Complex Mosaic Landscapes: Novel Methodologies to Understand Dynamics of Cocoa Farming in Ghana

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Abstract

Complex mosaic landscapes are some of the most prolific and important in the tropics. Often consisting of a mixture of small scale agriculture, natural vegetation and settlements, these areas support the livelihoods of hundreds of thousands of people and are the backbone of some globally important crops, such as cocoa. These landscapes are inherently complex due to the presence and interaction of numerous social and environmental factors across multiple spatial and temporal scales. Given the importance and abundance of these landscapes, disproportionately little is known about the patterns and processes which sustain or disrupt them.

This thesis aims to advance the understanding of complex mosaic landscapes by using novel methodologies to capture and analyse the patterns and processes of these systems. Cocoa farming landscapes surrounding Kakum National Park in southern Ghana are used as a case study. Data were acquired in three distinct regions surrounding the park, namely the area surrounding the villages of Aboabo , Ahomaho and Kwameamoabeng.

This thesis first presents detailed methods for undertaking Unmanned Aerial Vehicle surveys using commercially available equipment with RGB cameras. Next a detailed account of how to processes this imagery using commercially available softwares is outlined. The first data chapter of this thesis examines using machine learning approaches to classify land use within complex mosaic landscapes only using RGB drone imagery. These first chapters highlight the significant insights generated by

this thesis towards capturing the patterns of complex mosaic landscapes in the tropics. The later part of the thesis focuses on the dynamics and processes which govern complex mosaic landscapes by framing them as social-ecological systems. The second data chapter provides a detailed summary of land use in the area of study while also quantifying the impact of humans on the environment by calculating and comparing the Human Appropriated Net Primary Productivity between the three study regions. The final data chapter presents a study of the dynamics between humans and the environment during a climatic shock perturbation. Using combination of social, environmental and spatial data the resilience of households is assessed. Indicators of resilience are then compared at a regional scale to understand some of the multi-scale dynamics of resilience to the climate shock. The thesis is then concluded and future research directions are identified.

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1. Introduction

1.1 Background and Rationale

Much of the world's agriculture exists within complex smallholder mosaic landscapes. Approximately 85% of global farmers are smallholders, farming less than 2-5 hectares of land (Lowder, Skoet & Raney 2016). Smallholder farmers typically farm multiple crops on a single farm, consisting of both subsistence crops and livelihood cash crops, typically relying on rain-fed agricultural practices making them vulnerable to changes in weather conditions, and environmental shocks. Further, these farmers are often poor and food insecure with little economic buffering capacity (Morton 2007).

Many smallholder farmers are located in the tropics, where the impact of climate change is expected to result in increased likelihood of crop failures (Morton 2007; Sylla et al. 2018). Further, the difficulty of capturing the patterns and processes of these lanscapes underscore the need to employ innovative approaches to studying complex mosaic landscapes. As a result of both factors, understanding the dynamics of these landscapes is becoming increasingly important. However, certain regions, such as tropical West Africa, are understudied, and while broad land use patterns are understood at a national or regional scale, the nature of smallholder farming practices requires equally fine scale investigation to understand the complexity of these landscapes. Obtaining data to support the detailed study of complex landscapes can be a challenge.

Conventional ground-based approaches can provide data at the scale necessary to understand complex mosaic landscapes. However, collection of such data can be expensive and time consuming and regions of interest can be difficult to access. In recent years satellite-based remote sensing has emerged as a vital tool to gather large amounts of spatial imagery. However, remote sensing data can be rendered unusable by atmospheric features such as clouds, or haze. These factors are particularly prominent in tropical West Africa, where clouds from the coast and haze from the Sahara (Harmattan) can obscure the majority of satellite images. Some satellite imagery, are only available on relatively coarse spatial scale (>10m resolution), and data that are available on finer spatial scales (<10m resolution) are often not taken frequently enough capture sufficient clear images (Hall et al. 2018). As a result, a scale gap can emerge, where there are few data available to link ground collected data with remote sensing data.

One strategy that could address the apparent scale-gap is utilizing Unmanned Aerial Vehicles (UAVs or "drones") to capture landscape and regional scale land use data at extremely high resolutions (~10 cm). UAVs have the potential to offer low cost, high resolution imagery well suited to complex mosaic landscapes. Until recently this has rarely been exploited. UAV-derived data can eliminate the interference of factors such as clouds or haze, while providing users with large tracks (~1 km^2 per flight) of highly detailed landscape data. The resulting imagery can be used to scale up local and ground based data in such a way that comparison between ground-based data and satellite imagery becomes possible. Thus UAV imagery can fill the scale-gap which will allow comparison of field collected data with regional, national, and event global data.

Further, spatial scaling up of UAV imagery to encompass regions that are relevant to policy makers is possible. In order to accomplish this using UAV imagery alone, there are certain challenges which exist. The most significant of these challenges is due to the current area that an average flight can cover (due to necessary reception between the controller and the drone unit, as well as the battery power). This would require establishing several monitoring locations which are suitable and consistently accessible thus enabling the capture of consistent and standardized data. With the current acceleration of drone technology, it is likely that some of these issues will be addressed in the near future thus allowing monitoring of larger areas with off the shelf drones. Further, combining current and emerging approaches such as machine learning, Google Earth Engine and drone imagery has the potential to predictively upscale trends on the landscape to larger and larger areas.

Once fine scale data can be collected at a suitable rate, opportunities will emerge for more detailed assessments of complex mosaic landscape systems. Beyond classifying land use on a precise scale, further research can be undertaken to understand the dynamics of land use in this topography. The highly integrated nature of the social and ecological aspects of the diversified landscapes highlight the need for integrated study. Social-Ecological Systems (SES) theory offers a useful perspective, suggesting that to understand any elements of a natural resource system, one must consider the ecological and social components as interdependent, and equally important (Berkes, Folke & Colding 1998). In particular, integrated approaches which quantify these relationships can give insight into the operationalization of concepts such as resilience.

1.1.1 Case Study of Regions Surrounding Kakum National Park, Ghana

One of the most important crops produced in tropical West Africa is cocoa. Ghana is one of the largest cocoa producers in Africa, as well as globally, producing 18% of the World's cocoa (Laderach et al. 2013). Cocoa contributes approximately 9% of the Gross Domestic Product of Ghana (Goodman AMC 2017) and constitutes most of the household income for cocoa producers (Ntiamoah & Afrane 2008). The cocoa sector in Ghana employs over 800,000 smallholder farm families and the number of cocoa farm owners in Ghana is estimated at 350,000 (Anim-Kwapong & Frimpong, 2008). Farmers often utilize some portion of their land for subsistence crops along with cocoa cultivation. Understanding the extent of cocoa cultivation and the social-ecological dynamics of these landscapes in Ghana are important to local farmers, the national government, and global chocolate supply chains. Further, typically cocoa is grown in warm and moist regions, however cocoa crops grown in West Africa are grown near the warm/dry threshold for cocoa viability. This means increased temperatures and decreased precipitation threatens the future viability of the crop throughout the entire West African region (Laderach et al. 2013). When considering this factor in conjunction with the potential impacts of global climate change on agriculture in the tropics, the urgency for such research becomes even more apparent.

To further understand some of the knowledge gaps of complex cocoa landscape in Ghana, the ECOLIMITS project was established in 2014. The project sought to understand the various dynamics of the cocoa landscape in Ghana by studying the complex relationships between social and ecological factors within a cocoa growing region including ecosystem health, socio-economic opportunity, and agriculture development (Hirons et al. 2018c; Morel et al. in review).

This thesis was undertaken in collaboration with the ECOLIMITS project, and seeks to scale up the social and ecological data, using innovative methods to capture the extent and pattern of not only cocoa production, but also other land uses. Further, by integrating both social and ecological data, this project seeks to quantify the impact of human land use on this landscape as well as spatial resilience of the cocoa farmers.

1.2 Aims and Objectives

This doctoral thesis aims to apply novel UAV-based methodologies to map the patterns and process of a complex small holder mosaic agricultural landscape in West Africa. The thesis focuses on the cocoa growing region surrounding Kakum National Park in the Central Region of Ghana.

To achieve this aim, the following broad objectives were identified, with the specific objectives further outlined.

1. Utilize basic UAV imagery, and machine learning, to capture and classify land use in a complex mosaic landscape.
    i. Develop more affordable monitoring methods for local actors
    ii. Undertake detailed surveys of three distinct regions surrounding Kakum National Park using a conventional commercial drone equipped with a high resolution RGB camera.

iii. Classify the land use in each region using ground-truthed manual classification, and use this data to train and test random forest and neural network machine learning approaches in order to compare the success, strengths and weaknesses of each.

2. Increase the understanding of the relationship between humans and the environment in complex mosaic landscapes by quantifying the level of human impact on the region.
    i. Quantify the level and diversity of human impact on the regional ecosystem using Human Appropriated Net Primary Productivity (HANPP) as the focal metric.

3. Investigate the how social, environmental and spatial factors impact the resilience of farmers during a disturbance event.
    i. Investigate the spatial resilience within and between each region using a social-ecological lens and combining geospatial metrics and social survey data collected during a climate shock (2015/2016 El Nino).

1.3 Related Publications

The following first author journal papers form the main substantive content of the DPhil Thesis. The papers are themselves integrated into the thesis through their inclusion as Chapters 3-6. Paper contribution statements, signed by all co-authors, are located in Appendix A. A description of each paper, including its status in terms of publication, is given below:

I. Moore, C., Kruitwagen, L., Ramirez-Mendiola, J. L., Morel, A. C. & Malhi, Y. Classifying Land Use in Complex Mosaic Tree Crop Landscapes using Drone Imagery and Machine Learning. *Remote Sensing and the Environment.* In review.

II. Moore, C., Morel, A. C., Asare, R. A., Sasu, M. A., Adu-Bredu, S., & Malhi, Y. Human Appropriated Net Primary Productivity of Complex Mosaic Landscapes. *Frontiers in Forests and Global Change*. In review.

III. Moore, C., Morel, A. C., Aronson, J., Hirons, M., Messina, J., Asare, A. C., Queye, M., Mason, J., Norris, K., & Malhi, Y. Resilience of farmer households in a complex mosaic landscape: A case study of Ghanaian cocoa and El Niño. People and Nature. In review.

1.4 Outline of the Thesis

The thesis is divided into seven chapters. Following the introduction, Chapter 2 provides a literature review that underpins the primary themes and the theoretical and methodological development of the thesis. This includes an outline of global change, social-ecological systems and resilience, smallholder agriculture in Ghana, measuring complex mosaic landscapes, and analyzing complex mosaic landscapes.

Chapter 3 presents a detailed outline of the UAV or drone based methodologies which are central to chapters 4, and 5. Additionally, relevant methodologies of the broader ECOLIMITS project not covered in depth in Chapters 4, 5 or 6 are presented.

Chapter 4 responds to research objective one by presenting a methodology for classifying land use in a complex mosaic landscape using simple RGB UAV imagery and comparing three machine learning approaches. Classifying land use in tropical regions can be notoriously difficult, due the broad homogeneity of the landscape (dense vegetation, few settlements, small colour variation). As such, this chapter seeks to investigate the success of a number of machine learning approaches, including a standard random forest approach, a neighbourhood random forest approach, and a novel neural network machine learning approach. The results indicate that the novel neural network machine learning approach, titled ResUNet, was consistently the most successful at classifying the land use data, with the neighbourhood random forest being the next most successful. This chapter is presented through the related publication [I] Classifying Land Use in Complex Mosaic Tree Crop Landscapes using Drone Imagery and Machine Learning.

Chapter 5 responds to research objective two by presenting a quantitative analysis of the level of human impact in the region of study. This chapter measures Human Appropriated Net Primary Productivity (HANPP) in three regions surrounding Kakum National Park. While all regions are considered cocoa growing regions, all had different land use patterns and average HANPP values. The HANPP for the three cocoa regions studied was found to be approximately 6.69 MgC/ha, 8.00 Mg C/ha and 9.85 Mg C/ha. The findings of this study are higher than those which have been reported in other publications, and possible reasons for this are discussed. This chapter is presented through the related publication [II] Human Appropriated Net Primary Productivity of Complex Mosaic Landscapes.

Chapter 6 responds to research objective three by presenting an analysis of the relationship between farmer resilience and spatial, social and environmental factors during a climate shock caused by the 2015/2016 El Nino. This chapter investigates resilience by considering the resistance to the shock and recovery from the shock as two separate responses. Social, environmental and spatial data are studied using a general linear model to determine how these might interact to lead to households which show resistance to the shock and those which show recovery from the shock. The results indicate that those households with wetter ground on their primary farm and a fewer people in their household were more resistant to the climate shock; while those with wetter ground, closer proximity to the urban centre of Assin Focu and a male primary decision maker were more able to recovery from the climate shock. This chapter is presented through the related publication [III] Resilience of farmer households in a complex mosaic landscape: A case study of Ghanaian cocoa and El Nino.

Chapter 7 presents the conclusions of the thesis. Firstly, by summarizing the thesis followed by an outline of the main research and applied contributions of the work. Finally, potential future work in this area is outlined.

2. Literature Review

The literature reviewed in this chapter is divided into four separate focuses. The first is on global change, specifically climate change, and how to study its impacts on connected human and natural systems. Further, the concept of resilience is introduced as a way to frame the study and adaptation suggestions of these impacts. The second literature describes the importance of small holder agriculture in Ghana, particularly in cocoa production. The third literature focuses on the measurement, and classification of complex mosaic landscapes, while the fourth focuses on how these landscapes can be analysed to gain insights into the dynamics of these systems. The data chapters of this thesis (Chapters 4, 5 and 6) rely on one or more of these distinct literatures.

2.1 Global Change, Social-Ecological Systems and Resilience

Anthropogenic influence on the earth is clear, from habitat destruction to climate change, the world is changing at an unprecedented rate. The planet has entered the Anthropocene, where human actions have become the central drivers of environmental change (Steffen 2007, Rockstrom et al. 2009). Large-scale changes have occurred in globally significant biomes including tropical forests via land conversion (Malhi et al. 2014), oceans via overfishing (Scheffer et al. 2005) and grasslands via changes in fire regime and grazing patterns (Goetze et al. 2006). Further, all of earth’s biomes are now influenced by climate change via alterations in atmospheric composition including increases in greenhouse gases such as CO_2 and methane (Solomon et al. 2009). Anthropogenic climate change is already associated with increasing global temperatures, ocean acidification as well as increasingly severe weather events such as droughts, storms and shifts in precipitation regimes (IPCC 2018, James et al. 2018; Mba et al. 2018; Mitchell et al. 2016; James, Washington & Jones 2015). Climate change in the last few decades has had widespread impacts on human and natural systems, indicating the sensitivity of these systems to a changing climate (IPCC 2018).

Global change, via climate change and other anthropogenic drivers, has already begun to directly impact both human and natural systems (IPCC 2018). However, the influence of direct impacts is seldom straightforward, and will likely include an array of processes including indirect impacts, feedback loops and knock-on effects (Norberg & Cumming 2008). The compounded and tangled nature of these impacts reflects the complexity inherent within both human and natural systems, as well as the complexity of connections between them (Berkes, Colding & Folke 2003). As such, many emerging and ongoing resource and environmental problems can be viewed as complex systems problems (Levin 1999). A complex systems approach studies the interactions of interrelated elements within a system, and the emergent properties of the entire system, rather than focusing on individual elements of the system (Mitchell 2009). Systems theory provides a conceptual framework to understand the dynamics of integrated systems (Norberg & Cumming 2008).

The two prevailing approaches which involve the study of humans and the environment as a single, complex system are as Coupled Human and Natural Systems (CHANS) or Social-Ecological Systems (SES) (Liu et al. 2007). Originating from separate fields of study, but ascribing to similar principles, both approaches seek to integrate social and ecological sciences to study human and environment interactions (Liu et al. 2007; Berkes, Colding & Folke 2003). Given the ubiquity of the terms, for the remainder of this thesis SES will be used to describe such systems. While the properties of such systems are complex, nonlinear and dynamic, advances have been made towards understanding these complexities (Rogers et al. 2013; Moore et al. 2014; Biggs, Schutler & Schoon 2015). Within the context of multi-scaled global change, understanding the complex dynamics of social-ecological systems is imperative (Norberg & Cumming 2008). Humans depend upon natural resources and ecosystem services however the complexity of natural and social systems make mapping the interactions between them and how they might respond to global change challenging (Liu et al. 2007).

Modelling potential longitudinal change in atmospheric conditions due to climate change is particularly complex, and studies are frequently adjusting models to improve predictions (Allen et al. 2018). Using these studies as the basis for understanding the potential impacts of climate change on social-ecological systems can involve many assumptions and uncertainties. However, disturbances due to climate change are already increasing in frequency and severity and can provide insights into potential future changes and conditions (Otto et al. 2018, Philip et al. 2018). Further, these disturbances can also occur on a timescale which can enable the direct study of such events on social-ecological systems (Lugo 2018). As such, using disturbances due to climate change, or disturbances which mimic expected long-term climate change impacts, can help assess and provide insight into the future sustainability of social-ecological systems under climate change.

Climate change is expected to impact peoples and ecosystems unequally, amplifying existing risks or vulnerabilities as well as introducing new ones (IPCC 2018). Those in disadvantaged communities are most at risk and, by extension, so are the ecosystems they are most connected to (Adger 2006). In many developing regions, people rely directly on the environment for food, shelter and medicine, with those who are most disadvantaged being most reliant due to an inability, either through lack of money or access, to exploit alternatives, such as buying food or medicine from a market or shop (Kaimowi & Sheil 2007). As such, decreases in ecosystem function, such as a loss in soil fertility, will impact those most reliant on the land creating a positive feedback between losses in ecosystem function and poverty (Barbier 2000)

While system vulnerability typically focuses on the susceptibility of that system to harm, the contrasting notion of resilience focuses on the ability of a system to persist. While in many ways these concepts are a product of differing origins (social vs. ecological science), there is substantial conceptual convergence of the concepts of vulnerability and resilience (Miller et al. 2010; Turner 2010). The concept of resilience has become an increasingly popular lens with which to assess directional change in social-ecological systems (Folke 2006; Chapin et al. 2010; Gunderson 2010). While many definitions of resilience exist, from the metaphorical to specific (Carpenter 2001), the basic concept was originally proposed as the ability of an ecosystem to absorb changes, or bounce back from disturbance, and still exist (Holling 1973). Recent definitions tend to elaborate on this original idea, and includes the capacity of social, economic and/or environmental systems to cope with hazardous event(s), trend(s) or disturbance(s), and maintain their essential structure, function and identity (Carpenter 2001; Walker et al. 2004; Cumming 2005; IPCC 2018).

The perceived vulnerability or resilience of a system to climate change and associated disturbances can vary significantly based on the bound and scale of assessment or analysis. Just as communities which are disadvantaged are most at risk to the impacts of disturbance, further dynamics within communities, such as access to resources or positions of influence, predispose certain households or individuals to greater risk (Bennett et al. 2016; Dumenu & Obeng 2016; Hirons et al. 2018c). Similarly, ecosystems or ecosystem components, such as certain tree species, can be perceived as being at greater or lesser risk given the scale and context of analysis (e.g. within a farmers plot vs. a national park for example). The importance of scale when studying resilience in social-ecological systems unifies different disciplinary perspectives of complex systems research (Cash et al. 2006; Cumming et al. 2006; Scholes et al. 2013).

Patterns and processes as well as individuals and networks exist within contexts that vary in dimensions. A combination of these dimensions is what defines a single scale, and it is at this scale that empirical observations are made (Cumming et al. 2006). However, couplings within and among social-ecological systems take place across scales (Liu et al. 2007) thereby making traditional single scale approaches unsuitable to sufficiently capture and represent the system complexity. For example, a single scale study would focus only on the household, town or regional level (inclusive of multiple towns or villages), while a multi-scaled approach would include a focal scale (such as a town), as well as smaller scales (such as households) and/or larger scales (such as regions). It should be noted that to scale up from small to large is not a simple process of aggregation, due to the nonlinear processes that organize the shift from one range of spatial and/or temporal scales to another (Holling & Gunderson 2002). In order to account for scaling and cross scale feedbacks, studies of social-ecological systems must seek to account for multiple scales during analysis, at a minimum accounting for the scale directly above and below the scale of interest (Cumming et al. 2006).

2.2 Smallholder Agriculture in Ghana

Agriculture is particularly important in supporting rural livelihoods in Africa, where it is typified by smallholder agriculture (Collier & Dercon 2014). Smallholder agriculture generally involves rural producers whose farm is maintained by family labour and the farm constitutes the primary source of income for the household. Subsistence agriculture, on the other hand, is that which is undertaken for the primary objective of consumption by farmers themselves (Morton 2007). Farmers will often undertake some combination of smallholder farming (e.g. cash crop or farming) and subsistence farming, especially in regions where poverty is prevalent. This type of agriculture is particularly vulnerable to climatic events because farmers often lack the financial means to install irrigation or other infrastructure systems which could provide stability in times of environmental disturbance such as drought (Danso-Abbeam, Addai & Ehiakporl 2014). This vulnerability is even more pronounced in the tropics, where most crops are rain-fed, and climate change has the potential to significantly influence crop productivity (Slingo et al. 2005, IPCC 2018).

One of the most important crops produced in tropical West Africa is cocoa. The global cocoa industry is dependant on the cocoa produced in this region and consequently cocoa is central to the economies of a number of countries there, including Ghana (Schroth et al. 2016). Ghana, along with neighbouring Cote d'Ivore, are two of the largest cocoa producers in Africa, as well as globally, producing 70 % of the worlds cocoa (Vigneri & Kolavalli 2018, Laderach et al. 2013). Cocoa contributes approximately 3.4 % of the GDP of Ghana (FAO 2008), 10 % of agricultural GDP, and can represent between 70-100 % of the annual household income for cocoa farmers (Ntiamoah and Afrane 2008). Even though cocoa-harvested land has increased from one million hectares in 1995, to 1.6 million in 2010, most cocoa farms in Ghana remain small and are typically 2 hectares or less (Wessel and Quist-Wessel 2015), however the general definition of small holder farming can include farms up to 10 hectares in size (FAO 2012). The cocoa sector in Ghana employs over 800,000 smallholder farming families and the number of cocoa farm owners in Ghana is estimated at 350,000 (Anim-Kwapong and Frimpong, 2008).

While Ghana was the largest global producer of cocoa in the 1960s, their contribution to global market shares decreased and approached insignificance in the 1980s due in part to large bush fires which destroyed many coca farms. Since then cocoa production has increased consistently, and at times rapidly. Cocoa is credited with helping Ghana achieve large reductions in unemployment and poverty (Kolavalli & Vigneri 2011). However, poverty persists amongst many cocoa farmers and remains a principal challenge for achieving a sustainable cocoa sector. This is in turn exacerbated by poor rural infrastructure and services, a rapidly aging farming population, and weak organizational and management skills among cocoa cooperatives (Hainmueller 2011). This poverty continues to persist, even in the face of increasing global importance of cocoa products. This, along with the dependence of cocoa farming systems on sensitive climatic parameters, highlights the vulnerability and uncertainty facing Ghanaian cocoa farmers and possibly other cocoa farming regions under climate change (IPCC 2018)

The majority of cocoa farmers only cultivate relatively small farms (approximately 2 – 5 ha). Generally, the productive lifetime of cocoa trees is between 30 and 40 years. Once a farm has begun to decrease in productivity due to age, there are two approaches farmers can undertake. The first is to plant new trees on the same area or to attempt to rehabilitate the farm to extend the productivity for a few extra years using better management practices such as applying fertilizers or undertaking integrated pest and disease control (Wessel & Quist-Wessel 2015). Some farmers may choose to leave old farm areas to fallow for some years to enable the soils to replenish, while others may immediately plant again due to constraints of land access or land tenure (Hirons 2018a). While historically, farmers would preferentially cultivate areas of native tropical forest this is not the case any more. Primary forest remnants in the cocoa growing regions of Ghana are all heavily protected, thus forcing farms to look to fallowed lands (Wessel & Quist-Wessel 2015) . However, The ability of a farmer to undertake such farm shifting and expansion would be broadly dependant on land tenure and ownership laws and practices in their region.

Some farmers use a portion of their farms to cultivate a range of subsistence crops for their own family, while others may use some portion to grow vegetables for the local market. Additionally, farmers will often utilize multiple crops to not only maximize the productive capacity of their land, but also to accommodate the growth and development of their most important crops (Assiri et al. 2012). For example, when farmers have cleared an area specifically for cocoa cultivation, they will also plant plantain and a mixture of other vegetables amongst the young cocoa seedlings. Farmers will plant plantain in particular, because it provides substantial shade for the cocoa seedlings and keeps the soil cooler and wetter, thereby accommodating the growth and development of the cocoa. As a result, the landscape itself, at a broad scale is relatively homogenous, consisting of remaining forest stands and various forms of agriculture. However, at a fine scale the landscape is very heterogeneous, with plots adjacent to each other being used for vastly different agricultural activities.

2.3 Measuring Complex Mosaic Landscapes

Land-use patterns in small holder agriculture systems are highly heterogeneous and often appear as a mosaic on the landscape (Norris et al. 2010). However, understanding and capturing the patterns and processes of such a mosaic landscape is highly difficult. The sheer number of actors or households involved, combined with a diversity of agricultural approaches create a complex system of social, environmental and spatial processes (Padoch & Sunderland 2013). As such, many of the regions which produce cocoa in Ghana could be considered complex mosaic landscapes. While these areas consist primarily of cocoa plots, they also contain a range of villages of different sizes and a dispersion of other crops and agricultural activities. Further, given the historical coverage of this region by tropical forest, remnant large native trees remain which many farmers actively maintain to either provide shade for their agricultural crops, or as an investment to be sold for timber in the future (Hirons et al. 2018b).

Understanding, measuring and analyzing the dynamics of complex mosaic agricultural landscapes, particularly in the tropics has proven difficult (Lasseur et al. 2018; Reed et al. 2017; Pfund 2010). The first step in this process is to capture the pattern of land use in the region of interest. There are two common approaches which would normally be used to capture land use, one land based and one air based. Land based methods consist of ground surveys as the principle technique which entail walking transects and using GPS technology to record land use at designated distances (Fuller et al. 1998). However, the rural location of many complex mosaic landscapes in Ghana, along with the unstable transport infrastructure, make many such systems difficult to access to undertake ground level surveys. Further, the large geographic extent of the regions can make property censusing and cataloguing land use from the ground impossibly expensive and impractical (Pundt & Brinkkotter-Runde 2000).

Satellite based methods available for the mapping of complex mosaic landscapes include using remote sensing (RS) imagery, particularly satellite derived RS imagery. This is one of the primary ways that information can be obtained over large spatial scales. The term 'remote sensing' can be used to describe any method of data collection where data are obtained where the sensor is not in physical contact with the subject matter, but is most often used to describe data which are collected from an aircraft or satellite (Cracknell 2007). A variety of platforms offer a large degree of precision of images and the opportunity to capture detailed temporal dynamics (Matese et al. 2015). Since as early as 1900, aerial photography or air photos have been the best way to obtain information of larger spatial scales than are allowed by standard ground based methods. While aerial photography is still utilized today, it remains expensive, and can become prohibitively costly and time consuming as the area of study increases (Smith, Chandler & Rose 2009).

Since the 1960s, the field of remote sensing has become increasingly dominated by the study of data collected from satellites. The Landsat and MODIS image collections owned by NASA are the most widely known and used. The data are freely available and provide information at 30 m, 250 m and 1000m resolutions, respectively (Garcia-Mora, Mas & Hinkley 2012; Hansen & Loveland 2012). In the last two decades, the price and accessibility of satellites has decreased substantially and have resulted in a large number of additional satellite image collections. Many of these are owned by private companies and can provide data at extremely high resolution (>10cm resolution) (Schreier & Dech 2005).

Remote sensing has resulted in major breakthroughs of scientific discovery in recent decades. However, there are remaining regions of the planet where remote sensing remains a difficult methodology for studying landscapes (Sanchez-Azofeifa et al 2009). One of the primary limitations with remote sensing imagery from satellites is the inability of the most sensors, such as Optical data and LiDAR, to penetrate cloud cover. It should be noted that RADAR sensors can penetrate cloud cover, however RADAR is only available on a small subset of satellites currently and may be at too coarse a scale to provide insight into complex mosaic agriculture landscapes (Chen et al. 2017). As a result, tropical areas can often be extremely difficult to study, given the large amount of atmospheric scatter and cloud coverage characteristic of tropical forest landscapes (Hilker et al. 2012, Shrestha, Saepuloh & van der Meer 2019). Some of these issues can be overcome by combining images into cloud free composites representative of broader year or multi-year time periods. Further, recent advances in processing platforms, such as Google Earth Engine, allow investigators to even combine cloud free pixels to generate mosaics (Gorelick et al. 2017). However, even given these advances, the presence of perennial clouds restrict the applicability of satellite remote sensing as a method.

These issues are further exacerbated when trying to assess tropical small scale agriculture. Further, in regions where tree crops such as cocoa or coffee are prominent, the issue of classification using remote sensing becomes even more difficult. The inefficiency of sensors to detect the differences between heterogeneous agriculture landscapes and heterogeneous forest landscapes has often lead to misclassifications of these regions in the past (Hansen et al. 2013, Tropek 2014). This can result in agricultural landscapes being labeled as forest, to the detriment of the accuracy of global land-use surveys like Hansen and colleagues (2013) original forest coverage map (it should be noted that more recent iterations of this project have become increasingly successful at classifying forest agriculture). However, even recent iterations of large scale global studies continue to misclassify land use (Mendenhall & Wrona 2018). The use of private high resolution image collections, such as Rapideye or WorldMapper, has the potential to solve some of the issues associated with misclassification of land-use, and further provide ideal data for which to describe detailed small-scale land-management. However, the frequent cloud coverage as well as the expensive cost of such images constrains their use.

In recent years, the utility of small lightweight unmanned aerial vehicles (UAVs) or drones has gained increasing popularity as a practical approach to ecological monitoring. Drones have been used for diverse projects including mapping malaria vector habitats (Hardy et al. 2017), assessing the impact of species reintroductions (Puttock et al. 2015), assessing forest biodiversity (Getzin et al. 2012), and community based forest monitoring (Paneque-Galvez et al. 2014). Drones can be flown under clouds and their flight height can be adjusted easily allowing them to be used to capture images under otherwise restrictive conditions for other remote sensing approaches. While satellite imagery is more systematic and consistent, drones are more flexible and offer the operator or authority the opportunity to dictate the frequency of data collection. Further, drones can be of particular value in tropical areas where such utility can be more reliable than satellite RS images, due to the impact of clouds or atmospheric haze which can render some RS images unusable. In particular, drones area necessary compliment to, ground surveys and satellite RS images, specifically filling the scale gap between the approaches. This is particularly true when trying to get a dynamics and complex and heterogeneous landscapes.

The cost of collecting drone imagery in comparison to other survey methods, such as satellite based remote sensing imagery, can initially be expensive, however these costs quickly decrease. For example, the primary expense for collecting drone imagery is the purchase of the drone itself. Thus while the initial cost would be high (depending on the drone this could range from approximately 500 pounds to several thousand pounds), the subsequent use of the drone would be low, only including the cost of accessing a launch site, and the cost of the operators time. One cost related criticisms of drone use could the be the costs associated with surveying a large area. However, purchasing and deploying drones to various locations is a possible solution, which would include a large upfront cost, but again relatively low running costs. This would also allow monitoring at any desired temporal scale. Conversely, the use of remote sensing imagery (where possible) would incur the same cost for each image acquired, thereby possibly outpacing the cost of the drone monitoring after some amount of time.

Drones have been used successfully in a number of land classification studies. Drones are routinely used to classify urban land use (Feng, Liu & Gong 2015; Koeva et al. 2016) and have been used to investigate vegetation composition in North America (Ahmed et al. 2017), and South East Asia (Kalentar et al. 2017). Recently, Hall et al. (2018) used UAVs to classify maize in a complex small holder farming system in Eastern Ghana. Their study used a combination of Red-Green-Blue (RGB) and Near Infrared (NIR) drone imagery over an ~.8 hectare area to classify maize location up to a high accuracy using object oriented image classification methods. While this study highlights the utility of such tools in understanding mixed small holder landscapes, the applicability over larger areas was not investigated. These previous studies highlight the immense utility of drones for classifying land use, however, specific application of such tools has not taken place in cocoa growing regions with the express purpose of classifying cocoa (among other land uses). The complexity, small scale heterogeneity of land use, and the homogeneity of land cover (namely dense, green vegetation) underscore the need to undertake drone surveys in cocoa growing regions.

Classification of remote sensing imagery, including via satellite or other methods such as aerial surveys, drone surveys etc., has advanced significantly in the last few years. Historically, the primary approach was to use pixel-based unsupervised or supervised classification to classify imagery. In unsupervised classification, pixels from an image are clustered based on their spectral properties using one of a number of clustering algorithms. It is referred to as unsupervised because the user does not input any information such as examples of class types, but rather just dictates the number of classes to produce. The clustering algorithms used to generate classes based on the structure of the data, such that elements in the same cluster (or class) are more similar to each other than they are to different clusters. There are several commonly used algorithms, such as k-means, and hierarchical clustering. Each use slightly different approaches to group data, with k-means assuming that similarity between data points (or pixels) is the opposite of the distance between points using squared Euclidian distance Alternately, hierarchical clustering which can be either divisive or agglomerative, where pixels either begin as once single cluster (divisive) and are iteratively separated into more clusters or where each pixel begins as its own cluster (agglomerative) and are iteratively grouped based on cluster dissimilarity (Jain 2010). In supervised classification, the user selects representative samples of each land cover class. The spectral signature for each class as well as an algorithm, such as standard maximum likelihood or minimum distance estimators, is then used to classify the remaining area. In maximum likelihood algorithms, it is assumed that the statistics for each class in each spectral band follows a normal distribution, where each pixel is assigned to the class with the highest probability of matching it. Alternately, a minimum distance classifier will generate a mean point in digital parameter space which is based on the pixels from the known class. This is done for each class, and unknown (or unclassified) pixels are assigned to the class which is arithmetically closest when the digital values of the different bands are plotted. Both supervised and unsupervised classification methods (Richards, 2012) can have limited success on particularly complex landscapes where multiple land-use classes have similar spectral signatures (such as in complex small holder landscapes) (Tutu Benefoh et al. 2018). In the late 90s, Object-Based image classification shifted from pixel level classification to grouping pixels beside each other into homogeneous image objects. While this method is often more successful than supervised or unsupervised classification, this approach also struggles in regions where spectral signatures are similar amongst object classes, and where the density of objects is high and diverse (Liu & Xia 2010).

Recently, computer vision techniques, including convolutional neural networks, deep learning and machine learning, have been rapidly advancing. Computer vision techniques use image processing algorithms to recognize patterns to interpret images. These techniques take an image as an input and provide a classification as an output, which could be anything from distinguishing between a dog or a cat in an image, to identifying features such as size or colour (Everingham et al. 2010). As these techniques have developed, the ability to utilize such sophisticated approaches has spread into applied studies in ecology and have shown promise in land-use classification (Kumar et al. 2012, Dell et al. 2014, Weinstein 2017). One of the most utilized approaches has been the Random Forest model (Cutler et al. 2007). While originally designed for the machine learning community, this technique has been used in a number of different studies such as classifying salt marsh vegetation (Beijma, Comber & Lamb 2014), species distributions (Evans et al. 2011) and Sclerophyll forest (Mellor et al. 2013), and is now often programmed within conventional geospatial softwares such as ArcGIS, QGIS, and Google Earth Engine. Random Forest models use a number of ensemble decision trees which are generated using a randomly selected subset of training data features, which are then merged together to generate a more stable and accurate prediction (Belgiu & Dragut, 2016).

Further success in classification has been achieved by applying deep learning models to image classification, due in part to the inclusion of hyperparameters (a parameter of prior distribution), which Random Forest models lack. Deep learning models are a class of convolutional neural network. Neural networks have emerged to challenge the primacy of Random Forest machine learning models. For supervised learning problems, neural networks receive a data sample as an input and predict an output label. The inputs are processed via hidden layers (where more layers = deeper network) which use weights (or connections) and biases to produce intermediate activations corresponding to derived features of the sample. Deep learning models are those which use a number of hidden layers. A thorough introduction to neural networks can be found via LeCun, Bengio & Hinton (2015) or Olden, Lawler and Poff (2008).While deep learning models are some of the most advanced at the moment, most require a large amount of processing power, large numbers of input images and expertise to design. However, once a machine learning model is developed, trained and validated on an image set, it is relatively easy to apply this model to similar image processing tasks (i.e. Similar regional context, temporal analysis etc.) to a high degree of specificity.

