ABSTRACT

Title of Dissertation: INTERDISCIPLINARY GEOSPATIAL ASSESSMENT OF MALARIA EXPOSURE IN ANN TOWNSHIP, MYANMAR

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Despite considerable progress toward malaria elimination in Myanmar, challenges remain owing to the persistence of complex focal transmission reservoirs. Nearly all remaining infections are clinically silent, rendering them invisible to routine monitoring. Moreover, limited knowledge of population distributions and human activity on the landscape in remote regions of Myanmar hinders the development of targeted malaria elimination approaches, as advocated by the World Health Organization (WHO). This is especially true for Ann Township, a remote region of Myanmar with a high malaria burden, where a comprehensive understanding of local exposure, which includes the characterization of environmental settings and land use activities, is crucial to developing successful malaria elimination strategies. In this dissertation, I present an interdisciplinary approach that combines satellite earth observations with two separate on-the-ground surveys to assess human exposure to malaria at multiple scales. First, I mapped rural settlements using a fusion of Landsat imagery and multi-temporal auxiliary data sensitive to human activity patterns with a classification accuracy of 93.1%. A satellite data-based map of land cover and land use was then used to assess landscape-scale malaria exposure as a function of

environmental settings for a subset of ten villages where a malaria prevalence survey was carried out. While multiple significant associations were discovered, the relationship found between malaria exposure and satellite-measured village forest cover was the most significant. Finally, a separate detailed survey that explored a variety of land use activities, including their frequency and duration along with testing for clinical or subclinical malaria, was used to identify and quantify factors promoting an individual's likelihood of malaria infection regardless of the environmental settings. This analysis established strong associations between malaria and individual land use activities that bring respondents into direct contact with forested areas. These results highlight that the current Myanmar malaria elimination strategies, which focus on prevention from within the home (i.e., bednets and indoor spraying), are no longer sufficient to remove remaining malaria reservoirs in the country. A paradigm shift in malaria elimination strategies towards targeted interventions that can disrupt malaria transmission in the settings where the exposure occurs are critical to achieving country-wide malaria elimination.

INTERDISCIPLINARY GEOSPATIAL ASSESSMENT OF MALARIA EXPOSURE IN ANN TOWNSHIP, MYANMAR

by

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Dissertation submitted to the Faculty of the Graduate School of the
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Dedication

For Chip and Posy – my biggest distractions and greatest joys.

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To Lucas, for being my partner in this, and in everything else.

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List of Abbreviations

API	Annual Parasite Incidence
CDC	Centers for Disease Control
CI	Confidence Interval
CSO	Central Statistical Organization (Myanmar)
DEM	Digital Elevation Model
DMSP	Defense Meteorological Satellite Program
ETM+	Enhanced Thematic Mapper
EVI	Enhanced Vegetation Index
GIS	Geospatial Information Science/Geographic Information Systems
GFC	Global Forest Change
GFSAD	Global Food Security Support Analysis Data
GHS	Global Human Settlement
GMIS	Global Man-made Impervious Surface
GMS	Greater Mekong Subregion
IPCC	Intergovernmental Panel on Climate Change
LaSRC	Land Surface Reflectance Code
LCLU	Land Cover Land Use
LUI	Land Use Index
MIMU	Myanmar Information Management Unit
MODIS	Moderate Resolution Imaging Spectroradiometer
MPHC	Myanmar Population and Housing Census
MSAVI	Modified Soil-Adjusted Vegetation Index
NASA	National Aeronautics and Space Administration
NBR	Normalized Burn Ratio
NDMI	Normalized Difference Moisture Index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NIR	Near Infrared
NMCP	National Malaria Control Programme (Myanmar)
OLI	Operational Land Imager
OR	Odds Ratio
SAVI	Soil-Adjusted Vegetation Index
SRTM	Shuttle Radar Topography Mission
SWF	Surface Water Fraction
SWIR	Shortwave Infrared
TIRS	Thermal Infrared Sensor
TM	Thematic Mapper
TOA	Top of Atmosphere
UNDP	United Nations Development Programme
usPCR	Ultrasensitive Polymerase Chain Reaction
VHR	Very High Resolution
VI	Vegetation Index
VIIRS	Visible Infrared Imaging Radiometer Suite
WHO	World Health Organization

Chapter 1: Introduction

For over 500,000 years, malaria, a mosquito-borne infectious disease caused by parasites in the blood, has plagued humankind. Very few civilizations have been able to escape its wrath. Egyptian mummies have been found showing signs of malaria (Miller et al., 1994). There is evidence that Alexander the Great may have died of malaria (Cunha, 2004), and George Washington and Abraham Lincoln both suffered from malaria (Nicolay, 2016; Randall, 1998). During World War II, high rates of malaria in the Pacific Theater contributed to an estimated loss of 9 million working days (Bruce-Chwatt, 1985). Today, despite enormous control efforts over several decades, malaria still rampages across the globe. In the most recent World Health Organization (WHO) malaria report from 2018, there were 228 million malaria cases and 405,000 deaths (WHO, 2019). Although tremendous scientific advances in preventing and treating malaria have been made for over a century, the global community remains unable to meet the WHO's goal of malaria elimination: the interruption of local transmission of malaria in a defined geographical area. Further still are we from the goal of eradication: complete and permanent worldwide reduction to zero new cases.

Five known malaria parasite species can infect humans: *Plasmodium malariae, P. vivax, P. ovale, P. knowlesi,* and, the most deadly and devastating, *P. falciparum.* These parasites have been evolving and adapting for hundreds of thousands of years. The human genome has adapted as well, through mutations like the Duffy and sickle-cell genes, which, while protective against malaria, bring with them a host of other medical challenges. Therefore, the primary strategies for malaria elimination have focused on prevention and treatment. However, the speed at which malaria adapts presents an ever-moving target. For example, research on artemisinin drugs, found to be useful for the treatment of malaria, was first published in 1979 (Qinghaosu Antimalaria Coordinating Research Group, 1979), but then only adopted by the WHO as an accepted malaria treatment in 2006 (White et al., 2015). Unfortunately, parasites resistant to artemisinin have already been reported in the Greater Mekong Subregion (GMS) (Ashley et al., 2014).

Further complicating matters is the relative lack of knowledge regarding the geography of malaria transmission. In his classic malaria textbook, L.W. Hackett (1937) wrote,

> *"…the best method to control malaria in one place may be the worst possible thing to do only forty miles away. A mosquito, harmless in Java, is found to be the chief vector in the interior of Sumatra. A method of treatment unusally [sic] effective in India is almost without effect in Sardinia. The half-mile radius, sufficient for larval control in Malaya, has to be quintupled in the Meditteranean [sic] basin. A village in Spain, in which half the population is in bed with chills and fevers in August, turns out to be less infected than a village in Africa where virtually no one has to abandon work on account of malaria at any time. Everything about malaria is so moulded [sic] and altered by local conditions that it becomes a thousand different diseases and epidemiological puzzles. Like chess, it is played with a few pieces, but is capable of an infinite variety of situations".*

While Hackett's observation was published over 80 years ago, this quote demonstrates the same spatial heterogeneity observed for modern malaria. Due to the complex mechanisms of malaria transmission involving coupled human and natural systems, in order for malaria elimination strategies to be locally-viable, they must be firmly rooted in an understanding of region-specific malaria ecology. This understanding is best captured through a multi-disciplinary approach. The complexity of malaria does not lend itself well to study by a single scientific discipline. Methodologies and approaches from disciplines such as geography, biomedical sciences, public health, epidemiology, entomology, ecology, anthropology, and more are all crucial to understanding the nuances of regionally-specific malaria. This dissertation seeks to use an interdisciplinary approach to assess malaria exposure for a constricted geographic location, Ann Township, Rakhine State, Myanmar.

1.1 Background and Motivation

Eliminating malaria from a country or region depends on that area's ability to interrupt the local transmission of malaria. Some of the world's largest intergovernmental organizations have committed considerable resources to achieve this goal. In 2013 the United Nations released its ambitious Sustainable Development Goals for the year 2030. Goal 3, Target 3.3 directly relates to malaria by setting a goal to "*end the epidemics of AIDS, tuberculosis, malaria, and neglected tropical diseases*" (Griggs et al., 2013). Similarly, the WHO released its own ambitious goal for malaria in 2016, namely at least a 40% reduction in malaria cases by 2020, at least 75% by 2025, and at least 90% by 2030 (WHO, 2015a). However, as we enter into the first milestone year of the WHO's plan, only 31 countries out of the 92 where malaria is endemic are on track to achieve that goal (WHO, 2019).

In response, the WHO shifted its priorities to a new aggressive plan titled *High burden to high impact: a targeted malaria response* (WHO, 2019). Four key elements define this new plan, the second of which includes moving away from a "one-size-fits-all" approach and instead using data-driven methodologies to pinpoint where to deploy the most effective malaria control tools for maximum impact. Where some of this impact has been felt the strongest is within the GMS. Alongside the release of the targeted WHO 2030 goals, the organization also developed the *Strategy for Malaria Elimination in the Greater Mekong Subregion* (WHO, 2015b). Since the implementation of this strategy, malaria cases have fallen dramatically across the region.

One of the greatest success stories from the GMS is the country of Myanmar. From 2012 – 2018, Myanmar saw a reduction of 82% of all malaria cases (Figure 1-1) (WHO, 2018). However, the country is facing numerous challenges which could inhibit its forward progress, including artemisinin-resistant parasites, insecticide-resistant malaria vectors (WHO, 2018), and lengthy borders with other malarious countries (Bhumiratana et al., 2013; Kounnavong et al., 2017; Parker et al., 2015).

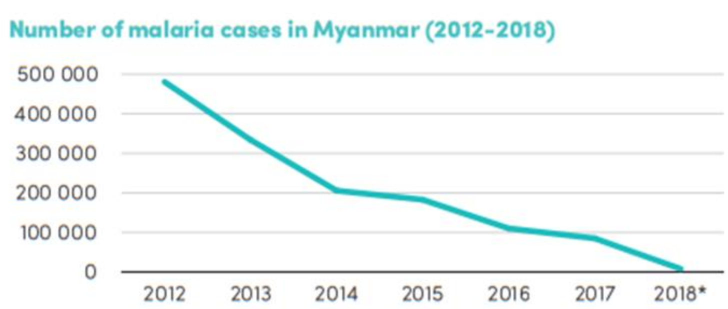


Figure 1-1: Number of Malaria cases in Myanmar (2012-2018). Malaria in the country has fallen by 82% since 2010 (WHO, 2018)

With this incredible progress, Myanmar is now classified as having "low malaria transmission," which presents significant challenges to driving out the last few malaria hotspots. When Myanmar was considered to have "high malaria transmission," broad coverage malaria interventions like providing bed nets to citizens were highly effective. Now though, the remaining malaria prevalence across Myanmar is heterogeneous, patchy, and complex. Following the call from the WHO to pinpoint malaria control for the highest impact and the urgency of keeping momentum in Myanmar, now more than ever, it is critical to find feasible ways to identify populations that are most at risk of malaria for targeted intervention.

Further complicating matters is the high prevalence of asymptomatic, low-density malaria infections (Adams et al., 2015; Imwong et al., 2015, 2014). While symptomatic cases are more likely to seek treatment, allowing for easier monitoring and, therefore, disruption of transmission, asymptomatic carriers are unaware of the need to seek treatment and therefore represent a silent and long-lasting reservoir that can significantly hinder elimination efforts (Lindblade et al., 2013). Strategies that rely on self-reporting of infection to track malaria hotspots will be insufficient when seeking to eliminate the last few pools of malaria remaining in the country. While a census level collection of blood samples would be the ideal way to identify these remaining parasite pools, such an undertaking would be extremely costly and challenging to implement. A framework of risk, which can be used to identify likely hotspots of infection, is needed to inform the sampling scheme necessary to capture the few remaining malaria reservoirs.

1.1.1 Malaria Transmission Risk Framework

There are many definitions, equations, and frameworks to describe the concept of risk. In simple, statistical terms, risk is the probability of a given (frequently negative) outcome. In epidemiology, risk is defined as the probability that a particular outcome will occur *following a specific exposure* (Last et al., 2001). These definitions are helpful from a medical and health perspective. For example, smoking increases a person's risk of developing lung cancer. However, when discussing the risk of a population-wide outbreak of malaria, these definitions fall short. Malaria is a disease that combines both human and environmental elements. Therefore, a framework of risk that assesses the impacts of Climate Change, another socio-ecological phenomenon, can be a useful tool in conceptualizing malaria risk.

The Intergovernmental Panel on Climate Change (IPCC) defines risk as *"the possibility of adverse effects in the future; derived from the combination of physical hazards and the vulnerabilities of exposed elements"* (IPCC, 2014). The hazard event is not the only determinant of risk; risk is also governed by the vulnerability and exposure of societies and social-ecological systems. When thought of in these terms, risk can be explained as a function of hazard, vulnerability, and exposure (Figure 1-2).

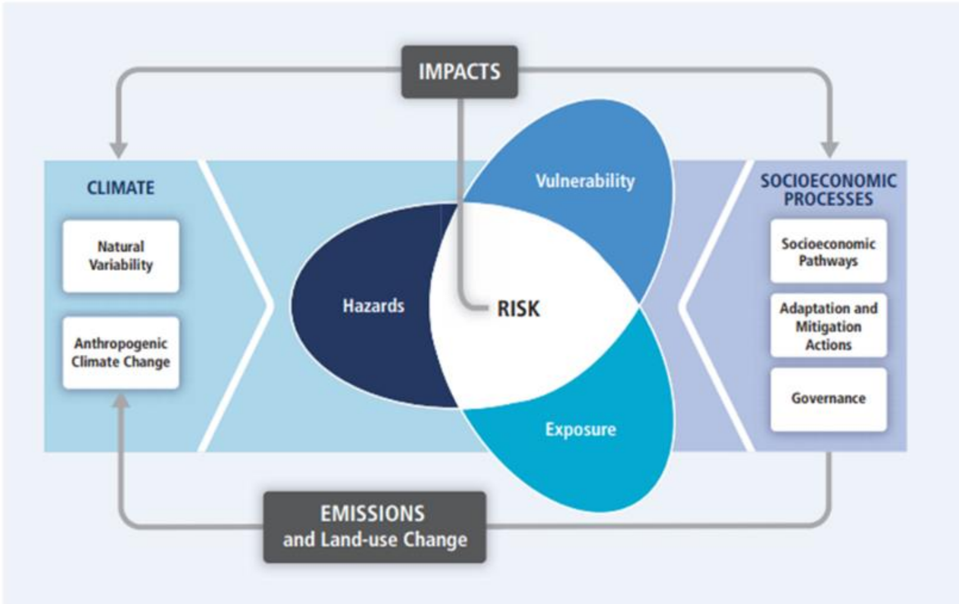


Figure 1-2: IPCC Risk Framework (IPCC, 2014)

While the IPCC framework also includes socio-economic processes and climate variabilities which influence risk from the outside, the inner Venn diagram of risk, composed of hazards, vulnerability, and exposure, is the framework highly applicable to malaria (Figure 1-2). The IPCC defines a hazard as "*a natural or human-induced event or trend that may cause loss of life, injury, or other health impacts.*" Within this framework, vulnerability is defined as "*situation-specific propensity or predisposition to be adversely affected. Includes sensitivity (susceptibility to harm) and coping capacity (positive features of people or society that may reduce the risk posed by a certain hazard)*." The final piece of the framework, exposure, is defined as "*the inventory of elements (people, infrastructure, etc.) in an area in which hazard events may occur*." While these three terms – exposure, vulnerability, and hazard – are widespread among the climate change science community (Cooper et al., 2019; Kakota et al., 2011; Krishnamurthy et al., 2014; Mach et al., 2016; Silva et al., 2015), they are more rarely found in malaria research, where a propensity towards equating malaria risk to vector abundance exists. While vector abundance may be a suitable proxy for malaria risk in hyperendemic areas, within low transmission regions, a more nuanced understanding of risk is required. Indeed, previous research has shown that vector abundances do not translate well to malaria prevalence (Mwakalinga et al., 2016; Ngom and Siegmund, 2010).

For my dissertation, I have adjusted the IPCC framework for the goal of malaria elimination – the disruption of local malaria transmission in a defined geographical area. Risk within this dissertation is defined as the risk of malaria occurrence (i.e., parasites present in the blood of a human). When risk is framed this way, the interconnected facets of risk – hazards, exposure, and vulnerability are defined slightly differently than they are for the original IPCC framework (Figure 1-3).

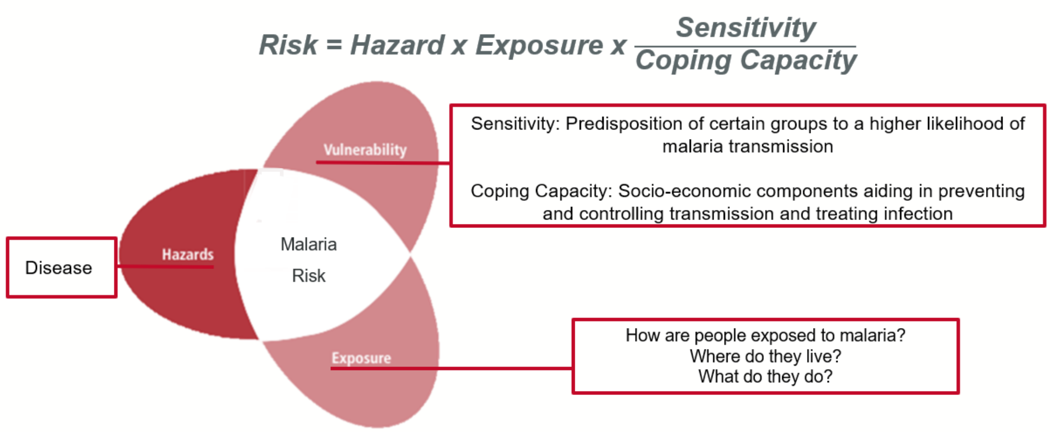


Figure 1-3: Adaptation of the IPCC Risk Framework for Malaria Risk

1.1.1.1 Risk Framework: Hazard

The hazard portion of this framework is the most easily defined and has also received the highest level of attention within the malaria research community. The hazard here is defined as the disease itself, specifically the combination of the malaria parasite (*Plasmodium spp.*) and a mosquito vector (*Anopheles spp.*). Five of the 100 species of

Plasmodium have been recognized to infect humans in nature: *P. malariae, P. knowlesi, P. ovale, P. vivax*, and *P. falciparum* (CDC, 2017). Roughly 70 of the 430 different species of *Anopheles* can transmit malaria (Shah, 2010). These different malaria and mosquito species can be found in nearly all parts of the world (except Polynesia east of Vanuatu), with each species exploiting a slightly different ecological niche (Shah, 2010). For example, *P. falciparum*, which needs continuous infection and spreading to survive and reproduce, can be spread by *An. gamibae,* which prefers year-round warm temperatures and sunny puddles for egg-laying (Shah, 2010). *P. vivax*, which can remain dormant in the liver for years (Huldén et al., 2008), can be spread by *An. labrinachae*, a European mosquito capable of hibernating over winter (Shah, 2010). *An. dirus,* the primary malaria vector in Southeast Asia, prefers forests and wells (Oo, Storch and Becker 2004), while *An. minimus*, another common Southeast Asian vector, can be found in foothills and areas with extensive irrigation systems (Oo et al. 2004).

Plasmodium spp. is a true parasite, which implies that the individuals cannot survive outside of the host body for any length of time. At no point in the parasite life-cycle is malaria contagious between humans. Moreover, the parasites undergo different stages of development within the mosquito and human hosts. In humans, the parasites grow and multiply first in the liver and then later in red blood cells. Once the parasite reaches the blood-stage, it becomes contagious and can be ingested by a female *Anopheles spp.* mosquito. Within the mosquito, the parasites mate and grow for 10-18 days before sporozoites migrate to the salivary glands of the mosquito. Once that occurs, and the mosquito bites another human, the sporozoites are injected and migrate to the liver, starting the cycle all over again (CDC, 2019). Thus, although there may be a strong link between mosquito abundance and the potential for malaria occurrence, the relationship is not strongly predictive, as illustrated by the general lack of malaria in the southeastern US despite the high abundance of *Anopheles spp.* mosquitoes. Therefore, while *Anopheles spp.* abundance is a critical factor in the disease transmission and spread within the presented framework is serves as a constituent of the hazard component of the framework.

1.1.1.2 Risk Framework: Vulnerability

Vulnerability combines sensitivity and coping capacity. Sensitivity here is defined as the predisposition of certain groups to a higher likelihood of malaria infection, referring directly to demographics, health status, and genetics. For example, in high malaria transmission regions, children aged 1 – 5 are the most sensitive to malaria infection (Sachs and Malaney, 2002). Pregnancy has been shown to lower malaria immunity as well, increasing sensitivity for pregnant women (WHO, 2002). HIV infection has also been implicated as increasing a person's sensitivity to malaria (French et al., 2001). Genetically, certain ethnic groups have been shown to possess higher malaria antibodies than similarly exposed groups (Modiano et al., 1999), and certain genetic mutations, such as the sickle-cell gene, can reduce malaria sensitivity (Aidoo et al., 2002).

Coping capacity refers to socio-economic components that aid in the prevention and control of malaria transmission or treatment of infection. These include factors such as socio-economic status, political stability, health care accessibility, education, and government prevention programs (Bates et al., 2004, 2004).

1.1.1.3 Risk Framework: Exposure

The definition of exposure within my risk framework (Figure 1-3) is the most dissimilar to the definition provided by the IPCC. It is more similar instead to the concept of exposure from the field of epidemiology, which defines exposure as contact with some agent at the boundary between humans and the environment, at a specific concentration, over an interval of time, which can be harmful or beneficial to a subject’s health (Wallace, 1995). Therefore, exposure within my framework refers to the ways that people come into contact with malaria (i.e., the hazard of parasites plus mosquitos) as a function of where they live and what they do throughout the day.

Unfortunately, measuring the specific concentrations of malaria exposure is impossible without the ability to quantify how many mosquitoes (infected with parasites at the exact right life cycle stage for sporozoite production) a person comes into contact with each day. However, we do have the ability to measure where people are living and estimate how often they are venturing into landscapes where exposure to the malaria hazard is likely to be higher. Therefore, the relevant proxy variables which can be used to describe exposure are population distribution and local environment (where they live), and land use, occupation, and mobility (what they do). Each of these proxies varies with local processes of landscape use, similar to how exposure varies locally. Regarding population distribution, Sturrock et al. (2013) note that at large spatial scales, infections tend to cluster into foci related to environmental, climatic, and ecological suitability for vectors and transmission. However, at smaller scales within these foci, "hotspots," which consist of a household or groups of households, maintain higher transmission of malaria and are a consistent reservoir of parasites throughout the year. Therefore, in low transmission areas, especially, fine-scale population distribution data will be needed for successful targeted interventions.

In terms of what people do throughout their day that increases their likelihood of exposure to a malaria vector, exciting work is being done which assesses malaria risk through the lens of human mobility and migration (Chang et al., 2019; Li et al., 2020; Rodrigues et al., 2018; Ruktanonchai et al., 2016; Sorichetta et al., 2016). Much of the work that has been done in terms of land use, however, has focused on land use and its relationship to vector ecology (Pope et al., 2005; Vanwambeke et al., 2007), primarily assessing which areas (croplands, forests, etc.) have the highest abundances of mosquitoes. What these studies fail to capture is if, when, and how often humans engage with those areas of high mosquito abundance, thereby increasing their exposure.

A few studies have sought to capture this by investigating occupations and livelihoods. For example, Zaw et al. (2017) found a higher prevalence of asymptomatic malaria among Myanmar workers with forest-related occupations, with an odds ratio approximately ten times greater than study participants whose occupation was not forest-related. Soe et al. (2017) found high associations between malaria morbidity and occupation, with fire woodcutters at the highest risk and night-time rubber tree tappers at the lowest risk. What these studies fail to capture are the other ways that people are engaging with their landscapes throughout the day that are not directly related to their occupation (i.e., conducting chores, tending to subsistence crops, etc.).

This dissertation seeks to understand better the human behaviors which influence malaria exposure. Specifically, my goal is to use innovative satellite remote sensing techniques alongside comprehensive qualitative survey data to assess exposure as a function of population distribution, landscape environmental settings, and human land use activities.

1.1.2 Disease Risk Mapping and Modeling using Remote Sensing Technologies

Satellite remote sensing (technologies and methods which quantify the physical properties of the Earth's surface through satellite collection of reflected or emitted electromagnetic energy) has been promoted over the past two decades as a useful tool for public health and epidemiological studies (Curran et al., 2000; Hay, 2000; Rochon et al., 2010). Imagery and data captured by satellites and the tools and methodologies used to analyze that data have prompted many advances in epidemiological exposure assessment. As a result, many epidemiological studies are using remotely sensed data to quantify or improve the quantification of acute environmental exposures, such as wildfire smoke (Mirzaei et al., 2018; Yao and Henderson, 2014) and extreme temperature events (Buscail et al., 2012; Johnson et al., 2009), or more chronic exposures like air pollution (Kloog et al., 2012; Puett et al., 2019; Yanosky et al., 2018).

Remotely sensed data and technologies have also been used for malaria risk mapping, forecasting, and hotspot targeting since the early 1990s (Pope et al., 1994; Rahman et al., 2010; Rogers et al., 2002; Sithiprasasna et al., 2003; Thomson et al., 2006). These studies have used remote sensing primarily for its capacity to measure environmental variables, which are associated with the habitat suitability and population dynamics of the malaria mosquito vector, such as temperature, rainfall, and land cover. When these environmental variables are forecast over space and time, predictive maps of vector densities can be created. However, previous studies have shown that models that rely solely on vector densities are only loosely associated with actual malaria prevalence. Models that incorporate factors relating to human behavior and human population, alongside vector densities, align better with observed malaria distribution (Moffett et al., 2007; Mwakalinga et al., 2016; Ngom and Siegmund, 2010).

While the satellite remote sensing field has been dominated by the physical sciences since its earliest inception, exciting work is being conducted in the social sciences using satellite remote sensing. Remotely sensed imagery is being integrated with socio-economic data in innovative ways to study issues such as poverty (Jean et al., 2016; Silva et al., 2018), natural disaster impacts (Dennis et al., 2005; Ghaffarian et al., 2018), macroeconomic change (Ying et al., 2019), and even the ability to detect looting at cultural heritage sites (Agapiou et al., 2017). The most substantial contribution to social science through satellite remote sensing though has been through population mapping. There exists a long history of innovative uses of satellite data to map human population distribution and quantify population density (Bartholomé and Belward, 2005; Bhaduri et al., 2007; Doxsey-Whitfield et al., 2015; Elvidge et al., 2001; Gaughan et al., 2013; Pesaresi et al., 2013)

Perhaps the most critical benefit of satellite remote sensing is its global coverage. Satellite remote sensing is of particularly high value for developing data-poor countries. Environmental or surveyed data are typically more challenging to locate or collect in marginalized areas. For Myanmar specifically, before the 2014 census, the last census was conducted in 1983. Additionally, the USAID Demographic and Health Surveys program, which has been in operation since 1985, only conducted its first Myanmar survey in 2015. For research conducted between censuses or without the aid of survey data, it is crucial to determine the feasibility of using data with a high temporal resolution with broad areal coverage, such as that offered by various remote sensing satellites.

Considering that surveying is often prohibitively expensive and often not feasible in remote hard-to-reach areas, many of the parameters describing potential malaria exposure can be captured through satellite-based land cover and land use (LCLU) mapping. Land cover (LC) describes the physical properties of the landscape (tree, shrub or grass cover, open water, impervious surface, etc.). In contrast, land use (LU) describes how humans are using the land in question (plantation, natural forest, built structures, cropped areas). In combination, LCLU maps can be used as a proxy for human activity on the landscape, allowing for incorporating exposure metrics into malaria models.

1.1.3 Ann Township, Rakhine State, Myanmar

While recent research has been published on the area of Myanmar bordering Thailand (Imwong et al., 2015; Parker et al., 2015) – little research is available regarding malaria in the western states of Myanmar. The westernmost of these is Rakhine State. Rakhine exhibits a high malaria burden; the estimated malaria Annual Parasite Incidence (API) for Rakhine is 9.54 in 1,000 population (NMCP, 2017), which is much higher than the estimated API of 0.14 and 0.29 for neighboring regions Magway and Bago, respectively. The state is also politically unstable, which has implications for limiting government services and access to medical care, which aids in the persistence and spread of malaria. An estimated 41.6% of people in Rakhine live in poverty (CSO, UNDP, and WB, 2018), which reduces residents coping capacity. However, the socio-economic profile of Myanmar overall is shifting rapidly, after the dissolution of the military junta in 2011 and greater integration between the country and the broader financial world.

I have chosen to focus my dissertation on Ann Township (Figure 1-4), a small township within Rakhine, similar in size and scope to that of a county in the United States.

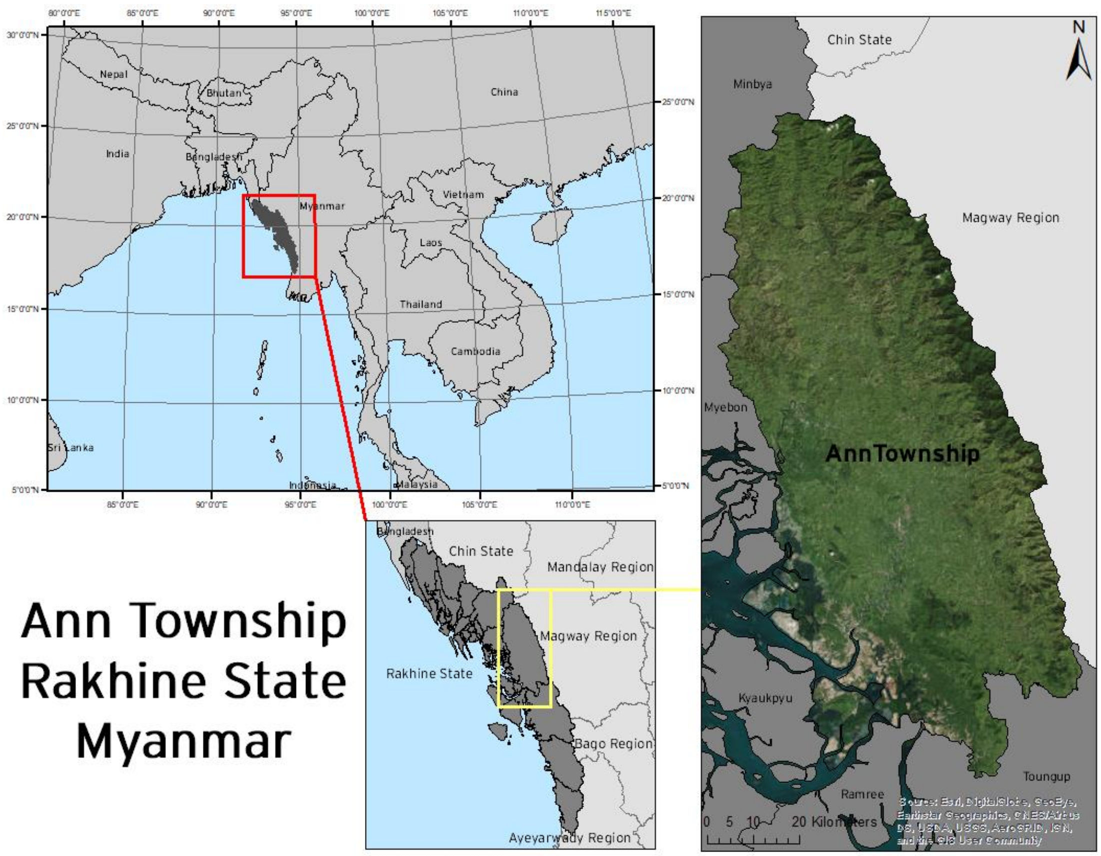
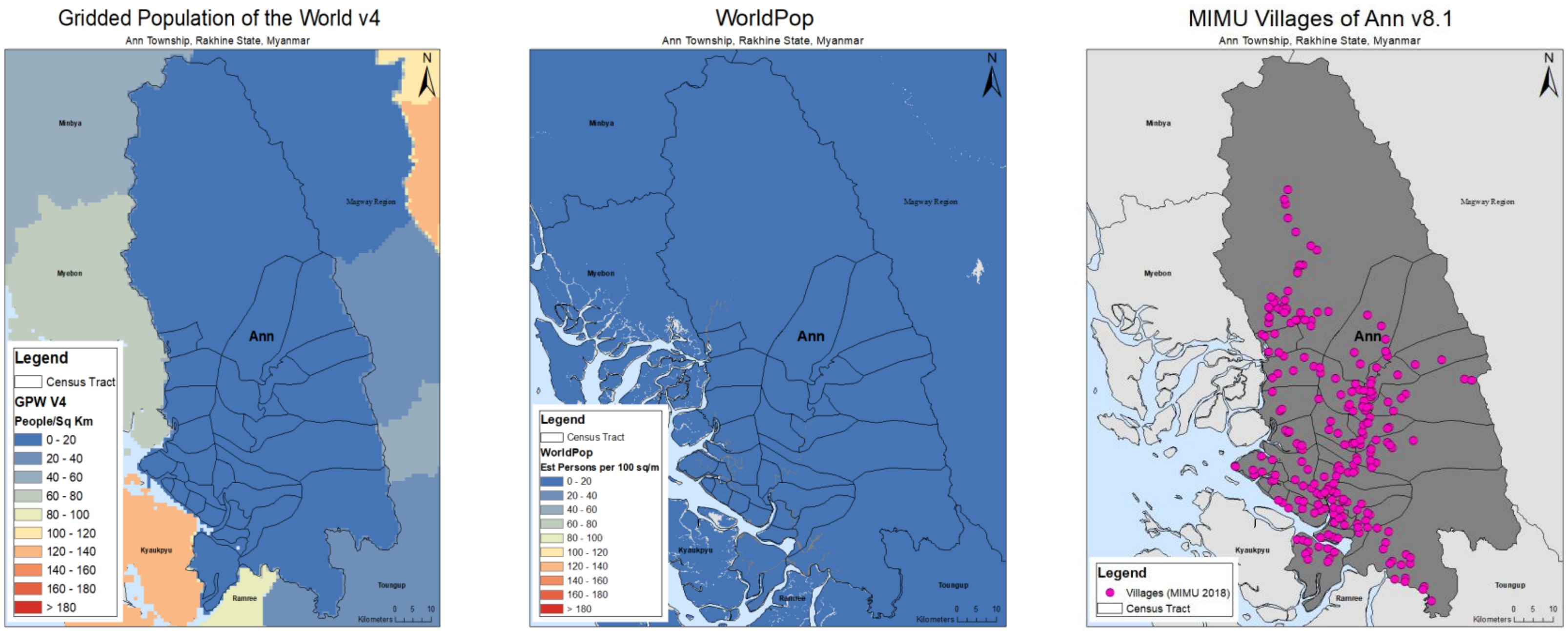


Figure 1-4: Map detailing the location of the study area: Ann Township, within Rakhine State, within the country of Myanmar.

