A Practical Exploration in Classifying High-Resolution Multispectral Images of Coffee Agroecosystems in Puerto Rico

by

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Abstract:

Highly diverse agroecosystems are becoming increasingly of interest to researchers and government organizations as more light is shed on the invaluable ecosystem services that these farms support. Accompanying the increased agroecosystem research is an increased use of uncrewed aerial systems (UAS) in remote sensing research. UAS allow for finer spatial resolution imagery, and they also have the capacity to revisit sites faster than traditional satellites. With the combined utility of UAS and interest in diverse agroecosystems, there exists an opportunity to meld fields of study and understand the practicality of UAS in highly biodiverse settings.

In this study, we utilized UAS to collect fine-resolution 10-band multispectral imagery of coffee agroecosystems in Puerto Rico. We then used the imagery to create a pixel-based supervised classification of each farm. After classifications were completed, accuracy assessments were performed. The average overall accuracy (53.9%), while relatively low, was expected for such a diverse landscape with such fine-resolution data, and does not eliminate the utility of the land-cover classifications for certain actors. Furthermore, in order to evaluate the land cover classifications, we conducted interviews with farmers to understand their thoughts on how these maps may be best used to support their land management. We shared printouts of the multispectral imagery and the land cover classifications with land managers and found that while the imagery and maps may have been a point of pride or curiosity for farmers, using the maps as part of farm management was perceived as inapplicable currently. These findings highlight that while remote sensing of diverse agroecosystems may provide a quick way of estimating land cover classes (and subsequent ecosystem services), these maps may only be of use to those who do not regularly work in these environments.

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Introduction:

Unlike the highly input-dependent monocultures that make up the largest part of the food production system (Foley et al., 2011), diversified agroecosystems are increasingly touted as invaluable systems against climate change. Agroecosystems, in the context of this study, have the capacity to maintain ecosystem services, biodiversity, and farmer livelihoods indicating that the highly diverse farms of this paper are part of more sustainable practices (Iverson et al., 2019; Mayorga et al., 2022; Saj et al., 2017). Coffee agroecosystems are ecologically, economically, and politically significant to the neotropics (Perfecto & Armbrecht, 2003). Ecologically, coffee is significant because of the species richness it has the potential to promote. While there exists a gradient from which coffee is grown, ranging from unshaded monocultures to shaded polycultures and agroforestry systems, many coffee farms in the neotropics promote biodiversity by planting coffee in the shade of overstory vegetation. This overstory vegetation and other cultivated plants intercropped with coffee can provide habitat for wild flora and fauna and regulate ecosystem services necessary for other plant life (Jha et al., 2014; Moguel & Toledo, 1999; Perfecto et al., 1996). Economically, roughly a third of the world's coffee production takes place in Latin America (ITC [International Trade Center], 2011; Rice, 1999). Because of the significant economic impact that coffee exports have on the neotropics, government policy has frequently encouraged high-intensity production at the expense of more ecologically sound agroecosystems (Borkhataria et al., 2012).

Because of the significance coffee agroecosystems carry, there are increased efforts to study and understand the heterogeneity of farms that have traditionally been classified as forested (Helmer et al., 2002). The task of understanding coffee agroecosystems becomes especially important in the context of Puerto Rico post-Hurricane Maria. Hurricane Maria highlighted the lack of knowledge about food production in Puerto Rico. When it made landfall in Puerto Rico as a Category 4 hurricane, flooding, landslides, and overall damage were prevalent in the coffee-growing mountainous region of Puerto Rico (National Weather Service & National Oceanic and Atmospheric Administration, 2017). Understanding the resistance and resilience of coffee agroecosystems to such catastrophic events requires an understanding of the land change that occurred due to the natural disaster (Perfecto et al., 2019).

Foundational to understanding land change post-climatic disaster is having accurate land cover classifications maps before and after such events. The advent of uncrewed aircrafts (UA), or drones, means that remote sensing imagery can be captured with a much finer spatial resolution, well under a meter resolution and often on the order of tens of centimeters (Jay et al., 2019), than that of traditionally used satellites like Sentinel-2A MSI and Landsat 8 OLI, which have resolutions of 10-20 meters and 30 meters per pixel respectively (Cerasoli et al., 2018). In addition to the increased spatial resolution, drones do not have defined return times and can be employed whenever desired, as well as move across the terrain and around many obstacles. The flexibility and increased spatial resolution of drones mean that UAs have the potential to create vastly more accurate land cover classifications.

While the use of auxiliary data and finer-resolution data may aid in improving classification accuracies, in some cases these classifications only benefit researchers and other outside actors, who hold implicit biases about the land that they are studying (Laso & Arce-Nazario, 2023). In order to derive practical tools and analyses from classifications, it is necessary that farmers be included in the mapping and classification of their land. This becomes especially important in such diversified systems, as more nuance can exist in what does and does not constitute a “crop”. In mapping with farmers, we also affirm that our work is done in collaboration with the land stewards of what we map (Laso & Arce-Nazario, 2023). Working in partnership with farmers does lend itself to the potential of misestimating the amount of a certain land cover class in favor of another due to different actors placing significance on certain land cover types. However, to a large extent, this is considered to be outweighed in terms of the benefits of including farmers in the mapping process (Laso & Arce-Nazario, 2023).

This thesis was written with the intention of adding more information to the growing literature on the classification of diversified coffee agroecosystems, with an emphasis on the utility of UA and farmer participation in this effort. Our goals were to quantify the accuracy of classifications performed on fine-resolution multispectral data and to explore how speaking with farmers may change the methods or results in which classification occurred initially. It is our hope that should similar research continue, farmer involvement will happen at an earlier stage, and more often so that a better knowledge exchange can occur.

Methods:

Study area:

Our study took place in the coffee-growing mountainous areas of central-Western Puerto Rico. More specifically, farms were surveyed in Utuado, Adjuntas, Jayuya, and Yauco (see **Figure 1)**. Farms in these regions experienced normal, between 177-229 cm of annual rainfall (National Weather Service, n.d.) and are classified as submontane and lower montane wet forests (Helmer et al., 2002). Soils present in the coffee-growing region include ultisols, inceptisols, and oxisols (Alvarez-Torres, 2020). Farms surveyed were a part of long-withstanding coffee agroecosystem research in the region and spanned across a gradient of coffee production intensification (Moguel & Toledo, 1999). Other commonly found crops in these diverse agroecosystems include citrus trees, bananas, and plantains. The farms surveyed had an average slope of 15.4 degrees. Farms ranged from 0.8-56.7 hectares in size. More information can be found in **Table 1.**

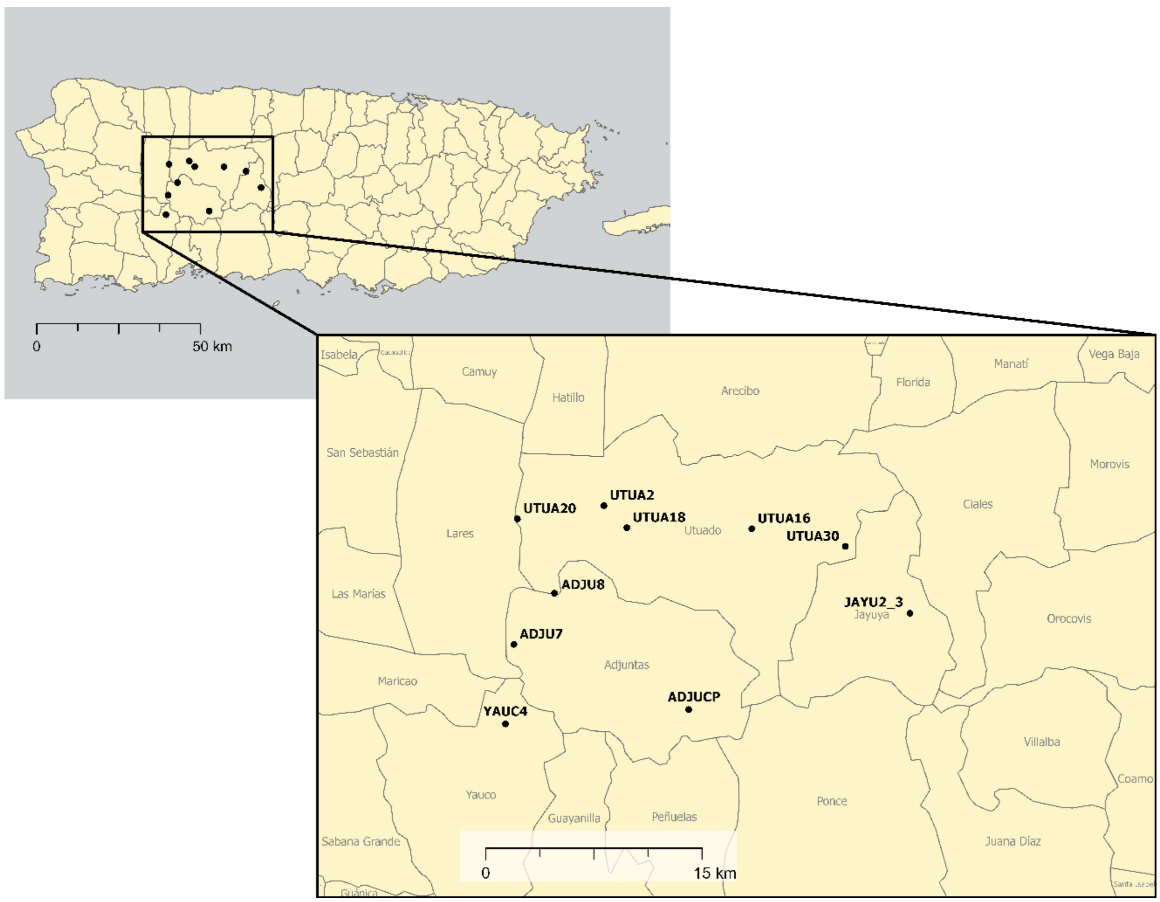


Figure 1. Study sites within the central-Western coffee growing region of Puerto Rico. Municipalities layer from UN Office for the Coordination of Humanitarian Affairs. The figure is projected to "StatePlane Puerto Rico Virgin Isl FIPS 5200 (Meters)," a version of the Lambert conformal conic projection, and has a datum of NAD 1983.

Table 1. Information on farm size, aspect, slope, and classification based on Moguel and Toledo's (1999) coffee growing gradient.

Farm	Size (ha)	Aspect	Median Slope (°)	Classification
UTUA2	1.64	West-facing	7	Commercial polyculture
UTUA16	0.96	South-facing	12	Traditional polyculture
UTUA18	2.13	East-facing	16	Traditional polyculture
UTUA20	1.63	South-facing	18	Commercial polyculture
UTUA30	0.82	West-facing	25	Traditional polyculture
YAUC4	2.47	North-facing	12	Traditional polyculture
ADJUCP	3.45	North-facing	12	Commercial polyculture
ADJU8	41.97	East-facing	16	Shaded monoculture
JAYU2_3	56.05	South-facing	17	Shaded monoculture

Uncrewed aircraft (UA) flights occurred in 2021, 2022, and 2023 to collect LiDAR (Light Detection and Ranging) and 10-band multispectral imagery. Before 2021, numerous preliminary data-gathering missions occurred with the use of fixed-wing and multirotor UA. Ground data collection, which includes the GPS and plant characteristic data, occurred in 2021, 2022, and 2023. Interviews with farmers were conducted in May of 2023 and were subject to review and approval by the Institutional Review Board (IRB) of the University of Michigan.

Ground data collection:

Ground data collection was conducted over the course of multiple field campaigns and had multifaceted goals each year. Depending on the field campaign, either ESRI Collector or ESRI Field Maps was used to capture data. The preferred data capture software was linked to an external GPS receiver. In earlier campaigns, the Trimble R1 Catalyst was used, and in later campaigns, a BadElf Flex was used. Both of these external GPS receivers were placed on a 2-meter tall survey pole in order to ensure an appropriate satellite connection. Both external receivers increased GPS accuracy (as compared to integrated GPS in the smartphones used to capture data), but steep topography meant that strong connections to satellites were not always met, resulting in decreased GPS accuracy. The Trimble R1 Receiver typically receives submeter accuracy (Trimble R1 GNSS Receiver, n.d.), whereas the Bad Elf Flex receives 30-60cm accuracy on average (Bad Elf, n.d.). Because of the steep topography, typically accuracies of below 1 meter were accepted. On very few occasions, accuracies were accepted at around 1.5 meters if a given surveyor had waited five minutes with no increase in accuracy.

At a given crop or plant of interest, the survey pole with attached external GPS was placed as close to the base of the plant as possible. Using a smartphone and either ESRI's Field Maps or Collector, a GPS point was recorded. The data capture software recorded various information for each GPS point. If the plant of interest was coffee, information on the coffee leaf rust (CLR) and leaf miner level was recorded. Other information collected included the plant type, specific plant species if relevant, farm code, percent of plant covered by vines, notes about the surrounding canopy, date and time of point collection, and a photo of the plant or surroundings if desired. Information collected on CLR, leaf miner levels, and vine coverage by plants was retained for other studies.

