability."

4. DISCUSSION AND CONCLUSIONS

4.1 Crop mapping: A strategy to overcome climate change challenges

This study uses remotely-sensed imagery from satellites and advanced machine learning techniques to produce crop maps for millet and groundnut in the Groundnut Basin of Senegal. Crop mapping can play a multifaceted role in overcoming the threats posed by climate change and soil degradation to agriculture.

Accurate monitoring and assessment of agricultural lands are among the most significant benefits of crop mapping using satellite imagery. The regular production of crop maps enables precise tracking of land use dynamics, offering detailed insights into crop health, soil conditions, and changes in land cover. This level of detail is crucial for identifying areas most severely affected by soil degradation, thereby enabling targeted interventions to restore soil fertility and prevent further land degradation.

In addition to monitoring, crop mapping contributes substantially to optimizing resource management. By understanding the specific conditions and needs of individual fields, farmers can apply water, fertilizers, and other agricultural inputs more efficiently. This precision is especially important in the context of climate change, which introduces increased variability and unpredictability in weather patterns. Improved input management not only reduces waste and costs but also enhances crop yields, thereby supporting more sustainable farming practices.

Moreover, crop mapping plays a direct role in promoting climate-resilient agricultural practices. It allows for the identification of suitable areas for implementing techniques such as crop rotation, intercropping, or agroforestry. These practices are essential for maintaining soil health, improving water retention, and increasing crop resilience to the effects of climate change. By guiding the adoption of such strategies, crop mapping supports long-term sustainability and productivity in agriculture.

Another important application of crop mapping is its integration into early warning systems. When combined with weather forecasts and other environmental data, crop maps can support the development of systems that provide alerts for droughts, pest infestations, and other potential risks. These early warnings enable farmers to take proactive measures to protect their crops, minimizing losses and maintaining productivity amid increasing climate variability. Early interventions based on accurate and timely information are crucial to safeguarding food security.

Finally, crop mapping provides a valuable data foundation for informed decision-making by policymakers. With comprehensive information on crop performance, environmental conditions, and land use trends, decision-makers are better equipped to design effective policies and strategies. These insights can be instrumental in addressing production shocks, managing agricultural risks, and ensuring the welfare of populations that rely heavily on farming for their livelihoods.

4.2 Future directions for research

This study highlighted significant changes in groundnut cultivation in the Groundnut Basin of Senegal over the five years from 2018 to 2023. The decline in the area dedicated to groundnut farming indicates the challenges posed by climate change, soil degradation, and possibly other socio-economic factors. These findings underscore the importance of implementing strategies to mitigate these challenges, such as adopting climate-resilient agricultural practices and improving soil management techniques. Our use of remote sensing and machine learning for crop mapping is shown to be a practical and timely approach to capturing these dynamics. The probabilistic mapping strategy used provides valuable insights into the current state of groundnut and millet cultivation and offers a powerful tool for predicting future trends. This predictive capability is crucial for policymakers and farmers who must make informed decisions in changing environmental conditions.

Future research should focus on two areas. First, the scope of such research should be expanded to include other crops and regions within Senegal and across West Africa, which would provide a better and more comprehensive understanding

of agricultural trends in the region. Second, the crop maps should be used to explore the socio-economic factors influencing land use changes in the Groundnut Basin. A deeper understanding of the interplay between climate change, economic pressures, and agricultural practices is crucial for informing policy and the design of strategies to mitigate the adverse effects of these factors. In addition, such understanding will also enable the development of more powerful machine learning models for mapping crops in Senegal and elsewhere in West Africa.

4.3 Conclusion

This study employed remotely-sensed imagery from satellites and advanced machine learning techniques to map groundnut and millet cultivation in the Groundnut Basin of Senegal. The results show that groundnuts occupy a larger cultivated area than millet. Our analysis, covering the period from 2018 to 2023, reveals a notable decrease in the land area dedicated to groundnut cultivation in the Groundnut Basin.

Our findings suggest that using a probabilistic strategy for crop mapping offers significant advantages for policymakers. It enables them to make informed decisions with the precision needed to identify groundnut locations and, potentially, to estimate yields before the end of the season. The crop maps developed through this study can serve multiple purposes for policymakers and farmers, enabling them to adapt to climate change and promote sustainable agriculture. These findings offer detailed insights into the evolving patterns of groundnut farming, providing valuable information for optimizing cultivation practices and informing regional policy decisions.

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