High Frequency Monitoring: The Use of Drone Imagery to Generate Training Data for Crop Modeling in the Konni Irrigation Perimeter

2019–2025 Final Report

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Contents

Figures

Number **Page**

Tables

Number **Page**

List of Acronyms

MCA	Millennium Challenge Account
MCC	Millennium Challenge Corporation
NASA	National Aeronautics and Space Agency
RTI	RTI International
UAV	Unmanned Aerial Vehicle
SARL	Société à Responsabilité Limitée
GIS	Geographic information system
ICRISAT	International Crops Research Institute for the Semi-Arid Topics
IPDA	Irrigation Perimeter Development Activity
M&E	Monitoring and evaluation
NDVI	Normalized Difference Vegetation Index
SMS	Short message service
DAS	Drone Africa Service

Executive Summary

Executive Summary

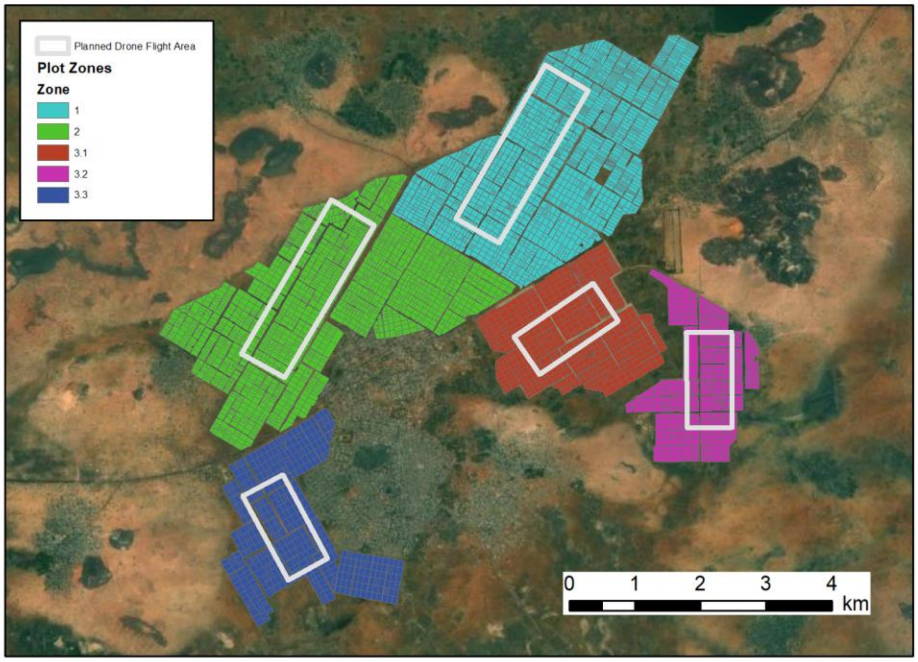
RTI International built upon its crop modeling work in Rwanda (Chew et al., 2020; Hegarty-Craver et al., 2020) to apply the use of drones (also known as unmanned aerial vehicles or UAVs) to generate crop type labels in the Konni region of Niger and use them to develop machine learning models that predict crop types. Drone data offer the ability to see and label crops at high resolution (~2 cm) at multiple intervals during a given growing season, providing a potential alternative to in-person field data collection. RTI captured and used the drone data for the area of investigation to create large crop label datasets containing multiple crop examples at specific locations and times. These labeled data in turn provided the training data for satellite-based crop type models that can be applied over large areas. These models can be run multiple times during a compact as part of a project's monitoring and evaluation strategy so that a shift in crop types and extents can be detected more quickly than with traditional survey-based methods, allowing for program intervention and recalibration if needed.

Goals

Our main goal was to obtain drone imagery, for both the dry and rainy seasons, starting in the 2021 dry season and ending in the 2023 dry season. With the help of expert agronomists, we aimed to classify fields by crop type and provide those data for training satellite-based crop type prediction models, all to support the determination of whether the provisioning of water to the Konni Irrigation Perimeter resulted in a shift toward higher-value crops.

Methods

The Konni area is not very large and is contained within a single satellite image (scene). To use satellite imagery to predict the type of crop over a larger area, we chose a subset of the Konni Irrigation Perimeter area over which to fly our drones. The fields serviced by the irrigation perimeter are divided into five zones. We chose a smaller area inside of each of the zones to ensure we captured crops that were prevalent in the Konni area as a whole.



We contracted with Drone Africa Service

(Niamey, Niger) who operate several fixed wing and quadcopter-style drones equipped with high-resolution cameras. These drones fly at a low altitude and capture high-resolution vertical and oblique (taken at an angle) visible-spectrum images. Drone missions were timed to capture crops at two growth stages: early- to mid-season, and mid- to late-season. The two sets of imagery allowed analysts to see the crops at different points in the growing season, which helped differentiate similar crops, as well as capture at least one image of planted crops for each field sampled in case crops were either planted late or harvested early. Traditional vertical images were acquired and used, but the additional oblique imagery that was captured proved to be an invaluable complementary source of information that helped improve crop identification. The oblique imagery did not cover the entire study area as the vertical imagery did, but it was taken at a lower altitude as well as at an angle. This allowed analysts to see the crops in greater detail and gave us greater confidence in our crop labels. This project demonstrated that integrating oblique drone imagery into the work flow is essential and should be adopted as best practices.

Imagery was processed by RTI into mosaics and then published as image services to RTI's external Esri Portal. Portal is a core component of Esri's ArcGIS Enterprise software and allows web-based viewing and annotation of GIS layers. The image services were displayed in a web map, along with field, zone, and satellite boundaries. Analysts were then asked to delineate fields by crop types. In general, most fields within a farmer's plot were monocrops, but we did capture and use examples where intercropping was present.

The purpose of delineating known locations of crops is to train a satellite model with those data to predict the locations of those same crops across a larger area. RTI created a point layer derived from the centroids of satellite cells and intersected them with the field boundaries, transferring the crop type to each point, and thus labeling each satellite cell with the crop type found on the ground. The percentage of the cell covered by the primary crop type was recorded, so that cells below a certain percent (e.g., 80%) could be removed from the training dataset during modeling if desired (i.e., to train the model on more uniform cells).

Crop labels derived from the drone imagery are the key component to satellite-based machine learning models for crop type prediction. These models use multiple satellite spectral bands, combinations of bands, and ancillary computed spatial data (such as distance to a well) to form a relationship between the input values and the crop type. The training data were divided into two parts: 80% of the data were used to train the model, and 20% were used to evaluate the model's predicted crop type against a location where the crop type is known.

Results

Our modeling results were excellent. In all cases we achieved an accuracy of greater than 90%, meaning that the crop predictions over the entire study area are very reliable and can be used to determine crop type changes.

As far as changes in crop types and extents, we noted multiple changes. There was a large decrease in cereal crops between the 2023 and 2024 rainy seasons with land shifting into non-cereal crops and fallow. Cereal crops accounted for 97.90% of the study area during the 2023 rainy season, but only 73.64% of the study area during the 2024 rainy season. Non-cereal crops increased from 0.31% to 10.33% of the study area between these seasons, while the fallow area increased from about 1.77% to 16.01% of the study area. There were also large shifts in land allocation between the 2024 and 2025 dry seasons. In the 2024 dry season, there did not appear to be irrigation water flowing based on drone imagery and approximately 99.60% of the study area was fallow with about 0.02% planted in cereal crops and the other 0.38% in non-cereal crops. In the 2025 dry season, when irrigation water was available, the fallow area fell to 50.82% of the study area while 35.32% of the study area was planted in cereal crops and the other 13.85% was allocated to non-cereal crops. The large increase in non-cereal area in the rainy season is in line with the expectation that farmers with greater access to water will shift their production to higher-value cash crops. The positive dry season result strongly suggests that farmers with greater access to water will grow cereal or non-cereal crops, rather than leave their fields fallow.

Lessons Learned

During our work, we noted several findings that will improve our methodology moving forward. In terms of drone imagery acquisition, we found that having two passes at different periods is sufficient to capture enough identifiable crop examples for training data. We also found that higher-resolution (~2 cm) drone imagery, although more expensive and larger in file size, is noticeably better than the 3 cm imagery we initially specified, and therefore allows crops to be identified with greater confidence. In addition, combining low-altitude oblique drone imagery with vertical drone imagery yielded more reliable crop labels. Lastly, hiring a trained agronomist with local cropping systems knowledge to guide our work and provide quality control was essential.

Although we did not get a chance to do so, we strongly recommend that seasonal crop prediction models trained on *multiple* years of input data be created and evaluated for accuracy. This has the potential to produce significant savings of both time and money once stable models that can be effectively transferred across growing seasons and areas are developed.

Section 1: Background

1. Background

The main goal of this study was to perform high frequency monitoring of crops in the Konni Irrigation Perimeter area to augment traditional monitoring and evaluation (M&E). This high frequency monitoring was not meant to replace traditional M&E, but rather improve aspects such as time-to-insight. The following defines how we think about traditional M&E and enumerates its various facets.

1.1 Monitoring and Evaluation

The disciplines and practices once known simply as "monitoring and evaluation" have undergone multiple rounds of rebranding over the last decade.[1] Regardless of the specific label being applied, the core aim remains the same: to rigorously understand the relationship between a program's implementation and its outcomes. Given that understanding, program designers and implementers can tweak their approaches to meet any of several goals. The sections below describe the central tenets of traditional M&E.

1.1.1 Triangulation

Traditional M&E makes heavy use of human-centered methods like surveys, questionnaires, and interviews. Whether administered by field enumerators or conducted via short message service (SMS), as is increasingly common, these methods are subject to bias at the respondent level. The shortcomings of these methods—as well as various mechanisms for partially mitigating those shortcomings—have been extensively documented in the social scientific literature (Larsen et al., 2002; Bogner & Landrock, 2016).

1.1.2 Reproducibility

Traditional enumerator-driven M&E methods require pairing careful instrument development with significant investments in training to achieve good inter- and intra-rater reliability.[2] The former becomes increasingly difficult as the size of the workforce scales; the latter suffers when fatigue, difficult terrain, and other environmental conditions come into play.

1.1.3 Cost

Initial data collection

The costs of initial data collection using traditional M&E methods are driven by human labor (wages, per diem, and lodging) and other direct costs (materials, vehicle rental, fuel). The collection is typically done by teams with a supervisor, increasing the cost.

[1] M&E became monitoring, evaluation, and learning (MEL), which in turn became monitoring, evaluation, *adaptation*, and learning (MEAL), which in turn became monitoring, evaluation, *research*, learning, and adaptation (MERLA). In some contexts, the term "CLA" (for collaborating, learning, and adapting) is used instead.

[2] *Inter*-rater reliability refers to the consistency between different assessors measuring the same input, often concurrently. *Intra*-rater reliability is the consistency over time of a given assessor's repeated measures on the same input.

Data processing and analysis

The increasing adoption of electronic data capture—collecting data via digital forms on mobile phones or tablets, or through interactive voice response, SMS, etc.—has substantially reduced digitization or data entry costs associated with traditional M&E. Much of the data processing, cleaning, and analysis, however, continues to be implemented in spreadsheets using labor-intensive manual techniques. While some efficiencies can be gained over time as analysts gain experience, this typically means that subsequent rounds of data analysis incur substantial additional labor costs. It is, of course, possible to deploy reproducible data cleaning, processing, and analytics techniques in traditional M&E contexts. Doing so would also yield significant benefits in cost, quality, and timeliness. Such approaches have not historically been a feature of traditional M&E teams, however, and may require a significant effort to successfully introduce.

1.1.4 Time-to-Insight

A perennial issue with traditional M&E methods is the substantial delay between data collection and decision-making. Fieldwork alone often takes many days, if not weeks. If electronic data collection is used, data entry can be foregone; otherwise, it often takes several more days or weeks. Once the data are ready, analysis can begin, and typically takes multiple days. The end result is that M&E data are often presented to program leaders months after they were collected, at which point they may no longer reflect reality on the ground.

1.2 Niger Compact

1.2.1 History of Compact

The compact between the United States via the Millennium Challenge Corporation (MCC) and the Republic of Niger was signed on July 29, 2016, entering into force roughly 18 months later, on January 26, 2018.[3] Its initial term of 5 years was extended by 12 months through a 2022 amendment intended to address the disruptions and delays occasioned by the global COVID-19 pandemic.[4] The compact closed on January 26, 2024.[5]

1.2.2 Agricultural Focus of Compact

The MCC’s *Niger Constraints Analysis* of January 2014 identified *access to water for agriculture and livestock* as a binding constraint on economic growth in Niger.[6] Accordingly, over $256 million dollars (nearly 58% of the compact’s total funding of $442.6 million, but over 71% of its programmatic allocation) was earmarked for an *Irrigation and Market Access Project*.

> The Compact aims to increase rural incomes through improvements in agricultural productivity and sales resulting from modernized irrigated agriculture with sufficient trade and market access; and to increase incomes for small-scale agriculture-dependent and livestock-dependent families in eligible municipalities

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[3] Compact between MCC and Niger. July 29, 2016. Accessed 2025-04-04.
[4] Niger Compact Amendment. February 10, 2022. Accessed 2025-04-04.
[5] Niger Compact. Accessed 2025-04-04.
[6] Niger Constraints Analysis. Accessed 2025-04-04.

> in rural Niger by improving crop and livestock productivity, sustaining natural resources critical to long-term productivity, and increasing market sales of targeted commodities through two projects: the Irrigation and Market Access Project and Climate-Resilient Communities Project.[7]

At the signing of the compact, the *Irrigation Perimeter Development Activity (IPDA)* and the *Management Services and Market Facilitation Activity* were jointly projected to directly benefit nearly 40,000 Nigeriens.[8] The IPDA focused on rehabilitating the Konni irrigation system and developing new irrigation infrastructure in the Dosso-Gaya area.

1.3 Konni Irrigation Perimeter

The Konni Irrigation Perimeter was first constructed in 1976 with additional infrastructure added in 1982. Since that time, as the perimeter fell into disrepair, the agricultural community grew, along with the need for irrigation during increasingly frequent dry periods. Therefore, as part of the Niger Compact, MCC provided funding to improve the perimeter—repairing existing infrastructure and building new irrigation to connect the entire area to a reliable source of water.

1.3.1 Goals of the High Frequency Monitoring Project

Data on the areas planted with different crops in the current growing season and projected yields are important for public- and private-sector decision-makers to allocate resources, plan logistics, anticipate commodity production and prices, and prepare for any potential food security concerns. In addition, these data can be used as part of impact evaluations assessing the effects of agricultural programs and policies.

Many countries utilize farmer surveys and collection of remote-sensing data to gather these data. Drone imagery is widely used to map and monitor agriculture (Hall et al., 2018). Not only can drone imagery be used to delineate extents, it can also be used to determine if and where crops need additional water or fertilizer, or are suffering from disease or pests. These types of data can both aid in yield prediction as well as inform interventions to mitigate potential yield reductions due to crop stressors. However, in resource-poor parts of the world, estimates of planted area by crop type and projected crop yields may not be available in a timely fashion due to sparse data collection and administrative lag times. As a result, there may be insufficient data to analyze the impacts of agricultural development program implementation on crop mix and yields prior to availability of data collected in surveys administered at program midpoints or endpoints. By the time survey data are processed and analyzed, it may be too late to substantively adjust the program implementation based on evaluation findings.

