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Understanding Agricultural Output in Mozambique

Using remote sensing to initiate a discussion on development

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Understanding Agricultural Output in Mozambique
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Prepared by Kelsee Bratley and Alexis Meyer-Cirkel*

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ABSTRACT: This paper presents a comprehensive analysis of the agricultural land coverage in Mozambique by harnessing advanced remote sensing technologies and draws on successful agricultural development examples to propose strategic pathways for Mozambique. The study leverages Sentinel-2 satellite imagery coupled with a machine learning algorithm to accurately map and assess the country's agricultural land, revealing that agriculture accounts for only 12 percent of Mozambique's land area. By examining the agricultural transformation or "green revolution" that some countries have experienced, it is possible to distill regularities and necessary conditions, which can then be compared to the state-of-affairs in Mozambique. This study not only offers a model of how emerging technologies like remote sensing can inform agricultural state of affairs, it also provides important insights into which concrete bottlenecks are likely to be holding back Mozambique's agricultural development.

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WORKING PAPERS

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Contents

1. Introduction

Mozambique has the foundational elements for a thriving agricultural sector, with an extensive land area, compared to its relatively low population density, not too arid climate conditions, and a long coast, making its geostrategic position covetable to access other African or Asian consumer markets. Despite these advantages and strong agricultural dependence, with about 70 percent of the population heavily reliant on agriculture for their livelihoods, the nation faces significant challenges in harnessing its agricultural potential. Mozambique's poor ranking on the global hunger index, where it stands at 113th out of 125 countries[1], highlights the stark gap between potential and actual agricultural productivity, underlining the urgency of maximizing Mozambique's agricultural output

The primary motivation for this paper is to illuminate the reasons behind a low agricultural output in Mozambique. While numerous factors may contribute to this issue, this study focuses on two fundamental questions: i) Is the country utilizing sufficient land for agricultural purposes? and ii) Is the output per hectare reasonable compared to global benchmarks and what are the driving forces behind that output?

Hence, Part A of the paper focuses on better understanding how much land is being used for agriculture. Accurate maps depicting the extent of agriculture in Mozambique remain notably absent. Additionally, there are no reliable quantitative estimates, with associated uncertainties, of cultivated areas. Improving the spatial understanding of Mozambique's agricultural extent is critical given its potential to drive economic growth. The agricultural sector is not merely a means of subsistence; it can also serve as a catalyst for rural development and poverty alleviation. Realizing this potential, however, will require targeted interventions that address the red tape, governance problems, infrastructure deficits, market inefficiencies, and financial barriers that currently exist.

Satellite remote sensing presents a transformative solution for Mozambique, where limited infrastructure and resources pose challenges for ground-based data collection. By using satellites or airborne sensors to capture high-resolution, up-to-date images across vast areas, remote sensing provides a scalable and cost-effective means of accurately assessing agricultural land use, overcoming the infrastructure limitations that would otherwise hinder data collection (Moran et al., 1997).

Previous mapping efforts in Mozambique have been limited to either small regional-scale maps (Mananze et al., 2020; Bofana et al., 2022; Rufin et al., 2022) or broad-scale global maps (Karra et al., 2021; Potapov et al., 2022; Zanaga et al., 2022). Regional maps, while detailed, cover only specific areas within Mozambique, offering valuable localized insights but leaving substantial gaps in the national perspective. These fragmented maps make it difficult to understand the full agricultural landscape, limiting their usefulness for national policy and strategic planning. Conversely, broad-scale global maps provide extensive coverage but are constrained by their broad scope and lack the nuanced detail a national-level analysis requires. What is still needed is a comprehensive national map that not only captures the full extent of Mozambique's agricultural areas but also provides the granular detail necessary for informed, effective agricultural planning and intervention across the country. This paper leverages Sentinel-2 remote sensing data to map agricultural land use in Mozambique, providing a critical foundation for understanding current agricultural practices across the country.

[1] https://www.globalhungerindex.org/ranking.html

Part B then focuses on understanding Mozambique's agricultural output in a global and historic context. Agriculture is a vital sector for economic development, especially in the context of a growing global population that demands more food and renewable resources. From 1800 to 2000, the world population increased significantly, while agricultural production expanded even more rapidly, leading to improved food security and reduced famine occurrences. Historically, agriculture employed a large portion of the labor force, but in advanced economies, that share has dwindled to below 2.5%. This transformation has been driven by various technological, chemical, economic, social, and environmental factors, which have collectively enhanced agricultural practices and productivity.

Despite these international advancements, challenges such as infrastructure gaps, corruption, inadequate or uncoordinated institutions, underdeveloped input markets, and limited access to finance hinder Mozambique's agricultural advancement. The named challenges create a complex environment that hinders not only the growth of the agricultural sector but also, by extension, the overall economy. Addressing these impediments is essential for improving productivity and achieving food security, especially in a country where agriculture remains the primary source of income for a significant portion of the population.

The structure of this paper is as follows: the next section (Chapter 2) delves into the methodology applied to complete a remote sensing exercise for the entire extension of Mozambique. In Chapter 3 the results are laid out and maps presented, while Chapter 4 discusses and interprets these outcomes in more detail. In Chapter 5, the paper examines how agricultural development has occurred in other countries, the key drivers of change, and highlights specific case studies that exemplify particularly impressive stories of agricultural development. Chapter 6 Concludes.

Part A – Agricultural Land Usage

2. Methodology in Remote Sensing in Mozambique

Active agricultural land in Mozambique for 2022 was mapped using Sentinel-2 Level-2A Surface Reflectance imagery. The study was done in three main steps. First, data preparation involved creating image composites and calculating spectral indices and temporal statistics. Second, an agricultural land use map was created using a machine learning algorithm; specifically, a modified version of the Digital Earth Africa (DEA) continental cropland mask workflow (available at https://github.com/digitalearthafrica/crop-mask/tree/main). Finally, map accuracy was assessed, and land cover class areas were estimated following the good practice guidelines outlined in Olofsson et al. (2014; Figure 2.1). The analysis was performed on two platforms: image classification was conducted on the DEA Sandbox, while training data collection, accuracy assessment, and area estimation were conducted on Google Earth Engine (GEE).

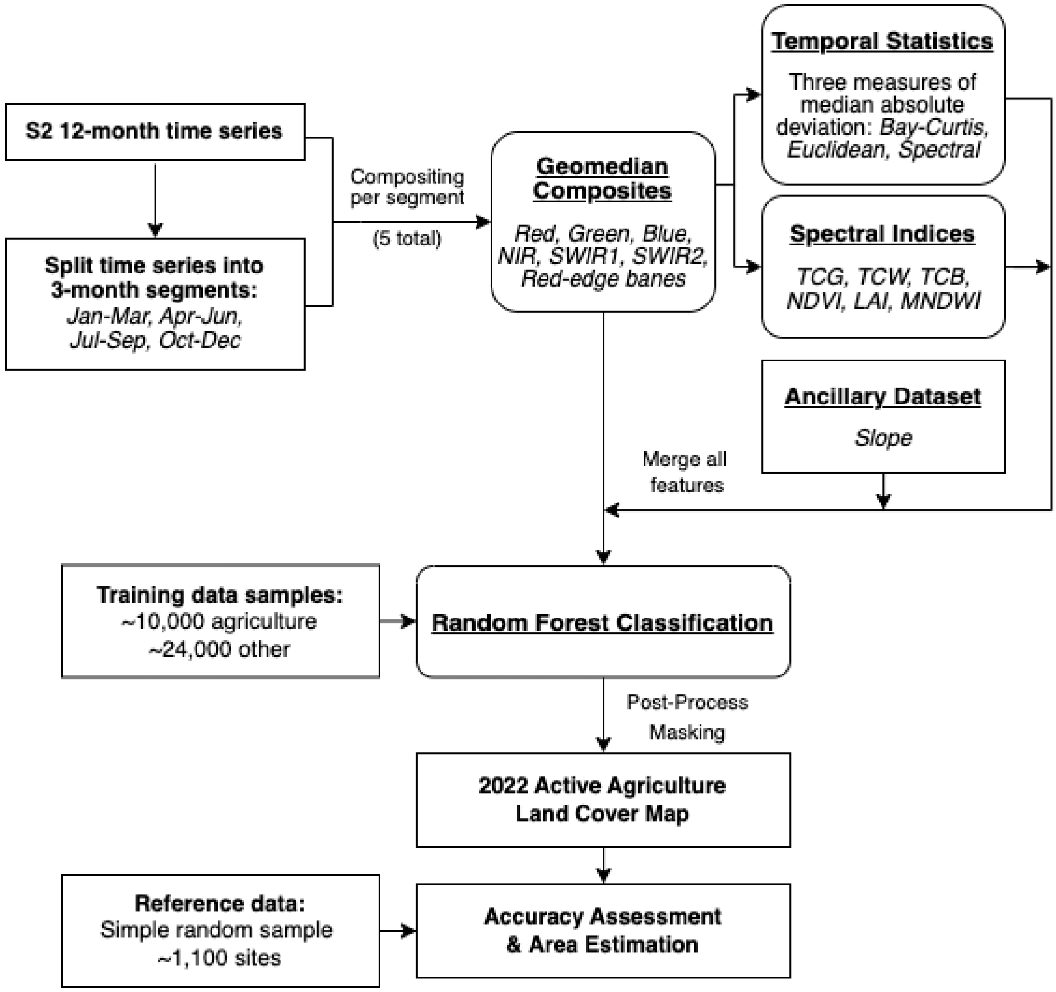


Figure 2.1. Methodology workflow for generating the 2022 Active Agriculture Land Cover Map.