Ann Township stretches from the west coast eastward to mountainous terrain. Ann specifically carries a high malaria caseload, in comparison with other GMS locations, and the largest asymptomatic reservoir, detected by sensitive molecular techniques (unpublished data, Nyunt), despite an overall low transmission rate. The primary malaria vector is the forest-dwelling *Anopheles dirus*, which displays a post-monsoon transmission season (peak in October). The secondary is the foothill and valley-dwelling *Anopheles minimus*, with a well-marked pre-monsoon transmission season (peak in May and June) and a post-monsoon incidence (peak in November and December) (Oo et al., 2004). Malaria parasites *Plasmodium vivax* and *P. falciparum* are most commonly identified in the region; however, *P. knowlesi* has been recently identified elsewhere in Myanmar (Ghinai et al., 2017; Jiang et al., 2010).

The population of Ann is dynamic and distributed across the landscape in a highly uneven pattern. This results in isolated groups of people that can serve as primary drivers of infectious diseases (in this case, malaria) into previously disease-free regions upon migration or travel (Martens and Hall, 2000). While most of the population lives in the southwest coastal area, visual analysis of very high resolution imagery shows that small to medium settlements of 2 – 20 homes or structures extend well north into the mountains. Known village locations provided by the Myanmar Information Management Unit (MIMU), display a population distribution pattern that is poorly represented by publicly available population gridded datasets (Figure 1-5).



(a) (b) (c)

Figure 1-5: Comparison of two popular gridded global population products with locations of known settlements in Ann. (a) Gridded Population of the World v4; (b) WorldPop; (c) MIMU v8.1

As a remote and isolated region with a current high malaria burden, this Township has the potential to become a notable source of malaria infection across Myanmar and South Asia (particularly towards bordering Bangladesh and India). With the anticipation of a more open Myanmar society and a greater integration in the country-wide and regional economic activity, malaria control within Ann Township is a crucial component of a successful malaria elimination agenda in Southeast Asia and globally.

1.2 Research Questions

A full understanding of local malaria exposure is crucial to develop successful targeted malaria elimination strategies. As described in Section 1.1.1.3, exposure within the scope of this dissertation will focus on where people live (population distribution and village environment) and what they do (land use and occupation). Therefore, the overarching research question that this dissertation seeks to answer is,

What landscape ecological factors and individual land use activity patterns are contributing to the observed differences in malaria presence and prevalence between the villages of Ann Township in Rakhine State, Myanmar?

To answer this question, I will conduct three integrated studies to examine the heterogeneous and complex malaria exposure patterns within Ann Township. These studies will encompass the dual facets of malaria exposure (i.e., where people live and what they do), while also taking into consideration the three geographic scales that govern exposure. Namely, regional scale (population distribution), village scale (village environmental settings), and individual scale (land use and occupation). While these three integrated studies will be guided primarily by science questions, each study will also include a component of methodological advances from the field of satellite remote sensing. As I explain in Section 1.1.2, many proxies of malaria exposure can be captured through satellite remote sensing data – which remains one of the most readily-available sources of data for developing countries, which are also the countries disproportionately affected by malaria. The interconnectedness of scale, primary science questions, secondary methodological advances, and the overarching research question is illustrated in Figure 1-6.

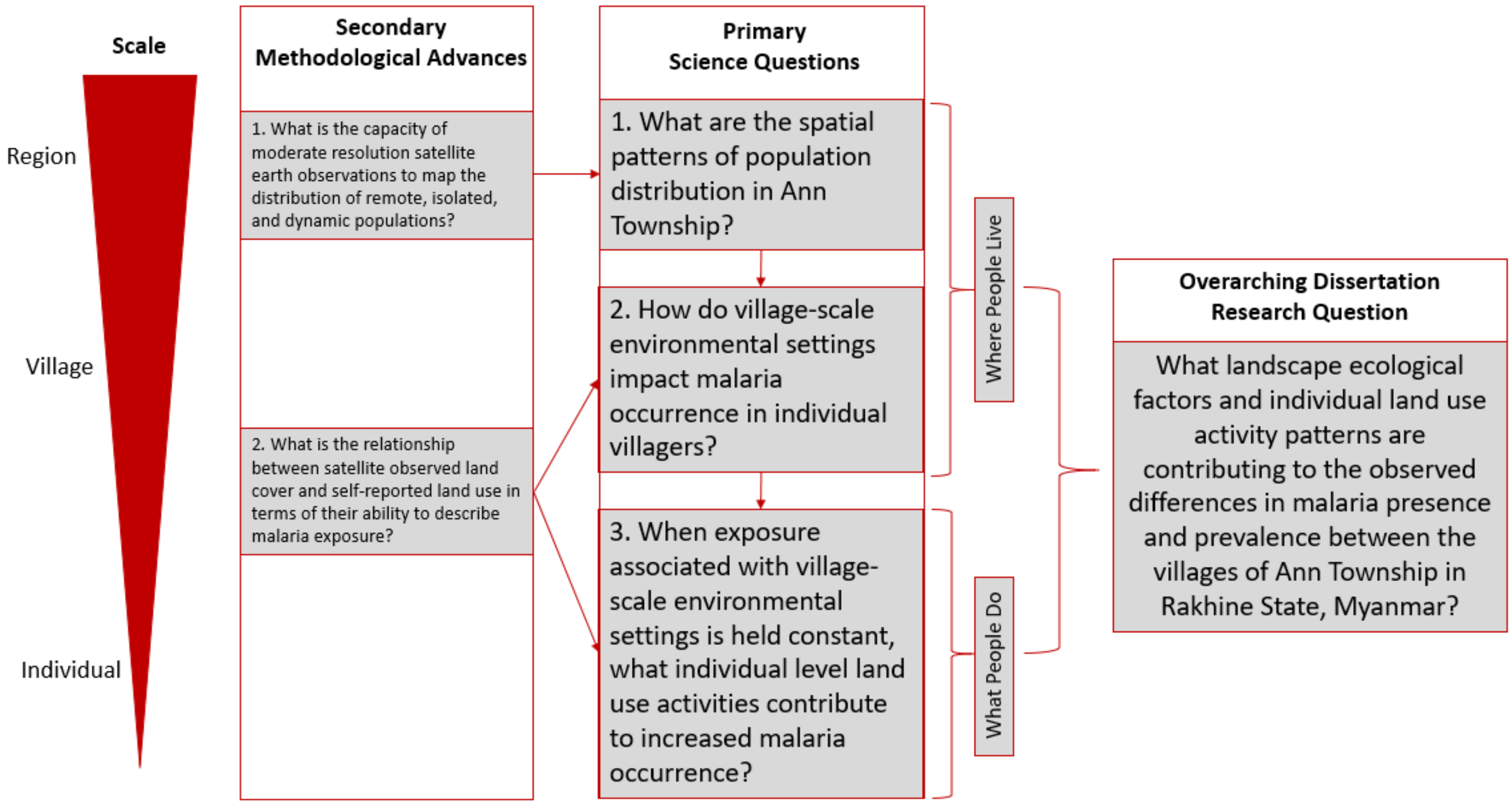


Figure 1-6: Conceptual diagram of dissertation science questions

Primary Science Question 1 addresses the regional scale component of the first facet of malaria exposure (where people live) by asking,

1. What are the spatial patterns of population distribution in Ann Township?

As noted in the introduction, Ann Township, like many remote regions of malaria-endemic countries, is data-poor and suffers from a lack of reliable population maps. This question seeks to discover where people are living across the landscape using a novel methodology that incorporates moderate resolution satellite earth observations. Therefore, the secondary question situated within Primary Science Question 1 is, *what is the capacity of moderate resolution satellite earth observations to map the distribution of remote, isolated, and dynamic populations?* This question addresses the feasibility of using moderate resolution data to map rural settlements, which is generally considered to have insufficient resolution for the task.

Primary Science Question 2 will assess exposure at the next finest scale – the village level. While still focusing on the first facet of malaria exposure (where people live), this question seeks to address the relationship between malaria exposure and the environmental settings of where a person lives by asking,

2. How do village-scale environmental settings impact malaria occurrence in individual villagers?

This will be answered using another novel methodological approach involving the use of satellite remote sensing, contextualized by a qualitative land use survey. In this way, I can determine if the ecological settings surrounding a village are associated with malaria prevalence, regardless of how people may specifically interact with those land covers (i.e., does merely living near forest influence the likelihood of malaria – even for people who do not work in the forest?). The secondary question for Primary Science Question 2 is, *what is the relationship between satellite observed land cover and self-reported land use in terms of their ability to describe malaria exposure?* With this question, I will contextualize satellite-derived environmental village settings with land use survey data to assess the relationship between satellite-derived metrics and malaria exposure.

This contextualization will also support Primary Science Question 3, which will use the results of Question 2 to control for the impact of the environment while analyzing a detailed land use survey to assess exposure at the finest scale – the individual level. Question 3 will address the second facet of exposure (what people do) by asking,

3. When exposure associated with village-scale environmental settings is held constant, what individual level land use activities contribute to increased malaria occurrence?

This final question will address individual-level land use activities that cannot be captured with satellite remote sensing but are a crucial component of malaria exposure. Namely, how often (frequency) and for how long (duration) do village residents engage in the land use activities which contribute to higher malaria exposure. This question controls for village-level environmental settings in order to capture the complexity of individual activities and their relationship to malaria exposure.

1.3 Dissertation Structure

Chapter 1 of this dissertation provides the background, motivation, research questions, and structure that will guide the rest of the dissertation.

Chapter 2 of this dissertation answers Question 1. This chapter introduces a novel algorithm that allows for the mapping of rural populations with a high level of accuracy using moderate resolution remotely sensed data – which was previously thought to be insufficient for this purpose. This chapter has been peer-reviewed and published in *Remote Sensing of Environment* (Hoffman-Hall et al., 2019).

Chapter 3 of this dissertation answers Question 2. I contextualize land cover and land use metrics by pairing a satellite-data based land cover and land use map with on-the-ground survey data and laboratory analysis (survey collection and laboratory analysis performed by researchers at the Duke Global Health Institute and Myanmar's Department of Medical Research) in order to assess the effect of village-level environmental settings on malaria exposure. This chapter is being prepared for submission to *GeoHealth*.

Chapter 4 of this dissertation answers Question 3. Building on statistically significant relationships found between village-level environmental settings and malaria exposure in Chapter 3, in Chapter 4, I controlled for those factors in order to assess associations between individual-level land use activities and malaria exposure by analyzing a detailed land use survey. This chapter is also being prepared for submission to *GeoHealth.*

Chapter 5 presents the major conclusions of this doctoral dissertation. The findings of Chapters 2, 3, and 4 are summarized, and additional insights are provided regarding the contribution of this work to remote sensing for public health, implications for malaria elimination strategies, and future research directions.

Chapter 2: Mapping Remote Rural Settlements at 30 m Resolution Using Geospatial Data Fusion[1]

2.1 Introduction

The 2013 Ebola outbreak across West Africa brought into focus a major information gap that impeded effective response to the crisis – a lack of reliable population maps (Koch, 2016). Accurate and timely population distribution maps are critical to addressing health epidemics, but are also heavily used for natural disaster response and impact assessment (Chakraborty Jayajit et al., 2005; Deville et al., 2014), to track global changes for environmental conservation (Venter et al., 2016), and to address human rights issues (Gueguen et al., 2017; Jean et al., 2016). Many countries and territories across the globe lack the infrastructure and resources to map their population consistently and accurately, especially in remote rural areas. The location and spatial extent of large urban centers are comparatively well established. In contrast, the more dynamic populations living in peri-urban or rural settlements present mapping challenges which are difficult to overcome using traditional censusing or generalized land cover mapping.

[1]This chapter has been published as a multi-authored paper in the Remote Sensing of Environment as *Hoffman-Hall, A., Loboda, T. V., Hall, J. V., Carroll, M. L., & Chen, D. (2019). Mapping remote rural settlements at 30 m spatial resolution using geospatial data-fusion. Remote Sensing of Environment, 233, 111386.*
Amanda Hoffman-Hall was the primary researcher and algorithm developer. She conducted all mapping and validation activities with advisory input from other authors of the manuscript.

Censuses are rarely collected with a temporal frequency high enough to capture the dynamics of rural populations, particularly those which are marginalized through either remote geography or civil conflicts. Previous research has shown that the isolation of rural settlements enhances their vulnerability to natural disasters and substantial modifications of the environment (Blaikie, 1994; Cannon, 1993; Cross, 2001). Isolated populations experience a disproportionate share of negative health outcomes (Suwonkerd et al., 2013) and can serve as the main drivers of infectious disease transmission, such as malaria, into previously disease-free regions (Martens and Hall, 2000). In some data poor regions, the difficulty and cost of mapping these isolated populations has resulted in inaccurate or incomplete maps of existing settlements which can further exacerbate their vulnerability. Beyond creating a single point-in-time map the cost of mapping remote populations is further exacerbated by the dynamicity of such populations. Natural population growth, migration for better economic opportunities, post natural disaster relocation, cultural preferences, and other factors can result in the movement of rural peoples across a landscape. To date, many low-income countries have been unsuccessful in attempts to continually update maps detailing the locations of remote settlements.

For example, the southeast Asian country of Myanmar has attempted three recent censuses (1973, 1983, 2014), each of which has been plagued by political instability, civil wars, and/or boycotts. Following the dissolution of the military junta in 2011, changes in the political landscape have launched a series of rapid political and economic reforms which increased the numbers of people moving across the landscape for new opportunities. The United Nations estimates that 70% of Myanmar’s population lives in rural areas, where an estimated 52% of people live below the poverty line. The population of Myanmar is extremely ethnically diverse, with 135 recognized ethnic groups speaking over 100 different languages and dialects. The most remote areas of Myanmar, typically the mountainous border regions, are home to minority ethnic groups such as the Shan, Rohingya, and Chin, where vague land tenure policies result in dynamic settlements which are constantly moving to locate work. Accurately and consistently mapping the population is critically important, but nearly impossible via census under current conditions.

Development of a cost-effective approach to mapping and monitoring population, with a previously un-emphasized focus on rural areas, is a critical component in designing improved delivery of services and efficient resource management. Satellite remote sensing offers a means to achieve this goal in a cost-effective and repeatable way. Previous work from the remote sensing community has focused on urban and peri-urban regions at global scales. Examples include low spatial resolution datasets (~1km – 250 km) such as maps based on Defense Meteorological Satellite Program (DMSP) nighttime lights data (Elvidge et al., 2001) or Moderate Resolution Imaging Spectroradiometer (MODIS) data (Bartholomé and Belward, 2005). Other attempts have combined satellite data with auxiliary inputs (census data, land cover, etc.) such as LandScan (Dobson et al., 2000), WorldPop (Gaughan et al., 2013), Gridded Population of the World (Doxsey-Whitfield et al., 2015), and Esri’s World Population Estimate (Frye et al., 2018). While such datasets are useful for studies conducted at sub-continental to global scales, their coarse spatial resolution limits their ability to identify small, isolated rural settlements.

More recent approaches to mapping rural areas involve the use of Very High Resolution (VHR) imagery. While there is no single accepted definition, it is generally accepted that VHR imagery includes everything with a spatial resolution below 5 m, although the majority of recent VHR acquisitions are available at much higher (sub-meter) resolutions. These recent advances in VHR data availability offer promising results in mapping rural settlements moving forward but face major challenges. Currently there exists no VHR dataset that has a high repeat frequency and is freely available, limiting the usability of VHR by resource-poor regions. Additionally, data-poor regions lack highly accurate Digital Surface Models and field-collected Ground Control Points required in order to ensure minimal ground displacement errors in VHR data (Pesaresi et al., 2013; Toutin, 2004). However, most importantly, although the first commercial VHR data from Ikonos goes back to 1999 and some areas of the globe have benefitted from extensive VHR imaging, substantial global VHR data archives cover only the past decade which limits historical analyses. In contrast, global archives of moderate spatial resolution datasets (Landsat 4 – 8) extend to the early 1980s offering a potential for multi-decadal studies aimed at assessing landscape population distributions through time.

Moderate spatial resolution remote sensing data (10 – 90 m) offers a compromise between the fine spatial resolution of VHR data and the frequent temporal resolution of low spatial resolution data. Landsat's Thematic Mapper (TM) (Landsat 4 & 5), Enhanced Thematic Mapper Plus (ETM+) (Landsat 7), and Operational Land Imager (OLI) (Landsat 8) instruments provide observations of land surface at 30 m spatial resolution. The repeat frequency of each of these satellites individually provides an opportunity for data collection every 16 days. During time periods when more than one Landsat satellite has been in operation, for example Landsat 5 and 7 between 1999 and 2013 and Landsat 7 and Landsat 8 between 2013 and present day, the imagery is collected every 8 days.

However, image availability is often limited by cloud cover, particularly in tropical regions. Hansen et al. (2016) found that during the rainy season in subtropical Peru, cloud free observations covered only 20% of the country. Lastly, all imagery collected during the Landsat program is freely available for public use since December 2009. Also within the moderate resolution realm, the Sentinel 2 mission has been collecting similar spectral bands to Landsat at resolutions of 60, 20, and 10 meters since 2015. While the finer spatial resolutions available through Sentinel 2 are an improvement over Landsat, at the time of this publication cloud masking issues limited the reliability of Sentinel 2 top-of-atmosphere (TOA) to surface reflectance conversion methods (Claverie et al., 2018). Therefore, we chose to use Landsat for this research, under the assumption that, if successful at 30 m spatial resolution, the methodology would be scalable to the finer resolution of Sentinel 2 once fully available.

To date, the only publicly available global population dataset with a spatial resolution similar to Landsat is the Global Human Settlement (GHS) Built-Up Grid (Pesaresi et al., 2015), which boats a spatial resolution of 38 m and was created as part of the global GHS Settlement Grid project (Pesaresi and Freire, 2016). While this dataset performs consistently well within urban areas, it underestimates the presence of human activity and structures across rural and remote regions. Landsat has been successfully used to study urban sprawl and urban change many times (Brown de Colstoun et al., 2017; Goldblatt et al., 2018; Lu and Weng, 2005; Patel et al., 2015; Song et al., 2016; Wang, 2017; Wieland and Pittore, 2016) however, the classification of more rural, remote, and isolated populations with Landsat has not received focused attention. At this spatial resolution, nearly all urban and especially rural settlements will present a mixed spectral signal of roof material, trees, bare ground, and other minor signals (e.g. shadows of 3-dimensional objects, very small water bodies, etc.) (Figure 2-1). For this reason, Landsat and other moderate resolution datasets have been considered insufficient to map small human settlements (particularly those < 30 m across in size, as is the case with some in Ann Township). Certainly, mapping structural properties (such as metal roofs vs thatched roofs) is not possible due to these spectral constraints, however humans leave a footprint on a landscape that goes beyond buildings. Our approach relies on combining spectral signatures with contextual regionally specific information to bolster the limited spectral separability of fine-scale built environment signal within 30 m pixels.

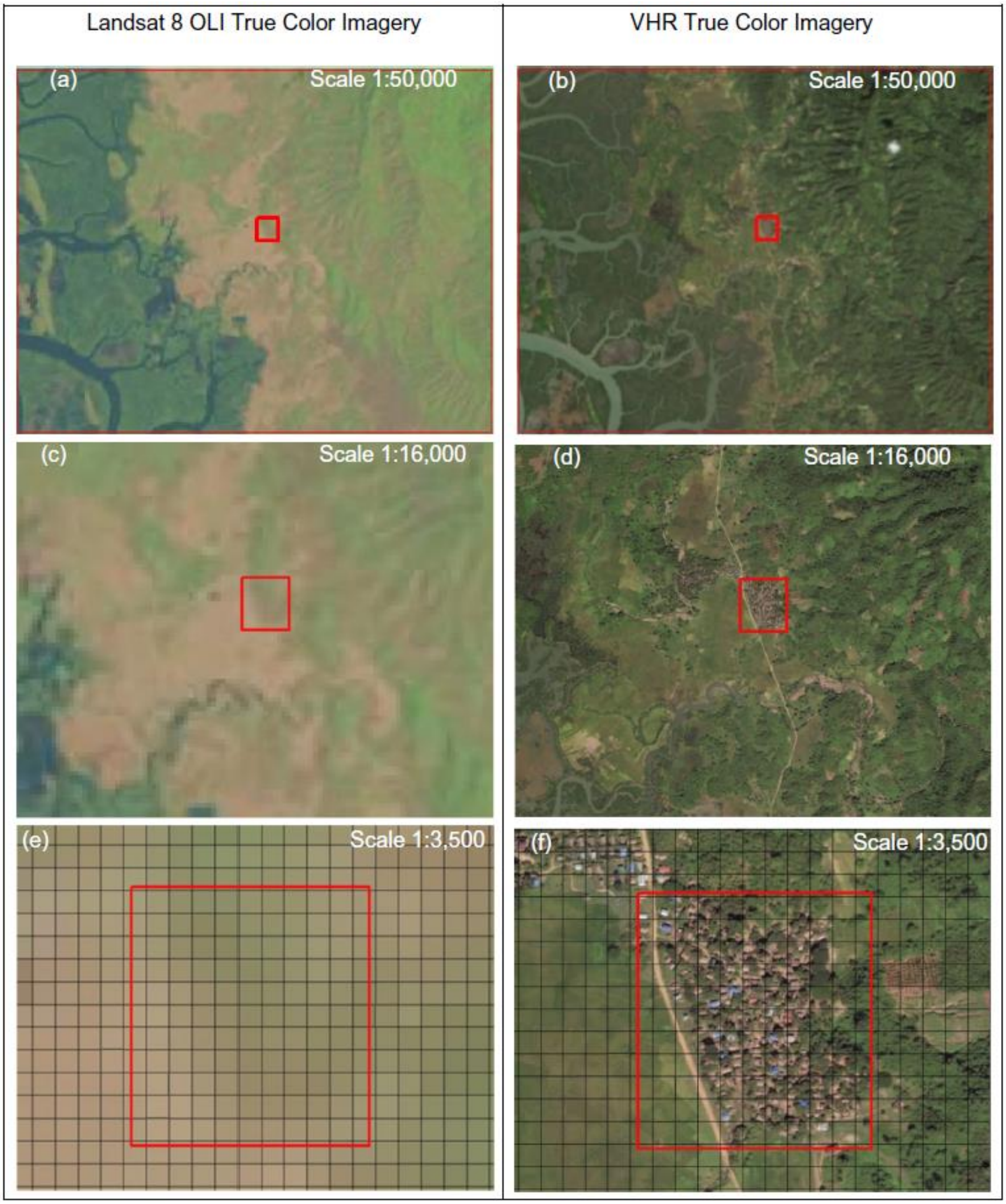


Figure 2-1: Comparison of the same village shown at differing scales with Landsat 8 OLI True Color Imagery (a, c, and e) and Very High Resolution Imagery (b, d, and f). Images (e) and (f) are overlaid with a 30 m grid corresponding to Landsat spatial resolution. (VHR Imagery Source: Service Layer Credits: Esri, Digital Globe, GeoEye, Earthstar, Geographics., CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community).

Understanding regional specifics that pertain to both vegetation dynamics and human activity is a key component in our methodology's ability to accurately map human settlements across Ann Township. Previous studies focused on identifying human settlements (both ancient and contemporary) frequently rely on auxiliary geospatial information, either in conjunction with or without spectral data (Kohler and Parker, 1986; Scianna and Villa, 2012). For example, archaeological sites tend to appear in environments with favorable settlements conditions, such as an area of shallow slopes with close proximity to fresh water. By incorporating these so-called "locational metrics" archaeologists can increase their chances of discovering an archaeological site, even in the absence of remotely sensed imagery (Warren, 1990). A similar thought process can be applied to many contemporary cities and/or rural areas. This is particularly true in Ann Township. For example, out of 205 known settlement locations within Ann Township, 75% of those settlements are located less than 200 meters away from a water body.

Similarly, auxiliary geospatial data can improve mapping accuracy when used alongside remotely sensed imagery. Costa et al. (2018) created a land cover map of Portugal based on Landsat data by including previously mapped data of wind farms, quarries, burnt areas, and elevation. Stevens et al. (2015) utilized remotely sensed data alongside a wide variety of auxiliary geospatial data, such as elevation, slope, previously mapped land cover, distance to roads, and distance to rivers data, to disaggregate census data to more accurately map population distributions in three data-poor regions. Similarly, Wieland and Pittore (2016) concluded that while Landsat 8 was sufficient to map built-up urban areas, the inclusion of manually mapped settlement point data would have improved their classification.

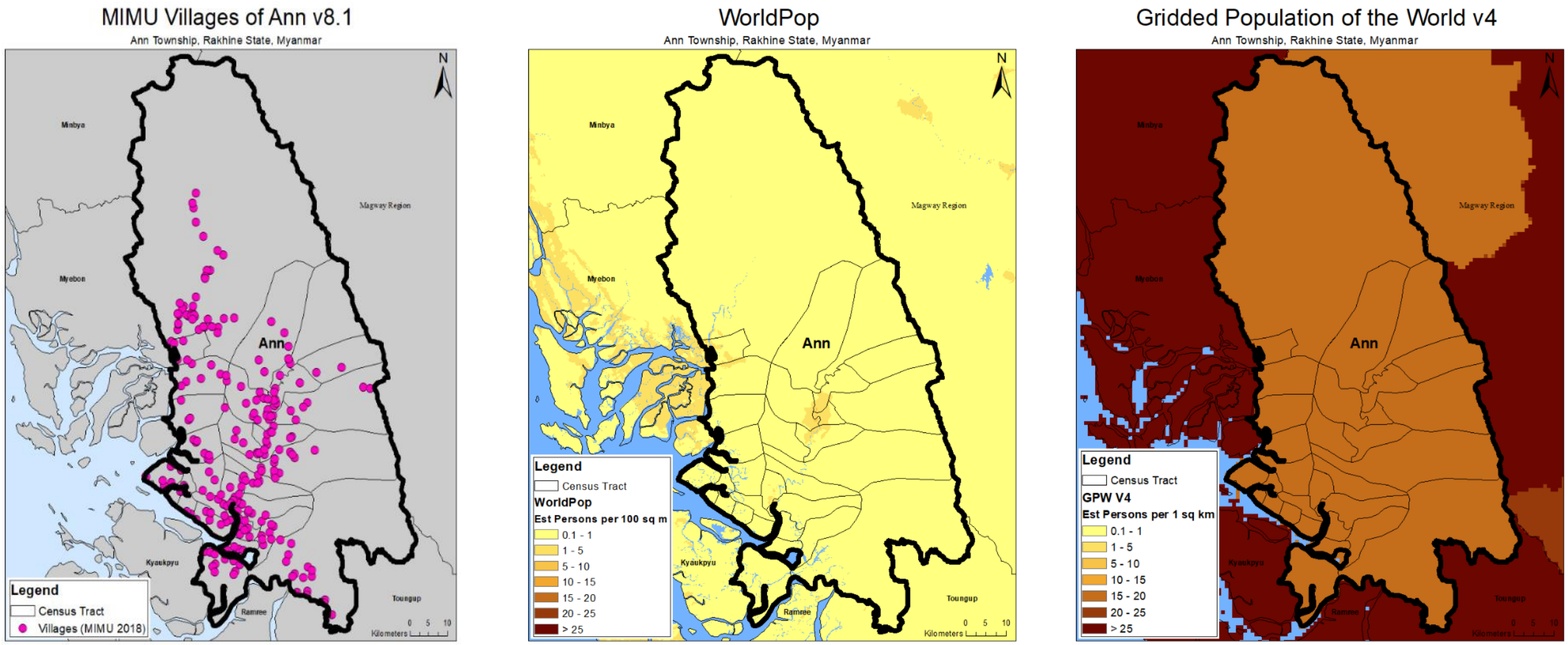
For our methodology most of the variables incorporated describe relationships common to human settlements across the globe, i.e. distance to roads, distance to water sources, and elevation. However, we bring this reasoning a step further by incorporating a novel variable that is regionally specific: distance to recent active fire. Based on our field reconnaissance trips to Ann Township, slash-and-burn is the primary management tool for crop residue management and for subsistence plantation clearance. Fire is not a common natural component of ecosystem functioning in deciduous tropical forests, such as those found in Ann (Murphy and Lugo, 1986). Therefore, the presence of fire is most likely related to agricultural burning indicating human activity.

Here we present a prototype for a machine learning and remote sensing methodology for mapping the locations of human settlements using a challenging example region comprised of very small, remote, and dispersed rural settlements at a 30 m scale. Our primary goal is to identify locations where people may be living in an easily reproducible methodology so that aid or services can reach them. The objective is to map locations, rather than settlements size or extent, with a method that can be adapted to capture the dynamicity of rural settlements annually.