Satellite-based crop type and yield models hold the promise of facilitating much more frequent monitoring of outcomes that can be observed remotely. For instance, by developing a satellite-based crop analytics framework that can be updated whenever new imagery becomes available to generate estimates of crop extents, it may be possible to generate actionable metrics earlier

[7] Niger Compact Amendment.
[8] Niger Compact.

in a program's implementation when small changes to an intervention may produce a higher return on investment. These model estimates are not meant to replace traditional M&E but complement it and provide input at more frequent intervals.

RTI's primary goal was to collect drone data during multiple growing seasons and use those data to calibrate satellite-based crop analytics models for the Konni Irrigation Perimeter. This would then inform MCC evaluation of the effectiveness of the irrigation components of this compact.

1.3.2 Partners

The larger work on this project was divided into three main components: the collection of crop yield data and farmer surveys, the generation of ground truth data used for training and validating satellite-based models, and the modeling itself. The three components were each led by a different organization: Mathematica, RTI, and NASA respectively.

- Mathematica has broad experience designing and implementing agricultural surveys in developing nations.
- RTI has experience using drones to develop crop type model training data, as well as modeling expertise, and survey design and implementation.
- NASA has extensive experience in satellite-based crop mapping, including work in Burkina Faso and Senegal.

Based on each organization's experience and skill sets, the work was broadly divided as indicated in **Table 1**.

Table 1. Division of Tasks Among Team Members

Task	Mathematica	RTI International	NASA
Farmer surveys and crop yields	●		
Drone imagery acquisition and crop label generation		●	
Satellite model development		●	●

In addition to doing their own tasks, data were shared between team members: RTI provided crop type locations to Mathematica to help them plan their crop cut implementation and to NASA to support their model development; Mathematica shared their crop cut data with NASA to help train a crop yield model; and NASA shared the predictive surfaces which were generated by the models. None of the team members could have performed all these tasks on their own. The results of this project were only made possible by contributions of each organization.

1.4 Drone Imagery

Low-altitude, high-resolution drone imagery taken over agricultural crops can make crop type and extent identification faster, more efficient, and less costly than traditional on-the-ground sampling. By identifying where certain crops are being grown, a satellite-based predictive model can be built using these crop locations as training data.

While visible-spectrum (0.38 µm–0.75 µm) RGB imagery is sufficient for crop delineation, aerial cameras with additional bands such as red edge (0.68 µm–0.75 µm) and near-infrared (0.78 µm–1.4 µm) can provide information about relative crop stress, and potentially enhance the ability to discriminate between crops. Ideally, imagery would include these additional bands, but these cameras are not yet standard and are not available in all cases.

The resolution of the aerial camera and the drone flight altitude combine to create an image of a certain ground resolution. In the case of crop identification, a pixel resolution of less than 3 cm is necessary to reliably identify crop types.

A given plant will have different physical characteristics depending on its life cycle stage (phenology). To enhance plant type identification, it is preferable to get imagery at several points during the growing season. Just before harvest is the ideal time for crop identification because the leaves are at their largest and fruit may be visible. It is also helpful to have imagery of specific known crop types during the middle of the growing season to be able to see how similar crops may differ visually. This also guards against missing crop examples due to early harvest or crop failure. Therefore, if budgets allow, two or three UAV flights per growing season are recommended.

Orthorectified drone imagery is viewed in a geographic information system (GIS) application in which a trained analyst identifies examples of crop types, including monocrops and intercrops. Monocrops are a single crop found in a given field, whereas intercrops are a mixture of two or more. The analyst draws a polygon around the field and then, using a spatial join in a GIS, extracts the crop type and ancillary metadata collected to each satellite cell centroid. These centroids then form the training dataset upon which satellite-based machine learning models are created and evaluated.

Section 2:
Phase 1

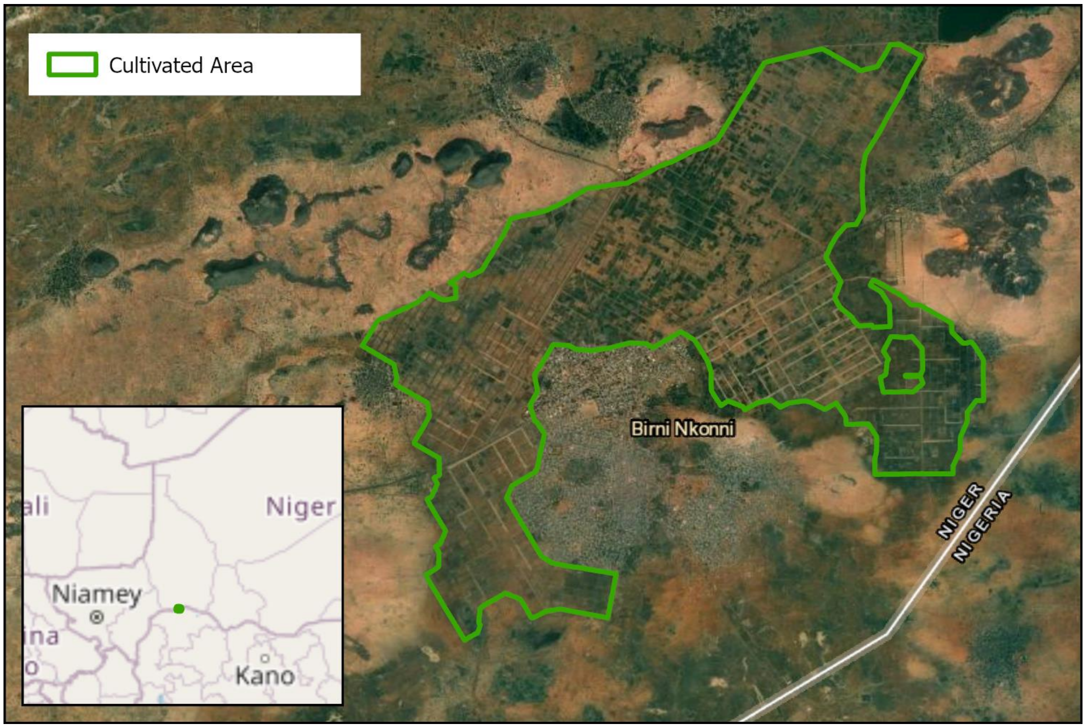
2. Phase 1

2.1 Feasibility Study

Phase 1 of this project was to determine the feasibility of augmenting traditional monitoring and evaluation by using satellite models to perform high frequency monitoring of agriculture in the Konni Irrigation Perimeter in Niger. This idea meshes with MCC's desire to explore ways to obtain higher-quality, higher-frequency, and lower-cost project monitoring data. More frequent data collection that occurs before, during, and after specific program interventions would allow MCC to know earlier in the process if the intervention is having the desired effects and allow for program changes that potentially would lead to improved outcomes.

Part of MCC's Niger Compact included the rehabilitation and extension of the Konni Irrigation Perimeter to provide water to agricultural plots (**Figure 1**), as well as other programs intended to boost agricultural productivity and increase the value of farmers' crops. RTI proposed to use satellite imagery paired with ground truth information to measure changes in crop mix and crop extents and use this information to evaluate the potential to monitor/map crop yields and soil moisture in this area of Niger.

Figure 1. Cultivated Area Within the Konni Irrigation Perimeter



2.2 Scoping Trip to Niamey, Niger

RTI traveled to Niamey, Niger in December 2019 along with our MCC partners to meet with local officials working in the agricultural sector. The overall objective of this trip was to determine the feasibility of augmenting traditional monitoring and evaluation by using satellite-based predictive models to perform high frequency monitoring of agriculture in the Konni Irrigation Perimeter in Niger. Specifically, the objectives were to:

1) Meet with local drone operators to gauge their capacity to capture low-altitude aerial imagery that would facilitate crop identification and produce training data
2) Meet with local stakeholders to determine their interest in providing agronomy interpretation of the drone imagery
3) Meet with local stakeholders to determine their interest in providing site-specific productivity data and soil moisture data.

This trip had two additional overarching goals. The first was to form a basis for collaboration with the various government agencies and nongovernmental organizations (NGOs) that would foster future cooperation and sharing of resources. The second was to gauge interest in and capabilities for building long-term capacity to take ownership of this methodology and implement it going forward.

We visited Drone Africa Service, a Niamey-based company that has been in business for approximately 9 years. The owner, Mr. Aziz Abdul Kountche, constructs his own drones (**Figure 2**) using components purchased from Europe and the United States. He has performed work for many local NGOs, government agencies, and universities.

We also had a telephone conversation with a second drone operator, Mr. Assadeck of Éspace Geomatique, based in Ouagadougou, Burkina Faso. Their office in Niamey was not yet operational.

In addition, we identified and visited several local institutions that could (1) provide ground truth information on crops, crop yields, and soil moisture, (2) check the work of local students doing crop identification, and (3) build capacity so that the technology can be used to measure agricultural outcomes and soil moisture beyond the end of the compact.

The institutions we visited were:

- Ministry of Agriculture and Livestock (MAGEL)—government
- *L'Office National des Aménagements Hydro-Agricoles (ONAHA)*—government
- Abdou Moumouni University—education
- *Haute Commissariat à L'Initiative 3N (HC3N)*—government
- SERVIR/AGRHYMET—research institute
- National Network of Chambers of Agriculture (RECA)—local NGO
- United Nations World Food Programme (WFP)—international NGO

All institutions expressed a willingness to be part of a small coordination and collaboration group that would be set up and administered by MCC/Millennium Challenge Account (MCA)-Niger. In return for data sharing, knowledge transfer, and provision of equipment and training that will ultimately lead to sustainability, the institutions indicated that they could help with our project needs.

Figure 2. Fixed Wing Drone Used by Drone Service Africa

2.3 Feasibility Results

Before proceeding with Phase 2, RTI evaluated several criteria in Phase 1 to make a judgment of Phase 2 feasibility. These included the ability to acquire drone imagery, acquire suitable satellite imagery, create ground truth data, and ultimately create models that predict crop types and therefore provide additional monitoring and evaluation data points.

2.3.1 Drone Imagery Providers

Our assessment was that there were at least three firms capable of capturing low-altitude, high-resolution aerial imagery using a drone as the platform. Drone Africa Service based in Niamey, Niger has successfully completed work for many NGOs, Nigerien government entities, and universities. Their clients have included the UN High Commission for Refugees (Niger), the Red Cross of Luxembourg, the International Crops Research Institute for the Semi-Arid Topics (ICRISAT), the Delegation of the European Union to the Republic of Niger, and Abdou Moumouni University of Niamey. Their rates were within budget and they were very familiar with the process to apply for and obtain drone authorization from the Ministry of Defense, the Ministry of the Interior, and the National Agency for Civilian Aviation (ANAC).

Two additional service providers identified were Charis Unmanned Aerial Solutions (Charis) based in Kigali, Rwanda, and Éspace Geomatique (S.A.R.L.) based in Ouagadougou, Burkina Faso. RTI has used Charis previously for work performed in Rwanda and found them to be highly competent and able to complete work on schedule and within budget. Éspace Geomatique is a Burkina-Faso–based company that has good experience and has a branch office in Niamey, Niger. Both were capable of flying drones in Niger and had comparable rates to Drone Africa Service.

2.3.2 Drone Imagery Mission Parameters

Although drones can be equipped with a variety of sensors, including infrared, thermal, and radar, the purpose of drone imagery for this project was to create labeled point data of crop types, and so it only needed to carry a high-resolution camera capable of capturing imagery in the visible spectrum.

We learned from agricultural consultants in Niamey that while some areas of Niger farm continuously throughout the year, mixed farming areas like Konni have two distinct seasons: the dry season and the rainy season, each with their own distinct mixture of crop types. The dry season generally runs between November and April, while the rainy season occurs between May and October. We therefore determined that it was necessary to acquire drone imagery during each of the two growing seasons at multiple intervals. This strategy would allow us to develop sufficient high-quality training data for crops that may leaf out or be harvested at different times.

2.3.3 Ground-Based Observations

For crop type identification, corroborative ground-based observations are valuable as they can be used to confirm the crop type identification done through drone imagery by a trained analyst. Our experience in Rwanda suggested that combining ground-based observations with drone imagery produces highly accurate crop type labels. This allows the creation of a knowledge base, and thus the majority of labeled training data can be derived from the drone imagery alone using an online GIS viewer. RTI's scoping trip to Niamey identified a network of government agencies, NGOs, and universities that possess existing ground-based crop data, as well as the ability to collect future ground-based crop data. Specifically, we understood that they would be able to provide crop identification confirmation, crop yield data, and soil moisture data upon which the satellite models are based. The coordination of the data collection and provision was to be done by the MCA-Niger staff in Niamey.

2.3.4 Sources of Satellite Imagery

RTI has previously had good success using Sentinel 2 imagery from the European Space Agency for mapping crop types in similar smallholder contexts. This imagery has a high spatial resolution (10 m), the sensor constellation revisits the same place on Earth every 5 days, and there is no cost to obtain or use it. There are several other sources of satellite imagery that are available at no cost through an agreement with MCC such as Maxar's Worldview data and Planet Labs' PlanetScope. Therefore, access to appropriate satellite imagery as an input to seasonal crop prediction models was not an issue and we could focus on the alignment with higher-resolution UAV flights and field data collection campaigns.

The modeling software used for RTI's Rwanda Grand Challenge was well suited to create agricultural measures in the Konni area. Specifically, we believed that machine learning models (e.g., random forest classification) developed with ground truth satellite data and implemented on the highly scalable and accessible Google Earth Engine platform had the highest probability of success. Random forest was selected because it is a mathematically robust and transparent model. However, the success of this approach ultimately hinged on the quantity and quality of ground truth data.

2.3.5 Summary

Based on our scoping trip to Niamey and a review of current best practices in terms of data inputs and modeling environments, RTI found no significant barriers to performing high frequency monitoring of agriculture in the Konni Irrigation Perimeter area. Ground truth data in the form of labeled crop type locations on drone imagery were obtainable. There were no impediments in terms of capacity, permitting, cultural sensitivity, security, or cost. Crop yield and soil moisture calibration data are more challenging to acquire, especially in the quantity needed to develop reliable models. But local in-country organizations expressed a willingness to provide these data, so it was potentially possible to develop these models as well. We also believed that the methodology developed can be applied outside of the Konni area and be carried out beyond the end of the compact by in-country stakeholders, as long as the necessary training and equipment are provided.

Section 3:
Phase 2

3. Phase 2

Based on the findings from Phase 1, we began the implementation of our data collection, processing, and analysis that comprised the bulk of the work in Phase 2.

3.1 Implementation

MCC's goal was to develop satellite-based models that would detect a change in water usage, crop types, crop extents, and crop yields. To achieve this goal, we needed to collect the appropriate training data. The water usage question is difficult to answer because water comes from three sources—rain, wells, and irrigation canals—and we do not know how much comes from each source. The health of crops depends in part on the quantity and timing of available water. All things being equal, a good way to determine if farmers are increasing their use of irrigated water is to measure the type and extents of crops, especially in the dry season when there is less rainfall. The types and extents of crops can be determined from drone imagery taken during each growing season. For crop yields, the best training data comes from crop cuts, a small (~0.1 ha or smaller) representative area that is harvested and weighed, which were planned and administered by our colleagues at Mathematica. The intention is that these data will be made available to future partners, so that crop yield models can be developed.

