REMOTE SENSING-BASED CHARACTERIZATION OF BIODIVERSITY SUPPORTING STRUCTURES ON COFFEE FARMS IN ZIMBABWE

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July, 2024

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ABSTRACT

Coffee is an important commodity crop in international trade and mainly produced in tropical areas where deforestation is reported to be happening. There is a growing market demand for sustainable coffee that is deforestation free and supports ecosystem services among other social and environmental requirements. Current methods of assessing indicators of sustainability rely on sending assessors and this is expensive, time consuming and often subjective. The goal of this project was therefore to develop an accurate remote-sensing based method to map and quantify biodiversity supporting structures (BSS) on coffee farms to support coffee certification. Field data on the location, extend and other features of five BSS (hedgerows, shade trees, coffee, forests, and wetlands) were collected at two farms (Crake Valley and Jersey) in Zimbabwe. A random-forest based classification routine for optical data (Pléiades and GeoEye-1) and radar (Sentinel-1) data was implemented using the field data collected using spectral bands and vegetation indices. The separability of BSS using bands, indices and radar metrices was tested then the best performing indices were used for the mapping and quantification of the BSS from the remote sensing data. Using the mapped BSS, a change assessment was then implemented to assess if there are changes in the BSS at the two farms. Using the Fishers linear discriminant analysis on optical data, three vegetation indices (NDVI, NDWI and GNDVI) at Crake Valley ranked the most discriminant while SAVI, EVI and B3 were the most discriminant at Jersey. Different Sentinel-1 radar based data types were tested to see if using them in mapping BSS would improve the accuracy but it was concluded that this approach was not successful because the low spatial resolution to recognize small BSS. Applying the best discriminating features to map the BSS at Crake Valley produced an overall accuracy of 73.1% and 52.0% for optical and radar respectively. At Jersey, the overall accuracy was 64.9% and 38.5% for optical and radar respectively, with coffee and forest being difficult to distinguish. It was concluded from this that the optical methods are better in mapping BSS in coffee farms and were applied to detect if there were changes in these at the two farms. Crake Valley had higher density of BSS in relation to coffee compared to Jersey meaning increased ecosystem services. It is concluded from this study that it is possible to map and quantify BSS on coffee farms with high resolution optical remote sensing data to support sustainability assessments with an accuracy above 64%. Further work is required to standardize the methods across farms and to include other indicators in the assessment.

Key words: coffee, certification, sustainable sourcing, shading

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1. INTRODUCTION

1.1. Coffee production and sustainability

Coffee is an important agricultural commodity traded globally, playing a pivotal role in the global economy (Wahyudi et al., 2020). Approximately 125 million people rely on coffee for their livelihood, highlighting its significance as a major economic driver (Krishnan, 2017). The global coffee industry has been on an upward trajectory for decades. Annually, over 10 million tons of coffee are produced, originating from more than 70 tropical countries (Statistics | Food and Agriculture Organization of the United Nations, 2023.) This growth is fueled by an increasing demand driven by a thriving coffee culture and a growing preference for specialty and artisanal coffees. Consequently, coffee production has become a major industry, contributing significantly to the economies of coffee-producing and consuming countries(Takesure, 2018).

To meet this growing demand, some coffee farmers particularly those engaged in commercial and large-scale operations, resort to unsustainable farming practices such as deforestation, monoculture, excessive use of pesticides, and poor water management. These practices have adverse impacts on the environment, leading to biodiversity loss, soil degradation, and water pollution (Anand et al., 2008; Hylander et al., 2013; Ngugi & Mbaria, 1995). Addressing the environmental effects of unsustainable coffee farming is crucial for preserving biodiversity, preventing deforestation, ensuring soil and water quality and mitigating climate change effects. Unsustainable coffee farming inflicts wide-ranging and adverse consequences on the health, livelihoods, and overall well-being of communities (Hunt et al., 2020). It places the health of these communities at risk, often involving the heavy use of pesticides and chemicals that contaminate local water sources and lead to various health as highlighted by Merhi et al., (2022).

On a local scale, coffee farming forms a crucial part of Zimbabwe's agricultural landscape. While Zimbabwe may not be among the largest global coffee producers but it has a unique coffee-growing history and tradition. Over the years, coffee has emerged as a valuable crop in the country, providing livelihoods to many local communities and contributing to their economic stability. The coffee industry in Zimbabwe, showcases the potential to enhance local economies. Recent statistics indicate that Zimbabwe's coffee production has been revitalized through initiatives such as Nespresso's Tamuka MuZimbabwe programme, which has increased production by 7% (Nespresso, 2023). As of 2022, Zimbabwe's coffee production was 661 metric tons and produced from over 2500 ha of planted area (Figure 1). Therefore, on average over half a million kilograms of coffee are produced every single year in the country with production and area harvested statistics showing an increasing trend. A further growth is projected as both government and private initiatives continue to support the sector (Knoema, 2023). The government aims to boost coffee output to 10,000 tons by 2030 through investments and the establishment of new plantations (Nespresso, 2023).

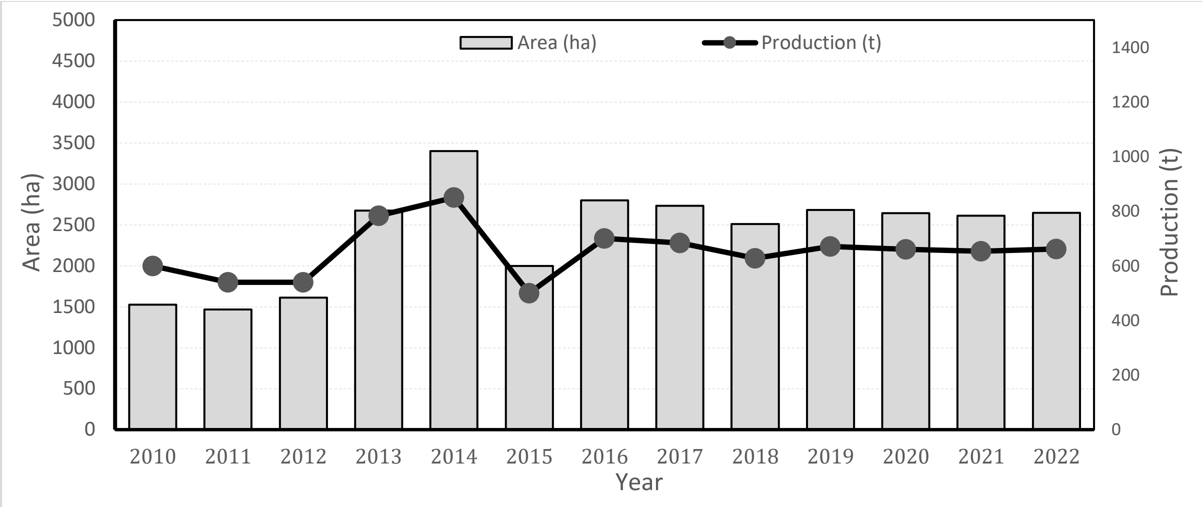

Figure 1: Zimbabwe Coffee Production Trends (2010-2022). This graph illustrates the annual coffee production in Zimbabwe, measured in metric tons, from 2010 to 2022 and the area measured in ha. Data sourced from the Food and Agriculture Organization of the United Nations (2023).

This increase in coffee output aligns with the global demand for coffee. However, the market is increasingly demanding coffee that adheres to sustainable practices. This now requires mechanisms to ensure that coffee supply chains are environmentally and socially responsible. Zimbabwean coffee farmers are responding to this global market trend by moving towards sustainable certification as recent trends indicate that sustainable certification can enhance market access and profitability. Initiatives like Nespresso's Tamuka MuZimbabwe exemplify how market-driven sustainability efforts can benefit both the environment and the local economy by providing training, resources, and financial support to smallholder farmers. This approach not only meets the global demand for sustainable coffee but also promotes long-term ecological and economic stability in coffee-producing regions (Nespresso, 2023). This is because sustainably-produced coffee has the capacity to promote conservation of mammals, birds, pollinators and provide other ecosystems services such as carbon sequestration, erosion prevention and act as biological corridors, in addition to being profitable for producers as it receives a premium on the market.

This market-driven need for certified sustainable coffee consequently requires methods to make certification more accessible and standardized. Certification is often expensive due to extensive fieldwork and varied metrics that are prone to subjective assessment as highlighted by the U.S Department of Agriculture (2023). There is therefore need for developing more efficient and less expensive but consistent certification methods for use in the coffee sector. Beyond understanding current practices, challenges and solutions in coffee sustainable assessments, it is essential to examine the dynamic changes in biodiversity within these farms over extended periods. Coffee plants take roughly 4 to 5 years to reach maturity (Ukers, 2016). There is therefore need for a long-term perspective to fully capture its ecological impacts and assess the effectiveness of sustainable practices. Thus, a decade-long focus is vital for this study (2013-2023). This timeframe not only encompasses the biological growth cycle but also coincides with significant shifts in agricultural policies and market demands for sustainability during this period. The importance of a decadal timeframe is underscored by research by Perfecto (2015) highlighting the long-term influence of shade management practices on coffee farm biodiversity.

1.2. Assessing sustainable farming practices and certification standards

Coffee producers across the world are increasingly adopting certification standards in their agricultural practices to be recognized as sustainable coffee producers. This involves a verification process where independent certification agency inspectors conduct physical field visits to ensure farmers adhere to sustainability criteria. The certification process involves substantial costs that can range from a few hundred to several thousand dollars, according to the U.S. Department of Agriculture (2023). Additional sources like the Dutch Centre for the Promotion of Imports from developing countries (CBI, 2021) and the Rainforest Alliance (2023) also highlight the financial burden of certification which is often born by the producers.

Certification encompasses economic, social, and environmental dimensions, each critical for satisfying the increasing global demand for sustainable coffee. This demand is evidenced by the significant growth in certified coffee exports from only 8% being certified sustainable in 2009 (International Trade Centre, 2011) to more than 40% in some countries such as The Netherlands in recent years (Global Coffee Platform, 2022). This rise is driven by consumer expectations and corporate responsibility initiatives that require producers to adhere to stringent environmental and ethical standards. These standards not only help farmers access international markets but also encourage practices that reduce environmental impacts. Such trends underscore the importance of developing and applying innovative assessment methods, including remote sensing technologies, to efficiently verify compliance with these diverse certification criteria.
Certification programs as detailed by Giovannucci & Ponte (2005) and supported by recent updates from Gourmesso Coffee (2023), enforce guidelines that cover three focus areas (Figure 2) which are:

i. Environmental Standards: These focus on conserving high biodiversity areas and integrating biodiversity-supporting structures (BSS) like shade trees and buffer zones on coffee farms. These practices aim to prevent deforestation, protect soil and water quality and reduce greenhouse gas emissions, thus maintaining ecological balance and supporting diverse species habitats.
ii. Labor Standards: These ensure decent working conditions, fair wages, and prohibit child labor. These standards are essential for improving the livelihoods of farm workers and enhancing the social well-being of communities involved in coffee production.
iii. Social Standards: These address broader issues such as community development and respect for local cultures. This often includes implementing social projects like education and healthcare initiatives to support surrounding communities.

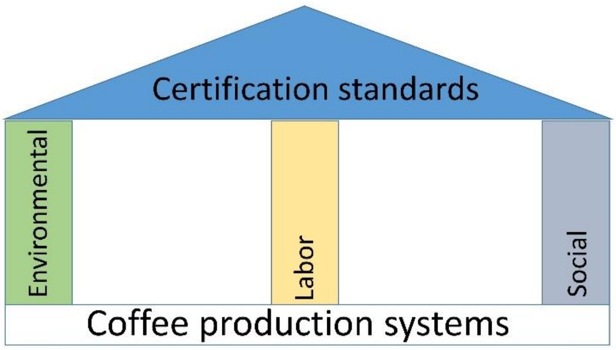

Figure 2: The three interacting pillars of coffee certification programs that are used to assess producers.

1.3. Environmental criteria for certification

To promote sustainable coffee farming practices, certification programs mainly emphasize a variety of environmental criteria designed to ensure ecological sustainability. These are sustainable farm management practices, conservation of high biodiversity areas, incorporation of BSS and vegetational buffer zones on coffee farms.

- Sustainable farm management practices: Certification programs emphasize sustainable farm management practices that minimize the environmental footprint of coffee production. This includes the responsible use of water resources, reduction of chemical inputs, and the implementation of soil conservation techniques. Sustainable management practices are vital for maintaining soil fertility and preventing land degradation (International Trade Centre, 2011).

- Conservation of high biodiversity areas: Certification standards require the conservation and restoration of high biodiversity areas. This involves protecting natural vegetation, fauna, soil, and water sources. Maintaining these areas helps preserve ecological balance and supports various species' habitats, ensuring that coffee farming does not lead to biodiversity loss (Lentijo & Hostetler, 2011)
- Incorporation of BSS: Coffee farms are encouraged to integrate BSS, such as shade trees and buffer zones, which help create a habitat for wildlife and contribute to soil and water conservation. These structures also mitigate the effects of erosion and improve the resilience of coffee farms against environmental changes (Giovannucci & Ponte, 2005)
- Vegetational buffer zones: Maintaining vegetational buffer zones near rivers, streams, lakes, and erosion-prone areas is a critical element of these certification standards. These buffer zones act as natural barriers that prevent soil erosion, filter pollutants, and provide a habitat for various plant and animal species. They play a significant role in maintaining water quality and overall ecosystem health (CBI, 2021)

By adhering to these standards, coffee farms not only contribute to global sustainability goals but also enhance their appeal to consumers who prioritize environmentally friendly products. Farmers also get higher income from selling their certified coffee which they can invest into other biodiversity and social programs. The precision and objectivity offered by remote sensing technologies provide an opportunity to assess these crucial environmental elements systematically and efficiently. This potentially reduces the need for physical site visits and thereby lowering the overall costs of certification while offering a more objective assessment that can be implemented over long time periods (Takahashi & Todo, 2014).