Multispectral and LiDAR data collection with Uncrewed Aircraft Systems (UAS):

UAS work and subsequent methods documentation were done by Embry-Riddle Aeronautical University in accordance with Federal Aviation Administration's (FAA) 14 CFR Part 107 regulations. Highly variable topography within the coffee-growing region of Puerto Rico required significant mission and flight planning in order to collect quality multispectral and LiDAR data. Mission planning was completed prior to arrival in Puerto Rico, and included tasks such as identifying appropriate equipment and sensors for the specific terrain and creating standardized procedures. Google Earth Pro was first utilized to identify farm boundaries and areas within farms that may be of special interest. In addition, Google Earth Pro was used to identify potential divisions for farms that were too large to be imaged with a single drone flight.

Based on the results of the Google Earth Pro exploratory analysis, a fixed-wing UA or multirotor UA was selected for a given farm for preliminary data-gathering operations. After the 2020 data-gather missions, it was decided that fixed-wing UA was no longer a viable option, and all later missions utilized multirotor UAS. This is predominantly because multirotor UAs are able to recover vertically, navigate smaller volumes of air, adapt to changing terrain, hold heavier payloads, and fly discontinuously. The use of multirotor UA in instances of abrupt topography change ensured that acceptable ground sampling distances were maintained.

A DJI Inspire 2 was outfitted with a multispectral imaging sensor and a DJI Matrice 600 UA was outfitted with a LiDAR sensor. Multispectral imaging for relevant field campaigns was done using a MicaSense RedEdge-MX Dual Camera Imaging System, which included 10 synchronized bands that spectrally overlapped with Sentinel-2A MSI and Landsat 8 OLI imagery (detailed in **Table 2**). In addition to the multispectral sensor, a downwelling light sensor aided in radiometrically calibrating images. Infrared radiation was pulsed and gathered subsequent returns of up to 400 points per meter from on-the-ground objects and terrain. Three integrated global navigation satellite system (GNSS) receivers, an inertial measurement unit (IMU), and internal sequencing and intensity combined to assign each return a specific XYZ location, scan angle, and calibration value. Returns were then processed to create a dense point cloud.

Table 2. Spectral band information for the MicaSense RedEdge-MX Dual Camera Imaging System as compared to Sentinel-2A MSI and Landsat 8 OLI

Sentinel-2A MSI		Landsat 8 OLI		MicaSense RedEdge-MX Dual Camera Imaging System	
Spectral Region	Wavelength range (nm)	Spectral Region	Wavelength range (nm)	Spectral Region	Wavelength range (nm)
Blue	458–523	Blue	435–451	Blue	430-458
Green peak	543–578	Blue	452–512	Blue	459-491
Red	650–680	Green	533–590	Green	524-538
Red edge	698–713	Red	636–673	Green	546.5-573.5
Red edge	733–748	NIR	851–879	Red	642-658
Red edge	773–793	SWIR1	1566–1651	Red	661-675
NIR	785–899	SWIR2	2107–2294	Red Edge	700-719
NIR narrow	855–875			Red Edge	711-723
SWIR	1565–1655			Red Edge	731-749
SWIR	2100–2280			NIR	814.5-870.5

Flight planning, unlike mission planning, occurred on site. Upon arrival at a given farm, a temporary shelter was established with a generator and charging station. A site survey was completed by considering persons and property, airspace restrictions, local weather conditions, topography, and any obstructions. Site surveys were especially interested in the specification of the minimum safe altitude (MSA) for each flight, or the lowest altitude the UA can fly without encountering any obstructions.

After establishing the temporary shelter, a waypoint-defined flight plan was created in DJI Ground Station Pro on a mobile tablet. The size of the farm, data needs, and underlying surface were considered in determining whether a single or double grid (cross-hatch) flight pattern was flown (**Figure 2**).

Figure 2. Depiction of a single and double grid flight plane (PIX4D, 2019).

Flight plans also took into consideration the speed, altitude, direction, launch, recovery, and line of sight of the UA. In addition, flight planning included the appropriate emergency action should a lost link action occur. Emergency planning included a return-to-home altitude and approach profile. In all emergency and general flight plans, extra consideration was given to altitude given the steep topography and the effect the altitude had on data quality. When possible, flight plans were reused across farms assuming that no new obstructions were present. Lastly, flight plans were created alongside flight schedules. Schedules ensured that proper image-capturing thresholds were met. For instance, multispectral imaging is sensitive to sun angle and therefore occurred as close to solar noon as possible.

Prior to farm classifications, basic image processing was done in Agisoft Metashape in order to create a georeferenced orthomosaic (*MicaSense RedEdge MX Processing Workflow [Including Reflectance Calibration] in Agisoft Metashape Professional*, n.d.). The default processing was done utilizing the GPS data generated by the UAS and MicaSense dual camera data capturing process, with no additional manual ground control point input. Reflectance calibration was performed, but no reflectance normalization was performed across flights or farms.

Classifications:

It was decided that in order to produce the most current classification, only 2022 images would be utilized. These images were the most recent imagery pre-processed in time to interview farmers in 2023. In order to run comprehensive, farm-level classifications, it was determined that for farms that had multiple multispectral images (UA flights), the various images should be mosaiced to create one image per farm. All individual images for a given flight were loaded into ERDAS IMAGINE. Using the MosaicPro tool, each image was loaded into the view, with an "overlay" overlap function specified. Seamlines were created using the default "optimal seamline" generation option. After, color corrections were set to "histogram matching". The tool was run and the resulting mosaicked image was saved. In order to run classifications without error, ERDAS IMAGINE's spatial model editor was used to change "NODATA" values to "0".

Pixel-based supervised classifications were run in ArcGIS Pro 3.1. In addition, one farm (UTUA18) was classified twice, once using the default pixel-based classification, and then again using object-based classification. The intention in creating a single object-based classification was to quickly evaluate if an object-based classification varied significantly from the pixel-based classification. After loading in the mosaicked farm image, the ground control points (GCPs) from three field campaigns were also layered on top. A classification schema was created to encompass relevant crops and land cover types. This schema included the following ten classes: coffee, citrus, banana, palms, low herbaceous vegetation/grass, bare earth, pavement, buildings, water, and overstory vegetation. These ten classes were selected because researchers familiar with the farms indicated that these were the dominant land cover types across farms. For each class, training site polygons were drawn using GCPs as a reference. For instance, if creating a training site for coffee, a polygon was drawn around whichever coffee plant(s) a GCP identified as coffee. For farms that may be larger, significant areas of land would have no GCPs. In order to create representative training sites across the entirety of a farm, polygons were drawn in areas without GCPs that were visually confirmed to match plants with associated GCPs. Prior to running the object-based classification on UTUA18, segmentation was completed. For more information regarding the number of training sites and pixels for each class for each farm, see **Tables 6-9**. After creating ample training sites for each class within each farm, a support vector machine (SVM) classifier was run on the entirety of the farm. SVM classifiers assume no assumptions are made about the data distribution (Mountrakis et al., 2011). The selection of an SVM classifier was done with the understanding that many farms would have limited training classes for a given class and that SVM is built to be less susceptible to an imbalance in training samples (*Train Support Vector Machine Classifier (Spatial Analyst)—ArcGIS Pro | Documentation*, n.d.).

For some farms, the classification was slightly misaligned with the farm boundary. In order to remedy this, a clip was run to trim the classification down to the farm boundary. After classifications were completed, accuracy assessments were run. In order to create testing sites to check for accuracy, the same process for creating training sites was followed. For each farm, roughly the same number of testing sites and training sites were created for a given class. As much as possible, testing sites did not overlap with previously created training sites, with a few exceptions. For instance, farms with water bodies typically only had one small pond. A training site was created for that land cover classification, and a testing site was typically made on the same body of water. Testing sites were used as reference data for the accuracy assessments, which were then run.

After running the initial classifications, principal component analyses (PCAs) were run for each farm as a means of obtaining more relevant spectral information. The PCAs were generated in Erdas Imagine and 10 principal components were selected as the output. A second round of land cover classifications was conducted on farms UTUA2, UTUA16, UTUA18, AND UTUA20 utilizing all 10 principal components of the previously created PCAs. In all iterations of classifications, the same training and testing sites were utilized. A third iteration of classifications was conducted on farms UTUA2, UTUA16, and UTUA18 using a layer stack of the multispectral imagery bands 5, 6, and 7 layered with principal components 1, 2, and 3. Similarly, on farm UTUA20, a classification was conducted utilizing a layer stack of multispectral imagery bands 5, 6, 7, and 8 layered with principal components 1, 2, and 3. Two additional classifications were performed on farm UTUA2, including a layer stack of multispectral bands 5-10 and principal components 1 and 2, and multispectral bands

5-7 layered with principal components 1-3 and a previously created NDVI. These iterations are listed in **Table 3.**

Table 3. Improved classification iterations applied on 2022 farm imagery

Iteration name	Multispectral bands	Principal components	Other layers	Farms layer stack was performed on
Iteration A	1-10	—	—	UTUA2, UTUA16, UTUA18, UTUA20, UTUA30, YAUC4, ADJU8, JAYU2
Iteration B	—	1-10	—	UTUA2, UTUA16, UTUA18, UTUA20
Iteration C	5-7	1-3	—	UTUA2, UTUA16, UTUA18
Iteration D	5-8	1-3	—	UTUA20
Iteration E	5-10	1, 2	—	UTUA2
Iteration F	5-7	1-3	NDVI	UTUA2

<u>Interviews:</u>

After each initial classification was run, posters of each farm's multispectral imagery and classifications were created in ArcGIS Pro 3.1. These posters were then printed on 32” x 40” matte paper. In the 2023 field campaigns, at each farm, a semi-structured interview was conducted with farmers, land managers, and owners, with references made to the multispectral imagery and the classifications. (See **Appendix A** for more information on the interview script.) These interviews were done with the intention of better understanding land use history, farmers' spatial relationships with their farms, and how remote sensing or land cover classifications may improve the management or understanding of such complex agroecosystems. Interviews were conducted onsite at farms, or at homes on farm property with teams of 2-3 researchers. Interviewees were asked if they consented to both the interview itself, as well as being recorded during the interview using an audio recorder.

Our interviews were based on the assumption that we would be referencing the printed orthomosaics and classifications, but many interviews included walking areas of the farm with farmers as they pointed out specific crops or landmarks. Interview length varied greatly, with some interviews under an hour and others over two and a half hours. This length variation is primarily because interviews were farmer guided, with respondents addressing topics they felt relevant. After a series of questions that were intended to orient researchers to the specifics of a given farm, the multispectral image was shown to the farmers. This was intended to show the farmers what the UA had collected, as well as compile any preliminary thoughts the farmers had on the UA itself. In earlier interviews, tracing paper was laid on top of the multispectral image and farmers were encouraged to annotate any areas they felt important or of general interest. This was later removed as part of the interview process, as farmers were often more comfortable speaking generally about the land. After viewing the multispectral image, the classification image was brought out, and farmers were asked questions about the utility of the classification in their management. Viewing the classification map was largely considered to be the conclusion of the interview, and farmers were asked if they had any questions for the researchers. Both the multispectral imagery and the classification maps were left with interviewees at the conclusion of the discussions.

After the interviews were completed, they were uploaded into transcription software and transcribed in Spanish. Researchers then translated the transcriptions from Spanish to English, making corrections to the transcriptions where the software failed to capture any regional language differences or language not otherwise captured. A content analysis was run on the interviews, which included coding each interview transcript individually, as well as synthesizing notes from interviews that were not recorded. In order to conduct an effective content analysis, each theme was clearly defined by researchers. Examples or quotes from interviews were highlighted and sorted into relevant themes. Each example was again reviewed by researchers to ensure that a given example fit into the theme it was assigned to. Each theme was linked to a more generalized research finding from the interviews, and the relevancy of each theme to the project at large was defined. Results were then summarized and put into a content matrix.

Results:

Ground data and image capturing:

The results of drone flights for 2022 were largely successful. 10 farms were surveyed with both LiDAR and multispectral imagery. **Table 4** details the number of flights flown per farm. Of these 10 farms, all but two (ADJUCP and ADJU7) were classified. ADJUCP was not classified as we were unsure if an interview would occur with land managers, and ADJU7 was not classified as large amounts of water were highly reflective and changed the color balance of the farm mosaic.

Table 4. The number of flights flown for each farm in the 2022 field campaign.

Farms	Number of flights
UTUA2	1
UTUA16	1
UTUA18	1
UTUA20	1
UTUA30	2
YAUC4	1
ADJUCP	2
ADJU7	3
ADJU8	7
JAYU2_3	8

The results of the ground data field campaigns are listed in **Table 5.** In 2021, time constraints meant that ground control points were not able to be taken in UTUA16. In 2023, GPS errors on farms UTUA30 and ADJU8 were unable to be resolved in a timely manner, therefore little to no GPS ground truths were collected. Additionally in 2023, no points were collected in YAUC4 due to a thunderstorm that made it unsafe for researchers to conduct ground research. The most points taken occurred in farm JAYU2_3 in 2021. UTUA2 had the most points taken throughout the field campaigns, seemingly because of its proximity to researcher housing.