2.4 Analysing Complex Mosaic Landscapes

The emergence of methods, such as the use of drones and machine learning, which are capable of capturing and classifying complex mosaic landscapes, is relatively recent, specifically in the tropics (Mithal et al. 2018; Hethcoat et al. 2019). As such, there remains a dearth of literature which address the analysis of such landscapes which specifically try to incorporate the inherent complexity. Given the interconnectedness of social and environmental patterns and processes, methodologies which would be most successful are those which are capable of considering social and ecological components of the system as well as the connections between them.

Unifying the social and ecological literatures has proven, and continues to prove, problematic. The quantitative approach of ecology and the natural sciences is dependent on measurement, as it connects empirical observation and mathematical expression of quantitative relationships. However, quantitative approaches are criticized for being overly reductionist, sacrificing holistic insight for measurable features (Dambacher et al. 2003). Conversely the approaches favoured in the social sciences are more qualitative, and focus on gathering an in-depth understanding of human behaviour (Denzin & Lincoln 2005). As a result, the study of complex mosaic landscapes as social-ecological systems must seek to unify separate, often contrasting pedagogues in order to build upon the wealth of previous compartmentalized scholarship (Chapin et al. 2010; Allen et al. 2014).

One such interdisciplinary method has emerged which seeks to quantify the extent to which humans have harnessed environmental productivity, by measuring human appropriated net primary productivity (HANPP). The significance of this crosses all scales from global trends in land conversion to local trends in land use. The use of land in complex mosaic landscapes is dependent on numerous factors such as cultural, social and political trends or ideologies in the region. However, crop yields, and resulting decisions about what might be most productive is also based on the land's natural biological productivity, in other words it's Net Primary Productivity per area. HANPP has emerged as a primary indicator which explicitly addresses the social-ecological nature of human use of land systems (Haberl, Erb & Krausmann 2014). HANPP gives a measure of the impact of humans on the natural environment, using land use and land use change as the indicator to determine levels of human impact. The indicator is a measure of the difference between the NPP of the potential vegetation (NPPpot) (had the ecosystem not been altered by humans) and the NPP of the actual vegetation (NPPeco) present.

HANPP has been used in a variety of studies assessing the impact of humans on the biosphere. The majority of studies have investigated HANPP at a global scale. These studies have estimated the human appropriation of NPPpot have ranged from ~20 – 40 % (Anderson et al. 2015). Vitousek et al. (1986) proposed low, intermediate and high estimates of HANPP based on measures from the 1970's. The low estimate, which only included biomass consumed by humans and livestock, estimated HANPP to be approximately 3 %. However, the intermediate estimate, which also considered the entire NPP of human-dominated ecosystems, and the high estimate, which further considered human impacts, were estimated to be 27 % and 39 %, respectively. A more recent study conducted by Krausmann et al. (2013) estimated that between 1910 and 2005 HANPP doubled from 13 % to 25 %. These studies have provided a large amount of insight into the global trends in HANPP.

Using similar methodological approaches HANPP has also been assessed at the national (Kastner 2009; Fetzel, Gradwohl & Erb, 2014) and regional scales (O'Neill et al. 2007; Andersen et al. 2015). Further, Andersen and colleagues (2015) conducted a watershed scale HANPP estimation in the southeastern United States. The authors reported a net decrease in HANPP between 1968 and 2011, primarily attributed to changes in land use.

While HANPP is a widely accepted indicator, with many studies cross validating one another's results (Haberl, Erb and Krausmann 2014) few studies use field collected, embedded data to assess HANPP which could then be scaled up with relative accuracy to provide a scale of assessment comparable to regional, national and global HANPP studies. The need for such approaches is particularly marked in regions of mixed agriculture, where small holder farms are the most common land use. One recent study of cocoa production in Ghana gathered embedded data from farm plots of differing intensities within a complex mosaic landscape, as well as generating HANPP measures for an adjacent tropical forest national park to serve as a baseline (Morel et al. in press). However, studies such as this are intensive and require a large amount of field work and processing to generate accurate measures. In order to scale the findings of such studies to many of the most significant studies of HANPP (Haberl et al. 2007, Krausmann 2013), other approaches are needed which can both capture the complexity of such landscapes, while doing so on a scale which is comparable to global analyses.

2.4.1 Dynamics of complex mosaic landscapes

Literature on Social-Ecological Systems (SES) has progressed significantly in recent years, and has been regarded as an important approach to operationalizing the transdisciplinary research of connected human-environment systems (Ostrom 2007). However, methods to study and understand these complex systems has lagged significantly behind the conceptual progress in the study of SES (Bodin & Tengo 2012, Filatova 2013). There are numerous reasons for this including difficulty integrating social and ecological methods and discourse, complexity of study systems as well as the hierarchical multi-scaled (spatial and temporal) nature of these systems.

Of particular relevance are studies which have used remote sensing to understanding landscape structure and social surveys to understand human land use and drivers of landscape change such as mangrove degradation (Dahdouh-Guebas et al. 2004), deforestation (Mertens et al. 2000), human induced forest fires (Dennis et al. 2005), as well as the impacts of climate variability (Galvin et al. 2001). Further understanding can be gained by building models which integrate social, spatial and environmental factors.

Perhaps the most significant obstacle for the derivation of methods to study complex mosaic landscapes is the very complexity of the systems themselves. Complexity arises due to interactions between components of a system, and is a product of the relationships between components rather than properties of the components themselves (Cilliers et al. 2013). Cillers (1998) indicates that the central characteristics of a complex system are that it consists of a large number of components, it is an open system, that it changes in time and that the components interrelate based on dynamic interactions. These dynamic interactions are (at least partially) nonlinear, and create feedback loops (Liu et al. 2007; Levin et al. 2013).

When considering the predicted longitudinal impacts of climate change in complex mosaic landscapes, many models can underestimate the interconnections between system components and the resulting feedback loops (Heimann & Reichstein 2008; Mollmann et al. 2008; Hedwall, Brunet & Rydin 2017). Further, uncertainty within models of such unprecedented trends and conditions (Soden, Collins & Feldman 2018) means attempts to model the impacts or responses of local or regional scale processes can create a large amount of uncertainty in the model itself or result in substantial simplification of the system (Cillers et al. 2013). An approach which can both provide insights into the potential impacts of longitudinal change, like that associated with global climate change, while also incorporating the dynamics and complexity of such a system is to frame the assessment around a single disturbance event.

Disturbance events, in the ecological sense, are those events which are discrete in time and disrupt ecosystem, or ecological communities and change resource availability or the physical environment itself (Pickett & White 1985). Expanding this concept for social-ecological systems accommodates the inclusion of social and cultural structures, and process, and the resulting feedbacks between the social and ecological system components (Osterblom et al. 2011). By studying the impact of discrete events on social-ecological systems, significant understanding about their short term resilience, as well as predications relating to their long term resilience can be derived. Resilience theory has led to many advances in understanding the concept of critical thresholds within natural resource use systems in recent years, and offers an opportunity to draw on a wealth of theoretical literature to inform practical study (Carpenter et al. 2001; Folke et al. 2010; Ostrom & Cox 2010).

Incorporating the concept of space into the study of resilience in complex social ecological systems is of particular importance when considering complex mosaic landscapes. The substantial spatial heterogeneity, as well as the impact of ecological process such as connectivity and ecological memory are considerably tied to the spatial organization of features on a landscape (Johnstone et al. 2016). Further, spatial heterogeneity in the location, manifestation of, and responses to environmental change makes spatially explicit approaches to disturbances necessary (Allen et al. 2016). Spatial resilience can also be more explicitly considered as the spatial arrangement of, differences in, and interactions among, internal and external elements of a system (Cumming 2011). The spatial distribution of people, ecological features, and infrastructural assets across a landscape influence the exposure of humans to climate change associated hazards. However, further factors such as land management, land tenure household practices or cultural practices could act to mitigate or enhance potentially adverse outcomes of climatic hazards. In essence, when attempting to capture climatic resilience in complex mosaic landscapes, using variables that capture space can facilitate further understanding of the potential of harm to arise from climate change interacting with the local context. In addition, climate change is likely to alter the spatial and temporal distribution of climate hazards, further highlighting the need to incorporate aspects of space into assessments of resilience in complex mosaic landscapes (Preston et al. 2011).

3. Methods

The methods utilized in this thesis include a diverse array of spatial, social, ecological and modelling approaches. The methods used in each chapter are covered in depth within said chapter, however broad methods which apply to one or more chapters that warrant additional explanation or introduction are presented here. This chapter begins by introducing the study site where all chapters of the thesis are focused. It will then outline a specific and exhaustive account of the drone data methods which were used when collecting, and processing the drone data which are central to the thesis. Finally, it will provide an overview of the ECOLIMITS project, which provided data directly for use during this project, as well as serving as the umbrella organisation under which the work was undertaken.

3.1 Study Site

This study was carried out in the Central Region of southern Ghana. This region was historically covered in tropical forest, however the current landscape is heavily transformed by agroforestry with most remaining forest patches only present within protected areas. Rainfall in the entire Central Region is typical of a tropical region, and averages around 1500 mm per year. The majority of the rainfall takes place during the rainy seasons which are typically from May to June, and from September to November (Whitfield 2019). The specific area studied in this thesis is characterized by moist semi-deciduous forest with an annual precipitation of 1300 mm (slightly lower than the regional average) and average temperatures of 24°C to 27°C. In addition, the region typically experiences the Harmattan, a dust laden wind which blows from the Sahara between November and March. The Harmattan can cause foggy or hazy conditions, especially in the mornings, and significantly decreases air quality (De Longuevile et al. 2010).

This project focused specifically in and around six communities bordering the northern section of Kakum National Park (KNP) (5°33′53″N, 1°20′42″W; See Figure 3.2). This area was an excellent location to undertake the research conducted in this project for a number. The range of distances of households and communities from KNP enabled the study of the influence of the ecosystem services provided by the park. Further, the configuration of the park (Figure 3.2) delineates the environment into three distance regions, which are also all governed by different chiefs and thus land use and tenure measures. The park contains a large track of continuous tropical rainforest, and constitutes a portion of the broader Kakum Conservation Area which covers an area of 350 km^2 (Combey and Kwapong 2016). The park is large enough that it has the ability to impact the local weather system, often sustaining cloud for long periods, and also cooling temperatures closer to the park border. The park is also legally inaccessible to the public, as it is seen as a completely protected area. This has resulted in a hard border existing between the park itself and the surrounding agroforestry landscapes (Figure 3.1).

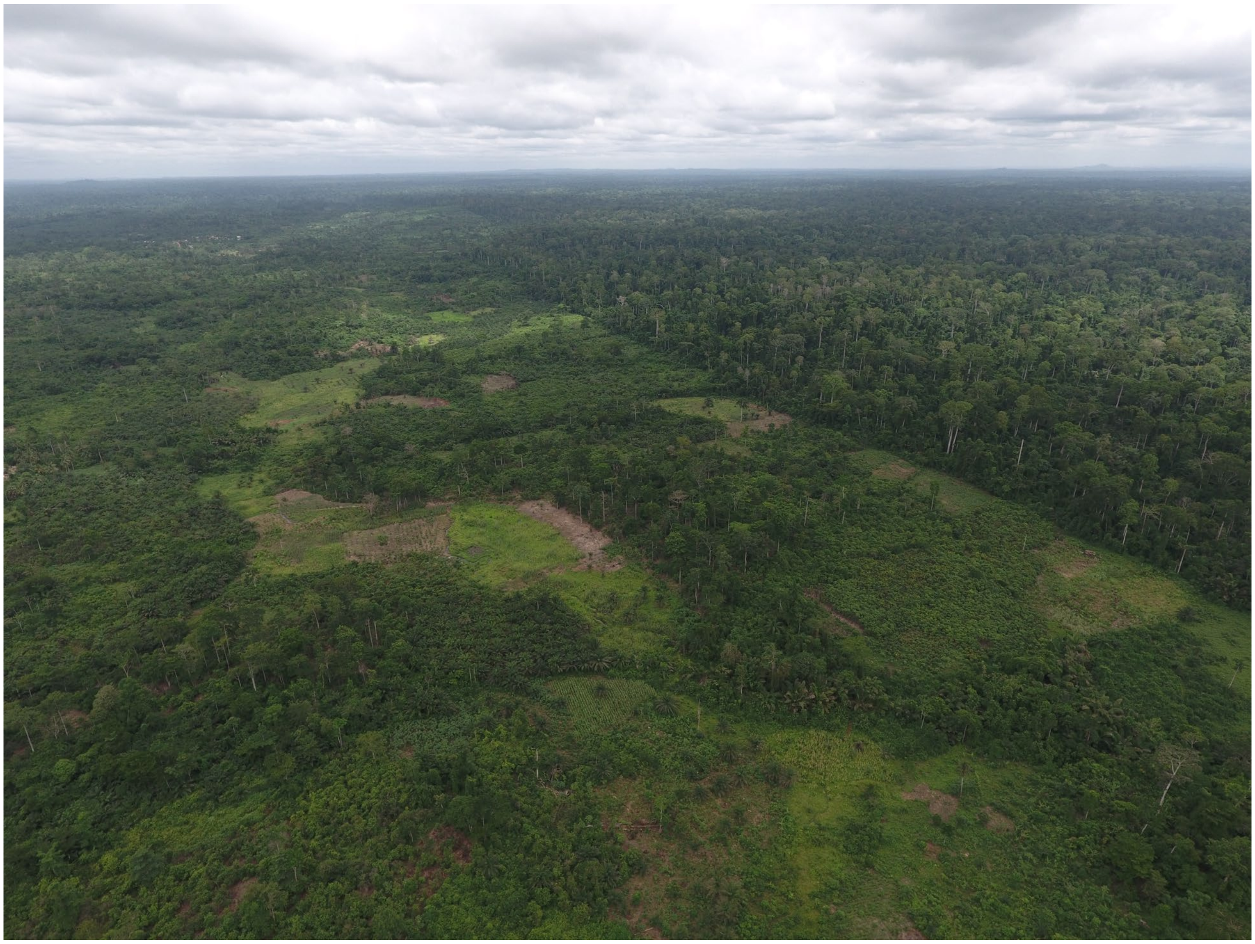

Figure 3.1 Picture of the hard border between KNP and the surrounding landscape taken by a drone. (Picture by Yadvinder Malhi)

The primary land use and livelihood strategy in the area is agroforestry, principally cocoa farming, interspersed with oil palm and subsistence crops. The primary remaining remnant of the broader tropical forest landscape outside of the formal Kakum Park boundary is the persistence of some large trees species, such as Wawa (*triplochiton scleroxylon)* and Edinam (*Entandrophragma angolense*), which are actively maintained on farms for shade or in anticipation of future revenue from their sale for timber on the informal market (Hirons et al. 2018b, Morel et al. in press). Cocoa farming in the region has been the primary land use for decades, and historically farmers could cultivate additional lands of wild forest for cocoa farms once their farms had become unproductive (Ruf & Schroth 2004). However, that practice is now essentially impossible due to the lack of available uncultivated wild forest.

The study area was further subdivided into three distinct regions, each inclusive of two focal villages and the surrounding land use areas (Figure 3.2). Each of these regions is naturally delineated from each other due to the configuration of the park itself. Further, each region is governed by a different chieftaincy or 'stool' which dictate different land use rules and land tenure agreements." These regions are: AB (including the villages of Aboabo and Asorefie), HM (including the villages of Ahomaho and Nsuoekyi) and KA (including the villages of Kwamoabeng and Tumfokrom) (Figure 3.2).

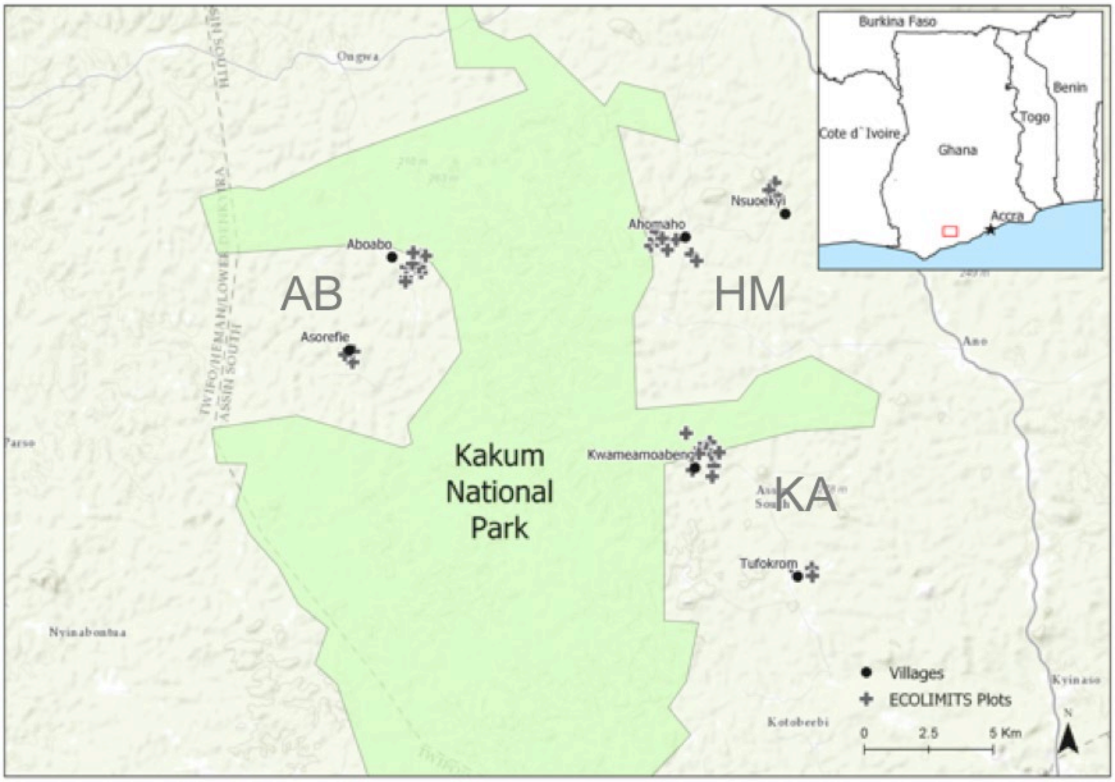

Figure 3.2 Study sites for the ECOLIMITS project surrounding Kakum National Park in southern Ghana. ECOLIMITS ecological plots (+) were intensively monitored for three years between 2014 and 2017. Household surveys for the ECOLIMITS project were conducted at six villages (●).

3.2 - ECOLIMITS Project Methods

The work was carried out as a part of the larger ECOLIMITS project which collected data between 2014 and 2017 to better understand the relationship between poverty and ecosystem services (see www.ecolimits.org). The project constituted a concerted effort to investigate the primary research questions around the ecosystem limits of poverty alleviation using interdisciplinary and integrated approaches, namely viewing the system as a socio-ecological system. As such, while there were both social and ecological components, these were highly integrated, by incorporating qualitative and quantitative data collection from the same households, within the defined regions (AB, HM and KA) surrounding Kakum National Park.

The initial focus of the project was adjusted due to the area experiencing an extended dry season and subsequent drought, which were caused by the 2015/2016 El Niño Southern Oscillation. Due to the data collection beginning prior to the climate shock, there was an unique opportunity to further the bounds of the original study to investigate questions of vulnerability and resilience. The specific impacts of the El Niño resulted in changes to the typical rainfall pattern in the entire area during the latter part of 2015 and the early part of 2016. The first impacts of the El Niño included a delay in the re-starting of the rains in September (during the second rainy season of 2015), and higher than normal rainfall the following rainy season (the first rainy season of 2016). In addition, during the Harmattan period (November to March), the area experienced drier than average conditions which, when combined with higher temperatures drove heightened vapour pressure deficits which are typically associated with leaf wilting of vegetation due to root water uptake being incapable of keeping up with leaf evapotranspiration. This deficit would drive low soil water availability (Morel et al. in review, Whitfield et al. 2019).

While the ECOLIMITS project aimed to pursue an overall interdisciplinary research trajectory, this included distinct ecological and social facets. The ecological facets of the project focused on the detailed monitoring of 36 cocoa farm plots across a forest to cocoa-dominated landscape gradient surrounding the park, with 12 plots in each of the three regions (AB, HM, KA). One forest plot was established within Kakum National park approximately 800 meters in from the edge of the forest, which was deemed to represent 'intact forest'. An additional forest plot was established with the Antandiaso shelter belt, which is currently undergoing both legal and illegal logging, and was deemed to represent ‘logged forest’. All plots were approximately 0.36 ha (60 m x 60 m). Within each region, 12 plots were monitored, with three plots at each of four distances from the edge of the forest (100 m, 500 m, 1 km, 5 km) along the forest to cocoa gradient respectively. The plots were monitored continuously from October 2014 to October 2017. Each plot consisted of nine sub-plots of 20 m x 20 m. Cocoa trees and shade trees species were counted and monitored consistently during that time period. Monitoring included measuring canopy Net Primary Productivity (NPP) using litter fall traps, measuring woody NPP by summing coarse root, stem growth and branch turnover, measuring root NPP by evaluating deep in growth cores quarterly and measuring cocoa pod NPP by assessing total pod production of each cocoa tree . In addition, soil samples of the top 30cm of soil were collected in each plot as well as cocoa tree canopy gap (by calculating the average leaf area index (LAI) using photos taken at 4.5 m above ground (i.e. above the cocoa trees) for all nine subplots). The NPP data collected during this monitoring was calculated for all plots (and sub-plots), and these data formed the basis for Chapter 4 (*Human Appropriated Net Primary Productivity of a Complex Mosaic Landscape*).

Net Primary Productivity (NPP) is often used as a measure to describe the functionality of an ecosystem, or the production of biomass. For this study, NPP was estimated following the protocols of the Global Ecosystems Monitoring network (Marthews et al. 2012), with minor modifications. Three components of NPP were estimated for forest/shade trees which were canopy NPP (leaves, twigs, flowers, seeds etc.), woody NPP (stems, coarse roots and branches) and fine root NPP. In addition, for cocoa farms cocoa pod production was estimated. Annual NPP values were calculated by summing monthly and seasonal measures of individual NPP components. Standard errors were computed for each component at each time step and propagated through quadrature for every calculation (as in Malhi et al. 2015). Further, highly detailed descriptions of how biomass was estimated for each of the components can be found in Morel et al. (in press).

The ecological data described above were complimented by the collection of qualitative data aimed at understanding social facets of households responsible for each of the farm plots, in addition to other cocoa farmers within each region. The social data were collected during the same broad time scale as the ecological data, and included interviews, focus groups, and a household survey (n = 106). The goal of this survey was to quantify the different dimensions of poverty at the household level. The data primarily utilized by this thesis were those collected during the household survey. The survey was conducted once a year (August 2015, August 2016, and May 2017) and was administered at the home of each respondent by a research assistant fluent in the local language. The survey was designed by Mark Hirons, and was based on Oxford Poverty and Human development Initiative (OPHI) multidimensional poverty surveys and his own past work (Mark Hirons, 2019, pers. comm. August 14). The first iteration of the survey was focused on capturing demography of each household, as well as measures of assets, income, ability to meet critical expenditures, land management, cocoa yield, non-timber forestry products (NTFPs) utilised by the household, shocks, social group membership and satisfaction. The two subsequent iterations of the survey also included questions relating specifically to the impacts of the drought and adaptive measures undertaken by households to cope with it.

3.3 Detailed Drone Imagery Collection and Processing Methods

3.3.1 Machinery

The drones used to conduct the fieldwork were both DJI Phantom 3 Professionals (Figure 3.3). The drone is capable of ascending at 5 m/s and flying at 16 m/s while at a steady altitude. Each unit is equipped with GPS, which is typically accurate to 0.1 m. The machinery is equipped with one of the best cameras available for drones of this variety, which can capture 12.4 M pixels.

Figure 3.3 Drones used for all drone data collection. Droney McDroneface (left) and Leonard Drohen (right) are both DJI Phantom 3 Professional models.

3.3.2 Site data

All drone flights were carried out between November 2016 and January 2017. A number of test flights were initially undertaken to determine the possible metrics which could be standardized across flights. The software used to undertake the flights was Pix4D (www.pix4d.com) with some early prospecting work done using the DJI GO app (https://www.dji.com/uk/goapp).. This software was designed to allow full image coverage of a designated area. When data are available this can be done with the aid of satellite imagery (Figure 3.4) however, in rural areas, maps can be downloaded beforehand. Each battery is capable of flying for approximately 20 − 25 minutes. This means that a balance between a number of different parameters needs to be struck in order to optimize the area covered, while ensuring sufficient image overlap. These included:

1. Area or extent covered - The square area to be covered by the drone on its flight.
2. Flight height - The height at which the drone will undertake the entire flight plan. Drone height can be dictated by the pilot/investigator, however laws exist in some countries which limit the maximum height drones can be flown at.
3. Image overlap - this determines the frequency that images should be taken along the flight path. It also dictates the number of rows the drone must fly on the flight plan.
4. Flight speed - How quickly the drone will fly during the flight plan.

Figure 3.4 An example of the flight plan section of the Pix4D software (University Parks, Oxford, UK). The user can designate the area covered (light green square), and by using this information as well as the image overlap set by the user, the software determines the number of rows that must be flown by the drone over the designated area (in this case seven rows are indicated). The measured area is displayed as well as time of flight plan (grey box, centre bottom). The area covered here is 145 m x 149 m and will take approximately 10 minutes and 27 seconds. The altitude can be set using the slider on the left side of the screen, and is set to 40 m in this example.

3.3.3 Sampling Design

It was important the drone data collected captured the ecological monitoring sites for the ECOLIMITS project (to allow for integration of the all social, ecological plot data and drone data). Thus drone sampling was prioritized in areas surrounding and including the ECOLIMITS ecological plots. A 1km buffer zone was established around each plot, with many buffers merging to create areas of particular interest and priority (Figure3.5A) A series of 2 km, 3 km and 4 km buffers zones were established around each grouping (Figure 3.5A), where closer buffers were considered more important to sample as completely as possible. Actual sites were selected based on accessibility. Selecting the site for each flight was based on the criteria of, location within the buffer zones as well as proximity to previous flights (to ensure some degree of overlap between flights), while also attempting to capture as much of the landscape as possible. . Figure 3.5A was loaded into a GPS to allow some estimation of where the I was with relation to the target areas while determining sampling locations. Given that each flight would capture approximately 1km2 of area, a 1km grid was overlaid on the buffer zones to aid in selecting sites which would meet our criteria. The goal was to collect 20 km^2 of landscape data from each region, with 12 km^2 collected around the near villages (Aboabo, Ahomaho, and Kwamoabeng) and 8 km^2 collected around the far groups (Asorefie, Nsuoekyi, Tumfokrom) (Figure 3.5B). However, due to the nature of the rural landscape and lack of roads or paths, some areas were deemed inaccessible so sampling was adjusted (eg. nine sites sampled in the far KA rather than 8, due to difficulties accessing areas in the near KA site).

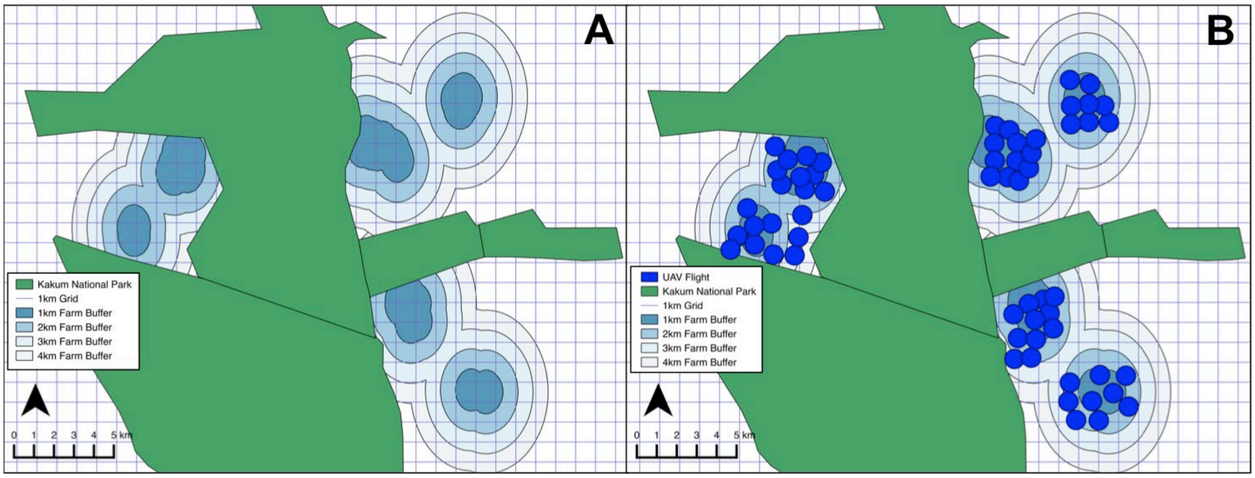

Figure 3.5 Guide used to determine areas of highest priority for drone surveying, and the subsequent outcome of the drone surveys. The areas surrounding and including the location of the ECOLIMITS ecological sites were prioritized, with decreasing priority for specific flight sites decreasing as distance to these sites increased. **(A)** Target areas for drone surveying with colour intensity of sequential 1km buffer zones indicating differing levels of importance (with the most intense colour indicating the most important areas). (B) Locations of eventual drone survey sites in relation to the target buffer zones.

Sites for flight take-off and landing were selected based on their location within 1km grid, their proximity to villages/ecological plots of interest, and their proximity to other flights. Additionally, sites needed to contain certain characteristics, specifically sufficient forest or vegetation gaps. Those areas with shorter crops in clearings, such as cassava or vegetables, were preferable for take-off and landing due to the need to ensure the radio signal between the remote and the drone unit could be maintained. Regions with electronic towers or wiring were avoided due the potential for interference between the remote and the drone. Once a site was selected, the area was cleared of bulky ground vegetation and covered with a 1 m x 2 m tarp which served as a landing pad. The remote was then connected to an iPad, and both were turned on. The drone unit was then turned on and placed on the landing pad. Once the remote and the drone had connected, the drone was calibrated to reset the 'home' location to the landing pad. The image overlap was set to 75 %, the speed set to 10 m/s and fast image capture mode (which allows the drone to continue flying, and not stop to take pictures) was selected. Once all parameters had been set and all proper checks had been done, the app was allowed to run, which controlled the drone operation autonomously.

Flights were initially carried out at an altitude of 300 m, however this was adjusted (to a range of 150 m − 250 m) because the higher altitude caused too much strain on the fan belt of the drone. The advantage of flying at a higher altitude is the ability to capture more of the study area in a single flight, however mechanical issues, remote-drone connectivity issues as well as atmospheric interference (likely from the Harmattan) usually constrained the area covered by each flight to a maximum of 1 km^2. The drone would fly to the designated height, rotate to a given corner, fly to that corner and begin following the track designated by the app. Once the flight plan was completed, the drone would return to the location where it took off (i.e. 'home'). The app allows the drone to land itself, however, this was often done manually to ensure the least possibility of collision with vegetation.

3.3.4 Data processing

A number of commercially available softwares are currently available for processing drone imagery. However, the use of many of these softwares proved ineffective and unsuceesful for this drone data. In order to produce a mosaic for each flight, most of the softwares request all images for a particular flight. They are then processed and you are presented with a final orthomosaic image. However, often this type of processing for these data would come back with a blank orthomosaic, indicating that none of the images had been successfully stitched together. Further, while some flight image sets did result in orthomosaic outputs, these would only be a small section of the entire area which it managed to mosaic successfully. Alternately, some outputs were heavily distorted mosaics possibly indicating that the software has interpreted certain points in different images as being the same, resulting in the software manipulating the output to fit this.

After consultations with several companies a few potential explanations were offered. The first was the land was relatively homogeneous (namely green vegetation) thus making it difficult for the software to detect distinct points in the landscape, which could be clearly detected in adjacent drone images. So even though the level of image overlap used in this work (75%) was far above the recommended 60%, most softwares failed to stitch any images at all. Another suggestion was that the flights were flown at a height which was too high for the softwares to work properly. It could also be that the softwares were not trained on image sets that resemble the image sets produced in this work, thus making the task too difficult for the software.

After trying a number of softwares and combinations of softwares, it was found that drone imagery could best be processed using a combination of softwares, including DroneDeploy (DroneDeploy 2018), Event 38 Unmanned Systems (DDMS 2018), ArcGIS 10.2 (ESRI 2018) and Affinity Photo (Serif 2018) (Figure 3.6). Drone images were processed in single flight batches, and the resulting orthomosaics varied in size from 750 m^2 to 1.6 km^2. Size variation was due to flight duration, flying height and conditions, such as wind, on the day of the flight.

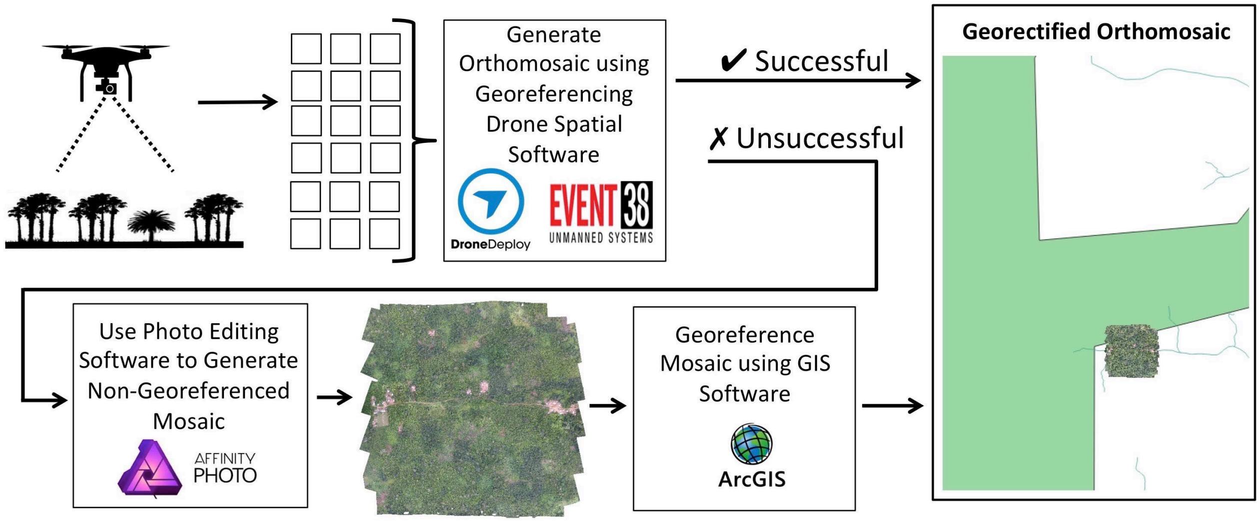

Figure 3.6 Drone Image Processing Workflow: Data are captured from the drone as individual images. These were then fed into drone spatial software capable of generating georectified orthomosaics (i.e. Drone Deploy, Event 38 unmanned systems). If these softwares were incapable of producing an orthomosaic, the images were fed into an advanced image editing software (i.e. Affinity Photo). The resulting orthomosaic is not georeferneced, so it was then uploaded to GIS software capable of georeferencing (i.e. ArcGIS). Within the GIS software, the georeferencing tool was deployed, using geospatial information embedded in each drone image as the reference points to produce a final georectified orthomosaic.

Chapter 4

The previous chapter detailed some of the methods used to acquire detailed land use imagery for a complex mosaic landscapes. Once the imagery has been acquired and processed, then comes the step of needing to classifying land use. As outlined in Chapter 3 there are several approaches to classifying imagery but many have their constraints. Many of these were not appropriate for classifying land use in this environment, which is homogenous at a broad scale, heterogeneous at a fine scale and where most vegetation would display similar spectral bands (namely those for identifying green). The recent advancement of machine learning, and success of other studies using machine learning approaches to classify land in more simplistic landscapes, indicate that this approach could provide significant insight. Thus, this chapter specifically addresses Objective 1: *Utilize basic UAV imagery, and machine learning, to capture and classify land use in a complex mosaic landscape.* One of my specific objectives for this study was to find a classification method which could be used on the most basic imagery, and would work over a large scale. This chapter compares a number of potential machine learning classification approaches to classify land use using only RGB imagery.