1.4. Role of remote sensing in assessing sustainability criteria

Remote sensing technology has become an invaluable tool in assessing sustainability criteria within agricultural landscapes, including coffee farms. The ability to gather extensive data over large areas, combined with advanced analytical techniques, allows for detailed monitoring and evaluation of various environmental parameters. To conduct a thorough analysis of biodiversity structures within coffee farms, it is essential to consider the specific characteristics of these structures, guiding the choice of remote sensing imagery and technology.

RS technologies offer a range of capabilities to capture detailed and diverse ecological information. High-resolution optical sensors, such as those provided by DigitalGlobe's WorldView-2 satellite, are crucial for fine-scale analysis. With a nominal resolution of 0.4 meters per pixel, this imagery is essential for identifying and mapping small and heterogeneous BSS, such as individual shade trees and vegetational buffers (Ducrot et al., 2015; Freudenberg et al., 2022). High spatial resolution enables the differentiation of individual trees, aiding in quantifying their contribution to biodiversity (Klemas, 2014). High-resolution imagery is particularly advantageous for detecting fine-scale features, which are often critical in biodiversity studies because they allow for a more detailed and accurate mapping of small, heterogeneous structures within coffee farms.

Moderate-resolution imagery from satellites like Landsat and Sentinel is beneficial for monitoring larger features like forest patches and extensive biodiversity areas. Landsat data, with a resolution of 30 meters, is effective for observing large-scale land cover changes (Wulder et al., 2008). Similarly, Sentinel data provides a holistic view of biodiversity patterns and is valuable for comprehensive land cover monitoring (Drusch et al., 2012). However, moderate-resolution imagery might not capture the fine details necessary for precise mapping of smaller BSS, making it less suitable for tasks that require high spatial accuracy.

Radar sensors such as those on Sentinel-1, offer critical data on surface roughness and moisture content. Sentinel-1's C-band radar, with a resolution of 10 meters, provides valuable insights into larger aggregated BSS. While its resolution is larger than individual small-scale structures like shade trees or hedgerows, it effectively captures broader vegetative patterns and moisture variations. Radar's ability to penetrate cloud cover ensures consistent data acquisition, vital in areas with frequent cloud cover (Asner & Vitousek, 2005). Additionally, the sensitivity of radar technology to surface roughness is critical in detecting BSS within coffee plantations (Baghdadi et al., 2002)

Despite these advantages, radar data alone may not provide sufficient detail for identifying specific small-scale structures, as its resolution is generally coarser than that of high-resolution optical imagery. The fusion of radar and optical data ensures that the shortcomings of one imagery are compensated by the strengths of the other, offering a more nuanced and detailed understanding of BSS (Freudenberg et al., 2022). For example, Maskell et al. (2021) demonstrated the effectiveness of combining Sentinel-2 and Sentinel-1 SAR data to map coffee production systems, achieving an overall accuracy of 89% for a binary coffee/non-coffee map.

From these RS imageries, spectral and texture characterization are critical components of this analysis. Spectral properties derived from optical sensors and texture properties obtained from radar sensors provide information that can distinguish BSS from other land cover types and themselves with the highest accuracy and most detailed separability. High-resolution imagery offers detailed insights into the spatial distribution and health of these structures. Additionally, radar data provides crucial information on surface roughness and moisture content, enhancing the accuracy of BSS identification.

1.5. Remote sensing-based approach for identifying and mapping BSS

Remote sensing plays a pivotal role in biodiversity mapping, offering detailed insights into land cover and ecological structures. Two predominant methods in remote sensing for image analysis and land cover characterization are pixel-based and object-based approaches.

Pixel-based methods operates on the premise that each pixel in an image is the smallest unit of analysis (Casals-Carrasco et al., 2000; Damla et al., 2011). It assigns class labels to individual pixels based on their spectral properties. This method is advantageous for its simplicity and computational efficiency, particularly when dealing with high-resolution imagery that captures detailed spectral information. Pixel-based approaches are highly effective for fine-scale analysis, making it suitable for detecting small and heterogeneous features such as BSS within agricultural landscapes (Duro et al., 2012a).

Object-based classification, on the other hand, involves segmenting an image into meaningful objects or regions before classification (Damla et al., 2011). This method considers not only the spectral properties of pixels but also their spatial context, such as shape, texture, and relationships with neighboring pixels. Object-based classification is often preferred for its ability to produce visually appealing and generalized representations of land cover classes (Liu & Xia, 2010). It can integrate contextual information, potentially improving classification accuracy for certain applications, such as large homogeneous areas or where spatial relationships are crucial.

Empirical evidence supports the efficacy of pixel-based approaches for land cover characterization and quantification of features. For example, a study by Duro et al., (2012) compared pixel-based and object-based image analysis using various machine learning algorithms for classifying agricultural landscapes. The findings indicated no significant difference in overall accuracy between the two methods ($p > 0.05$), suggesting that pixel-based approaches can also achieve high classification accuracies comparable to object-based methods but without the overall burden of complexity and strenuous processes.

Similarly, Berhane et al., (2018) demonstrated that pixel-based methods can achieve high accuracies comparable to object-based methods, particularly when using advanced machine learning algorithms like RF. In their study, the pixel-based RF approach achieved an overall accuracy of 87.9%, while the object-based RF approach achieved 90.4%. McNemar's test confirmed no statistically significant difference in overall accuracy between the pixel-based and object-based RF classifiers, suggesting that pixel-based approaches are sufficiently robust for high-accuracy feature identification.

Pixel-based classifications are less time-consuming and computationally intensive, requiring fewer variables and less processing time (Zehra et al., 2011). This efficiency is particularly advantageous when handling large datasets and multiple spectral bands from high-resolution imagery, making pixel-based methods a practical and robust choice for this research. Additionally, pixel-based approaches offer significant flexibility in data integration, seamlessly combining various data types (optical, radar) and multiple spectral bands as shown by (Duro et al., 2012b). This capability may enhance the detection and characterization of different BSS, allowing for a comprehensive analysis of the ecological landscape. The ability to integrate diverse datasets is particularly beneficial in the context of coffee farms, where the goal is to accurately map detailed and specific BSS (Widayati et al., 2002)

In the specific application of coffee farms in Zimbabwe, the fine-scale capabilities of pixel-based methods are especially advantageous. They enable precise mapping of critical ecological features supporting biodiversity conservation efforts. They provide a balance of accuracy, efficiency and simplicity, making them a suitable choice for this study. By leveraging high-resolution optical and radar imagery, pixel-based methods can deliver detailed and accurate maps of BSS (Berhane et al., 2017), thereby supporting biodiversity conservation efforts within coffee farming landscapes in Zimbabwe.

Given the utilization of two distinct datasets, optical and radar, data fusion becomes crucial for maximizing classification accuracy in this study of coffee farms. Two prominent approaches exist- pre-classification and post-classification fusion, each with its advantages and limitations (Pandit & Bhiwani, 2015) Pre-classification fusion integrates optical and radar data before the individual classification processes. This creates a comprehensive dataset that can capture the intricacies of the features being studied, potentially leading to higher classification accuracy as highlighted by (Chen et al., 2017). However, this method unlike post classification it does not allow for a clear understanding of how each data source contributes to the final classification (Zhang et al., 2023). This can be valuable for interpreting the results and identifying areas where one data type might be more informative than the other. Also, post-classification fusion is generally less computationally demanding compared to pre-classification fusion making it suitable for our analysis. Furthermore, by fusing after the classification, the study can apply decision rules after the individual classifications, potentially leveraging the strengths of both data sources.

1.6. Research objectives and research questions

1.6.1. Main objective

The main objective of this study is to develop a remote sensing-based method for accurately mapping BSS within coffee farms. The focus is on testing to what extent pixel-based approaches (optical and a fusion of radar and optical images) can identify and map BSS on coffee farms to support certification.

1.6.2. Specific objectives

1. Evaluate the effectiveness of pixel-based classification using Very High-Resolution optical imagery in detecting BSS within coffee farms in Zimbabwe.
2. Explore the integration of optical and radar data using post-classification fusion method to enhance the mapping accuracy of BSS.
3. Compare the presence of biodiversity supporting structures between 2013 and 2023 across coffee farms in Zimbabwe to assess changes over time.

1.6.3. Research Questions

1. How accurately can VHR optical imagery detect and map biodiversity supporting structures within coffee farms in Zimbabwe?
   Sub-question: Which optical bands/indices are most effective in distinguishing between different types of BSS?
2. To what extent does the fusion of optical high-resolution imagery and radar technology improve the accuracy in identifying and quantifying BSS within coffee farms. Which radar features and their derived metrics are most effective in distinguishing between different types of BSS?
3. To what extent have biodiversity supporting structures within coffee farms changed between 2013 and 2023?

2. DATA AND METHODS

2.1. Study area

The study area is the Manicaland Province of Zimbabwe, which falls under agroecological region 1, one of the five agroecological regions in the country. Manicaland province is geographically situated between latitudes 17°00' S to 20°00' S and longitudes 32°00' E to 33°30' E. It is a key agricultural hub known for its fertile soils and favorable climate. This region's agricultural productivity significantly contributes to Zimbabwe's food security and export earnings, with major crops including tea, coffee, tobacco and citrus fruits (Chingarande et al., 2020). Agroecological region 1 experiences a subtropical climate, characterized by warm, humid summers and mild, dry winters. The average annual temperature ranges from 18°C to 26°C, with the highest temperatures in October and November, and the lowest in June and July. Annual rainfall varies from 1000mm to 1500mm, with the wet season lasting from November to April and the dry season from May to October. These climatic conditions, combined with the region's fertile soils, make it particularly suitable for coffee cultivation, emphasizing Manicaland's critical role in Zimbabwe's agricultural landscape (ESDAC, 2024). This region is known for specialized and diversified farming, including intensive farming and forestry, which thrive due to the reliable and abundant rainfall. Coffee farming, in particular, benefits greatly from these conditions, making agroecological region 1 an ideal location for this crop. Importantly, almost all coffee farms in Zimbabwe are situated in Region 1, making it crucial to focus on this area.

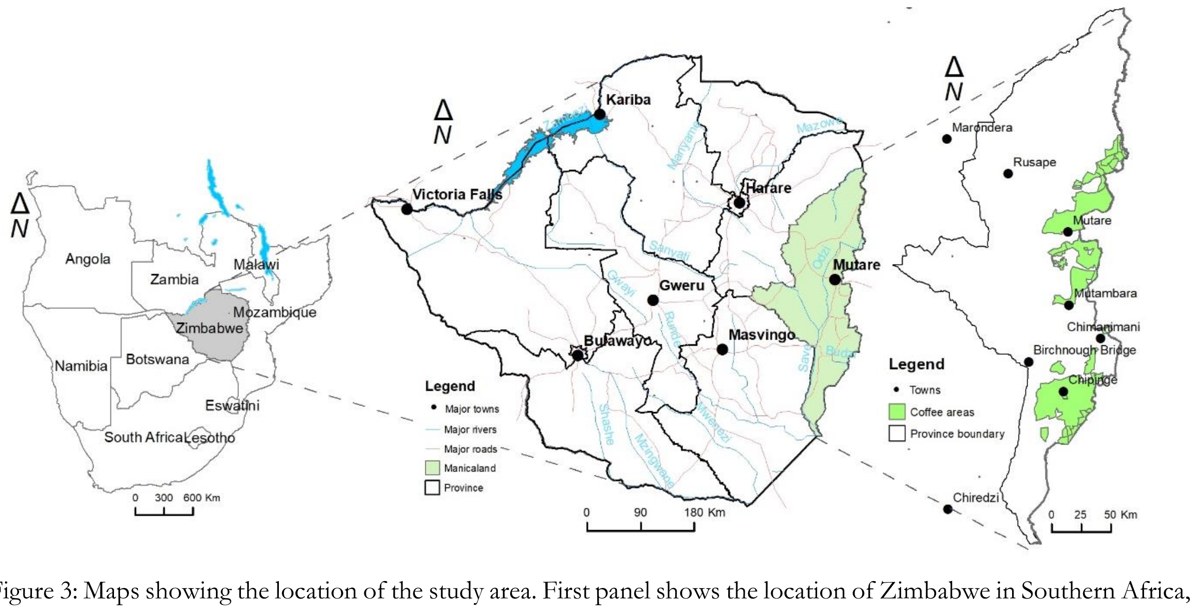

Figure 3: Maps showing the location of the study area. First panel shows the location of Zimbabwe in Southern Africa, the second shows the location of Manicaland province in Zimbabwe and the third shows the coffee production areas in Manicaland province.

2.2. Overview of methods

This section presents a comprehensive method for characterizing BSS on coffee farms in Zimbabwe through remote sensing. The study involved evaluating pixel-based approaches using very high-resolution optical imagery to map and quantify BSS on coffee farms. The study also explored the integration of optical and radar data through post-classification fusion methods then compared BSS presence between 2023 and 2014. Due to the variability in characteristics of BSS across different farms, farm-specific models were developed and validated to ensure accurate classification. The methodology includes field data collection, spectral and radar analysis, feature creation, model training, classification, data fusion, accuracy assessment, and temporal analysis. Each section elaborates on the specific methods and processes utilized.

2.3. Data

To support the analysis and classification of BSS on coffee farms, various datasets were utilized. These datasets provide comprehensive information through different remote sensing technologies and field survey data. Table 1 summarizes the datasets used in this study, showing their type, resolution date and source. All spatial data were projected using the WGS 84 / UTM zone 36S coordinate system which is particularly suited to the study area's geographic location in the southern hemisphere, providing a consistent framework for spatial analysis.