2.1 Data preparation

For this analysis we utilized the DEA publicly available Sentinel-2 geomedian composites in our classification. Five composites were included in the analysis: one annual geomedian composite, and four 3-month rolling geomedian composites representing sequential time periods for the year 2022 (i.e., Jan-Mar, Apr-Jun, Jul-Sept, and Oct-Dec).

The geometric median is a spectral transformation technique commonly used in remote sensing to create a single representative image (i.e., composite) from a collection of multi-spectral images (Roberts et al., 2017). The process involves computing the element-wise median across the spectral bands of the input images. The resulting geomedian composite synthesizes the most common spectral values at each pixel location, effectively reducing spatial noise and highlighting the dominant spectral characteristics of the landscape. By incorporating multiple composites at varying time intervals, we introduced greater spectral and temporal diversity into the classification.

To improve the image classification process, three Median Absolute Deviation (MAD) layers were calculated for each geomedian composite: Euclidean MAD (EMAD), spectral MAD (SMAD), and Bray-Curtis MAD (BCMAD). EMAD measures the distance of each pixel from the median pixel in multi-dimensional spectral space, providing a measure of spectral variability and texture. SMAD captures spectral variability between neighboring pixels, aiding in the identification of subtle spectral differences between land cover classes. BCMAD quantifies the compositional dissimilarity between pixels and their neighbors, offering information on the spatial arrangement and heterogeneity of land cover types. MAD layers were calculated for all five geomedian composites (Roberts et al., 2017).

Moreover, six spectral indices were calculated for each geomedian composite and included in the classification: Normalized Difference Vegetation Index (NDVI); Leaf Area Index (LAI); Modified Normalized Difference Water Index (MNDWI); Tasseled Cap Wetness (TCW); Tasseled Cap Brightness (TCB); and TCG. NDVI, MNDWI, and LAI are useful for monitoring vegetation changes in agricultural areas (Wiegand et al., 1991; Delegido et al., 2013; El-Asmar et al., 2013). The Tasseled Cap transformations (i.e., TCW, TCB, TCG) assist in differentiating different land-cover types, with TCG being particularly sensitive to soil and crop conditions, making it valuable for agricultural detection (Crist, 1984).

All spectral features were combined with a slope file derived from the Shuttle Radar Topography Mission (SRTM) to create the final dataset. The results in a merged image composed of five geomedian composites—four 3-month composites, and one annual composite— totaling 91 bands. These diverse spectral and temporal inputs, along with the MAD layers and spectral indices, provide a comprehensive foundation for agricultural land use classification.

2.2 Land cover mapping

The first step in creating the agricultural land use map involved collecting training data, which, along with the image data mentioned in the above section, served as input in our machine learning classifier. In remote sensing, training data typically consists of a collection of samples, each representing a small area or pixel in an image and is associated with a known land cover class. This data is essential for guiding the classification process, enabling the classifier to learn patterns and characteristics from the labeled samples and then assign land cover values to areas not included in the training set.

To ensure the quality and representativeness of our training data, collection occurred in two main phases. The first phase encompassed the bulk of the training data collection, where training points corresponding to either an *Agriculture* or *Other* class were collected in a province-by-province basis using Sentinel-2 and PlanetScope (Planet Team, 2017) imagery. In this study, we define *Agriculture* as a piece of land of minimum 0.16 ha that is sowed/planted and harvest-able at least once within the 12 months after the sowing/planting date. This definition, based off the DEA Cropland Classification Guide[2], excludes grasslands, unplanted pastures, and perennial/evergreen crops (e.g., mangoes, cashews, grapes, and citrus trees are all excluded by this definition) as these crop types are difficult for satellite imagery to differentiate from natural vegetation.

We use the 0.16 hectares threshold (about four 20-meter x 20-meter pixels) to ensure our results accurately reflect Mozambique’s agricultural landscape, where smallholder farming is the dominant model. The average farm size is approximately 1.27 hectares, with a substantial portion of farms occupying less than one hectare

[2] https://docs.digitalearthafrica.org/en/latest/data_specs/Cropland_extent_specs.html

(World Bank, 2018). Setting a higher minimum threshold would risk excluding a significant portion of these small-scale farms, which make up a large part of the agricultural landscape. By maintaining the 0.16-hectare threshold, we can better capture the diversity and scale of smallholder plots typical in Mozambique while also reducing classification noise. *Other* refers to any land cover that does not align with the *Agriculture* definition (e.g., forest, water, urban area).

A random forest classifier was applied to the merged image features and the training data to create the final map. The random forest classifier was chosen due to its ability to handle high dimensional and non-normally distributed data, specifically beneficial in image classification where the incorporation of different imagery sources and ancillary data are required (Kloiber et al., 2015). Steep slopes (>40°), water areas, and urban areas were masked from the random forest output using an SRTM derivative, the Water Observations from Space (WOfS) dataset (Mueller et al., 2016), and the 2019 World Settlement Footprint (WSF-2019) dataset (Marconcini et al., 2021), respectively.

In the second phase of training data collection, we used the classifier's preliminary outputs to identify areas with misclassifications and iteratively added more training data to improve accuracy. This process continued until the final map output achieved a visually acceptable level of accuracy.

2.3 Accuracy assessment and area estimation

Land cover maps, particularly those created over large areas, are inherently subject to errors. These inaccuracies often arise due to various factors, such as difficulty distinguishing fuzzy boundaries between different land cover types and gaps in available imagery (Stehman et al., 2009). The "pixel-counting" method for area estimation, which simply estimates area by counting pixels, does not account for these errors, rendering it generally unreliable and unsuitable for accurate analysis (GFOI, 2016). A more reliable approach involves calculating area estimates through an unbiased statistical estimation process based on a sample design. In this method, samples are drawn from different map strata and then compared to reference data that is more accurate than the map.

Given the potential for errors and biases in land cover maps, it is essential to apply a robust sampling strategy to assess map accuracy and estimate area. To this end, we selected a simple random sample of 1,200 pixels at the same 20m resolution as our final agricultural map. The sampling design was chosen for two main reasons: 1) the need for a probability sampling design, and 2) the ability to estimate standard errors without relying on variance approximations. Additionally, simple random sampling was particularly appropriate because the collection of reference data began before the final agricultural land use map was completed. As a result, the more common practice of stratified sampling, which relies on the completed map to define strata, was not feasible (Olofsson et al., 2014). Although simple random sampling can be less effective at accurately estimating very small map classes, this was not a significant concern in our case, as the final agricultural map was dominated by two larger map classes.

The total sample size was determined using the variance estimator solved for n as described in Cochran (1977), with a target margin of error of 10% of the *Agriculture* class. Trained interpreters assigned reference land use labels to each sample unit by examining time-series data of Sentinel-2 and PlanetScope (Planet Team, 2017) spanning 2019-2022, using the AREA2 toolbox (available at github.com/bullocke/area2). Incorporating imagery from previous years as supplemental data helped interpreters better understand the landscape and accurately assign land use labels for the target year, 2022. Without access to the final map, each sample was labeled as either *Agriculture* or *Other*, with a corresponding confidence level categorized into one of three levels. Samples with the lowest confidence values were re-examined at a later stage and either adjusted or removed. A stratified estimator was then applied to the interpreted reference samples to estimate area at 95% confidence intervals (Olofsson et al., 2014).

3. Results

We mapped active agricultural land in Mozambique for 2022 using a Random Forest machine learning classifier combined with five Sentinel-2 geomedian image composites. The mapping process involved three primary stages: 1) generating training data, 2) classifying and mapping agricultural areas, and 3) assessing accuracy and estimating class areas using high-quality reference data. The following section provides a summary of the results from each of these stages.

3.1 Training Data Collection

The nationwide training dataset includes 34,604 samples, each the size of a 20m Sentinel-2 pixel. These samples were visually interpreted and categorized as either *Agriculture* or *Other* for the year 2022 (Figure 3.1). The distribution of training sites is relatively uniform across the country, with slightly lower densities observed in larger provinces or areas dominated by uniform non-agricultural land cover. The variability in the training set reflects the natural variation in land cover across Mozambique. Of the total training sites, approximately 70% are labeled as *Other*, while 30% are classified as *Agriculture*.