The findings of the study are presented in the paper "Classifying Land Use in Complex Mosaic Tree Crop Landscapes using Drone Imagery and Machine Learning" which has been submitted for publication in the journal Remote Sensing of the Environment.

I am the main author and wrote the paper, conducted the fieldwork and carried out the data analysis with guidance from my supervisors Alexandra Morel and Yadvinder Malhi. Lucas Kruitwagen helped me apply the machine learning models to my data, and Jose Luise Ramirez-Mendiola helped me learn to use python and helped me with earlier iterations of this work.

4. Classifying Land Use in Complex Mosaic Tree Crop Landscapes using Drone Imagery and Machine Learning

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4.1 Abstract

Unmanned Aerial Vehicles (UAVs), or drones, have become an increasingly popular tool in environmental and ecological studies, particularly when studying land use classification. Drones can overcome many of the issues with satellite remote sensing approaches, namely giving the user more control over temporal and spatial scales of study. In addition, drones also can eliminate the interference from clouds by flying behest them to capture images, which is particularly vital in monitoring complex mosaic agriculture landscapes in cloudy tropical regions such as West Africa. Accessing and affording specialized drones, with multisensory cameras, remains difficult for many practitioners in tropical areas, where drones are most needed for monitoring. However, off the shelf drones with RGB cameras are increasingly inexpensive and easy to access, though the lack of extra sensors make classifying land use using common metrics (ie. NDVI or EVI) impossible. Image classification of RGB imagery using machine learning has advanced significantly in recent years for detecting diverse land use types such as infrastructure or palm oil plantations vs. logged forest. This paper examines whether it is possible to classify land use in a highly complex, small scale tropical agriculture using the most inexpensive drone machinery and basic high resolution RGB imagery with machine learning approaches. This paper presents the comparison of a number of machine learning approaches (Random Forest single pixel, Random Forest cluster pixel and ResUnet) to classify land use in a complex mosaic landscape in a cocoa landscape in southern Ghana. The random forest models and fully convolutional ResUnet network were trained on two datasets, one broadly classified dataset of >14,000 image tiles, and a second finely classified dataset of 1,280 image tiles. Classification of the landscape using

the broadly classified dataset was unsuccessful, however, the finely classified dataset showed considerable promise, particularly when trained on the ResUnet deep learning architecture. The precision of the ResUNet architecture varied from 100% (settlement) to 50% (cocoa), compared to 62% (other class) to 0% (settlement) precision of the Random Forest single pixel classifier and 64% (other class) to 4% (settlement) precision of the Random Forest cluster pixel classifier. All classifiers were less successful when using the stricter criteria of Intersection over Union (IoU), however again the ResUnet architecture outperformed both Random Forest classifiers, with crop classifications ranging from 34% to 2% compared to the RF models which ranged from 12% to 0%. Further, the ResUnet model was very useful at determining overall land use patterns in this complex mosaic landscape

4.2 Introduction

The use of unmanned flying vehicles (UAVs) or drones, for research in recent years has grown significantly. In particular, the utility of small, fixed-wing drones has gained increasing prominence as a practical approach to ecological monitoring. The potential of these machines to advance ecological study has been proposed for fields from plant conservation (Baena, Boyd & Moat 2018, Tay, Erfmeier &Kalwij 2018) to the monitoring of marine megafauna (Hensel, Wenclawski & Layman 2018) or nesting habitat of birds or reptiles (Evans et al. 2016, Borrelle & Fletcher 2017). Further, drones have already been used for diverse projects including mapping malaria vector habitats (Hardy et al. 2017), assessing the impact of species reintroductions (Puttock et al. 2015), assessing forest biodiversity (Getzin et al. 2012), and community-based forest monitoring (Paneque-Galvez et al. 2014).

Drones have been particularly embraced by researchers studying or monitoring land use (Kalantar et al. 2017). They are routinely used to classify urban land use (Koeva et al. 2016; Feng, Liu & Gong 2015) and have been used to investigate vegetation composition in North America (Ahmed et al. 2017, Cruzan et al. 2016), and South East Asia (Iizuka et al. 2018; Kalantar et al. 2017). Drones enable the user to acquire scale appropriate measures of land use and other ecological phenomena. Spatially, drones can be flown low, avoiding interference from clouds or other atmospheric impediments to capture ecological patterns. Temporally, drone flights can be repeated as often as the end user requires, capturing landscape images at sub-daily, daily, monthly or other intervals, enabling the study of ecological process (Anderson & Gaston 2013).

Acquiring spatially explicit data to study land use has been historically conducted using ground-based approaches, but in recent decades there has been an increasing reliance on satellite mounted remote sensors, resulting in ground breaking research such as a global map of forest cover (Hansen et al. 2013). Finer scale studies, conducted at the regional level and using higher resolution sensors such as RapidEye or QuickBird imagery can generate even more accurate measures of land cover change (Sannier, McRoberts & Fichet 2016; Milodowski, Mitchard & Williams 2017). However, even with substantial increase in the number of satellite sensors producing imagery, including publicly funded satellites such as the Sentinel program or private satellites such as RapidEye or WorldView, substantial issues remain. One such issue is the lack of precision in definition, such as vegetation over five meters in height being labeled as forest (Hansen et al. 2013, Tropek et al. 2014). In addition, clouds remain a primary barrier to universal reliance on satellite derived imagery, especially in the tropics (Reiche et al. 2016, Sannier et al. 2014, Potapov et al. 2012).

The lack of reliable remote sensing imagery is of particular concern in regions of tropical agroforestry. The cultivation of some crops, such as palm oil, which are more typically associated with large monocrop plantations, can be more easily detected using satellite sensors, and image composites in cloudy regions (Carlson et al. 2012, Cheng et al. 2018). Conversely, capturing the patterns and processes of small holder farming is markedly more difficult. This is particularly true for certain agroforestry crops such as cocoa or other forms of mixed agriculture in tropical regions. Capturing cocoa agroforestry is particularly difficult due to the spectral similarities between cocoa and natural forest, and the persistence of clouds in many cocoa growing regions (Tutu

Benefoh et al. 2018). While some progress has been made on mapping cocoa agroforestry in larger plantation-type scales (Tutu Benefoh et al. 2018), there remains a relative lack of studies of cocoa agroforestry in its most common form, complex mosaic landscapes.

Complex mosaic agriculture systems are prolific in the developing world, particularly in Africa (Mertz et al. 2012; Norris et al. 2010). On a broad landscape scale, these landscapes can focus on a primary land use of some crop such as cocoa, however on a local scale these areas are dominated by numerous smallholder farms, cultivating both cash and subsistence crops. Smallholder farms are those which are between 2 – 5 hectares in size, and often are a mosaic of intercropping of numerous crops (Cohn et al. 2017; Rapsomanikis, 2015). Small holder farming is the primary farming practice of cocoa farmers in the second largest cocoa producing nation, Ghana. It is estimated that the industry employs 3.2 million people along the supply chain, and is responsible for the primary income of approximately 800,000 households (Essegbey & Ofori-Gymfi 2012, Anim-Kwapong & Frimpong 2005). Given the predicted impacts of climate change on the region, namely increased temperatures, decreased precipitation and increased disturbance events (Sylla et al. 2018), capturing and monitoring these landscapes is of pressing local, national, and global consequence.

Some studies have managed to overcome the current dearth of reliable imagery for tropical complex mosaic agroforestry by using drones, notably by either using drones equipped with multispectral sensors (Hall et al. 2018) by combining drone data with reliable satellite imagery from the region of study (Szantoi et al. 2017). However, these methods may not be useful for those practitioners in tropical regions where the cost of multispectral or more sophisticated drones could be prohibitive, and where access to the expertise, and computation power necessary to marry drone and satellite imagery could be limited. However, low cost drones equipped with RGB cameras are continuing to decrease in cost, while also becoming widely available for purchase. These units could present a viable alternative for monitoring complex mosaic agroforestry landscapes in tropical regions, however classification of the imagery presents a hurdle.

While inexpensive RGB camera equipped drones can capture high resolution imagery, they do not capture spectral bands usually used for vegetation classification (Elvidge & Chen 1995). However, methods using machine learning and other computer vision models have emerged as being highly successful at classifying RGB imagery in the medical sciences (Greenspan et al. 2016), engineering (Varghese et al. 2017) and biology (Seymour et al. 2017). These studies demonstrate the possibility of using the simplest imagery from the cheapest equipment to derive highly specialized information about complex mosaic landscapes using machine learning or other computer vision models.

4.2.1 Image classification using Machine Learning

Recently, computer vision techniques and machine learning, including deep learning with convolutional neural networks, have been rapidly advancing. As these techniques have developed, the ability to utilize such sophisticated approaches has spread into applied studies in ecology and have shown promise in land-use classification (Olden, Lawler and Poff, 2008; Weng et al. 2018). One of the most utilized approaches incumbent to CNNs has been the Random Forest model (Ho 1998, Breiman 2001).

Random Forest models are ensemble classifiers, whereby several classifiers are combined and used in conjunction to optimise outputs. The basic concept of a random forest model is that it uses a randomly selected subset of data features to produce multiple decision trees (hence forest) iterated over multiple rounds of variable selection with replacement and testing of samples (Ho 1998, Breiman 2001). Random Forest classifiers have been used in a numerous of different studies (extensive review can be found in Belgiu and Dragut 2016) and are now often implemented for pixel classification within conventional geospatial software such as ArcGIS, QGIS, and Google Earth Engine. The basis for Random Forest models is that a number of ensemble decision trees are generated using a randomly selected subset of training data features, which are then merged together to generate a more stable and accurate prediction (Belgiu & Dragut, 2016). The success of Random Forest models is due to a number of factors including the quick speed of training the model on modest datasets, the versatility of the approach on data types, the robustness of the model to mislabels and the fact that models often produce some of the best results in comparison to other approaches (Caruana, Karampatziakis & Yessenalina, 2008). While Random Forest has been used successfully in a number of studies, specifically those utilizing remote sensing satellite data (Belgiu & Dragut, 2016), it can be computationally expensive and slow with larger datasets.

Even though neural networks have been used for decades (Werbos 1975), recent advancements in NN development have positioned them to surpass the success of Random Forest machine learning models. For supervised learning problems, neural networks receive a data sample as an input and predict an output label. The inputs are processed via hidden layers (where more layers = deeper network) which use weights (or connections) and biases to produce intermediate activations corresponding to derived features of the sample. Importantly, layers assess activations sequentially, whereby the outputs of layer 2 become the inputs of layer 3, and so on. Back propagation of error between the predicted class outputs and the sample label allows network parameters to be simultaneously optimised for minimal error. A thorough introduction to neural networks can be found via LeCun, Bengio & Hinton (2015) or Olden, Lawler and Poff (2008).

Convolutional neural networks (e.g. LeCun et al 1998) have emerged as the leading method for computer vision problems including image classification, object localisation, and semantic segmentation (Fukushima 1980; LeCun et al. 1989; Krizhevsky, Sutskever & Hinton 2012). Convolutional neural networks are a class of deep neural networks which train small kernels of neurons to extract consistent feature information from a small area of an image or similarly-arranged data. Multiple convolutional layers can be combined with other intermediary layers to extract higher-order features prior to model output. Fully-convolutional neural networks produce outputs matching the dimensional space of the input, allowing the semantic segmentation of an input image. These methods allow a 1-to-1 mapping of input RGB pixels with an output class, a method used in similar land-use classification problems (Castelluccio et al. 2015, He et al. 2015).

Specifically, deep learning computer vision models are the leading methods for generic object segmentation tasks in diverse fields including medical imaging (Greenspan et al. 2016) and self-driving vehicles (Triebel et al. 2016; Huval et al. 2015), and they are now being adapted to remote sensing applications (Fu et al. 2018; Sa et al. 2018; Zhu et al. 2017). While deep learning models are some of the most advanced at the moment, they do require a large amount of processing power and expertise to design. However, once a machine model is developed, trained and validated on an image set, it is relatively easy to apply this model to similar image processing tasks (i.e. similar regional context, temporal analysis etc.) to a high degree of specificity. Early progress with convolutional neural networks sought to successfully label images with one or more of several thousand classes based on a training corpus of millions of images (Russakovsky et al. 2015). Unet (Ronneberger, Fischer & Brox 2015) is a full convolutional neural network architecture developed with the express purpose of achieving high accuracy on specialist problems, where the number of classes is small (<10) and the training corpus is moderates (in the thousands of samples). Unet's novelty lies in the concatenation of lower level features on to higher level features during deconvolution. Low level features are typically comprised of simple patterns and colour detections, while higher level features are more sophisticated patterns up to and including whole objects. Higher level features identify combinations of lower level features up to and including whole objects. For example, if the image that Unet was processing was a human face, a lower level feature might be a line, where as a mid-level feature might be the nose while a high level feature would be most of the face including the eyes, nose and mouth. Thus, UNet's utility in this example would be that features such as a line or edge, could be resampled onto the human face higher level feature to improve the outcome. Unet has demonstrated considerable success in segmentation problems featuring fixed perspective imagery with few samples and classes, for example biomedical images (Ronneberger, Fischer & Brox 2015). Another model advancement comes from ResNet (He et al. 2015), which add a sparse identity 'short-circuit' to a conventional convolutional layer. This innovation delivers information to deeper layers of the network, reducing training time and minimising vanishing gradients. With these improvements, more layers can be added to image classification models, extracting higher-order features and improving performance. Zhang et al. (2017) combine these innovations into ResUnet, a Unet architecture with residual ‘short circuits’. Like Unet, ResUnet is computationally inexpensive (compared to other very deep image classification models), can successfully train on relatively few images and parameters, while facilitating accurate image classification. Zhang et al (2017) used this approach to successfully extract road networks from remote sensing data.

The aim of this study is to examine whether the cheapest remote sensing equipment (namely an off-the-shelf drone with a high resolution RGB camera) can be used to accurately classify land use in a highly complex tropical agroforestry landscape using machine learning. With the steady advancement of machine learning classification, matched with the increasing availability and affordability of drones, we hypothesize the utility of such technologies could soon stand alone, without the need to supplement with further satellite-generated remote sensing data. To achieve this end, this research study examines the application and success of three machine learning approaches to classify land use in a complex mosaic landscape obtained via a conventional RGB drone. The three models explored in this study include a conventional Random Forest Model (single pixel), a clustered Random Forest Model (3x3 pixel) and a deep learning ResUnet model. The specific questions this study seeks to address are:

1. How well does each model classify land use in a tropical complex mosaic landscape using evaluation criteria such as precision and recall?
2. Is there a difference in model success at the finest pixel scale or at a broader tile/image scale for detecting land uses?
3. Do any of the models perform well enough to be operationalised for landscape-level monitoring of cocoa expansion in a diverse, smallholder context?
4. Can only RGB imagery derived from a drone and machine learning effectively classify land use in a tropical complex mosaic agriculture landscape?

4.3 Methods

4.3.1 Case study location

This work was carried out in southern Ghana in the region surrounding Kakum National Park. The region was previously covered by tropical forest, however much of this has been converted to small holder agriculture, interspersed with protected areas of remnant tropical forest (including Kakum) (Figure 4.1). This work is situated within the broader ECOLIMITS project which seeks to understand the ecological limits of poverty alleviation in small holder cocoa production in Ghana (Hirons et al. 2018c; Morel et al. in review). Land use in this region consists of a mix between cash crop production (cocoa and palm) and subsistence agriculture (cassava, plantain, banana, vegetables etc.). The forest zone in this region is designated as moist semi-deciduous, however, the landscape consistently contains highly-productive, evergreen vegetation with only a small amount of area taken up by settlements.

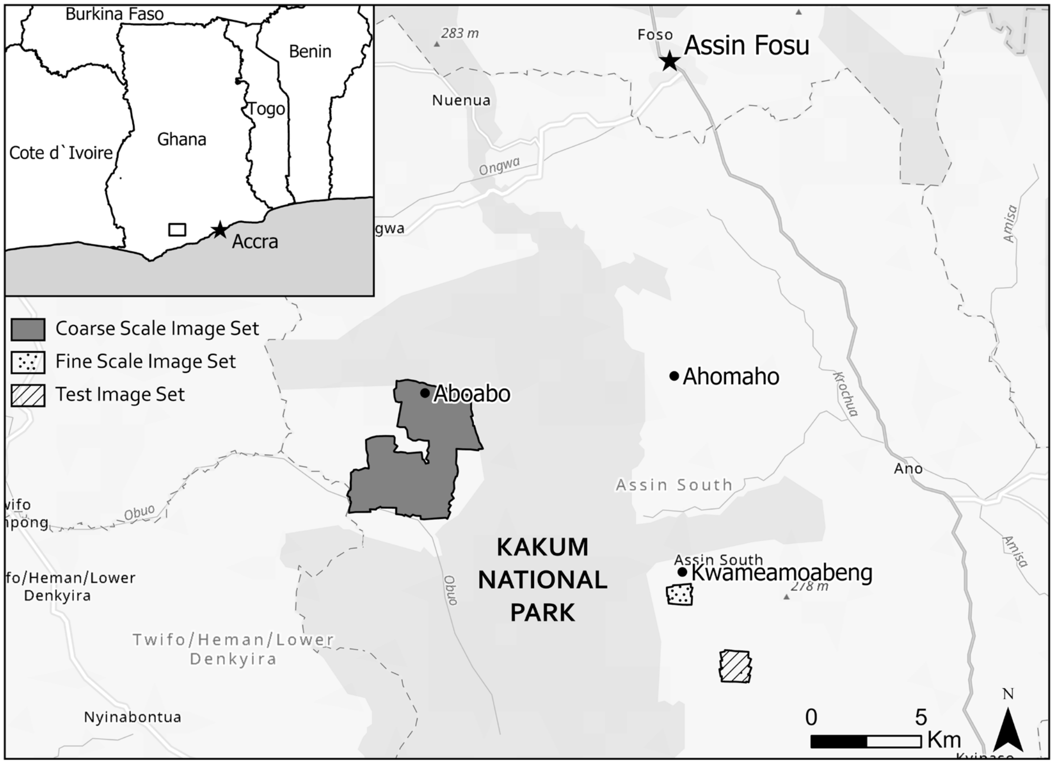

Figure 4.1 Areas surrounding Kakum national Park used to derive image sets. The coarse scale image set was derived from drone imagery collected surrounding the town of Aboabo. The fine scale image set was derived from drone imagery collected surrounding the town of Kwameamoabeng, as was the test image set.

4.3.2 Data collection

Data were collected between November 2016 and February 2017. All drone imagery data were collected using a DJI Phantom 3 Professional drone. The camera on this drone is an RGB camera, with 12M effective pixels, a 1/2.3" CMOS sensor and an

ISO range of 100-1600. The program used to undertake the flights was the Pix4D application (https://www.pix4d.com/) with some early prospecting work done using the DJI GO app (https://www.dji.com/uk/goapp). The primary limiting factor of using drones is the short battery life which limits each flight to 20-25 minutes. Therefore, a balance between a number of different parameters (flight height, image overlap, and flight speed) needed to be achieved in order to optimise the area covered, while ensuring sufficient image overlap to generate orthomosaics. The primary objective of this data collection was to cover as large an area as possible for each flight, which meant maximizing area coverage and flight height. Flight height was set by considering conditions such as presence of fog, haze or clouds as well as the vegetation density in the area of take-off and landing and ranged from 150 m to just under 300 m. All flights had a minimum overlap of 70% side overlap and 60% forward overlap.

The drones used to conduct the fieldwork were both DJI Phantom 3 Professional models. The drone is capable of ascending at 5 m/s and flying at 16 m/s while at a steady altitude. Each unit is equipped with GPS, which is typically accurate to 0.1 m. The machinery is equipped with one of the best cameras available for drones of this variety, which can capture 12.4 megapixels.

4.3.3 Data processing

Each flight produced between 60 and 130 images (depending on flight height, image overlap, and drone speed). Images from each flight were then joined into multi-picture mosaics of either an entire row of images, or where possible (without distortion) the full flight (6-8 rows of images). The data captured for this study were processed into orthomosaics using a number of different softwares. This was necessary due to the difficulty of processing images in this region due to some combination of the green homogenous landscape, along with the drones being flown at a very high altitude (120-300m). The first software attempted was Drone Deploy (DroneDeploy, 2018), which gives users a georeferenced orthomosaic, and where a student license accommodating a large amount of processing was available. If this was unsuccessful, Event38 Unmanned Systems (DDMS 2018) was used, which also produced a georeferenced orthomosaic, but did not offer a student license. If these failed, the images were stitched together using Affinity Photo 1.6.6 photo processing software (Serif 2018), which could produce mosaic images, which were not georeferenced. These were then georeferenced using ArcMap 10.2 GIS software (ESRI 2018). This process can be seen in further detail in Moore et al. in review.

4.3.4 Image classification

This study was originally designed to use two distinct image sets. The first image set consists of over 14,000 image tiles, and the classification is done to a broad scale of specificity. The second image set consists of 1’280 image tiles, and the classification is done to the most specific land use scale. Both sets are then tested against the same validation sets consisting of approximately 1 km^2 of data.

Land use was labeled manually using QGIS software. This was accomplished by having a single person (the lead author) classifying all images by sight and ground-truthed data. Much of the drone imagery was of such a high resolution and clarity, that determining land use was a simple task, however over 100 ground truthed samples collected in the field with GPS were also used to enhance the accuracy of the labeling. All images were classified to create shape files of land use within one of eight categories (cocoa, palm, settlement, cassava, banana/plantain, fallow, grassy fallow, or vegetables), with some area left unclassified due to uncertainty of land use or distortion of imagery. For model classification, each land-use was binned into one of six classes (7 class bin) or one of three classes (4 class bin) (Table 4.1).

For the 7-class bin, all classified land use information was used, and the total area used to train the models was ~16 km^2. These land-uses were defined at a scale of ~1 m, and needed to represent the majority (>75%) of the land use within the classification boundary. Most land use is on a coarser scale than specific plants, and this image set tried to capture this. For example, an area of cassava could be interspersed with other vegetables, but the majority of the area is cassava and would be classified as such by both users and researchers using remote imagery. Thus functionally, the area would be classified as cassava, and this image set was testing whether the models could still detect the broader patterns without the finest scale classifications.

For the 4-class bin, a much smaller area was used to train the models (~2 km^2), and only cocoa, palm and settlements were included. This image set was designed in accordance with standard protocol for many machine learning training sets, namely that it must be as specific and fine scale as possible. Thus, these land-uses were defined at the maximum possible scale (>10 cm resolution) and the area within a land-class boundary represented 100% of the land class. The results for all models for the 7-class bin were found to be very poor and the specific results are not presented, with only the results for the 4-class bin being covered in detail. The primary reason for the lack of success for all models using the 7-class bin dataset likely relates to the lack of specificity in the training data. By definition, the coarsely defined data only required 75% of an area to be the class of interest for it to be classified as that class. As a result, up to 25% of a particular class could include other classes, with different land covers and mixed spectral signatures. Thus, the classifiers were likely confused by this mixture of data, resulting in the lack of success in all models. The lack of success was determined by examining two functions over sequential epochs. The first function is loss, which measures the inconsistency between the predicted class and the actual class, while the second is accuracy which measures the algorithms performance. If a model is even remotely successful, there should be some amount of convergence between the loss of the training and validation data. However, models trained using the 7-class bin data never converged, and indicated that all were not successful.

Table 4.1 Land use classifications along with acronym as well as how the land use was binned according to the 7 class bin dataset and the 4 class bin dataset. Each class bin included an Other (OTH) class which included regions which were not classified, or classified as something other than the target land uses. Further, a 5th class Null was included to account for edges, or areas of the orthomosaic which were black/not covered by imagery.

Land Use Type	**Land Use Acronym**	**7 class bin**	**4 class bin**
Cocoa	CCO	CCO	CCO
Palm	PLM	PLM	PLM
Settlement	SET	SET	SET
Plantain/Banana	PLB	VEG	*OTH*
Cassava	CSV	VEG	*OTH*
Vegetables	VEG	VEG	*OTH*
Fallow	FAL	FAL	*OTH*
Grass	GRS	GRS	*OTH*
Edge/Null	NUL	NUL	NUL

4.3.5 Random Forest Models

Random Forest models are ensemble classifiers, whereby several classifiers are combined and used in conjunction to optimise outputs. The basic concept of a random forest model is that it uses a randomly selected subset of data features to produce multiple decision trees (hence forest) iterated over multiple rounds of variable selection with replacement and testing of samples (see Belgui & Dragut 2016 for detailed model description). Two distinct random forest models were utilised in this study. The first was a standard single pixel random forest classification model, henceforth referred to as RF1x1x3, where the classification was carried out at the single pixel scale (1x1) across the three RGB colour bands. The second random forest model used a pixel neighbourhood approach. Rather than assessing each pixel in isolation, each pixel is samples with its 8 adjacent neighbours, creating a 27 feature sample for each pixel. This ensures each pixel is classified using information relating to its 'neighbourhood'. This model is henceforth referred to as RF3x3x3. The number of samples for each RF model is effectively the number of pixels. For the entire image set, preliminary analysis indicated that the percentage of pixels assigned to each class are as follows: 56% are cocoa, 11% are palm, >1% are settlement and 56% are classified as other land uses. Each tile is 370 pixels by 370 pixels, with each tile containing a total of 136'900 pixels.

4.3.6 Deep Learning Model

A fully-convolutional neural network is used to segment land use classifications in the drone imagery. The model architecture used in this study is ResUNet (Zhang et al. 2017), a recent architectural innovation combining the context-capture of UNet (Ronneberger, Fischer & Brox 2015) with the residual blocks of ResNet (He et al. 2015). The ResUNet architecture adapted for this study is hosted at github.com/Lkruitwagen. The architecture is trained and run using Python, Tensorflow and Keras. The ResUNet was trained on an Amazon Web Services P3 instance (NVidia Tesla V100) for 500 epochs. The training set was 60% of the total image set (768 image tiles or samples), with 20% used for model performance cross-validation, and 20% reserved as a final out-of-sample test set.

4.3.7 Evaluation Criteria

The results of each classifier were assessed based on three parameters which are typical of many machine learning problems, and a fourth used in image localization and segmentation problems. The first three of these used here include Precision, Recall and F1. Precision is a measure of how accurate the model is in detecting positive results. This measure highlights how many of the predicted positive measures, were actually positive (Equation 1). Recall captures how many true positives are captured in the model. This criteria considers false negatives, and thus is useful when the cost of a false negative is high (Equation 2). The third metric is F1, and can be considered a blend of precision and recall, as it is calculated by finding the harmonic average of precision and recall (Equation 3).

$$\text{Precision} = \frac{TP}{TP+FP} \tag{1}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{2}$$

$$F1 = 2*(\frac{Precision + Recall}{Precision * Recall}) \quad (3)$$

Where TP = True Positive, FP = False Positive, FN = False Negative.

The fourth criteria used for cross-model comparison is the Jaccard Index (or Intersection-over-Union, IoU). IoU is a common metric for evaluating model proficiency in image segmentation problems, defined for a given class as the intersection of the label and prediction divided by union of the same (Equation 4). The IoU metric is particularly strict - the denominator includes both the false positives and false negatives, and in a multi-classifier, a mislabeling will definitionally reduce the IoU for both the true and falsely-labelled class. IoUs greater than 50% will be considered successful, and greater than 65% very successful.

$$IoU_C = \frac{L_C \cap P_C}{L_C \cup P_C} = \frac{TP_C}{TP_C + FN_C + FP_C} \quad (4)$$

Where $L_C \cap P_C$= the area of overlap, $L_C \cup P_C$= union of total area, TP = True Positive, FP = False Positive, FN = False Negative.

It should be noted that accuracy was not used as an evaluation criteria in this study. Accuracy is a measure of the number of true positives and true negatives divided by the sum of true positives, true negatives, false positives and false negatives. For example, if we were testing for settlement pixels, if a pixel which should be classified as palm, is classified as cocoa, this would still be considered a true negative, because it did not classify the pixel as settlement (even though the classification was incorrect). As a result accuracy is highly skewed by the presence of a large number of true negatives. Due to the number of variables we were attempting to detect, we found the accuracy often presented an inflated indication of how well each model was performing, and as such it was not included as an evaluation criteria.

4.3.8 Pixel Distribution

Pixel distribution will also be tested, giving an indication of not how individual pixels are doing at capturing land use but rather how the tiles themselves are doing. This pixel distribution will give a measure of the proportion of land use types detected by the models versus what the input classifications indicate. This will be able to test how the models, at a coarser scale, are able to detect land use and land use patterns.

4.4 Results

The deep learning ResUNet model was consistently the most successful at classifying land use using conventional drone imagery, when compared to the single pixel (1x1x3RF) and neighbourhood pixel (3x3x3RF) classifiers (Figure 4.2). The precision of all models was modest, with the ResUNet model showing the greatest success (40-100% precision), while both RF models performed less well, in particular for settlements (Figure 4.3). Similarly, the recall of both RF models was very low for the variables of interest, namely cocoa, palm and settlements. The ResUNet model performed substantially better, with particular regard to palm where it achieved 82% recall. Again, the ResUNet model performed the best when considering F1 (the balance between recall and precision), particularly with regard to palm and cocoa (57% and 47% respectively). All models performed poorly with regard to the final, and most stringent metric, IoU. While again the ResUNet model performed the most successfully, the metrics of interest, namely palm, cocoa and settlements, only achieved 34%, 25% and 2% respectively (Figure 4.3).

A further criteria to consider is the distribution of pixels between models. For the training and test classifications, roughly 50% of the pixels were 'Other' class, 18% were cocoa, 12% were palm, 16% were 'null' and 0% were listed as settlement. When assessing the distribution of pixel classes between the models, ResUNet performed much better than the other models for all land classes (though slightly underestimating cocoa (14%) and overestimating palm (21%)) (Figure 4.2).

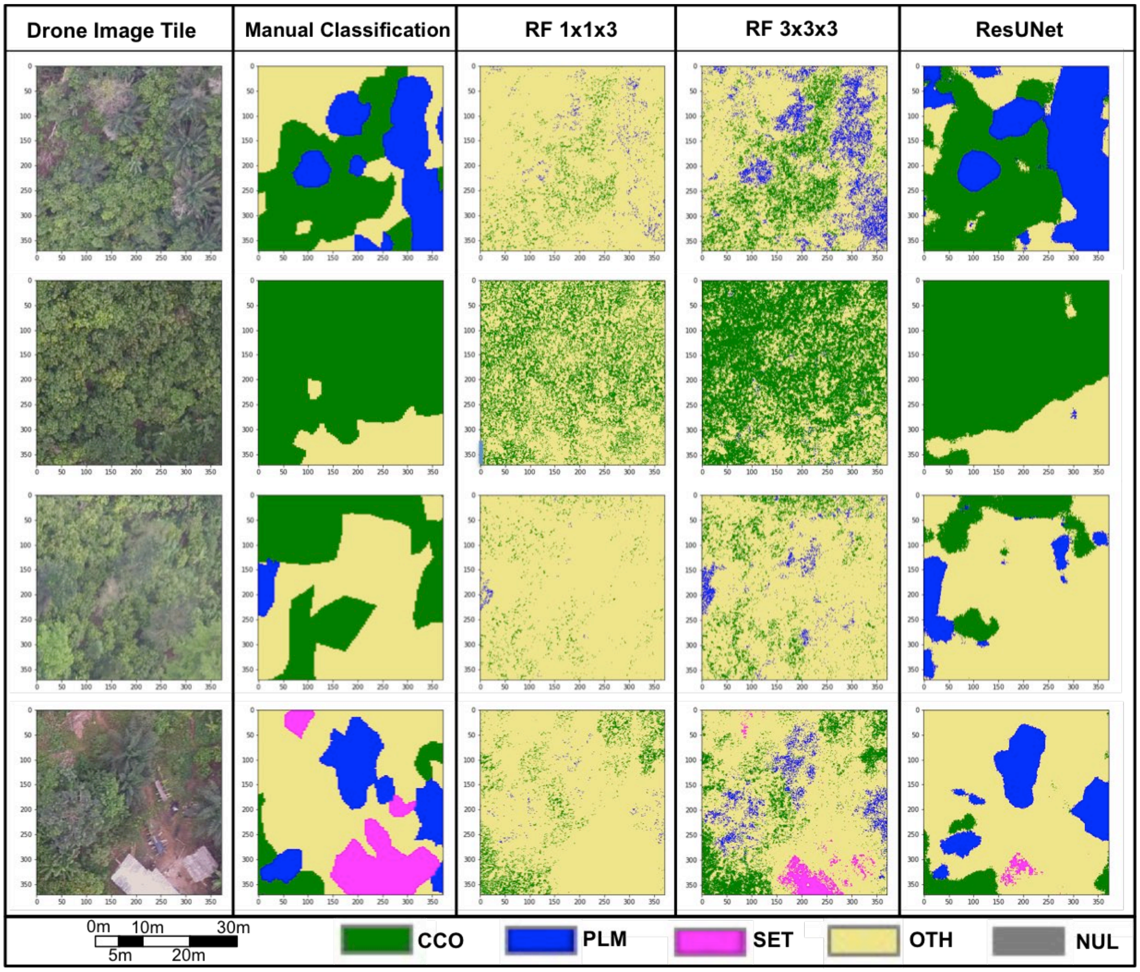

Figure 4.2 Classification overlays of selected drone image tiles using machine learning models. Manual classification is the baseline that served as the correct baseline for each model. RF1x1x3 is a random forest model using single pixel assessment, RF3x3x3 is a random forest model using 3x3 pixels clustered as the assessment scale, while ResUNet is the fully convolutional neural network model. In all overlays, green represents cocoa, blue represents palm trees, pink represents settlements, and yellow represents other land uses. Both axes are in number of pixels.

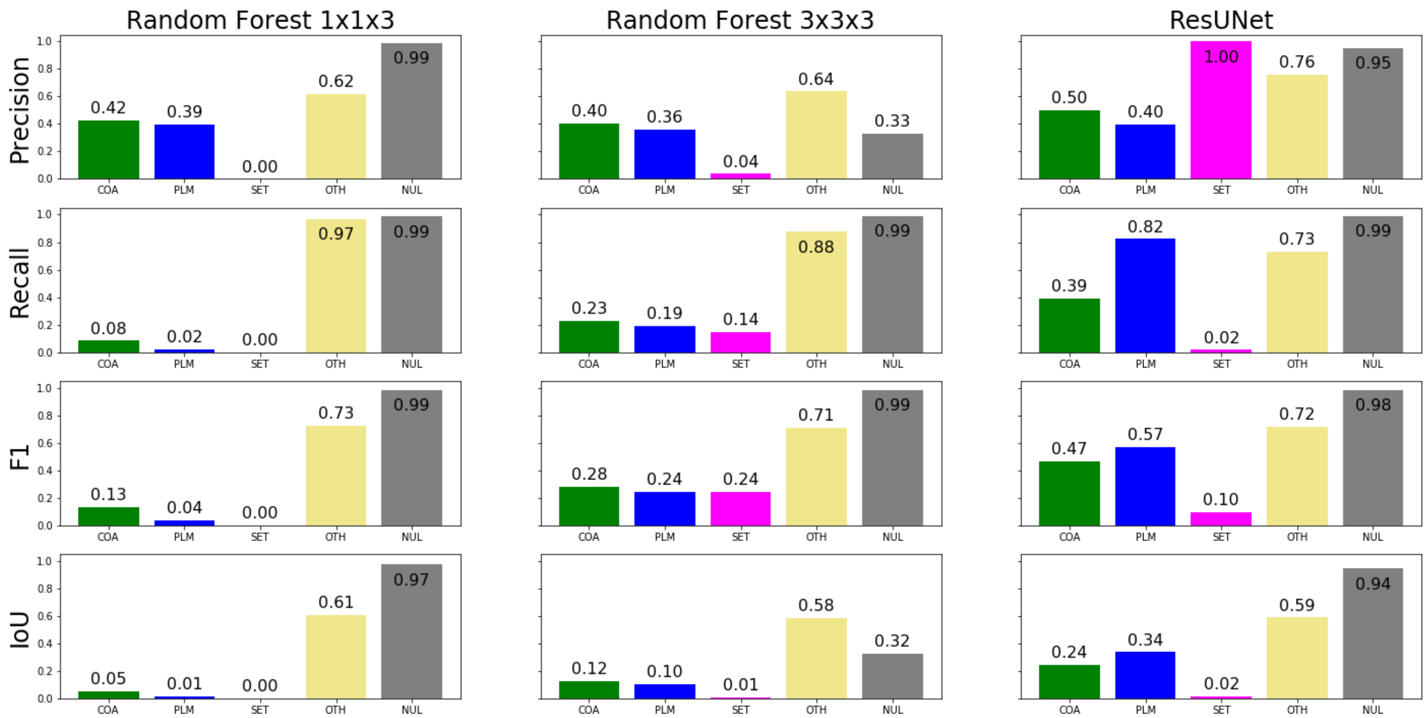

Figure 4.3 Precision, Recall, F1 and IoU results for each land use class from each model. In all graphs, green represents cocoa, blue represents palm trees, pink represents settlements, and yellow represents other land uses.