Table 1: Summary of datasets used for analysing and classifying BSS on coffee farms.

Name	Type, Resolution & Format	Date	Source of Data
Coffee Farm Boundaries	Vector (polygon) [.shp]	2023	Surveyor General
Field Survey Data	Text Data [.csv, .xlsx]	2024	Field work
GeoEye-1 Satellite Image	Raster (PAN 0.5m, Multispectral 2m) [.tif]	2012, 2023	GeoEye-1, DigitalGlobe
Pléiades Neo, Pléiades	Raster (PAN 0.5m, Multispectral 2m) [.tif]	2013, 2023	Airbus and European Space Agency (ESA)
Sentinel-1 Radar Data	Raster (10m) [.tif]	2012, 2023	European Space Agency (ESA)

2.4. Field data collection

Initially, five coffee farms in Zimbabwe were selected for field sampling based on the presence of BSS and their variability. These farms were chosen to represent a variety in terms of sustainability and geographical distribution across the coffee producing areas in Zimbabwe. Out of the five selected farms, access was granted to three farms but sufficient samples were obtained from only two farms – Crake Valley and Jersey.

2.5. Sampling design

To gather sample data of the BSS on coffee farms, the study employed a stratified random sampling strategy. This approach began with an initial assessment using Google Earth Pro to identify specific strata in which BSS are found namely monocrop coffee fields, coffee fields with shadow trees or intercropping, forest patches and wetland. Based on these identified BSS the farms were then divided into distinct strata. Then within each stratum, random sample points were chosen. This two-step process ensured a representative sample across the entire farm and prevented any bias towards specific areas. The goal was to gather accurate data on the overall BSS conditions.

Following the initial field data collection, additional sample points were identified and collected from high-resolution imagery to create a more comprehensive and balanced dataset. These points were selected based on preliminary analysis of the initial data, targeting underrepresented or challenging areas such as dense forests and wetlands as shown by Figure 4.

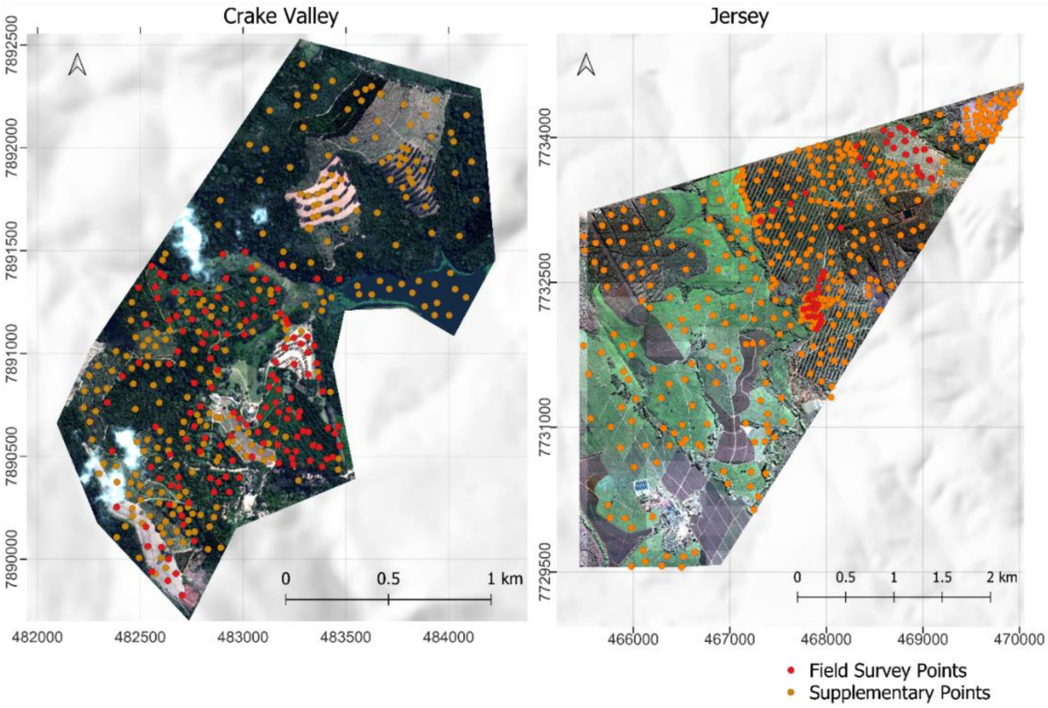

Figure 4: Spatial distribution of sample and supplementary points at Crake Valley and Jersey.

Table 2 below shows the distribution of all the points across the different BSS. By integrating these additional points with the initial dataset it ensured a more balanced representation of all BSS types across the study area thus improving the overall quality and comprehensiveness of the dataset.

Table 2: Field and supplementary data summary

Farm	BSS type	Number of points
Crake Valley	Shade Trees	82
	Hedgerows	172
	Forest	99
	Wetlands	58
	Bare	34
	Coffee	116
Jersey	Shade trees	6
	Forest	108
	Hedgerow/ Macadamia	68
	Bare	67
	Tea	92
	Coffee	224

2.6. Optical remote sensing data processing

2.6.1. Data acquisition

The study aimed to use very high-resolution optical imagery with a resolution of less than 1 meter. However, the availability of suitable satellite imagery varied between Crake Valley and Jersey. There was no single satellite platform offering consistent coverage for both locations. Furthermore, the available satellites had different spectral bands available with some bands not offered consistently across both sites. Despite these limitations, Red Green Blue and Near infrared bands were common across the available satellite options at a resolution of 0.5 meters and were chosen. This choice ensured the best possible uniformity in data quality and spectral properties across different sites, despite the differences in satellite platforms.

For Crake Valley, imagery from GeoEye-1 was selected with specific acquisitions on June 29, 2023 (Image ID 1050010034A06A00), and May 3, 2013 (Image ID 1050410000BF7900), each featuring a 4-Band Bundle (PAN, BLUE, GREEN, RED, NIR1) at a resolution of 50/60 cm and processed as Map-Ready (Ortho) at a scale of 1:12,000. For Jersey, Pléiades imagery from August 18, 2023 (Segment ID: ACQ_PNEO4_03234008365230), and September 16, 2013 (Segment ID: DS_PHR1A_201309160808024_FR1_PX_E032S21_0819_06169) was utilized, also processed to the same specifications.

2.6.2. Pan-sharpening

To enhance the spatial resolution of the VHR images, a pan-sharpening process was applied using the Gram-Schmidt spectral-sharpening algorithm with default settings. The Gram-Schmidt algorithm was selected based on its superior performance in enhancing image clarity and preserving spectral characteristics (*Pansharpening Function*, n.d.) The pan-sharpened images were saved in GeoTIFF format, exhibiting improved spatial resolution and clarity compared to the original multispectral imagery.

Pan-sharpening is used to enhance remote sensing images by combining the high-resolution detail of panchromatic images with the colour information from lower-resolution multispectral images. This process increases the clarity and detail of the images, making it easier to identify smaller features on the ground. Additionally, it improves the visual quality of images, making them sharper for interpretation. This enhancement facilitates more accurate data analysis and thus improving the overall effectiveness of the imagery for BSS characterization.

2.6.3. Reflectance Value Calculation

To convert the digital number (DN) values from GeoEye-1, Pléiades, and Pléiades Neo imagery to reflectance, specific calibration factors and extraterrestrial solar irradiance (ESUN) values are used for each sensor. The process involves the following steps:

1. Convert DN to Radiance:

$$L(b) = \frac{DN(b)}{rescale\ gain(b)} + rescale\ bias(b)$$

2. Calculate reflectance:

$$R(b) = \frac{\pi \times L(b) \times d^2}{ESUN\ (b) \times \cos(\theta)}$$

Where:

- $L(b)$s the spectral radiance for band b
- π is the mathematical constant pi.
- d is the Earth-Sun distance in astronomical units.
- ESUN(b) is the extraterrestrial solar irradiance for each band.
- θ is the solar zenith angle in degrees.

2.6.4. Calibration factors

Table 3: Calibration factors and ESUN values used in image processing.

Calibration factors	**Sensor**	**Blue**	**Green**	**Red**	**NIR**
	GeoEye-1	0.008919	0.0120281	0.0056679	0.0134302
	Pléiades	0.009	0.011	0.011	0.012
	Pléiades Neo	0.009	0.011	0.011	0.012
ESUN Values	GeoEye-1	1993.18	1828.83	1491.49	1022.58
	Pléiades	1969.0	1823.0	1512.0	1055.0
	Pléiades Neo	1986.0	1812.0	1501.0	1042.0

2.6.5. Vegetation Indices

To enhance the accuracy of vegetation mapping and the detection of BSS within coffee farms, specific vegetation indices are utilized as input features. These indices are Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Normalized Difference Water Index (NDWI), Soil Adjusted Vegetation Index (SAVI), and Green Normalized Difference Vegetation Index (GNDVI). They are critical for assessing vegetation health, water content, and other ecological characteristics. The selection of these indices is based on their proven effectiveness in differentiating between various types of vegetation and land cover, and their compatibility with the available 4-band imagery (BLUE, GREEN, RED, NIR1). Using these indices allows for a comprehensive and accurate ecological assessment (Ducrot et al., 2015; Freudenberg et al., 2022).

Normalized Difference Vegetation Index (NDVI)

NDVI assesses vegetation health by measuring the difference between near-infrared (NIR) and red bands, where healthy vegetation strongly reflects NIR and absorbs red light.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

Normalized Difference Water Index (NDWI)

NDWI monitors changes in vegetation water content and soil moisture by using the green and near-infrared (NIR) bands. It is particularly useful for detecting water stress in plants.

$$NDWI = \frac{(G - NIR)}{(G + NIR)}$$

Enhanced Vegetation Index (EVI)
EVI improves sensitivity in high biomass areas and reduces atmospheric influences. It uses a gain factor to enhance the vegetation signal and reduce noise from the atmosphere and soil.

$$EVI = 2.5 \times \frac{NIR - R}{NIR + 6 \times Red - 7.5 \times Blue + 1}$$

Soil Adjusted Vegetation Index (SAVI)
SAVI adjusts for soil brightness influences, suitable for areas with sparse vegetation. It uses a soil brightness correction factor (L), typically set to 0.5.

$$SAVI = \frac{NIR - Red}{NIR + Red + L} \times (1 + L)$$

Green Normalized Difference Vegetation Index (GNDVI)
GNDVI assesses chlorophyll content in vegetation by measuring the difference between NIR and green bands. It is particularly useful for detecting variations in leaf chlorophyll concentration.

$$GNDI = \frac{NIR - Green}{NIR + Green}$$

These indices were selected based on their specific applications to assessing ecological characteristics relevant to BSS and their compatibility with the 4-band imagery available for this study. By employing a range of indices, the study determined which indices provide the highest accuracy in mapping BSS, aligning with our research question on optimizing vegetation mapping techniques.
These indices were calculated using high-resolution optical imagery from GeoEye-1, Pléiades, and Pléiades Neo. The calculations were performed using QGIS with an EnMap plugin called Awesome spectral indices (EnMAP, n.d.)

2.7. Radar remote sensing data processing

2.7.1. Data acquisition

Sentinel-1 GRD data were obtained for the Crake Valley and Jersey using vertical transmit and vertical receive (VV) and vertical transmit and horizontal receive (VH) polarization. The data was already pre-processed in the Sentinel Application Platform (SNAP) to apply the orbit file, perform thermal noise removal, radiometric calibration, and terrain correction using SRTM30 (*Introducing Sentinel-1*, n.d.)
Image ids - S1A_IW_GRDH_1SDV_20230626T031722_20230626T031747_049151_05E912_F849.SAFE for Crake Valley captured on 26 June 2023
S1A_IW_GRDH_1SDV_20230825T031751_20230825T031816_050026_0604D5_6E1A_COG.SAFE for Jersey captured on 25 August 2023

2.7.2. Resampling radar data

This step involved resampling radar data from 10 meters to match the high spatial resolution of optical data, which is set at 50 cm. This resampling is achieved through bilinear interpolation, a technique that preserves the integrity of the original data while increasing its resolution. By harmonizing the spatial resolutions of radar and optical datasets, this step facilitates the seamless integration of the two data sources, enhancing the accuracy and reliability of subsequent analyses and classifications. The effectiveness of bilinear interpolation in improving the spatial characteristics of data has been well-documented in various studies (Kusano et al., 2011; Shrestha et al., 2021).

2.7.3. Texture variables calculations

To enhance the characterization of BSS types, eight Gray Level Co-occurrence Matrix (GLCM) texture variables were calculated for the median composite of the descending VH series. According to Haralick et al., (1973) and Jenicka & Suruliandi, (2014) GLCM texture measures capture the spatial relationships of pixels by identifying patterns based on the specified neighbourhood size. The resultant matrices store the occurrence frequency of pixel pairs with specific grey levels or pixel brightness values. These measures are commonly used in image classification to improve the accuracy of detecting and differentiating surface types. The integration of GLCM texture variables enhances the detail and reliability of the radar and optical data fusion, facilitating more precise land cover and surface type classification.

This textural analysis was based on the method by Haralick et al. (1973), using a 5 × 5 moving window with a displacement of 1, and averaged over four spatial orientations. The 5 × 5 window was chosen as it was used in similar studies for agroforestry mapping, such as in a cocoa landscape landscape (Numbisi et al., 2019) The selected window size is particularly suitable for this study because the BSS to be mapped were similar in size and shape to the objects analyzed in these previous studies. This ensures that the texture features accurately capture the characteristics of BSS within the coffee farms.