3.1.1 Drone Imagery Acquisition

Our intention was to acquire drone data for six growing seasons (three rainy and three dry) starting in March 2021. It is possible to train a crop type model with training data generated in a single season. The model could then be used with satellite data from future years, as well as against past satellite data, to predict the type and locations of crops identified in the training data. However, acquiring additional drone data gives the opportunity to develop separate training data and separate models for each season/year, as well as to combine models across multiple years. Additional drone-derived training data allows us to measure how well a model trained using previous years' training data performs in the current year. This gives us the flexibility to use the models with the best performance and therefore the ability to determine if the crop mix and crop extents were changing to higher-value crops that require more water but also generate a higher income for the farmers, as irrigation water became more readily available.

The first drone mission was flown over a portion of the irrigation perimeter and along the canal that links the Mijoyo River to the irrigation perimeter (**Figure 3**). The purpose of these flights was to (1) determine what crops were growing on the irrigation perimeter during the dry season before any irrigation infrastructure construction began, and (2) determine if drone imagery could be used to identify/quantify the amount of water being drawn by farmers along the canal before it reached the irrigation perimeter (**Figure 4**).

Figure 3. Areas Covered by Drone Imagery, Dry Season 2021

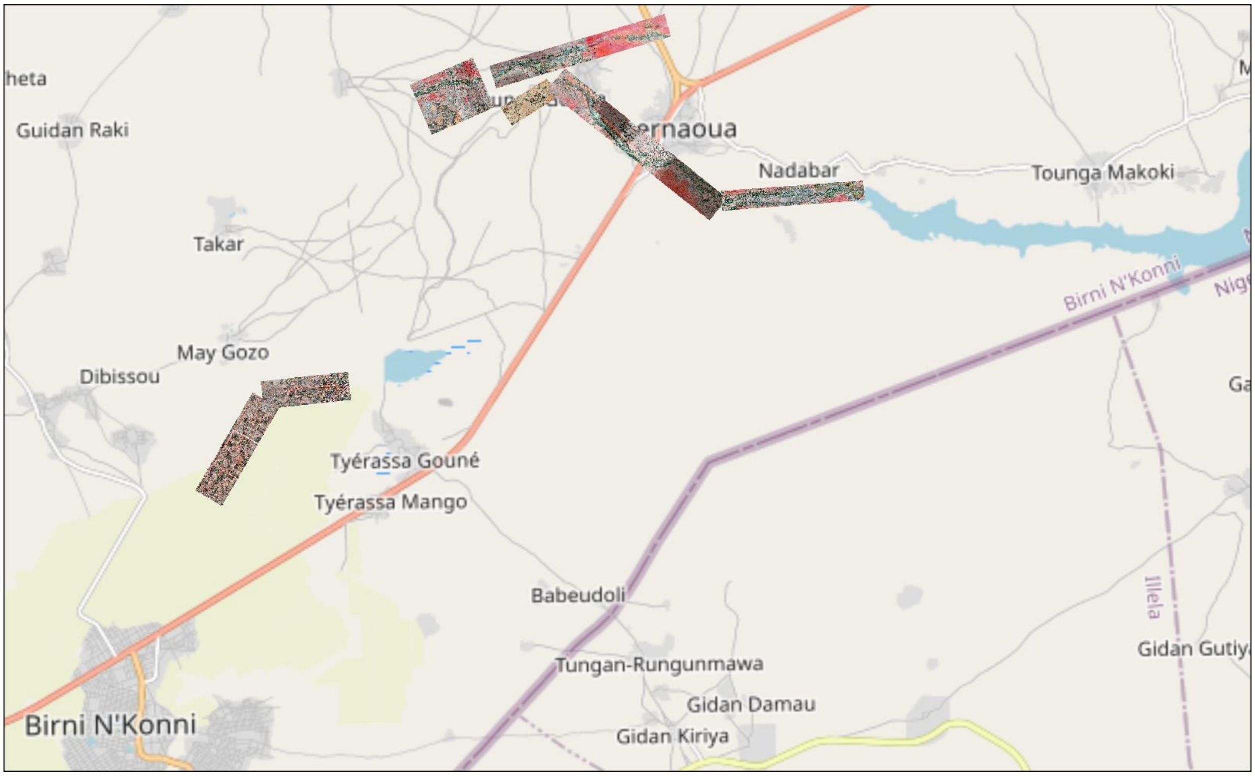


Figure 4. Example of Farmers Pumping Water from Canal before It Reaches the Konni Irrigation Perimeter

We solicited quotes from the three drone operators who we were confident could do the work, and ultimately chose Éspace Geomatique for the first drone mission, as they were the least expensive. This work was completed to our mission specifications, and we were able to generate an image service that was displayed within our online crop labeler application.

3.2 Project Delays

Our drone schedule and subsequent crop labeling and model development was impacted by several events in the early part of the project. MCC's intention was to suspend farming on a portion of the irrigation perimeter while it was being rehabilitated and expanded. Farming was to continue in those portions not under construction while those farmers not able to farm would be compensated for their losses. However, due to construction delays and the COVID-19 epidemic, we were advised by MCC that there was no cultivation between the 2021 rainy season and the 2022 dry season. Therefore, we did not acquire any drone imagery during this time. Beginning in the rainy 2022 growing season, there were indications that part of the perimeter was under cultivation while construction was fast tracked. However, the drone imagery showed little to no activity. The same was the case for the 2023 dry season. During the 2023 rainy season widespread cultivation returned to the perimeter, although construction was still ongoing. Access to irrigated water started following the 2024 dry season after MCC provisionally accepted the completed construction works. The drone imagery acquired during each growing season is presented in **Table 2**.

Table 2. Drone Imagery Captured by Year/Season

Year	Season	Month	Resolution	Labels Created	Vendor	Notes
2021	Dry	March	3 cm	Yes	Éspace Geomatique	Includes areas along canal where water extraction suspected
2021	Rainy	N/A	N/A	N/A	N/A	N/A
2022	Dry	N/A	N/A	N/A	N/A	N/A
2022	Rainy	August	2 cm	Yes	Drone Africa Service	Plots were almost all fallow
2023	Dry	March	2 cm	No	Drone Africa Service	All zones unplanted
2023	Rainy	August	2 cm	Yes	Drone Africa Service	Mapillary imagery acquired
2023	Rainy	September	2 cm	Yes	Drone Africa Service	Mapillary imagery acquired
2024	Dry	March	2 cm	Yes	Drone Africa Service	Oblique imagery acquired, almost all plots were unplanted or abandoned
2024	Rainy	August	2 cm	Yes	Drone Africa Service	Oblique imagery acquired
2024	Rainy	September	2 cm	Yes	Drone Africa Service	Oblique imagery acquired
2025	Dry	March	2 cm	Yes	Drone Africa Service	Oblique imagery acquired

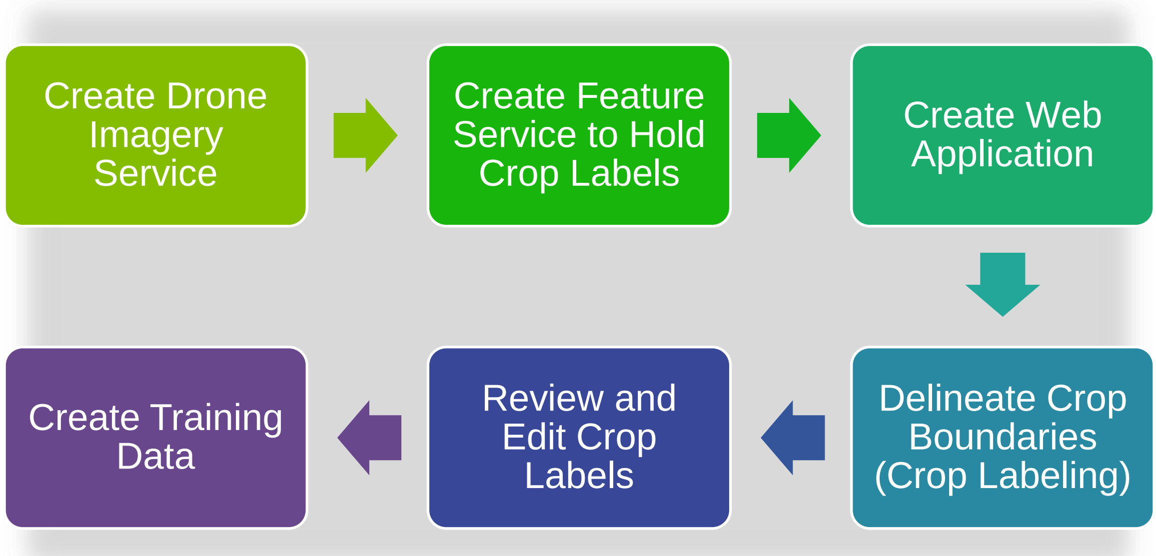
Note: Mapillary is a platform for hosting ground-based imagery.

On July 26, 2023, the Nigerien military staged a coup d'état deposing the country's elected president and taking control of the government. The military suspended government services and closed the borders and air space which eliminated non-Nigerien drone operators thus forcing us to use Drone Africa Service. Despite this, the DAS provided a reasonable quote and was able to obtain the required permits in time to perform the first drone flights for the 2023 rainy season.

3.3 Crop Labeling

RTI created a web application that displayed the drone imagery overlaid with farmer plot boundaries and Sentinel 2 satellite pixel extents. The application allowed an analyst with an account and an internet connection to access the imagery from anywhere in the world. There was the ability to label individual Sentinel 2 cells, as well as delineate polygons of fields with the same crop or crop mix. The general workflow for each season is presented in **Figure 5**.

Figure 5. Crop Labeling Workflow



To improve efficiency, in the web application, we added drop-down lists of commonly found crops, their condition, their growth stage, if they were present with any other crops, and our confidence in the accuracy of the label (**Figure 6**).

Figure 6. RTI Crop Labeler Interface

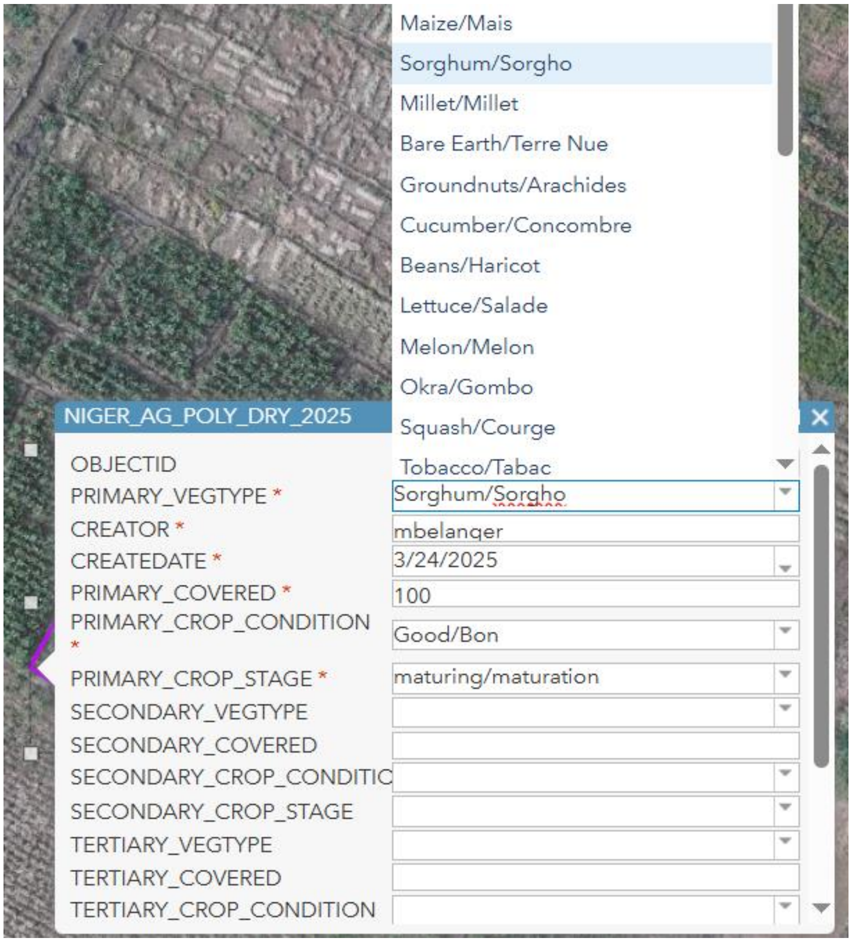
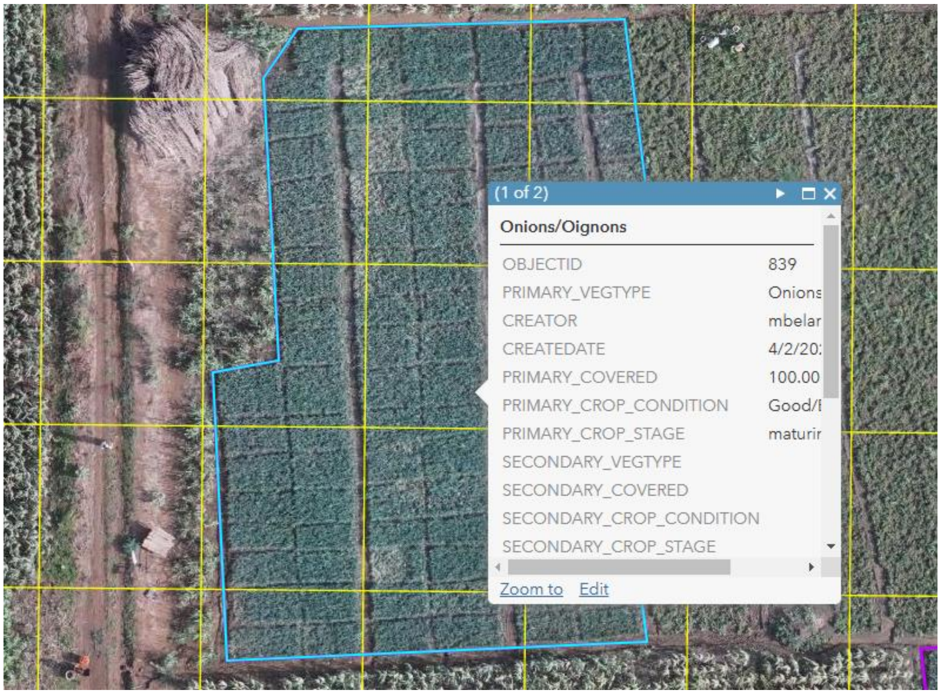


Figure 7 shows an example of an onion field and the Sentinel cells it intersects. Each of the intersected cells becomes a crop label with a measure of cell overlap. Cells completely inside the field get a value of 100%, while those along the edges receive a value of less than 100%. The modeler can then select only labels above a given threshold to train and evaluate the model in an effort to maximize accuracy.

Figure 7. Crop Labeling Workflow



There are roughly 5,000 agricultural fields in our drone sample area. Accordingly, our goal was not to label every single field, but rather to accumulate a sample of all crop types present at various growth stages and conditions. This strategy represented a balance between the need to be thorough but also to be time efficient. The results of the crop delineation were stored in an enterprise geodatabase comprised of ArcGIS Server and Microsoft SQL Server.

3.3.1 Challenges

We initially engaged with volunteer agricultural consultants with whom we had made contact through the MCA office in Niamey. We set up accounts, created a labeling guidance document, and provided several online training sessions, all in French. We asked that consultants delineate fields and attribute them with crop type and the other related information. The consultants had difficulty with their internet connection speed and did not feel confident providing crop identification on their own. We then set up interactive sessions, where RTI used the app, shared its screens via an online meeting, and did the crop delineation with guidance from the consultants. This was better but progress was slow because we could only get 1–2 hours of the volunteers' time every few weeks.