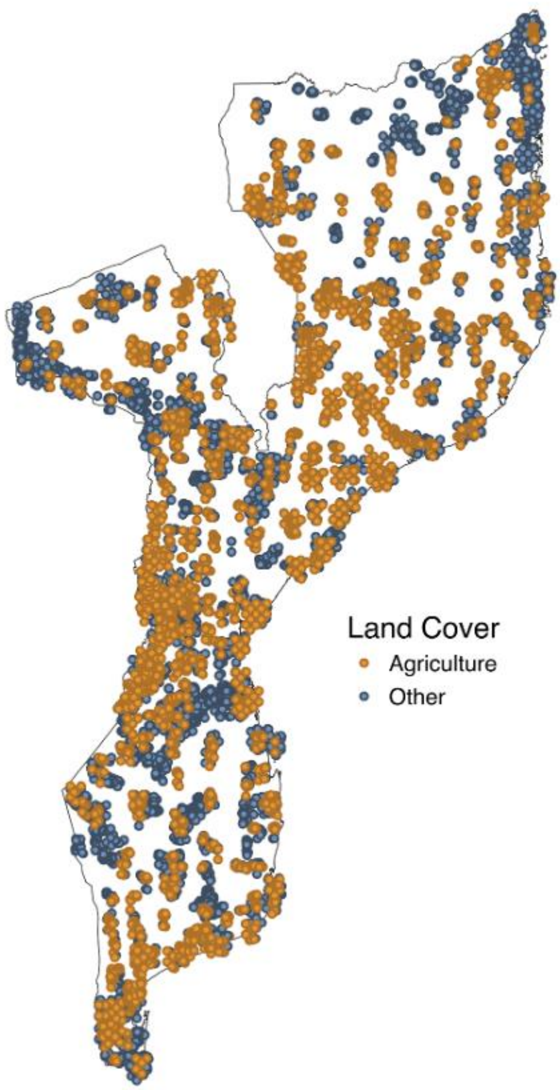


Figure 3.1. Training site dataset created for Mozambique. The training data is classified into two categories: *Agriculture* and *Other* (includes all non-agriculture land covers).

3.2 Mozambique 2022 Active Agriculture Mapping Results

Mapped areas of active *Agriculture* at 20m spatial resolution for 2022 are displayed in Figure 3.2. The distribution of agricultural land use shows significant spatial variability, with field size and density varying across the country. Subsets 3A and 3B highlight regions of densely populated smallholder farms in the provinces of Nampula and Zambezia, while Subset 3C depicts an area with lower field density and slightly larger average field sizes. Notably, most agricultural areas were found close to urban areas, often forming clusters around settlements.

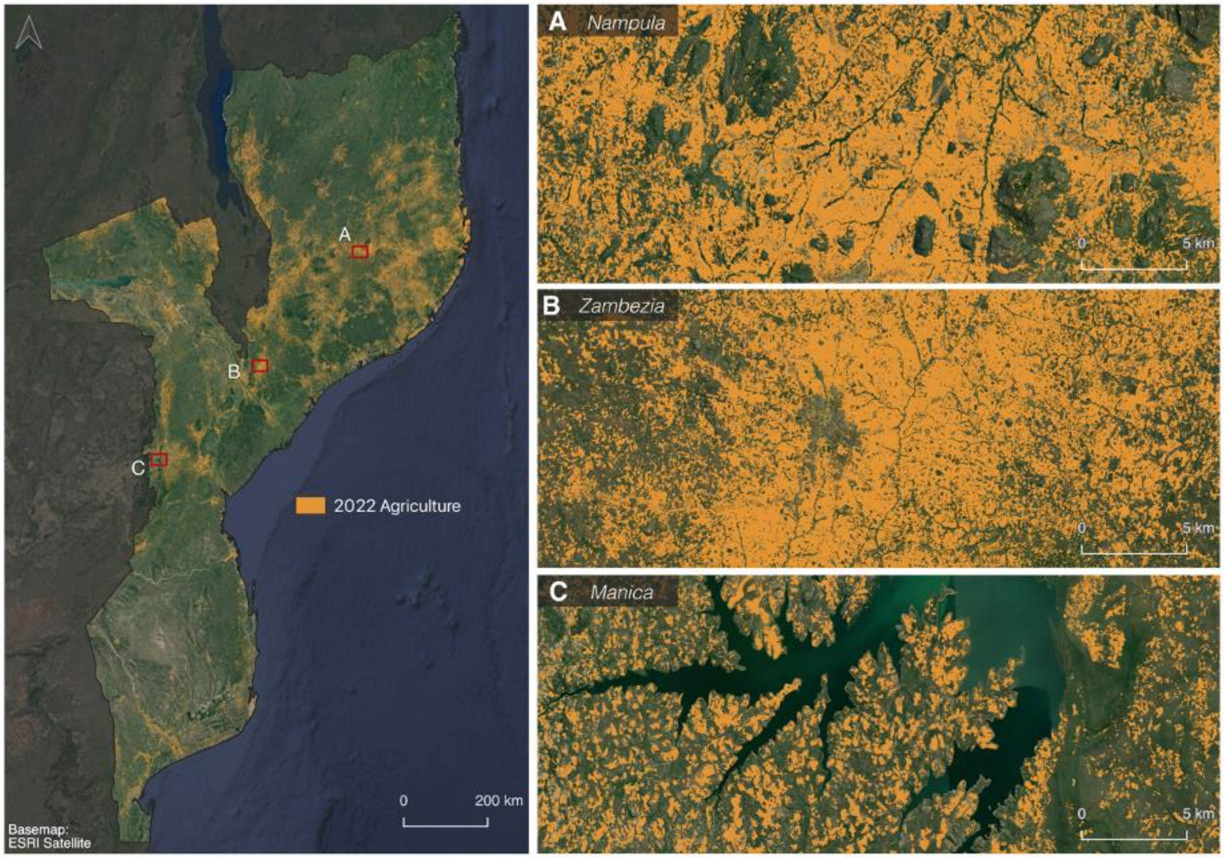


Figure 3.2. Map of 2022 active agriculture in Mozambique. Active agriculture (shown in orange) is defined as a piece of land of minimum 0.16 ha that is sowed/planted and harvest-able at least once within the 12 months after the sowing/planting date. This definition excludes grasslands, unplanted pastures, and perennial/evergreen crops as these crop types are difficult for satellite imagery to differentiate from natural vegetation. Subsets A and B are in the provinces of Nampula and Zambezia, respectively, which boast the highest agricultural land area in the country. Both regions display dense concentrations of small holder agricultural areas. In contrast, subset C is in the province of Manica, characterized by comparatively lower agricultural density.

In 2022, agriculture accounted for 12% of Mozambique's total area, covering 90,680.57 km² ± 8,127.49 km² (Table 1). Of this agricultural land, roughly 60% was concentrated in three provinces: Nampula (25%), Zambezia (20%), and Tete (15%), as shown in Figure 4A. Notably, these provinces also had the highest population concentrations (Figure 4B): Nampula (20%), Zambezia (18%), and Tete (10%), based on 2022 projections from the 2017 national census (IV RGPH, 2017). This suggests a correlation between agricultural activity and population distribution across Mozambique.

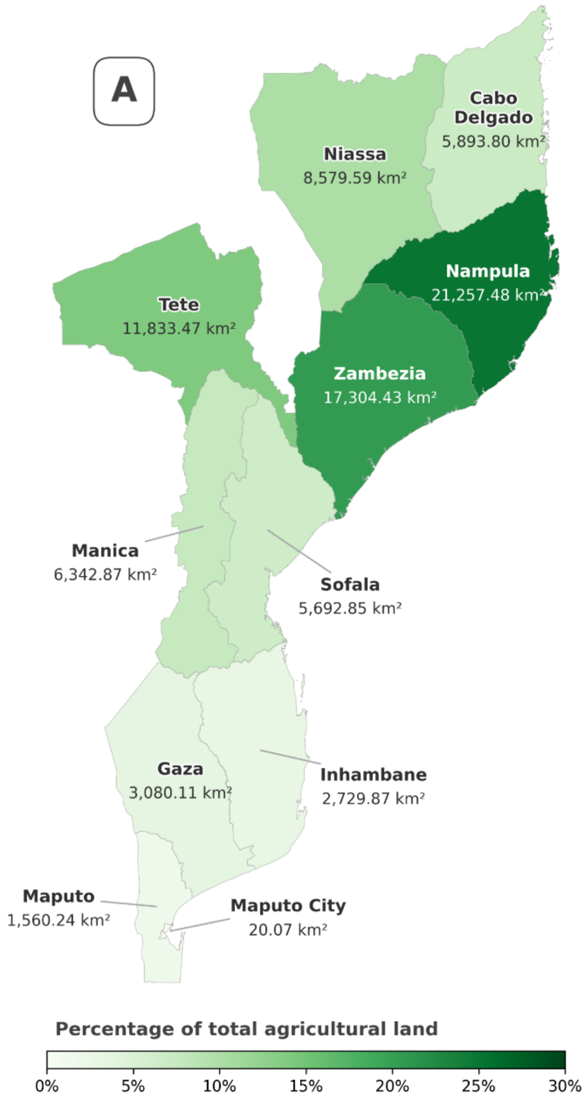


Figure 3.3. Percentage of the total 2022 active agricultural land per province (A) compared to the percentage of total 2022 population per province (B). Provinces Nampula, Zambezia, and Tete exhibit the highest populations and the largest quantities of agricultural land per unit area. The agricultural area is determined using the results from Figure 3, which exclude fallow lands and agroforestry systems. The 2022 population data represents projected data and was obtained from the 2017 US Census (IV RGPH, 2017).