Table 5. Ground control points collected by year.

	Year			
Farm	**2021**	**2022**	**2023**	**TOTAL**
UTUA2	69	112	73	254
UTUA16	-	20	52	72
UTUA18	41	32	21	94
UTUA20	49	41	31	121
UTUA30	51	24	-	75
YAUC4	51	28	-	79
ADJU8	63	44	1	108
JAYU2_3	140	63	30	233
TOTAL	464	364	208	1036

Classifications and accuracy assessments:

As part of the classification workflow, training and testing sites were generated for each farm. These are detailed in **Tables 6-9.** "UTUA18_obj" refers to the one object-based classification done on farm UTUA18. For this farm, different training sites were selected between classification methods, but the testing site remained consistent between classifications. Both training and testing sites are quantified in two forms: polygons and pixels. Polygons designates the number of sites drawn, and pixels refer to the total number of pixels across all polygons.

Table 6. Number of training sites for each class in each farm. Each site is a polygon drawn around one representative site.

Farm	sites/polygons										
	coffee	citrus	banana	palm	grasses/low herb	bare earth	paved	buildings	water	overstory veg	total
UTUA2	16	9	3	3	6	6	2	4	0	1	50
UTUA16	3	0	2	5	1	1	1	2	1	2	18
UTUA18	0	0	4	0	3	3	2	2	0	3	17
UTUA18_obj	6	0	2	0	2	3	3	3	0	2	21
UTUA20	4	7	4	0	2	4	2	3	0	2	28
UTUA30	10	0	8	0	2	4	4	4	0	4	36
YAUC4	9	0	6	0	8	5	4	3	0	3	38
ADJU8	14	0	14	0	10	10	3	6	2	7	66
JAYU2_3	22	0	14	11	10	12	7	10	2	11	99

Table 7. Number of pixels in training sites per class in each farm classification.

Farm	pixels										
	coffee	citrus	banana	palm	grasses/ low herb	bare earth	paved	buildings	water	overstory veg	total
UTUA2	15420	89118	17989	148768	60581	47051	20753	185462	0	130191	715333
UTUA16	22218	0	219318	164487	46675	13170	4615	85679	26321	448878	1031361
UTUA18	0	0	29439	0	21740	113898	8102	54437	0	246623	474239
UTUA18_obj	19621	0	14374	0	52909	161456	18481	60649	0	427093	754583
UTUA20	4467	24900	218041	0	28145	20922	13867	176316	0	346139	832797
UTUA30	9420	0	45587	0	37646	18861	23754	55815	0	1339405	1530488
YAUC4	13393	0	74659	0	63188	49843	107538	142527	0	983011	1434159
ADJU8	36804	0	10892	0	96113	48835	23161	99930	45674	424707	786116
JAYU2_3	60510	0	42551	47663	361668	163092	57446	142129	10865	635097	1521021

Table 8. Number of testing sites per class for each farm. Each site is a polygon drawn around one representative site.

Farm	**sites/polygons**										
	coffee	citrus	banana	palm	grasses/low herb	bare earth	paved	buildings	water	overstory veg	totals
UTUA2	9	4	4	3	5	5	3	3	0	2	38
UTUA16	0	0	3	3	2	3	2	2	1	2	18
UTUA18	7	1	3	0	4	9	5	5	0	4	38
UTUA18_obj	7	1	3	0	4	9	5	5	0	4	38
UTUA20	6	0	4	1	3	9	5	5	0	3	36
UTUA30	11	0	4	2	3	3	4	3	0	2	32
YAUC4	11	0	5	3	6	7	3	2	0	3	40
ADJU8	16	0	13	0	10	10	3	3	2	4	61
JAYU2_3	22	0	15	4	12	12	7	4	1	5	82

Table 9. Number of pixels in testing sites per class for each farm.

Farm	**pixels**										
	coffee	citrus	banana	palm	grasses/low herb	bare earth	paved	buildings	water	overstory veg	totals
UTUA2	3810	17091	18297	80214	54190	10729	38281	125668	0	203356	551636
UTUA16	0	0	7781	61145	41312	9343	9845	11010	37650	233632	411718
UTUA18	2493	4121	59215	0	28739	22514	32468	80595	0	260498	490643
UTUA18_obj	2493	4121	59215	0	28739	22514	32468	80595	0	260498	490643
UTUA20	2793	0	21690	24840	9667	23540	6096	99500	0	239493	427619
UTUA30	2483	0	2546	38088	35111	22465	22665	31082	0	137590	292030
YAUC4	7746	0	34838	79386	10584	52144	24292	5484	0	367339	581813
ADJU8	18869	0	43640	0	49656	69418	14798	51844	56798	306815	611838
JAYU2_3	14095	0	41412	28680	51561	35116	33236	337495	16366	296676	854637

The following figures **(Figures 3-11)** are the results of classifications on all farms. Scales of farms vary widely, as do classes present across farms. Legends present in map layouts indicate which of the ten potential farm classes were found on each farm. All maps shown are projected in the coordinate system “StatePlane Puerto Rico Virgin Isl FIPS 5200 (Meters),” a version of the Lambert conformal conic projection, and have a datum of NAD 1983. This is consistent with the coordinate system utilized by others working in Puerto Rico.

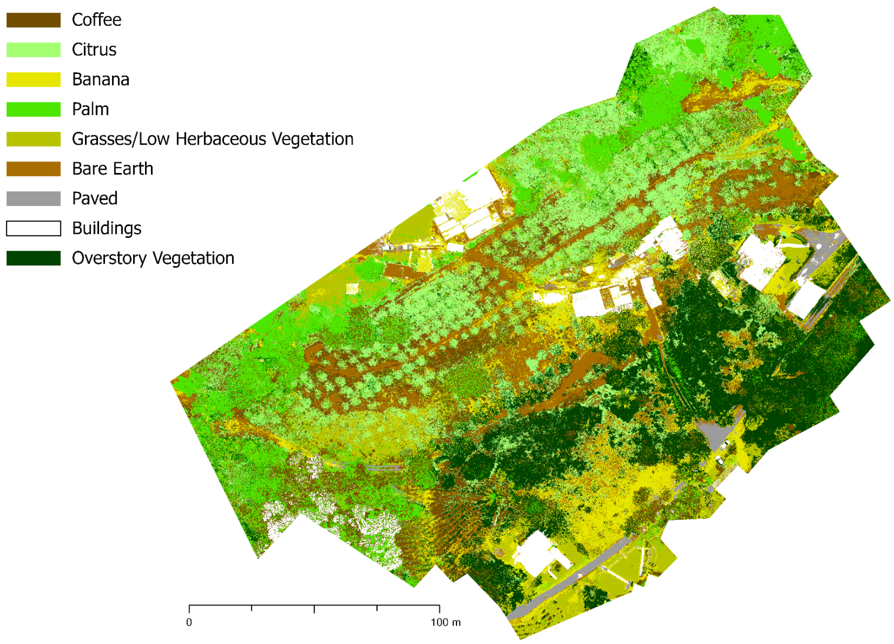


Figure 3. Land cover classification of farm UTUA2 using 2022 multispectral imagery.

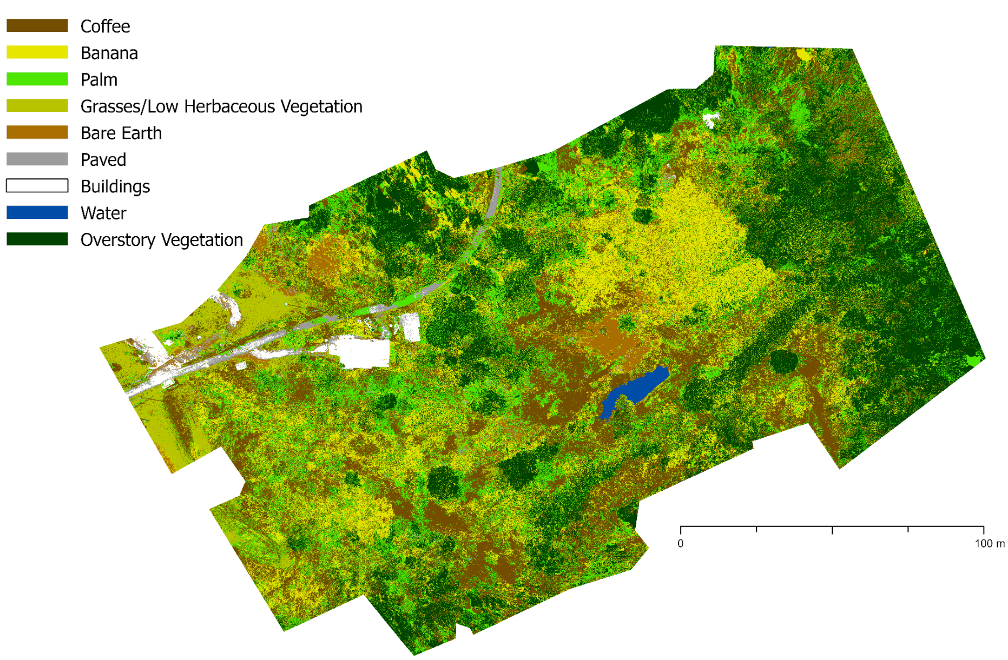
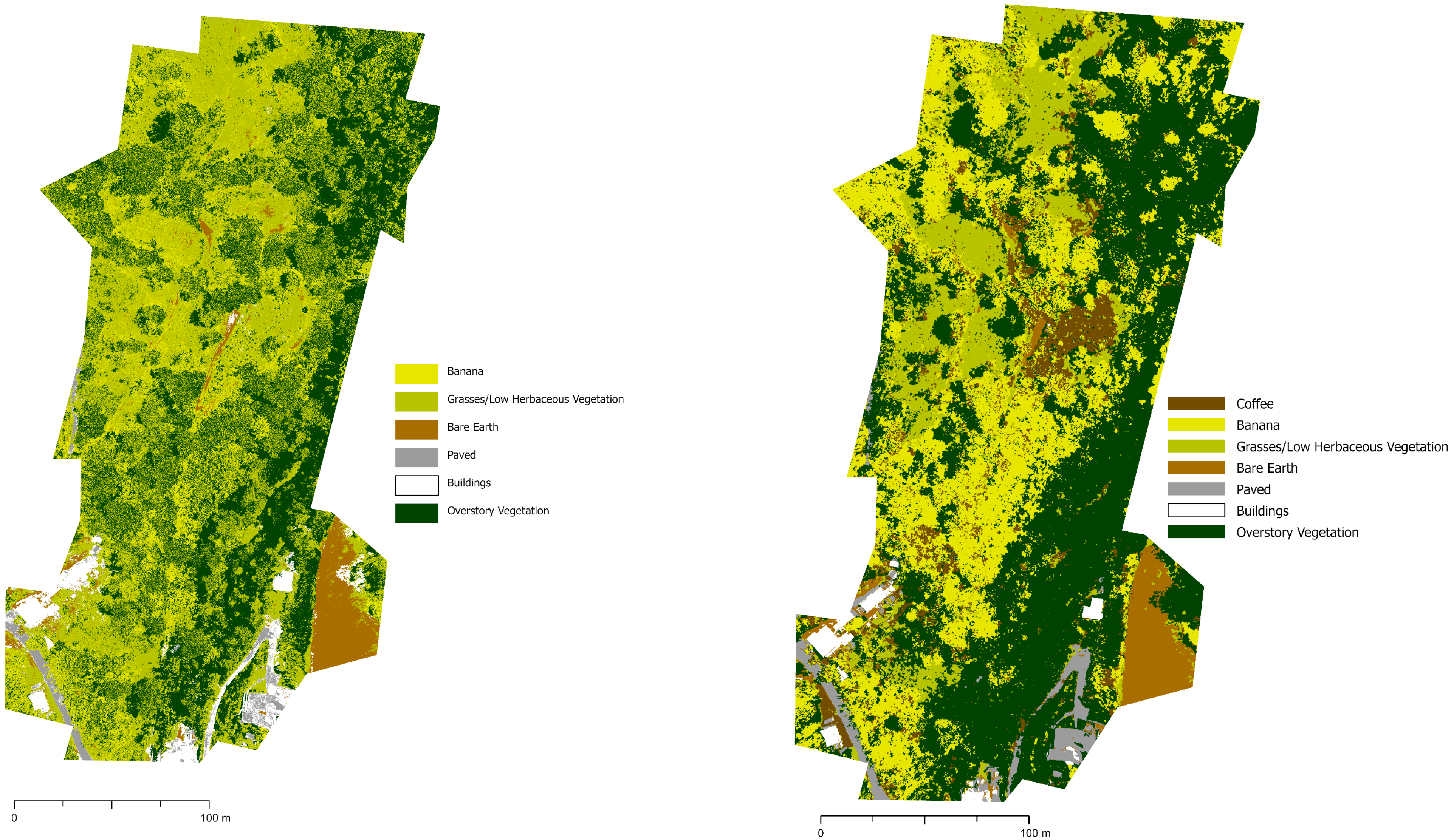


Figure 4. Land cover classification of farm UTUA16 using 2022 multispectral imagery.