2.8. Model development

Given the variability in BSS characteristics across different farms, farm-specific models were developed to ensure accurate classification. The spectral and radar properties of BSS need to be carefully characterized to distinguish them not only from surrounding land cover but also from each other. Feature selection was a critical step in this process, identifying the most relevant features for accurate classification. Various methods were considered for feature selection as described below:

2.8.1. Fisher's linear discriminant ratio (FLDR)

Fisher's Linear Discriminant Ratio (FLDR) is a statistical method used to measure the discriminatory power of features. It evaluates the ratio of between-class variance to within-class variance to identify features that maximize class separability. FLDR is effective in identifying features that provide better class separability, making it highly suitable for remote sensing applications. It has been widely used to enhance classification accuracy by selecting features that significantly distinguish land cover types (Kavzoglu, 2009). FLDR however has limitations. It primarily focuses on maximizing class separability and may not consider the statistical significance of the features. The need to distinguish between different types of BSS was critical for this study. FLDR is particularly effective in identifying features that maximize the separation between different BSS types. However, to enhance the robustness of the feature selection process and address the limitation of FLDR regarding the lack of statistical confirmation. FLDR was complemented with ANOVA. ANOVA added a layer of statistical validation to ensure these features were significantly different across BSS types providing a balanced and thorough approach to feature selection.

2.8.2. Analysis of variance (ANOVA)

Analysis of Variance (ANOVA) is a statistical method used to determine whether there are significant differences between the means of different classes. ANOVA is applied to these features to test whether the differences in means among groups are statistically significant or merely due to random variation. If significant differences are found, Tukey's HSD test is used to perform pairwise comparisons among the groups, pinpointing exactly which pairs of means are significantly different. This method ensures that selected features are not only effective in differentiating between classes but also statistically validated, thereby enhancing the accuracy and reliability of the classification model.

2.8.3. Spectral and radar features

The different feature categories were calculated and these were in four types (bands, vegetation indices, radar features and textural variables (Table 4). Spectral bands are the fundamental units of multispectral and hyperspectral imagery, where each band captures light within a specific segment of the electromagnetic spectrum. Different bands can highlight various aspects of the landscape such as vegetation, water bodies, and soils. Vegetation indices are calculated from the spectral bands and are designed to enhance the signal of interest, typically related to vegetation health and vigour and soil. Textural variables describe the texture of the image and are derived from the spatial arrangement of pixel values within an image, providing information about patterns, structure, and regularity. Textural features are important in distinguishing between similar land use types that might not be clearly separable through spectral data alone(Haralick et al., 1973; Moreira et al., 2013)

Table 4: Summary of feature categories, descriptions and data sources used for classifying BSS on coffee farms.

Feature Category	Feature Description	Source
Spectral Bands reflectance	Blue, Green, Red, NIR	GeoEye-1, Pléiades, Pléiades Neo
Vegetation Indices	Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Enhanced Vegetation Index (EVI), Soil Adjusted Vegetation Index (SAVI), Green Normalized Difference Vegetation Index (GNDVI)	Calculated from GeoEye-1, Pléiades, Neo
Radar Data	Vertical Transmit and Vertical Receive (VV), Vertical Transmit and Horizontal Receive (VH) Polarizations	Sentinel-1
Texture Variables	VH Gray Level Co-occurrence Matrix Variance (VH_glcm_variance), VH Standard Deviation (VH_sd), VH Gray Level Co-occurrence Matrix Mean (VH_glcm_mean), VH 75th Percentile (VH_75), VH 25th Percentile (VH_25), VV Gray Level Co-occurrence Matrix Variance (VV_glcm_variance)	Calculated from Sentinel-1 Data

2.8.4. Sample points dataset

Features for the sample points were extracted to create farm-specific datasets. These features included optical spectral bands (Blue, Green, Red, Near-Infrared), vegetation indices (NDVI, NDWI, EVI, SAVI, GNDVI), and radar features (VV, VH polarizations, VH_glcm_variance, VH_sd, VH_glcm_mean, VH_75, VH_25, VV_glcm_variance) as shown by table 4 above. Two distinct datasets for each farm were prepared: one with only optical features and the other combining both optical and radar features. These datasets form the foundation for model creation and classification processes.

2.8.5. Feature Selection Process

From the sample points datasets created, FLDR was calculated for all optical features (spectral bands and vegetation indices) and radar texture features. Features with the highest FLDR values were prioritized for classification. ANOVA was then performed on the features identified by FLDR to statistically assess their significance followed by Tukey's Honestly Significant Difference. Features with p-values less than 0.05 and high F-values are selected for their strong evidence in differentiating BSS classes. This process was conducted separately for each farm because of variability in BSS characteristics across different farms. This allowed for more precise and farm-specific feature selection.

2.8.6. The Random forest (RF) algorithm

The choice of an appropriate classification algorithm is crucial for accurately identifying and mapping BSS within coffee farms. Various machine learning algorithms were considered to determine the most suitable approach for this study. Each algorithm has unique strengths and weaknesses, making it important to evaluate them based on their performance, computational efficiency, and ability to handle the specific characteristics of the dataset. After considering the support vector machine, k-Nearest Neighbors (k-NN) and the Random Forest (RF), the later was selected for image mapping BSS on coffee farms in Zimbabwe.

Random Forest is an ensemble learning method that combines the predictions of multiple decision trees to produce a more accurate and stable result. It reduces the risk of overfitting and handles both numerical and categorical data well (Berhane et al., 2017; Y. ; Zhang et al., 2022). Studies have consistently shown that RF outperforms other classifiers, particularly in complex classification tasks in remote sensing (Belgiu & Drăgu, 2016). RF is well-suited for large datasets, which are common in remote sensing applications. It efficiently manages large volumes of data without a significant increase in computational cost, making it ideal for high-resolution imagery analysis. Additionally, RF provides insights into the importance of different features used in the classification process, which is valuable for understanding which spectral bands and indices contribute most to identifying BSS. RF is also less sensitive to noisy data and outliers, enhancing its reliability in real-world applications where data quality may vary. (Ghimire et al., 2012; Gislason et al., 2006).

Conclusively, to perform the characterization of BSS within coffee farms in Zimbabwe we used RF for its superior performance and suitability for the task. RF was also selected due to its ability to handle large datasets efficiently and its robustness to noise and outliers. By combining multiple decision trees, RF enhances accuracy and stability, which is crucial for the complex task of studying BSS in remote sensing data.

2.9. Farm-specific models

Separate models were developed for each of the two accessible coffee farms, using data specific to each farm. These models will account for farm-specific characteristics and management practices. To train the Random Forest (RF) model, the dataset for each farm was divided into training (70%) and validation (30%) sets. The RF model was configured to utilize 500 decision trees, a commonly used parameter setting that balances computational efficiency with model performance. Hyperparameters, such as the number of variables randomly selected at each split (mtry), were fine-tuned to optimize the model's performance. A 10-fold cross-validation strategy was employed for robust evaluation.

2.10. Characterization of coffee BSS

2.10.1. Random Forest Classification

Following model training and validation, the trained RF model was applied to classify land cover based on the collective set of input features. This classification process involved assigning each pixel in the imagery to a specific type of BSS. The resulting classification maps provided insights into the spatial distribution and extent of various land cover types within the study area.

2.10.2. Classification scheme for BSS on coffee farms

To classify the BSS on the coffee farms a classification scheme was developed. This scheme was designed to define how these categories will be labelled in the detailed land cover maps that will be created. Table 5 provides an overview of the classification categories and how they were represented in the land cover maps. Each classification category was labelled as specified in the table below. This provided a comprehensive view of the land cover types within Crake Valley and Jersey.

Table 5: Classification categories used in the detailed land cover map, with example high-resolution imagery from Google Earth for reference.

BSS	**Example Imagery**		
Shade Trees		Wetlands	
Tea		Coffee	
Hedgerows		Bare land	
Forest			

2.10.3. Reclassification with decision rules

After the initial classification of satellite imagery was completed, a targeted reclassification using decision rules followed up. This was specifically done to enhance the accuracy of identifying BSS within Crake Valley and Jersey farms. In this refined process, areas initially classified as forests within coffee plots were reclassified as shade trees. This adjustment was based on the understanding that trees within coffee plots are typically intended to provide shade and other ecological benefits to the coffee plants, rather than constituting a forest in the conventional sense. Conversely, trees identified as shade trees but located outside coffee plots were reclassified as forest.

These specific decision rules were applied to ensure that the classification accurately reflects the dual role of tree cover in agricultural landscapes—both as part of managed agricultural practices (shade trees) and as elements of the natural environment (forest). After this confusion matrices were calculated to assess the classification accuracy, using metrics namely overall accuracy, producer's accuracy, consumer's accuracy.

2.10.4. Density of BSS in relation to coffee

the density of BSS in relation to coffee was quantitatively assessed to evaluate the extent of ecosystem services available for coffee cultivation. The density calculations were performed by dividing the total area occupied by each specific BSS by the total area covered by coffee within the same region. This ratio provides a measure of BSS density per hectare of coffee. This method was applied consistently across two different regions, Crake Valley and Jersey.

2.11. Temporal analysis

A comprehensive temporal cross-tabulation analysis was conducted to assess changes in the presence and size of BSS within coffee fields at Crake Valley and Jersey between 2013 and 2023. The study used image subtraction on classification maps from 2013 and 2023, which were generated using optical data. By overlaying these maps, it was possible to pinpoint exact locations where changes in BSS presence occurred over the ten-year period. This involved not only identifying the size of areas where BSS presence changed but also areas where no change occurred, thereby providing a detailed view of the spatial distribution of these changes.

Specific metrics calculated include the area of each BSS category in both years and the net changes between them. These quantitative measures provided critical insights into the effectiveness of implemented sustainable farming practices, indicating whether there has been a reduction or expansion in BSS affected areas, and assessing sustainability at Crake Valley at Jersey.

3. RESULTS

The results of the study are presented in this section, structured to address the three main research questions and their respective sub-questions. The results are organized to provide a comprehensive overview of the findings, starting with the sub-processes followed by the final outputs for each research question.

3.1 Separability assessment of BSS

3.1.1 Separability with optical remote sensing features from GeoEye-1 and Pléiades Neo

In order to understand the spectral characteristics of the indicators of BSS at Crake Valley and at Jersey estate, separability tests were conducted for optical bands and vegetation indices. The results from the Fisher's linear discriminant analysis show that the separability of BSS varied between the two farms with higher separability at Crake Valley compared to Jersey for all bands and vegetation indices assessed (Figure 1). In addition, the most discriminating features are different between the two sites, with higher feature discrimination at Crake Valley than at Jersey. At Crake Valley, three vegetation indices (NDVI, NDWI and GNDVI) ranked the best in distinguishing coffee BSS. In terms of spectral bands, B3 and B4 were the best at Crake Valley. On the other hand, at Jersey, the most discrimination remote sensing features are SAVI and EVI vegetation indices with the B3 band also important (Figure 5). No contribution was observed in terms of the spectral ability of GNDVI and NDWI at Jersey although these are ranked high at Crake Valley. Spectral features that showed importance for both Crake Valley and Jersey are B3, SAVI and EVI.

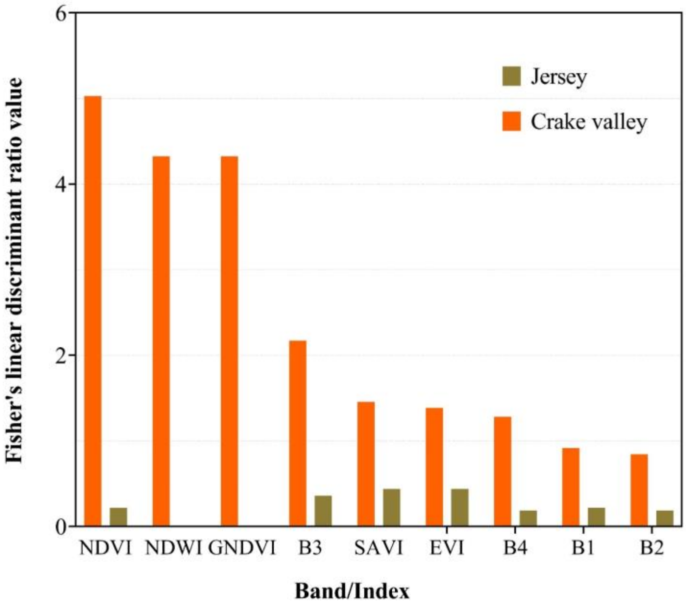

Figure 5: Fisher's linear discriminant ratio values for various optical bands and indices at Crake Valley (orange) and Jersey (brown).

Further statistical tests were conducted to assess the significance of the differences in optical spectral features of BSS and the pairwise differences. At Crake Valley, significant differences were observed among BSS when using NDWI, B4, and SAVI ($p < 0.05$, Figure 6). As expected, the wetland feature had the highest NDWI, while the least were for coffee, hedgerow and shade trees which were not significantly different from each other. For B4 and SAVI, coffee had the highest reflectance followed by hedgerow and forest while the least was for wetland (Figure 6a,c). Overall, the results show that the BSS that are found in coffee fields (coffee, hedgerow and shade trees) and those outside of fields (forest, wetland and bare) can be distinguished by using all the NDWI, SAVI and B4 at Crake Valley, corresponding to the results of the linear discriminant analysis.