3.3 Accuracy Assessment and Area Estimation

Central to this study is the area estimates with 95% confidence intervals of both map classes. To evaluate the accuracy of the 2022 Active Agriculture land use map (Figure 3.2), we utilized a simple random sample of 1,200 reference observations collected across Mozambique (Figure 3.4). All reference observations underwent quality assurance checks to ensure the accurate labeling of reference data. Results from comparing the reference data with the agriculture map are shown in Table 1.

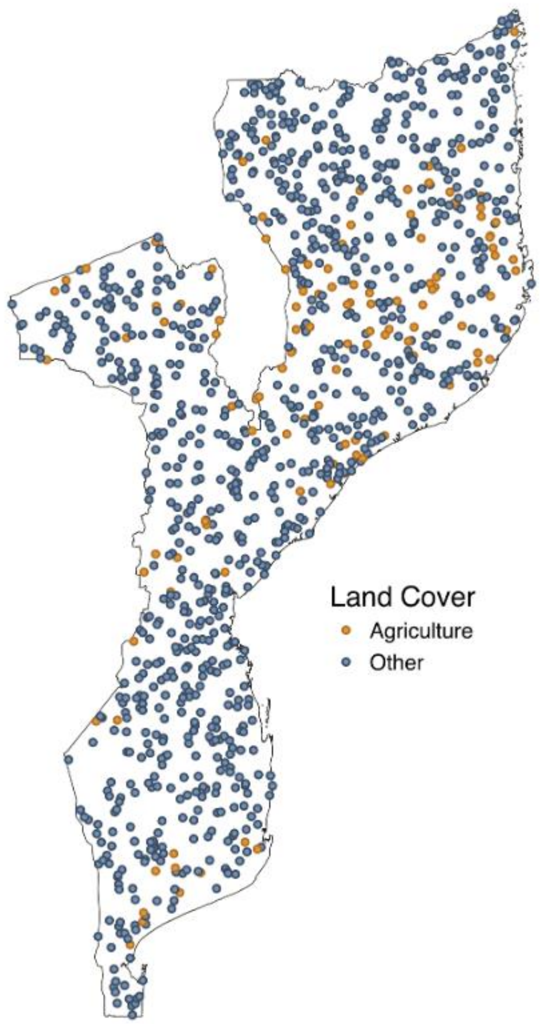


Figure 3.4. Map showing location of reference sites selected by simple random sampling. These sites were used to assess the accuracy of the 2022 active agriculture land use map (Figure 3).

		Reference		
	Class	**Agriculture**	**Other**	**Total**
Map	Agriculture	92	11	103
	Other	22	982	1,004
	Total	114	993	1,107
	User Accuracy	89.32%	97.81%	
	Producer Accuracy	83.02%	98.71%	
	Area Estimate [km^2]	90,680.57	696,309.07	
	Area 95% Confidence Interval [km^2]	8,127.49	8,127.49	
	Margin of Error [%]	8.96%	1.17%	
	Overall Accuracy	96.90%		

Table 1. Accuracy Assessment and Area Estimation Results. This table presents the accuracy error matrix, including user and producer accuracy, along with area estimates, confidence intervals, and margin of error values for the respective land use categories. Data was collected using a simple random sampling strategy and sourced from Sentinel-2 and high-resolution PlanetScope imagery (Planet Team, 2017). The accuracy metrics evaluate the correct classification rates for the *Agriculture* and *Other* map classes, while the area estimates account for map errors and biases. All strata achieved a margin of error below the 10% target, indicating reliable area estimation across the study area.

The overall map accuracy, or the percentage of reference points correctly identified, is 96.09%. The user accuracies (i.e., commission error, or the percentage of area erroneously included in the land cover class being evaluated) are 89.32% and 97.81% for the *Agriculture* and *Other* classes. The producer accuracies (i.e., omission error, or the percentage of area erroneously excluded in the land cover class being evaluated) are 83.02% and 98.71% for the *Agriculture* and *Other* classes. All map classes not only exceed our goal of achieving accuracies above 70%, but they also meet our additional objective of staying below a 10% margin of error. This provides strong evidence for a highly accurate and reliable land cover map, as well as precise area estimates for all classes. However, it's worth noting that the slightly lower values for the *Agriculture* class indicate the challenges involved in accurately mapping cropland in this particular region. Further discussion on this topic can be found in Section 4.2.

4. Discussion

4.1 Agricultural Extent in Mozambique: Validation and Comparison

Our remote sensing-based analysis estimates Mozambique's agricultural land at approximately 9.1 million hectares, providing the first national-level estimate based on rigorous accuracy assessment and area estimation methods. In an era where timely and accurate agricultural data is critical for decision-making, our remote sensing approach offers clear advantages over traditional methods. Field surveys, while valuable for localized insights, are often constrained by their limited geographic scope and infrequent repetition. Remote sensing provides a powerful and efficient alternative, enabling comprehensive data collection across vast areas at consistent intervals. By automating the process and reducing reliance on manual interpretation, remote sensing enables comprehensive data collection over large areas at consistent intervals, automating data processing and reducing reliance on manual interpretation to improve accuracy, reproducibility, and reliability in agricultural assessments.

Despite these remote sensing advantages, there has been limited exploration of mapping agriculture at the national scale for Mozambique, with most applications focusing only on small regions (Mananze et al., 2020; Bofana et al., 2022; Rufin et al., 2022). Consequently, the current understanding of Mozambican agriculture extent heavily relies on global mapping products or field survey estimates. Here, we validate the accuracy of our 2022 Active Agriculture map by comparing it to both global agricultural maps and field survey data, highlighting the strengths of a nuanced, national-level remote sensing approach.

To evaluate the accuracy of our 2022 Active Agriculture map against other agricultural products, Figure 4.1 presents a side-by-side comparison with two global mapping products: the Environmental Systems Research Institute (ESRI)/Impact Observatory (IO) Land Cover product for 2022 (Row 2; Karra et al., 2021), and the European Space Agency (ESA) WorldCover map for 2021 (Row 3; Zanaga et al., 2022). Both global maps were modified to only display their agriculture class. Results show that the ESRI product significantly underestimates agricultural areas across all three examples compared to our 2022 map. In contrast, the ESA product aligns closely with outr map in all locations but consistently underestimates smallholder agriculture, resulting in a lower overall agricultural land estimate. Accurately capturing smallholder farms is crucial for effective land management, and our 2022 Active Agriculture map includes these areas, providing a detailed and reliable national-scale assessment. While global products are useful, their broad mapping strategies are too broad for a comprehensive national-scale assessment, often lacking the nuanced understanding of agriculture patterns that a national-scale approach would offer.