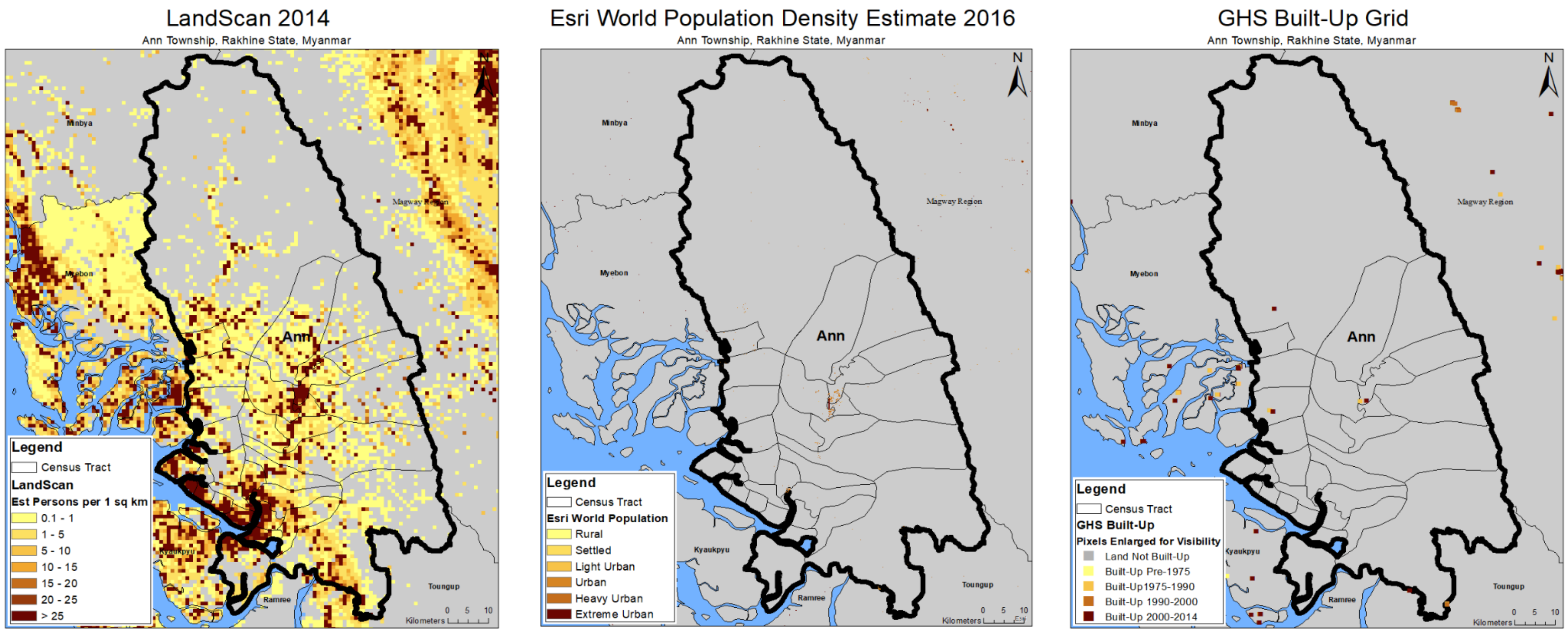
2.2 Materials and Methods

2.2.1 Study Area

The population of the remote mountainous Ann Township within Rakhine State, Myanmar (Figure 1-4) is distributed across the landscape in a highly uneven pattern. While most of the population lives in the southwest coastal region of Ann, visual analysis of VHR imagery shows that small to medium settlements of 2 – 20 homes or structures extend well north into the mountains. Known village locations provided by the Myanmar Information Management Unit (MIMU) are displayed in Figure 2-2a. MIMU is a service organization to the United Nations (UN) Country Team and Humanitarian Country Team, under the management of the UN Resident and Humanitarian Coordinator (http://themimu.info/). The known village location data was created in coordination with the General Administrative Department of the Myanmar Government. The mapped villages display a clustered pattern not fully represented by currently publicly available gridded datasets (Figure 2-2). LandScan and Esri's World Population Density Estimate appear to be the most representative, but both lack the precision that a 30 m map could provide with spatial resolutions of 1 km and 162 m respectively (Figures 2-2d and 2-2e). The 38 m GHS Built-Up Grid which, like our methodology, also derives built areas from Landsat, captures only 7 pixels of built area in all of Ann Township (Figure 2-2f)


MIMU Villages of Ann v8.1
Ann Township, Rakhine State, Myanmar
Minbya
Myebon
Magway Region
Ann
Kyaukpyu
Ramree
Toungup
Legend
Census Tract
Villages (MIMU 2018)
Kilometers
WorldPop
Ann Township, Rakhine State, Myanmar
Legend
Census Tract
WorldPop
Est Persons per 100 sq m
0.1 - 1
1 - 5
5 - 10
10 - 15
15 - 20
20 - 25
> 25
Gridded Population of the World v4
Ann Township, Rakhine State, Myanmar
Legend
Census Tract
GPW V4
Est Persons per 1 sq km
0.1 - 1
1 - 5
5 - 10
10 - 15
15 - 20
20 - 25
> 25

(a) (b) (c)



(d) (e) (f)

Figure 2-2: Comparison of gridded global population products with locations of known settlements in Ann. (a) Known settlement locations via MIMU v8.1; (b) WorldPop; (c) Gridded Population of the World v4; (d) LandScan; (e) Esri's World Population Density Estimate 2016; (f) Global Human Settlement (GHS) Built-Up Grid (built-up pixels artificially enlarged for visibility).

The primary goal of this work is to map the presence of settlements in Ann Township at a 30 m spatial resolution rather than their spatial extent. Here a settlement is defined as any location containing a structure where people may shelter at any time (including homes, schools, military barracks, industrial buildings, etc.). While some settlements within Ann are dense and can span more than 25 square kilometers, many are small and may only contain a few homes/structures spanning less than 30 m across (Figure 2-3).

(a)

(b)

(c)

*Figure 2-3: Examples of Ann Settlements ranging from (**a**) most densely populated/built (example shows town of Ann); (**b**) medium density (example settlement located ~4 km southwest of town of Thaphanbin); (**c**) low density/most remote (example settlement located ~8 km southwest of town of Ann). Red polygon used to highlight settlement location.*

2.2.2 Random Forest Algorithm

Decision Trees are a robust and widely applied machine learning method of supervised imagery classification. However, individual decision trees are highly sensitive to the input dataset, resulting in large differences in classification output for relatively small changes in input (Bishop, 2006). Random Forest (RF) is an algorithm designed to moderate the high sensitivity of individual decision trees through the use of consensus in classifiers based on a random selection of training subsets of data with an ensemble of trees (Breiman, 2001). Each decision tree within the RF is trained on different input datasets generated through a bagging procedure, ultimately creating an ensemble of independent experts. The output of the RF is determined by a majority vote of the trees within the ensemble (Gislason et al., 2006).

The data used to train the RF were chosen by overlaying a 30 m grid georeferenced to Landsat pixels on freely available VHR imagery from Esri ("World Imagery," n.d.). "Settlement" pixels were defined as pixels which were covered at least 25% by structures. "Other" land cover pixels included anything deemed to not be a settlement through VHR visual analysis (trees, low vegetation, water, etc.). The training dataset was comprised of 1,031 "settlement" pixels and 2,691 "other" land cover pixels. Upon initial testing the "other" category was subdivided into "agriculture/bare ground" (agriculture here is defined as primarily cropped lands) and "other" due to an initial confusion between agriculture, bare ground, and settlements. The final set of training pixels contained 1,031 settlements, 872 agriculture/bare, and 1,817 other. The algorithm was implemented within the randomForest package in R statistical software. The final model used a default of 500 trees and 9 variables tried at each split. The output was a raster where each pixel value was the probability of the pixel being a settlement. This raster was then converted into a binary Settlement/Not Settlement map by imposing a cut-off value of 65% probability of settlement presence (the rationale behind this threshold value is described in Section 2.3.1).

2.2.3 Data

2.2.3.1 Landsat Surface Reflectance

Our random forest algorithm ingests 84 different freely-available data inputs to identify settlements. Spectral data used for analysis includes the National Aeronautics and Space Administration (NASA) developed Landsat 8 Surface Reflectance Code (LaSRC) Product (Vermote et al., 2016) Surface Reflectance data for Operational Land Imager (OLI) Bands 1-7 (spatial resolution 30 m) and Top of Atmosphere (TOA) Brightness Temperature for Thermal Infrared Sensor (TIRS) Bands 10 - 11 (spatial resolution 100 m resampled to 30 m). TOA reflectance was also downloaded for Bands 1 - 7 for use in deriving indices such as the Tasseled Cap transformation (the equations developed by Baig et al. (2014) are not accurate for surface reflectance), but was not used in algorithm development otherwise.

The climate of Myanmar can be conditionally divided into 3 primary seasons: dry-hot (February – April), wet-monsoon (April – October), and dry-cold (November – January) (Aung and Thoung, 1985). The persistent cloud cover during the monsoon season severely limits Landsat image availability from May to October. However, temporal trajectories of surface signature within natural and human-managed land covers (e.g. flooding of rice paddies or senescence within deciduous broadleaved forests) provides important contextual information which can aid in identifying human footprint on the landscape. We obtained the LaSRC data for the dry seasons of 2014 including a cloud free image from March 9 and, due to the unavailability of any cloud-free data for the dry-cold season, November 20, December 6, and December 22 were mosaicked to obtain a cloud- and shadow-free composite. To ensure the full removal of clouds a 20-pixel buffer was added to the LaSRC cloud mask for each image. Any pixel falling within the mask or buffer were removed. The clear-surface pixels from December 6 and 22 were used to fill in the resultant gaps in the November 20 image with the preference given to the December 6 as the closest in time to the primary image. Due to overlapping areas of cloud cover in the dry-cold season, we were unable to fill 52,584 pixels in the final dry-cold composite, representing less than 0.7% of the total image. However, we found no human presence within cloud-impacted areas through a visual examination of the Google Earth collection of VHR imagery and subsequently selected to proceed with mapping without adding cloud-free observations from 2015.

2.2.3.2 Spectral Indices

Spectral indices for this study were specifically chosen to reflect the regionally-specific vegetation and human activity characteristics of Ann Township. Using a suite of vegetation, water, and soil-based indices provides the random forest more information to separate pixels containing anthropogenic structures from pixels containing natural vegetation, surface water bodies, and cropped areas within two dry seasons (Table 2-1).

Table 2-1: Spectral Indices Used as Inputs during Algorithm Development. All indices described were calculated for the dry-hot season LaSRC image and the dry-cold season LaSRC image. B# refers to the numbering system used by the Landsat 8 Science Mission (ex. B4 is the Red Landsat 8 band, B5 is the Near Infrared Landsat 8 band, etc.).

Index	Citation	Equation	Use
Normalized Difference Vegetation Index (NDVI)	(Rouse, 1974)	$\frac{B5-B4}{B5+B4}$	Discriminate natural/managed vegetation
Enhanced Vegetation Index (EVI)	(Liu and Huete, 1995)	$2.5* \frac{B5-B4}{B5+6*B4-7.5*B2+1}$	Discriminate natural/managed vegetation
Soil Adjusted Vegetation Index (SAVI)	(Huete, 1988)	$1.5* \frac{B5-B4}{B5+B4+0.5}$	Discriminate natural/managed landscapes where vegetation cover is low (< 40%)
Modified Soil Adjusted Vegetation Index (MSAVI)	(Qi et al., 1994)	$\frac{2*B5+1-\sqrt{(2*B5+1)^2-8*(B5-B4)}}{2}$	Discriminate natural/managed landscapes where vegetation cover is low (< 40%)
Normalized Difference Moisture Index (NDMI)	(Wilson and Sader, 2002)	$\frac{B5-B6}{B5+B6}$	Discriminate wetlands and other land covers that contain high levels of plant moisture
Normalized Burn Ratio (NBR)	(García and Caselles, 1991)	$\frac{B5-B7}{B5+B7}$	Discriminate areas which have recently been burned, likely indicating human activity nearby
Normalized Burn Ratio 2 (NBR2)	(Vermote et al., 2016) *Landsat Surface Reflectance Derived Spectral Indices Product Guide*	$\frac{B6-B7}{B6+B7}$	Discriminate areas which have recently been burned, likely indicating human activity nearby

Normalized Difference Water Index (NDWI)	(McFeeters, 1996)	$\frac{B3-B5}{B3+B5}$	Discriminate natural/managed vegetation
Normalized Difference Water Index using SWIR (NDWI6)	(Gao, 1996)	$\frac{B5-B6}{B5+B6}$	Discriminate natural/managed vegetation
Normalized Difference Water Index using SWIR (NDWI7)	(Gao, 1996)	$\frac{B5-B7}{B5+B7}$	Discriminate natural/managed vegetation
Tasseled Cap Brightness	(Baig et al., 2014; Crist and Cicone, 1984)	(B2* 0.3029)+ (B3*0.2786)+ (B4*0.4733)+ (B5*0.5599)+ (B6*0.0508)+ (B7*0.1872)	Discriminate natural/managed vegetation
Tasseled Cap Greenness	(Baig et al., 2014; Crist and Cicone, 1984)	(B2* -0.2941)+ (B3*-0.243)+ (B4*-0.5424)+ (B5*0.7276)+ (B6*0.0713)+ (B7*-0.1608)	Discriminate natural/managed vegetation
Tasseled Cap Wetness	(Baig et al., 2014; Crist and Cicone, 1984)	(B2* 0.1511)+ (B3*0.1973)+ (B4*0.3283)+ (B5*0.3407)+ (B6*0.7117)+ (B7*-0.4559)	Discriminate natural/managed vegetation

2.2.3.3 Textural Metrics

Due to the spatial resolution of Landsat imagery, many of the buildings in Ann Township, particularly those used as residential dwellings, are smaller than a single Landsat pixel (30 m). Thus, the inherent land cover signal mixing within a single pixel makes it nearly impossible to discriminate buildings from other features using spectral signatures alone. The sparse distribution of settlements across the landscape also results in large swaths of natural or managed vegetation usually spread between settlements. By incorporating textural metrics covering a 3 x 3 pixel window, the algorithm is able to exclude homogenous swaths of non-settled lands from further consideration. To discriminate the large swaths of similar vegetation (i.e. natural, non-settled forest lands), the near-infrared (NIR) band was used to calculate First-Order (Occurrence) Metrics (data range, mean, variance, homogeneity, and contrast) for both the dry-hot and dry-cold imagery based on the methodology and equations of Anys et. al (1994). Second-Order (Co-Occurrence) Metrics (mean, variance, homogeneity, contrast, dissimilarity, entropy, 2nd moment, and correlation) were similarly calculated for the NIR band, based on the methodology and equations of Haralick et al. (1973).

2.2.3.4 Seasonal Metrics

The spectral signature of settlements generally varies less throughout the year compared to that of non-settled areas which can vary widely throughout the seasons. By capturing the changes across the landscape between seasons, the algorithm can more successfully identify areas which do not experience change and are therefore more likely to be settlements. In addition, multi-seasonal observations highlight vegetation development patterns that help in separating natural vegetation phenology from that of more managed plant landscapes (i.e. farms, plantations, rice paddies, etc.). For example, rice farming in Myanmar relies on the monsoon season to flood the rice paddies. While these paddies will appear dry during the pre-monsoon dry-hot season, they will appear flooded during the post-monsoon dry-cold season. As can be expected, managed landscapes are found in the immediate proximity to settled areas – this can cause confusion in the algorithm if one only investigates locational metrics like those described in more detail in Section 2.3.5. For this reason, it is extremely important to capture seasonal change across both settled and non-settled areas.

Five seasonal change metrics were calculated using Equation 2-1, where VI is a spectral band or index relevant to seasonal changes in vegetation (specifically, Landsat 8 OLI red band, Landsat 8 OLI NIR band, TC Brightness, TC Wetness, and TC Greenness). VI_d is the value of the index/band during the pre-monsoon dry-hot season, while VI_c is the value of the index/band during the post-monsoon dry-cold season.

$$dVI = |VI_d - VI_c| \qquad \text{Equation 2-1}$$

2.2.3.5 Locational Metrics

To further bolster the limited power of spectral separability, we included regionally specific "location metrics" datasets. The locational metrics chosen for this study were based on two factors: 1) knowledge of settlement patterns and livelihood practices in Ann, and 2) data availability. The chosen metrics encompass those which are universally applicable to settlement patterns, such as elevation and slope (Shuttle Radar Topography Mission (SRTM) 1-arc second digital elevation model (DEM)), and some more unique to Ann. For example, during our field visits to the area we observed a wide prevalence of slash and burn agriculture in the region. Therefore, proximity to a recent active fire (as mapped by either the Moderate Resolution Imaging Spectroradiometer (MODIS) or Visible Infrared Imaging Radiometer Suite (VIIRS) active fire products from 2013-2014) was included in the suite of auxiliary data. The MODIS and VIIRS point data were buffered out to 500 m and 187 m, respectively, to represent the spatial resolution of the data products. Fire proximity was then mapped as Euclidean distance to the buffers on a 30 m grid matching the Landsat pixels.

The final 3 locational metrics are limited by poor data availability but their strong influence on settlement patterns necessitates their inclusion: proximity to roads, proximity to waterbodies, and proximity to a 3rd order or greater waterway. For proximity to roads, any available road data was collected for Ann and its neighboring townships from Open Street Map on February 22nd, 2018. This road data was merged with a more detailed road network of the area primarily surrounding Ann Airport, manually mapped using VHR imagery by a team of researchers at the Center for Geospatial Information Science at the University of Maryland (Li et al, unpublished data).

A comprehensive map of waterways in Ann Township was not available prior to this project. Therefore, water was mapped using a combination of two methodologies which relied on freely available data. The first method involved creating a flow accumulation model with the Spatial Analyst extension in ArcGIS based on the SRTM DEM. Any pixel which, according to the DEM, would have 1000 or more other pixels flow into it was classified as a waterway, resulting in rivers mapped as single pixel width polylines. While this resulted in well mapped connectivity for rivers, the polylines pose a problem when conducting proximity analysis to possible settlements. Many of the rivers in Ann are multiple pixels wide (i.e. wider than 30 meters across). The polylines created by the flow accumulation model were often situated on one side of where the actual river is located, not down the center. If the polyline ran along only one side of the actual river it would influence the proximity of a settlement situated on the other side of the river, making it appear further away.

To overcome this limitation, the output of the flow accumulation model was combined with a Landsat based map of water. The Surface Water Fraction (SWF) algorithm (DeVries et al., 2017) estimates sub-pixel water fraction using Landsat data and requires no external training. The resulting output was fairly accurate for large rivers and waterbodies but missed some of the small or more ephemeral streams. These smaller streams were however captured by the flow accumulation model. The combination of the flow accumulation plus the SWF ensured a water network which most closely resembled the connectivity, width, and expanse of all waterbodies. The streams were also ordered via the Strahler Stream Order method (Strahler, 1952). Ultimately two water source auxiliary datasets were created: 1) Euclidean distance to any waterway and 2) Euclidean distance to any Strahler 3rd order or greater stream. This was based on the reasoning that while all settlements require a reasonably accessible water source, settlements are more likely to be found in close proximity to larger water bodies and streams (3rd order or greater) which can be used as both sources of water and transportation. All proximity metrics were mapped as Euclidean distances across a 30 m grid.

Finally, we included two derived data products to enhance the separability of settlements including Landsat Tree Cover Continuous Fields (Sexton et al., 2013) and 30 m Global Bare Ground 2010 (Hansen et al., 2013). Each of these datasets had the added benefit of being Landsat-based so their spatial resolutions are the same as our intended map output.

2.2.4 Pixel Based Accuracy Assessment

Freely available VHR imagery through Google Earth, Esri, and other entities has been widely used for both collecting training samples and validating classification results (Bhagwat et al., 2017; Gong et al., 2011; Yu and Gong, 2012). However, the temporal mismatch between the timing of acquisition of VHR imagery and the mapping dates within this project creates a challenge in using freely available VHR images for validation of the mapping results. In our accuracy assessment approach, we had to ensure that all settlements mapped by our algorithm were in existence prior to the date of the earliest Landsat scene used, March 9th, 2014. The possibility of new buildings appearing between the dry-hot and dry-cold seasons imagery is acknowledged but virtually impossible to verify without more frequent VHR imagery collection.

Stratified random sampling was used to select 1000 pixels to be assessed. Of these 1000 pixels, 197 were verified visually as settlements by a trained analyst with Esri and/or Google Earth VHR imagery. The remaining 803 pixels were considered the "other" class. While agriculture/bare ground was considered a separate class in the training data it was combined into "other" for the accuracy assessment since the goal of the classification was solely to map settlements.

2.2.5 Location Based Accuracy Assessment

While a per-pixel accuracy assessment is generally the accepted mechanism for assessing land cover raster map accuracy, the goal of this research was to map settlement presence, rather than their spatial configuration and extent. While Figure 2-4a could be used for settlement size/footprint analysis as it fully encompasses the settlement's extent, the mapped pixels of Figure 2-4b do not cover the entirety of the settlement area and could not be used similarly. If the red square in Figure 2-4b was assessed during the per-pixel assessment it would fail and contribute to omission error. However, as our goal was to map locations and not extents, it is clear that the settlement in Figure 2-4b was located by the algorithm, despite not being mapped to its true extent. Therefore, a secondary accuracy assessment was undertaken that more closely assessed the identification of locations of human presence.

(a)

(b)

Figure 2-4: Results of the mapping algorithm displaying: (a) a result suitable for footprint analysis and (b) a result not suitable for footprint analysis but achieving the goal of settlement location.

For the locational accuracy assessment, each pixel that was mapped into the “Settlement” class was buffered in ArcGIS by 500 m. This distance was chosen because it is large enough to cover most small and large settlements, while also being small enough that a hypothetical aid worker visiting a mapped pixel on the ground could easily locate the actual settlement. The same 1000 points used in the per-pixel assessment were re-assessed. If a point location intersected the new buffered settlement layer and a visually verified settlement was contained within the 500 m buffer intersecting said point, it was concluded to be correctly mapped as “Settlement” (Figure 2-5a, assessed point shown in red). If a point location intersected the new buffered settlement layer but the 500 m buffer did not contain a verified settlement, it was concluded to be incorrectly mapped as “Settlement” (Figure 2-5b). If an assessed point did not intersect with the new buffered settlement layer and also did not overlay a visually verified settlement, it was concluded to be correctly mapped as “Non-Settlement” (Figure 2-5)). If an assessed point did not intersect the new buffered settlement layer but overlaid a visually verified settlement, it was concluded to be incorrectly mapped as “Non-Settlement” (Figure 2-5d).

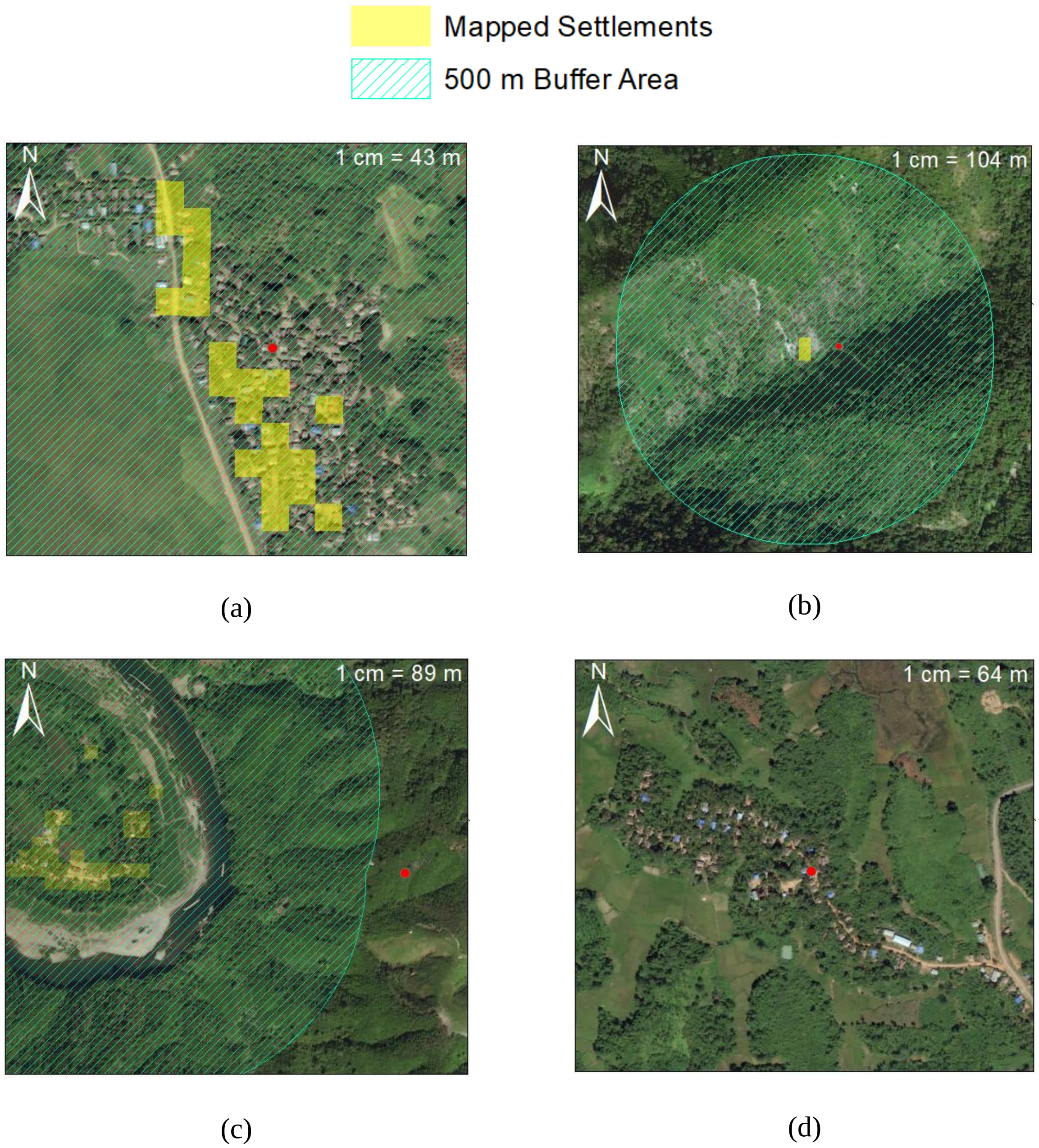


Figure 2-5: Examples of scenarios assessed in locational accuracy assessment. For each image the red point would be assessed for accuracy. (a) Correctly mapped as "Settlement"; (b) Incorrectly mapped as "Settlement"; (c) Correctly mapped as "Not Settlement"; (d) Incorrectly mapped as "Not Settlement".

2.3 Results

2.3.1 Accuracy Assessment

The internal metrics of the RF algorithm showed an overall high settlement identification rate. The overall out-of-bag (OOB) error reported from the RF model was 11.7%. For settlements specifically, the reported misclassification rate was 18.8%. A similar overall error rate (13.5%) was found through the VHR validation accuracy assessment, where the "agriculture/bare" and "other" classes used to train the model were combined in a single "Non-Settlement" class. For this accuracy assessment the "Settlement" class was defined as any pixel with a reported RF probability of 65% or more of being a settlement (Table 2-2). It is noted though that while the overall accuracy remained high, the accuracy of settlement mapping decreased from the reported OOB error.

Table 2-2: Confusion Matrix of Points Assessed during Per-Pixel Accuracy Assessment. Settlement class defined as any pixel with an RF probability of being in the Settlement class equal to or over 65%.

		Mapped			
		Settlement	**Non-Settlement**	**Total**	**Producer's Accuracy**
Visually Verified	**Settlement**	119	78	197	60.41%
	Non-Settlement	57	746	803	92.90%
	Total	176	824	1000	
	User's Accuracy	67.61%	90.53%		**Overall Accuracy 86.50%**

The cut-off value of 65% was possible because the RF output is not binary and instead classified pixels as likelihood of settlement presence values (ranging from 0% - 100% probability). The overall classification accuracy, and the specific settlement accuracy, changes when different probability thresholds are selected. This allows for some accuracy improvement in certain areas dependent on the user's intended goal. Table 2-3 below shows that there is an inverse relationship between Producer's and User's Accuracy for the settlement class when different threshold probabilities are applied.

Table 2-3: Producers and Users Accuracies for the Settlement Class Dependent on Different Cut-Off Thresholds of the RF Probability for Settlement Class. Cut-off value used for analysis (65%) is highlighted in gray.

Cut-Off Threshold Applied	Producer's Accuracy for Settlement Class	User's Accuracy for Settlement Class
90% probability	6.09%	100.00%
85% probability	12.69%	100.00%
80% probability	24.37%	90.57%
75% probability	32.49%	86.49%
70% probability	48.73%	78.05%
65% probability	60.41%	67.61%
60% probability	74.11%	57.48%
55% probability	88.83%	50.14%
50% probability	96.45%	36.47%

Pixels which were classified as equal to or greater than 65% likely to be a true settlement were ultimately those chosen for the final product. While users of the data may choose a probability value more suitable for their needs, a threshold of 65% balanced the Producer's and User's accuracy in the most meaningful way for the goals of this study (i.e. mapping locations of settlements, not areas). From this point forward all results are reported only for pixels at or above 65% probability for the "Settlement" class.

In comparison to the per-pixel assessment, the location-based assessment resulted in a much higher overall accuracy (93.1%) and significantly increased the Producer's and User's accuracy for the "Settlement" class (Table 2-4).

Table 2-4: Confusion Matrix of Points Assessed during Locational Accuracy Assessment

		Mapped			
		Settlement	**Non-Settlement**	**Total**	**Producer's Accuracy**
Visually Verified	**Settlement**	457	11	468	97.65%
	Non-Settlement	58	474	532	89.10%
	Total	515	485	1000	
	User's Accuracy	88.74%	97.73%		**Overall Accuracy 93.10%**

2.3.2 Distribution of Settlements

Figure 2-6(a) shows the distribution of mapped settlements across Ann. As expected, the settlements are most prevalent along the coast and near to the largest town of Ann. Very few settlements were located near the eastern mountainous border with the Magway Region. Conversely, many settlements were located near the borders with other Rakhine State districts, Mybeon, Kyaukpyu, Ramree, and Toungup in particular, with relatively few bordering the Minbya District. Mapped settlements varied widely in size. Our algorithm was able to locate settlements ranging from the smallest at only ~3 structures across (Figure 2-6(b)), to medium settlements (Figure 2-6(c)), to those spanning multiple kilometers (Figure 2-6(d)).

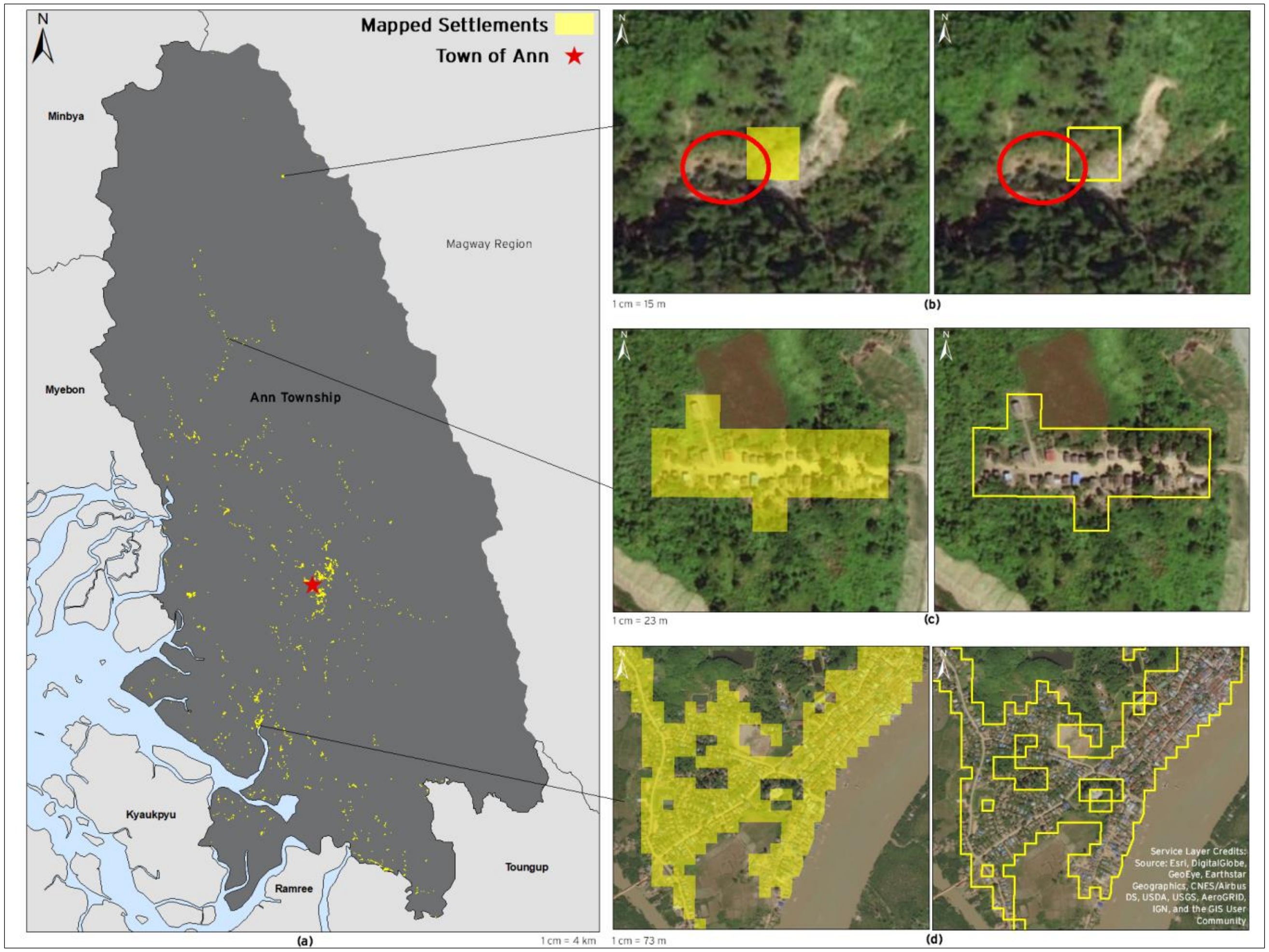


*Figure 2-6: Results of the mapping algorithm(**a**) entirety of Ann Township; (**b**) small mapped settlement, red ellipse included to aid viewing of structures on the ground; (**c**) medium mapped settlement; (**d**) large mapped settlement. Mapped pixels are the same for all inset maps, those on the right show the footprint outline to enable the viewer to see the high-resolution imagery underlaid.*

Our algorithm mapped a total of 6,323 pixels as settlements. These pixels represent 0.1% of the total land area of Ann Township, further emphasizing how remote these settlements are. The 500 m buffers used in the locational accuracy assessment were dissolved to merge overlapping buffers. After this process, 256 separate objects remained – these objects can be thought of as a proxy to a village.