4.4.1 Pixel Distribution

When assessing the broader scale classification success of each model, ResUNet was more successful than the other models (Figure 4.4). This indicates that even if the pixel values are not high, the model is doing a successful job of grouping pixels such that the broader land use features are being captured well.

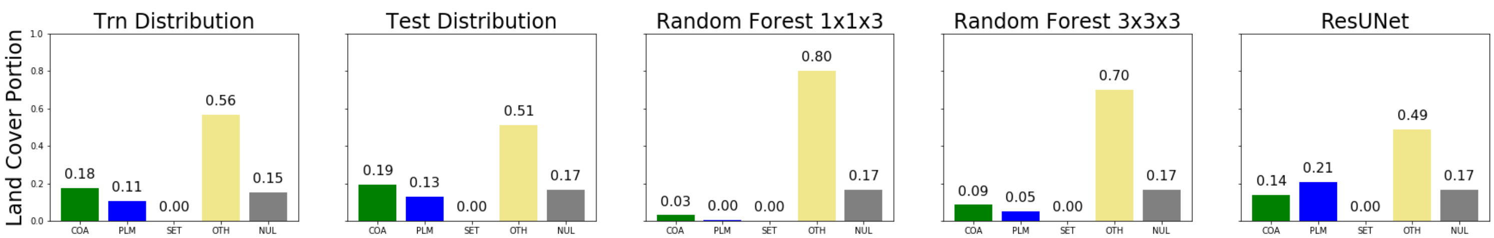

Figure 4.4 Pixel distribution by land class type for the training data (Trn), test data (Test) and the three machine learning models. In all graphs, green represents cocoa, blue represents palm trees, pink represents settlements, and yellow represents other land uses.

4.5 Discussion

The machine learning models tested varied in their ability to detect different land uses. The best performance according to all measures was by the ResUnet model. This performance was followed by the RF3x3x3 model and then the RF1x1x3 model. The success of the ResUnet model indicates the potential of the approach. While, some results presented here are not sufficiently or consistently high to be considered successful for some applications, other results underscore the utility of the approach in it's current form. The improved performance of the two models which consider regional context (RF3x3x3 and ResUnet) highlight the importance of proximity and context in detecting crop types, even in such a complex mosaic landscape – spatial information is a critical complement to spectral information.

Cocoa was very difficult for the models to detect, with all achieving 40-50% precision in detecting the crop. The values for the recall of cocoa dropped for all models, particularly for the RF1x1x3 model (42% for precision to 8% for recall), indicating presence and influence of false negatives in all models. While F1 values for the ResUnet were substantially higher than the other two models (47% compared with 13 and 25%). This once again highlights the superiority of the ResUnet model, and points to it being close to a usable standard. For IoU, the most strict evaluation criteria, cocoa had a low detection for all models. However, the highest of which was the ResUnet model, which successfully detected cocoa 24% of the time. While this measure is impressive, it does not meet our minimum threshold of 50% to be considered successful.

Palm appeared more easily detectable than cocoa for the ResUnet model, consistently outperforming the detection of cocoa on all evaluation criteria except for precision. Notably, the recall for palm in the ResUnet model was 82%, and for F1 was 57%. The success of these criteria highlight that palm may be easier to detect on the landscape when using the ResUnet model. However, both RF models were less successful at detecting palm across all evaluation criteria.

Settlements appeared to be difficult to detect, with all models performing poorly in detecting and identifying the land class. For the ResUnet model, the discrepancy between the precision and recall of settlements (100% to 2%), highlights the number of areas which should have been classified as settlements, but were not. While all models performed poorly in settlement detection, according the most strict IoU statistic (2% to 0%), the RF3x3x3 model was more successful at detecting settlements when using the F1 evaluation criteria. It should be noted that settlements were severely underrepresented in the dataset (making up less than 1% of land area) and this is what likely lead to the low scores of detection. This is generally descriptive of the region, where very few settlements exist in the landscape, and people tend to cluster in villages. However, a small number of settlements and homesteads are located directly amongst the agriculture landscape, and thus their detection remains important. It was assumed that settlements would be the easiest to detect given the stark differences between settled areas (exposed brown soil, presence of structures and contrasting colours) and vegetated land areas. In future evaluations, datasets should be supplemented with additional data for land uses which fall beneath a particular threshold of the land area. In this case, hard positives (areas of known to represent a given classification, but located outside of the original dataset) could be added. A minimum threshold for all land classes should be included to ensure poor model performance is due to difficulty in detecting the land class itself, rather than a lack of land class information in the training data.

While the pixel-based evaluations did not perform successfully given our IoU criteria (>50%), the pixel distribution did yield some encouraging results. While both RF models did not perform sufficiently well, both greatly over estimating 'Other' land classes and underestimating the land classes of interest (cocoa, palm and settlement), the ResUnet model performed well. While the ResUnet model slightly underestimated the presence of cocoa (14% vs. 18.5%) and overestimated the presence of palm (21% vs. 12%), it generally was able to capture the approximate landscape land use proportions. This result is very important, as while the ResUnet model is not perfect at detecting individual instances of vegetation per pixel, it does a fairly good job at accurately classifying the land use data for the training area in a highly heterogeneous complex landscape. This is an important step towards beginning to understand these landscapes, and the patterns of land use within them. Many studies of this region of west Africa tend to broadly classify the entire landscape as mixed agriculture however, at a fine scale the dynamics are far more complex (Moore et al. in review). From a practical standpoint, in this region of Ghana both cocoa crops and palm oil crops can represent the primary or sole income for many households (Hirons et al. 2019, Essegbey & Ofori-Gymfi 2012). This method could be used in the monitoring of climate smart cocoa programs (Vaast et al. 2016), or deforestation due to cocoa expansion (Ordway, Asner & Lambin 2017). Further, monitoring the spatial impacts of climate change related disturbance events, such as the 2015/2016 El Nino, is urgent and could benefit from a refined version of this approach (Moore et al. in review).

There are a number of substantial benefits to the methods and approaches proposed in this study than those widely used. Firstly, working with drone images is easier than many remote sensing platforms, and they can be analysed using widely available image editing software (e.g. Photoshop, Affinity photo etc.) and basic GIS software, as well as Python and the Tensorflow machine learning framework.

Secondly, drone imagery overcomes many of the shortcomings in satellite remote sensing imagery, and the utility of inexpensive drones as well as free software would increase the access of such technology to practitioners in areas where the technology is needed most. Finally, advances in cloud computing make it possible for such an approach to be utilized in places where these images are produced (e.g. West Africa) as long as they can be uploaded. Large amounts of data can be undoubtedly useful, but these data must be capable of answering the desired research or practical questions. Finally, the cost of the drones used in this study are not prohibitively expensive, and are easy to use. The number of apps which allow autonomous flight for systematic monitoring of designated areas, such as the Pix4D app used here, is growing and many are free or very inexpensive.

While the research study presented here indicates the substantial potential of machine learning models in classifying conventional drone imagery, there still remain some substantial issues. Random forest models do not scale well with samples or features. Generating the model ensemble required parallel training across 50 nodes of a high performance computing cluster and took approximately 20 hours. As well as a steeper learning curve, training the deep learning model required access to a GPU cloud instance and took approximately 36 hours. Further, the drone imagery was computationally difficult to process, given the high failure rate of the most convenient softwares, Drone Deploy and Event38 Unmanned systems (further description can be found in Chapter 3), this task proved very time intensive. In addition, drone imagery also faces other issues which also impact tradition remote sensing approaches, namely aerosols in the blue band and the influence of features such as shadows. However, the methods proposed here have been more fine-tuned, and would be recommended to other researchers in the future. These two features, computation and temporal expense, remain barriers for the easy and wide utilization of the approaches proposed in this study. However, the continual substantial advancement of cloud computing resources highlights the potential for these resources to be both cheaper, and more easily accessible in the very near future.

In conclusion, this study successfully used an advanced machine learning approach (ResUnet) to classify land use in a high complex landscape using only RGB imagery from an inexpensive, off-the-shelf drone. For pixel based classification, the lack of success of the RF models approaches to image classification is consistent with other studies. Further the relative success of the ResUnet model highlights the substantial potential that machine learning, and specifically deep learning approaches have in advancing the approaches of land use classification. Additionally, the success of the ResUnet model in coarser land use classification is highly encouraging, and indicates that this approach has current utility in the most complex landscapes. Many other studies have overcome some of the classification shortfalls described in this study by incorporating remote sensing imagery or other bands (Near Infrared or Infrared). However, this study demonstrates the potential for successful land use classification in highly complex landscapes, using only RGB images from an inexpensive off-the-shelf drone by using a sophisticated machine learning approach.

Chapter 5

This second data chapter addresses Objective 2 *Increase the understanding of the relationship between humans and the environment in complex mosaic landscapes by quantifying the level of human impact on the region.* To achieve this objective, I used all of the drone data processed using the methods described in Chapter 3. I used the metric of Human Appropriated Net Primary Productivity (HANPP) to quantify the approximate levels of impact of each land use on the ecosystem. I used information from the literature to derive HANPP values for most land uses, while the HANPP values for cocoa were derived using field collected data from sites around Kakum National Park as part of the ECOLIMTIS Project. The findings of the paper are presented in a paper entitled "Human Appropriated Net Primary Productivity of Complex Mosaic Landscapes" which is currently under review by the journal *Frontiers in Forests and Global Change*.

The original intention was to have the machine learning approach to classify the imagery in all regions, however there was a lack of success in classifying subsistence crops using these techniques. Since I wanted to capture a range of land uses beyond just cash crops, which were more successfully classified using the machine learning approach, I decided to manually classify all the drone data to include subsistence crops such as plantain, cassava and vegetables.

I am the main author and wrote the paper, conducted the drone fieldwork in Ghana and carried out all other analysis with the guidance from my supervisors Alexandra Morel and Yadvinder Malhi. This work could not have been possible without

the support and coordination of our partners in Ghana: Rebecca Asare, Micheal Sasu and Stephen Adu-Bredu.

5. Human Appropriated Net Primary Productivity of Complex Mosaic Landscapes

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5.1 Abstract

Quantifying human impact on the environment is increasingly important and particularly so in complex mosaic landscapes. Such landscapes are prolific in the developing world, notably in West African, small holder cocoa farming communities. Human Appropriated Net Primary Productivity (HANPP) is a metric which has been developed to quantify the human impact on the environment and has been used in a number of studies globally. However, most operationalization's of HANPP have been done on a coarse global scale or a very local scale, and few studies exist of complex mosaic landscapes. This study utilizes Unmanned Autonomous Vehicles (UAV), or drones, to classify land use and HANPP for three cocoa farming regions in Ghana's Central Region. The results of the study indicate while all regions differ in land use composition, the primary crop for all is cocoa, followed by palm and then land that was previously cultivated which has been left to fallow. The average HANPP was 44% for all measured regions, calculated using net primary productivity (NPP) values of an adjacent natural tropical forest. The HANPP for the three cocoa regions studied was found to be approximately 6.69 MgC/ha, 8.00 Mg C/ha and 9.85 Mg C/ha. These values are higher than those that have been reported in some widely accepted global studies, and highlight the need for more regional and landscape scale studies to supplement global assessments of HANPP.

5.2 Introduction

Understanding and quantifying human impact on the biosphere is increasingly important in the face of global climate change and large-scale land conversion. It is of particular importance in areas which have historically benefited from stable and predictable temperature and rainfall regimes, such as tropical regions including West Africa. Under climate change, it is predicted that these tropical regions will experience increases in inter-annual variability of seasonality, accompanied by increasing uncertainty around the intensity, arrival and duration of rainfall events (Feng, Porporato & Rodrigez-Iturbe 2013). Further, these regions have undergone, and continue to undergo, significant land conversion, often resulting in highly biodiverse landscapes being replaced with large-scale monocropping systems or small-scale mixed cropping systems (Laurance, Sayer & Cassman 2014). As a result, understanding the dynamics between humans and the biosphere is of particular urgency and importance in the tropics.

Significant research has been done on the conversion of tropical regions to large scale monocropping systems, including regions of SE Asia (Fox et al. 2014; Cove & Wilcove 2008) and the Amazon (Bonini et al. 2018). The dynamics of land use and land conversion in the tropical regions of West Africa have received less attention. One reason for this is the nature of land conversion, which is dominated by small-scale mixed agriculture and complex small holder farming systems (Collier & Dercon 2014). Farmers in this region typically keep farms of less than five hectares, and also undertake primarily rain-fed agriculture practices (Rapsomanikis, 2015; Morton 2007). These factors, combined with extensive poverty amongst farmers, result in highly complex, and potentially vulnerable agriculture systems.

Most human uses of land are dependent on the land's biological productivity, in other words it's Net Primary Productivity (NPP) per area, which is the annual rate of production of living biomass (Imhoff et al. 2004). However, this metric alone cannot provide sufficient evidence for the relationship between the NPP of a natural landscape, and the NPP of the human modified landscape. Understanding and quantifying this distinction is of principle importance when seeking to understand the complex relationships between humans and the biosphere. As a result, Human Appropriation of Net Primary Productivity (HANPP) has emerged as a primary indicator which explicitly addresses the social-ecological nature of human use and conversion of land systems. The indicator is a measure of the difference between the NPP of the potential vegetation (NPPpot) had the ecosystem not been altered by humans and the unexploited NPP of the actual vegetation (NPPeco) present (Figure 5.1). HANPP can be further dissociated into $HANPP_{harv}$ which describes the biomass which is exploited from the ecosystem (either as harvest material which is removed from the system, or unused harvest [e.g slash] that remains in the ecosystem) and the land-use change-associated $HANPP_{luc}$ which describes the difference in total ecosystem NPP caused by the conversion of the native vegetation to the current land use (Haberl et al. 2014).

Values for HANPP can vary substantially based on the background NPP, (natural vegetation), the level of conversion which has occurred and the level of inputs in the form of fertilizers, irrigation etc. HANPP is often displayed as a percentage of NPP potential, where urban areas which have undergone substantial land use conversion might have a value close to 100% HANPP. For diverse tropical systems, it is rare to observe values of

HANPP for converted landscapes which exceed that of the background vegetation (Figure 5.1). For example, agriculture in these regions is primarily rain fed, and many farmers lack the ability to input fertilizers on a consistent basis which may artificially decrease the percent of HANPP. Conversely, the input of fertilizers or irrigation can make some landscapes more productive than the baseline natural vegetation, for example agriculture in Saudi Arabia can generate HANPP values in excess of -100% (in other words at least 100% more productive than the background landscape) (Haberl, Erb and Krausmann 2014).

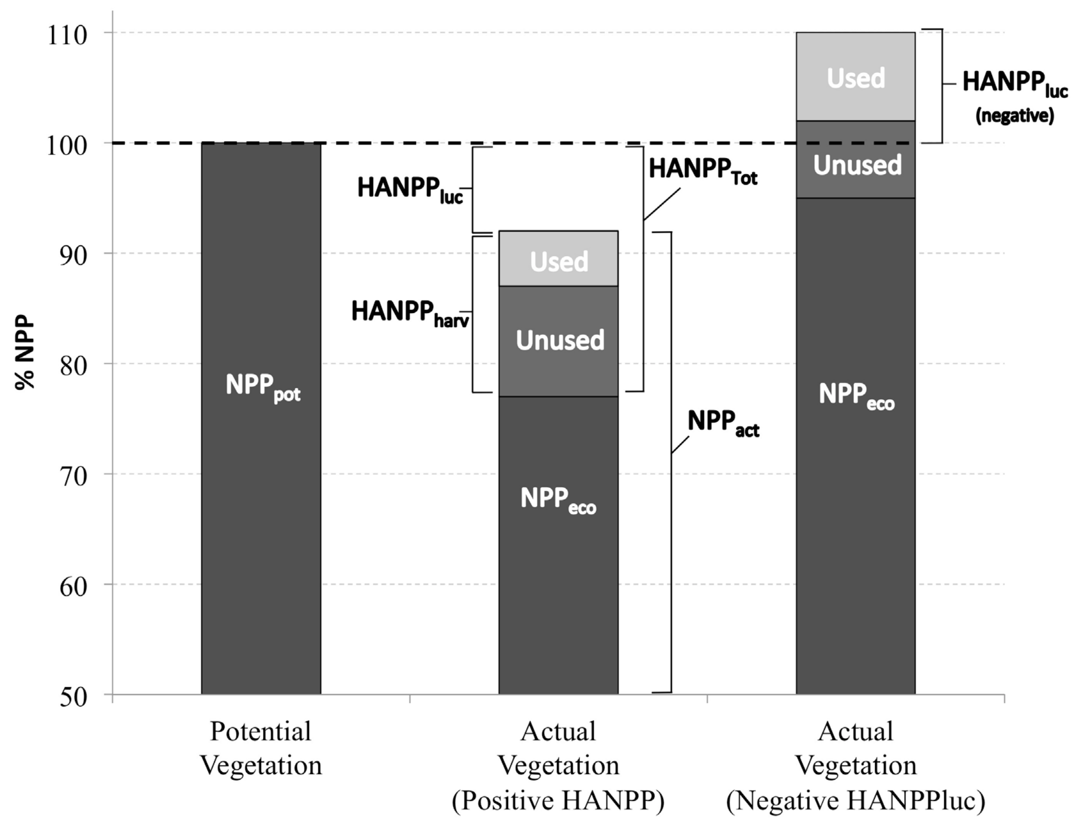

Figure 5.1 How to measure the HANPP of a landscape. HANPP is a combination of HANPPharv [the NPP harvested, whether it is used (removed from the landscape) or unused (left in the landscape)] and HANPPluc (the change in NPP induced by conversion of the native ecosystem to the current land). The actual NPP of the converted landscape includes both the NPPeco (NPP of the current ecosystem) and HANPPharv. If the combination of HANPPharv and NPPeco are lower than NPPpot, HANPPluc is postive and added to generate HANPPTot. However, if the combination of NPPeco and HANPPharv is higher than NPPpot, HANPPluc is then subtracted to determine HANPPTot.

HANPP has been used in a variety of studies assessing the impact of humans on the biosphere. The majority of these studies have investigated HANPP at a global scale, and have estimated the human appropriation of potential NPP to be approximately 20-40% (Anderson, Donovan & Quinn 2015). Vitousek et al (1986) first introduced the concept of HANPP, and proposed low, intermediate and high estimates of HANPP based on measures from the 1970's. The low estimate, which only included biomass consumed by humans and livestock, estimated HANPP to be approximately 3%. However, the intermediate estimate, which also considered the entire NPP of human-dominated ecosystems, and the high estimate, which further considered human impacts, were estimated to be 27% and 39%, respectively. A more recent and spatially explicit study conducted by Krausmann et al. (2013) estimated that between 1910 and 2005 HANPP doubled from 13% to 25%. These studies have provided a large amount of insight into the global trends in HANPP.

Using similar methodological approaches HANPP has also been assessed at the national (Fetzel, Gradwohl & Erb, 2014; Haberl et al. 2012; Kaster 2009) and regional scales (O'Neill et al. 2007; Andersen, Donovan & Quinn 2015). Further, Andersen, Donovan and Quinn (2015) conducted a watershed scale HANPP estimation in the Southeastern United States, and reported a net decrease in HANPP between 1968 and 2011, primarily attributed to changes in land use.

While HANPP is a widely accepted indicator, with many studies cross validating one another's results (Haberl, Erb and Krausmann 2014; Haberl et al. 2007), many of these global studies to not include ground validated data. As an example, the seminal Haberl et al. (2007) study derived HANPP values using a standard "Dynamic Global

Vegetation Model" (DGVM), with gridded data on climate and soil as input data to determine NPPpot. To determine NPPact and NPPharv, the authors used statistical data on country scale data on livestock, agricultural yields and wood harvest as well as land use data at a 10kmx10km resolution. While the authors make a concerted effort to include the best data available at a large scale, most features are collected at a very coarse scale, and several assumptions are used about the broad applicability of statistics and data. While such global studies are important, there remains a dearth of research studies using field collected, embedded data to assess HANPP. Further, any measures of HANPP from such data need to be scaled up with relative accuracy to provide a scale of assessment comparable to regional, national and global HANPP studies.

While the inclusion of field collected data is highly desirable and should remain a priority, there are complications which arise when trying to utilize field collected data for landscape or regional (or larger) scale HANPP studies. The collection of field data itself is often expensive, time consuming and can be impossible in certain landscapes. Further, scaling up such data must be done with caution, certainly in areas where remote sensing data is sparse or unreliable (e.g. tropical regions prone to cloudiness). The need for innovative approaches is particularly marked in regions of mixed agriculture, where small holder farms are the most common land use. Widely used remote sensing image collections (i.e. MODIS, Landsat etc) are often at too coarse of a resolution to detect and map patterns of small-scale agriculture in order to make accurate predictions about the land use intensity (Kuemmerle et al. 2013), and thus generalized measures of HANPP for such regions may be inaccurate. There is a clear need to develop methods which can incorporate and scale up ground based assessments of HANPP.

One strategy which could address this apparent scale-gap, is utilizing novel Unmanned Ariel Vehicles (UAVs, commonly referred to as drones) to capture landscape and regional scale land use data, at extremely high resolutions (~10cm^2). Today, commercial UAVs offer low cost and high-resolution imagery well suited to complex mosaic landscapes, but have until recently rarely been exploited to address this challenge. UAV-derived data can eliminate the interference of factors such as clouds or haze, while providing users with moderately large tracks (~1km^2 per flight) of highly detailed landscape data. The resulting imagery can be used to scale up local and ground based HANPP data in such a way that comparison between ground based data, and satellite imagery becomes possible. Thus, UAV imagery can fill the scale gap which allows comparison of field collected data with the standard global scale HANPP maps which have served as the basis for most HANPP studies thus far.

This kind of approach is particularly needed in tropical West Africa, where smallholder agriculture is the primary driver behind land change (USGS 2018, Vittek et al. 2014). While many people in rural areas cultivate numerous subsistence crops such as cassava or plantain, substantial land transformation has occurred to support the cultivation of cocoa trees (Kolavallli & Vigneri 2011). Together, Cote d'Ivoire and Ghana produce 70% of the world's cocoa, much of which is grown in regions which were historically tropical forest. In Ghana, cocoa beans and associated products account for approximately 60% of export earnings. Further, cocoa contributes approximately 10% of the agricultural GDP, providing employment to over 800,000 households (Vigneri & Kolavalli 2018). Farmers in the cocoa zones of these two countries typically cultivate farms of less than 5 ha, and often utilize their plots for a diversity of crop types. As a result, while cocoa trees dominate the landscape, the remaining land is used to cultivate a variety of other subsistence crops, interspersed with fallow land and large shade trees. This results in highly complex and fine-scale landscape of cocoa, subsistence crops, remnant tropical forest and fallowed areas. The importance of understanding the land use in these regions cannot be understated, especially when considering the lack of success many global products have at detecting and mapping deforestation in tropical areas (Grainger 2008). As such, operationalizing the measure of HANPP at a scale which is comparable with both local and global surveys is of particular relevance.

In order to determine the HANPP of such a mosaic landscape, detailed measures of HANPP of cocoa must be determined. Recent work by Morel et al. (2019a) generated detailed site-level data of NPP and HANPP in cocoa farms in the Central Region of Ghana. The study reported a strong relationship between cocoa farm characteristics, namely shade tree density and cocoa tree density, and HANPP. The high level of correlation between these factors indicate that if the cocoa density and shade tree density can be measured at a larger scale, HANPP for an entire cocoa mosaic landscapes could be accurately predicted.

Here we present a novel medium-scale study of HANPP in a mosaic tree crop and agricultural landscape in West Africa. Our work combines results from detailed *in situ* studies of NPP and HANPP, with landscape extrapolation based on maps of vegetation cover generated from high resolution imagery collected from a UAV. Further, this study is the first attempt to reliably scale up ground-based measures to a scale comparable to the grain size of benchmark global studies of HANPP.

We address the following questions:

- What are the patterns of land use in our case study tropical mosaic landscape, and how much does cocoa dominate this landscape?
- What is the HANPP associated with this landscape, and how does it vary across the landscape?
- How well do large scale products capture the HANPP that we have quantified at the fine scale?

5.3 Methods

5.3.1 Study Site and Supporting Materials

This study was carried out in the Central Region of southern Ghana around six communities bordering Kakum National Park (5°33’42.712” N, 1°20’ 55.234” W ; See Figure 5.2). The area of study was further subdivided into three distinct regions, each inclusive of two focal villages and the surrounding land use areas, following the sampling design of Morel et al (in review). These regions are: AB (including the villages of Aboabo and Asorefie), HM (including the villages of Ahomaho and Nsuoekyi) and KA (including the villages of Kwamoabeng and Tumfokrom).

The entire region is typified to a high extent by small holder cocoa farmers, who produce cocoa, as well as oil palm (which is native to this region and is a food crop), and subsistence crops such as vegetables (Hirons et al. 2018a). The work was carried out as a part of the larger ECOLIMITS project which collected data between 2014 and 2017 to better understand the relationship between poverty and ecosystem services (Hirons et al. 2018b). The project intensively monitored two forest plots within Kakum National Park as well as eight cocoa farm plots under varying levels of management intensity for NPP and HANPP over three years as well as collected above ground biomass and cocoa yield data for 28 additional plots (Morel et al. 2019a). Each of the intensive plots was 60m x 60m (0.36 ha), and field measurements followed the Global Ecosystems Monitoring (GEM) protocol (Marthews et al. 2012). For shade trees, three components of NPP were estimated (canopy NPP, woody NPP and fine root NPP) and summed to determine NPP. These components were also measured for cocoa trees in addition to the estimated NPP of cocoa pod production, with all four components being summed to determine NPP.. Detailed descriptions of the full methods used to generate the NPP of cocoa farms as well the background forest NPP can be found in Morel et al. (2019a). NPP values for the cocoa farms were then compared to NPP values collected for the conservation area forest plots (~17 Mg C ha^{-1} yr^{-1}) to generate an estimate of HANPP of the cocoa farms. While based on one forest plot, we assumed a uniform NPP across the landscape for our HANPP calculations. We feel this was justifiable as our forest NPP was within 5% of a similarly measured forest in Ghana by Moore et al (2018). In addition, while this value is high, these values are comparable to several other tropical regions and other studies have confirmed that West Africa has very high NPP values (Moore et al. 2018). Further, this value sits within upper bounds calculated for synthesis studies of tropical forest NPP (Clark et al. 2001).

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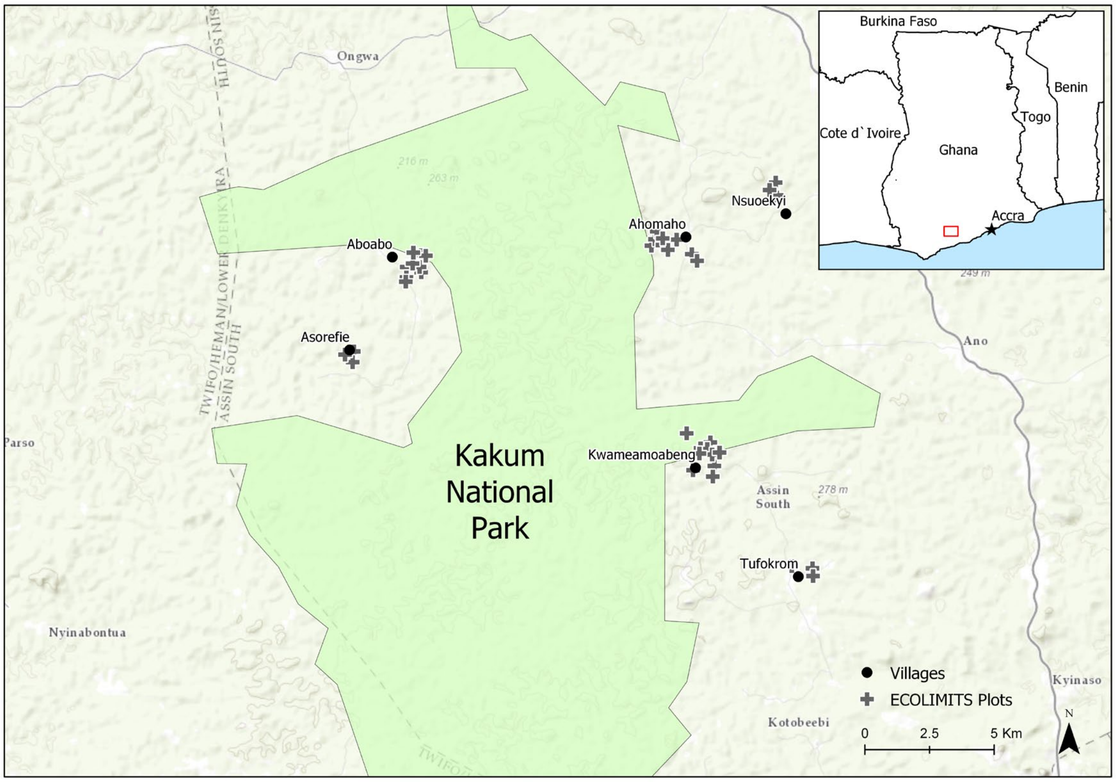

Figure 5.2 Study sites for the ECOLIMITS project surrounding Kakum National Park in southern Ghana. ECOLIMITS ecological farm plots (+) were intensively monitored for three years between 2014 and 2017. Farm sites were selected at 100m, 500m, 1km and 5km distances from the national park (Morel et al. in review). Six villages (•) where the household surveys for the ECOLIMITS project were conducted. Drone surveys were prioritized for the areas containing the villages of households surveys and the location of their farm plots.

5.3.1 Drone Image Collection and Processing

Image Data Collection

Aerial data were collected between November 2016 and January 2017. Data were collecting using DJI Phantom 3 Professional drones (www.dji.com). Each drone is equipped with a 12.4 Megapixel RGB camera. Areas surrounding each community were divided into 1 km^2 grids. Flights were then conducted as close to the centre of these grids as possible. Each flight aimed to capture ~1 km^2 area. Flights were flown at 150-300 m above ground level, where flight height was dependent on factors such as cloud cover, and Harmattan (dry season Saharan dust haze) conditions. The drone operation softwares DJI GO and Pix4D were used to carry out the drone surveys. Data were captured as individual pictures taken sequentially, with minimum 70% side overlap, and minimum 60% top/bottom overlap. This level of overlap is consistent with expert opinion on the overlap needed to generate orthomosaic images of each flight (where all individual images are rendered together to create a single, large GeoTIFF of each flight).

Drone Data Processing

After trying a number of options and facing several challenges, it was found that drone imagery could best be processed using a combination of software, including DroneDeploy (DroneDeploy, 2018), Event 38 Unmanned Systems (DDMS 2018), ArcGIS 10.0 (ESRI 2018) and Affinity Photo (Serif 2018) (Figure 3). Drone images were processed in single flight batches, and the resulting orthomosaics which were produced varied in size from 0.75 km^2 to 1.6 km^2. Size variation was due to flight duration, flying height and conditions, such as wind, on the day of the flight.

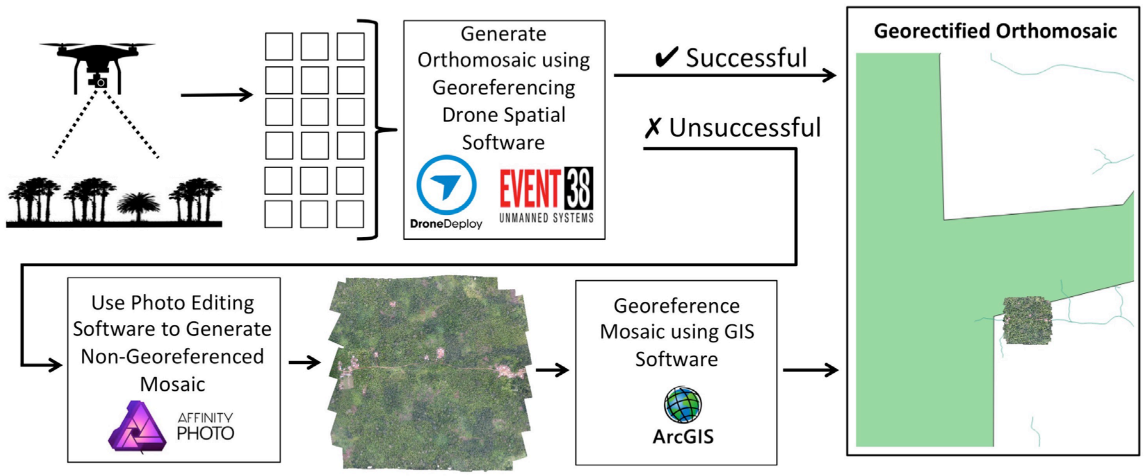

Figure 5.3 Drone image processing workflow: data were captured from the drone as individual images. These were then fed into drone spatial software capable of generating georectified orthomosaics (i.e. Drone Deploy, Event 38 unmanned systems). If these softwares were incapable of producing an orthomosaic, the images were fed into an advanced image editing software (Affinity Photo). The resulting orthomosaic was not georeferenced, so it was then uploaded to GIS software capable of georeferencing (ArcGIS) to produce a final georectified orthomosaic. Within the GIS software, the georeferencing tool was deployed, using geospatial information embedded in each drone image as the reference points

5.3.2 Land Use Classification and Cocoa Data Processing

Land-use categories and classification

Land use was determined by undertaking manual classification of the drone images using QGIS software to produce a land use vector layer. The very high resolution of the imagery made it possible to easily distinguish different land use types. Classification was carried out by one individual (the lead author), who trained using ground truth points to establish confidence in the resulting land use classifications. Land use was partitioned into nine categories: Cocoa (CCO), Cocoa with Timber Trees (CTT), Cassava (CSV), Fallow (FAL), Grass (GRS), Palm (PLM), Plantain/Banana (PLB), Settlement (SET), and Vegetables (VEG) (Table 5.1).

Table 5.1 Description of dominant land use classes in regions surrounding Kakum National Park

Land Use Name	Land Use Acronym	Description	Example
Cocoa	CCO	>75% coverage of cocoa trees (*Theobroma cacao*).	
Cassava	CSV	>75% coverage of cassava (*Manihot esculenta*)	
Fallow	FAL	An area dominated by wild vegetation including trees and shrubs, shows no evidence that it is being actively maintained.	
Grass	GRS	An area dominated by short wild grassy vegetation, shows no evidence that it is being actively maintained.	

Palm	PLM	>75% coverage of palm trees. This is inclusive of all trees from the Arecaceae, though tends to be dominated by *Elaeis guineensis,* the oil palm.	
Plantain/Banana	PLB	>75% coverage of plantain or bananas stocks (the *Musa* family). Plantain and banana are indiscernible using areal imagery of this scale, and as such were grouped together.	
Settlement	SET	>75% coverage of a settlement or obvious human occupation. The surrounding ground or cleared urban space is also captured.	
Vegetables	VEG	>75% coverage of vegetables including tomatoes, garden eggs, peppers etc.	