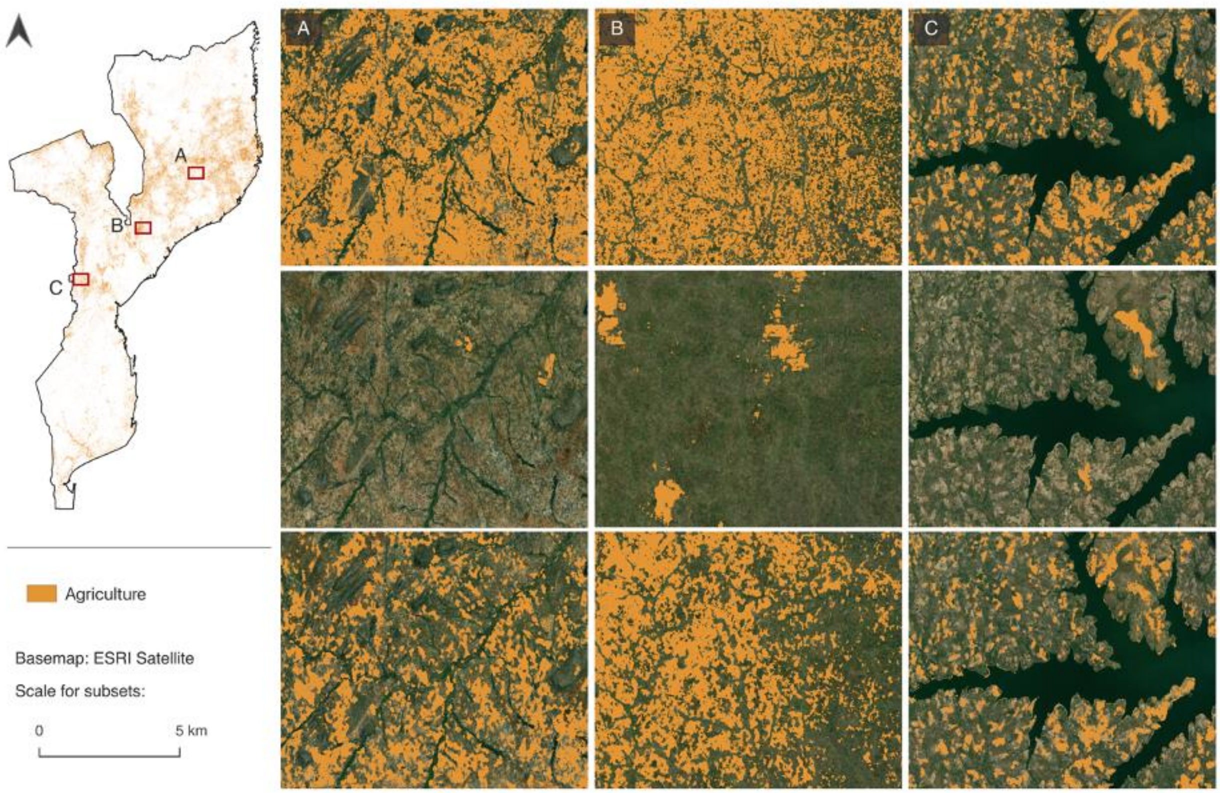


Figure 4.1. Comparison of the 2022 Active Agriculture land use map from this study (1st row), with the Environmental Systems Research Institute (ESRI)/Impact Observatory (IO) Land Cover product for 2022 (Karra et al., 2021) (2nd row), and the European Space Agency (ESA) WorldCover map for 2021 (Zanaga et al., 2022) (3rd row), for locations in Nampula (A), Zambezia (B), and Manica (C).

To further validate and contextualize our findings, we compared them with other national estimates, highlighting methodological differences and limitations. The Mozambique Ministry of Agriculture's 2023 census estimates that small and medium farmers utilize approximately 6.9 million hectares, representing about 8.7% of the country's total area. This estimate is notably lower than our remote sensing-based finding (11.5%), likely due to two main factors: first, the Ministry's definition of agricultural land excludes large farming enterprises; and second, their methodology relies on a sampling approach through field surveys, which, while informative, does not capture the complete agricultural landscape. Field surveys are also resource-intensive, demanding significant time and financial investment. In contrast, our remote sensing approach offers an efficient, comprehensive national assessment, allowing for repeated data collection with minimal reliance on manual input.

Similarly, the Food and Agriculture Organization (FAO) estimates that 5.6 million hectares of land are currently cultivated in Mozambique, representing about 7.1% of the country's total area. The FAO relies on annual questionnaires, which depend heavily on self-reported data. This introduces variability in accuracy and completeness, especially in areas with limited survey reach. Additionally, differing definitions and reporting practices across countries reduce comparability and can obscure the true extent of agricultural land—a gap our remote sensing approach addresses with its nuanced national-level focus.

Both the Ministry's and FAO's estimates share notable limitations. First, neither provides accuracy assessments or error terms, an important metric for understanding potential variations or uncertainties in area estimates. Additionally, both estimates lack spatially explicit information on the exact locations of agricultural land. While the Ministry of Agriculture offers data at the provincial level, this lacks the spatial granularity needed for detailed land management, which our remote sensing approach addresses by producing precise agricultural maps across the national landscape. Nevertheless, as shown in Table 2, all estimates, despite their differences, indicate a relatively low agricultural land usage rate in Mozambique compared to other countries with significant agricultural output, underscoring a potential for growth and increased productivity within the existing land base.

Country	Country area (in 1,000 ha)	Agriculture area (in 1,000 ha)	Share of agri. land use
United States	983,151	427,475	43%
China	960,001	521,395	54%
Brazil	851,577	228,489	27%
Australia	774,122	377,002	49%
India	328,726	178,528	54%
Argentina	278,040	117,679	42%
South Africa	121,909	96,341	79%
France	54,909	28,524	52%

Source: FAO

Definitions: "Country area": Area under national sovereignty. It is the sum of land area, inland waters and coastal waters. It excludes the exclusive economic zone. "Agriculture": Land used for agricultural purposes, including for cultivation of crops and animal husbandry, farm buildings, etc. The total of areas under “Agricultural land” and “Farm buildings and Farmyards”.

Table 2. Estimates of arable land utilization across countries where agriculture is a relevant economic sector.

4.2 Land cover mapping challenges

The study's results demonstrate that agricultural areas for 2022 were successfully mapped with high accuracy. However, given that accuracy and area estimation of agricultural land are the principal goals of this study, it is interesting to examine the errors present in the final land cover map.

A significant challenge in land cover mapping is the presence of sub-pixel mixtures of land cover. This challenge becomes particularly pronounced in regions with sparse or low-stature vegetation, such as grasslands or mixed open forests, which are common in Mozambique. Agriculture omission errors were primarily observed along agricultural transition zones, specifically (1) along borders of fields and (2) within fields with dispersed non-plantation tree cover. The absence of high spatial resolution imagery, such as Google Earth or drone imagery (i.e., both <1m spatial resolution), as a guide in the mapping process makes it challenging to distinguish active agriculture along transition boundaries at the pixel scale. Consequently, the resulting land cover reference labels have systematically lower confidence, leading to the removal of 93 reference points from the final reference dataset.

Moreover, distinguishing between grasslands and agriculture at the pixel scale is also challenging, especially in areas of rain-fed agriculture, as their spectral characteristics are relatively similar throughout the year. Agriculture commission errors were predominantly observed in grassland areas, which is unsurprising given that Mozambique's agricultural sector is ~70% rain-fed (Silva & Matyas, 2014). Including the DEA 3-month rolling geomedian composites in the final classification helped mitigate *Agriculture* commission errors, as the incorporation of more time periods (i.e., seasons) helped capture the subtle differences between the two land covers. However, further exploration and integration of other high-resolution datasets may offer additional opportunities for enhancing precision and understanding the intricacies of agricultural landscapes. Despite the above limitations, we suggest our approach to mapping agricultural land cover in Mozambique is successful, as indicated by the results of our accuracy assessment (Table 1).

4.3 Leveraging Remote Sensing for Agricultural Monitoring and Infrastructure Insights

As global climate change intensifies, agricultural systems—particularly in vulnerable regions like Mozambique—face growing threats. Remote sensing is a powerful tool for monitoring not only agricultural systems but also the broader environmental and infrastructure factors that shape agriculture productivity. Its capacity to deliver large-scale, real-time data makes it especially effective for monitoring environmental changes that directly affect agriculture, such as flooding or prolonged droughts (Bofana et al., 2022; West et al., 2019). By capturing and analyzing this data, remote sensing enhances the precision of land-use assessments and plays a critical role in advancing long-term sustainability and resilience strategies. Integrating remote sensing into climate change monitoring systems, including econometric models, helps improve decision-making and supports adaptive strategies to protect agricultural productivity and food security amid growing climate challenges.

Future remote sensing research should consider adopting dynamic time series models in conjunction with the data generated in this study to better understand Mozambique's spatiotemporal agricultural dynamics. While this study represents a significant achievement by producing the country's first national-scale agricultural extent map, it offers a static snapshot limited to 2022. Time series methods, such as Continuous Change Detection and Classification (CCDC), provide a powerful approach for capturing ongoing land-use changes and environmental shifts (for technical background, see Zhu & Woodcock, 2014; for implementation tools, see Arevalo et al., 2020). These models allow for continuous monitoring of agricultural trends, enabling the detection of patterns such as land abandonment, crop rotation, and climate-related disruptions with greater accuracy. By utilizing the dataset from this study, future time-series change assessments can provide deeper insights into historical trends and future shifts, supporting the development of adaptive strategies to protect agricultural productivity and strengthen climate resilience in Mozambique.

Beyond monitoring agricultural extent, the resulting dataset also provides a valuable foundation for further applications of remote sensing to address infrastructure challenges in Mozambique. For example, proxy indicators derived from satellite data could help identify likely irrigated areas (Xie & Lark, 2021), complementing the agricultural extent analysis. Additionally, advancements in high-resolution imagery, such as PlanetScope data, offer opportunities to assess rural road networks, which are critical for improving market connectivity and agricultural productivity, and are difficult to map using moderate-resolution imagery. By building on this study's findings, future work can leverage remote sensing to deliver broader insights into the link between agriculture and infrastructure, supporting targeted interventions to drive sustainable development.

Part B – Understanding Agricultural Output in Mozambique

5. Agricultural development - a historic perspective

Agriculture is arguably the most fundamental of economic sectors. A continuously expanding population is not only demanding more food but also a series of renewable material sources to provide everything from packaging to construction material. A finite supply of land requires managing resources well and working towards continuous technological improvements that allow increasing output. Humanity has proven to manage the agricultural challenge well so far: from 1800 to 2000 the population has risen about six to seven-fold, from less than one billion to over six billion. At the same time, agricultural production has expanded much faster, with at least a tenfold output increase. On average, people are fed much better today and famines have become rare events, while they have haunted humanity in the pre-industrial times. Even more remarkable has been the developments around the labor force employed in agriculture. In traditional agrarian societies, agriculture employed over 75 percent of the total labor force, and in the 1950s about two-thirds around the world. Today, in the advanced economies the share of the workforce employed in agriculture is less than 2.5 percent (Federico 2005).