2.4 Discussion

2.4.1 Comparison with Previous Settlement Mapping Efforts

The dataset produced in this study relies on a few assumptions. For example, the use of satellite imagery prohibits the ability to ascertain building or structure use and inhabitant count. Therefore, industrial structures, schools, military bases, and temporary settlements such as plantation or mining camps are included in the “Settlement” class and would be counted as correctly mapped for the accuracy assessment. It is also possible that some mapped settlements have been abandoned or are not currently in use. Every effort was made to ensure that the imagery used in the VHR validation accuracy assessment corresponded to 2014 or prior.

Prior to this research, the best publicly available dataset detailing the location of settlements within Ann Township was provided by the Myanmar Government’s General Administration Department in coordination with the United Nations Myanmar Information Management Unit (MIMU). At the time of this research the latest available MIMU dataset was created in March 2015, and therefore a good map for comparison with our efforts to map the year 2014. However, as of the time of writing a new version was released by MIMU in December 2018. This new version significantly improved from the 2015 version, removing 2 settlements and adding 81 settlements. The removed settlements could have been abandoned, destroyed, or incorrectly mapped in 2015, while the added settlements could be those missed in 2015 version or newly built. Metadata is not available which categorizes changes. For comparison with our dataset we focus on the 2018 dataset because a comparison with our mapped dataset showed that most of the new MIMU points were likely missed in the 2015 version, as opposed to newly built.

Figure 2-7 shows a comparison of our raster map compared to the vector 2018 MIMU village point data. Though it is generally not advisable to compare data of differing formats this way, it is evident that there are many areas where the MIMU layer is in agreement with our dataset and some areas where it is not. MIMU defines the term village similarly to how we define settlement, i.e. “any populated place” (“Rakhine State Village Points,” n.d.) and therefore our goals in mapping settlements are similar.

Our results reveal that people live much further east within the township than previously acknowledged, primarily in extremely small/isolated settlements (Figure 2-7). While our data mapped approximately 256 villages, MIMU only lists 227 villages in the 2018 dataset (148 villages in the 2015 dataset). A quantitative comparison with MIMU 2018 revealed that 185 out of 227 (81%) village points mapped by MIMU are within 500 m of our mapped village data. The remaining 42 MIMU points were visually inspected and include 32 villages that were missed by our algorithm, 5 villages that were newly built post 2014, 4 villages that were incorrectly mapped by MIMU, and 1 village (Wa Maw/Ah Yoe Taung) that was visible in 2004 imagery viewed using Google Earth but was no longer visible in the next available Google Earth imagery from 2015.

The 32 MIMU villages missed by our algorithm drops to 8 missed villages if you lower the probability of settlement presence threshold of the RF output to 50% as opposed to the 65% value used for this analysis. By dropping the threshold cut-off to 50%, the omission error drops from 39.59% to 3.55% (Table 2-3), explaining the better alignment with MIMU. However, the commission error increases from 32.39% to 63.53% (Table 2-3). Interestingly, among the 8 MIMU villages that our algorithm missed, 3 were located along a major road that spans the township, the Minbu-Ann Road. This road was included as a polyline in our road network data, but the wide expanse of the road bears a similar spectral signature to bare ground which may have confused our algorithm.

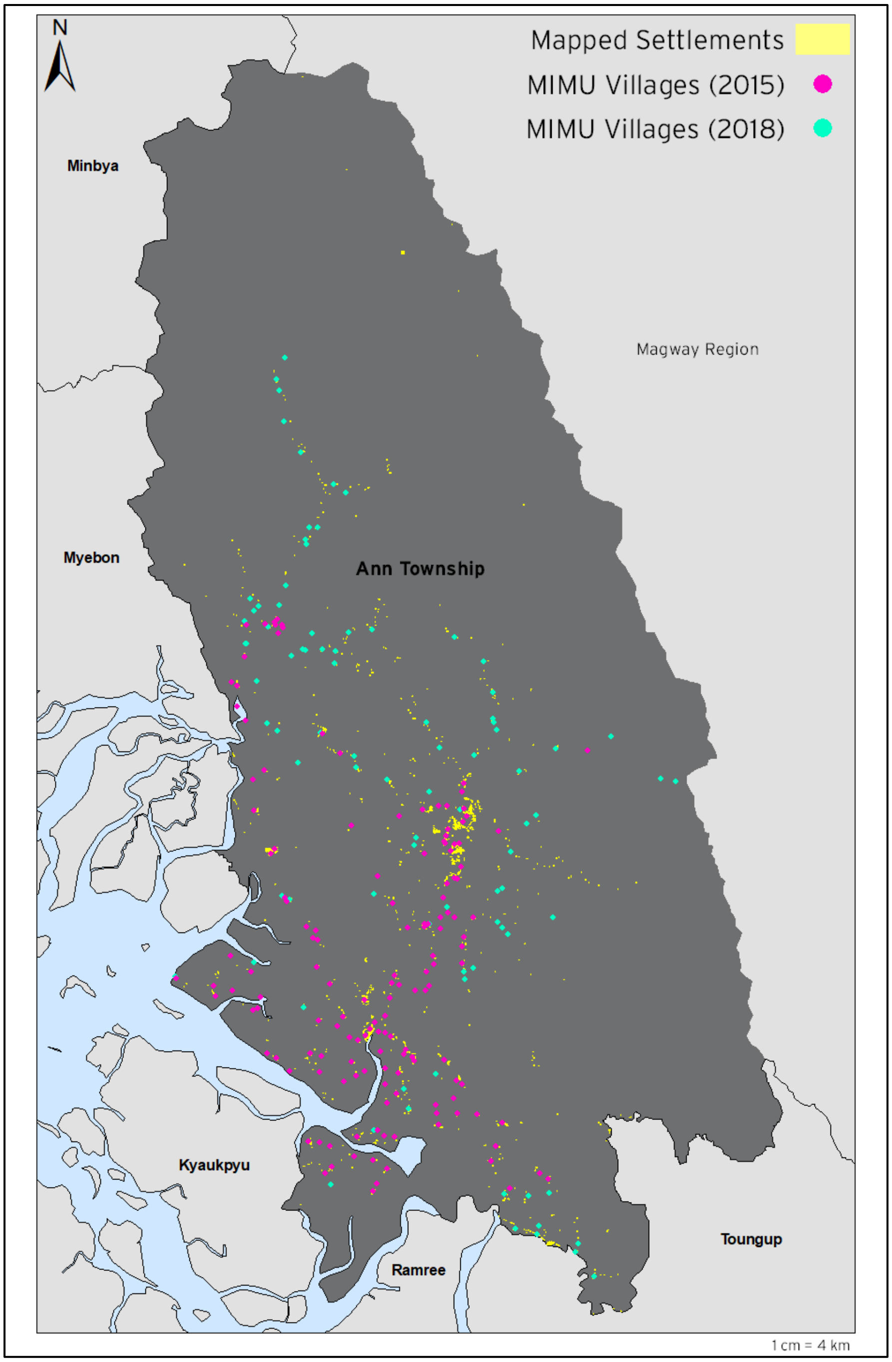


Figure 2-7: Comparison of settlements as mapped by our algorithm with settlements mapped by MIMU in 2015 and 2018. 2015 MIMU layer is displayed on top of the 2018 MIMU layer. All but 2 of the 2015 MIMU settlements are included in the 2018 layer, therefore the blue dots representing 2018 MIMU can be considered as the 81 settlements added for the version.

2.4.2 Contribution of Variables to Mapping

Of the 84 variables used within the RF algorithm, the top 20 which contributed most to the identification of the "Settlement" class, and the bottom 5 which contributed the least are shown in Figure 2-8. A full listing of the contribution for each of the 84 variables is available in Table A1 in the Appendix. The top 20 variables can be subdivided into 3 general categories: 1) those describing seasonal changes in natural and/or managed plant phenology, 2) those describing slash-and-burn agricultural management practices, and 3) those describing a settlement's physical location. The first two categories may not seem immediately relevant to the identification of settlements; however, they do describe the influence of human activity on a landscape and which are often found in the same locations as settlements (i.e. a dwelling and an agricultural field are both likely to be situated near water). Indeed, during our first attempts at mapping settlements there appeared to be a substantial amount of confusion between settled areas and agricultural areas. Therefore, the inclusion of variables which describe seasonal plant changes and agricultural practices was crucial in differentiating between areas where people lived as opposed to areas they farmed (fields, plantations, rice paddies, etc.).

Those variables which describe natural and/or managed (rice paddies, crops, etc.) plant phenology contributed highly across the top 20. The Normalized Difference Water Index (NDWI) and Landsat 8 OLI's SWIR 2 band are influenced by plant water content, while the Landsat 8 TIRS bands are influenced by soil moisture. Moisture again appears in the top 20 through the inclusion of the Tasseled Cap Wetness Index for the dry-cold season as well as the different in Tasseled Cap Wetness from the dry-hot to the dry-cold season. The contributions of these variables highlight the dramatic changes that the monsoon season brings to managed landscapes in between the two dry seasons. Finally, it is assumed that the inclusion of the Landsat Tree Cover Continuous Fields Product was instrumental in delineating the large swaths of natural forest present between areas of human activity.

The most surprising finding within this research is the contribution of variables which describe the prevalence of slash-and-burn agriculture in the region. While the inclusion of these variables in the first place was intentional, we were somewhat surprised to learn how large their contribution was. The Normalized Burn Ratio 2 Index for the dry-cold season image contributed the 3rd highest mean decrease in accuracy. Distance to Recent Active Fire (from both MODIS and VIIRS data), the Landsat 8 TIRS bands, and NBR2 for the dry-hot season image all also appear in the top 20. While the Landsat 8 TIRS bands have already been mentioned in relation to soil moisture, they are likely important for this reason too as thermal bands. In addition, the inclusion of proximity to active fire locations has greatly improved the model's predictive capability in identifying human settlement patterns. Clearly, mapping the human footprint on a landscape can be enhanced through incorporating local land use practices into the conceptual design for algorithm development. This is particularly applicable at the local to subcontinental scales where land use practices are shared across the region. In this study, satellite observations of fire activity from slash and burn agriculture strongly improved the predictive capabilities of the algorithm. Slash and burn agriculture and crop residue burning across more permanent cropping regions is common in South East Asia and was particularly helpful in algorithm design as fire activity within this climatic setting is limited to human use. However, this metric will have less predictive power across areas with substantial natural fire activity (e.g. boreal regions) or other uses of fire as a management tool (e.g. fuel reduction practices). Field visits provide a good opportunity to identify land use practices that can be combined with satellite observations to improve the detection of human footprint on the landscape. However, the information can frequently be obtained through collaborations with regional experts or through peer reviewed literature.

Finally, variables which described a settlements physical location appeared often in the top 20, including: Distance to Roads, Distance to Water, Elevation, Distance to a Waterway 3rd Order or Greater, and Texture: NIR Mean Occurrence. Distance to Roads is perhaps the least surprising variable to appear in the top 20 – it is clear that a more detailed/complete road network dataset would greatly improve this and any future analysis, though often in data poor regions a lack of settlement data means there is likely little to no road data as well. However, while road data presents an obstacle, the other variables discussed here are all either available freely on a global scale (elevation through SRTM DEMs) or can be created with standard GIS software capabilities using freely available global data (Distance to Water, Texture).

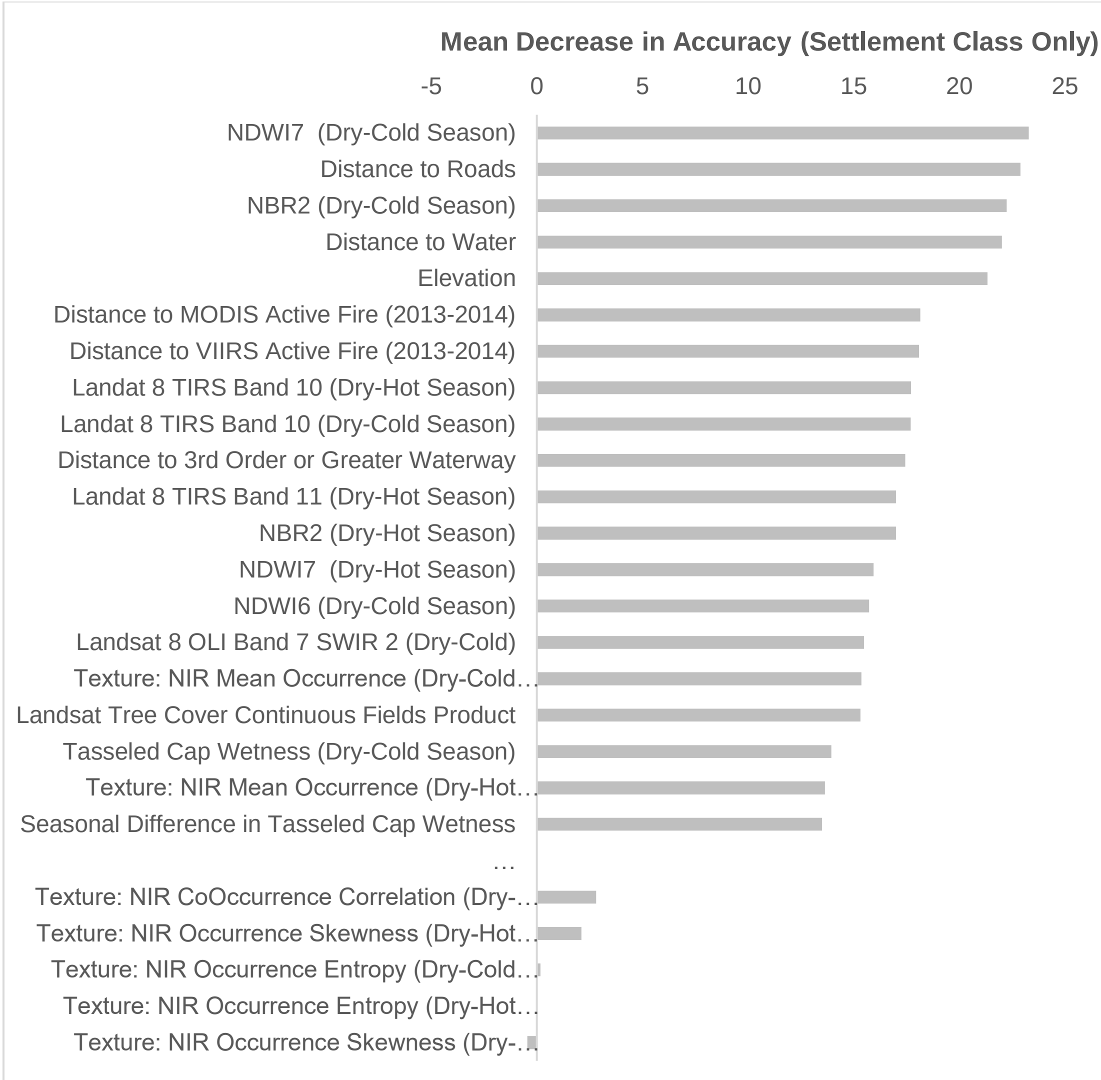


Figure 2-8: Mean decrease in accuracy of the RF algorithm for top 20 variable contributors to model and bottom 5 variable contributors for "Settlement" class only. The decrease in accuracy is calculated as if the variable in question has been excluded from the RF algorithm. The more the accuracy decreases due the exclusion of that variable, the more important/contributory it is deemed to be.

The 5 variables which contributed the least to the classification are shown at the bottom of Figure 2-8, with the bottom two contributing conversely to the overall accuracy. All 5 variables shown are part of the Textural metrics that were calculated. Skewness (a measure of symmetry around the mean pixel value of a 3x3 kernel) and Entropy (a measure of disorder among pixel values within a 3x3 kernel) were particularly not contributory. This is likely due to a combination of their measures not being of particular use in settlement classification mapping and any potential contribution likely being correlated with another variables more influential contribution (such as the Texture: NIR Mean Occurrence appearing in the top 20).

The inclusion of all 84 variables was necessary for the purposes of elucidating the contributions of each but did impose limitations on the presented method in terms of necessary computing power and efficiency of data collection (though all data used is free, organization and storage takes time). These could present insurmountable challenges to those who might wish to apply this method to other data poor regions. Therefore, an analysis was conducted to determine the feasibility of reducing the number of input variables by removing those which did not contribute highly and those which correlated strongly with a higher contributing variable. Specifically, our goal was to identify a model with minimal number of variables with an acceptable level of loss of model performance. During this analysis, a forward stepwise selection process was implemented based on the variable importance as revealed in Table A1. We started with a model that contained only one variable, being NDWI7 (Dry-Cold Season) whose importance was the highest. Additional variables were added into the model sequentially following the suggested importance order after passing a test for correlation, which was designed to filter out variables that were overly correlated with the existing variables. For this test, the Pearson Correlation coefficient was calculated. If the variable in question was statistically significantly ($p < 0.05$) correlated with any of the existing variables and the correlation coefficient was larger than 0.5, it was excluded from further analyses. Each time a variable was confirmed to be included, a new random forest model was created and the OOB error rates for the overall model and settlement class were calculated.

Ultimately, an algorithm using 5 variables was determined to result in the smallest increase in the reported OOB error (14.1% vs 11.7% for the full model). The 5 variables included in the paired down algorithm are: NDWI7 (Dry-Cold Season), Distance to Roads, Distance to Water, Distance to a Recent Active Fire (MODIS), and Landsat 8 TIRS Band 10 (Dry-Hot Season). This method severely limited the use of spectral data and relied more heavily on locational metrics. While the OOB error increased by only 2.4%, a per-pixel accuracy assessment that we conducted revealed larger increases in error. Table 2-5 compares the results of the per-pixel accuracy assessments, where the overall accuracy of the map decreased by 6.0% and the Producer's and User's accuracies for the "Settlement" class decreased by 17.77% and 17.01% respectively. Dependent on user goals, computing power, and data availability (particularly road network data) this may or may not be an acceptable amount of accuracy loss.

Table 2-5: Per-Pixel Accuracy Assessment Results of Full RF Model and Limited RF Model

	Full RF Model (84 Variables Included)	**Limited RF Model (5 Variables Included)**
Overall Map Accuracy	86.50%	80.50%
Producer's Accuracy for Settlement Class	60.41%	42.64%
User's Accuracy for Settlement Class	67.61%	50.60%

2.4.3 Future Directions

One of the primary goals of this research was to develop a methodology that could be reproducible elsewhere. Our overall approach and input variable suite are appropriate for locating settlements across Myanmar, and likely across the monsoonal range of SE Asia. However, we are aware of substantial contextual differences in settlement distribution at national and regional scales. It is likely that the existing algorithm will perform well across other remote mountainous regions of Myanmar (e.g. Chin, Kachin, and Shan states) but additional training samples would be required to represent lowland cropland-dominated landscapes which contextually and spectrally differ from the example of Ann Township used in this manuscript. For this iteration of our algorithm, we collected 3720 sample pixels, which represent just 0.025% of the ~14.5 million pixels that cover Ann when imaged at 30 m resolution. This is promising for limiting the time intensity of training data collection for expansion to larger regions. Also promising is that data availability in general is better across the lowland areas of Myanmar than it is for the remote mountainous regions. However, it is those regions, including Ann, which are particularly affected by a lack of precise settlement distribution data. Our algorithm without any further modification is likely to make a considerable contribution to the state of settlement mapping for these regions.

The use of Landsat data in this research provides exciting opportunities to conduct historical settlement pattern analysis given the long history of Landsat data collection. Perhaps more exciting though, is the ability to adapt this methodology to new moderate resolution datasets in the future, including Landsat 9 (launch scheduled for 2020) and Sentinel 2 (2015 – present). The Sentinel 2 mission collects similar spectral bands to the

Landsat 8 mission, however it also includes a higher repeat frequency and, for many bands, a finer spatial resolution (10 m, 20 m, and 60 m). The finer spatial resolution could alleviate some of the challenges to mapping settlements with Landsat while remaining computationally feasible over large areas, which remains a challenge when using VHR data. Work is well underway to create a harmonized Landsat and Sentinel 2 data product, known as HLS (Claverie et al., 2018). The goal of HLS it to combine the observations from both Landsat and Sentinel 2 so that a user may examine any given pixel as a near-daily reflectance time series, as though it came from a single sensor (Claverie et al., 2018). This dataset could improve our methods accuracy by increasing the likelihood of obtaining cloud free composites. This would be of particular utility for Ann and other subtropical regions where an image closely following the monsoon season would be helpful in identifying rain-fed agricultural practices across the landscape.

2.5 Conclusions

Through this research we have shown that Landsat data can be successfully used to map rural, remote, and isolated populations which was previously considered insufficient for this purpose due to the limitations of Landsat's spatial resolution. Through incorporating key contextual metrics that are sensitive to regional trends in human activity we were able to overcome the challenges inherent in mapping settlements which are generally comprised of structures smaller than that of a single Landsat pixel. For Ann Township specifically, the presence of fire was strongly associated with human activity and greatly improved settlement mapping accuracy. This presents an exciting opportunity for future work as data availability increases across all fields. In the present, however, the methodology presented here is reproducible, both over time and space. By using Landsat as the primary data input the ability to expand to all of Myanmar, or other countries/regions, is now possible. Furthermore, long term study could now feasibly be undertaken given the long history of the Landsat archive, which will also presumably advance into the future with the current plans for the launch of Landsat 9 in 2020 as well as the newly released Harmonized Landsat and Sentinel 2 surface reflectance dataset.

The resultant map provides a useful augmentation to similar mapping efforts being undertaken in the region. While our map would not be adequate for footprint and/or population count analysis, it does provide critical insights into where people live so that aid and services are better able to locate them in times of crisis or to provide routine assistance and services (e.g. healthcare, education, etc.). Marginalized people often live separated from the rest of the world, which can be the result of oppression, or cultural, religious, and other personal preferences against integrating with adjacent communities, or more simply because governmental and/or aid agencies are unaware that they exist. Through revealing these isolated populations, researchers, NGOs, and government agencies will be able to more decisively respond in the face of a crisis, monitor human induced changes to the environment, and provide appropriate health and poverty alleviation programs.

Chapter 3: Contextualizing Malaria Exposure in Myanmar by Combining Satellite-Derived Land Cover and Use Observations with Field Surveys[2]

3.1 Introduction

Despite considerable progress towards elimination in the past decades, malaria remains a significant global public health burden and priority. In 2013 the United Nations released its ambitious Sustainable Development Goals for the year 2030. Goal 3, Target 3.3 directly relates to malaria by setting a goal to “end the epidemics of AIDS, tuberculosis, malaria, and neglected tropical diseases” (Griggs et al., 2013). Similarly, the World Health Organization (WHO) released its own ambitious goal for malaria in 2016, namely at least a 40% reduction in malaria cases by 2020, at least 75% by 2025, and at least 90% by 2030 (WHO, 2015a). As we approach the first milestone year for WHO’s ambitious plan, progress has unfortunately stalled (WHO, 2019). In response, the WHO shifted its priorities to a new aggressive plan titled “High burden to high impact: a targeted malaria response” (WHO, 2019). Four key elements define this new plan, the second of which includes moving away from a “one-size-fits-all” approach and instead

[2]This chapter has been written with the intention of submission as a multi-authored paper in the journal *GeoHealth.* Authors include: Amanda Hoffman-Hall, Robin Puett, Julie A. Silva, Dong Chen, Allison Baer, Kay Thwe Han, Zay Yar Han, Aung Thi, Thura Htay, Zaw Win Thein, Poe Poe Aung, Christopher V. Plowe, Myaing Myaing Nyunt, Tatiana V. Loboda
Amanda Hoffman-Hall was the primary researcher and conducted all data analysis with advisory input from other authors of the manuscript. Data collection was supervised by Dr. Myaing Nyunt.

using data-driven methodologies to pinpoint where to deploy the most effective malaria control tools for maximum impact.

Although the number of malaria-driven deaths is highest in Africa, the urgency of malaria elimination is equally high in South East Asia, where there has been a documented emergence of Artemisinin resistant *Plasmodium falciparum* parasites (WHO, 2015a). For this reason, the WHO also released the "Strategy for malaria elimination in the Greater Mekong Subregion (GMS)" (WHO, 2015b). Since the implementation of this strategy, malaria cases have fallen dramatically across the GMS. However, forward momentum must continue to reach full eradication. The country of Myanmar has been a success story, with a decrease of 82% of malaria cases in the country from 2012-2017 (WHO, 2018). However, the country is facing numerous challenges which could inhibit its forward progress, including artemisinin-resistant parasites, pyrethroid-resistant malaria vectors (WHO, 2018), lengthy borders with other malarious countries (Bhumiratana et al., 2013; Kounnavong et al., 2017; Parker et al., 2015), and health care access issues for mobile/migrant populations (NMCP, 2017, 2016).

Following the call from the WHO to pinpoint malaria control for the highest impact and the urgency of keeping momentum in Myanmar, now more than ever, it is critical to find feasible ways to implement targeted intervention strategies. Similar to other low-transmission areas, malaria prevalence across Myanmar is heterogeneous, patchy, and complex. Further complicating matters is the high prevalence of asymptomatic, low-density malaria infections (Adams et al., 2015; Imwong et al., 2015, 2014). Using an ultrasensitive reverse transcription PCR (usPCR) assay (Adams et al., 2015), we are finding that the prevalence of malaria at sites within and bordering Myanmar is highly heterogeneous. Villages with high prevalence are often close to villages with little or no malaria. While acute cases are more likely to seek treatment, allowing for easier monitoring and disruption of transmission, asymptomatic carriers are unaware of the need to seek treatment and therefore represent a silent and long-lasting reservoir that can significantly hinder elimination efforts (Lindblade et al., 2013). Strategies that rely on self-reporting of infection to track malaria hotspots will be insufficient when seeking to eliminate the last few pools of malaria remaining in the country. While a census level collection of blood samples would be the ideal way to identify these remaining parasite pools, such an undertaking would be extremely costly and challenging to implement. An intermediary that can target likely hotspots of infection is needed to inform the sampling scheme necessary to capture the few remaining malaria reservoirs.

Spatial statistical modeling has been deployed in multiple countries for malaria forecasting (Rogers et al., 2002; Thomson et al., 2006). Such models typically rely on environmental variables that are associated with the habitat suitability and population dynamics of the malaria mosquito vector. When these environmental variables are forecast over space and time, predictive maps of vector densities can be created. However, previous studies have shown that models that rely solely on vector densities are only loosely associated with actual malaria prevalence. Models that incorporate factors relating to human behavior and human population, in conjunction with vector densities, align better with observations of malaria distribution (Mwakalinga et al., 2016; Ngom and Siegmund, 2010).

An example of human behavior associated with malaria is occupation or livelihood. How people live, work, and move through their landscape can increase or decrease their risk of contracting malaria. For example, Zaw et al. (2017) found a higher prevalence of asymptomatic malaria among Myanmar workers with forest-related occupations, with an odds ratio approximately ten times greater than study participants whose occupation was not forest-related. Soe et al. (2017) found high associations between malaria morbidity and occupation, with fire woodcutters at the highest risk and night-time rubber tree tappers at the lowest risk. While no country-wide datasets describing occupational exposure exist and obtaining those data via surveys is prohibitively expensive and frequently not feasible in remote hard-to-reach areas, many of the parameters describing potential occupation- or livelihood-related malaria exposure can be captured through satellite-based land cover and land use (LCLU) mapping. Land cover (LC) describes the physical properties of the landscape (tree, shrub or grass cover, open water, impervious surface, etc.) while land use (LU) describes how humans are using the land in question (plantation, natural forest, built structures, cropped areas). In combination, LCLU maps can be used as a proxy for human activity on the landscape, allowing for incorporating livelihood exposure metrics into malaria models.

Within Myanmar, the patterns of LCLU are incredibly variable in space and time. Myanmar is a rapidly developing economy that rejoined the global markets relatively recently. Rapid land cover change is occurring across the country, with estimates of nearly 2 million hectares (Mha) of intact forest lost occurring annually (Bhagwat et al., 2017). With such rapid changes occurring, satellite remote sensing offers a methodology for capturing the composition of land cover and land use while also monitoring the change in the environmental conditions both related to vector dynamics and population exposure.

Moderate-resolution remote sensing instruments, such as Landsat, are particularly well-suited to collect data at scales relevant to human activity, specifically the smaller scale patterns of LCLU within remote regions of Myanmar where the majority of malaria pools persist. However, satellites are unable to capture the full scope of how people engage in various land uses. This research seeks to contextualize moderate resolution remotely sensed land cover data using survey data that questions how people use the land for a remote township within Myanmar. The goal of this research is to define criteria for easy-to-implement remote sensing methodologies that can increase the efficiency of targeted malaria elimination strategies.

3.2 Materials and Methods

3.2.1 Study Area

Five remote villages dispersed across sub-tropical Ann Township, an administrative region (similar to a county) within Rakhine State, Myanmar (Figure 3-1), were surveyed. Rakhine State carries a high malaria burden for the region, with an estimated Annual Parasite Incidence (API) of 9.54 in 1,000 population for any malaria according to the Vector Borne Disease Control Annual Report 2016 compiled by the National Malaria Control Programme (NMCP), Ministry of Health and Sports, Myanmar (NMCP, 2017). This incidence rate is much higher than the estimated API of 0.14 and 0.29 for neighboring regions Magway and Bago, respectively.

Ann Township stretches from the west coast eastward to mountainous terrain. Ann specifically carries a high malaria caseload, in comparison with other GMS locations, and the largest asymptomatic reservoir), detected by sensitive molecular techniques (unpublished data, Nyunt), despite an overall low transmission rate. The primary malaria vectors are forest-dwelling *Anopheles dirus* and foothill and valley-dwelling *Anopheles minimus* (Oo et al., 2004). Malaria parasites *Plasmodium vivax* and *P. falciparum* are most commonly identified in the region; however, *P. knowlesi* has been recently identified elsewhere in Myanmar (Ghinai et al., 2017; Jiang et al., 2010).

The population of Ann is dynamic and distributed across the landscape in a highly uneven pattern, with human settlements covering less than 0.1% of the total land area (Hoffman-Hall et al., 2019). This uneven distribution results in isolated groups of people that can serve as primary drivers of infectious diseases (in this case, malaria) into previously disease-free regions upon migration or travel (Martens and Hall, 2000). Eliminating malaria from these isolated populations (transmission "sources") is difficult as NMCP is often unable to reach and engage with them; however, left untreated, these groups could hinder overall elimination progress. The next step, therefore, must be to discover which characteristics, identifiable via remote sensing, influence malaria transmission in these populations to facilitate the quick and efficient identification of areas in need of targeted elimination interventions.