Manual classification of the landscape yielded classifications for 90% of the captured land cover (Figure 5.4). The remaining 10% of land-use could not be discerned confidently using the drone imagery, however the areas were classified into one of two additional classes via manual classification, so that landscape level estimates of land use could be determined. The two additional classifications which were included were listed as distorted and unknown. Distorted was the class given to areas of the landscape where the images had become distorted, typically during the mosaic stitching process, or were too blurry to classify with confidence (often due to the drone changing direction). Additionally, Unknown was used to classify areas of the landscape which could not be classified with confidence, and could potentially include any of the utilized land use types, but if those were presenting in a non-standard way (ie. potentially very young cocoa) or alternate land-use types, such as rice.

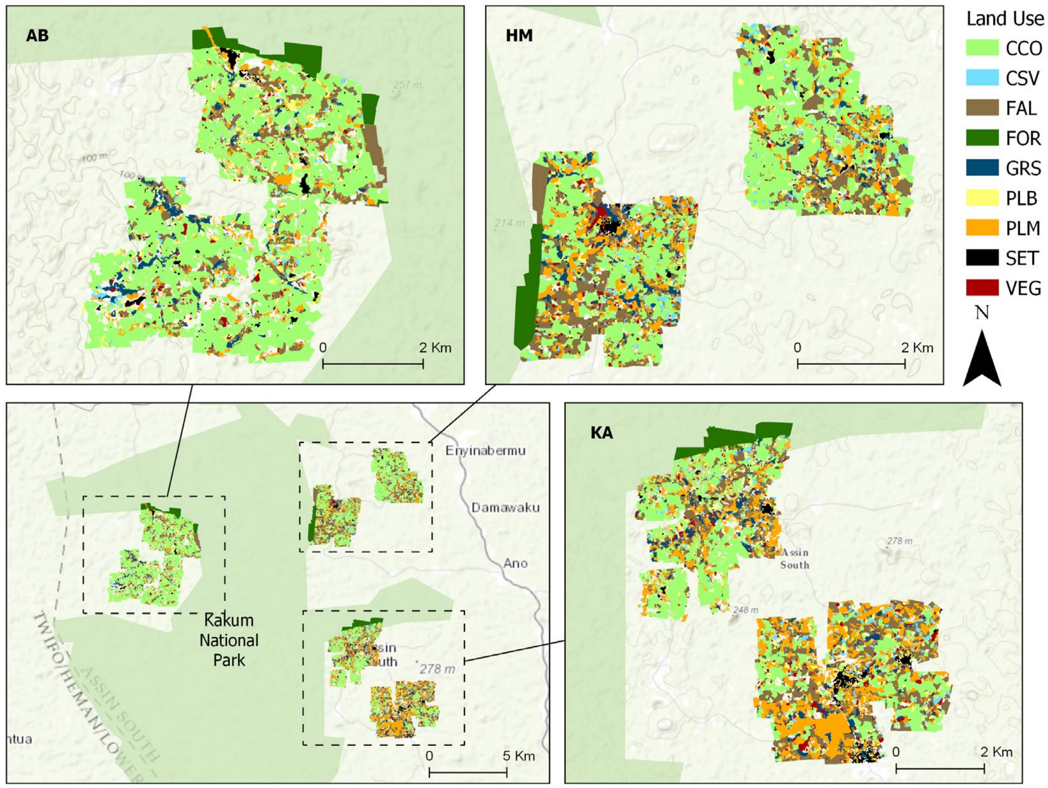

Figure 5.4 Land use classifications in the Aboabo (AB), Ahomaho (HM) and Kwameamoabeng (KA) regions of the Central Region of Ghana captured using drone imagery. Land use classifiations include cocoa (CCO), cassava (CSV), fallow (FAL), forest (FOR), grassy fallow (GRS), plantain/banana (PLB), palm trees (PLM), settlements (SET) and vegetables (VEG)These communities border Kakum National Park which can be seen in the bottom left inset, depicted in green.

Detailed processing of cocoa

The land use classifications were used to clip the drone mosaics to produce rasters for analysis. Cocoa land use was further clipped from the rasters to generate cocoa only rasters. These rasters were then examined in detail and timber trees were isolated, while also removing other land-uses which were not captured in the original classification. To focus NPP/HANPP calculations on solely cocoa areas, bare ground visible between cocoa trees was removed using interactive supervised classification in ArcGIS Map 10.0.

Cocoa density was determined by comparing different estimates of cocoa density with ground-truthed data from the eight cocoa farm plots. The cocoa density measures were then calibrated using these data, and then scaled up to determine the cocoa density per hectare for the drone-sampled area.

5.3.3 HANPP Calculations

Measures of HANPP for Cocoa

Calculations described by Morel et al. (2019a) indicate that HANPP for cocoa could be estimated with relatively high accuracy from cocoa tree density and number of shade trees (Figure 5.5). Values for HANPP varied from −4.6 to 5.2 Mg C ha-1 yr-1 across the plots, with the negative values being recorded at a particularly shade-tree dense, young cocoa farm, and an older farm managed largely for timber. The model suggests that density of shade trees is the largest driver of HANPP in cocoa farms, followed to a lesser extent by cocoa tree density (R2 = 0.859, $p < 0.01$; Figure 5). As both, or either, of the variables increase, the level of HANPP decreases. The model suggests that density of shade trees is the largest driver of HANPP in cocoa farms, followed to a lesser extent by cocoa tree density. As both, or either, of the variables increase, the level of HANPP decreases. These equations are based on using normalized values of cocoa and shade tree density (Figure 5.5). To accomplish this, scaling factors were applied for both cocoa density (μ=591.92, sd=266.56) and number of shade trees (μ=47.63, sd=33.62) measured per hectare. Cocoa density could not be accurately determined using the drone data, so two values for cocoa density were used initially used. The first value was 600 trees/ha which was the average cocoa tree density reported by Morel et al. (2019a). The second was 719 trees/ha which was the maximum cocoa tree density reported by Morel et al. (2019a). This value was chosen due to the removal of ‘ground' from cocoa raster's described above, thereby resulting in a higher than average cocoa density.

$$\mathbf{HANPP = 3.32 - 0.993*Cocoa\ Density - 2.4*\ Number\ of\ Shade\ Trees} \quad \mathbf{(1)}$$

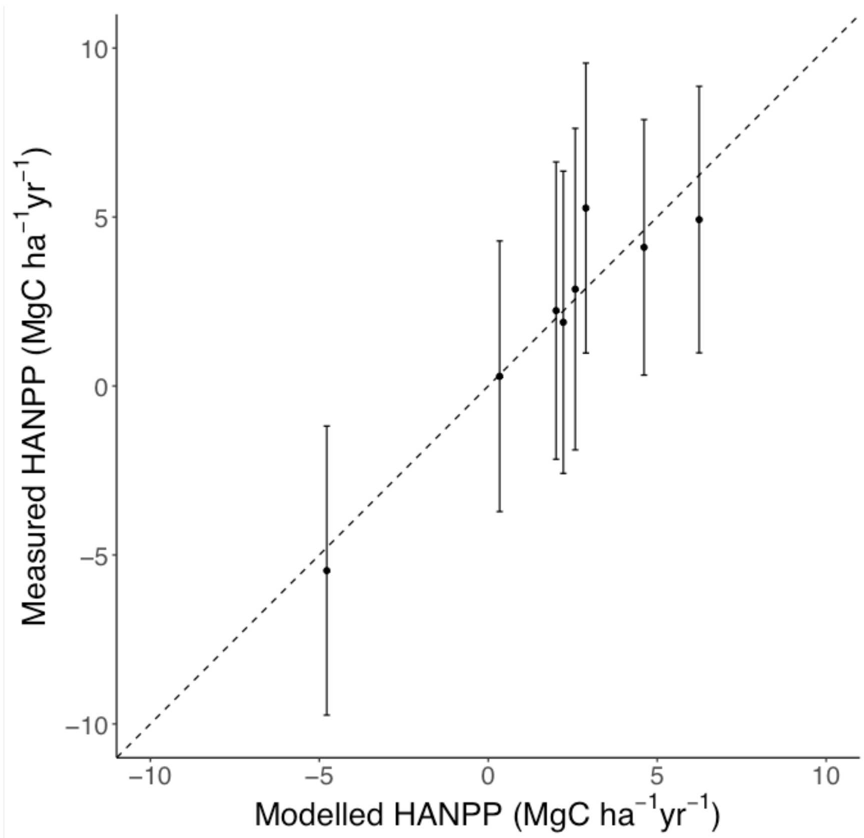

Figure 5.5 The relationship between measured HANPP and modeled HANPP using cocoa density and shade tree density per hectare as indicators (r^2= 0.86). Adapted from Morel et al. (2019a).

HANPP values for cocoa were calculated using a 1 ha grid overlaid over all study regions. In order to decrease random bias which may emerge from using a single grid, the results of this grid were compared to three other grids, each offset by 0.5 ha from the original, as well as a tessellated 0.25 ha grid. There was found to be no significant difference between the grid approaches, so the first grid was used.

HANPP levels for other land-use

HANPP levels for the remaining classified land uses were derived from NPP estimates taken from multiple literature sources for each land use. HANPP was then calculated by subtracting the resulting average NPP value for each land use from the natural NPP levels from Kakum National park, measured by Morel et al. (2019a) to be 17 Mg C ha−1 yr−1 (Table 5.2). The calculation of HANPP normally explicitly includes the land use and harvested components of NPP, however the calculation used here automatically combines those two factors due to the harvested component (yield) already being accounted for in the calculation of NPP from literature values.

HANPP values for Cassava, Plantain/Banana, Oil Plam, and Vegetables were determined using methods proposed by Monfreda et al. (2008), along with average yield estimates from various sources (detailed in Table S1). HANPP values for fallow and grassy fallow were derived using values from the literature (Haberl et al., 2007; Olson et al., 2013), while the HANPP value proposed by Haberl et al. (2007) for urban was used as a proxy for settlement (Table 5.2; Appendix C, Table C1). Detailed accounts of each calculation are provided in Appendix C.

Table 5.2 Mean NPP and HANPP values for land uses within the study region. HANPP is also displayed as a percent (%) of the potential NPP. Value calculated using: *Ramankutty et al. 2008, §Haberl et al. 2007, °Olsen et al. 2013

	NPP Mean (Mg C ha^{-1} yr^{-1})	HANPP Mean (Mg C ha^{-1} yr^{-1})	HANPP as % of potential NPP (17 Mg C ha^{-1} yr^{-1})
Cassava*	4.01 ± 0.3	12.99	76.5
Plantain/Banana*	3.22 ± 0.7	13.78	81.1
Oil Palm*	14.40 ± 2.6	2.60	15.3
Grassy Fallow°	6.11 ± 1.6	10.89	64.1
Veg*	1.79 ± 1.5	15.21	89.5
Fallow§	14.79 ± 3.0	2.21	13
Settlement§	0	17.0	100

NPP values for Cassava, Plantain/Banana, Oil Palm and Vegetables were determined using an equation for estimating NPP from Ramankutty et al. (2008):

$$\boldsymbol{NPP_i} = \frac{\boldsymbol{EY_i \times DF_i \times C}}{\boldsymbol{HI_i \times RS_i}} \tag{2}$$

where i is the specific crop, NPP is net primary production, EY is the metric tons of economic yield per hectare, DF is the dry proportion of the economic yield, and C is the carbon content (0.45 g C g dry matter^{-1}). HI refers to the harvest index, a standard measure of the proportion of total aboveground biological yield allocated to the economic yield of the plant (Donald and Hamblin, 1976). The root:shoot ratio, RS, indicates the ratio of below to aboveground production. Measures for economic yield for each crop were estimated using literature and policy documents for Ghana or similar tropical environments (Table B1).

Although HANPP values for oil palm were determined using Ramankutty et al. (2008) as a guide, it should also be noted that it is not possible to determine whether the palm trees observed are used for palm oil or for palm wine. However given the rapid expansion of the palm oil industry in Ghana in the last ~20 years, with harvested areas now exceeding ~350’000 ha per year (FAO, 2018), it was assumed that palm oil production was the primary purpose for the palm observed in the landscape, though much of the oil palm production in this region is for local consumption. Further, research suggests that palm trees are often eventually used for palm wine when they have become less productive for palm oil (Meikle et al. 1996).

Settlement was assigned a 100% value of HANPP (17 Mg/ha). Fallow was estimated using Haberl et al. 2008 as a guide. No measure could be found to determine the NPP of fallow, as such it was assigned an average of the HANPP percentage values for grazing land (19.4%) and forestry (6.6%). The rationale for using these values is the varied nature of fallow lands, which include multiple vegetation classes from scrubby brush to trees. The resulting HANPP percentage value for fallow of 13% was applied to the forest baseline NPP (17 Mg C/ha), resulting in a HANPP value of 2.21 MgC/ha, and an NPP value of 14.79 Mg C/ha. To account for the uncertainty in this value, the standard error was set to ± 25% of the NPP value (Table 5.2). Uncertainty was set to 25% as this was considered sufficiently high enough to capture the potential variability of this land use type, as it would assume 68% of values would fall between 11.09 Mg C/ha and 18.49 Mg C/ha, which is a substantial range considering the range for other values derived in this study.

The NPP value for grassy fallow was estimated values from the Oakridge National Laboratory (Olson et al. 2013). The total NPP value averaged over tropical/grassland C4 biome was found to be a maximum of 7.25 MgC/ha/yr and a minimum of 4.97 MgC/ha/yr (μ=6.11). Due to the fallow nature of these grassy areas, it was assumed that they are not being harvested for human consumption or use.

Overall HANPP Calculations

Median HANPP values were derived for each region using derived cocoa values and values from the literature as described above. Due to relatively small sample sizes for each of the literature-derived values, Monte Carlo simulation was carried out to propagate uncertainty of the values presented.

5.4 Results

General Summary Information

The total area covered by the drone surveys for the all regions ranged from 20.62 km^2 for AB, to 17.73 km^2 for HM, to 21.88 km^2 for KA, approximately 62km^2 in total (Table 5.3). On average, 90% of the land use in each region was classified (~54km^2 in total). Cocoa was the most prominent crop in each area: the proportion of cocoa varied from 52.78% in AB, to 40.24% in HM to 26.60% in KA. In the AB and HM regions, the next most dominant land class was fallow lands which constituted 11.11% and 21.58% respectively. For both regions the following most dominant land class was palm oil at 8.78% and 15.75% respectively. The KA region varied from the others most notably both in the proportionally smaller cocoa crop area, but also the much higher presence of palm oil (25.81%), a similar land area to the cocoa crops (Figure B1).

Table 5.3 Land use codes, area covered per land use and percent land use for all the regions.

		AB region		**HM region**		**KA region**	
Crop	**Code**	**Area (ha)**	**% Area**	**Area (ha)**	**% Area**	**Area (ha)**	**% Area**
Cocoa	CCO	10.88	52.78	7.13	40.24	5.82	26.60
Cassava	CSV	0.3	1.43	0.57	3.24	0.66	3.01
Plantain/Banana	PLB	0.89	4.31	0.73	4.13	0.82	3.76
Oil Palm	PLM	1.81	8.78	2.79	15.75	5.65	25.81
Vegetables	VEG	0.26	1.27	0.53	2.97	0.69	3.16
Settlement	SET	0.38	1.83	0.22	1.23	0.53	2.42
Fallow	FAL	2.29	11.11	3.83	21.58	4.38	20.00
Grassy Fallow	GRS	0.84	4.07	0.96	5.42	1.15	5.24
Subtotal		**15.92**	**85.59**	**16.76**	**94.56**	**19.70**	**90.00**
Unknown	DK	2.25	10.89	0.54	3.05	1.30	**5.95**
Distorted	DST	0.72	3.52	0.43	2.39	0.89	**4.05**
Total		**20.62**	**100**	**17.73**	**100**	**21.88**	**100**

Cocoa Density and HANPP

The HANPP levels for cocoa were calculated using two different cocoa densities, 600 trees/ha, and 719 trees/ha. When assuming a cocoa density of 600, overall average HANPP was 6.15 ± 0.73 Mg C ha-1 yr-1, with the regional average HANPP values ranging from 6.41 ± 0.86 Mg C ha-1 yr-1 for AB to 5.95 ± 0.86 Mg C ha-1 yr-1 for HM to 5.98 ± 0.85 Mg C ha-1 yr-1 for KA (Figure S2). The average HANPP value as a percent of NPPpot was 36%, with each region being 38%, 35% and 35%. When assuming a cocoa density of 719, overall average HANPP was 5.71 ± 0.73 Mg C ha-1 yr-1, with the regional average HANPP values ranging from 5.97 ± 0.36 Mg C ha-1 yr-1 for AB to 5.51 ± 0.86 Mg C ha-1 yr-1 for HM to 5.54 ± 0.85 Mg C ha-1 yr-1 for KA (Figure S2). These values were slightly lower as a percentage of NPPpot, with an average value of 34%, with each region being 35%, 32% and 33%. Henceforth we report using only results with a cocoa density of 600 trees/ha, the mean cocoa density reported for our study

Total NPP and HANPP

NPP values per region varied as expected depending on the percent land use of each type (Figure 5.6, Figure B3). Cocoa was the most dominant land use in all areas, and therefore had a disproportionate influence on the average NPP per hectare. With a cocoa density of 600 trees/ha, the median NPP per hectare was 10.31 ± 0.48 MgC/ha , 9.00 ± 0.96 MgC/ha and 7.15 ± 1.39 Mg C/ha for AB, HM and KA respectively. The distributions of NPP values in each area peaked around 11-12 MgC/ha due to the dominance of cocoa on the landscape. This peak was particularly notable in the AB region. The distribution of NPP values in KA also had a second peak around 2-3 MgC/ha due to the prevalence of palm trees within that region (Figure B4).When using 17MgC/ha as the baseline NPP for the natural forest, the median HANPP values were then calculated to be 6.69 MgC/ha, 8.00 Mg C/ha and 9.85 Mg C/ha for AB, HM and KA respectively (Figure 5.7). These values represent 39%, 47% and 56% of the NPPpot.

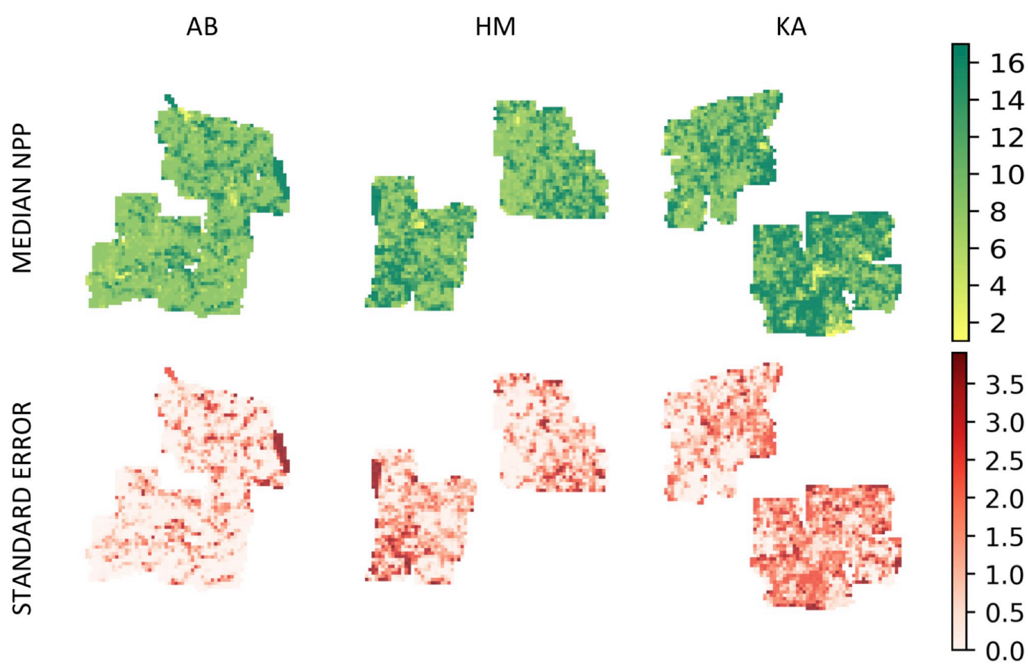

Figure 5.6 NPP and standard deviation values per hectare of the AB, HM and KA regions assuming a density of 600 trees per hectare.

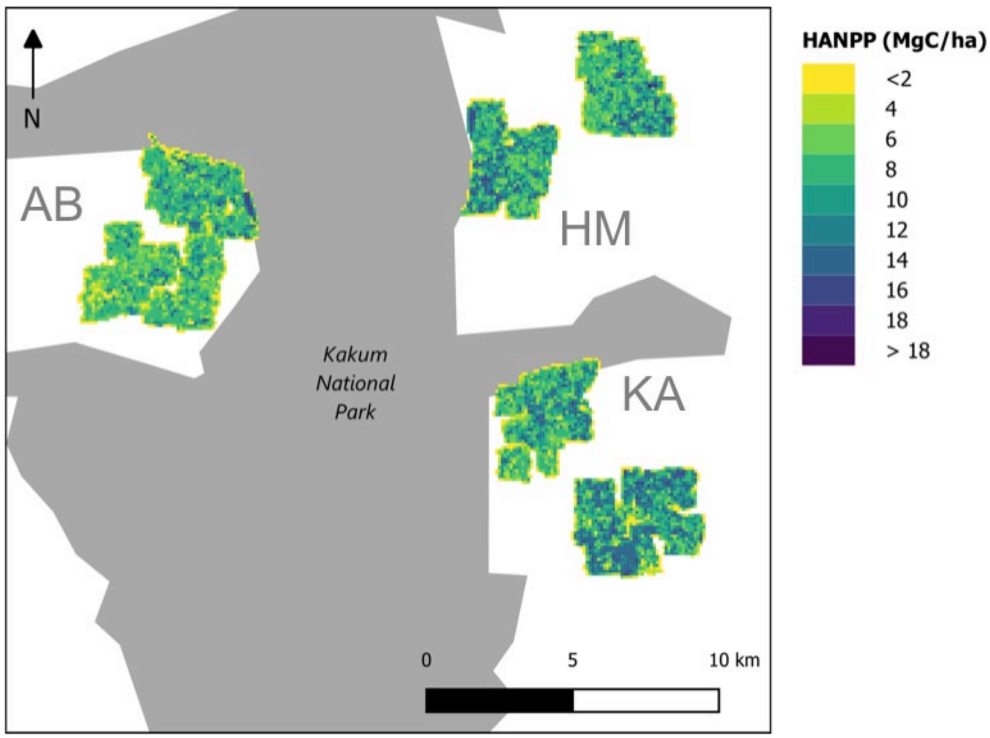

Figure 5.7 HANPP for all measured regions surrounding Kakum National Park.

5.5 Discussion

The results of this study highlight the significant and diverse land use practices in this complex mosaic landscape. Further, the application of HANPP as a focal metric, demonstrates the intensity of land use in the region, while also highlighting the diversity of land use practice and intensity within and between three regions surrounding Kakum National Park. Finally, the use of a novel UAV approach to capture data was successful, capturing a substantial area of land (~62 km^2), where 90% was classified by land use (~54 km^2) to a very high degree of resolution (<10 cm^2).

Diversity of land use across regions

Each region of study surrounding the Kakum Conservation Area displayed a diversity of different land use practices. In all regions of study, the most dominant crop was cocoa, constituting ~53%, ~40% and ~27% of overall land cover in Aboabo, Ahomaho, and Kwamoabeng. Given the prominence of cocoa production in the region, it could have been assumed that cocoa production may have been more uniform between regions and more prominent. However, the high resolution imagery used in this study indicates a much more complex and diverse scenario. The westernmost region containing the villages of Aboabo and Asorefie (Figure 3, AB) had the highest density of cocoa farms. Both this region and the HM region (north eastern region containing the villages of Ahomaho and Nsuoekyi; Figure 3, HM) were dominated by cocoa trees. The next most dominant land use types in both areas were fallow areas followed by palm trees.

The third region in the south east, containing the villages of Kwamoabeng and Tofukrom (Figure 3, KA), had considerably different land use practices. The area of the land which was cocoa (~27%) was only marginally larger than the area which was used for palm tree cultivation (~26%). It is probable that there are some portions of the palm tree cultivation in all areas, but especially in the KA region, which are also used for the production of palm wine. Palm wine production involves completely felling the trees, but some farmers only use palm trees for the production of palm wine after a tree has surpassed its peak production for palm oil (Taabazuing et al. 2012). This could be assumed to be the common practice for all regions, but within the KA region there is a much larger emphasis on the production of palm wine, than in the other regions. This may explain the proportionally higher density of palm production in the region. Further, the KA region is under different land tenure arrangements than the other study regions. For example, it is not a requirement to cultivate cocoa in the KA region, while in the AB and HM regions it is a requirement of many of the land tenure agreements.

Following cocoa and palm, fallowed areas were found to occupy the next most significant proportion of the landscape in each of the regions studied. In Ghana, given the availability of land for agriculture, and the expense of products such as fertilizer and pesticides, the primary mechanism for farmers to increase yields is by fallowing. However, due to uncertainty associated with a lack of land tenure rights, farmers with fewer land tenure rights tend to fallow land for shorter periods of time (Goldstein and

Udry 2008). This could provide a possible explanation for the relatively smaller proportion of fallowed and grassy fallow land (~14%) in the AB region, than in the other regions (~26%). Alternately, considering the high levels of poverty amongst farmers in all regions studied (Hirons et al. 2018a), it is likely that many farmers need to re-establish their income stream from cocoa as quickly as possible, thus they decide to immediately replant rather than fallow their land.

Contribution of Cocoa to HANPP

The average HANPP values for cocoa for each region were 6.41 ± 0.86 MgC/ha for AB to 5.95 ± 0.86 MgC/ha for HM to 5.98 ± 0.85 MgC/ha for KA, when assuming a cocoa density of 600 trees per hectare. Each value decreased by approximately 0.4 MgC/ha when the cocoa density was assumed to be 719 trees per hectare. The cocoa density did not appear to have a significant impact on the variation in HANPP values for each region.

The number of shade trees, on the other hand, had a substantial impact on the HANPP values for cocoa. The highest number of shade trees recorded in a single grid square was 38 trees, with many grids indicating no shade trees. However, when normalizing for cocoa area, such that the density of shade trees per hectare for each grid cell should be determined, the highest shade tree density rose to 140 shade trees per hectare. It should be noted that using this method only allowed for the detection of emergent shade trees. When comparing the values recorded via drone imagery with those collected by Morel et al. (2019), the shade tree densities were generally smaller, some substantially so.

Therefore, it is probable there was a greater density of other trees that were not visible using conventional drone data. This could have implications for HANPP estimates, likely overestimating them in the case of underestimating the number of shade trees. In order to measure the presence of all trees both above and below the canopy, a drone equipped with LiDAR technology would be necessary.

NPP and HANPP of Complex Mosaic Landscape

The median HANPP values for each region ranged from 6.69 MgC/ha for AB to 9.85 MgC/ha for KA. These values did not vary substantially when the cocoa density was increased to 719 trees per hectare, where the values ranged from 6.25 MgC/ha for AB to 9.68 MgC/ha for KA. These values vary substantially from those presented in some of the benchmark global studies of HANPP. For these same regions, the global map of Haberl et al. (2007) estimates the value of HANPP as being 2.79 MgC/ha for AB, 2.75 MgC/ha for HM and 2.64 MgC/ha for KA for the year 2000. Our values are significantly higher than those found in the Haberl study, with an approximate difference of ~4 MgC/ha per region. The results presented here suggest that there is significant underestimation of HANPP for this cocoa growing region in Ghana. This is probably due to the evergreen nature of cocoa and palm trees, which may present a similar spectral signal to tropical forest. In addition, the highly fine scale mixed use agriculture in the region may distort results from areas such as these. Alternately, given the resolution of the data (~85 km2) presented by Haberl et al (2007), the results presented here could highlight that by not being able to differentiate these high resolution dynamics of land use, such large scale studies may be under-estimating the scale of HANPP.

The results of this study highlight how global studies of HANPP, and potentially other global assessments, need to take special care when studying the tropics, most notably areas where mixed agriculture land uses are common. Such underestimation of HANPP is likely to be a feature of most smallholder tree crop mosaics, leading to substantial underestimation in regional HANPP. Curtis et al. (2018) recently reported that all of African deforestation was due to slash and burn agriculture as opposed to being commodity-driven, which is certainly not the case in tropical regions of Africa. While global assessments provide substantial and important insight into drivers of global change, these studies must continue to be complimented or challenged by regional and local scale studies such as this one.

HANPP is a useful metric to help quantify the impact of humans on the biosphere. Decreasing HANPP is increasingly important, because lower levels of HANPP relate to higher levels of productivity, high levels of biomass and nutrient availability to support biodiversity, and possibly higher capacity to sequester carbon. Studies such as that by Krausmann et al. 2013 highlight that between 1910 and 2005, the global HANPP doubled from 13 to 25%. The results presented here indicate an average HANPP of 44% in this landscape, compared to natural topical forest. This value highlights the need to attempt to decrease HANPP where possible in tropical mosaic landscapes. While this study did not focus on cocoa density, the variations in density which were applied tended to have a relatively small influence on HANPP value. Alternately, the influence of shade tree density on HANPP values was substantial. The most important strategy for decreasing

HANPP in cocoa dominated landscapes is to encourage the cultivation of shade trees. Research has also shown that cocoa yields can increase with increasing canopy cover provided by shade trees (Asare et al. 2018, Schroth 2016), further strengthening the case that the key to climate smart strategies for cocoa is the presence of shade trees. Increasing shade tree cover not only reduces HANPP, but has other benefits such as more resilience of the cocoa crop to climate extremes and regional warming (Schroth 2016, Schroth 2011, Rice & Greenberg 2000) and increased biodiversity. Bolstering biodiversity on cocoa farms not only provides benefits to the surrounding ecosystems, but also has many associated benefits to the crops themselves, such as increased pollination, increased soil health and decreases in crop disease (Barrios 2018).

Conclusions

This study utilized novel field- and UAV-based methods to undertake a detailed, large scale assessment of HANPP in a mixed agriculture region of West Africa. This is the first study of its kind, and the results suggest the importance of detailed studies of land use in tropical areas. HANPP as metric of human impact on the biosphere is well-established, but it still lacks ground validated measures to a scale that is comparable to the benchmark global analyses. This study is the first attempt to significantly scale up ground measures of NPP and HANPP to a scale comparable with these global studies. Further, this work was carried out in a region which should require special attention in the future due both to paucity of reliable remote sensing images (due to clouds or haze) as well as the fine-scale patterns of land use. This work demonstrates how low-cost drone based approaches can help address the scale gap when looking at land use in complex mosaic landscapes with small scale farming. Such approaches could be widely applicable and useful.

Chapter 6

The third data chapter addresses Objective 3 of the thesis: *Investigate how social, environmental and spatial factors impact the resilience of farmers during a disturbance event.* In seeking to increase the understanding of social-ecological processes in complex mosaic landscapes, I undertook a study of how households might vary in their response to a climate shock disturbance event. Disturbance events can occur over a short enough time span, and can perturbate the routine functioning of systems enough that dynamics may be easier to detect. Further, there exists a rich theoretical literature on the resilience of social-ecological systems which I wanted to test in a practical study.

I wanted to explore various indicators, which could provide evidence of the importance of social, environmental and/or spatial factors in these responses. Further, the findings of Chapter 5 suggested that there were regional differences between land use activities and land use intensities across the three study regions surrounding Kakum National Park. This, along with work conducted by Hirons and colleagues (2018a), suggested that while the regions are generally regarded as being similar, there could be significant differences between them.

For this study I used a dataset of household surveys, which I further cleaned and processed, freely available published datasets, farm perimeters which were collected by my project partners, and some results from Chapter 5. The findings of this study are presented in a paper entitled *Resilience of farmer households in a complex mosaic* *landscape: A case study of Ghanaian cocoa and El Niño*. Which has been submitted for publication in People and Nature.

I am the main author, conducted all the analysis and wrote the paper under the guidance of my supervisors Alexandra Morel and Yadvinder Malhi. Jonathan Aronson aided in the conceptual development of the study, and processing of the data, Mark Hirons collected the household survey data used, Jane Messina assisted with the statistical analysis and Marvin Quaye was responsible for collecting the farm perimeter data. Alexandra Morel, Mark Hirons and Ken Norris were responsible for the overall coordination of the ECOLIMITS project with our in country collaborators in Ghana: Rebecca Asare and John Mason.

6. Resilience of smallholder farmers in a complex mosaic landscape: A case study of Ghanaian Cocoa and El Niño.

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6.1 Abstract

The impacts of climate change in tropical west Africa are expected to cause an increase in temperature, a disruption of precipitation regimes and an increase in disturbance or shock environmental events. The impacts of such conditions will disproportionately negatively impact rural small holder farmers, as a result of their direct reliance on rain fed agriculture for their livelihoods, as well as high levels of poverty which limit household buffering capacity to such shock events. Understanding which factors enable households to be resilient to shock climatic events can provide insights into future resilience of households and communities to projected climate change impacts. Quantifying this household resilience using a central unified metric remains a challenge. However, breaking down the concept of resilience into more detailed components, such as resistance to impact and recovery from impact, represents a tangible way to assess the resilience of households to shock events. An El Nino event in 2015/2016 caused a shift in precipitation patterns and a general increase in temperature in tropical West Africa. This study examines the household resilience of rural agroforestry farmers in three regions (AB, HM, KA) in southern Ghana to the impact of the climatic shock event caused by the 2015/2016 El Nino. Data collected during a household survey carried out in August 2015 was used to generate baseline social, environmental and spatial indicators of farmer household resilience. Data collected during subsequent 2016 and 2017 surveys was used to generate resistance and recovery metrics based on perceived negative impacts due to the shock event. Indicators associated with household resistance and recovery were determined using a general linear model (GLM). The results indicate that those who have wetter ground at their primary farm, and have fewer members in their household

were more resistant to the impacts of the shock. While those who have wetter soils at their primary farm, are closer to an urban centre and have a male primary decision maker displayed better recovery from the climatic shock. Indicators were then compared at a regional scale using Kruskal Wallis tests. Regional variation between the farms was detected for ground wetness, access to an urban centre, number of cocoa plots, number of subsistence crops, total number of plots and the intensity of land use at the primary farm. Differences in negative impact from the shock event between two regions, seemingly showing one as more resilient to the shock than the other, highlight the importance of distinguishing between resilience to and resistance from disturbance events.

6.2 Introduction

Climate change in tropical Africa is predicted to result in increased temperatures, decreased length of wet seasons, overall decreases in precipitation and an increase in climatic extreme events (Sylla et al. 2018). These changes have the potential to significantly impact both social and ecological systems in the region. Ecologically, historical conditions in tropical regions of the continent are typified by highly seasonal precipitation regimes and interannual variation in precipitation and temperature (Badr et al. 2016). The population in Africa as a whole has been described as "vulnerable to the impacts of projected changes because poverty limits adaptive capabilities" (IPCC 2018).

Agriculture is particularly important in supporting rural livelihoods in Africa and is typified by smallholder or subsistence systems (Tittonell & Giller 2013). Smallholder agriculture involves rural producers whose farms are maintained by family labour and where the farm constitutes the primary source of household income (Rapsomanikis 2015). Smallholder farmers in particular, are at risk to the impacts of climate change due to a lack of physical, agricultural, economic and social resources to moderate its impacts on production (Morton 2007). This vulnerability is even more pronounced in the tropics, where most crops are rain-fed, and climate change has the potential to significantly influence crop productivity and thereby livelihoods in general (Slingo et al. 2005).

One of the most important smallholder crops grown in tropical West Africa is cocoa. Approximately 70 % of the global cocoa supply is produced in this region and consequently cocoa is central to the economies of a number of countries there, including Ghana (Schroth et al. 2016). Even though total cocoa harvested land in Ghana has increased from one million hectares in 1995, to 1.6 million in 2010, most cocoa farms remain small and are typically 5 hectares or less (Wessel and Quist-Wessel 2015). The Ghanaian cocoa sector employs over 800,000 households, for whom cocoa contributes from 70 to 100 % of the annual household income (Ntiamoah and Afrane, 2008). While the cocoa produced in Ghana has become globally important, the farmers who produce it remain in poverty. Cocoa production in Ghana lies at the hot and dry end of the biogeographical range of cocoa viability (Laderach et al. 2013). This, along with the dependence of the cocoa farming systems on varying climatic parameters (e.g. moist soil, cooler tropical conditions etc.), highlights the vulnerability and uncertainty facing West African cocoa farmers and cocoa farming regions generally under climate change (Laderach, 2013).

