Exploring the Role of Agrobiodiversity on Drought Stress in Coffee Fields in Vietnam with Remote Sensing

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Abstract

Vietnam is the second largest coffee producer in the world but is challenged by an increase in the frequency and severity of droughts. At the same time, coffee production is associated with negative impacts on the environment. Various coffee sustainability programs emphasise the inclusion and conservation of biodiversity in coffee fields to improve sustainability. Assessing biodiversity with exclusive use of field visits is challenging. Moreover, it is uncertain whether a correlation between agrobiodiversity and drought stress in coffee plants exists. Using remote sensing is promising as it offers a transparent and efficient method for both biodiversity assessments as well as drought stress assessments. Therefore, this thesis uses multi-spectral remote sensing to explore (1) its ability to assess agrobiodiversity in coffee fields with the use of image classification, (2) its ability to assess drought stress in coffee plants with NDVI and VCI indices, and (3) if a relationship between agrobiodiversity and droughts can be established with this approach. To validate the remote sensing results, fieldwork was used to (1) collect ground truth points for the image classification, and (2) examine correlations between agrobiodiversity traits and the health of coffee plants. Using the commune Quang Hiep as a case study area, field data revealed that an increase in shade from intercrop or shade trees was highly correlated with an increase in coffee plant health (r=0.70). The image classification results revealed that high-resolution SPOT 6 imagery, with NDVI as vegetation index and a Random Forest classifier, can distinguish between high-shade, low-shade, and no coffee areas with an overall accuracy of 80.03%. The drought stress analysis revealed that the NDVI map derived from Sentinel-2 imagery is moderately correlated with the observed health of coffee plants from the field data collection (r=0.34). Lastly, after comparing NDVI and VCI indices for the high-shade and low-shade intercrop coffee classes, results show higher values for high-shade intercrop coffee fields. Thus, healthier vegetation can be found in the areas classified as high-shade intercrop coffee. Although more research on optimal shade levels is necessary, these findings suggest that more shade in coffee fields may reduce drought stress. This research contributes to sustainable coffee farming practices, emphasising the possible benefits of agrobiodiversity for climate adaptation in agriculture and the possible use of remote sensing to assess this.

Keywords: Agrobiodiversity, Droughts, Remote Sensing, Sustainable coffee production

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 The Challenges of Coffee Production

Coffee is one of the most traded commodities in the world. It contributes significantly to the livelihoods of more than 100 million people worldwide and its production has doubled in the last 30 years (Y. Pham et al., 2019). It is a source of income for millions of smallholders in tropical countries that depend on the production for their livelihoods (Utrilla-Catalan et al., 2022). Vietnam is the second largest coffee producer in the world, with around 17% of the global production (Son et al., 2023). On a national level, coffee is the second largest export crop after rice. The Robusta variety is especially popular, with 40% of global Robusta yield being produced in Vietnam (Hung Anh et al., 2019). Within the country, particularly the Central Highlands region of Vietnam is a fundamental coffee-growing region, as 97% of the coffee production is located in this area (Byrareddy et al., 2021). However, despite the economic importance of coffee, there have been various stressors that make the production of coffee challenging. These stressors include but are not limited to market price volatility, extreme weather events, and plant diseases and pests (Rhiney et al., 2021). At the same time, unsustainable cultivation methods, such as overuse of chemical fertilisers, deforestation and intensive water usage, affect and cause stress to the local environment of coffee producing areas (G. Nguyen & Sarker, 2018). A full overview of the challenges is visible in the Causal loop diagram in Figure 1.1.

1.1.1 Environmental Impacts of Coffee Production

The coffee production in Vietnam has various environmental impacts. First of all, the Robusta coffee variant that is mostly grown in Vietnam thrives under intense fertiliser usage (Giovannucci et al., 2004). However, agricultural intensification in the form of excessive nitrogen fertiliser use is reducing soil and water quality while increasing emissions (Hung Anh et al., 2019). Intensive fertiliser usage causes contamination of water resources due to its chemical runoff, which consequently spreads throughout the environment (Giovannucci et al., 2004). Another environmental impact is intensive water use that is threatening to deplete groundwater resources for agricultural production (Amarasinghe et al., 2015; Byrareddy et al., 2020). The depletion of deepwater reserves is a major concern for the agriculture of Vietnam as agriculture accounts for 73.1% of Vietnam's water demand (Q. Pham et al., 2023). Lastly, deforestation and the decrease in shade coffee, thus coffee growing under the shade of taller trees, is decreasing the available habitat for biodiversity. The growth in coffee production and many new coffee plantings were often the result of forest clearance (Meyfroidt et al., 2013). While other species of coffee thrive under the canopy of larger trees, the Robusta variant, which is mostly grown in Vietnam, can manage to grow under full sun exposure (Giovannucci et al., 2004). A major benefit of growing coffee under full sun exposure is its potential of higher yield production in ideal environmental circumstances (DaMatta, 2004). Besides, harvesting of mono-cultures is easier than with more diversified systems (Liu et al., 2018). Thus, growing Robusta in dense monocultures has benefits, but at the cost of forests and biodiversity (Meyfroidt et al., 2013).

1.1.2 Climate Change and Coffee Production

Besides the environmental impacts, climate change is also affecting the coffee production. Specifically, due to climate change, the increasing frequency of droughts causes declines in coffee yields and loss of areas optimal for coffee production (Byrareddy et al., 2021). In the Central Highlands region of Vietnam, where coffee production is concentrated, coffee fields were largely affected by droughts. In 2016, more than 56,000 ha (27.5%) of the total coffee area of Dak Lak province experienced severe drought stress (Y. Pham et al., 2020). This has severe consequences for farmers who depend on coffee production for their livelihoods (Utrilla-Catalan et al., 2022). To add on, it is expected that climate change will increase the distribution of pests and diseases that could affect coffee cultivation (Y. Pham et al., 2019). Various major coffee pests and diseases, such as the coffee white stem borer and the coffee berry borer, are expected to increase reproductive rates and distribution as a result of changing long-term temperature and precipitation patterns (Kutywayo et al., 2013; Magrach & Ghazoul, 2015). Longer-term changes in precipitation patterns and temperature have already been argued to contribute to recent spikes in coffee leaf rust in several countries across Latin America and the Caribbean (Rhiney et al., 2021). Epidemics from plant diseases, such as coffee leaf rust, make globalised coffee systems more vulnerable and threaten the produce (Rhiney et al., 2021).

1.1.3 Socio-economic Challenges and Coffee Production

From a social and economic perspective, coffee farmers are also facing severe challenges regarding coffee production. In 1989 a global regulated quota system that ensured stable prices ended (Kolk, 2013). Because of this, price volatility in the coffee market became inevitable and causes vulnerability in producers' income (De Fontenay et al., 2002; Kolk, 2013). Non-governmental organizations (NGOs) correlated this to declining income levels for farmers, and poor working and living conditions (Kolk, 2013). Particularly ethnic minorities and economically disadvantaged individuals are facing these challenges, as the dominant coffee-producing region is also the region with many socio-economically vulnerable minority groups (De Fontenay et al., 2002; Khuc et al., 2018).

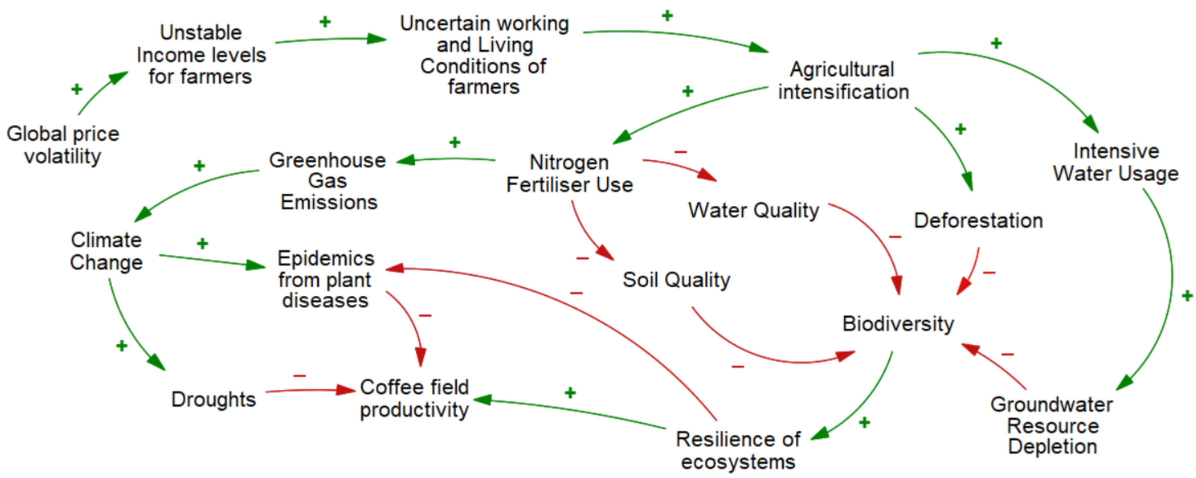


FIGURE 1.1: Causal loop diagram visualising the main factors of the NRM problem.

1.2 Biodiversity, Droughts and Farmlands

1.2.1 The Role of Agrobiodiversity on Farms

It can be argued that the issues regarding the sustainability of coffee fields in Vietnam, partly arise by producing coffee at the cost of biodiversity as a consequence of agricultural intensification. There has been a worldwide growing realisation of the importance of biodiversity for both environmental conservation as well as agricultural production (Dinesh et al., 2022; Dulloo, 2019; Thrupp, 2000). Agricultural biodiversity (agrobiodiversity) is essential for a healthy farming system. Agrobiodiversity can be defined as "the variability of animals, plants, and micro-organisms that are used directly or indirectly for food and agriculture, including crops, livestock, forestry, and fisheries" (Dulloo, 2019).

Agrobiodiversity has multiple benefits for a healthy farm system, which have the potential to improve the sustainability of coffee production in Vietnam. An example is supporting the naturally occurring insects, bacteria, fungi, and birds that make it possible to control epidemics such as insect pests and diseases (Dinesh et al., 2022; Thrupp, 2000). To add on, insects, birds, and other animals also play an essential role in pollination and fertilisation (Anderson et al., 2016). Besides, organic matter is provided by the loose leaves or die-off from other plants (Kuzyakov, 2010). Furthermore, supporting soil organisms is essential for the quality of soil that is used for production, decreasing dependence on fertilisers (Thrupp, 2000). Soil fauna, such as worms, are also responsible for decomposition which is essential for providing plants with nutrients (Bhadauria & Saxena, 2010). Lastly, adding a variety of species, such as different vegetation types, can support ecosystem services, such as pest control and stability of the farms with climate and water regulation (Thrupp, 2000). All of these are important in supporting overall ecosystem health and resilience.

1.2.2 Biodiversity and Drought Resilience

While biodiversity that provides ecosystems resilience to climate change has to be further explored, various papers suggest there could be a relationship between biodiversity and drought resilience (Adams et al., 2022; De Keersmaecker et al., 2016; Isbell et al., 2015; Wright et al., 2021). What is already known, is that there are so-called "insurance effects" of biodiversity. When ecosystems have higher diversity in species, it is also more likely that they contain species that are more robust against extreme climate conditions. Thus, when more vulnerable species are affected by extreme climate conditions, the robust species can compensate for their losses (Isbell et al., 2015). In biodiversity ecosystem functioning research, the stress-gradient hypothesis is a topic of interest. This hypothesis suggests that ecological interactions between organisms become more positive to support each other's survival, for example, by providing shade, improving soil moisture, or sharing nutrients (Adams et al., 2022). According to the hypothesis, drought-sensitive species may be buffered against climate extremes when growing under two requirements. For the first condition, they have to grow in either higher diversity or higher biomass plant communities. The second one states they should grow near drought-resistant neighbours. The reason for this is that higher-diversity communities can be more productive in the provision of greater shade, cooler air temperatures, increased relative humidity, increased likelihood of deep-rooted species and increased surface moisture at the community level (Wright et al., 2021).

A study by Isbell et al. (2015) explored the relation between grassland plant diversity and droughts. For a broad range of climate events, including wet, dry, moderate, and extreme events. In all situations, the productivity of low-diversity communities that only included one or two species changed by approximately 50%. In contrast, high-diversity communities with 16 – 32 species were more resistant to the events and only changed by approximately 25%. However, a year after each climate event, the productivity of both high- and low-diversity had recovered. This study suggests that biodiversity mainly stabilises the productivity of ecosystems (Isbell et al., 2015). In another study by Wright et al. (2021), a variety of plant species were tested under mono-culture and higher-diversity mixture conditions. The species that grew in mono-cultures during dry years were suppressed in their growth. In contrast, when the same species grew in a higher-diversity mixture, they were unaffected by drought. The study suggests that biodiversity should be used as a tool to protect individual species, e.g. crops grown in mono-cultures, from drought conditions (Wright et al., 2021). In a study by De Keersmaecker et al. (2016), semi-natural grasslands were compared to intensively managed agricultural grasslands in response to climate anomalies. This study concluded that the more species-rich semi-natural grasslands were more resistant to droughts and climate anomalies as compared to the agricultural grasslands, stating that increasing species-richness may result in stability against climate extremes.

1.3 Societal Response to Negative Impacts of Coffee Production

Sustainable coffee production by focusing on environmentally friendly cultivation practices is necessary from both a socio-economic as well as an environmental perspective. As a consequence of the worldwide growing concerns on coffee production, certification programs, and labels have emerged to set a standard for sustainable coffee production (Kolk, 2013). Certification programs exist to ensure that the production of coffee takes into account at least one or more aspects of sustainability. These aspects include the economic viability of coffee for farmers, that coffee is produced in a healthy environment and promotes fairness among farmers and workers. There exist various coffee certification programs that all have different main objectives. Nevertheless, they share common traits in providing economic incentives and a voluntary certification process to farmers and sustainable production methods, that are verified by independent certification agency inspectors (Lentijo & Hostetler, 2011).

1.3.1 Coffee Certification Programs

There are various internationally known coffee certification programs (Lentijo & Hostetler, 2011). To begin with, there is Organic. Organic certification focuses on ensuring that no synthetic chemicals are used during production in agriculture (Organic, n.d.). Another well-known certification program is Fairtrade. Fairtrade is focused on strengthening the organisation of small producers by ensuring fair prices and providing stability within trade relationships (Fairtrade International, n.d.). Next, there is Rainforest Alliance, which focuses on coffee grown by farmers that are located in conserved forests, soils, rivers, and wildlife. Their focus is on ensuring that coffee is grown under tree shade and fair working conditions for farmers (Rainforest Alliance, 2024). Furthermore, there is Bird-Friendly, which focuses on promoting shade-grown organic coffee, as this plays an essential role in conserving trees and migrating birds (Bird Friendly, n.d.). Moreover, Starbucks has a certification program known as Starbucks C.A.F.E. Practices. This program makes sure that the coffee that is specifically grown for Starbucks takes into account economic, social, and environmental aspects of production (C.A.F.E., 2020). Finally, there is the Common Code for the Coffee Community (4C), which addresses social, economic, and environmental standards for all stakeholders in the supply chain of coffee production (Lentijo & Hostetler, 2011). While other certification programs have one particular focus, it can be argued that 4C takes a more overarching approach by focusing on the whole process and supply chain of coffee production. The general process in which the certification programs work is with independent verification systems that perform physical audits on coffee fields. Various certification programs, such as 4C include the environmental dimension in their assessments. For example, in the audit checklist of 4C, "protection of biodiversity and high carbon stock areas" is mentioned as a criterion, as well as "primary forests and protected areas are protected" (4C Services, 2024).

1.3.2 Sustainable Farming Practices, Biodiversity, and Drought Stress in Vietnamese Coffee Fields

Currently, unsustainable farming practices are still widely used in the Vietnamese coffee production system. Such as the intensive use of water that depletes groundwater resources (Amarasinghe et al., 2015; Byrareddy et al., 2020) and the overuse of chemical fertilisers (G. Nguyen & Sarker, 2018). Nevertheless, There is an increase in attempts to improve sustainability in coffee fields, such as with intercropping, water-saving technologies, and mulching.

For example (UNEP, 2020) launched a report on addressing the smallholder resilience in coffee production in the Central Highlands of Vietnam. The report describes the economic benefits of transitioning from intensive Vietnamese Robusta cultivation to avocado, durian, or pepper intercropping models. Not only will diversification result in economic benefits by reducing the impacts of low coffee prices, but it will also lead to increased biodiversity and improved soil structure. In return, the economic profitability rises by reducing the requirement of irrigation and agricultural inputs (UNEP, 2020). A study by Clément et al. (2023) supported these findings. This study focused on transitioning from mono-culture to mixed cropping systems in Vietnam. Results indicated that farmers are increasingly integrating multiple crops into their fields. Particularly, coffee, pepper, and fruit trees such as avocado, durian, and macadamia are grown in the same field. These changes were primarily driven by government incentives and market prices. Benefits included increased economic resilience to price fluctuations and a decreased need for fertilisers and pesticides.

Other farm-scale strategies to increase sustainability are focused on improving irrigation efficiency (Amarasinghe et al., 2015; Byrareddy et al., 2020) and irrigation techniques to decrease the depletion of groundwater resources (Ho et al., 2022). Moreover, conservation of soil moisture through mulching, thus spreading a layer of litter such as pruned branches and leaves on top of the soil around the plant, increases coffee production resilience and can result in an economic benefit of 10.2% as compared to farmers that do not apply this practice (Byrareddy et al., 2021). Furthermore, shade management, by providing more shade to coffee trees with other tree species or agroforestry is a practice that can improve sustainability and adds biodiversity in fields (Boreux et al., 2016).

Coffee farmers in Vietnam continue to adapt and apply more sustainable cultivation methods. However, it is largely unknown how effective their strategies are for the mitigation of droughts (Byrareddy et al., 2021). A multitude of these methods directly increase plant biodiversity in the fields, such as adding intercrop species and shade trees (Boreux et al., 2016; Clément et al., 2023; UNEP, 2020). Previous research suggests that there may be a relationship between biodiversity and drought stress (Adams et al., 2022; De Keersmaecker et al., 2016; Isbell et al., 2015; Wright et al., 2021). However, the correlation between agrobiodiversity, such as intercrop species and undergrowth of grass and herbs, and drought stress experienced by coffee plants in Vietnam has not been extensively researched and has the potential to be explored further.

1.4 Wickedness

A wicked problem can be defined as a problem that involves uncertain knowledge and disagreement among involved stakeholders. This makes it challenging to propose a suitable solution (Balint et al., 2011). In the case of sustainable coffee production in Vietnam, the primary wickedness is that the stakeholders who are involved in Vietnamese coffee production have various opinions on how to define, what to prioritise, and how to implement sustainability within coffee production (Rhiney et al., 2021). This results in stakeholders that are willing to participate in the transition to sustainable coffee production, but have different focal points, such as environmental concerns (Kolk, 2013; World Bank Group., 2015), social concerns (Kolk, 2013) or the potential economic benefits (Hung Anh et al., 2019).

To begin with, the national government of Vietnam has played a significant role in the rapid increase in coffee production in the country. Since the late 1970s, the government actively encouraged coffee production by removing restrictions and allowing private firms to participate fully in the market (Giovannucci et al., 2004). An example is having a low import tax for fertilisers (Giovannucci et al., 2004). However, in more recent years, the Vietnamese government realised the importance of sustainable agriculture and is working together with the World Bank to make coffee production more sustainable (World Bank Group., 2015). An example is governmental support for an intensive coffee program that focuses on improved farm management practices. The aim is to maintain current levels of production while using less land, water, and material inputs to decrease impacts on surrounding forests (World Bank Group., 2015). Another governmental action includes supporting sustainable coffee rejuvenation and replanting practices, as the uncontrolled industry expansion has led to coffee fields in areas that are not suitable for its production (World Bank Group., 2015). The Vietnamese Ministry of Rural Development and Agriculture recently released a vision report on transitioning to sustainable agriculture by 2050 (UNDP, 2023). The concerns about sustainability also led to the emergence of a variety of voluntary standards for sustainable coffee production. This is the result of NGOs and sometimes industry-accompanied concomitant certification programs. The various standards that exist, such as Fairtrade, Organic, and Rainforest Alliance. All have different requirements and priorities for what they consider to be sustainably produced coffee (Kolk, 2013). For coffee farmers, the most important reason to participate in sustainable agricultural practices is because of the potential economic benefits (Hung Anh et al., 2019). Moreover, farmers who have experienced soil erosion and a lack of irrigation water also show interest in incorporating sustainability initiatives into their methods of production and processing (G. Nguyen & Sarker, 2018). Lastly, research on the willingness to pay for sustainable coffee by consumers, shows that consumers value agrochemical management, such as pesticide-free coffee, more than other features of sustainability, such as biodiversity protection (Gatti et al., 2022).

For these reasons, it can be argued that the various stakeholders that are involved in the coffee production of Vietnam have various reasons to participate in sustainable coffee production. This agreement between the stakeholders on increasing sustainability makes the topic seem less wicked. However, there are different opinions on what sustainability in coffee production entails (Kolk, 2013). As a result, the aspect of agrobiodiversity on coffee farms becomes overshadowed, reducing the overall awareness and emphasis on its significance within the broader context of sustainable practices. Besides the possible economic benefits, the benefits and disadvantages of having other species on the field are less obvious (Vogt, 2020). Consequently, the wickedness of the problem increases, as there is no stakeholder consensus on the value of agrobiodiversity and also uncertainty on the role of agrobiodiversity in coffee fields. Raising awareness and understanding on the topic of agrobiodiversity in coffee fields could therefore decrease the wickedness.

1.5 Potential Use of Remote Sensing in Biodiversity Assessments and Crop Monitoring

1.5.1 Remote Sensing for Agrobiodiversity Assessment

Assessing and monitoring agrobiodiversity in coffee fields is an essential part of sustainability certification. However, Nagendra (2001) argues that by only using field visits, it is nearly impossible to acquire enough information for a complete biodiversity assessment. Remote sensing is suggested as a solution as this can provide a systematic, synoptic view of the earth cover, that proves to be useful for biodiversity assessment. Another advantage of the use of remote sensing for agrobiodiversity assessment is that it is not necessary to assess one field at a time. In fact, with the use of remote sensing images, a multitude of fields can be assessed, as larger areas at a time can be covered by one image. This offers benefits of cost and time efficiency as well as a transparent way of assessing fields (Read, 2006).

There are challenges when it comes to mapping coffee fields in the Central Highland region of Vietnam. Mapping coffee fields in this region is especially challenging due to the persistent cloud cover in the 'coffee belt'. To add on, the spectral characteristics of coffee are similar when compared to other agricultural land and tree crops. Apart from this, coffee production systems themselves also appear to be diverse, making it challenging to find a universal classification method to use (Maskell et al., 2021). For example, the method of growing Robusta in Vietnam differs from the methods that are used for the production of Arabica coffee in Latin American countries. While the Arabica grows under the shade of other trees, Robusta does not necessarily require the inclusion of shade from other vegetation (Giovannucci et al., 2004). But even within Vietnam, there are various types and structures of coffee production systems. Despite the challenges, there has been previous success in the mapping of coffee fields in Vietnam (Kpienbaareh et al., 2021; Maskell et al., 2021; Zhou et al., 2017). A study by Maskell et al. (2021) integrated sentinel optical and radar data to map smallholder coffee production systems in Vietnam, which resulted in an overall accuracy of 89% (Maskell et al., 2021). Another study used a combination of Landsat and digital elevation model (DEM) data for the mapping of multidecadal changes in coffee in the Central Highlands region of Vietnam. This resulted in an overall accuracy of 86.9% (Son et al., 2023).

Since coffee farms in Vietnam generally consist of small fields, high-resolution multispectral sensors of less than 5 meters become particularly useful for coffee mapping (Hunt et al., 2020). Agrobiodiversity in Vietnamese coffee fields can be characterised by a large variety of intercrop species that are grown with the coffee plants in various structures (Clément et al., 2023). This large heterogeneity in spectral signatures makes it almost impossible to classify distinct intercrop species to assess agrobiodiversity (Bégué et al., 2018). A more general approach to map agrobiodiversity within coffee fields would be to map different field structures, such as distinguishing between high-shade and low-shade intercrop coffee fields. The quality of shade depends on tree crown sizes, density, and compactness (Tscharntke et al., 2011). Thus, mapping different structures of intercrop coffee fields, such as distinguishing between high-shade and low-shade fields has the potential to reveal different forms of agrobiodiversity in coffee fields, but the mapping of this has not yet been explored.