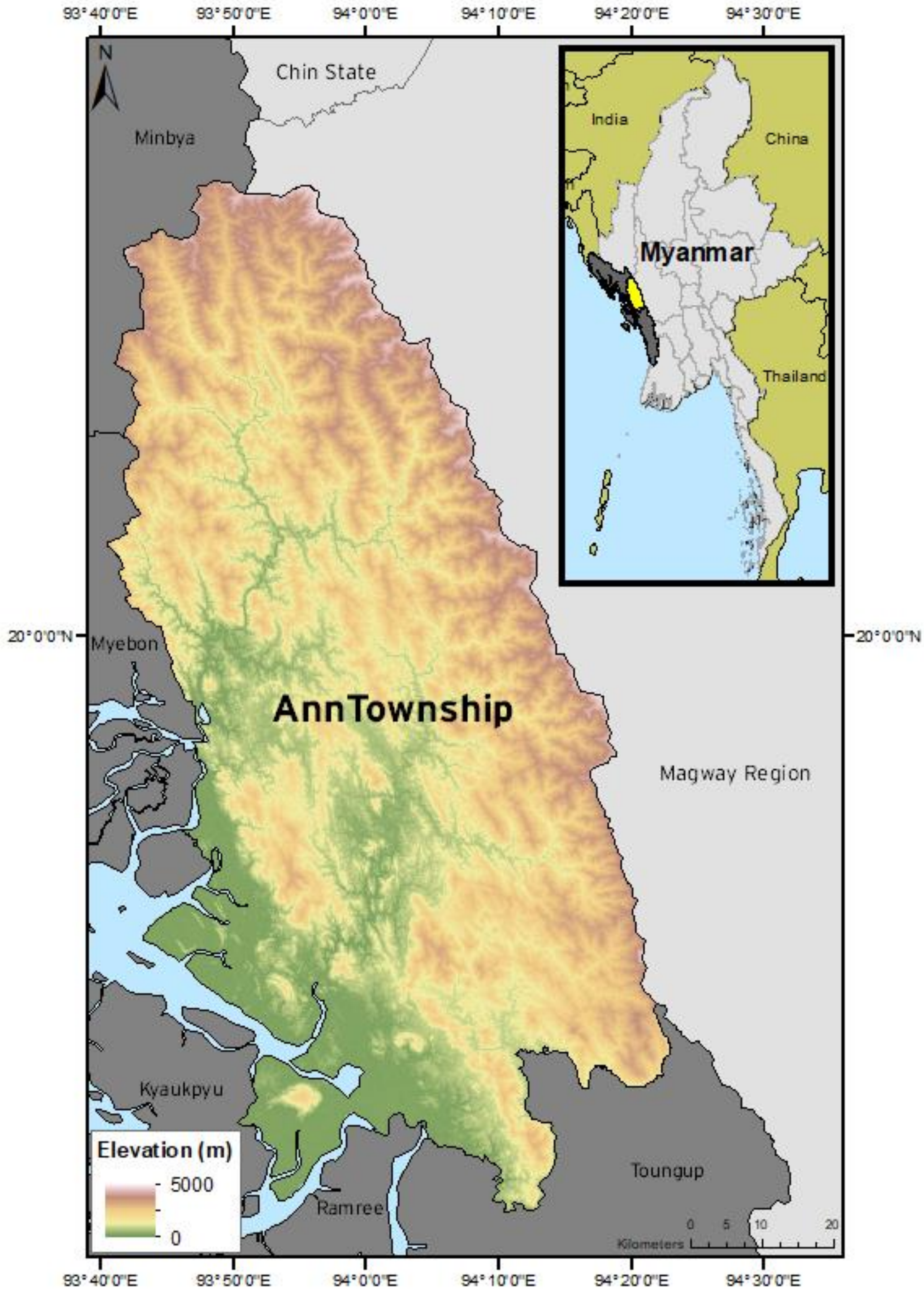


Figure 3-1: Map detailing the location of the study area: Ann Township, Rakhine State, Myanmar

3.2.2 Data

3.2.2.1 Malaria Prevalence

A prospective cross-sectional study was conducted in March – June 2016 to estimate the prevalence of malaria in five remote villages in Ann township in Rakhine State. The study was independently reviewed and approved by the Institutional Review Boards of the Myanmar Department of Medical Research, Duke University, and the University of Maryland College Park. The village selection was based on known or suspected malaria burden and research team capability to ensure the integrity of the study data and samples. Inclusion criteria included age at least six months old, compliance with study procedure, and written informed consent. Community outreach was conducted twice before the study to ensure community buy-in and adequate dissemination of knowledge about the upcoming study. The primary means of study recruitment was word of mouth, recognized as effective in previous studies (Huang et al., 2017). A two-stage household- and individual-based randomization scheme was used to approximate the local population as closely as possible. Households were selected using a random number randomization method, until a target sample size was reached, assuming that each household was composed of 4.5 (ranging between 2 and 12) members on average, based on the census data. From each household, if the household contained four or fewer, everyone was sampled, or four individual members were randomly selected from larger households using a random number method. Written consent was obtained from a designated head of the household and each participant. If a potential participant refused or was unavailable, the next nearest household was selected. Data were collected using a standardized and validated questionnaire (see below) by trained study personnel. Finger prick blood was collected for malaria testing using a rapid diagnostic test (RDT) and transferred on to a filter paper for laboratory molecular analysis using an ultrasensitive polymerase chain reaction (usPCR) method. The result of the RDT was documented in real-time. Filter paper blood samples were labeled and air-dried. These dried blood spot (DBS) samples were placed in an individual ziplock bag containing desiccant and stored in a refrigerator until transport to a central lab. *P. falciparum*, *P. vivax*, and mixed infections were all identified by usPCR (Zainabadi et al., 2017).

A total of 990 participants were enrolled and completed the study successfully. No unexpected or severe adverse events were reported. Only one case of *P. falciparum* was identified by RDT and was treated by a referred care team, following the national treatment guidelines. The characteristics of the study population, study villages, and village-based malaria prevalence for *P. falciparum* mono-infection, *P. vivax* mono-infection, and mixed infection are summarized in Table 1. Those with usPCR-positive malaria were not treated since treatment is not recommended by the Myanmar national program or the WHO, nor is there a clear understanding of a risk-benefit ratio for treating them.

3.2.2.2 Data on Malaria Risk

A questionnaire was developed to collect demographic information for each participant, based on malaria literature which commonly identifies the following variables as potential confounders: age (Wendy P. O'Meara et al., 2008), pregnancy status (Desai et al., 2007), travel status ("have you traveled outside of the village in the past six months?") and family travel status ("has anyone in your family traveled outside the village in the past six months?") (Wesolowski et al., 2012). Sex was also assessed as a possible confounder and effect modifier (Ayele et al., 2012). Each participant was also surveyed about their prior symptoms to assess the subclinical nature of malaria infection. Prior symptoms included fever, headache, body ache, nausea, vomiting, abdominal discomfort, decreased appetite, or fatigue, all within the previous two months, as well as fever within the previous 24 hours. Axillary body temperature of each participant was recorded at the time of data collection.

3.2.2.3 Exposure: Land Use, Land Cover, and Forest Cover Change

As part of the questionnaire, participants were asked about their land use in areas relevant to malaria exposure. Specifically, they were asked if they visited any of the following locations frequently (defined as at least twice a week or continuous two weeks): farm, forested area, plantation, mine, refugee camp.

Satellite-based LCLU data was derived from a 30 m LCLU map of Ann in 2016 created for this research. Eight classes were identified in the following order: 1) water, 2) human infrastructure, 3) croplands, 4) managed forest (i.e., plantations), 5) natural forest, 6) topographic depressions, 7) shrub and grass, and 8) bare ground. The water class was mapped using the Landsat Surface Water Fraction algorithm (DeVries et al., 2017). Human infrastructure was a combination of impervious surface mapped by the Global Man-made Impervious Surface (GMIS) data product (Brown de Colstoun et al., 2017) and Ann Township villages mapped at 30 m resolution by Hoffman-Hall et al. (2019). The croplands class was mapped using the Global Food Security-support Analysis Data (GFSAD) Cropland Extent 30 m dataset (Oliphant, A., 2017). The managed forest class was mapped by capturing areas of forest change from 2001 – 2016 via the Global Forest Change (GFC) 30 m product (Hansen et al., 2013). The natural forest class was mapped using the Landsat Vegetation Continuous Fields product (Sexton et al., 2013). Topographic depressions were determined based on surface curvature and flow accumulation calculated using the Shuttle Radar Topography Mission (SRTM) 1-arc second digital elevation models (DEM). These six classes were combined into a single map hierarchically based on the order priority mentioned above. Specifically, the classification began with the class with the highest priority (water) and continued following the order of priority. If a pixel had already been assigned a class value with higher priority, it would no longer be eligible for subsequent classification. All remaining pixels that were not mapped into any of the first six classes were classified into either shrub/grass or bare ground, based on the Landsat-derived Normalized Difference Vegetation Index (NDVI) with a threshold value of 0.5 (shrub/grass: > 0.5, bare ground: ≤ 0.5).

The resultant map was assessed for accuracy using the assessment methodology based on the fuzzy set theory developed by Woodcock and Gopal (2000). The total weighted accuracy for the map is 81.73% when fuzziness (i.e., tolerance for error) is considered. For the land covers of primary interest, natural forests, managed forests, and croplands, the accuracies are 90%, 48%, and 84%, respectively. The full results of the accuracy assessment can be found in Appendix Table A2.

For each village surveyed, we derived a satellite-based characterization of village environmental settings by calculating the area of each mapped LCLU category within a 2 km radius of the center of the village. The rationale of choosing 2 km as our buffer distance is grounded in the flight dispersal of the major malaria vectors in the region, *An. minimus* and *An. dirus*, which have estimated flight ranges of 1 km and 2 km, respectively (Dev et al., 2004; Marchand et al., 2004).

We also analyzed forest cover change. We calculated the area of forest loss within 2 km of each village for the year 2016 (the year of survey data collection) derived from the GFC 30 m product described above. We also calculated the annual rate of forest loss for the previous five years (2012-2016) and the total area of forest loss within that period.

3.2.3 Statistical Analysis

Of the 990 participants, 11 were excluded due to missing age (n=5) or unknown pregnancy status (n=6). Univariate and multivariate logistic regression analysis was chosen to understand the association between the exposure variables and outcome (presence of malaria parasites in the blood sample). Due to the low overall prevalence of malaria (9.40%, n=92), *P. falciparum*, *P. vivax,* and mixed infections were all considered as a positive case. Univariate analysis was performed to assess the relationship between individual malaria and each subset of exposure variables, including self-reported land use (frequent visits to farms, forests, and plantations), satellite-based environmental village settings (area of croplands, natural forests, and managed forests in square kilometers), and forest cover change variables (area of recent forest loss, rate of forest loss, and area of 5-year-cumulative forest loss). The variables of frequent visits to refugee camps or mines were not analyzed because no participants responded affirmatively to those questions.

For each univariate model where the assessed exposure variable was found to be significantly associated with malaria ($p < 0.05$), potential confounders were progressively added (age, age squared, sex, pregnancy status, travel status, family travel status). Biologically plausible confounders found to be significant remained in the final adjusted model while non-significant variables were removed. Within the fully adjusted models, interactions by sex were examined via interaction terms. If interactions were significant stratified models were considered. Odds ratios (ORs) and 95% confidence intervals (CIs) were calculated for the resultant adjusted and stratified models. All data analysis was undertaken in R statistical software packages.

Finally, we conducted three sensitivity analyses to evaluate the robustness of our findings. Sensitivity Analysis I sought to examine Village D's impact on the results by removing Village D from the study sample and comparing these results to those of the main analysis. The respondents from Village D were all working-aged males – very different than the respondent demographics from the other villages, which more closely follow the general demographics of Myanmar (MPHC, 2014). Sensitivity Analysis II assessed the influence of village environmental settings on malaria infection in those participants who reported no to frequently visiting farms, forests, or plantations (i.e., the participants answered “no” to every land use question, *see section 2.3.2*) and presumably primarily remained in the village during the past six months. Sensitivity Analysis III was conducted to evaluate further the relationship found between forest loss metrics and malaria. In this analysis, we removed Village C from the dataset because the amount of forest loss surrounding that village was significantly higher than for the other four villages (See Section 3.3.5).

3.3 Results

3.3.1 Demographics: Confounders and Effect Modifiers

As shown in Table 3-1, 9.4% (n=92) of our study population tested positive for malaria parasites via usPCR testing. *P. vivax* malaria is more prevalent in this region: 30.4% (n=28) tested positive for *P. falciparum* while 63.0% (n=58) tested positive for *P. vivax*, with the remaining 6.5% (n=6) identified as mixed infections. Nearly every positive case was asymptomatic/subclinical. While debate exists regarding the confirmed definition of asymptomatic malaria, the most widely-used criteria are the presence of parasites in peripheral thick blood smears, an axillary temperature <99.5°F, and no evidence of malaria-related symptoms (Laishram et al., 2012). Of the 92 positive cases, only one case reacted positively to RDT testing. No respondent had a fever at the time of data collection, though a few respondents claimed to have had a fever within the past 24 hours (n=4) or past two weeks (n=6). Similarly, low numbers were reported for other symptoms experienced in the past two weeks, including headache (n=34), body aches (n=31), nausea (n=3), vomiting (n=5), abdominal pain (n=15), loss of appetite (n=5), and fatigue (n=6).

Our sample population skewed male (60.4%) because participants from Village D were all male. Otherwise, each village was split approximately equally between male and female participants. Sex was not determined to be a significant cofounder within our study; however, a significant interaction was evident between sex and farmland use. Therefore, models stratified by sex are presented for farm-related variables below.

The participant age distribution generally follows the age distribution of Myanmar (MPHC, 2014), with slightly more participants in the 25 – 54 age group (52.2%) when compared to the country overall (42.51%) and slightly less in all other groups. This is again due primarily to Village D, where the sample is composed entirely of working-aged males. A non-linear relationship between age and probability of malaria infection was discovered (Fig 3-2). Age and age-squared proved to be significant confounders and are therefore included in each adjusted model presented.

Six women reported being pregnant during the time of sample collection. However, despite low overall malaria prevalence, malaria infection within the pregnant cohort was high at 50% (n=3). For this reason, pregnancy status is included in all fully-adjusted models presented and within any female stratified models.

For travel status, 463 (47.3%) participants reported traveling outside the village within the past 6 months, with the majority of those (n=198) reporting from Village D. Mobility of family members (although not necessarily the participants themselves) was nearly equally high: 390 (39.8%) participants reported having a family member from their household traveling outside the village within the past 6 months. Neither of these variables was determined to be significantly associated with malaria infection through univariate logistic regression and were therefore not adjusted for in the final models.

Table 3-1: Descriptive statistics of the sample population.

Village	A	B	C	D	E	Total
Population Sampled, n	193	198	192	199	197	979
Sex: n (% of sample village population)						
Female	96 (49.7%)	108 (54.5%)	93 (48.4%)	0 (0%)	91 (46.2%)	388 (39.6%)
Male	97 (50.3%)	90 (45.5%)	99 (51.6%)	199 (100%)	106 (53.8%)	591 (60.4%)
Age: n (% of sample village population)						
0 – 14	60 (31.1%)	60 (30.3%)	80 (41.7%)	0 (0%)	33 (16.8%)	233 (23.8%)
15 – 24	33 (17.1%)	27 (13.6%)	34 (17.7%)	24 (12.1%)	34 (17.3%)	152 (15.5%)
25 – 54	71 (36.8%)	80 (40.4%)	65 (33.9%)	170 (85.4%)	125 (63.5%)	511 (52.2%)
55 – 64	17 (8.8%)	17 (8.6%)	6 (3.1%)	5 (2.5%)	4 (2.0%)	49 (5.0%)
65+	12 (6.2%)	14 (7.1%)	7 (3.6%)	0 (0%)	1 (0.5%)	34 (3.5%)
Pregnancy Status: n (% of sample village female population)						
Pregnant	1 (1.1%)	1 (0.9%)	0 (0%)	0 (0%)	4 (4.4%)	6 (1.5%)

Not Pregnant (excludes males)	95 (98.9%)	107 (99.1%)	93 (100%)	0 (0%)	87 (95.6%)	382 (98.5)
Travel: n (% of sample village population)						
Participant travelled outside village in past 6 months	86 (44.6%)	75 (37.9%)	52 (27.1%)	198 (99.5%)	52 (26.4%)	463 (47.3%)
Family member(s) of participant travelled outside village in past 6 months	112 (58.0%)	115 (58.1%)	83 (43.2%)	39 (19.6%)	41 (20.8%)	390 (39.8%)
Self-Reported Exposure: n (% of sample village population)						
Frequently visits forest areas	44 (22.8%)	54 (27.3%)	24 (12.5%)	75 (37.7%)	52 (26.4%)	249 (25.4%)
Frequently visits plantations	0 (0%)	3 (1.5%)	24 (12.5%)	109 (54.8%)	67 (34.0%)	203 (20.7%)
Frequent visits farms	79 (40.9%)	91 (46.0%)	91 (47.4%)	14 (7.0%)	8 (4.1%)	283 (28.9%)
Did not select any land use option	107 (55.4%)	100 (50.5%)	99 (51.6%)	74 (37.2%)	112 (56.9%)	492 (50.3%)
Malaria Prevalence: n (% of sample village population)						
***P. falciparum* mono**	9 (4.7%)	3 (1.5%)	13 (6.8%)	1 (0.5%)	2 (1.0%)	28 (2.7%)
***P. vivax* mono**	9 (4.7%)	6 (3.0%)	22 (11.5%)	12 (6.0%)	9 (4.6%)	58 (5.9%)
Mixed *P. falciparum* & *P. vivax*	1 (0.5%)	1 (0.5%)	4 (2.1%)	0 (0%)	0 (0%)	6 (0.6%)
Any malaria	19 (9.8%)	10 (5.1%)	39 (20.3%)	13 (6.5%)	11 (5.6%)	92 (9.4%)

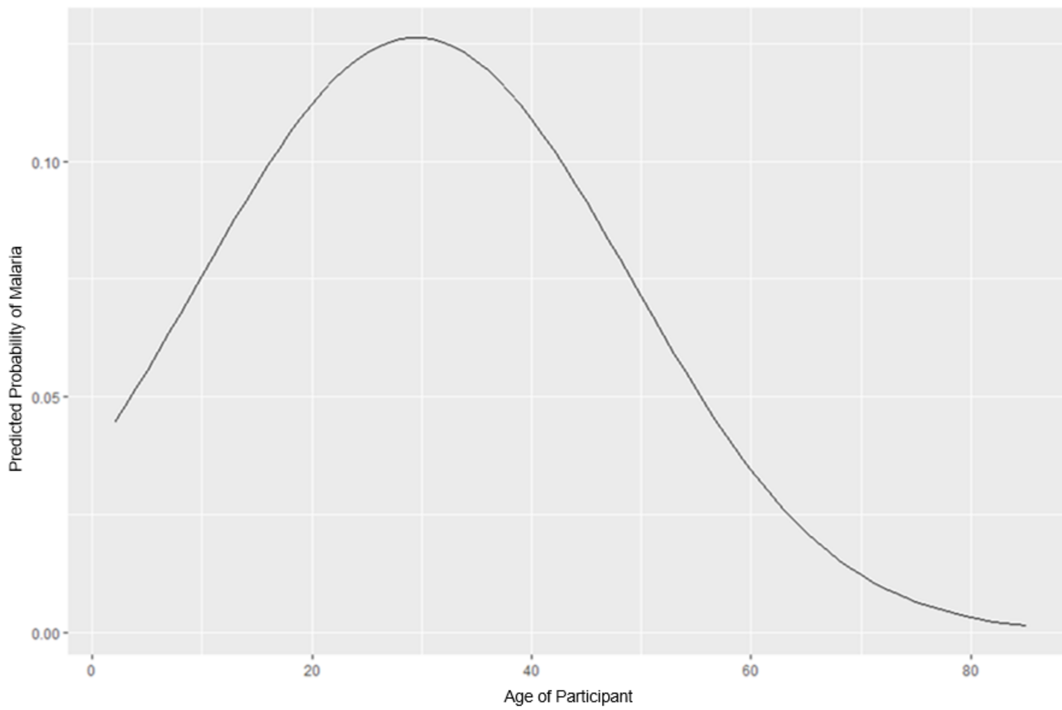


Figure 3-2: Logistic regression univariate model derived relationship between malaria risk and age

3.3.2 Sensitivity Analysis Demographics Comparison

The sensitivity analyses altered the demographics of our study sample in different ways (Table 3-2). The exclusion of Village D (Sensitivity Analysis I) resulted in demographics more similar to the overall demographics of Myanmar (MPHC, 2014), in terms of both age and sex distribution. Roughly half of the Primary Analysis group answered “No” to frequenting farms, forests, or plantations. When these respondents were grouped for Sensitivity Analysis II, the age distribution skewed much younger, with very few children removed from the sample. Sensitivity Analysis III was conducted to investigate the link to forest loss; therefore, the exclusion of Village C had less to do with demographics and more to do with the landscape of the village, which is further explained in Section 3.3.5; however, the changes in demographics are shown here.

Table 3-2: Demographic information of Primary Analysis compared to Sensitivity Analysis I, II, and III

Village	Primary Analysis	Sensitivity Analysis I (Village D Excluded)	Sensitivity Analysis II (Answered No to All 3 LU Questions)	Sensitivity Analysis III (Village C Excluded)
Population Sampled (n)	979	780	492	787
Sex: n (% of sample population used in analysis)				
Female	388 (39.6%)	388 (49.7%)	233 (47.3%)	295 (37.5%)
Male	591 (60.4%)	392 (50.3%)	259 (52.6%)	492 (62.5%)
Age: n (% of sample population used in analysis)				
0 – 14	233 (23.8%)	233 (29.9%)	215 (43.7%)	153 (19.4%)
15 – 24	152 (15.5%)	128 (16.5%)	81 (16.5%)	118 (15.0%)
25 – 54	511 (52.2%)	341 (43.7%)	166 (33.7%)	446 (56.7%)
55 – 64	49 (5.0%)	44 (5.6%)	10 (2.0%)	43 (5.5%)
65+	34 (3.5%)	34 (4.4%)	20 (4.1%)	27 (3.4%)
Pregnancy Status: n (% of sample female population used in analysis)				
Pregnant	6 (1.5%)	6 (1.5%)	4 (1.7%)	6 (2.0%)
Not Pregnant (excludes males)	382 (98.5%)	382 (98.5%)	229 (98.2%)	289 (98.0%)
Travel: n (% of sample population used in analysis)				
Participant travelled outside village in past 6 months	463 (47.3%)	265 (34.0%)	186 (37.8%)	411 (52.2%)
Family member(s) of participant travelled outside village in past 6 months	390 (39.8%)	351 (45.0%)	216 (43.9%)	307 (39.0%)
Self-Reported Exposure: n (% of sample population used in analysis)				
Frequently visits forest areas	249 (25.4%)	174 (22.3%)	0 (0%)	225 (28.6%)
Frequently visits plantations	203 (20.7%)	94 (12.1%)	0 (0%)	179 (22.7%)
Frequent visits farms	283 (28.9%)	269 (34.5%)	0 (0%)	192 (24.4%)
Did not select any land use option	492 (50.3%)	418 (53.6%)	492 (100%)	393 (50.0%)
Malaria prevalence: n (% of sample population used in analysis)				
***P. falciparum* mono**	28 (2.9%)	27 (3.5%)	7 (1.4%)	15 (1.9%)
***P. vivax* mono**	58 (5.9%)	46 (6.3%)	29 (5.9%)	36 (4.6%)
Mixed *P. falciparum* & *P. vivax*	6 (0.6%)	6 (0.8%)	2 (0.4%)	2 (0.3%)
Any malaria	92 (9.4%)	79 (10.1%)	38 (7.7%)	53 (6.7%)

3.3.3 Self-Reported Use of Landscape

Fully-adjusted models (adjusted for age, age-squared, and pregnancy) were created for each of the self-ported use of landscape variables, and ORs were calculated (Table 3-3). Frequent visits to a forest were not associated with malaria (OR: 1.26, 95% CI: 0.76 – 2.04). However, frequent visits to a plantation were found to be protective for malaria (OR: 0.51, 95% CI: 0.27 – 0.92). The association between frequent visits to a farm and malaria was modified by sex; therefore, we present fully-adjusted models stratified by sex. Within stratified models, we observed no relationship between frequent visits to a farm and malaria for females (OR: 1.36, 95% CI: 0.57 – 3.26), but a strong positive relationship was observed among males (OR: 3.86, 95% CI: 2.13 – 7.06). These results were reinforced by Sensitivity Analysis I, except for frequent plantation visits no longer being significantly protective.

Table 3-3: Model results expressing the risk of Plasmodium presence in the blood as a function of self-reported LU visit frequency. Blue cells indicate protective associations, red cells indicate risk associations, while white cells indicate non-significant associations.

	Primary Analysis		Sensitivity Analysis I (Village D Excluded [All Male Village])	
Variable	OR (95% CI)	p-value	OR (95% CI)	p-value
Frequently visits forest areas	1.26 (0.76 – 2.04)	0.3571	1.29 (0.73 – 2.21)	0.3683
Frequently visits plantations	0.51 (0.27 – 0.92)	0.0318	0.58 (0.24 – 1.22)	0.1820
Frequently visits farms – Female	1.36 (0.57 – 3.26)	0.4794	1.11 (0.36 – 3.59)	0.8605
Frequently visits farms – Male	3.86 (2.13 – 7.06)	< 0.001	2.74 (1.46 – 5.25)	0.0019

3.3.4 Village Environmental Settings

The results of the satellite-based LCLU mapping revealed large swaths of natural forests and croplands dominating the surrounding landscapes of the study villages within the 2 km buffer. All village landscapes contained some area of managed forests (between 2% to 7% of the total area mapped), but Village C was distinctive in that 24% of its landscape was covered by managed forest (Table 3-4). An inverse relationship between the area of natural forest and croplands was observed among the villages (Figure 3-3). Villages with expansive areas of natural forest (Villages A, C, and D) had comparatively small areas of croplands. Villages with large areas of croplands similarly have less area of natural forest (Villages B and E). A weak negative correlation was found between proximal croplands and village level malaria prevalence (R^2 = 0.56) (Figure 3-4a), while a positive correlation was found between proximal natural forest and village level malaria prevalence (R^2 = 0.73) (Figure 3-4b).

Table 3-4: Areas of relevant LCLU classes (percentage of total land) within 2 km of a village center in sq km.

Village	**A**	**B**	**C**	**D**	**E**
Croplands	1.58 (12.6%)	5.90 (47.0%)	0.26 (2.1%)	1.89 (15.1%)	3.09 (24.5%)
Managed Forests	0.74 (5.9%)	0.84 (6.7%)	2.97 (23.6%)	0.67 (5.4%)	0.28 (2.3%)
Natural Forests	7.19 (57.2%)	2.96 (23.5%)	8.14 (64.8%)	4.03 (32.1%)	1.53 (12.2%)

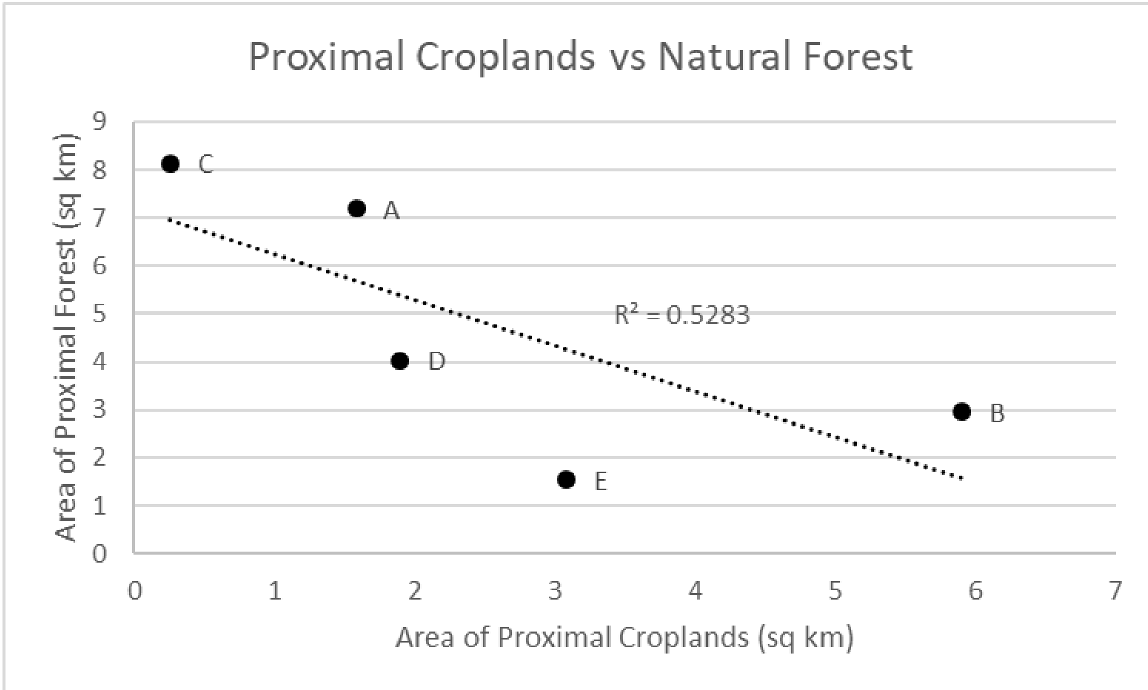
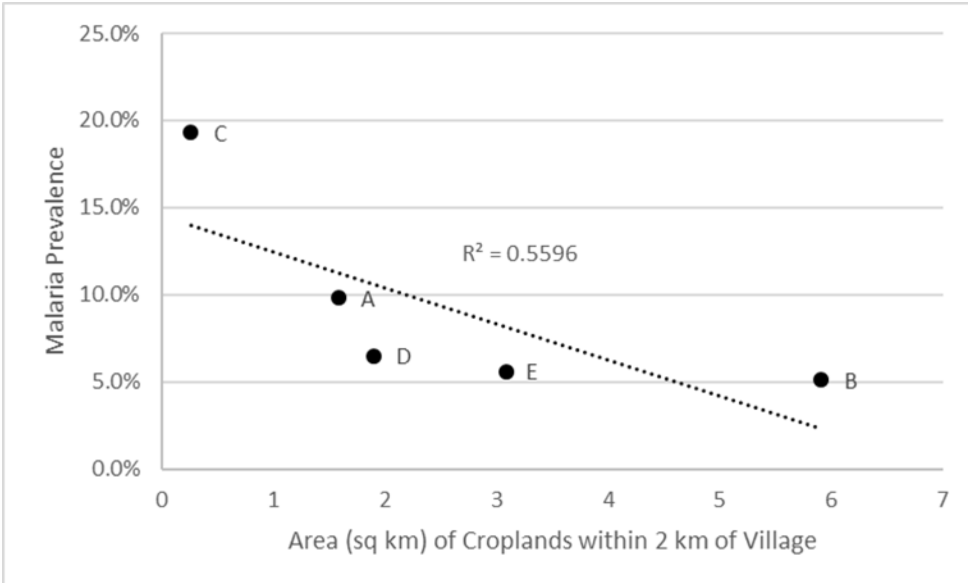
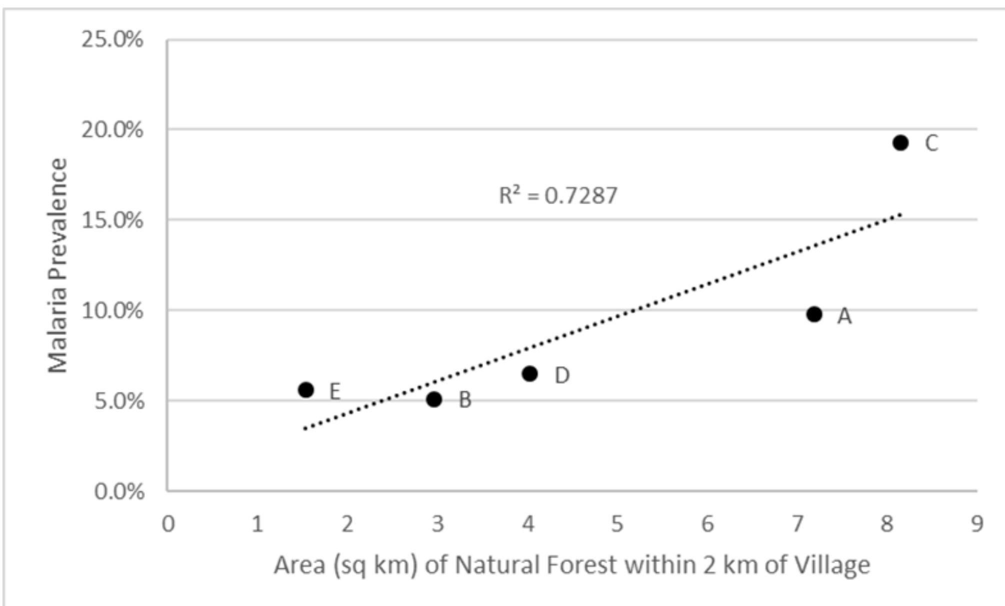


Figure 3-3:Relationship between the area of natural forest and croplands among the villages



(a)



(b)

Figure 3-4: Relationships between malaria village prevalence and (a) area of croplands within 2 km of a village and (b) area of natural forest within 2 km of a village.

Fully-adjusted models assessed the relationship between malaria and each of the village environmental settings variables of interest. Area of natural forest within 2 km of a participant's village and area of managed forest within 2 km of a participant's village were found to be strongly associated with increased risk of malaria (OR: 1.96, 95% CI: 1.60 – 2.41 and OR: 1.35, 95% CI: 1.23 – 1.50 respectively). We found that sex modified the relationship between malaria and area of croplands within 2 km of a participant's village, and thus we present stratified results. Among females, proximal croplands were found to be strongly protective (OR: 0.52, 95% CI: 0.37 – 0.69), whereas a much weaker suggestive protective effect was observed among males (OR: 0.82, 95% CI: 0.67 – 1.00) (Table 3-5). The results were reinforced by Sensitivity Analysis II, which only analyzed data on study participants that did not claim to frequently visit any of the three land covers investigated (demographics for Sensitivity Analysis II compared to the Primary Analysis can be found in Section 3.3.2, Table 3-2).

Table 3-5: Model results expressing the risk of Plasmodium presence in the blood as a function of village proximal LC.Blue cells indicate protective associations, red cells indicate risk associations, while white cells indicate non-significant associations.