Figures 5 and 6. Land cover classification of farm UTUA18 using 2022 multispectral imagery. The left shows the default pixel-based classification, right shows the object-based classification.

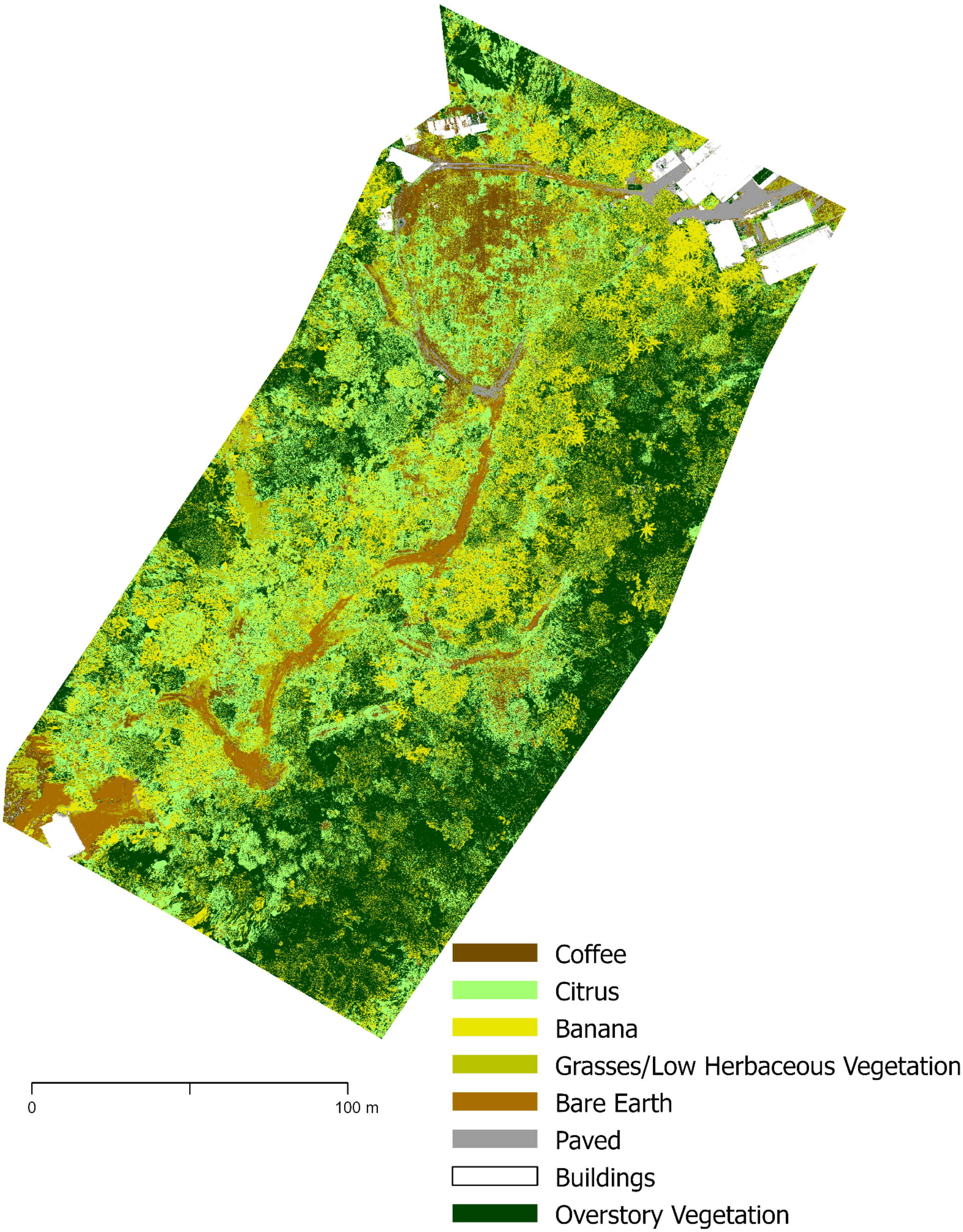


Figure 7. Land cover classification of farm UTUA20 using 2022 multispectral imagery.

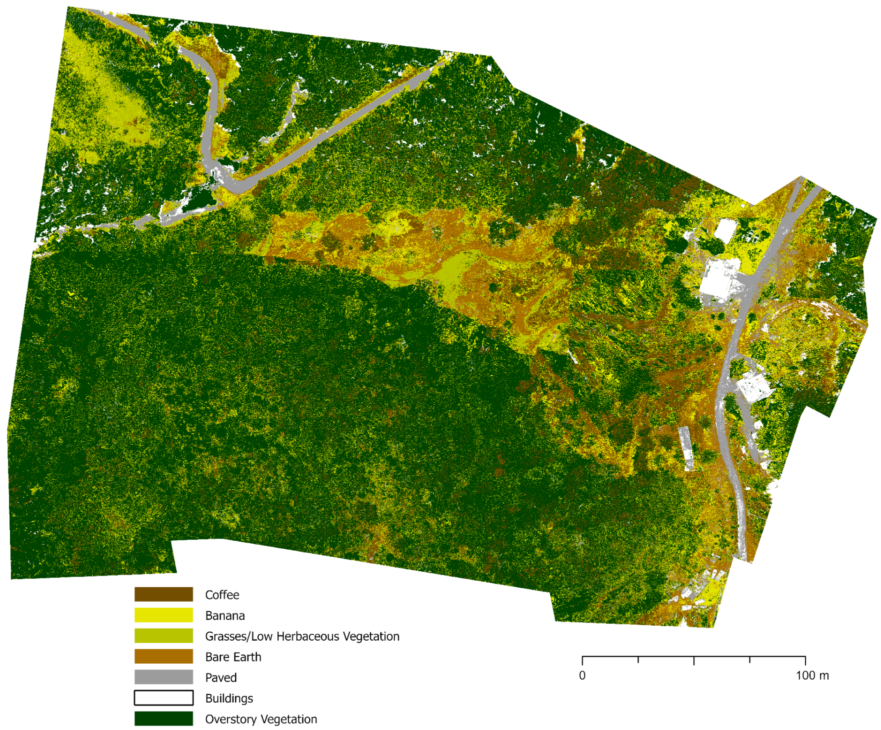


Figure 8. Land cover classification of farm UTUA30 using 2022 multispectral imagery.

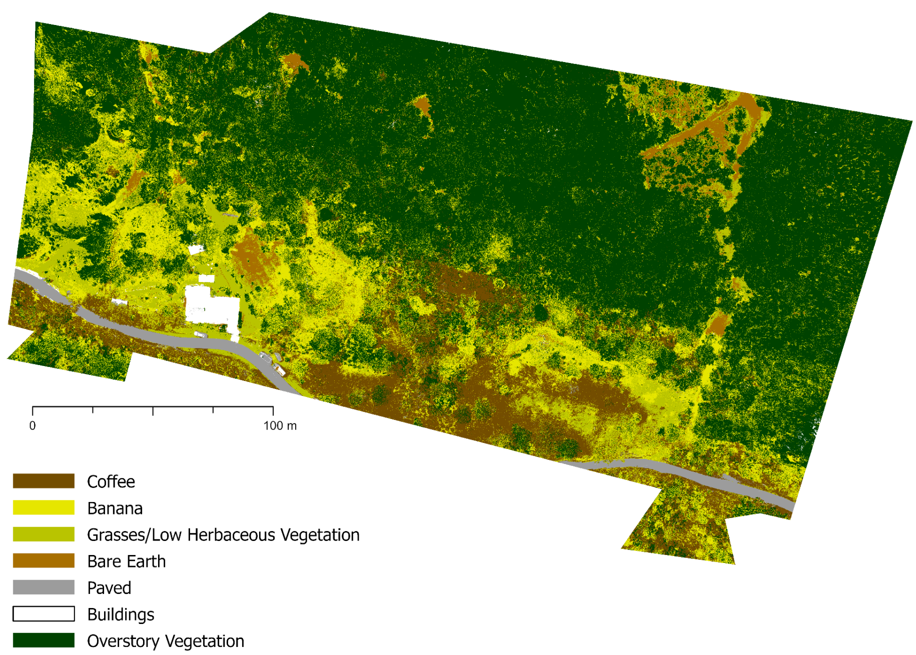


Figure 9. Land cover classification of farm YAUC4 using 2022 multispectral imagery.

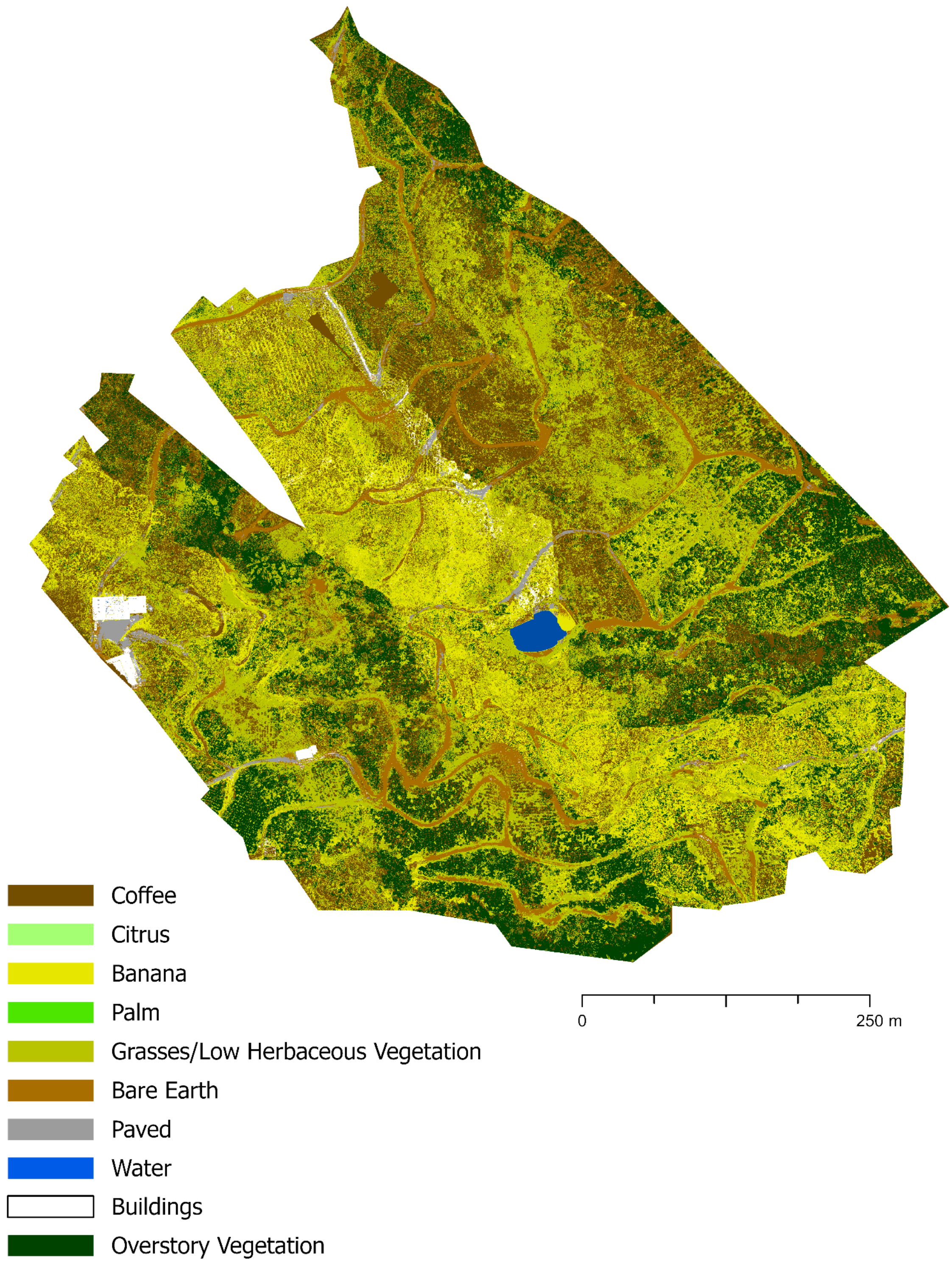


Figure 10. Land cover classification of farm ADJU8 using 2022 multispectral imagery.