Another challenge was that even though the process worked well overall, a trained agronomist using 2 cm resolution RGB imagery may still have had difficulty determining with certainty the crop type growing at a given location. This is due in part to the fact that many crops look similar on the imagery. The timing of the drone flights also led to problems. If a flight is too early in the growing season when leaves are small and there may not be any fruit to see, it may not be possible to discern one crop from another. If it is too late in the growing season, crops may have already been harvested and thus do not appear at all. And because not all crops of a given type are planted at the same time, whenever drone flights are scheduled, some may be too immature to identify, while others may have already been harvested.

3.3.2 Strategies to Overcome Challenges

We initially relied on crop image examples from past missions to train geospatial analysts to do the crop labeling. After having difficulty getting volunteer Nigerien agronomists to help with our crop labeling, we hired a Rwandan agricultural consultant with whom we previously had worked. Since he was familiar with Nigerien crops and farmers' growing strategies across Sahel countries, he was able to thoroughly review the labels to correct any errors and ensure consistency. Having a paid, trained agronomist was crucial in ensuring our crop training data were created in a timely fashion and were as accurate as could be.

Bracketing the growing season with multiple sets of drone imagery is the best way to avoid getting imagery that is too early or too late. A minimum of two passes is recommended, while three is better if the budget allows it. For Konni, we planned for an early/mid set, as well as a mid/late set. While not perfect, it gave us sufficient examples of multiple crops at multiple growth stages and minimized the number of immature and harvested fields.

Higher-resolution imagery (2 cm) also helped us to better identify crop types. Our first mission completed by Éspace Geomatique was flown at 3 cm, and the difference between this and subsequent missions flown at 2 cm was noticeable. It also increased the size and therefore reduced the ease of file transfer and processing of the datasets as well as the online viewer performance, but it was worth the tradeoff in our experience.

We also augmented our vertical drone imagery with two other types of imagery. We theorized that having a second set of either ground-based or oblique images from a low-altitude drone would aid in interpretation. We contracted with our drone operator to take ground-based images with his phone and post them to the image-sharing website Mapillary (similar to Google StreetView). This did not yield very much actionable imagery as the photos tended to be too far from the crops of interest and only captured crops in the first few meters. Low-level (15–20 m above terrain) drone imagery taken at an angle (oblique) (**Figure 8**), however, proved to be *very* useful. This imagery did not encompass the entire project area, but was done in irregular transects of regularly spaced photos. Incorporating these images into our online viewer proved to be invaluable, as it gave a second view of a given crop and allowed us to label larger fields with higher confidence.

Figure 8. Example of Low-Altitude Oblique Drone Imagery

3.4 Modeling

Although our NASA colleagues were tasked with doing the bulk of the satellite modeling, RTI was also encouraged to develop models that would accurately predict the types and extents of the crops growing in the Konni Irrigation Perimeter during the various growing seasons. This activity was in addition to our primary task of developing training/evaluation data.

We trained multiple model variations using publicly accessible satellite imagery (Sentinel and LandSat data) with data derived from drone imagery. We primarily trained random forest models; the benefits of random forests include quick training speed and ease of extracting variable importance metrics, which allowed us to assess the impact of the input satellite wavelength bands we used.

We used free and open-source software (R and QGIS) to train these models and predict output crop cover. To tune the model parameters and better characterize the performance of the model, we performed five-fold cross-validation using the R package caret. We partitioned the training set into five equal-sized subsamples, or folds, creating five subsampled datasets (each using four folds for training data and one for testing data—the commonly used 80/20 split).

The model used multiple predictive parameters, mostly individual satellite bands. For each parameter value we wanted to analyze, we trained a separate model; for example, five-fold cross-validation with four parameter values results in 20 total model runs. Using caret, we determined which parameter values maximized the model performance. Finally, using the best parameter values, we trained the final model using the entirety of the training set (i.e. all five folds) and validated using the test set.

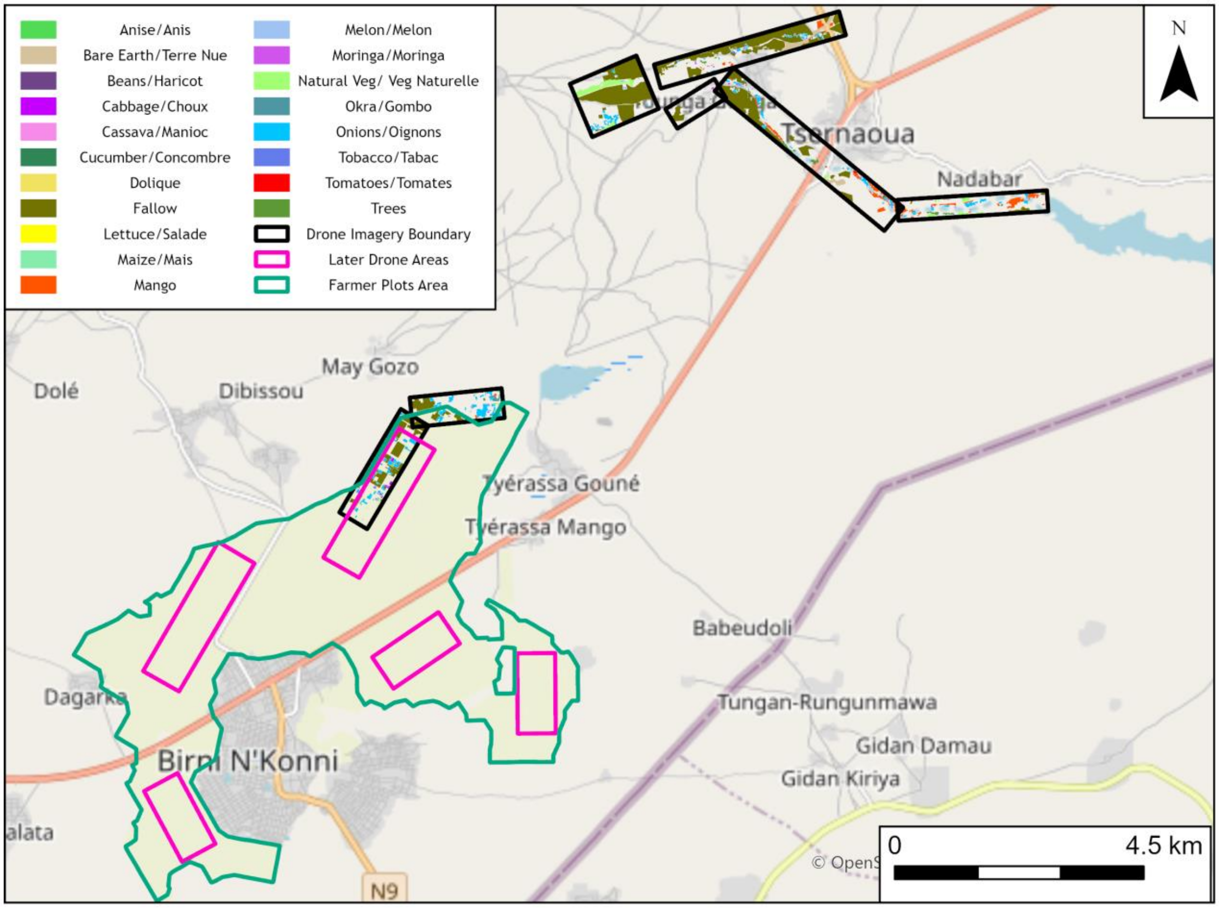
Section 4: Results

4. Results

4.1 2021 Dry Season

While one of the purposes of the drone imagery taken in March 2021 was to assess its utility in quantifying water extraction from the canal linking the Mijoyo River to the irrigation perimeter, we also used it to identify crops being grown on and off the perimeter. A large percentage of the land was fallow, but there were many examples of onions and cabbage (**Figure 9**). These data were shared with NASA and they used them to train and evaluate a satellite-based crop type predictive model. We did not perform any modeling using these training data. The drone imagery showed areas where water was being extracted from the canal and used to irrigate crops but was not useful in quantifying the amount.

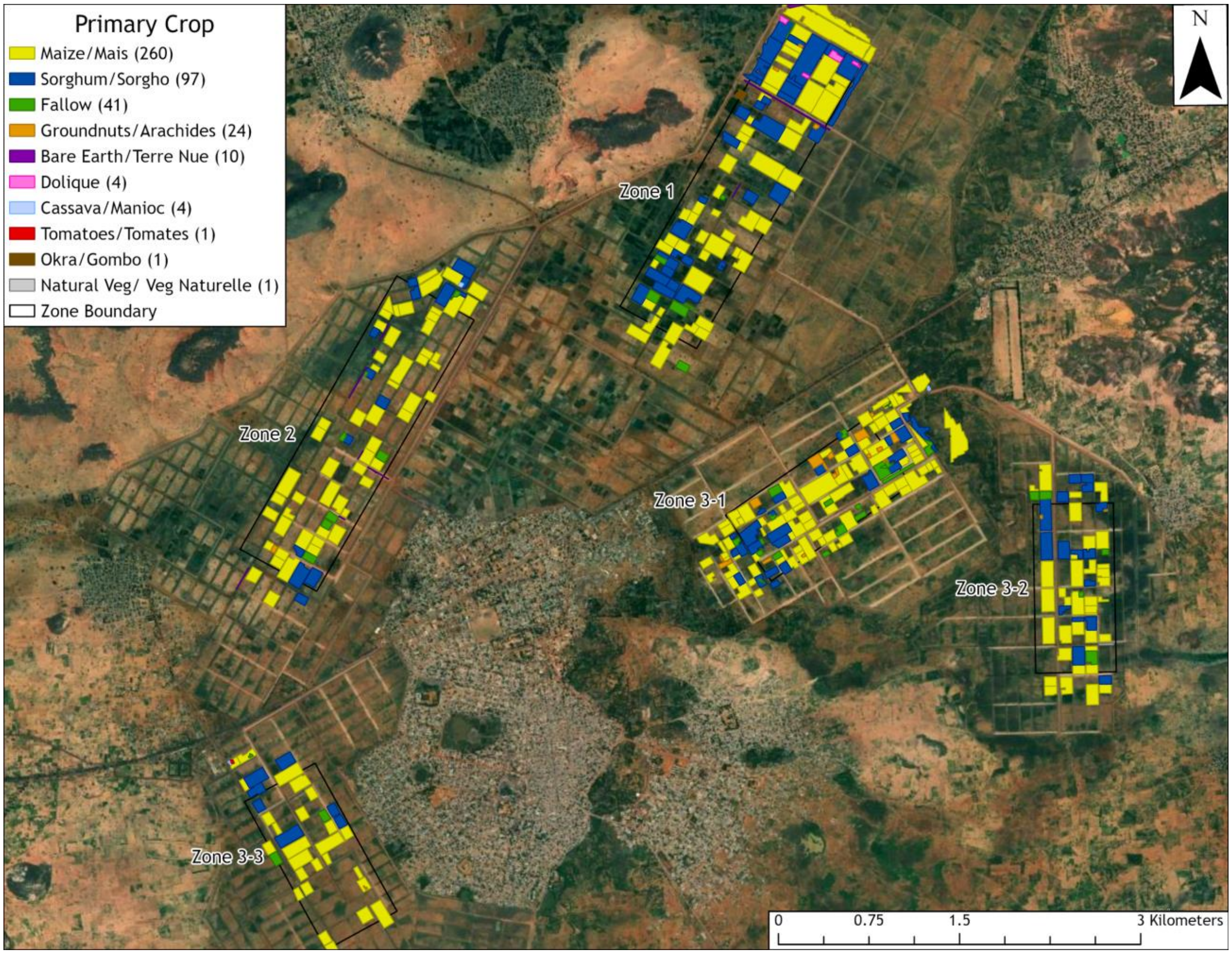
Figure 9. Fields Labeled by Crop Type Dry Season 2021



4.2 2023 Rainy Season

The 2023 rainy season marked the first time that widespread cultivation occurred in the Konni Irrigation Perimeter since the beginning of the rehabilitation and expansion. At this time, construction was still ongoing and irrigation from the works was not available. Our drone imagery was concentrated within the five zones that comprise the fields that surround Konni. We contracted for two sets of drone imagery: one in early August 2023 and the second in late September 2023. Using these sets of images in image services publishing to our external Esri Portal, we classified fields with the crops present. Most fields were planted with cereal crops, specifically maize and sorghum. We did not see many examples of non-cereal crops. There was however, a fairly large number of fields that were left unplanted (fallow). The types and extents of the crops present are shown in **Figure 10**.

Figure 10. Fields Labeled by Crop Type, Rainy Season 2023

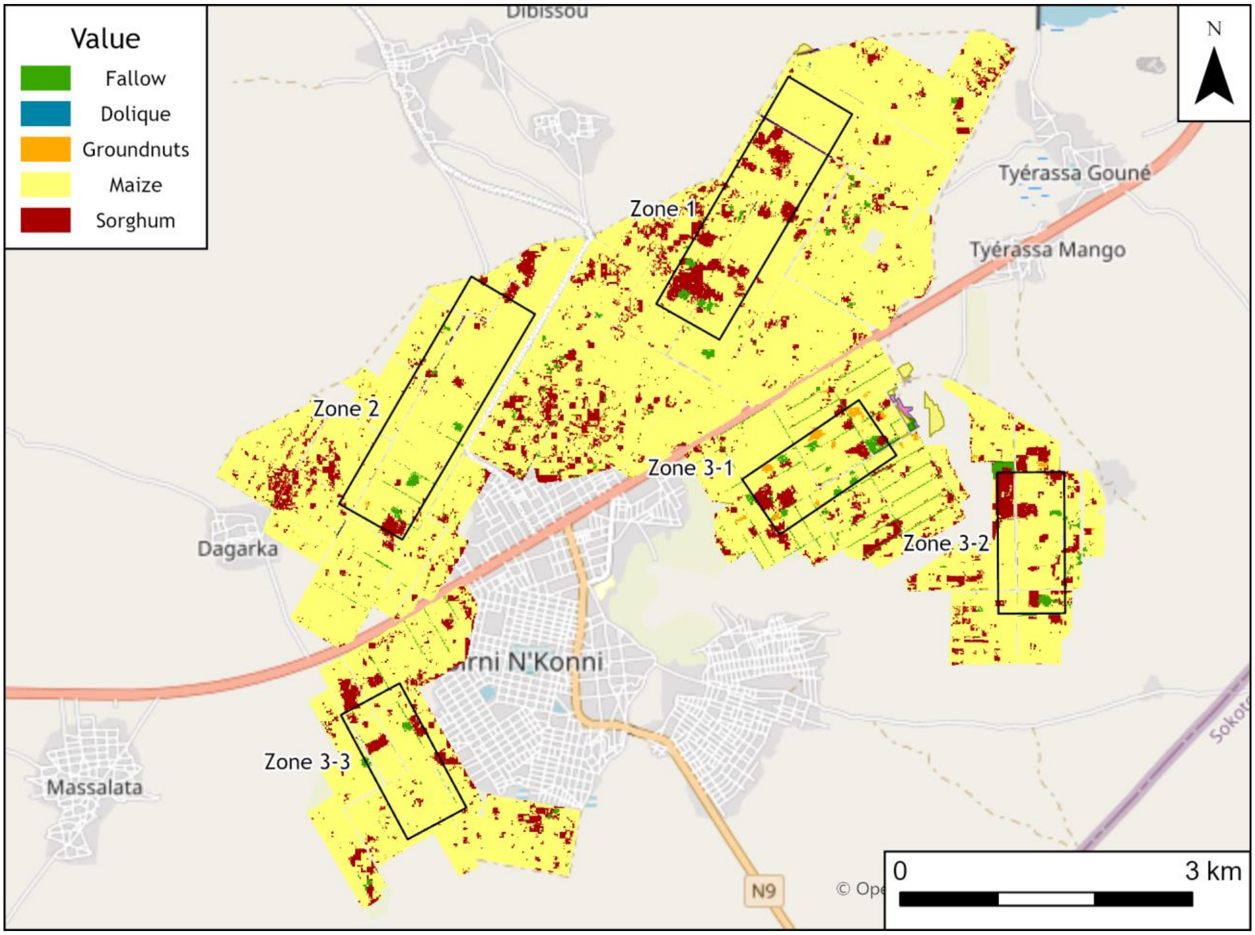


We generated a crop type model that was trained on five main land covers/crops: maize, sorghum, dolique, groundnuts, and fallow. This model was greatly influenced by the large numbers of fields of maize and sorghum in the training data, consequently producing an overall accuracy of 95%. However, the overall accuracy may not reflect the reality of how and where misclassifications occur, especially in models trained on data with class imbalances such as this one. Since we labeled so much maize, it is not surprising that the model mostly (and correctly) predicted maize.