5.1. The sources of agricultural development

The developments in agricultural output have been shaped by a combination of technological, economic, social and environmental drivers. These drivers have collectively transformed agricultural practices, increased productivity, and influenced the global food system. Below are some of the key drivers, including those with a negative impact, of agricultural development during this period:

Technological and chemical innovations

Mechanization[3]. Mechanization in agriculture refers to the use of various machines and equipment to automate and improve the efficiency of agricultural processes. This transformation has significantly changed the way farming operations are carried out, leading to numerous benefits including increased productivity, reduced labor requirements, and enhanced crop management. First, the world has seen extensive improvements in plowing and tilling (faster and more efficient soil preparations), planting (increased precision and speed), and irrigation (automated system, including sprinkler and drip technology, allow optimizing water usage and crop health). Second, the harvesting efficiency has undergone tremendous change. Combined harvesters are able to perform multiple tasks such as reaping, threshing, and winnowing in a single operation, and specialized harvesters have been engineered to streamline specific crops (e.g. potato diggers, cotton pickers). Third, the capacity to monitor and manage crops has also experienced momentous change. Drones and satellites enable remote monitoring of crop health, soil conditions, and environmental factors, enabling optimal decision making. At the same time precision agriculture using GPS and GIS technologies improve field-level management in terms of crop farming – precision application of water, fertilizers and pesticides, improving efficiency of resource use and minimizing environmental impact. Fourth, sorting and grading machines have been developed, which allow adequate separation and improving marketability, and reducing post-harvest loss. While storage and preservation has been improved through mechanized facilities that control atmosphere exposure and extend shelf life of agricultural

[3] Agricultural Mechanization - an overview | ScienceDirect Topics

products. Fifth, better transportation and logistics have allowed automated conveyance systems to facilitate movement of produce from field to storage and market, thereby reducing manual labor and handling costs. Sixth, enormous improvements in energy efficiency, also through renewable energy powered machinery, support general efficiency. See also Emami et al (2018), and Daum (2023)

Chemical inputs and biotechnology. Along mechanical innovations, the integration of continuously improved chemical inputs into agriculture have been a key factor in increasing productivity, plant health, nutritional quality of food, and controlling pests and diseases. The invention of synthetic fertilizers in the early 20th century, particularly the Haber-Bosch process for synthesizing ammonia, revolutionized agriculture by significantly increasing the availability of nitrogen, a critical nutrient for plant growth. This led to substantial increases in crop yields and agricultural productivity (Smil 2001). In the more recent decades, the main improvements in chemical inputs have been: first, Enhanced Efficiency Fertilizers[4], which reduce nutrient loss to the environment and improve nutrient use efficiency by crops. Second, the holistic Integrated Pest Management approach combines biological, cultural, physical, and chemical tools to minimize the impact of pests on crop production while reducing the reliance on chemical pesticides. Third, biological and botanical pesticides, derived from natural sources such as plants, bacteria, and fungi, offer an alternative, more environmentally friendly and target specific, to synthetic and chemical pesticides. Fourth, nanotechnology[5] has been applied to develop nano-formulation of fertilizers and pesticides, which are more efficient[6], require lower doses, reduce environmental risks, and can be designed to release their active ingredients in response to specific environmental triggers or plant demands. Fifth, soil improvement products enhance soil structure, water retention, and microbiome health, contributing to healthier and more resilient crops. Sixth, water-soluble fertilizers[7] have facilitated the integration of fertilization with irrigation systems, allowing a more uniform distribution and efficient use of nutrients by crops. Seventh, genetically modified crops have allowed to foster insect resistance, reducing the need for the usage of chemicals, and herbicide tolerance, permitting efficiency increases (Qaim, 2009).

Economic and Policy Factors

Agricultural policies. Governments across the globe implement agricultural policies with the aim of achieving various economic, social, and environmental goals, which in turn have profound effects on agricultural practices, market dynamics, and food security. These policies include subsidies and support programs that provide financial assistance to farmers for inputs like fertilizers and seeds, or through direct payments, potentially making farming more economically viable but also possibly distorting market prices and trade (Orden et al., 1999). Preferential tariffs and trade agreements are used to boost international trade and allow a wider market for domestic farmers, increasing their real incomes (Anderson et al., 2006). But tariff barriers are also employed to shield domestic agriculture from international competition, yet they can provoke trade disputes and impact global food prices (Anderson and Martin, 2006). Environmental regulations aim to protect the ecosystem, influencing agricultural methods towards sustainability, albeit sometimes increasing operational costs for farmers. Lastly, land use policies affect the availability and cost of agricultural land and the adoption of sustainable practices, shaping the agricultural landscape and its future direction.

Focus on Research and Development. Over the past few decades, Research and Development (R&D) in agriculture has been instrumental in enhancing productivity, sustainability, and resilience to challenges such as climate change. Innovations including high-yield crop varieties, precision agriculture technologies, and biofortified foods have significantly contributed to food security and nutritional improvement (Pingali, 2012). Efforts in developing climate-resilient crops and sustainable agricultural practices are pivotal in adapting to environmental

[4] https://www.fertilizer.org
[5] https://www.nature.com/nnano/
[6] https://nifa.usda.gov/precision-agriculture
[7] https://pubs.acs.org/journal/jafcau

changes (Lobell et al., 2011). Moreover, R&D has facilitated value addition and economic development within the agricultural sector (Fuglie et al., 2011). The progress achieved has been underpinned by both public and private investment, highlighting the need for continued support and equitable access to innovations. Addressing future challenges will require a sustained focus on R&D to ensure global food security for a growing population, while navigating ethical and social implications of new technologies (Godfray et al., 2010; Qaim, 2009).

Social and demographic changes

Population growth and urbanization. The speed at which the global population has grown over the past centuries is notable – while in 1800 there were about one billion people sharing the planet, today there are more than 8 billion among us. This has translated into a related increase in demand for food and other agricultural resources, such as renewable silvicultural systems. As a response, the land use for agriculture increased as did the need to increase land productivity. While the population increased, there was also a migration from the rural to the urban centers, in search for higher salaries and better working conditions (Stark, 1991). This has had a dual socioeconomic impact, on the one hand less labor was available on the countryside and at the same time an increased demand for a greater variety of products and processed foods with longer shelf life. Both factors contributed to the rapid search for productivity improvements.

Market access, energy and input costs

Transportation networks and energy infrastructure. The improvement of transportation networks supports agricultural output from a series of angles. It allows farmers to reach markets beyond their local community and thereby expand scale and types of crops, as the consumer market becomes larger and more diverse. The expansion of railroads in the 19th century and then highways and roads in the 20th century revolutionized the capacity for farmers in more remote places to offer their products and be integrated into broader value chains (Wolmar, 2012). All of which leading to increased competition, a more rapid diffusion of know-how, and cheaper input factors. Furthermore, the electrification of rural areas allowed farmers to make use of more advanced technology and machinery, as described above, facilitating processing and packaging and thereby easing storage and distribution.

In tandem, Globalization has significantly impacted agriculture by fostering interconnectedness and interdependence among the world's markets and businesses. It has enabled market expansion, allowing farmers to access and sell their products in broader international markets, potentially increasing their income by meeting global standards. Countries have specialized in producing agricultural goods for which they have a comparative advantage, enhancing global production efficiency. However, this integration into global markets has also introduced price volatility, influenced by changes in global supply and demand, exchange rate fluctuations, and international trade policies. Additionally, globalization has facilitated the transfer of agricultural technologies across borders, aiding productivity improvements in developing countries, and contributing to the overall modernization of agricultural practices. See also Anderson (2000), Pingali (2007), McMichael (2005), Reardon and Timmer (2007), and Swinnen and Maertens (2007).

5.2. Green Revolution – the fast catching up of some countries

The Green Revolution marked a pivotal moment, profoundly influencing global hunger and agricultural advancement. Its impact on the growth paths of many countries, especially in Asia, was considerable. Nations that faced acute food shortages in the 1950s through 70s have transformed into middle-income emerging economies, with some rapidly progressing towards high-income status, and the rapid improvement in agricultural productivity has certainly played a role. Imagining the state of the developing world without the Green Revolution is difficult. Despite its achievements, the specter of food insecurity still looms large over the global community, and high levels of malnutrition are prevalent in many regions, including in Mozambique. A considerable portion of the rural population in developing regions, notably in Sub-Saharan Africa and South Asia, remains reliant on low productivity agriculture and lives in poverty. There is a continuous push for investments from donors and national governments to replicate the successes of the Green Revolution (Pingali, 2023).