Understanding the potential impacts of climate change on smallholder cocoa farmers in tropical West Africa requires a framework which considers both humans and the environment. Such a framework must also capture the interconnectedness of humans and the environment, and the flows, feedbacks and dynamics that come along with it. This social-ecological systems (SES) perspective presents a useful lens with which to understand complex interconnected humans and natural systems (Holling, 1974). SES theory suggests that in order to understand any elements of a natural resource use system, one must consider the ecological and social components as interdependent, and equally important (Berkes & Folke, 1998, Ostrom 2009). Given the deeply integrated nature of the social and ecological components of smallholder farming landscapes, utilizing SES theory is prudent. SES theory is particularly useful when trying to understand the potential impacts of climate change, due in large part to the rich literature on resilience.

The concept of resilience has emerged in the last decade as one of the central foci of many interdisciplinary studies investigating natural resource management systems, social-ecological systems and the potential impacts of climate change (Anderies, Ryan & Walker, 2006; Auclair et al. 2015; Speranza 2013; Postigo 2014; Renaud et al. 2014). One issue with the increase in resilience literature, is the abundance of unique definitions for the concept. One of the original definitions of resilience was proposed by Holling (1974) and focused on the ability of a system to persist in the face of change, whether that be long term change or through absorbing disturbance in response to shocks while essentially maintaining the same structure and function. Many definitions have since emerged and built on this concept, increasingly incorporating the notions of transformation, dynamics, complexity and adaptation (Scheffer et al. 2001, Folke et al. 2004, Folke et al. 2010). Resultantly, many metrics and indices have also emerged which claim to measure resilience (Standish et al 2014) however others argue that resilience cannot be captured in a single metric (Hodgson, McDonald & Hosken 2015). Walker et al. (2004) outlined four crucial aspects of resilience: latitude (the maximum amount a system can be changed before losing its ability to recover), resistance (the ease or difficulty of changing the system), precariousness (how close the current state of the system is to a limit or threshold) and panarchy (the influence of cross scale interactions, and of scales above and below the focal scale). Even this example outlines the problematic task of translating the theoretical concept of resilience into operationalized factors which can be measured and researched in empirical studies. Hodgson, McDonald & Hosken (2015) contest that the most important, and tangible, components of resilience are resistance and recovery. The authors argue that operationalizing the resilience concept in empirical studies will require not the development of new metrics, but rather an embracing of the most basic principals and components of resilience, namely the resistance of a system to disturbance, and the recovery of that system following such a disturbance.

Another aspect which plays an important role in understanding the resilience of social-ecological systems is the influence of spatial factors. The incorporation of spatial analysis when assessing resilience can help build understanding about climate resilience and how geographic factors influence this resilience (Cumming 2011). The spatial distribution of people, ecological features, and infrastructural assets across a landscape influences the exposure of humans to climate change associated hazards. Additionally, factors such as land management, land tenure, and household or cultural practices could either mitigate or enhance these potentially adverse outcomes. In essence, when attempting to understand resilience to climate changes, including variables which capture spatial factors can enhance our understanding of potential climate change impacts interacting with the local context (Whitfield et al. 2019). In addition, climate change is likely to alter the spatial and temporal distribution of climate-associated hazards, further highlighting the need to incorporate aspects of space into assessments of resilience (Preston et al. 2011).

This study seeks to understand how social, spatial, and environmental factors lend themselves to predicting the resilience (specifically resistance to disturbance and recovery from it) of households in a tropical smallholder agroforestry region in West Africa. In 2015/2016 an El Niño Southern Oscillation event resulted in a substantial climatic shock in the region, leading to an extended dry season and changes in rainfall patterns in much of the cocoa growing region of West Africa (Whitfield et al. 2019). While El Nino events can be viewed as cyclical, the frequency and impacts of such events are far more uncommon and uncertain in west Africa than other regions (Malhi & Wright 2004) thus strengthening the argument that this event represented a genuine, unexpected disturbance. In this study, the El Niño and subsequent impacts are framed as a disturbance event to gain an understanding of the features related to the resilience of the social-ecological system. Resilience is studied by considering the resistance of farmers to the disturbance impacts, and/or the recovery of farmers from this disturbance across a number of parameters. The study focuses specifically on six communities across a cocoa growing region in southern Ghana, adjacent to a large national park. Using multi-temporal household surveys collected before, during and after the climate shock, along with farmer and region specific spatial and environmental data, this study aims to establish which factors were associated with households who were resistant to the climate shock, or able to recover from the climate shock and those who were not/did not. Specifically, this study seeks to answer the following research questions:

- How resistant were farmers to the recent climate shock? (e.g. what were the household responses to the El Niño driven conditions)
- Were farmers who were impacted by the climate shock, able to recover from the shock?
- What were the social, environmental and spatial factors that influenced their resistance or recovery?
- Were there any spatial concentrations of resistance or recovery to the climate shock across regions?

6.3 Methods

6.3.1 Study Area

Data for this study were collected in three regions surrounding Kakum National Park (KNP) in southern Ghana (Figure 6.1). The three regions included the village of Aboabo (AB) west of KNP, Ahomaho (HM) north-east of KNP and Kwameamoabeng, east of KNP (KA). All regions are generally regarded as cocoa growing, with large tracts of complex mosaic agroforestry landscapes interspersed with small settlements.

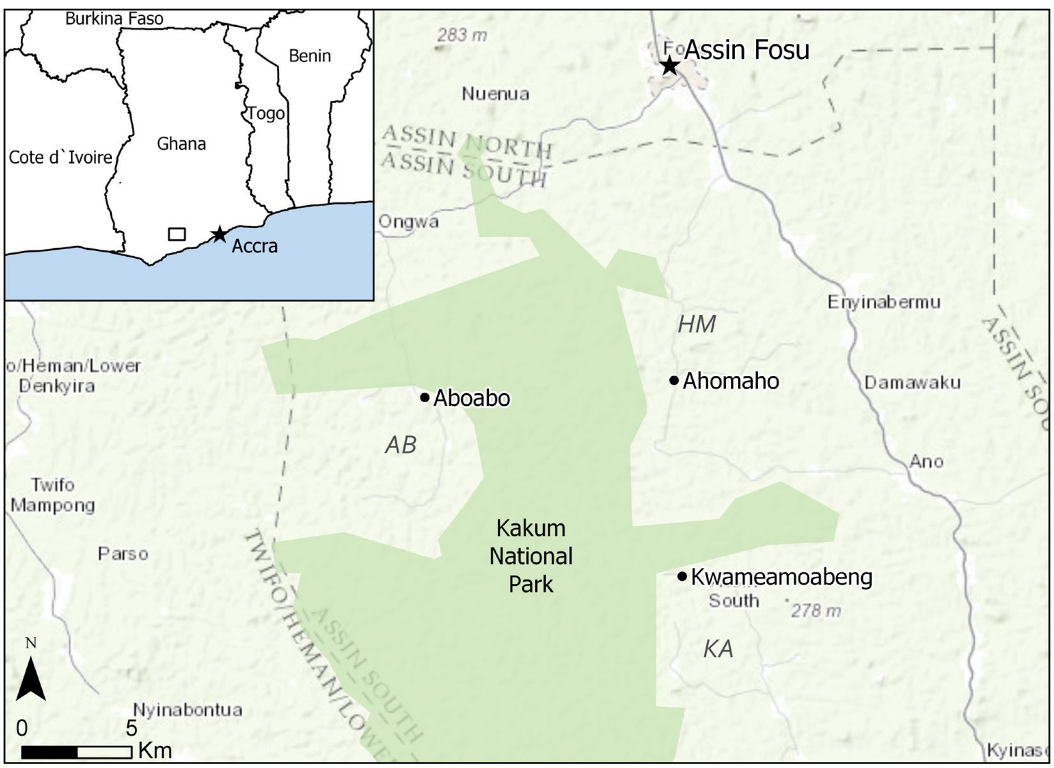

Figure 6.1 The study area with the villages of Aboabo, Ahomaho, and Kwameamoabeng, as well as the regions of AB, HM and KA indicated. Assin Fosu, the closest urban center is also indicated.

6.3.2 Data Collection

Data for this study were collected as part of the ECOLIMITS project (Hirons et al. 2018c, Morel et al. in review) which originally set out to document the relationship between poverty and ecosystem services, with dedicated ecological and social components. The project began in 2013 and data collection began in 2014 and concluded in 2017. During the course of the project, the region was directly impacted by hotter and drier conditions, as well as a shift in the intensity and timing of the rainy seasons, associated with the 2015/2016 El Niño. As such, this event enabled research examining in detail the impact and response of the households and regions to the subsequent drought-like conditions caused by this climate shock. The region typically experiences a bi-modal wet season, with rains from April to June, and again from September to November. During this climatic shock, the restarting of the rains in September 2015 were delayed. This was then followed by the Harmattan period (during which dry and dusty Saharan winds blow in from the north) which was drier than average and also had elevated temperatures, which resulted in heightened vapor pressure deficits (VPD) and low soil water availability (Whitfield et al. 2019; Morel et al. 2019b). VPD is described as the driving force for transpiration in plants, where higher VPD results in greater levels of transpiration, resulting in moisture loss and heighted mortality of tree seedlings (Will et al. 2013).

Social Data

Household surveys (n=106) were conducted within each of the regions in August 2015, August 2016 and May 2017, where respondents were requested to give information about the preceding 12 months. The survey was administered at the household level, where the primary decision maker for the household provided responses for the entire household. This study utilized two different aspects of the overall household survey. As this study was conducted to understand those social, environmental or spatial components which potentially predispose households to resilience or a lack of resilience to environmental perturbation, the first aspect comprised responses given during the 2015 survey, in other words the 'pre-shock' period. These responses were seen to represent a baseline of operation for the household, in essence giving a 'normal' reflection of the economic, social and environmental activities of the household. This premise is based on work (Whitfield et al. 2019, Morel et al. 2019b) which highlights the anomalous nature of the El Nino conditions, and provide substantial evidence, both globally and locally, that this event represented a climate shock. Given that the focus of this work is to assess the impact of the shock, it is assumed that the social data collected in 2015 (which describes conditions in 2014), can be used to describe the 'pre-shock' conditions, as the shock effects had not yet begun. The questions of focus here are those which give some basic reflection of the demographics of the household (e.g. household size, income diversity and gender of principal decision maker). Additionally, household survey questions which related to the households interaction with, and dependence on, the environment were included (e.g. number of farm plots, number of subsistence crops across all plots, number of cocoa crops across all plots). The second aspect of the survey utilized were questions which indicated the impact of the climate shock (2016 responses) and/or the long term impact of the shock conditions (2017 responses) on different aspects of the household. All survey questions used in this study are provided in Appendix D.

Spatial Data

Data from the household surveys were supplemented with additional geospatial data. Each survey was conducted at the home or homestead of each household. During the course of the survey the house location was recorded using GPS. During 2016 each farmer was asked to indicate the location of their primary or most important farm. A research assistant then accompanied each farmer to the location of this farm, and walked with the assistant around the perimeter of the farm while using a GPS to document the location and spatial extent of the farm. While all farmers were requested for these data, only a subset were able to accompany the field assistant to the plot which reduced the sample size for the study (n=80).

This farm perimeter data were overlaid with data from Moore et al. (in review) which gives an estimate of Human Appropriated Net Primary Productivity (HANPP) for the farm. These data were derived using high resolution drone data covering approximately 60 km2 of the study region, as well as ground level measures of HANPP for cocoa crops (Morel et al. 2019a) and other literature sources for the remaining crops (Moore et al. in review). The data have a resolution of 1x1 hectare. Only a subset of the farm perimeters were covered by these data, and thus to consider this metric the sample size was reduced again (n=72).

Supplementary Datasets

Two supplementary datasets were used to provide additional context specifically to the spatial data. The first dataset from Weiss et al. (2017) is a global dataset which gives an approximate measure of the travel time to cities for 2015 at a spatial resolution of approximately 1 x 1 km. This dataset utilized a number of layers which give an indication of movement rates using multiple surfaces which include distance, transport infrastructure and distribution of cities, to calculate the amount of time it would take to move between the spatial locations and cities. The second dataset from Fan, Li & Miguez-Macho (2013) is a global dataset which gives a measure of water table depth in meters at 1 km resolution. The data were generated using government archives and literature, with data gaps being filled using a groundwater model derived from modern climate, terrain and sea level. While this study is specifically observing hotter and drier conditions, it is assumed that those areas which are wetter relative to the rest of the landscape during non-drought times would also be wetter during drought times.

6.3.3 Variable selection and treatment

Resistance and Recovery Metrics

Both variables were constructed using the same questions posed as a part of the 2016 and 2017 household survey. These questions asked how the climate shock had impacted a particular aspect of the farmers' livelihood, or farm. A suite of these questions related directly to food security, while two additional variables (access to education and healthcare) were considered as measures of well-being.

Food security is often cited as one of the most important basic requirements for reducing poverty (UN, 2015). When considering the resilience of food security during perturbations, it can be defined as the ability to maintain the production and provision of sufficient and nutritious food in the face of chronic or acute perturbations (Suweis et al. 2015). In complex mosaic agricultural landscapes systems, like that found in the region surrounding Kakum National Park, this resilience can manifest over multiple scales from regional to field scale (Bullock et al. 2017). In order to consider the importance of spatial scale to the household resilience in all regions studied, two spatial scales were examined in detail: the regional scale (AB vs. HM vs. KA) and the household scale. Three questions were asked which were incorporated into measuring the resilience of food security. These encompassed (i) food availability; (ii) food variety and (iii) food quality, and how these were impacted by the climate shock (Appendix D)

While education is officially free in Ghana, it can remain inaccessible to those in poverty. Children require uniforms, materials, and lunches, the availability of which can vary on a monthly basis for many in poor rural areas of Ghana. Not sending children to school can be one of the first responses by households to reduce expenses during times of difficulty (Kurosaki 2006, Zereyesus et al. 2017). Healthcare is another important facet of wellbeing, which can be affected by a household's attempt to cope during times of reduced income or struggle. While many healthcare services are provided by the government, these are often perceived as being inaccessible to rural farmers (Peters et al. 2008; Poku-Boansi, Ekekpe & Akua Bonney 2010). In particular, during the rainy season it can be difficult and expensive to access clinics or hospitals located in more urban areas due to faults in infrastructure, such as washed out roads. Further, the cost of medication in Ghana is perceived to be very high and unaffordable for the much of the population (Adua et al. 2017). As such this was determined to be a relatively good indicator of resilience because those in poverty will often forgo medical treatment or medications during times of struggle.

During the survey, participants were asked if each of the features listed above were negatively impacted by the climate shock in 2016 and then in 2017 were asked if each of the features were longer-term negatively impacted by the conditions (Supplementary Data Table 1). If the respondent indicated they were negatively impacted, a score of one was given, while a score of zero was given if they indicated they were not negatively impacted. These scores were totalled for each year and each household was given an impact score for that year out of a possible score of five. Given that the questions specifically asked about the impact of the climate shock, all households were given a baseline score of zero for the year of 2015 (as the shock had not occurred yet). As such each household had three scores relating to each year of the survey, representing pre-shock (where each household had a score of 0), during-shock and post-shock time periods.

The calculation of the resistance and recovery metrics were undertaken using the scores reported for each household. The resistance variable seeks to capture how many times the farmers reported that they had been impacted by the climate shock. Thus, this was simply calculated by summing the scores reported by each household. For example, if the household reported a score of three for 2016 (thus having been impacted in three areas during the 2015-2016 year) and a score of two for 2017 (thus having been impacted in two areas during the 2016-2017 year), the household was given a resistance score of five. Lower scores indicated more resistant households (Figure 6.2).

To calculate recovery, , those which reported fewer impacts in 2017 than in 2016 were considered to have recovered to some extent, with those who ‘bounced back’ most significantly (i.e. From 5 in 2016 to 1 in 2017) considered the most recovered. Those who were either most detrimentally impacted in 2016, then remained impacted, or those which were further negatively impacted in 2017 were considered to have shown a lack of resistance or recovery (Figure 6.2).

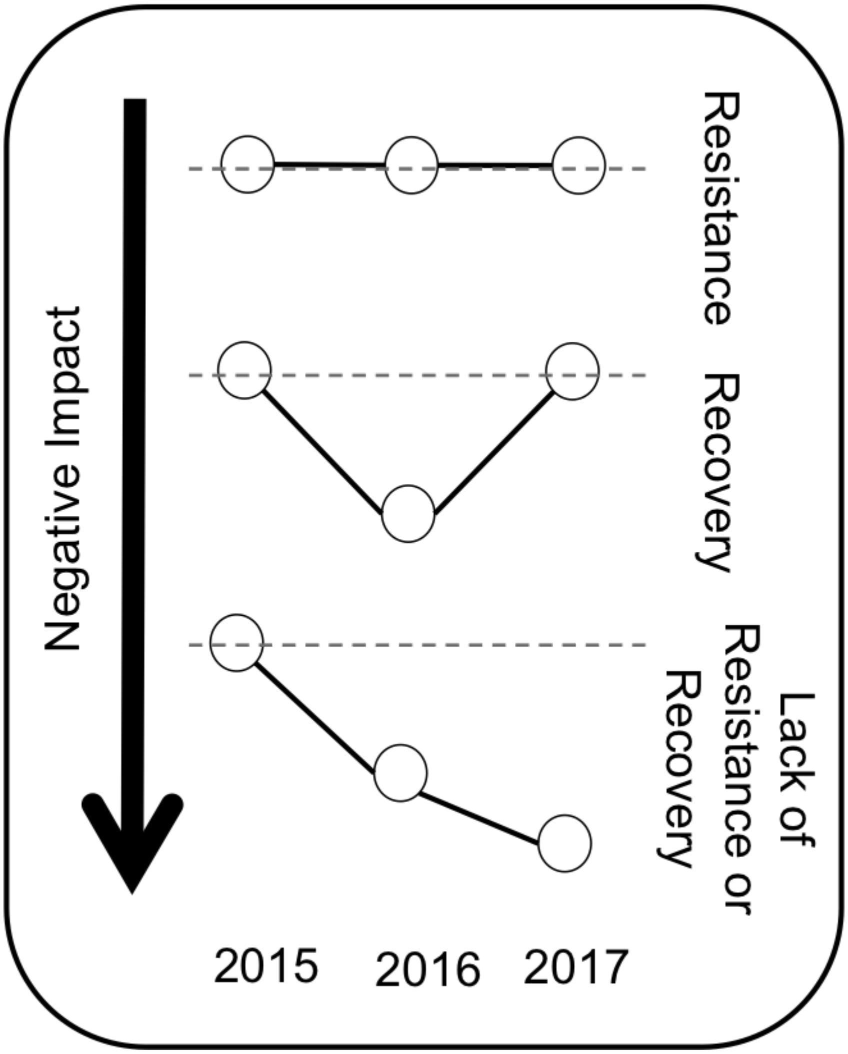

Figure 6.2. Configurations of total negative impacts for households during the climate shock. The dotted line indicates the 2015 baseline score. The configurations which show a positive slope (bounce back) in 2017 were considered more resilient, while those show a negative slope (further decline) were considered less resilient.

In order to calculate recovery each household's scores were treated in a standard way. The normalized difference of the 2016 and 2017 scores was calculated, then the 2017 score was added to this value to account for those households which were able to recover (Equation 6.1).

$$\left(\frac{a-b}{a+b}\right)+a \tag{6.1}$$

Where a is the 2017 score, and b is the 2016 score.

It is important to note that due to the way in which the both the resistance and recovery metrics were calculated, when these metrics are lowest, the indicator is most closely associated with high resistance or recovery. Therefore those factors which show a negative association with the metric (i.e. indicator increases while the resilience metric decreases), are actually showing a correlation with higher resistance or recovery.

Indicators

A group of eleven indicators were selected to assess whether any were important drivers of the resilience of households and broader regions during the 2015/2016 El Niño induced climate shock. These variables were selected to encompass a mixture of social, spatial and environmental variables (Table 6.1).

The first set of metrics were chosen to give a sense of the state of the household before the shock. Household size is often linked to poverty and food insecurity (Ahmed et al. 2017; Lanjouw & Ravllion 1995) whereby those households which are larger tend to be more impoverished. This can at times be further linked to a dependency ratio, which is a ratio of the number of dependents (in this case children under the age of 13 or 18) to the number of adults in the household. However preliminary analysis of our data indicated that it was not a useful indicator, while household size was found to be influential. The second metric of household demographics was income diversity in 2015. Income diversity has been cited as being important to improve the resilience of households (Opiyo, Wasonga & Nyanito 2014; Niehof 2004), where supplementary incomes are regarded as a potential adaptive measure to buffer against vulnerability of any single income source to a shock. Finally, the gender of the principal decision maker was included because this has been found to be linked to climate resilience in Kenya (Opiyo, Wasonga & Nyanito 2014), Tanzania (Van Aelst & Holvoet 2016, Muthoni & Wangui 2013) and Ghana (Friedman, Hirons & Boyd 2018).

Due to the predominance of agriculture on the livelihoods of each of the households surveyed, coupled with the impacts of the El Niño climate shock on agricultural productivity, it was important to consider factors which could capture this dynamic. The first factor considered was land tenure. The impacts of land tenure on the resilience of farmers has been studied in numerous contexts, and research suggests that the more ownership and agency a farmer has over their land, the more resilient they can be (Daniel et al. 2019; Hirons et al. 2018a; Goldstein & Udry 2008). In these regions there are over twenty land tenure arrangement types, however these can all be considered in basic terms as relating to ownership or sharecropping of some kind (Hirons et al. 2018a). Thus, this variable was treated as binary relating to whether the farmer owns the majority of plots they use (owners) or are under some kind of share cropping arrangement on the majority of plots they use (share croppers). The second factor considered was the number of individual, isolated plots each farmer had, which was asked of each farmer in 2015. How each farmer used these plots was also considered, with questions asking which crop or combination of crops are grown on each plot. Previous work has highlighted the importance of both cocoa and subsistence crops to farmers in this area (Hirons et al. 2018c), and as such both were included as variables in this study. To determine the number of each crop the farmer had, each time a farmer indicated a subsistence or cocoa crop was cultivated on a different plot, a one was added to the overall score. These were them summed to generate the number of cocoa and subsistence crops the farmer had before the climate shock occurred.

Given the extended dry season and climate shock, it was important to quantify how this might have impacted a farmer. Thus, using a global dataset of water table depth (Fan, Li & Miguez-Macho 2013), along with the perimeter boundary of the farmers primary farm, an average value of ground water depth for each farm plot was determined, where smaller values are associated with wetter land. In order to include a quantified assessment of the farmers land use, average Human Appropriated Net Primary Productivity (HANPP) values were estimated for a subset of farm perimeters which overlapped a dataset from Moore et al. (2019). HANPP is a way of quantifying the human impact on the environment, and it takes into account the historical land cover of the region (in this case tropical forest), the current land use, and also the biomass which is harvested.

In rural areas, issues surrounding access to resources (including farms, water, markets, etc) and other spatial features (such as proximity to roads, biodiversity or pollinator sources (such as Kakum National Park)) have the potential to greatly impact the livelihoods and general wellness of a farming household. One of the most significant factors which can impact farmers is access to urban areas. Often in rural areas in Ghana, medicines, school supplies and other key provisions are only accessible in urban areas.

As such, the duration it takes for someone to traverse the landscape to access these resources can potentially impact their ability be resilient to drought or shock conditions. To capture this, a global map of travel times to urban centers (Weiss et al. 2017) was used to determine the amount of time it would take each farmer to move from their homestead to the nearest urban centre (Assin Fosu, Central Region, Ghana).

The final metric, region, was also included as several studies specifically highlight the importance of considering different scales when assessing resilience (Maciejewski et al. 2015, Cumming et al. 2013, Carpenter et al. 2001). By including region as a variable in the model, this study can consider the impact of regional location on the resistance and recovery of each household.

Table 6.1 Description of social, environmental and spatial indicator variables.

Dimension	Indicator	Data Description	Data type (Social, spatial, environmental)	Source or Reference
Household Demographic Information	Household Size	Number of people in the household	Social	Ahmed et al. 2017; Lanjouw & Ravllion 1995
	Income Diversity	Total number of different income sources for the entire household	Social	Opiyo, Wasonga & Nyanito 2014; Niehof 2004
	Principal Decision Maker Gender	Binary indicator of the gender of the primary decision maker in the household (1=male, 2=female)	Social	Opiyo, Wasonga & Nyanito 2014; Van Aelst & Holvoet 2016; Muthoni & Wangui 2013; Friedman, Hirons & Boyd 2018
Farm Information	Land Tenure	Land ownership of farm plots and harvests (1=ownership, 2=share cropping)	Social, Environmental	Daniel et al. 2019; Lokonon 2018; Hirons et al. 2018; Goldstein & Udry 2008
	Number of plots	Number of farming plots owned by the household	Social, Environmental	Hirons et al. 2018c
	Cocoa Crops	Number of cocoa crops cultivated by the household across all plots	Social, Environmental	Hirons et al. 2018c
	Subsistence Crops	Number of subsistence crops cultivated by the household across all plots	Social, Environmental	Hirons et al. 2018c

	Ground Water Depth at Primary Farm	Average ground water depth of primary farm in meters (where 0 m is exposed water, and 10 m is very dry land)	Environmental, Spatial	Fan, Li & Miguez-Macho 2013
	HANPP at Primary Farm	Human Appropriated Net Primary Productivity at primary farm. Values ranging from 17 Mg/ha/year for primary forest, to 0 mg/ha/year for settled areas without any vegetation	Environmental, Spatial	Moore et al. 2019
Location Information	Access	Travel time from the household or homestead to a city in the shortest accessible journey with consideration for infrastructure, distance etc. in minutes	Spatial	Weiss et al. 2017
	Region	Region of household and farm plots (AB, HM, KA)	Spatial	Maciejewski et al. 2015, Cumming et al. 2013, Carpenter et al. 2001

6.3.4 Analysis

Collinearity

All indicator variables were tested for collinearity using variance inflation factors (VIF) which is a measure of the inflation in the variances of the parameter estimates due to collinearities that exists between the indicator variables. All variables used in the final model were found to be below four (Appendix E Table E1), which is regarded as a very strict threshold for VIF, and below which non-collinearity can be assumed (O'brian 2007).

Generalized linear model for indicators at farm level

To explore the relationships between the indicator variables and the resistance and recovery metrics, a generalized linear modelling framework (GLM) was used. The initial model was run with all 11 indicator variables, however the process was streamlined using Likelihood Ratio Test (LRT) stepwise model selection. This eliminates independent variables (indicators) and compares the log likelihood ratios of the models, selecting the model with the lower ratio. This process is then integrated automatically to indicate the best performing model. The model was then run again after removing HANPP as a variable, in order to include a larger number of samples (HANPP dataset n=72, non-HANPP dataset n=80). All resulting models were then cross validated using model AIC values to determine the model of best fit (Appendix E Table E2 and E3).

Kruskal Wallis Test for indicators at Region Level

In order to measure the variation of all of the indicator variables across the regions, each variable was tested using a Kruskal Wallis H test, due to the non-parametric nature of some of the variables. Wilcoxon tests were run as a post-hoc analysis to determine the pair-wise relationships which were significant

6.4 Results

The spatial distribution of the negative impacts of the drought on each household shows some spatial clustering, with higher impact values in the KA and AB regions (Figure 6.3). The average impact reported by households in 2016 were 3.17 (sd =1.73), 2.93 (sd =1.65) and 3.53 (sd =1.78) for AB, HM and KA respectively. The average impacts reported by households in 2017 were less for each region at 1.75 (sd =1.30), 2.14 (sd=1.36) and 2.11 (sd=1.43) for AB, HM and KA respectively. The resistance and recovery metrics were fairly dispersed across the landscape, without any obvious spatial clustering (Figure 6.4 & Figure 6.5).

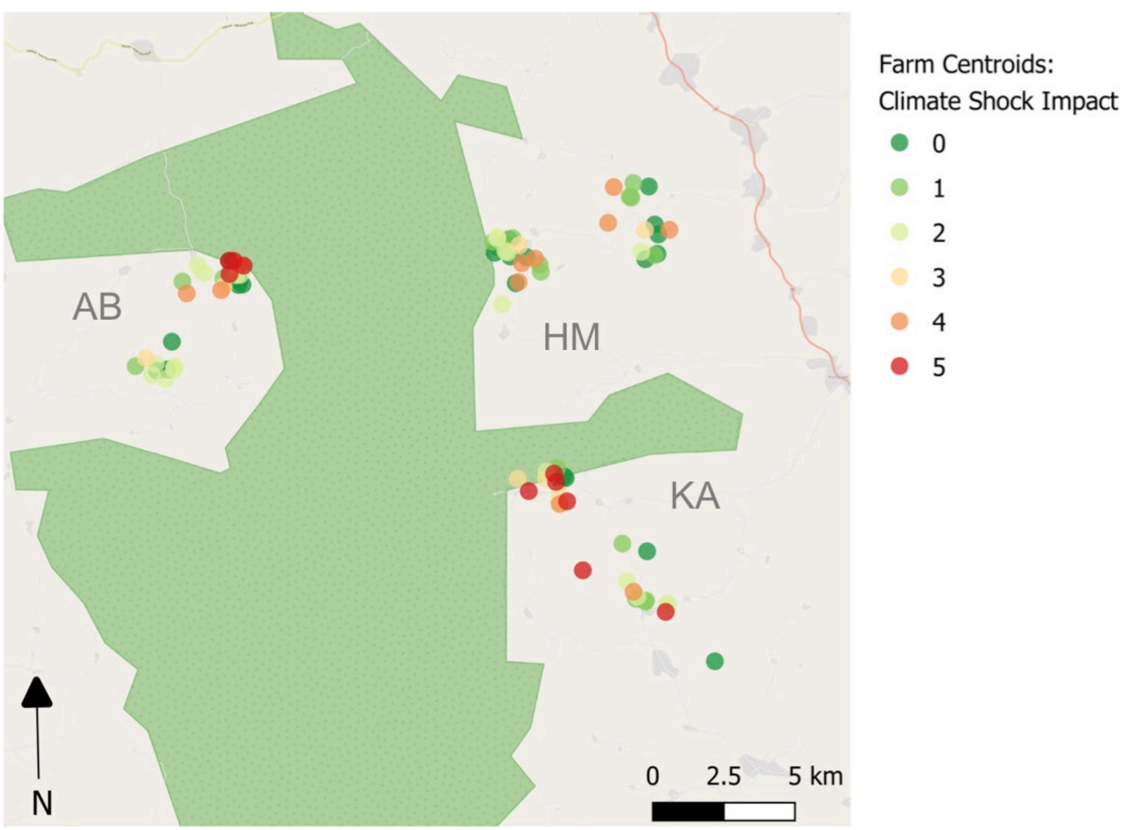

Figure 6.3. The spatial distribution of the negative impact in 2016 of the El Niño on households, as displayed via the locations of their primary farms. Circles which are red indicate higher levels of impact, while those that are green indicate lower levels of impact.

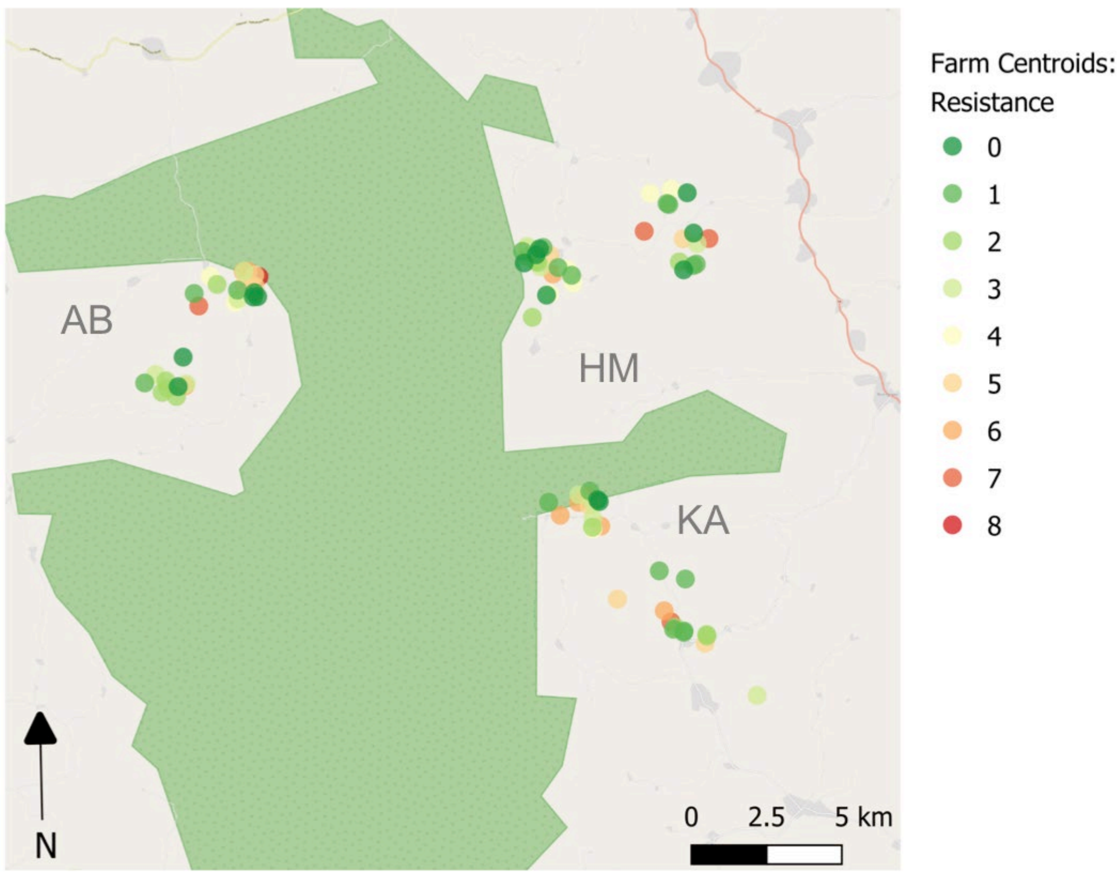

Figure 6.4. The spatial distribution of resistance scores where the green denotes high resistance to the impacts of the 2016 El Niño and the red denotes low resistance.

Figure 6.5. The spatial distribution of resilience scores. Circles which are red indicate higher resilience, while those that are green indicate lower resilience scores.

6.4.1 Generalized Linear Model for Indicators at Farm Level

Model Outcomes – Resistance

The model with the best performance included ground water depth, number of members of the household and the HANPP value within a 25m buffer of the primary farm (including the farm itself) (Table 6.2) with an AIC value of 344.93 (Appendix E, Table 2E). Due to the directionality of the resistance metric, those values which are smaller are associated with greater levels of resistance.

Table 6.2 Result of general linear model (GLM)testing the resistance metric against a number of indicator variables for farming households. Those variables which display a significant relationship are indicated with an asterisk (*).

Indicator	Estimate	SE	Lower CL	Upper CL	t value	Pr(>|t|)
(Intercept)	0.28694	0.75369	-1.764	-1.190	-0.381	0.705
Ground Water Depth (m)	-0.22313	0.07855	0.069	0.377	2.841	0.006**
Household Size	-0.09276	0.0422	0.010	0.175	2.198	0.031*
HANPP25m	-0.13156	0.06845	-0.003	0.266	1.922	0.058

Model Outcomes - Recovery

The model with the best performance included only the variables for ground water depth, access, number of plots, number of subsistence crops, the dummy HM regional variable, and principal decision maker (Table 6.3) with an AIC value of 94.26 (Appendix E, Table 3E). Due to the directionality of the recovery metric (smaller/more negative values = more resilient), those values which are negatively associated with the metric show higher levels of resilience.

Table 6.3 Result of the general linear model (GLM) testing the recovery metric against a number of indicator variables for farming households. Those variables which display a significant relationship are indicated with an asterisk (*).

