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Evaluating the Impact and Recovery of Hurricane Matthew on the Agricultural Sector of the Sud and Grand'Anse Department, Haiti.

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EVALUATING THE IMPACT AND RECOVERY OF HURRICANE MATTHEW ON THE AGRICULTURAL SECTOR OF THE SUD AND GRAND'ANSE DEPARTMENTS, HAITI.

By

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ABSTRACT

Hurricanes present a significant threat to food insecurity in geographically vulnerable nations, such as Haiti, that are heavily reliant on agriculture. Despite this, there is a lack of data collected within Haiti, specifically in the Sud and Grand'Anse department, to implement sound disaster risk management plans against hurricanes. This prevents building resilience against one of the largest threats to food insecurity. Consequently, this research presents a desk-based methodology employing the common satellite derived Vegetation Index, Normalised Difference Vegetation Index (NDVI) to evaluate the immediate impact and long-term recovery of agricultural vegetation following Hurricane Matthew. Analysis of NDVI before and after hurricane Matthew identified the communes and agricultural land covers that sustained the most damage in the immediate aftermath of the hurricane, alongside their long-term recovery. The findings conclude that Hurricane Matthew inflicted widescale damage, with agricultural land covers, *Agroforestry* and *Dense Agriculture,* and the communes of Torbeck and Camp-Perrin sustaining the most severe damage. Consequently, more severe damage is predominantly linked to species taller in height with a wider surface area and coastal or inland flooding of river valleys associated with a storm surge or heavy precipitation. In the long-term, findings suggest that agricultural vegetation made a full recovery by 6 months post-hurricane. The findings of this research highlights areas of vulnerability to hurricanes in Haiti. This is useful to governments and locals to inform changes to agricultural practices and policy to build resilience and reduce food insecurity. If tested, this methodology can be utilised in any region of the world, investigating the impact of not only hurricanes but other climatic-related hazards such as flooding and droughts.

Keywords: Hurricane Matthew; Haiti; Agricultural Vegetation; NDVI; Impact and Recovery; time-series analysis; Land Covers

Word Count: 32,967

DECLARATION AND ACKNOWLEDGMENTS

DECLARATION

I hereby declare that this project is entirely my own work and where I have used the work of others it has been referenced correctly. I can also confirm that the project has been completed in compliance with the University ethics policy and that the information that was supplied with the original ethics document handed in with the project proposal corresponds with the work conducted for the project.

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ACROYMNS

BAP- Best Available Pixel

C2L2- Collection 2 Level 2

CC- Cloud Cover

EC – Electrical Conductivity

GEE- Google Earth Engine

kNN- k-Nearest Neighbour

LAI- Leaf Area Index

NDSI- Normalised Difference Salinity Index

NDVI- Normalised Difference Salinity Index

NIR- Near Infrared

RF- Random Forest

SAVI- Soil Adjusted Vegetation Index

SI- Salinity Indices

SI2- Salinity Index 2

SR- Surface Reflectance

SS- Soil Salinity

VI- Vegetation Indices

VSSI- Vegetation Soil Salinity Index

CHAPTER 1

1. INTRODUCTION

1.1. HURRICANES AND FOOD SECURITY

One thing is known for certain; hurricanes can challenge food security within countries on both a local and regional scale. It is seen repetitively, across countries that are vulnerable to hurricanes, that the sheer force of wind, in conjunction with heavy rainfall and a potential storm surge, can cause immediate loss of agricultural vegetation. This was seen in 2017 when Hurricane Irma made landfall in Florida; the estimated total agricultural losses equated to $2.5 billion (Bond and Perez 2018). Similarly, losses in rice production from 1970-2018 in the Philippines amounted to an average of $42 million per cyclone event (Yuen *et al.* 2022). It is clear that post-hurricane literature regarding agricultural damage (e.g. Bond and Perez 2018; Yuen *et al.* 2022) tends to focus on the commodity side of impacts; quantifying damage in relation to the yield lost and the associated costs. Whilst useful information to know in terms of the immediate impact this has on food security, it is not helpful for countries that rely on agriculture predominantly for self-sufficiency (e.g., smallholder-farming). Typically, these countries are most vulnerable to food insecurity. Furthermore, research does not consider the long-term implications of the shock and stress that a hurricane can inflict on the land. Therefore, alongside immediate commodity loss, the foundations for agricultural productivity can be impacted, and reduce the health of vegetation in the long-term. Thus, understanding the logistics behind vegetation health post-hurricane should be a priority in the long-term process of battling food insecurity.

Gaining information regarding the pattern and severity of damage to agricultural vegetation immediately post-hurricane, rather than obtaining just the area and loss of yield, can support preparedness, mitigation, and recovery efforts for future hurricanes. This is because identifying patterns of damage can determine areas of higher vulnerability, thus what regions need more support. This, in the long term, will contribute to building resilience. Additionally, literature does not monitor the long-term recovery of the land, thus there is no understanding of the patterns of recovery within the agricultural sector post-hurricane. This knowledge would, once again, aid mitigation and recovery efforts. For example, understanding if one region recovers quicker than another and why is insightful for amending future agricultural practices. Overall, gaining further knowledge regarding the immediate impact and long-term recovery of hurricanes on agricultural vegetation, as opposed to quantifying the impact economically, can help build resilience against future hurricanes. It is with the hope that in the long-term this will decrease the impact on food insecurity within vulnerable regions.

1.2. FOOD SECUIRTY IN THE CARIBBEAN

For many nations such as Haiti, food security does not purely rely on commodity crop production and importing of goods. This is evident throughout the global south and in the Caribbean where smallholder farms are the main producers of food for domestic consumption and local market trade, thus, is the main source of food security.

Smallholder farms, a common practice in Haiti, can be defined as farmers with less than 2ha (Csaki and De Haan 2003), producing food for their own consumption and local markets. Indeed, within the Sud and Grand'Anse departments (the ROI for this research), Haiti, agriculture is the main economic activity; 80% and 84% of households in Sud and Grand'Anse (respectively) have access to land for agriculture (RTAC 2021). Agroforestry is also a common practice within Haiti, typically this practice is found on the slopes of the country (CIESIN 2022). In lower elevations, dense agricultural systems can be found, with the main crops produced being maize, rice, legumes, roots and tubers, plantains, and fruits (RTAC 2021). In the 2009 agricultural census, approximately 85% of farms had a total area of less than 2.5ha (Rodrigues-Eklund *et al.* 2021). On average farms consist of 1.8 parcels; an agricultural parcel can be defined as a continuous area of land declared by one farmer that includes no more than one crop (Rodrigues-Eklund *et al.* 2021). Usually, these parcels are located several kilometres away from each other, with the average size of a parcel being 0.54ha. This structure of farming modelled in Haiti is common throughout the Caribbean and the global south.

Years of history has shaped how Caribbean countries, including Haiti, now practise agricultural production to conquer their food and nutritional security challenges. Although the benefits of smallholder agriculture can be seen through data concluding that they have higher land productivity and yields, due to the informality of smallholder farms, there are several factors that prevent their sustainability. Challenges include limitations of low-level technology, and absence of barriers to prevent entry of pests and animals. The main challenge which this research focuses on is their vulnerability to climate and annual shocks that are beyond their control and poorly prepared and mitigated against. This relationship between food insecurity/rural poverty and climate change vulnerability is cyclical and if not addressed and mitigated against could have a significant negative impact on sustainable food production and thus, food security (Ewing-chow 2020). This additionally limits their ability to compete in domestic markets that are flooded with imports. Consequently, the food produced by smallholder farms tend to not contribute to the global commodity chain, thus have a less significant impact on global food security. However, using around 24% of the worlds agricultural land, smallholder farms are estimated to produce around 29% of total crop production, measured in Kilocalories (Ritchie 2021; Shroff 2022). This, in conjunction with the local context, smallholder farming has a vital role to play in food security, health and fighting against hunger (Saint Ville, Hickey and Phillip 2015). Jamaica's investment and export promotion agency states that with investment in climate resilient agriculture, production could double (Ewing-Chow 2020). Thus, monitoring the immediate impact and recovery of climate-induced hazards (e.g., hurricanes) on smallholder agriculture is equally as important as it would be for regions where larger scale commercial commodity farming is practiced, thus is vital to build resilience and increase food security.

1.3. THE IMPACT OF HURRICANES ON FOOD SECURITY IN HAITI

One country that is challenged with food insecurity and is also susceptible to hurricanes is Haiti. Haiti is currently the poorest country in the western hemisphere and has a heavy reliance on agriculture; with 29% of Haiti's population working within this sector (The World Bank 2019). Despite this, 1.3 million Haitians suffer from severe hunger; which is one of the highest levels of food insecurity in the world (IPC 2022; World Food Program 2022). Alongside Haiti's political instability and other challenges limiting its development, Haiti is geographically vulnerable (IPCC 2014). Consequently, the country experiences many natural disasters, one of which is hurricanes. Since 1951, 6 hurricanes of more than category 3 have made landfall in Haiti (Thompson 2016), including Hurricane Matthew (2016). This repetitive subjection to damage from hurricanes is a hindrance to not only the country's development but further challenges food security. One of the most recent hurricanes to cause wide-scale destruction was Hurricane Matthew. Hurricane Matthew was a category 4 event that made landfall on the 4th October 2016 in the Sud department, travelling north through Grand'Anse. The hurricane had a severe impact; an estimated 2.2 million people were affected, over 500 people lost their lives, up to 90% of homes were destroyed, and the damage to critical water and sanitation infrastructure contributed to an increase in the number of cholera cases (Marcelin, Cela and Shultz 2016; British Red Cross 2017; Action Aid 2022). In regard to agriculture and food insecurity, over 90% of crops were destroyed, with damage to the agricultural sector estimated to be $580 million (FAO 2016; The World Bank 2017; Action Aid 2022). This resulted in 806,000 people suffering an extreme level of food insecurity (Action Aid 2022). Research associated with Hurricane Matthew in Haiti (e.g. Shultz *et al.* 2016; Marcelin, Cela, and Shultz 2016; Khan *et al.* 2017; Pasetto *et al.* 2018; Kianersi *et al.* 2021) does not acknowledge the impacts of the hurricane on agricultural vegetation immediately post-hurricane or in the long-term, despite there being evidence of long-term impacts on the health of the land, affecting agricultural productivity. Furthermore, there is a lack of data collected within Haiti, specifically in the Sud and Grand'Anse department, to implement sound disaster risk management plans (Cohen and Sing 2014). Thus, research to investigate the immediate impact and long-term recovery of Hurricane Matthew on agricultural vegetation would be beneficial. It would quantify damage, identifying regions of higher vulnerability, thus understanding where mitigation and recovery efforts need to be focused in the future to reduce the impact on food insecurity. Therefore, this research holds importance to both locals, government bodies and policy makers.

1.4. AIM & OBJECTIVES

Considering the current literature (e.g., Shultz *et al.* 2016; Marcelin, Cela, and Shultz 2016; Khan *et al.* 2017; Pasetto *et al.* 2018; Ewing-Chow 2020; Ritchie 2021; Kianersi *et al.* 2021; Shroff 2022) and Haiti's challenges, this desk-based study aims to assess the impact of Hurricane Matthew on the agricultural sector of the Sud and Grand'Anse departments, Haiti. This aim will be met by the following objectives:

1. Develop and test a methodology that utilises remote sensing data to assess changes in vegetation following Hurricane Matthew.
2. Critically assess the immediate impact of Hurricane Matthew.
3. Monitor the long-term recovery between 2016 and 2021.
4. Assess the vulnerability of land cover types across agricultural dependant communes.

To begin with, the literature review will establish the current situation in relation to food insecurity and hazards such as hurricanes, highlighting the links and the importance of the issue at hand. To follow, a detailed review of the different impacts of hurricanes on agricultural land will take place, accompanied by the methods used to monitor the impacts. The methodology will address the study site, data collection, and pilot studies as well as the final methods used to produce the results. The results will then be presented, outlining the immediate impacts, followed by the long-term recovery. The discussion will debate the findings of the research, as well as provide a detailed evaluation of the methods and results with particular focus on the challenges of data access within Haiti. Finally, the research will be summarised.

CHAPTER 2

2. LITERATURE REVIEW

2.1. THE CURRENT CLIMATE OF WORLD HUNGER

World hunger is a complex issue. Hunger can be defined as periods when populations experience severe food insecurity. Consequently, families may experience entire days without eating due to a lack of money and resources or restricted access to food (World Health Organisation 2021). There are different categorisations of hunger worldwide, as well as a lack of resources to register birth rates, displacement rates and to record health data, leading to inaccurate figures regarding hunger. In politically vulnerable nations, figures released nationally and internationally can be shaped by an agenda which inevitably impacts the categorisation of a country's situation.

The Integrated Food Security Phase Classification (IPC), however, is a respected measurement of world hunger employed by governments, NGO's, and UN agencies. The IPC is beneficial for countries such as Haiti as it is used to determine the severity and magnitude of acute and chronic food insecurity, and acute malnutrition situations to inform emergency responses as well as medium- and long-term policy and programme (IPC 2022). Figure 1 shows that based on the Acute Food Insecurity Scale, Catastrophe/Famine (Phase 5) describes the most serious situation concerning food insecurity (Oxfam 2021; IPC 2021). Although not impossible, it is rare for regions to surpass the emergency phase into the famine threshold (>20% of households with extreme food gaps, >30% of children acutely malnourished, and Crude Death Rate > 2/10,000/day) (IPC 2021). Today, it is estimated that 0.46 million are in Phase 5 worldwide (IPC 2022) whereas between 10-45 million people are facing emergency conditions (Phase 4) according to research by agencies such as Oxfam (2021), The World Food Program (2021) and IPC (2022). Although these statistics are alarming, other types of hunger such as 'stress' and 'crisis' are more prevalent across a broad range of countries (IPC 2022; FEWS NET 2022). The Global Report on Food Crisis (GRFC) (2022) reports that the majority suffering from hunger are concentrated within 48 countries (Global Network Against Food Crisis 2022), all of which are in the 'global south' (GRFC 2022). One country demonstrating evidence of 'crisis' and 'emergency' states of hunger is Haiti with one of the highest levels of food insecurity in the world (IPC 2022; World Food Program 2022). In February 2022, worldwide, 34.94 million were in a state of emergency (Phase 4), 1.3 million of which were Haitians. Furthermore, 3 million/128.03 million worldwide in a state of crisis (Phase 3) were Haitians (IPC 2022). Although the 3 million Haitians account for <2.5% of individuals suffering from crisis worldwide, 3 million accounts for more than a quarter of the country's population (The World Bank 2021). Thus, food security is a major threat to Haiti.

Figure 1. Acute Food Insecurity Scale (IPC 2021).

Haiti is a Caribbean country with a warm tropical climate and shares the island of Hispaniola with the Dominican Republic. It is the least developed nation in the Western Hemisphere (World Bank 2021); ranked the 15th lowest in the 2020 Human Development Report whereby countries are measured and ranked by development indicators such as education and life expectancy. Haiti's complex history regarding political stability, conflict, and repetitive subjection to natural hazards create challenging circumstances for development (Council on Foreign Relations 2021). Haiti is additionally reliant on agriculture, particularly for smallholder farming, and in the Sud and Grand'Anse departments agriculture is the main economic activity (RTAC 2021). Despite this, inferred by the Acute Food Insecurity Scale, Haiti struggles with food insecurity, with a total of 4.5 million Haitians in need of urgent assistance (IPC 2022). Alongside this, food insecurity acts as a consequence of and hindrance to development in Haiti. Statistics presented by organisations (e.g., Global Hunger Index 2021; IPC 2021; IPC 2022; World Food Program 2022; FEWS NET 2022) highlight the severity of food insecurity within countries such as Haiti, and although it's a complex topic, research efforts and global unity can work together to prevent the issue from growing.

In recent years, unifying efforts have been made to tackle world hunger. In 2015 the UN updated the Sustainable Development Goals (SDGs) with the 2nd goal, 'Zero Hunger', aiming to 'end hunger, achieve food security, improve nutrition and promote sustainable agriculture' by 2030 (United Nations 2020). Targets to achieve this goal include doubling the agricultural productivity of small-scale producers (United Nations 2020). As well as implementing resilient agricultural practices that will increase productivity and production and strengthen the capacity for adaption to climate change and associated climatic-related hazards that degrade land and soil quality (United Nations 2020). Despite countries including Myanmar and Rwanda showing constructive movement toward these targets (IFPRI 2016), globally, statistics show that the world is far from the UN's SDGs 2030 target. Indeed, from 2014 to 2019 the UN (2021) reported an increase of up to 60 million people suffering from hunger. For Haiti, indicators of hunger are showing little improvement (Sachs *et al.* 2022). Specifically, scores of under-nourishments, stunting in children, cereal yields and the nitrogen management index are decreasing, stagnant, or increasing at less than 50% of the required rate (Sachs *et al.* 2022), highlighting that the food insecurity crisis has made little progress since the SDG's were updated. Despite strategic plans being proposed by organisations such as the World Food Program for 2019-2023 (World Food Program 2022), there is no data suggesting that efforts have been effective. Indeed, IPC (2017, 2019, 2022) (Figure 2) suggest that food insecurity has increased in Haiti since 2017. Thus, it is evident that more research needs to be completed to gain a better understanding of why, in a technologically advancing world, food insecurity is still escalating.

Figure 2. Acute Food Insecurity Phases, Haiti 2017, 2019 and 2022 (IPC 2017, 2019, and 2022).

2.2. REASONS BEHIND HUNGER

To understand the reasons for food insecurity globally and the lack of progress with the associated SDG's including 'Zero hunger', the causes behind hunger need to be explored. The factors contributing to food insecurity are extensive. Politics, governance, conflict, rising food prices, income, race/ethnicity, trade policies, access to land/resources, climate, and natural disasters, individually and as a combination, all impact hunger (Pawlak and Kolodiziejczak 2020). Many countries, including Haiti, are challenged by several of these factors such as conflict leading to food insecurity/blockages on imports or aid, which makes establishing a solution more challenging. Generally, countries that experience a range of socioeconomic challenges such as conflict, poverty, lack of investment in agriculture and rural development, and poor governance, tend to suffer from increased food insecurity (Pawlak and Kolodiziejczak 2020; Global Hunger Index 2021); this is the case for Haiti. Haiti, in addition also experiences environmental challenges such as natural disasters and more severe impacts of climate change, exacerbated by their geographical vulnerability. Past marginal gains economically have been undone recently by Covid-19, climatic shocks like Tropical Strom Grace and the assassination of their President, Moise. Haiti now sees 52.3% of the country living below the poverty line of US$3.2 per day (World Bank 2022). In Haiti, as with nations with a similar geography and socio-economic make-up, all of these factors work hand-in-hand; climatic-related and natural hazards can be a catalyst for socioeconomic challenges, restricting development and thus worsening food insecurity. Therefore, food insecurity within a region like Haiti is a complex topic to understand (Wang, Kraay and Andree 2020).

Identifying the varying ways in which individual socioeconomic and environmental factors impact food security can assist in identifying mechanisms for managing it. Factors including regional policy decisions, inequality and unstable governance can negatively influence the distribution and access to food within and between countries (Smith 1998; Gregory, Ingram and Brklacich 2005; Concern 2021). It has been noted that economic and political inequalities, along with political agendas can dramatically shape food distribution systems; this, in turn, has prevented food from being received in areas that need it most (Smith 1998; Gregory, Ingram, and Brklacich 2005). In contrast, other factors such as land degradation affect the direct source of food, impacting the production and productivity of the land (Gregory, Ingram, and Brklacich 2005; Concern 2021). However, certain factors affect each stage of the food system, once again increasing the complexity of the situation. Conflict and climate change are examples of this as they can impact the access and distribution of food, yet also have a direct impact on the production and productivity of the land. In some cases, these issues can have a long-term impact on the health of the land, thus impacting the productivity of agricultural practices. This can broadly be referred to as land degradation. Over the past 7 decades over 35% of arable land worldwide has been degraded (Gupta 2019); this adversely impacts citizens' livelihoods, with most people affected living in poverty in developing countries (Olsson *et al.* 2019). This is because developing countries, such as Haiti, have a large reliance on agriculture, consequently making them more susceptible to the threat of food insecurity associated with land degradation. Considering the loss of arable land to land degradation it can be determined that food insecurity associated with land degradation is a major, wide-scale concern. Specifically, in regions more vulnerable to climate change as this exacerbates the rate and magnitude of several ongoing land degradation processes and introduces new degradation patterns (Olsson *et al.* 2019). Consequently, understanding the key foundations in maintaining a healthy agricultural system, the causes of land degradation, and how land degradation threatens agricultural land is vital.

2.2.1. LAND DEGRADATION

Generally, it can be stated that good soil health, diversity, a predictable and favourable climate, and clean groundwater are all key foundations in upkeeping a healthy agricultural system, thus increasing agricultural productivity. Healthy soils, in particular, are essential to production; soil supplies essential nutrients, water, oxygen, and root support that vegetation needs to grow and flourish (FAO 2015). Healthy soil can be defined as soil that functions as a living system; working in conjunction with microscopic and larger organisms that can perform vital functions such as converting dead organic matter and minerals to plant nutrients (nutrient cycling), controlling pests and diseases, and improving soil structure; having a positive impact on soil water/nutrient holding capacity (FAO 2015). Finally, healthy soil will mitigate the effects of climate change by maintaining or increasing its carbon content.

Despite being aware of the qualities and characteristics needed to sustain healthy agricultural practices, land degradation poses a severe threat, especially to soil health. Land degradation is the process in which the value of the biophysical environment is undesirably affected by a combination of human-induced processes acting upon the land; including human-induced climate change (IPCC 2019; Olsson *et al.* 2019). The undesirable effects referred to include direct damage to plants, soil degradation, deforestation, groundwater contamination, and biodiversity loss. In relation to soil health, the FAO (2015) estimates that soil erosion removes 25-40 billion tonnes of topsoil every year. These impacts have a direct or secondary impact on soil health, impacting agricultural productivity. This is detrimental to those who rely on agriculture, exacerbating hunger.

As mentioned in Section 2.2, land degradation can be a product of conflict, urban development, and climate-related hazards induced by climate change; and although it is currently a prominent issue, it is likely to worsen. One of the largest concerns contributing to land degradation and exacerbating world hunger is climate change. Indeed, by 2050, land degradation interlinked with climate change is predicted to reduce crop yield by up to 10% globally and up to 50% in certain regions (Head 2019). Degraded land is less productive as it reduces the soils' ability to absorb carbon (Head 2019). Therefore, degraded land is a catalyst for climate change, while climate change, in turn, exacerbates land degradation by increasing the intensity of extreme weather events and climate-related hazards, intensifying the rate and magnitude of degradation (Olsson *et al.* 2019). Consequently, land degradation, as both a catalyst and result of climatic-related hazards pose serious threats to the health and productivity of agricultural land, increasing food insecurity.

2.2.2. CLIMATE CHANGE AND CLIMATIC-RELATED HAZARDS

It has been established that climatic-related hazards can result in a large decline in agricultural production due to land degradation and also cause direct damage to crops. This results in a loss of subsistence agriculture (Gomez 2005; Olsson *et al.* 2019); in turn, decreases access to food, increasing food prices, contributing to food insecurity (FEWS NET 2015). In agricultural terms, climatic-related hazards can inflict both shock and stressors onto agricultural land (Farming First 2014). Shocks are sudden events, such as hurricanes, flooding, droughts, and wildfires, that can have a direct impact on the crop, reducing yield. Whereas stress is a prolonged impact that can reduce a plant's health. Stress can result from an unhealthy environment after a shock and can constrain a crop from reaching full health. This is supported by Lunt *et al.* (2016) who predicted that global crop yields of maize could decrease by 10% in the near future based on an analysis of historical agricultural production shocks. Unfortunately, shocks inflicted by climatic-related hazards associated with climate change, are something that society have less control over. Over the last few decades, we have created irreversible damage to our climate that will be felt for years to come (van der Geest and van den Berg 2021). One consequence of irreversible damage is the increase in the frequency and intensity of climatic-related hazards, such as hurricanes. The annual occurrence of disasters is now more than three times that of the 1970s and 1980s (United Nations 2021). Additionally, human-induced factors, ironically including the global food system, are raising temperatures by 0.2 °C per decade (IPCC 2018), amplifying the risk of increased intensity storms. This is due to the increased heat in the atmosphere in conjunction with warmer ocean temperatures, resulting in more intense winds during tropical storms (USGS N.D). This, combined with the rising sea levels consequent of global warming, expose more locations to flooding and more intense storm surges associated with hurricanes (USGS N.D).

A recent analysis shows that by 2050 climate change (without the current climate crisis) could increase the number of chronically hungry people by 78 million (Global Hunger Index 2021). This reinforces that climate change is a serious threat to world hunger on a global and local scale. Additionally, events associated with climate change and geographic vulnerability detract focus from investing in sustainable food systems, further exacerbating environmental degradation, preventing high productivity. This can create further tension and conflict within communities and highlight poor governance within a country. Undeniably, climate change and its associated hazards have a major influence on food insecurity. In the short term, they have a direct impact on the harvest, yet in the long term can contribute to land degradation, thus impacting the health of agriculture. Indeed, in Ethiopia, it was found that land degradation in the form of soil erosion, deforestation, and reduction of pastureland was one of the main factors affecting crop productivity (Taddese 2018). Furthermore, 12 million hectares of agricultural land across Europe suffer from severe erosion resulting in a 0.43% decrease in crop productivity annually; equating to €1.2 billion (Panagos *et al.* 2018). Consequently, the role of preparation, mitigation, and recovery is key to building resistance and resilience in vulnerable areas, with the long-term goal of reducing hunger (Uphaus 2008) and increasing food availability.

Although climate change is a global phenomenon, some countries are more vulnerable than others. This is due to a country’s geographic vulnerability; the degree of exposure to which a community, structure, or service is likely to be damaged or disrupted by a climatic-related hazard. These can be areas that already have a challenging climate, or regions that are more susceptible to the effects of climate change; for example, small island nations (IPCC 2014; Mohan 2016). Indeed, Mohan (2016) found that hurricanes have a negative impact on agriculture, with smaller islands appearing to be more severely impacted. For example, in the Caribbean, disaster impacts convert to a loss of 975 calories per capita per day, accounting for 40% of recommended daily intake (United Nations 2021). In conjunction, these developing nations have a high dependence on natural resources such as crops, increasing their vulnerability and limiting their capacity to cope (Harrold *et al.* 2002), exacerbating the effect of climatic-related hazards. This is the case for Haiti; which in addition to the issues related to development, is a small island nation in the Atlantic hurricane path, exacerbating their vulnerability to climate change (IPCC 2014). Consequently, Haiti's agricultural system is more vulnerable to the shock of hurricanes and long-term stressors like land degradation. Indeed, in Haiti, land degradation, exacerbated by hurricanes and their associated impacts such as wind and flooding, contributes to an annual soil loss of around 36 million tons (reliefweb 2004). Finally, sea level rise in conjunction with hurricanes can cause severe damage, particularly in low elevated coastal regions like Les Cayes and Torbeck in the Sud department. Regions such as these are more susceptible to coastal flooding associated with storm surges (Cohen and Singh 2014), further exacerbating soil erosion through the salinisation of soils (Cohen and Singh 2014).

Overall, it is evident that hurricanes and their associated impacts pose a major threat to agriculture immediately post-hurricane and in the long-term. Subsequently, considering Haiti's consistent struggle with food insecurity and its vulnerability to hurricanes, both the short and long-term impacts of hurricanes on agricultural vegetation need to be understood. Bridging the existing knowledge gap and understanding how the agricultural sector is affected by disasters, specifically hurricanes, is key to building resilience and reducing the impact on food insecurity (Cohen and Singh 2014; FAO 2017). Agricultural resilience is based on equipping farmers with the capacity to absorb and recover from shocks and stresses to their agricultural production and livelihoods. Consequently, to do this, there needs to be an in-depth understanding of how hurricanes impact agricultural land.

2.3. HURRICANES, ASSOCIATED IMPACTS & RECOVERY

Hurricanes, also known as tropical cyclones and typhoons, are amongst the most destructive natural disasters to affect specific regions around the globe (Gomez 2005). A hurricane is a storm that forms over tropical waters, bringing strong winds, flooding, and a storm surge(s), causing large-scale and long-lasting damage. Hurricanes have both short- and long-term impacts on agricultural land, reducing productivity, and increasing food insecurity. GFDL (2021) identified a positive statistical relationship between Atlantic Sea Surface Temperature and the power dissipation index that measures the intensity of a hurricane due to climate change. This means that storm intensity increases in conjunction with sea surface temperatures. Subsequently, within the next century, it is likely that hurricanes in the Atlantic will have higher amounts of rainfall and intense wind speed than the average present-day hurricane. If conditions persist, damage associated with hurricanes is likely to increase, therefore food insecurity as an impact of hurricanes will be an ongoing issue. Without monitoring the immediate impacts and long-term recovery, appropriate mitigation and preparedness strategies will not be implemented, and resilient agricultural systems will not be established.

When a hurricane makes landfall, the impacts are extensive. The process of damage arises from the three main hazards: strong winds, flooding associated with heavy rain and a high storm tide linked to storm surges. The force and impact of a hurricane can result in wide-scale socio-economic damage, however, specific to this research the impacts of a hurricane can have both short- and long-term impacts on agricultural vegetation (Gomez 2005; Arya, Mandal and Muley 2006; Chen 2009; Williams 2009; Wang *et al.* 2010; Brun and Barros 2013; Kaiser *et al.* 2013; Mohan 2016; Mohan and Strobl 2017; Hu and Smith 2018; Feng *et al.* 2018). Therefore, hurricanes can be linked to and associated with the persisting issue of food insecurity.

One of the main impacts affecting agricultural land associated with hurricanes is the intrusion of saline waters due to storm surges (Gomez 2005; Arya, Mandal and Muley 2006; Rodgers, Murrah and Cooke 2009; Brun and Barros 2013; Kaiser *et al* 2013; Phonphan *et al.* 2014; Goto *et al.* 2015; Scudiero *et al.* 2016; Gorji, Sertel and Tanik 2017; Dharanirajan *et al.* 2018; Rahman *et al.* 2018; Davis, Wang, Dow 2019; Gorji *et al.* 2019; Nguyen *et al.* 2020; Tripathi and Tiwari 2021). The intrusion of saline waters on land can result in an increase in Soil Salinity (SS), i.e. the content of salt within the soil. The process of increasing salt content, both via natural occurrence and human-induced, is known as soil salinisation. In agriculture, soil is considered saline when there is a sufficient amount of salt dissolved within the root zone, with an Electrical Conductivity (EC) > 0.2 considered unsuitable for agriculture (Goto *et al.* 2015). Soil salinisation causes ion toxicity, osmotic stress, nutrient deficiency, and oxidative stress on plants, consequently limiting water uptake from the soil (Shrivastava and Kumar 2014). With this knowledge, it is recognised that soil salinisation has a negative impact on plant health and soil quality, consequently resulting in soil degradation, a loss of arable land and low crop productivity (Phonphan *et al.* 2014; Goto *et al.* 2015; Das *et al.* 2016; Scudiero *et al.* 2016; Gorji, Sertel and Tanik 2017; Rahman *et al.* 2018; Davis, Wang, Dow 2019; Gorjo *et al.* 2019; Nguyen *et al.* 2020; Tripathi and Tiwari 2021).

Soil salinisation is a hazard that is increasingly inescapable within a climate that experiences high evaporation and low precipitation (Gorji, Sertel and Tanik 2017), therefore, the hazard commonly strikes in arid/semi-arid environments. However, due to sea level rise and natural hazards such as hurricanes resulting in storm surges inundating land with seawater, similar soil impacts that are seen in arid/semi-arid regions are more commonly being identified across coastal regions (Goto *et al.* 2015; Morshed, Isla and Jamil 2016; Rahman *et al.* 2018; Davis, Wand and Dow 2019). This is due to the higher salt concentration present within seawater, 35,000 ppm, 35 grams of salt per litre (USGS N.D). However, the degree of salinisation is dependent on the duration of exposure to sea water, climate, and soil type. For example, sandy soils have a high infiltration rate, resulting in contamination to a low depth, yet the capacity for this soil to retain the salt is limited as minimum freshwater can leach the salt out from the soil profile (FAO 2005). Conversely, clay soils are less sensitive, but in cases of prolonged exposure the damages can become increasingly severe. Additionally, freshwater is a determining factor of resilience; where there is no freshwater source (rain or irrigation), it will take the soils longer to recover as they cannot be flushed out.

Due to these varying factors, the impact of coastal flooding on SS varies globally. For example, Goto *et al.* (2015) found a strong negative correlation between the Normalised Difference Vegetation Index (NDVI) and post-flooding EC values following Typhoon 9918 (Southern Japan) in 1999. This indicates that increased SS was accountable for decreased plant health. Furthermore, following Hurricane Katrina, NDVI in the Weeks Bay Reserve, Alabama, decreased by 64% along the coast (Rodgers, Murrah, and Cooke 2009). This decrease in NDVI was linked to increased salinity due to the storm surge and persisted for 8 months (Rodgers, Murrah, and Cooke 2009). This inland saltwater intrusion post-Hurricane Katrina caused rice crop productivity to decrease by 20% (Williams 2009), highlighting the severity of impact soil salinisation can have on crop productivity. Furthermore, Dharanirajan *et al.* (2018) found that an extreme seawater intrusion associated with the Indian Ocean tsunami (2004), affected crop productivity in India. The high saline conditions persisted due to drought conditions post-inundation making this a long-term issue affecting agricultural land. The attention to the climatic conditions post-hurricane highlights that salinisation could only be a long-term issue if drought conditions follow an event. Similarly, research investigating the same event, but in Thailand found the same negative effect of saltwater intrusion, emphasising that large patches of grassland and agricultural plantations such as coconut trees and orchards were affected (Kaiser *et al.* 2013).

The fragile nature of water sources' impact on agricultural land was highlighted particularly well after the Boxing Day Tsunami (2004). In Southeastern India salinity levels were raised by approximately one-quarter of the salinity of seawater, with conditions persisting for more than 10 months, despite the inundation and retreat lasting just 5 minutes (Violette, Boulicot and Gorelick 2009). In contrast, in Sri Lanka, damage was less extreme than the humanitarian sectors had assumed; by the Yala Season (May), 65% of the affected area was ready for cultivation as far as salinity is concerned, and by the start of the Maha season (September), 90% was ready for cultivation (FAO 2005). This highlights how conditions and persistence of salinity vary; some research suggests that land can take up to 2 years, potentially longer, to recover (Williams 2009; Brun and Barros 2013; Gould *et al.* 2020), whilst others suggest that it could be as little as 2 weeks to a year (Violette, Boulicot and Gorelick 2009; Kaiser *et al.* 2013). As we know, this is dependent on climate conditions (Dharanirajan *et al.* 2018), duration of exposure, and soil type (FAO 2005). However, it is evident that soil salinisation can have a negative impact on crop productivity and have long-lasting impacts on the condition of the land. Therefore, it would be an important factor to monitor.

Other impacts associated with hurricanes are high wind speeds and flooding induced by intense rainfall. This too can result in the total loss and damage of vegetation (Walker 1991; Ramsey *et al.* 2001; Gomez 2005; Staben and Evans 2008; Ito 2010; Zhang *et al.* 2013; Hoque *et al.* 2016; Marzen *et al.* 2017; Feng *et al.* 2018; Hu and Smith 2018; Bellanthudawa and Chang 2021; Estoque *et al.* 2021). Furthermore, as well as the immediate impacts, in the long-term reduced vegetation cover induced by wind/flooding on understory communities (the underlying layer of vegetation growing below a canopy) and soil, are extensive (Breda 2008). Increased soil exposure from a reduced canopy cover can result in more severe land degradation, which also results in decreased productivity (Section 2.2.2). Therefore, both wind and flooding can have direct and indirect impacts on the health of the land. Flooding usually takes place due to intense rainfall but is exacerbated in areas that are not well drained or have less impermeable surfaces such as clayey soils (Gomez 2005). This can increase the volume and velocity of flooding, increasing the severity of the damage. The impacts of flooding on vegetation are three-fold. Firstly, depending on the velocity and volume of the flood, crops can be damaged/washed away, immediately destroying the harvest. For example, a 28.35% increase in barren land was recorded post-Hurricane Maria in Puerto Rico in 2017 (Hosannah *et al.* 2020), highlighting the immediate loss of crops associated with a hurricane. Secondly, flooding can result in soil erosion, decreasing the available nutrients. Water quality surveys conducted following Hurricane Katrina, at a station that drains agricultural land in Florida, showed an increased nutrient input consequent from increased runoff (Zhang *et al.* 2009). Concentrations of nitrate and soluble phosphate increased by 7- and 10-fold, respectively (Zhang *et al.* 2009). This highlights that large volumes of nutrients were removed due to the runoff/soil erosion following rainfall from Hurricane Katrina, leading to a decrease in productivity as the foundations of the land post-hurricane were not as healthy. Finally, persisting flood conditions can result in waterlogging, reducing the amount of oxygen available to the plant resulting in asphyxiation (Gomez 2005). This can ultimately lead to damage or death of vegetation, depending on the crop type and duration of flooding. This can also create suitable conditions for pests and diseases to develop (Gomez 2005). Overall, it can be concluded that the related impacts of flooding such as immediate damage/loss of harvest, soil erosion, waterlogging, and the development of pests can result in long-term stress on agriculture, reducing health and productivity.

In regards to wind associated with hurricanes, typically, wind causes defoliation and snapping of trees, with the latter being the main cause of a reduced canopy cover (Walker 1991; Ito 2010). Dense and taller vegetation such as forests have been found to be more sensitive to damage (Walker 1991; James 2010; Hu and Smith 2018; Charrua 2021). The severity of damage inflicted by wind has been found to positively correlate with the duration and force of wind; higher durations of critical wind speed increase the severity of damage (Ramsey *et al.* 2001). This finding was supported by Hu and Smith (2018), who found that vegetation damage in Puerto Rico caused by Hurricane Maria was highly correlated with distance from the storm centre. This conveys that land closest to the hurricane eye was exposed to a higher critical wind speed and, therefore, experienced higher levels of vegetation damage. Additionally, the wind associated with hurricanes has been found to cause damage by airborne sea salt transference. In particular, strong winds can carry sea salt up to 200-300 m inland from the coast, preventing the growth of crops sensitive to salt (Gomez 2005). This being said, most research focuses on the impact of wind on trees/forests (e.g. Feng *et al.* 2018; Hue and Smith 2018) as it is known that they are more severely impacted. However, as mentioned, snapping and uprooting of trees can result in a long-term loss of canopy which increases bare soil exposure, leaving understory communities vulnerable. This optimises conditions for land degradation (Breda 2008). Considering this, there is little known about the short and long-term impacts of wind on agricultural land associated with hurricanes and the potential long-term implication on understory communities.

It is apparent that the hazards associated with hurricanes have a detrimental effect on all vegetation, including agriculture. However, dependant on factors such as climate and the severity of damage, impacts such as salinity and loss of nutrients due to soil erosion consequent from flooding and wind can persist long-term. These combined threats create a stressed agricultural system, challenging the agricultural sector by reducing productivity, contributing to food insecurity, and thus, hunger on a local scale. Preservation of agricultural health can be approached in the form of mitigation and preparedness. Reducing the initial impact, but also developing strategies to recover efficiently can be key to agricultural resilience. Therefore, it is imperative that the impacts of hurricanes in relation to agricultural land are explored to improve resilience.

Research that works closely with farmers and locals within the community strive to understand the recovery of their agriculture to inform preparedness and prevention against the associated impacts of future hurricanes. Indeed, employing simple field techniques, Holt-Giménez (2001) conducted a study to measure farmers agroecological resistance to Hurricane Mitch in Central America. Agroecological refers to sustainable farming that employs a holistic and integrated approach, seeking to optimise interactions between plants, animals, humans and the environment (FAO 2023). Measurements of key agroecological indicators on 1,804 plots (paired under the same topographical condition) concluded that sustainable farming practices were more resilient against Hurricane Mitch. On average, 'agroecological' plots on sustainable farms sustained lower economic losses after the hurricane than on conventional farms and could lower vulnerability to such events. Agroecological plots tended to have 30-40% more topsoil, higher field moisture, and one-fifth more vegetative cover. Additionally, there were fewer incidents and smaller losses of arable land in relation to landslides, and less rill/gully erosion than conventional plots (Holt-Giménez 2001). These statistics highlight the benefits of agroecological farming, and the increase in resilience they have against extreme events such as hurricanes. Further research, post-Hurricane Maria supports the notion that agroecology is the backbone of agricultural recovery (Felix and Holt-Gimenez 2017).

Agroecological farming practises include structural, agronomic and agroforestry techniques. Structural techniques encompass contour ploughing, ditches, and terraces to aid soil and water conservation management. Agronomic practices include relay cropping, intensive in-row tillage, compost, vermiculture, animal manure, and integrated pest management. These benefit fertility, soil health, weed/pest control, water conservation and soil protection. Finally, agroforestry is centred around woodlots, multistorey/alley cropping, vegetive strips and live fences. Agroforestry techniques provide fuel, timber, and fruit, reduce run off mitigating erosion, enhance the nutrient cycle, and provide habitats for beneficial insects (Holt-Giménez 2001; Altieri et al. 2015).