A common approach for coffee mapping with optical data is the use of spectral pixel-based methods. These methods classify the image pixels into land cover classes based on spectral signatures of the land cover types in the study area (Hunt et al., 2020). Often vegetation indices are used to extract more information from the satellite data. The most widely used index for this purpose is the Normalised Difference Vegetation Index (NDVI) (Chemura et al., 2017; Hunt et al., 2020). However, the NDVI is shown to be sensitive to soil colour and brightness, clouds, atmospheric effects, and shadows (Xue & Su, 2017). To account for atmospheric effects, the Atmospherically Resistant Vegetation Index (ARVI) was developed (Xue & Su, 2017), which has also been used for coffee mapping (H. Nguyen et al., 2016; Phi & Hoa, 2022). Another index that was derived from the NDVI index and is less sensitive to soil brightness is the Soil Adjusted Vegetation Index (SAVI) (Xue & Su, 2017). However, reducing the atmospheric effects or the soil brightness effects may increase the other effects. To counter this, the Enhanced Vegetation Index (EVI) was developed, which is also used in coffee mapping (Bernardes et al., 2012). Thus, a broad range of useful vegetation indices for mapping coffee exist. However, there is no universal classification method. This raises the question of which vegetation index is the most useful for mapping different structures of intercrop coffee fields in Vietnam.

1.5.2 Remote Sensing for Drought Stress Assessment

Remote sensing is also suitable for drought impact monitoring. While traditional methods for drought monitoring fully relied on rainfall data, which was sometimes difficult to obtain, developments in remote sensing technology offer an efficient and rapid view of droughts at various scales (AghaKouchak et al., 2015; Zargar et al., 2011).

The NDVI has become a primary tool for the description of vegetation health with remote sensing because of its ability to distinguish healthy vegetation with high NDVI values from unhealthy vegetation with low NDVI values (AghaKouchak et al., 2015; Kogan, 1995). This became the basis for various remote sensing drought indicators, such as the Vegetation Condition Index (VCI) (Kogan, 1995; Zargar et al., 2011). The VCI scales NDVI values between their minimum and maximum values over multiple years to separate the short-term weather signals from the long-term condition (Kogan, 1995). Several studies have been using the VCI for drought monitoring (Dutta et al., 2015; Liang et al., 2017; Quiring & Ganesh, 2010; Zambrano et al., 2016), and has been proven especially useful for the monitoring of agricultural drought (AghaKouchak et al., 2015). This raises the question if these indices without the use of further data are able to accurately assess drought stress in coffee plants in Vietnam.

1.6 Problem Statement

Coffee production is associated with various negative environmental impacts and improving sustainability in coffee production is challenging. Different types of coffee production systems exist, such as a variety of intercropping patterns and structures. Thus, coffee fields may substantially differ in the level of agrobiodiversity. Previous research has shown there may be a relationship between biodiversity and the level of drought stress. Both intercrop coffee field types and drought stress have the potential to be assessed with remote sensing. The use of vegetation indices, derived from high-resolution imagery is a promising approach. However, it is uncertain how well these remote sensing-based assessments perform and if a relationship between biodiversity and drought stress can be established with this approach.

1.7 Research Objective and Research Questions

The goal of this research was to assess if different types of intercrop coffee fields respond differently to drought stress. First, different high-shade and low-shade intercrop coffee fields were classified with the use of various vegetation indices. Next, the impacts of droughts on the field level were calculated using NDVI and VCI indices. Finally, the outcome of these analyses were used to explore possible correlations between the agrobiodiversity within coffee fields and drought stress. This led to the following main objectives:

- **RO1:** To test the suitability of high-resolution multispectral remote sensing imagery for mapping intercrop coffee fields and drought stress in coffee plants.
- **RO2:** To investigate the effect of agrobiodiversity on the drought resilience of coffee fields in Vietnam.

This is answered with the following research questions:

- **RQ1:** Which vegetation index provides the highest accuracy in distinguishing high-shade and low-shade intercrop coffee fields with high-resolution multispectral remote sensing imagery?
- **RQ2:** To what extent can high-resolution multispectral remote sensing imagery with NDVI and VCI indices be used for detecting drought stress in coffee plants?
- **RQ3:** What is the relationship between agrobiodiversity and the level of drought stress in coffee fields?

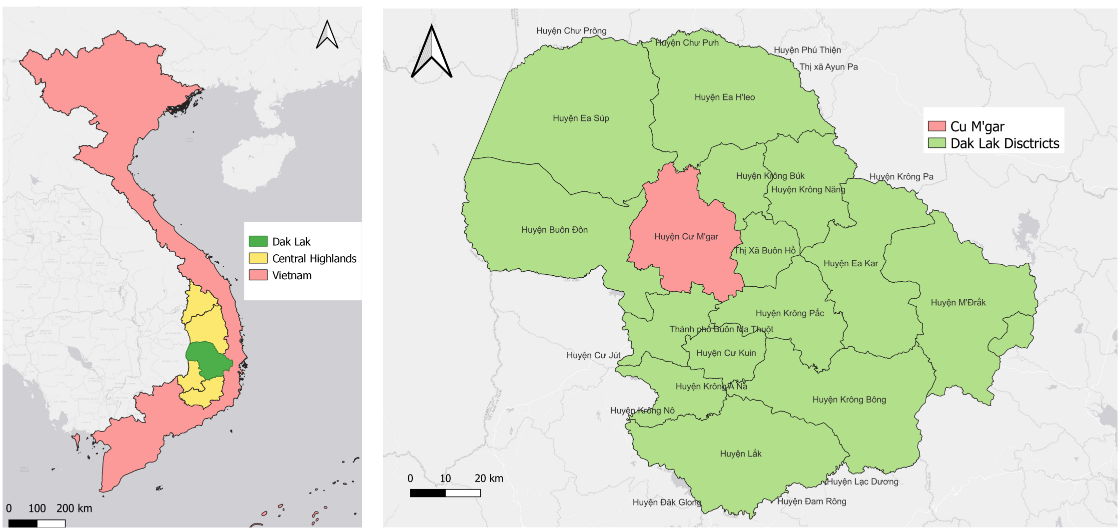
Chapter 2

Materials and Methods

In this chapter, the materials and methods that were used to answer the research questions are explained.

2.1 Study Area

In Figure 2.1 A, the Central Highlands and Dak Lak province of Vietnam are visible. The Central Highlands is the main coffee-producing region in Vietnam, The Dak Lak province in particular is known to be the coffee province of the country, as one-third of the total coffee production in Vietnam originates from Dak Lak (G. Nguyen & Sarker, 2018). The average coffee farm size is 1.63 ha with an average of 978 coffee trees per ha (Kuit et al., 2020). Dak Lak consists of multiple smaller districts, as visible in Figure 2.1 B. In the districts of Krong Pak, Cu M'gar and Buon Ho, Robusta coffee production is the main source of income (Hung Anh et al., 2019). According to an expert organisation in the province (Nyguen Thanh Tam from TMT consulting, personal communication, 17 January 2024), Cu M'gar, as visible in Figure 2.1 B, was at the time of this research a primary coffee-producing district. However, for fieldwork, the local authorities granted permission exclusively to one of the communes, known as Quang Hiep. For this reason, Quang Hiep was the case study area of this research. The exact location of Quang Hiep is visible in Figure 2.2.



(A) Vietnam and Central Highlands

(B) Dak Lak and Cu M'gar District

FIGURE 2.1: Maps of the study area.

Cu M'gar is located in the center of the Dak Lak province in the Central Highlands of Vietnam and is subdivided into seventeen wards and communes. It is a district of 824.43 km^2 and had a population of 173,024 inhabitants in 2022 (Cu M'gar Government, 2022). Most of the area in Cu M'gar is planted with coffee, pepper, durian, and annual crops (Cu M'gar Government, 2022). The climate is categorised by the highland tropical monsoon climate. There are two distinct seasons in a year. During the rainy season from May to October, 92% of the yearly precipitation happens, which foresees water for crop growth and development. The dry season is from November to April, precipitation during this season is limited (Vietnam Institute for Building Science and Technology, 2022). This, in combination with low air humidity and a large amount of evaporation further increases potential drought stress.

FIGURE 2.2: The district of Cu M'gar with the study area Quang Hiep.

2.2 Materials

During fieldwork, a GPS system of type Garmin eTrex was used to keep track of the location of the sample points. A measurement tape with a length of 50 meters was used to make transects from the sides of the coffee fields toward the center of the coffee fields. Printed-out fieldwork forms were used together with a pencil to make notes of the fieldwork observations. After fieldwork, this data was converted to an Excel file and shapefile.

For analysis of the sub-questions, multiple satellite images were used. These included a high-resolution SPOT 6 image as well as a collection of Sentinel-2 images from 2017 till 2024.

SPOT 6 Image

The SPOT satellite image was collected from the archive of the European Space Agency and had the ID number ID number ORT_SPOT6_20240223_030159400_000. The specific product is a SPOT 6 image that was orthorectified, pansharpened and contains four spectral bands. These include, blue, green, red and near-infrared. It has a spatial resolution of 1.5 meters, which is very high in comparison to other satellite image sources. The repeat cycle of SPOT 6 is 26 days, and this specific image was captured on 2024-02-23:03:01:54.6. Thus, the image was captured around the same time as the fieldwork phase of the research. Since the SPOT image has both a high resolution and a similar timing to the fieldwork phase, it was appropriate to select this specific image for this research. The coordinates are in UTM zone 48N. Figure 2.3, visualises the original satellite image with 7343 rows and 8442 columns of pixels, clipped to the study area Quang Hiep with true colour composite.

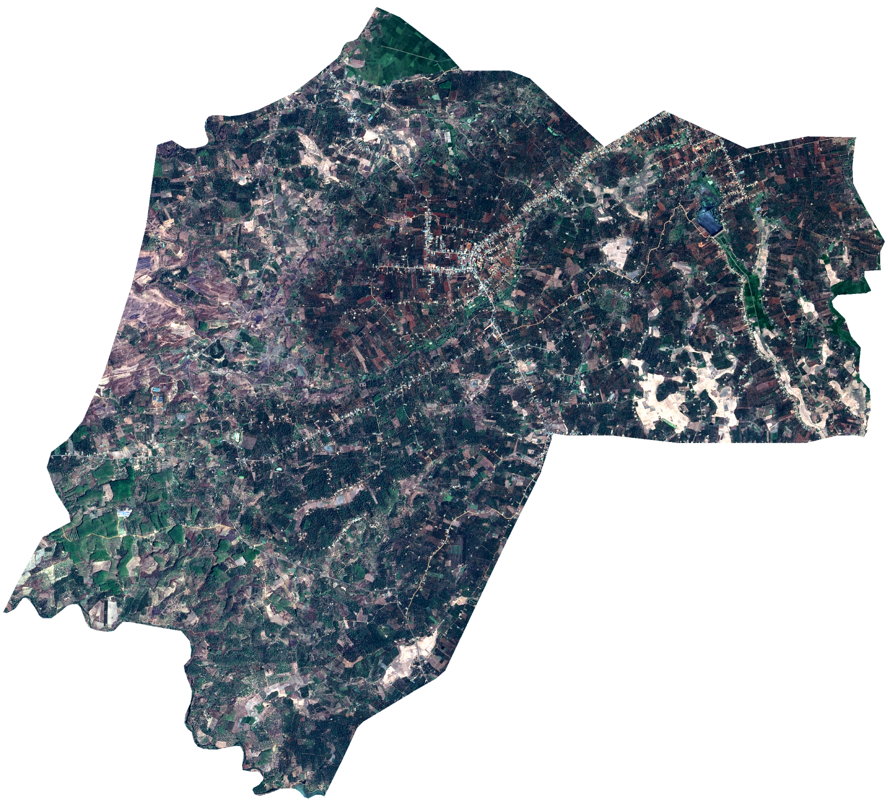


FIGURE 2.3: SPOT 6 satellite image clipped to the study area Quang Hiep in true colour composition, captured on 24-02-23.

Sentinel-2 Imagery

The Sentinel-2 satellite images were collected from the online Sentinel Hub platform. The specific product collection consisted of Sentinel-2 level 2A imagery that was orthorectified and contained 13 spectral bands in total. These included ultra blue, blue, green, red, multiple visible near-infrared bands, and multiple short-wave infrared bands. The bands have different spatial resolutions with the highest resolution of 10 meters for the blue, green and red bands. The lowest spatial resolution is 60 meters for ultra-blue and short-wave infrared bands. The spatial resolution is therefore considerably lower in comparison to the SPOT 6 image product. The earliest available image for the Quang Hiep study area is from 2017, which is why a time series from 2017 to 2024 was selected. The coordinates are in UTM zone 48N. Table 2.1 shows the exact dates of every acquired Sentinel-2 image.

Table 2.1: Exact dates of the collected Sentinel-2 images from 2017 to 2024.

Year	Month	Day
2017	February	7th
2018	February	7th
2019	January	28th
2020	January	23rd
2021	February	16th
2022	January	22nd
2023	March	8th
2024	February	16th

Software

Software that was used for the analysis includes Python version 3.9.12, R version 4.2.3, and Q-GIS version 3.22.10. The integrated terminal of the code editor Visual Studio Code was used to run the Python scripts with various libraries. These included, scikit-learn, Rasterio, Pandas, GeoPandas, NumPy, Matplotlib, seaborn, and SciPy. To run the R code, R studio was used with the terra library. Q-GIS was used for the creation of the maps in this research.

2.3 Methods

This study consisted of four main phases. To begin with, field data was used to enable and validate the analysis, by collecting samples of coffee plants and ground truth points (GTPs). Secondly, image classification of high-resolution remote sensing imagery was used to map high-shade intercrop coffee, low-shade intercrop coffee and no coffee classes. Next, remote sensing imagery was used to analyse the drought stress that is experienced on coffee plantations, by calculating the NDVI and VCI. Lastly, a descriptive statistical and correlation analysis was conducted to search for potential patterns between biodiversity and drought conditions. A workflow of the study design of this thesis is visible in Figure 2.4.

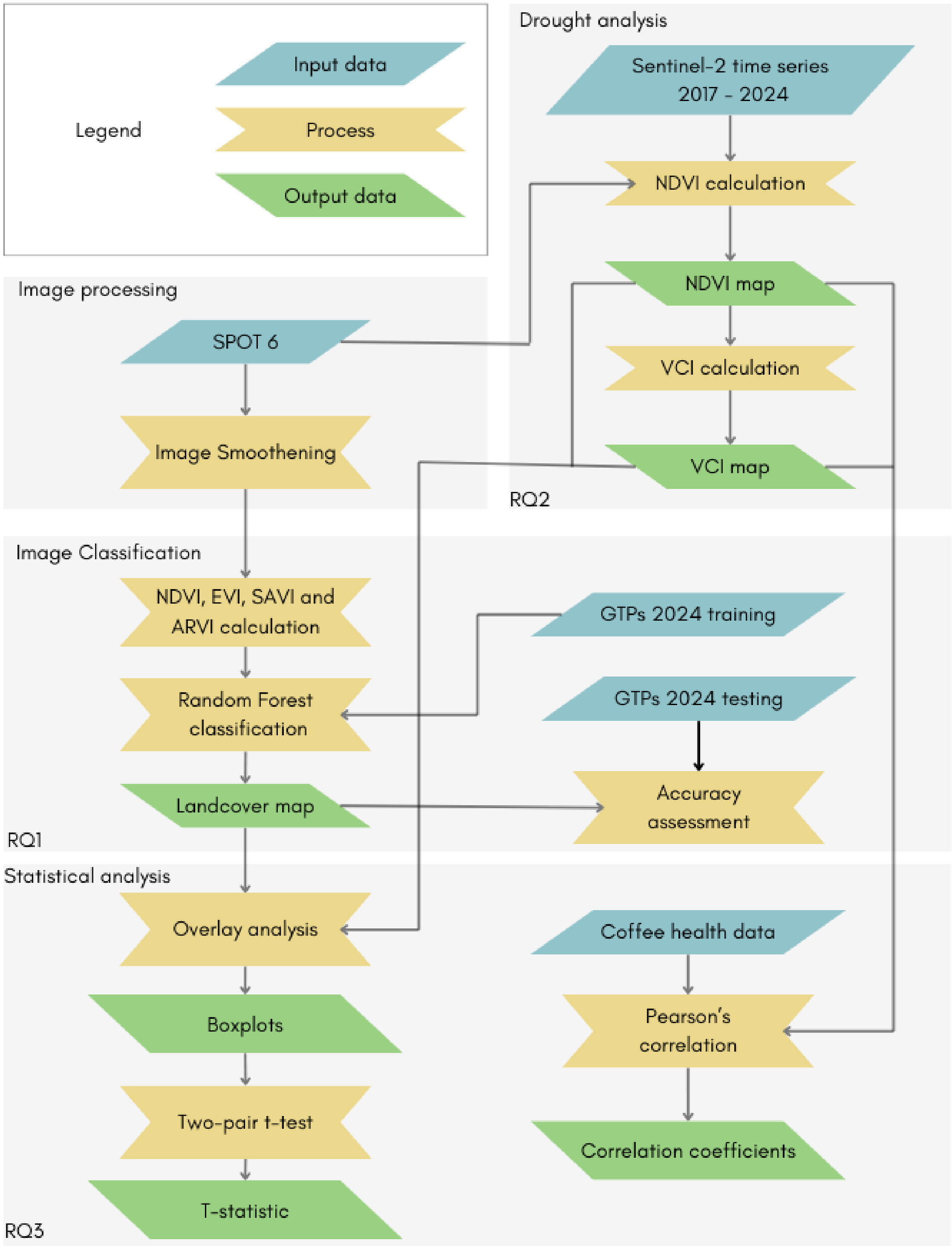


FIGURE 2.4: Workflow of the study design, including the different methods, steps and how each research question was answered.

2.3.1 Data Collection

Fieldwork sampling design

The exact timing of the field data collection was from the 3th of March untill the 20th of March 2024. this is during the dry season of the study area. Instruments for the fieldwork included a GPS system, measurement tape of 50 meters, and two field work forms for the collection of coffee health data and GTPs. There was no previous selection of farms to visit, because there was no information or spatial outlines on coffee farms available. Instead, a member from a farmers cooperative known as Quet Tien cooperative guided us to randomly selected coffee farms in the area, taking into account that the locations needed to be spread out over the study area.

For the coffee health dataset, points were collected every 10 meters in a transect from the side of a coffee field to the center, using the measurement tape and GPS. The GTPs were focused on the collection of points of other land cover types in the study area. For this, random points were selected and the location was tracked using the GPS. Both dataset collections are in detail discussed in the following sections.

In total, 88 coffee health sample points and 163 GTPs of various classes were collected. This is visible in Figure 2.5 and a more zoomed-in version that shows the distribution points on a field level is visible in 2.6. Approximately 15 farms with multiple coffee fields containing different characteristics were visited. These characteristics ranged from mono-culture fields with a lot of sun exposure, to large intercrop trees that provided a lot of shade. Even within the fields, there was variation in planting structures visible. All fieldwork data sheets were converted into a database in Excel.

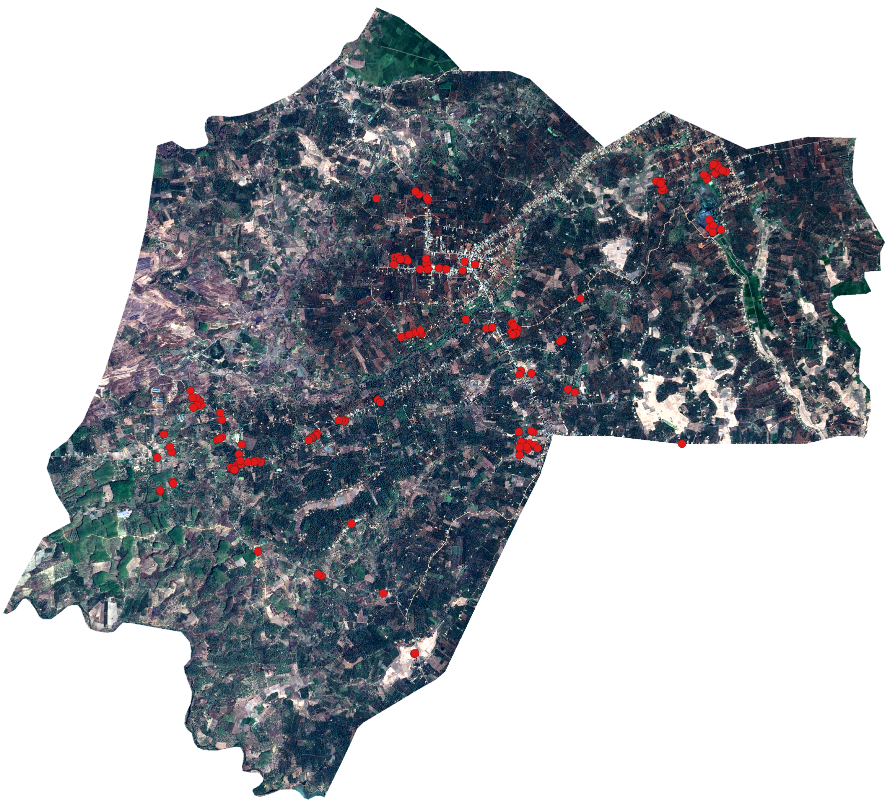


FIGURE 2.5: Distribution of collected sample points in the fieldwork phase.

FIGURE 2.6: Zoomed-in version of the distribution of collected sample points in the fieldwork phase.

Coffee health data collection

The first type of data that was collected during fieldwork was the coffee health data. This was done by collecting points every 10 meters in a transect from the side of a coffee field to the center, to see if there were gradual changes within a field. Because the coffee fields are randomly distributed and quite small (this varies between 0.5 hectares to 1.5 hectares), one transect per field was carried out to collect data.

By filling in the data collection form as visible in A.2, at every point, data was collected on the health state of the coffee shrubs based on observable characteristics. A study by Evizal and Prasmatiwi (2022) describes observable traits of nutrient deficiencies in Robusta coffee that were especially present after a long drought season in non-shaded coffee fields in Sumatra. A symptom of nitrogen deficiency is the presence of yellow leaves. Furthermore, magnesium deficiency is visible with yellow-brown to light brown necrotic spots (Evizal & Prasmatiwi, 2022). Abu-Mettleq and Abu-Naser (2019) further indicates that coffee plants can suffer from severe leave loss and branch dieback during dry seasons when water is lacking. The health of the observed coffee plant samples was evaluated quantitatively, using a percentage-based scoring system from 0 to 100. Figure 2.7 shows an overview of the mainly observed different characteristics. The sampled coffee plants received a score between 0 and 100. A score of 0 indicated the least healthy condition, while a score of 100 denoted optimal health.

Plants scoring between 75 and 100 were categorized as "healthy". These samples exhibited uniformly bright green leaves with no yellow leaves, brown spots, or other stress indicators. Scores in the range of 50 to 75 indicated plants with moderate health issues, characterized by the presence of some yellowing or brown spotting on the leaves, but retaining a majority of green foliage. As the score approached 75, fewer yellow leaves were observed, while scores closer to 50 indicated a greater prevalence of such symptoms. Plants with scores ranging from 25 to 50 demonstrated more pronounced stress, primarily marked by a predominance of yellow leaves. Lower scores within this range indicated an increased presence of yellowing. Scores below 25 were assigned to plants showing severe stress symptoms, such as significant leaf loss and the presence of predominantly yellow or brown visibly dried-out leaves.

(A) Health score between 75 and 100

(B) Health score between 50 and 75

(C) Health score between 25 and 50

(D) Health score between 0 and 25

Figure 2.7: Examples of health scores for coffee samples based on appearance. (A) A coffee plant with exclusively bright green leaves. (B) A coffee plant with mostly green but also yellow leaves. (C) A coffee plant with predominantly yellow leaves with few green leaves. (D) A coffee plant with very few leaves, of which all leaves are yellow.