	Primary Analysis		Sensitivity Analysis II (Answered No to all 3 LU Questions)	
Variable	OR (95% CI)	p-value	OR (95% CI)	p-value
Area of Natural Forest	1.96 (1.60 – 2.41)	< 0.001	3.09 (2.12 – 4.63)	< 0.001
Area of Managed Forest	1.35 (1.23 – 1.50)	< 0.001	1.50 (1.27 – 1.81)	< 0.001
Area of Croplands – Female	0.52 (0.37 – 0.69)	< 0.001	0.47 (0.29 – 0.69)	0.0007
Area of Croplands – Male	0.82 (0.67 – 1.00)	0.0576	0.32 (0.14 – 0.64)	0.0046

3.3.5 Forest Loss

Each village exhibited very different patterns of forest cover change. While all have experienced some amount of forest loss, Village 3 lost by far the highest amounts of forest in the year of data collection (2016) and the five years preceding our survey (Figure 3-5). When compared to village level malaria prevalence, a high positive correlation was found between malaria prevalence and the rate of deforestation surrounding a village (km^2 year^{-1}) (Figure 3-6). This was further corroborated by the fully adjusted models, which found recent (2016) deforestation (OR: 3.97, 95% CI: 2.57 – 6.13), rate of deforestation (OR: 14.30, 95% CI: 6.20 – 32.99), and total deforestation over five years (OR: 1.70, 95% CI:1.44 – 2.01) were all strongly associated with increased malaria risk. However, these results were not reinforced by Sensitivity Analysis III, wherein none of the relationships remained significant when Village C was removed (Table 3-6).

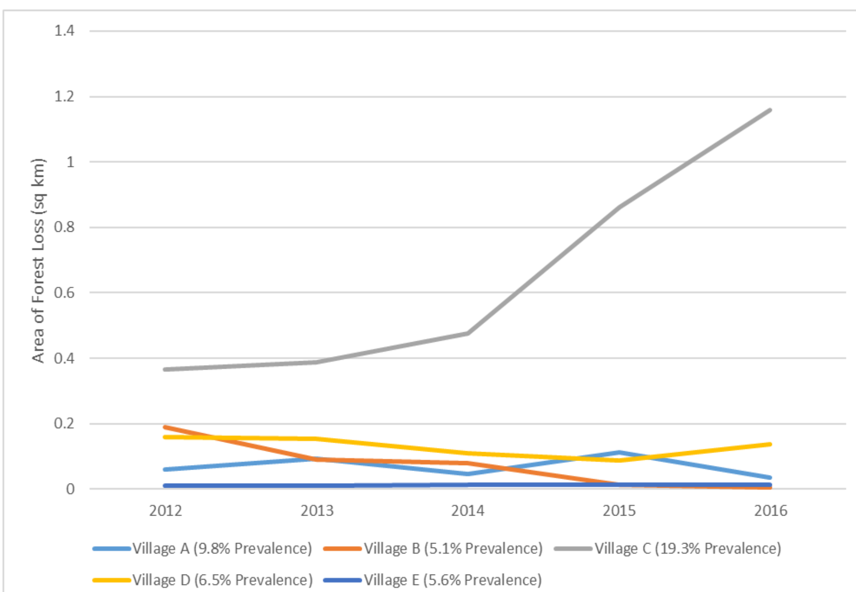


Figure 3-5: Annual area of forest loss in sq km within 2 km of each village over the five years preceding the survey data collection. Village level malaria prevalence included in the key.

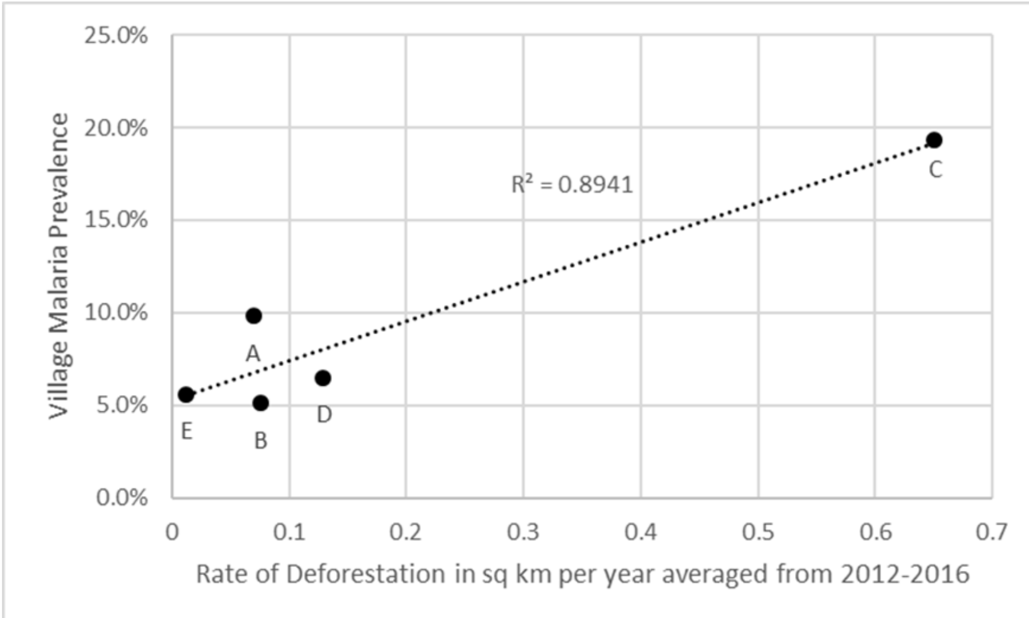


Figure 3-6: Relationship between village-level malaria prevalence and the average rate of deforestation (sq km/year) over the five years preceding survey data collection

Table 3-6: Model results expressing the risk of Plasmodium presence in the blood as a function of village proximal deforestation. Blue cells indicate protective associations, red cells indicate risk associations, while white cells indicate non-significant associations.

	Primary Analysis		Sensitivity Analysis III (Village 3 Removed)	
Variable	OR (95% CI)	p-value	OR (95% CI)	p-value
Area of Deforestation (2016) Sq Km	3.97 (2.57 – 6.13)	< 0.001	0.19 (0.00 – 37.64)	0.5503
Rate of Deforestation (2012-2016) Sq Km/Year	14.30 (6.20 – 32.99)	< 0.001	1.77 (0.003 – 1228.7)	0.8616
Total Deforestation (2012-2016) Sq Km	1.70 (1.44 – 2.01)	< 0.001	1.12 (0.31 – 4.15)	0.8616

3.4 Discussion

The challenge posed by asymptomatic reservoirs for malaria elimination is illustrated by this study's findings that only 1 out of the 92 malaria cases identified was detected by the standard test used for routine surveillance and clinical diagnosis. Routine testing found a prevalence of just 0.1% across five villages, while more sensitive molecular testing uncovered villages with up to more than 20% prevalence of low-density malaria infections. No cases exhibited signs of fever at the time of data collection, and very few reported any recent physical symptoms. Although data are limited, a growing body of evidence highlights the critical importance of all malaria infections, symptomatic or asymptomatic, in continued and sustained transmission. This study further highlights the growing need to identify these infection reservoirs for targeted interventions with a method not solely reliant on routine testing and self-reporting.

One such criterion that should be considered when implementing a targeted elimination strategy is the amount of natural forest cover surrounding a village. Our findings further corroborate the association between malaria risk and forest cover found in other studies (Tipmontree et al., 2009; Zaw et al., 2017). While previous work has established a link between forest workers and malaria risk, our research expands upon this by revealing that persons living in villages where the dominant land cover is natural forest are at an increased malaria risk, regardless of whether or not they work or spend time in forested areas. This is further supported by our sub-sample of participants who did not claim to frequently visit a forested area (Sensitivity Analysis II) but experienced a high positive association with malaria infection relating to the area of natural forest coverage near their village.

Conversely, persons living in villages with high areas of croplands experience decreased malaria risk, unless they are explicitly working/frequenting those areas. This is especially true for men, for whom our results indicate a substantial increase in risk for frequent farm visitors, but a strong protective effect for men who merely live close to large areas of croplands (Sensitivity Analysis II) but do not frequently visit those lands. We do not believe that proximal croplands are necessarily "protective" for malaria. Instead, we surmise that the protective effect of croplands is in reality due to the minimizing of the "riskier" land cover, natural forest. We found that villages with high areas of proximal croplands also have comparatively low areas of proximal natural forest (Section 3.3.4, Figure 3-3). Villages with higher percentages of croplands than natural forests, Village B (3% forest, 47% cropland) and Village E (12% forest, 25% cropland), have the lowest rates of malaria at 5.1% and 5.6% respectively. Similarly, areas with higher percentages of natural forest than croplands, Village A (57% forest, 13% cropland), and Village C (65% forest, 2% cropland) have the highest village level prevalence of malaria at 9.8% and 19.3% respectively. One potential explanation for this relationship may have to do with the dominant vector species in Ann Township. *An. dirus* – a forest-dwelling species - has a longer flight range (~2 km) than the other dominant malaria vector in Ann Township - *An. minimus*, which prefers lowland areas and has a flight range half as long (~1 km) (Dev et al., 2004; Marchand et al., 2004). Therefore, the forest-dwelling *An. dirus* is more easily able to reach persons living close to its natural habitat, whereas *An. minimus* is less likely to travel far enough to bite anyone that does not explicitly visit its habitat (i.e., cropland).

The observed differences between the sexes in farm work associated risk was an unexpected finding but could be explained by the work-related gender dynamics of the villagers. While women who report frequenting farms do not experience an increase in risk, there is a substantial increase in risk for men (OR: 3.86, 95% CI: 2.13-7.06). Akter et al. (2017) found that men and women share many of the same roles in rice farming. However, some roles are gendered, with men participating more in land preparation and fertilizer/pesticide application, and women participating more in seedling transplanting and food preparation for laborers. This gendered dynamic to land preparation could result in males spending comparatively longer periods in the fields, though we currently have no evidence of this. Although it is also possible, and semi-supported by our data, that men in this region often take on multiple livelihood roles. Within our sample, 32% of women and 27% of men reported frequenting a farm, indicating that slightly more women participate in farm work than males. However, 53% of men who reported frequenting a farm also reported frequenting a forest, compared to only 31% of the women who frequented farms. Therefore, men who farm are also more likely to frequently engage in other activities that could increase their risk of malaria exposure.

The interactions between frequenting plantations and managed forest land cover are essentially the inverse of the farm/cropland discussion above. Frequent visits to a plantation were found to be a protective factor, while in contrast, high areas of plantation land cover surrounding a village increased risk. Literature indicates that plantation jobs (fruit, rubber, and teak) in Southeast Asia typically increase risk (Singhasivanon et al., 1999). This is in-line with our results on the amount of proximal managed forest coverage. Indeed, Village C displays the highest proportion of managed forest (24%) and also the highest prevalence of malaria (19.3%). Interestingly, the villages with the lowest proportions of managed forest, Village D (5.4%) and Village E (2.3%) counterintuitively report the highest numbers of respondents saying they frequent plantations (n=109 and n=67, respectively). Village C, in comparison, had only 24 respondents frequenting plantations. Overall, malaria prevalence rates in Villages D and E were low (6.5% and 5.6% respectively). When viewed via satellite imagery, Villages D and E appear much less isolated than the other villages, both being relatively close to the only airport within Ann Township and having much higher percentages of human infrastructure than the rest of the villages. Secondly, Villages D and E are very close to each other. Approximately five sq km of overlapping area exists between the 2 km buffers created for the villages. This leads us to believe that there is a confounding variable influencing the plantation workers from these two villages that we were unable to capture in our study.

While the static LCLU mapped and calculated for this study revealed interesting relationships, LCLU is rapidly changing across Myanmar as the economy grows and expands. One of the most prominent areas of change is forest loss, with estimates of nearly 2 million hectares of intact forest lost occurring annually (Bhagwat et al., 2017). Since we discovered that both proximal natural forest and managed forest land cover increased malaria risk, it seemed logical that any significant changes to those land cover types could also influence malaria risk. We identified strong associations between multiple different metrics of forest cover loss and malaria risk. However, Village C has experienced a significantly higher amount of forest cover loss than any of the other villages, which profoundly influenced the results. No significant associations were identified when Village C was removed from the analysis. We believe, though, that

Village C is less of an outlier and instead represents a different type of village than the others included in our study. Preliminary results from on-going projects in the region (data not presented here) indicate that other villages are experiencing similar levels of forest cover loss and high prevalence of malaria, though more research is necessary for this area.

Some limitations of this research include the moderate resolution of the satellite imagery and potential confusion in questionnaire responses. Finer spatial resolution satellite data would have been welcome, particularly in identifying managed forest cover, for which our mapped accuracy was only 48%. However, the goal of this research was to identify criteria that could be used easily to locate reservoirs of malaria. In essence, fine spatial resolution LCLU mapping is more time consuming, complicated, and costly than moderate resolution mapping. The mapping methodology presented here relies on freely-available public data and can be easily replicated for other locations and dates.

Within our questionnaire, it is unclear if our definitions of land use match the respondents' perceptions. For example, we intended for frequent visits to a farm to mean a rice paddy or large cropped field. However, it is possible that for our respondents, subsistence agricultural plots near to their homes could be considered as farms. It is also possible that farming in our respondents' interpretation refers to forest-related work (Zaw et al., 2017) or foraging for wild vegetables in forested areas (Cornish and Ramsay, 2018). These potential differences in definition could impact the interpretation of our results. However, the results gleaned from the remotely sensed land cover variables are less vulnerable to misinterpretation, which helped contextualize the questionnaire results.

3.5 Conclusions

As malaria transmission declines, targeted interventions will become the highest priority to malaria elimination in Southeast Asia. Considering the highly heterogeneous and rapidly changing prevalence of asymptomatic malaria, identifying areas to target is growing in difficulty. By pairing remotely sensed indices with survey data, we were able to contextualize land cover and land use metrics to form a cohesive picture of malaria within Ann Township that can bolster elimination efforts. Primarily, villages with high natural or managed forest cover in their immediate proximity are the locations where one is most likely to find persons with malaria, with considerations for age and pregnancy status. For villages with large areas of croplands, prevention strategies should consider focusing on men, particularly those working on farms.

More research is needed to assess the causal link between forest cover and malaria in Myanmar. While we hypothesize that it may have something to do with the land cover preferences of the two dominant mosquito species, entomological data for the region is sparse. Without more information on this link, it will be difficult to ascertain how forest cover change will influence malaria infections for the region. As the economy of Myanmar grows, likely, the conversion of natural forests to teak, rubber, or other plantations will accelerate. Understanding the relationship between malaria and deforestation and forest conversion will be critical to eliminating malaria under these rapidly changing socio-economic conditions.

Now more than ever, models that allow for the identification of likely reservoirs of malaria, but are disconnected from symptomatic carriers seeking treatment or broad coverage in-situ rapid diagnosing, are needed to proceed forward with targeted interventions. Remote sensing offers a means to quickly locate areas that meet the land cover criteria discussed and provides promising data and methodologies to explore other LCLU that may influence malaria risk.

Chapter 4: Malaria Exposure in Ann Township, Myanmar as a Function of Land Use

4.1 Introduction

Effecting over 200 million people a year, the life-threatening vector-borne disease, malaria, remains a global health crisis (WHO, 2019). However, many regions have reached low transmission status through the work of some of the world's largest intergovernmental agencies, local governments, NGOs, researchers, and public health workers. A significant success story is found in the country of Myanmar. Since 2012, Myanmar has reduced its number of malaria cases by a monumental 82% (WHO, 2018). However, the remaining malaria transmission foci in Myanmar are heterogeneous and complex, with many remaining infections clinically silent, rendering them invisible to routine monitoring (Adams et al., 2015; Imwong et al., 2015, 2014). Therefore, targeted prevention strategies have been implemented across Myanmar to eliminate these remaining reservoirs.

Within the elimination strategies currently in use in Myanmar, the two principal vector control measures for malaria prevention implemented within the National Plan for Malaria Elimination in Myanmar (NMCP, 2016) focus on prevention from within the home. Measure 1 includes universal population coverage and usage of long-lasting insecticidal nets (LLINs), while measure 2 (employed to a lesser extent) suggests indoor residual spraying (IRS). While these measures have likely been partially responsible for the 82% drop in malaria cases across the country, within the remote region of Ann

Township, Rakhine State, Myanmar, malaria prevalence has remained at nearly 10% of the population from 2016 – 2019 (Chapter 3 and Chapter 4).

It is reasonable to assume that this remaining malaria pool may not be suitably eliminated through these home-centric strategies. However, little is known about how people live, work, and move through their landscape in Ann Township, especially as it relates to their exposure to malaria. Although, some village-level associations with the environment surrounding a village have been discovered. For example, Chapter 3 of this dissertation found that the area of natural forest surrounding a village was highly linked to malaria prevalence. Chapter 3 also found that deforestation was associated with malaria risk, but this was not confirmed by a sensitivity analysis.

Many other studies have researched the influence of deforestation on malaria risk; however, the results have been ambiguous (MacDonald and Mordecai, 2019; Tucker Lima et al., 2017). While multiple studies have observed increases in malaria alongside increases in deforestation (Garg, 2019; MacDonald and Mordecai, 2019; Santos and Almeida, 2018), others have observed high malaria prevalence alongside high natural forest coverage (Vittor et al., 2006; Chapter 3) and claim that efforts to combat deforestation may increase malaria burden (Valle and Clark, 2013).

Much of the ambiguity is due to a lack of understanding of the mechanism behind forest clearing and malaria. Multiple studies suggest that after a forest is cleared, the mosquito ecology shifts (Do Manh et al., 2010; Parker et al., 2015). However, comparatively little research has looked at if the relationship is instead not wholly or even partially due to an ecological shift, but due instead to increased interaction between humans and the natural forest landscapes where malaria exposure is high during forest clearing periods. In this chapter, I seek to investigate the role of human land use activities with malaria prevalence, specifically how people engage with their landscape in terms of frequency, duration, and time of day, in a region known for both its high amount of natural forest and rapidly increasing deforestation pressure (Bhagwat et al., 2017).

4.2 Materials and Methods

4.2.1 Study Population

This study employed a nested case-control study design, which analyzes a geographic subset of participants from a larger longitudinal study, on-going as of 4/22/2020 (Nyunt et al., 2018). The longitudinal study aims to describe the dynamics of low-density subclinical malaria across multiple sites in Myanmar, Bangladesh, and along the China-Myanmar and India-Myanmar borders. The study was independently reviewed and approved by the Institutional Review Boards of the Myanmar Department of Medical Research and Duke University. The village selection was based on the known or suspected malaria burden and research team capability to ensure the integrity of study data and samples. Inclusion criteria included age at least six months old, compliance with study procedure, and written informed consent.

The broader longitudinal study aims to collect data on up to 6000 participants, with anywhere from 1 to 5 follow up visits per participant. Within the nested case-control study, I restricted the sample to baseline visit data collected in Ann Township, a small administrative region (similar to a county) within Rakhine State, Myanmar (Figure 4-1). Cases were those participants who tested positive for any malaria (*P. vivax* and/or *P.*

falciparum) via ultrasensitive polymerase chain reaction (usPCR) methods (Zainabadi et al., 2017), while controls were those that tested negative. A total of 1000 participants were enrolled and completed the study successfully for use in the nested case-control study.

4.2.2 Study Site

Five remote villages in southwestern Ann Township were surveyed (Figure 4-1). Ann has a subtropical climate, with a distinct monsoon season that stretches from April through October. The population of Ann is generally isolated, with highly uneven patterns of settlements covering less than 0.1% of the total land area (Hoffman-Hall et al., 2019). Previous research has shown that isolated settlements experience disproportionate shares of adverse health outcomes (Suwonkerd et al., 2013) and can serve as the main drivers of infectious disease transmission into previously disease-free regions (Martens and Hall, 2000).

According to the Vector Borne Disease Control Annual Report 2016 compiled by the National Malaria Control Programme (NMCP), Ministry of Health and Sports, Myanmar, Rahkine State carries a much higher malaria load than its neighboring regions. The estimated Annual Parasite Incidence (API) for Rakhine is 9.54 per every 1,000 persons, compared to just 0.14 and 0.29 for neighboring regions Magway and Bago, respectively (NMCP, 2017).

Ann Township is primarily dominated by two malaria vectors, forest-dwelling *Anopheles dirus,* and foothill and valley-dwelling *Anopheles minimus* (Oo et al., 2004). Commonly identified malaria parasites include *Plasmodium vivax* and *P. falciparum,* but

P. knowlesi has been identified elsewhere in Myanmar (Ghinai et al., 2017; Jiang et al., 2010). For Ann specifically, the majority of infections are subclinical. In essence, infected persons show little to no symptoms, and the parasites can only be detected through ultrasensitive laboratory techniques as opposed to in-field Rapid Diagnostic Testing (RDT) (Chapter 3).

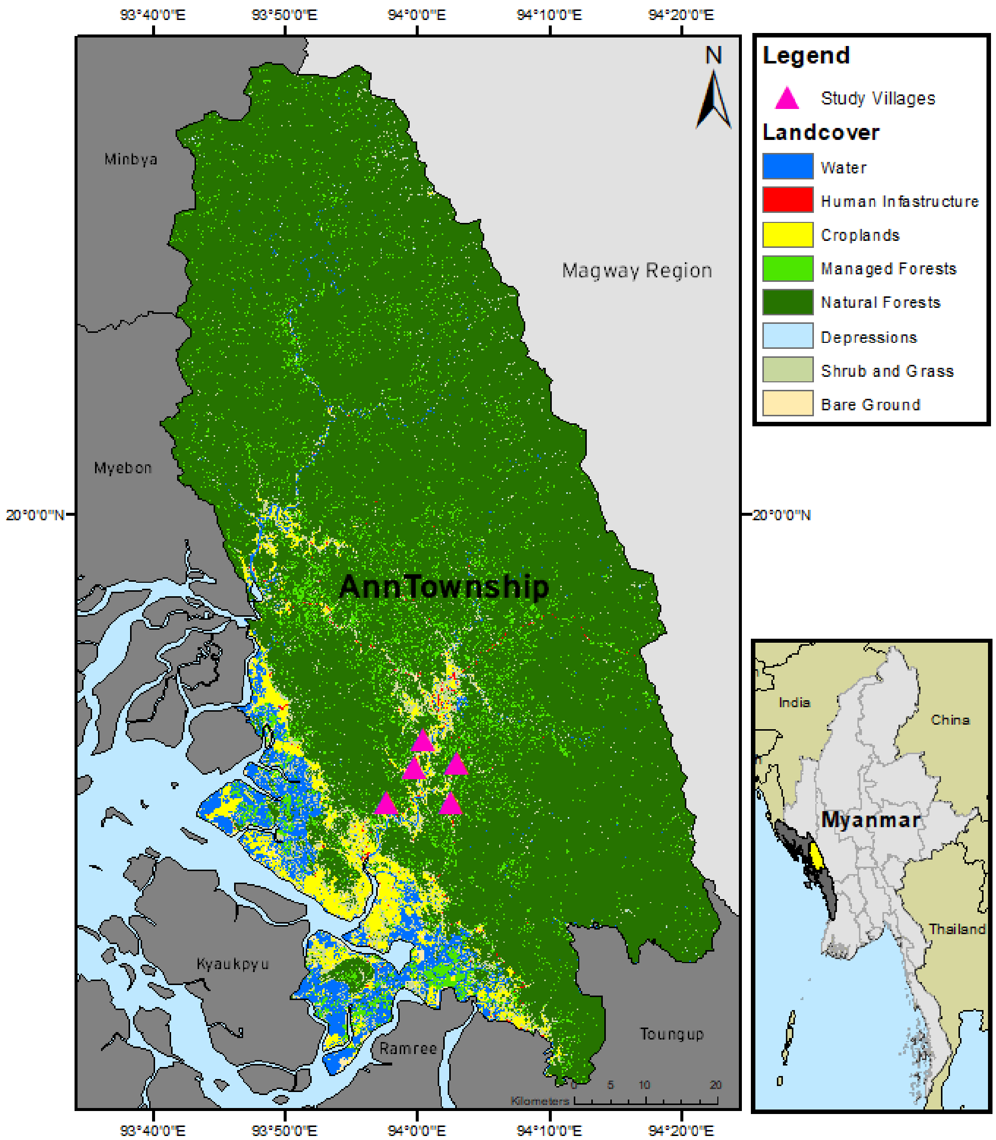


Figure 4-1: Surveyed villages (offset and unlabeled to preserve privacy) overlaid a landcover map of Ann Township, Rakhine State, Myanmar.

4.2.3 Outcome: Malaria Prevalence

Baseline surveying across the five Ann Township villages was conducted August 2018 through February 2019, in both the rainy and dry seasons. The full protocol can be found at www.clinicaltrials.gov, Identifier: NCT03483571. The primary aim of the broader longitudinal study that the data derives from was not to obtain an unbiased measurement of malaria prevalence, which was anticipated to be low in many sites. Instead, it was to identify the target number of cases of subclinical malaria infection, which are expected to be rare. People and locations suspected or known to harbor malaria based on previously collected data and government reports were targeted for screening. As data collection continued, household and workplace contacts of RDT+ and usPCR+ cases were traced to find more infected individuals. This targeted data collection means that the overall sampling framework is neither random nor fully representative of every village. However, unbiased prevalence estimates of *P. falciparum* and *P. vivax* infection were collected for Villages A, B, and E, where all eligible villagers were sampled. Villagers were eligible for inclusion in the study if they: 1) were aged six months or older at baseline visit; 2) were able to provide written consent (from the parent/guardian if the subject is less than 18 years old). Detailed descriptions of consent processes can be found in Diallo et al. (2005). Additionally, analysis of the nested case-control data is conducted at the individual level, not the village level, since unbiased village prevalence does not exist for each village.

Community outreach was conducted before the study to ensure the community buy-in and adequate dissemination of knowledge about the upcoming study. Written consent was obtained from a designated head of the household and each participant. If refused or unavailable, the nearest next household was selected. Data were collected using a standardized and validated questionnaire by trained study personnel. Finger prick blood was collected for malaria testing using a rapid diagnostic test (RDT) and on to a filter paper for molecular analysis of malaria using usPCR. RDT test results were documented in real-time. Filter paper blood samples were labeled and air-dried. These dried blood spot (DBS) samples were placed in an individual Ziplock bag containing desiccant and stored in a refrigerator until transport to a central lab. *P. falciparum*, *P. vivax*, and mixed infections were all identified by usPCR.

No unexpected or severe adverse events were reported as of 4/22/2020. Any cases identified by RDT were treated by a referred care team, following the national treatment guidelines. The characteristics of the study population, study villages, and village-based malaria prevalence for *P. falciparum* mono-infection, *P. vivax* mono-infection, and mixed infection are summarized in Table 1. Those with usPCR-positive malaria were not treated since treatment was not recommended by the national program or the WHO, nor is there a clear understanding of a risk-benefit ratio for treating them.

4.2.4 Data on Malaria Risk: Potential Confounders and Effect Modifiers

Demographic and other relevant risk factor information was collected using the questionnaire, which included a range of questions based on malaria literature which commonly identifies the following variables as potential confounders: age (W. P. O'Meara et al., 2008), sex (Ayele et al., 2012), pregnancy status (Desai et al., 2007), resident status ("have you lived in this village for > 6 months?") (Wesolowski et al., 2012), and the seasonality of the participant's occupation ("does your main occupation vary seasonally in the past one year?") (Canavati et al., 2016). Sex was also assessed as a possible effect modifier. Each participant was surveyed about their prior symptoms, including fever, headache, body ache, nausea, vomiting, abdominal discomfort, decreased appetite, or fatigue within the previous two months, as well as fever within the previous 24 hours. Axillary body temperature of each participant was recorded at the time of data collection, and participants were asked if they had recently been tested for malaria. Finally, each participant was surveyed about their bednet usage, precisely what type of bednet they used, and if they had slept under it the night before the survey.

4.2.5 Exposure: Village-Level Natural Forest Cover & Forest Cover Loss

The results from Chapter 3 show that the area of natural forest cover surrounding a village is highly associated with an increase in malaria risk, even for villagers who did not report to visit the forest. The first priority of this study was to test if an association was also present between the villages in this study and their respective levels of natural forest coverage, and if so, control for natural forest cover in the statistical modeling to allow for the isolation of individual land use associated risks. Area of natural forest cover was quantified based on the 30-meter landcover map of Ann Township circa 2016 derived from satellite earth observation datasets (see Chapter 3). The accuracy of the natural forest class for the map is 90%.

An area with a 2 km radius around each village was used to calculate the total area of proximal natural forest, following the estimated flight range of the major malaria vectors in the region - *An. minimus* and *An. Dirus* - 1 km and 2 km, respectively (Dev et al., 2004; Marchand et al., 2004). I updated the 2016 map to account for likely change in land cover composition by 2018, when the malaria surveys were collected. To update the extent of proximal natural forest cover, Global Forest Change (GFC) data from 2017 and 2018 (Hansen et al., 2013) was used to remove any areas of natural forest which were deforested between 2016 and the start of 2019.

In addition, I calculated the area of forest loss within 2 km of each village for the year between 2014 and 2018, derived from the GFC dataset. The annual rate of forest loss for the previous five years (2014-2018) and the total area of forest loss within that period were added as metrics of landscape-level proximal forest loss to the analysis.

4.2.6 Exposure: Individual-Level Land Use & Occupation

Participants were surveyed on the frequency, duration, and timing of six land use activities within Ann Township: 1) attending to crops/farming; 2) work at plantations; 3) work at mining areas; 4) travel to refugee camps; 5) conducting household chores that involve trips to the water; and 6) conducting household chores that involve trips to the forest (e.g., hunting, firewood and construction material collection, fruit gathering). If a respondent indicated that they had participated in one of the activities within the past three months, they were able to choose between three frequency options: 1) rarely (special cases, e.g., burial); 2) usually (at least once a month); 3) often (almost every day). They then selected between three duration options: 1) less than an hour; 2) several hours; 3) all-day; and four timing options: 1) before sunrise; 2) morning; 3) day-time; 4) after dark. Each participant was also asked what their primary occupation was and if that occupation was primarily indoor or outdoor. The options provided for occupation were:

Dependent, Student, Vendor, Soldier, Refugee, Farmer, Plantation worker, Mineworker, Logger, and Other (Specify).

While each of these variables was assessed independently, their combination was likely to reflect the actual landscape-scale activity of a participant more accurately. Therefore, the questions regarding land use, frequency, and duration were combined into a Land-Use Index. This index is different from published indices which seek to quantify the diversity of landscapes (Blüthgen et al., 2012; Yoshida and Tanaka, 2005), and instead seeks to quantify the diversity in how a single person engages with the landscape. Equation 4-1 was used to calculate the Land-Use Index.

$$
\begin{aligned}
LUI = \\
X_{farm}(F_{farm} + D_{farm}) + X_{plantation}(F_{plantation} + D_{plantation}) + \\
X_{mining}(F_{mining} + D_{mining}) + X_{water}(F_{water} + D_{water}) + \\
X_{forest}(F_{forest} + D_{forest})
\end{aligned}
\qquad \textit{Equation 4-1}
$$

Where, X equals one if a respondent indicated that they did participate in that land use activity (farming, plantation work, mining, chores near water, chores in the forest – no respondents indicated visiting refugee campus), or 0 if they indicated that they did not. F refers to the frequency of that activity, with values of 1 for often, 0.5 for usually, and 0.1 for rarely. D refers to the duration of that activity, with values of 8 for all day, 4 for several hours, and 1 for less than 1 hour.

For example, participated in forest chores, often, for less than one hour, and also participated in plantation work, usually, all-day, their score would be 10.5 (Equation 4-2).

$$LUI = 0 + 1*(0.5 + 8) + 0 + 0 + 1*(1 + 1) = 10.5 \qquad \textit{Equation 4-2}$$

If a respondent indicated that they did not participate in any of the land use activities within the study, their LUI score would be zero. Hypothetically, the maximum LUI score would be 45. However, this is impossible to achieve because it would not be feasible for a person to participate in all five land use activities, often (nearly every day), for 8 hours a day. A more reasonable maximum score would be 20, which could be explained by participating in 2 land use activities, often (nearly every day), all-day, and an additional land use activity (likely water chores) for 1 hour per day. Though this will likely not be achieved in reality, unless the participant engages in seasonal work would could explain being able to engage in two land use activities all-day.

4.2.7 Statistical Analysis

Univariate and multivariate logistic regression analysis was chosen to understand the association between the land use exposure variables and malaria prevalence outcome. Due to the low overall prevalence of malaria (9.60%, n=96), *P. falciparum*, *P. vivax*, and mixed infections were all considered as a positive case. Univariate analysis was performed initially to assess the relationship between each explanatory variable including proximal natural forest coverage, binary yes/no responses to the land use activities described in Section 4.2.5, land use frequency, land use duration, land use timing, primary occupation, indoor/outdoor nature of that occupation, and their LUI score with individual malaria infections. All analyses are conducted at the individual level due to the non-representative village level sample. The variable of visiting a refugee camp was not analyzed because no participants responded affirmatively to that category.