Furthermore, diversification has a large impact on resilience against various types and degrees of shock (Altieri *et al.* 2015). When agroecosystems are simplified, it affects their capacity to respond to change and generate ecosystem services. Consequently, a practise with increased biodiversity enhances ecosystem functions as different species and genotypes perform slightly different and have different niches. This diversity acts as a buffer against failure due to environmental fluctuations, resulting in a more predictable and aggregated community response, increasing resilience (Marrero et al. 2021). Indeed, Chen (2009) concluded that increased diversification and changes in cropping patterns can improve resilience to hurricanes and reduce sector-wide agricultural damage by up to $650 million. Additionally, in a literal sense, crop diversification can diffuse natural disaster risk by providing products that can be harvested in fewer months such as plantain or chilli peppers, or even weeks such as lettuce or cilantro (Marrero et al. 2021). Agroforestry, for example, is a practice built around diversification and was seen to sustain less damage in comparison to their conventional monoculture neighbours post-hurricane Mitch (Holt-Giménez 2001). Therefore, agronomic practices that focus on diversification tends to increase resilience to shocks such as hurricanes.

Research such as this highlights the importance of knowledge surrounding resilient agricultural practices that reduce stress and improves the condition of agricultural land, achieving a productive landscape. Unfortunately, across many underdeveloped countries, there is a lack of understanding and education regarding appropriate agricultural practices as well as the impacts and recovery of agricultural land related to natural hazards (FAO 2017), this is the case in Haiti (Cohen and Singh 2014). Therefore, communities are not adapting agricultural practices to prepare for or reduce the impacts of challenges such as hurricanes. As a result, this can make underdeveloped countries that rely heavily on agriculture even more vulnerable. Therefore, a key requirement is to bridge existing knowledge gaps and expand the current understanding of how the agricultural sector is affected by hurricanes (FAO 2017) and identify what regions are more vulnerable than others. Fortunately, of the factors driving land degradation and fuelling world hunger, climate change, and associated hazards is one we have the best chance of predicting through science (UN Food System Summit

2021). This provides the opportunity to build agricultural resilience against hurricanes. Consequently, using Haiti as the study site, this research aims to expand the current understanding of how agricultural land is affected by hurricanes by investigating the immediate impact and long-term recovery of the Sud and Grand'Anse departments following Hurricane Matthew (2016).

2.4. HURRICANE MATTHEW (2016)

Hurricane Matthew was a category 4 hurricane that made landfall in Haiti on the 4th October 2016. The hurricane hit the southern peninsular and travelled through the Sud and Grand'Anse departments. The storm caused winds of up to 145 MPH for prolonged periods, heavy rain, and a storm surge, resulting in swollen rivers, flash flooding, landslides, and the destruction of agriculture and infrastructure (Stewart 2017; The World Bank 2017). Furthermore, although the height of the storm surge along the coastline of Haiti is unknown, Hurricane Matthew caused the most powerful storm surge to affect Haiti in recent history, submerging land entirely (Shultz *et al.* 2016). Consequently, the agricultural sector was deemed to be one of the most damaged sectors with up to 90% of crops lost in some regions (Action Aid 2022). Along the southern coast of the Sud department, it is estimated that 90% of coconut trees were knocked down and entire coffee and cocoa plantations were destroyed (Stewart 2017). As both departments have a dependence on agriculture, this made them even more susceptible to food insecurity as a result of Hurricane Matthew (RTAC 2021). Rapid interventions such as the rehabilitation of irrigation systems, new seeds provided to 2,500 farmers, and cash transfers to cover damage to commercial crops helped minimise the loss of the winter harvest and prevent widespread famine (ReliefWeb 2017). However, these are only short-term solutions and do not take into account the potential long-term effects on the land that may impact the productivity of future growing seasons. Similarly, the majority of post-hurricane assessments only considered the short-term impacts and quantified them by economic loss or area (Stewart 2017; The World Bank 2017; World Vision 2018; Wisly N.D; Action Aid 2022).

Although short-term damage assessments were needed to quantify and understand the immediate impact of Hurricane Matthew on food security, the patterns and severity of damage to agriculture are important, as well as the long-term effects on the land. Despite this, there are no studies that monitor the short- and long-term impact on agricultural vegetation post-Hurricane Matthew even though this could be detrimental to the long-term productivity of agriculture, contributing to food insecurity within Haiti. Indeed, research that is linked to Haiti post-Hurricane Matthew focuses on the cross between microfinance and food insecurity (Kianersi *et al.* 2021), governance and community response (Marcelin, Cela, and Shultz 2016), the cholera outbreak (Khan *et al.* 2017; Pasetto *et al.* 2018), and the psychosocial impact (Shultz *et al.* 2016). Consequently, Cohen and Singh (2014) state that in hurricane-vulnerable low-lying areas such as the Sud department, not enough data has been collected to create sound disaster risk management plans. Therefore, regarding the known impacts of hurricanes on vegetation and the potential long-term effects (e.g. Walker 1991; Gomez 2005; Violette, Boulicot and Gorelick 2009; Williams 2009; Ito 2010; Zhang *et al.* 2013; Hoque *et al.* 2016; Marzen *et al.* 2017; Mohan and Strobl 2017; Dharanirajan *et al.* 2018; Hu and Smith 2018; Bellanthudawa and Chang 2021; Estoque *et al.* 2021), research needs to be conducted in the Sud and Grand'Anse Departments to explore the short- and long-term impacts and recovery of Hurricane Matthew on agricultural vegetation, enabling suitable adaptations to better agricultural practices and build resilience against hurricanes (World Bank 2022). To achieve this, there needs to be an understanding of how the impacts of hurricanes can be monitored.

2.5. MONITORING THE IMPACTS OF HURRICANES

Monitoring the impacts of hurricanes is an essential part of the disaster management cycle that builds resilience. An effective disaster management cycle (Figure 3) highlights four phases- response, recovery, prevention/reduction, and preparedness (Hoque, Phinn and Roelfsema 2017). The latter phases, prevention/reduction and preparedness include appropriate measures and planning that reduce the likelihood and impact of hurricanes becoming disasters. Consequently, by monitoring the impact and recovery of hurricanes, this research aims to contribute towards knowledge that can guide practice to be more prepared, prevent/reduce damage and inform policy change. In a review of tropical cyclone disaster management using remote sensing and spatial analysis (Hoque, Phinn and Roelfsema 2017) it was concluded that there significantly less research assessing the overall impact and recovery of the landscape caused by tropical cyclones using remote sensing. This is echoed by Singh and Choen (2014) who acknowledged that there is a lack of information on the impacts of hurricanes in Haiti, debilitating the ability to effectively work towards sound disaster management plans. Attaining this information can influence adaptations in agricultural practices and enable mitigation efforts to be focused on regions of higher vulnerability, thus reducing the impacts of future hurricanes and minimise their effect on food security.

Figure 3. The Hurricane Disaster Management Cycle (Hoque, Phin and Roelfsema 2017).

It is more common for the impact and recovery of hurricanes on agricultural land to be assessed on a local community scale as opposed to a national scale. Typically, a social science approach is employed, working closely with farmers and the local community who manage the agricultural vegetation daily to understand the recovery of their agriculture to inform preparedness and prevention. This was the direction Holt-Giménez (2001) took; by networking with local farmers made possible by Movimiento Campesino a Campesino (a farmer movement for sustainable agriculture) and simple field techniques, a study was conducted to measure farmers agroecological resistance to Hurricane Mitch in Central America (Holt-Giménez 2001). The benefits of looking into the short-term impact and long-term recovery of hurricanes from a social science perspective is fourfold. It gives locals a voice, informs, educates, and spreads knowledge. However, in many cases the work completed can only take place on a local scale because it is time consuming, intensive, cannot monitor near-real time impacts nationally, and does not identify the overall impact and recovery of landscapes contributing to regional scale knowledge. Furthermore, due to limitations and restrictions some research cannot afford to carry out primary, grassroot research. Thus, many studies adapt, taking a desk-based remote approach. Desk-based approaches can provide a method that allows the rapid assessment of damage which is a key response in providing aid; this over a regional scale is critical.

Over the past few decades, remote sensing and spatial analysis have become increasingly popular in supporting all 4 phases of the disaster management cycle to aid building resilience. Considering the scale of damage hurricanes can inflict, remote sensing and spatial analysis offers a suitable approach to monitor the regional impact of hurricanes on agricultural land (Hu and Smith 2018), as it is both cost-effective and time-efficient. Today, there are many freely available and accessible data sources alongside machine learning tools that are powerful for data gathering and analysis (United Nations 2021). Remote sensing enables changes in the land to be identified by monitoring reflective characteristics of the earth's surface; these changes can be highlighted with change detection tools (Hoque, Phinn and Roelfsema 2017; L3Harris 2022). Finally, with a range of open-source satellite imagery available, imagery with a good resolution can be employed, increasing the detail of outputs.

Several studies (e.g., Wang *et al.* 2010; Hoque *et al.* 2017; Feng *et al.* 2018; Hu and Smith 2018; Tay *et al.* 2020; Charrua *et al.* 2021) have demonstrated the utility of remote sensing to monitor damage and recovery associated with hurricanes. Many of the studies employ Vegetation Indices (VIs) which combine values of surface reflectance at two or more wavelengths to highlight a particular property of vegetation (L3Harris 2022). Hu and Smith (2018), for example, found that the health of vegetation returned to 'near normal' 1.5 months after Hurricane Maria in Dominica and Puerto Rico. The term 'near normal' refers to an NDVI value that is not representative of when the land cover is under stress or exposed to shock. In particular, comparisons of NDVI values showed that forests were the most affected land cover with damage highly correlated to the distance from the storm centre (Hu and Smith 2018). Similarly, Wang *et al.* (2010) assessed damage to forests following Hurricane Katrina using the Normalised Difference Infrared Index (NDII). In total, 86.2% of pixels classified as trees were damaged, with damage to taller vegetation being more severe. Finally, monitoring the change in Non-Photosynthetic Vegetation (NPV), Feng *et al.* (2018) estimated that Hurricane Maria caused mortality and severe damage to 23-31 million trees in Puerto Rico. Although there was a focus on assessing damage to forests, the methods employed provide an insight into how the impact and recovery of agricultural land following a hurricane can be monitored using remote sensing.

2.6. MONITORING CHANGES IN LAND COVER

Land cover classifications help monitor how the land has changed. High wind speeds and flooding, both coastal and inland have immediate and long-term impacts on agricultural land. In the short term, this can result in agricultural loss, resulting in a loss of canopy, thus a change in land cover. Furthermore, soil salinisation and the loss of vegetation cover induced by wind and flooding have long-term impacts on understory communities, by inducing higher rates of soil erosion, reducing plant health and productivity (Breda 2008). If the health of the land is severely impacted by the hurricane and is not producing substantial yields, this could result in long-term changes in land cover. Land may be abandoned in some regions and agricultural expansion could take place in others (Singh and Cohan 2014). Consequently, assessing immediate and long-term land cover change is important to understand what regions sustained crop losses and which crops are more resilient.

The approach employed to monitor land cover change can be referred to as image classification; the two main approaches to classifying land are 1) Pixel-Based (PB) classification (Lam *et al.* 2011; Reif, Macon and Wozencraft 2011; Cherjarla *et al.* 2016; Grybas and Congalton 2015; Hu and Smith 2018; Charrua *et al.* 2020), and 2) Object-based Image Analsis (OBIA). (LaMantia-Bishop 2010; Badjana *et al.* 2015; Grybas and Congalton 2015; Phiri, Morgenroth and Xu 2019). PB methods consist of individual pixels being classified by considering the spectral information they hold compared to the spectral signatures of the land cover/land use classes derived from training data (Tassi et al. 2021). Conversely, OBIA is based on image segmentation. The segmentation process takes into consideration both spectral and textural information given by the pixels to segment the image into homogenous objects (Tassi et al. 2021). The segments are then assigned to a class based on the training data. Over recent years, there has been a shift to OBIA for land cover classifications, as it has been proven successful in improving land cover classification accuracy in vegetated areas (Zhang *et al.* 2018; Tassi *et al.* 2021). Additionally, PB classifications encounter issues when dealing with high spatial resolution images (Gao and Mas 2008). Despite this, PB classification still performs well using moderate resolution imagery like Landsat.

Across both classification methods, there are a range of classification algorithms such as Random Forest (RF), and k-Nearest Neighbour (kNN) that can be used to produce land cover maps. These two non-parametric classifiers have been reported as performing with the highest accuracy (Noi and Kappas 2017). Indeed, due to its improved accuracy and reliable outputs, alongside good processing speeds (Le Louarn *et al.* 2017; Charrua *et al.* 2021), RF was chosen to classify the impact of Tropical Cyclone Idai on the vegetated landscapes of Mozambique (Charrua *et al.* 2021). RF is frequently employed to assess landscapes and plant species due to the tuning parameters such as "number of features" and the maximum number of trees (Li *et al.* 2019). Additionally, the algorithm is not sensitive to noise, therefore, complex and homogeneous plant groups are classified successfully (Ok, Akar, and Gungor 2012). Furthermore, Hu and Smith (2018) used kNN to monitor the land cover of Dominica and Puerto Rico as they state that the classifier is respectable for images that are composed of spectrally similar classes that are not well separated (Hu and Smith 2018). Due to canopy structure in agricultural practices being similar in Haiti, some agricultural covers may have similar spectral signatures, especially if they are in the same phonological status (Kumar 2013), therefore kNN would be beneficial to explore for this study. With regards to location, topography, and vegetation, Hu and Smiths' (2018) study site shares similarities with Haiti, thus suggesting that kNN would produce similar high accuracy results when performing land cover classification.

In regards to assessing the immediate change in land cover post-hurricane, research that focuses on the impacts of wind dismisses agricultural land and typically focuses on tree species. Defoliation is a common occurrence in tropical and subtropical regions, as hurricanes result in the shredding of leaves and branches (Ito 2010). Walker (1991) and Estoque *et al.* (2021) have demonstrated the possibility to assess changes in vegetation cover by monitoring the canopy cover of large tree species remotely. However, canopy cover is defined as the percentage of ground area covered by the vertical projection of tree crowns (Whiteside and Boggs 2009), therefore does not accommodate non-tree species, including many agricultural products. Despite the definition of canopy cover, some literature studying canopy cover uses a PB approach (Ma, Su and Guo 2017; Celine 2019; Estoque *et al.* 2021). It can be argued that the output of this method is not just the measure of canopy cover but all land covers (Whiteside and Boggs 2009). Indeed, Sahebjalal and Dashtekian (2013) employed pixel-based classification in Ardakan, Iran, finding that agricultural land decreased by 8.39% from 1990-2006. Similarly, it was employed to classify tree cover and was effective in monitoring the loss of canopy (Ma, Su and Guo 2017). PB classification is considered a successful method to classify land cover (Sahebjalal and Dashtekian 2013; Ma, Su, and Guo 2017), thus it would enable comparisons from pre- to post-hurricane to be made, allowing changes to agricultural land to be identified. However, it must be remembered that the results will not objectively indicate how the loss of vegetation took place, i.e., wind. Despite evidence suggesting that PB classification is successful in monitoring changes in vegetation, the spatial resolution of imagery being analysed contributes to the overall accuracy. Ma, Su, and Guo' (2017) employed WorldView-2 to obtain a very high spatial resolution satellite imagery of 2 and 0.5 m to compare canopy cover to LIDAR estimates; in contrast, Sahebjalal and Dashtekian' (2013) employed Landsat, with a coarser resolution of 30 m to analyse land use-land cover changes in Iran. Subsequently, Ma, Su, and Guo (2017) achieved a very high overall accuracy of 93% in comparison to a lower accuracy of >81% achieved by Sahebjalal and Dashtekian (2013). It can be assumed that the higher spatial resolution reduced spectral mixing within a pixel, thus increasing the accuracy of the outputs. Consequently, although both studies prove PB classification to be successful, employing imagery with a higher resolution will increase accuracy, thus the reliability of the results.

In contrast to PB classification, OBIA has frequently been employed to monitor the loss of canopy cover (Johansen *et al.* 2009; Whiteside and Boggs 2009; Chehata *et al.* 2014; Chong *et al.* 2017). It has been stated that to ensure high accuracy outputs, OBIA requires very high spatial resolution data. In particular, to accurately identify the row structure within banana plantations, Johansen *et al.* (2009) stated that the spatial resolution of imagery needed to be ≤2.5 m. Alternatively, OBIA could be used to identify areas of agricultural land rather than the individual species/objects alone. For example, OBIA was used to map land cover types for both pre- to post- Cyclone Sidr (2007) in Bangladesh using lower resolution Spot-5 imagery (10 m spatial resolution) (Hoque *et al.* 2016). Employing the outputs, a post-classification comparison change detection algorithm was employed to identify changes in the landscape from pre- to post-cyclone. Through a trial-and-error approach, and visual inspection the object-based method was considered successful in identifying the extent and type of change induced by Cyclone Sidr (Hoque *et al.* 2016). This highlights that OBIA can be employed to produce land cover maps identifying agricultural types at a field scale, that can be used for further analysis. This omits the requirement for very-high spatial resolution data as seen in Johansen *et al.* (2009), which is typically not open source.

Overall, it can be concluded that both PB and OBIA can be used to monitor land cover change; in the short-term assessing the loss of vegetation, and in the long-term investigating land cover change associated with the long-term impacts of the hurricane on the land. Consequently, both methods of classification will be trialled within a pilot study.

2.7. MONITORING CHANGES IN VEGETATION

Change in vegetation can be monitored to a high standard using VIs applied to remotely sensed multi-spectral imagery. In particular, NDVI has the ability to quickly delineate vegetation and vegetative stress (Huang et al. 2020). Through chlorophyll absorption taking place in the red band and reflection in the Near-Infra Red (NIR) band, NDVI determines the density of green on a patch of land (NASA 2000), ranging between -1 and 1. Due to this appeal, in conjunction with its simplicity and reliance on easily obtainable multi-spectral bands, NDVI quickly became one of the most popular VIs (Wang *et al.* 2010; Huang et al. 2020). Amongst studies that employ NDVI, its use and therefore the meaning of the values derived from it vary. Studies have demonstrated that NDVI is effective in estimating various vegetation properties such as Leaf Area Index, biomass, chlorophyll concentration in leaves, plant productivity and stress (Huang et al. 2020). However, these have all been assessed by correlating remotely sensed NDVI values with on-the-ground measured values of these variables. On a local scale and across the same class of vegetation it is commonly used as a direct indicator of vegetation health (Huang et al. 2020). Aligning with this study, NDVI has also been employed to investigate vegetation damage inflicted by hurricanes (Hu and Smith 2018; Charrua et al. 2021); when Hurricane Maria made landfall in Dominica and Puerto Rico, post-hurricane NDVI was compared to reference years to monitor damage and establish when the vegetation returned to 'near normal' (Hu and Smith 2018). Charrua et al. (2021) applied a similar methodology when monitoring Cyclone Ida's impact on Mozambique; the paper concluded that change in NDVI from pre- to post-cyclone varied from -0.07 to -0.46, with the most damaged land cover being dense vegetation. Consequently, comparing a pre-hurricane NDVI with a post-hurricane NDVI (Hu and Smith 2018) would highlight if certain properties of agricultural vegetation had changed post-Hurricane Matthew, allowing the severity of damage and change in vegetation to be quantified, identifying regions of vulnerability. Therefore, NDVI can be used to monitor damage and recovery of vegetation.

Whilst the use of NDVI can be highly effective, it's limitations and capabilities need to be understood to avoid misuse. NDVI has been found to be sensitive to the atmosphere and background soil brightness (Xue and Su 2017), especially in areas where vegetation cover is low (<40%) and the surface soil is exposed. Darker soil background may produce larger NDVI index values (Bausch 1993); this is something to be considerate of post-hurricane, as due to damage and vegetation being washed away, soil exposure may increase, influencing NDVI. Furthermore, NDVI is sensitive to areas of high biomass, resulting in saturated NDVI values. Despite this, many studies (e.g., Rodgers, Murrah and Cooke 2009; Wang 2012; Li *et al.* 2016; Hu and Smith 2018; Taillie *et al.* 2020) have employed NDVI to monitor the impacts of hurricanes on vegetation. In particular, VIs have been used to measure the severity of vegetation damage subsequent to events such as hurricanes and associated salinity damage (Goto *et al.* 2015; Hu and Smith 2018; Charrua 2021). Indeed, utilising the pre- and post-hurricane NDVI, change in NDVI can be calculated (Hu and Smith 2018) (Equation 2) and the relative change in vegetation activity can be quantified by the NDVI ratio (NDVI% - Equation 3); where a higher NDVI% represents more serious hurricane damage. This method was implemented to investigate vegetation damaged in response to hurricanes (Hu and Smith 2018; Charrua 2021), as well as monitor the long-term effects of salinity on vegetation post-flooding induced by a typhoon (Goto *et al.* 2015). Indeed, Hu and Smith (2018) found that the mean NDVI of vegetative land significantly decreased from a pre-hurricane value of 0.91 to 0.70 post-hurricane. Additionally, forest land cover sustained the most damage, in contrast, natural grassland was the least impacted. Methods that can identify what land covers/regions are more severely impacted are useful in building resilience as it highlights areas of vulnerability, focusing mitigation efforts on the correct regions. Therefore, within this study, NDVI values would be used to infer the damage inflicted by Hurricane Matthew and monitor how long it takes for agriculture to return to a 'near normal' state (NDVI value that is representative of when the land cover is not under stress or exposed to shock).

$$NDVI = \frac{(NIR-Red)}{(NIR+Red)}$$ Eq 1. NDVI

$$\Delta NDVI = NDVI_{Pre} - NDVI_{Post}$$ Eq 2. Change in NDVI

$$NDVI\% = \frac{\Delta NDVI}{NDVI_{Pre}} x100\%$$ Eq 3. NDVI Ratio

Furthermore, the outputs of NDVI can be analysed and presented in a range of different ways. One example includes thresholding NDVI. This is when the NDVI is split into ranges and given a class, for example, 'Very Healthy Vegetation'= >0.66 (USGS 2018; Earth Observing System 2019). This method has been used as a tool to compare changes in vegetation (e.g., Gammal, Ali and Samra 2014; Walcker *et al. 2019*). This enables quantitative measures to be extracted about the area of land that has changed from one class to another. Similarly, change detection can be utilised to monitor the change in NDVI from the initial to final state over the same geographic extent (L3Harris 2022). This method allows quantitative values to be given regarding the severity of damage within specific regions.

The second VI, the Enhanced Vegetation Index (EVI) (Equation 4) is a modified version of NDVI that accounts for soil brightness to reduce inaccuracies. As can be seen in Equation 4, EVI includes a constant term that accounts for the soil background that NDVI is sensitive to; the soil adjustment factor 'L'. Although this omits the issue of soil background, the soil adjustment factor 'L' makes it more sensitive to topographic correction, therefore, the topographic effect on the EVI must be accounted for (Matsushita *et al.* 2007). While EVI accounts for soil background, this index is not appropriate in Haiti because it has been shown to be more effective in regions with minimum topographic variability (Earth Observing System 2019); as we know, Haiti's terrain is comprised of rugged mountains with small coastal plains and river valleys (Library of Congress 2010).

$$EVI = G\ x\ \frac{(NIR - Red)}{(NIR + C1\ x\ Red - C2\ x\ Blue + L)} \qquad \text{Eq 4. EVI}$$

Whereby G = 2.5, C1 = 1, C2 = 7.5, L = 1, NIR = Near Infrared, Red = red band, Blue = Blue band, $\Delta NDVI$ = Change in NDVI.

2.8. MONITORING CHANGES IN SOIL SALINITY

As mentioned in Section 2.3, storm surges associated with hurricanes increase SS, thus having a long-term impact on agricultural productivity. Consequently, monitoring SS to assess the long-term impact on recovery would be beneficial. There are two approaches used to monitor SS remotely, 1) the most used, 'direct approach', focuses on surface SS by measuring the spectral reflectance of bare soil (Ivushkin *et al.* 2017), and 2), the indirect approach whereby vegetation reflectance is used as an indicator of SS. Method two can be used when vegetation prevents seeing the soil. To meet the desired outcome, the latter approach would be more efficient as the canopy cover reflects the conditions of the root zone. Thus, if the canopy is not as healthy following a storm surge, it can be assumed that salinity is higher within the root zone for example. The root zone, in particular, determines vegetation health and is therefore better suited to assess agricultural lands, consequently it is suggested that attention should be directed towards the indirect method (Scudiero *et al.* 2016; Scudiero *et al.* 2017; Tripathi and Tiwari 2021). Despite this, conditions immediately post-hurricane make the indirect approach of estimating salinity through indices of canopy cover unachievable due to total loss of vegetation. Vice versa, when recovery begins to take place, canopy cover will prevent direct estimations using soil. Therefore, indices for both direct and indirect approaches need to be considered.

There are varying methodologies that have proven to be effective when monitoring SS over large spatial extents with repetitive measurements (e.g., Das *et al.* 2016; Gorji, Sertel and Tanik 2017; Ivushkin *et al.* 2017; Davis, Wang and Dow 2019; Nguyen *et al.* 2020; Rajendran *et al.* 2021; Zhu *et al.* 2021). The most common approach demonstrates the advantages of combining satellite image analysis with field data to assess the accuracy of SS estimates (Das *et al.* 2016; Morshed, Islam and Jamil 2016; Gorji, Sertel and Tanik 2017; David, Wang and Dow 2019; Nguyen *et al.* 2020; Omori *et al.* 2021; Rajendran *et al.* 2021; Tripathi and Tiwari 2021; Zhu *et al.* 2021). However, this is counterproductive, as the advantage of remote sensing is that you do not have to be present at the study site to conduct research. Consequently, a range of salinity indices, VIs, and bands have been evaluated to identify the proxies that are most sensitive to and correlate with Electrical Conductivity (EC). However, research that explores SS in alternate climatic (other than arid/semi-arid) zones is limited (. In a review of remote sensing approaches for monitoring salinity (Gorji *et al.* 2019), only 4 out of 100 studies took place in a similar tropical climatic region to Haiti (Gorji *et al.* 2019). The few studies that have been completed highlight that the indices do not perform as well for a region other than for which they were developed (Das *et al.* 2016; Morshed, Islam, and Jamil 2016), and those doing so have found much lower correlations and predictive power than reported for the initial application (Ivushkin *et al.* 2016). Indeed, Morshed, Islam, and Jamil (2016) investigated 13 indices in Bangladesh, a similar tropical climate to Haiti. Overall, the NIR band, Salinity Index 2 (SI2), NIR/R ratio, and the Soil Adjusted Vegetation Index (SAVI) had the best relationship with EC field samples, achieving a correlation of 0.64, 0.62, 0.73, and 0.68 respectively. However, these correlations are relatively low, meaning that there is a reasonable chance that salinity estimates will not be an accurate representation of the true EC. Furthermore, the different indices and ratios used to monitor SS across the study sites (e.g. Gorji, Sertel and Tanik 2016; Morshed, Islam and Jamil 2016; Asfaw, Suryabhagavan and Argaw 2018) show no consistency in regard to how well the indices perform. For example, Salinity Index 1 (SI1) (Equation 5), utilising the green and red band, performed well in monitoring salinity in Turkey (Gorji, Sertel and Tanik 2016) and Ethiopia (Asfaw, Suryabhagavan and Argaw 2018). Yet when applied in Bangladesh, returned low correlations with field data (Morshed, Islam and Jamil 2016). Similar inconsistencies are observed with the Normalised Difference Salinity Index (NDSI) (Equation 6). NDSI allows the brightness values in white encrustation to be analysed (Das *et al.* 2016) by utilising the Red and NIR bands as they are most sensitive to soil ions causing salinity. Nguyen *et al.* (2020) found that NDSI had a very low correlation with EC in Vietnam, whereas Das *et al.* (2016) reported high accuracies. The exceptions of inconsistency are the NIR band and Red band (together and alone), and the Vegetation Soil Salinity Index (VSSI). The Red and NIR bands, in particular, are useful to assess SS (Morshed, Islam and Jamil 2016; Corwin and Scudiero 2019; Nguyen *et al.* 2020; Zhu *et al.* 2021). This means that plants stressed by saline soils are characterised by a lower NIR reflectance than other non-stressed plants. This is reinforced by the fact that many indices include the NIR band. Therefore, a simple ratio of bands, including the NIR and Red band has proven to estimate SS adequately. Although this approach has not been frequently applied, Morshed, Islam, and Jamil (2016) found that out of the 13 indices assessed, the NIR/R ratio achieved the highest correlation. Similarly, Nguyen *et al.* (2020) showed that the NIR band had a very high correlation with EC. Additionally, VSSI (Equation 7) performed well across two studies in similar climatic regions to Haiti employing Landsat data (Nguyen *et al.* 2020; Hassan *et al.* 2021). Despite these few exceptions, the inconsistencies regarding the performance of these indices/ratios make the outputs estimating SS unreliable, thus the outputs would have to be validated with on-the-ground data.

$SI1 = \sqrt{Green + Red}$ Eq 5. SI1 Equation

$NDSI = \frac{(RED-NIR)}{(RED+NIR)}$ Eq 6. NDSI Equation

$VSSI = 2\ x\ Green - 5\ x\ (Red + NIR)$ Eq 7. VSSI Equation

Although it has been established that estimation of SS through remote sensing is possible, due to the inconsistency in the performance of indices and their poor correlations in non-arid environments, if the methods were to be applied to this research, on-the-ground data would be required to validate the findings. However, in Haiti there is a lack of environmental data collected to validate the findings. The reasons for a lack of data collection are broad and vary from country to country. However, in Haiti, the two main reasons contributing to a lack of data collection are conflict and the country's history, resulting in a lack of trust in external bodies (Daut 2021; Ground Truth Solutions 2022). Firstly, the ongoing conflict can make the data collection process unsafe. Secondly, Haiti's history consists of subjection to centuries of debt, exploitation, and violence, leading to a lack of trust throughout the country towards external organisations that can aid research and data collection (Ground Truth Solutions 2022). Consequently, although assessing SS would have been beneficial to understanding the long-term effects on the land, and thus the productivity of agriculture, the method would require validation with on-the-ground data. This is something that this study does not have access to, therefore assessing salinity is not a valid approach as it cannot be measured with high confidence, consequently, it will be excluded from this research.

2.9. SUMMARY

Overall, from reviewing the literature it has been established that despite efforts and global unity, food insecurity within certain countries, including Haiti, is not improving. The factors contributing to food insecurity are vast and interlinked, making it a complex issue. However, hurricanes, a hazard due to an increase in frequency and intensity due to climate change, pose a large reoccurring threat to food insecurity. Haiti has experienced the repetitive threat of hurricanes first-hand, and understanding the impacts of this threat is vital to build resilience. Reviewing the impacts of hurricanes demonstrated that the hazard can inflict both immediate damage on agricultural land as well as have secondary effects in the long-term. Despite this, literature that monitors the impacts of hurricanes tends to only quantify the short-term damage by loss of yield and associated costs. Consequently, the impact on agricultural vegetation and its long-term recovery is disregarded. Based on these findings, this research seeks to assess the impact of Hurricane Matthew on the agricultural sector of the Sud and Grand'Anse departments, Haiti, by utilising remote sensing. Although this research has a specified region of interest, it aims to develop a methodology that when tested, can be used universally to investigate and understand the short and long-term impacts of hurricanes and other climatic-related hazards worldwide. The outputs of such research can provide insight into the patterns and severity of damage, informing policy change and better agricultural practices, with the end goal of building resilience against food insecurity. Consequently, this research aligns with the SDG Zero Hunger, specifically targeting 2.3 and 2.4, as well as 17.16; 'enhancing global partnership for sustainable development that mobilise and share knowledge, expertise, and technology to support the development of SDGs in all countries, specifically developing countries' (United Nations N.D).

CHAPTER 3

3. METHODOLOGY

3.1. INTRODUCTION TO THE METHODS

This methodology employed a desk-based quantitative research approach to fill the knowledge gap highlighted in the literature review on the short and long-term impacts of hurricanes on agricultural vegetation. Although the benefits of working within and amongst communities/alongside farmers is understood and would benefit this study, as mentioned, there are various factors that made primary data collection unattainable; the main circumstance being that conflict present within the ROI makes on-the-ground research high-risk. Additionally, for the aim of the research and scale of the ROI, in-the-field research would not have been cost or time effective, nor achievable for the scope of this research. Thus, the methodology employs satellite imagery to assess the ROI.

This chapter outlines the methodology for this research. There were many challenges when working towards the results, including the lack of, and access to data and limitations of the software. Consequently, this chapter will demonstrate how these challenges were overcome. The chapter will start by introducing the study site, data sources and data collection process, and explain the pilot studies that go on to create the foundations for the methods of this research. The final methods employed to monitor the impact and recovery of Hurricane Mattew will then be explained, followed by how the data was analysed and a conclusion of the methodology.

3.2. DEFINING THE REGION OF INTEREST (ROI)

Within this research 3 ROIs will be assessed; 1) regional scale, across agricultural land of the Sud and Grand'Anse departments, 2) land covers; *Agroforestry, Dense Agriculture and Moderately Dense Agriculture*, alongside *Forest* and *Savanna with Others,* and 3) locally defined agriculturally dependant communes.

Figure 4 shows the Sud and Grand'Anse Departments, Haiti, clipped to a 70km buffer from Hurricane Matthews track; this defines the regional scale ROI. Hurricane Matthew made landfall in the west of the Sud department, Haiti, travelling north through Grand'Anse (NOAA 2016), consequently these departments are the focus of this research as they sustained the most damage. To ensure all changes to agricultural land are associated with the impact of the hurricane, the departments have been clipped to a 70km buffer from Hurricane Matthews track. This buffer is based on findings associated with Hurricane Maria, a category 4 hurricane (comparable to Hurricane Matthew) whereby changes in mean NDVI were detected up to 70km away from the hurricanes track (Hu and Smith 2018).

In order to meet objective 4 (assess the vulnerability of land cover types across agricultural dependant communes), agricultural land covers and agricultural dependant communes needed to be defined in the ROI. There is a lack of on-the-ground and secondary data defining land covers within Haiti, therefore it is hard to separate specific agricultural land covers from other wild flora species. A national data set, Haiti Data (2017), met these requirements which utilised SPOT satellite imagery to produce a Biota Land Cover map that identified areas of *Dense Agriculture*, *Agroforestry*, and *Moderately Dense Agriculture, Forest and Savanna with Others,* which are required for this research (Haiti Data 2017). This dataset is comparable to other sources such as the Agricultural Land Use map produced by the Haiti Ministry of Agriculture, Natural Resources and Rural Development (1998) as well as the land use/cover map produced by the FAO (2010) (see Appendix 8.1 and 8.2). Subsequently, the land cover data (Haiti Data 2017) was downloaded in shapefile format allowing land covers to be selected for individual land cover assessment.

Furthermore, 7 communes in the ROI that are vulnerable to food insecurity, therefore requiring community agricultural support (RTAC 2021) were chosen to be assessed (Table 1). Commune boundaries were downloaded in shapefile format from HDX Data (2018). In-depth analysis of the communes enables areas of vulnerability to be highlighted, addressing objective 4.

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Figure 4. Map of ROI. Sources to Create the Map Include Sud and Grand'Anse Department and Communes' Shapefiles (HDX 2018), and Land Cover Shapefiles (Haiti Data 2017), Clipped to 70km from the Hurricane Track (NOAA 2016).

Table 1. Defined Communes Undergoing In-Depth Analysis and their IPC Phases (IPC 2022).

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3.3. ACQUISITION OF SATELLITE IMAGERY

Due to the extent of the study area, satellite imagery was the primary source of data for this research. When employing satellite imagery, it is important to understand what is required of the imagery and the user's needs. Being aware of characteristics such as spatial resolution; the physical dimensions that represent a pixel, as well as temporal resolution; how often data is collected in the same area, is key. Within this study, a higher spatial resolution is prioritised as it can improve the accuracy of results (Bouaziz, Matschullat and Gloaguen 2011; Morshed, Islam and Jamil 2016). However, time-series analysis is the focus of this research, therefore the most important aspects of data collection are imagery that is atmospherically corrected, imagery that provides a cloud mask and data continuity. Atmospheric correction improves the comparison between multiple images over the same region by removing the scattering and absorption effects of the atmosphere, including clouds and aerosols (L3Harris 2015). Most satellites now provide Surface Reflectance (SR) products, whereby removal of atmospheric effects takes place by measuring the fraction of incoming solar radiation reflected from the earth's surface to the sensor (USGS N.D). Therefore, SR products are desired as they are suitable for time-series analysis. In terms of data continuity, it is important that, where possible, the same imagery is being employed for consistency. This can be challenging for time-series analysis that takes place over several years.

Various data sources were explored including Planet Labs, Sentinel, Landsat and MODIS. Planet Labs and Sentinel were explored first due to the desired higher resolution data (3.7m and 10m respectively) (Planet 2021). Although they provide the surface reflectance product, prior to 2018 Planet did not provide their Usable Data Mask 2.0 (UDM2) to mask Cloud Cover (CC) and Sentinel was not launched until 2015 which would cause issues in data continuity. Landsat and MODIS provided both data continuity and cloud masks, therefore were explored further.

3.3.1. LANDSAT DATA

Landsat 8 Collection 2 Level 2 (C2L2) provides surface reflectance imagery with a 30 m spatial resolution. Despite a lower resolution, Landsat is one of the longest-running, resolution-consistent satellites and therefore is frequently chosen to investigate environmental change over time. Since the launch of Landsat 4-5 in 1984 (EO 2021) the Landsat series has consistently provided 30m spatial resolution data with a revisit time of 16 days. Landsat collates data in swath paths of 185 x 180km (USGS N.D), subsequently, the Sud and Grand'Anse Departments cross over two paths (009 and 010), and therefore are collected at different times. This difference in data collection results in different atmospheric conditions across the tiles, thus increasing the importance of the SR product. Additionally, the accompanying QA pixel band was critical to overcome issues associated with cloud covering large areas. Overall, Landsat 8 has a good spatial resolution and can be downloaded with surface reflectance alongside the accompanying QA pixel band for cloud masking, making it an effective data source for a time series analysis.

Despite this, Landsat 8 launched in 2013, therefore years prior to its launch require imagery from either Landsat 7/4-5. Landsat 7 was not appropriate due to a scan line corrector failure resulting in incomplete images (USGS N.D). Although data can be downloaded with masks that infill the missing data, the masks are an estimation and therefore are not as accurate, thus Landsat 7 could not be used. Furthermore, it was established that there was no SR data collected from Landsat 4-5 for the growing seasons between the years 2010-2014.

3.3.2. MODIS DATA

Due to the lack of imagery in the pre-hurricane data collection period for Landsat, MODIS Surface Reflectance (MODIS/006/MOD09GA) was employed alongside Landsat to calculate the pre-hurricane reference mean NDVI from 2010-2015 (Section 3.5.1). MODIS data is collected daily, with atmospheric correction and surface reflectance applied. However, MODIS has a coarse spatial resolution of 463m. Nevertheless, this was the most reliable and accessible product that could be employed alongside Landsat.

3.3.3. DATA COLLECTION

To meet objectives 2 and 3, data was collected immediately pre- and post-hurricane, to enable the assessment of the impact, as well as every 6 months post-hurricane from 2016 to 2021 to monitor long-term recovery. Additionally, data was collected from 2010-2015 to calculate a reference mean NDVI to aid the analysis of the impact and recovery. When investigating agricultural vegetation, due to plant phenology and its impact on VIs, it is imperative to consider the time of data collection. Due to Haiti's climate and subsistence farming being the dominant practice, growing seasons are not clearly defined. However, as Haitian agriculture relies on rain for irrigation (Abraham 2015), the two main growing seasons coincide with the rainy periods. The first takes place in spring starting from April to July and the second lies from September to December (FEWS NET 2015). This coincides with The Famine Early Warning System (2015) typical annual growing calendar for Haiti (Figure 5), consequently defining the time frames in which data was collected. Employing this as a reference, imagery was acquired during the peak of the growing season, prior to harvest, to ensure consistency in vegetation phenology. This would ensure the truest reflection of recovery possible.

Figure 5. Seasonal Calendar in a Typical Year (FEWS Net 2015).

3.4. PILOT STUDIES

3.4.1. CLOUD COVER PILOT STUDY

When exploring and collecting data sources, an issue identified across all imagery was Cloud Cover (CC). For some time now, CC has been a constraint associated with the collection of satellite imagery globally (Marshall, Dowdeswell, and Rees 1994; Hu and Smith 2018; Man *et al.* 2018; Rahman *et al.* 2018; Tran *et al.* 2018; Sun et al. 2019; Qui, Zhu and Woodcock 2020; Rahman and Di 2020). Figure 6 shows the average CC in Haiti throughout the year (Weather Sparks N.D), highlighting that the months with high CC fall in the data collection period. CC and cloud shadow present within satellite imagery can reduce data consistency between images, significantly reducing the area of the study site and making time-series analysis difficult (Robinson, Rosser, and Walters 2019; Qiu, Zhu, and Woodcock 2020). Furthermore, cloud shadows decrease the reflectance capability of target objects (Earth Observing Systems 2021). Therefore, finding the best approach to mask or reduce CC and associated shadows is essential.