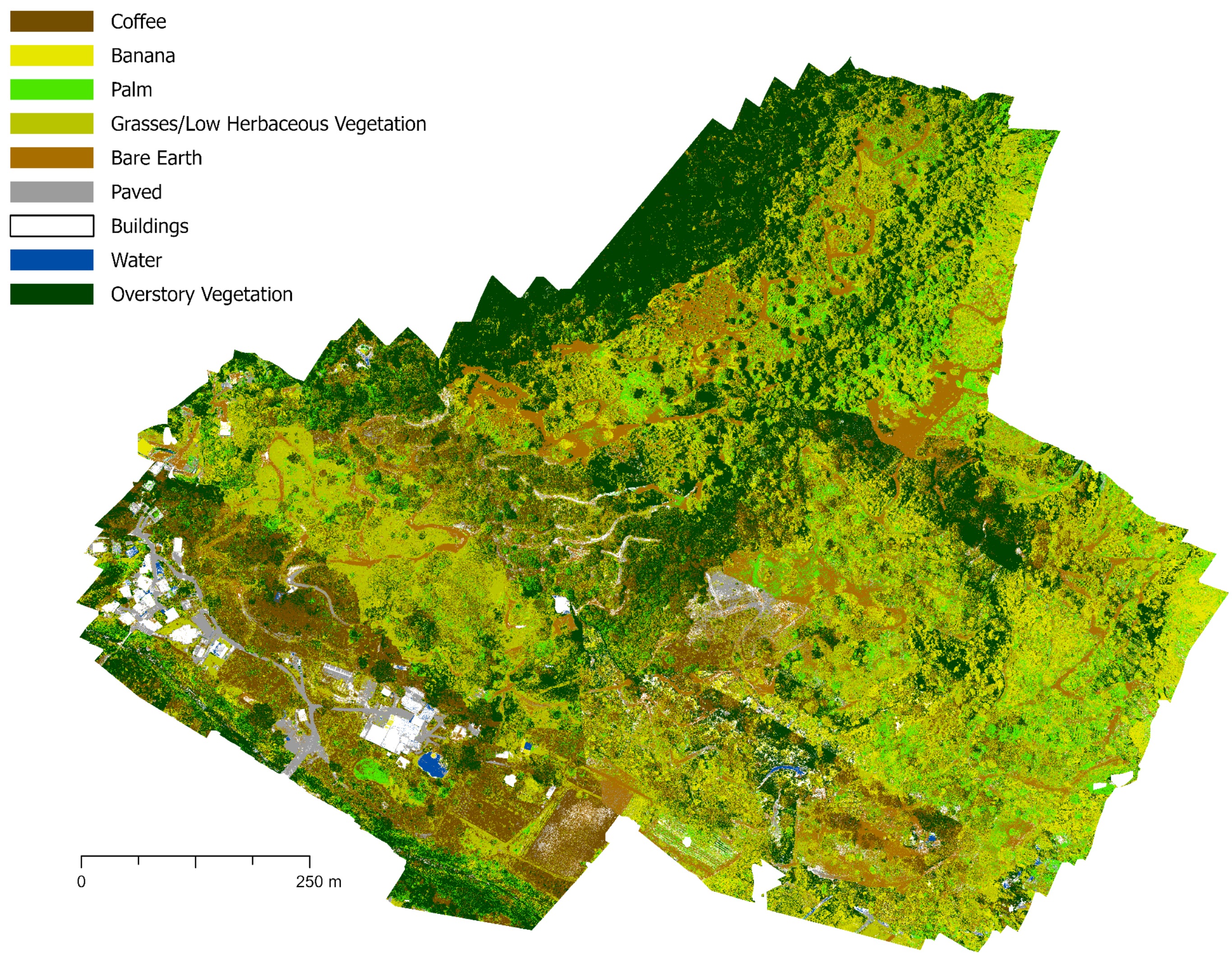


Figure 11. Land cover classification of farm JAYU2_3 using 2022 multispectral imagery.

The initial landcover classifications **(Figures 3-11)** were all assessed for accuracy. **Table 10** details both the overall accuracy of the classification, as well as the Cohen's Kappa statistic. The Kappa statistic incorporates errors of commission and omission and is regarded as more nuanced than that of overall accuracy (Congalton, 1991). Kappa is reported on a scale of -1 to +1, with values closer to +1 indicating a stronger classifier. A classifier is considered strong if it has a high accuracy while taking into account the expected accuracy of a random classifier (Rosenfield & Fitzpatrick-Lins, 1986).

The average overall accuracy across all farms was 53.9% and the average Cohen's Kappa statistic across all farms was 0.409. Farm YAUC4 had the highest overall accuracy, as well as the highest Kappa statistic. The object-based classification had the lowest overall accuracy and Kappa statistic at 36.8% and 0.221 respectively. Excluding the object-based classification, the lowest accuracy and Kappa statistic for pixel-based classification was farm UTUA16. Individual accuracy assessments, including users' and producers' error, can be found in **Appendix B**.

Table 10. Accuracy of farm classification using 2022 imagery. The table details the overall accuracy of each farm along with Cohen's Kappa statistic.

Farm	**Overall Accuracy (%)**	**Kappa (κ)**
UTUA2	57.0	0.4625973054
UTUA16	49.4	0.3688443615
UTUA18	58.4	0.4474540204
UTUA18_obj	36.8	0.220849049
UTUA20	52.4	0.3878268491
UTUA30	51.3	0.391198044
YAUC4	74.0	0.5085924504
ADJU8	53.5	0.4634190585
JAYU2_3	52.6	0.4295536256

For the purposes of this thesis, we did not include figures of secondary classifications as the level of detail was so high that differences in classification maps were largely not visible at the scale of the initial classification figures and therefore not perceivable in this paper. However, accuracy assessments are summarized in **Table 11,** and in addition, individual accuracy assessments for improved classifications can be found in **Appendix C**.

Our secondary classification results were similar to those of the initial classification. Results showed that Iteration B had an average overall accuracy of 52.7% and an average kappa statistic of 0.402. Iteration C had an average overall accuracy of 47.8% and an average kappa statistic of 0.354. Averaging all the secondary classifications (Iterations B-F) resulted in an average overall accuracy of 49.8% and an average overall kappa statistic of 0.378. Iteration B of farm UTUA18 had the highest accuracy of the secondary classifications with an accuracy of 55.3% and a kappa statistic of 0.424981.

Iteration C of farm UTUA2 had the lowest overall accuracy of 45.4% and Iteration C of farm UTUA18 had the lowest kappa statistic of 0.323879.

Table 11. Accuracy of secondary classifications. The table details the overall accuracy of each farm along with Cohen's Kappa statistic.

Iteration	Farm	Overall Accuracy (%)	Kappa
	UTUA2	51.3	0.399000
	UTUA16	51.6	0.389000
	UTUA18	55.3	0.424981
B	UTUA20	52.7	0.395061
	UTUA2	45.4	0.360941
	UTUA16	51.2	0.376000
C	UTUA18	46.9	0.323879
D	UTUA20	50.9	0.371676
E	UTUA2	47.3	0.380003
F	UTUA2	45.6	0.358437

Farmer interview content analysis:

We conducted a total of nine interviews, six of which were recorded on an audio recorder. Using the recorded interviews and notes from the interviewees who did not consent to be recorded, the following content matrix (**Table 12)** was created.

The themes highlighted included utility, novelty, orientation, biodiversity, clarity, and land management. Farmers found the maps interesting and exciting, but were on sure if they were applicable to land management of their farms. Many farmers struggled to orient themselves, especially when landmarks the farmers were familiar with weren't overtly visible in the map. Many farmers noted a lack of biodiveristy or crops present in the map. Despite the lack of diversity present in maps, it was believed by researchers that concise formatting supported legibility of maps by farmers who were unfamiliar with the information displayed in this manner. Lastly, while viewing maps many farmers noted current or future management decisions they consider. These were included in the findings as they may inform future iterations or methodologies of classifications.

Table 12. Content matrix summarizing interview findings.

Themes	Quote/Example	Research Finding	Subthemes	Relevance to land cover classification map and methodology
Utility	"What is the purpose of us seeing this?"	Many farmers were unsure how the classification maps could fit into the farm management but were excited about the maps, and being able to keep them.	Beauty	Landcover maps are created with the intention of better understanding the makeup of a given area to enhance land management. However, there were no clear farmer-generated ideas on the implementation of the maps in their own management, nor any motivation to implement the ones suggested by researchers.
Novelty	The majority of farmers provided excited exclamations when presented with a map. "You can think you know everything. On the contrary, huh. Technology advances, Knowledge is continuous."	Farmers are open to the use of maps and the classification and visuals in their present form.	Pride, Technology	There is still excitement about the prospect of utilizing drone imagery and classifications but there still exists a gap in understanding the applicability of relatively new technology in these contexts.
Orientation	"I don't know where it is." "Oh, there's my lake!" or "I let myself be led by the buildings."	When relevant personal landmarks were noted, farmers often used them to orient themselves. In the case that they were not present, their absence was noted and farmers then used other points or direction from interviewers to orient themselves.	Movement, Landmarks, Perspectives	In connection to novelty and utility, a lack of orientation means that the imagery or classification maps may not be implemented and may instead become a barrier for farmers engaging with this technology.
Biodiversity	Many farmers noted that other food crops and vegetation were present on the farm but had not been mapped (i.e. peppers, guaraguao trees, smaller citrus, mangoes).	Within diversified farming, there is a wealth of food crops and non-food crops that farmers prioritize.	Food Crops, Land Management	While capturing biodiversity present in diverse agroecosystems is desired, maps created that highlight such diversity may also be overwhelming or imperceivable to those who have not yet had an introduction to this type of imagery.
Clarity	"I know the farm, but that's not exactly it, but it's not because I really see it there." Visual representation provided in a concise formatting supported outward expressions of map legibility.	While farmers express wanting representation of the entirety of crops and vegetation, a cursory introduction to the maps in a simplified form aids synthesis of imagery and content.	Digestibility, Simplification	Understanding the audience of a map is a principal element of cartography. In a setting such as this study, creating a simpler iteration may serve as a tool with which to foster connections and understand where to expound upon classifications or tools in the future.
Land Management	A farmer speaking to the increased heat noted they needed to plant more plants to shade coffee. Farmers intercropped coffee with citrus as a means of protecting the coffee (their primary crop).	Land management techniques often include practices to address climatic conditions. By diversifying crops, farmers are better shielded from economic downturns and a rapidly changing environment.	Crop Selection, Crop Placement	Land management may inform classifications by creating more targeted areas for ground truthing and testing sites. For example, if a farmer noted that coffee was planted under an area of dense canopy, it may make sense to ground truth the area heavily and test the degree to which the coffee in that area was present in the classification.

Discussion:

Classifications:

We obtained an average kappa value across all farms of 0.409, meaning that the classifiers, generally, are fair in comparison to a random classifier (Fleiss et al., 2003; Landis & Koch, 1977). Many of the farms have a sizeable disagreement between overall accuracy and the kappa index, like for instance farm YAUC4, which had an accuracy of 74% (or 0.74) and a kappa statistic of 0.51. This disagreement between kappa and overall accuracy could be because there are classes present that make up a majority of the classification, and these classes are also accurate in the classification. In the case of my classifications, the overstory vegetation class often had more training and testing sites made of larger segments. For YAUC4, the overstory vegetation class made up around 70% of all training pixels, meaning it had a greater effect on the accuracy than other classes. Even though the overstory vegetation may have skewed overall accuracy, the kappa statistic takes into account the relative impact of each class, meaning that it is not skewed by a single well-represented class (Congalton, 1991; Manel et al., 2001; Rosenfield & Fitzpatrick-Lins, 1986), in this case, overstory vegetation. Relatedly, the classification results often contained large, uninterrupted patches of the overstory vegetation land cover class toward the edges of the farm boundary. In addition, because training and testing sites for the overstory vegetation class were often areas of dense canopy, there is less of a chance that pixels associated with a different land cover were misclassified as overstory vegetation. It is worth noting, in this paper and otherwise, that while overall accuracy and the kappa statistic are common ways to evaluate land cover classifications in the remote sensing field, more recent literature (Foody, 2002; Olofsson et al., 2014) has highlighted that confusion matrices are not entirely reliable and need to be analyzed with some understanding that the accuracies reported are not absolute.

Somewhat expectedly, many of the vegetation classes (i.e. coffee, citrus, banana, palm, and overstory vegetation) were misclassified as other vegetation classes. Because these classes are spectrally similar, and because the initial classifications utilized all ten bands, including those that have little separation between classes, it can be anticipated that there would be some confusion amongst these classes. **Figure 12** illustrates the spectral similarities across vegetation training classes. Another area of confusion was between the pavement and building classes. Across many of the farms, buildings and pavements were misclassified as one another, but were less often misclassified as bare earth and vegetation.

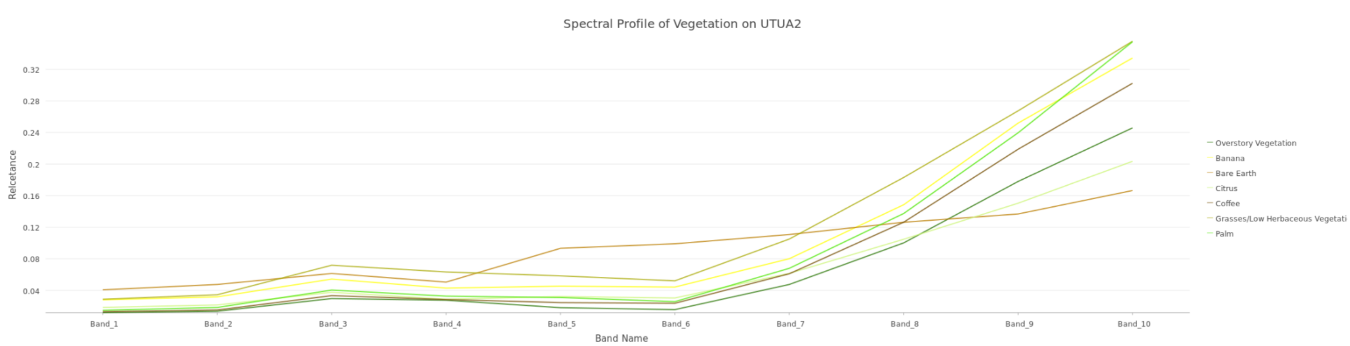


Figure 12. The spectral profile of vegetation classes for farm UTUA2.