Case studies

Mexico. The Green Revolution in Mexico, initiated in the mid-20th century, represents a pivotal moment in agricultural history, marking the transition towards modern agricultural practices that significantly enhanced food production capabilities. Spearheaded by Norman Borlaug, an American agronomist working under the auspices of the Rockefeller Foundation, this transformative period saw the development and implementation of high-yielding, disease-resistant wheat varieties. Borlaug's groundbreaking work in wheat breeding led to the production of semi-dwarf varieties that were more productive than traditional strains, resistant to common diseases, and responsive to chemical fertilizers. The adoption of these varieties, alongside advances in irrigation techniques and the use of chemical fertilizers, enabled Mexico to achieve remarkable increases in wheat production. By the early 1960s, Mexico had not only attained self-sufficiency in wheat but also became an exporter, showcasing the potential of scientific innovation to address food security challenges – see also Perkins (1997), Shubinski (2022).

The success of the Green Revolution in Mexico served as a blueprint for other countries grappling with similar issues of food scarcity and agricultural productivity. It underscored the role of scientific research in agriculture and demonstrated the global applicability of the innovations developed in Mexico. However, while the Green Revolution brought about significant yields and reduced hunger, it also introduced environmental and sustainability concerns, such as the overuse of chemical inputs and water resources, along with a reduction in agricultural biodiversity. These challenges have prompted ongoing discussions about sustainable agriculture that seeks to balance high productivity with environmental preservation. The legacy of Mexico's agricultural transformation is thus a complex one, highlighting both the achievements and the unintended consequences of rapid technological adoption in agriculture (Pingali, 2012).

India. The Green Revolution in India started in the second half of the 1960s and allowed the country to quickly achieve self-sufficiency in food supply within a decade. But in this first phase of rapid output increase, the success was confined to a concentrated selection of wheat crops and to the northern regions of India, which limited the immediate overall socioeconomic impact. A fortunate discovery revealed that the high-yielding varieties (HYVs) of wheat, specifically the Mexican semi-dwarf varieties developed in Mexico, were well-suited to the climatic conditions of northern India, particularly in regions like Punjab. But then, the second wave of rapid agriculture development, involved almost all crops including rice, it covered the majority of the country, and it allowed raising agricultural income and alleviating poverty substantially.

A pivotal element in the widespread adoption of these new agricultural technologies, coinciding with the global diffusion of new seed-fertilizer technologies, was the proliferation of private tube-wells, which facilitated the use of groundwater for irrigation. This technological synergy, especially beneficial for wheat cultivation, led to a rapid dissemination of new seed-fertilizer methods across northern India. Within roughly a decade, these advancements propelled India towards achieving food self-sufficiency, barring periods of drought (Fujita, 2010).

Brazil. Over the past five decades, Brazil has undergone a remarkable transformation in its agricultural sector, evolving from a net importer of food to one of the world's leading agricultural producers and exporters. This dramatic shift was fueled by several factors, including significant advancements in agricultural technology, strategic policy reforms, and substantial investments in infrastructure. The establishment of the Brazilian Agricultural Research Corporation (EMBRAPA) in 1973 was a turning point, leading to the development of crop varieties adapted to Brazil's varied climates, particularly enabling the cultivation of the *cerrado*, a once underutilized savanna region. The widespread adoption of no-till farming, genetically modified organisms (GMOs), and precision agriculture techniques further enhanced productivity. Government initiatives providing subsidies, credit, and tax incentives, alongside efforts to stabilize the economy and improve land tenure security, created a conducive environment for agricultural growth – see also Calil and Ribeira (2019), Correa and Schmidt (2014), Gasques (2017)

Brazil's agricultural boom has not only bolstered the country's economy but also positioned it as a dominant player on the global food market, exporting commodities like soybeans, beef, sugar, coffee, and orange juice. The expansion into the *cerrado* and the adoption of export-oriented strategies have been central to this success. However, this rapid development has come with its share of challenges, including environmental concerns like deforestation in the Amazon and *cerrado* regions, as well as social issues related to land rights and the displacement of indigenous communities. While Brazil's agricultural revolution has been a model of growth and innovation, addressing these environmental and social challenges remains crucial for ensuring the sustainability and equity of its agricultural sector in the future (VanWey et al., 2013).

5.3. Linkage between agricultural progress, broader economic development and poverty alleviation

When reviewing the literature on agriculture and development, a strong linkage between agricultural progress and broader economic development can be posited. Particularly agricultures' pivotal role in low-income countries where a significant portion of the population relies on farming has been underscored. Agricultural development can be seen not only as a means of increasing food production and achieving self-sufficiency but also as a catalyst for economic growth and poverty alleviation. This narrative underscores that advancements in agriculture, such as those seen during the Green Revolution, have led to substantial increases in agricultural productivity. These increases, in turn, have contributed to higher rural incomes, improved food security, and reduced poverty levels. Agriculture's contribution extends beyond the rural economy, as it provides affordable food supplies to urban areas and generates demand for non-agricultural goods and services, thereby fueling overall economic growth.

Furthermore, the dynamics of agricultural growth and its implications for poverty alleviation are very important. The adoption of high-yielding varieties and improved farming practices not only enhances food production but also creates employment opportunities in rural areas where the majority of the poor reside. This, coupled with income diversification opportunities through the rural non-farm sector, facilitates a reduction in poverty by providing alternative sources of income and employment. Furthermore, agricultural development leads to structural transformation by releasing labor from agriculture to other sectors of the economy, thus contributing to a broader economic development and transition towards a more diversified economic base. This structural transformation is critical for sustained economic growth and reduction in poverty over the long term.

The literature establishes a clear linkage between agricultural progress, broader economic development, and poverty alleviation, advocating for integrated policies that target both the agricultural and rural non-farm sectors. Such policies are essential to harness the full potential of agricultural development in driving economic growth and reducing poverty – see also World Bank (2022), and Dethier and Effenberger (2012) for a literature review. Figure 5.1 below shows the larger impact growth has on poverty in the agricultural compared to other sectors. Furthermore, that poverty-growth elasticity is larger for Mozambique than in other countries in the region (Figure 5.2).

Figure 5.1. Agriculture has the Greatest Poverty Mitigation Potential
(Poverty-growth elasticities across sectors in Mozambique)

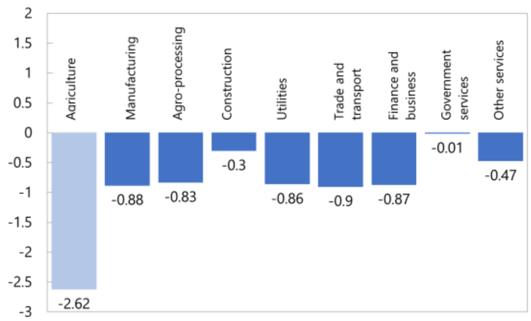
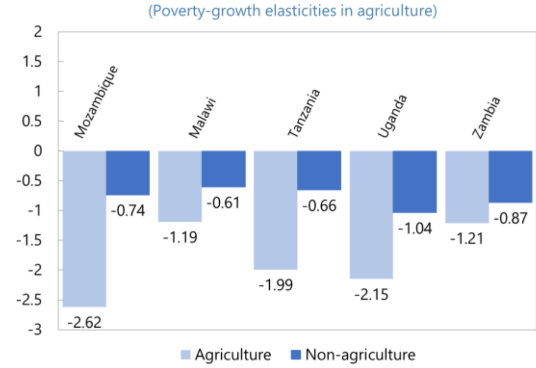


Figure 5.2. Mozambique's Agriculture has Higher Growth Mitigation Potential than Wider Region
(Poverty-growth elasticities in agriculture)



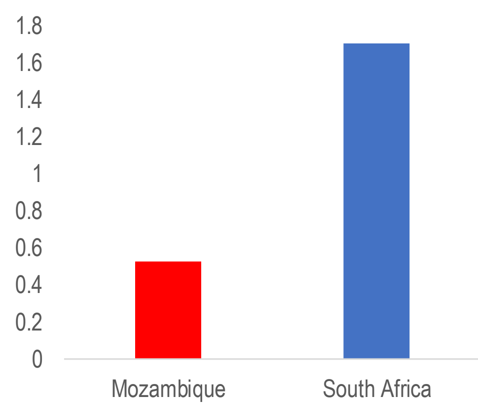
Source: Dorosh and Thurlow (2018)

5.4. Lessons for Mozambique and the macro criticality of agriculture

It is commonly accepted that the Green Revolution was propelled by a combination of factors aimed at addressing food insecurity and spurring agricultural development. Key among these were the introduction of high-yielding varieties (HYVs) of staple crops like wheat and rice, which significantly increased food production. This was complemented by the expansion of irrigation infrastructure, ensuring that crops received adequate water. The widespread use of chemical fertilizers and pesticides further boosted crop yields by providing essential nutrients and protecting against pests and diseases. Furthermore, supportive government policies played a crucial role, offering subsidies for agricultural inputs and investing in agricultural research and development. This combination of factors, including the mechanization of farming practices and the development of agricultural markets, collectively contributed to the dramatic increase in agricultural productivity, marking the era of the Green Revolution.