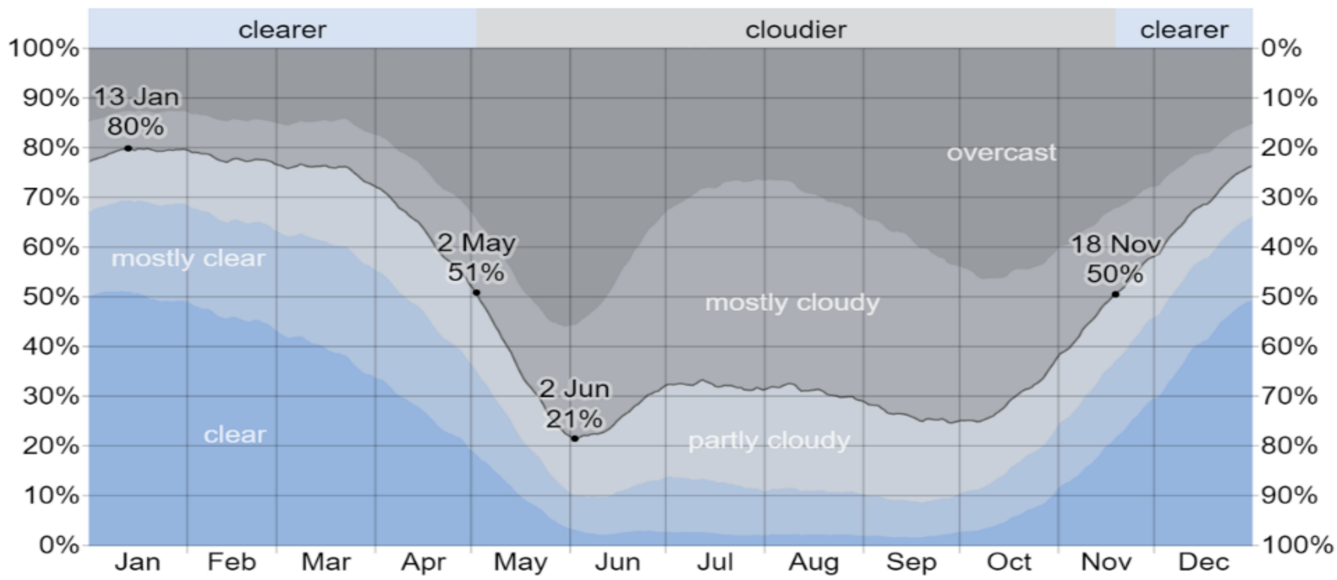


Figure 6. Cloud Cover Categories in Haiti (Weather Sparks N.D); Harvest Months July and November.

To reduce CC and subsequently increase the accuracy and consistency of the time-series analysis, various software and methods were explored to resolve the challenge of CC. As this is a global problem when working with satellite imagery, tools and algorithms have been developed to perform cloud masking at the pre-processing stage (Zhu, Wang, Woodcock 2015; Qui, Zhu and Woodcock 2020; QGIS 2021). Cloud masking was the first method explored, which essentially prepares imagery for processing and improves product generation (Earth Observing System 2021). One of the most widely used methods for cloud masking was the Fmask Algorithm (Hu and Smith 2018; Davis, Wang and Dow 2019; Sun *et al.* 2019). This method can be completed in ENVI or QGIS using the Cloud Mask plugin.

Both ENVI and QGIS were trialled to mask CC using data collected from the same date to assess accessibility and the quality of the output. Within ENVI, due to accessibility issues, the QA pixel band was processed manually to remove the CC, in contrast, the QGIS plugin completed this process automatically. Figure 7 compares the difference between the QGIS plugin and ENVI outputs; it shows that the cloud mask in ENVI covered a larger area, masking both cloud and cloud shadows. The red cross point sits on a region of cloud shadow that was identified in ENVI but not by QGIS, despite also selecting 'cloud shadow' to be masked. Consequently, because the QGIS plugin did not identify all the shadows within the imagery, this could result in skewed data values as the shadow is not a true value of the surface reflectance (Fisher 2014). Therefore, QGIS was unreliable for performing spectral analysis.

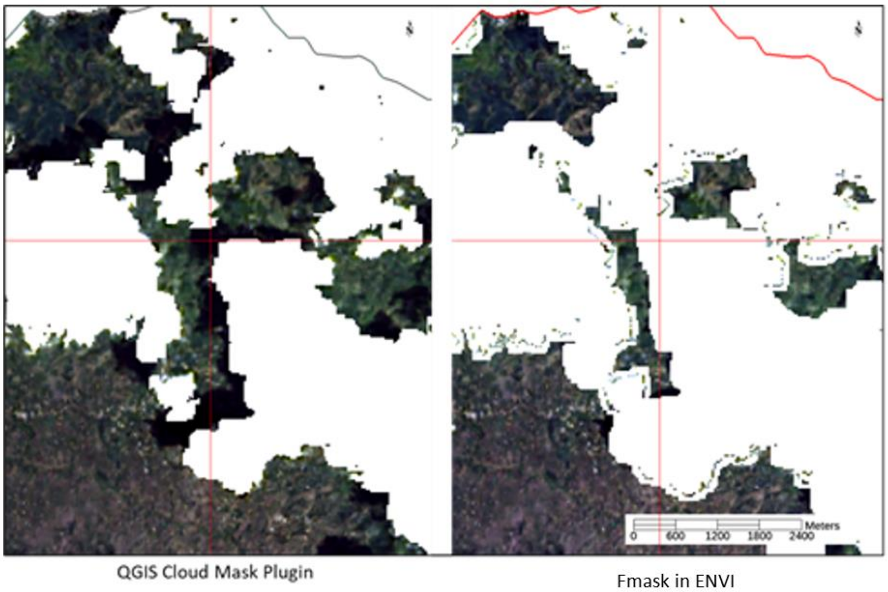


Figure 7. Difference Between QGIS Cloud Mask Plugin and Fmask Tool in ENVI Outputs from Imagery of the Same Dates.

Figure 8 shows the Sud and Grand'Anse Departments with the QGIS cloud mask applied across the pre-hurricane, post-hurricane (immediate), 6- and 12-months post-hurricane imagery. When selecting the data for this pilot study, metadata was used to select imagery with the least amount of on-land CC. Despite this, some images still had over 42% of land covered by clouds. The area being masked significantly reduced the area of the ROI that could be assessed. Additionally, when comparing the pre-hurricane to the post-hurricane imagery for analysis, the CC is dissimilar across the imagery (regarding its location and area), further reducing the area that can be analysed. Consequently, cloud masked outputs alone were not suitable for analysis.

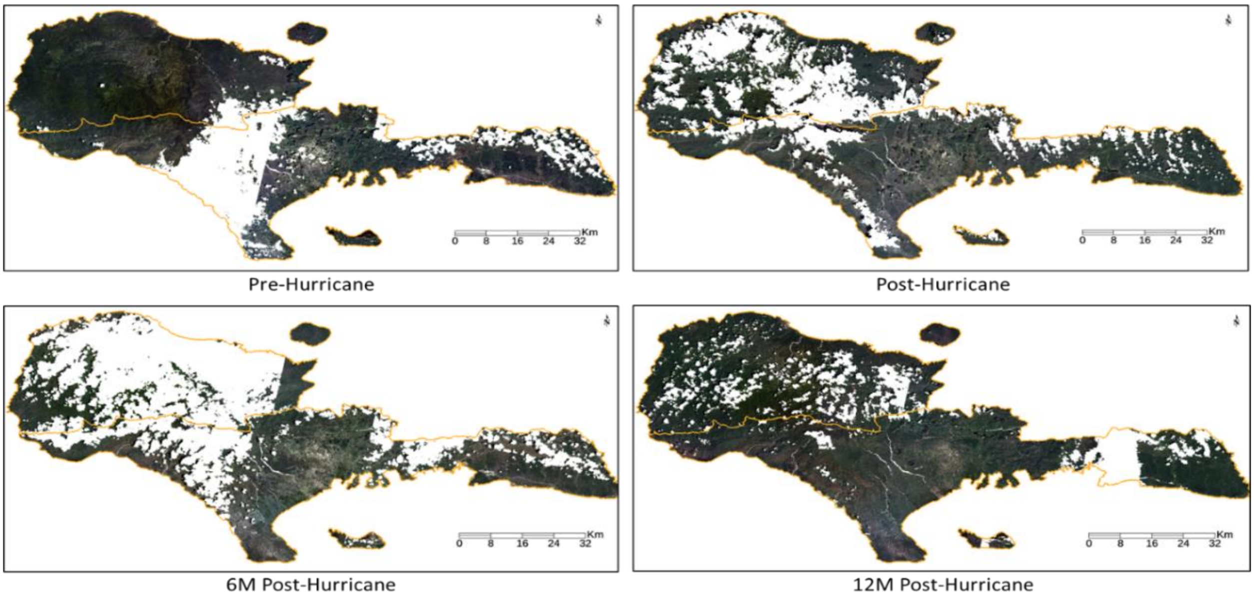


Figure 8. QGIS Cloud Masking Plugin Applied to Pre and Post Hurricane Landsat Imagery (USGS 2016, USGS 2017, HDX 2018, QGIS and ENVI).

To resolve this, the creation of a cloud-masked composite was explored to produce the most complete image possible. Recently, Best-Available-Pixel (BAP) compositing methods have been proposed to eliminate the effects of CC (Man *et al.* 2018; Hosannah *et al.* 2020). BAP methods replace cloud pixels with the best-quality pixels from a set of images within a defined period (Man *et al.* 2018). A composite image can be produced by mosaicking imagery to produce a cloud-free time series (Man *et al.* 2018; Hosannah *et al.* 2020). Processes such as this can be performed in ENVI, however, downloading imagery from multiple dates and pre-processing would significantly increase processing time. To avoid this issue Google Earth Engine (GEE) was employed. GEE combines a multi-petabyte catalog of satellite imagery with planetary-scale analysis capabilities (Google Earth Engine N.D), enabling instant access to and use of satellite data and a significant reduction in the computation time of batch processes. Therefore, this platform is particularly useful when handling large quantities of data (Carrasco *et al.* 2019; Tassi, and Vizzari 2020; Tassi *et al.* 2021). Consequently, a pilot study in GEE to explore creating a cloud-masked composite, increasing the area of land that can be consistently analysed was the next appropriate course of action.

To create the cloud masked composite, a method was developed by adapting scripts and processes applied in previous research; key influences were methods outlined by Tassi and Vizzari (2020) and

Tassi *et al.* (2021). Figure 9 shows the process employed to produce the reduced cloud composite image. Firstly, the data source was specified (Landsat 8 L2C2) and dates of collection were filtered (Table 2). Topographic correction was required to remove the influence of topography on the surface reflectance (Tassi *et al.* 2021). It must be acknowledged that although Landsat data includes terrain correction, this is dissimilar to topographic correction. Terrain correction ensures each pixel is displayed as viewed from directly above regardless of topography or view angle, therefore does not account for the variations in reflectance values that topography can inflict upon the land (Young *et al.* 2017). Regarding masking CC, similar to the processes in ENVI and QGIS, GEE utilises the QA_PIXEL band (CFMask) to mask cloud pixels. Finally, imagery that was collected within the defined time frame was then coded to be cloud masked and stacked together to create a composite image whilst applying the 'lastNonNull' reducer. The 'lastNonNull' function ensures that the last date in the time series that is not null of data is prioritised (Google Earth Engine N.D). This is essential as the latest possible date before the harvest begins is desired to produce the NDVI, as this is the most accurate representation of vegetation at peak phenology. Figure 10 presents the cloud masked composite in comparison to the individual imagery used to make the composite. This demonstrates the effectiveness of this method to produce a cloud-reduced image, increasing the area of land that can be assessed. Therefore, GEE will be employed to produce cloud masked composites to assess the impact and recovery of agricultural land post-Hurricane Matthew.

Table 2. Data Sources and Filtered Dates of Collection for Composite Images.

Data Source & Use	**April-July Growing Season**	**September-November Growing Season**
Landsat 8 for NDVI Analysis Immediately Pre vs Post-Hurricane	-----	• 2016-08-15 to 2016-10-04 • 2016-10-05 to 2016-11-30
Landsat 8 for Post-Hurricane Long-Term Recovery	• 2017-04-01 to 2017-07-30 • 2018-04-01 to 2018-07-30 • 2019-04-01 to 2019-07-30 • 2020-04-01 to 2020-07-30 • 2021-04-01 to 2021-07-30	• 2017-09-15 to 2017-11-30 • 2018-09-15 to 2018-11-30 • 2019-09-15 to 2019-11-30 • 2020-09-15 to 2020-11-30 • 2021-09-15 to 2021-11-30
Landsat 8 for Pre-Hurricane Average	• 2015-04-01 to 2015-07-30 • 2014-04-01 to 2014-07-30 • 2013-04-01 to 2013-07-30	• 2015-09-15 to 2015-11-30 • 2013-09-15 to 2013-11-30
MODIS for Pre-Hurricane Average	• 2012-04-01 to 2012-07-30 • 2011-04-01 to 2011-07-30 • 2010-04-01 to 2010-07-30	• 2014-09-15 to 2014-11-30 • 2012-09-15 to 2012-11-30 • 2011-09-15 to 2011-11-30 • 2010-09-15 to 2010-11-30

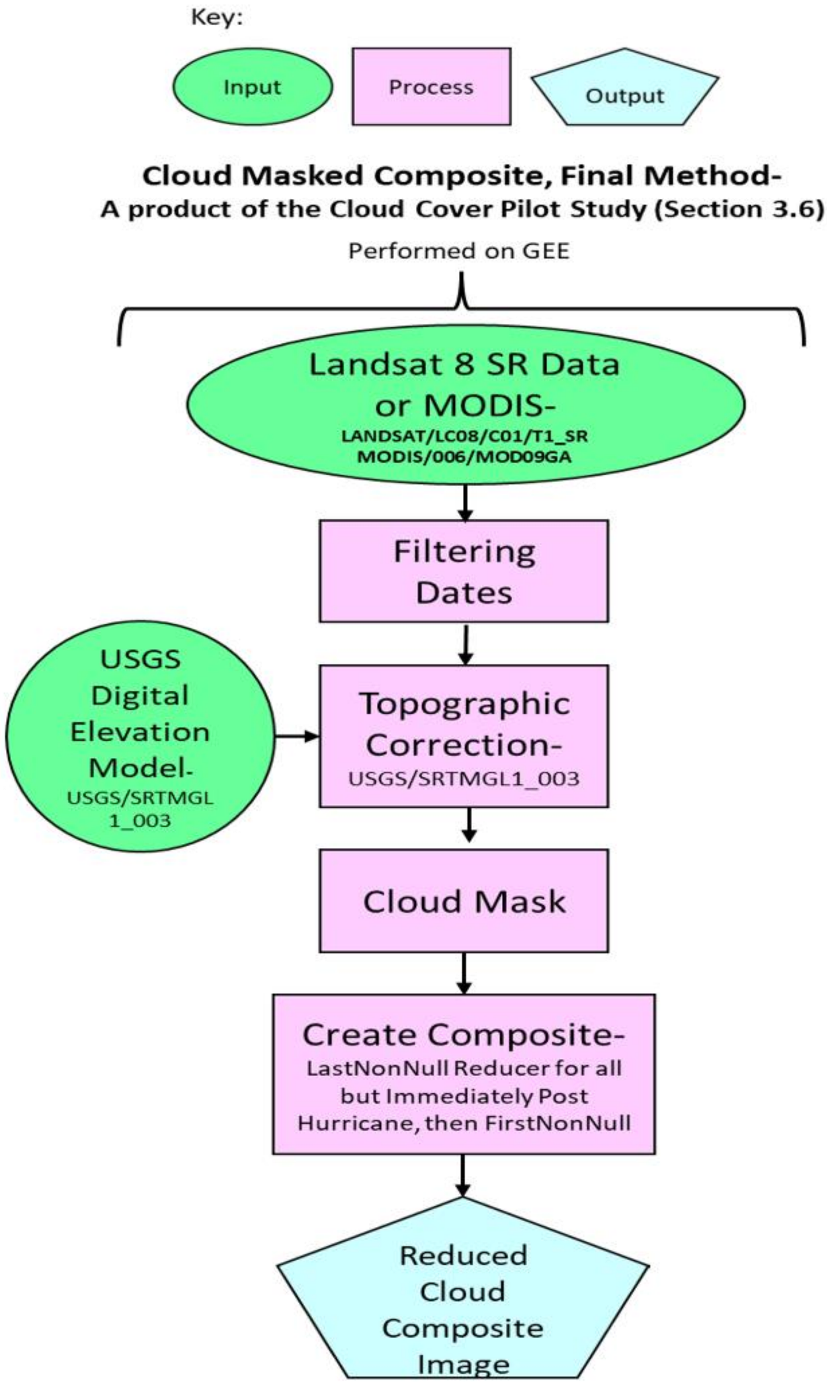


Figure 10. Data Flow Diagram to Create the Reduced Cloud Cover Composite Image. The Filtered Dates Referred to in the DFD are Highlighted in Table 2.

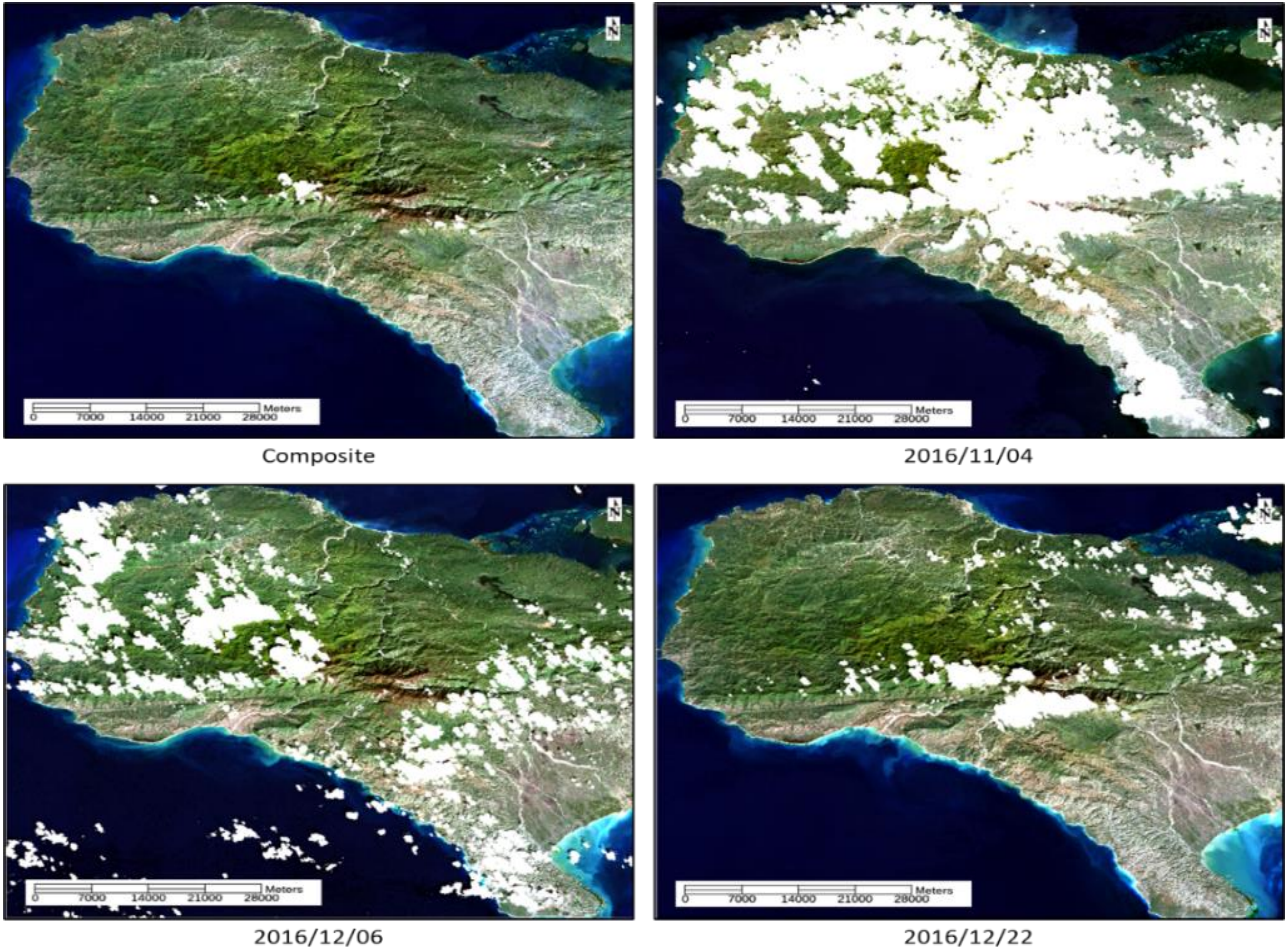


Figure 11. Cloud Cover Masked Composite vs Individual Images (Landsat 2016, GEE and ENVI); Composite % of On-Land CC= <0.5, 2016/11/04 % of on-land CC= 26.8, 2016/12/06 % of on-land CC= 7.77 , 2016/12/22 % of on-land CC= 2.9.

3.4.2. ASSESSING THE IMPACTS PILOT STUDY

The literature review identified that there were three parameters that could be explored to study the impacts of hurricanes on agricultural land: 1) the impact of a storm surge on soil salinisation and subsequently plant productivity, 2) change in land cover, where short-term change is associated with defoliation and the immediate destruction of crops, and long-term change results in permanent damage, thus potential land abandonment, and finally 3) change in vegetation from wind and flooding. It was established in the literature review (Section 2.8) that due to the lack of on-the-ground data to validate findings, soil salinisation cannot be measured with high confidence, therefore will not be included in this study. However, methods to assess changes in land cover and changes in vegetation were explored. The findings of the pilot study finalised the method that was employed to meet the aim and objectives of this research.

The first method explored was image classification. Image classification allows changes in land cover to be assessed, identifying patterns of land cover/land-use change after Hurricane Matthew. Short-term, this would identify immediate changes to the canopy, whereas long-term change could be associated with permanent damage to agricultural lands, such as land degradation. Additionally, image classification can be used to distinguish between crop types. This would allow an analysis of what species are more resilient or recover quicker, thus informing adaptions in agricultural practices. From reviewing image classification methods in the literature review, both Pixel-Based (PB) and Object Based Image Analysis (OBIA) methods were explored to establish which is more effective for meeting the study's objectives.

GEE was employed to trial both methods; the recent machine learning algorithms available in GEE such as Random Forest and Support Vector Machine have demonstrated higher performance and accuracy compared to the traditional maximum likelihood algorithm (Ghimire *et al.* 2012; Nery *et al.* 2016; Tassi and Vizzari 2020), and do not rely on the data having a normal distribution (Tassi and Vizzari 2020). The process used to perform the image classifications closely followed methods from Tassie *et al.* (2021), a method proven to produce high accuracy land cover classifications, Figure 11. The classification trialled drew upon a collation of spectral information, this can be referred to as a 'data cube'. Producing the data cube included employing multispectral bands, the calculation of spectral indices such as NDVI and textural indices e.g., the Gray Level Co-occurrence Matrix (GLCM), a matrix function of the angular relationship and distance between two neighbouring pixels (L3Harris 2022). Including such layers in classifications, as well as utilising the panchromatic band to complete

RGB pan-sharpening, has been shown to increase accuracy (Mohanaiah *et al.* 2013; Godinho, Guiomar and Gil 2018; Mananze, Pocas, Cunha 2020; Tassi *et al.* 2021). Due to the collection of primary data not being possible, and the lack of detailed on-the-ground data regarding land cover, the training data used to classify the images was validated by employing very high-resolution imagery, Planet Labs and Google Earth Pro. After evaluating both image classification methods and including the data cube the findings concluded that OBIA performed better, achieving a higher kappa value (Figure 12).

Figure 12. Data Flow Diagram of Tassie et al. (2021) Methodology (Pixel-Based, PB; Pixel Based including the image textural information, PBT; Object-Based, OB; Object-Based using the L8 15m Panchromatic band, OBP).

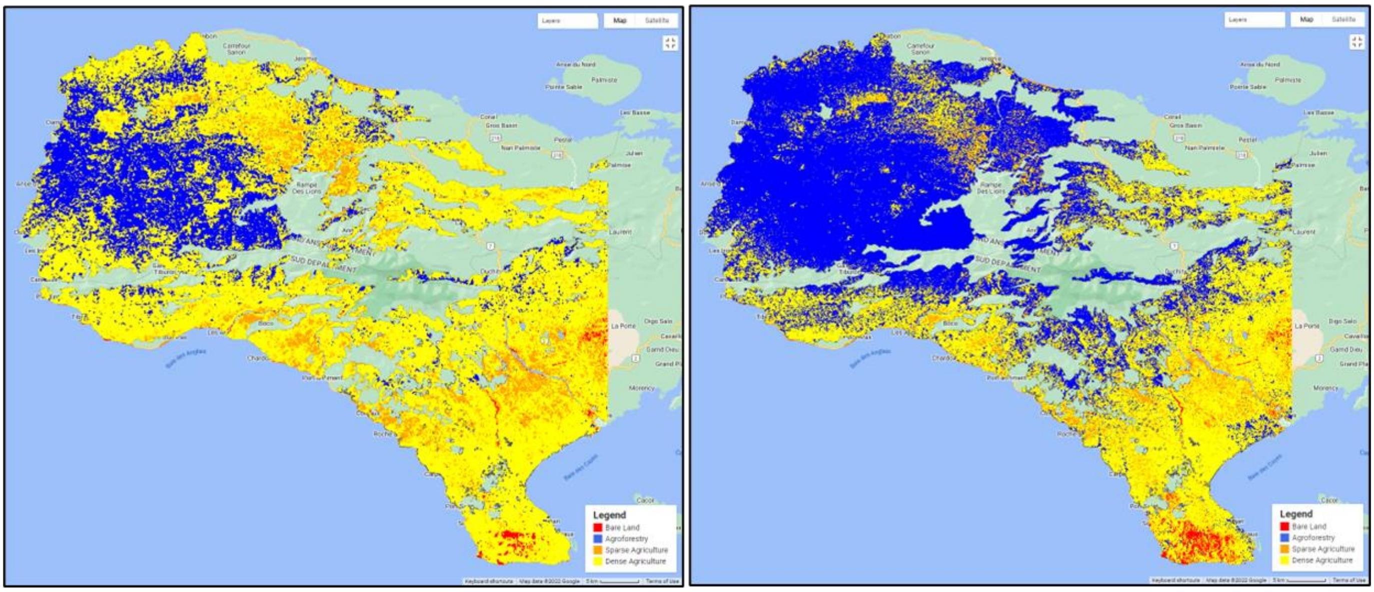


Figure 13. OBIA (Left), Kappa Value: 0.76, vs PB Classification (Right), Kappa Value: 0.60.

The second method explored NDVI. NDVI can be employed to assess change in vegetation from pre- to post-hurricane and monitor the long-term recovery consequent of Hurricane Matthew. The aim of this in the short-term was to assess the impact of the hurricane on the change in vegetation to gauge the severity of damage. In the long-term, assessing change in vegetation can inform how long it takes for the vegetation to recover; from this it can be inferred if the hurricane inflicted long-term damage (land degradation) onto the land, thus impacting vegetation productivity.

As mentioned in Section 3.3.1, collection of pre-hurricane data was challenging as in some years (2010-2014) Landsat imagery was not available, thus MODIS was employed to assess NDVI. To make sure MODIS produced similar outputs to Landsat despite the difference in spatial resolution, a comparison of NDVI from the same timeframe was carried out between both sources. Extraction of the NDVI mean, minimum, maximum, and standard deviation were assessed for a subset of the study area to assess the variability in NDVI. Overall, the two sources share a similar mean, with MODIS reporting higher NDVI values by 0.02 (Figure 13). This higher mean NDVI reflects the higher minimum NDVI in contrast to Landsat (Table 3). It can be assumed that the differences in the NDVI between Landsat and MODIS is due to the spatial resolution; larger pixels (MODIS) suppress the detail of smaller regions, that would be identified in a 30x30 m pixel, that is of a lower NDVI in comparison to surrounding land. Despite MODIS mean NDVI being slightly higher than Landsat, the difference is not enough to skew reference mean NDVI calculations, thus producing reliable NDVI outputs.

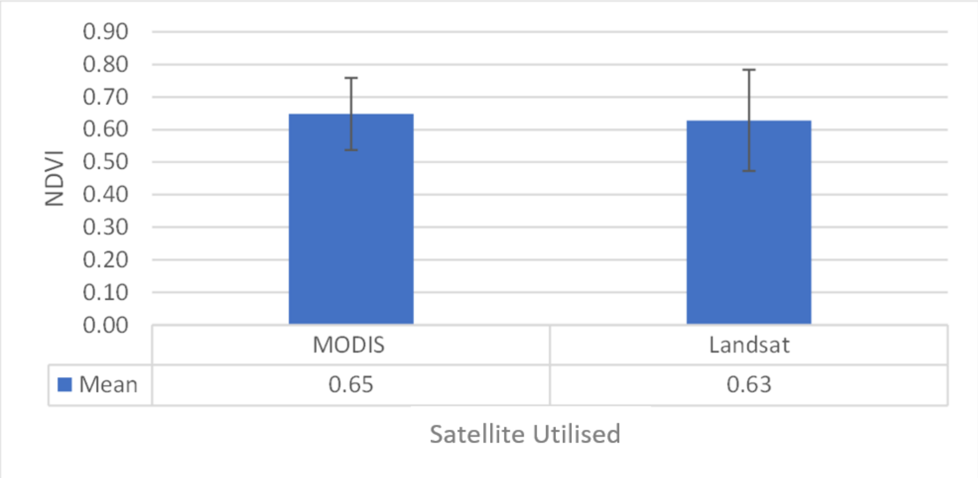


Figure 14. Comparison of MODIS and Landsat mean NDVI. Error Bars Highlight the Standard Deviation Around the Mean, Showing Little Difference.

Table 4. NDVI Statistics MODIS vs Landsat for Agricultural Land September-November 2015.

	MODIS	**Landsat**
Mean	**0.65**	**0.63**
Min	**-0.04**	**-0.56**
Max	**0.91**	**1.00**
StdDev	**0.11**	**0.16**

Although both image classification methods were successful, the outputs produced were compared to the subset of the study region for NDVI. It was concluded that the image classification outputs were similar to NDVI. This was due to the lack of on-the-ground data, meaning specific vegetation types were not able to be determined. Consequently, the training classes for the classification were vague, for example, 'dense vegetation' and 'sparse vegetation'. Classes such as this can be determined using NDVI, a reliable index based on quantitative information, whereas image classification outputs rely on the knowledge of the user. Therefore, employing NDVI and applying thresholding (i.e., defining NDVI ranges) decreases the chance of human error and bias. Furthermore, consequent of the issue regarding the lack of on-the-ground/secondary data, when classifying the image, specific land covers (e.g., crop types) could not be defined. This takes away the main purpose of the land cover classification, as findings cannot conclude which crops sustained less damage, therefore are more resilient, and which agriculture recovered quicker. Nor could they identify land abandonment, as there was no way to distinguish between wild flora and agricultural vegetation, especially with the resolution of satellite imagery available. Consequently, although the image classification could determine the change in land cover, the outputs could not deduce the detail that was initially desired without on-the-ground/secondary data. Although NDVI cannot specify crop type, it is more reliable than an image classification that solely relies on the knowledge of the user to train the data. Therefore, NDVI will be employed to assess changes in agricultural vegetation from pre- to post-hurricane and monitor the long-term recovery of agricultural land post-Hurricane Matthew.

3.4.3. CONCLUDING THE METHODS PILOT STUDIES

The pilot studies set out to effectively reduce and mask CC and evaluate methods to assess the impact and recovery of Hurricane Matthew. To conclude, the cloud mask alone produced unsatisfactory outputs; the area of land that could be assessed was significantly decreased and remnants of cloud shadow still occupied the imagery. Subsequently, GEE was employed to create a mosaic of cloud-free imagery.

Regarding methods to assess impact and recovery, due to the lack of and accessibility to on-the-ground/secondary data regarding land cover in Haiti, the image classifications did not produce the desired outputs. The lack of secondary data had a large influence on the methods and thus the findings of this study therefore will be discussed further in Sections 5.4-5.5. Consequently, this pilot study determined that employing image classification to assess land cover change did not meet the aim and objectives of this study. Consequently, change in vegetation was taken forwards into the final methodology.

3.5. ASSESSING THE IMPACT & RECOVERY OF HURRICANE MATTHEW IN HAITI

The pilot studies completed prior to finalising the methods built the foundations for this research and thus the results. Recapping from the CC Pilot Study (Section 3.4.1), data was collected, pre-processed, and cloud-masked in GEE. The Image Classification Pilot Study concluded that image classification was not a suitable method and that assessing change in vegetation using NDVI was the most effective way to meet the aim and objectives. The subsequent sections in this chapter will explain how NDVI was produced utilising GEE and describe the methods employed to analyse the short-term impacts of Hurricane Matthew, followed by an explanation of the methods used to assess the long-term recovery. Figure 14 presents a Data Flow Diagram (DFD) summarising the methods employed.

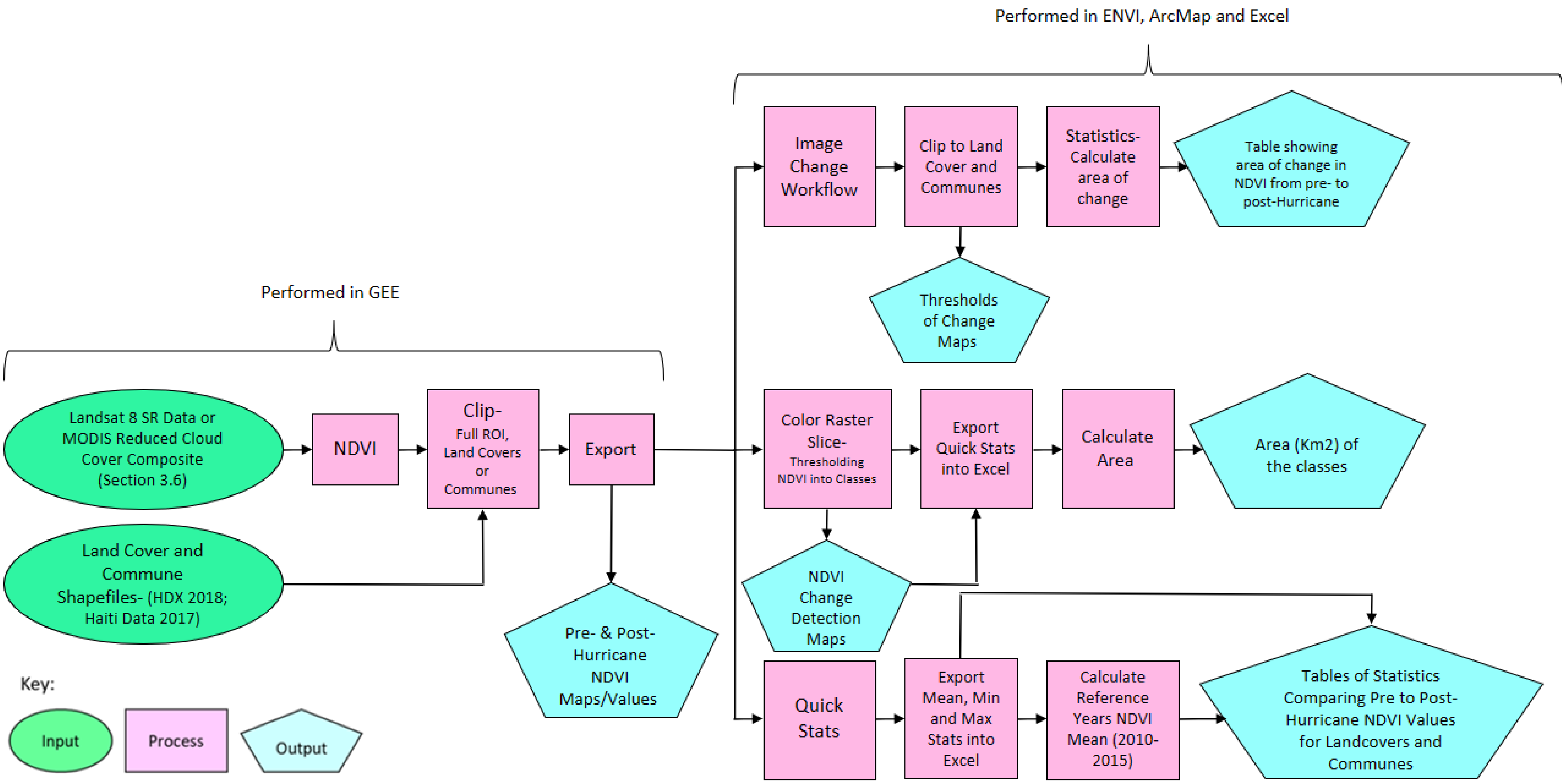


Figure 15. Data Flow Diagram of Methods Used to Produce Results. The filtered Dates are Highlighted in Table 2.

3.5.1. NDVI

As already established NDVI was the chosen VI employed to assess the impact and recovery of agricultural land subsequent to Hurricane Matthew. As seen in the literature review, Equation 1 shows how NDVI is calculated by employing the Red and NIR band.

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \qquad \text{EQ.1. NDVI}$$

Regarding data processing, NDVI was produced in GEE. Utilising the script produced to create the cloud masked composite, NDVI (EQ1) was coded and applied to the composite images. NDVI data was produced for immediately pre- and post-hurricane, as well as every 6 months post-hurricane (within both growing seasons) to monitor the long-term recovery. The 'lastNonNull' reducer was utilised for the immediately pre-hurricane composite and the 'firstNonNull' for the immediately post-hurricane composite. This means that the values from the last image prior to Hurricane Matthew and the first image post-hurricane were used to produce the NDVI unless null, ensuring the most immediate cloud free image was used. In contrast, when collecting data to monitor the long-term recovery (every 6 months post-hurricane) the latest image prior to harvest was used employing the ‘lastnonNull’ reducer; this ensured that NDVI reflected peak agricultural productivity to monitor recovery against the reference mean NDVI. Additionally, NDVI data was produced for 6 years (2010-2015) pre-hurricane (for each growing season) to aid calculation of a reference mean NDVI. Collating 6 years of data omits and accounts for any abnormalities within the data that may have been influenced by annual variations or meteorological conditions (Hu and Smith 2018; Tassi *et al.* 2021). The reference mean NDVI allows for post-hurricane NDVI to be compared to an NDVI that is reflective of a ‘near normal’ status. Within this study, ‘near normal’ refers to a status of vegetation that is not under stress or shock. NDVI values not returning to a near normal state may suggest that the hurricane inflicted long-term damage on the land (i.e., land degradation). For example, if a post-hurricane mean NDVI exceeds the reference mean NDVI, it highlights that vegetation has recovered/has exceeded what is deemed as a ‘near normal’ vegetative status for that region. The NDVI data was then exported from GEE so that further analysis could be conducted.

Once the data was processed, the mean NDVI across each individual ROI (regional, land cover and commune scale) was extracted. This was completed for both the pre- and post-hurricane data. The mean NDVI shows the average NDVI within each commune and land cover across each timeframe. Equation 8 shows how the reference mean NDVI was calculated from the pre-hurricane NDVI data.

These mean NDVI values were taken forwards to analyse the change in NDVI to assess the immediate impact and long-term recovery.

$$Reference\ Mean\ NDVI\ = \frac{2010\ MN + 2011\ MN + 2012\ MN + 2013\ MN + 2014\ MN + 2015\ MN}{6}$$ *Equation 8.*

Reference Mean NDVI Calculation Applied to Each Growing season, Whereby MN Stands for Mean NDVI.

3.5.2. ANALYSING THE CHANGE IN NDVI

The methods employed to analyse the NDVI data include 1) change detection, 2) threshold maps showing change in NDVI, and 3) comparison of NDVI mean, minimum and maximum values from immediately pre- to post-hurricane (to infer severity of damage) and long-term, against the reference mean NDVI to monitor how long it takes vegetation returned to a 'near normal' state.

The first method used to both visually and descriptively analyse the data was the classification of NDVI values into classes to produce change detection maps. Thresholding into classes of health has been applied in several studies to quantify damage and aid interpretation (Sahebjalal and Dashtekian 2013; Gammal, Ali and Samra 2014; Walcker *et al. 2019*). For different climatic regions, the NDVI ranges determining the health of a class differ (Gammal, Ali and Samra 2014; Aquino *et al.* 2018; USGS 2018; Earth Observing System 2019; Walcker *et al. 2019).* Table 4 shows the NDVI ranges associated with vegetation health that have been adapted from various studies and applied to reclassify the NDVI for this research and calculate the total area for each class (Gammal, Ali and Samra 2014; Aquino *et al.* 2018; USGS 2018; Earth Observing System 2019; Walcker *et al. 2019*). This enabled changes in NDVI to be quantified in terms of both area and mode of change (i.e., an area changing from 'very healthy' to 'moderately healthy').

Table 5. NDVI Ranges Associated with Vegetation Health (Earth Observing Systems 2019).

	Class	Range
Health	Dead/Inanimate Vegetation	-1 – 0
	Unhealthy	0 – 0.33
	Moderately Healthy	0.33 – 0.66
	Very Healthy	>0.66

$$Area\ (Km^2) = \frac{(Pixel\ Count\ of\ Class \times 900)}{1{,}000{,}000}$$ *Equation 9. Area (Km^2)*

Where 900 is the area of a Landsat pixel (m^2) and 1,000,000 is the conversion of m^2 to km^2.

The second approach employed 'Image Change Workflow' tools in ENVI to produce threshold maps showing change in NDVI from pre- to post-hurricane. This tool assesses the difference between the pre-hurricane and post-hurricane image to present the change that has occurred, classifying the change in NDVI experienced in each pixel into thresholds (for example, an increase in NDVI of 0.05-0.1). The thresholds were customised, employing the most effective interval ranges to present this set of data; classes for change detection increased by 0.05 until the class '>0.3'. This fixed increase accounts for both the smaller and larger changes in NDVI, enabling the area and severity of damage to be determined, ultimately allowing patterns of impact to be identified. Furthermore, the number of pixels within each threshold range can be extracted enabling calculations to be made that highlight the area (km^2) of land that has experienced a specific change in NDVI from pre- to post-hurricane. This data can be analysed in conjunction with the land cover attribute, enabling the land cover that sustained the most severe damage to be determined.