For each univariate model where the assessed variable was found to be significant ($p < 0.05$), potential confounders (age, age squared, sex, pregnancy status, resident status, bednet usage, occupation seasonality, the season of data collection [rainy/dry]) were added progressively. Biologically plausible confounders found to be significant remained in the final adjusted model while non-significant variables were removed. Within the fully adjusted models, interactions by sex were examined via interaction terms. If interactions were significant stratified models were considered. Odds ratios (ORs) and 95% confidence intervals (CIs) were calculated for the resultant adjusted and stratified models. All data analysis was undertaken in R statistical software packages.

Finally, I conducted multiple sensitivity analyses. Sensitivity Analysis I is intended to determine the robustness of the findings concerning the relationship between proximal natural forest cover and malaria. I conducted Sensitivity Analysis I on a subset of the study sample participants that claimed to never participate in chores that occur in the forest, because in Chapter 3 the association between village proximal forest coverage and malaria risk was observed, even for participants who indicated that they did not frequently visit forested area. Sensitivity Analyses II and III are conducted on the population subset by age, with Sensitivity Analysis II covering participants aged 0 – 14 and Sensitivity Analysis III covering participants 15+.

4.3 Results

4.3.1 Land Use & Occupation Demographic Analysis

The results of the survey indicate that land use practices vary across Ann, both spatially and demographically. When viewed broadly, different patterns of land use practices and occupations appear across the five surveyed villages. Focusing further, differences appear regarding gender and age groupings. One important distinction to make, however, is that reported primary occupation does not directly translate to land use engagement. For example, many respondents who chose Farmer as their primary occupation indicated that they participate in Farming, but also Plantation Work, during the land use portion of the survey (Figure 4-2b). Additionally, some respondents who chose Farmer as their primary occupation did not report engaging in any farming activities within the three months before the survey (Figure 4-2a).

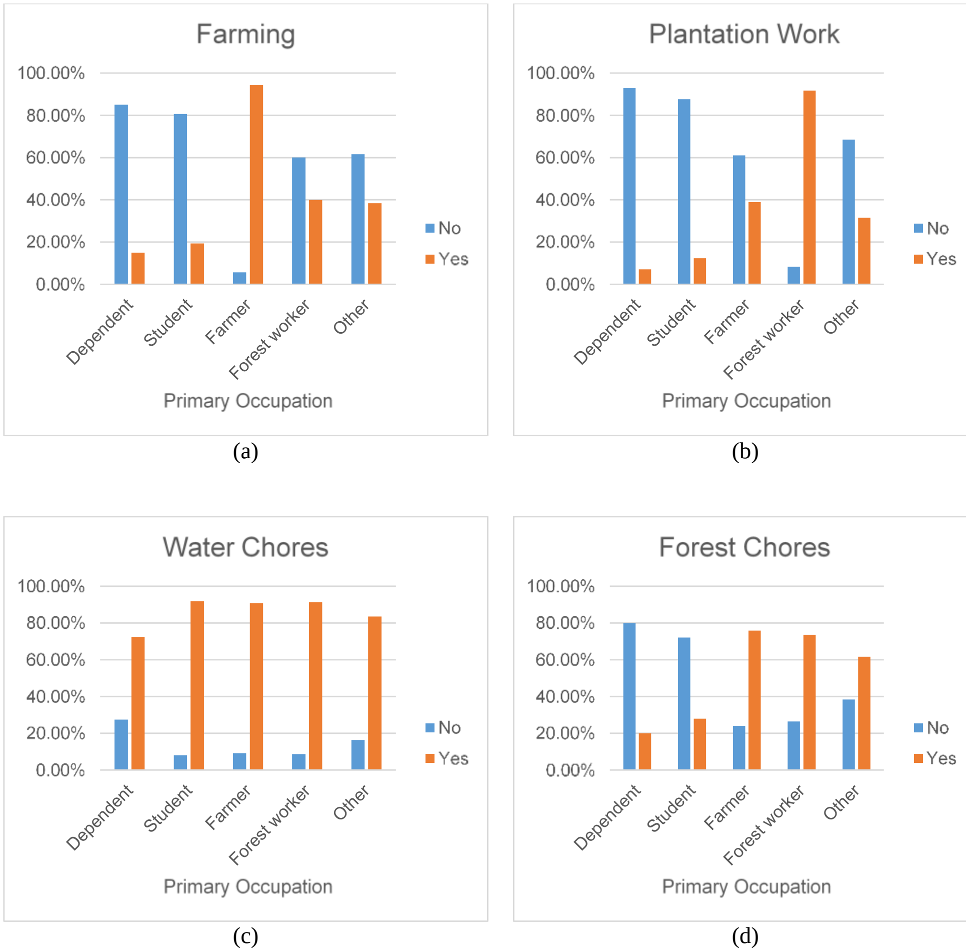


Figure 4-2: Proportion of surveyed villagers' land use engagement based on their primary reported occupation. The proportion of the total surveyed village population per occupation is shown on the y-axis.

4.3.1.1 Land Use & Occupation Demographic Analysis by Village

The patterns of reported primary occupations within the surveyed villages varied geographically (Figure 3). Village C reports the highest proportion of Forest Workers (43.7%), while Village B claims the highest proportion of Farmers (22.0%) (Figure 4-3). Village B was also the only village with a higher proportion of Farmers than Forest Workers. Overall though, Dependents and Students dominated the reported primary occupations, with 49.8% of the total sample population claiming those categories as their primary occupation.

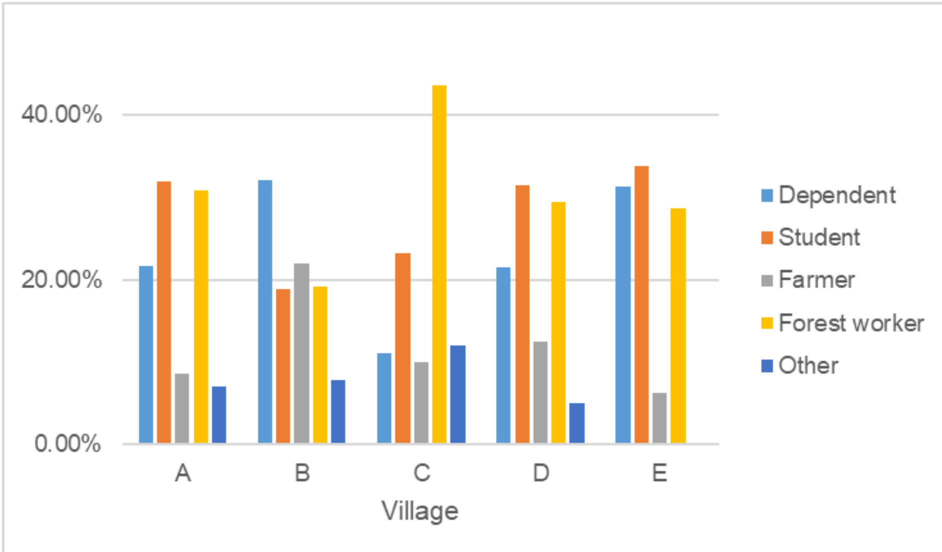


Figure 4-3: Proportion of surveyed villagers' primary occupations. *The proportion of the total surveyed village population is shown on the y-axis.*

When participants were asked about specific land use practices, the responses varied slightly less geographically, but still in significant ways. For example, similar proportions of the sample populations of Villages C and E responded affirmatively to engaging in Plantation Work, with 55.8% and 57.5% of each village, respectively (Figure 4-4b). This is despite the marked differences in the proportion of Forest Worker occupations in Villages C and E (Figure 4-3), which were 43.7% and 28.8%, respectively. Engaging in Water Chores was the most commonly selected land use practice, with 86.3% of the total study population reportedly engaging in that activity within the past three months.

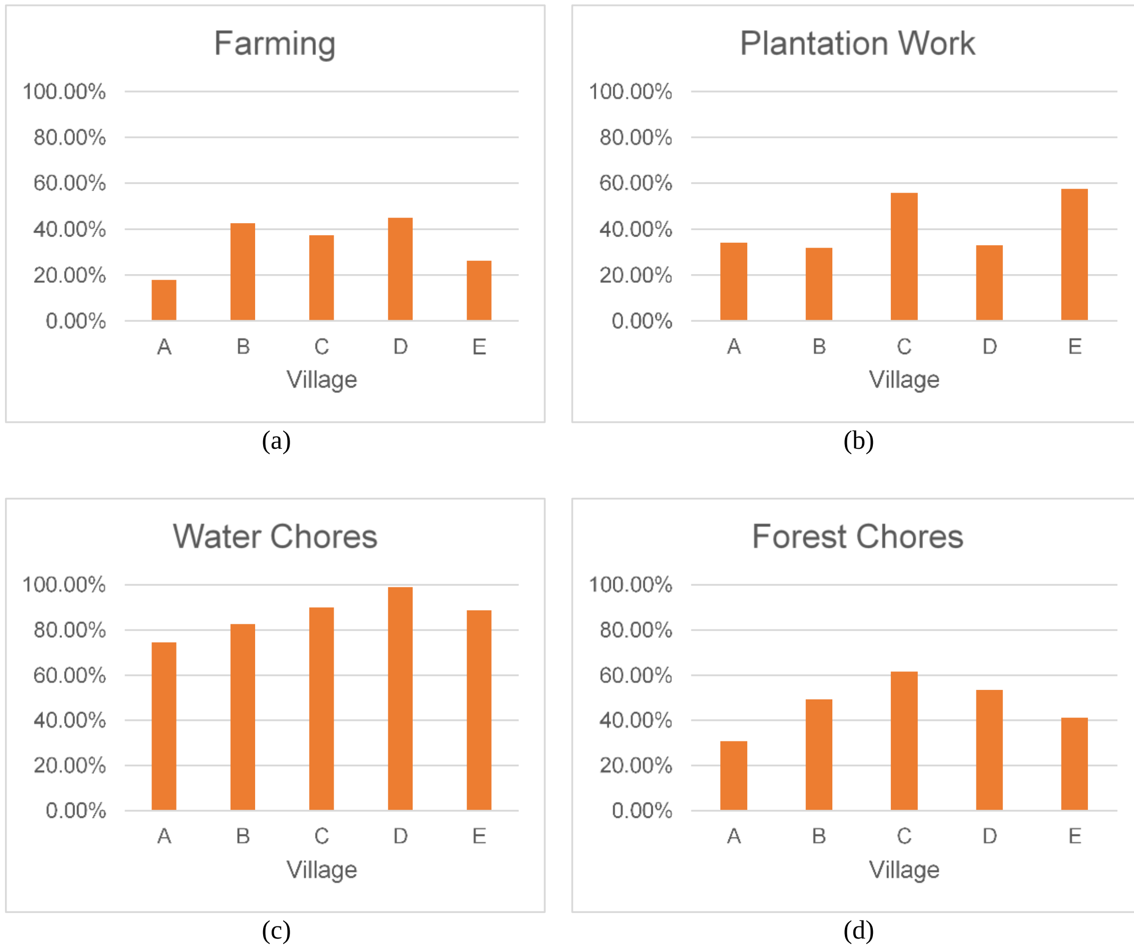
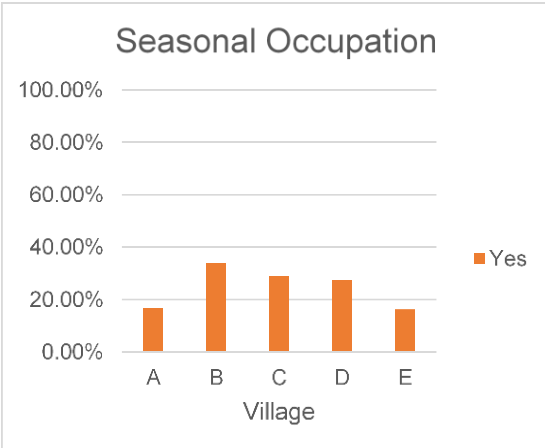
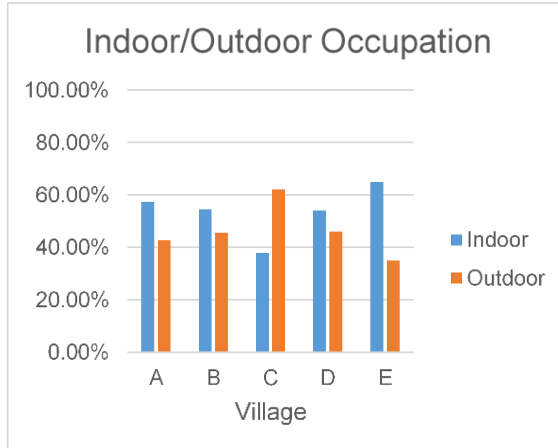


Figure 4-4: Proportion of surveyed villagers who answered "Yes" to engaging in (a) Farming, (b) Plantation Work, (c) Water Chores, and (d) Forest Chores within the past three months. The proportion of the total surveyed village population is shown on the y-axis.

Most of the reported occupations were not seasonal (Figure 4-5a), with only 27.1% of respondents indicating that their primary occupation varies seasonally. The distinction between indoor and outdoor occupations, though, was nearly split in half, with 52.6% reporting an indoor occupation and 47.4% reporting an outdoor occupation. Village E had the most considerable observed disparity between indoor and outdoor jobs, with 65.0% of respondents claiming indoor occupations (Figure 4-5b). This is in line with the high proportion of students and dependents surveyed in Village E. Village C was the only village to claim more outdoor occupations than indoor, reflective of the high proportion of Forest Workers in the village.



(a)



(b)

Figure 4-5: Proportion of surveyed villagers who answered "Yes" to (a) having a primary occupation that varied seasonally and (b) having an indoor or outdoor job. The proportion of the total surveyed village population is shown on the y-axis.

4.3.1.2 Land Use & Occupation Demographic Analysis by Gender

Within our sample population, gender differences were observed within the reported primary occupations. Women were much more likely than men to classify their primary occupation as Dependent (30.3% for women, 17.0% for men). In comparison, men were slightly more likely than women to classify themselves as Students (22.9% for women, 29.0% for men) and Forest workers (25.4% for women, 32.6% for men) (Figure 4-6). For the categories of Farmers and Others, no gender differences were observed (Figure 4-6). Small differences were also noted in occupational seasonality and indoor/outdoor, with women slightly more likely than men to report indoor (56.4% for women, 48.3% for men), non-seasonal occupations (76.0% for women, 69.5% for men) (Figure 4-7).

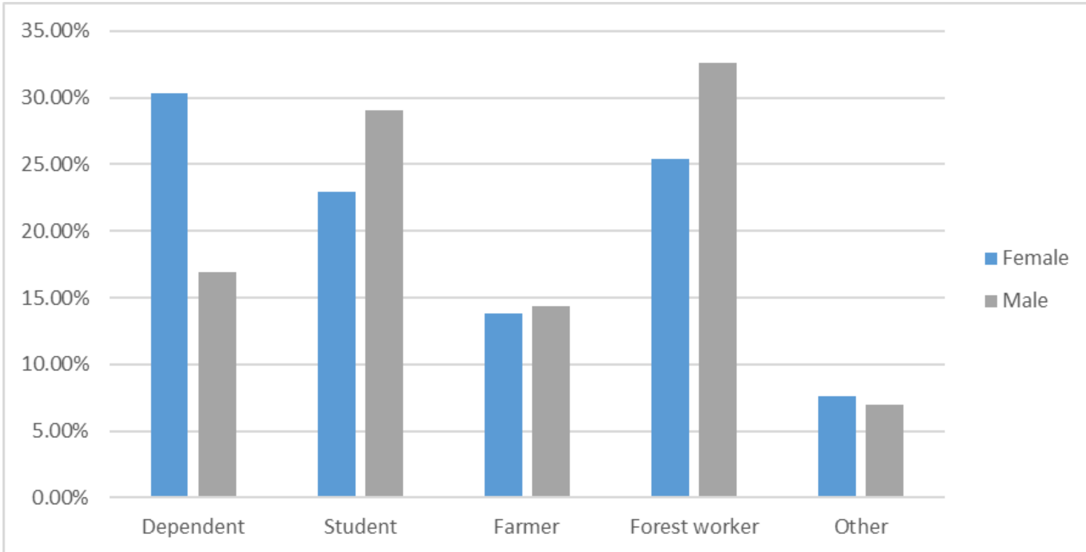


Figure 4-6: Proportion of surveyed villagers' primary occupations, separated by gender. The proportion of total surveyed village population (male or female) is shown on the y-axis.

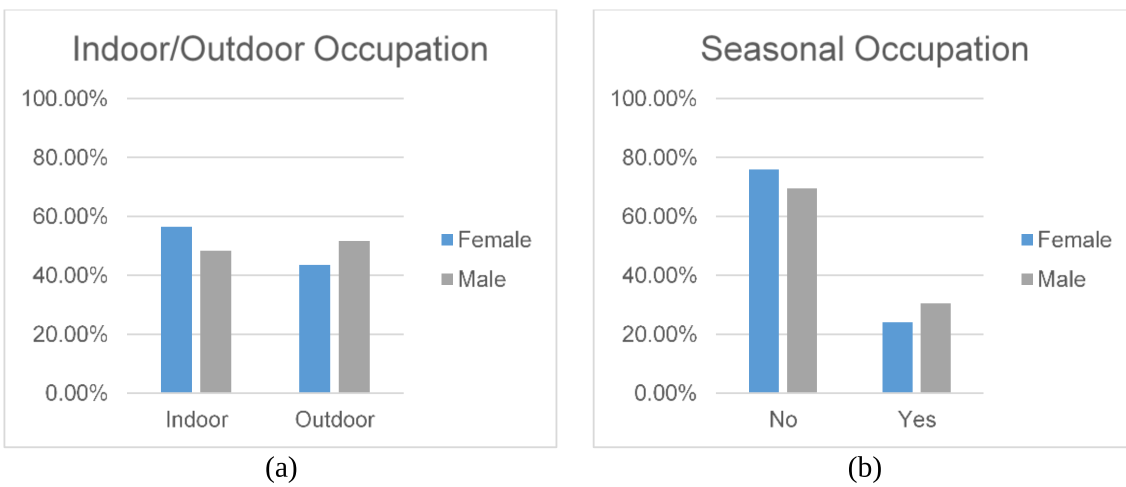
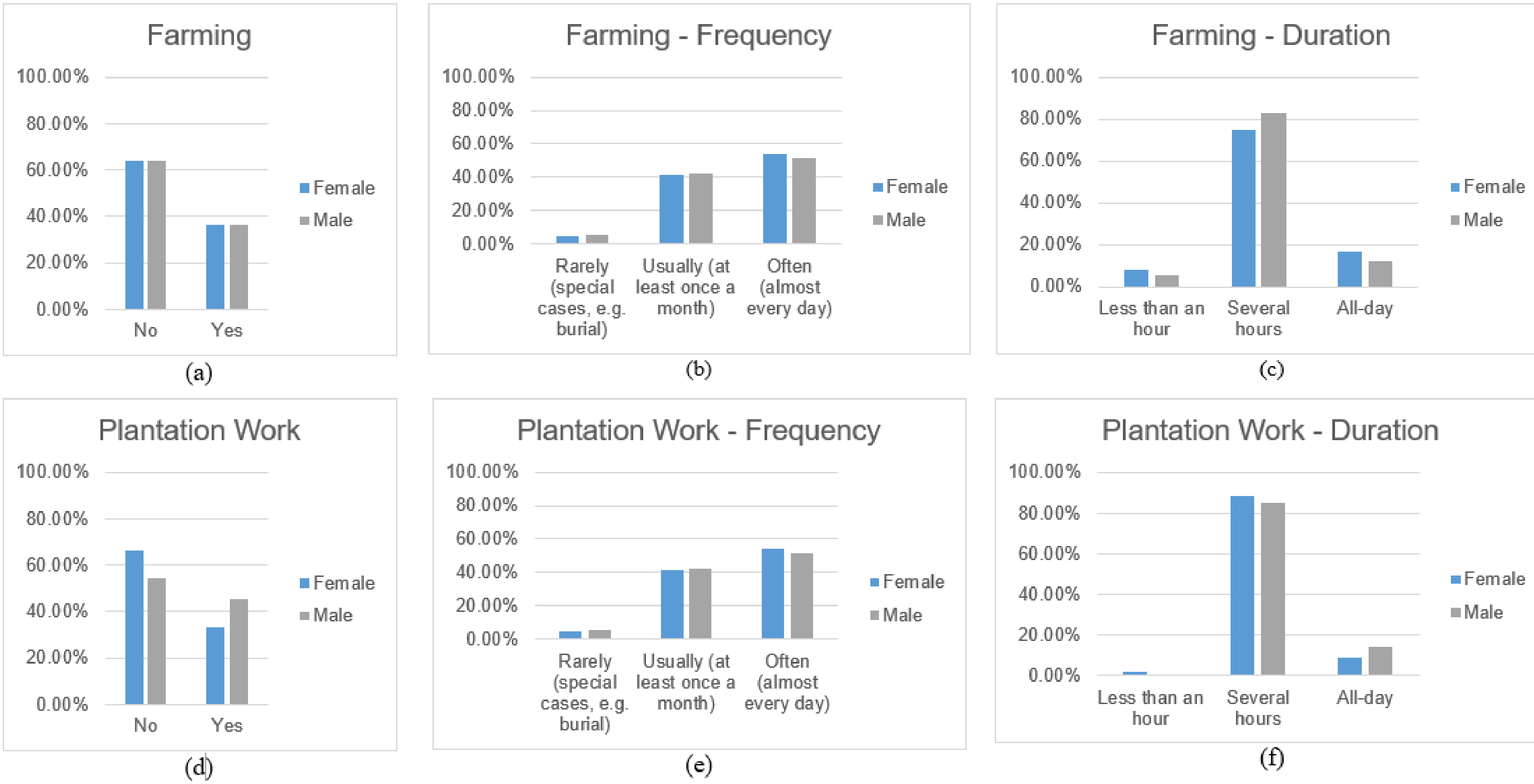


Figure 4-7: Proportion of surveyed female and male villagers who answered "Yes" to (a) having a primary occupation that varied seasonally and (b) having an indoor or outdoor job. The proportion of the total surveyed male and female village population is shown on the y-axis.

While the gender differences observed in the reported primary occupations extend to the reported engagement with Farming (equal for men and women, Figure 4-8a) and Plantation Work (men more likely to participate, Figure 4-8d), virtually no observable gender difference was present for water or forest chores (Figures 4-8g and 4-8j).

Additionally, there were no observable differences between men and women in terms of the frequency or duration of engaging in these land use activities, except for a small proportion of men reporting engaging in forest chores all-day (4.5%) compared to zero women. Additionally, while “several hours” appears to be the standard duration of most land use practices, chores near the water were the lone exception, with the overwhelming majority reporting less than one hour spent there (Figure 4-8i).


Farming
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
No
Yes
Female
Male
(a)
Farming - Frequency
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
Rarely (special cases, e.g. burial)
Usually (at least once a month)
Often (almost every day)
Female
Male
(b)
Farming - Duration
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
Less than an hour
Several hours
All-day
Female
Male
(c)
Plantation Work
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
No
Yes
Female
Male
(d)
Plantation Work - Frequency
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
Rarely (special cases, e.g. burial)
Usually (at least once a month)
Often (almost every day)
Female
Male
(e)
Plantation Work - Duration
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
Less than an hour
Several hours
All-day
Female
Male
(f)

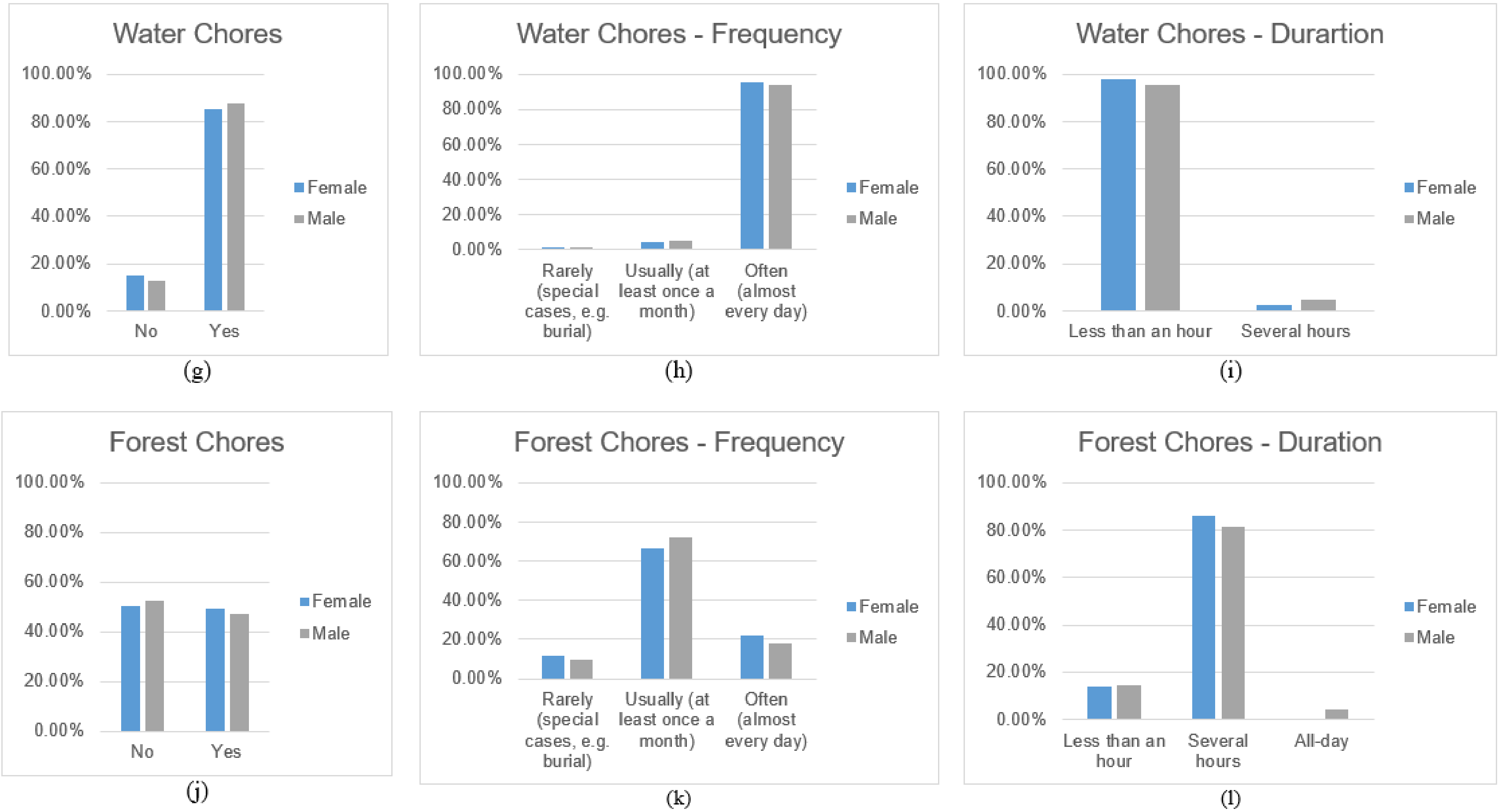


Figure 4-8: Proportion of surveyed villagers who answered "Yes" to engaging in (a) Farming, (d) Plantation Work, (g) Water Chores, and (j) Forest Chores within the past three months, separated by gender. The frequency of land use activities (b, e, h, k) and duration of land use activities (c, f, i, l) are similarly shown separated by gender. No participants reported spending all-day engaged in water chores. The proportion of the total surveyed population engaging with each land use is shown on the y-axis.

4.3.1.3 Land Use & Occupation Demographic Analysis by Age

Very distinct differences were observed among age groups in terms of their reported primary occupations, with some notable relationships with gender as well. While a higher proportion of females claiming to be Dependents was noted in Section 3.1.2, Figure 4-9 reveals that this difference can be explained by the proportion of females aged 15 – 54 who report themselves as Dependents (32.7%) much more often than men in the same age group (4.4%).

Students are the overwhelming majority of the 0-14 age group (69.5%), with very few students remaining in the 15 – 24 age group (6.5%) (Figure 4-9). It appears that this population joins the workforce typically around 14 – 15 years of age. Participants claiming Student as their primary occupation dwindled significantly among late-teen year participants, ranging from 92% – 94% of 10 – 13 year-olds claiming Student as their primary occupation, to only 63% of 14 year-olds, 53% of 15 year-olds, 7% of 16 and 17 year-olds, and 0% of 18 year-olds.

Also notable is that, while men and women aged 25 – 54 claimed Forest Occupations nearly equally (13.4% for women, 15.4% for men), a sharp difference is evident for men and women aged 55+ (7.8%), with women dropping out of the Forest Occupation workforce and men remaining (22.4%) (Figure 4-9).

Young people were much more likely to claim an indoor occupation (98.6% indoors), while people of "working age" (15 – 54) were more likely to work outdoors (61.0% for 15-24 and 84.7% for 25-54) (Figure 4-10a). Older people (55+) were equally likely to work indoors (49.1%) or outdoors (50.9%) (Figure 4-10a). People aged 25 – 54 were the most likely to report a seasonal job (49.3%). However, all groups were still more likely to report a non-seasonal occupation over a seasonal one (Figure 4-10b).

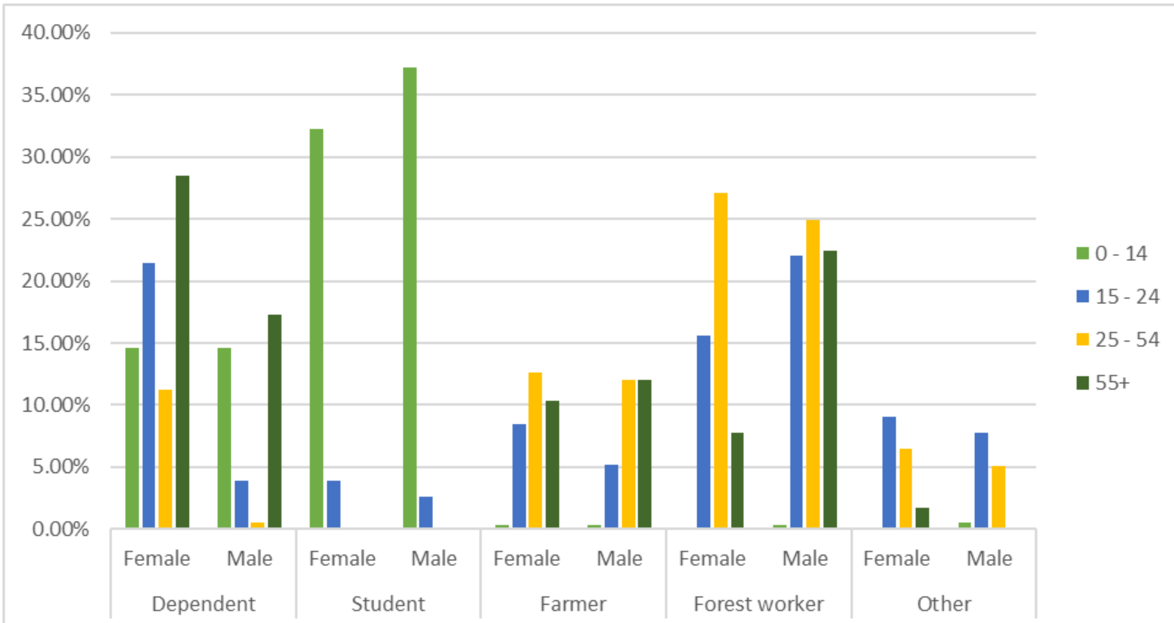
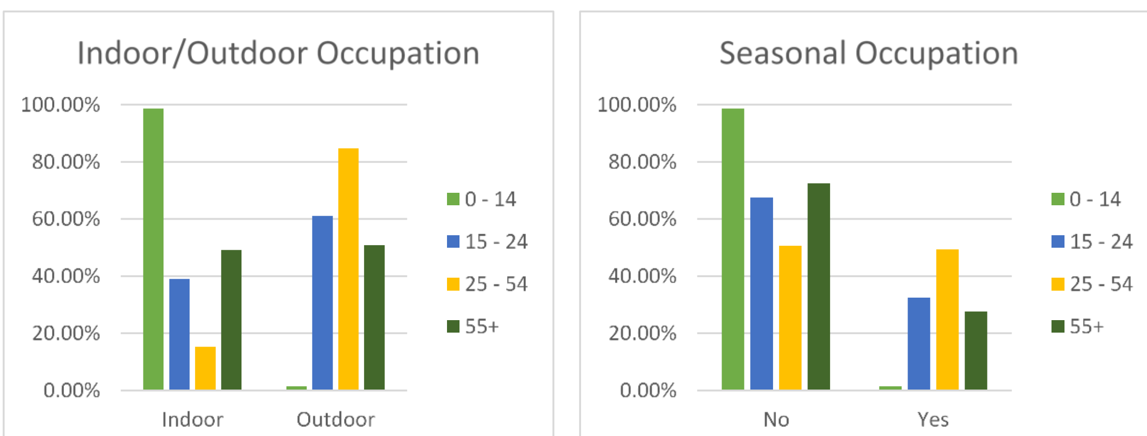


Figure 4-9: Proportion of surveyed villagers, separated by female/male and occupation, shown in differing age groups. The proportion of the total surveyed village population is shown on the y-axis.