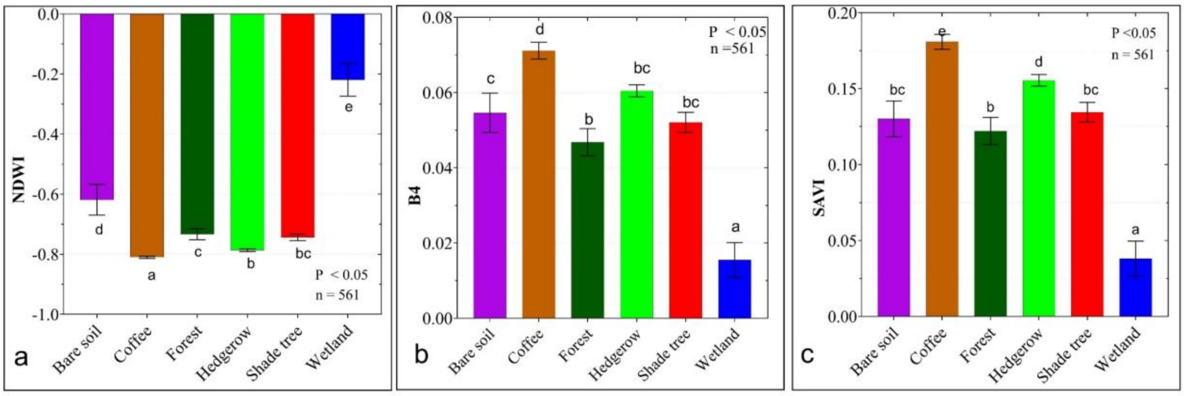

Figure 6: Separability of BSS using NDWI(a), B4(b), and SAVI(c) Indices at Crake Valley using ANOVA. Similar letters above the intervals indicate non-separability of the classes while different letters indicate significant pairwise separability of the classes using Tukey's test.

Similarly, at Jersey, significant differences were observed among BSS when using SAVI, NDVI, B1 (p < 0.05, Figure 7). The effectiveness of SAVI, NDVI, B1 was assessed with the results confirming their suitability for distinguishing BSS despite overall lower FLDR separability scores compared to Crake Valley. SAVI was the common index for the two farms and the results show that, unlike at Crake Valley, at Jersey shade tree, hedgerow and forest had the highest values, with the lowest being bare soil (there was no wetland class at this site). For NDVI, vegetation classes such as shade trees, coffee, hedgerows and forest had higher values but surprisingly, for this site the bare areas also showed high NDVI values (Figure 7). The least value for NDVI was for the class tea. The highest for B1 was for the class bare while the classes coffee, hedgerow, shade tree and tea were not significantly different from each other after Tukey's test (p>0.05). With these results, it should therefore be possible to use these combinations of optical spectral features (NDWI, EVI and SAVI at Crake Valley and SAVI, NDVI and B1 at Jersey) to distinguish between the different BSS in coffee farms with remote sensing data.

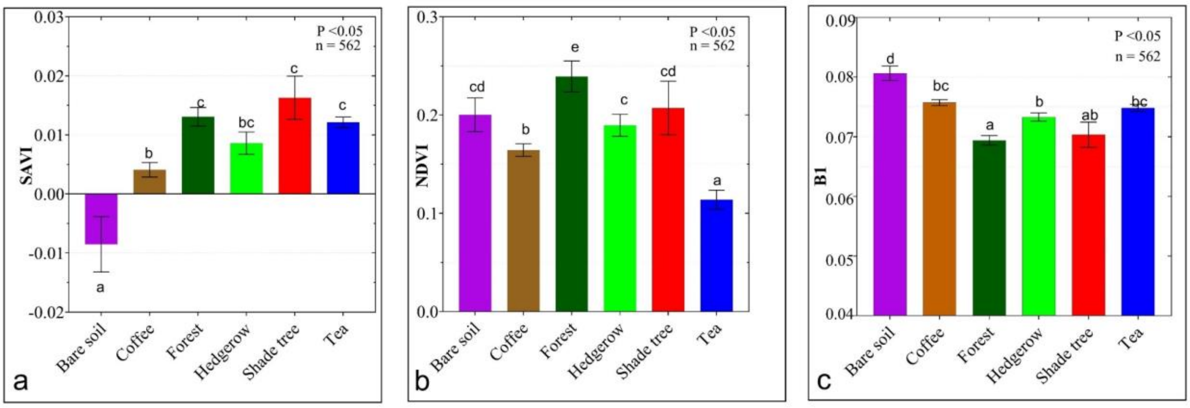

Figure 7: Post Hoc Tukey Test results for SAVI(a), NDVI(b), and B1(c) Indices across different BSS at Jersey. Similar letters above the intervals indicate non-separability of the classes, different letters indicate separability of the classes.

3.1.2 Separability using radar remote sensing features

The study also calculated the discriminatory power of each radar feature. Most types of radar features exhibit significant variability in discriminating between different BSS at Crake Valley as indicated by their high Fisher's linear discriminant ratio values (Figure 8a). The best discriminating radar feature at Crake valley was the VH_d_glcm_homogeneity. Other important radar features for discrimination BSS in coffee at Crake Valley were VV_d_glcm_variance, VH_d_glcm_mean, VH_d_glcm_entropy and VH_d_25. By looking at these top 5 discriminating features at Crake valley, the results show that the VH band characteristics are more important than the VV which only appears once in the top 5 bands (Figure 8). The least discriminating radar features at Crake Valley were the VV_d_glcm_second moment and the VH_d_glcm_contrast features (Figure 8a).

At Jersey, the best discriminating radar feature is the VH_d_glcm_mean, followed by the VH_d_glcm_variance, VV_d_glcm_mean and VV_d_glcm_variance, while the least discriminating is the VH_d_sd, VV_d_glcm_contrast and the VH_d_glcm_contrast (Figure 8b). The results show that at Jersey, like for optical features, the radar features show lower discriminant ratio values, indicating less variability and effectiveness in distinguishing BSS. Assessing for consistency of features across the two sites shows that VV_d_glcm_variance is among the best discriminating features while VH_d_glcm_contrast is ranked low at both sites. There is no outstanding group of radar features as homogeneity, variance, entropy, mean and dissimilarity features appear rather randomly in the ranking, except that there are no contrast features in the top 5 features at both sites (Figure 8).

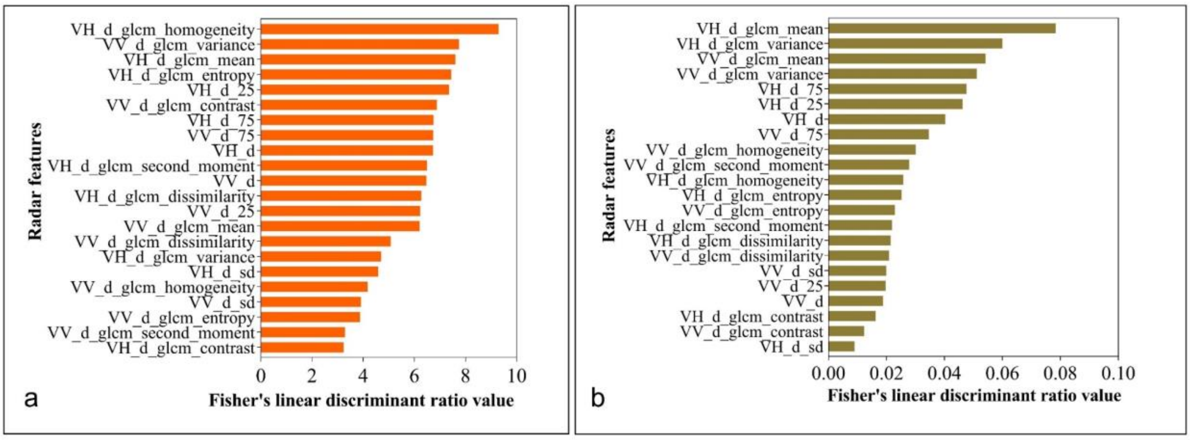

Figure 8: Fisher's linear discriminant ratio values for radar features at (a) Crake Valley and (b) Jersey.

Further statistical analysis using ANOVA and Tukey's HSD post hoc tests provided quantitative backing for the separability of the radar features. Results show that VH_d_25, VV_d_glcm_variance and VH_d_glcm_variance were identified as having significant differences across various BSS ($p < 0.05$, Figure 9). For VH_25, Figure 9a bare had the highest backscatter value and was significantly different from all other features. Forest had the lowest backscatter value followed by wetland. Bare soil exhibited the highest VV and VH variance figure 9b&c while forest, hedgerow and shade tree had the lowest variance which were not significantly different from each other. In summary, the results demonstrate that all BSS at Crake Valley can be identified by using VH_d_25, VH and VV glcm_variance, in line with the linear discriminant analysis's findings. However, there is a common challenge in distinguishing between more vegetated classes such as forest, hedgerow and coffee because of similar radar signatures.

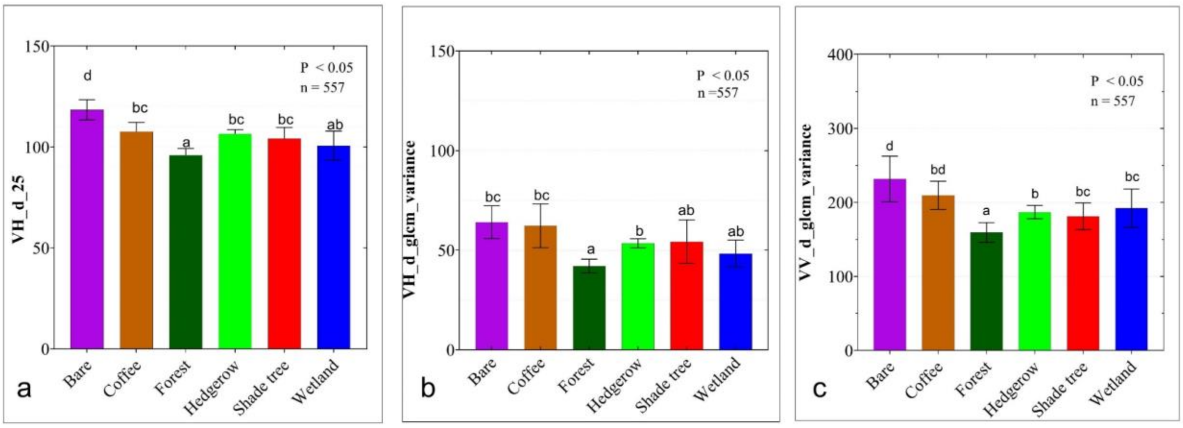

Figure 9: Post Hoc Tukey Test results for VH_d_25(a), VV_d_glcm_variance(b), and VH_d_glcm_variance(c) features across different BSS at Crake Valley. Similar letters above the intervals indicate non-separability of the classes, different letters indicate separability of the classes.

At Jersey farm, significant differences were observed among BSS when analyzing VH_d_glcm_variance, VH_d_glcm_second_moment, and VV_d_glcm_variance ($p < 0.05$, Figure 10). The results indicate that, despite overall FLDR separability scores, VH_d_glcm_variance showed that tea had the highest values, closely followed by bare soil and hedgerow, which were not significantly different from each other. In terms of VH_d_glcm_second_moment, the highest values were observed for shade trees, while tea and bare soil had the lowest and were not statistically different from each other. For VV_d_glcm_variance, similar to findings at Crake Valley, bare soil at Jersey exhibited the highest values, with forest showing the lowest (Figure 10c). Notably, there was no wetland class at Jersey to compare.

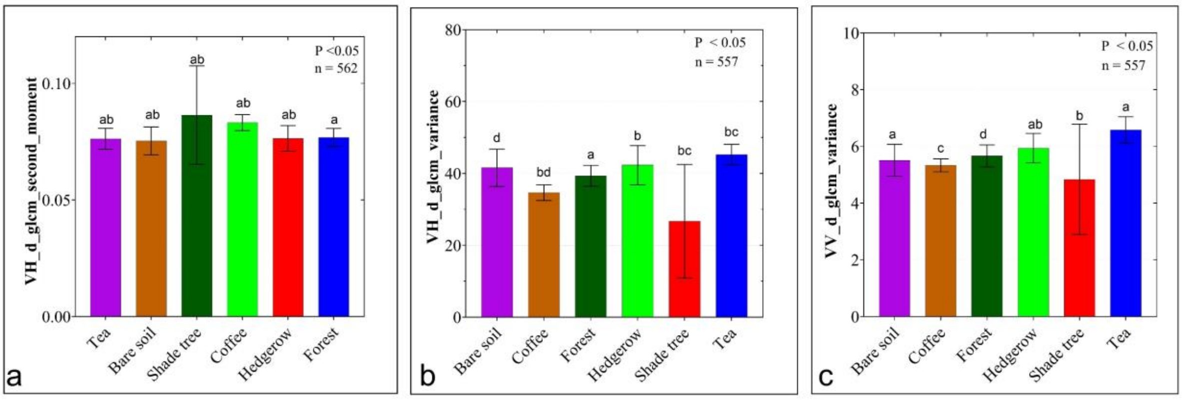

Figure 10: Post Hoc Tukey Test results for VH_d_glcm_variance(a), VH_d_glcm_second_moment(b), and VV_d_glcm_correlation(c) features across different BSS at Jersey. Similar letters above the intervals indicate non-separability of the classes, different letters indicate separability of the classes.

3.2 Remote sensing-based mapping of BSS

To achieve a robust mapping of BSS within Crake Valley and Jersey, the study utilized the best-performing spectral indices and radar-derived features identified in the separability tests features.

3.2.1 BSS mapping at Crake Valley

An overall accuracy of 73.1% was achieved at crake valley (Table 6) with the most accurately identified BSS being forest (80.6% and 61.7% for user and producer accuracy respectively) for optical. Radar data had a dismal performance in mapping BSS in coffee at Crake valley achieving a measly overall accuracy of 52%. The most misidentified BSS were coffee itself and shade trees (Table 6). The accuracy assessment for Crake

Valley therefore revealed that using optical data generally outperforms using radar data in classifying BSS. Bare Soil and Wetland classes showed high user and producer accuracies with optical data. Coffee also demonstrated high producer accuracy (80%) with optical data, although with some misclassification with hedgerows and shade trees. Shade trees had the lowest accuracy as the tree crowns were misidentified as hedgerows. Coffee showed perfect producer accuracy but lower user accuracy (34.8%) using radar data showing that the approach was wrongly identified non-coffee features as coffee.