The final approach employed to analyse change in vegetation consisted of extracting the NDVI mean, minimum and maximum values across each of the ROIs, similar to Hu and Smith (2018). These values were extracted for immediately pre- and post-hurricane, and every 6 months post-hurricane from 2016 to 2021 within the peak growing seasons (April-July and September-November). Additionally, the mean NDVI from both growing seasons (2010-2015) were extracted to calculate the reference mean NDVI, as mentioned previously. Analysing both the minimum and maximum alongside the mean gives more detail of the range of change experienced from pre- to post-hurricane. Data was extracted in ENVI employing the 'Quick Stats' tool and was investigated further in Excel. Comparing post-hurricane NDVI to the reference mean NDVI enabled conclusions to be drawn regarding whether agricultural vegetation had returned to a 'near normal' status, inferring if Hurricane Matthew had a long-term impact on agricultural productivity. For example, the productivity of the newly planted crops in a new growing season would be dependent on the health of the land. Therefore, if the NDVI of agriculture declined post-hurricane, it could indicate long-term land degradation associated with Hurricane Matthew, in the form of soil erosion, or soil salinisation, for example. Thus, allowing conclusions to be drawn about the land covers/communes that were more severely impacted, meeting the 4th objective.

A key element of analysis is determining changes that are a result of the hurricane and not related to variability in the data. For example, analysis of pre-hurricane September-November mean NDVI (Table 5) show a difference of 0.052, thus any change in NDVI recorded post-hurricane <0.05 cannot be linked to the impact of the hurricane with certainty, as it could be considered natural variation. Therefore, to avoid addressing changes in NDVI that could be classed as seasonal fluctuations when assessing the impact post-hurricane, a rounded significance level of 0.05 was established. Thus, any change in mean NDVI recorded post-hurricane <0.05 cannot be linked to the impact of the hurricane with certainty, as it could be considered natural variation.

Table 6. September-November Growing Season Pre-Hurricane Mean NDVIs

	September-November Mean NDVIs					
Stats	2010 (MODIS)	2011 (MODIS)	2012 (MODIS)	2013 (Landsat)	2014 (MODIS)	2015 (Landsat)
Mean	0.757	0.763	0.745	0.781	0.730	0.762

3.6. CONCLUSION OF METHODS

To successfully meet the aim and objectives of this research, pilot studies were carried out to ensure that the most effective methods were employed. The first pilot study sought to find the best approach to mask and reduce CC; this was a major issue when collecting data, as it significantly reduced the area of the study site that could be assessed. The pilot study concluded that cloud-masked composite images were the most effective method to create cloud-reduced imagery. The second pilot study evaluated methods to assess impact and recovery, and concluded that due to a lack of/access to on-the-ground data, images could not be classified to the detail that was desired. Consequently, the final methodology was based on the analysis of NDVI to monitor changes in vegetation. The methods employed meet the aim and objectives, assessing the immediate impacts and monitoring the long-term recovery whilst assessing the vulnerability of land cover types across agriculturally dependant communes.

CHAPTER 4

4. RESULTS

The findings of this research will be addressed in the order of the objectives. Firstly, the pre-hurricane reference mean NDVI for each growing season will be presented, followed by the results of the immediate impacts, finishing with the long-term recovery. The results will go in-depth, comparing the communes and land covers (Figure 15) to aid understanding of the impacts and recovery of Hurricane Matthew across the Sud and Grand'Anse departments.

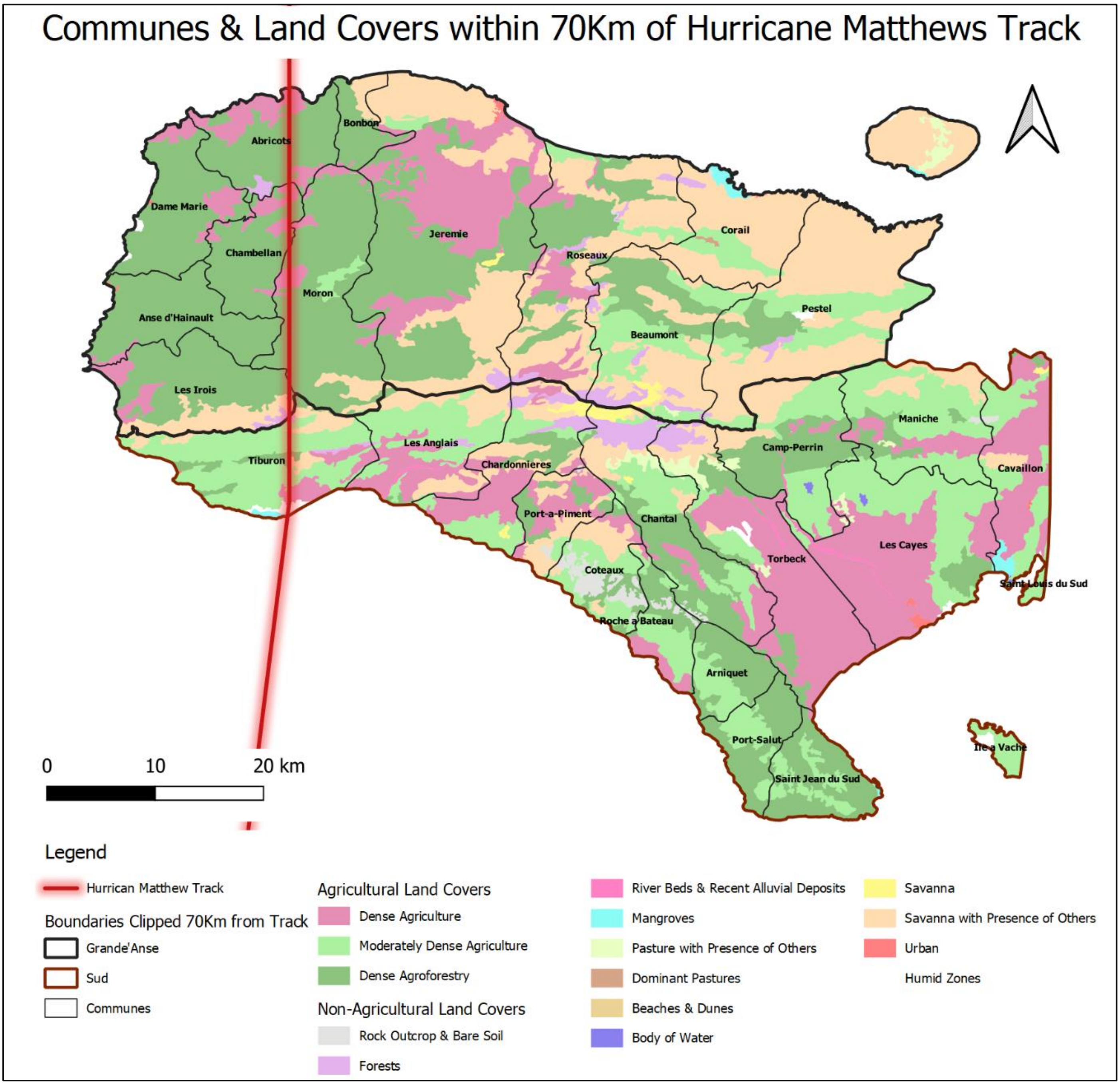


Figure 16. Map of ROI; Communes and Land Covers within 70km of Hurricane Matthews Track (As Found in Section 3.2).

4.1. PRE-HURRICANE VEGETATION

Pre-hurricane Reference Mean NDVIs were employed to assess when agricultural vegetation had returned to near normal, i.e., a mean NDVI above the reference mean NDVI. The reference mean NDVI data shows that consistently, across all agricultural land, communes, and land covers, the reference mean NDVI was higher in the September-November growing season than in April-July growing season (Table 6). Chambellan had the highest average NDVI within both growing seasons with Dame Marie reporting values 0.005 below Chambellan. In contrast, Les Cayes had the lowest reference mean NDVI, with the September-November reference mean NDVI being 0.659. Regarding agricultural land covers, *Agroforestry* had the highest reference mean NDVI, however, including non-agricultural land covers both *Forest* and *Savanna with Others* was higher than *Agroforestry*, showing that on average 'natural' land cover has higher NDVI values.

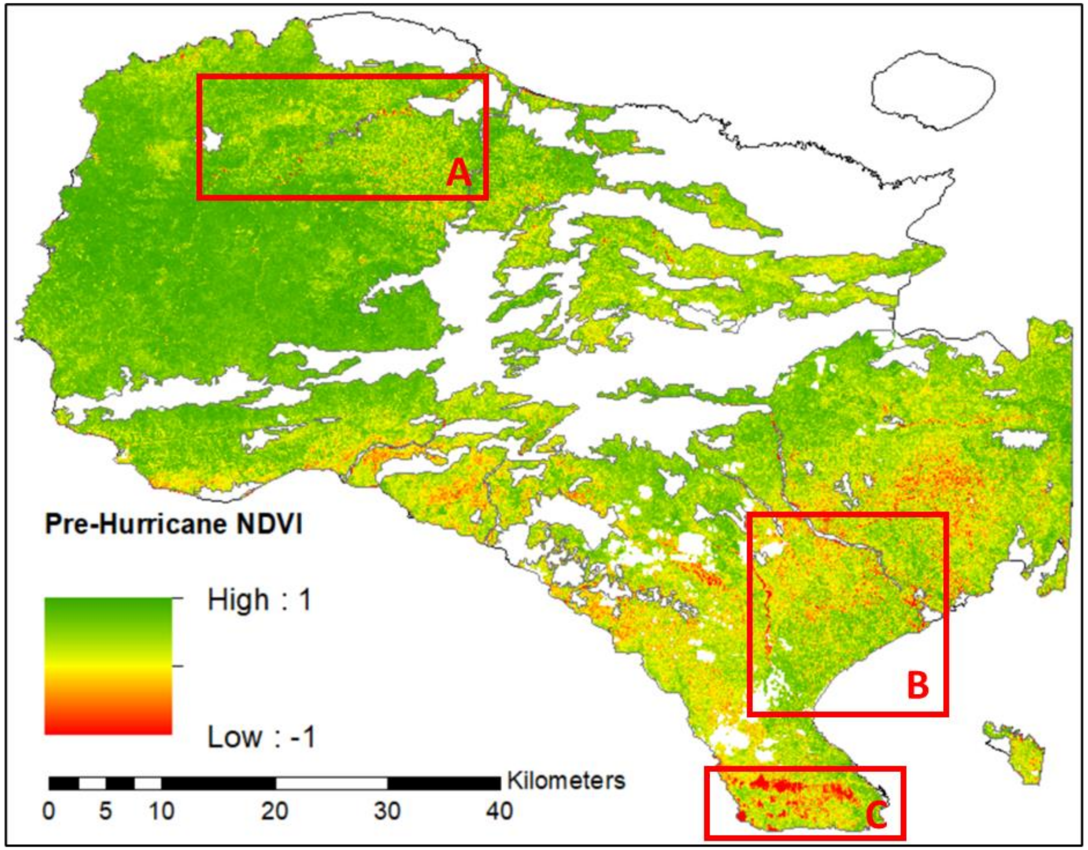
Table 7. Reference Mean NDVI for Each Growing Season, Including Land Covers and Communes.

	Sep - Nov Growing Season Reference Mean NDVI	April - July Growing Season Reference Mean NDVI
Agricultural Land	0.756	0.675
Non-Agricultural Land	0.784	0.711
Commune Agricultural Land		
Arniquet	0.701	0.591
Camp-Perrin	0.749	0.668
Chambellan	0.842	0.790
Dame Marie	0.835	0.785
Les Anglais	0.734	0.620
Les Cayes	0.659	0.568
Torbeck	0.707	0.629
Land Covers		
Agroforestry	0.792	0.724
Dense Agriculture	0.715	0.630
Moderately Dense Agriculture	0.737	0.642
Forest	0.808	0.748
Savanna with Others	0.800	0.727

4.2. IMMEDIATE SHORT-TERM IMPACT

4.2.1. COMPARISON OF PRE- AND POST-HURRICANE NDVI

To assess the immediate impact, the NDVI from pre- to post-hurricane was assessed and compared (Figure 16). Pre-Hurricane agricultural land, specifically in the north Grand'Anse Department, a region dominated by *Agroforestry*, had a high NDVI with the majority of NDVI values >0.75. Whereas pre-hurricane NDVI in the Sud Department was less consistent and, in some regions, NDVI values range from 0.2-0.3. However, on close inspection of agricultural land in the Torbeck commune, for example, many regions of *Dense Agriculture* report NDVI values >0.70. In the post-hurricane agricultural land NDVI, although subtle on a regional scale, generally, there is a decrease in NDVI; this is more prominent in the Sud department. In the northwest region of Grand'Anse (labelled 'A'), there is a decrease in NDVI seen within the valleys of the mountains. In certain regions, NDVI post-hurricane is <0.2, in contrast to pre-hurricane values in the same location >0.7. Within the southeast region, specifically, the communes of Les Cayes and Torbeck (labelled 'B') a decrease in NDVI is experienced throughout the region, with NDVI in many areas <0.5, particularly around river channels. Despite this overall decrease, there are some isolated clusters of *Dense Agriculture* near the coastline where NDVI values remain similar to pre-hurricane and in some cases increase (>0.75). Finally, the peninsular in the south (C), pre-hurricane has dense patches of negative NDVI reaching values <0.2 which have a higher NDVI post-hurricane.



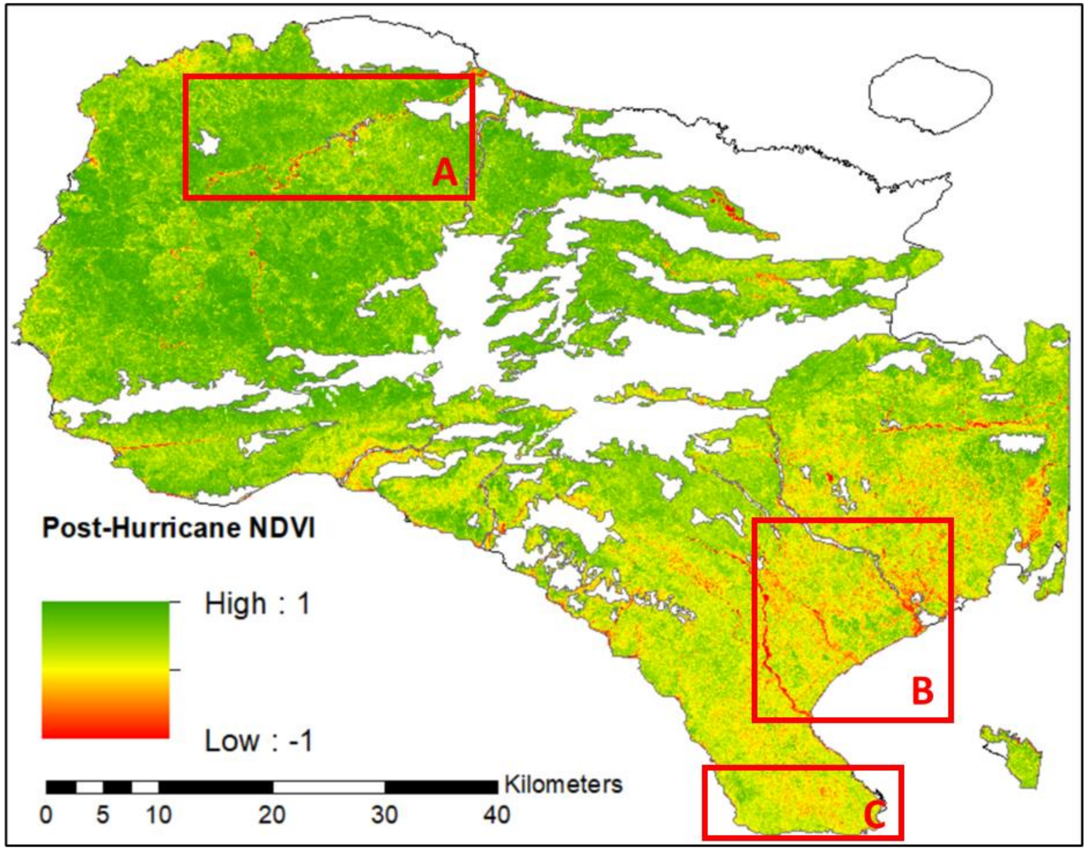
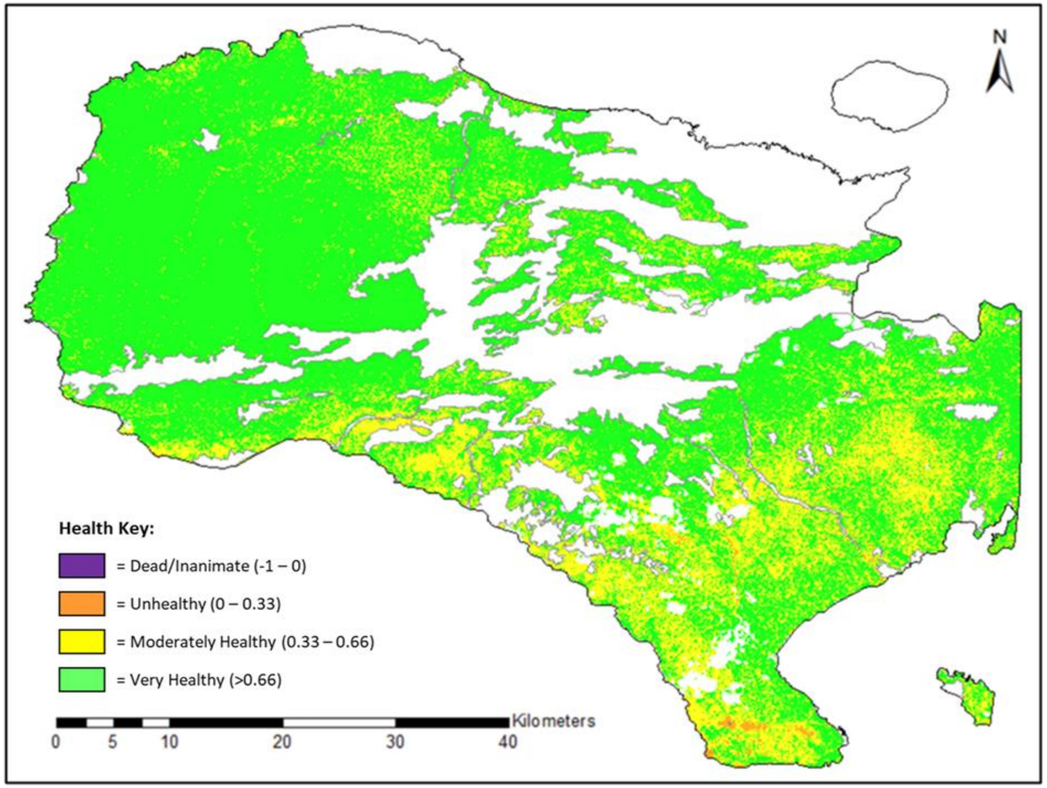


Figure 17. Pre-Hurricane NDVI (Left), Post-Hurricane NDVI (Right).

4.2.2. CHANGE DETECTION

Figure 17 highlights that overall, the NDVI of vegetation decreased, specifically in the Sud department, with large regions shifting from ‘very healthy vegetation’ to ‘moderately healthy vegetation’. This decrease is related to isolated areas of vegetation post-hurricane being classed as ‘unhealthy’ parallel to river courses within the Sud department. As seen in Figure 18, ‘very healthy’ vegetation decreased by 381.7 km^2, and ‘moderately healthy’ and ‘unhealthy vegetation’ increased by 406.9 km^2 and 37.5 km^2 respectively, from pre- to post-hurricane. Therefore, it can be confirmed that the area classed as ‘very healthy vegetation’ decreased post-Hurricane Matthew. Changes in NDVI from pre- to post-hurricane are largest within river valleys in the Grand’Anse department, and along the coastline of the Torbeck. For example, within valleys of the Grand’Anse department, decreases of 0.55 were seen (0.84 pre-hurricane to 0.29 post-hurricane). However, the average decrease in NDVI was 0.053 from pre- to post-hurricane, therefore, as seen in Figure 17, much of the land remains in the same class.



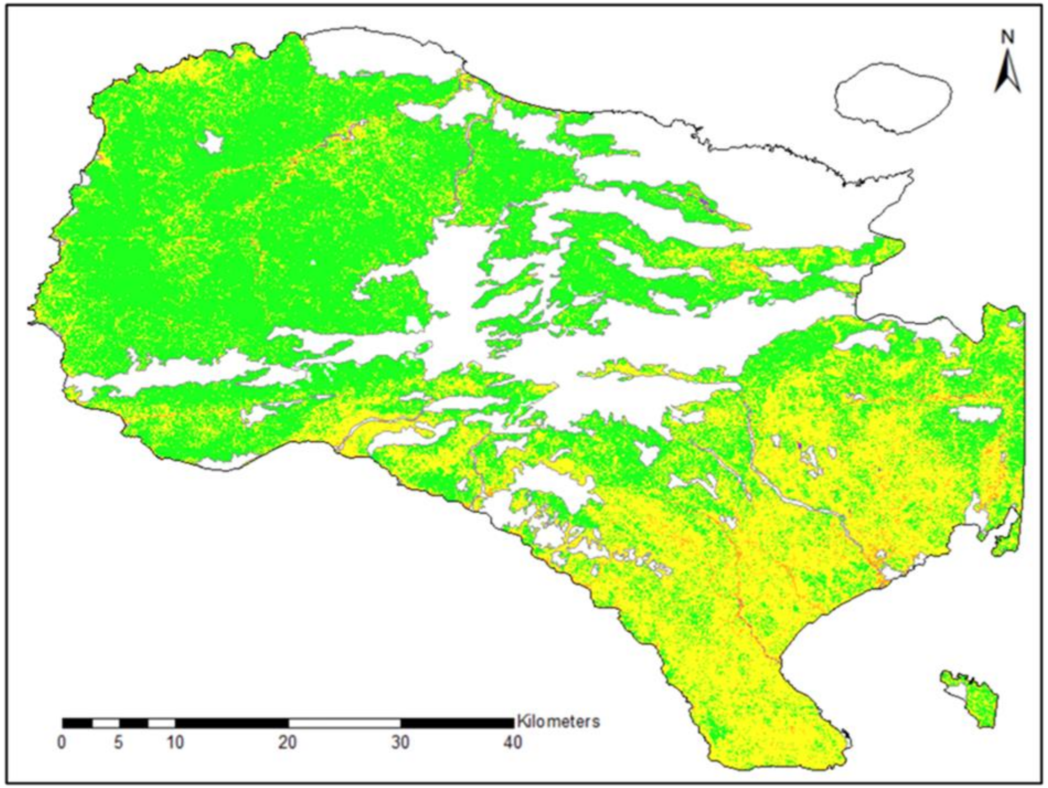


Figure 18. Pre-Hurricane (Left) vs Post-Hurricane (Right) NDVI Change Detection.

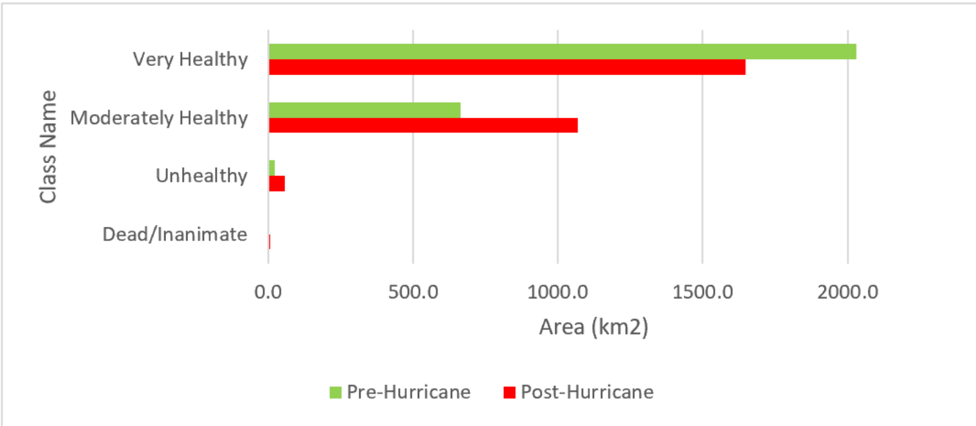


Figure 19. Pre vs Post-Hurricane NDVI Health Change Detection Area (km2).

4.2.3. NDVI MEAN, MINIMUM, AND MAXIMUM & THRESHOLD MAPS SHOWING CHANGE IN NDVI

Figure 19 highlights areas of damage across the ROI. Negative values of change, which this study is more concerned with are represented in tones of red. Whereas areas that have experienced a positive change are highlighted in green. Within the thresholds of change maps, all areas that are classed as 'Unclassified' (areas of white within the imagery with no border around) are regions of cloud that were masked, but not filled in the creation of the composite; therefore, they contain no value. Figure 19 emphasises the isolated incidents of damage running parallel/surrounding river channels, as well as the more widespread damage seen in the Sud department. The most significant damage (decrease in NDVI >0.3) was experienced within the communes of Camp-Perrin and Torbeck, along the coastline and within river valleys. For example, parallel to Torbeck's coastline, NDVI in regions of Dense Agricultural land decreased from values >0.83 to <0.43. Conversely, there are some regions that have increased in NDVI; one region where the NDVI increased from pre- to post-hurricane is along the south coast in the commune of Tiburon. There is a vertical band of *Moderately Dense Agriculture*, whereby regions of NDVI pre-hurricane were <0.47, however post-hurricane were >0.81.

In conjunction with change detection, the mean, minimum, and maximum NDVI statistics of both agricultural and non-agricultural land covers and agriculturally dependent communes were extracted and compared to further understand the overall impact. Assessing the change in NDVI from pre- to post-hurricane and the difference between post-hurricane NDVI and the reference mean NDVI across land cover types and communes highlights what regions sustained more damage (Table 7), enabling further understanding of the overall impact.

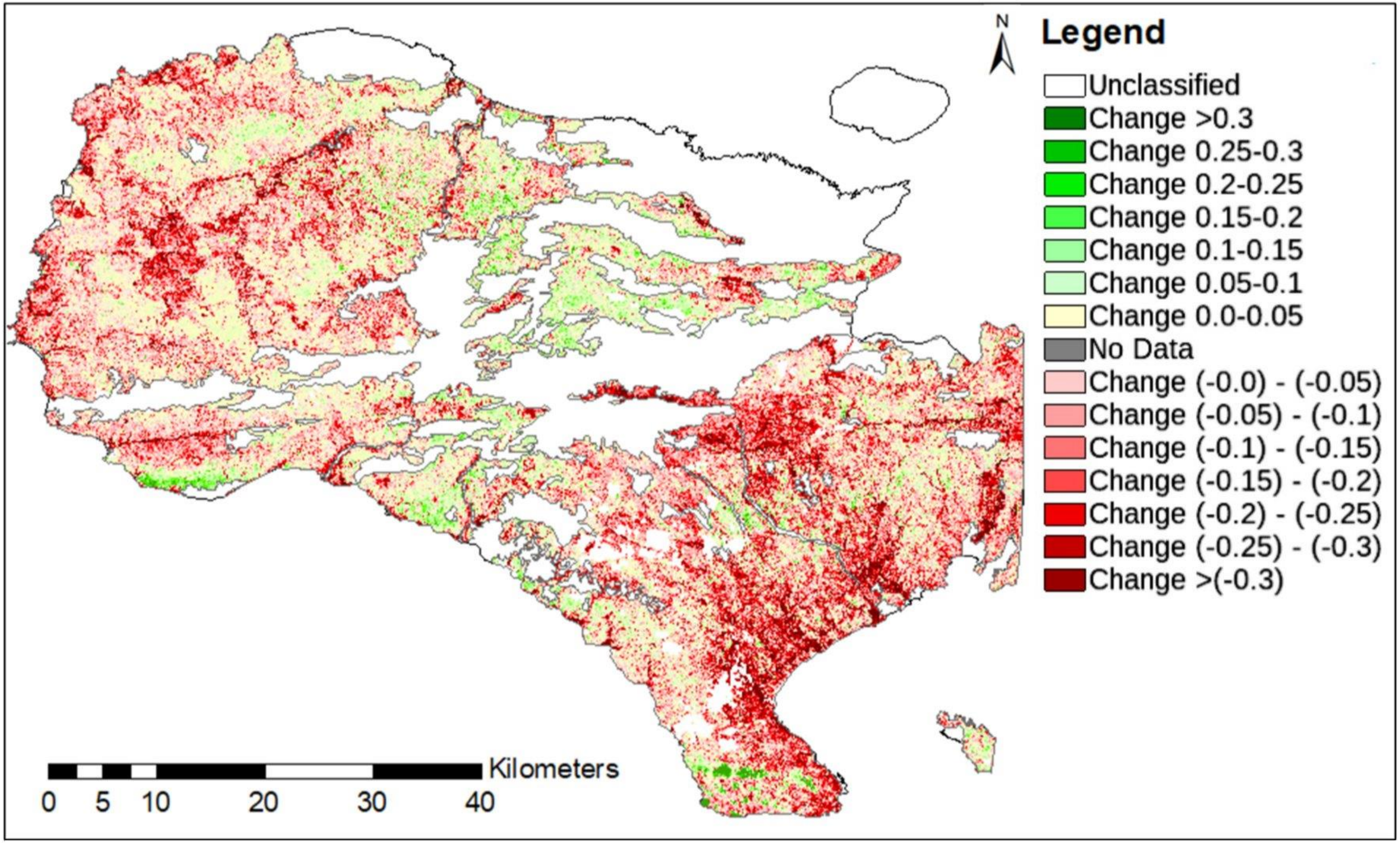


Figure 20. Threshold Map Highlighting the Change in NDVI from Pre to Post-Hurricane Matthew.

Table 8. A) Land Covers, Change in NDVI Pre to Post-Hurricane Ranked; B) Land Covers, Difference Between Post-Hurricane NDVI and Reference Mean NDVI Ranked; C) Communes, Change in NDVI Pre to Post-Hurricane Ranked; D) Communes, Difference Between Post-Hurricane

A		
Land Cover	**Change in NDVI from Pre- to Post-Hurricane**	**Rank**
Forest	-0.086	1
Dense Agriculture	-0.064	2
Agroforestry	-0.063	3
Moderately Dense Agriculture	-0.034	4
Savanna with Others	-0.012	5

B		
Land Cover	**Difference Between Post-Hurricane NDVI and Reference mean NDVI**	**Rank**
Forest	-0.099	1
Dense Agriculture	-0.090	2
Agroforestry	-0.078	3
Moderately Dense Agriculture	-0.077	4
Savanna with Others	-0.052	5

C		
Communes	**Change in NDVI from Pre- to Post-Hurricane**	**Rank**
Chambellan	-0.125	1
Torbeck	-0.110	2
Camp-Perrin	-0.106	3
Les Cayes	-0.088	4
Arniquet	-0.062	5
Dame Marie	-0.062	5
Les Anglais	-0.040	6

D		
Communes	**Difference Between Post-Hurricane NDVI and Reference mean NDVI**	**Rank**
Torbeck	-0.140	1
Camp-Perrin	-0.124	2
Arniquet	-0.121	3
Les Cayes	-0.112	4
Chambellan	-0.083	5
Les Anglais	-0.074	6
Dame Marie	-0.072	7

Table 8 and Figure 19 show that overall, there was a larger negative impact across agricultural land, with the mean NDVI decreasing by 0.055 from pre- to post-hurricane, in comparison to only 0.025 (pre- to post-hurricane) in non-agricultural land. This is also reinforced by the minimum value where the minimum NDVI decreased by 0.075 from pre- to post-hurricane in comparison to non-agricultural land only decreasing by 0.013.

Table 9. Pre- vs Post-Hurricane NDVI Statistics Across Agricultural Land vs Non-Agricultural Land.

	Agricultural Land			Non-Agricultural Land		
Stats	Pre-Hurricane	Post-Hurricane	Difference Between Pre and Post	Pre-Hurricane	Post-Hurricane	Difference Between Pre and Post
Mean	0.731	0.676	-0.055	0.741	0.716	-0.025
Min	-0.915	-0.991	-0.075	-0.973	-0.985	-0.013
Max	1.000	1.000	0.000	1.000	1.000	0.000

The commune of Arniquet is ranked the 5th most damaged commune based on the difference in mean NDVI from pre- to post-hurricane. However, based on the difference between minimum NDVI values pre- to post-hurricane, Arniquet is ranked 1st, with the minimum NDVI decreasing by 0.918 (Table 9). It can be inferred that some regions within this commune have sustained severe damage, however, the area experiencing the damage is only a small region, therefore did not have a large influence on mean NDVI. Coupled with the threshold map (Figure 20), it is apparent that significant damage has occurred within the east and west of the commune, in particular, running parallel to River Carpentier. In comparison, the central region sustained little damage, with some areas of agricultural land experiencing increases in NDVI. Thus, reducing the influence of severe damage on mean NDVI.

Table 10. Arniquet Pre- vs Post-Hurricane NDVI Statistics.

Communes	Arniquet			
Stats	Pre-Hurricane	Post-Hurricane	Difference Between Pre and Post	Difference Between Post-Hurricane Mean & Reference Mean NDVI
Mean	0.642	0.580	**-0.063**	**-0.121**
Min	0.229	-0.689	**-0.918**	
Max	0.889	0.903	**0.014**	

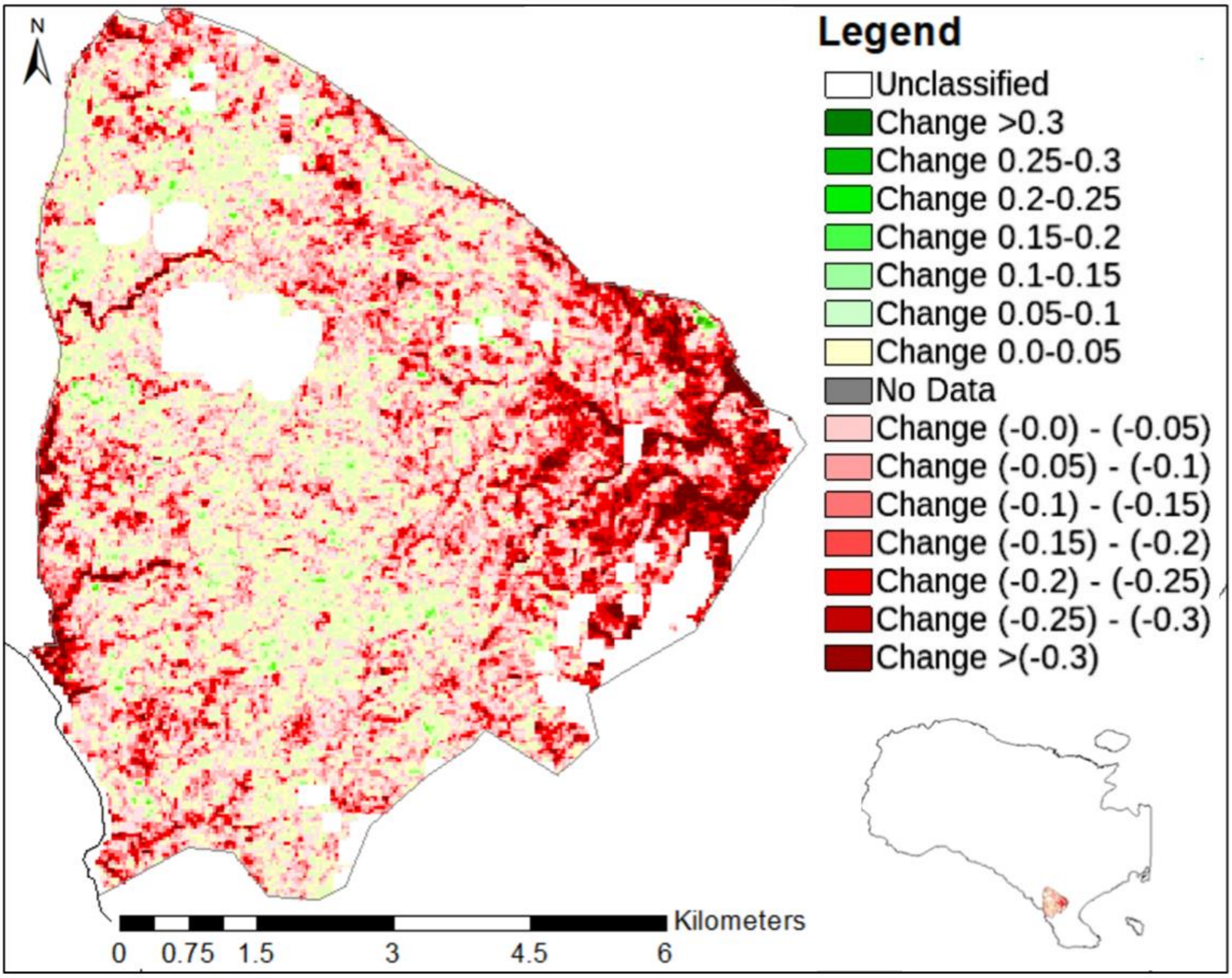


Figure 21. Threshold Map of Arniquet Agricultural Land.

By assessing the change in mean and minimum NDVI values pre- to post-hurricane alongside the difference between mean NDVI post-hurricane and the reference mean NDVI, the two most impacted communes are Torbeck and Camp-Perrin. Torbeck's mean NDVI (Table 10) is the lowest below the reference mean NDVI and experiences the largest change in mean NDVI from pre- to post-hurricane (decreasing by 0.112). Additionally, the commune showed a considerable decrease in minimum NDVI (0.361) from pre- to post-hurricane. Figure 22 shows that damage took place on a wide scale within the commune, with dense areas of negative change in NDVI >0.3 lying close to the coastline. The area of damage experiencing a decrease in NDVI >0.3 appears to reduce moving inland with the decrease in NDVI typically being <0.2.

Table 11. Torbeck Pre vs Post-Hurricane NDVI Statistics.

Communes	Torbeck			
Stats	Pre-Hurricane	Post-Hurricane	Difference Between Pre and Post	Difference Between Post-Hurricane & Reference Mean NDVI
Mean	0.679	0.568	**-0.112**	**-0.139**
Min	-0.533	-0.894	**-0.361**	
Max	0.993	0.956	**-0.038**	

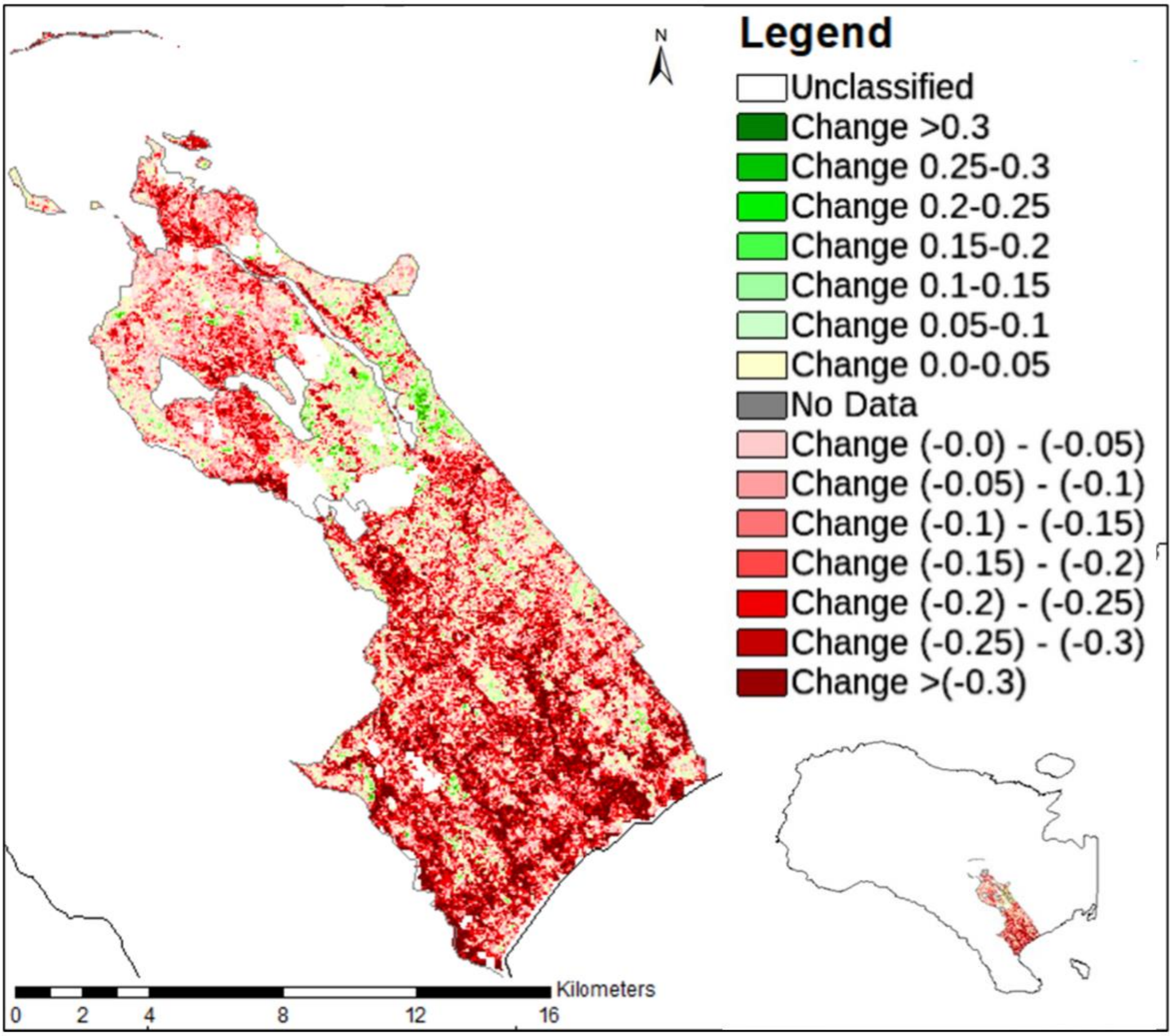


Figure 21. Threshold Map, Torbeck Agricultural Land.