Appendix A.1 shows a breakdown of the confusion matrix and accuracies by crop type, allowing us to interpret the accuracy with more nuance. The confusion matrix provides data about how often the predictive surface crop either (1) agrees with the human-labeled satellite grid cell, or (2) is confused and predicts a different crop type at the location of the human-labeled grid cell. The confusion matrix indicates that the model is 99% accurate when identifying maize and 87% accurate when identifying sorghum; however, these high accuracies are a result of the overall abundance of cereal crops and come at the expense of accuracy when identifying dolique, groundnuts, and fallow land.

The predictive crop type surface produced by the model is shown in **Figure 11**.

Figure 11. Predicted Crop Types over Entire Study Area, Rainy Season 2023



In terms of hectares, maize and sorghum comprised almost all the planted area (**Table 3**). Some fields were left fallow, and the only non-cereal crop of note was groundnuts (8.37 ha).

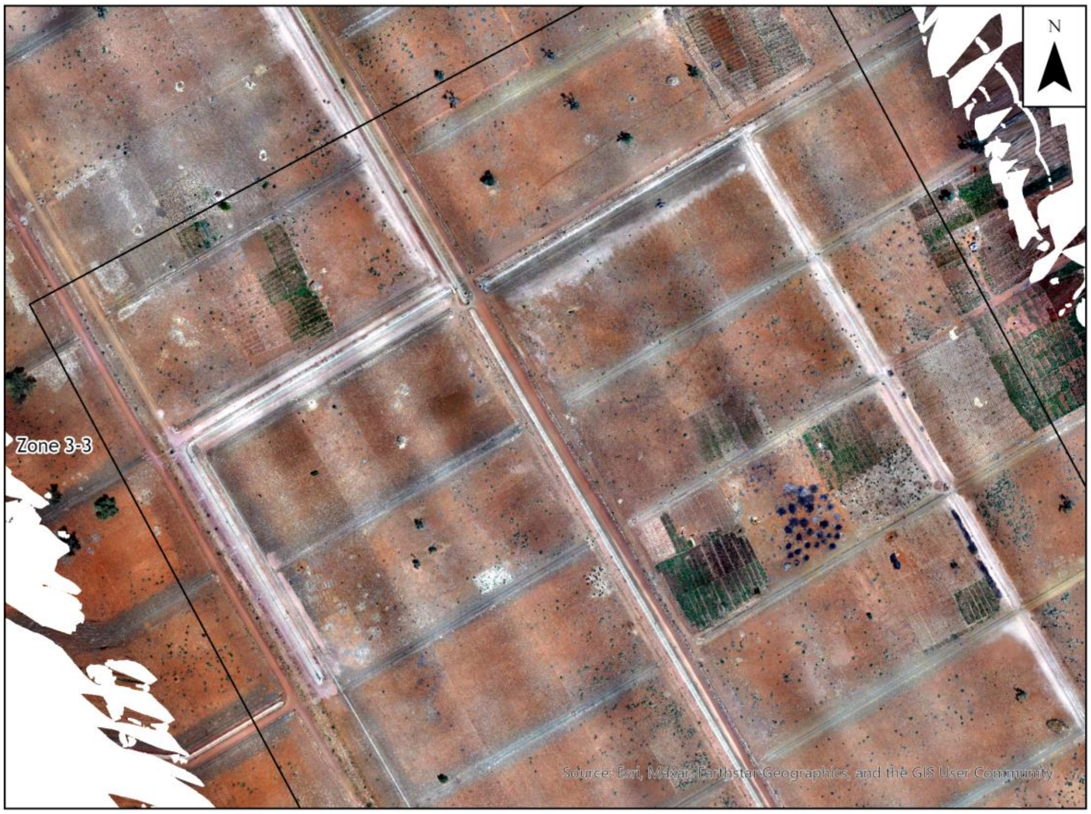
Table 3. Area of Predicted Crop Types (Konni Perimeter), Rainy Season 2023

Crop Type	Hectares	Percent Area	Model Accuracy Percent
Maize	2388.62	87.73	99.06
Sorghum	277.48	10.19	87.45
Fallow	48.15	1.77	72.78
Groundnuts	8.37	0.31	70.86
Dolique	0.09	0.00	33.33

4.3 2024 Dry Season

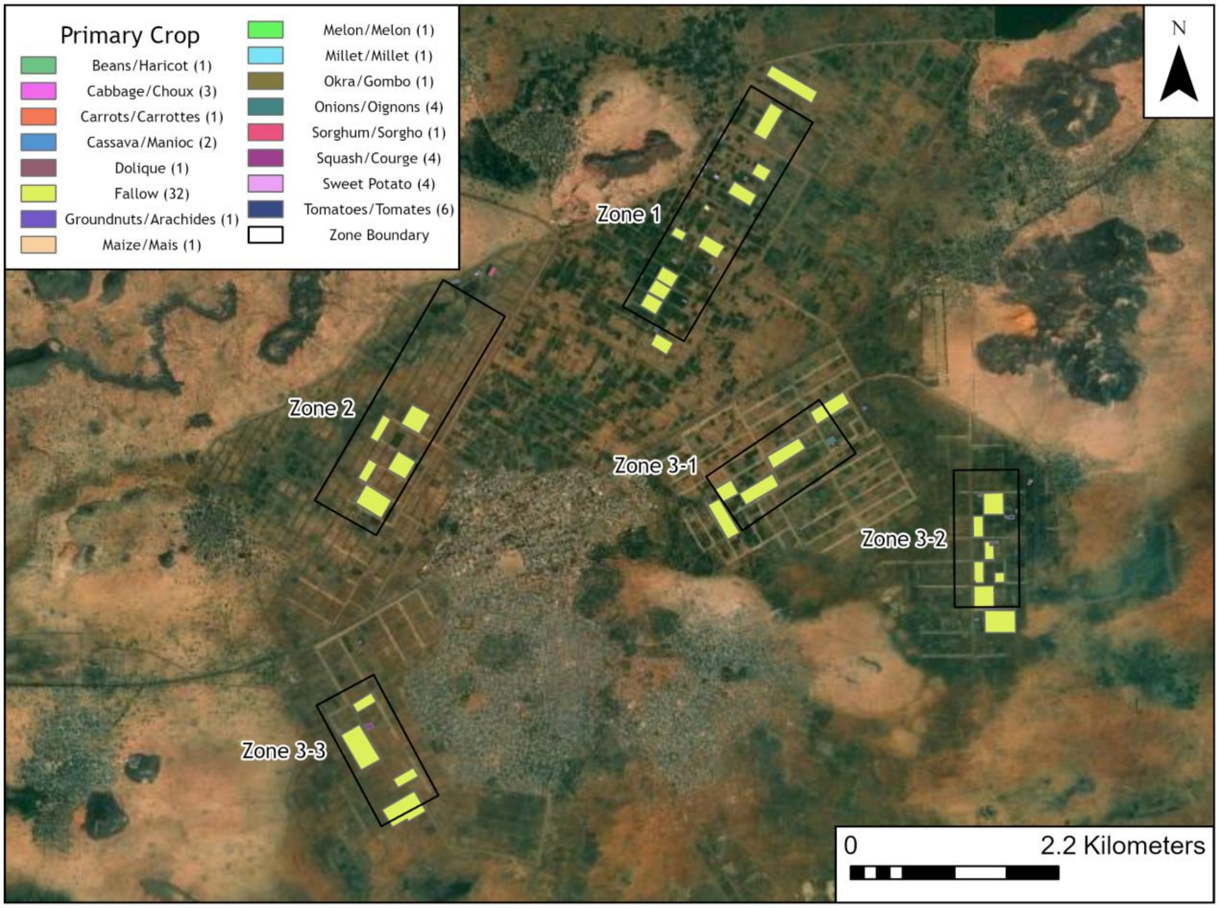
We intended to obtain two sets of drone imagery for the 2024 dry season. After receiving and processing the first set from mid-March, it was apparent that almost all the fields had either been left unplanted, or the crops had been abandoned. **Figure 12** shows an example of the state of cultivation within the irrigation perimeter during the 2024 dry season. From the drone imagery, there did not appear to be any water flowing in the irrigation canals, which may explain the lack of cultivation during this dry season

Figure 12. Typical Condition of Fields, Dry Season 2024



We created labels for the few fields that were actively being farmed as well as examples of fallow/abandoned fields (**Figure 13**) and shared these ground truth data with our NASA colleagues.

Figure 13. Fields Labeled by Crop Type, Dry Season 2024



We also did our own modeling to generate a predictive crop surface and generated a map shown in **Figure 14**. The model's confusion matrix and accuracies are provided in Appendix A.2. The overall accuracy was very high, but this is because the model was trained with almost all fallow examples. Given that the drone imagery showed extremely limited cultivation, it is entirely expected that the model produced a surface that identified bare earth/fallow as 99.6% (**Table 4**) of the land use within the irrigation perimeter

Figure 14. Predicted Crop Types over Entire Study Area, Dry Season 2024

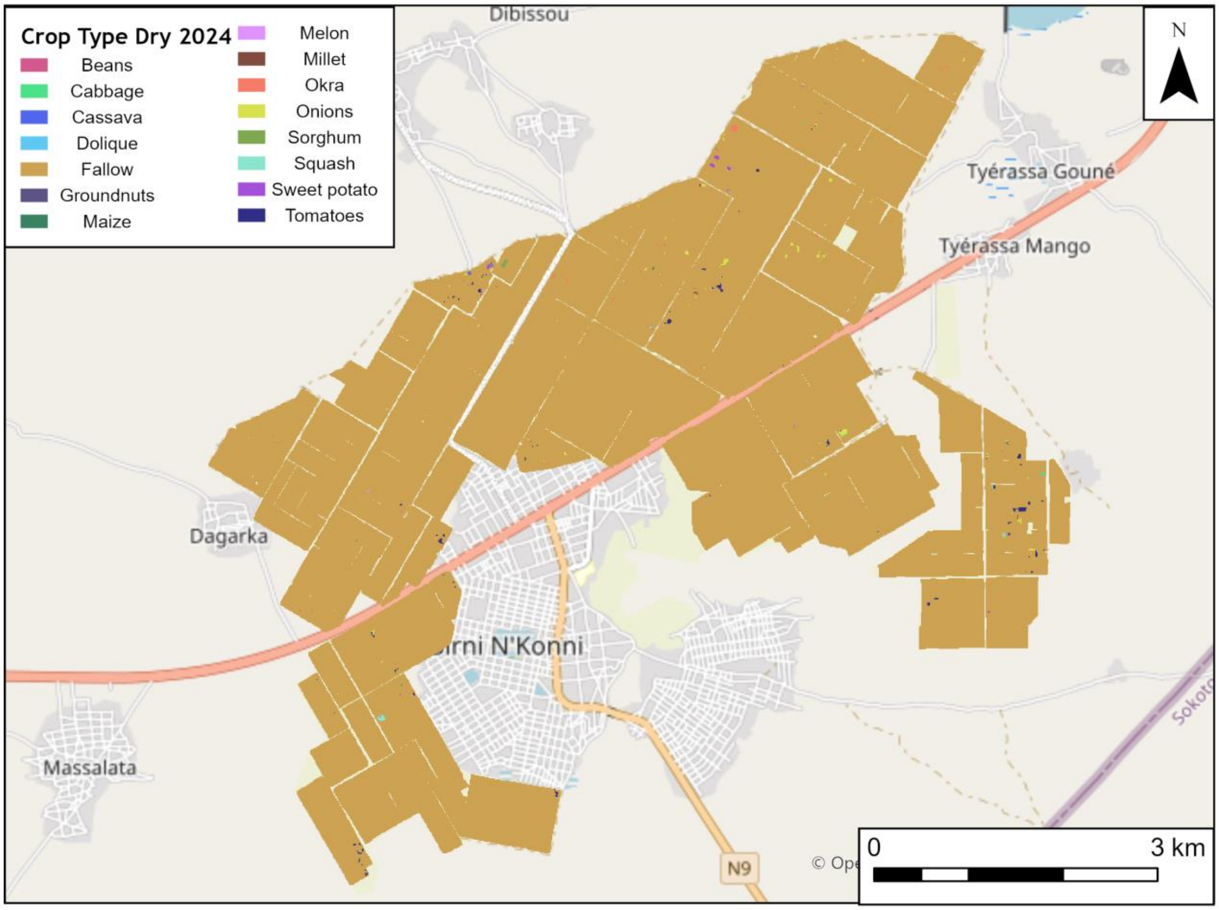


Table 4. Area of Predicted Crop Types (Konni Perimeter), Dry Season 2024

Crop Type	Hectares	Percent Area	Model Accuracy Percent
Fallow	2712.99	99.60	100.00
Tomatoes	3.41	0.13	88.89
Onions	3.15	0.12	54.17
Okra	1.41	0.05	90.91
Sweet Potato	0.96	0.04	47.06
Squash	0.7	0.03	33.33
Sorghum	0.59	0.02	77.78
Cabbage	0.21	0.01	66.67
Cassava	0.18	0.01	40.00
Groundnuts	0.13	0.00	100.00
Millet	0.07	0.00	100.00
Beans	0.06	0.00	50.00
Melons	0.06	0.00	0.00
Maize	0.04	0.00	0.00
Dolique	0.03	0.00	0.00