Moreover, the height of the coffee plants, surface cover type and cover percentage, intercrop/shade tree type and cover percentage, the distance between the intercrops, and species count information were collected. For the species count, all unique plant species within a radius of 3 meters around the coffee shrub were counted. A local expert supported the recognition and distinction of various intercrop species during the fieldwork. The coffee height, intercrop cover percentage, surface cover percentage, and the distance between intercrops were estimated, based on visual interpretation. A full overview of the collected variables is visible in Table 2.2.

Table 2.2: Information collected for the coffee health dataset during fieldwork.

Field	**Description**
ID	Unique identifier for each sample point.
Coordinates	GPS coordinates of the sample point.
Distance from the side of the field (m)	Measured distance from the edge of the field to the sample point.
Coffee Height (m)	Average height of the coffee plants in the three meter radius of the sample point.
Coffee Health	Assessment of the average health of the coffee plants from 0 to 100 in the three meter radius of the sample point.
Surface Cover Type	Type of surface cover in the three meter radius of the sample point.
Surface Cover	Percentage of surface area that is not bare soil in the three meter radius of the sample point.
Intercrop Type	Type of intercrop present in the three meter radius of the sample point.
Intercrop Coverage	Percentage of area covered with shade from the intercrop in the three meter radius of the sample point.
Intercrop Height	Average height of the intercrops in the three meter radius of the sample point.
Distance Between Intercrops (m)	Distance between individual intercrop plants on the sample point location.
Species Count	Count of all unique plant species present in the three meter radius of the sample point.

Ground Truth Points data collection

The second dataset that was collected during fieldwork served as GTPs for the image classification to create a land cover map. This was done to improve the distinction between coffee fields and other types of fields in the classification process of the remote sensing image. Random points of various land cover types were collected. The land cover types that were included in the observations were selected before the fieldwork and consisted of: bare soil, shrubland, grassland, cropland, wild trees, other plantations, various intercrop species in coffee fields, mono-culture coffee, newly planted coffee and water. For this, the data collection form was filled in and the GPS was used to track the sample locations. Moreover, a picture of the land cover type was taken at each location. A full overview of the collected data is visible in Table 2.3. A local expert supported the recognition of the predominant observed plant species in sample locations. The species count information included all observed plant species on a sample location. The canopy cover was estimated, based on an on-sight visual interpretation. The fieldwork form that was used for this is visible in A.1.

TABLE 2.3: Information collected for the GTP dataset during fieldwork.

Field	**Description**
ID	Unique identifier for each data point.
Coordinates	GPS coordinates of the sample.
Land Cover Type	Classification of the land cover.
Dominant Species	Predominant species observed.
Species Count	Total number of species recorded.
Canopy Cover	Percentage of canopy cover.
Description	Additional description of the area.

In Table 2.4 a full overview of the data that was used for this research is visible. This consisted of the data collected during the fieldwork phase of this research, and the collected satellite images from the European Space Agency and Sentinel Hub.

TABLE 2.4: Dataset and Source Information

Dataset	**Source**
Ground truth points	Collected during fieldwork
Coffee health	Collected during fieldwork
SPOT image	European Space Agency
Sentinel-2 images	Sentinel Hub

2.3.2 Field data processing

The GTP dataset originally consisted of the following classes: bare soil, shrubland, grassland, cropland, wild trees, other plantations, various intercrop coffee classes, mono-culture coffee, newly planted coffee, and water. It was tested whether a classification with distinct intercrop species in coffee fields was possible. However, the accuracy of classifying distinct intercrop classes was too low for further analysis. Instead, the classes were generalised to high-shade intercrop coffee, low-shade intercrop coffee, and no coffee classes. The distinction between high-shade and low-shade intercrop coffee classes was based on the collected data on canopy cover percentages. If the intercrop coffee sample had a canopy cover percentage of over 50%, the sample was classified as high-shade intercrop coffee. If the class had a canopy cover percentage that was lower than 50%, it was classified as low-shade intercrop coffee. Also, the mono-culture coffee class, which had a canopy cover percentage of 0%, was merged with the low-shade intercrop coffee to have a larger number of samples for the classification process.

2.3.3 Image Processing

Preprocessing of the SPOT image

Before the classification, the image was filtered with a Gaussian smoothing filter using the SciPy library and .ndimage package for multidimensional image processing. The smoothening process was necessary because when zooming into the SPOT image, small irregularities in pixel values became visible which lowered the accuracies in the tested classification results. To smoothen out these small irregularities and increase the accuracy of the classification, the Gaussian smoothening filter was used. The Rasterio and NumPy libraries were used the process the raster image.

The Gaussian smoothing filter works by creating a normalised kernel, which is a matrix based on the Gaussian distribution. The size of this kernel and the sigma decide on the amount of smoothening that is applied to the image. This kernel is moved over the image to calculate the weighted average of the pixel values for every pixel based on the kernel. Because this filtering technique uses a weighted average, in which weights gradually decrease towards the outer pixels, larger objects are preserved while noise is reduced (Gonzalez & Woods, 2017). For smoothening of the SPOT 6 image, the selected sigma was 2, with an alpha of 1.5 to preserve the edges of coffee fields.

Image Classification

For the classification of the SPOT image, several Python libraries were used: Rasterio for geospatial raster data manipulation, GeoPandas for handling and analysing geospatial datasets, NumPy for efficient array operations, and Scikit-learn for implementing machine learning algorithms.

The dataset comprised 163 samples, and thus only limited samples per class were available. Therefore, it was crucial to have a good balance between training and testing sets, as estimating errors on validation datasets with limited samples is very sensitive (Xu & Goodacre, 2018). According to Xu and Goodacre (2018), the splitting strategy is data-dependent and cannot be decided a priori. For that reason, to have a stable model performance, different distributions of training and validation data were explored before selecting a splitting strategy. This was done by running an initial Random Forest model with different data splitting strategies and comparing the results. From this pre-analysis, 80% training and 20% validation, and 70% training and 30% validation sets resulted in unstable model performances with either very high or very low overall accuracies. 50% Training and 50% validation set resulted in low overall accuracies, which could be due to the minimal samples in the training set. For this reason, 60% training and 40% testing sets were selected. Random stratification was used to ensure that 40% of the samples for all classes were used as testing set. An overview of the number of training and validation samples for each class is visible in Figure 2.5

Table 2.5: Total number of training and validation samples per class.

Class	Training	Validation
High-shade intercrop coffee	16	11
Low-shade intercrop coffee	24	17
No coffee	57	38

From the SPOT 6 image, all available bands (blue, green, red, and NIR) were used as features to train the model. Alongside the regular SPOT 6 bands, a multitude of vegetation indices including NDVI, EVI, SAVI, and ARVI were tested on their performance. This was done by developing models that include the regular SPOT 6 bands as a feature set as well as one of the selected vegetation indices and a model that combined all vegetation indices. An overview of how each index was calculated is visible in Table 2.6.

TABLE 2.6: Vegetation index formulas where NIR, RED, and BLUE represent the near-infrared, red, and blue spectral bands, respectively. L is the soil conditioning index, which varies from 0 to 1 depending on the density of the vegetation that is being analysed (Xue & Su, 2017). In this research L = 0.5 was adopted to account for the differences of high-shade and low-shade intercrop coffee fields.

Index	Formula
NDVI	$\text{NDVI} = \dfrac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}$
EVI	$\text{EVI} = 2.5 \times \dfrac{\text{NIR} - \text{RED}}{\text{NIR} + 6 \times \text{RED} - 7.5 \times \text{BLUE} + 1}$
SAVI	$\text{SAVI} = \dfrac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED} + L} \times (1 + L)$
ARVI	$\text{ARVI} = \dfrac{\text{NIR} - (2 \times \text{RED}) + \text{BLUE}}{\text{NIR} + (2 \times \text{RED}) + \text{BLUE}}$

The Random Forest algorithm was used for classification. This is an ensemble classifier that combines the results of multiple decision trees to make a final class prediction. It is often used for classification in the field of remote sensing due to the accuracy of the classifications. Its benefits include that it is fast and insensitive to overfitting, has ease of parameterisation, and its the ability to handle high data dimensionality (Belgiu & Drăguţ, 2016). A grid search algorithm to optimise the parameters for each model and enhance their predictive performance was used. Each algorithm underwent 100 iterations of training and testing to account for variability due to random data splitting, thus ensuring a robust evaluation. Hereafter, the models with the highest overall accuracy, for each of the vegetation indices were further analysed with their precision, recall, and F1 scores. These measures give better insights into the specific classes when the data is imbalanced (Juba & Le, 2019). These evaluations provided a detailed comparison to select a model of which the resulting land cover map would be further used in the analysis. The selected model was finally investigated with a confusion matrix.

2.3.4 Analysis

Drought Analysis

Drought analysis was performed using the terra library in R to process SPOT 6 and Sentinel-2 imagery. The analysis utilised two key indicators: the Normalized Difference Vegetation Index (NDVI) and the Vegetation Condition Index (VCI).

The NDVI calculation was conducted for both the SPOT 6 as well as the Sentinel-2 images. This was done to compare the resulting NDVI map from the SPOT 6 image from 2024 and the Sentinel-2 image from 2024. Additionally, the mean and median NDVI values were calculated using the Sentinel-2 imagery from 2017 to 2024 to understand if the plant conditions in 2024 are similar to those of the previous seven years. With the resulting NDVI maps for the years 2017 to 2024 from the Sentinel-2 images, the VCI for the conditions of the Sentinel-2 image of 2024 was computed with the formula:

$$\mathrm{VCI} = 100 \times \frac{\mathrm{NDVI} - \mathrm{NDVI}_{\mathrm{min}}}{\mathrm{NDVI}_{\mathrm{max}} - \mathrm{NDVI}_{\mathrm{min}}}$$

where $\mathrm{NDVI}_{\mathrm{min}}$ and $\mathrm{NDVI}_{\mathrm{max}}$ are the minimum and maximum NDVI values observed over the period. VCI provides a relative measure of vegetation health by comparing the current NDVI to historical extremes (Kogan, 1995). This temporal analysis supported the assessment of drought conditions and their effects on coffee plant health by comparing extreme values from the previous 8 years during the dry season with the conditions of the 2024 dry season.

Correlation Analysis

For the correlation analysis, R was used as well as Python. Pearson's Correlation Coefficient was the primary statistical tool used to analyse the relationships between agrobiodiversity variables and coffee plant health. This method was selected for its ability to measure the strength and direction of linear relationships between continuous variables (Sedgwick, 2012). Pearson's correlation is a standard function of R and uses the formula as visible below.

$$r_{xy} = \frac{\mathrm{cov}(x, y)}{\mathrm{SD}_x \times \mathrm{SD}_y}$$

Pearson's correlation is the most common correlation method that uses the covariance of two normalised variables by the product of their standard deviations (Makowski et al., 2020). To begin with, Pearson's correlation coefficients were computed for all continuous variables that were collected during fieldwork and the coffee health scores. This included the variables: intercrop cover percentage, the height of the intercrop, the distance between intercrop plants, surface cover percentage, and species count. This analysis supported the recognition of the role agrobiodiversity variables have on coffee plant health. From these results, the significant continuous variables were further analysed to explore possible correlations between each other. R was used to compute the Pearson's correlation coefficients.

For the categorical variables, which included intercrop types and surface cover types, another approach had to be used to analyse possible correlations with the coffee health scores. For every unique category, binary variables were created, using 0 for absence and 1 for presence of the category. This was used to compute correlation matrices with R. Thus, for all categories, its presence or absence was correlated with the health of coffee plants.

Overlay Analysis

Overlay analysis was used to quantify the relationship between the classified land cover map and the NDVI and VCI maps that were generated in the previous steps of the analysis. For this, various Python libraries were used, including Rasterio, NumPy, Scipy.stats, Matplotlib, and Statsmodels. After reading in the land cover, NDVI, and VCI maps, the NDVI and VCI values were calculated for every pixel of the high-shade intercrop coffee and low-shade intercrop coffee classes. Descriptive statistics, including the mean and median NDVI and VCI scores per class, were calculated and plotted with a boxplot. To analyse if the high-shade and low-shade intercrop coffee groups were significantly different from each other, a two-sample t-test was used, using the sample means $\bar{X}_1$ and $\bar{X}_2$, sample variances s_1^2 and s_2^2, and samples sizes n_1 and n_2, of the two coffee classes. The formula is visible below.

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

2.4 Ethical Considerations and Data Management

Before the start of the fieldwork, the ethical considerations were approved by the ITC GEO Ethics Committee. Researching small-holder coffee fields in Vietnam raises the geo-ethical concern of privacy. For that reason, the owner of every visited coffee field was informed about the research and asked for consent before data in the field was collected. Owners of the visited fields remained anonymous.

The coffee health data collection contains detailed information regarding coffee health and other crops that are grown in the field. These specific GPS coordinates of farms can be sensitive because they reveal the exact position of private properties. Moreover, the results of mapping the various intercrop systems and information on coffee health may expose farming practices and potential vulnerabilities. Making this data open-source gives organisations and external researchers access to information that could potentially impact the livelihoods of farmers. To ensure privacy of farmers, the data that was collected during this research was stored in a secure OneDrive folder and in the local environment of the author's computer. The data can be shared based on specific requests and will be based on the motivation and purpose of the request.

Chapter 3

Results

In this chapter, the results of the analysis are discussed to understand the role of plant biodiversity in coffee fields and its possible correlation with drought stress.

3.1 Descriptive Statistics of the Field Data

In this first section, the results that were obtained from fieldwork are discussed with descriptive statistics. This includes the observations on coffee plant health, and other observed biodiversity in the fields.

As visible in Figure 3.1, most of the observed coffee samples have a health score that is centered around 70%. This indicates that these plants do show some signs that can be interpreted as stress, such as the presence of yellow leaves or brown spots that prevent the plants from being classified as completely healthy. Nevertheless, the predominant colour of the leaves of the plants is green. This indicates that while the plants might experience stress that affects their appearance, this is not to a severe extent.

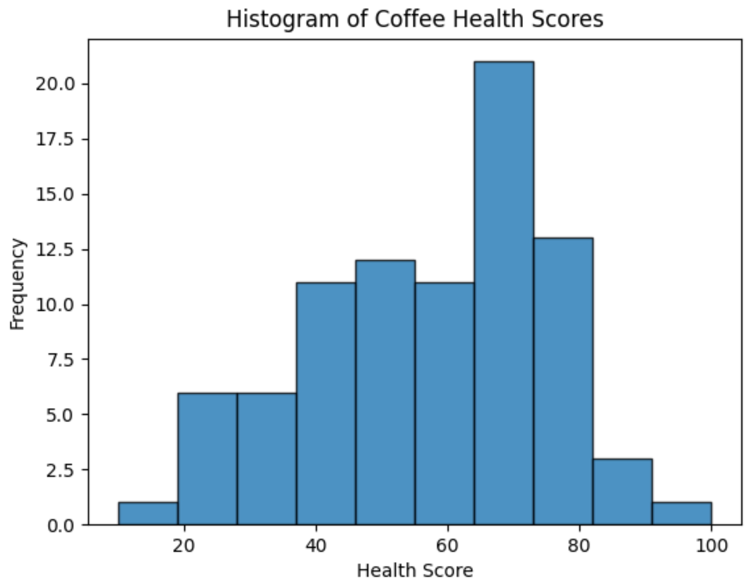


FIGURE 3.1: Distribution of coffee plant health scores for each sample that was collected during fieldwork.

To test if the coffee health scores were normally distributed, a Q-Q plot was used, which is visible in Figure 3.2. From this result, in which the points follow a pattern close to a straight line, the study assumes that the coffee health scores are normally distributed.

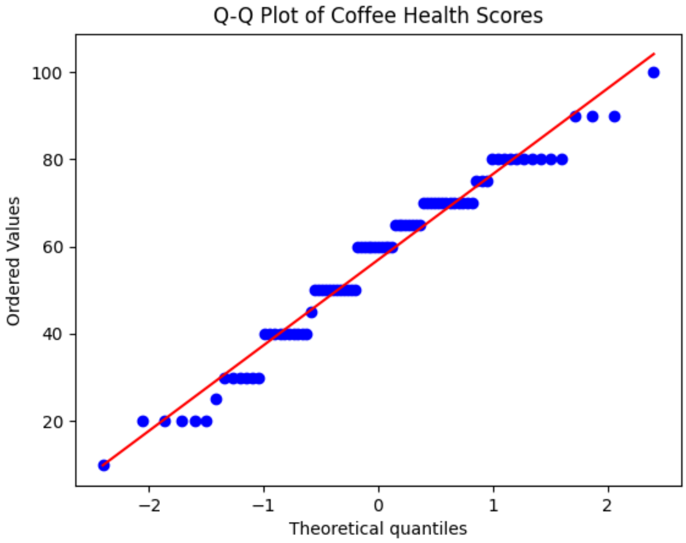


FIGURE 3.2: Q-Q plot to test if the coffee health scores are normally distributed. The blue data points fall mostly along the straight red line and are not skewed.

3.1.1 Biodiversity in Coffee Fields

During the fieldwork, it was observed that other forms of plant biodiversity primarily consisted of other intercrop species. The presence of other vegetation such as ground cover from herbs and grass was limited. For this reason, this section primarily focuses on the different intercrop species that were observed during fieldwork.

In Figure 3.3 a visualisation of the different observed intercrop species is visible. Various intercrop species were observed in combination with coffee plants. Black pepper grown on poles was the most frequently observed intercrop. Following this, cashew trees were commonly found to be intercropped with coffee. Additional intercrops, such as durian, were also noted, although less frequently. Intercrop species observed only once or twice were categorised into "other". This category includes tamarind trees, banana trees and jackfruit trees. In multiple instances, coffee was intercropped with a variety of intercrop species simultaneously, as represented by the multiple intercrop species category. This typically involved combinations such as black pepper with cashew or pepper with durian. While a variety of intercrop species were observed during fieldwork, mono-culture coffee cultivation was less prevalent, and only limited samples of mono-culture coffee fields were collected. Even less prevalent was the presence of shade trees. In this study, shade trees are defined as trees that were planted for shade provision and do not serve as an intercrop.

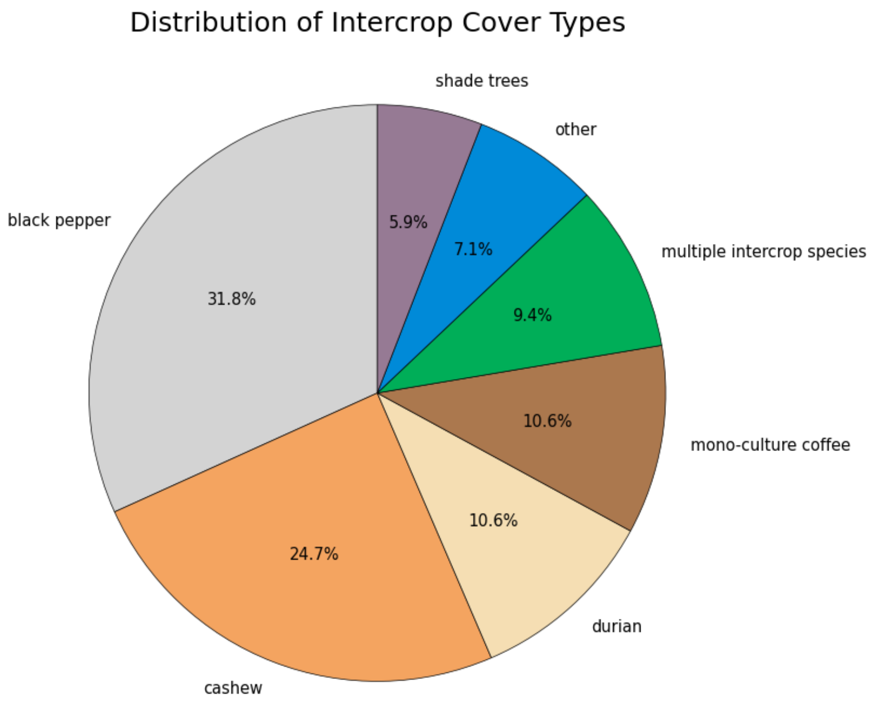


FIGURE 3.3: Piechart visualising the distribution of mono-culture coffee plants and intercrop species that were observed during fieldwork at each sample point.

In Table 3.1 the different intercropping types that were observed in the coffee fields are visible. Notably, shade trees have the highest mean height, followed by the "other" category and cashew trees. These three categories also have the highest maximum height values. Moreover, shade trees also have a very high mean cover percentage. Thus, they generally provide more shade to coffee plants than other categories. The maximum cover percentage for each intercrop type does not show large differences.

TABLE 3.1: Mean and maximum height values in meters and mean and maximum cover percentages for different types of intercrops.

Intercrop Description	**Mean Height (m)**	**Max Height (m)**	**Mean Cover (%)**	**Max Cover (%)**
Shade trees	9.4	10.0	82.0	90
Other	8.7	20.0	28.33	70
Black Pepper	6.56	12.0	20.19	80
Cashew	8.14	20.0	46.67	80
Durian	3.94	6.0	27.78	60
Multiple intercrop species	3.50	5.0	30.00	60

In Figure 3.4 the different surface cover types that were observed during fieldwork are visible. The plant biodiversity for surface coverage was very limited. Most ground coverage consisted of litter consisting of dead leaves. In some instances grass and herbs were visible. Healthy green-looking grass and herbs were categorised differently than instances with dried-out yellow and brown grass, which was the least observed surface cover type.

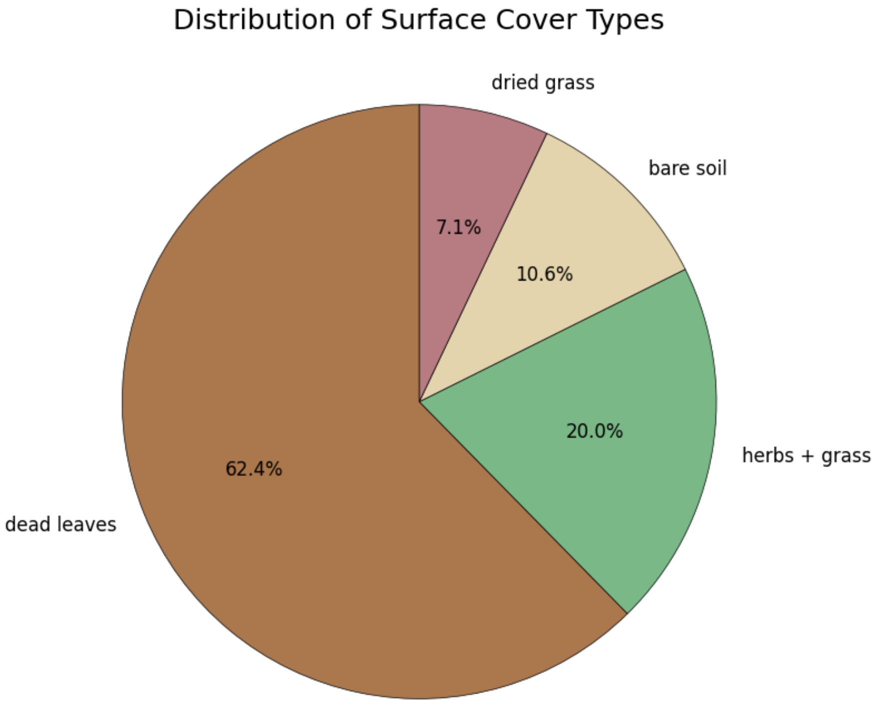


FIGURE 3.4: Different surface cover types observed during fieldwork at each sample point.

3.2 Correlating Observed Biodiversity and Coffee Health

With the collected fieldwork data, correlation analysis was conducted using the observed coffee health scores and the other biodiversity variables. To begin with, the correlation between the coffee health scores and the intercrop data was tested. These intercrop variables include (1) the type of intercrop, (2) the amount of shade the intercrop provided to the coffee plant, (3) the height of the intercrop, and (4) the distance between intercrop plants. From these results, the intercrop variables that had significant correlation coefficients were further analysed. The surface cover types were also tested for correlation with coffee health scores. Lastly, correlation analysis with the overall number of plant species surrounding the coffee samples was conducted.

3.2.1 Correlating Mono-culture Coffee and Intercrop Types with Coffee Health

In Figure 3.5, the mean health score of the coffee plants for mono-culture coffee and the different intercrop types is visible. Noticeably, the mean health for mono-culture coffee plants scored lowest, while shade trees stand out with the highest mean coffee health scores. The second-highest mean coffee health scores can be found in cashew intercropping. However, there is a relatively limited difference in mean coffee health scores between cashew, multiple intercrops, durian, and black pepper intercrops.