Similarly, Camp-Perrin was the second most impacted commune based on the mean and minimum change in NDVI from pre- to post-hurricane and the difference between mean NDVI post-hurricane and reference mean NDVI (Table 11). Consequently, the mean NDVI is 0.125 below the September-November growing season reference mean NDVI and the minimum NDVI value decreased by 0.597 post-hurricane. Figure 23 highlights that the most severe damage is concentrated within the centre of this commune running from east to west with certain regions experiencing a decrease in NDVI >0.38 from pre- to post-hurricane. In contrast, regions to the north and south experience an increase in NDVI >0.2.

Table 12. Camp-Perrin Pre- vs Post-Hurricane NDVI Statistics.

Communes	**Camp-Perrin**			
Stats	**Pre-Hurricane**	**Post-Hurricane**	**Difference Between Pre and Post**	**Difference Between Post-Hurricane & Reference Mean NDVI**
Mean	0.731	0.625	**-0.107**	**-0.125**
Min	0.037	-0.560	**-0.597**	
Max	1.000	0.985	**-0.015**	

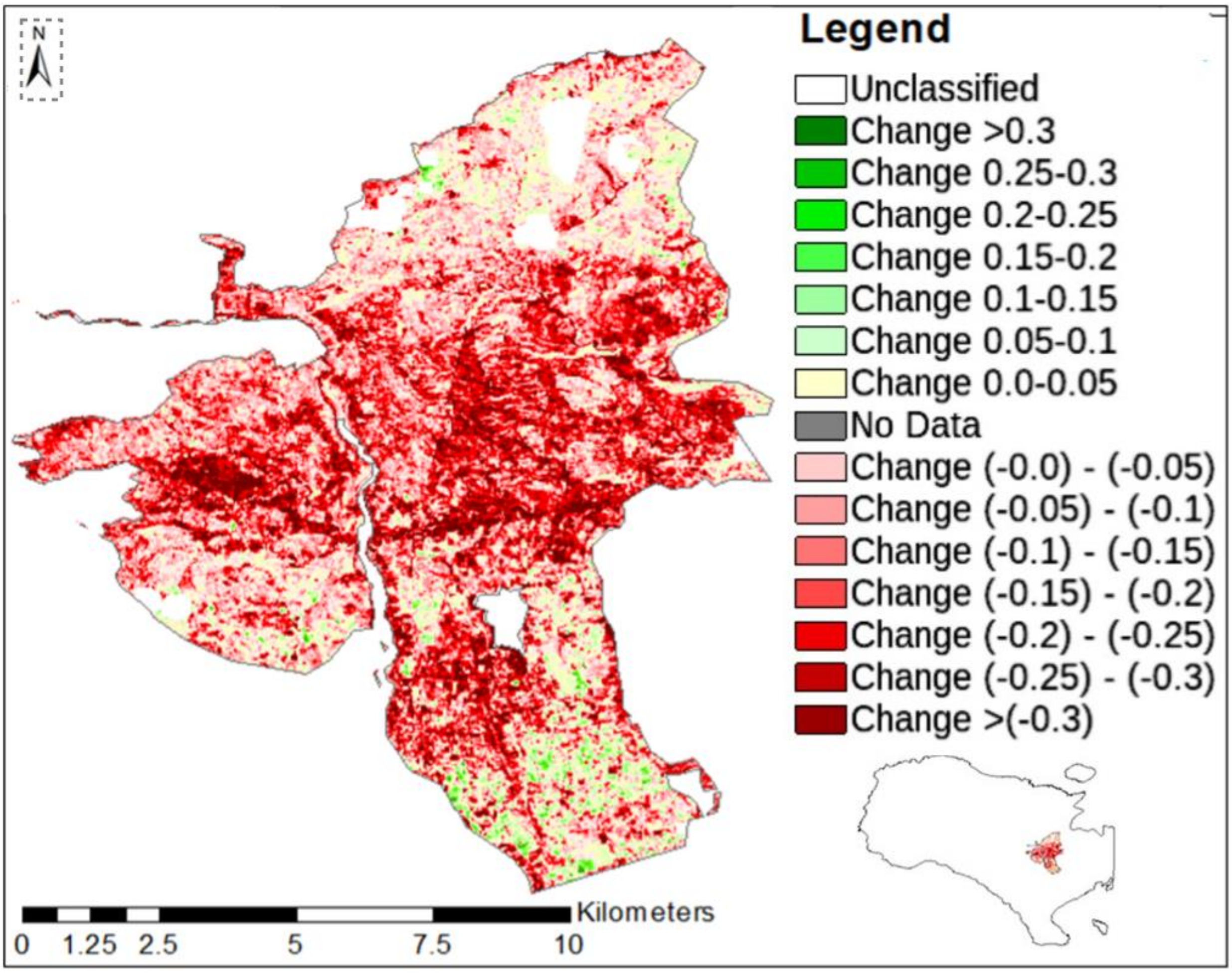


Figure 22. Threshold Map, Camp-Perrin Agricultural Land.

Les Cayes was the commune that experienced the smallest difference in the minimum NDVI from pre- to post-hurricane, decreasing by 0.053 (Table 12). Despite this, the mean NDVI decreased by 0.088 post-hurricane, 0.112 below the reference mean NDVI for the September to November growing season. Figure 24 shows that dense areas of damage (decrease in NDVI >0.3) are concentrated around/to the north of the main urban area circled in the figure. Additionally, the large negative changes in NDVI within this commune follow the patterns of valleys and channels.

Table 13. Les Cayes Pre vs Post-Hurricane NDVI Statistics.

Communes	**Les Cayes**			
Stats	**Pre-Hurricane**	**Post-Hurricane**	**Difference Between Pre and Post**	**Difference Between Post-Hurricane & Reference Mean NDVI**
Mean	0.635	0.547	**-0.088**	**-0.112**
Min	-0.786	-0.839	**-0.053**	
Max	0.982	0.979	**-0.003**	

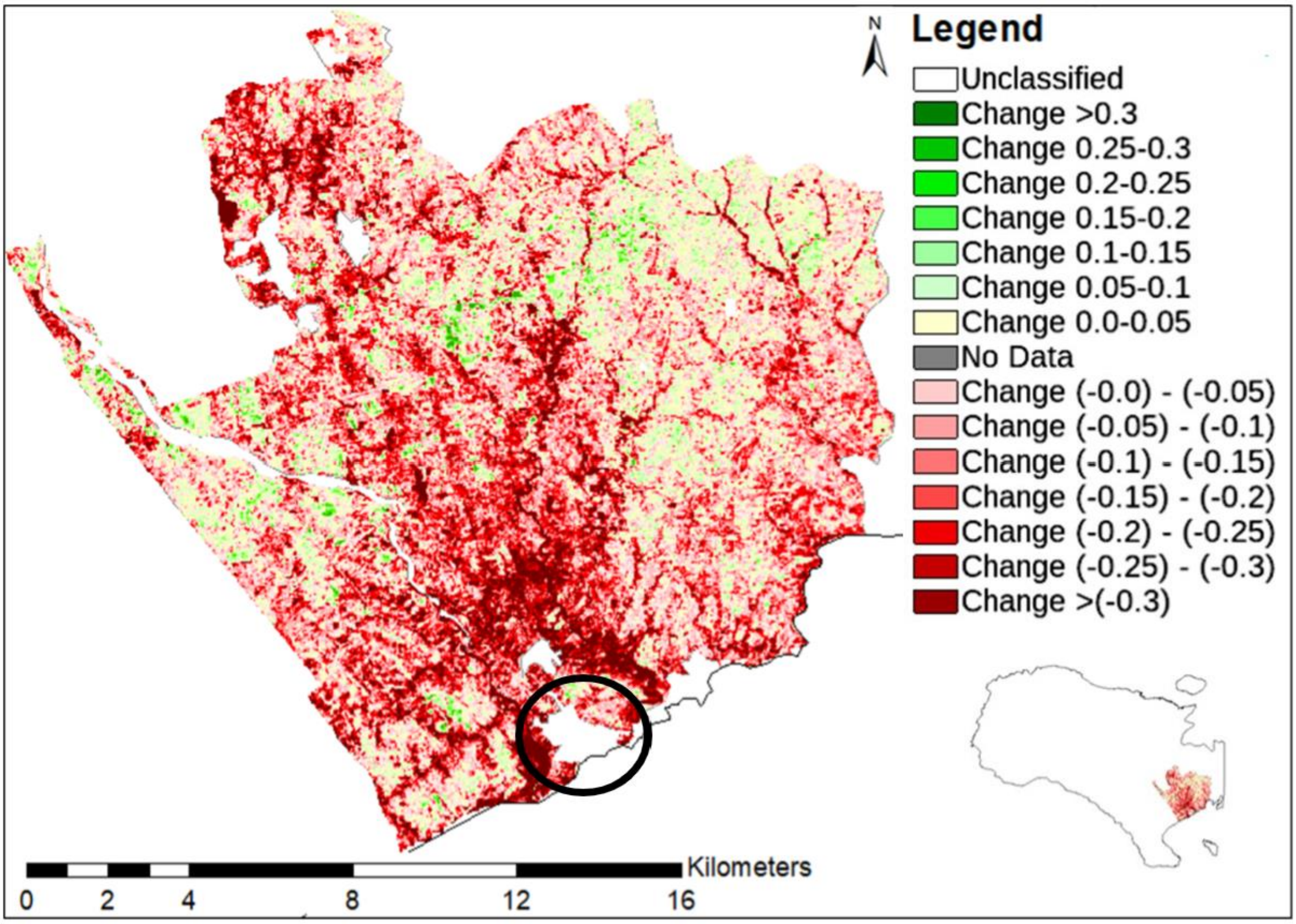


Figure 23. Threshold Map, Les Cayes Agricultural Land.

Finally, Dame Marie and Chambellan emphasise the severe damage that can be seen running parallel to the coast and around river channels. Dame Marie experienced a 0.400 decrease in the minimum NDVI from pre- post-hurricane (Table 13), highlighting that some regions sustained significant damage. Figure 25 shows that change in NDVI >-0.3 was common, along the coastline and to the northeast/southeast of the town of Dame Marie, circled in the figure. In contrast, the more severe damage in Chambellan surrounded valleys (Figure 26). Although areas of damage within this commune are large, with some areas of damage decreasing from >0.87 pre-hurricane to <0.36, the mean NDVI was only 0.083 below the reference mean NDVI (Table 14). This could be because there are increases in NDVI post-hurricane in the north of the region.

Table 14. Dame Marie Pre vs Post-Hurricane NDVI Statistics.

Communes	Dame Marie			
Stats	Pre-Hurricane	Post-Hurricane	Difference Between Pre and Post	Difference Between Post-Hurricane & Reference Mean NDVI
Mean	0.825	0.763	**-0.062**	**-0.071**
Min	-0.408	-0.807	**-0.400**	
Max	0.993	0.991	**-0.002**	

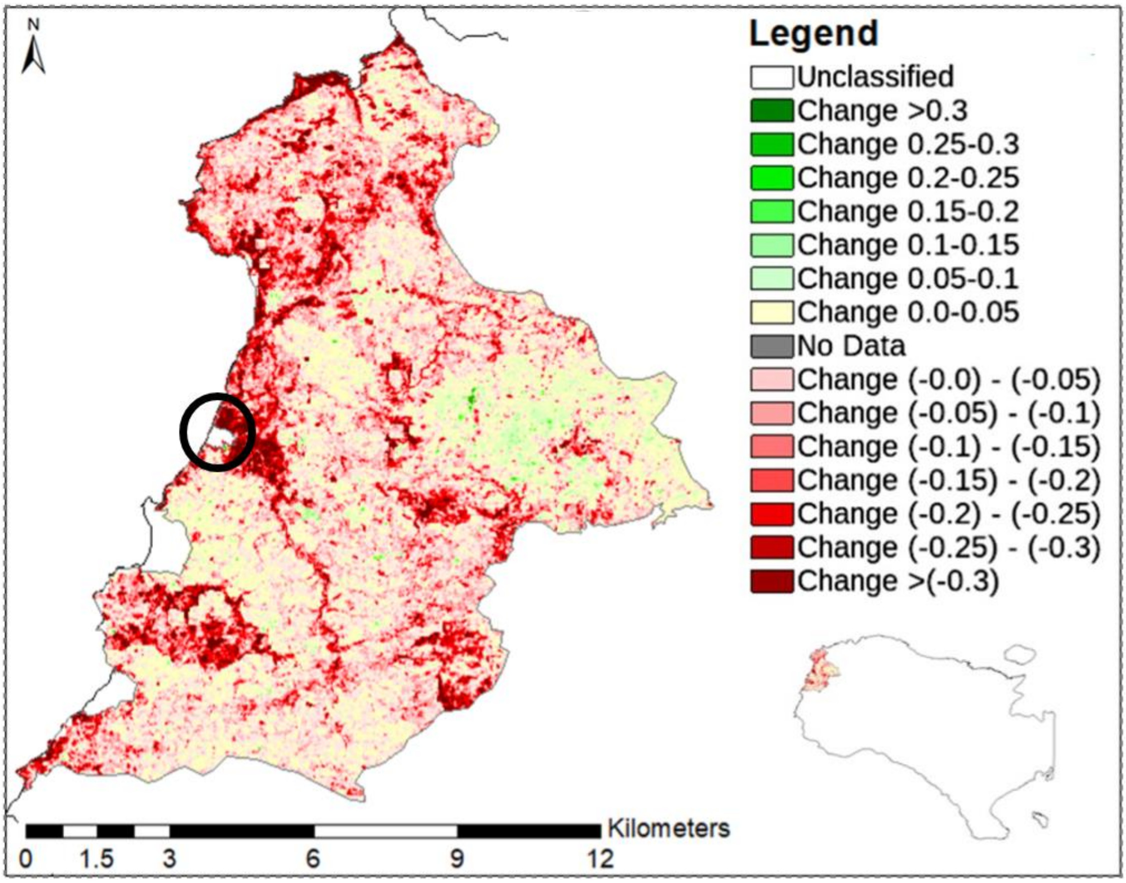


Table 15. Chambellan Pre vs Post Hurricane NDVI Statistics

Figure 24. Threshold Map, Dame Marie Agricultural Land.

Communes	Chambellan			
Stats	Pre-Hurricane	Post-Hurricane	Difference Between Pre and Post	Difference Between Post-Hurricane & Reference Mean NDVI
Mean	0.844	0.759	**-0.086**	**-0.083**
Min	0.039	-0.152	**-0.191**	
Max	0.995	0.989	**-0.006**	

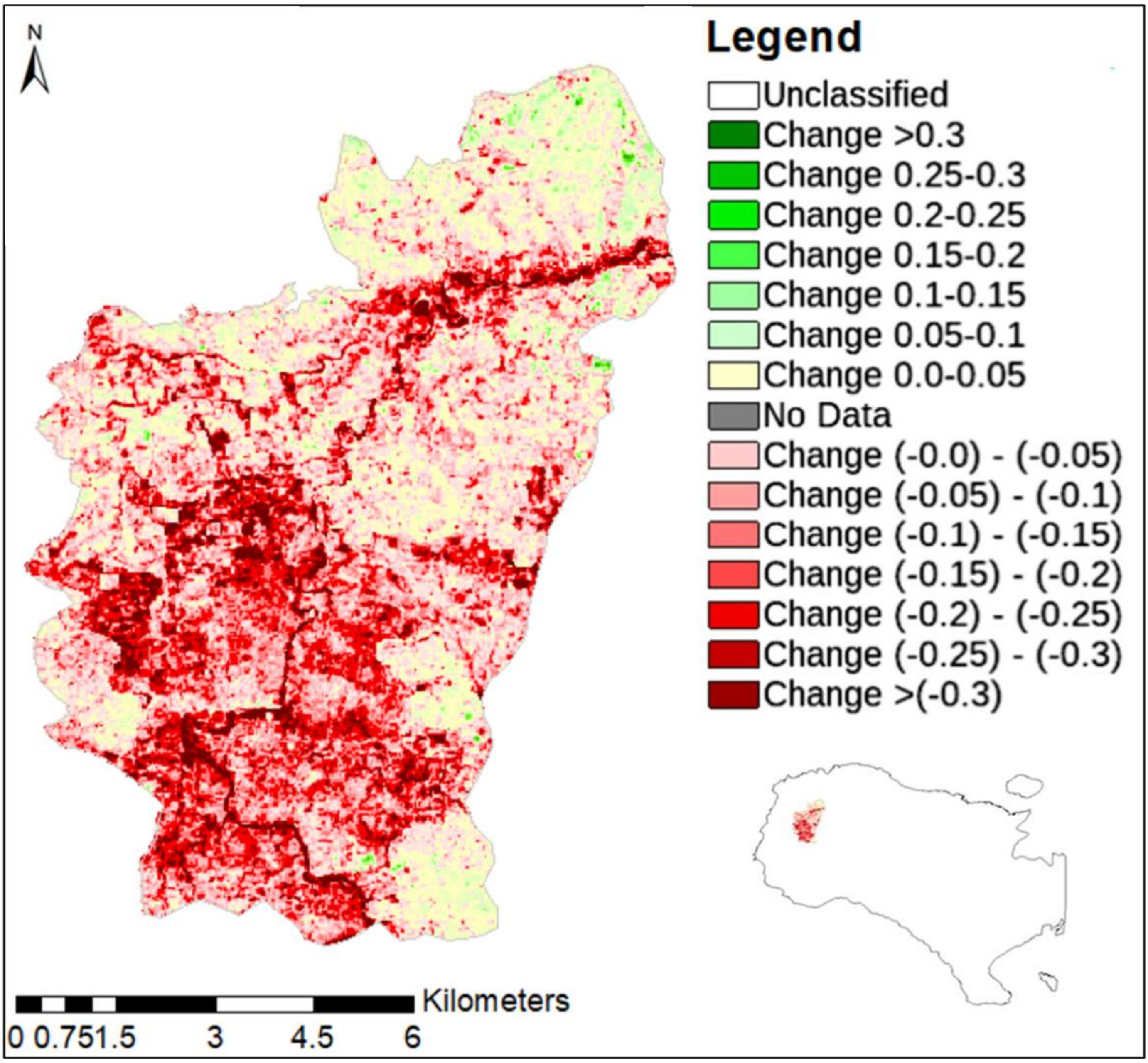


Figure 25. Threshold Map, Chambellan Agricultural Land.

In regard to land cover, the results of the difference between the mean NDVI post-hurricane compared to the reference mean NDVI showed that *Dense Agriculture* was the most severely damaged agricultural land cover (Table 15). *Dense Agriculture*'s mean NDVI was 0.089 below the reference mean NDVI with most damage being in the Torbeck commune (Figure 27). In contrast, *Agroforestry*'s mean NDVI post-hurricane was 0.078 below the average (Table 16). Despite this, *Agroforestry* had a larger decrease in minimum NDVI (decreasing by 0.369) which is considerably more than what is seen across the other two agricultural land covers. This large decrease was concentrated in certain regions circled in Figure 28; A) Dame Marie/Chambellan, B) Camp-Perrin and C) Saint Jean De Sud. Within all these regions, decreases in NDVI >0.3 are experienced, for example, regions along the coastline of Saint Jean De Sud decreases in NDVI from 0.90 to 0.45. Similar values are recorded in the valleys of 'A' and within the region labelled 'B'.

Table 16. Dense Agriculture Pre vs Post-Hurricane NDVI Statistics.

Land Covers	**Dense Agriculture**			
Stats	**Pre-Hurricane**	**Post-Hurricane**	**Difference Between Pre and Post**	**Difference Between Post-Hurricane & Reference Mean NDVI**
Mean	**0.689**	**0.625**	**-0.063**	**-0.089**
Min	**-0.786**	**-0.975**	**-0.189**	
Max	**0.999**	**1.000**	**0.001**	

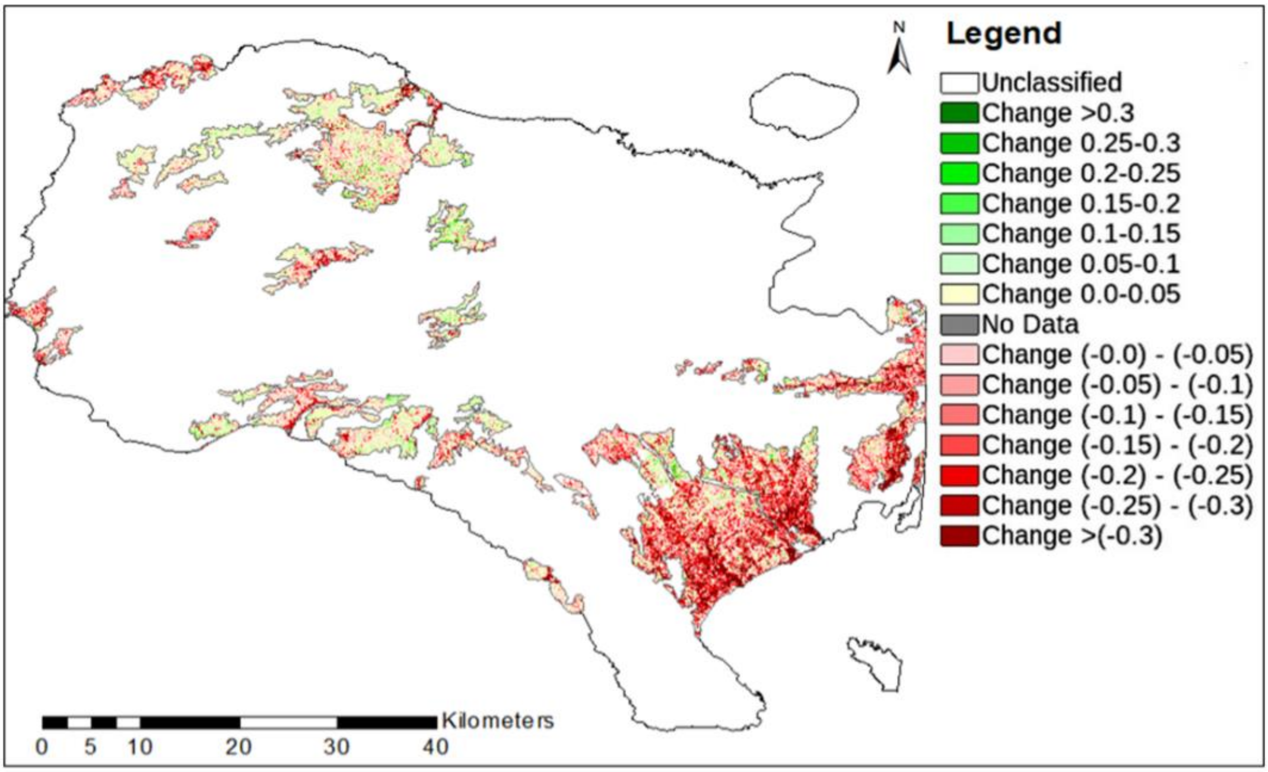


Figure 26. Threshold Map, Dense Agriculture.

Table 17. Agroforestry Pre vs Post-Hurricane NDVI Statistics.

Land Covers	Agroforestry			
Stats	Pre-Hurricane	Post-Hurricane	Difference Between Pre and Post	Difference Between Post-Hurricane & Reference Mean NDVI
Mean	**0.777**	**0.714**	**-0.064**	**-0.078**
Min	**-0.622**	**-0.991**	**-0.369**	
Max	**1.000**	**1.000**	**0.000**	

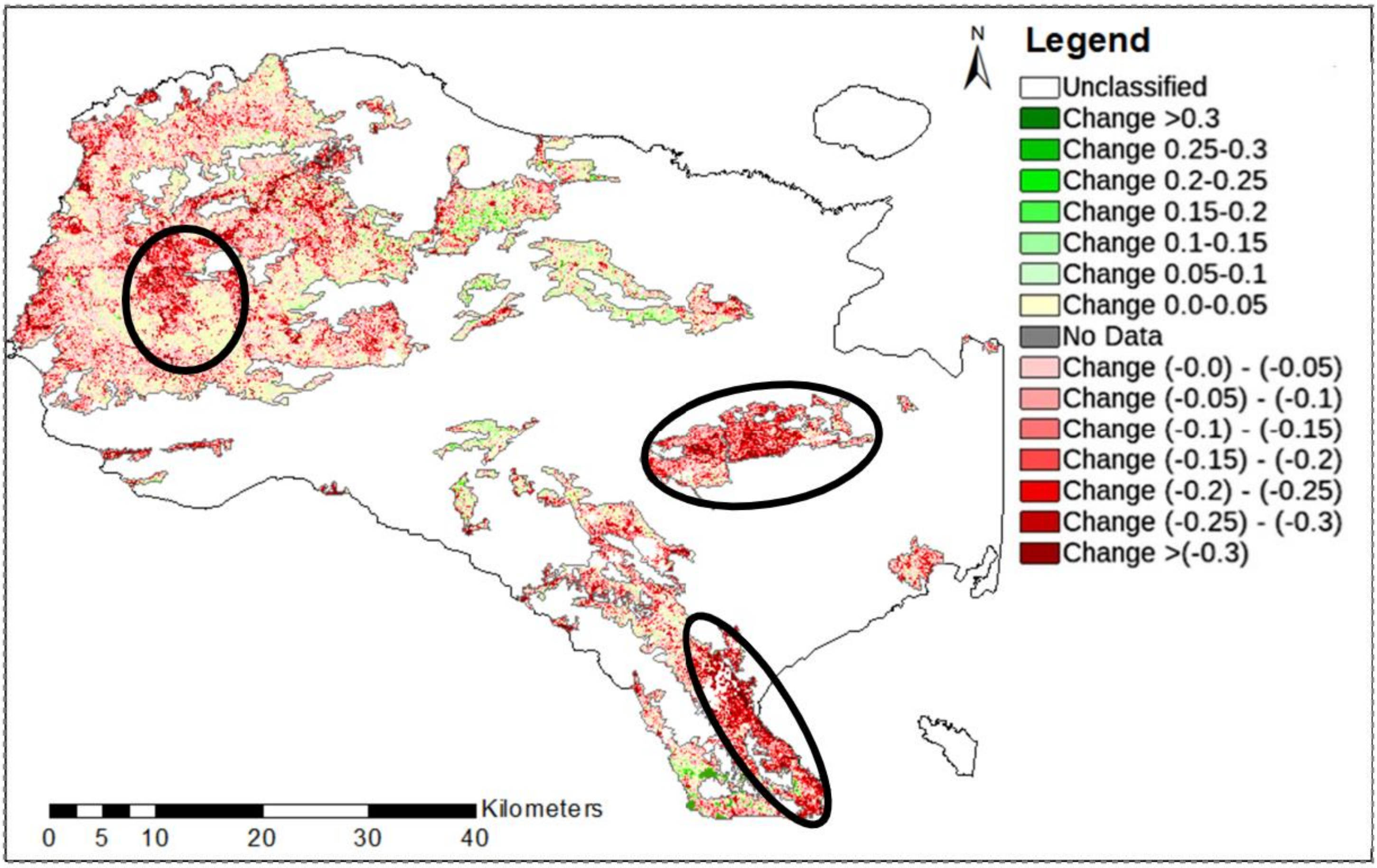


Figure 27. Threshold Map, Agroforestry.

The NDVI statistics for non-agricultural land cover, *Forest*, and *Savanna with Others*, allowed for further comparison of the severity of damage. Out of all land covers, *Forest* was the most damaged with the minimum NDVI decreasing by 0.733 from pre- to post-hurricane, consequently, the mean NDVI decreased by 0.086 (Table 17). *Forest* lies predominantly within the centre of the ROI, with dense regions of damage within the east (Figure 29).

Table 18. Forest Pre vs Post-Hurricane NDVI Statistics.

Land Covers	Forest			
Stats	Pre-Hurricane	Post-Hurricane	Difference Between Pre and Post	Difference Between Post-Hurricane & Reference Mean NDVI
Mean	0.795	0.709	-0.086	-0.098
Min	0.114	-0.619	-0.733	
Max	0.996	1.000	0.004	

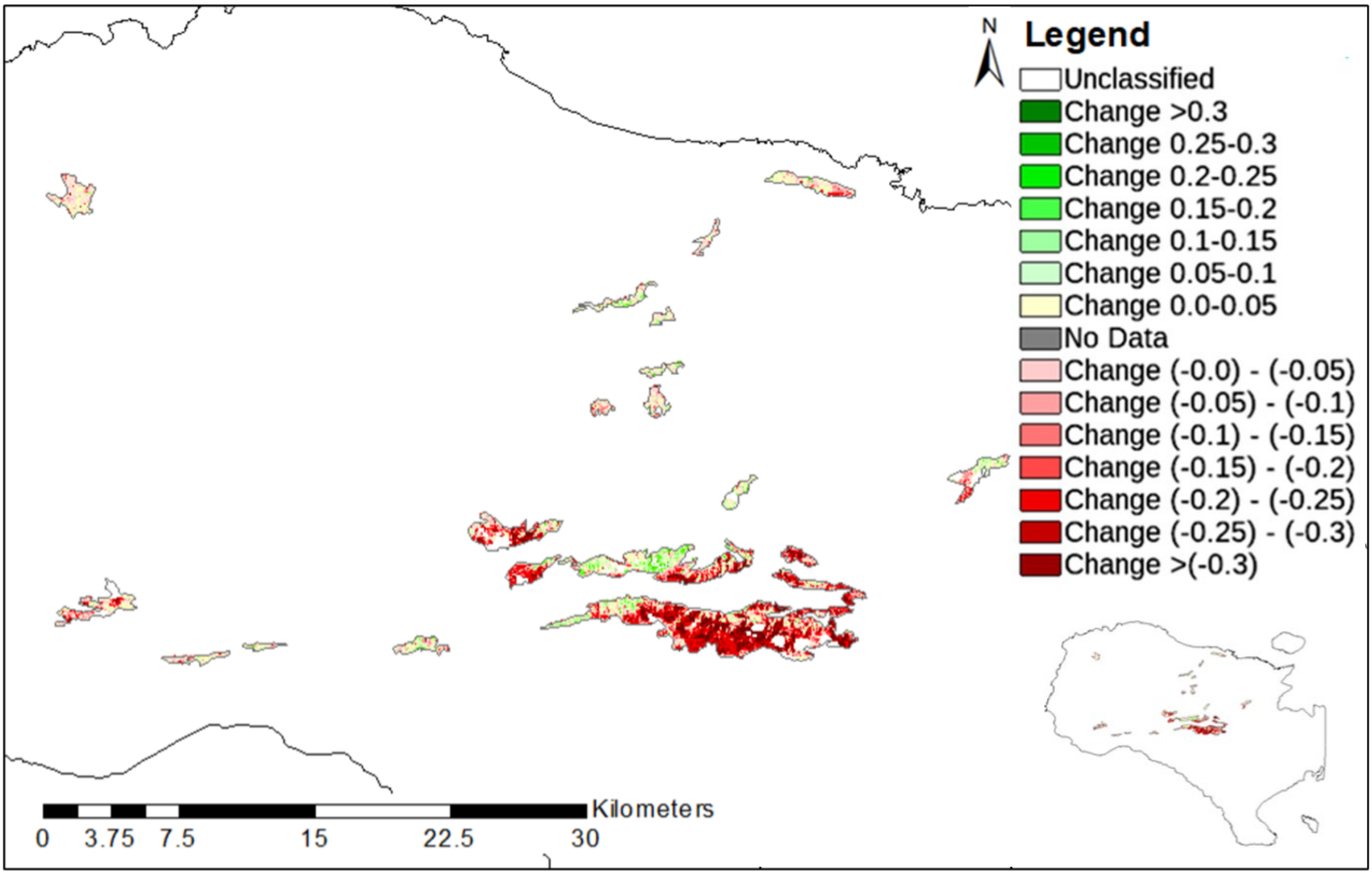


Figure 28. Threshold Map, Forest.

Across the ROIs assessed, Les Anglais (0.040), Moderately Dense Agriculture (0.034) and Savanna with the Presence of Others (0.012) experienced a change in mean NDVI from pre- to post-hurricane <0.05. Therefore, based on the significance level established in section 3.5.2., the changes experienced (Figures 30-32 and Tables 18-20) are not likely to be the result of the hurricane.

Table 19. Les Anglais Pre vs Post-Hurricane NDVI Statistics.

Communes	Les Anglais			
Stats	Pre-Hurricane	Post-Hurricane	Difference Between Pre and Post	Difference Between Post-Hurricane & Reference Mean NDVI
Mean	0.700	0.660	**-0.040**	**-0.074**
Min	-0.182	-0.315	**-0.133**	
Max	0.995	0.958	**-0.038**	

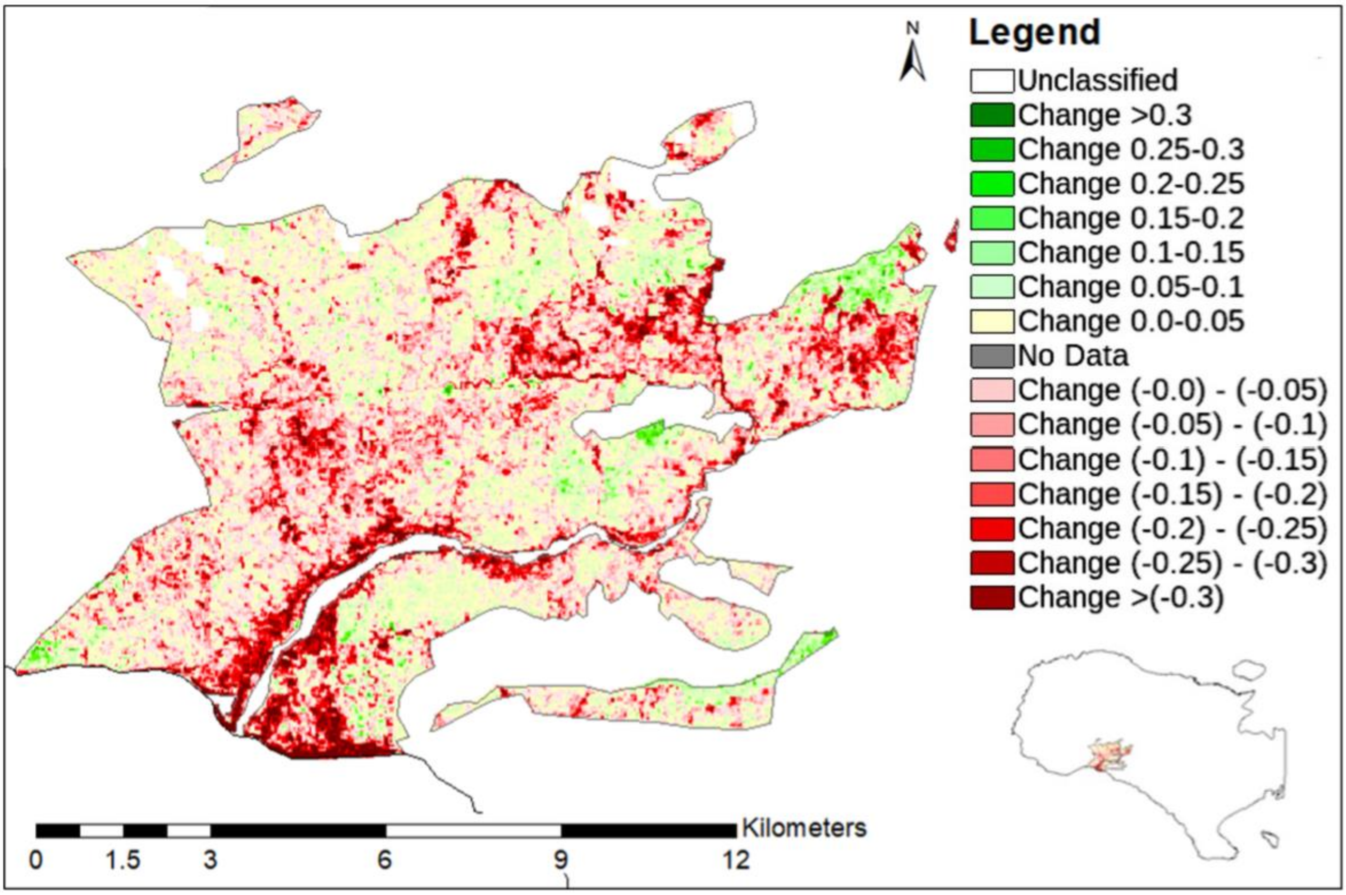


Figure 29. Threshold Map, Les Anglais Agricultural Land.

Table 20. Moderately Dense Agriculture Pre vs Post-Hurricane NDVI Statistics.

Land Covers	Moderately Dense Agriculture			
Stats	Pre-Hurricane	Post-Hurricane	Difference Between Pre and Post	Difference Between Post-Hurricane & Reference Mean NDVI
Mean	**0.694**	**0.660**	**-0.034**	**-0.077**
Min	**-0.915**	**-0.980**	**-0.064**	
Max	**1.000**	**1.000**	**0.000**	

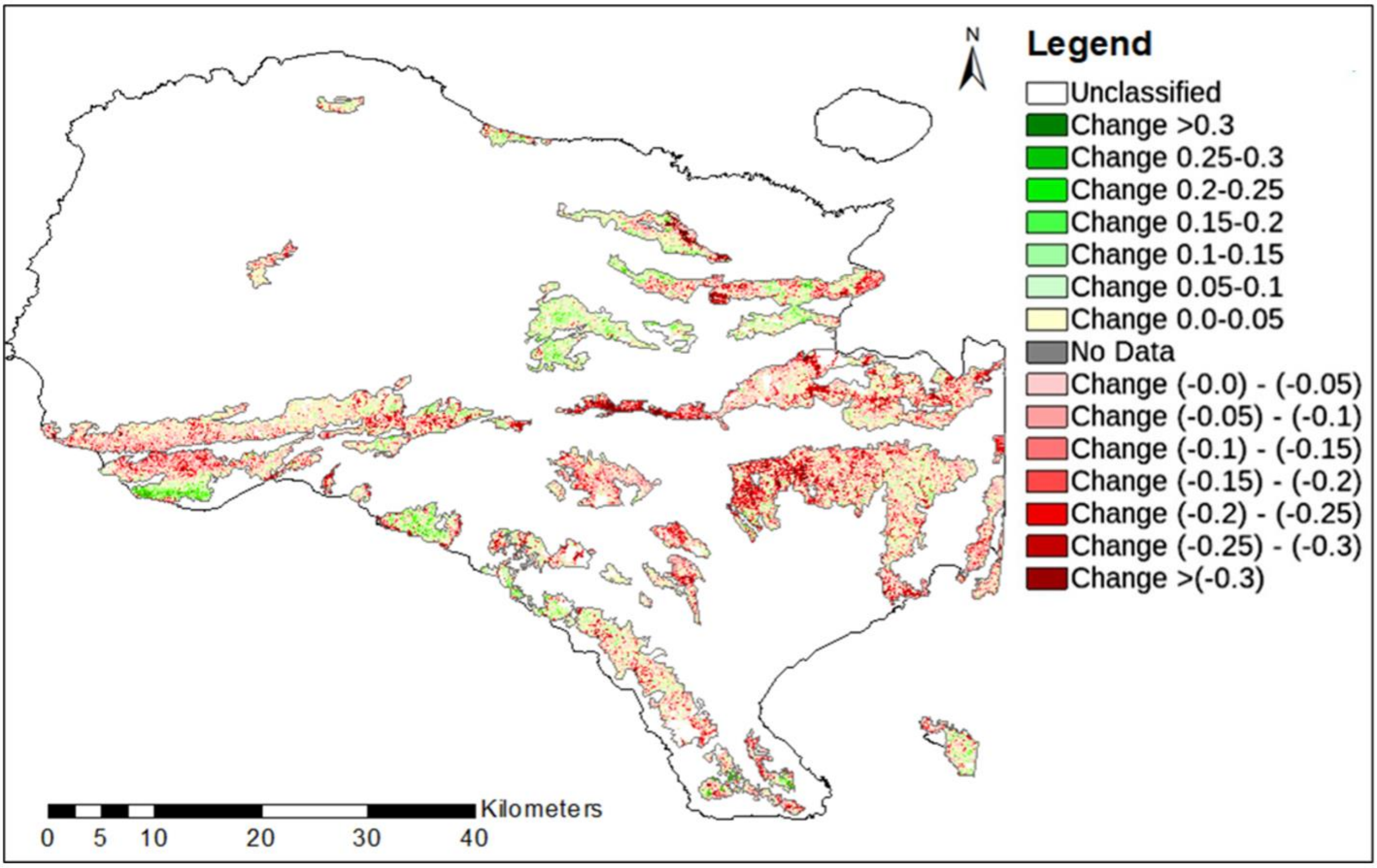


Figure 30. Threshold Map, Moderately Dense Agriculture.