4.4 2024 Rainy Season

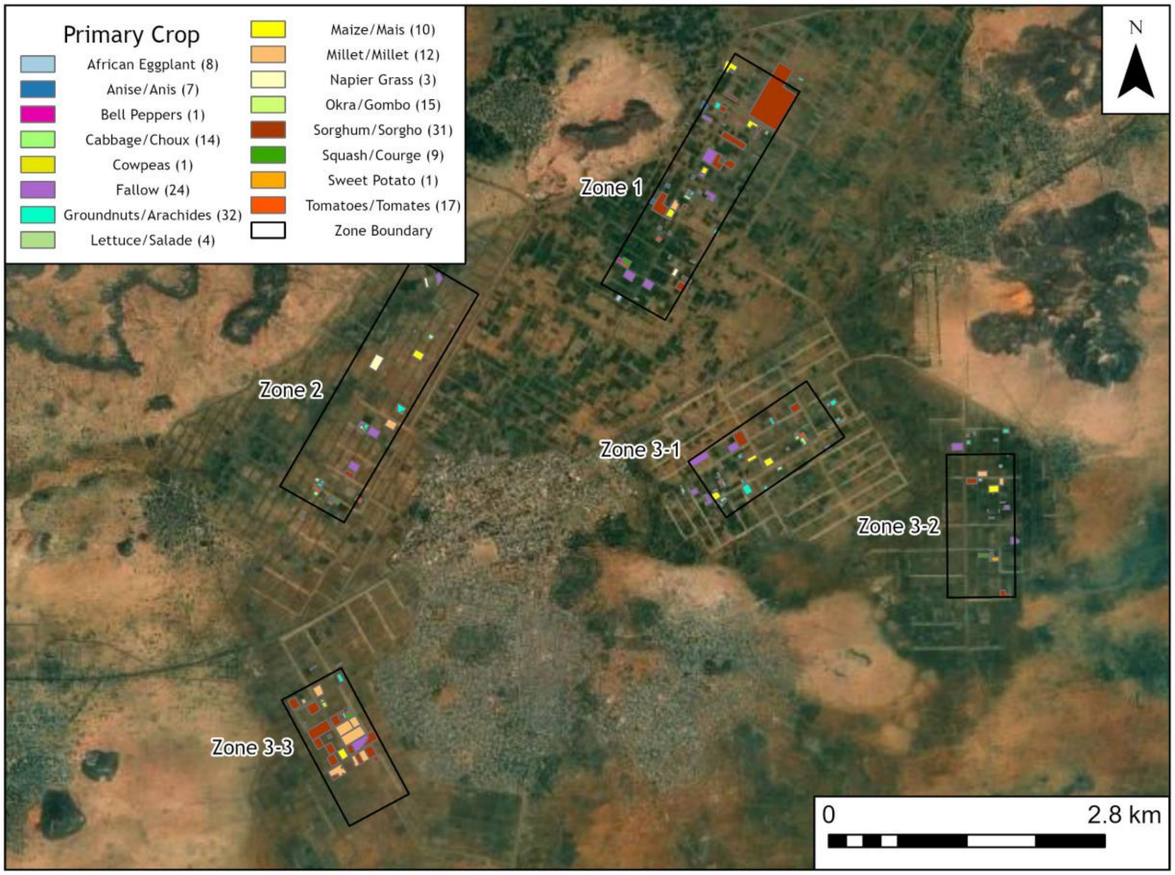
The 2024 rainy season marked the first time we obtained oblique drone imagery to complement our vertical imagery. Oblique imagery is typically taken at a lower altitude than the vertical imagery and the camera points toward the ground at an oblique angle (**Figure 15**). The coverage is continuous along the flight path, but the flight paths do not cover the entire drone area the way that the vertical imagery does. It is meant to augment the vertical imagery, not replace it.

We again contracted for two sets of drone imagery: one in early August 2024 and the second in late September 2024. This included collection of both vertical and oblique imagery.

Figure 15. Example of Oblique Drone Imagery

All sets of images were published to our external Esri Portal and, using our online crop labeler, we classified fields to generate a cross section of crops present. The oblique imagery turned out to be an invaluable resource. Because it was taken at a lower altitude and we could see the relative height and the shape of the tops of plants, we were able to label more crops with higher confidence. As in 2023, most fields were planted with cereal crops in 2024 (mostly sorghum, but also millet and maize). In addition, we saw many examples of non-cereal (cash) crops (**Figure 16**).

Figure 16. Number of Fields Labeled by Crop Type, Rainy Season 2024



These ground truth data trained the rainy season 2024 model, which produced the crop type predictive surface shown in **Figure 17**. Our model produced an overall accuracy of 91% (Appendix A.3), which was largely driven by large numbers of labels for sorghum, maize, millet, fallow, and groundnuts. Of these, maize (86%) and groundnuts (88%) achieved lower accuracies, although they were still quite good. In general, the cereal crops produced higher accuracies than non-cereal crops. This is mostly because these fields tend to be larger than non-cereal crops and therefore generate more crop labels inside their boundaries Geographically, there does not appear to be any spatial pattern. Sorghum was planted throughout the irrigation perimeter along with millet and maize, with some cash crops interspersed between.

Figure 17. Predicted Crop Types, Rainy Season 2024

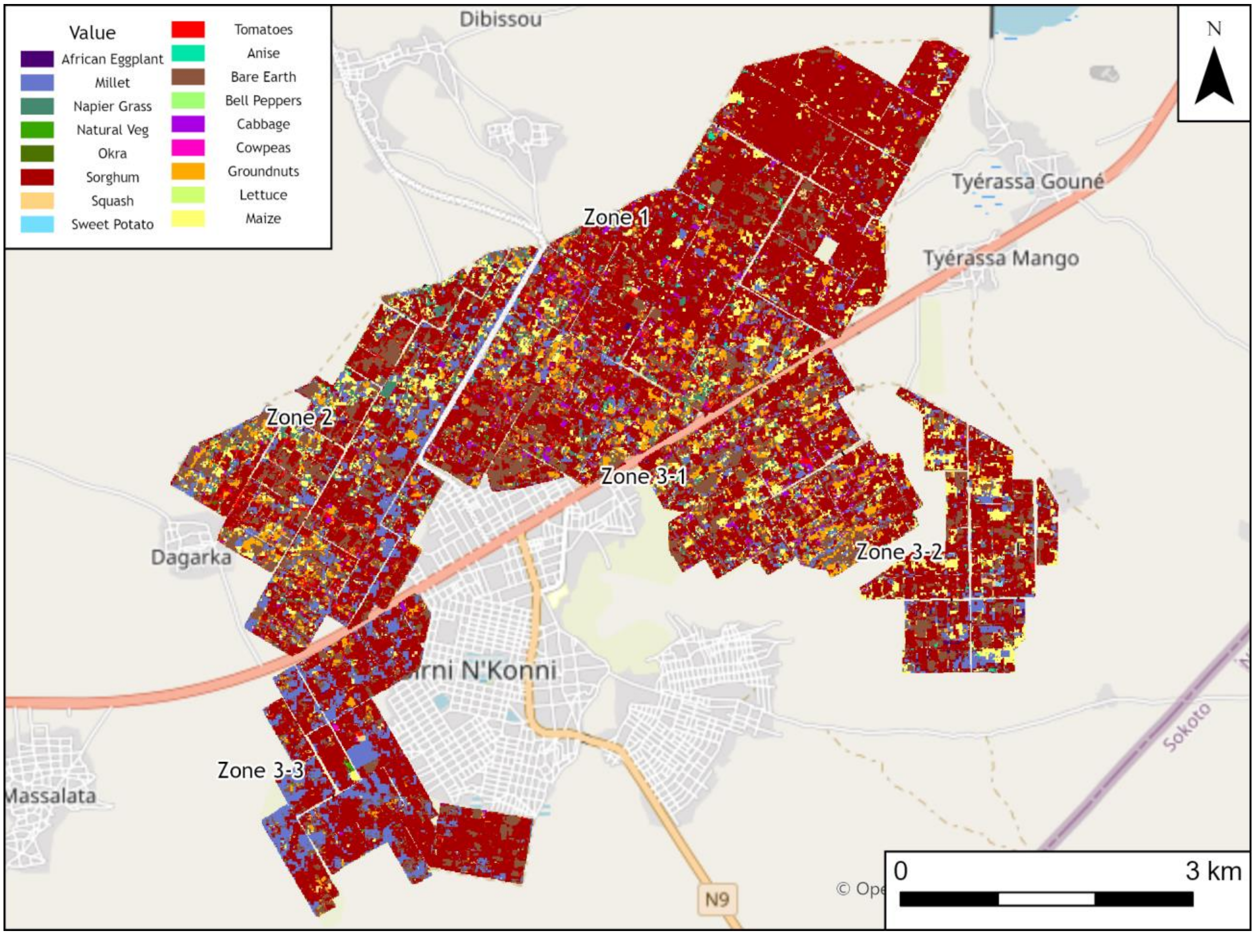


Table 5 displays the crop areas in hectares and their corresponding percentages of the planted area. As suggested by the map, sorghum makes up the largest crop by area, followed by bare earth/fallow, and then two additional cereal crops: millet and maize. The most prevalent non-cereal (cash) crop was groundnuts, with 5.39% of the cultivated area.

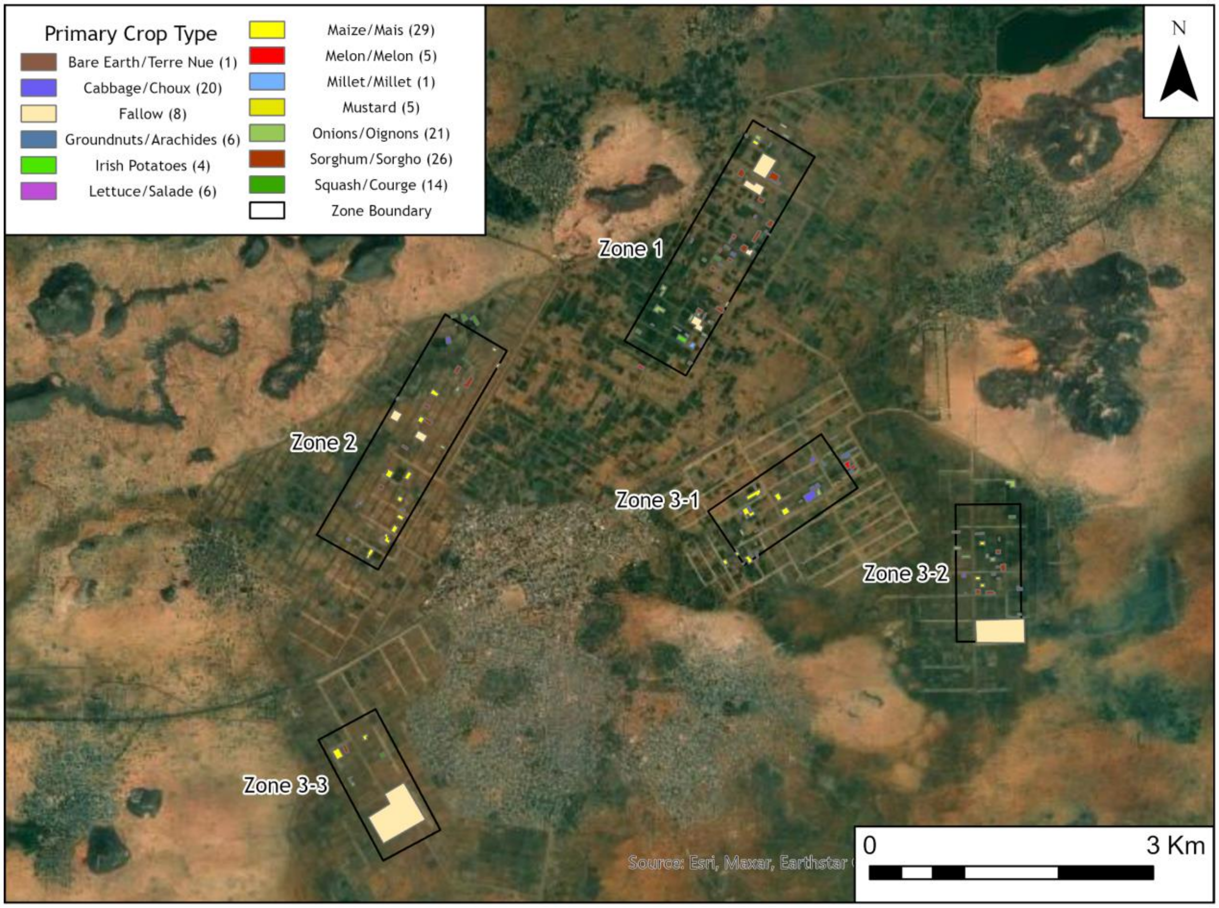
Table 5. Area of Predicted Crop Types (Konni Perimeter), Rainy Season 2024

Crop Type	Hectares	Percent Area	Model Accuracy Percent
Sorghum	1,468.94	54.26	98.08
Bare Earth	428.98	15.85	89.25
Millet	258.37	9.54	93.27
Maize	205.26	7.58	86.49
Groundnuts	145.95	5.39	88.46
Napier Grass	62.28	2.30	93.10
Cabbage	58.14	2.15	72.97
Tomatoes	41.26	1.52	72.46
Anise	10.72	0.40	65.63
African Eggplant	8.88	0.33	73.08
Squash	7.86	0.29	69.39
Okra	5.57	0.21	58.33
Natural Veg	1.91	0.07	58.33
Sweet Potato	1.56	0.06	87.50
Cowpeas	0.63	0.02	83.33
Bell Peppers	0.45	0.02	60.00
Lettuce	0.23	0.01	33.33

4.5 2025 Dry Season

For the 2025 dry season, we followed the same method we used for the creation of the 2024 rainy season crop labels, which was to use the oblique drone imagery in conjunction with the vertical imagery. The distribution of the labeled fields is shown in **Figure 18**. There were more fields under cultivation during the 2025 dry season as compared to the 2024 dry season. The presence of water in many of the irrigation canals suggests that either (1) water was flowing from the main irrigation canal, or (2) it had recently rained. Water availability is likely the reason for the noticeably increased cultivation.

Figure 18. Number of Fields Labeled by Crop Type, Dry Season



We used these crop labels to create a dry season model and produce a predictive surface (**Figure 19**). It is immediately evident that there was still a large area within the irrigation perimeter that was left fallow, but there were also many plots growing sorghum and maize. The overall model accuracy was excellent at 95% (Appendix A.4). This number was driven by the large number of bare earth/fallow, sorghum, and maize labels. For the cereal crops, sorghum (94%), maize (93%), and millet (63%) were predicted with high accuracy. Millet is lower because of the low number of training labels. For the non-cereal crops, the model performed very well for onions (88%), cabbage (76%), groundnuts (89%), and squash (97%).