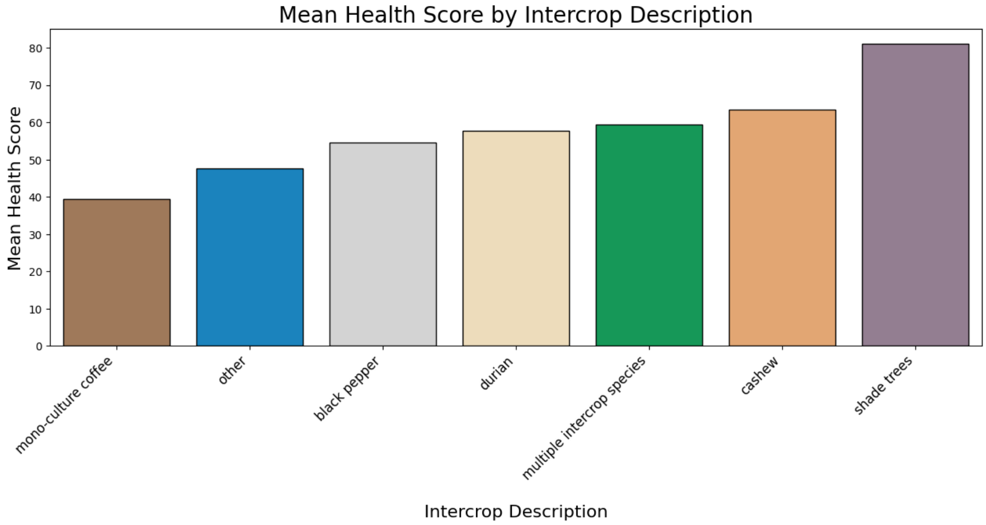


FIGURE 3.5: Histogram visualising the mean health scores of coffee plants for mono-culture coffee plants and coffee plants growing with different intercropping types.

In Table 3.2, results of a computed correlation matrix between coffee health and different intercropping types are visible. The correlation with mono-culture coffee shows the most substantial negative correlation with coffee health scores. Thus, according to this result, growing coffee in mono-cultures tends to produce coffee plants with lower health scores as compared to when coffee plants are grown with another intercrop. The highest positive correlation can be found with growing coffee and shade trees in the same field. Moreover, although the correlation scores are relatively low, there may be a limited positive correlation between growing both coffee and cashew trees in a field. Pepper, durian, multiple intercrop species, and other intercrop types show almost no correlation with the coffee health scores.

TABLE 3.2: Correlation values between coffee health scores and intercrop types computed with a Correlation Matrix.

Intercrop Type	Correlation Coefficient (r)
Pepper	−0.08
Durian	0.01
Cashew	0.19
Shade trees	0.31
Other	−0.13
Mono-culture coffee	−0.31
Multiple intercrop species	0.04

3.2.2 Correlating Intercrop Cover, Height, and Distance with Coffee Health

In Figure 3.6 the Pearson's correlation between the amount of shade that is provided by the intercrop in cover percentage, and the coffee health is visible. The relatively high correlation coefficient of 0.7 and the very small p-value indicate that there is a positive correlation between the amount of shade provided by the intercrop and the coffee health score. Thus, the more shade that is provided by the intercrop species, the higher the coffee health score is, according to this result.

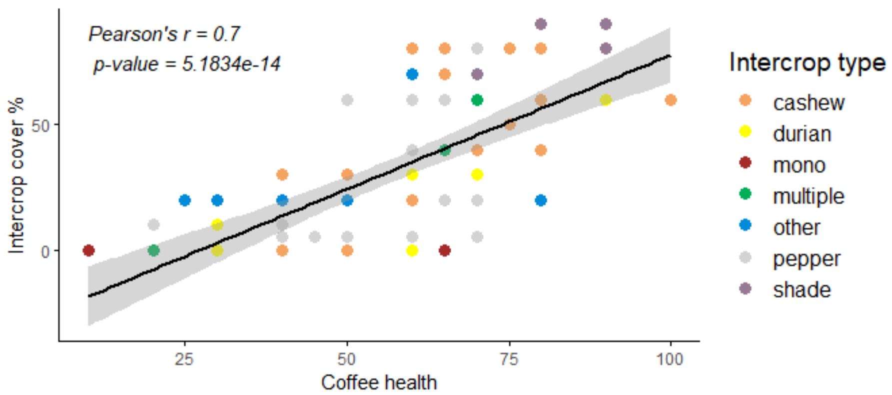


FIGURE 3.6: Pearson's correlation between the intercrop cover percentage and coffee health scores.

In Figure 3.7 the Pearson's correlation between the height of the intercrop and the coffee health is visible. Although the correlation scores are lower as compared to the amount of shade that is provided by the intercrop, the result suggests a moderate positive correlation with a correlation coefficient of 0.5. This is supported by the small p-value. Thus, an increase in intercrop height, suggests a small increase in coffee health.

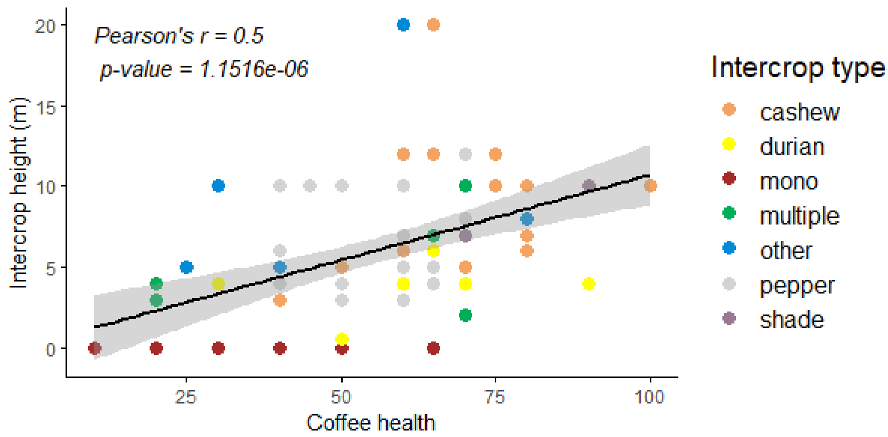


FIGURE 3.7: Pearson's correlation between the intercrop height in meters and coffee health scores.

The correlation between the distance between two intercrop species within a coffee field and the coffee health score had a correlation coefficient of 0.18 and had a high p-value of 0.11. This result suggests that there is no significant correlation between the distance between intercrops and coffee health. The measured distance from the edge of the field to the sample point also showed no significant correlation with the health of the coffee sample with a correlation coefficient of -0.05 and p-value of 0.66.

3.2.3 Intercrop Characteristics Correlation

To further understand the intercrop variables, a correlation analysis was conducted between the significant intercrop characteristics from the correlation analysis with coffee health scores. This included the intercrop species type, shade provision, and height of the intercrop.

To begin with, the correlation between the type of intercrop and the intercrop cover was computed in a correlation matrix. The results of Table 3.3 indicate that there are positive correlations between cashew trees (0.29) and shade trees (0.43) and the amount of shade that is provided. This indicates that these trees have a positive effect on the shade in coffee fields. On the other hand, the strongest negative correlation was found with black pepper as intercrop (-0.27), indicating that when pepper is used as intercrop species, there is limited shade in the coffee field.

TABLE 3.3: Correlation values between intercropping type and intercrop cover percentage computed with a correlation matrix.

Intercrop Description	Correlation Coefficient (r)
Multiple intercrop species	0.12
Other	-0.03
Shade trees	0.43
Cashew	0.29
Durian	-0.05
Pepper	-0.27

The next analysis focused on the Pearson's correlation between the height in meters of the intercrop and the intercrop cover percentage, as visible in Figure 3.8. From this analysis, the results indicate that that is a moderate positive correlation between the height of the intercrop and the cover percentage it provides with a correlation coefficient of 0.46. Thus, taller intercrop species are generally able to provide more shade according to this result.

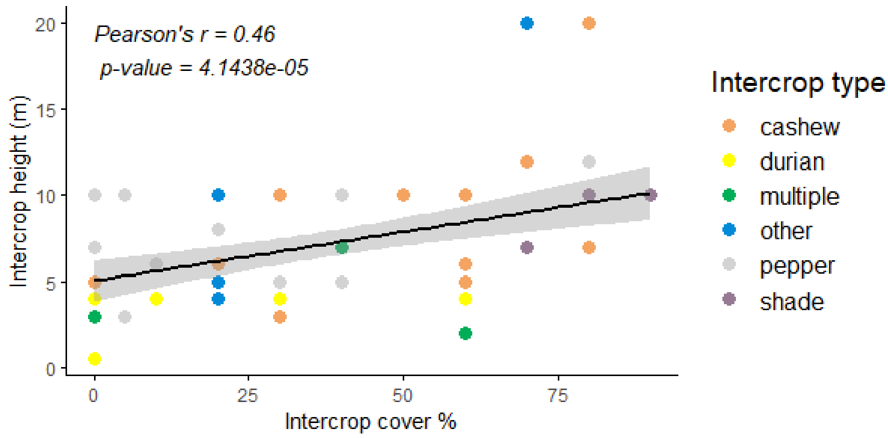


FIGURE 3.8: Pearson's correlation between intercrop height and intercrop cover percentage.

3.2.4 Correlating Surface Cover Types and Coffee Health

In examining the influence of the type surface cover on coffee plant health, a correlation matrix was used. In Figure 3.9 the mean coffee health scores per surface cover type are visible. The dead leaves cover category has the highest mean coffee health score. This is followed by the herbs and grass category, and bare soil. Dried grass shows a very low mean for coffee health scores in comparison to the other surface cover types.

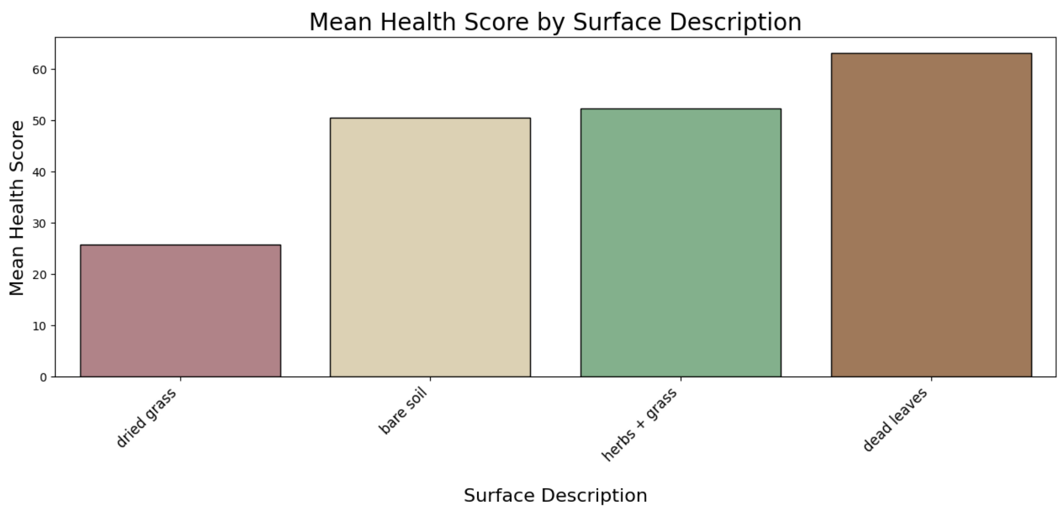


FIGURE 3.9: Histogram visualising the mean health scores of coffee plants for different surface types at each sample point.

In Table 3.4 the correlation scores for different surface cover types are visible. Dead leaves show a positive correlation indicating that the presence of dead leaves on the surface is associated with higher coffee health scores. Dried grass has a strong negative correlation with coffee health scores. This indicates that its presence is associated with lower health scores. The bare soil, and herbs and grass categories show limited correlation with the coffee health scores.

Table 3.4: Correlation values between coffee health scores and surface cover types computed with a correlation matrix.

Surface Type	Correlation Coefficient (r)
Bare soil	−0.11
Dead Leaves	0.40
Dried Grass	−0.44
Herbs and Grass	−0.12

3.2.5 Number of Species

With the number of plant species that were counted on the location of the coffee plant, including intercrop species as well as surface cover plants, no correlation could be found with coffee health scores. The p-value for this was 0.2495 and thus higher than the 0.05 threshold. The correlation score was -0.126. Thus, no significant correlation between the plant species count and coffee health could be found.

3.2.6 Highlights of the Descriptive Statistics of the Field Data

The highest correlation was found between coffee health scores and the amount of shade that is provided by intercrop species. The type of intercrop was less relevant than the amount of shade that was provided by the intercrop. However, the amount of shade that each intercrop type is able to provide is found to be significantly different. The height of the intercrop species also appears to affect the cover percentage. Because the cover percentage resulted in the highest and most significant correlation values, the amount of shade in a coffee field was selected as the focus for the next parts of the analysis.

3.3 Classifying High-shade and Low-shade Fields

From section 3.2 it was concluded that the most important feature of other plant biodiversity on coffee health is the amount of shade that is provided by other plant species. For this reason, the classification process focused on classifying high-shade and low-shade coffee fields to explore if there is a link with drought stress and the level of shade in these types fields.

For the classification of the SPOT 6 image, a supervised classification approach was used with a Random Forest algorithm. For the training and testing of the model, the ground truth data that was collected during the fieldwork was used. A selection of vegetation indices were tested on their performance. To assess the accuracy of the models, precision, recall, F1 scores, and a confusion matrix were used as metrics.

3.3.1 Model Comparison using Different Vegetation Indices

Different models were used to test the performance of various feature sets. All models included the regular bands of the SPOT image and one of the vegetation indices from the selection NDVI, SAVI, ARVI, EVI and a combined model. Each model was run 100 times and each time the accuracy was assessed. In Figure 3.10, boxplots of the overall accuracies for each model are visible. The model using the standard bands and NDVI as vegetation index achieved the highest overall accuracy result and is followed by the combined model. However, the mean overall accuracy from the ARVI model is higher and has a smaller interquartile range. While the highest ARVI overall accuracy is similar to the highest SAVI accuracy, the SAVI and EVI models generally scored the lowest accuracies. To select a model for the coffee classification task, the precision, recall, and F1 metrics of the best-performing models for each vegetation index were compared.

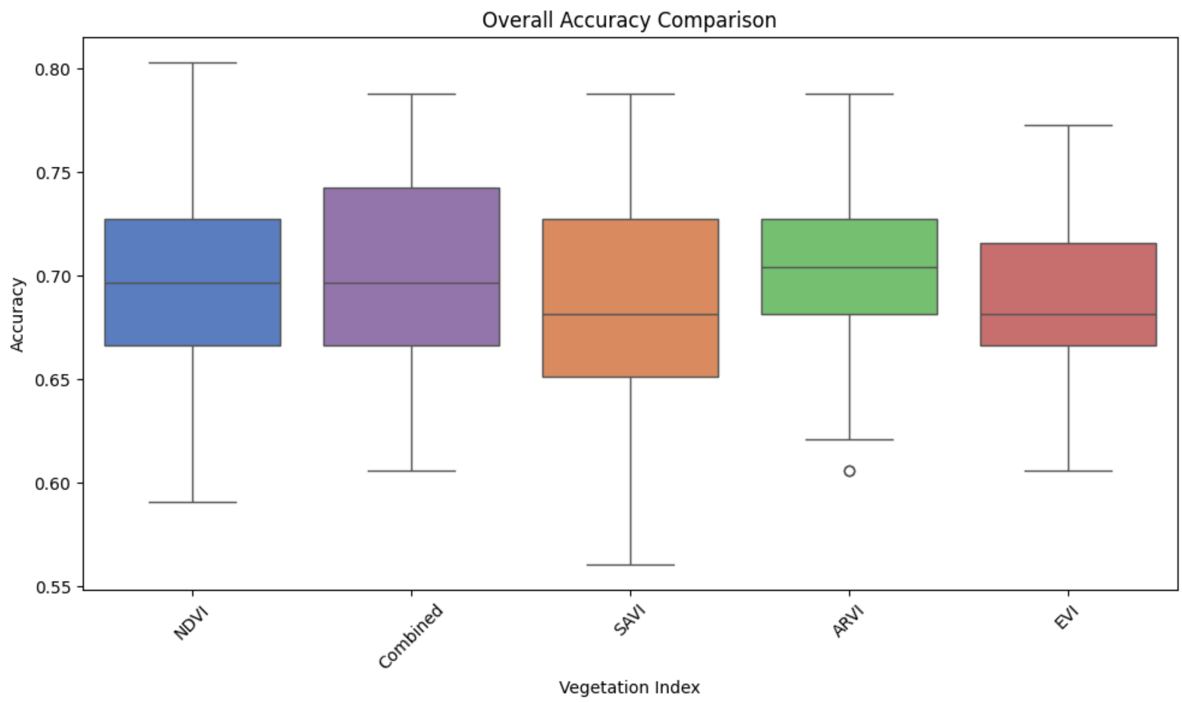


FIGURE 3.10: Boxplots visualising the overall accuracies after running the models for each vegetation index with Random Forest classifier 100 times.

3.3.2 Precision, Recall and F1 Scores

In Table 3.5 the precision scores for each class per model are visible, as well as the number of validation samples that supported the assessment. The precision score represents the number of correctly classified samples from a class divided by all samples that are classified as belonging to this class (Tharwat, 2021). Thus, this gives a measure of how many samples per class are correctly classified. Overall, the NDVI model scored higher than 0.70 for all three classes. The Combined model scored highest for the low-shade intercrop coffee class, but lower for the high-shade intercrop coffee clas. While the EVI model precision scored very high on the high-shade coffee field class (0.89), it scored lower on the low-shade coffee field class (0.67). The SAVI model was not able to reach a score higher than 0.7 for the coffee classes, and the ARVI model scored low on the low-shade coffee intercrop coffee class (0.58).

Table 3.5: Class-specific precision for the best-performing model of each vegetation index.

Class	NDVI	SAVI	EVI	ARVI	Combined	Support
High-shade intercrop coffee	0.73	0.69	0.89	0.71	0.67	11
Low-shade intercrop coffee	0.75	0.67	0.67	0.58	0.8	17
No coffee	0.84	0.85	0.78	0.83	0.81	38

In Table 3.6, the recall scores for the best-performing models are visible. The recall scores are defined as the correctly classified samples from a class divided by the total number of samples that should have been classified as belonging to the class (Tharwat, 2021). Generally, the recall for the no coffee class is high for all models with scores centered around 0.80. The models also generally have high recall scores for the high-shade intercrop coffee class with scores over 0.70. The ARVI model is an exception to this, as it has a recall score of 0.45 for the high-shade intercrop coffee class. For the low-shade intercrop coffee class, all models scored relatively low with scores centered around 0.50. Thus, the models tend to classify low-shade intercrop coffee as other classes. The ARVI model performs better than the other models with a recall score of 0.65 for low-shade intercrop coffee.

Table 3.6: Class-specific recall for the best-performing model of each vegetation index.

Class	NDVI	SAVI	EVI	ARVI	Combined	Support
High-shade intercrop coffee	0.73	0.82	0.73	0.45	0.73	11
Low-shade intercrop coffee	0.53	0.47	0.47	0.65	0.47	17
No coffee	0.95	0.92	0.92	0.87	0.95	38

In Table 3.7 the F1 score for the best-performing models are visible. This measure combines the precision and recall scores in one harmonised mean value of the two other measures (Tharwat, 2021). All models, except for the ARVI model, score high on the high-shade intercrop coffee class. The EVI model outperforms the other models with an F1 score of 0.80 for high-shade intercrop coffee. The NDVI and SAVI models, have similar F1 scores for the high-shade coffee class, wich are 0.73 and 0.75 respectively. The ARVI model has a very low score of 0.56 for this class, as compared to the order models. The F1 scores of the models for the low-shade coffee class are lower. The NDVI model outperforms the other models with an F1 score of 0.62 for low-shade intercrop coffee. All models perform relatively well on the no coffee class with F1 scores of at least 0.84.

TABLE 3.7: Class-Specific F1 Scores for the best-performing model of each vegetation index.

Class	NDVI	SAVI	EVI	ARVI	Combined	Support
High-shade intercrop coffee	0.73	0.75	0.80	0.56	0.70	11
Low-shade intercrop coffee	0.62	0.55	0.55	0.61	0.59	17
No coffee	0.89	0.87	0.84	0.85	0.88	38

The NDVI model was able to achieve the highest overall accuracy from all tested models. Moreover, the precision, recall and F1 scores for the three classes were well-balanced for the three classes in comparison to the other models. For these reasons, the resulting landcover map of this model was selected for further use in the analysis.

3.3.3 Confusion Matrix

The results of the best NDVI model outcome are further explained in Table 3.8, which presents the confusion matrix for three classes. The classification results indicated a high overall accuracy of 80.3%. Despite the limited and unequal number of samples for each class, the Kappa coefficient was calculated to be 0.64, suggesting substantial agreement between the classified map and the reference data. As visible in the confusion matrix, most confusion is caused by low-shade intercrop coffee pixels that are classified as no coffee.

TABLE 3.8: Confusion matrix of NDVI model.

Actual/Predicted	High-shade intercrop coffee	Low-shade intercrop coffee	No coffee	Total
High-shade intercrop coffee	8	2	1	11
Low-Shade intercrop coffee	2	9	6	17
No coffee	1	1	36	38
Total	11	12	43	66

3.3.4 Visualisation of the classification result

In Figure 3.11, the landcover map from the NDVI model classification result is visible. During the field visit, it was observed that also within coffee fields the structure can vary. One coffee field could contain both high-shade and low-shade areas. This is also visible in the classification result in which the classified high-shade and low-shade intercrop coffee fields are intertwined. This highlights the potential for high-resolution SPOT imagery to classify variation within coffee fields.