Table 21. Savanna with Presence of Others Pre vs Post-Hurricane NDVI Statistics.

Land Covers	Savanna with Others			
Stats	Pre-Hurricane	Post-Hurricane	Difference Between Pre and Post	Difference Between Post-Hurricane & Reference Mean NDVI
Mean	**0.759**	**0.747**	**-0.012**	**-0.052**
Min	**-0.650**	**-0.880**	**-0.231**	
Max	**1.000**	**1.000**	**0.000**	

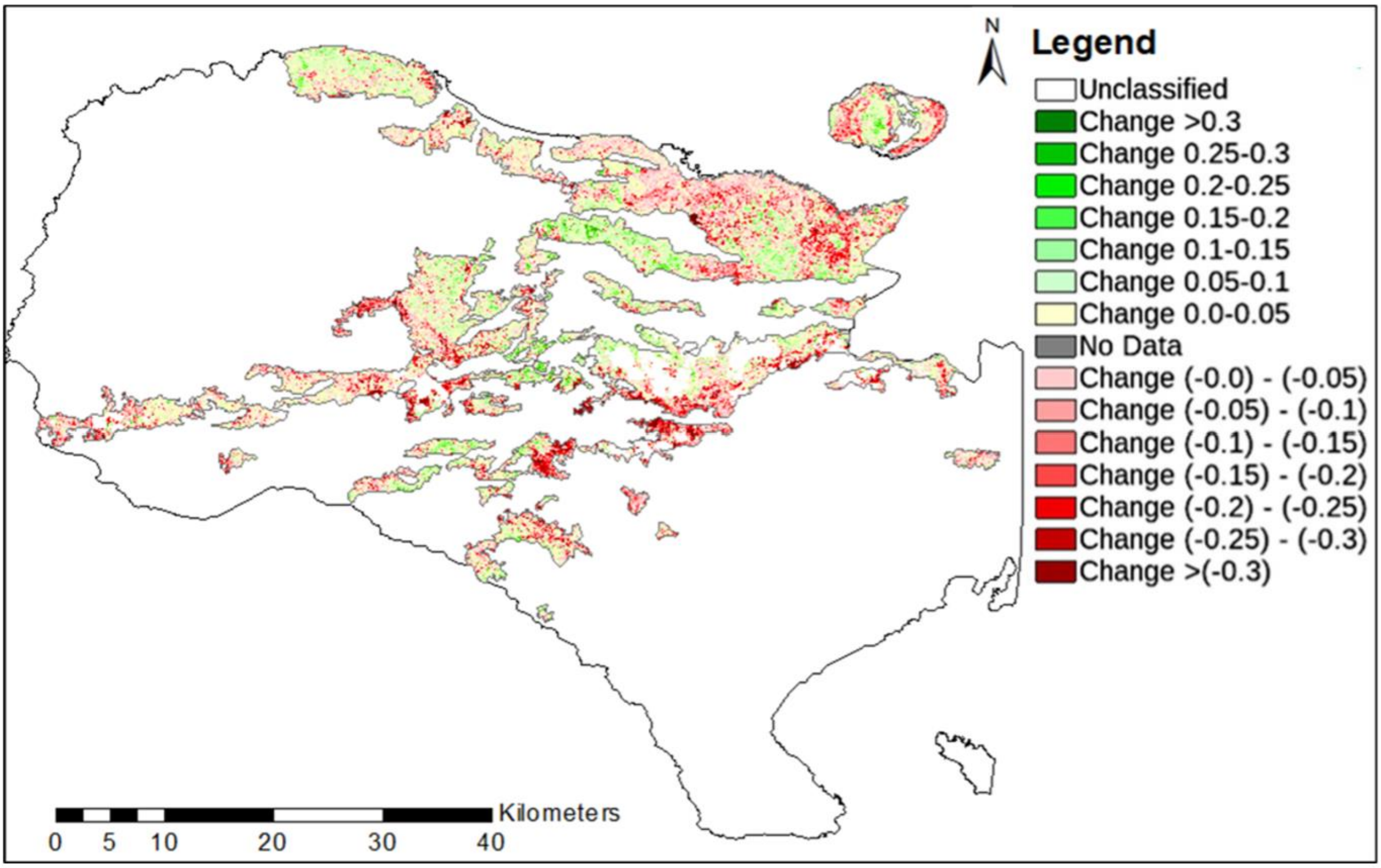


Figure 31. Threshold Map, Savanna with Presence of Others.

4.2.4. THRESHOLD MAP DATA EXTRACTION

The area (km^2) of each change in NDVI threshold for agricultural land (presented in Figure 19) is presented in Table 22. The results show that overall, the area of agricultural land that sustained a negative impact on NDVI was larger than the areas that increased in NDVI post-hurricane. Considering the significance level established in section 3.5.1., a total area of 1,252.6 km^2 experienced a decrease in NDVI that can be associated with the impact of the hurricane. The area of land that experienced an increase in NDVI was 911.2 km^2. The trend in Table 20 shows that as the change in NDVI increased (positive or negative), the area of land experiencing the change decreased, with the exception of the last two class ranges, (+ and -) 0.25-0.3 and >0.3. Therefore, the area of agricultural land experiencing a significant impact is smaller than the area experiencing more subtle damage. Employing the data associated with Table 21 and the land cover class files, the agricultural land cover that has the largest area of severe negative change (>0.3 change in NDVI) was identified. Consequently, Figure 33 presents that *Agroforestry* was the agricultural land cover that sustained a more severe change in vegetation with 43 km^2 decreasing in NDVI by >-0.3. *Dense Agriculture* followed, with *Moderately Dense Agriculture* sustaining the smallest area of land experiencing a change in NDVI >-0.3.

Table 22. Area of Agricultural Land Change in NDVI Classes.

Agricultural Land Thresholds of Change in NDVI	
Threshold	Area (km2)
Change >0.3	12
Change 0.25-0.3	11.2
Change 0.2-0.25	24.8
Change 0.15-0.2	55.2
Change 0.1-0.15	116.7
Change 0.05-0.1	239.9
Change 0.0-0.05	451.4
No Data	0
Change (0.0) -(-0.05)	537.3
Change (-0.05) -(-0.1)	436.6
Change (-0.1) -(-0.15)	305.9
Change (-0.15) -(-0.2)	201.4
Change (-0.2) -(-0.25)	129.9
Change (-0.25) -(-0.3)	80.2
Change > (-0.3)	98.6

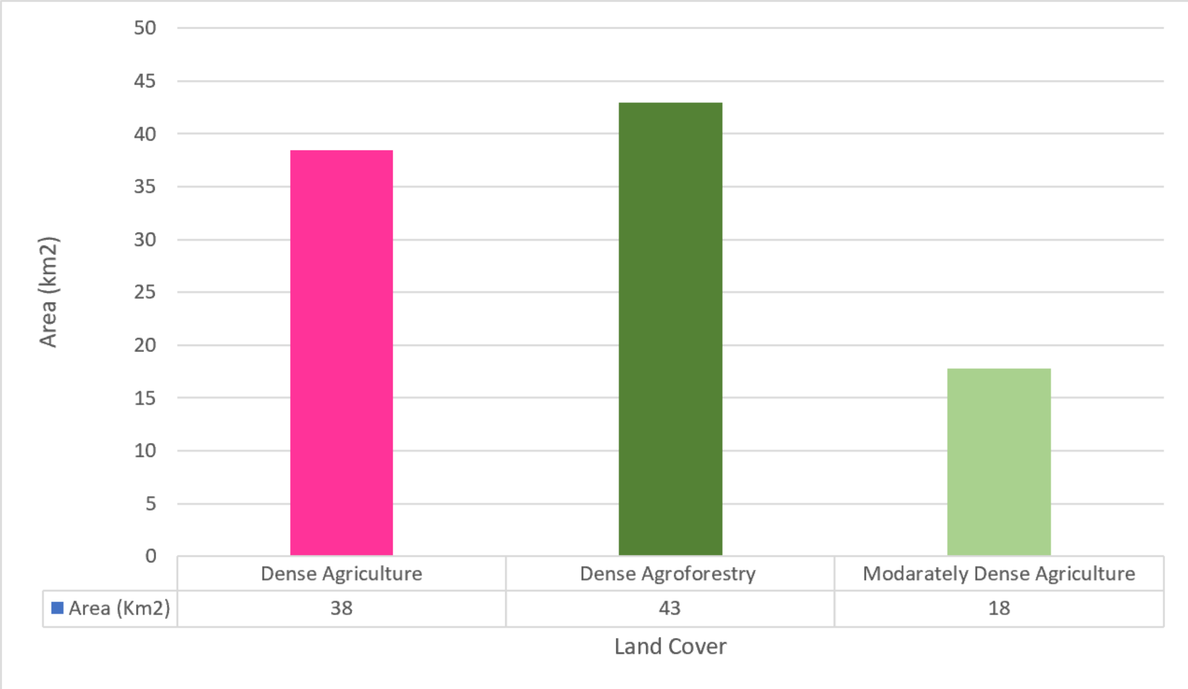


Figure 32. Area Experiencing >-0.3 Change in NDVI Across Agricultural Land Covers.

4.3. LONG-TERM IMPACT RESULTS

Table 22 accompanied by Figure 34 show that by 6 months post-hurricane (April to July 2017 growing season), the mean NDVI was 0.032 more than what was recorded immediately post-hurricane and was 0.033 and higher than the reference mean NDVI for the April to July growing season. Additionally, Figure 34 shows that the mean NDVI 12 months post-hurricane exceeded the Sep-Nov reference mean NDVI highlighting that there were no long-term impacts on the foundations of the land affecting the agricultural vegetation from reaching ‘near normal’ status.

Table 23. Long-Term Recovery NDVI Mean, Minimum, Maximum, and Growing Season NDVI Averages.

Stats	Pre-Hurricane	Immediately Post-hurricane	6 Months Post-Hurricane (Apr-Jul 2017)	12 Months Post-Hurricane (Sep-Nov 2017)	18 Months Post-Hurricane (Apr-Jul 2018)	24 Months Post-Hurricane (Sep-Nov 2018)	30 Months Post-Hurricane (Apr-Jul 2019)	36 Months Post-Hurricane (Sep-Nov 2019)	42 Months Post-Hurricane (Apr-Jul 2020)	48 Months Post-Hurricane (Sep-Nov 2020)	54 Months Post-Hurricane (Apr-Jul 2021)	60 Months Post-Hurricane (Sep-Nov 2021)
Mean	0.731	0.676	0.708	0.773	0.603	0.767	0.666	0.773	0.679	0.757	0.735	0.768
Min	-0.915	-0.991	-0.998	-1.000	-0.960	-0.999	-0.999	-0.996	-0.785	-1.000	-1.000	-1.000
Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
StdDev	0.127	0.151	0.137	0.144	0.142	0.131	0.147	0.132	0.139	0.151	0.140	0.157
Sep-Nov/April-July Growing Season Reference Mean NDVI	0.756	0.756	0.675	0.756	0.675	0.756	0.675	0.756	0.675	0.756	0.675	0.756

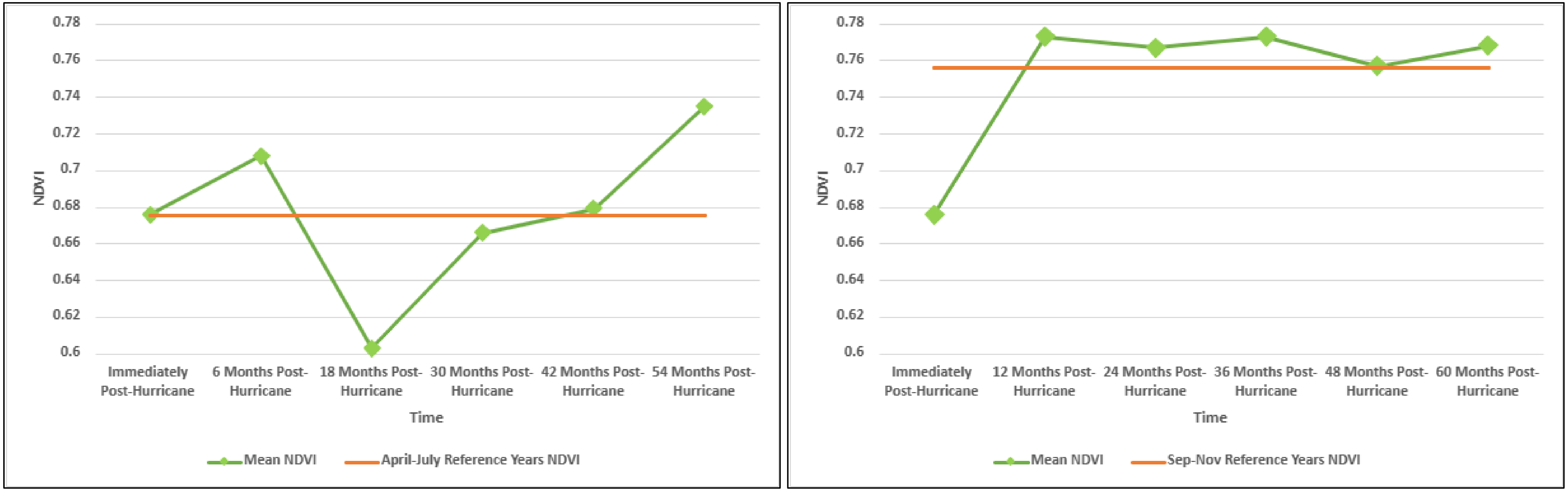


Figure 33. April-July (Left) and September-November (Right) Growing Season Long-Term Recovery Compared with the Growing Season Reference Mean NDVI.

Threshold maps comparing immediately post-hurricane NDVI with 6 months post-hurricane NDVI shows that NDVI did not increased in all regions by 6 months post-hurricane. Table 23 shows that 1646 km^2 of land increased in NDVI and 1002.9 km^2 decreased in NDVI from immediately post-hurricane to 6 months post-hurricane. Although the 'decreased in NDVI' area is considered large, Figure 35 demonstrates that the areas that have experienced a decrease in NDVI are <0.1. In contrast, Figure 36 highlights that the decrease in NDVI from immediately post-hurricane to 12 months post-hurricane is significantly lower, with a total area of only 409 km^2 decreasing in NDVI (Table 24), in contrast to 1002.9 km^2 6 months post-hurricane.

Table 24. Area of Agricultural Land Increase/Decreasing in NDVI from Immediately Post-Hurricane to 6 Months Post-Hurricane.

Class	Area (km2)
Increased NDVI	**1646.0**
Decreased NDVI	**1002.9**

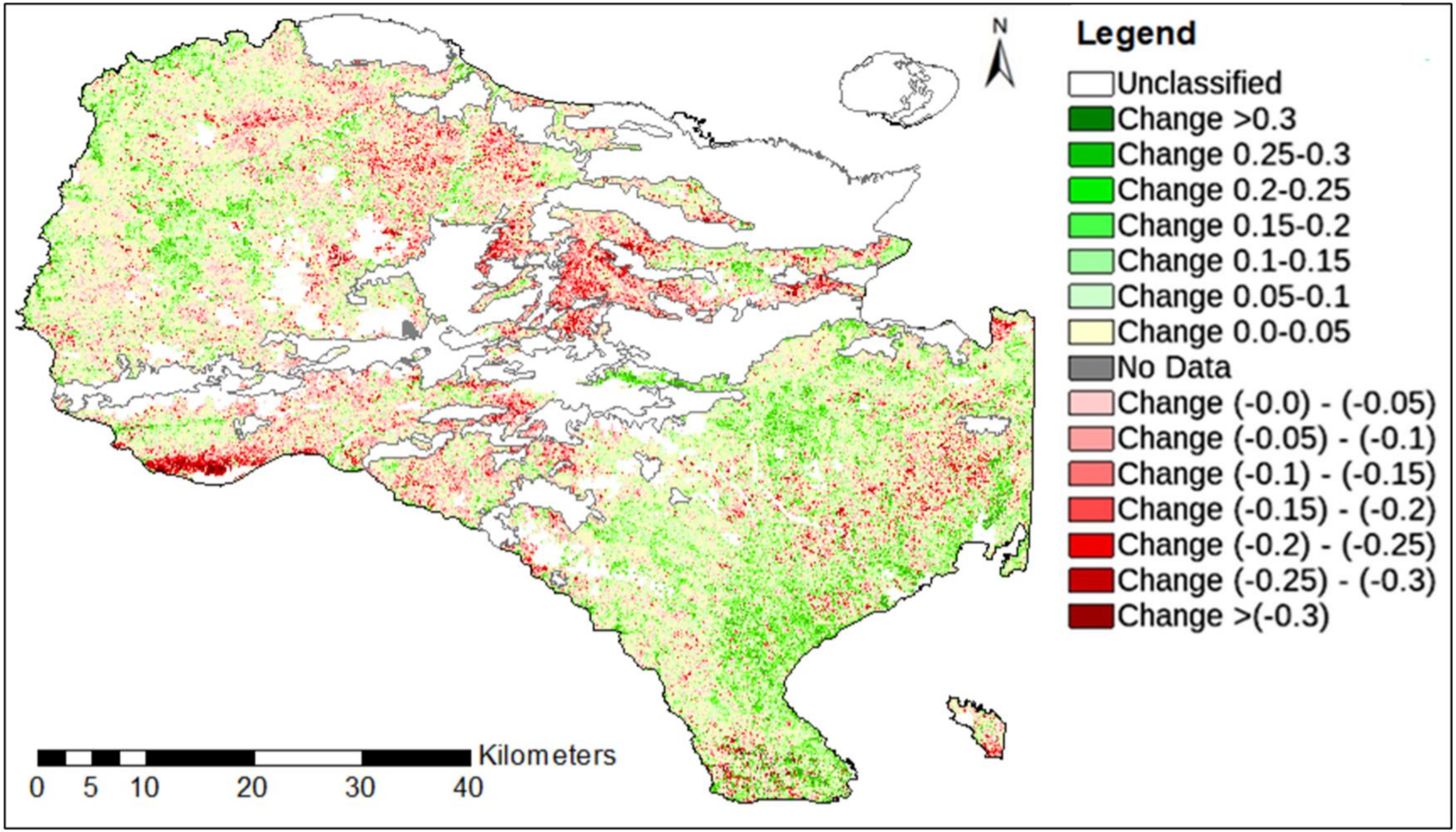


Figure 34. Threshold Map, Agricultural Land Immediately Post-Hurricane to 6 Months Post-Hurricane.

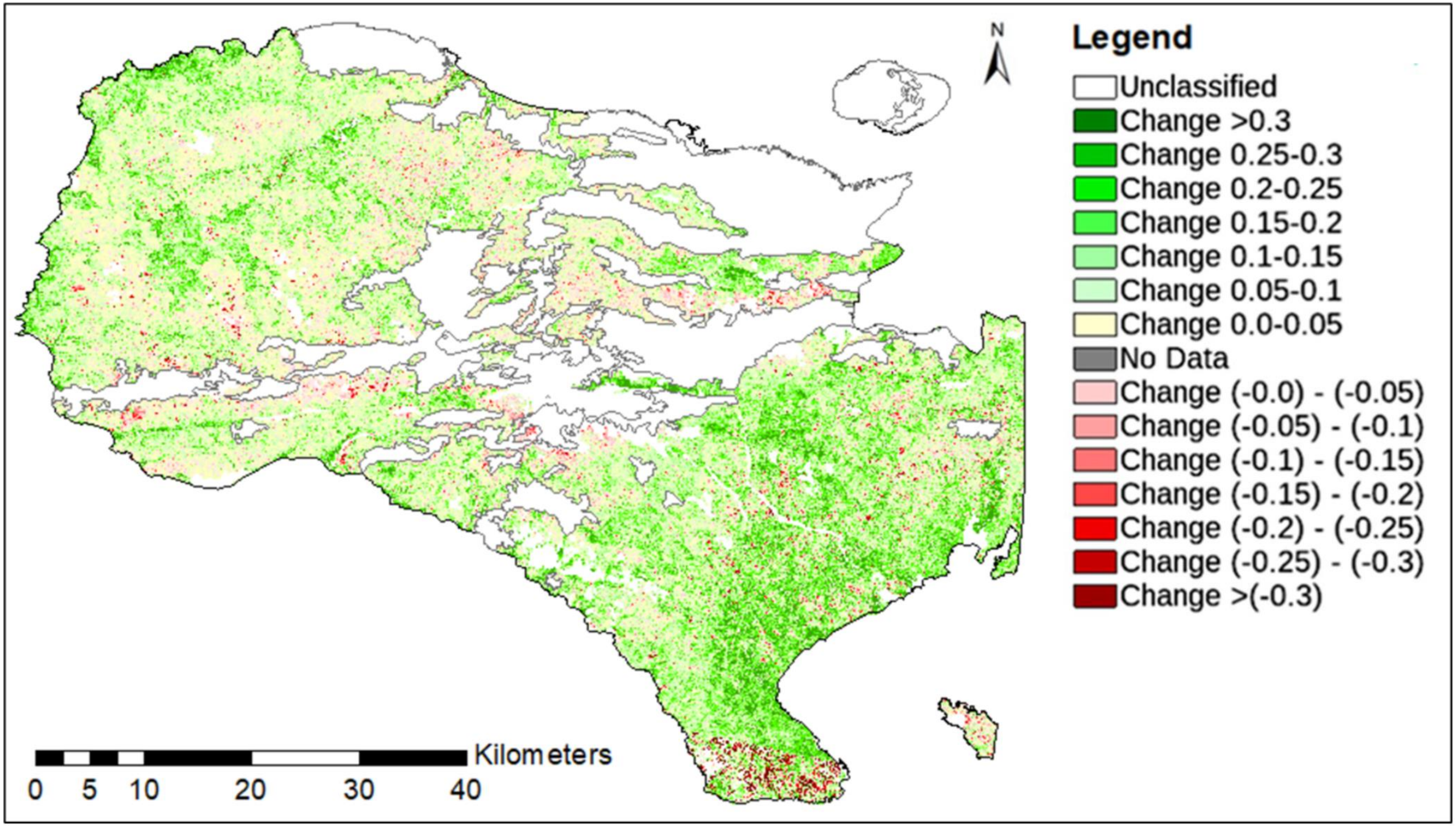


Figure 35. Threshold Map, Agricultural Land Immediately Post-Hurricane to 12 Months Post-Hurricane.

Table 25. Area of Agricultural Land Increase/Decreasing in NDVI from Immediately Post-Hurricane to 12 Months Post-Hurricane.

Class	Area (km2)
Increased NDVI	**2323.8**
Decreased NDVI	**409.6**

Tables 25 and 26 present the change in the mean, minimum, and maximum NDVI for each commune and land cover from post-hurricane to 6 months post-hurricane, as well as the difference between the 6 months post-hurricane (April-July 2017) mean NDVI value and the reference mean NDVI April-July growing season values found in Table 6. Table 25 shows that for all commune's 6-month post-hurricane mean NDVI values are >0.024 higher than the April-July growing season average, once again suggesting that a full recovery was made. Additionally, apart from Les Anglais, all communes had 6-months post-hurricane mean NDVI values >0.054 higher than what was recorded immediately post-hurricane. Similarly, in regard to land cover (Table 26), the mean NDVI was >0.029 higher 6 months post-hurricane (April-July 2017) than the April to July growing season NDVI average for agricultural land.

Table 26. Communes Immediately Post-Hurricane vs 6 Months Post-Hurricane NDVI Statistics.

Communes	Torbeck				Les Anglais				Camp-Perrin				Dame Marie			
Stats	Post-Hurricane	6 Months Post-Hurricane (April-July 2017)	Difference Between Post and 6 Months Post	Difference Between 6 Months Post-Hurricane & Reference Mean NDVI	Post-Hurricane	6 Months Post-Hurricane (April-July 2017)	Difference Between Post and 6 Months Post	Difference Between 6 Months Post-Hurricane & Reference Mean NDVI	Post-Hurricane	6 Months Post-Hurricane (April-July 2017)	Difference Between Post and 6 Months Post	Difference Between 6 Months Post-Hurricane & Reference Mean NDVI	Post-Hurricane	6 Months Post-Hurricane (April-July 2017)	Difference Between Post and 6 Months Post	Difference Between 6 Months Post-Hurricane & Reference Mean NDVI
Mean	**0.568**	**0.657**	**0.089**	**0.028**	**0.660**	**0.644**	**-0.016**	**0.024**	**0.625**	**0.715**	**0.090**	**0.047**	**0.763**	**0.826**	**0.063**	**0.041**
Min	**-0.894**	**-0.260**	**0.634**		**-0.315**	**-0.148**	**0.167**		**-0.560**	**-0.085**	**0.475**		**-0.807**	**-0.642**	**0.165**	
Max	**0.956**	**0.929**	**-0.03**		**0.958**	**0.988**	**0.031**		**0.985**	**0.997**	**0.013**		**0.991**	**0.999**	**0.009**	

Communes	Arniquet				Chambellan				Les Cayes			
Stats	Post-Hurricane	6 Months Post-Hurricane (April-July 2017)	Difference Between Post and 6 Months Post	Difference Between 6 Months Post-Hurricane & Reference Mean NDVI	Post-Hurricane	6 Months Post-Hurricane (April-July 2017)	Difference Between Post and 6 Months Post	Difference Between 6 Months Post-Hurricane & Reference Mean NDVI	Post-Hurricane	6 Months Post-Hurricane (April-July 2017)	Difference Between Post and 6 Months Post	Difference Between 6 Months Post-Hurricane & Reference Mean NDVI
Mean	**0.580**	**0.638**	**0.058**	**0.047**	**0.759**	**0.831**	**0.073**	**0.041**	**0.547**	**0.601**	**0.054**	**0.033**
Min	**-0.689**	**-0.168**	**0.520**		**-0.152**	**-0.090**	**0.062**		**-0.839**	**-0.347**	**0.492**	
Max	**0.903**	**0.931**	**0.028**		**0.989**	**0.999**	**0.010**		**0.979**	**0.998**	**0.019**	

Table 27. Land Covers Immediately Post-Hurricane vs 6 Months Post-Hurricane NDVI Statistics.

Land Cover	Agricultural Land											
	Dense Agriculture				Moderately Dense Agriculture				Dense Agroforestry			
Stats	Post-Hurricane	6 Months Post-Hurricane (April-July 2017)	Difference Between Post and 6 Months Post	Difference Between 6 Months Post-Hurricane & Reference Mean NDVI	Post-Hurricane	6 Months Post-Hurricane (April-July 2017)	Difference Between Post and 6 Months Post	Difference Between 6 Months Post-Hurricane & Reference Mean NDVI	Post-Hurricane	6 Months Post-Hurricane (April-July 2017)	Difference Between Post and 6 Months Post	Difference Between 6 Months Post-Hurricane & Reference Mean NDVI
Mean	**0.625**	**0.659**	**0.034**	**0.029**	**0.660**	**0.678**	**0.018**	**0.037**	**0.714**	**0.756**	**0.042**	**0.032**
Min	**-0.975**	**-0.350**	**0.625**		**-0.980**	**-0.984**	**-0.004**		**-0.991**	**-0.998**	**-0.007**	
Max	**1.000**	**0.998**	**-0.002**		**1.000**	**1.000**	**0.000**		**1.000**	**1.000**	**0.000**	

Land Cover	Non-Agricultural Land							
	Forest				Savanna With Others			
Stats	Post-Hurricane	6 Months Post-Hurricane (April-July 2017)	Difference Between Post and 6 Months Post	Difference Between 6 Months Post-Hurricane & Reference Mean NDVI	Post-Hurricane	6 Months Post-Hurricane (April-July 2017)	Difference Between Post and 6 Months Post	Difference Between 6 Months Post-Hurricane & Reference Mean NDVI
Mean	**0.709**	**0.755**	**0.045**	**0.006**	**0.747**	**0.757**	**0.010**	**0.030**
Min	**-0.619**	**0.003**	**0.622**		**-0.880**	**-0.469**	**0.412**	
Max	**1.000**	**0.986**	**-0.014**		**1.000**	**1.000**	**0.000**	

Finally, although it has been established that a full recovery was made by 6 months post-Hurricane Matthew, the long-term NDVI outputs drew attention to other significant events that impacted agricultural vegetation. Firstly, as mentioned in Section 4.1, across the agricultural land cover, the mean NDVI is consistently lower in the April-July growing season in comparison to the September to November growing season. This is clear, visually, in the April-July (6, 18-, 30-, 42-, and 54-months post-hurricane) NDVI maps (Figure 37). Additionally, the NDVI 18 months post-hurricane (April-July 2018) is considerably lower than what is seen across other growing seasons. The mean NDVI was 0.603, which is 0.072 below the reference mean NDVI (Table 22 and Figure 37). Additionally, the mean NDVI value of 0.603 was lower than what was recorded immediately, post-Hurricane Matthew. In the April-July growing season NDVI values in the Torbeck region for example typically are >0.7, however, 18 months post-hurricane values generally are <0.6, this decreases further in communes such as Les Anglais with NDVI values <0.4 in some regions. Thus, these results drew attention to other significant events that may be impacting food security.

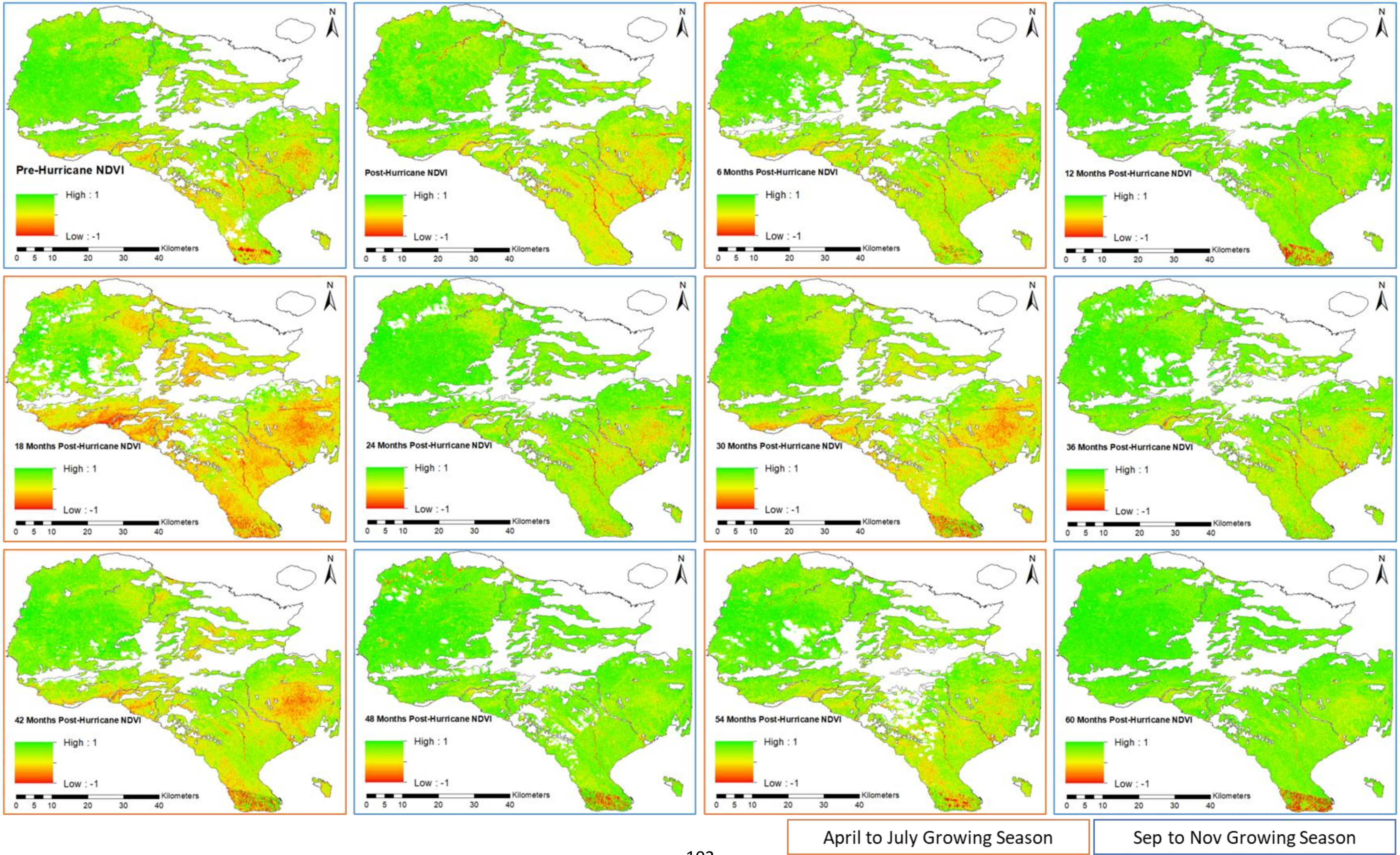


Figure 36. Long-Term Agricultural Land NDVI.

4.4. SUMMARY OF THE RESULTS

Firstly, the reference mean NDVI results highlighted the seasonal fluctuations in NDVI between the April-July and the September-November growing season. NDVI within the September-November growing season was consistently higher than the April-July growing season.

To conclude, Hurricane Matthew had an immediate impact on agricultural vegetation, specifically in the Sud department. Patterns of severe damage were concentrated along the coastline and running parallel to valleys. The two most impacted communes were Torbeck and Camp-Perrin, conversely, Les Anglais was the least impacted. In regard to agricultural land cover, *Dense Agriculture* and *Agroforestry* sustained a larger area experiencing a decrease in NDVI >0.3 than *Moderately Dense Agriculture*. Overall, across agricultural land, the area that decreased in NDVI from pre- to immediately post-hurricane amounted to 1789.9 km^2, compared to 911.2 km^2 that increased in NDVI. Therefore, Hurricane Matthew had a negative immediate impact on the agricultural land cover of the Sud and Grand'Anse Departments of Haiti.

In the long-term, agricultural vegetation returned to near normal by 6 months post-hurricane, with the mean NDVI values being above the reference mean NDVI by 6 months post-hurricane. This finding was consistent across all communes and land covers. Despite the threshold maps highlighting that some regions decreased in NDVI from immediately post-hurricane to 6 months post-hurricane, these decreases were small and can be associated with the seasonal fluctuations between the April-July and September to November growing seasons. Finally, the long-term NDVI highlighted a significant decrease in NDVI 18 months post-hurricane (April-July 2018), suggesting that there are other climatic events taking place that are significantly impacting the status of agricultural vegetation.

CHAPTER 5

5. DISCUSSION

This chapter will first interpret and describe the short-term impacts, acknowledging the potential reasons for the changes in NDVI. This will be followed by the long-term recovery and discussion of what the short/long-term impact results mean for building resilience in Haiti's agricultural sector. Within both sections, the land covers and communes will be discussed. Finally, there will be a thorough evaluation of this research, identifying the successes of the study as well as limitations, with suggestions for future research.

Evidence has shown that the severity of hurricane damage on agriculture can contribute to food insecurity. Within Haiti, this has been exacerbated by a lack of research on the country's geographical vulnerability (Cohen and Singh 2014). That being said, little has been acknowledged regarding the socio-economic and geo-political factors (including access to/availability of secondary data) that have influenced this further. Throughout the discussion, consideration will therefore be made to Haiti's complex history and associated socio-economic and political issues (Edmonds 2013; Daut 2021; The World Bank 2022).

5.1. HAITI'S SOCIO-ECONOMIC & POLITICAL HISTORY, AND CURRENT STATUS

Haiti's socio-economic position continues to be hindered by uncertainty, environmental fragility, political instability, and associated violence (The World Bank 2022). Haiti is the poorest nation in the western hemisphere, with a GDP per capita of US$1,815 in 2021 (World Bank 2021), with approximately 1.2 million suffering from severe hunger (World Food Program 2022). Whilst Haiti's food insecurity has largely been associated with the reoccurring environmental shocks that it has been subjected to, including Hurricane Matthew (FEWS NET 2015 The World Bank 2017; Olsson *et al.* 2019; Council on Foreign Relations 2021); barriers to social and economic development have been heavily shaped by years of political instability.

Haiti's path to development can be traced back to 1804 when Haiti gained independence from France. Haiti was the first country to be founded by formerly enslaved people and in order to stem their growth further and prevent potential threats to the current state of norm regarding colonialism and slavery, a sizeable debt was enforced on the country amounting to what would be $21 billion dollars today (Edmonds 2013; Daut 2021). Haiti, in effect, were being made to pay for their freedom twice, first through conflict and loss of life, and then financially, only paying for the debt in 1947.

A period of structural adjustment occurred during this period, with infrastructure starved, preventing necessary investment in education, health and transportation, key to a country's socio-economic development. Moreover, Haiti's history laid the foundation for a lack of trust amongst the government and locals towards other countries and is predominantly responsible for the underfunding of the country's education and healthcare in the 20th century (Daut 2021). The repercussions of Haiti's trouble history have been reflected most in their approach to governance. Haiti is currently fighting one of its worst outbreaks of violence since 1986 when the Anti-Duvalier protest movement took place (Human Rights Watch 2020). Gender inequality and gender-based violence have also arguably been exacerbated by created gender hierarchies adopted from colonialism (Mannell 2022). Indeed, Gage (2005) found that out of a sample of 2000 women, 29% experiences some form of intimate partner violence in the past 12 months. It is therefore important to acknowledge the wider historical context of a place when truly understanding the complexity of the impacts of sever hurricane damage.

Haiti's past, which has paved its current status, is capping future generations' potential and preventing adequate preparedness and resilience-building mechanism against threats such as hurricanes from being put in place (World Bank 2022). It is no surprise, therefore, that Haiti does not have the capacity to prioritise future threats over current ones that are unfolding today. Without access to education, funding, and resources, the preparation and mitigation to build resilience against threats such as hurricanes, which aid food insecurity will be challenging to achieve. This, in retrospect, elevates the importance of this research as Haiti itself does not have the funding or resources to conduct similar research. Indeed, Cohen and Singh (2014) state that due to these reasons, there has been a lack of research assessing the vulnerability of regions to hurricanes and their impacts on Haiti. Consequently, the findings of this research will be valuable, informing stakeholders about specific vulnerabilities, which will be discussed further in this chapter. Consequently, considering the significance of the socioeconomic/political history and current status of Haiti, this should not be overlooked when interpreting and discussing the findings of this research.

5.2. IMMEDIATE IMPACT

Chapter 4 provides evidence that Hurricane Matthew had a severe negative immediate impact on the agricultural vegetation of the Sud and Grand'Anse Department, Haiti. The discussion of the immediate impacts is separated into sub-categories to highlight and compare the change in NDVI values across the communes and land covers.

5.2.1. IMMEDIATE IMPACT- LAND COVER SUBSETS

The immediate impact of Hurricane Matthew demonstrated that, overall, agricultural land cover sustained more substantial damage than non-agricultural land covers (including *Forest* and *Savanna with Others*). Despite this, out of all land covers, *Forest* was the most severely impacted, experiencing the largest change in the mean and minimum NDVI from pre- to post-hurricane (Table 17). Although the most severely impacted, the area of *Forest* within the study site was very small (70.8 km^2). In comparison, the second non-agricultural land cover, *Savanna with the Presence of Others* was the least impacted land cover and covered a larger area of 793.5 km^2. Consequently, this lower area of impacted land cover would have neutralised the large changes in NDVI present in *Forest*, subsequently decreasing the change in mean NDVI when assessing non-agricultural land as a whole. This is why agricultural land cover appeared more damaged as a whole despite *Forest* being the most impacted land cover overall.

In the order of the most impacted land covers, it appears there is a relationship between the intensity of damage and the surface area/height of vegetation (n.b. this assumption does not consider other influential variables such as distance from the hurricane). This relationship was acknowledged in Section 2.5, stating that taller trees sustained more damage subsequent to Hurricane Katrina (Wang *et al.* 2010). It is known that a larger surface area captures more energy from the wind, consequently, trees of a smaller height/smaller surface area require higher wind speeds to cause damage/breakage (Walker 1991; James 2010). Similarly, taller trees are more likely than smaller species to experience defoliation (Walker 1991). The results presented in Section 4.1

supports this. Figure 33 highlights that *Agroforestry* (assumed to have the largest surface area out of the agricultural land covers) sustained the largest area that experienced a decrease in NDVI >0.3; meaning that *Agroforestry* was the most severely impacted land cover. Additionally, considering non-agricultural land covers, as mentioned above, *Forest* suffered the most damage (Table 17) and can be assumed to have an even larger surface area than *Agroforestry*. This is assumed due to the species present in Haiti's forests, such as *Cordia alliodora* and *Catalpa longissimi* with dense crown canopies and heights of up to 40 and 29 meters, respectively (Timyan 1996). Conversely, *Savanna with the Presence of Others* would be assumed to have species with the smallest surface area. *Savanna* is defined as a mixed woodland-grassland ecosystem with an open canopy, primarily including scrub, herbaceous grasses, and the occasional tree (The American Heritage Science Dictionary 2011). Thus, *savanna* is predominantly covered by species of a small surface area/height, consequently experiencing the smallest mean change in NDVI from pre- to post-hurricane, as seen in Table 20. Findings such as these could justify why *Forest* was the most impacted landcover followed by *Agroforestry* and *Dense Agriculture,* as they have taller and more dense species capturing more energy from the wind, thus experiencing more intense damage.