Indicator	Estimate	SE	Lower CL	Upper CL	t value	Pr(>|t|)
(Intercept)	2.210	0.406	1.414	3.005	5.445	<0.001***
Ground Water Depth (m)	-0.043	0.020	-0.082	-0.004	2.325	0.0347*
Access from homestead (min)	-0.011	0.005	-0.020	-0.001	2.046	0.0353*
Number of plots	-0.047	0.028	-0.101	0.007	1.450	0.0933
Number of subsistence crops	0.040	0.024	-0.006	0.086	-1.540	0.0934
HM Region	-0.360	0.100	-0.664	-0.006	2.191	0.0171*
Gender of Principal Decision Maker	-0.245	0.155	-0.442	-0.048	2.172	0.0230*

Household demographics

Income diversity was found to have no significant relationship with either the resistance or recovery metrics. Household size was found to be significantly related to resistance, such that the fewer individuals in the household, the greater the resistance to the shock event ($p>0.05$). While households where the primary decision maker was male were significantly more likely to recover than households where the primary decision maker was female ($p<0.05$).

Farm Information

Average ground water depth at the primary farm of each household was found to be significantly related to both resistance and recovery.. Namely, those farms which were wetter, or had lower values for ground water depth, were significantly ($p<0.05$) more likely to be resistant to the impacts of the climate shock and/or able to recover from the shock. Those farms with a lower level of HANPP (or with less intensive land use) on their own farm and in the 25m surrounding it, displayed a relationship with increased resistance, however this was not significant. Both the number of plots and the number of subsistence crops showed a relationship with the recovery metric, such that more plots and fewer subsistence crops were associated with recovery, however these were not significant. The land tenure and number of cocoa crops showed no relationship with either metric.

Location Information

The accessibility of farmer's homes and homesteads to urban areas was found to be significantly related to recovery. The closer a home or homestead of a farmer was to an urban centre the more able to recover from the climate shock that household would be ($p<0.05$). The farmers in the region of HM were found to be significantly less able to recover than those in KA ($p<0.05$). There was no relationship which was found between farmers in KA and AB. Neither accessibility or region metrics showed a relationship with household resistance.

6.4.2 Kruskal Wallis test for Indicators at Region level

Kruskal-Wallis tests were conducted to examine the differences in indicators of resilience by region. Significant differences were recorded for ground water depth where HM values were significantly lower (wetter) than KA (Figure 6.6a). All three regions were significantly different to each other when considering access of homes or homesteads to urban areas, with HM having the shortest travel time and AB having the longest (Figure 6.6b). Further, for cocoa crops, HM farmers had significantly fewer cocoa farms than KA and AB (Figure 6.6c), while for subsistence crops, AB farmers had significantly more subsistence crops than HM and KA (Figure 6.7a). HM farmers also had significantly fewer farming plots than farmers in the KA region (Figure 6.7b). HANPP was found to be significantly higher in the HM region than the KA region, with no significant relationship in the AB region (Figure 6.7c)

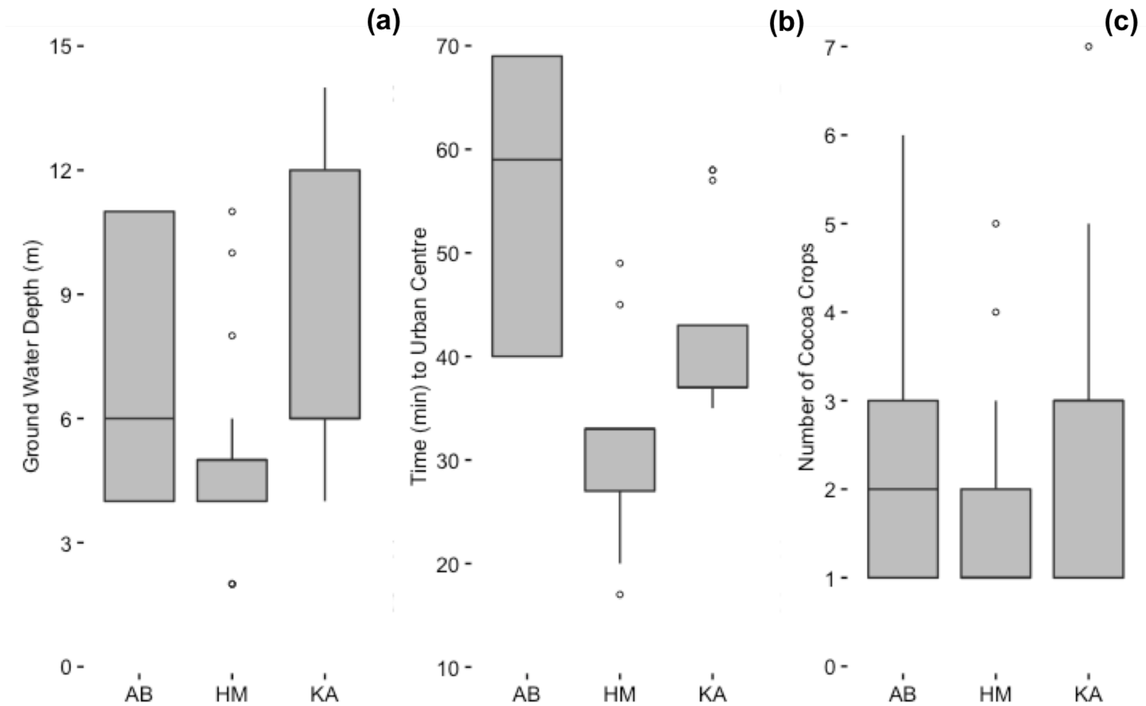

Figure 6.6 Variances in (a) ground water depth, (b) Time to urban centres [or access] (min) and (c) number of cocoa crops for farmers in the regions of AB, HM and KA.

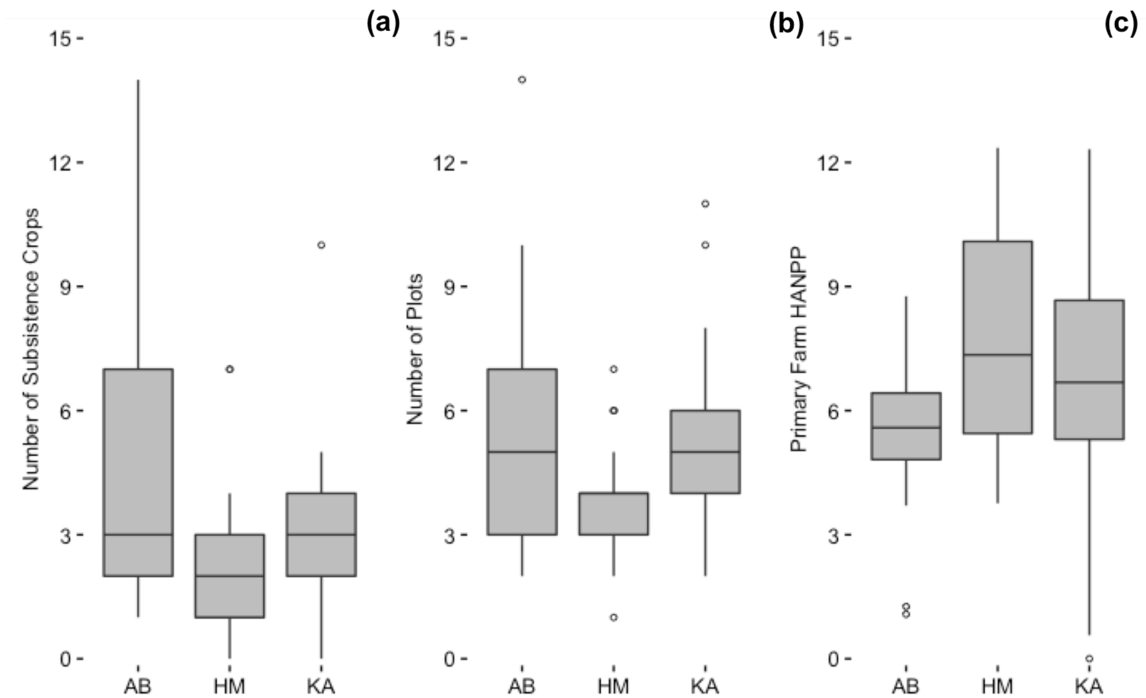

Figure 6.7 Variances in number of subsistence crops (a), number of plots (b) and the Human Appropriated Net Primary Productivity of the primary farm for farmers in the regions AB, HM and KA.

6.5 Discussion

This paper highlights indicators that relate to resistance to and recovery from a climate shock, both at a household and regional scale, using a dataset which spanned before, during and post phases of a shock climatic event. At the household level, households which had wetter land at their primary farm and contained fewer people were more resistant to the impacts of the climate shock. While households which had wetter land at their primary farm, were closer to an urban centre and had a male primary decision maker were found to be more able to recover from the shock. According to the recovery metric, those households in HM are significantly less likely to recover than those in KA. However, when considering this finding in conjunction with the differences in average impact between the regions (HM: 2016 =2.93, 2017 =2.13; KA: 2016=3.52, 2017=2.11), farms in KA were much more impacted than those in HM. Thus given the relatively lower impact reported by households in HM, it is possible these households may did not have as severe impacts to recover from. When considering the relationship between the indicators and region, there did not appear to be a clear trend which explained the differences in recovery between households in the HM vs. KA region however there are a few possible explanations for this, which are explored below.

6.5.1 Household Level Resistance and Recovery

Farmers whose primary farm had a lower ground water depth, in other words had wetter ground, were more resilient during the climate shock, namely by being less likely to be impacted by the shock, and if they were impacted, they were more likely to recover. This finding is consistent with observations made by farmers in the region about the importance of 'wet lands' during the shock event (Hirons et al. 2018a). Ground water availability has the potential to mitigate some of the atmospheric processes which can influence crop health during times of increased heat. Further, when one considers the increase in atmospheric VPD in the region during the shock (Whitfield et al. 2019; Morel et al. 2019b), this finding suggests that ground water depth could also play an important role in mitigating some of the atmospheric processes which influence plant transpiration and mortality (Will et al. 2013).

Those households which were most resistant to the impacts of the climate shock, also tended to have smaller households. Research suggests that those households which are smaller are both less vulnerable to shock events, but also that they have an increased chance to reduce their poverty level (Meyer & Nishimwe-Niyimbanira 2016; Agbaje et al. 2013), which would be consistent to being resistant to this shock event.

While the level of HANPP at the primary farm, and within 25m of the farm, did not display a significant relationship with resistance, it trended towards higher levels of HANPP (less intensive land sue and land use change) being associated with resistance of households. As this relationship was not significant, it does not bear further assessment, however the potential of the metric is displayed and should be looked into further in future work.

Access to urban centres was significantly related to the recovery of households. Those farmers who were able to more easily and quickly access the closest urban centre (Assin Fosu) from their homes, were could recover more. Generally, a lack of access to resources and opportunities in urban centres such as hospitals and markets presents a major barrier to wellbeing and overall improved livelihoods (Weiss et al. 2017). In this instance, it is also possible that households which were closer to the urban centre were able to more easily find alternate sources of income or access resources which could aid them in recovering from the climate shock.

The gender of the principal decision maker was also significantly related to the recovery of households. Households which were headed by a woman were significantly less resilient, than those headed by a man. Research has suggested that women generally face greater barriers to development and access to opportunities, thereby making them generally more vulnerable to climate shocks (Sujakhu et al. 2019; Lawson et al. 2019; Flato et al. 2017; Arora-Jonsson, 2011). This is often exacerbated in rural or poor regions, where farmers can incur additional costs, and infrastructure is poorly maintained. For example, one female farmer in this region reported that she must hire men to carry her cocoa beans if the roads are washed out due to rains (Friedman, Hirons and Boyd 2018).

It was a surprise that certain metrics, such as diversity of income, land tenure or cocoa crops were found to have no significant relationship with resistance or recovery, as asserted by the literature (Opiyo, Wasonga & Nyanito 2014; Lin 2011; Barns 2009;

Niehof 2004). When considering income diversity without a measure of the vulnerability of each income source to the climate shock, this metric may not be adequately capturing qualitative differences in income sources and underlying dynamics, which may be masking the benefit of certain income sources to the resilience of a household. For land tenure, the variable used was only binary, considering if the majority of the farmers plots were owned or sharecropped. However, ownership and land tenure are highly complex in this region. For example, in this 'share cropping' actually included over 18 different tenure arrangements. Given the diversity and complexity of the metric (and the feature it represents) it would be advisable to investigate tenure via more qualitative approaches. For cocoa crops, it is possible that a lack of sufficient variation between farmers would highlight a lack of power of this particular metric amongst this sample of farmers. Additionally, there is evidence to suggest that while young cocoa trees had a higher incidence of mortality (Hirons et al. 2018a), most mature trees actually produced more cocoa pods (Morel et al. in review). The possible explanation for this is the that it could be a physiological response of the trees to the shock where they will attempt to flower more and spread its genetic material, thus creating a higher density of cocoa pods in the process (Niether et al. 2017). For subsistence crops, while there was more variation, the variation was still relatively minor with the average of three subsistence crops per farmer and most farmers having between one and four subsistence crops. In addition, just as with the diversity of income, without specific information about the vulnerability of each crop to the climate shock, it is possible that the hardiness of some crops is masking the vulnerability of others.

Looking at households from a broader perspective, those in the HM and KA regions were found to have significantly different recovery scores than each other, with the KA region households generally showing greater. This regional variability is consistent with other studies from the region which have reported extensive differences in land use (Moore et al. 2019) and also differences in land tenure arrangements (Hirons et al. 2018a). In order to understand which factors may be contributing to the difference observed between the HM and KA regions, all indicators were compared across the three regions.

6.5.2 Regional Level Variability

Ground water depth was found to be significantly deeper in the KA region farms than in the HM and AB region farms. This means that those farms in the KA region are significantly drier than the other regions. Observations made by Moore et al. (in review) showed KA to have substantially fewer cocoa crops than the other regions, as well as substantially more oil palm crops. Oil palm is generally considered a hardy crop to some of the predicted impacts of climate change, however a number of studies have highlighted the susceptibility of the crop to soil water deficit (Smith 1989; Pirker et al. 2016). Yields in water limited areas have been found to be significantly lower (more than 50 %) than yields in other wetter regions (Woittiez et al. 2017). While farmers reported that the oil palm in all study regions was not affected by this climate shock (Hirons et al. 2018a), the combination of drier lands and hotter conditions in the future could lead to decreased resilience (both due to less resistance and lower recovery) within the KA region.

All regions were found to vary significantly in the minutes it takes to access the nearest urban centre, with HM taking the shortest amount of time and AB taking the longest. The range of travel times for those in HM and KA did not vary significantly with the majority taking 25-35 minutes, and 35-45 minutes respectively. The range of AB however was substantially larger, with the majority taking 40-70 minutes. The amount of time people in this region need to travel to access the nearest urban center is also significantly impeded during the wet seasons, due to the major road being routinely washed out for long periods. This could enhance the vulnerability of households in this region and present a significant barrier to the resistance and recovery under future climate shocks, such as the heavier than normal rains observed at the end of the El Niño event (Whitfield et al. 2019).

The farmers in the AB region also had significantly more subsistence crops than those in the other regions. In general, farmers in this region had an average of 4 subsistence crops per household versus 2.2 or 2.9 in HM and KA respectively. This could potentially highlight the cultivation of subsistence crops as an adaptive strategy, considering the difficulty these farmers would have accessing the large market in Assin Fosu (Figure 6.1).

This study found that Human Appropriated Net Primary Productivity (HANPP) was significantly higher for the HM region than the AB region, with no significant relationship to AB. HANPP can give an indication of how intensively land is being used by humans, where higher values of HANPP indicate a greater intensity of land use (Haberl, Erb & Krausmann 2014). The farms in the HM region also had fewer plots per household, and also had fewer numbers of cocoa crops. This suggests that those farms in the HM region are more intensively farming their land. This study found that HANPP levels at farmers' main farm had no significant relationship to household-level resistance or recovery, the differences between regions highlight the importance of scale when considering using the metric.

6.5.3 Resilience vs. Resistance and Recovery

This study used the metrics of resistance and recovery to attempt to quantify which variables are associated with household resilience to a climate shock. When assessing recovery of households, one of the surprising results of the study was that the farms in HM were significantly less able to recover than the farms in KA according to our recovery metric. The surprising aspect of this is that farms in HM were significantly wetter and had greater access to the closest urban center than those farms in KA. Given this finding, and the lower levels of impact reported for the HM region, it was suspected that these households were displaying resistance to the climate shock. When attempting to understand this, it is helpful to refer to the spatial distribution of both the negative impacts reported in 2016 (Figure 6.3) and the recovery metric itself (Figure 6/5). Also notable were the differences in negative impacts between the two regions for 2016 and 2017; with HM less negatively impacted in 2016 and KA more negatively impacted in 2016 but bouncing back in 2017. It is fairly clear that the farms in HM did not experience as many negative impacts from the drought as farms in the other regions. However, region did not display a significant relationship to our resistance metric. It is possible these households were more resilient to the drought but that it is not be captured by the metrics or variables used in this study.

The resistance and recovery metrics used in this study have provided insight into the spatial distribution of impacts of a climate shock on households, and the traits of farms which are beneficial during times of stress or disturbance. This study has demonstrated that there is additional benefit to breaking down resilience into further measureable components, as outlined by Hodgson, McDonald and Hosken (2015), namely resistance and recovery. As shown in this study, both are important independent processes which can provide valuable insight into the findings of empirical studies seeking to study resilience.

6.5.4 Limitations

While the findings of this study are useful in understanding the farmers studied, and could be used as an indicator of potential factors of importance relating to future climatic resilience in the region, the findings should be regarded with some caution. Firstly, the situation is highly complicated and there are far more factors at play than could be captured in this study. While this study used quantitative methods on a qualitative dataset, much of the associated data from focus groups or interviews highlight the nuance resilience in such complex systems. Land tenure and income diversity, for example, were assessed as simplified variables, and could give further insight if they were broadened to include more detail. However, it would be difficult to have adequate representation of each new group (ie. over 20 land tenure groups) given the sample size of this study. The sample size for the study is relatively small and as a result is not necessarily representative of the communities in the regions of study, let alone the entire cocoa agroforestry industry in Ghana. However, studies like this one are vital in grasping some of the more complex features which may be descriptive of the broader system within which it is embedded.

This work highlights that some factors may have an impact across scales, such as ground water depth, however others such as income diversity may be more complex than what can be captured in a single metric. It should also be noted that many of the metrics studied here were derived from self reported responses. When considering the impacts of the climate shock, there are likely several dynamics which may not have been captured by the household survey. However, even with that caveat, the results here do show an important interaction between social, ecological and spatial factors when assessing resilience by studying resistance and recovery.

6.5.5 Conclusion

The research presented in this study outlined the utility of assessing resilience of small holder farming households using data from before, during and immediately following a climate shock by using resistence and recovery as focal metrics. The first aims of the study were to determine how resistant farmers were to the climate shock caused by the 2015/2016 El Nino and how able they were to recovery from the shock. The results indicate that households varied substantially in their ability to cope during and after the shock event. The study found a combination of social, environmental and spatial factors, contributed to a greater resilience for some farming households, namely wetter soils at the primary farm, smaller household sizes, access to the nearest urban centre and a male head of household, thereby addressing the third aim of the study. The fourth aim of this study was to determine whether any spatial concentration in regions was associated with resilience. This study found that households in one region (HM) were less able to recover from the climate shock then households in another (KA) according to the recovery metric. However, comparing the negative impacts reported during 2016 and 2017 for the two regions highlighted that while KA was in fact resilient, those households in HM tended to have more traits of resilience, namely wetter soils, greater access and more male decision makers.

This study highlights the importance of using multiple scales of analysis to understand the resilience of households to climate shocks. Further, the combination of social, environmental and spatial factors demonstrate the complexity of many features of resilience. Finally, this study also provides insight into the need for resilience studies to be flexible when considering a resilience metric, highlighting that greater insight into the resilience of households to climate shock events can be gained by using the metrics of resistance and recovery.

7. Conclusion

7.1 Summary of thesis

The thesis presented herein develops methodology and analysis for better understanding the pattern and process of complex mosaic landscapes in tropical regions. A site in southern Ghana, where the primary livelihood is cocoa agroforestry, is used as a case study with which to frame the aims of the thesis. The thesis first focuses on improving methods for capturing patterns in complex mosaic landscapes (Chapters 3 and 4). The later focus is on understanding some of the processes of complex mosaic landscapes by using a social-ecological lens (Chapters 5 and 6).

The first part of the thesis focused on capturing and classifying land use in complex mosaic landscapes. The first obstacle to the study of complex mosaic landscapes in tropical regions are the particularly persistent clouds and atmospheric interference, which make the use of satellite based remote sensing imagery unviable. A methodology using drones to capture and process imagery is presented, which underpins each subsequent chapter of the thesis. The imagery derived from the drones is first used to test multiple machine learning models for image classification. Two image sets are tested using all models. The first is a broad scale image set of >14,000 image tiles, which are classified in a manner similar to what would normally be acceptable for manual classification of land use (~5m resolution). Seven levels of land class were included, including cocoa, palm, settlement, plantain etc. The second image set is classified to a high resolution (~10cm), which is similar to the recommended level outline in many computer vision approaches.

Besides the null and other categories for each image set, the fine scale image classification included cocoa, palm oil and settlement, while the coarse scale included the aforementioned as well as plantain, vegetables, and cassava. None of the models were able to perform well using the coarse image tiles, indicating the unsuitability of coarsely classified images for machine learning classification. However, the fine scale images were found to be most adequately classified using a deep learning convolutional neural network called ResUNet. The model was more successful at broadly classifying land use proportion rather than specific pixel classification. The model slightly underestimated cocoa presence (14% vs. 18.5%) and overestimated palm (12% vs. 21%). These findings highlight the utility of the approach to classify cocoa, and palm at a broad scale (ie. not pixel by pixel or tree by tree). The initial intention was to use the methods developed in Chapter 4 to classify the large areas of imagery acquired for Chapter 5. However, due to the lack of success in classifying all land classes of interest (including plantain, cassava etc), all classification had to be done manually.

The later part of the thesis focused on analyzing the interplay between humans and ecosystems inherent to complex mosaic landscapes. This thesis framed these landscapes as social-ecological systems, as the framework highlights the duality of importance of both the human and ecosystem components of the system. The thesis presented an analysis of both pattern and process of complex mosaic landscapes. Where patterns are the structure of the landscape at any given time, such as the land use and processes are the dynamics of the landscape. There is a cyclical relationship between these as processes give rise to patterns, while patterns influence subsequent processes. Thus capturing and analysing both were a priority for this thesis. This was achieved by first focusing on quantifying the pattern of the landscape by estimating the human impact on the environment. By calculating the Human Appropriated Net Primary Productivity (HANPP), this thesis was able to display the variance of human impacts on three regions. HANPP varied across the three regions from 6.69 MgC/ha/yr to 8.00 Mg C/ha/yr to 9.85 Mg C/ha/yr. These values were both significantly higher and more varied than those presented in the most widely accepted study of HANPP globally, which vary from 2.64 MgC/ha/yr to 2.79 MgC/ha/yr for the same regions. The study also identified a large variance in land use between each of the regions, which would normally have been considered highly similar cocoa agroforestry landscapes.

To analyse some of the dynamics (or processes) of complex mosaic landscapes, a disturbance event was used to frame the assessment of the resilience of the system. The 2015/2016 El Nino caused a climate shock in the region leading to a change in precipitation as well as increases in temperatures. To try to capture some of the complexities of the landscape, the impact of the climate shock was assessed using social, environmental and spatial indicators at a household scale. These indicators were also compared at a regional scale. Three years of survey data collected for each household were used to generate the dataset, the first year to establish potential base level indicators and the later two years to determine the short and longer term perceptions of the impacts of the climate shock. The analysis indicated that a mixture of social, environmental and spatial factors at a household scale contributed to a decrease in negative impact from the shock. Specifically, those farmers who had wetter ground at their primary farm (ground water depth), were closer to the nearest urban center (Assin Fosu) and had a male head of household, were found to be more resilient. At a regional scale, it was found that while one region displayed an increase in resilience to the climate shock conditions, another displayed resistance to the climate shock in the first place, highlighted in diminished negative impacts in the region.

7.2 Main research contributions

The main research contributions of the thesis are as follows:

- Captured approximately 60 km^2 of high resolution imagery in a landscape which has a relative lack of reliable remote sensing imagery.
- Developed methods to capture and process RGB drone imagery in a tropical landscape.
- Developed monitoring methods for local actors which can give can give them more control over their monitoring regime, especially if they are in a region where clouds can make satellite based remote sensing approaches difficult and/or if they are seeking very fine scale data covering a moderate amount of area.
- Developed a method to generate land use data using an advanced machine learning approach and simple RGB imagery from a basic drone.
- Provided detailed land use information for three regions of complex mosaic landscapes, and uncovering previously unknown differences between these regions in the process. While all regions are considered cocoa agroforestry landscapes, the percent of cocoa on each landscape varied from 53% to 40% to 27%.
- Generated a quantified measure of human impact in a complex mosaic landscape

effectively scaling up detailed field derived measures to multi-kilometer scale.

- Generated an assessment of household resilience to a climate shock in a complex mosaic landscape using a combination of social, environmental and spatial factors.

7.3 Future Research Directions and Activities

Despite the contributions of this thesis, there remains much practical work to do to truly understand complex mosaic landscapes and importantly, to understand the potential future impacts of climate change in these regions. The following paragraphs provide a selection of future research directions and activities which will help improve this understanding and ensure that the practical and theoretical insights of this thesis have the best chance of impacting researchers and policy makers in tropical regions, and globally.

- This thesis focused very specifically on one region of Ghana, within cocoa agroforestry complex mosaic landscapes. The findings of the study highlight the stark variations between these regions normally considered homogeneous. Future work in areas like this should seek to understand broad patterns, but also should not make assumptions about the fine scale dynamics and how those might impact seemingly identical regions differently.
- While this thesis made significant progress towards capturing the patterns of a complex mosaic landscape, further work could substantially benefit form

repeating the surveys completed here. Specifically, the drone imagery only provides a snapshot of one period of time, and a large amount of knowledge could be gained through repeat surveys of this region.

- This thesis makes significant progress towards understanding the fine scale patterns of complex mosaic landscapes. By generating this data over a large area, it enables the scaling up of findings more precisely than was previously possible. Research, especially in the tropics, should continue to not just see large scale or fine scale studies as the only options, and should continue to attempt to bridge this gap using methods like those developed here.
- Processing of drone imagery was one of the major complications of this work. While many commercial drone imagery products offer to produce georectified orthomosaics, most failed to be functional in this tropical landscape. More work needs to be done incorporating more sophisticated algorithms which are usable in broadly homogenous landscapes.
- Given that the drones used in this thesis were only equipped with standard GPS technology (accuracy to 15m), further study could benefit from using differential GPS (accuracy to 10cm). This would be particularly relevant when attempting to combine drone imagery with high resolution satellite imagery, to develop detailed, and reliable land use information on a larger scale.
- Remote sensing imagery, even when generated at a very high spatial resolution, is not a panacea. The importance of incorporating embedded and ground based data with larger regional or global studies should continue to be a priority.
- Partnerships between computer scientists and remote sensing communities should

be actively pursued to a greater extent. The methods used in this thesis for image classification are cutting edge, and have been present in the machine learning community for over 3 years. However, the work here is the first to use these methods in an ecological study. The nurturing of cross disciplinary relationships, specifically with computer science, will ensure the rapid and effective uptake of the latest and best computational advancements.

- More studies should pursue the practical applications of social-ecological systems theory. While theoretical principles continue to be advanced, the operationalization of the theory continues to lag behind, specifically with regard to resilience. Greater interdisciplinary partnerships between complex systems scientists, and social-ecological theorists would go a long way towards generating more practical applications and general operationalization of social-ecological systems theory.

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Appendix A: Co-author Paper Contribution Statements

The following statements provide details of the contributions made by co-authors to papers included in this thesis:

Certificate of Authorship of Dissertation Work for Christine Moore

To the Director of Graduate Studies: School of Geography and the Environment, University of Oxford.

I hereby certify that Christine Moore carried out the majority of the work contained in the articles described below, which form part of her DPhil thesis:

- *Classifying Land Use in Complex Mosaic Tree Crop Landscapes using Drone Imagery and Machine Learning.*
- *Appropriated Net Primary Productivity of Complex Mosaic Landscapes.*
- *Resilience of farmer households in a complex mosaic landscape: A case study of Ghanaian Cocoa and El Nino.*

Name: Professor Yadvinder Malhi

Affiliation: Environmental Change Institute, School of Geography and the Environment, University of Oxford, Oxford, UK

Signature:

Date: 25th April 2019

Certificate of Authorship of Dissertation Work for Christine Moore

To the Director of Graduate Studies: School of Geography and the Environment, University of Oxford.

I hereby certify that Christine Moore carried out the majority of the work contained in the articles described below, which form part of her DPhil thesis:

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- *Appropriated Net Primary Productivity of Complex Mosaic Landscapes.*
- *Resilience of farmer households in a complex mosaic landscape: A case study of Ghanaian Cocoa and El Nino.*

Name: Dr. Alexandra Morel

Affiliation: Institute of Zoology, Zoological Society of London, London, UK.

Signature:

Date: 17/4/2019

Certificate of Authorship of Dissertation Work for Christine Moore

To the Director of Graduate Studies: School of Geography and the Environment, University of Oxford.

I hereby certify that Christine Moore carried out the majority of the work contained in the articles described below, which form part of her DPhil thesis:

- *Appropriated Net Primary Productivity of Complex Mosaic Landscapes.*
- *Resilience of farmer households in a complex mosaic landscape: A case study of Ghanaian Cocoa and El Nino.*

Name: Dr. Rebecca Ashley Asare

Affiliation: Nature Conservation Research Centre, Accra, Ghana

Signature: Rebecca A Asare

Date: 17/04/2019

Certificate of Authorship of Dissertation Work for Christine Moore

To the Director of Graduate Studies: School of Geography and the Environment, University of Oxford.

I hereby certify that Christine Moore carried out the majority of the work contained in the articles described below, which form part of her DPhil thesis:

- *Classifying Land Use in Complex Mosaic Tree Crop Landscapes using Drone Imagery and Machine Learning.*

Name: Mr. Lucas Kruitwagen

Affiliation: Smith School of Enterprise and the Environment, University of Oxford, Oxford, UK.

Signature:

Date:

Certificate of Authorship of Dissertation Work for Christine Moore

To the Director of Graduate Studies: School of Geography and the Environment, University of Oxford.

I hereby certify that Christine Moore carried out the majority of the work contained in the articles described below, which form part of her DPhil thesis:

- *Resilience of farmer households in a complex mosaic landscape: A case study of Ghanaian Cocoa and El Nino.*

Name: Mr. Jonathan Aronson

Affiliation: Independent Researcher

Signature:

Date: 17 April 2019

Certificate of Authorship of Dissertation Work for Christine Moore

To the Director of Graduate Studies: School of Geography and the Environment, University of Oxford.

I hereby certify that Christine Moore carried out the majority of the work contained in the articles described below, which form part of her DPhil thesis:

- *Appropriated Net Primary Productivity of Complex Mosaic Landscapes.*

Name: Dr. Stephen Adu-Bredu

Affiliation: Nature Conservation Research Centre, Accra, Ghana

Signature:

Date: 17TH APRIL, 2019

Certificate of Authorship of Dissertation Work for Christine Moore

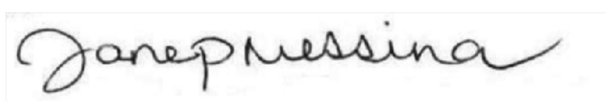
To the Director of Graduate Studies: School of Geography and the Environment, University of Oxford.

I hereby certify that Christine Moore carried out the majority of the work contained in the articles described below, which form part of her DPhil thesis:

- *Resilience of farmer households in a complex mosaic landscape: A case study of Ghanaian Cocoa and El Nino.*

Name: Dr. Jane Messina

Affiliation: School of Geography and the Environment, University of Oxford, Oxford, UK

Signature: 

Date: 17 April 2019

Certificate of Authorship of Dissertation Work for Christine Moore

To the Director of Graduate Studies: School of Geography and the Environment, University of Oxford.

I hereby certify that Christine Moore carried out the majority of the work contained in the articles described below, which form part of her DPhil thesis:

- *Resilience of farmer households in a complex mosaic landscape: A case study of Ghanaian Cocoa and El Nino.*

Name: Mr. John Mason

Affiliation: Nature Conservation Research Centre, Accra, Ghana

Signature:

Date: 17/04/2019

Appendix B: Supplementary Figures and Tables for Chapter 4

Appendix C: Supplementary Figures and Tables for Chapter 5

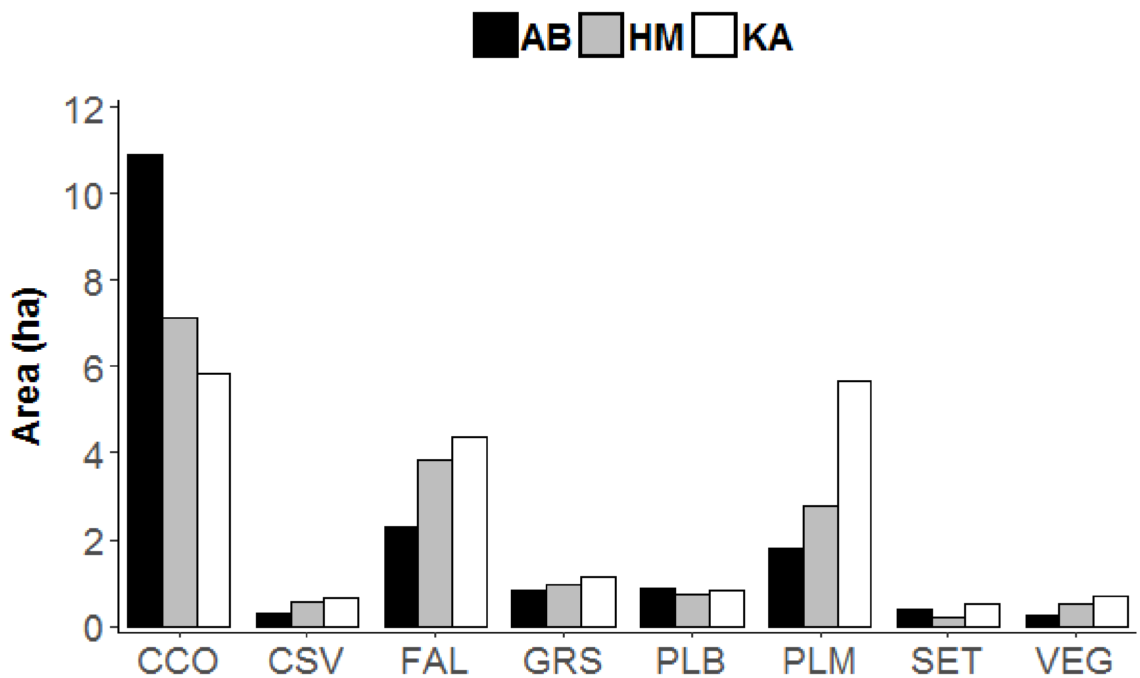


Figure B1. The area of each measured land use in the AB, HM and KA regions.