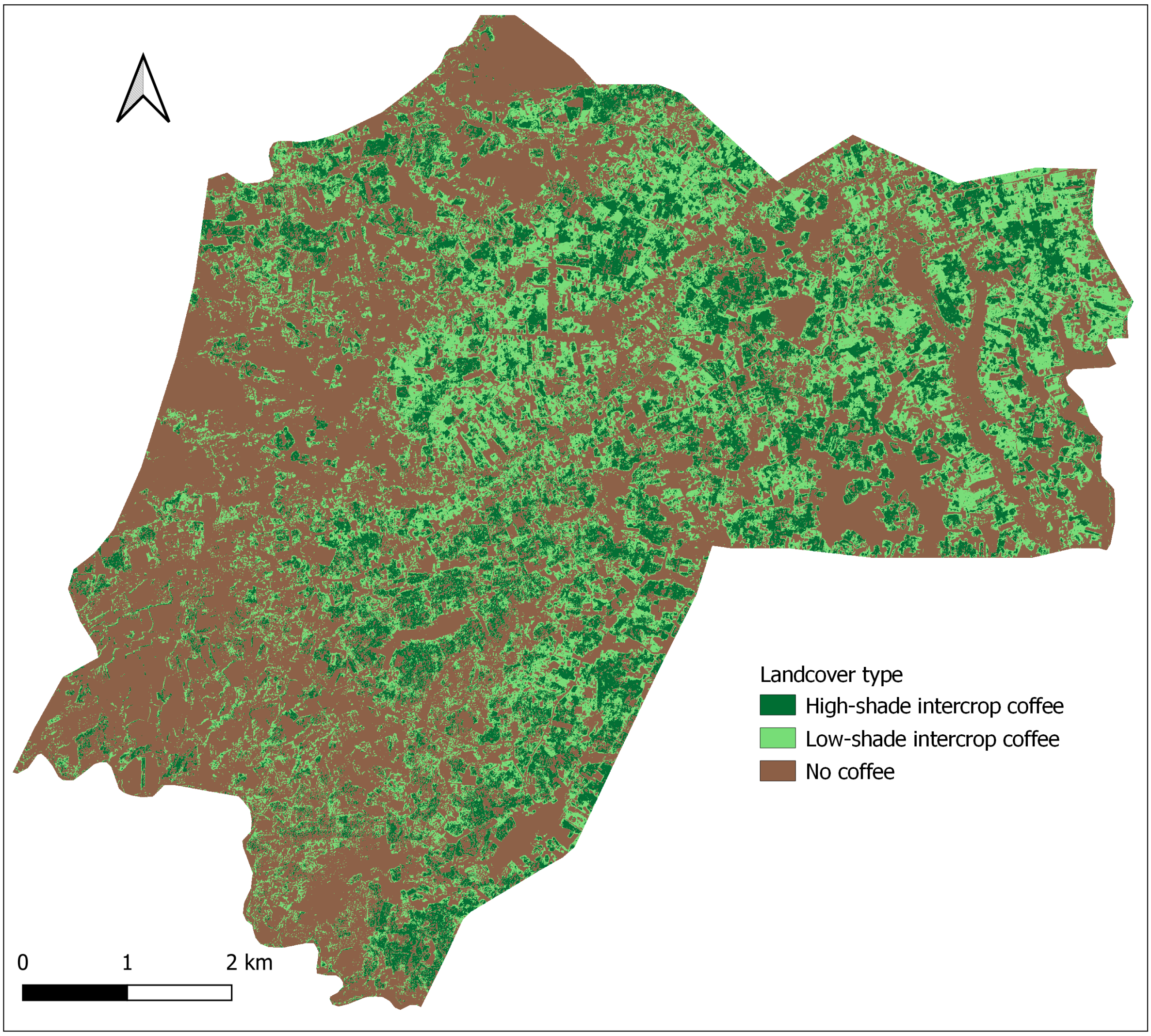


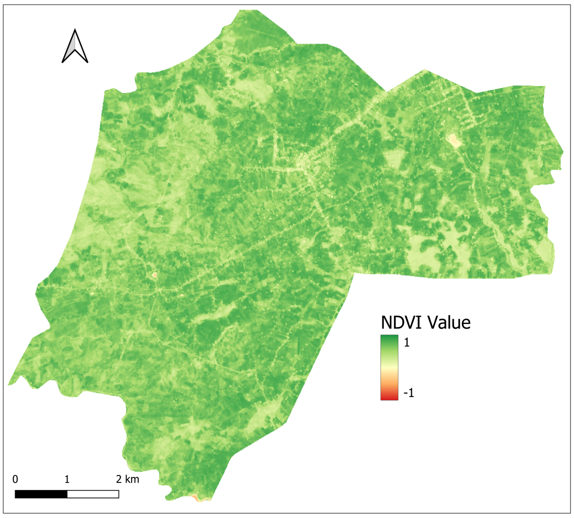
FIGURE 3.11: Landcover map derived from classifying a SPOT 6 image, using a Random Forest algorithm with the regular image bands and NDVI index as features.

3.4 Drought analysis

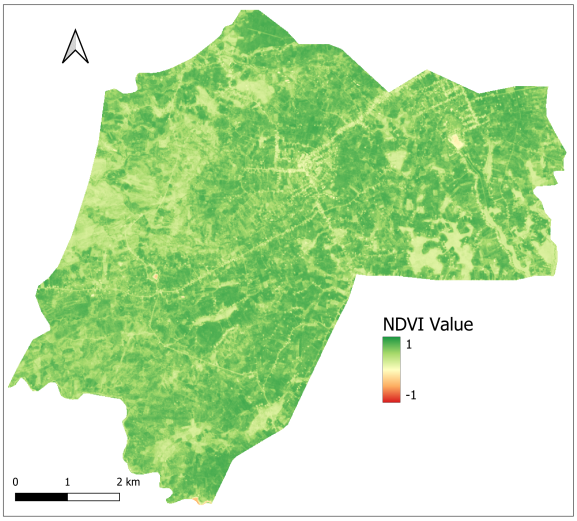
For the assessment of the drought stress in the study area, The collected SPOT image was used, as well as a time series of Sentinel-2 images from 2017 to 2024. The time of the images varies from the end of January till mid-March, ensuring the images are in proximity to the fieldwork dates. From these images, the NDVI and VCI were calculated and used as primary indicators of vegetation health and drought stress.

3.4.1 NDVI

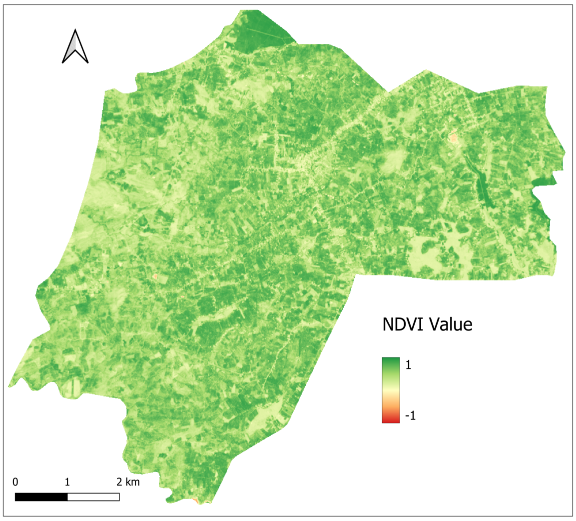
The median and mean NDVI for the years of the Sentinel-2 images from 2017 to 2024 was calculated. Furthermore, the NDVI values for the SPOT image were also calculated. This resulted in the NDVI maps as visible in Figure 3.12. Noticeable is that the SPOT NDVI has lower values as compared to the other NDVI maps. The Sentinel 2 NDVI also has lower values when compared to the mean and median NDVI from 2017 to 2024. However, the difference is especially noticeable in the SPOT NDVI map.



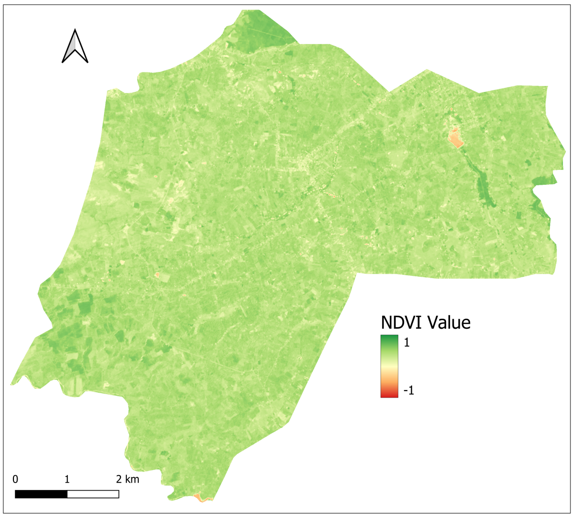
(A) Mean NDVI from Sentinel-2 time-series images from 2017 - 2024 with dates ranging from the end of January till mid-March.



(B) Median NDVI from Sentinel-2 time-series images from 2017 - 2024 with dates ranging from the end of January till mid-March.



(C) Sentinel-2 NDVI for February 16th 2024.



(D) SPOT 6 NDVI for 23 February 2024.

FIGURE 3.12: NDVI maps from SPOT6 and Sentinel-6 images.

3.4.2 VCI

The Sentinel 2 images were also used for the calculation of the Vegetation Condition Index (VCI) of 2024. In Figure 3.13 the VCI map is visible. According to Kogan (1995), VCI values that are lower than 35 can be argued to be areas of drought stress. In the VCI map for 2024 that is derived from Sentinel 2 satellite images from 2017 to 2024, it is visible that a large area with Quang Hiep is experiencing drought stress according to this threshold.

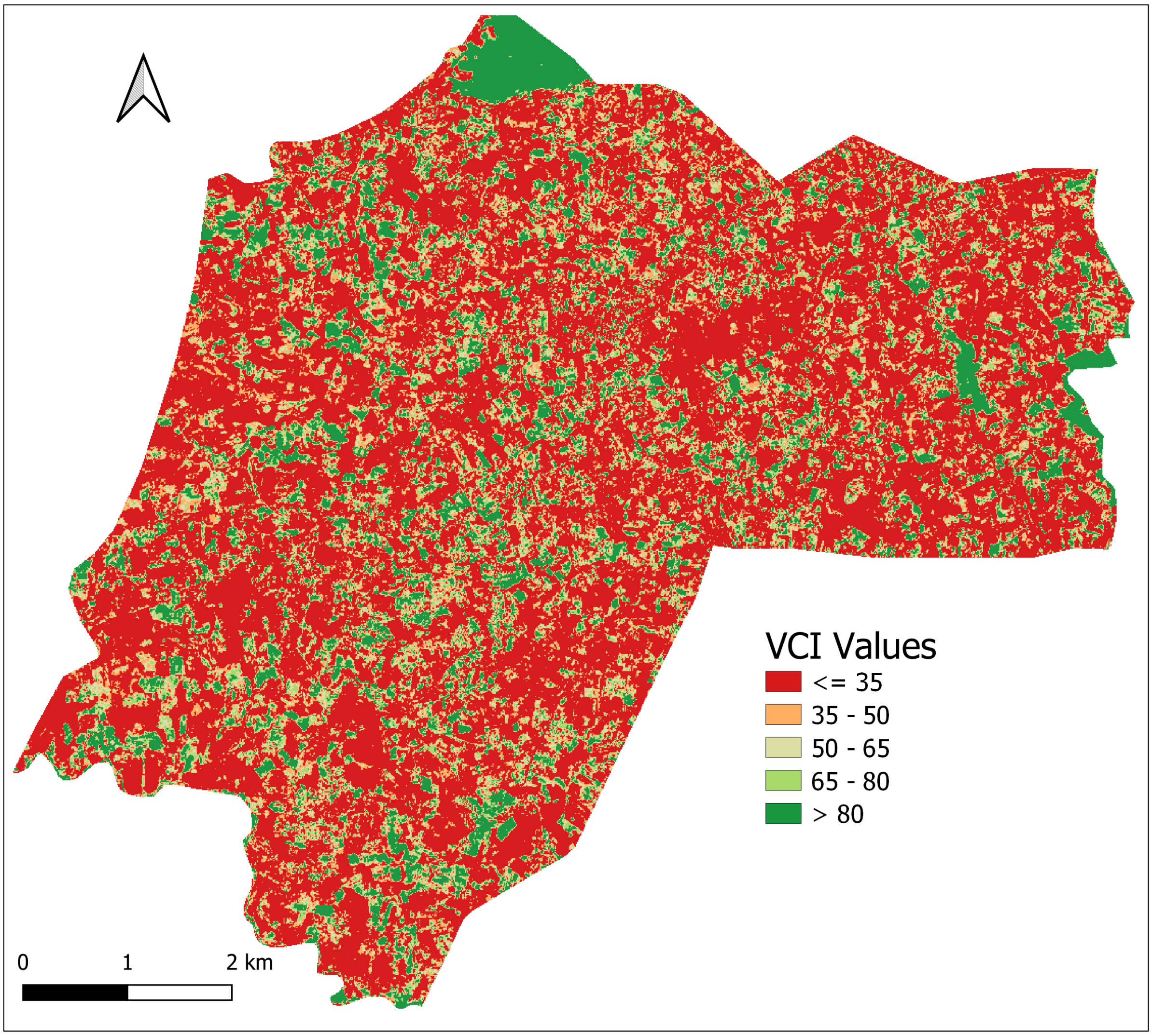


FIGURE 3.13: VCI 2024 map derived from Sentinel-2 images from 2017 till 2024. Values lower than 35 could be the result of drought stress according to Kogan (1995).

3.5 Coffee Fields and Drought Stress

Finally, the relationship between biodiversity and the level of the drought stress indicators in coffee fields was explored. First, the correlation between the observed coffee health scores and the NDVI and VCI indices was analysed. Next, the landcover map and both the NDVI and VCI maps were used to analyse differences between the high-shade and low-shade coffee field classes.

3.5.1 Observed coffee health and drought indices

As visible in Figure 3.9, performing a Pearson's correlation analysis reveals a moderate positive correlation between coffee plant health scores and the NDVI values from all sources. The median NDVI shows the highest correlation with a correlation coefficient of 0.354 and a p-value of 0.0001. This is followed by the Sentinel-6 NDVI image with a correlation coefficient of 0.344 and a p-value of 0.001. These findings indicate that NDVI, particularly from Sentinel-2 and the median NDVI value from a time-series of Sentinel-2 images, can moderately reflect the health status of coffee plants as observed in the field. The SPOT NDVI showed a weaker but still significant correlation with a correlation coefficient of 0.252 and a p-value of 0.020. This suggests that while it can also be useful, it may be less accurate for assessing the health of a coffee field than the Sentinel-2 NDVI sources. In contrast, the VCI demonstrated a very weak and non-significant correlation with coffee plant health ($r = 0.1318618$, $p = 0.229$). Thus, the VCI index is not directly suitable for assessing coffee health as observed during fieldwork.

Table 3.9: Correlation coefficients and p-values for different vegetation indices and the observed coffee health samples.

Vegetation Index	Correlation Coefficient (r)	p-value
Median NDVI	0.35	0.0009
Sentinel-2 NDVI	0.34	0.0012
SPOT 6 NDVI	0.20	0.0201
VCI	0.13	0.2290

3.5.2 Comparing the landcover map and NDVI values

For all the pixels that were classified as high-shade intercrop coffee and low-shade intercrop coffee, descriptive statistics of their NDVI values from the SPOT 6 image were calculated. In Figure 3.14 the boxplots of the classified coffee fields and their NDVI values are visualised. High-shade intercrop coffee has the highest mean NDVI value (0.47), while low-shade intercrop coffee has a mean NDVI value of 0.40. These findings suggest that low-shade coffee fields generally have lower NDVI values than high-shade coffee fields. However, this difference in mean values is minimal. Nevertheless, the results of the two-sample t-test demonstrate that it's difference is significant with a t-statistic: 2957.19 and p-value of less than 0.05.

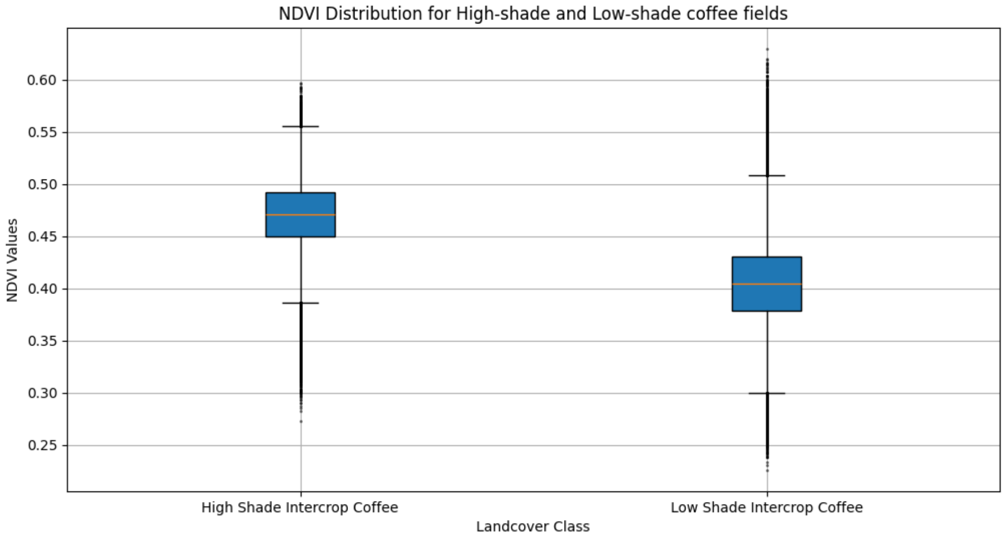


FIGURE 3.14: Boxplots visualising the SPOT 6 NDVI values per type of classified coffee field.

To further test this, the same descriptive statistics were computed for the land cover classes and the NDVI values of the Sentinel-2 image, as visible in Figure 3.15. The mean of high-shade intercrop coffee was 0.70, while the mean for low-shade intercrop was 0.58. For this result, the two-sample t-test also resulted in a large t-statistic of 2651.25 and a p-value of less than 0.05. This further proves that these intercrop classes have significantly different NDVI values.

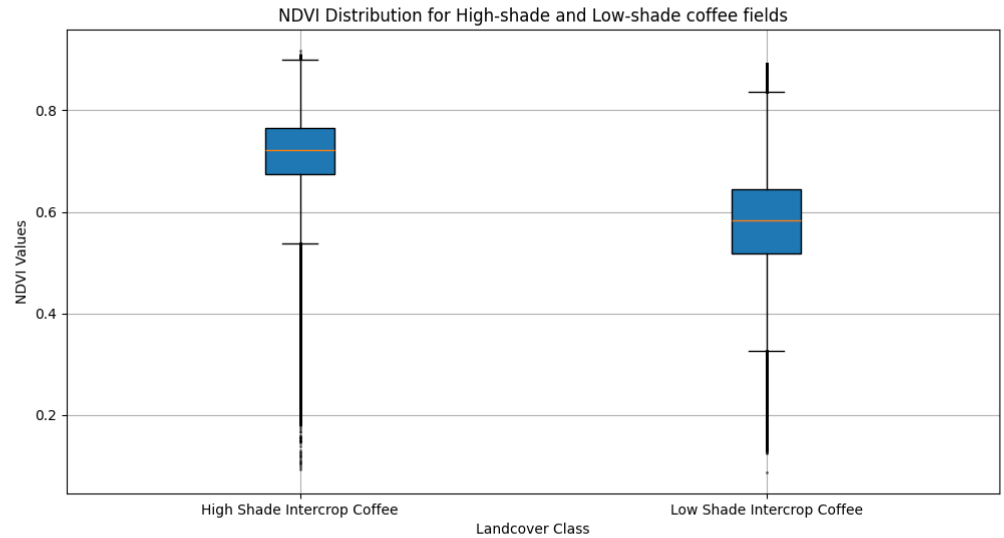


FIGURE 3.15: Boxplots visualising the Sentinel-2 NDVI values per type of classified coffee field.

3.5.3 Comparing the Landcover Map and VCI values

In Figure 3.16, boxplots of the different coffee field types and their VCI values are visualised. These discriptive statstics are based on the total number of pixels that were classified as high-shade and low-shade intercrop coffee fields. For high-shade intercrop coffee, the mean VCI value was 47.02, which is higher than the VCI drought stress threshold of 35. For low-shade intercrop coffee, the mean had a value of 30.36, which is below the VCI drought stress threshold. According to these findings, high-shade intercrop coffee fields generally have higher VCI values than low-shade coffee fields. Thus, these fields may experience less drought stress than low-shade intercrop coffee fields. The two sample t-test revealed a high t-statistic: 912.73 and low p-value of less than 0.05, further proving significant differences.

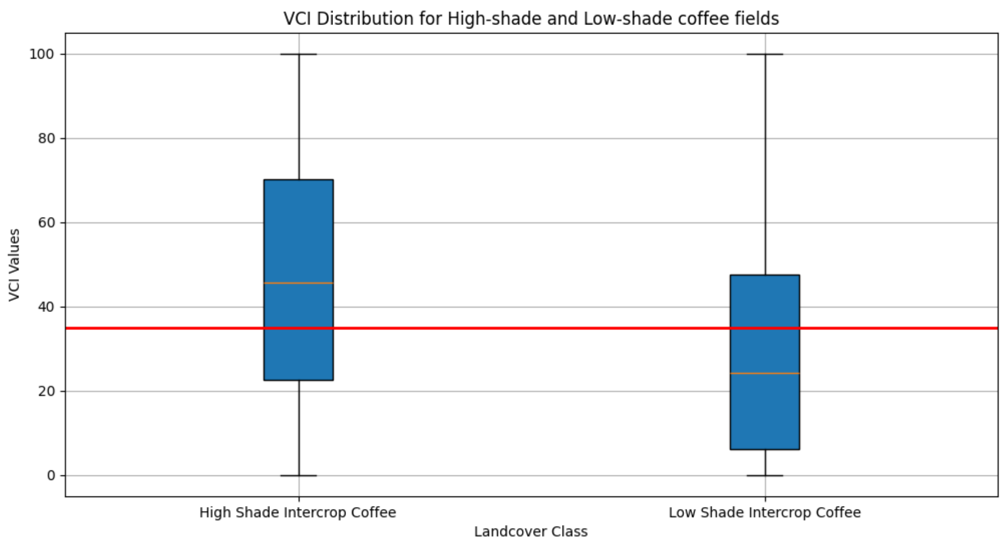


FIGURE 3.16: Boxplots visualising the VCI values per type of classified coffee field. The red line represents the threshold for drought stress, with any values lower than 35 indicating drought stress according to Kogan (1995).

Chapter 4

Discussion

This chapter aims to answer the research questions from the key findings presented in the Results chapter. Moreover, limitations and recommendations are discussed.

4.1 Classification of Different Types of Coffee Fields

In this section, the performance of the vegetation indices for the classification of different intercrop coffee fields is compared and discussed. This answers research question one (RQ1).

The Random Forest model with regular SPOT 6 bands and NDVI index, was able to achieve a high overall accuracy of 80.3%, demonstrating it's ability to distinguish high-shade intercrop, low-shade intercrop and no coffee classes from each other. Despite the sensitivities of the NDVI for soil colour and brightness, atmospheric effects, clouds, and shadows (Xue & Su, 2017), it outperformed the other models in terms of the highest overall accuracy. By comparing the precision, recall, and F1 scores, the Random Forest model with NDVI index was selected over the SAVI, ARVI, EVI, and combined indices models for further analysis. Noticeably when comparing these metrics, some vegetation index models scored very high on one intercrop class, but lower for the other class. An example is the EVI model that outperformed the other models with high-shade intercrop coffee predictions, but scored low on the low-shade intercrop class in comparison to other models. This highlights that the selection of vegetation indices is case dependent.

However, mapping low-shade intercrop coffee was challenging for all models as the recall scores for low-shade intercrop coffee were low, leading to an underestimation of the presence of this class. This difference in accuracy per intercrop class might be attributed to the types of intercrops that can be found in high-shade and low-shade intercrop coffee fields. For high-shade intercrop fields, common intercrop types that were present in the field were intercrop types with large tree crowns, such as mature cashew, durian, and shade trees. For low-shade intercrop coffee fields, the intercrop types that could be found were very diverse, ranging from younger cashew and durian trees to pepper, avocado, and even passionfruit. A random distribution of various plant species and sizes causes a wide range of heterogeneity in spectral signitures, making the classification challenging (Bégué et al., 2018).

Limited previous studies have attempted to classify different coffee planting structures. Two studies focused on the distinction between shade and mono-culture coffee with lower-resolution Landsat imagery. Cordero-Sancho and Sader (2007) achieved a maximum overall accuracy of 65%, while Ortega-Huerta et al. (2012) had an overall accuracy of 76%. One previous study by Maskell et al. (2021), used Sentinel-2, and SAR data, to map mono-culture coffee, intercropped coffee and young coffee systems in Vietnam. This resulted in an overall accuracy of 72%, as well as user accuracies of 65% for mono-culture coffee and 56% for intercropped coffee. As far as this research is aware, no studies focused on the distinction between different levels of shade within coffee fields. With an overall accuracy of 80.3%, SPOT 6 imagery with the use of NDVI has shown potential for mapping distinctions within small-holder coffee fields in Vietnam. Especially for high-shade intercrop coffee, the recall and precision scores are promising. However, low-shade intercrop coffee was more difficult to distinguish from other classes. To improve the accuracy of the results, more sophisticated image classification techniques could be explored. One potential technique would be to fuse synthetic aperture radar (SAR) data with SPOT 6 imagery. SAR data allows for a texture-based approach to capture aspects of canopy structure, this been proven to be particularly useful for classifying coffee (Hunt et al., 2020; Maskell et al., 2021). Since the SPOT 6 imagery that was used for this research has shown potential for the classification of different intercrop coffee fields, a combined approach with SAR data could improve the accuracy of the results.

4.2 Detecting Drought Stress in Coffee Plants

In this section, the key findings from the drought analysis are discussed, as well as the performance of SPOT 6 imagery for this assessment. This answers the second research question (RQ2). Furthermore, the limitations of the used methodology and potential future research are discussed.