Figure 19. Predicted Crop Types, Dry Season 2025

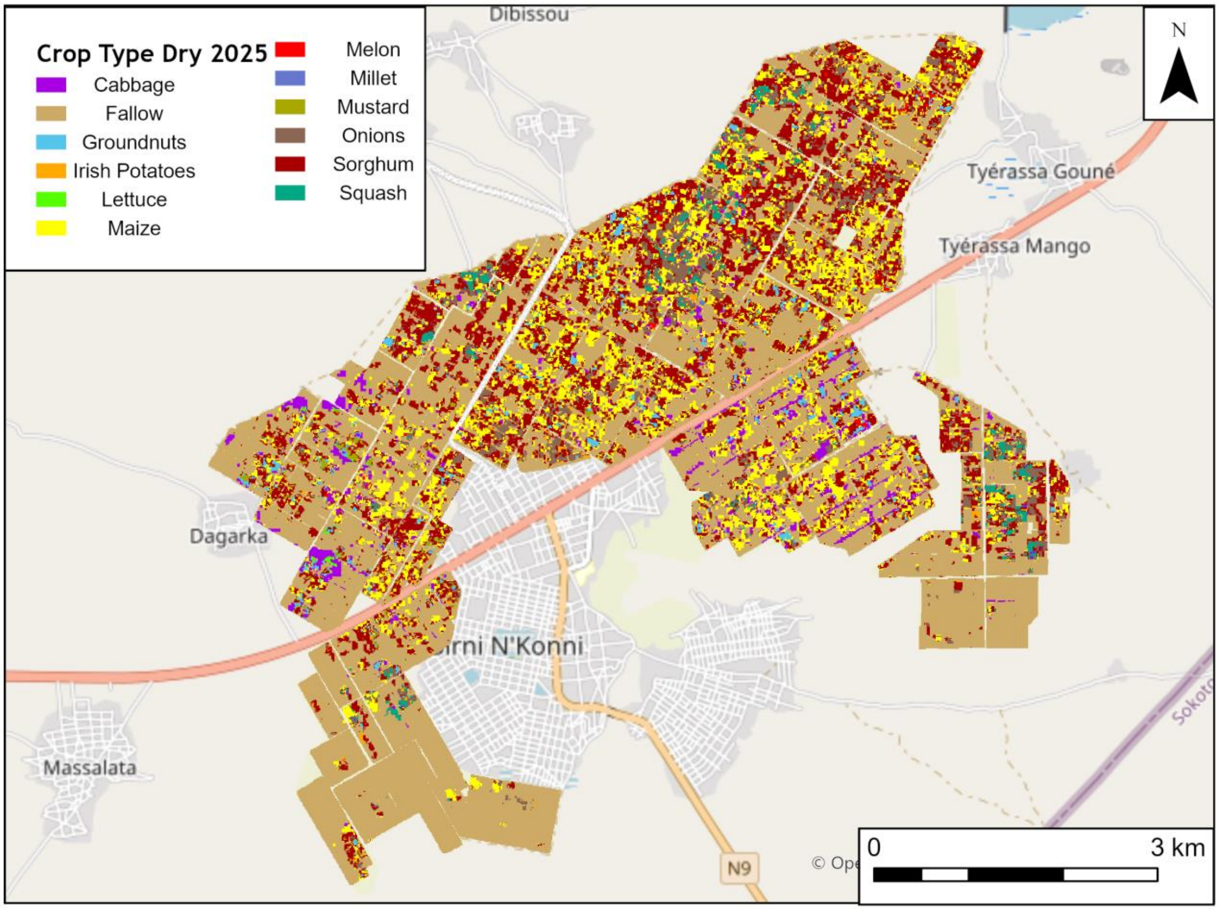


Table 6 shows the number of hectares and the corresponding percent of the study area predicted for each of the crops for which we trained the model. After sorghum and maize, we saw a small amount of onions (6%) and cabbage (3%). Though grown on small areas, it was unusual to see melons and Irish potatoes grown during the dry season in this area. These crops require significant amounts of water to grow and are not normally a dry season crop, which indicates that least some farmers are using irrigation to grow crops for additional income. Irish potatoes in particular are a high value cash crop in Niger.

Table 6. Area of Predicted Crop Types (Konni Perimeter), Dry Season 2025

Crop Type	Hectares	Percent Area	Model Accuracy Percent
Fallow/Bare Earth	1384.41	50.82	99.58
Sorghum	521.64	19.15	94.42
Maize	439.1	16.12	93.10
Onions	167.9	6.16	87.90
Cabbage	84.17	3.09	75.58
Groundnuts	49.3	1.81	88.89
Squash	33.84	1.24	97.06
Mustard	14.17	0.52	81.82
Melon	13.03	0.48	76.67
Irish Potatoes	12.27	0.45	86.21
Lettuce	2.84	0.10	60.00
Millet	1.32	0.05	62.50

4.6 Changes

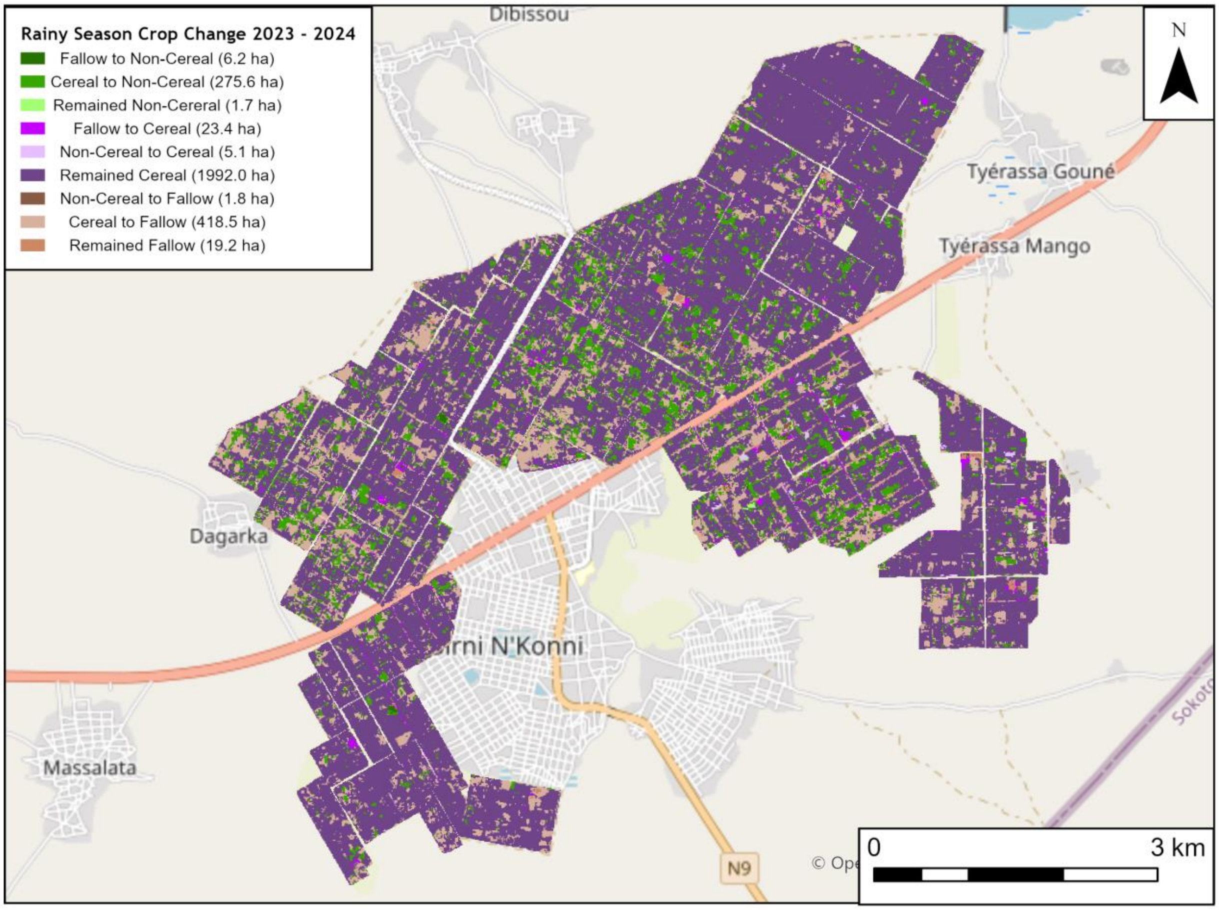
4.6.1 Rainy Season Changes

The crop types identified by the model for the 2023 and 2024 rainy growing seasons were not identical, thereby making change calculations difficult. To resolve this, and to limit the number of possible combinations, we combined crops/land covers into the following categories:

1. Fallow = fallow, bare earth, natural vegetation
2. Cereal Crops = maize, millet, sorghum
3. Non-Cereal Crops = all others

Figure 20 shows a map of the nine possible combinations. The map shows that the majority of the cultivation remained in cereal crops (dark purple) between 2023 and 2024, with some cereal crop areas being left fallow, and some cereal crops moving to non-cereal (cash) crops.

Figure 20. Cereal/Non-Cereal Crop Change, Rainy Seasons 2023–2024



Crop change category areas and percentages are presented in **Table 7**. As the map indicated, 72.61% of cultivated land remained in cereal crops between 2023 and 2024. Approximately 15% of land was left fallow in 2024 as compared with 2023, and about 10% of the 2023 cereal crop area was converted to non-cereal crops in 2024. The other types of changes amounted to only about 2% of the total area under cultivation.

Table 7. Changes in Cereal/Non-Cereal Crops, Rainy Seasons 2023–2024

Change Description	Area (ha)	Percent
Remained Cereal	1992.04	72.61
Cereal to Non-Cereal	275.55	10.04
Cereal to Fallow	418.52	15.25
Non-Cereal to Cereal	5.12	0.19
Fallow to Cereal	23.44	0.85
Fallow to Non-Cereal	6.16	0.22
Remained Fallow	19.24	0.70
Remained Non-Cereal	1.71	0.06
Non-Cereal to Fallow	1.78	0.06

To calculate the ***net*** change from 2023 to 2024 by category, we added the amount of area that was converted ***into*** each category, and subtracted the amount of area that was converted ***out of*** each category. The results of this calculation are presented in **Table 8**.

Table 8. Net Change in Cereal/Non-Cereal Crops, Rainy Seasons 2023–2024

Net Crop Category Change	Area (ha)	Change in Percentage of Total Area
Cereal	-665.51	-24.26
Non-Cereal	274.81	10.02
Fallow	390.7	14.24

Overall, there was a large decrease in cereal crops, which accounted for 97.90% of the study area during the 2023 rainy season, but only 73.64% of the study area during the 2024 rainy season. Non-cereal crops experienced a very large increase from 0.31% to 10.33% of the study area between these seasons, while the fallow area increased from about 1.77% to 16.01% of the study area. While an increase in non-cereal crops is one of MCC's goals, an increase in fallow area is not. Given that these changes are between two *specific* rainy seasons, any trends should be interpreted with caution. There may be other factors at play besides water availability.

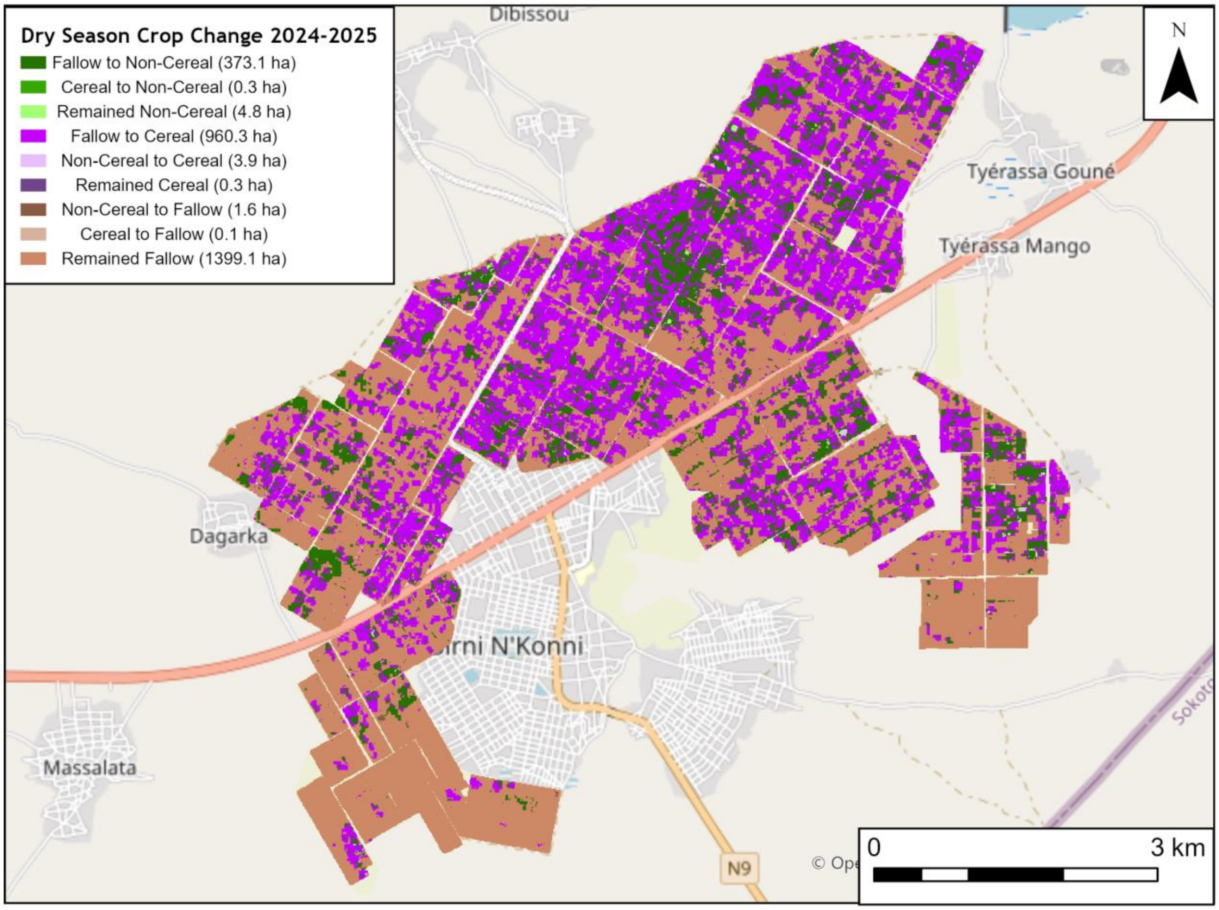
4.6.2 Dry Season Changes

The crop types identified by the model for the 2024 and 2025 dry growing seasons were also not identical, thereby again making change calculations difficult. To resolve this, and to limit the number of possible combinations, we again combined crops/land covers into the same three categories:

1. Fallow = fallow, bare earth, natural vegetation
2. Cereal Crops = maize, millet, sorghum
3. Non-Cereal Crops = all others

Figure 21 shows a map of the nine possible combinations. The map shows that most of the cultivation remained fallow (medium brown) between 2024 and 2025, with some cereal crop areas being left fallow, and some cereal crops moving to non-cereal (cash) crops.

Figure 21. Cereal/Non-Cereal Crop Change, Dry Seasons 2024–2025



Crop change category areas and percentages are presented in **Table 9**. As the map indicates, approximately 50% of cultivated land remained fallow between 2023 and 2024. This is a large decrease from the 2024 dry season when over 99% of the cultivated land was left fallow. Most of the previously fallow land was planted with cereal crops (35%), but we also note a significant increase in non-cereal crops (13.6%) as well.

Table 9. Changes in Cereal/Non-Cereal Crops, Dry Seasons 2024–2025

Change Description	Area (ha)	Percent
Remained Cereal	0.3	0.01
Cereal to Non-Cereal	0.27	0.01
Cereal to Fallow	0.13	0.00
Non-Cereal to Cereal	3.94	0.14
Fallow to Cereal	960.33	35.00
Fallow to Non-Cereal	373.12	13.60
Remained Fallow	1399.1	51.00
Remained Non-Cereal	4.8	0.17
Non-Cereal to Fallow	1.57	0.06

To calculate the ***net*** change between 2024 and 2025 by category, we added the amount of area that was converted ***into*** each category, and subtracted the amount of area that was converted ***out of*** each category. The results of this calculation are presented in **Table 10**.

Table 10. Net Change in Cereal/Non-Cereal Crops, Dry Seasons 2024–2025

Net Crop Category Change	Area (ha)	Change in Percentage of Total Area
Cereal	963.87	35.13
Non-Cereal	367.88	13.41
Fallow	-1331.75	-48.54

Overall, there were also very large shifts in land allocation between the 2024 and 2025 dry seasons. In the 2024 dry season, there did not appear to be irrigation water flowing based on drone imagery and approximately 99.60% of the study area was fallow with about 0.02% planted in cereal crops and the other 0.38% in non-cereal crops. In the 2025 dry season, when irrigation water was available, there was a huge increase in cropped area with fallow area falling to 50.82% of the study area while 35.32% of the study area was planted in cereal crops and the other 13.85% of the study area allocated to non-cereal crops. This is a marked increase in cultivation, as compared with the 2024 dry season. The 2025 drone imagery revealed much more area under cultivation and water in most of the irrigation ditches. Therefore, it is not surprising to see a dramatic decrease in fallow area. Most of the increases were seen in traditional cereal crops, rather than non-cereal crops suggesting that farmers returned to what they normally grow.