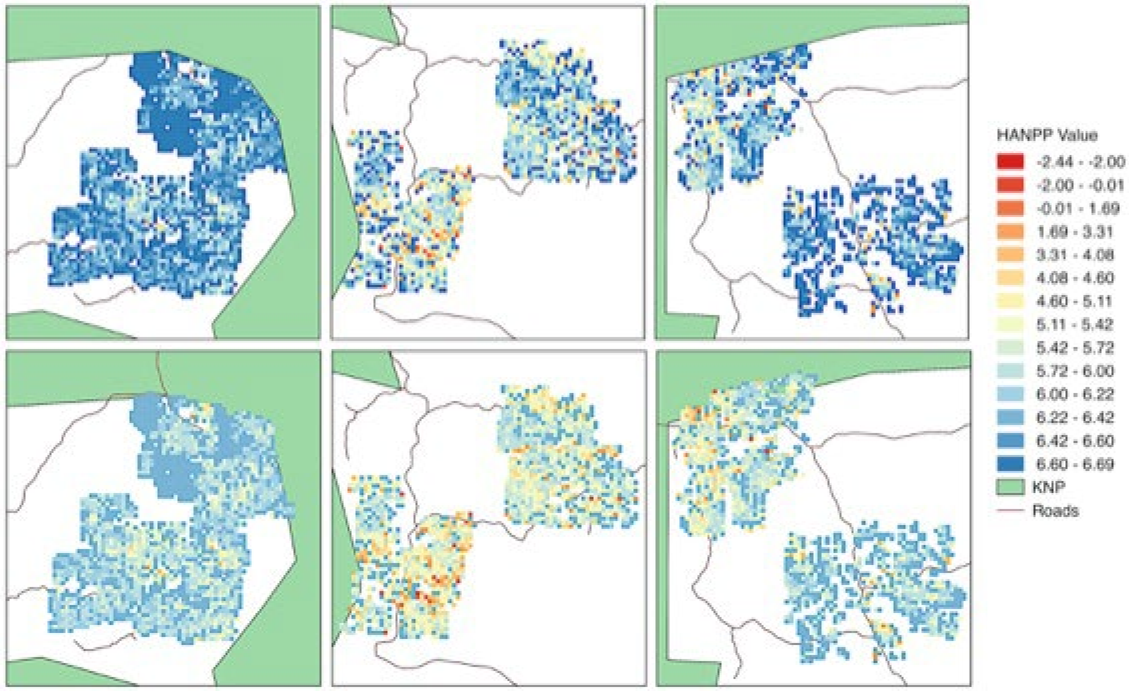


Figure B2. Cocoa only HANPP values for estimated cocoa densities of 600 trees/ha (top) and 719 trees/ha (bottom) for AB, HM and KA regions.

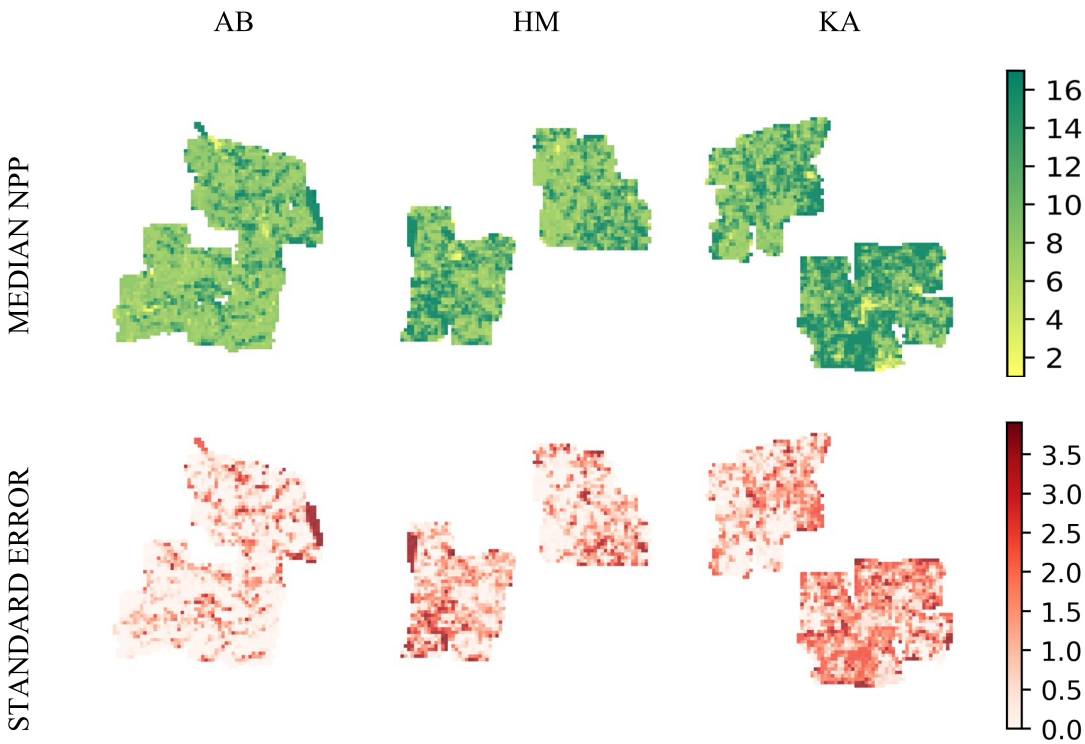


Figure B3 NPP and standard deviation values per hectare of the AB, HM and KA regions assuming a density of 719 trees per hectare.

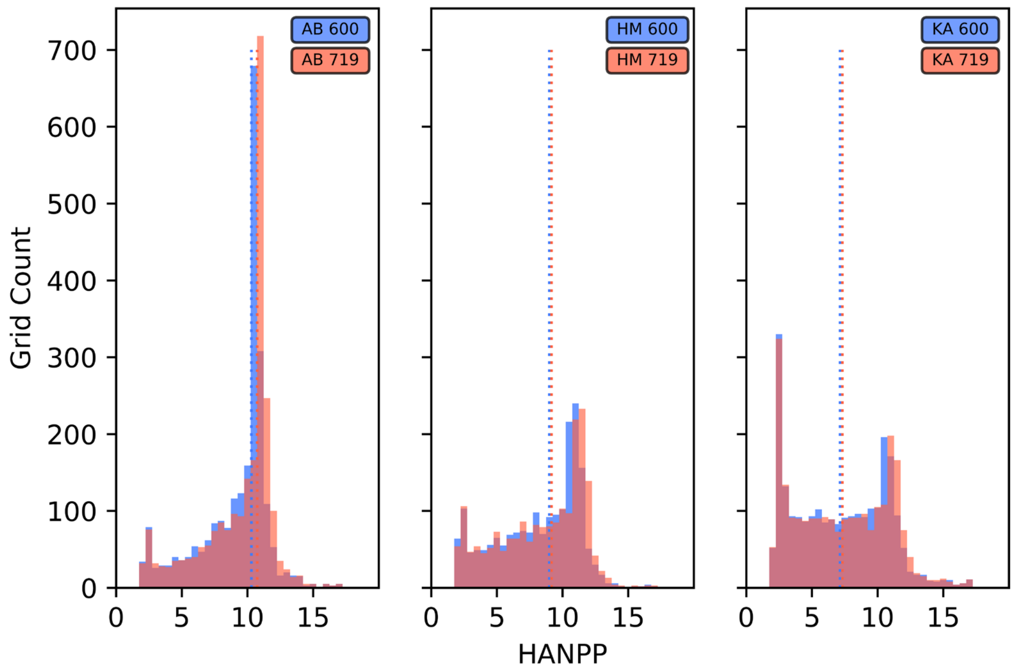


Figure B4 Number of grid cells with each value of NPP for all three regions, for cocoa densities of 600 trees per hectare (blue) and 719 trees per hectare (orange).

Table 1C Yield values for crops used to calculated NPP (see: Equation 1 [from Ramenkutty 2008]).

Crop		Yield Value (Mg ha^{-1})	Source
Cassava		11.9	Breisinger et al. 2008
		10.8	FAO, 2013
Plantain/Banana		8.1	Breisinger et al. 2008
		10.5	FAO, 2012
		8.2	FAO, 2012
		5.7	Norgrove & Hauser, 2014
		7.8	Norgrove & Hauser, 2014
Oil Palm		5.8	Rhebergen et al. 2016
		5.1	IPNI, 2015
		6.9	IPNI, 2015
		4.6	MASDAR, 2011
Vegetables	Yam	12.4	Breisinger et al. 2008
	Cocoyam	6.7	Breisinger et al. 2008
	Maize	1.5	Breisinger et al. 2008
	Tomatoes - Rainfed	25	Breisinger et al. 2008
	Okra	10.9	MOFA,2013
	Tomatoes	6	FAO, 2013
	onions	16.7	FAO, 2013
	Chillies and green pepper	6.5	FAO, 2013
	Chillies and green pepper	8.3	FAO, 2013

Appendix D: Social Survey Questions

SECTION LIST	COLOUR CODE
GENERAL DATA AND IDENTIFIERS	Asked in 2015
SECTION A - HOUSEHOLD DEMOGRAPHICS, PROFILE AND MIGRATION DATA	Asked in 2016
SECTION B - ASSETS AND ASSET RESPONSE TO DROUGHT	Asked in 2017
SECTION D - ABILITY TO MEET CRITICAL EXPENDITURES	Asked in 2015 and 2016
SECTION E - EXPENDITURE (poverty proxy)	Asked in 2016 and 2017
SECTION F - HOUSEHOLD INCOME SOURCES	Asked in all years
SECTION G = LAND QUESTIONS	
SECTION K = COCOA YIELD QUESTIONS	
SECTION M = OTHER CROP YIELD QUESTIONS	
SECTION Q - SHOCKS	

Section	QUESTION CODE	Description of question and codes for answer
GENERAL DATA AND IDENTIFIERS	UUID	
	DATE	
	LATTITUDE	
	LONGITUDE	
	VILLAGE	Village (1 = Ahomaho; 2 = Nsuoekyi; 3 = Kwameamoabeng; 4 = Tufokrom; 5 = Aboabo; 6 = Asorefie
	PLOTCODE	Ecology plot reference
	HOUSEHOLD CODE	
	EL NINO	
SECTION A - HOUSEHOLD DEMOGRAPHICS, PROFILE AND MIGRATION DATA	QA001	Gender (1 = Male; 2 = Female)
	QA002	Age
	QA003	Marital Status (1 = married; 2 = single; 3 = divorced; 4 = widowed; 5 = other)
	QA006	Second decision maker gender (1 = Male; 2 = Female)
	QA012	Children in household aged 0-5
	QA013	Children in household aged 6-12
	QA014	Children in household aged 13-17
	QA015	Other adult males (>18) in household
	QA016	Other adult females (>18) in household
	QA017	Years in village
	QA023	Has there been an increase in the number of people in your household during the last year? (0 = no; 1 = yes)
	QA024	Number of arrivals
	QA027_n	What is their age?
	QA030	Has there been a decrease in the number of people in your household? (0 = no; 1= yes)
	QA031	Number of departures
	QA034_n	What is their age?
SECTION B - ASSETS AND ASSET RESPONSE TO DROUGHT	QB001	Electricity (0 = no access to electricity; 1 = on grid; 2 = share from grid; 3 = own generator)
	QB002	Sanitation (0 = no; 1 = yes; 2 = share)
	QB003	Clean drinking water (0 = no; 1 = yes; 2 = share)
	QB004	Floor (0 = no; 1 = yes; 2 = share)
	QB005	Radio (0 = no; 1 = yes; 2 = share)
	QB006	TV (0 = no; 1 = yes; 2 = share)
	QB008	Bicycle (0 = no; 1 = yes; 2 = share)
	QB009	Motorbike (0 = no; 1 = yes; 2 = share)
	QB015	Bank account (0 = no; 1 = yes)
	QB018	House/plot elsewhere (0 = no; 1 = yes)
	QB021	Cattle (number)
	QB022	Sheep
	QB023	Chickens
	QB024	Goats
	QB025	Pigs
	QB026	Horses
	QB027	Donkeys
SECTION D - ABILITY TO MEET CRITICAL EXPENDITURES	QD001	Food amount (1 = no; 2 = yes - did not get enough food)
	QD002	Jan (food amount)
	QD003	Feb (food amount)
	QD004	Mar (food amount)
	QD005	Apr (food amount)
	QD006	May (food amount)
	QD007	Jun (food amount)
	QD008	Jul (food amount)
	QD009	Aug (food amount)
	QD010	Sep (food amount)
	QD011	Oct (food amount)
	QD012	Nov (food amount)

	QD013	Dec (food amount)
	QD014	Food variety (1 = no; 2 = yes - did not get adequate variety of food)
	QD015	Jan (food variety)
	QD016	Feb (food variety)
	QD017	Mar (food variety)
	QD018	Apr (food variety)
	QD019	May (food variety)
	QD020	Jun (food variety)
	QD021	Jul (food variety)
	QD022	Aug (food variety)
	QD023	Sep (food variety)
	QD024	Oct (food variety)
	QD025	Nov (food variety)
	QD026	Dec (food variety)
	QD027	Education (1 = no; 2 = yes - missed school; 3 = N/A)
	QD028	Jan (food variety)
	QD029	Feb (food variety)
	QD030	Mar (food variety)
	QD031	Apr (food variety)
	QD032	May (food variety)
	QD033	Jun (food variety)
	QD034	Jul (food variety)
	QD035	Aug (food variety)
	QD036	Sep (food variety)
	QD037	Oct (food variety)
	QD038	Nov (food variety)
	QD039	Dec (food variety)
	QD040	Medicines (1 = no; 2 = yes - did not get medicines when needed)
	QD041	Jan (medicines)
	QD042	Feb (medicines)
	QD043	Mar (medicines)
	QD044	Apr (medicines)
	QD045	May (medicines)
	QD046	Jun (medicines)
	QD047	Jul (medicines)
	QD048	Aug (medicines)
	QD049	Sep (medicines)
	QD050	Oct (medicines)
	QD051	Nov (medicines)
	QD052	Dec (medicines)
	QD053	Health centre (1 = no; 2 = yes - did not get access to health centre when needed)
	QD054	Jan (health centre)
	QD055	Feb (health centre)
	QD056	Mar (health centre)
	QD057	Apr (health centre)
	QD058	May (health centre)
	QD059	Jun (health centre)
	QD060	Jul (health centre)
	QD061	Aug (health centre)
	QD062	Sep (health centre)
	QD063	Oct (health centre)
	QD064	Nov (health centre)
	QD065	Dec (health centre)
	QD066	Funeral expenses (1 = no; 2 = could not afford)
	QD067	Jan (funerals)
	QD068	Feb (funerals)
	QD069	Mar (funerals)
	QD070	Apr (funerals)
	QD071	May (funerals)
	QD072	Jun (funerals)
	QD073	Jul (funerals)
	QD074	Aug (funerals)
	QD075	Sep (funerals)
	QD076	Oct (funerals)
	QD077	Nov (funerals)
	QD078	Dec (funerals)

SECTION E - EXPENDITURE (poverty proxy)	QE001	Cedis spent on food per week
	QE002	Cedis spent on sugar per week
	QE003	Cedis spent on oil per week
	QE004	Cedis spent on soap per week
	QE005	Cedis spent on water per week

	QF005	Cocoa farming (0 = no; 1 = yes)

	QF008	Cocoa income (cedis annual)
	QF009	Cocoa trading (PC) (0 = no; 1 = yes)
	QF012	Cocoa trading income (cedis annual)
	QF013	Annual crop farming (0 = no; 1 = yes)
	QF016	Annual crop farming income (cedis annual)
	QF017	Vegetable farming (0 = no; 1 = yes)
	QF020	Vegetable farming income (cedis annual)
	QF021	Rearing livestock (0 = no; 1 = yes)
	QF024	Rearing livestock income (cedis annual)
	QF025	Trading (0 = no; 1 = yes)
	QF032	Trading income (cedis annual)
	QF033	Preparing food/drink (0 = no; 1 = yes)
	QF035	Preparing food/drink income (cedis annual)
	QF036	Collecting fuelwood (0 = no; 1 = yes)
	QF038	Collecting fuelwood income (cedis annual)
	QF039	Charcoal (0 = no; 1 = yes)
	QF042	Charcoal income (cedis annual)
	QF043	Timber (0 = no; 1 = yes)
	QF045	Timber income (cedis annual)
	QF046	Chainsaw operating (0 = no; 1 = yes)
	QF048	Chainsaw operating income (cedis annual)
	QF049	Daily labouring (cocoa) (0 = no; 1 = yes)
	QF052	Daily labouring (cocoa) income (cedis annual)
	QF053	Daily labouring (food crops) (0 = no; 1 = yes)
	QF056	Daily labouring (food crops) income (cedis annual)
	QF057	Daily labouring (other) (0 = no; 1 = yes)
	QF060	Daily labouring (other) income (cedis annual)
	QF061	Oil palm (0 = no; 1 = yes)
	QF064	Oil palm income (cedis annual)
	QF065	Driving (0 = no; 1 = yes)
	QF067	Driving income (cedis annual)
	QF068	Remittances (0 = no; 1 = yes)
	QF071	Remittances income (cedis annual)
	QF072	Salaried position (0 = no; 1 = yes)
	QF076	Salaried position income (cedis annual)
	QF077	Pension (0 = no; 1 = yes)
	QF079	Pension income (cedis annual)
	QF080	NTFPs (0 = no; 1 = yes)
	QF083	NTFPs income (cedis annual)
	QF084	Sale of land (0 = no; 1 = yes)
	QF085	Sale of land income (cedis annual)
	QF086	Skilled labour (0 = no; 1 = yes)
	QF090	Skilled labour income (cedis annual)
	QF091	Making/selling wood products (0 = no; 1 = yes)
	QF093	Making/selling wood products income (cedis annual)
	QF094	Interest from loans (0 = no; 1 = yes)
	QF096	Interest from loans income (cedis annual)
	QF097	Small-scale mining (0 = no; 1 = yes)
	QF100	Small-scale mining income (cedis annual)
	QF101	Other income sources (0 = no; 1 = yes)
SECTION F - HOUSEHOLD INCOME SOURCES	QF103	Other income income (cedis annual)

	QG001	Homestead area (acres) (1 pole = 0.8 acres)
	QG002	Homestead crops (1 = no crops; 2 = Fallow; 3 = Cocoa; 4 = Oil Palm; 5 = Cassava; 6 = Plantain; 7 = Yam; 8 = Vegetables; 9 Maize; 10 = Sorghum; 11 = Coconut; 12 = Oranges; 13 = Other fruit; 14 = Trees for timber; 15 = cotton)
	QG003	Homestead crops (1 = no crops; 2 = Fallow; 3 = Cocoa; 4 = Oil Palm; 5 = Cassava; 6 = Plantain; 7 = Yam; 8 = Vegetables; 9 Maize; 10 = Sorghum; 11 = Coconut; 12 = Oranges; 13 = Other fruit; 14 = Trees for timber; 15 = cotton)
	QG004	Homestead crops (1 = no crops; 2 = Fallow; 3 = Cocoa; 4 = Oil Palm; 5 = Cassava; 6 = Plantain; 7 = Yam; 8 = Vegetables; 9 Maize; 10 = Sorghum; 11 = Coconut; 12 = Oranges; 13 = Other fruit; 14 = Trees for timber; 15 = cotton)
	QG005	Homestead crops (1 = no crops; 2 = Fallow; 3 = Cocoa; 4 = Oil Palm; 5 = Cassava; 6 = Plantain; 7 = Yam; 8 = Vegetables; 9 Maize; 10 = Sorghum; 11 = Coconut; 12 = Oranges; 13 = Other fruit; 14 = Trees for timber; 15 = cotton)
	QG006	Homestead crops (1 = no crops; 2 = Fallow; 3 = Cocoa; 4 = Oil Palm; 5 = Cassava; 6 = Plantain; 7 = Yam; 8 = Vegetables; 9 Maize; 10 = Sorghum; 11 = Coconut; 12 = Oranges; 13 = Other fruit; 14 = Trees for timber; 15 = cotton)
	QG007	Homestead crops (1 = no crops; 2 = Fallow; 3 = Cocoa; 4 = Oil Palm; 5 = Cassava; 6 = Plantain; 7 = Yam; 8 = Vegetables; 9 Maize; 10 = Sorghum; 11 = Coconut; 12 = Oranges; 13 = Other fruit; 14 = Trees for timber; 15 = cotton)

	QG008	Homestead crops (1 = no crops; 2 = Fallow; 3 = Cocoa; 4 = Oil Palm; 5 = Cassava; 6 = Plantain; 7 = Yam; 8 = Vegetables; 9 Maize; 10 = Sorghum; 11 = Coconut; 12 = Oranges; 13 = Other fruit; 14 = Trees for timber; 15 = cotton)
	QG009	Homestead crops (1 = no crops; 2 = Fallow; 3 = Cocoa; 4 = Oil Palm; 5 = Cassava; 6 = Plantain; 7 = Yam; 8 = Vegetables; 9 Maize; 10 = Sorghum; 11 = Coconut; 12 = Oranges; 13 = Other fruit; 14 = Trees for timber; 15 = cotton)
	QG010	Homestead crops (1 = no crops; 2 = Fallow; 3 = Cocoa; 4 = Oil Palm; 5 = Cassava; 6 = Plantain; 7 = Yam; 8 = Vegetables; 9 Maize; 10 = Sorghum; 11 = Coconut; 12 = Oranges; 13 = Other fruit; 14 = Trees for timber; 15 = cotton)
	QG011	Homestead crops (1 = no crops; 2 = Fallow; 3 = Cocoa; 4 = Oil Palm; 5 = Cassava; 6 = Plantain; 7 = Yam; 8 = Vegetables; 9 Maize; 10 = Sorghum; 11 = Coconut; 12 = Oranges; 13 = Other fruit; 14 = Trees for timber; 15 = cotton)
	QG012	Plots
	For each plot, the following questions were asked:	
	QG013_1	Plot area (acre)
	QG014_1	Plot distance (minutes walking)
	QG016_1	Main land-use (1 = Cocoa; 2 = Oil palm; 3 = Vegetables; 4 = Maize; 5 = Sorghum; 6 = Cassava; 7 = Plantain; 8 = Coconut; 9 = mixed food crops; 10 = Oranges; 11 = other fruit; 12 = trees for timber; 13 = Building; 14 = Primary forest; 15 = secondary forest; 16 = Millet; 17 = Sweet potato; 18 = sugar cane; 19 = rice; 20 = Yam/coco yam; 21 = Pepper; 22 = Groundnut; 23 = Fallow; 24 = don't know)
	QG017_1	Secondary land-use (1 = Cocoa; 2 = Oil palm; 3 = Vegetables; 4 = Maize; 5 = Sorghum; 6 = Cassava; 7 = Plantain; 8 = Coconut; 9 = mixed food crops; 10 = Oranges; 11 = other fruit; 12 = trees for timber; 13 = Building; 14 = Primary forest; 15 = secondary forest; 16 = Millet; 17 = Sweet potato; 18 = sugar cane; 19 = rice; 20 = Yam/coco yam; 21 = Pepper; 22 = Groundnut; 23 = Fallow; 24 = don't know)
	QG019_1	Land tenure (1 = Land owner; 2 = Land will be shared once cocoa matures; 3 = Receives share of yield abunu (1:1); 4 = Shares yield abunu (1:1); 5 = Receives share of yield abusa (1:2); 6 = Receives share of yield abusa (2:1); 7 = Receives share of yield abusa (1:1:1); 8 = Shares yield abusa (1:2); 9 = Shares yield abusa (1:2); 10 = Shares yield abusa (1:1:1); 11 = Pays annual rent to landowner (renting); 12 = Receives annual rent in cash; 13 = Land will be shared once oil palm matures; 14 = Land will return to landowner once oil palm or other crop has matured; 15 = proceeds used to maintain cocoa farm; 16 = Yield shared among family; 17 = All production is for the farmer; 18 = Owner comes occasionally for crops; 19 = Land with cocoa will be returned to once cocoa matures (Farmer keeps food crops while cocoa is established); 20 = Included as part of rental for another part of land)
	QG031	Has the land available to you for farming cocoa increased in the last year? (0 = 0; 1 = 1)
	QG032	Land area (acre)
	QG036	Has the land available to you for farming cocoa decreased in the last year? (0 = no; 1 = yes)
	QG037	Land area (acre)
	QG042	Has the land available to you for farming oil palm increased in the last year? (0 = no; 1 = yes)
	QG043	Land area (acre)
	QG047	Has the land available to you for farming oil palm decreased in the last year? (0 = no; 1 - yes)
	QG048	Land area (acre)
	QG053	Has the land available to you for farming annual crop increased in the last year? (0 = no; 1 = yes)
	QG054	Land area (acre)
	QG058	Has the land available to you for farming annual crop decreased in the last year? (0 = no; 1 = yes)
QG = Land questions	QG059	Land area (acre)

	QK001	Passbook available (1 = yes; 2 = no)
	QK002	Harvest last year - kg (May 2014-April 2015) '2015'
	QK003	Harvest (kg) May-July 2014
	QK004	Harvest (kg) Aug-Oct 2014
	QK005	Harvest (kg) Nov 2014 - Jan 2015
	QK006	Harvest (kg) Feb-Apr 2015
	QK007	Harvest (kg) 2014
	QK008	Harvest (kg) 2013
	QK009	Harvest (kg) 2012

QK = Cocoa yield questions	QK010	Harvest (kg) 2011
	QK011	Harvest (kg) 2010
	QK012	Harvest (kg) 2009
	QK026	How much cocoa did the farmer harvest in the last year (May 2015-June 2016) (kg)
	QK027	What has the impact of the extended dry season been on your yield of cocoa this year (light crop)? (0 = 100% less; 0.33 = Two-thirds less; 0.5 = Half less; 0.66 = One-third less; 0.75 = Quarter less; 1 = No change; 1.25 = Quarter more; 1.33 = One-third more; 1.5 = Half more; 1.66 = Two-thirds more; 2 = 100% more; 2 = More than 100% more; dn = Don't know)
	QK031	How much cocoa did the farmer harvest in the last year - heavy crop season August 2016 - March 2017) (kg)
	QK032	Compared to 2015-2016 heavy crop season (with the extended dry season), how is the yield of cocoa this heavy crop season (Oct- to date)? (0 = 100% less; 0.33 = Two-thirds less; 0.5 = Half less; 0.66 = One-third less; 0.75 = Quarter less; 1 = No change; 1.25 = Quarter more; 1.33 = One-third more; 1.5 = Half more; 1.66 = Two-thirds more; 2 = 100% more; 2 = More than 100% more; dn = Don't know)

	QM001	What has been the impact of the extended dry season on your maize? (1 = No change from a typical year; 2 = Some spoiling or crop loss (up to a third); 3 = A lot of spoiling or crop loss (between a third and two thirds); 4 = Very significant spoiling or crop loss (More than two thirds); 5 = Complete failure; 6 = Don't know/don't grow)
	QM003	In a normal dry season what proportion of your maize do you sell? (%)
	QM004	What proportion did you sell in this extended dry season? (%)
	QM005	What has been the impact of the extended dry season on your cassava? (1 = No change from a typical year; 2 = Some spoiling or crop loss (up to a third); 3 = A lot of spoiling or crop loss (between a third and two thirds); 4 = Very significant spoiling or crop loss (More than two thirds); 5 = Complete failure; 6 = Don't know/don't grow)
	QM007	In a normal dry season what proportion of your cassava do you sell? (%)
	QM008	What proportion did you sell in this extended dry season? (%)
	QM009	What has been the impact of the extended dry season on your plantain? (1 = No change from a typical year; 2 = Some spoiling or crop loss (up to a third); 3 = A lot of spoiling or crop loss (between a third and two thirds); 4 = Very significant spoiling or crop loss (More than two thirds); 5 = Complete failure; 6 = Don't know/don't grow)
	QM011	In a normal dry season what proportion of your plantain do you sell? (%)
	QM012	What proportion did you sell in this extended dry season? (%)
	QM013	What has been the impact of the extended dry season on your tomatoes? (1 = No change from a typical year; 2 = Some spoiling or crop loss (up to a third); 3 = A lot of spoiling or crop loss (between a third and two thirds); 4 = Very significant spoiling or crop loss (More than two thirds); 5 = Complete failure; 6 = Don't know/don't grow)
	QM015	In a normal dry season what proportion of your tomatoes do you sell? (%)
	QM016	What proportion did you sell in this extended dry season? (%)
	QM017	What has been the impact of the extended dry season on your oil palm? (1 = No change from a typical year; 2 = Some spoiling or crop loss (up to a third); 3 = A lot of spoiling or crop loss (between a third and two thirds); 4 = Very significant spoiling or crop loss (More than two thirds); 5 = Complete failure; 6 = Don't know/don't grow)
	QM019	In a normal dry season what proportion of your oil palm do you sell? (%)
	QM020	What proportion did you sell in this extended dry season? (%)
	QM024	Has there been a lasting impact of the extended dry season on your maize? (1 = No lasting/noticable difference; 2 = Some spoiling or crop loss (up to a third); 3 = A lot of spoiling or crop loss (between a third and two thirds); 4 = Very significant spoiling or crop loss (More than two thirds); 5 = Complete failure; 6 Don't know/don't grow)
	QM026	Has there been a lasting impact of the extended dry season on your cassava? (1 = No lasting/noticable difference; 2 = Some spoiling or crop loss (up to a third); 3 = A lot of spoiling or crop loss (between a third and two thirds); 4 = Very significant spoiling or crop loss (More than two thirds); 5 = Complete failure; 6 = Don't know/don't grow)

	QM028	Has there been a lasting impact of the extended dry season on your plantain? (1 = No lasting/noticable difference; 2 = Some spoiling or crop loss (up to a third); 3 = A lot of spoiling or crop loss (between a third and two thirds); 4 = Very significant spoiling or crop loss (More than two thirds); 5 = Complete failure; 6 Don't know/don't grow)
QM = other crop yield questions.	QM030	Has there been a lasting impact of the extended dry season on your tomatoes? (1 = No lasting/noticable difference; 2 = Some spoiling or crop loss (up to a third); 3 = A lot of spoiling or crop loss (between a third and two thirds); 4 = Very significant spoiling or crop loss (More than two thirds); 5 = Complete failure; 6 = Don't know/don't grow)

	QQ001	Drought (0 = no; 1 = yes)
	QQ002	Drought impact (0 = no impact; 1 = negative; 2 = very negative)
	QQ006	Drought NTFP importance (0 = do not use/not important; 1 = not very important; 2 = quite important; 3 = important; 4 = very important; 5 = essential)
	QQ076	How has household health been affected by the extended dry season? (0 = Not applicable (e.g. they don't grow the crop); 1 = Much worse; 2 = A bit worse; 3 = No impact; 4 = A bit better; 5 = Much better)
	QQ078	How has the extended drought affected the household's ability to meet educational needs? (0 = Not applicable (e.g. they don't grow the crop); 1 = Much worse; 2 = A bit worse; 3 = No impact; 4 = A bit better; 5 = Much better)
	QQ080	How has the amount of available food been affected by the extended dry season? (0 = Not applicable (e.g. they don't grow the crop); 1 = Much worse; 2 = A bit worse; 3 = No impact; 4 = A bit better; 5 = Much better)
	QQ082	How has the quality of food been affected by the extended dry season? (0 = Not applicable (e.g. they don't grow the crop); 1 = Much worse; 2 = A bit worse; 3 = No impact; 4 = A bit better; 5 = Much better)
	QQ084	How has the variety of food been affected by the extended dry season? (0 = Not applicable (e.g. they don't grow the crop); 1 = Much worse; 2 = A bit worse; 3 = No impact; 4 = A bit better; 5 = Much better)
	QQ086	How has the availability of clean drinking water been affected by the extended dry season? (0 = Not applicable (e.g. they don't grow the crop); 1 = Much worse; 2 = A bit worse; 3 = No impact; 4 = A bit better; 5 = Much better)
	QQ088	How has income from cocoa been affected by the extended dry season? (0 = Not applicable (e.g. they don't grow the crop); 1 = Much worse; 2 = A bit worse; 3 = No impact; 4 = A bit better; 5 = Much better)
	QQ090	How has income from oil palm been affected by the extended dry season? (0 = Not applicable (e.g. they don't grow the crop); 1 = Much worse; 2 = A bit worse; 3 = No impact; 4 = A bit better; 5 = Much better)
	QQ092	How has income from annual crops been affected by the extended dry season? (0 = Not applicable (e.g. they don't grow the crop); 1 = Much worse; 2 = A bit worse; 3 = No impact; 4 = A bit better; 5 = Much better)
	QQ095	Are there lasting impacts of the extended dry season on household health? (0 = no; 1 = yes)
	QQ097	Are there lasting impacts of the extended dry season on the household's ability to meet educational needs? (0 = no; 1 = yes)
	QQ099	Are there lasting impacts of the extended dry season on food availability? (0 = no; 1 = yes)
	QQ101	Are there lasting impacts of the extended dry season on the quality of food? (0 = no; 1 = yes)
	QQ103	Are there lasting impacts of the extended dry season on the variety of food? (0 = no; 1 = yes)
	QQ105	Are there lasting impacts of the extended dry season on the availability of clean drinking water? (0 = no; 1 = yes)
	QQ107	Are there lasting impacts of the extended dry season on income from cocoa? (0 = no; 1 = yes)
	QQ109	Are there lasting impacts of the extended dry season on income from oil palm? (0 = no; 1 = yes)
	QQ111	Are there lasting impacts of the extended dry season on income from annual crops? (0 = no; 1 = yes)

QQ - Shocks	QQ113	Have you been affected by any other shocks this year? (0 = No; 1 = Too much rain/flood; 2 = Storms; 3 = Pests or diseases that affected the crop catastrophically before harvest; 4 = Pests or diseases that affected the crop during storage; 5 = Cocoa bean theft; 6 = Livestock death; 7 = livestock theft; 8 = Input price increase; 9 = Fire; 10 = Forced migration; 11 = Contract disputes regarding land; 12 = Unexpected death)

Appendix E: Supplementary Model Results for Chapter 6

Table 1E. Result of the VIF analysis (test of colinarity) for all variables included in any model

Variable Name	Variable Description	VIF Score
D_House	Distance between main plot and homestead	1.424324
D_Forest	Distance between main plot and Kakum National Park	1.967497
GW_D	Ground Water Depth at main plot	1.710206
HAccess	Access to the nearest urban center (Assin Fosu) from homestead	1.927855
HouseHoldSize	Number of people in household	1.577449
HouseHoldSizeCng	Change in the number of people between 2015 and 2017	1.388671
a2015DR13	Dependency Ratio	1.485037
Asset_Change	Change in bulk assets (ie. tv, car, sprayer etc) between 2015 and 2017	1.479888
IncomeDiversity	Number of sources of income	1.665288
NumPlots	Total number of plots (including cocoa, subsistence and palm)	2.516911
CCOCrop	Number of cocoa crops	2.382077
SubCrop	Number of subsistence crops	2.207822
AvePlotD	Average distance between homestead and plots	1.233146

WetLand	Percieved access to wetlands during climate shock	1.445357
FoodSecurity2015	Perception of overall food security in 2015	1.736121
HealthLikert2015	Perception of access to health services in 2015	1.538263
Assets2015	Perception of access to new assets in 2015	1.854789
Education2015	Perception of access to education in 2015	1.66805
SatisfactionLikert2015	Overall satisfaction with life in 2015	1.514044
PDM	Gender of the principal decision maker	1.503087
SimpDiv	Simpsons Diversity Index of crops across all plots	2.104429
HANPP25m	HANPP score within a 25m buffer of main plot (including main plot)	1.609433
PalmOil	Number of plam oil crops	1.548413
Land_Tenure	Land tenure (1=ownership, 2=shared tenure)	1.581273

Table 2E. Results of the LRT Stepwise regression for the Resistance metric with AIC values, where * indicates variables included in the model, and darkened cells indicate variables which have been removed from the models.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
HouseHoldSize	*	*	*	*	*	*	*	*	*	*
IncomeDiversity	*	*	*	*	*	*	*	*	*	
PDM	*	*	*	*	*					
LandTenure	*									
NumPlots	*	*	*							
CCOCrop	*	*								
SubCrop	*	*	*	*						
GW_D	*	*	*	*	*	*	*	*	*	*
HANPP25m	*	*	*	*	*	*	*	*	*	*
Haccess	*	*	*	*	*	*				
DummyAB	*	*	*	*	*	*	*			
DummyHM	*	*	*	*	*	*	*	*		
AIC	**359.7**	**357.72**	**355.76**	**353.88**	**351.99**	**350.13**	**348.24**	**347.1**	**345.65**	**344.93**

Table 3E. Results of the LRT Stepwise regression for the Recovery metric with AIC values, where * indicates variables included in the model, and darkened cells indicate variables which have been removed from the models.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
HouseHoldSize	*	*	*	*	*				
IncomeDiversity	*	*							
PDM	*	*	*	*	*	*	*	*	*
LandTenure	*	*	*	*					
NumPlots	*	*	*	*	*	*	*		
CCOCrop	*	*	*						
SubCrop	*	*	*	*	*	*	*	*	
GW_D	*	*	*	*	*	*	*	*	*
HANPP25m	*	*	*	*	*	*			
Haccess	*	*	*	*	*	*	*	*	*
DummyAB	*								
DummyHM	*	*	*	*	*	*	*	*	*
AIC	105.65	103.65	101.68	106.21	99.74	97.82	95.92	94.96	94.26