SPOT 6 imagery was used to detect drought stress in coffee fields, with differing results. First of all, the NDVI values of the SPOT image were noticeably lower than the Sentinel-2 NDVI values. This can be explained by the Red and NIR spectral bands that both data sources use. For SPOT 6, the wavelength of the Red band is in the range 0.625 to 0.695 µm, and NIR 0.760 to 0.890 µm (Airbus, 2013). For Sentinel-2, the Red band has a more narrow value of 0.665 µm, and the NIR band ranges from 0.705 to 0.865 (European Space Agency, 2015). A study by Teillet et al. (1997) compared the spectral characteristics of different sensors on vegetation indices. This study demonstrated that spectral bandwidth, especially for the Red band, significantly affects the NDVI. Therefore, the difference in NDVI values for the SPOT 6 and Sentinel-2 images may be explained by the bandwidth of the Red band. A study that focused on rice plant health, in which SPOT 6, and Sentinel-2 NDVI values were compared, also resulted in generally lower values for the SPOT 6 dataset (Octavia & Supriatna, 2022)

Using Pearson's correlation to to determine the strength of the relationship between the observed coffee health scores with the NDVI values, the highest and most significant correlation coefficients were found with the Sentinel-2 NDVI products. The correlation with the SPOT NDVI image was less high but still significant. From these results, it can be argued that the lower-resolution Sentinel-2 images perform better than the SPOT 6 image for detecting vegetation health in the study area. Sentinel-2 has proven to be significant in vegetation health mapping in a multitude of other studies. Examples include vegetation stress assessments (Shukla et al., 2019), crop monitoring (Ghosh et al., 2018), and pest detection (Haghighian et al., 2022). While Spot 6 imagery was useful for the mapping of different intercrop coffee fields in this study, it is less useful for vegetation health monitoring.

To further analyse the drought stress in coffee plants, the VCI index was used. The VCI, which was derived from Sentinel-2 images from 2017 till 2014 showed no significant correlation with the observed coffee health. Previous studies that used the VCI for drought monitoring had mixed results. A study assessed agricultural drought using the VCI and the Standardized Precipitation Index (SPI). This study found a high correlation coefficient ($r>0.75$) between the VCI and yield of major rain-fed crops and concluded that the VCI was efficient in assessing agricultural drought (Dutta et al., 2015). In contrast, a study by Quiring and Ganesh (2010) found no high correlation between the VCI and station-based meterological drought indices in Texas. They argued that the VCI is strongly affected by climate region, as well as land use/land cover, amount of irrigation and soil properties (Quiring & Ganesh, 2010). During field data collection in Vietnam, various irrigation techniques were observed that likely influenced the results from the drought analysis, as the coffee grown in these fields is not rain-fed.

The NDVI and VCI indicators were able to show that high-shade and low-shade intercrop coffee fields significantly differed in NDVI and VCI values, with high-shade intercrop coffee having a higher mean for both indices. While the NDVI and VCI indicators are efficient and non-complex methods for drought assessments, these indicators have their limitations as they only use remote sensing data. A more comprehensive drought analysis would involve more data from various resources, such as temperature data or precipitation data. This would allow for a more complete drought assessment. For example, to monitor droughts in Vietnam, various studies used the Vegetation Health Index (VHI), which combines the VCI and the Temperature Condition Index (TCI), based on land surface temperature data (Du et al., 2018; Tran et al., 2017). In Ha et al. (2016), local climate factors, including seasonal average temperature, rainfall and length of the dry season, and land-use data were combined to analyse drought in the Central Highlands of Vietnam. These methods are promising approaches for future research.

4.3 Relationship between Agrobiodiversity and Drought Stress

In this section, the relationship between agrobiodiversity and drought stress in coffee fields is explored with results from the field data analysis and the remote sensing analysis. This answers the third research question (RQ3).

4.3.1 Intercrop Shade Cover

With the collected fieldwork data, a correlation analysis between the observed health of coffee plants and a variety of agro-biodiversity variables was conducted. The results that were derived from this analysis, showed that the highest and most significant correlation can be found between coffee health and intercrop canopy cover. Research shows various benefits of shade coffee, such as the preservation of biodiversity, and potential decline in diseases (Van Long et al., 2015). Moreover, shade trees create a micro-climate by buffering temperature in the understory, which in turn can reduce water and heat stress within coffee fields (Boreux et al., 2016). To add on, shade trees can improve soil water infiltration and soil conservation when adequate management practices are used (Byrareddy et al., 2021). Van Long et al. (2015) investigated the effects of various shade tree types on the production of Robusta coffee in Vietnam. Results demonstrated that the number of flowers that were produced by the coffee plant in shaded and unshaded sites was similar. However, under shaded conditions, there was less premature fruit fall than coffee that was grown under full sun exposure (Van Long et al., 2015). Ultimately, the combination of these benefits may lead to increased production. Results from the overlay analysis of this thesis show that high-shade intercrop coffee has higher mean values for the NDVI and VCI indices as compared to low-shade intercrop coffee. This indicates that high-shade intercrop coffee is associated with healthier vegetation as compared to the low-shade intercrop coffee. These findings support the initial assessment of the field data analysis and provide further support that more shade tends to be correlated with healthier coffee fields.

However, this result must be nuanced. Experts from TMT noted that if the crop is intercropped with a fairly thick density, it will also affect the growth and development of coffee trees, causing the plant to be obstructed, not enough light for photosynthesis to feed fruits, branches and leaves and prone to pests and diseases due to high humidity. Therefore, it is necessary to pay attention to what percentage of shade is present in the field (Duong Van Hoai from TMT consulting, personal communication, 22 March 2024). Other studies also argue that shade trees may decline coffee yield. One reason is shade causes less stimulus for the growth and number of flower buds while focusing more on vegetative growth (DaMatta, 2004; Van Long et al., 2015). In Costa Rica, the decrease in coffee yield because of shading has shown to be between 18% and 30% (Siles et al., 2010). Similar studies have shown a 28% decrease in Central America (Haggar et al., 2011) and 50% in Brazil (Campanha et al., 2004). This thesis did not focus on the relationship between shade and yield from coffee production. Potential future research could focus on finding a balance between the amount of shade and light intensity for sustainable coffee growth. Thus, how shade from intercrop species can be used to limit the impact of extreme weather events while not compromising the growth and yield development of coffee plants.

While yield maximisation with unshaded coffee fields is a major economic benefit, this comes with drawbacks that need to be considered. To begin with, unshaded coffee leads to biennial production. This means that coffee shrubs can provide a high yield for one year, but are exhausted during the production, with a decline in yield production in the following year as a result (DaMatta, 2004). Thus, the yield per year is unstable. Since the coffee market experiences global price volatility (Kolk, 2013), this can increase uncertainty in income levels for Vietnamese coffee farmers. With shaded coffee production, the produced yield is stabilised (DaMatta, 2004). Another drawback of sun coffee production is that it may be maintained with the use of large external inputs, such as fertilisers and intesive water usage, but this is often at the expense of the environment (Boreux et al., 2016). As the agricultural sector in Vietnam is challenged with groundwater resource depletion and droughts (Byrareddy et al., 2020; Y. Pham et al., 2019), further decline of groundwater levels is unfavorable.

DaMatta (2004) states that the advantages and disadvantages of adding shade trees to coffee production systems ultimately depend on the site conditions and management. Unshaded coffee fields are favorable when coffee is grown under ideal environmental conditions, as this will result in higher yields than shaded coffee fields can provide ideal environmental conditions. However, the benefits of shaded coffee fields increase as the site conditions become less favorable for coffee cultivation. The benefits of shade trees particularly increase in regions that suffer from soil and/or atmospheric droughts. Therefore, it can be argued that in the Central Highlands of Vietnam, conditions are becoming less favorable with the increasing frequency of droughts (Y. Pham et al., 2020). These unfavorable climatic conditions can explain the correlation that was found between coffee health and shade from other plant species in this thesis.

The topic of adding shade trees to coffee production systems and its potential benefits and disadvantages have been widely discussed in scientific research. However, The interactions and functioning between coffee and different kinds of shade trees are complex and remain a challenge to fully investigate (Boreux et al., 2016; Byrareddy et al., 2021). Based on existing literature, the increasing pressure of droughts, and the results of this thesis, shade tree inclusion in Vietnamese coffee fields may lead to increased benefits. Thus, while the outcomes of this thesis align with the literature on the benefits of shade trees, more research, such as on optimal levels of shade, is necessary for a full understanding of the topic.

4.3.2 Species Count

The number of unique plant species that were found in proximity to the coffee plant, did not affect the plant health significantly according to the results of this research. A previous study by Teixeira, Bianchi, Cardoso, Tittonell, and Pena-Claros (2021) investigated coffee productivity and agro-ecological coffee management and could also not demonstrate a causal link. However, they did conclude that coffee maintained under agroecological management had higher biodiversity and maintained similar coffee productivity as compared to conventionally managed farms. (Teixeira et al., 2021). this means that higher biodiversity may lead to satisfactory crop yields that can be maintained without intensive use of external inputs, which is beneficial for farmers in terms of cost and labour efficiency.

4.3.3 Intercrop Type

Noticeable, is that the intercrop type is of less importance for coffee health according to the results of this study. A previous study by Opoku-Ameyaw et al. (2003) focused on the effects of different intercrop species on Robusta coffee in Ghana. Results found significant differences in coffee growth, yield, and economic benefits by intercropping coffee with either jack bean, cowpea, cassava, or plantain. Future research could use a similar approach to further analyse the differences and effects of commonly used intercrop species on Robusta coffee in Vietnam, such as black pepper, cashew, and durian. Nevertheless, this thesis found a significant difference in the mean cover percentage of each intercrop type. For example, cashew trees had a positive correlation (0.29) with the intercrop cover percentage, while black pepper had a negative correlation (-0.26) with the intercrop coffee percentage. This finding indicates that the type of intercrop can affect the shade that is present in the fields. Also, the height of the intercrop significantly affects the cover percentage ($r = 0.56$). Thus, a field with taller cashew trees could be more beneficial for shade provision in coffee fields than shorter black pepper intercrop species.

4.3.4 Surface Cover

Correlation analysis between coffee health and the presence of litter from dead leaves showed a moderate positive correlation. Teixeira et al. (2021) argues that soil litter cover can be related to higher soil quality. Thus, this may be a reason for the positive correlation between litter from dead leaves and coffee health. The presence of herbs and grass did not have a significant impact on the coffee health scores. According to Teixeira et al. (2021), higher weeding intensity does not necessarily result in more coffee productivity. Therefore, while herbs and grass may not directly have added benefits for coffee fields, it's removal through weeding practices may not be necessary.

4.4 Addressing the Wickedness

This master thesis explored the use of image analysis for intercrop coffee mapping and drought assessment in coffee fields. These results were related to field observations to understand the role of agrobiodiversity in Vietnamese coffee production. The topic of agrobiodiversity is often overshadowed in sustainable coffee production as the involved stakeholders have differing opinions on what sustainability in coffee production entails (Kolk, 2013; Vogt, 2020). Research on agrobiodiversity can decrease uncertain knowledge on the topic. With more evidence on the benefits of agrobiodiversity, stakeholder agreement on the value of agrobiodiversity might increase, which makes the problem less wicked. From the results of this master's thesis, it can be concluded that there is a correlation between coffee plant health and shade from other plant species. Certain intercrop types, such as cashew, are correlated with more shade provision as compared to other intercrop types, such as pepper. Although optimum levels of shade have yet to be determined, these results suggest that planting shade trees is promising for the health of coffee plants in Vietnamese coffee fields.

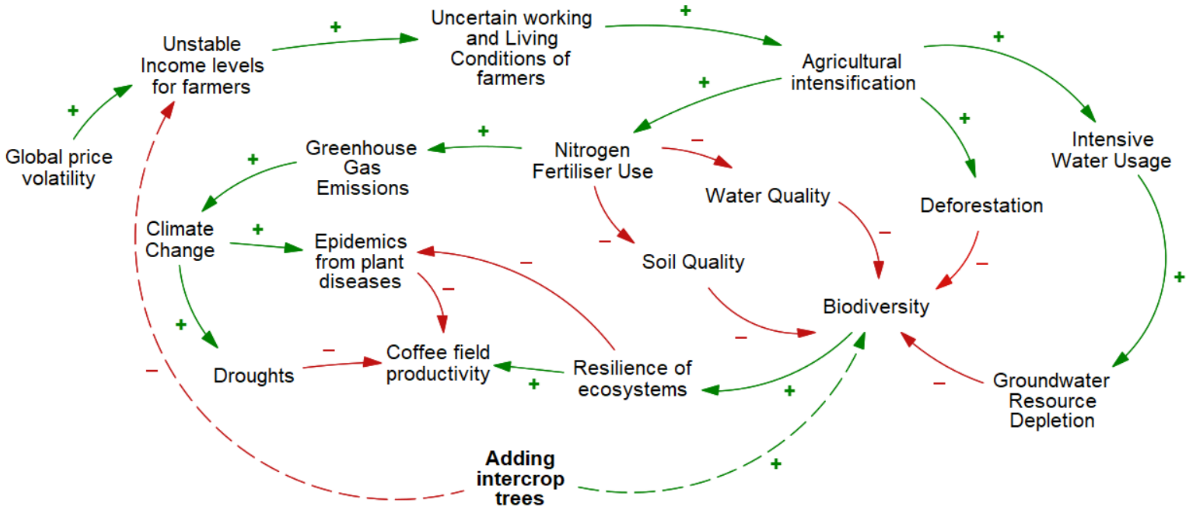


FIGURE 4.1: The role of intercrop species in the Causal loop diagram visualising the main factors of the NRM problem.

This master's thesis therefore opens a pathway for more focus on the topic of agrobiodiversity in coffee fields. In Figure 4.1, the causal loop diagram that visualized the NRM problem in the Introduction chapter of this thesis is visible. However, this causal loop diagram also shows how the addition of intercrop trees can affect the system, which benefits multiple stakeholders.

On a national level, the Vietnamese Ministry of Agriculture and Rural Development worked on a Sustainable Agriculture and Rural Development Strategy 2021-2030 Vision to 2050 (UNDP, 2023). More emphasis on intercropping is aligned with the Ministry's ambition to increase sustainability. Adding intercrop trees to coffee fields increases biodiversity. As biodiversity can increase the resilience of ecosystems, and therefore also coffee production systems, the overall sustainability of these agricultural fields can improve. The findings of this research may be used by policymakers to further explore the inclusion of intercrop trees within coffee fields. Similarly, organisations and certification programs focused on biodiversity conservation may use these insights to promote for the transition away from large-scale monocultures in favor of shade coffee systems as they may offer various environmental benefits. Coffee certification programs can also benefit from the methodology of this research as it allows for transparent assessment of the state of intercrop coffee fields by separating high-shade intercrop and low-shade intercrop coffee without extensive field visits by auditors. This allows for general but efficient assessments of agrobiodiversity in small-scale coffee fields. For coffee farmers, who are challenged with unstable income levels, adding intercrop trees has the potential to decrease this instability. Not only will the inclusion of intercrop trees result in a diversification of income that makes the farmers less reliant on coffee production, but it also has the potential to improve the health of the coffee shrubs and spread the risk of crop loss by a pest or disease. To add on, there are market benefits, as shade coffee cultivation is associated with sustainability and organically produced coffee (DaMatta, 2004; Van Long et al., 2015). Further research on what intercrop types can be combined with coffee plants for increasing economic benefits can benefit the farmers.

Thus, the topic of agrobiodiversity and the information provided in this thesis may be of interest for multiple stakeholders in the sustainable coffee production chain. An increase in knowledge on the benefits of agrobiodiversity for different stakeholders may lead to more consensus on its value. This ultimately decreases the wickedness of sustainable coffee production.

4.5 Limitations and Recommendations

In this section, limitations and recommendations for further research are discussed.

4.5.1 Field Data Collection

A limitation that made the classification of intercrop coffee fields challenging and introduced uncertainty is the limited number of samples that were collected during fieldwork. Due to constrains in time and accessibility of locations during fieldwork, a limited number of samples could be collected for both the GTP dataset, as well as the coffee health datasest. Also the locations of the samples that were collected in Quang Hiep were dependent on where the local farmers guided us and no maps of coffee farms were available. This made it challenging to collect well-distributed data. For more reliable classification results, a larger number of samples should be used for training and testing of the models.

Moreover, the study area became smaller than originally anticipated. The original study area consisted of the whole district of Qu M'gar. However, the permission that was received from the local authorities allowed for research exclusively in the commune Quang Hiep. As a result, only a small area of Vietnam could be researched, which does not fully represent the variety of conditions that can be found in the country, province of Dak Lak, or even district of Cu M'gar. For example, the commune of Quang Hiep had limited groundwater sources in the area. Some of the other communes in Cu M'gar had relatively more groundwater availability, which may result in less drought stress. Besides, Clément et al. (2023) mentioned integration of various intercrop species within coffee fields. Some of the mentioned intercrop species, such as macadamia was not observed in Quang Hiep. Moreover, the topography varies throughout Vietnam, while Quang Hiep had a slightly hilly topography, there are locations with mountains of high altitudes. Lastly, all visited farms in Quang Hiep were not certified by coffee certification programmes. Local experts in the study area indicated that in other communes, some coffee farms are certified (personal communication, TMT consultancy). Therefore, this research could be conducted in larger or more study areas in Vietnam. This would allow for a more comprehensive overview of the conditions of coffee fields in Vietnam and to make comparisons between different regions.

The field observations on coffee health were performed by the author of this paper, who is no expert in the recognition of coffee health conditions. Although literature was used in support of the recognition, it is possible that certain observable characteristics were either not recognised or misinterpreted. Involving expert on this topic during the field data collection could increase the quality and reliability of the data.

Another limitation that is necessary to consider is the presence of spatial autocorrelation. The small geographic extent of this study area means that any spatial autocorrelation might result from field-level patterns. For example, the coffee fields within the Quang Hiep commune may have similar environmental conditions, such as soil type and climate. This could cause other coffee fields in Quang Hiep to have similar coffee health scores or levels of intercrop shading. This might introduce bias, making it difficult to distinguish the effects of different variables on coffee health. However, the small study area also means that the potential for spatial variation is reduced, such as variety in climatic conditions, which could simplify the interpretation of results. In future research, spatial analysis techniques can be applied to measure potential spatial autocorrelation. Examples of methods that can support spatial autocorrelation analysis include Moran's I, or variograms to detect whether spatial patterns exist (Getis, 2009).

4.5.2 Methods

A limitation of the classification approach was that while the presence of shade from intercrop species can be linked with the presence of agrobiodiversity in coffee fields, this approach did not account for the species richness that can be found within the fields. For this, a numerical approach, such as with a specific biodiversity index is more suitable. One such approach could be measuring Rao's Q, as proposed in Rocchini, Marcantonio, and Ricotta (2017). Another research direction for more specific agrobiodiversity mapping is to classify specific intercrop types within the coffee fields. For this, unmanned aireal vehicle (UAV) imagery are a suitable approach. UAV data has been used in multiple studies for the detection of intercrop species, with reliable results (Jamil et al., 2022; Parra et al., 2022; Shi et al., 2022). Nevertheless, for this research, high-shade and low-shade coffee fields were appropriate to perform statistical analysis on to further analyse the effect of shade in coffee fields.

Another limitation of this research is that the remote sensing analysis is only able to capture NDVI and VCI indicators of the top layer of canopy. This means that the NDVI and VCI of coffee plants under the canopy of taller trees could not be analysed with remote sensing. This was taken into account with the correlation analysis between the coffee health and intercrop cover percentage. The results of this analysis indicated that more shade resulted in healthier coffee. Thus, it is assumed that the classified high-shade coffee type generally includes healthier coffee than the low-shade and mono-culture coffee classes. However, more research on the relationship of understory vegetation and canopy is necessary to prove this assumption.

Finally, coffee health is affected by more factors that were not researched in this thesis. While this research exclusively focused on agro-biodiversity and droughts, other factors, such as nutrients in the soil and pests can also affect the coffee health, but were not taken into account in this study. Another potential future research could focus on the coffee-related health factors that were not focused on in this research. This includes research on soil nutrients, pests, and diseases.

Chapter 5

Conclusion

This research focused on the role of agrobiodiversity on drought stress in coffee fields in Vietnam and the suitability of remote sensing data to assess this. The first research objective was to test if high-resolution remote sensing imagery was suitable for mapping intercrop coffee fields and drought stress assessments. Results indicate that SPOT 6 imagery with regular bands and NDVI index can be used to distinguish between high-shade and low-shade intercrop coffee fields with F1 scores of 0.73 and 0.62 respectively. Therefore, high-resolution optical remote sensing imagery has shown potential for distinguishing different types of coffee intercrop structures. For drought stress assessment in coffee plants, the correlation coefficients of the Sentinel-2 imagery were more aligned with field observations than those of SPOT 6 imagery. This indicates that Sentinel-2 imagery may be more suitable for drought stress monitoring of coffee plants. To improve on these results, the use of UAV data is recommended for more accurate mapping of agrobiodiversity, intercropping in particular, in coffee fields. Moreover, for drought assessments, the use of more data, such as surface temperature data, might increase the alignment with field observations. The second objective of this research was to investigate the effect of agrobiodiversity on the drought resilience of coffee fields in Vietnam. Results indicate that there is a high correlation between the observed health of coffee plants and the shade that intercrop species provide for coffee plants. This was further supported by the results from the classified coffee field types and the drought indicators. High-shade intercrop coffee fields had a significantly higher mean and median value for the NDVI and VCI indicators than the low-shade intercrop coffee fields. The type of intercrop and the number of plant species that were present on the farm were not significantly relevant for the observed coffee plant health. However, some types of intercrop species, such as cashew, were more effective than other species in providing shade. To add on, the height of the intercrop species was also found to be significant for the shade provision. Although the optimal shade conditions have yet to be determined, these results underscore the added value of agrobiodiversity with high shade cover for coffee fields.