Upon closer inspection of the mean and minimum NDVI, Agroforestry only experienced a decrease in the minimum NDVI of 0.369, compared to 0.733 in *Forest*, as well as a smaller change in mean NDVI. This could be due to the combination of trees/shrubs planted amongst crops in the *Agroforestry* practice. As mentioned in section 2.3, the diversity agroforestry provides can increase resilience against extreme storm events such as hurricanes (Chen 2009; Lin 2011; Felix and Holt-Gimenez 2017; Sridhar and Chaturvedi 2017) and has been said to reduce damage in comparison to conventional practices (Holt-Giménez 2001; Altieri, Funes-Monzote, and Petersen 2012). Therefore, it is thought that the larger species protected the smaller ground level species, thus the minimum NDVI post-hurricane had a smaller decrease due to the protected, less damaged ground species. Subsequently, *Agroforestry* experienced a reduced change in minimum NDVI from pre- to post-hurricane compared to *Forests*. This supports that *Agroforestry* practises are more resilient and protect understory crops from more severe damage (Holt-Giménez 2001; Lin 2011; Altieri et al. 2015; Altieri, Funes-Monzote, and Petersen 2012; Sridhar and Chaturvedi 2017). Therefore, although regarding the change in mean NDVI *Agroforestry* sustained a negative impact and decrease by -0.063 from pre- to post-hurricane, it is more than likely that this practice prevented further damage to understory communities and therefore is a more sustainable agricultural practice. However, it must be acknowledged that if the trees within the agroforestry system are cash crops trees, fruit loss will be one of the main impacts of a hurricane (Daley *et al.* 2020) but will still protect understory communities.

Being able to identify which land covers are more severely affected by hurricanes is beneficial for building resilience through preparedness, mitigation, and implementation of more sustainable agricultural practices, as it highlights what land covers are more vulnerable to the impacts of hurricanes (USDA 2022). This can also be useful on a regional scale for developing frameworks and informing policy changes. Amongst research studying the effects of hurricanes, Forests are the predominant land cover assessed as the large negative effects on forests are known and recorded (Philpott *et al.* 2008). Although forests provide many ecosystem services and are beneficial to communities in many ways (Chazdon 2008), agricultural production plays a large direct role in food security. Yet, with the exception of Philpott *et al.* (2008), little research is completed on the impact of hurricanes on different agriculture types/land uses. Knowledge of the effect of hurricanes on different agricultural species would be transformative to building resilience against hurricanes. For example, knowing what species are flood tolerant or more flexible and thus can withstand strong winds without breakage could reduce the severity of damage to the agricultural sector post-hurricane, thus alleviating the impact on food insecurity. Although the land cover classes assessed within this research are broad and do not identify specific crop types due to the lack of on-the-ground data (elaborated on in Section 5.6), the findings presented in this study begin to give an insight into the effects of a hurricane on different agricultural land covers. The results highlighted that *Agroforestry* and *Dense Agriculture* sustained more damage, thus are more vulnerable requiring mitigation to reduce the impacts in the future. However, more research needs to be conducted regarding *Agroforestry*. Although it was recorded that from pre- to post-hurricane there was a decrease in NDVI in the agroforestry land cover, compared to other land covers assessed, it experienced a smaller decrease in the minimum NDVI, suggesting that the diversity of the practise provided protection, reducing damage. To gain clarity it needs to be understood if most damage takes place to the upper canopy of the larger species, thus protecting the understory community of crops, reducing a loss of harvest.

5.2.2. IMMEDIATE IMPACT- COMMUNE SUBSETS

In addition to the individual land covers assessed, an in-depth analysis of specific communes took place. Changes in mean NDVI from pre- to post-hurricane, in particular, reflect that certain communes' such as Torbeck, and Camp-Perrin, suffered the largest negative impact on agricultural vegetation. Conversely, Les Anglais sustained the smallest change in NDVI. Torbeck, which lies in the east of the Sud department and is predominantly classified as *Dense Agriculture*, experienced the largest change in NDVI from pre- to post-hurricane. What is more, regarding the difference between the mean NDVI post-Hurricane and the reference mean NDVI, *Dense Agriculture* was the most impacted agricultural land cover. This land cover represented 122.7 km^2 of 156.9 km^2 of the agricultural land within the Torbeck commune. Consequently, the predominant land cover of *Dense Agriculture* could be contributing to the significant damage experienced within Torbeck. Furthermore, when observing the change in NDVI in Torbeck (Figure 22), to the eye, the damage looks more intense closer to the coastline. Dense regions of decreases in NDVI >0.3 lie close to the coast, moving inland these decreases typically reducing to <0.2. This could be due to the low elevation within this region in conjunction with a storm surge, causing severe flooding (Mersereau 2015; Oppenheimer *et al.* N.D; World Vision 2018). Elevation was proven to be a crucial variable in forecasting the impact of hurricanes after the coastal damage that was inflicted by Hurricane Sandy in 2012 (USGS N.D). Furthermore, generally, a storm surge will be higher on a concaved coastline (curved inwards) (NOAA N.D), similar to the coast of the Torbeck and Les Cayes, thus causing more intense damage parallel to the coast. To understand how coastal flooding may have impacted the change in NDVI, further analysis considered the elevation and shape of the coastline, for the region of Torbeck. This analysis looked into the distance from the coast in 2 km intervals and extracted the mean elevation and mean change in NDVI for every interval. It was concluded that moving away from the coastline up to 14 km inland the damage decreased. Interestingly, from 14 km inland, the mean change in NDVI increased with the damage becoming more severe. This is despite the mean elevation continuing to rise up to 24 km inland. It can be assumed that the pattern seen within the first 14 km inland is associated with the storm surge (World Vision 2018) and that the rise in elevation prevented the surge from moving further inland. Consequently, coastal flooding contributed to the severity of damage within the Torbeck commune.

Considering that coastal flooding is a major threat associated with hurricanes (Rodgers, Murrah, and Cooke 2009; Goto *et al.* 2015), as seen in Torbeck, it would be expected that the coastal commune of Dame Marie would sustain similar damage along the coast, however, this was not the case. In this case, Hurricane Matthew's approach ran parallel to the coastline (Figure 15), which decreased the severity of the hazard (NOAA N.D). Thus, this region did not experience as intense damage in comparison to regions such as Torbeck that sit perpendicular to the track. Understanding the approach of hurricanes, in conjunction with the shape of the coastline and the elevation can be useful for preparedness and mitigation. This can enable mitigation efforts to be focused in the correct places. For example, mitigation directly targeting soil salinisation can include gypsum application, switching to a more salt-tolerant rotation, or using grass leys to improve soil structure and salt-flushing potential (Gould *et al.* 2020). Additionally, hard and green engineering techniques can be employed to mitigate the direct threat of the storm surge. Hard engineering structures such as levees and storm surge barriers are the most common, however soft engineering approaches are becoming more common such as wetland creation and mangrove restoration (Horn 2015). Indeed, organisations such as Just One Tree have partnered with the Eden Reforestation Project to plant mangroves to build a natural defence against storm surges (Just One Tree 2022). During storms, as waves enter the mangrove forest the root branches reduce the wave's energy, this, in turn, reduced the distance a wave can travel inland (Just One Tree 2022). Preventing the storm surge from reaching further inland will not only reduce the long-term threat of salinisation but also mitigate against the immediate destruction of crops associated with coastal flooding.

Despite a widescale decrease in NDVI, there were anomalies of small, isolated patches of land near the coastline that increased in NDVI in Torbeck (Figure 38). This suggests that vegetation within these regions coped well with flooding conditions, thus experiencing an increase in NDVI post-hurricane. One staple crop that Haiti has cultivated for many years is rice (RTAC 2021). This crop is well known to be able to flourish in flooded soils whereas other crops would die (Eckardt 2017). This appears to be the case post-Hurricane Matthew, where the health of rice paddies within the Les Cayes and Torbeck region improved coinciding with flooding. Figure 38 demonstrates the coincidence of rice paddies with the areas that increased in NDVI. Therefore, rice is a resilient crop to the short-term hurricane impacts. Thus, for future mitigation against hurricanes, particularly in regions susceptible to flooding, rice would be a good alternative to plant. This would decrease the immediate impact of a hurricane on the loss of harvest, potentially increasing food security on a local scale. This is an example of the benefit of identifying crops that are more resilient to the impacts of hurricanes (as mentioned in Section 5.2.1), helping build toward more resilient agricultural practices.

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Figure 37. Top: Les Cayes/Torbeck Threshold Map, Bottom: Land Use Map (SERTIT 2018).

Camp-Perrin was also severely impacted following Hurricane Matthew. However, due to the commune's location inland the damage was not related to the storm surge. Further investigation suggests that the severity of damage is associated with land cover types and rainfall patterns. The middle of the commune is dominated by *Agroforestry*, with the north and south mainly *Moderately Dense Agriculture*. The changes in NDVI in comparison to the land cover map (Figure 39) demonstrate that there is a relationship between land cover and the severity of the damage. Most severe damage can be seen in the region dominated by *Agroforestry*, and the less severe damage in the regions of *Moderately Dense Agriculture*. Figure 33 further supports this statement, highlighting that *Agroforestry* sustained the largest area of damage decreasing in NDVI by >0.3, whereas *Moderately Dense Agriculture* sustained the smallest area of damage. As we know from Section 5.2.1, the more severe damage in *Agroforestry* can be associated with the larger surface area/taller species present within this land cover, meaning they capture more energy from the wind and thus experience more severe damage (Walker 1991; James 2010). Subsequently, Camp-Perrin is a prime example of the land cover type determining the severity of the damage experienced within a commune and further supports the results highlighting that *Agroforestry* is a more severely impacted commune. Finally, in Hurricane Matthews's case, the majority of the rainfall fell to the east of Hurricanes Matthews's track, due to the storm's counterclockwise circulation engaging with the island topography (NASA 2016). Camp-Perrins positioning to the east of the track could have contributed to the increased severity of damage linked to flooding within this commune, a factor that could have also contributed to the damage in Torbeck.

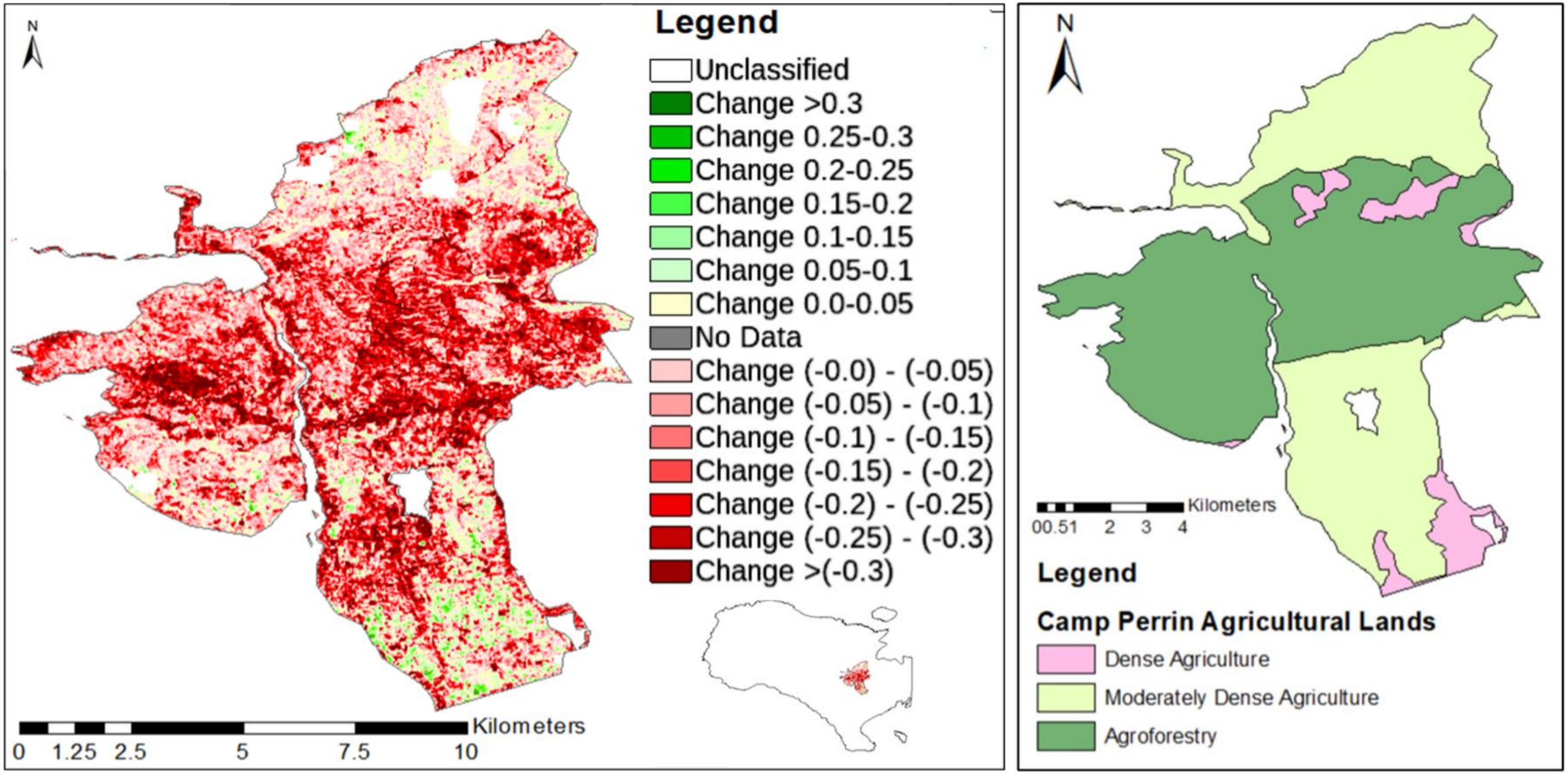

Figure 38. Camp-Perrin Threshold Map Compared to a Map Highlighting the Agricultural Land Covers.

Evidence showed that Les Anglais, on the other hand, experienced a change in mean NDVI below the significance level of 0.05, therefore it cannot be said with certainty that the change was subsequent of the impact of Hurricane Matthew, as it falls within the range of seasonal variation. Despite this, individual regions of a negative change in NDVI >0.2 within Les Anglais reflect that the threat associated with Hurricane Matthew that inflicted the greatest change in NDVI was flooding. Previous events of flooding associated with hurricanes have been recorded to cause destruction to agriculture (Gomez 2005; Hoque *et al.* 2016; Marzen *et al.* 2017; World Vision 2018), and this was one of the consequences of the heavy precipitation associated with Hurricane Matthew (The Guardian 2016; The World Bank 2017; World Vision 2018). Figure 40 highlights that the most severe damage runs parallel to the Les Anglais River and along the coast. It should also be noted that along the coast there is an area of *Agroforestry* that aligns with the largest changes in NDVI, thus the land cover may be contributing to the severity of the damage. Regardless of land cover type, the pattern of decreases in NDVI >0.2 in Les Anglais reinforces the patterns that severe damage is common along the coast and runs parallel to river channels. This indicates that most of the damage within this region is associated with flooding, be that coastal or from heavy precipitation.

Analogous patterns can also be seen across other communes. Dame Marie, for example, experienced some of the most severe damage around the main town, aligning with the mouth of the Dame Marie River. Furthermore, in Chambellan, the highest negative change in NDVI (>0.25) follows the River Bras Gauche that progresses to the River Grand'Anse. Figure 40 highlights isolated areas of severe damage caused by the flooding of river channels, consequently flooding and damaging agricultural vegetation in the surrounding area. It can be assumed that the heavy precipitation associated with Hurricane Matthew caused rivers to swell, consequently flooding surrounding agricultural land (The Guardian 2016; The World Bank 2017; World Vision 2018). This is a prominent threat to the health of vegetation, confirmed by the fact there were large decreases in the NDVI from pre- to post-hurricane within these regions. This supports literature such as Gomez (2005), Hoque *et al.* (2016), Marzen *et al.* (2017), and Li *et al.* 2021 that highlights the severity of damage flooding can inflict. In particular, Li *et al.* (2021), states that agricultural land is the most affected by flooding associated with Typhoons in Taiwan. Consequently, croplands were selected as adaptation targets undergoing multiple engineering and non-engineering strategies to reduce the potential impacts (Table 27). Results found that even when considering the costs, all adaptation options yielded higher benefits than the 'do nothing' option. Thus, regions vulnerable to flooding in Haiti need Disaster Risk Management (DRM) frameworks to be implemented to mitigate against the threat or adapt practices to ensure resilient recovery (OECD 2021). The research method developed in this study and subsequent results can identify areas that are vulnerable to flooding, enabling mitigation efforts to be focused in the correct regions. Considering Haiti's socioeconomic status and environment, some mitigation options presented in Table 27 would not be feasible. For example, 'Adjustment of Agricultural Production Periods' may be hard to implement as many Haitians rely on natural irrigation for agricultural production (Abraham 2015), thus explaining why the growing seasons coincide with the rainy seasons. However, the outputs of Li *et al.* (2021) research in conjunction with the result of this study highlights the importance of mitigating against flooding as it can reduce yield loss, consequently reducing the impacts of hurricanes on food insecurity. These results provide key information that can be used to inform where mitigation needs to be implemented; this method can also be employed within other regions to identify areas of vulnerability.

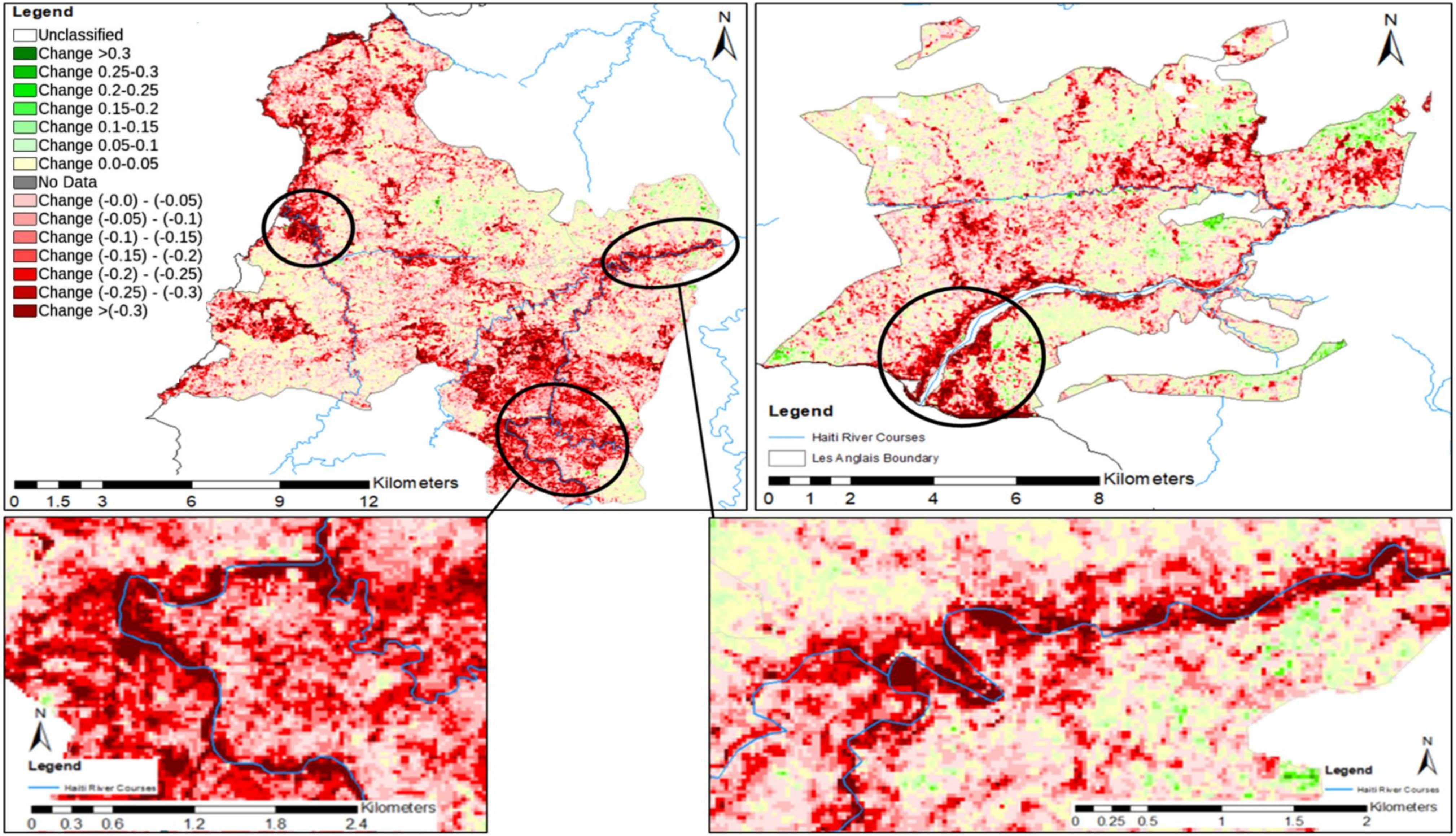

Figure 39. Chambellan, Dame Marie and Les Anglais Communes with a River Shapefile Overlaid Showing the Correlation Between River Courses and Damage Post-Hurricane.

Table 28. Adaptation Methods for Reducing Flooding Impacts on Agricultural Farmland (Li et al. 2021).

Method	Concept	Benefits
	Engineering Methods	
Improving Drainage systems	Improve drainage and sewer systems.	Increase the infiltration volume of the paving and build a reservoir to reduce the chance of damage to agricultural products.
Heightening Farmland	Add 10-60 cm more to the height of the farmland ridge.	Reduce the flood risk area.
Adding Food Control and Strengthening Structural Capacity	Add pumping stations in urban parks or wasteland.	Reduce flooding in key areas.
	Non-Engineering Methods	
Adjustment of Agricultural Production Periods or Changing Crops	Avoid flood seasons or change cropping patterns in flood-prone areas.	Reduce the probability of losing agricultural output due to flooding.
Fallowing	Encourage fallowing in areas prone to flooding and provide subsidies.	Avoid losing agricultural output due to flooding.
Create Protected Areas	Land acquisition program to delimit protected lands.	Restore flood-prone area to its ecological condition, therefore reducing agricultural losses due to flooding.

Despite the risk that flooding associated with hurricanes has on agricultural land, there are many benefits to utilising floodplains for agricultural production, therefore many communities utilise the land surrounding river channels. For example, close proximity is beneficial for irrigation purposes, especially in regions with sparse or seasonal rainfall (National Geographic Society 2022), like Haiti. Additionally, the land tends to be rich in nutrients, increasing fertility, making it a good foundation for agricultural production (Gangashe 2020; National Geographic Society 2022). Both factors are particularly important to improving agricultural productivity; something that is needed in Haiti due to the food insecurity epidemic. Thus, many locals accept the risk of flooding to gain the advantages of growing agriculture on floodplains. However, with climate change increasing the intensity of such events (GFDL 2021) the benefits and challenges of agricultural production near water courses should be weighed up to assess whether the advantages outweigh the risks associated with flooding.

Typically, the wettest month in Haiti is May, averaging around 190mm of rain in the Grand'Anse Department (World Weather Online 2022), therefore, with the average climate, flooding tends not to be a major concern. Unless, associated with events such as storms and hurricanes, which due to climate change are increasing in intensity (GFDL 2021). In Hurricane Matthews's case, over 800mm of rain was recorded across regions in Haiti (NASA Earth Observatory 2016). Heavy rainfall events such as this increases surface run-off as the ground is saturated, therefore the water reaches the river faster, resulting in flooding. Additional variables such as steep topography, impermeable geology, and anthropogenic factors such as poor drainage or deforestation can further increase the threat of flooding. This research has already identified that Haiti is a mountainous region, therefore has steep topography (Library of Congress 2010). Yet it is also known that large areas of the Sud and Grand'Anse Department's geology are Oceanic Basalt (Valls and Geo 2019; DesRoches *et al.* 2011), which can be impermeable depending on the cooling rate (Waite Roebuck *et al.* 1999). Impermeable geology such as this increases surface runoff, exacerbating flooding. Finally, poor drainage infrastructure contributed to the severity of flooding within the region (Balaraman 2016). Therefore Haiti's environmental characteristics along with poor infrastructure contributed to the flooding associated with Hurricane Matthew. In most cases, vegetation cannot withstand the overflow associated with the flooding and in extreme events it can cause vegetation to become broken and uprooted, decreasing the health of vegetation as inferred by the NDVI (Gangashe 2020). In particular, cultivated areas are particularly vulnerable (Gangashe 2020). This is why the results show more intense damage running parallel to river channels and in surrounding areas.

Knowing that this is where significant damage is concentrated allows flooding mitigation and preparedness strategies to be implemented, such as adapting crop types to reduce future impacts, thus building back stronger. It has been stated that reforestation and planting stabilising vegetation that reduces erosion is key to reducing flooding in Haiti (Benge N.D). Reforestation removes water from the catchment by increasing the amount of precipitation that gets intercepted. Additionally, roots increase ground-through flow, reducing the amount of precipitation reaching the river, consequently reducing the risk of flooding. Previous governmental efforts mitigating against flooding include planting close to 9 million trees and working with farmers to plant more resistant crops that prevent erosion (UNDP 2014). Additionally, organisations such as Eden Reforestation Projects have been established with the goal of working towards reforesting the country (Eden Reforestation Project 2022). Nevertheless, flooding associated with Hurricane Matthew highlighted how large of an issue this is for agricultural through the decreasing NDVI values, thus it must be mitigated to build resilience.

Overall, from the results it can be concluded that there are three significant factors that can determine the severity of damage that a commune sustains immediately post-hurricane. The first is land cover; generally, *Dense Agriculture* and *Agroforestry* sustain more damage than *Moderately Dense Agriculture*. Camp Perrin demonstrates this well, as there is a clear distinction between the severity of damage recorded in *Agroforestry* compared to *Moderately Dense Agriculture*. Secondly, water courses within a commune/if the commune is coastal. Potential flooding associated with high rainfall or a storm surge can significantly damage surrounding agricultural land. Dame Marie, Chambellan, and Les Anglais are all examples of damage to agriculture associated with flooding of rivers, whereas Torbeck demonstrates the damage of a storm surge. Finally, the approach of the hurricane, to the coast can determine the impact of storm surges and rainfall patterns (considering topography), thus having an influence on the severity of damage in a commune.

5.2.3. IMMEDIATE IMPACT- CONCLUSION

Overall, the assessment of immediate short-term changes following Hurricane Matthew can be considered successful. The results allowed conclusions to be drawn about what communes and land cover types were impacted more severely, identifying regions of vulnerability and addressing objective 4. To conclude it can be said that the immediate impacts associated with Hurricane Matthew on the agricultural land of the Sud and Grand'Anse departments caused significant damage, with communes such as Torbeck and Camp Perrin being more severely impacted than Les Anglais. The large decreases in NDVI >0.3 concentrated around river channels and the coastline identified that flooding associated with heavy precipitation, or storm surges can cause severe damage to agricultural vegetation. Additionally, regions with the predominant land cover of *Agroforestry* or *Dense Agriculture* are likely to be more significantly impacted due to the species being taller/having a larger surface area. Consequently, this research has drawn attention to areas of vulnerability and highlighted immediate impacts associated with hurricanes that require mitigation.

5.3. LONG-TERM IMPACT

Objective three of this research set out to monitor the long-term recovery of agricultural land. The mean NDVI results showed that compared to the reference mean NDVI, agricultural land had fully recovered and had a higher mean NDVI by 6 months post-hurricane at a regional scale. As highlighted in Figure 35, not all agricultural land returned to near normal 6 months post-hurricane. Although the 'decreased in NDVI' area is considered large, Figure 35 demonstrates that the areas that have experienced a decrease in NDVI are <0.1. Section 4.1 results established that there are seasonal fluctuations between the two growing seasons; the agricultural land September-November growing season has a higher NDVI average of 0.756 than the April to July growing season of 0.675. This pattern is consistent across both pre and post-hurricane data, across all communes and land covers. Therefore, the areas of land decreasing in NDVI from immediately post-hurricane to 6 months post-hurricane is assumed to be due to the natural seasonal fluctuations. Figure 36 supports this, highlighting that the decrease in NDVI from immediately post-hurricane to 12 months post-hurricane is significantly lower, with a total area of only 409 km^2 decreasing in NDVI (Table 24), in contrast to 1002.9 km^2 6 months post-hurricane. However, upon closer inspection of certain regions it is unknown if this is due to the seasonal fluctuations highlighted by this research, or due to the long-term impacts of soil-salinisation (Rodgers, Murrah, and Cooke 2009; Violette, Boulicot and Gorelick 2009; Gould *et al.* 2020). For example, small, isolated regions of *Dense Agriculture* along the coastline of Torbeck prior to Hurricane Matthew had an NDVI >0.79. Post-hurricane, NDVI decreased to values <0.2, and by 6 months post-hurricane, although there was an increase in NDVI, it was still considerably lower than pre-hurricane values (<0.4). By 12 months post-hurricane, the NDVI had returned to the pre-hurricane value. This data was extracted from a region that sustained coastal flooding, therefore it is possible that the low NDVI observed 6 months post-hurricane could be associated with the effects of soil salinisation or water logging on the health of the vegetation (Gomez 2005; Arya, Mandal, and Muley 2006; Rodgers, Murrah and Cooke 2009; Brun and Barros 2013; Kaiser *et al* 2013; Phonphan *et al.* 2014; Goto *et al.* 2015; Scudiero *et al.* 2016; Gorji, Sertel and Tanik 2017; Dharanirajan *et al.* 2018; Rahman *et al.* 2018; Davis, Wang, Dow 2019; Gorji *et al.* 2019; Nguyen *et al.* 2020; Tripathi and Tiwari 2021). However, without on-the-ground data, validation cannot take place confirming that the decrease in NDVI was associated with soil salinisation and not a result of the seasonal fluctuations. Despite minor fluctuations such as this, the results confirm that agricultural land made a full recovery by 6 months post-hurricane. The small regions such as the one referred to above that sustained negative impacts in the first growing season post-Hurricane Matthew returned near normal by 12 months post-hurricane.

Although the findings of objective three (to monitor the long-term recovery of agricultural land from 2016-2021) are minor and indicate no widescale long-term damage, these findings should still be reported. This is because impacts associated with hurricanes have been found to have long-term effects on agricultural land, consequently affecting the health and productivity of agricultural vegetation (Reliefweb 2004; Breda 2008; Violette, Boulicot and Gorelick 2009; Gould *et al.* 2020), with potential impacts on food insecurity. In this instance it can be concluded that in the short-term Hurricane Matthew caused wide-scale destruction across agricultural land, however, in the long-term on a regional scale agricultural vegetation NDVI was above average, therefore returned to a near normal status within 6 months post-hurricane. From this, we can infer that the long-term impacts on agricultural land such as soil erosion and salinisation, did not have a significant impact on the health of agriculture and by 12 months post-hurricane, small regions of decline in NDVI, potentially linked to salinisation had recovered. In Haiti's case, NDVI returned to normal status in the majority of the study site by the following growing season. However, this may not be the case for all regions vulnerable to hurricanes. As we know from Chapter 2, annual soil loss, exacerbated by hurricanes amounts to 36 million tonnes (Reliefweb 2004). This can wash away vital nutrients vegetation requires to remain healthy (Zhang *et al.* 2009), leading to a long-term decrease in productivity. Furthermore, soil salinisation subsequent to coastal flooding can have long-term impacts on vegetation health, persisting for years after the event (Violette, Boulicot, and Gorelick 2009; Gould *et al.* 2020). In particular, the longevity of salinisation has been suggested to be linked to climatic conditions after the intrusion of saline waters (Dharanirajan *et al.* 2018). Indeed, drought conditions can enable salinisation to persist for longer, as there is no precipitation to 'flush' out the soil. Therefore, although in the case of Hurricane Matthew it can be inferred that Haiti did not sustain any detrimental long-term damage to agricultural land, this may not be the case for every region susceptible to hurricanes. Therefore, long-term recovery should still be assessed in addition to the immediate impacts. Furthermore, the long-term effects of hurricanes broadly referred to as 'land degradation', are a threat that will build up to be more severe over time causing more significant issues in the future than they do now. Thus, long-term threats should still be considered and monitored post-hurricane.

5.3.1. LONG-TERM IMPACT- LAND COVER AND COMMUNES

Across the communes (Table 25) and land covers (Table 26), although each returned to near normal, there were variations in recovery. Across all land covers, the mean NDVI was higher 6 months post-hurricane (April-July 2017) than the April to July growing season NDVI average. Additionally, the mean NDVI was higher than what was recorded immediately post-hurricane. The long-term NDVI mean, min, and max, show that canopies that would be assumed to obtain a higher NDVI such as *Forest* and *Agroforestry* (due to more dense green chlorophyll) (Zaitunah *et al.* 2018), make larger increases in NDVI from immediately post-hurricane to 6 months post-hurricane. This may be because there is a higher chance of defoliation due to the species present within these land covers as they are taller/denser (Walker 1991; Ito 2010; James 2010; Wang *et al.* 2010). Therefore, the increase in NDVI when new leaf and branch production has taken place is more noticeable. Walker (1991) confirms that new leaf production can begin as soon as 2 weeks post-hurricane. Additionally, *Forest* and *Dense Agriculture* had the largest increase in minimum NDVI from immediately post-hurricane to 6 months post-hurricane, showing that the regions of severely low NDVI have increased. For example, areas of *Dense Agriculture* in the Torbeck had an NDVI of 0.79 pre-hurricane, suggesting very healthy agricultural vegetation. Immediately post-hurricane, the same region had an NDVI value of 0.45, which 6 months later had an NDVI >0.7. Highlighting that regions of *Dense Agriculture* that had a low NDVI post-hurricane have improved by 6 months post-hurricane. Finally, *Moderately Dense Agriculture* NDVI was higher above the reference mean NDVI than any other land cover, suggesting that areas of *Moderately Dense Agriculture* were significantly healthier in the April-July 2017 growing season than usual. Overall, employing the mean, minimum, and maximum NDVI, each land cover was seen to make a full recovery by the following growing season (6 months) post-hurricane, April-July 2017. Therefore, although land covers sustained different severities of immediate damage, they all recovered in the long-term, with the NDVI performing above the reference mean NDVI.

In regard to the long-term recovery of the communes, results show that the NDVI of agricultural vegetation was better than the reference mean NDVI 6 months post-hurricane. Additionally, all communes, bar Les Anglais had higher mean NDVI 6 months post-hurricane was recorded immediately post-hurricane. Les Anglais was one of the least impacted communes immediately post-hurricane, therefore had a higher NDVI than most communes. Considering the trend of the April-July growing season consistently having a lower NDVI than the September to November growing season, the fact that an increase in NDVI was not recorded 6 months post-hurricane from immediately post-Hurricane is not a concern, as the decrease in NDVI from immediately post-hurricane to 6 months post-hurricane is most likely linked to the seasonal fluctuations. The communes sustaining the most severe damage such as Torbeck and Camp Perrin, accompanied by Les Cayes and Arniquet have the largest change in NDVI from immediately post-hurricane to 6 months post-hurricane. It can be assumed that this is due to the planting of new crops and regrowth of vegetation sustaining defoliation as this can take place within the months following a hurricane (Walker 1991; Howard and Schokman 1995; Ostertag, Scatena and Silver 2003), thus significantly increasing the NDVI across communes that are dominated by dense vegetation such as *Agroforestry*. Once again, as seen across the individual land cover subsets, the communes all make a full recovery by 6 months post-hurricane.

5.3.2. LONG-TERM IMPACTS IN THE WIDER CONTEXT

The finding that agricultural land can recover by 6 months post-hurricane could be considered a reassuring finding to communities and government. Firstly, it highlights that long-term threats such as increased SS (Rodgers, Murrah, and Cooke 2009; Han *et al.* 2018) are not impacting agricultural land in the long-term. This is supported by figure 36 as 12 months post-hurricane no long-term damage was identified around the coast. Furthermore, with the recovery of agricultural vegetation taking place naturally within 6 months, it means that efforts can be focused directly on mitigating the short-term immediate impacts of hurricanes. Mitigation techniques have been briefly mentioned in Section 5.2.2. Mitigation can include engineering or non-engineering techniques (Li *et al.* 2021), as seen in Table 27 for mitigation techniques against flooding. However, due to the weak fiscal situation Haiti's government is in, there is a lack of funding in the agricultural sector for disaster management and preparedness (The World Bank 2013; Cohen and Singh 2014; Jean, Mary and Lei Win 2022). Subsequently, support for DRM, mitigation, and preparedness is from international NGO's such as ActionAid (Jean, Mary and Lei Win 2022). Indeed, ActionAid is trying to reduce inequality and increase agricultural production by working with Haitian women, teaching them how to grow and sell food, purchase land and mitigate the effects of climate change. In particular, they train farmers to diversify their crops with the hope of building resilience (ActionAid 2022), as it was stated that farmers continue to use the same crop varieties instead of adapting to the changing climate (Cohen and Singh 2014). Besides from NGO's, government plans have been proposed, but rarely materialise; this could be due to the lack of data collected regarding hurricane vulnerable areas (Cohen and Singh 2014). Therefore, it is with the hope that new information provided by this research can aid in planning for DRM, mitigation, and preparedness. This will ensure communities are more resilient in the long-term, ensuring less severe immediate impacts and a shorter recovery period.

To a community so dependent on agriculture, although the results show there are no long-term impacts on agriculture, the 6-month recovery period would be crucial. Xiao (2011) and Mohan and Strobl (2017) and (2021) have shown that hurricanes can directly impact individuals' livelihood; many people would be out of work, and rising food prices increase food insecurity and related health issues, all of which could have a long-term impact. Indeed, Mohan and Strobl (2021) found that the negative impact on unemployment rates post-hurricane can persist for up to 4 years in the Caribbean. Therefore, although there is little to no long-term impact directly on agricultural vegetation, the short-term impacts on agricultural vegetation and consequent repercussions alone are enough to further damage the socioeconomic structure of the region (discussed in Section 5.1). This can cause rising tensions within communities due to a lack of resources, increased unemployment, and highlight weaknesses such as unstable governance, inequality, and the lack of resources and support. This reinforces the importance of this research and the method developed because helping identify severely impacted regions enables focus and support to be directed to vulnerable communities, encouraging them to build back stronger and increase resilience for the future threats that they face. In the long-term this will prevent and reduce the socioeconomic pressures linked to agricultural land post-hurricane. This is becoming increasingly important in the face of climate change as the intensity of climate-related hazards such as hurricanes are increasing (GFDL 2021). Indeed, from 2000-2019, Haiti ranked 3rd amongst the countries most affected by extreme weather events (World Food Program 2022). Being a country that is repeatedly impacted by such hazards makes it challenging for regions to recover in all environmental/socioeconomic aspects before being subjected to another hazard (United Nations 2021). Therefore, although individual hurricane events do not have a long-term impact on agricultural land, the indirect long-term socioeconomic effects and reoccurrences of such events deepen vulnerabilities and can have a long-term impact on livelihoods. Therefore, reducing the short-term consequences, may reduce the socio-economic implications and relieve longer-term impacts.

Despite the quick recovery of agricultural land following Hurricane Matthew, both the Sud and Grand’Anse Departments continue to suffer from food insecurity. As of June 2022, 4.5 million Haitians suffer from food insecurity, with the Sud department being classified in a state of emergency (IPC 2022). This number has increased since 2016 (World Food Program 2016), despite support scattered throughout the communes. With the knowledge that the agricultural land can return to the reference mean NDVI value quickly post-hurricane, there are more influential factors contributing to the consistent threat of food insecurity within Haiti. As discussed in Section 5.1, Haiti is an underdeveloped nation that has many socioeconomic and political challenges. The social structure of the country may have the largest influence on how the communities respond to such events. Thus, although the hurricane causes the direct loss of food, how the country responds is aiding the persisting issue of food insecurity. The 2010 Haiti earthquake is a prime example (Savard, Sael, and Clormeus 2020) of how Haitian public institutions and an unstable government did not anticipate such risks, thus planning and recovery efforts were weak. Consequently, over ten years later the country is still trying to recover (Savard, Sael, and Clormeus 2020). This reinforces that if citizens do not have the tools or resources to improve preparedness for disaster (Samhsa 2017), or build back stronger and utilise the land to its full potential, then regardless of whether agriculture can recover, the communes will be in a constant state of food insecurity. Therefore, evaluating the different variables that are creating a persisting environment for food insecurity is required, as further knowledge is needed on how to help this situation.

Within Section 5.3, the term 'recovery' has been referred to. Recovery can be defined as a return to a normal state, replicating the environment prior to the shock. Within this research, the normal state of health has been defined by the reference mean NDVI of each growing season, therefore results of communes or land covers where the mean NDVI matches or exceeds the reference mean NDVI can be declared as 'recovered'. Considering the status of food insecurity in Haiti prior to and post-Hurricane Matthew (World Food Program 2022), it can be argued that recovery is not enough in these circumstances to reduce food insecurity. Indeed, agricultural practices pre-Hurricane Matthew were not sufficient in sustaining food security, therefore recovery suggests maintaining these issues. This research monitors the long-term impacts and recovery to draw attention to areas of vulnerability. Identifying such patterns and susceptibility lays the foundations for building resilience, therefore the long-term goal is to improve agricultural practices to alleviate food insecurity. Understanding and reaching recovery is key to doing this.