Table 6: Accuracy assessment table of biodiversity supporting structures mapping at Crake Valley using Geoeye-1 and Sentinel 1 data.

	Optical			***Radar***		
BSS	Count	User Accuracy (%)	Producer Accuracy (%)	Count	User Accuracy (%)	Producer Accuracy (%)
Forest	29/36	80.6	61.7	7/17	41.2	50.0
Shade Tree	20/36	55.6	54.1	4/7	57.1	16.0
Hedgerow	12/22	54.5	63.2	11/35	31.4	47.8
Coffee	40/59	67.8	80.0	8/23	34.8	100.0
Wetland	15/19	78.9	78.9	5/7	71.4%	62.5
Bare	55/62	88.7	88.7	3/5	60.0%	18.8
Overall accuracy		73.1			52.0%	

Figure 11 illustrates the spatial distribution of BSS at Crake for the year 2023 with decision rules applied. For Crake valley three maps were produced but only two accuracies were provided (one for optical data and one for radar) as the third accuracy for fusion mirrors the accuracy of the best-performing dataset which was optical data. The maps show that forest areas are located in the north and eastern parts of the farm with coffee in the north-eastern, central and southern parts of the farm, with hedgerows and shade trees inside the coffee fields (Figure 11).

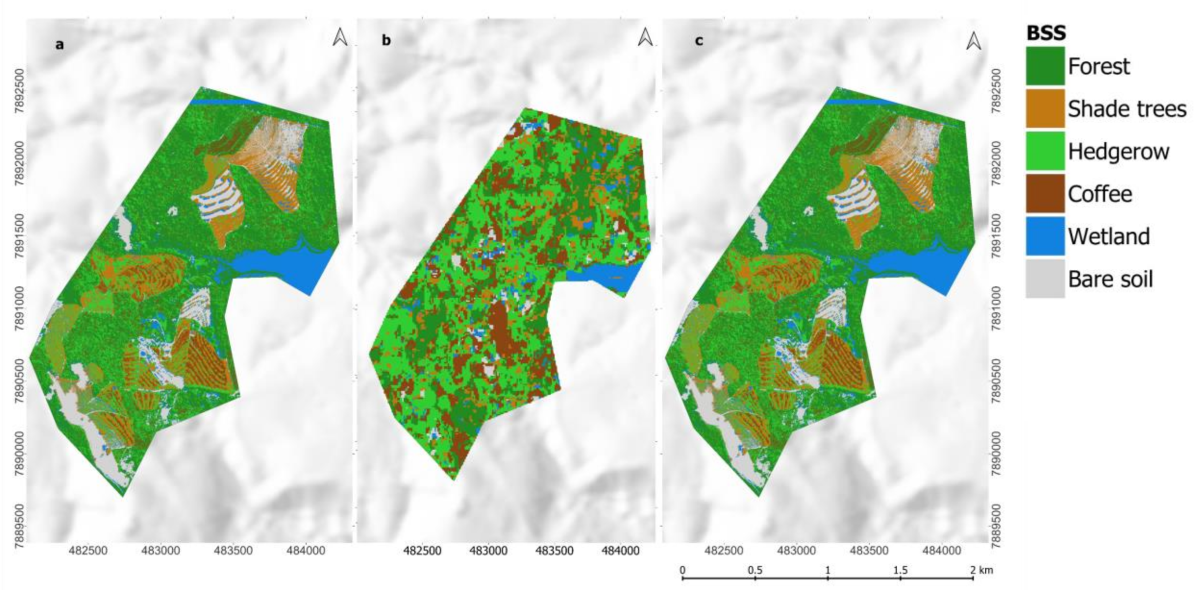

Figure 11: BSS classification maps of Crake Valley (2023) using GeoEye-1 NDWI, SAVI and B4 (a) 0.5m resolution, Sentinel-1 Radar VH_d_25, VV_d_glcm_variance, and VH_d_glcm_variance (b) and Geoey-1 and Sentinel 1 Radar fused post classification (c), generated with a pixel-based Random Forest classifier.

Figure 12 below showcases specific classification challenges and successes in BSS mapping, (a) in the eastern part of the Crake Valley close to the edge accurately identifies shade trees but misclassifies their central parts as hedgerows and shadows as wetlands, (b) eastern part of Crake Valley exhibits correct identification of coffee. (c) Successfully delineated hedgerows in the northern part (d) in the western part represents a forest with misclassified pixels identified as hedgerow, and coffee. Below each classified panel, the corresponding original satellite imagery provides a real-world reference, highlighting the discrepancies and accuracies of the classification approach used.

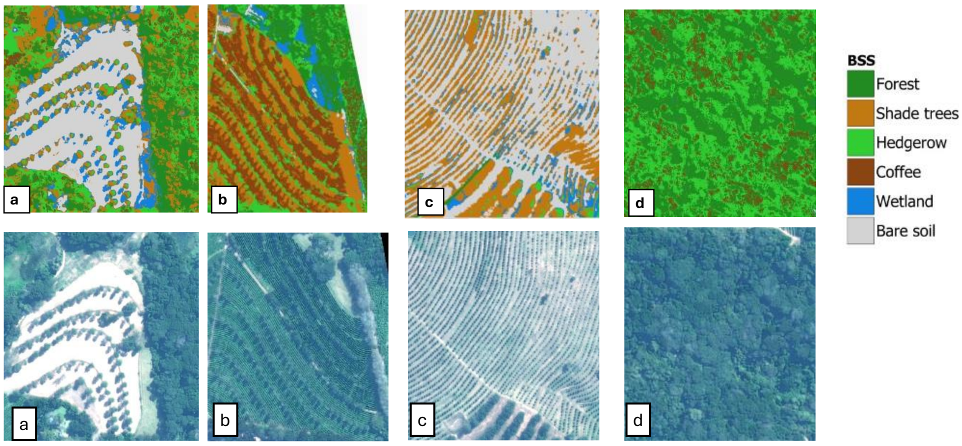

Figure 12: Classification verification with VHR imagery at Crake Valley

3.2.2 BSS mapping at Jersey

The accuracy assessment reveals that optical data generally outperformed radar data in classifying various land cover classes at Jersey. While radar data showed competitive producer accuracies in classes like coffee, its lower user accuracies indicate challenges in correctly identifying specific BSS. Forest class by using optical data achieved a user and producer accuracy and radar data showed lower accuracies as well. Forest was being misclassified a coffee in most cases. Bare Soil achieved high accuracies user and producer accuracy using optical data as it was easily separable from all the classes whereas radar data performed poorly with 11.1% user accuracy and 5.0% producer accuracy due to similar radar signals as the other classes.

Table 7: Accuracy assessment table of biodiversity supporting structures classification at Jersey using Pléiades Neo and Sentinel 1 data.

	Optical			**Radar**		
BSS	Count	User Accuracy (%)	Producer Accuracy (%)	Count	User Accuracy (%)	Producer Accuracy (%)
Forest	11/28	39.3	34.3	4/14	28/6	12.5
Hedgerow	1/8	62.5	26.3	1/7	14.3	5.2
Coffee	17/85	62.3	79.1	20/113	46.0	77.6
Bare soil	1/17	88.2	78.9	3/9	11.1	5.0
Tea	2/27	85.1	85.1	2/23	26.1	22.2
Overall accuracy		64.9			38.5	

Figure 13 below shows the spatial distribution of BSS and coffee at Jersey with decision rules applied. At this site, tea is the dominant feature occupying the western and central parts of the site. Coffee is identified from the central to the east and north east of the site. Forest patches are also identified across the study site.

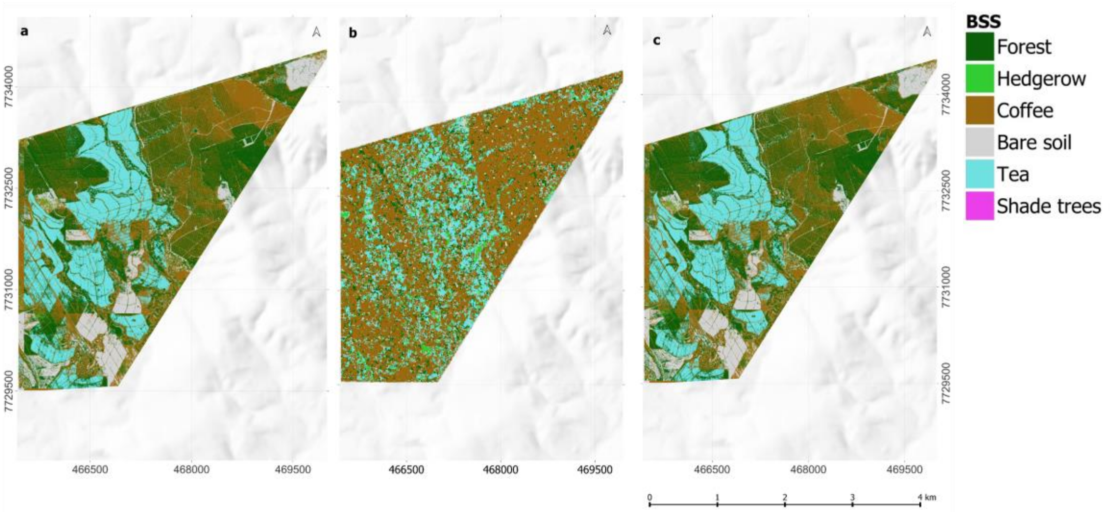

Figure 13: BSS classification maps of Jersey (2023) using Pléiades Neo NDVI, SAVI and B1 (a) 0.5m resolution, Sentinel-1 Radar(b) VH_d_glcm_variance, VH_d_glcm_second_moment, and VV_d_glcm_correlation) and Pléiades Neo and Sentinel 1 Radar fused post classification (c), generated with a pixel-based Random Forest classifier.

Figure 14 below shows specific identification challenges and successes in BSS mapping, (a) accurately identifies tea, (b) exhibits correct classification of coffee and hedgerows, (c) shows the mixed classification of forest and coffee. The related actual satellite imagery, which shows the differences and accuracy of the classification method employed is displayed beneath each class as a real-world comparison.

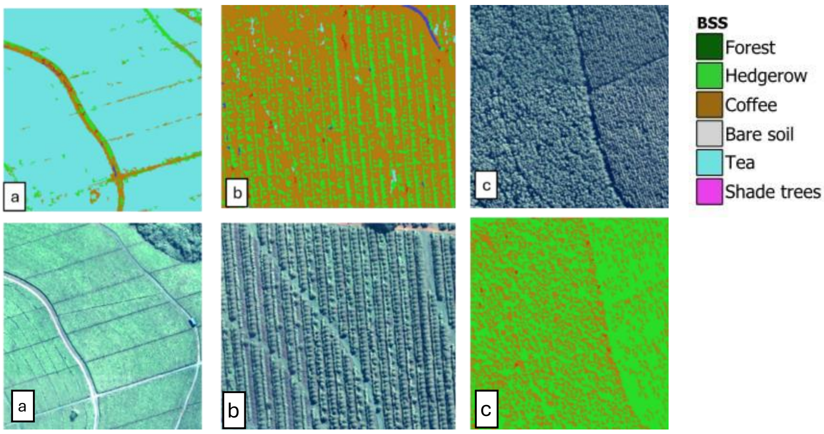

Figure 14: Classification verification with VHR imagery at Jersey

Further analysis showed that the area under coffee was different at the 2 farms with over one third of the area at jersey covered by coffee while only 7% at Crake Valley (Figure 15). However, the percentage under forest was relatively the same under the 2 farms as it was between 30 and 35%. Crake valley had more BSS than Jersey as it had more hedgerows, shade trees and wetland. However, Crake Valley had more bare soil areas.

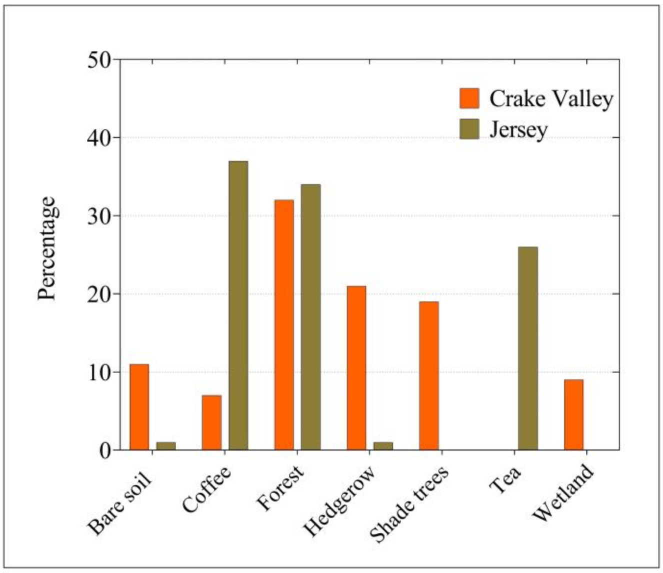

Figure 15: Percentage area covered by each BSS at Crake Valley and Jersey.

The density of BSS in relation to coffee was calculated by dividing the area of each BSS by the area of coffee from the mapping. Crake Valley had higher densities of BSS compared to those found at Jersey. The most common BSS at crake valley was forest where for every hectare of coffee there was 4.43 hectares of forest. All BSS densities were above 1 meaning that there was more of each BSS supporting coffee. At jersey all densities were below 1 meaning there is more coffee than all the BSS (Table 8).