For Mozambique, there is an enormous opportunity to reap the benefits of an expansion of the underutilized agricultural area, while also working towards improving on the low levels of productivity seen. Over the past few decades not much has changed in terms of the country's dependence on importing foodstuffs from abroad to cover the population's consumption needs. Mozambique has imported about double the amount of food in terms of value, compared to what it has exported. This stands in stark contrast to its neighbor, South Africa, which has exported about 70 percent more than it paid for the import of food products (Figure 5.3).

Figure 5.3: Ratio of Agricultural Exports over Imports, average 2018-22



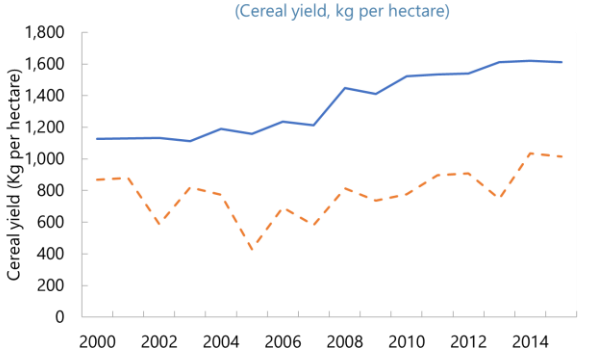
Source: Harvard, https://atlas.cid.harvard.edu/

Currently, agriculture is the main source of income for more than 70 percent of the population, while it provides employment for about 80 percent of the workforce[8] and contributes to over a quarter of the country's GDP. The World Bank's *Mozambique Rural Income Diagnostic* from 2020 also delineates clearly how connected and dependent the rural

[8] IFAD 2024: https://www.ifad.org/en/web/operations/w/country/mozambique#:~:text=Agriculture%20is%20the%20main%20source,generating%20income%20for%20their%20families.

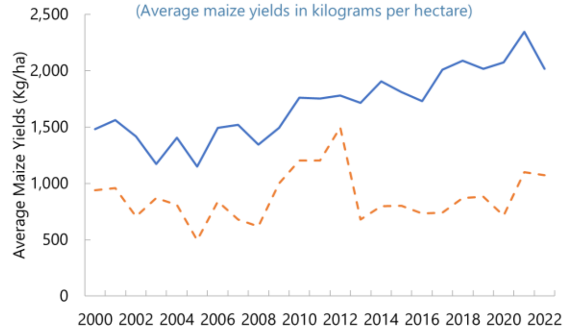
population is to their small plots of land. Non-farming labor opportunities are basically not available for the majority of those and therefore the best channels to target poverty runs through productivity improvements in agriculture. As can be seen in Figure 5.4 and 5.5 the gap in yields for cereals in general, or a staple crop as maize is very large between the output per hectare in Mozambique compared to its neighbors.

Figure 5.4. Mozambique's Productivity Lower than SSA
(Cereal yield, kg per hectare)



Source: WB WDI, FAO
Notes: Cereal yield, measured as kilograms per hectare of harvested land, includes wheat, rice, maize, barley, oats, rye, millet, sorghum, buckwheat, and mixed grains. Production data on cereals relate to crops harvested for dry grain only. Cereal crops harvested for hay or harvested green for food, feed, or silage and those used for grazing are excluded.

Figure 5.5. Mozambique's Productivity Lower than Neighbors
(Average maize yields in kilograms per hectare)



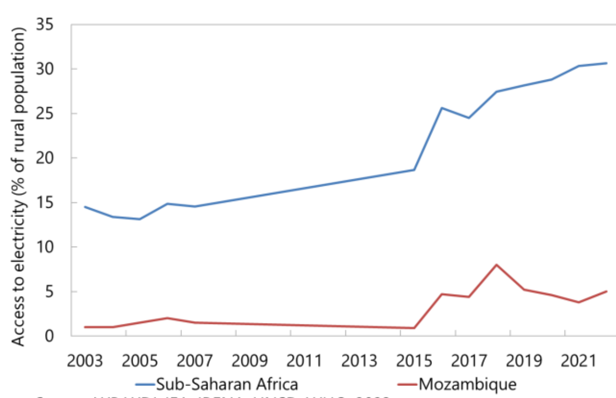
Source: FAOSTAT data

Impediments to Mozambique's agricultural development

While there is debate among experts on the importance of individual factors and their weight in explaining what is hindering Mozambique's agricultural development, there is a broad consensus that the below items play an important role (World Bank 2020, 2022):

- Key Infrastructure Gaps: Investment gaps in various types of infrastructure, including rural roads, electricity (figure 5.6), irrigation, and ICT, negatively impact farm gate prices, input prices, and market access.
- Underdeveloped Input Markets: Limited supply, weak demand, high prices, and low quality of inputs hinder smallholders' utilization of improved inputs and weakens commercialization incentives.
- Poor Organization and Functioning of Output Markets and Value Addition: Weak commercialization, high marketing and transaction costs, low farm gate prices, and limited incentives for productive investments hinder smallholders' access to markets.
- Lack of Access to Finance: Limited access to credit, lack of agricultural insurance markets, and exposure to weather risks hinder smallholders' ability to invest in productive activities.

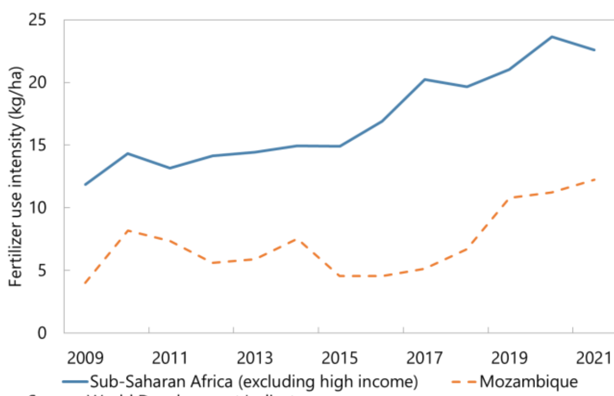
Figure 5.6. Mozambique Limited Access to Electricity



Source: WB WDI, IEA, IRENA, UNSD, WHO. 2023.

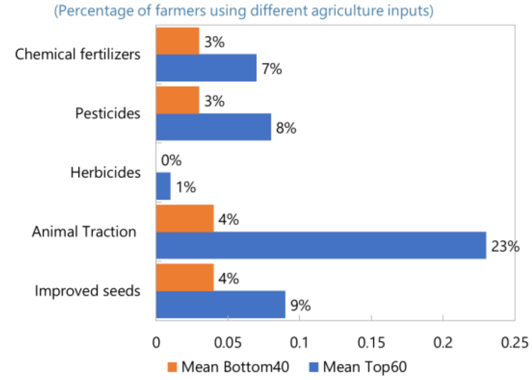
Without going into too much detail, it is still worth to look at some of the stylized facts around the listed impediments to growth. As a sign of both "underdeveloped input markets" is the large gap in fertilizer usage between Mozambique and its regional peers (Figure 5.7). While Figure 5.8 shows that there might be a link between lack of access to funding/financing and the usage of relevant inputs – we see that as the farmer's wealth increases, there is a larger propensity to utilize all necessary inputs and tools to achieve higher agricultural productivity.

Figure 5.7. Mozambique Contained Fertilizer Usage



Source: World Development Indicators

Figure 5.8. Input utilization Constrained by Wealth
(Percentage of farmers using different agriculture inputs)



Source: World Bank (2020)

The listed impediments to agricultural development have been spelled out particularly having the smallholder ownership structure in mind, which is the widely dominant form of cultivating farmland in Mozambique. However, while there are a few commercial agricultural and silvicultural enterprises engaged in the country, the big question raised often relates to the reasons behind the limited presence of large-scale agribusiness ventures. Many of the impediments to small scale farmers also apply to larger ventures, including gaps in public infrastructure, underdeveloped input markets, among others. But important impediments go beyond the rural sector. A recent Growth Diagnostic study conducted by the London School of Economics in Mozambique[9] point out three main bottlenecks: (i) infrastructure, (ii) red tape and governance problems, and (iii) lack of accountability and coordination between government agencies.

6. Conclusion

Over the past few decades, Mozambique has not seen fast agricultural development. On the one side, based on conducted household surveys, the usage of land by smallholder farmers has not increased substantially, and this study shows that the agricultural land coverage is contained to a minimal fraction of the overall available land. On the other side, productivity of Mozambican farmers is, on average, very low compared to the wider region and it has not improved markedly over the recent past.

Over 70 percent of the workforce depends on agriculture to sustain lives and livelihoods. The outside options in the labor market are broadly non-accessible to the rural population due to a lack of education and a labor market in the urban centers that does not have enough demand for rural, low-skilled workers.

Finally, the impact on poverty of growth in the agricultural sector is higher than in any other sector of the economy. Hence, improving agricultural output should be a front-and-center policy objective of any Mozambican government. There are many impediments to the sector and the government should try and address all of them, but an early prioritization and impact assessment is recommendable.

[9] https://www.mef.gov.mz/index.php/publicacoes/relatorios/2161-growth-diagnostics-mozambique-final-report-eng/file

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