Throughout farms, vegetation classes considered to be crops (coffee, citrus, and banana) often had low user's accuracies. In the case of coffee, the average user's accuracy was around 17.7%. Farms that had higher user's accuracies for coffee than the average of 17.7% included YAUC4 and ADJU8. Notably, coffee training sites in these two farms included clusters of coffee plants easily distinguishable from the grasses or bare earth surrounding them. Other farms that contained coffee training sites that were closer to the edges of dense canopies or had less clustered coffee training sites did not boast the same user's accuracies. The same phenomenon can be found while viewing the user's accuracy for the banana class in farm YAUC4. The average user's accuracy for the banana class across all farms was a little under 18%, but farm YAUC4 had a user's accuracy of 43.2% with training sites for the class clustered and in an area relatively distanced from other vegetation classes. Farm UTUA18 also had a higher user's accuracy for the banana class, but had training sites for bananas drawn around bananas within an overstory vegetation canopy. In addition, more conservative drawing of training sites across farms and given classes (i.e., drawing training sites closer to the edges of a plant or class) may create better training sites and therefore has the potential to lead to more accurate classifications. This may indicate that more careful drawing of training sites leads to less inclusion of pixels unrelated to the class being targeted in the training site. However, it is worth noting that using an object-based classification instead of a pixel-based one would in part address this issue within the segmentation step, where spectrally similar objects are grouped and considered to be a single object (Liu & Xia, 2010; Walsh et al., 2008).

There exists a myriad of reasons why the land cover classifications of this paper may be considered "inaccurate", many of which have been alluded to earlier in this discussion. One reason the accuracies of each farm classification may have been lower than anticipated was my own bias in testing sites. The creation of training sites and classification were done prior to my own visit to farms. This meant that my training classes were built around GCPs and not around my experiences. Testing sites, however, were created after visiting the farms, and when creating testing sites I could recall areas of a farm and be more discerning when utilizing the GCPs. For instance, on farm UTUA20 I created training classes for citrus based on a GCP labeled as such. However, while visiting the farm, I noticed that there was very little citrus. We took no GCPs at the few citrus trees that existed, and I made no testing sites for the citrus class because of both the lack of GCPs and also the lack of citrus I found on the farm generally. After running an accuracy assessment, the citrus class had 0% accuracy, driving down the total accuracy. In future work, I would instead throw out this class within this farm and rerun the classification entirely.

Another limitation of this study is that no radiometric normalization occurred prior to the image mosaicking process. Radiometric normalization may have created more consistency across flights and farms (Tuia et al., 2016). While the histogram equalization occurred during the mosaicking process, the resulting mosaics still had visible radiometric differences. Radiometric normalization, if applied earlier, could have created the opportunity to classify farm ADJU7, which was thrown out due to spectral imbalances present after histogram equalization, by reducing the bright spots present in one flight. In addition, if radiometric normalization occurred earlier in the process, it may have been feasible to train the classifier on only one farm and then apply it across farms. This would reduce the work to create a large number of training sites across farms, and instead, more attention could be paid to creating higher-quality training sites on one farm. Additionally, classifications may be improved by using ground control points in orthomosaic creation. During the processing of imagery in Agisoft Metashape, only the internal UA GNSS system was used to georeference raw images. By including ground control points collected with a more precise external GPS receiver in the image processing methodology, multispectral imagery may have been better aligned with ground control points collected for building training sites.

To a large extent, many issues could be addressed through another field campaign, with fewer time constraints and more precise objectives. Training sites were often generated around the previously collected ground control points, which were often clustered spatially and were also focused on one or another plant type between field campaigns. With more time at each study site, more plants across the farm could be surveyed, across the breadth of the farm. This would create more competitive opportunities for training sites to be drawn and encompass a greater variety of spectral properties per class. However, it is worth noting that part of the interest in remote sensing and land cover classification lies in the fact that remote sensing has the potential to operate without needing to do a complete land cover survey. Ground truthing each and every plant on such a highly diversified farm is extremely time-consuming and labor-intensive, and while the GPS instruments in this study boast sub-meter resolution, in certain areas of given farms the GPS instrument would require a given researcher to stand for five to ten minutes to wait for sufficient satellite connectivity to collect a point. Therefore, surveying more points to increase a given classification's accuracy may not be worth the effort and somewhat negate the advantage of a supervised classification.

Secondary classifications were completed using several alternate band combinations, but overall, the new layer stacks did not lead to an increase in accuracy. With the exception of three classifications (Iteration B of farm UTUA16, Iteration B of farm UTUA20, and Iteration C of UTUA16), overall accuracies of secondary classifications were lower than the initial classification, although the differences in all cases were only marginal. When considering Iteration A accuracies alongside Iterations B-F, the average overall accuracies cannot be directly compared because not all farms initially classified were used in the secondary classifications. However, when comparing Iteration A to each of Iterations B, C, and D, and filtering to only the relevant farms, the accuracy for Iteration A maintained a higher overall average than the respective secondary classifications. While disappointing, the lowered accuracies of secondary classifications were somewhat anticipated. It has been documented (e.g. Whiteside et al., 2011) that ancillary data works well to enhance object-based classifications. Still, the effects are not as strong as on pixel-based classifications because pixel-based classifications lack the "objects" that ancillary data can contextualize (Whiteside et al., 2011).

Interviews:

Analyzing the interview recordings and notes allowed for a more nuanced understanding of the remote sensing work done in this thesis. It became very apparent during interviews that farmers and land managers were extremely excited to view, talk about, and keep the map printouts. Many remarked that the images of their farms were beautiful and were excited to display the printouts for others to see, but were unsure of how the maps or products derived from the maps could be implemented in regular management. One farmer noted that they planned to hang imagery in a cafe for visitors to see, but when questioned about the utility of the map in their work, they indicated that they would instead be more interested in utilizing the drone to evenly distribute pesticides.

While the beauty and excitement of images and landcover classification maps are often overlooked as an aspect of utility in the remote sensing field, we understood this subtheme to be an extremely important one as it became more evident that farmers and researchers could build further rapport by addressing the beauty of the images and the farms that land managers work so hard to maintain. Connection building in the context of this thesis is extremely relevant as land cover classifications are regarded as an iterative process. By fostering better connections between researchers and farmers, we can more intimately understand the ways in which our work fits into farmers' management and make adjustments to maps accordingly. In many of our interviews, interviewees often pointed out a lack of diversity or missing landmarks. Without having conversations with land managers, researchers are limited to making changes that may not be useful to farmers and instead only serve to increase classification accuracies for schemas that were flawed themselves.

Farmers who communicated to us that maps were lacking relevant information also had more difficulty orienting themselves during interviews. One farmer remarked that he had often regarded his land as a square parcel, and viewing it as the roughly rectangular shape the imagery was captured as led him to become disoriented. The farmer also noted that he might have been able to orient himself in spite of his perception of the parcel, but only if landmarks he passed by daily had been included and labeled as such. When farmers are not able to orient themselves to the imagery, implementation of the maps in management becomes even farther-fetched.

While many farmers indicated absent crop and vegetation diversity in the land cover classification map, we felt that sharing a more simplistic map first actually enhanced the feedback we received and farmers' own understanding of the maps. Because the map shared was simpler, farmers noted specific areas where they were interested in seeing more detail, where they were practicing a given land management technique, or where they had a few personally relevant crops. In addition, we believe that the lack of detail present allowed for quicker orientation and better clarity of understanding of the maps. This was extremely important as we understood that land managers had not ever seen their land displayed in this manner and needed some time to relate the imagery to land they were intimately familiar with.

Future considerations:

Including interviews as part of this project greatly enhanced the findings of this thesis and would enhance any future work in similar settings. Colloredo-Mansfeld et al. (2020) found similar results in their work, noting that participatory drone mapping allowed researchers to ascertain broader and more relevant information about land management. In addition, the authors found that conducting land cover classification maps allowed them to understand sensitive areas of farms (e.g. where young plants were growing) and establish rapport between researchers and farmers. Unlike Colloredo-Mansfeld et al., (2020) our project did not contain more than one round of interviews. Nevertheless, it is clear that more knowledge sharing between researchers and farmers would benefit the work. One farmer noted during our interview that while she was extremely excited about participating in the research, she was disappointed that she had no proof of the drones being on the property to share with a friend. By leaving her with the printout of the map and a description of the work we had done, the farmer may be more likely to continue working with researchers. In return, we received valuable feedback on the crops and vegetation relevant to her on her property. Future iterations of land cover classifications would incorporate this feedback, and even more iterations of knowledge-sharing and classifications could continue.

The detailed nature of the high-resolution imagery was seemingly part of the interest that farmers had in interacting with the printouts. While the pixel-based supervised land cover classifications were mildly accurate, switching to an object-based classification would likely increase the overall average accuracy, as it is documented that object-based classifications perform better, especially at finer resolutions (Baker et al., 2013). However, fine-resolution data like that present in this thesis comes at a cost. Through each step of image processing and classification, the processing power required meant that analyses often took time to run. Whiteside et al., (2011) note that object-based classifications may require even more computational power, especially at the segmentation step.

Classification maps may also be enhanced with the addition of elevation or surface data, like the LiDAR data that was collected together with the multispectral imagery. Farmers interviewed often noted that they oriented themselves using peaks and valleys present on farms, something not reflected in the printout of the multispectral imagery or land cover classification maps. However, including data like this may mandate a more dynamic format in which to present maps to farmers. While digital elevation and surface models are something many in remote sensing are intimately familiar with, viewing elevation data on a 2D plane may still present some challenges for those who have not seen maps like it before. This could potentially be remedied by creating a 3D model of the surface or elevation data and viewing it together with farmers on a computer.

Conclusion:

This thesis was completed in order to better understand pixel-based supervised land cover classifications of diverse agroecosystems, and the utility they serve as management tools. We applied this exploration to coffee agroecosystems in Puerto Rico, and while this thesis was broad, it contributed to the growing literature on using fine-resolution imagery collected by UAS in remote sensing. This thesis found that while our land cover classifications are only moderately accurate they have the potential to become more accurate by utilizing different methodologies and better ground truths. In addition, we concluded that while farmers were unsure about using the maps as a farm management tool, they were still excited about the technology being applied to their land. In addition, we found that sharing our maps with farmers, even with their flaws, generated better communication between researchers and farmers and created the opportunity to "be attentive to the 'social position of the new map and how it engages institutions' " (Kim, 2015; Laso & Arce-Nazario, 2023).

However, there still exist many opportunities for which this research to be expanded and improved upon. Improving remote sensing methodologies includes further exploring object-based classifications in the context of Puerto Rican coffee agroecosystems, and improving interviews could include viewing more map iterations in more dynamic forms. Both remote sensing and interview methodologies would be improved by visiting farmers and their land more often. We hope this thesis encourages further exploration of fine-resolution remote sensing in coffee agroecosystems. We also hope that this thesis encourages more work alongside farmers to create classification schemes and products better suited to the needs of farmers.

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<u>Appendix A:</u>
English Version of Interview
Note: The interviews will be conducted in Spanish, but we have included the English version for IRB review purposes.

Hello, my name is Nayethzi Hernandez and this is my colleague Gwen Klenke. We're both graduate students at the University of Michigan. And this project is in collaboration with Ivette Perfecto, who you know. Thank you for taking the time to participate in this study. As Warren let you know, our team is looking into diverse Puerto Rican coffee farms and agroecology systems. As someone who is so knowledgeable, I really appreciate your time.

Through interviews, we're just looking for generalizable information, and none of this will be identifiable. If that's still okay with you it'll take us roughly 1 hour. Before we begin I want to confirm that it's okay that I record our conversation.

Please let me know if anything comes up during the interview you just let me know. Excellent! Let's begin talking a bit about your land.

Question group 1: Land history and farm management

Can you tell me a bit about how you started growing coffee?

When it comes to your farm, what are your goals with your crops?

Could you tell me a little bit about how you decided to put which crops where?

What type of knowledge or techniques influence how you manage the farm?

Could you tell me about some of the environmental changes that you've experienced while farming this land?

What are some goals you have for your farm?

Question group 2: Show farmers the map

Translate what Gwen says about how the maps are made

When you first look over the map what are some of your thoughts?

Question group 3: Map review

After looking over the map, what are areas of the map that are of interest to you?

Are there any changes you would like to consider when looking over this map?

If this technology was available to you would it be helpful for farm management?