Table 8: Density of BSS in relation to coffee area at Crake Valley and Jersey.

BSS	Crake Valley	Jersey
Bare soil	1.52	0.04
Forest	4.43	0.93
Hedgerow	2.93	0.04
Shade trees	2.60	0.00
Tea	0.00	0.71
Wetland	1.27	0.00

3.3 Assessment of changes in BSS over time

Using the best approach from the mapping of BSS at Crake Valley and Jersey coffee farms, changes in BSS over the ten-year period from 2013 to 2023 was assessed using the RF classifier trained with field data. By comparing maps from these two specific years, the study visualizes and quantifies changes in BSS (Research question 3).

3.3.1 Change assessment of BSS at Crake Valley

Figure 16 & 17 show how the BSS changed between 2013 and 2023 at Crake Valley and Jersey respectively. From these maps, it is noticeable that some bare areas in 2013 became coffee areas in the lower central fields while some coffee areas in the western parts of the farm became bare in 2013 at Crake Valley. The shade trees also increased from 2013 to 2023 mostly appearing in the central fields of the coffee farm.

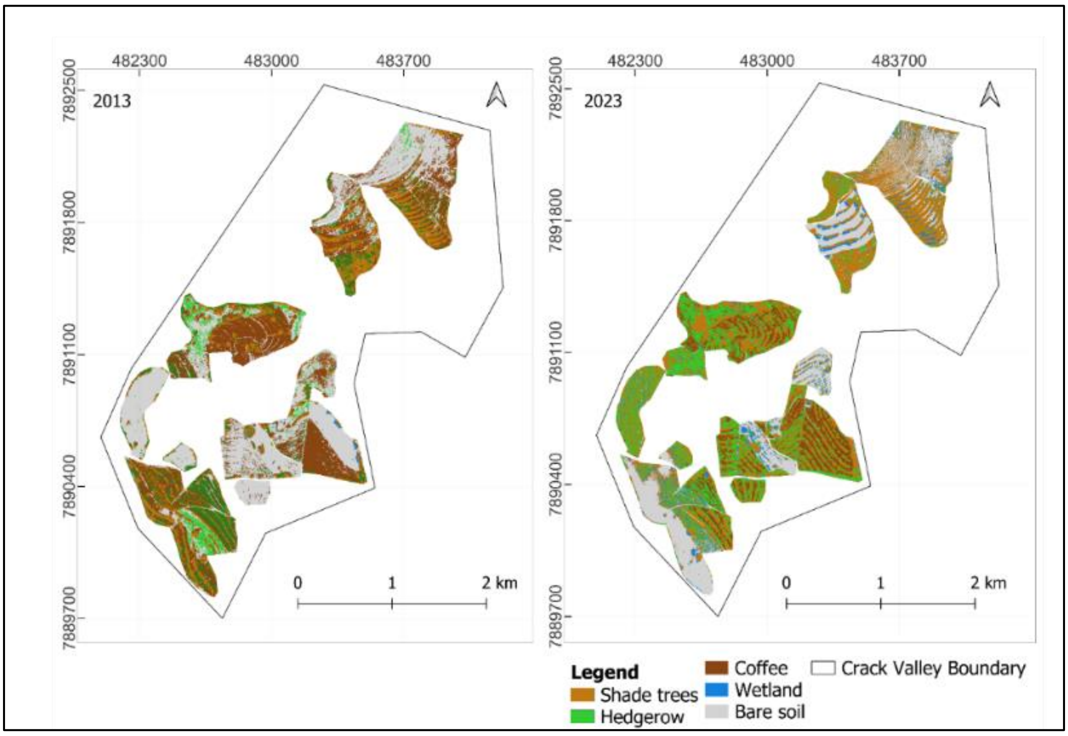

Figure 16: Spatial distribution of BSS within the coffee fields of Crake Valley for 2013 and 2023, generated using GeoEye-1 (0.5m)- Band 4, NDWI and SAVI and a pixel-based Random Forest classifier.

At Crake valley the majority of the area initially covered by shade trees remains as shade trees. This shows a stable or well-maintained shade tree coverage. The integration of shade trees into coffee plantations is also reflected. Coffee also expanded receiving significant portions of land from bare soil this implies a shift towards coffee cultivation. Conversion from bare soil to hedgerows can be seen from the statistics. Fieldwork observations reveal that hedgerows in the farm are primarily composed of sorghum and millet. This change reflects a broader trend towards sustainable agricultural practices, particularly use of shade trees in coffee.

Table 9: Transitions between BSS and coffee at Crake Valley (2013 to 2023) area in hectares. The diagonal shows the total area of a class which did not change.

From/To	Shade Trees	Hedgerow	Coffee	Wetland	Bare Soil
Shade Trees	14.63	4.64	1.52	2.22	5.64
Hedgerow	1.50	1.28	7.05	0.38	0.72
Coffee	12.68	0.00	4.63	2.12	8.54
Wetland	0.22	0.02	0.02	0.04	3.35
Bare Soil	15.67	9.99	4.12	3.35	10.56

3.3.2 Change assessment of BSS at Jersey

Figure 17 shows the change in BSS at Jersey from the remote sensing mapping. The results the gradual change of the coffee areas into hedgerows by 2023 especially in the northern and central parts of the coffee farms. This finding is confirmed by field observations during fieldwork, where it was observed that macadamia nuts are slowly replacing coffee as they grow. These hedgerows initially covered a significant area with a large portion remaining as hedgerows (47.31 ha). However, a substantial amount has been converted to new coffee plantations (54.88 ha), indicating a significant shift towards coffee cultivation.

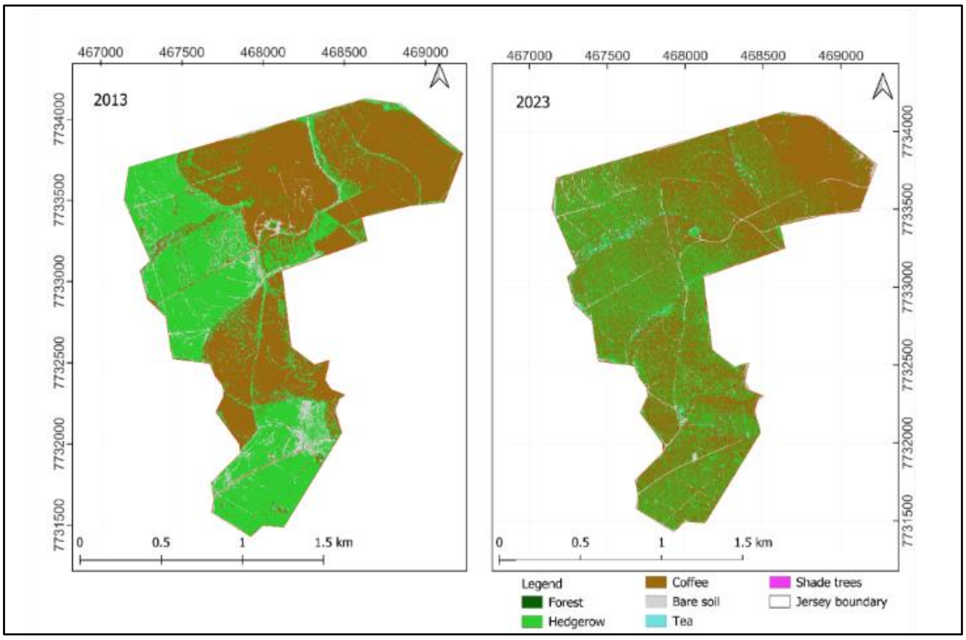

Figure 17:Spatial distribution of BSS within the coffee field at Jersey generated using Pléiades (2013) and Pléiades Neo (2023) at 0.5m resolution - Band 4, NDVI and SAVI and a pixel-based Random Forest classifier

Coffee at Jersey expanded considerably, absorbing land from hedgerows, bare soil. The high retention of coffee areas (91.78 ha) suggests that once established, coffee plantations are maintained likely due to their economic value. The conversion from other land uses to coffee points to a focused effort on increasing coffee production. Shade trees show no significant area in the initial data, suggesting that there was no shade tree. From the observation points only 6 shade trees were identified and therefore the classification failed to identify shade trees within the farm.

The integration of macadamia nuts into hedgerows also indicates a shift towards intercropping practices. Visually, the landscape in 2013 showed hedgerows (macadamia) were in 2 distinct sections, the eastern part and southern, but in 2023 there was a blend between these 2 classes.

The following table 10 summarizes the transitions between different BSS and coffee from 2013 to 2023 in hectares.

Table 10: Transitions between BSS tea and coffee at Jersey (2013 to 2023) area in hectares. The diagonal shows the total area of a class which did not change.

From/To	Hedgerow	Coffee	Bare Soil	Tea
Hedgerow	47.31	54.88	3.73	1.70
Coffee	31.52	91.78	3.49	1.00
Bare Soil	5.51	9.07	1.69	0.37
Tea	0.72	1.15	0.10	0.18

4. DISCUSSION

The study explored how well VHR optical imagery can identify and map biodiversity supporting structures (BSS) within coffee farms in Zimbabwe by identifying and applying the most effective optical bands and indices. It also examined if fusing optical imagery with radar data enhances accuracy and identified the most effective radar features. Finally, it investigated changes in BSS within these farms from 2013 to 2023.

4.1 Remote-sensing based mapping of BSS on coffee farms

The goal of this study was to develop and apply a remote-sensing based approach to map BSS on coffee farms with primary focus on supporting coffee certification but with other potential applications in ecological, conservation and ecosystem services assessments in agricultural landscapes. Overall, this study showed that it is possible to map shade trees, hedgerow, coffee plots, wetlands and other cover types on cover types, but with some challenges. The demonstrated effectiveness of very high resolution (VHR) optical imagery in detecting and mapping BSS highlights the potential of it in enhancing and sustainable agricultural practices. Achieving a high overall accuracy of 73.1% at Crake Valley and a modest 64.9% with optical data shows that BSS can be reliably mapped on coffee farms. This mapping of BSS is increasingly becoming important to satisfy the growing demand of certified and sustainably produced coffee in the global market(Jena & Grote, 2022; Souza et al., 2021) It is also expected that this demand will continue to grow in the coming years(Grabs, 2017; Willer et al., 2022) requiring development of these assessment tools to be fast-tracked and scaled up.

Given the expensive nature of these sustainability assessment, developing a reliable remote sensing based approach is important for both consumers and producers of coffee. For consumers, it ensures rapid assessment of coffee farms for sustainability indicators such as BSS while providing verifiable and traceable information on the performance of various coffee producers on these indicators. In this way coffee consumers will develop confidence that their coffee is not contributing to deforestation and other ecosystem degradation processes in areas where it is produced. On the other hand, for producers, this method ensures that the assessment process is less expensive as arduous fieldwork would have been cut while providing an objective appraisal of their productive system. These benefits have been demonstrated in Ethiopia (Takahashi & Todo, 2017) and Vietnam (Maskell et al., 2021) where remote sensing has been applied to assess coffee's contribution to deforestation or expansion into sensitive areas. This study therefore takes the assessment of coffee sustainability beyond just focusing on deforestation but to actual identification and quantification of BSS on coffee farms that are the pillars of environmental assessment of coffee farms. The factors contributing to the success and challenges in the process of mapping BSS on coffee farms are further analysed in detail in the following sections.

4.2 Spectral feature selection for BSS mapping.

It was demonstrated that vegetation indices outperformed spectral bands in discriminating BSS with remote sensing data at both sites but mainly at Crake Valley where only vegetation indices were the best performing discriminators of BSS. This is not surprising and was expected since many of the BSS are vegetation cover types (shade trees, hedgerows, coffee, forest, tea) which have contrasting reflectance peaks at various portions of the spectrum for which vegetation indices are designed for. For example, NDVI was considered an important variable for discriminating BSS at Crake Valley because is widely recognized for its ability to measure and monitor vegetation conditions by quantifying the difference between near-infrared and red light reflectance, making it a robust tool for various applications in agriculture, forestry, and ecology (Huang et al., 2021; Robinson et al., 2017). The same applies for NDWI and SAVI which were developed to deal with the saturation and soil background effect challenges of using NDVI.

In this case, it is interesting to note that although the BSS are mainly vegetation cover types, it is expected that vegetation indices should be able to distinguish between these vegetation types. This is because coffee is planted in straight rows and managed for productivity by pruning and fertilising which is not done on other vegetation cover types. In addition, the morphology and physiology of coffee is distinct as a tree/shrub that can reach up to 2m height and 1.5m width in the fields but with gaps for management (Winston et al., 2005). This contrasts with trees used as hedgerows or in forests as they can have more height depending on their ages. The spectral signature of shade trees is also expected to be different from that of either coffee or forest alone. This is because below the shade trees are coffee plants which contribute to the spectral signature, and thus this BSS is a combination of forest and coffee signature together. The results in this study confirmed this because when adjusted of soil background effect in SAVI, the value of shade trees approximated the sum of coffee and forest value, indicating that it is benefiting from both. In radar data, the values of shade were always between that of coffee alone and of forest alone, making it distinct. The same applies for wetland areas where the influence of water on the spectral signature was expected to interact with the influence of vegetation to enable separation. Therefore, the ability of vegetation indices and bands in optical and radar metrices to distinguish between the BSS is supported by their distinct characteristics relative to each other and the background.