Overall, it can be concluded that Hurricane Matthew did not have a long-term impact on agricultural land in the Sud and Grand'Anse Department and a full recovery was made 6 months post-hurricane. Although this is a positive finding, the short-term impacts in conjunction with Haiti's susceptibility to hazards, both climatic-related and non-climatic related (as evidenced by the 2010 earthquake and the 2018 drought) and their socioeconomic instability are resulting in repetitive damage that could have long-term consequences. A prime example of this is in Jamaica; their economy has grown 0.8% in the past 4 years; however, it would have grown by 4% without the impacts of hurricanes (United Nations 2021). Subsequently, the recovery of agriculture is not the prevailing issue that is causing the consistent threat of food insecurity. There is a socioeconomic and political structure that can be deemed more complex (Council on Foreign Relations 2021; Daut 2021; Human Rights Watch 2020), resulting in the continuity of food insecurity in Haiti. Indeed, unstable governance, a lack of funding and resources, and conflict are all present in Haiti (Edmonds 2013; Daut 2021; Human Rights Watch 2020). However, by providing information on the areas that were initially damaged, at-risk land covers that can be assumed to be vulnerable in the future can be identified and efforts in building resilience can be made. Building back stronger mitigates against more severe immediate damage for future events. This prevention of loss and quicker recovery can subsequently increase the rate of development and reduce a country's vulnerability in the long term (United Nations 2022). This narrative is more complex than can be measured currently in this research, however, it is something to consider. As mentioned prior, a multivariable analysis would be a beneficial piece of research to complete, to understand the broader picture of all factors (socioeconomic and environmental) that influence the amount of damage inflicted by hurricanes.

5.3.3. LONG-TERM IMPACT FINDINGS NOT ASSOCIATED WITH HURRICANE MATTHEW

In addition to the impacts and recovery of the hurricane, this research identified variations in NDVI that were not associated with Hurricane Matthew that could have a direct impact on food insecurity. The largest drop in NDVI was identified 18 months post-hurricane (April to July 2018 growing season); the mean NDVI was 0.603, consequently it was 0.072 below the reference mean NDVI (Figure 41). Additionally, the mean NDVI 18 months post-hurricane was lower than the NDVI that was recorded immediately post-hurricane by 0.73. This indicates that this growing season was less productive in comparison to the average and the land was more severely impacted than post-Hurricane Matthew. Further investigation identified that a severe drought affected Haiti in 2018 (ReliefWeb 2019; Thin 2020), consequently leading to a decline in vegetation health, thus, agricultural production. The drought was reported to be due to the El Nino phenomenon. El Nino is an event that typically takes place every 2-7 years, whereby the sea-surface temperature is warmer than average, causing drought conditions (Klingaman and Keat 2018). This event typically develops in May, reaching its maximum strength between December and February, therefore it can be assumed that the NDVI would reflect the drought conditions in the September 2018 to November 2018 growing season (24 months post-hurricane), as well as in the April 2019 to July 2019 growing season. However, based on the mean, minimum and maximum NDVI this was not the case for the September 2018 to November 2018 growing season. Figure 41 shows that the mean NDVI for the

September 2018 to November 2018 growing season was 0.011 above the reference mean NDVI. Therefore, highlighting that drought conditions did not appear to impact agricultural vegetation in the September 2018 to November 2018 growing season as expected. Despite this, the drought had a large impact on the April-July 2018 growing season. Events such as this are predicted to worsen (Met Office N.D) and it is projected that future years will show a declining trend, with rainfall totals decreasing by as much as 6% (RTAC 2021). Consequently, drought will become an increasing threat for the country and could have more severe effects on agriculture than what was inflicted between April 2018-July 2018. As a result, droughts are another environmental issue that needs to be addressed and investigated further in Haiti. It can be assumed that due to the impact on agriculture reflected in the results, events such as these are contributing to the food insecurity throughout Haiti.

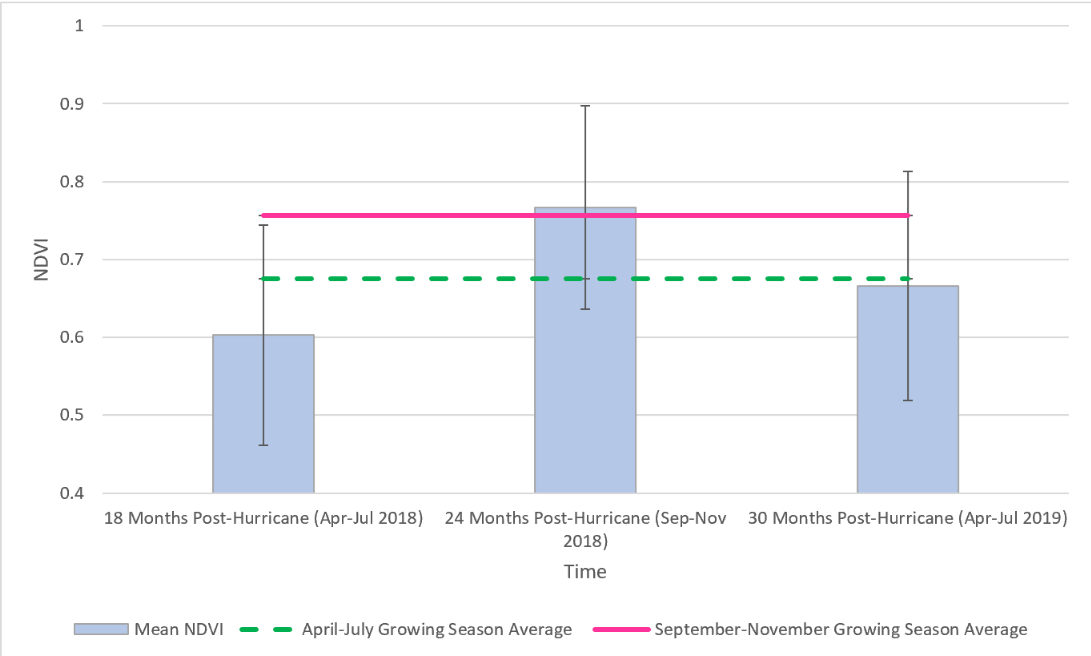

Figure 40. Mean NDVI of 18-, 24- and 30-Months Post-Hurricane Compared to the Reference Mean NDVIs.

5.3.4. LONG-TERM IMPACTS CONCLUSION

To conclude, based on the mean NDVI, agricultural land made a full recovery by 6 months post-hurricane at a regional scale. Upon close investigation, some areas, for example, Torbeck had not reached near normal by 6 months post-hurricane. This could have been because of soil salinisation from the storm surge or seasonal fluctuations between growing seasons as highlighted in the results; without on-the-ground EC data to validate, it cannot be confirmed if the lower NDVI values 6 months post-hurricane were due to salinisation. However, by 12 months post-hurricane, these regions returned to normal. In the wider context, although vegetation returned to normal, it was established that the immediate impacts alone are enough to contribute to and exacerbate long-term socioeconomic issues. Despite this, the results confirm that efforts can be focused on mitigating the immediate impacts rather than trying to bring the agricultural land back to full health post-hurricane. Finally, the long-term results highlighted other climatic-related hazards such as drought that had a larger impact on NDVI, as seen 18 months post-hurricane. This event impacted agricultural land more than what was seen immediately post-hurricane, thus highlighting the threat associated with drought and its potential impacts on food insecurity.

5.4. EVALUATION

The findings of this research meet the aim and objectives of this study, providing a reliable account of the immediate impacts and long-term recovery of Hurricane Matthew on the Sud and Grand'Anse Department, Haiti. However, an evaluation of the study brings attention to areas of the study that could be strengthened for future results to provide more reliable findings.

Firstly, considering that the main agricultural practice in Haiti is smallholder farming, if this research was repeated on a more recent period, satellite imagery with a higher spatial resolution could have been employed. Although Landsat imagery has a consistent spatial resolution suitable for time series analysis, a surface reflectance product, and a QA pixel band for the purpose of cloud masking, the spatial resolution (30m) does not deliver the detail required for smallholder farming. Recent advances have generated wider availability of very-high resolution data (Rivas-Fandiño et al. 2023), such as Sentinel 2 and Planet Lab, however, these datasets did not cover the study period. Sentinel 2 for example has a 10m spatial resolution, a revisit frequency of 6 days, and a surface reflectance product but was launched in 2015, making it unsuitable for this study period. Despite Landsat's spatial resolution being too coarse to monitor individual fields for smallholder farms, it is sufficient for broader landscape analysis. Haiti Data (2017) identified land cover types which could be detected by Landsat. Therefore, until on-the-ground data can be collected to accurately identify more specific land cover types for a smallholder farming scale, very-high-resolution data, although desired is not required.

In relation to CC being a large issue in the collection of data, CC composites were produced to mask and reduce CC for the time-series analysis (Section 3.4.1). This method reduced the risk of skewed data values from CC and increased the continuity of land that could be analysed across time series. The 'lastNonNul' function was employed to ensure that the last date in the time series that is not null of data is prioritised (Google Earth Engine N.D). This is essential as the latest possible date before the harvest begins is desired to produce the NDVI, as this is the most accurate representation of vegetation peak phenology. This means in the latest imagery (pre-harvest) if there were regions of CC, they would be presented as null. Subsequently, the imagery collected (roughly two weeks) prior would be employed to produce the NDVI. This meant that certain regions of NDVI were not reflecting full health prior to harvest. In some regions, this could have reduced the NDVI, impacting the mean, minimum, and maximum NDVIs that were extracted. Employing a satellite with a higher temporal resolution than Landsat (16 days) would reduce the severity of this issue as it would decrease the period between the imagery collected when the pre-harvest imagery is null due to CC. This would increase accuracy as it would be a truer reflection of full health prior to harvest. However, typically, increasing the temporal resolution compromises the spatial resolution and this would have decreased the detail of the findings. Therefore, with the resources available, the method employed to reduce CC was the most appropriate.

When investigating and analysing NDVI across different land covers and communes, similar to research by Hu and Smith (2018), extracting the mean was employed to monitor the immediate impact and long-term recovery of Hurricane Matthew. Firstly, it must be acknowledged that the NDVI can only be cross compared across regions of the same land cover. Secondly, NDVI is not considered to be linear as characteristics of the imagery such as CC, exposure to soil background, or high biomass can lead to saturation of NDVI, decreasing NDVI's sensitivity (Xue and Su 2017). This can result in some data values being skewed or in regions of high biomass for example, a point can be reached whereby NDVI no longer responds to variations in green biomass. Considering this, for future research, as opposed to the mean, alternative measures of NDVI could be explored (e.g., median, maximum with seasonal peak). For example, the median greatly reduces or removes the impact of outliers, especially in areas or land covers that are impacted by CC/cloud shadow or have high biomass saturating NDVI values. However, it must be mentioned that the median does not make use of all the information available in the data as it does not consider the precise value of each observation. Therefore, future assessments should assess which measure of NDVI is appropriate depending on the project focus. To address this issue in this research, minimum and maximum NDVI values were employed alongside mean NDVI to account for anomalies. Furthermore, indices such as EVI could have been considered to reduce inaccuracies as it accounts for soil brightness. EVI was not employed due to it being easily affected by topography, therefore should not be employed in mountainous regions (Matsushita *et al.* 2007; Earth Observing System 2019). However, studies have shown that topographic correction can reduce the effects of topography on EVI (Valeriano, Sanches, and Formaggio 2016; Chen *et al.* 2020), consequently it should be considered for future research.

Furthermore, to calculate the reference mean NDVI, data was collected from 6 years prior to Hurricane Matthew (2010-2015), mirroring the number of years recovery was being monitored (2016-2021). Due to reasons explained in Section 3.3.1, MODIS was employed in conjunction with Landsat to collect data for the reference mean NDVI. When comparing data sources, although the mean NDVI between the two sources were similar (Table 3), the MODIS mean was slightly higher. Therefore, employing MODIS in conjunction with Landsat could have slightly increased the reference mean NDVI values. Although employing MODIS alongside Landsat reduces consistency between years, considering the sources available, this was the most appropriate solution to the issues encountered. Preferably, Landsat would have been used consistently to ensure reliability throughout all results. Furthermore, there were low values of mean NDVI in the pre-hurricane data. Upon investigation it was identified that 2015 sustained the worst drought in the last 35 years (Reliefweb 2016). Climatic conditions such as this may skew the average and it is recommended for future research that the average should be calculated over a longer period to minimise the effect of variability. This will ensure more accurate representation of the reference mean NDVI.

Although objective 3 was successfully met, and it was determined that by 6 months post-hurricane agricultural land made a full recovery, a more detailed account of recovery would be beneficial. From Section 2.3, it has been concluded that a hurricane can increase SS and have a long-term impact on agricultural land. The method used in this study relied on extracting NDVI mean, minimum and maximum values to study the long-term recovery, therefore regional-scale quantitative outputs are derived, giving an overview of the land covers and communes. Alongside this, threshold maps were produced quantitively measuring the change in NDVI from post-hurricane to 6- and 12-months post-hurricane. This enabled identification of increases/decreases in NDVI to be located in association with the recovery, for example, looking at small regions of salinity intrusion in Section 5.3. Although attention could be drawn to specific regions of change, NDVI alone could not infer the reason behind the long-term changes. When working in regions such as Haiti where agricultural production tends to be smallholder farming (Rodrigues-Eklund *et al.* 2021), attention to finer details such as these need to be investigated. This is something that needs to be considered for future research; investigating smaller regions of interest (i.e., town-scale), with high-resolution imagery and on-the-ground data, because it would allow detailed patterns to be identified in the recovery.

The issues encountered within this study regarding spatial resolution, processing techniques and validation of data, although limiting, are ones that many studies encounter (Hoque, Phinn and Roelfsema 2017). However, with the expected advancements in the remote sensing and spatial analysis field, these challenges may be overcome in the upcoming years further advancing how it can be used to aid the disaster management cycle. Despite these areas of the study that could be strengthened, this methodology has highlighted how efficient remote sensing is on a regional/national scale at identifying changes in vegetation. Climate-related hazards such as hurricanes can have a widescale impact, therefore investigating these via fieldwork would not be efficient when trying to identify where efforts should be focused. Furthermore, hurricanes can cause damage to lines of communication and infrastructure, making it challenging and unsafe for on-the-ground research to be carried out. Thus, remote sensing is a safe and efficient way to monitor impacts on a regional scale in near-real-time (Brown *et al.* 2022). Instantly, it can be recognised that this methodology can be used for immediate response to hurricane events, yet it is also adaptable; with appropriate testing it could be used in regions worldwide. Additionally, because this index infers plant health from chlorophyll, it is not limited to assessing one type of disaster, therefore it can be used to monitor the damage of a plant under any shock, such as flooding or drought. Another important development from this methodology is the creation of the cloud composite, the method employed to mask and reduce CC, which increased the area that can be consistently assessed across the study site and should be considered for future research.

5.5. LIMITATIONS

The one major limitation of this research was the lack of/access to data. This is an issue for developing nations such as Haiti globally (The World Bank 2020). The reasons for a lack of data are broad and vary from country to country. In some regions there may be a lack of funding for data collection (Sarvajayakesavalu 2015), social and cultural clashes, or the collection process may be considered unsafe due to conflict/disease (The World Bank 2020). Some regions may not have the resources or infrastructure to conduct research themselves (Elahi 2008; Cohen and Singh 2014), and a lack of trust in foreign organisations would hinder any external bodies that wish to carry out research (Ortiz-Ospina and Roser 2016). Acknowledged in Section 5.1, many of these challenges are present in Haiti, creating a challenging environment for data collection, thus the lack of access to data. Currently, Haiti is fighting one of its worst outbreaks of violence since 1986 when the Anti-Duvalier protest movement took place (Human Rights Watch 2020). Violence alone makes data collection unsafe but complicity between politicians and gangs has further fuelled violence leading to a lack of trust within the country making even the risk of internal data collection higher. As mentioned in Section 5.1, Haiti's history has led to an unstable government and a lack of funding, both of which persist to be issues preventing their development, thus funding for data collection (Cohen and Singh 2014). This has prevented the funding for research and infrastructure needed to support it. Furthermore, Haiti's history could be considered the root cause of a lack of trust throughout the country towards external organisations. This was highlighted following the 2010 earthquake where an erosion of trust was seen towards NGOs, the media, and support services throughout communities; to earn this back it is said consistent open communication, transparency, and respect are needed (Ground Truth Solutions 2022). Although this is in reference to aid associated with the earthquake, it concludes attitudes towards foreign organisations, therefore anyone external coming to do research may be challenged in earning the trust of the community. Thus, considering the above reasons, it is clear to see why data collection in Haiti is challenging. This is an issue that will only be improved with changes in social and political structures throughout the country, aiding development, and building trust back both within the communities of Haiti and with external services, organisations, and individuals from foreign countries (Ground Truth Solutions 2022).

In relation to this study, the lack of access to data prevented the validation of NDVI. Unfortunately, for similar reasons, only 18% of research papers that employ satellite imagery to monitor the impacts of hurricanes validated their findings due a lack of access to data and safety concerns for primary data collection (Huang *et al.* 2021). Despite the above challenges to data access, and the limitations this has inflicted upon this study, the methodology presented in this research was effectively adapted and identified the immediate impacts of Hurricane Matthew, distinguishing regions of severe damage, and monitored the long-term recovery.

5.6. PROSPECTS FOR FUTURE RESEARCH BASED

As mentioned prior, due to limitations regarding time and resources, the scope of what this study could achieve was restricted. Hypothetically, this research would have benefitted from information sharing throughout the local community and working with a multidisciplinary team. Working within the local community, sharing information and data collation has numerous benefits, one being that it provides an opportunity for ground-truthing. Not only does ground truthing provide the opportunity to validate the findings, increasing the validity of the results, it allows for validation of new remote methodologies, expanding the capabilities of remote sensing. Indeed, a lack of on-the-ground data prevented the parameters of salinity and land cover from being explored remotely. Had the time scale for this study allowed salinity and land cover data could have been collected from local smallholder farms. Measuring SS post-hurricane is something that has not been monitored yet in tropical climates, yet it is known that salinity can impact plant health and productivity, both immediately and in the long-term (Violette, Boulicot and Gorelick 2009; Williams 2009; Goto *et al.* 2015). Collecting electrical conductivity measurements would enable correlations to the salinity indices, gauging if the index was representative of the true salinity. Indeed, Tran (2018) attempted to estimate salinity intrusion by correlating on-the-ground electrical conductivity values with spectral bands and salinity indices. Additionally, the lack of and access to data prevented a more detailed, in-depth analysis of the specific land covers and their recovery from Hurricane Matthew to be conducted. Using a secondary source (Haiti Data 2017), this research categorised agricultural land into three classes (*Dense, Moderately Dense Agriculture* and *Agroforestry*). Ideally, specific crop as well as their location would have been available. Consequently, relationships between damage and crop type could be established, allowing more detailed conclusions to be drawn about which crop is more resilient. Specifically, it could inform cropping patterns and more resilient practices to hurricanes. Collecting land cover data would enable training data with improved accuracy to conduct land cover classifications. With on-the-ground data, these methods could have been trialled and validated to provide a deeper understanding of the immediate and long-term impacts of parameters such as salinity post-hurricane. Findings such as this would contribute a wealth of knowledge to this discipline, therefore, collecting on-the-ground data to complete validation of these methods should be a focus of future studies.

Additionally, working with a multidisciplinary team builds a clearer picture of smallholder farming within the Caribbean, aids data interpretation, and provides a holistic view of this study and the impacts of hurricanes, further benefitting the community. In recent years, areas of study such as Plant Pathology have identified the need for an interdisciplinary approach; the complexity of challenges surrounding food security in relation to plant diseases now encapsulates agricultural and ecological sciences, national and global policies and regulations as well as the plant pathology discipline (Jeger *et al*. 2021). Similarly, this research would benefit from a team built from various disciplines, including agroecologists, earth observation and climate change scientist.

Finally, working within the local community, through workshops and round-table discussions, stories and practices in preparation and response to Hurricane Matthew could be shared. Spreading awareness of the ideas and techniques that individuals employed highlights areas of strength and weakness within the agricultural sectors resilience against hurricanes. This allows knowledge gaps to be identified, enabling research to be focused in these key areas. For example, focus groups held in response to Hurricane Michael (2018, Florida Panhandle) expressed the need for long-term and continuous planning for hurricanes, specifying a lack of scientific evidence informing the preparation of specific commodities for hurricanes (Wiener, Alvarez-Berrios and Lindsey 2020). Consequently, focus groups and round table discussions would be helpful to complete in the early stages of future research to identify knowledge gaps, aid understanding of the local context and the importance of the research to the community which it could have a direct benefit on.

For reasons discussed above, recommendations for future research within this discipline that aims to expand on this study is urged to connect with smallholder farmers and work collaboratively with a multidisciplinary team. Primary data collection is also key to expand the capabilities of remote sensing methods to effectivity study the impacts of hurricane on a national scale.

Finally, interpretation of results is based on individual variables supported by the findings of this research and published literature, however, the variables responsible for the varying degrees of damage across the ROI are broad. To have a thorough understanding of the different variables, both socio-economic and environmental, and the weight of influence they have on the impact of a hurricane would require a multivariable analysis. This would allow variables such as distance from the hurricane, land cover type, salinity, slope, access to resources, active organisations, and education to be assessed to determine the independent contribution of each of these risk factors to the change in NDVI experienced in each location. This would allow the most influential factor that determines the severity of damage to be identified. Determining the factors that play a significant role in increasing the threats associated with hurricanes, and sequentially food insecurity would increase clarity on the most effective ways to mitigate against hurricanes and the long-term threats to food insecurity. Consequently, this would be a very beneficial piece of research despite its complex and challenging nature. Research such as this can be time-consuming and not cost-effective over a large ROI, therefore, study sites may have to be refined. Nevertheless, this is a knowledge gap that needs to be assessed, as identifying the most influential variables that affect the severity of damage can highlight where efforts need to be focused to increase resilience against future hurricanes.

CHAPTER 6

6. CONCLUSION

This research sought to assess the immediate impact of Hurricane Matthew on the agricultural land of the Sud and Grand'Anse departments, Haiti, and monitor the long-term term recovery utilising remote sensing. Assessments of post-hurricane damage typically quantified agricultural damage as a loss of yield and the associated cost. Therefore, the immediate and long-term impacts of the change to vegetation were disregarded, despite having a large impact on food production, consequently increasing food insecurity. Therefore, although the results are the main findings to be concluded as they meet the aim and objectives, the method employed to complete this research is considered a vital part of this study as a methodology has been created that can be replicated for future research. Therefore, the methods alongside the findings will be acknowledged in the conclusion.

Overall, the assessment of immediate short-term changes following Hurricane Matthew can be considered successful. The methods used deduced findings that quantitively and qualitatively identified regions that sustained significant impacts post-Hurricane Matthew. This allowed conclusions to be drawn about what communes and land cover types were impacted more severely, addressing objective 4. The findings of this research can conclude that Hurricane Matthew had a large negative immediate impact on the agricultural vegetation in the Sud and Grand'Anse departments. More severe damage occurred in *Dense Agriculture* and *Agroforestry* land covers in comparison to *Moderately Dense Agriculture*. This finding is assumed to be associated with the relationship between wind and the height/surface area of the land cover species. Furthermore, communes such as Torbeck and Camp Perrin experienced more severe damage in comparison to Les Anglais, conveying which communes required more support post-hurricane. On closer inspection of change in NDVI, it was identified that some of the most severely impacted agricultural land was that running parallel to/surrounding river channels. This can be assumed to be due to flooding associated with the hurricane. Similarly, in some regions the impact of coastal flooding was clearly highlighted, this could be seen particularly well in the Torbeck region. These findings reinforce the destructive power of water on agricultural vegetation, making it one of the biggest potential threats associated with a hurricane. The short-term results provide an insight into the regions that are more vulnerable to the effects of hurricanes, and thus need more support and mitigation. Despite the damage seen across the region immediately post-hurricane, findings conclude that NDVI 6 months post-hurricane (April to July 2017) exceeded the April-July growing season NDVI average. This finding confirms that a full recovery of agricultural vegetation took place by the next growing season, 6 months post-hurricane. With the knowledge that this agricultural land can recover quickly, efforts can focus on preparedness and mitigation to reduce the severity of the immediate impact associated with hurricanes. This, in turn, will prevent the loss of agriculture. Additionally, results from monitoring the long-term recovery highlighted a significant drop in NDVI 18 months post-hurricane that was lower than that recorded immediately post-hurricane. This decrease in NDVI (sitting well below the reference mean NDVI), was associated with a drought event. Therefore, it can be assumed that in some cases drought can have a larger impact on agricultural vegetation than a hurricane, therefore posing as an equal, if not greater threat, acting as another component aiding to their food insecurity, vulnerability, and struggle of development in Haiti.

It can be concluded that this research effectively assessed the immediate impact and monitored the long-term recovery of Hurricane Matthew on the agricultural land of the Sud and Grand'Anse department by employing remote sensing. The findings of this research highlighted regions of agricultural vulnerability and have identified crucial patterns of damage that could reoccur under similar circumstances in the future. Therefore, these findings can be used to educate locals and inform changes to policy. Furthermore, the methods of this research can be employed across other study sites, immediately following a climate-related hazard to identify regions of severe damage and inform where resources and support need to be concentrated. Furthermore, despite finding that Hurricane Matthew had no long-term impacts on the agricultural land, the method still proved the ability to monitor the long-term changes in vegetation accurately. Therefore, although there was no long-term damage to agricultural vegetation at this study site, this may not be the case for all regions. For example, a storm surge in a more arid region may have a more detrimental long-term effect on SS, thus decreasing plant productivity which could be identified utilising this method. Although overall, the findings of this research have met the aim and objectives, the limitations of the methods and findings of this research have proven the need for a more in-depth analysis. It has been acknowledged that more detailed knowledge of the land covers and a multivariable analysis would be beneficial in determining the weight of influence different variables have on the impact of the hurricane. This would benefit the research by providing further in-depth analysis, however, this research did not have the time nor resources to complete this. The aim and objectives of this research were met successfully, and with further testing in different regions, the method developed will contribute to further research related to climatic hazards in different regions worldwide.

For Haiti, it is clear that in addition to their exposure to hurricanes, socio-economic setbacks are further contributing to food insecurity, mainly due to the lack of national support and funding for agriculture, DRM, mitigation, and preparedness. Furthermore, hurricanes are limiting economic development both in the short and long term. Moreover, a lack of research in Haiti regarding the impact of hurricanes and associated areas of vulnerability has prevented the implementation of resilient practices. The findings of this research however provide a clear insight into the immediate impacts and long-term recovery of Hurricane Matthew, highlighting areas of vulnerability that will inform and potentially direct where mitigation efforts need to be focused in the future. The research inevitably not only contributes to a literary and methodological gap but has the potential to support communities in Haiti and beyond, to work towards building resilience against future threats.

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8. APPENDIX

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Figure 42. FAO (2010)- Haiti Land Use/Cover Map

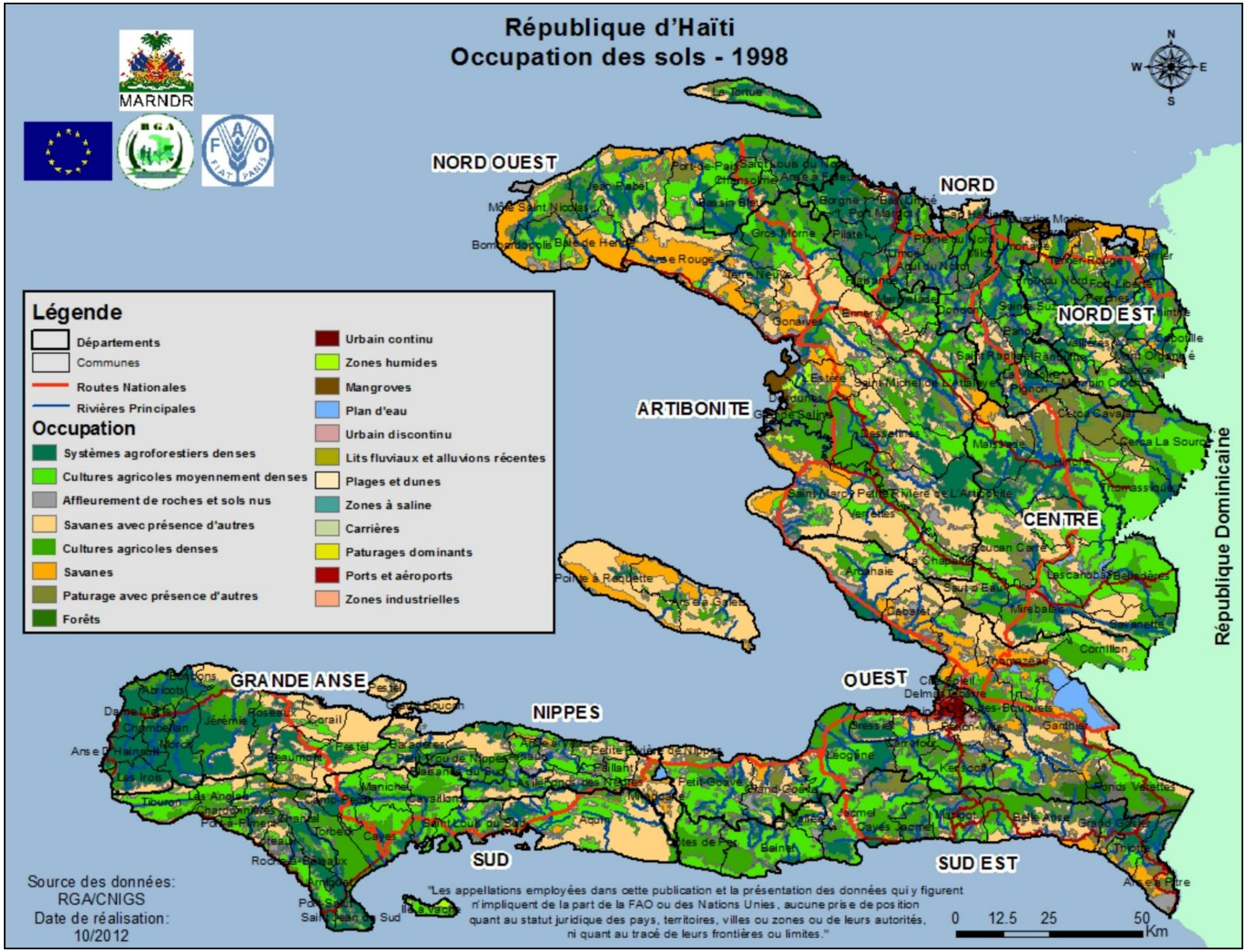

Figure 43. Ministry of Agriculture, Natural Resources and Rural Development (1998)- Land Cover/Use Map.

8.3. Link to GEE Code used to produce Post-Hurricane NDVI

https://code.earthengine.google.com/b21d8d5a5eb8c6f7bf75a87282793d52

```
Imports (1 entry)
var table: Table users/elliejowarburton231198/SudAndGrandAnseClippedToHurricaneTrack
//------Create Filters for time periods
{
var preHurricane = ee.Filter.date('2016-08-15','2016-10-04');
var postHurricane = ee.Filter.date('2016-10-05','2016-12-30');
var PH6M = ee.Filter.date('2017-04-01','2017-07-30');
var PH12M = ee.Filter.date('2017-09-15','2017-11-30');
var PH18M = ee.Filter.date('2018-04-01','2018-07-30');
var PH24M = ee.Filter.date('2018-09-15','2018-11-30');
var PH30M = ee.Filter.date('2019-04-01','2019-07-30');
var PH36M = ee.Filter.date('2019-09-15','2019-11-30');
var PH42M = ee.Filter.date('2020-04-01','2020-07-30');
var PH48M = ee.Filter.date('2020-09-15','2020-11-30');
var PH54M = ee.Filter.date('2021-04-01','2021-07-30');
var PH60M = ee.Filter.date('2021-09-15','2021-11-30');
}



//Input bands from L8
var inBands = ['B2','B3','B4','B5','B6','B7'];



var cloudFilter = 80;


//Bands for output
var outBands = inBands.concat("B2", "B3", "B4", "B5", "B6", "B7", "NDVI","NDBI","BSI","NRI_M","NDVI_M", "CVI_M","GARVI_M","elevation","slope","aspect");

Map.centerObject(table,10);



//-----------------------------------------------------
//Define parameters for the topographic correction
var demin = ee.Image("USGS/SRTMGL1_003");
var degree2radian = 0.01745;

// Define a boxcar or low-pass kernel.
var boxcar = ee.Kernel.circle({
  radius: 2, units: 'pixels', normalize: false
});
// Smooth DEM by convolving with the boxcar kernel.
var dem = demin.convolve(boxcar);


//Function for the topographic correction
var terrainCorrection = function(collection) {


  collection = collection.map(illuminationCondition);
  collection = collection.map(illuminationCorrection);

  return(collection);

  ////////////////////////////////////////////////////////////////////////////////
  // Function to calculate illumination condition (IC). Function by Patrick Burns and Matt Macander
  function illuminationCondition(img){

  // Extract image metadata about solar position
  var SZ_rad = ee.Image.constant(ee.Number(img.get('SOLAR_ZENITH_ANGLE'))).multiply(3.14159265359).divide(180).clip(img.geometry().buffer(10000));
  var SA_rad = ee.Image.constant(ee.Number(img.get('SOLAR_AZIMUTH_ANGLE')).multiply(3.14159265359).divide(180)).clip(img.geometry().buffer(10000));
  // Creat terrain layers
  var slp = ee.Terrain.slope(dem).clip(img.geometry().buffer(10000));
  var slp_rad = ee.Terrain.slope(dem).multiply(3.14159265359).divide(180).clip(img.geometry().buffer(10000));
  var asp_rad = ee.Terrain.aspect(dem).multiply(3.14159265359).divide(180).clip(img.geometry().buffer(10000));

  // Calculate the Illumination Condition (IC)
  // slope part of the illumination condition
  var cosZ = SZ_rad.cos();
  var cosS = slp_rad.cos();
  var slope_illumination = cosS.expression("cosZ * cosS",
                                          {'cosZ': cosZ,
                                           'cosS': cosS.select('slope')});
  // aspect part of the illumination condition
  var sinZ = SZ_rad.sin();
  var sinS = slp_rad.sin();
  var cosAziDiff = (SA_rad.subtract(asp_rad)).cos();
  var aspect_illumination = sinZ.expression("sinZ * sinS * cosAziDiff",
                                           {'sinZ': sinZ,
                                            'sinS': sinS,
                                            'cosAziDiff': cosAziDiff});
```

```
//-----Add NDVI
{
var addNDVI = function(image) {var ndvi = image.normalizedDifference(['B5', 'B4'])
  .rename('NDVI')
  .copyProperties(image,['system:time_start']);
  return image.addBands(ndvi);
}}

//-----First, for the year extract all information
var dataset = ee.ImageCollection('LANDSAT/LC08/C01/T1_SR')
    .filterBounds(table)
    .filterDate('2021-09-15','2021-11-30')
    //.filterMetadata('CLOUD_COVER', 'less_than', cloudFilter)
    .map(maskL8sr);

print(dataset, 'dataset');

//---- filtering bad dates 0
var start_bad_data = '2021-09-30T00:00:00';
var end_bad_data = '2021-10-02T00:00:00';
var bad_data_filter = ee.Filter.date(start_bad_data, end_bad_data);

// Select the bad data.
var L8_bad_data = dataset.filter(bad_data_filter);
// Select the good data.
var L8_good_data = dataset.filter(bad_data_filter.not());

// //---- filtering bad dates 1
// var start_bad_data1 = '2021-05-25T00:00:00';
// var end_bad_data1 = '2021-05-27T00:00:00';
// var bad_data_filter1 = ee.Filter.date(start_bad_data1, end_bad_data1);

// // Select the bad data.
// var L8_bad_data1 = L8_good_data.filter(bad_data_filter1);
// // Select the good data.
// var L8_good_data1 = L8_good_data.filter(bad_data_filter1.not());

var dataset1 = terrainCorrection(L8_good_data).select(inBands).map(divide);

print(dataset1,"Dataset1");

{
var datafirst = dataset1.filter(PH60M);
}

//----- NDVI Last
var collection_first = datafirst.select(inBands).map(addNDVI);
var ndvi_L = collection_first.select('NDVI').reduce(ee.Reducer.lastNonNull()).rename("NDVI_L");

Map.addLayer(datafirst.median().clip(table), {  min: 0, max: 0.3, bands: ['B4', 'B3', 'B2'],}, 'RGB_Topcorrected Median', true);

var clipped = ndvi_L.clipToCollection(table);
print(ndvi_L, 'NDVI_L');
Map.addLayer(clipped, {bands: ["NDVI_L"]}, 'NDVI_L');

// //----- NDVI first
// var collection_first = datafirst.select(inBands).map(addNDVI);
// var ndvi_F = collection_first.select('NDVI').reduce(ee.Reducer.firstNonNull()).rename("NDVI_F");
// var clipped = ndvi_F.clipToCollection(table);
// print(ndvi_F, 'NDVI_F');
// Map.addLayer(clipped, {bands: ["NDVI_F"]}, 'NDVI F');

Export.image.toDrive({
  image: clipped,
  region: table,
  description: '60MPHHurricaneNDVILast',
  scale: 30
});
```

Figure 44. Snapshots of GEE Code for Pre-Hurricane NDVI.

8.4. Link to GEE Code use to produce Pre-Hurricane Imagery

https://code.earthengine.google.com/d9933a2f448f89d05f6b22cf66268baf?noload=true

```
//----- periods of time for averge NDVI
//landsat 8
var aprJul2015 = ee.Filter.date('2015-04-01','2015-07-30');
var aprJul2014 = ee.Filter.date('2014-04-01','2014-07-30');
var aprJul2013 = ee.Filter.date('2013-04-01','2013-07-30');

//MODIS
var aprJul2012 = ee.Filter.date('2012-04-01','2012-07-30');
var aprJul2011 = ee.Filter.date('2011-04-01','2011-07-30');
var aprJul2010 = ee.Filter.date('2010-04-01','2010-07-30');

//landsat 8- sepNov
var sepNov2015 = ee.Filter.date('2015-09-15','2015-11-30');
var sepNov2013 = ee.Filter.date('2013-09-15','2013-11-30');

//MODIS
var sepNov2014 = ee.Filter.date('2014-09-15','2014-11-30');
var sepNov2012 = ee.Filter.date('2012-09-15','2012-11-30');
var sepNov2011 = ee.Filter.date('2011-09-15','2011-11-30');
var sepNov2010 = ee.Filter.date('2010-09-15','2010-11-30');


//Input bands from L8
var inBands = ['B2','B3','B4','B5','B6','B7'];
//(B2=Blue;B3=Green;B4=RED;B5=NIR;B6=SWIR1;B7=SWIR2)



//---------------------------------------------------
//Define parameters for the topographic correction
var demin = ee.Image("USGS/SRTMGL1_003");
var degree2radian = 0.01745;

// Define a boxcar or low-pass kernel.
var boxcar = ee.Kernel.circle({
  radius: 2, units: 'pixels', normalize: false
});
// Smooth DEM by convolving with the boxcar kernel.
var dem = demin.convolve(boxcar);


//Function for the topographic correction
var terrainCorrection = function(collection) {


  collection = collection.map(illuminationCondition);
  collection = collection.map(illuminationCorrection);

  return(collection);

  ////////////////////////////////////////////////////////////////////////////////
  // Function to calculate illumination condition (IC). Function by Patrick Burns and Matt Macander
  function illuminationCondition(img){

  // Extract image metadata about solar position
  var SZ_rad = ee.Image.constant(ee.Number(img.get('SOLAR_ZENITH_ANGLE'))).multiply(3.14159265359).divide(180).clip(img.geometry().buffer(10000));
  var SA_rad = ee.Image.constant(ee.Number(img.get('SOLAR_AZIMUTH_ANGLE')).multiply(3.14159265359).divide(180)).clip(img.geometry().buffer(10000));
  // Creat terrain layers
  var slp = ee.Terrain.slope(dem).clip(img.geometry().buffer(10000));
  var slp_rad = ee.Terrain.slope(dem).multiply(3.14159265359).divide(180).clip(img.geometry().buffer(10000));
  var asp_rad = ee.Terrain.aspect(dem).multiply(3.14159265359).divide(180).clip(img.geometry().buffer(10000));

  // Calculate the Illumination Condition (IC)
  // slope part of the illumination condition
  var cosZ = SZ_rad.cos();
  var cosS = slp_rad.cos();
  var slope_illumination = cosS.expression("cosZ * cosS",
```

```
//-----2014, for the year extract all information
var dataset1 = ee.ImageCollection('LANDSAT/LC08/C01/T1_SR')
    .filterBounds(table)
    .filter(aprJul2014)
    .filterMetadata('CLOUD_COVER', 'less_than', cloudFilter)
    .map(maskL8sr);

var topDataset1 = terrainCorrection(dataset1).select(inBands).map(divide);

{
var datafirst1 = topDataset1.filter(aprJul2014);


var collection_first1 = datafirst1.select(inBands).map(addNDVI);
var ndvi_L1 = collection_first1.select('NDVI').reduce(ee.Reducer.lastNonNull()).rename("NDVI_L");


Map.addLayer(datafirst1.median().clip(table), {  min: 0, max: 0.3, bands: ['B4', 'B3', 'B2'],}, 'RGB_Topcorrected Median', true);
}



var clipped1 = ndvi_L1.clipToCollection(table);
print(ndvi_L1, 'NDVI_L1');
Map.addLayer(clipped1, {bands: ["NDVI_L"]}, 'NDVI_L_aprJul2014');


Export.image.toDrive({
  image: clipped1,
  region: table,
  description: 'NDVI_L_aprJul2014',
  scale: 30
});
```

Figure 45. Snap Shots of GEE Code for Pre-Hurricane NDVI Used to Calculate Average NDVI.