If it's helpful to you, how often would you want an updated map?

Closing:
Thank you so much for your insights! We really appreciate your time. We invite you to keep the map if you'd like it.

Before we finish, is there anything you'd like to ask or say to us regarding the map or the interview?
I will provide you with my contact information if you have any questions for me about this study, or anything else.

Spanish Version of Interview

Hola, buenos dias/tardes. Yo me llamo Nayethzi Hernandez y ella es mi colega Gwen Klenke. Ambas estamos completando nuestras maestrías en la Universidad de Michigan. Este proyecto es en colaboración con la profesora Ivette Perfecto, que usted conoce. Me gustaría agradecerle por tomar este tiempo para conversar con nosotras. Como Don Warren le contó, nuestro equipo está estudiando diversos cafetales y sistemas de agroecología Puertorriqueños. Como alguien con un gran conocimiento, sinceramente agradezco su tiempo.

Por medio de entrevistas pretendemos generalizar información, y nada de lo que usted comparte conmigo será directamente conectado con su identidad. Si aún está de acuerdo, la entrevista será de una hora a lo más. ¿Antes de iniciar me gustaría confirmar que está bien si grabo el audio de nuestra conversación?

Si en algún momento durante la entrevista algo se le ocurre una duda, usted me dice.

¡Excelente! Avanzamos con el tema de su terreno.

Grupo de preguntas 1: historia y manejo de granja

¿Me puede contar un poco de cómo llegó a cultivar café?

Cuando se trata de su cafetal, ¿Cuáles son algunas de sus metas con su granja?

¿Me comparte un poco del proceso tras de cómo decide dónde plantar sus hortalizas y árboles?

¿Qué tipo de conocimiento y técnicas influyen como maneja la tierra?

¿Me cuenta acerca de los cambios en el medio ambiente que usted ha notado mientras ha estado trabajando estas tierras?

¿Cuáles son algunas de las metas que tiene para su cafetal?

Grupo de preguntas 2: presentar mapas

Traducir lo que Gwen dice de cómo se forman los mapas

¿Cuándo usted ve el mapa cuáles son algunas de sus ideas iniciales?

Grupo de preguntas 3: revisión de mapa

Después de revisar el mapa, ¿Qué áreas del mapa le interesan?

¿Hay cambios que gustaría considerar mientras lo ve?

¿Si esta tecnología estuviera disponible, usted siente que sería útil?

¿Si lo ve útil, a cada cuanto le gustaría un mapa actualizado?

Clausura:

¡Muchísimas gracias por compartir su perspectiva! Le agradecemos su tiempo. Si gusta, le invito a quedarse el mapa.

Antes de que terminemos la entrevista, ¿hay algo que le gustaría preguntarnos acerca del mapa o la entrevista?

Bueno, le comparto mi contacto por si tiene una pregunta acerca del estudio o de cualquier otra cosa.

Appendix B:

Table 1. Accuracy assessment of farm utua2.

Class Value	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_10	Total	Users Accuracy	Kappa
C_1 - Coffee	7	1	6	14	4	0	0	0	17	49	0.1428571429	0
C_2 - Citrus	1	10	3	12	6	0	2	2	19	55	0.1818181818	0
C_3 - Banana	1	0	5	7	5	3	0	6	2	29	0.1724137931	0
C_4 - Palm	0	2	0	3	4	0	0	0	16	25	0.12	0
C_5 - Grasses/Low Herbaceous Vegetation	0	2	0	3	24	0	0	0	2	31	0.7741935484	0
C_6 - Bare Earth	1	0	0	1	0	7	3	10	1	23	0.3043478261	0
C_7 - Paved	0	0	0	0	0	0	10	0	0	10	1	0
C_8 - Buildings	0	0	0	1	0	0	0	96	0	97	0.9896907216	0
C_10 - Overstory Vegetation	0	0	3	32	6	0	20	0	127	188	0.6755319149	0
Total	10	15	17	73	49	10	35	114	184	507	0	0
Producers Accuracy	0.7	0.6666666667	0.2941176471	0.04109589041	0.4897959184	0.7	0.2857142857	0.8421052632	0.6902173913	0	**0.5700197239**	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	**0.4625973054**

Table 2. Accuracy assessment of farm utua16.

Class Value	C_1	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_10	Total	Users Accuracy	Kappa
C_1 - Coffee	0	1	15	12	0	0	0	0	62	90	0	0
C_3 - Banana	0	8	16	4	0	0	1	0	67	96	0.08333333333	0
C_4 - Palm	0	1	26	10	0	0	3	0	33	73	0.3561643836	0
C_5 - Grasses/Low Herbaceous Vegetation	0	0	0	24	0	0	0	0	1	25	0.96	0
C_6 - Bare Earth	0	0	0	0	11	0	2	0	0	13	0.8461538462	0
C_7 - Paved	0	0	0	0	0	6	1	0	0	7	0.8571428571	0
C_8 - Buildings	0	0	0	0	0	6	5	0	0	11	0.4545454545	0
C_9 - Water	0	0	0	0	0	0	0	46	0	46	1	0
C_10 - Overstory Vegetation	0	0	17	0	0	0	1	0	121	139	0.8705035971	0
Total	0	10	74	50	11	12	13	46	284	500	0	0
Producers Accuracy	0	0.8	0.3513513514	0.48	1	0.5	0.3846153846	1	0.426056338	0	**0.494**	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	**0.3688443615**

Table 3. Accuracy assessment of farm utua18.

Class Value	C_1	C_2	C_3	C_5	C_6	C_7	C_8	C_10	Total	Users Accuracy	Kappa
C_1 - Coffee	0	0	0	0	0	0	0	0	0	0	0
C_2 - Citrus	0	0	0	0	0	0	0	0	0	0	0
C_3 - Banana	2	0	39	7	5	0	0	84	137	0.2846715328	0
C_5 - Grasses/Low Herbaceous Vegetation	4	6	11	17	11	0	0	27	76	0.2236842105	0
C_6 - Bare Earth	0	0	0	0	5	0	1	0	6	0.8333333333	0
C_7 - Paved	0	0	0	0	0	24	21	0	45	0.5333333333	0
C_8 - Buildings	0	0	0	0	2	9	60	0	71	0.8450704225	0
C_10 - Overstory Vegetation	4	4	10	5	0	0	0	154	177	0.8700564972	0
Total	10	10	60	29	23	33	82	265	512	0	0
Producers Accuracy	0	0	0.65	0.5862068966	0.2173913043	0.7272727273	0.7317073171	0.5811320755	0	**0.583984375**	0
Kappa	0	0	0	0	0	0	0	0	0	0	**0.4474540204**

Table 4. Accuracy assessment of farm utua18_obj (object-based classification).

Class Value	C_1	C_2	C_3	C_5	C_6	C_7	C_8	C_10	Total	Users Accuracy	Kappa
C_1 - Coffee	5	1	3	1	8	0	0	22	40	0.125	0
C_2 - Citrus	0	0	0	0	0	0	0	0	0	0	0
C_3 - Banana	4	0	31	7	2	0	0	176	220	0.1409090909	0
C_5 - Grasses/Low Herbaceous Vegetation	0	5	1	8	9	0	0	2	25	0.32	0
C_6 - Bare Earth	0	0	0	0	2	0	15	0	17	0.1176470588	0
C_7 - Paved	0	0	0	0	0	32	22	0	54	0.5925925926	0
C_8 - Buildings	0	0	0	0	0	0	45	0	45	1	0
C_10 - Overstory Vegetation	1	4	25	13	2	0	0	65	110	0.5909090909	0
Total	10	10	60	29	23	32	82	265	511	0	0
Producers Accuracy	0.5	0	0.5166666667	0.275862069	0.08695652174	1	0.5487804878	0.2452830189	0	**0.3679060665**	0
Kappa	0	0	0	0	0	0	0	0	0	0	**0.220849049**

Table 5. Accuracy assessment of farm utua20.

Class Value	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_10	Total	Users Accuracy	Kappa
C_1 - Coffee	1	0	0	2	7	14	0	5	3	32	0.03125	0
C_2 - Citrus	5	0	4	1	1	2	0	0	85	98	0	0
C_3 - Banana	0	0	14	16	2	0	0	0	57	89	0.1573033708	0
C_4 - Palm	0	0	0	0	0	0	0	0	0	0	0	0
C_5 - Grasses/Low Herbaceous Vegetation	0	0	0	1	0	7	1	1	0	10	0	0
C_6 - Bare Earth	0	0	1	0	0	5	2	1	1	10	0.5	0
C_7 - Paved	0	0	0	5	0	0	7	2	0	14	0.5	0
C_8 - Buildings	0	0	0	0	0	0	0	105	0	105	1	0
C_10 - Overstory Vegetation	4	0	6	4	0	0	0	2	134	150	0.8933333333	0
Total	10	0	25	29	10	28	10	116	280	508	0	0
Producers Accuracy	0.1	0	0.56	0	0	0.1785714286	0.7	0.9051724138	0.4785714286	0	**0.5236220472**	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	**0.3878268491**

Table 6. Accuracy assessment of farm utua30.

Class Value	C_1	C_3	C_4	C_5	C_6	C_7	C_8	C_10	Total	Users Accuracy	Kappa
C_1 - Coffee	4	5	5	7	4	0	0	48	73	0.05479452055	0
C_3 - Banana	0	3	22	42	5	0	0	31	103	0.02912621359	0
C_4 - Palm	0	0	0	0	0	0	0	0	0	0	0
C_5 - Grasses/Low Herbaceous Vegetation	0	0	0	1	0	0	0	2	3	0.3333333333	0
C_6 - Bare Earth	0	0	8	2	28	0	0	0	38	0.7368421053	0
C_7 - Paved	0	0	9	1	1	37	15	0	63	0.5873015873	0
C_8 - Buildings	0	0	1	0	0	2	38	4	45	0.8444444444	0
C_10 - Overstory Vegetation	6	2	20	7	0	0	0	151	186	0.811827957	0
Total	10	10	65	60	38	39	53	236	511	0	0
Producers Accuracy	0.4	0.3	0	0.01666666667	0.7368421053	0.9487179487	0.7169811321	0.6398305085	0	**0.5127201566**	0
Kappa	0	0	0	0	0	0	0	0	0	0	**0.391198044**

Table 7. Accuracy assessment of farm yauc4.

Class Value	C_1	C_3	C_4	C_5	C_6	C_7	C_8	C_10	Total	Users Accuracy	Kappa
C_1 - Coffee	9	9	0	4	0	0	0	0	22	0.4090909091	0
C_3 - Banana	0	16	2	2	15	0	0	2	37	0.4324324324	0
C_4 - Palm	0	0	0	0	0	0	0	0	0	0	0
C_5 - Grasses/Low Herbaceous Vegetation	1	2	1	4	17	0	0	5	30	0.1333333333	0
C_6 - Bare Earth	0	1	0	0	13	0	0	2	16	0.8125	0
C_7 - Paved	0	0	0	0	0	19	0	0	19	1	0
C_8 - Buildings	0	0	0	0	0	0	8	0	8	1	0
C_10 - Overstory Vegetation	0	2	65	0	0	0	2	307	376	0.8164893617	0
Total	10	30	68	10	45	19	10	316	508	0	0
Producers Accuracy	0.9	0.5333333333	0	0.4	0.2888888889	1	0.8	0.9715189873	0	**0.7401574803**	0
Kappa	0	0	0	0	0	0	0	0	0	0	**0.5085924504**

Table 8. Accuracy assessment of farm adju8.

Class Value	C_1	C_3	C_5	C_6	C_7	C_8	C_9	C_10	Total	Users Accuracy	Kappa
C_1 - Coffee	12	6	2	1	0	10	0	10	41	0.2926829268	0
C_3 - Banana	2	14	8	0	0	1	20	41	86	0.1627906977	0
C_5 - Grasses/Low Herbaceous Vegetation	0	6	26	2	0	3	0	35	72	0.3611111111	0
C_6 - Bare Earth	0	1	2	48	3	0	0	0	54	0.8888888889	0
C_7 - Paved	0	0	0	6	9	1	0	0	16	0.5625	0
C_8 - Buildings	0	1	0	0	0	27	0	1	29	0.9310344828	0
C_9 - Water	0	0	0	0	0	0	26	0	26	1	0
C_10 - Overstory Vegetation	1	8	3	0	0	0	0	38	50	0.76	0
Total	15	36	41	57	12	42	46	125	374	0	0
Producers Accuracy	0.8	0.3888888889	0.6341463415	0.8421052632	0.75	0.6428571429	0.5652173913	0.304	0	**0.5347593583**	0
Kappa	0	0	0	0	0	0	0	0	0	0	**0.4634190585**

Table 9. Accuracy assessment of farm jayu2_3.