When assessing the capabilities of various vegetation indices several studies provide comparative insights. It was shown in this study that SAVI was considered important at both Crake Valley and Jersey because other studies have shown that soil adjustment factor increases its sensitivity to topographic variations compared to NDVI, which generally ignores such effects (Matsushita et al., 2007). This finding is crucial for applications in rugged terrain like Crake Valley and Jersey. Another research offers a practical comparison across different vegetation stages, highlighting NDVI's vulnerability to soil colour and saturation, whereas SAVI and EVI present more reliable metrics, with reduced sensitivity to soil effects and less proneness to saturation. Additionally, a comparison of SAVI and NDVI points out that SAVI includes a soil brightness correction factor, making it more suitable for areas with sparse vegetation or varying soil conditions, thus providing more accurate vegetation indices. These studies collectively underscore the importance of selecting appropriate vegetation indices based on specific environmental conditions and the desired accuracy of vegetation monitoring and support the findings of this study.

This approach identified the most effective combinations for each farm highlighting the importance of region-specific calibration. The combination of NDWI, EVI and SAVI provided the highest separability in Crake Valley. Crake Valley is characterized by denser vegetation. NDWI's sensitivity to water content was particularly effective in distinguishing water-rich hedgerows and coffee from drier areas, while EVI and SAVI captured additional vegetation health information. Combining the different vegetation indices in the algorithm covers for the weaknesses of each method and therefore has potential to produce better accuracy. It is therefore a better approach to have different vegetation indices and bands than to have the traditional feature identification approaches that relied on bands only. Using different vegetation indices in classification has been done widely in remote sensing (Chafik et al., 2020; da Silva et al., 2020). In addition, it is also important to note that context matters as different variables were identified at the 2 sites. In Jersey, with less dense vegetation and an intercropping approach to coffee farming, the combination of SAVI, NDVI, and Band 1 (blue) proved most effective. SAVI and NDVI provided information on vegetation health, while Band 1 offered additional spectral information potentially aiding in differentiating between forest stands and hedgerows based on structural characteristics. Therefore, there is no one-size fits all when it comes to choosing spectral features for identifying BSS on coffee farms with remote sensing data. Additionally, results also differ due to the different sensors. Although the same resolution of 0.5m was used, the results are different because the spectral regions for the bands and sensitivities of the sensors is not the same. Therefore, an approach for characterising BSS on coffee farms developed at one farm cannot be simply transferred or generalised to another farmer/producer or to another sensor as it requires retraining.

4.3 Evaluating optical remote sensing accuracy.

The overall accuracy of optical remote sensing in Crake Valley was 73.1%, indicating a moderately high level of reliability for classifying BSS on coffee farms. This suggests that optical sensors, with their capacity to capture high-resolution spectral data, are generally effective in differentiating among the diverse landscape features. Forest and bares soil had producer and user accuracies above 80%. This excellent performance is attributed to the distinct spectral signatures associated with dense forest canopies and exposed soil surfaces, which are easily distinguishable by optical sensors. This has also been reported in other studies (Forkuo & Frimpong, 2012). The high reflectance of bare soil and the unique absorption and reflectance patterns of forest canopies due to their biomass and chlorophyll content are the factors enhancing classification success.

Hedgerows and shade tree classes showed a lower accuracy, with both around 54-63%. These figures indicate challenges in distinguishing these BBS from surrounding vegetation. Hedgerows and shade trees often integrate closely with other vegetation types, leading to spectral mixing that complicates clear classification. Their structural complexity and variability in density and species composition also contributed to these lower accuracies. Despite the high accuracy reported for wetland classification in Crake Valley, there was a notable issue with shadows of trees being misclassified as wetlands. This common error stems from the similar spectral signatures that shadows and water bodies may exhibit in optical imagery. Both appear darker than their surroundings due to reduced reflectance, water because of absorption and shadows due to lack of light. The probable misclassification of shadows as wetlands led to errors in change detection assessments where precise identification of wetlands is crucial for conservation efforts, water resource management, and maintaining biodiversity. This could be related to the time the image was taken at mid-morning when the shadow would be long relative to the angle of the sensor.

These findings provide a strong foundation for BSS classification in coffee farms using a limited band approach, that is 4 bands from GeoEye-1 or Pleiades satellites. However, an improved accuracy may be achieved by leveraging the rich information content from hyperspectral data. Hyperspectral data offers a much wider range of spectral bands compared to the limited bands typically used, allowing for a more nuanced analysis of vegetation characteristics and potentially more robust BSS classification. Various and narrower band width in hyperspectral data can therefore be considered in future studies of mapping BSS on farms. The finer spectral resolution allows for a more precise identification of subtle variations in characteristics of BSS that enable their separation and mapping (Escobar-López et al., 2022).

In addition to hyperspectral data, future research could explore integrating these findings with other data sources, such as LiDAR (Light Detection and Ranging). LiDAR provides three-dimensional information about vegetation structure, which could be particularly valuable for differentiating BSS types based on their height and canopy structure, especially when combined with the rich spectral information from hyperspectral data as highlighted by Balestra et al., (2024) and Pricope et al., (2022). It is expected that because the BSS have different heights and under-canopy features for forest, coffee, shade and hedgerows, LiDAR will be able to be effective in this regard. Exploring advanced feature selection techniques specifically designed for hyperspectral data analysis could also be valuable, helping identify the most informative spectral features for BSS classification even within the vast amount of data provided by hyperspectral sensors (Jia et al., 2013).

4.4 Evaluating radar data performance.

This study revealed that incorporating radar data after bilinear resampling from 10-meter resolution to 0.5m did not significantly improve the classification accuracy of BSS. This finding aligns with the observations Yumus & Ozkazanc, (2019) who reported challenges in using coarse resolution radar data for detailed land cover classification tasks. Chen et al., (2004) further emphasize how spatial resolution can significantly impact the accuracy of feature extraction and classification from remote sensing data, including radar. The integration of radar technology in this study was motivated by with recent advancements in remote sensing, where combining optical and radar data provided a more comprehensive understanding of complex agricultural ecosystems including in coffee landscapes (Maskell et al., 2021; Shrestha et al., 2021).It was therefore hypothesised that with its canopy penetrating capabilities, radar will be able to distinguish between BSS as texture metrics are able to capture more surface characteristics that define BSS in addition to utilising spectral features. However, radar data had a low spatial resolution to identify the small BSS like hedgerows.

Moreover, the limited contribution of radar data in this study might be attributed to the post-classification fusion approach used. This method may not have fully captured the complementary information from radar and optical sensors to produce a better classification, instead it introduced noise that reduce the accuracy of the optical alone. Pre-classification fusion, where data are combined before classification, is an alternative approach that we recommend for future studies as it has been demonstrated elsewhere (Cubaud et al., 2023).

Pre-classification fusion allows for a more synergistic extraction of features from radar, particularly those related to structure, and optical which could be crucial for accurate classification of BSS types. This approach might be particularly beneficial for capturing subtle structural details in BSS types, which could be crucial for accurate classification. Li et al., (2023) found that pre-classification methods generally outperform post-classification approaches in terms of image quality metrics, such as reducing the negative impacts of radar image shadows. This suggests that pre-classification fusion could potentially improve feature extraction for BSS classification tasks as well. Similarly, Zhang et al., (2012) compared pre-classification (feature-level) and post-classification (decision-level) fusion for land cover classification and found that pre-classification fusion often yielded better results.

Therefore, future research exploring the use of higher spatial resolution radar data and pre-classification fusion of optical and radar data might be more successful in exploiting the unique information provided by each sensor type for BSS classification. This approach could potentially improve the overall accuracy and capture more nuanced details in the classification of BSS types, particularly those with structural characteristics that radar data might be better suited to detect.

The results of the densities showed that 1 farm had higher density than the other. However, there are no comparable standards or thresholds of acceptable or expected densities of BSS for coffee farms. Therefore, the results from this study can be used as a benchmark for future studies on densities of BSS on coffee farms. It may not be expected that all densities be above 1 but it is preferable to have more BSS in relation to coffee areas in order to provide ecosystem services.

4.5 Changes in coffee areas and BSS between 2013 and 2023

In addressing the third objective, the study explored the extent to which BSS within the coffee fields in Crake Valley and Jersey have changed over the ten-year period from 2013 to 2023. This analysis was crucial for understanding changes of agricultural landscapes and the ecological impacts of farming practices over time. The study's findings indicate significant transformations in the BSS across both farms. In Crake Valley there was a noticeable reduction in bare soil areas, which indicates an increase in vegetation cover or changes in land use management that reduce soil exposure. Wetland areas showed an increase, suggesting enhancements in water conservation practices. Shade trees and hedgerow areas generally increased, reflecting possibly deliberate afforestation or natural succession where areas previously cleared for agriculture are reverting to their natural vegetative states. Coffee pixels showed a mixed pattern, with some plots experiencing decreases, possibly due to crop rotation practices or changes in coffee cultivation areas in favour of other crops specifically macadamia nuts.

Similar to Crake Valley, in Jersey there was a general increase in hedgerow areas, which might be due to conservation efforts and changes in land management strategies aimed at increasing biodiversity and enhancing ecological stability. Reductions in bare soil areas were also observed, suggesting improvements in soil management and a decrease in intensive agricultural activities that expose soil. The area under coffee showed an increase, which could be due to various factors including market demands, changes in farm management practices, or ecological factors influencing crop viability.

There is an expansion of coffee-growing areas, which could be due to factors like rising market demand for coffee as highlighted by the CBI (2021). This increase interestingly coincides with a transition from monoculture to intercropping. Both farms now intercrop their coffee with macadamia nut trees as hedgerows. This shift suggests a move towards more sustainable practices, potentially driven by a growing awareness of the environmental impact of agriculture. Intercropping offers several advantages for coffee cultivation, including improved soil health enhanced pest control through increased biodiversity and a more balanced ecosystem within the coffee fields (Rosado et al., 2021).

Changes towards more BSS reflect significant ecological shifts that indicates more sustainable agricultural practices. The increase in vegetative cover such as forests and hedgerows, coupled with the expansion of wetlands and the reduction in bare soil. This suggests an alignment with sustainable farming principles that enhance biodiversity, improve soil structure, and increase water retention. All of which contribute to reduced erosion and improved water quality (Plieninger et al., 2020). These developments not only foster diverse habitats for a range of species but also enhance the overall ecological integrity of the farming areas.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This study aimed at developing and applying a remote-sensing based approach for characterising BSS on coffee farms, using coffee farms in Zimbabwe as a case study. From the study it is concluded that it is possible to map BSS on coffee farms, an important advancement from previous studies that only mapped deforestation associated with coffee or coffee farms only. The accuracy achieved in the mapping could be improved by using other high-fidelity data sources such as LiDAR. It is also concluded that the performance of the approach in terms of accuracy vary depending on site and sensor (and the interaction of the two) and therefore retraining is required in applying this approach to other farms. It is also concluded that vegetation indices such as NDVI, SAVI, NDWI are better performing in mapping BSS in coffee compared to spectral bands only. In addition, optical sensors performed better than radar in assessing BSS at the two sites, indicating that there is potential in use of VHR optical sensors for this task. The results also showed some changes in BSS between 2013 and 2023, underlying the need for continuous mapping of BSS on coffee farms in sustainability assessments and other applications. The maps created from this study are the first RS-based maps of BSS ever their accuracy is still not optimal. However, they show how useful such RS based assessments are to monitor biodiversity support on farm. Overall, we conclude that it is possible to map BSS on coffee farms with acceptable accuracy for many applications including to support coffee certification schemes.

5.2 Recommendations

The research primarily utilized pixel-based classification approach as described in the methods section. It was found out that looking further into some specific RS based methods for further improving the mapping accuracy of BSS. One method is object-based analysis (OBIA) although other studies highlighted that there is no significant difference between the accuracy of OBIA and pixel based classification. When applied to coffee farms OBIA might enhance the accuracy and interpretability of remote the classification, especially in complex coffee farms. It groups pixels into meaningful objects based on their spectral and spatial characteristics. This method is particularly useful in coffee farms where distinct but spatially connected features such as shade trees, hedgerows and wetlands exist. OBIA can distinguish these features by considering the shape, texture and contextual relationship of areas, which might be overlooked in pixel-based analysis. The study's findings highlighted the effectiveness of optical features in classifying BSS with a moderately high accuracy using pixel-based methods. Integrating OBIA could potentially address some of the challenges encountered such as misclassification of shade tree crowns as hedgerows.

The exploration of LiDAR (Light Detection and Ranging) technology can significantly enhance the accuracy of the classification. The study's findings initially showed that while optical and radar data provide a good baseline for BSS classification, they sometimes fall short in accurately differentiating BSS with similar spectral signatures but different structural forms. At Jersey where there is intercropping of coffee and macadamia nuts as hedgerows, misclassifications were present. However, since coffee and macadamia nuts are spectrally similar but with differences in height, LiDAR could potentially distinguish these using highly accurate measurements of canopy height making their mapping more accurate.

The study initially employed a post-classification fusion approach combining optical and radar data results to classify BSS, which did not yield the expected improvements in classification accuracy. This outcome suggests that processing each data type separately before fusion may preserve inherent errors and limitations, thereby diluting the potential benefits of using multi-source data. To better capitalize on the complementary strengths of optical and radar data specifically their spatial and structural information a shift towards pre-classification fusion is recommended. By integrating these datasets before the classification process, a more robust feature set can be created and can enhance the classifiers' ability to accurately differentiate between BSS types. This potentially overcomes the drawbacks observed with post-classification fusion and leading to more precise and reliable results.

Radar imagery with higher spatial resolution has the potential to improve the mapping accuracy of BSS. Although the study resampled the radar data from 10m to 0.5, the image had poor edge detection, mixed pixels and resampling artifacts particularly blurring. By having radar data with a high resolution avoids these resampling issues thereby potentially improving the accuracy.

Certification bodies like 4C can adopt remote sensing technologies outlined in the research as a primary tool for certifying farms on the environmental aspect. This study's approach of using RS is a cost-effective alternative to traditional fieldwork, reducing the need for physical travel and subjective survey methods.

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