References

4C Services. (2024). *4c code of conduct.* Retrieved 2024-08-11, from https://www.4c-services.org/wp-content/uploads/2024/01/4C-Code-of-Conduct_v.4.1-3.pdf

Abu-Mettleq, A. S., & Abu-Naser, S. S. (2019). A rule based system for the diagnosis of coffee diseases. *International Journal of Academic Information Systems Research (IJAISR)*, *3*(3), 1–8. Retrieved from https://ssrn.com/abstract=3369019

Adams, A. E., Besozzi, E. M., Shahrokhi, G., & Patten, M. A. (2022). A case for associational resistance: Apparent support for the stress gradient hypothesis varies with study system. *Ecology Letters*, *25*(1), 202–217. Retrieved 2023-11-20, from https://onlinelibrary.wiley.com/doi/abs/10.1111/ele.13917

AghaKouchak, A., Farahmand, A., Melton, F. S., Teixeira, J., Anderson, M. C., Wardlow, B. D., & Hain, C. R. (2015, June). Remote sensing of drought: Progress, challenges and opportunities. *Reviews of Geophysics*, *53*(2), 452–480. Retrieved 2023-11-30, from https://agupubs.onlinelibrary.wiley.com/doi/10.1002/2014RG000456 doi: 10.1002/2014RG000456

Airbus. (2013, July). Spot 6 & spot 7 imagery - user guide [Computer software manual]. Retrieved from https://earth.esa.int/eogateway/documents/20142/37627/SPOT-6-7-imagery-user-guide.pdf

Amarasinghe, U. A., Hoanh, C. T., D'haeze, D., & Hung, T. Q. (2015). Toward sustainable coffee production in vietnam: More coffee with less water. *Agricultural Systems*, *136*, 96–105. Retrieved from https://doi.org/10.1016/j.agsy.2015.02.008

Anderson, S. H., Kelly, D., Robertson, A. W., & Ladley, J. J. (2016). Pollination by birds: A functional evaluation. In *Why birds matter: avian ecological function and ecosystem services.* University of Chicago Press. Retrieved from https://doi.org/10.7208/chicago/9780226382777.003.0004

Balint, P. J., Stewart, R. E., Desai, A., & Walters, L. C. (2011). Managing Wicked Environmental Problems. In P. J. Balint, R. E. Stewart, A. Desai, & L. C. Walters (Eds.), *Wicked Environmental Problems: Managing Uncertainty and Conflict* (pp. 207–217). Washington, DC: Island Press/Center for Resource Economics. Retrieved 2023-11-19, from https://doi.org/10.5822/978-1-61091-047-7_10

Bégué, A., Arvor, D., Bellon, B., Betbeder, J., De Abelleyra, D., PD Ferraz, R., … R. Verón, S. (2018). Remote sensing and cropping practices: A review. *Remote Sensing*, *10*(1), 99. Retrieved from https://doi.org/10.3390/rs10010099

Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS journal of photogrammetry and remote sensing*, *114*, 24–31. Retrieved from https://doi.org/10.1016/j.isprsjprs.2016.01.011

Bernardes, T., Moreira, M. A., Adami, M., Giarolla, A., & Rudorff, B. F. T. (2012). Monitoring biennial bearing effect on coffee yield using modis remote sensing imagery. *Remote Sensing*, *4*(9), 2492–2509. Retrieved from https://doi.org/10.3390/rs4092492

Bhadauria, T., & Saxena, K. G. (2010). Role of earthworms in soil fertility maintenance through the production of biogenic structures. *Applied and environmental soil science*, *2010*(1), 816073. Retrieved from https://doi.org/10.1155/2010/816073

Bird Friendly. (n.d.). *Bird friendly farm criteria.* Retrieved 2023-12-03, from https://nationalzoo.si.edu/migratory-birds/bird-friendly-farm-criteria

Boreux, V., Vaast, P., Madappa, L. P., Cheppudira, K. G., Garcia, C., & Ghazoul, J. (2016). Agroforestry coffee production increased by native shade trees, irrigation, and liming. *Agronomy for sustainable development*, *36*, 1–9. Retrieved from https://doi.org/10.1007/s13593-016-0377-7

Byrareddy, V., Kouadio, L., Kath, J., Mushtaq, S., Rafiei, V., Scobie, M., & Stone, R. (2020). Win-win: Improved irrigation management saves water and increases yield for robusta coffee farms in vietnam. *Agricultural Water Management*, *241*, 106350. Retrieved from https://doi.org/10.1016/j.agwat.2020.106350

Byrareddy, V., Kouadio, L., Mushtaq, S., Kath, J., & Stone, R. (2021, April). Coping with drought: Lessons learned from robusta coffee growers in Vietnam. *Climate Services*, *22*, 100229. Retrieved 2023-11-20, from https://www.sciencedirect.com/science/article/pii/S2405880721000170 doi: 10.1016/j.cliser.2021.100229

C.A.F.E. (2020). *C.A.F.E. Practices: Starbucks Approach to Ethically Sourcing Coffee.* Retrieved 2023-12-03, from https://stories.starbucks.com/press/2020/cafe-practices-starbucks-approach-to-ethically-sourcing-coffee/

Campanha, M. M., Santos, R. H. S., De Freitas, G. B., Martinez, H. E. P., Garcia, S. L. R., & Finger, F. L. (2004). Growth and yield of coffee plants in agroforestry and monoculture systems in minas gerais, brazil. *Agroforestry systems*, *63*, 75–82. Retrieved from https://doi.org/10.1023/B:AGFO.0000049435.22512.2d

Chemura, A., Mutanga, O., & Dube, T. (2017). Integrating age in the detection and mapping of incongruous patches in coffee (coffea arabica) plantations using multi-temporal landsat 8 ndvi anomalies. *International journal of applied earth observation and geoinformation*, *57*, 1–13. Retrieved from https://doi.org/10.1016/j.jag.2016.12.007

Clément, R., Tuan, D., Cuong, V., Le Van, B., quôc Trung, H., & Long, C. T. M. (2023). Transitioning from monoculture to mixed cropping systems: The case of coffee, pepper, and fruit trees in vietnam. *Ecological Economics*, *214*, 107980. Retrieved from https://doi.org/10.1016/j.ecolecon.2023.107980

Cordero-Sancho, S., & Sader, S. (2007). Spectral analysis and classification accuracy of coffee crops using landsat and a topographic-environmental model. *International Journal of Remote Sensing*, *28*(7), 1577–1593. Retrieved from https://doi.org/10.1080/01431160600887680

Cu M'gar Government. (2022). *Cong thong tin dien tu huyen cu m'gar, tinh dak lak.* Retrieved from https://cumgar.daklak.gov.vn

DaMatta, F. M. (2004). Ecophysiological constraints on the production of shaded and unshaded coffee: a review. *Field crops research*, *86*(2-3), 99–114. Retrieved from https://doi.org/10.1016/j.fcr.2003.09.001

De Fontenay, P., Leung, S., et al. (2002). Managing commodity price fluctuations in vietnam's coffee industry. *International and Development Economics Working Paper 02-4, Asia Pacific School of Economics and Government*. Retrieved from http://www.crawford.anu.edu.au/degrees/idec/working_papers/IDEC02-4.pdf

De Keersmaecker, W., van Rooijen, N., Lhermitte, S., Tits, L., Schaminée, J., Coppin, P., ... Somers, B. (2016). Species-rich semi-natural grasslands have a higher resistance but a lower resilience than intensively managed agricultural grasslands in response to climate anomalies. *Journal of Applied Ecology*, *53*(2), 430–439. Retrieved from https://doi.org/10.1111/1365-2664.12595

Dinesh, G. K., Priyanka, B., Anokhe, A., Ramesh, P. T., Venkitachalam, R., Keerthana Sri, K. S., ... Soni, R. (2022, October). Chapter 18 Ecosystem services and ecological role of birds in insect and pest control. In R. Soni, D. C. Suyal, & R. Goel (Eds.), *Plant Protection* (pp. 463–504). De Gruyter. Retrieved 2023-11-13, from https://www.degruyter.com/

document/doi/10.1515/9783110771558-018/html

Du, T. L. T., Bui, D. D., Nguyen, M. D., & Lee, H. (2018). Satellite-based, multi-indices for evaluation of agricultural droughts in a highly dynamic tropical catchment, central vietnam. *Water*, *10*(5), 659. Retrieved from https://doi.org/10.3390/w10050659

Dulloo, M. E. (2019, January). Maintaining Diversity of Plant Genetic Resources as a Basis for Food Security. In P. Ferranti, E. M. Berry, & J. R. Anderson (Eds.), *Encyclopedia of Food Security and Sustainability* (pp. 54–63). Oxford: Elsevier. Retrieved 2023-10-31, from https://www.sciencedirect.com/science/article/pii/B9780081005965222087

Dutta, D., Kundu, A., Patel, N., Saha, S., & Siddiqui, A. (2015). Assessment of agricultural drought in rajasthan (india) using remote sensing derived vegetation condition index (vci) and standardized precipitation index (spi). *The Egyptian Journal of Remote Sensing and Space Science*, *18*(1), 53–63. Retrieved from https://doi.org/10.1016/j.ejrs.2015.03.006

European Space Agency. (2015, July). Sentinel-2 user handbook [Computer software manual]. Retrieved from https://sentinel.esa.int/documents/247904/685211/sentinel-2_user_handbook (Accessed: 2024-08-06)

Evizal, R., & Prasmatiwi, F. E. (2022, apr). Nutrient deficiency induces branch and shoot dieback in robusta coffee. *IOP Conference Series: Earth and Environmental Science*, *1012*(1), 012073. Retrieved from https://dx.doi.org/10.1088/1755-1315/1012/1/012073

Fairtrade International. (n.d.). *Aims of the fairtrade standards.* Retrieved 2023-12-03, from https://www.fairtrade.net/standard/aims

Gatti, N., Gomez, M. I., Bennett, R. E., Scott Sillett, T., & Bowe, J. (2022, June). Eco-labels matter: Coffee consumers value agrochemical-free attributes over biodiversity conservation. *Food Quality and Preference*, *98*, 104509. Retrieved 2023-11-13, from https://linkinghub.elsevier.com/retrieve/pii/S0950329321003918

Getis, A. (2009). Spatial autocorrelation. In *Handbook of applied spatial analysis: Software tools, methods and applications* (pp. 255–278). Springer. Retrieved from https://doi.org/10.1007/978-3-642-03647-7_14

Ghosh, P., Mandal, D., Bhattacharya, A., Nanda, M. K., & Bera, S. (2018). Assessing crop monitoring potential of sentinel-2 in a spatio-temporal scale. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *42*, 227–231. Retrieved from https://doi.org/10.5194/isprs-archives-XLII-5-227-2018

Giovannucci, D., Lewin, B., Swinkels, R., & Varangis, P. (2004, June). *Socialist Republic of Vietnam Coffee Sector Report* [SSRN Scholarly Paper]. Rochester, NY. Retrieved 2023-11-13, from https://papers.ssrn.com/abstract=996116

Gonzalez, R. C., & Woods, R. E. (2017). Filtering in the frequency domain. In *Digital image processing, global edition.* Pearson Education Canada. Retrieved from https://elibrary.pearson.de/book/99.150005/9781292223070

Ha, T. T. N., Nhuan, T. M., Canh, D. B., & Thao, T. P. N. (2016). Mapping droughts over the central highland of vietnam in el nino years using landsat imageries. *VNU Journal of Science: Social Sciences and Humanities*, *32*(1S). Retrieved from https://js.vnu.edu.vn/SSH/article/view/4446

Haggar, J., Barrios, M., Bolaños, M., Merlo, M., Moraga, P., Munguia, R., ... others (2011). Coffee agroecosystem performance under full sun, shade, conventional and organic management regimes in central america. *Agroforestry Systems*, *82*, 285–301. Retrieved from https://doi.org/10.1007/s10457-011-9392-5

Haghighian, F., Yousefi, S., & Keesstra, S. (2022). Identifying tree health using sentinel-2 images: a case study on tortrix viridana l. infected oak trees in western iran. *Geocarto International*, *37*(1), 304–314. Retrieved from https://doi.org/10.1080/10106049.2020.1716397

Ho, T. Q., Hoang, V.-N., & Wilson, C. (2022). Sustainability certification and water efficiency in coffee farming: The role of irrigation technologies. *Resources, Conservation and Recycling*, *180*, 106175. Retrieved from https://doi.org/10.1016/j.resconrec.2022.106175

Hung Anh, N., Bokelmann, W., Nga, D., & Văn Minh, N. (2019, 07). Toward sustainability or efficiency: The case of smallholder coffee farmers in vietnam. *Economies*, *7*, 66. Retrieved from https://doi.org/10.3390/economies7030066

Hunt, D. A., Tabor, K., Hewson, J. H., Wood, M. A., Reymondin, L., Koenig, K., ... Follett, F. (2020, January). Review of Remote Sensing Methods to Map Coffee Production Systems. *Remote Sensing*, *12*(12), 2041. Retrieved 2023-11-19, from https://www.mdpi.com/2072-4292/12/12/2041 (Number: 12 Publisher: Multidisciplinary Digital Publishing Institute)

Isbell, F., Craven, D., Connolly, J., Loreau, M., Schmid, B., Beierkuhnlein, C., ... Eisenhauer, N. (2015, October). Biodiversity increases the resistance of ecosystem productivity to climate extremes. *Nature*, *526*(7574), 574–577. Retrieved 2023-11-20, from https://www.nature.com/articles/nature15374 (Number: 7574 Publisher: Nature Publishing Group)

Jamil, N., Kootstra, G., & Kooistra, L. (2022). Evaluation of individual plant growth estimation in an intercropping field with uav imagery. *Agriculture*, *12*(1), 102. Retrieved from https://doi.org/10.3390/agriculture12010102

Juba, B., & Le, H. S. (2019). Precision-recall versus accuracy and the role of large data sets. In *Proceedings of the aaai conference on artificial intelligence* (Vol. 33, pp. 4039–4048). Retrieved from https://doi.org/10.1609/aaai.v33i01.33014039

Khuc, Q. V., Tran, B. Q., Meyfroidt, P., & Paschke, M. W. (2018, May). Drivers of deforestation and forest degradation in Vietnam: An exploratory analysis at the national level. *Forest Policy and Economics*, *90*, 128–141. Retrieved 2023-12-03, from https://www.sciencedirect.com/science/article/pii/S1389934117303283

Kogan, F. N. (1995). Application of vegetation index and brightness temperature for drought detection. *Advances in space research*, *15*(11), 91–100. Retrieved from https://doi.org/10.1016/0273-1177(95)00079-T

Kolk, A. (2013, September). Mainstreaming sustainable coffee: Mainstreaming Sustainable Coffee. *Sustainable Development*, *21*(5), 324–337. Retrieved 2023-10-13, from https://onlinelibrary.wiley.com/doi/10.1002/sd.507

Kpienbaareh, D., Sun, X., Wang, J., Luginaah, I., Bezner Kerr, R., Lupafya, E., & Dakishoni, L. (2021, January). Crop Type and Land Cover Mapping in Northern Malawi Using the Integration of Sentinel-1, Sentinel-2, and PlanetScope Satellite Data. *Remote Sensing*, *13*(4), 700. Retrieved 2023-11-30, from https://www.mdpi.com/2072-4292/13/4/700 (Number: 4 Publisher: Multidisciplinary Digital Publishing Institute)

Kuit, M., Jansen, D. M., & Tijdink, N. (2020, December). Scaling up sustainable Robusta coffee production in Vietnam: reducing carbon footprints while improving farm profitability full technical report. *The Sustainable Trade Initiative*. Retrieved from https://www.idhsustainabletrade.com/uploaded/2021/03/Scaling-up-Sustainable-Robusta-Coffee-Production-in-Vietnam-full-tech-report_March-102021.pdf

Kutywayo, D., Chemura, A., Kusena, W., Chidoko, P., & Mahoya, C. (2013, August). The Impact of Climate Change on the Potential Distribution of Agricultural Pests: The Case of the Coffee White Stem Borer (Monochamus leuconotus P.) in Zimbabwe. *PLOS ONE*, *8*(8), e73432. Retrieved 2023-12-03, from https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0073432 (Publisher: Public Library of Science) doi: 10.1371/journal.pone.0073432

Kuzyakov, Y. (2010). Priming effects: interactions between living and dead organic matter. *Soil Biology and Biochemistry*, *42*(9), 1363–1371. Retrieved from https://doi.org/10.1016/j.soilbio.2010.04.003

Lentijo, G. M., & Hostetler, M. (2011, February). *WEC306/UW351: Evaluating Certified Cof-*

fee Programs. Retrieved 2023-11-29, from https://edis.ifas.ufl.edu/publication/UW351

Liang, L., Sun, Q., Luo, X., Wang, J., Zhang, L., Deng, M., ... Liu, Z. (2017). Long-term spatial and temporal variations of vegetative drought based on vegetation condition index in china. *Ecosphere*, *8*(8), e01919. Retrieved from https://doi.org/10.1002/ecs2.1919

Liu, C. L. C., Kuchma, O., & Krutovsky, K. V. (2018). Mixed-species versus monocultures in plantation forestry: Development, benefits, ecosystem services and perspectives for the future. *Global Ecology and conservation*, *15*, e00419. Retrieved from https://doi.org/10.1016/j.gecco.2018.e00419

Magrach, A., & Ghazoul, J. (2015, July). Climate and Pest-Driven Geographic Shifts in Global Coffee Production: Implications for Forest Cover, Biodiversity and Carbon Storage. *PLOS ONE*, *10*(7), e0133071. Retrieved 2023-12-03, from https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0133071 (Publisher: Public Library of Science)

Makowski, D., Ben-Shachar, M. S., Patil, I., & Lüdecke, D. (2020). Methods and algorithms for correlation analysis in r. *Journal of Open Source Software*, *5*(51), 2306. Retrieved from :https://doi.org/10.21105/joss.02306

Maskell, G., Chemura, A., Nguyen, H., Gornott, C., & Mondal, P. (2021, December). Integration of Sentinel optical and radar data for mapping smallholder coffee production systems in Vietnam. *Remote Sensing of Environment*, *266*, 112709. Retrieved 2023-11-17, from https://www.sciencedirect.com/science/article/pii/S0034425721004296 doi: 10.1016/j.rse.2021.112709

Meyfroidt, P., Vu, T. P., & Hoang, V. A. (2013, October). Trajectories of deforestation, coffee expansion and displacement of shifting cultivation in the Central Highlands of Vietnam. *Global Environmental Change*, *23*(5), 1187–1198. Retrieved 2023-12-03, from https://www.sciencedirect.com/science/article/pii/S095937801300071X doi: 10.1016/j.gloenvcha.2013.04.005

Nagendra, H. (2001, January). Using remote sensing to assess biodiversity. *International Journal of Remote Sensing*, *22*(12), 2377–2400. Retrieved 2023-11-07, from https://doi.org/10.1080/01431160117096 (Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/01431160117096)

Nguyen, G., & Sarker, T. (2018, January). Sustainable coffee supply chain management: a case study in Buon Me Thuot City, Daklak, Vietnam. *International Journal of Corporate Social Responsibility*, *3*(1), 1. Retrieved 2023-11-20, from https://doi.org/10.1186/s40991-017-0024-x

Nguyen, H., Mai, N. T., Bui, C. D., & Nguyen, T. (2016, December). Mapping Droughts Over the Central Highland of Vietnam in El Niño Years Using Landsat Imageries. *VNU Journal of Science: Social Sciences and Humanities*, *32*(1S). Retrieved 2023-11-22, from https://js.vnu.edu.vn/SSH/article/view/4446 (Number: 1S)

Octavia, M. T., & Supriatna, S. (2022). Rice plant health spatial study with sentinel and spot imagery in parakansalak district. In *Iop conference series: Earth and environmental science* (Vol. 1111, p. 012023). Retrieved from https://doi.org/10.1088/1755-1315/1111/1/012023

Opoku-Ameyaw, K., Oppong, F., Ofori-Frimpong, K., Amoah, F., & Osei-Bonsu, K. (2003). Intercropping robusta coffee with some edible crops in ghana: Agronomic performance and economic returns. *Ghana journal of agricultural science*, *36*(1), 13–21. Retrieved from https://doi.org/10.4314/gjas.v36i1.2059

Organic. (n.d.). *Organic Certification and Accreditation | Agricultural Marketing Service.* Retrieved 2023-12-03, from https://www.ams.usda.gov/services/organic-certification

Ortega-Huerta, M. A., Komar, O., Price, K. P., & Ventura, H. J. (2012). Mapping coffee plantations with landsat imagery: an example from el salvador. *International journal of remote sensing*, *33*(1), 220–242. Retrieved from https://doi.org/10.1080/01431161.2011.591442

Parra, L., Mostaza-Colado, D., Marin, J. F., Mauri, P. V., & Lloret, J. (2022). Methodology to differentiate legume species in intercropping agroecosystems based on uav with rgb camera. *Electronics*, *11*(4), 609. Retrieved from https://doi.org/10.3390/electronics11040609

Pham, Q., Nguyen, N.-H., Ta, T.-T., & Tran, T.-L. (2023, January). Vietnam's Water Resources: Current Status, Challenges, and Security Perspective. *Sustainability*, *15*(8), 6441. Retrieved 2023-12-04, from https://www.mdpi.com/2071-1050/15/8/6441 (Number: 8 Publisher: Multidisciplinary Digital Publishing Institute) doi: 10.3390/su15086441

Pham, Y., Reardon-Smith, K., Mushtaq, S., & Cockfield, G. (2019, October). The impact of climate change and variability on coffee production: a systematic review. *Climatic Change*, *156*(4), 609–630. Retrieved 2023-10-13, from http://link.springer.com/10.1007/s10584-019-02538-y doi: 10.1007/s10584-019-02538-y

Pham, Y., Reardon-Smith, K., Mushtaq, S., & Deo, R. C. (2020). Feedback modelling of the impacts of drought: A case study in coffee production systems in viet nam. *Climate Risk Management*, *30*, 100255. Retrieved from https://doi.org/10.1016/j.crm.2020.100255

Phi, D. C., & Hoa, N. H. (2022). Using atmospherically resistant vegetation index to detect forest cover change in lac duong district, lam dong province. *Journal of Forestry Science and Technology*(14), 129–140. Retrieved from https://jvnuf.vjst.net/en/article/view/237

Quiring, S. M., & Ganesh, S. (2010). Evaluating the utility of the vegetation condition index (vci) for monitoring meteorological drought in texas. *Agricultural and forest meteorology*, *150*(3), 330–339. Retrieved from https://doi.org/10.1016/j.agrformet.2009.11.015

Rainforest Alliance. (2024). *Rainforest alliance 2020 certification program auditing rules.* Retrieved 2024-08-11, from https://www.rainforest-alliance.org/wp-content/uploads/2024/08/SA-R-GA-5-V1-Auditing-Rules.pdf

Read, J. M. (2006). Satellite remote sensing for management and monitoring of certified forestry: An example from the brazilian amazon. In *Globalization and new geographies of conservation.* University of Chicago Press. Retrieved from https://press.uchicago.edu/ucp/books/book/chicago/G/bo3750630.html

Rhiney, K., Guido, Z., Knudson, C., Avelino, J., Bacon, C. M., Leclerc, G., ... Bebber, D. P. (2021, July). Epidemics and the future of coffee production. *Proceedings of the National Academy of Sciences*, *118*(27), e2023212118. Retrieved 2023-10-13, from https://pnas.org/doi/full/10.1073/pnas.2023212118

Rocchini, D., Marcantonio, M., & Ricotta, C. (2017). Measuring rao's q diversity index from remote sensing: An open source solution. *Ecological indicators*, *72*, 234–238. Retrieved from https://doi.org/10.1016/j.ecolind.2016.07.039

Sedgwick, P. (2012). Pearson's correlation coefficient. *Bmj*, *345*. Retrieved from https://doi.org/10.1136/bmj.e4483

Shi, Y., Gao, Y., Wang, Y., Luo, D., Chen, S., Ding, Z., & Fan, K. (2022). Using unmanned aerial vehicle-based multispectral image data to monitor the growth of intercropping crops in tea plantation. *Frontiers in Plant Science*, *13*, 820585. Retrieved from https://doi.org/10.3389/fpls.2022.820585

Shukla, G., Garg, R. D., Garg, P. K., Srivastava, H. S., Kumar, P., & Mohanty, B. (2019). Exploring the capabilities of sentinel-2 data in vegetation health/stress mapping. In *Igarss 2019-2019 ieee international geoscience and remote sensing symposium* (pp. 6652–6655). Retrieved from https://doi.org/10.1109/IGARSS.2019.8898052

Siles, P., Harmand, J.-M., & Vaast, P. (2010). Effects of inga densiflora on the microclimate of coffee (coffea arabica l.) and overall biomass under optimal growing conditions in costa rica. *Agroforestry systems*, *78*, 269–286. Retrieved from https://doi.org/10.1007/s10457-009-9241-y

Son, N.-T., Chen, C.-F., Chen, C.-R., Cheng, Y.-S., & Chen, S.-H. (2023). Multidecadal evaluation of changes in coffee-growing areas using landsat data in central highlands, vietnam. *Geocarto International*, *38*(1), 2204099. Retrieved from https://doi.org/10.1080/10106049.2023.2204099

Teillet, P., Staenz, K., & William, D. (1997). Effects of spectral, spatial, and radiometric characteristics on remote sensing vegetation indices of forested regions. *Remote Sensing of Environment*, *61*(1), 139–149. Retrieved from https://doi.org/10.1016/S0034-4257(96)00248-9

Teixeira, H. M., Bianchi, F. J., Cardoso, I. M., Tittonell, P., & Pena-Claros, M. (2021). Impact of agroecological management on plant diversity and soil-based ecosystem services in pasture and coffee systems in the atlantic forest of brazil. *Agriculture, Ecosystems & Environment*, *305*, 107171. Retrieved from https://doi.org/10.1016/j.agee.2020.107171

Tharwat, A. (2021). Classification assessment methods. *Applied computing and informatics*, *17*(1), 168–192. Retrieved from https://doi.org/10.1016/j.aci.2018.08.003

Thrupp, L. A. (2000). Linking Agricultural Biodiversity and Food Security: The Valuable Role of Sustainable Agriculture. *International Affairs (Royal Institute of International Affairs 1944-)*, *76*(2,), 265–281. Retrieved from http://www.jstor.org/stable/2626366

Tran, H. T., Campbell, J. B., Tran, T. D., & Tran, H. T. (2017). Monitoring drought vulnerability using multispectral indices observed from sequential remote sensing (case study: Tuy phong, binh thuan, vietnam). *GIScience & Remote Sensing*, *54*(2), 167–184. Retrieved from https://doi.org/10.1080/15481603.2017.1287838

Tscharntke, T., Clough, Y., Bhagwat, S. A., Buchori, D., Faust, H., Hertel, D., ... others (2011). Multifunctional shade-tree management in tropical agroforestry landscapes–a review. *Journal of Applied Ecology*, *48*(3), 619–629. Retrieved from https://doi.org/10.1111/j.1365-2664.2010.01939.x

UNDP. (2023). *Viet nam's steps toward sustainable agriculture and food systems at cop28.* Retrieved 2023-12-03, from https://www.undp.org/vietnam/news/viet-nams-steps-toward-sustainable-agriculture-and-food-systems-cop28

UNEP, U. N. (2020, July). *Addressing smallholder resilience in coffee production in the Central Highlands, Viet Nam.* Retrieved 2023-11-20, from http://www.unep.org/resources/case-study/addressing-smallholder-resilience-coffee-production-central-highlands-viet-nam (Section: publications)

Utrilla-Catalan, R., Rodríguez-Rivero, R., Narvaez, V., Díaz-Barcos, V., Blanco, M., & Galeano, J. (2022). Growing inequality in the coffee global value chain: a complex network assessment. *Sustainability*, *14*(2), 672. Retrieved from https://doi.org/10.3390/su14020672

Van Long, N., Ngoc, N. Q., Dung, N. N., Kristiansen, P., Yunusa, I., & Fyfe, C. (2015). The effects of shade tree types on light variation and robusta coffee production in vietnam. *Engineering*, *7*(11), 742–753. Retrieved from https://doi.org/10.4236/eng.2015.711065

Vietnam Institute for Building Science and Technology, H. (2022). *QUY CHUAN KY THUAT QUOC GIA VE SO LIEU ĐIEU KIEN TU NHIEN DUNG TRONG XAY DUNG.* Retrieved from https://datafiles.chinhphu.vn/cpp/files/vbpq/2022/10/02-bxd.pdf

Vogt, M. A. B. (2020). Developing stronger association between market value of coffee and functional biodiversity. *Journal of Environmental Management*, *269*, 110777. Retrieved from https://doi.org/10.1016/j.jenvman.2020.110777

World Bank Group. (2015, July). *Vietnam - Sustainable Agriculture Transformation Project (English).* Retrieved from http://documents.worldbank.org/curated/en/783441467998463415/Vietnam-Sustainable-Agriculture-Transformation-Project (Washington, D.C.)