Class Value	C_1	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_10	Total	Users Accuracy	Kappa
C_1 - Coffee	4	2	2	4	1	0	3	0	15	31	0.1290322581	0
C_3 - Banana	3	11	4	1	0	0	1	0	75	95	0.1157894737	0
C_4 - Palm	1	4	7	1	0	0	0	0	23	36	0.1944444444	0
C_5 - Grasses/Low Herbaceous Vegetation	1	3	1	20	1	0	0	0	13	39	0.5128205128	0
C_6 - Bare Earth	0	0	2	2	16	0	18	0	0	38	0.4210526316	0
C_7 - Paved	0	0	0	0	1	19	29	1	0	50	0.38	0
C_8 - Buildings	0	0	1	0	2	0	132	0	2	137	0.9635036496	0
C_9 - Water	0	0	0	0	0	0	14	9	0	23	0.3913043478	0
C_10 - Overstory Vegetation	1	4	0	2	0	0	0	0	46	53	0.8679245283	0
Total	10	24	17	30	21	19	197	10	174	502	0	0
Producers Accuracy	0.4	0.4583333333	0.4117647059	0.6666666667	0.7619047619	1	0.6700507614	0.9	0.2643678161	0	**0.5258964143**	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	**0.4295536256**

Appendix C:

Table 1. Accuracy assessment of Iteration B of farm UTUA2.

Class Value	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_10	Total	User's Accuracy	Kappa
C_1 - Coffee	6	0	3	12	2	0	0	0	27	50	0.12	0
C_2 - Citrus	1	14	9	6	2	0	0	3	22	57	0.245614	0
C_3 - Banana	2	0	4	13	4	2	0	10	6	41	0.097561	0
C_4 - Palm	1	0	0	7	8	0	0	3	29	48	0.145833	0
C_5 - Grasses/Low Herbaceous Vegetation	0	1	0	3	22	0	0	0	1	27	0.814815	0
C_6 - Bare Earth	0	0	0	0	0	8	0	7	0	15	0.533333	0
C_7 - Paved	0	0	0	0	0	0	9	0	0	9	1	0
C_8 - Buildings	0	0	0	0	0	0	2	91	0	93	0.978495	0
C_10 - Overstory Vegetation	0	0	1	32	11	0	24	0	99	167	0.592814	0
Total	10	15	17	73	49	10	35	114	184	507	0	0
Producer's Accuracy	0.6	0.933333	0.235294	0.09589	0.44898	0.8	0.257143	0.798246	0.538043	0	**0.512821**	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	**0.399021**

Table 2. Accuracy assessment of Iteration B of farm UTUA16.

Class Value	C_1	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_10	Total	User's Accuracy	Kappa
C_1 - Coffee	0	1	9	12	0	0	2	0	57	81	0	0
C_3 - Banana	0	8	21	1	2	0	0	0	70	102	0.078431	0
C_4 - Palm	0	1	20	2	0	0	0	0	25	48	0.416667	0
C_5 - Grasses/Low Herbaceous Vegetation	0	0	3	34	1	0	0	0	3	41	0.829268	0
C_6 - Bare Earth	0	0	0	1	8	0	3	0	0	12	0.666667	0
C_7 - Paved	0	0	0	0	0	9	1	0	1	11	0.818182	0
C_8 - Buildings	0	0	0	0	0	3	5	0	0	8	0.625	0
C_9 - Water	0	0	0	0	0	0	0	46	0	46	1	0
C_10 - Overstory Vegetation	0	0	21	0	0	0	2	0	128	151	0.847682	0
Total	0	10	74	50	11	12	13	46	284	500	0	0
Producer's Accuracy	0	0.8	0.27027	0.68	0.727273	0.75	0.384615	1	0.450704	0	**0.516**	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	**0.38892**

Table 3. Accuracy assessment of Iteration B of farm UTUA18.

Class Value	C_1	C_2	C_3	C_5	C_6	C_7	C_8	C_10	Total	User's Accuracy	Kappa
C_1 - Coffee	0	0	0	0	0	0	0	0	0	0	0
C_2 - Citrus	0	0	0	0	0	0	0	0	0	0	0
C_3 - Banana	2	1	34	10	6	0	0	90	143	0.237762	0
C_5 - Grasses/Low Herbaceous Vegetation	5	6	15	19	11	0	0	42	98	0.193878	0
C_6 - Bare Earth	0	0	0	0	6	0	0	0	6	1	0
C_7 - Paved	0	0	0	0	0	30	21	0	51	0.588235	0
C_8 - Buildings	0	0	0	0	0	3	61	0	64	0.953125	0
C_10 - Overstory Vegetation	3	3	11	0	0	0	0	133	150	0.886667	0
Total	10	10	60	29	23	33	82	265	512	0	0
P_Accuracy	0	0	0.566667	0.655172	0.26087	0.909091	0.743902	0.501887	0	**0.552734**	0
Kappa	0	0	0	0	0	0	0	0	0	0	**0.424981**

Table 4. Accuracy assessment of Iteration B of farm UTUA20.

Class Value	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_10	Total	User's Accuracy	Kappa
C_1 - Coffee	0	0	3	2	2	20	0	2	5	34	0	0
C_2 - Citrus	6	0	7	0	6	1	0	1	77	98	0	0
C_3 - Banana	2	0	12	23	0	0	0	0	63	100	0.12	0
C_4 - Palm	0	0	0	0	0	0	0	0	0	0	0	0
C_5 - Grasses/Low Herbaceous Vegetation	0	0	0	0	3	2	2	0	1	8	0.375	0
C_6 - Bare Earth	0	0	0	0	0	5	2	1	0	8	0.625	0
C_7 - Paved	0	0	0	0	0	0	5	2	0	7	0.714286	0
C_8 - Buildings	0	0	0	0	0	0	1	109	0	110	0.990909	0
C_10 - Overstory Vegetation	2	0	3	4	0	0	0	1	134	144	0.930556	0
Total	10	0	25	29	11	28	10	116	280	509	0	0
Producer's Accuracy	0	0	0.48	0	0.272727	0.178571	0.5	0.939655	0.478571	0	**0.526523**	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	**0.395061**

Table 5. Accuracy assessment of Iteration C of farm UTUA2.

Class Value	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_10	Total	User's Accuracy	Kappa
C_1 - Coffee	6	1	2	8	3	0	0	0	35	55	0.109091	0
C_2 - Citrus	0	11	4	24	4	0	4	1	39	87	0.126437	0
C_3 - Banana	2	2	5	1	11	1	15	2	5	44	0.113636	0
C_4 - Palm	0	0	1	16	6	0	0	0	46	69	0.231884	0
C_5 - Grasses/Low Herbaceous Vegetation	1	1	0	1	20	0	0	0	0	23	0.869565	0
C_6 - Bare Earth	0	0	0	2	0	9	2	18	0	31	0.290323	0
C_7 - Paved	0	0	0	0	0	0	11	0	0	11	1	0
C_8 - Buildings	0	0	0	1	0	0	0	93	0	94	0.989362	0
C_10 - Overstory Vegetation	1	0	5	20	5	0	3	0	59	93	0.634409	0
Total	10	15	17	73	49	10	35	114	184	507	0	0
Producer’s Accuracy	0.6	0.733333	0.294118	0.219178	0.408163	0.9	0.314286	0.815789	0.320652	0	**0.453649**	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	**0.360941**

Table 6. Accuracy assessment of Iteration C of farm UTUA16.

Class Value	C_1	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_10	Total	User's Accuracy	Kappa
C_1 - Coffee	0	4	20	14	0	0	1	0	41	80	0	0
C_3 - Banana	0	5	11	0	1	0	0	0	51	68	0.073529	0
C_4 - Palm	0	0	23	4	0	0	2	0	45	74	0.310811	0
C_5 - Grasses/Low Herbaceous Vegetation	0	0	2	32	0	0	0	0	11	45	0.711111	0
C_6 - Bare Earth	0	0	0	0	8	0	1	1	0	10	0.8	0
C_7 - Paved	0	0	0	0	2	5	6	0	0	13	0.384615	0
C_8 - Buildings	0	0	0	0	0	7	3	0	0	10	0.3	0
C_9 - Water	0	0	0	0	0	0	0	45	1	46	0.978261	0
C_10 - Overstory Vegetation	0	1	18	0	0	0	0	0	135	154	0.876623	0
Total	0	10	74	50	11	12	13	46	284	500	0	0
Producer's Accuracy	0	0.5	0.310811	0.64	0.727273	0.416667	0.230769	0.978261	0.475352	0	**0.512**	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	**0.375467**

Table 7. Accuracy assessment of Iteration C of farm UTUA18.

Class Value	C_1	C_2	C_3	C_5	C_6	C_7	C_8	C_10	Total	User's Accuracy	Kappa
C_1 - Coffee	0	0	0	0	0	0	0	0	0	0	0
C_2 - Citrus	0	0	0	0	0	0	0	0	0	0	0
C_3 - Banana	3	0	28	10	10	0	0	99	150	0.186667	0
C_5 - Grasses/Low Herbaceous Vegetation	4	10	11	18	6	0	0	53	102	0.176471	0
C_6 - Bare Earth	0	0	0	0	4	0	2	0	6	0.666667	0
C_7 - Paved	0	0	0	0	0	19	22	0	41	0.463415	0
C_8 - Buildings	0	0	0	0	3	14	58	0	75	0.773333	0
C_10 - Overstory Vegetation	3	0	21	1	0	0	0	113	138	0.818841	0
Total	10	10	60	29	23	33	82	265	512	0	0
Producer's Accuracy	0	0	0.466667	0.62069	0.173913	0.575758	0.707317	0.426415	0	**0.46875**	0
Kappa	0	0	0	0	0	0	0	0	0	0	**0.323879**

Table 8. Accuracy assessment of Iteration D of farm UTUA20.

Class Value	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_10	Total	User's Accuracy	Kappa
C_1 - Coffee	0	0	1	1	4	15	0	5	2	28	0	0
C_2 - Citrus	4	0	4	1	0	0	0	0	77	86	0	0
C_3 - Banana	0	0	15	23	3	0	0	0	63	104	0.144231	0
C_4 - Palm	0	0	0	0	0	0	0	0	0	0	0	0
C_5 - Grasses/Low Herbaceous Vegetation	0	0	1	0	3	5	2	1	2	14	0.214286	0
C_6 - Bare Earth	0	0	1	0	0	8	4	9	0	22	0.363636	0
C_7 - Paved	0	0	0	0	0	0	4	8	0	12	0.333333	0
C_8 - Buildings	0	0	0	0	0	0	0	93	0	93	1	0
C_10 - Overstory Vegetation	6	0	3	4	1	0	0	0	136	150	0.906667	0
Total	10	0	25	29	11	28	10	116	280	509	0	0
Producer's Accuracy	0	0	0.6	0	0.272727	0.285714	0.4	0.801724	0.485714	0	**0.508841**	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	**0.371676**

Table 9. Accuracy assessment of Iteration E of farm UTUA2.

Class Value	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_10	Total	User's Accuracy	Kappa
C_1 - Coffee	7	1	0	4	6	0	0	0	24	42	0.166667	0
C_2 - Citrus	2	10	4	28	4	0	2	1	27	78	0.128205	0
C_3 - Banana	0	1	8	6	7	1	16	8	7	54	0.148148	0
C_4 - Palm	0	0	0	13	3	0	0	0	58	74	0.175676	0
C_5 - Grasses/Low Herbaceous Vegetation	0	0	0	1	21	0	0	0	1	23	0.913043	0
C_6 - Bare Earth	1	0	1	2	0	9	0	13	1	27	0.333333	0
C_7 - Paved	0	0	0	0	0	0	16	2	0	18	0.888889	0
C_8 - Buildings	0	0	0	1	0	0	0	90	0	91	0.989011	0
C_10 - Overstory Vegetation	0	3	4	18	8	0	1	0	66	100	0.66	0
Total	10	15	17	73	49	10	35	114	184	507	0	0
Producer's Accuracy	0.7	0.666667	0.470588	0.178082	0.428571	0.9	0.457143	0.789474	0.358696	0	**0.473373**	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	**0.380003**

Table 10. Accuracy assessment of Iteration F of farm UTUA2.

Class Value	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_10	Total	User's Accuracy	Kappa
C_1 - Coffee	5	2	3	11	2	0	1	0	17	41	0.121951	0
C_2 - Citrus	1	9	3	21	4	0	1	0	27	66	0.136364	0
C_3 - Banana	3	2	6	4	8	1	18	4	9	55	0.109091	0
C_4 - Palm	1	0	1	11	7	0	0	0	61	81	0.135802	0
C_5 - Grasses/Low Herbaceous Vegetation	0	0	0	6	22	0	0	0	0	28	0.785714	0
C_6 - Bare Earth	0	0	0	5	0	8	5	16	2	36	0.222222	0
C_7 - Paved	0	0	0	0	0	0	8	0	0	8	1	0
C_8 - Buildings	0	0	0	0	0	1	0	94	0	95	0.989474	0
C_10 - Overstory Vegetation	0	2	4	15	6	0	2	0	68	97	0.701031	0
Total	10	15	17	73	49	10	35	114	184	507	0	0
Producer's Accuracy	0.5	0.6	0.352941	0.150685	0.44898	0.8	0.228571	0.824561	0.369565	0	**0.455621**	0
Kappa	0	0	0	0	0	0	0	0	0	0	0	**0.358437**