Section 5: Discussion

5. Discussion

This project produced several types of results that are worthy of discussion. Our main goal was to assess crop changes using high frequency monitoring. In addition, we wanted to know how well it augmented traditional monitoring and evaluation and to determine if our methods were sufficient to implement the augmentation. We also present lessons learned and look to modify our approach for future projects.

5.1 Crop Changes

With the delays in construction and resumption of cultivation in the Konni Irrigation Perimeter, we were only able to compare two rainy growing seasons (2023–2024) and two dry growing seasons (2024–2025). Fortunately, the construction works were provisionally accepted following the 2024 dry season, which allowed us to assess the cultivation before and after irrigation was provided. This is especially true for the dry season, when irrigation is essential.

5.1.1 Rainy Season Changes

Comparison of the rainy season crops, as combined into three categories (cereal, non-cereal, and fallow) revealed that there was a decrease in the overall share of the study area allocated to cereal crops of 24.26%. The corresponding increases were split between very large gains in fallow (+14.24% of total study area) and non-cereal crops (+10.02%). One of the impacts that MCC was anticipating as a result of increased access to irrigation is reallocation of crop mix from traditionally grown cereal crops toward non-cereal crops that require more water but that can be sold at higher market prices, thus increasing farmers' incomes. Based on our predictive crop type models, we are seeing a trend in that direction. Clearly this is a small sample size, and there are other factors that determine what a farmer decides to plant in any given growing season, but the results of this analysis indicate that provision of additional water is having a positive impact on rainy season non-cereal crop production.

5.1.2 Dry Season Changes

Comparison of the dry season crops, as combined into three categories (cereal, non-cereal, fallow) revealed that the amount of land left fallow decreased by almost 50%. The corresponding increases were split between cereal crops (+35.1% of total study area) and non-cereal crops (+13.4%). Given that most fields were either left unplanted or were abandoned in 2024, it was encouraging to see that half the irrigation perimeter was cultivated in 2025. Again, this is a small sample size but given that we saw water in the new irrigation canals, it is feasible that the availability of water during the dry season has allowed farmers to grow primarily cereal crops, but also some non-cereal (cash) crops. If this continues, and if the mix of crops shifts from cereal to non-cereal, then the impacts of the provision of additional water are in line with what MCC was expecting.

5.2 Augmentation to Traditional Monitoring and Evaluation

The remote-sensing approach discussed in this report complements more “traditional” M&E methods in several ways. This section discusses how using remote sensing at frequent intervals provides timely actionable data.

5.2.1 Triangulation

The findings of the remote-sensing approach will provide a line of sight into the empirical outcomes established by our team member Mathematica. Crop diversification measures generated using remote-sensing data will avoid social desirability bias, recall bias, and other forms of respondent-level bias that may mislead a program’s decision-makers. Analysts will use this visibility to estimate the nature and extent of the biases, enabling statistical adjustments that correct for them and thus yield more reliable estimates.

5.2.2 Reproducibility

Traditional enumerator-driven M&E methods require pairing careful instrument development with significant investments in training to achieve good inter- and intra-rater reliability.[9] The former becomes increasingly difficult as the size of the workforce scales; the latter suffers when fatigue, difficult terrain, and other environmental conditions come into play. Our approach, in contrast to traditional enumerator-driven M&E, has been shown in this study to be highly reproducible, and its performance is not typically affected by the same conditions that would affect enumerators. We were able to collect the drone data in the same way each season, and label it using the same tools with the same guidance. We were also able to write data processing scripts which provided consistent input into the crop type models. The models themselves were consistent, which allowed us to compare results from one season to the next.

5.2.3 Cost

Initial data collection

We are not able to directly compare the cost of obtaining drone data to crop type data collected by traditional enumerators since we did not produce crop labels both ways. The cost of imagery is approximately $10 per hectare, and this fell between quotes we received for comparable work in Rwanda and Zambia. These costs were reasonable and we budgeted accordingly. The imagery can be collected by a single individual, which keep costs to a minimum. Additionally, we do not have to return to the field if we need more data since we can derive additional labels from the drone imagery. However, to control costs, it is important to obtain multiple quotes when purchasing these services. We noted an uptick in costs, particularly the permits, when the coup

[9] *Inter*-rater reliability refers to the consistency between different assessors measuring the same input, often concurrently. *Intra*-rater reliability is the consistency over time of a given assessor’s repeated measures on the same input.

made it economically unfeasible for firms located outside Niger to perform the work and we had to go with a single vendor.

Data processing and analysis

The crop labeling process was computationally intensive and required a significant initial investment in building out the data cleaning and inference pipeline. However, we created reproducible processes that were applied to new datasets at significantly reduced costs. Thus, the methods and software written was used for multiple rounds of data collection. This significantly reduced processing and analytical costs and allowed us to conduct higher-frequency monitoring than would have been possible otherwise.

5.2.4 Time-to-Insight

Because of the various factors contributing to delays in this project (construction, COVID, and the military coup), we did not get to implement high frequency monitoring as often as we would have liked. However, we were able to establish our process and calculate the change between two dry seasons, and two rainy seasons. Based on the methods and software we created, we are confident that we could have modeled crop diversification on a regular six-month basis. This could have provided additional data points to program leaders and valuable complementary data to traditional M&E.

5.3 Additional Lessons Learned

While our experience in Rwanda taught us much about using drone imagery for crop identification, we also learned several things from our work in Niger. We knew that having multiple images of the same crops at different growth stages was essential to accurate crop identification. In Rwanda, we used three passes, but in Niger we found that two passes were sufficient. Not only did this reduce the cost of contracting drone imagery, but it also reduced the number of hours spent processing the imagery and reduced the storage space needed.

We also learned that the resolution of the drone imagery makes a difference. While 3 cm resolution was sufficient to identify most crops, imagery at 2 cm was noticeably better and allowed us to use leaf shape as a discriminator. We would specify 2 cm (or better) imagery in the future for all missions that require crop identification.

Another aspect of drone imagery acquisition is the scheduling of flights to capture crops at optimal points in the growing season. Scheduling the flights as far in advance as possible is very helpful, especially if the acquisition of the necessary permits from appropriate in-country aviation authorities is potentially slow. Some delays, such as weather, are impossible to predict but most can be avoided with good planning.

We envisioned using in-country personnel from the government agencies we contacted at the outset of this project to do the bulk of the crop labeling. However, expecting these staff to do the work on a volunteer basis proved to be unrealistic. We ended up hiring a trained agronomist to guide the crop labeling and providing final quality control. If we had set up this function at the outset of the project, it would have allowed us to quickly move through the drone imagery.

It became apparent that we needed a way to corroborate the crop types we were seeing in the vertical drone imagery with another form of identification. This was especially true of the cereal crops where millet, maize, and sorghum look very similar from directly above. One option we tried was using a mobile phone to capture ground images that could be viewed in the online platform Mapillary. While this platform is primarily for hosting dashcam videos, it can also be used for hosting images from someone walking along a route. This did not work very well, since only the crops in the foreground were discernible, and then only if the person was close enough. A much better solution was the inclusion of oblique drone imagery as a complement to the vertical imagery. By using these in tandem, we were able to discriminate between similar crops and greatly increase our labeling confidence.

5.4 Future Improvements

Future work of this type could benefit from additional technological and methodological improvements. The most important one is to determine if we can create accurate seasonal crop type models that span multiple years and extended geographies. We could do this by combining training data as well as satellite bands from multiple years. The model would have to be validated against ground truth data, so there would still be a need to collect some actual ground-based observations. But if the prediction accuracy is high enough, using a model to accurately predict crop types beyond a single season at a single location would save a significant amount of both time and money.

The second would be to use a sensor that captures more than just the visible spectrum. Having a sensor that also records reflected radiation in the red edge (0.68 µm–0.75 µm) and near-infrared (0.78 µm–1.4 µm) bands could help discriminate between crop types that look the same in the visible spectrum. This, and the ability to create vegetation indices such as Normalized Difference Vegetation Index (NDVI), might allow crops to be correctly identified, as well as indicate their health, which is directly related to available water.

Another improvement would be to reduce the area flown by the drone. This would reduce both costs and processing times, as well as reduce the time between imagery acquisition and model development and training. It would also reduce data storage costs since there would be less data. One caveat is that the area would still need to be representative of the study area as a whole. Careful sampling would have to be done so that all crops present are included.

A fourth improvement would be to use machine learning to create the crop type labels, which in turn would be used to train and evaluate the satellite models.[10] If a machine learning model could be trained to identify crop types on drone imagery, then a significant amount of labor could be saved. Caveats to this approach are that a large number of known examples would be needed for all crop types that exist in the study area and that these "synthetic" labels would still need to be reviewed by a trained agronomist before being released to train a satellite-based model.

[10] See Cajka et al. (2022) for additional discussion, https://cropanalytics.net/wp-content/uploads/2022/10/RTI-Rwanda-Case-Study_Final-Report_2022.pdf.

References

References

Bogner, K. & Landrock, U. (2016). *GESIS Survey Guidelines Response Biases in Standardised Surveys*. https://doi.org/10.15465/gesis-sg_en_016

Chew, R., Rineer, J., Beach, R., O'Neil, M., Ujeneza, N., Lapidus, D., Miano, T., Hegarty-Craver, M., Polly, J., & Temple, D.S. (2020). Deep neural networks and transfer learning for food crop identification in UAV images. *Drones, 4*, 7. https://doi.org/10.3390/drones4010007

Hall, O., Dahlin, S., Marstorp, H., Archila Bustos, M. F., Öborn, I., & Jirström, M. (2018). Classification of maize in complex smallholder farming systems using UAV imagery. *Drones, 2*, 22. https://doi.org/10.3390/drones2030022

Larsen, M. & Rasinski, K. (2002). The psychology of survey response by Roger Tourangeau; Lance J. Rips; Kenneth Rasinski. *Journal of the American Statistical Association, 97,* 358-359. https://doi.org/10.2307/3085796.

Appendix A – Model Metrics

A.1 Confusion Matrix Rainy 2023 Model

	Bare Earth/ Fallow	Dolique	Groundnuts	Maize	Sorghum	Total Predicted
Bare Earth/ Fallow	353	0	1	15	3	372
Dolique	0	1	0	0	0	1
Groundnuts	0	0	124	12	1	137
Maize	119	2	48	7793	238	8200
Sorghum	13	0	2	47	1686	1748
Total Actual	485	3	175	7867	1928	10458
Accuracy	0.7278	0.3333	0.7086	0.9906	0.8745	0.9521

A.2 Confusion Matrix Dry 2024 Model

	Beans	Cabbage	Cassava	Dolique	Bare Earth/ Fallow	Ground-nuts	Maize	Melon	Millet	Okra	Onions	Sorghum	Squash	Sweet Potato	Tomato	Total Predicted
Beans	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Cabbage	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	2
Cassava	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	2
Dolique	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bare Earth/ Fallow	1	1	2	0	3767	0	1	2	0	1	11	2	10	9	1	3808
Groundnuts	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	2
Maize	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Melon	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Millet	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
Okra	0	0	0	0	0	0	0	0	0	10	0	0	0	0	0	10
Onions	0	0	1	0	0	0	0	0	0	0	13	0	0	0	1	15
Sorghum	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	7
Squash	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	6
Sweet Potato	0	0	0	0	0	0	0	0	0	0	0	0	1	8	0	9
Tomato	0	0	0	0	0	0	0	0	0	0	0	0	1	0	16	17
Total Actual	2	3	5	0	3767	2	1	2	1	11	24	9	18	17	18	3880
Accuracy	0.5000	0.6667	0.4000	0.0000	1.0000	1.0000	0.0000	0.0000	1.0000	0.9091	0.5417	0.7778	0.3333	0.4706	0.8889	0.9884

A.3 Confusion Matrix Rainy 2024 Model

	African Eggplant	Anise	Bare Earth/ Fallow	Bell Peppers	Cabbage	Cow-peas	Ground-nuts	Lettuce	Maize	Millet	Napier Grass	Natural Veg	Okra	Sorghum	Squash	Sweet Potato	Tomato	Total Predicted
African Eggplant	19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19
Anise	1	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	23
Bare Earth/ Fallow	0	5	332	1	4	0	7	0	3	0	1	0	1	5	5	0	3	367
Bell Peppers	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	3
Cabbage	0	0	2	0	54	0	0	0	1	0	0	0	0	0	1	0	1	59
Cowpeas	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	5
Groundnuts	0	3	6	0	4	0	138	0	0	0	1	0	1	2	3	0	4	162
Lettuce	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
Maize	0	0	4	0	2	0	0	0	160	2	1	1	2	4	0	0	2	178
Millet	0	0	3	0	0	0	3	0	3	291	0	2	0	9	0	0	0	311
Napier Grass	0	0	0	0	0	0	0	0	1	0	54	0	0	0	0	0	1	56
Natural Veg	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	7
Okra	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	9
Sorghum	6	3	25	1	7	1	8	2	16	17	1	2	6	1124	5	1	7	1232
Squash	0	0	0	0	1	0	0	0	0	1	0	0	0	1	34	0	0	37
Sweet Potato	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	7
Tomato	0	0	0	0	2	0	0	0	1	1	0	0	0	1	1	0	50	56
Total Actual	26	32	372	5	74	6	156	3	185	312	58	12	19	1146	49	8	69	2532
Accuracy	0.7308	0.6563	0.8925	0.6000	0.7297	0.8333	0.8846	0.3333	0.8649	0.9327	0.9310	0.5833	0.5833	0.9808	0.6939	0.8750	0.7246	0.9119

A.4 Confusion Matrix Dry 2025 Model

	Labeled												
	Cabbage	Bare Earth/ Fallow	Ground-nuts	Irish Potatoes	Lettuce	Maize	Melon	Millet	Mustard	Onions	Sorghum	Squash	Total Predicted
Cabbage	65	0	1	0	0	1	1	0	0	1	1	0	70
Bare Earth/ Fallow	5	1172	0	0	0	8	1	2	0	2	1	0	1191
Groundnuts	0	0	24	0	0	0	1	0	0	0	0	0	25
Irish Potatoes	0	0	0	25	0	0	0	0	0	0	0	0	25
Lettuce	0	0	0	0	3	0	0	0	0	0	0	0	3
Maize	6	2	0	0	0	243	2	1	1	5	3	1	264
Melon	0	0	1	0	0	0	23	0	0	0	0	0	24
Millet	0	0	0	0	0	0	0	5	0	0	0	0	5
Mustard	1	0	0	0	0	0	0	0	9	0	0	0	10
Onions	7	1	0	0	0	0	0	0	0	109	4	0	121
Sorghum	1	2	1	1	2	9	1	0	0	4	203	1	225
Squash	1	0	0	3	0	0	1	0	1	3	3	66	78
Total Actual	86	1177	27	29	5	261	30	8	11	124	215	68	2041
Accuracy	0.7558	0.9958	0.8889	0.8621	0.6000	0.9310	0.7667	0.6250	0.8182	0.8790	0.9442	0.9706	0.9539