Wright, A., Mommer, L., Barry, K., & van Ruijven, J. (2021). Stress gradients and biodiversity: monoculture vulnerability drives stronger biodiversity effects during drought years. *Ecology*, *102*(1), e03193. Retrieved 2023-11-20, from https://onlinelibrary.wiley.com/doi/abs/10.1002/ecy.3193 (_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/ecy.3193) doi: 10.1002/ecy.3193

Xu, Y., & Goodacre, R. (2018). On splitting training and validation set: a comparative study of cross-validation, bootstrap and systematic sampling for estimating the generalization performance of supervised learning. *Journal of analysis and testing*, *2*(3), 249–262. Retrieved from https://doi.org/10.1007/s41664-018-0068-2

Xue, J., & Su, B. (2017). Significant remote sensing vegetation indices: A review of developments and applications. *Journal of sensors*, *2017*(1), 1353691. Retrieved from https://doi.org/10.1155/2017/1353691

Zambrano, F., Lillo-Saavedra, M., Verbist, K., & Lagos, O. (2016). Sixteen years of agricultural drought assessment of the biobío region in chile using a 250 m resolution vegetation condition index (vci). *Remote Sensing*, *8*(6), 530. Retrieved from https://doi.org/10.3390/rs8060530

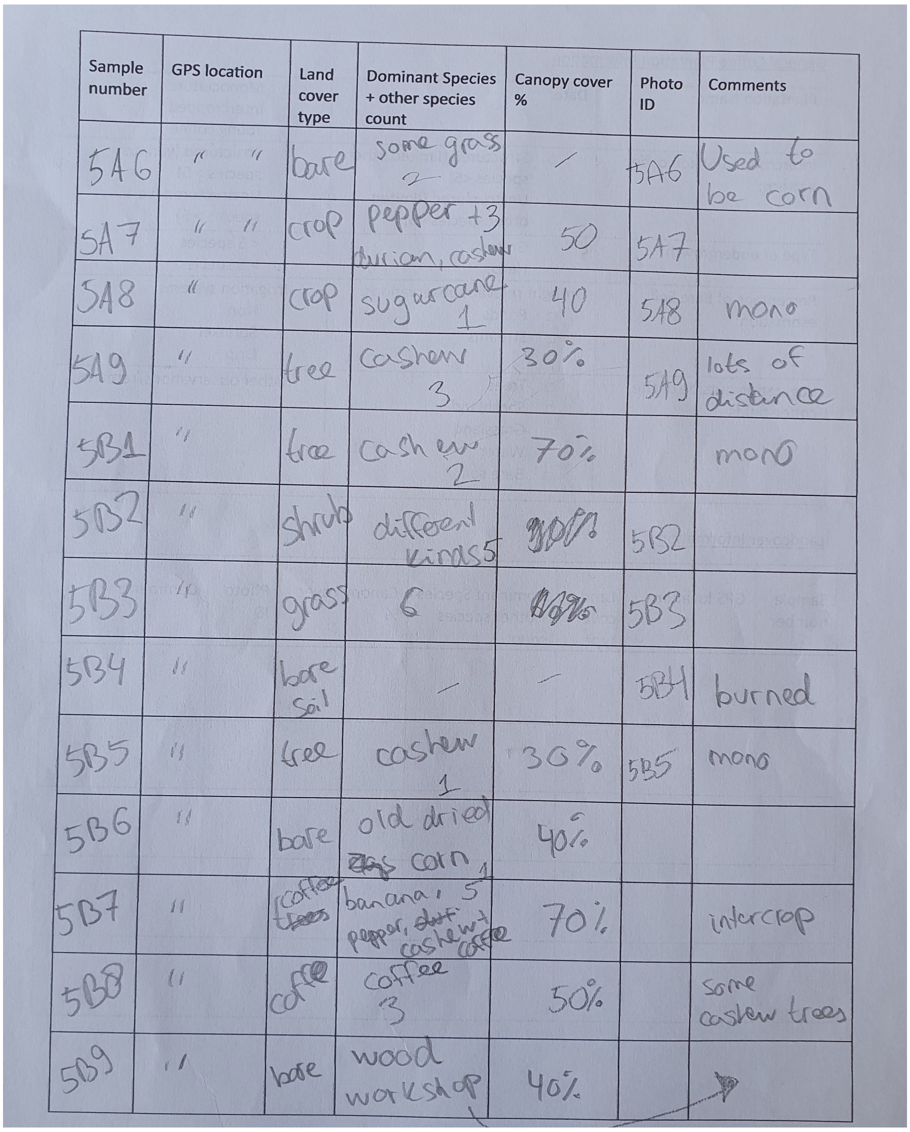
Zargar, A., Sadiq, R., Naser, B., & Khan, F. I. (2011). A review of drought indices. *Environmental Reviews*, *19*(NA), 333–349. Retrieved from https://doi.org/10.1139/a11-013

Zhou, T., Pan, J., Zhang, P., Wei, S., & Han, T. (2017, June). Mapping Winter Wheat with Multi-Temporal SAR and Optical Images in an Urban Agricultural Region. *Sensors*, *17*(6), 1210. Retrieved 2023-11-30, from https://www.mdpi.com/1424-8220/17/6/1210 (Number: 6 Publisher: Multidisciplinary Digital Publishing Institute)

Appendix A

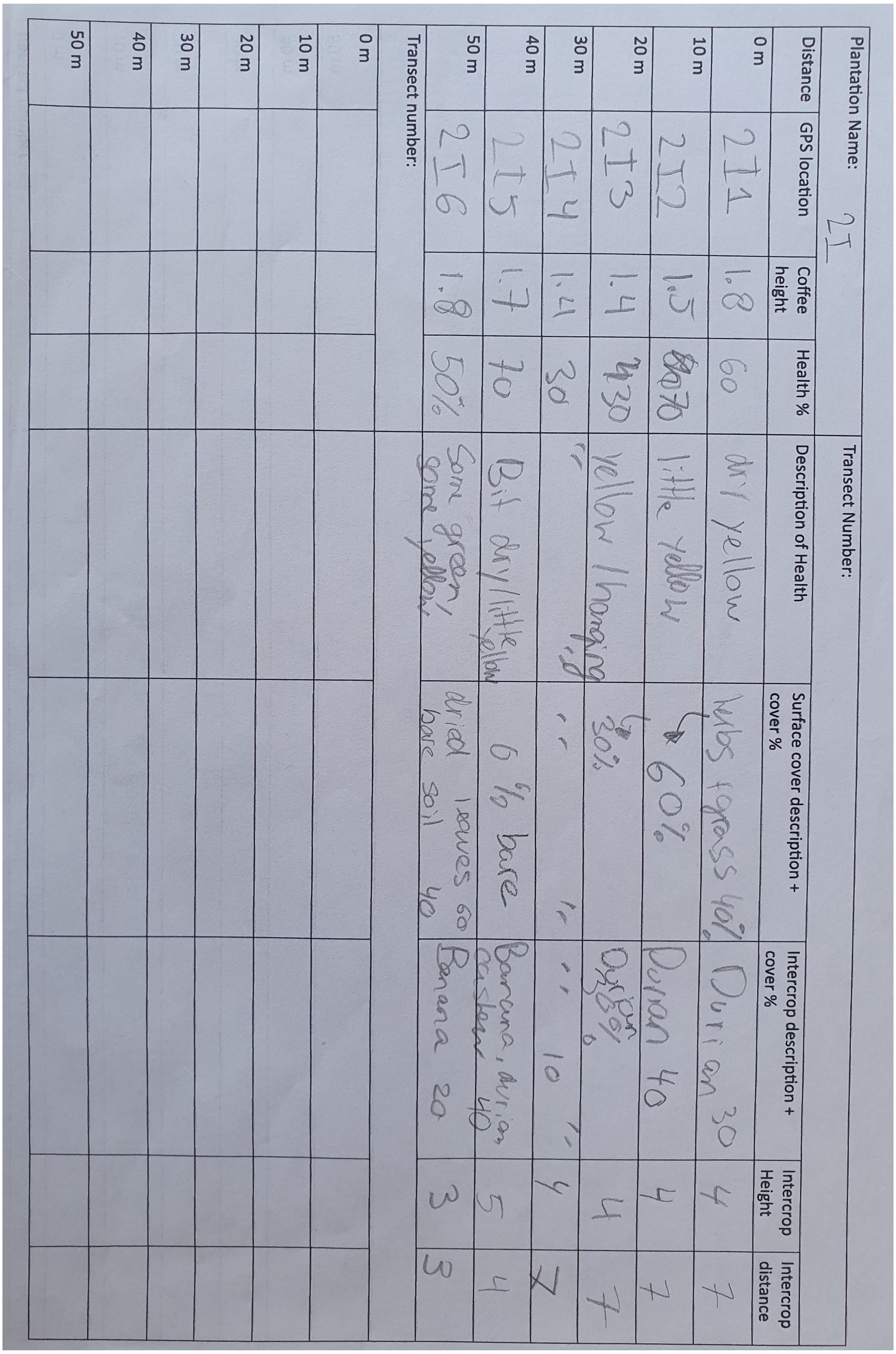
Fieldwork forms

In this section of the appendices, the field work forms for collection coffee health and the GTPs are visible.



Sample number	GPS location	Land cover type	Dominant Species + other species count	Canopy cover %	Photo ID	Comments
5A6	" "	bare	some grass 2	/	5A6	Used to be corn
5A7	" "	crop	pepper +3 durian, cashew	50	5A7	
5A8	"	crop	sugurcane 1	40	5A8	mono
5A9	"	tree	cashew 3	30%	5A9	lots of distance
5B1	"	tree	cashew 2	70%		mono
5B2	"	shrub	different kinds 5	[illegible]	5B2	
5B3	"	grass	6	[illegible]	5B3	
5B4	"	bare soil	/	/	5B4	burned
5B5	"	tree	cashew 1	30%	5B5	mono
5B6	"	bare	old dried ~~[illegible]~~ corn 1	40%		
5B7	"	coffee ~~trees~~	banana, pepper, ~~[illegible]~~ cashew, coffee 5	70%		intercrop
5B8	"	coffee	coffee 3	50%		some cashew trees
5B9	"	bare	wood workshop	40%		

Figure A.1: Picture of one of the filled-in fieldwork forms on collection coffee GTPs



Plantation Name: 2I

Transect Number:

Distance	GPS location	Coffee height	Health %	Description of Health	Surface cover description + cover %	Intercrop description + cover %	Intercrop Height	Intercrop distance
0 m	2I1	1.8	60	dry yellow	Mos grass 40%	Durian 30	4	7
10 m	2I2	1.5	70	little yellow	60%	Durian 40	4	7
20 m	2I3	1.4	30	yellow / hanging	30%	Durian 30%	4	7
30 m	2I4	1.41	30	"	"	" 10 "	4	7
40 m	2I5	1.7	70	Bit dry/little yellow	0% bare	Banana, durian, cashew 40	5	4
50 m	2I6	1.8	50%	Some green/ some yellow	dried leaves 60 bare soil 40	Banana 20	3	3

Transect number:

0 m							
10 m							
20 m							
30 m							
40 m							
50 m							

Figure A.2: Picture of one of the filled-in fieldwork forms on collection coffee health data

Appendix B

Landcover maps

In this section the other produced landcover maps from each model are visible.

B.0.1 SAVI model

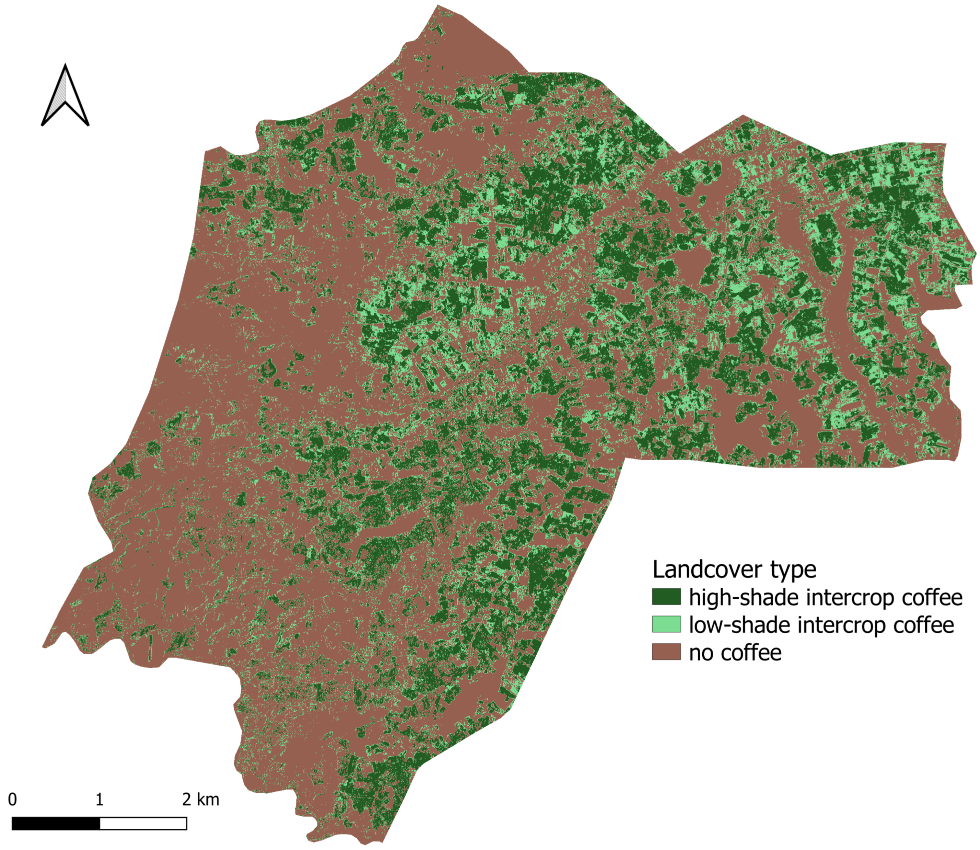


FIGURE B.1: Landcover map derived from classifying a SPOT 6 image, using a Random Forest algorithm with the regular image bands and SAVI index as features.

B.0.2 EVI model

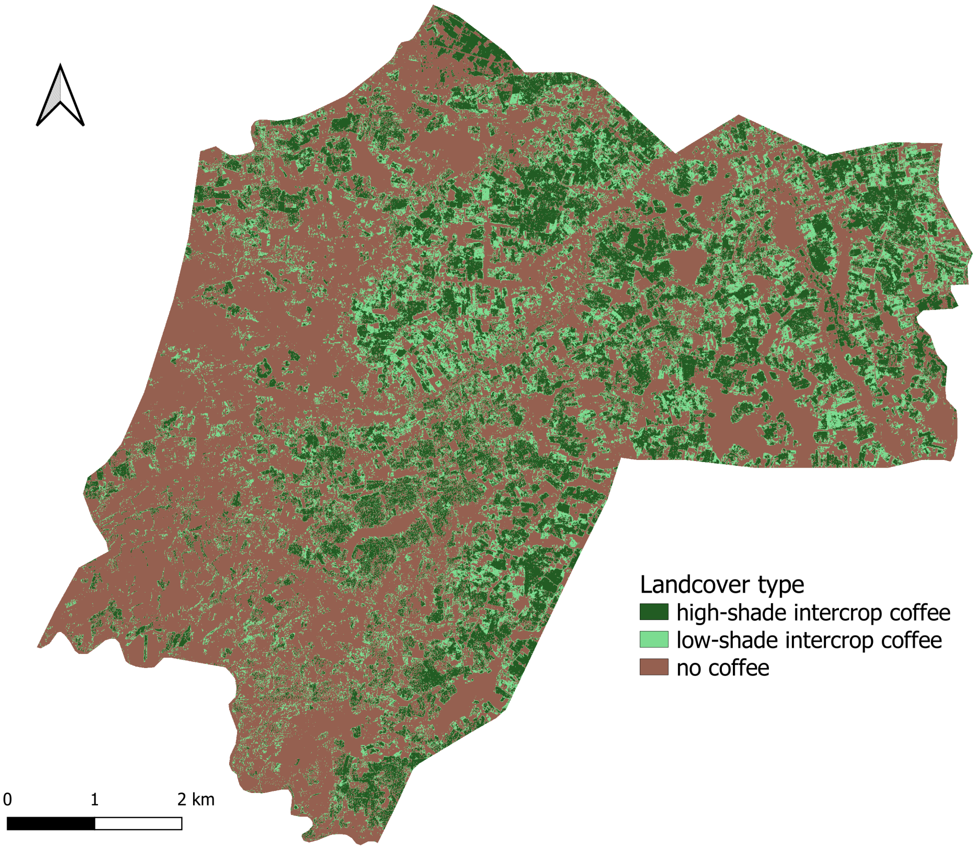


Figure B.2: Landcover map derived from classifying a SPOT 6 image, using a Random Forest algorithm with the regular image bands and EVI index as features.

B.0.3 ARVI model

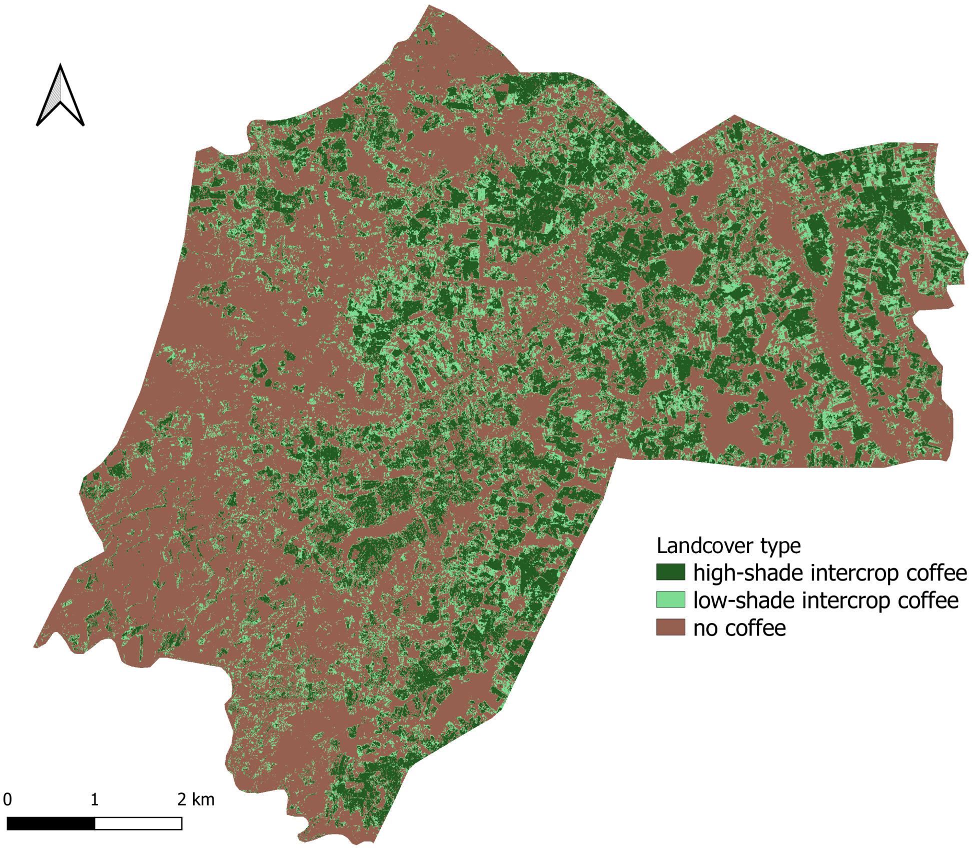


Figure B.3: Landcover map derived from classifying a SPOT 6 image, using a Random Forest algorithm with the regular image bands and ARVI index as features.

B.0.4 Combined model

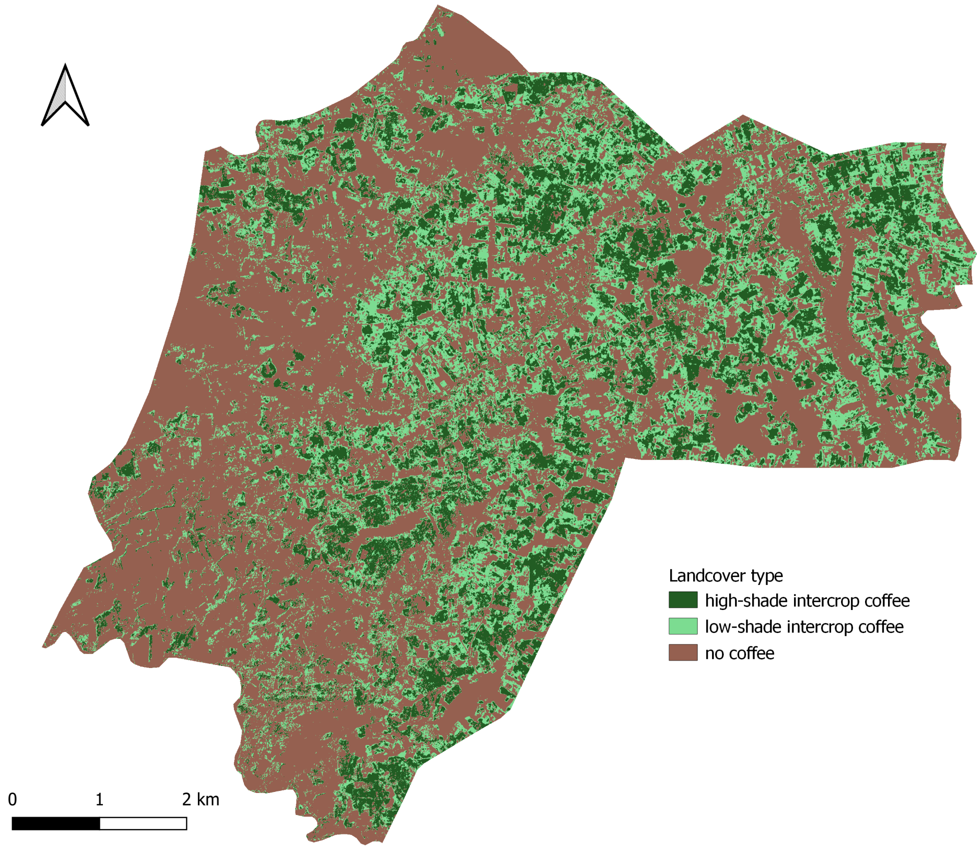


Figure B.4: Landcover map derived from classifying a SPOT 6 image, using a Random Forest algorithm with the regular image bands and the combination of NDVI, SAVI, EVI and ARVI indices as features.