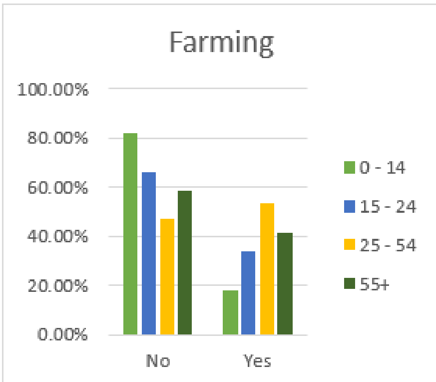


(a) (b)

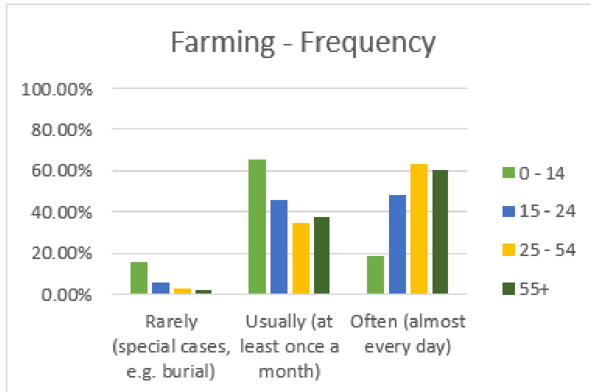
Figure 4-10: Proportion of surveyed villagers, separated by age, that answered "Yes" to (a) having a primary occupation that varied seasonally and (b) having an indoor or outdoor job. The proportion of the total surveyed population by age group is shown on the y-axis.

Unlike gender, where very few differences were observed in reported land use practices, frequency, and duration (except for Plantation Work), many differences were observed for the different age groups (Figure 4-11). Young people (0 – 14) were the least likely to engage in Farming (Figure 4-11a). If they did, they did so with little frequency (typically responding with the “Usually (at least once a month)” category), unlike the other age groups who were more likely to respond that they farmed nearly every day (Figure 4-11b). Plantation work followed a similar pattern (Figure 4-11d), though interestingly, the few respondents aged 0 – 14 who engaged in Plantation Work were the most likely of all the age groups to report working “All day” (Figure 4-11f).

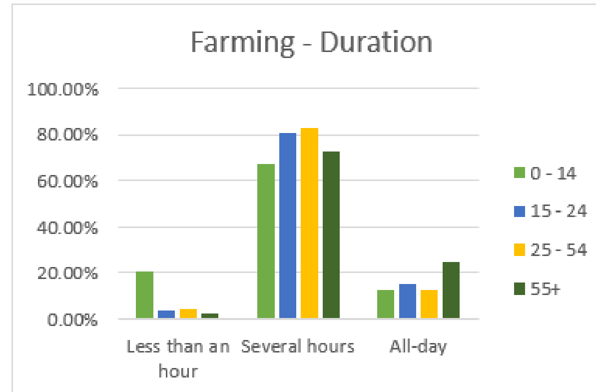
Participating in water chores was similarly highly reported across all age groups, with daily frequency and short duration (Figures 4-11h, 4-11i, 4-11j). Engaging in forest chores was most likely to be reported by persons aged 25 – 54 (Figure 4-11j). However, the frequency and duration of forest chore activity did not vary widely across age groups (Figures 4-11k, 4-11l).


Farming
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
No
Yes
0 - 14
15 - 24
25 - 54
55+

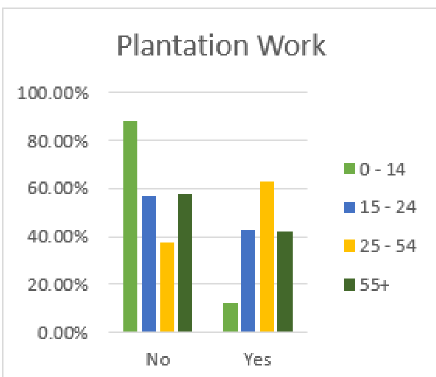
(a)


Farming - Frequency
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
Rarely (special cases, e.g. burial)
Usually (at least once a month)
Often (almost every day)
0 - 14
15 - 24
25 - 54
55+

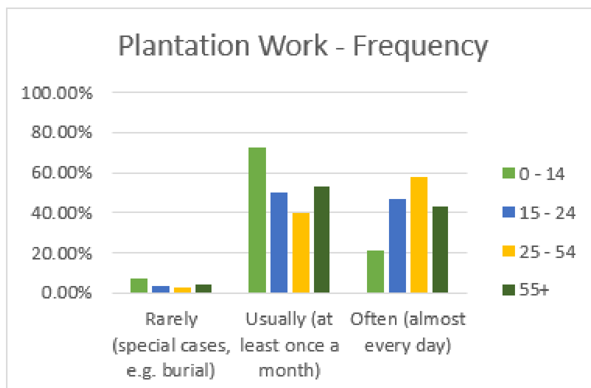
(b)


Farming - Duration
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
Less than an hour
Several hours
All-day
0 - 14
15 - 24
25 - 54
55+

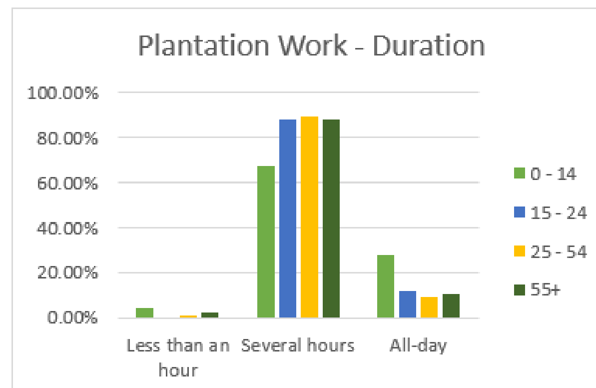
(c)


Plantation Work
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
No
Yes
0 - 14
15 - 24
25 - 54
55+

(d)


Plantation Work - Frequency
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
Rarely (special cases, e.g. burial)
Usually (at least once a month)
Often (almost every day)
0 - 14
15 - 24
25 - 54
55+

(e)


Plantation Work - Duration
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
Less than an hour
Several hours
All-day
0 - 14
15 - 24
25 - 54
55+

(f)

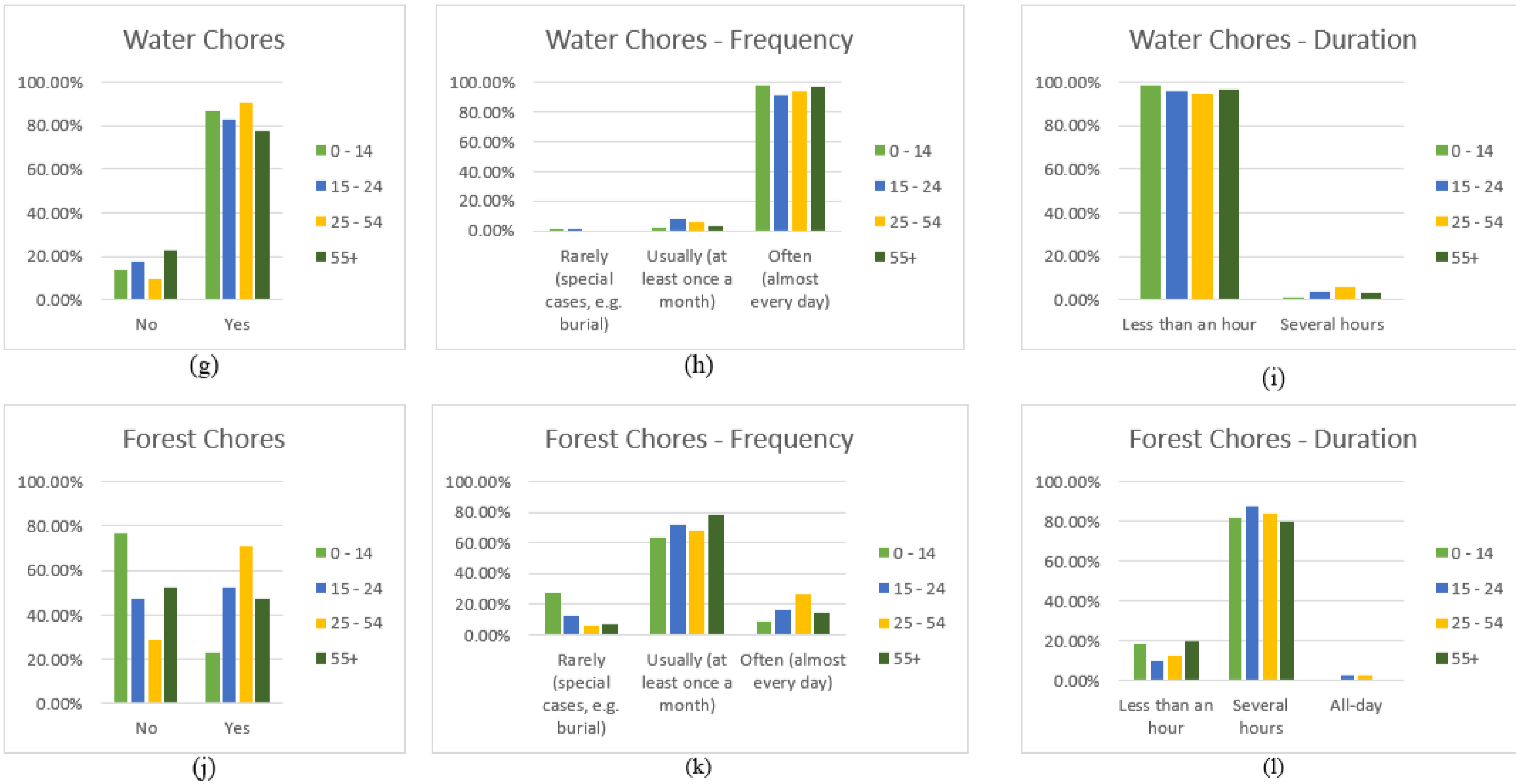


Figure 4-11: Proportion of surveyed villagers who answered "Yes" to engaging in (a) Farming, (d) Plantation Work, (g) Water Chores, and (j) Forest Chores within the past three months, separated by age group. The frequency of land use activities (b, e, h, k) and duration of land use activities (c, f, i, l) are similarly shown separated by age group. No participants reported spending all-day engaged in water chores. The proportion of the total surveyed population engaging with each land use is shown on the y-axis.

4.3.1.4 Land Use Time of Day Analysis by Village

The responses on the times of day that participants engage in the various land use activities were similar across land use activities and villages, with a few exceptions. While the more "occupation-based" land use activities (farming and plantation work) had some respondents reporting that they engaged in these activities before sunrise and after dark (Figures 4-12a, 4-12b), comparatively few respondents reporting engaging in chore work before sunrise or after dark (Figures 4-12c, 4-12d). This corresponds to the responses on duration, where a few participants indicated that they spend all-day farming or doing plantation work (Figures 4-11c, 4-11f). However, virtually no participants spend all day engaged in chores (Figures 4-11i, 4-11l).

Overwhelmingly though, most land use activity was evenly split between morning and day-time hours, with little variation of this theme amongst the villages (Figure 4-12). Respondents were allowed to select more than one time period, so many participants selected both morning and day-time. Similarly, all of the participants who reported engaging in farming or plantation work after dark, also selected the other three time period options, indicating that they engage in this work all day (except for two respondents).

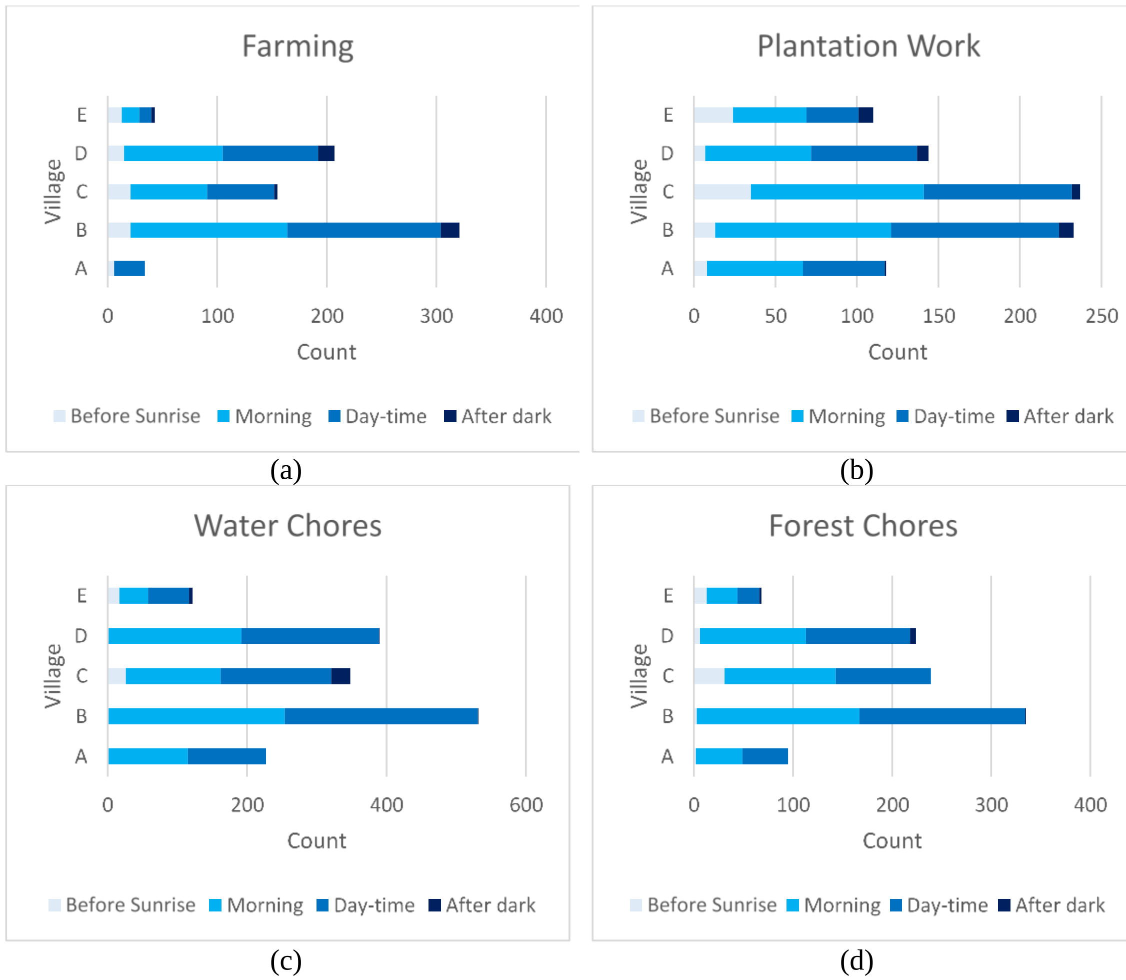


Figure 4-12: Count of villagers who selected each period for engagement with (a) Farming, (b) Plantation Work, (c) Water Chores, or (d) Forest Chores. Participants were allowed to select multiple periods.

4.3.2 Malaria Risk: Confounders and Effect Modifiers

As shown in Table 4-1, malaria prevalence among the study population was low, with only 9.6% (n=96) cases detected by usPCR. *P. vivax* was the most prevalent, with 53.1% (n=51) of cases testing positive for P. vivax, in comparison to only 39.6% (n=38) testing positive for *P. falciparum*. The remaining 7.3% of cases were mixed infections. The vast majority of cases were subclinical – only 5.2% (n=5) of cases were detected by

RDT. Each of the RDT positive tests identified *P. falciparum*; however, upon usPCR analysis, 3 of the five infections were mixed with *P. vivax*.

Data collection occurred August 2018 through February 2019, which leads to roughly half of our sample population was surveyed during the rainy season (48.1%) while the other half was sampled during the dry season (51.9%). Village 1 was surveyed only during the rainy season; Villages 4 and 5 were surveyed during the dry season; Villages 2 and 3 were split between the rainy and dry seasons (Table 4-1). Univariate analysis of season of data collection and malaria prevalence revealed a significant association; therefore, the season of data collection was included as a confounder in all further regression models.

The sample population skewed slightly female (52.8%) and young, with 35.7% of the sample under the age of 15. A nonlinear, but significant, association between age and malaria was observed, therefore age and age-squared were controlled for in adjusted models. The overall youth of the sample population (for example, 57.5% of the sample population in Village D is under the age of 15) necessitated separating the sample into 0 – 14 year old (Sensitivity Analysis II) and 15+ year old categories (Sensitivity Analysis III) for future analysis, which is presented in Section 4.3.4. During univariate analysis, sex was found to be weakly associated with malaria ($p = 0.063$). However, based on the results of Chapter 3 and the differences in land use activities observed among the genders, the decision was made to adjust for sex in the models regardless. No effect modification was found between sex and the other variables.

Only 9 (0. 9%) of the respondents indicated that they were pregnant at the time of data collection. Univariate analysis did not determine pregnancy to be a significant confounder, and it was, therefore, not included in adjusted models. Similarly, only 6 (0.6%) of the study population reported that they were not a resident of their village for the past six months. This was also not found to be a significant confounder and not included in adjusted models. A little over a quarter of the study population reported having a seasonal job (27.1%) ("Does your main occupation vary seasonally in the past year?"). Having an occupation that varies seasonally was found to be significantly associated with increased malaria risk and is therefore included in all adjusted models.

The final confounder included in the adjusted models was if participants had responded affirmatively to sleeping under a Long-Lasting Insecticide-treated Net (LLIN) the night before the survey. When sampled, participants were able to select multiple net types that they owned (Ordinary, LLIN, or Impregnated with Insecticide (ITN)). Ordinary nets were not found to be associated with malaria for this sample population. However, LLIN usage the night before the survey was found to be strongly protective and, therefore, is included in all adjusted models. High compliance with LLIN usage was found within the villagers, with 77.3% of participants sleeping under one the night before the survey (Table 4-1).

Table 4-1: Descriptive statistics of the sample population. Due to low response rates, pregnancy and residency status are not shown broken down for villages for the participants' privacy. For Occupation, the options of Vendor, Soldier, and Mine Worker were collapsed into Other in the table for participant privacy due to low response rates. Logger had similar low response rates (n=12), so it was combined with the significantly higher Plantation Worker option to create a Forest-Based Occupation category. For the Land Use data, Working in a Mine is not displayed due to the low response (n=2) that would not allow for anonymity. Percentages may not add up exactly to 100% due to rounding.

Village	A	B	C	D	E	Total
Population Sampled, n	185	345	190	200	80	1000

Malaria Prevalence: n (% of sampled village population)						
***P. falciparum* mono**	5 (2.7%)	16 (4.6%)	7 (3.7%)	7 (3.5%)	3 (3.8%)	38 (3.8%)
***P. vivax* mono**	13 (7.0%)	11 (3.2%)	9 (4.7%)	15 (7.5%)	3 (3.8%)	51 (5.1%)
Mixed *P. falciparum* & *P. vivax*	1 (0.5%)	2 (0.6%)	0 (0.0%)	4 (2.0%)	0 (0.0%)	7 (0.7%)
Any malaria	19 (10.3%)	29 (8.4%)	16 (8.4%)	26 (13.0%)	6 (7.5%)	96 (9.6%)
Season of Data Collection: n (% of sampled village population)						
Rainy	185 (100%)	185 (53.6%)	111 (58.4%)	0 (0.0%)	0 (0.0%)	481 (48.1%)
Dry	0 (0.0%)	160 (46.4%)	79 (41.6%)	200 (100.0%)	80 (100.0%)	519 (51.9%)
Sex: n (% of sampled village population)						
Female	87 (47.0%)	183 (53.0%)	106 (55.8%)	112 (56.0%)	40 (50.0%)	528 (52.8%)
Male	98 (53.0%)	162 (47.0%)	84 (44.2%)	88 (44%)	40 (50.0%)	472 (47.2%)
Age: n (% of sampled village population)						
0 – 14	74 (40.0%)	111 (32.2%)	38 (20.0%)	88 (44.0%)	46 (57.5%)	357 (35.7%)
15 – 24	31 (16.8%)	55 (15.9%)	36 (18.9%)	18 (9.0%)	14 (17.5%)	154 (15.4%)
25 – 54	66 (35.7%)	123 (35.7%)	97 (51.1%)	69 (34.5%)	18 (22.5%)	373 (37.3%)
55+	14 (7.5%)	56 (16.2%)	19 (10.0%)	25 (12.5%)	2 (2.5%)	116 (11.6%)
Pregnancy Status: n (% of sampled village female population)						
Pregnant	-	-	-	-	-	9 (1.7%)
Not Pregnant (excludes males)	-	-	-	-	-	519 (98.3%)
Residency Status: n (% of sampled village population) “Have you lived in the village for > 6 months?”						
Yes	-	-	-	-	-	994 (99.4%)
No	-	-	-	-	-	6 (0.6%)
Occupation Seasonality: n (% of sampled village population)						
Seasonal	31 (16.8%)	117 (33.9%)	55 (28.9%)	55 (27.5%)	13 (16.3%)	271 (27.1%)
Not Seasonal	154 (83.2%)	228 (66.1%)	135 (71.1%)	145 (72.5%)	67 (83.7%)	729 (72.9%)
Bednet Usage: n (% of sampled village population)						
Ordinary Net	88 (47.6%)	228 (66.1%)	161 (84.7%)	124 (62.0%)	68 (85.0%)	669 (66.9%)
Long Lasting Insecticide Net (LLIN)	169 (91.4%)	323 (93.6%)	185 (97.4%)	183 (91.5%)	72 (90.0%)	932 (93.2%)
Impregnated with Insecticide (ITN)	2 (1.1%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	2 (0.2%)
Slept Under any type of Bednet the Night Before Survey	164 (88.6%)	246 (71.3%)	182 (95.8%)	143 (71.5%)	76 (95.0%)	811 (81.1%)

Slept Under an LLIN the Night Before Survey	157 (84.9%)	230 (66.7%)	178 (93.7%)	138 (69.0%)	70 (87.5%)	773 (77.3%)
Natural Forest Cover: area sq/km (% of total village area within 2 km radius of village)						
Forest Cover	5.24 (41.8%)	5.17 (41.2%)	6.74 (53.7%)	8.01 (63.8%)	7.28 (58.0%)	-
Forest Loss: area sq/km (% of total village area within 2 km radius of village)						
Forest Loss 2017	0.48 (3.8%)	0.22 (1.7%)	0.88 (6.9%)	0.48 (3.8%)	0.64 (5.1%)	-
Forest Loss 2018	0.53 (4.3%)	0.42 (3.4%)	0.51 (4.1%)	0.37 (2.9%)	0.45 (3.6%)	-
Total Forest Loss 2014 – 2018	1.69 (13.5%)	1.32 (10.5%)	3.86 (30.7%)	1.98 (15.8%)	2.66 (21.2%)	-
Average Forest Loss Per Year 2014 – 2018	0.33 (2.7%)	0.24 (1.9%)	0.77 (6.1%)	0.40 (3.2%)	0.53 (4.2%)	-
Occupation Type: n (% of sampled village population)						
Indoor	106 (57.3%)	188 (54.5%)	72 (37.9%)	108 (54.0%)	52 (65.0%)	526 (52.6%)
Outdoor	79 (42.7%)	157 (45.5%)	118 (62.1%)	92 (46.0%)	28 (35.0%)	474 (47.4%)
Primary Occupation: n (% of sampled village population)						
Dependent	40 (21.6%)	111 (32.2%)	21 (11.1%)	43 (21.5%)	25 (31.3%)	240 (24.0%)
Student	59 (32.0%)	65 (18.8%)	44 (23.2%)	63 (31.5%)	27 (33.8%)	258 (25.8%)
Farmer	16 (8.6%)	76 (22.0%)	19 (10.0%)	25 (12.5%)	5 (6.2%)	141 (14.1%)
Forest-Based Occupation	57 (30.8%)	66 (19.1%)	83 (43.6%)	59 (29.5%)	23 (28.7%)	288 (28.8%)
Other	13 (7.0%)	27 (7.8%)	23 (12.1%)	10 (5.0%)	0 (0.0%)	73 (7.3%)
Land Use						
Attending to Crops/Farming						
Yes: n (% of sampled pop)	33 (17.8%)	147 (42.6%)	71 (37.4%)	90 (45.0%)	21 (26.3%)	362 (36.2%)
No: n (% of sampled pop)	152 (82.2%)	198 (57.4%)	119 (62.6%)	110 (55.0%)	59 (73.8%)	638 (63.8%)
Frequency: n (% of village respondents who said "Yes" to Attending to Crops/Farming)						
Rarely	2 (6.1%)	8 (5.4%)	3 (4.2%)	6 (6.7%)	0 (0.0%)	19 (5.3%)
Usually	10 (30.3%)	56 (38.1%)	29 (40.9%)	48 (53.3%)	9 (42.9%)	152 (42.0%)
Often	21 (63.6%)	83 (56.5%)	39 (54.9%)	36 (40.0%)	12 (57.1%)	191 (52.8%)
Duration: n (% of village respondents who said "Yes" to Attending to Crops/Farming)						
< 1 hour	0	15 (10.2%)	3 (4.2%)	3 (3.3%)	4 (19.1%)	25 (6.9%)
Several hours	30 (90.9%)	104 (70.8%)	64 (90.1%)	72 (80.0%)	14 (66.7%)	284 (78.5%)
All-day	3 (9.1%)	28 (19.1%)	4 (5.6%)	15 (16.7%)	3 (14.3%)	53 (14.6%)
Time of day: n (% not provided because participants could choose multiple options)						
Before Sunrise	6	21	21	15	13	76
Morning	30	143	70	90	16	349
Day-time	28	140	61	87	11	327
After dark	0	17	3	15	3	38
Working on a Plantation						
Yes: n (% of sampled pop)	63 (34.1%)	110 (31.9%)	106 (55.8%)	66 (33.0%)	46 (57.5%)	391 (39.1%)
No: n (% of sampled pop)	122 (66.0%)	235 (68.1%)	84 (44.2%)	134 (67.0%)	34 (42.5%)	609 (60.9%)

Frequency: n (% of village respondents who said "Yes" to Working on a Plantation)						
Rarely	2 (3.2%)	6 (5.5%)	2 (1.9%)	2 (3.0%)	0 (0.0%)	12 (3.1%)
Usually	17 (27.0%)	58 (52.7%)	43 (40.6%)	46 (69.7%)	19 (41.3%)	183 (46.8%)
Often	44 (69.8%)	46 (41.2%)	61 (57.6%)	18 (27.3%)	27 (58.7%)	196 (50.1%)
Duration: n (% of village respondents who said "Yes" to Working on a Plantation)						
< 1 hour	0 (0.0%)	2 (1.8%)	0 (0.0%)	0 (0.0%)	3 (6.5%)	5 (1.3%)
Several hours	60 (95.2%)	93 (84.6%)	94 (88.7%)	58 (87.9%)	34 (73.9%)	339 (86.7%)
All-day	3 (4.8%)	15 (13.6%)	12 (11.3%)	8 (12.1%)	9 (19.6%)	47 (12.0%)
Time of day: n (% not provided because participants could choose multiple options)						
Before Sunrise	8	13	35	7	24	87
Morning	59	108	106	65	45	383
Day-time	50	103	91	65	32	341
After dark	1	9	5	7	9	31
Conduct household chores that involve trips to water						
Yes	138 (74.6%)	285 (82.6%)	171 (90.0%)	198 (99.0%)	71 (88.8%)	863 (86.3%)
No	47 (25.4%)	60 (17.4%)	19 (10.0%)	2 (1.0%)	9 (11.3%)	137 (13.7%)
Frequency: n (% of village respondents who said "Yes" to Water Chores)						
Rarely	3 (2.2%)	1 (0.4%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	4 (0.5%)
Usually	18 (13.0%)	18 (6.3%)	0 (0.0%)	3 (1.5%)	1 (1.4%)	40 (4.6%)
Often	117 (84.8%)	266 (93.3%)	171 (100.0%)	195 (98.5%)	70 (98.6%)	819 (94.9%)
Duration: n (% of village respondents who said "Yes" to Water Chores)						
< 1 hour	126 (91.3%)	279 (97.9%)	170 (99.4%)	187 (94.4%)	71 (100.0%)	833 (96.5%)
Several hours	12 (8.7%)	6 (2.1%)	1 (0.6%)	11 (5.6%)		30 (3.5%)
All-day	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Time of day: n (% not provided because participants could choose multiple options)						
Before Sunrise	1	1	26	1	17	46
Morning	114	253	136	191	41	735
Day-time	112	277	159	197	59	804
After dark	0	1	27	1	5	34
Conduct household chores that involve trips to the forest						
Yes	57 (30.8%)	170 (49.3%)	117 (61.6%)	107 (53.5%)	33 (41.3%)	484 (48.4%)
No	128 (69.2%)	175 (50.7%)	73 (38.4%)	93 (46.5%)	47 (58.8%)	516 (51.6%)
Frequency: n (% of village respondents who said "Yes" to Forest Chores)						
Rarely	7 (12.3%)	21 (12.4%)	9 (7.7%)	14 (13.1%)	1 (3.0%)	52 (10.7%)
Usually	38 (66.7%)	120 (70.6%)	84 (71.8%)	74 (69.2%)	19 (57.6%)	335 (69.2%)
Often	12 (21.1%)	29 (17.1%)	24 (20.5%)	19 (17.8%)	13 (39.4%)	97 (20.0%)
Duration: n (% of village respondents who said "Yes" to Forest Chores)						
< 1 hour	19 (33.3%)	28 (16.5%)	13 (11.1%)	8 (7.5%)	0 (0.0%)	68 (14.1%)
Several hours	38 (66.7%)	141 (82.9%)	103 (88.0%)	93 (86.9%)	31 (93.9%)	406 (83.9%)
All-day	0 (0.0%)	1 (0.6%)	1 (0.9%)	6 (5.6%)	2 (6.1%)	10 (2.1%)
Time of day: n (% not provided because participants could choose multiple options)						
Before Sunrise	2	3	31	6	13	55
Morning	47	164	112	107	31	461
Day-time	46	167	96	105	22	436
After dark	0	1	0	6	2	9
Land-Use Index						
Maximum	11.5	17	21	17	17	21
Mean (sd)	3.1 (3.1)	4.3 (4.0)	5.3 (3.7)	4.7 (3.7)	5.1 (4.4)	4.4 (3.8)
Minimum	0	0	0	0	0	0

4.3.3 Natural Forest Cover & Forest Loss

The land cover distribution around each of the villages varied widely (Table 4-2, Figure 4-13), especially for the primary land cover of interest, natural forest. While natural forest was the dominant land cover of each village, its proportion within a 2 km radius ranged from a minimum of 41.2% in Village B to a maximum of 63.8% in Village D. The patterns of reported primary occupations within the surveyed villages (Figure 4-3) closely mirror the landscape. For example, Village C reports the highest proportion of Forest Workers (Figure 4-3), which is aligned with Village C, also reporting the highest area of managed forests (Table 4-2) and the highest amount of forest lost from 2014-2018 (Table 4-1). Similarly, Village B claims the highest proportion of Farmers (Figure 4-3) and the highest proportion of croplands (Table 4-2). Village B was also the only village with a higher proportion of Farmers than Forest Workers.

Table 4-2: Area in sq km (% of total area ~12.56 sq km) of each land cover type found within a 2 km radius of the village center.

Village	A	B	C	D	E
Natural Forest	5.24 (41.8%)	5.17 (41.2%)	6.74 (53.7%)	8.01 (63.8%)	7.28 (58.0%)
Managed Forest	1.76 (14.0%)	1.49 (11.8%)	4.37 (34.8%)	2.56 (20.4%)	3.11 (24.7%)
Human Infrastructure	0.14 (1.1%)	0.16 (1.3%)	0.15 (1.2%)	0.08 (0.7%)	0.11 (0.9%)
Croplands	2.01 (16.0%)	2.46 (19.6%)	0.24 (1.9%)	0.76 (6.1%)	0.87 (6.9%)
Shrub and Grass	2.64 (21.1%)	2.43 (19.4%)	0.90 (7.1%)	0.82 (6.5%)	0.99 (7.9%)
Water	0.47 (3.8%)	0.50 (4.0%)	0.04 (0.3%)	0.20 (1.6%)	0.05 (0.4%)
Bare Surface	0.30 (2.4%)	0.35 (2.7%)	0.12 (1.0%)	0.13 (1.0%)	0.16 (1.3%)

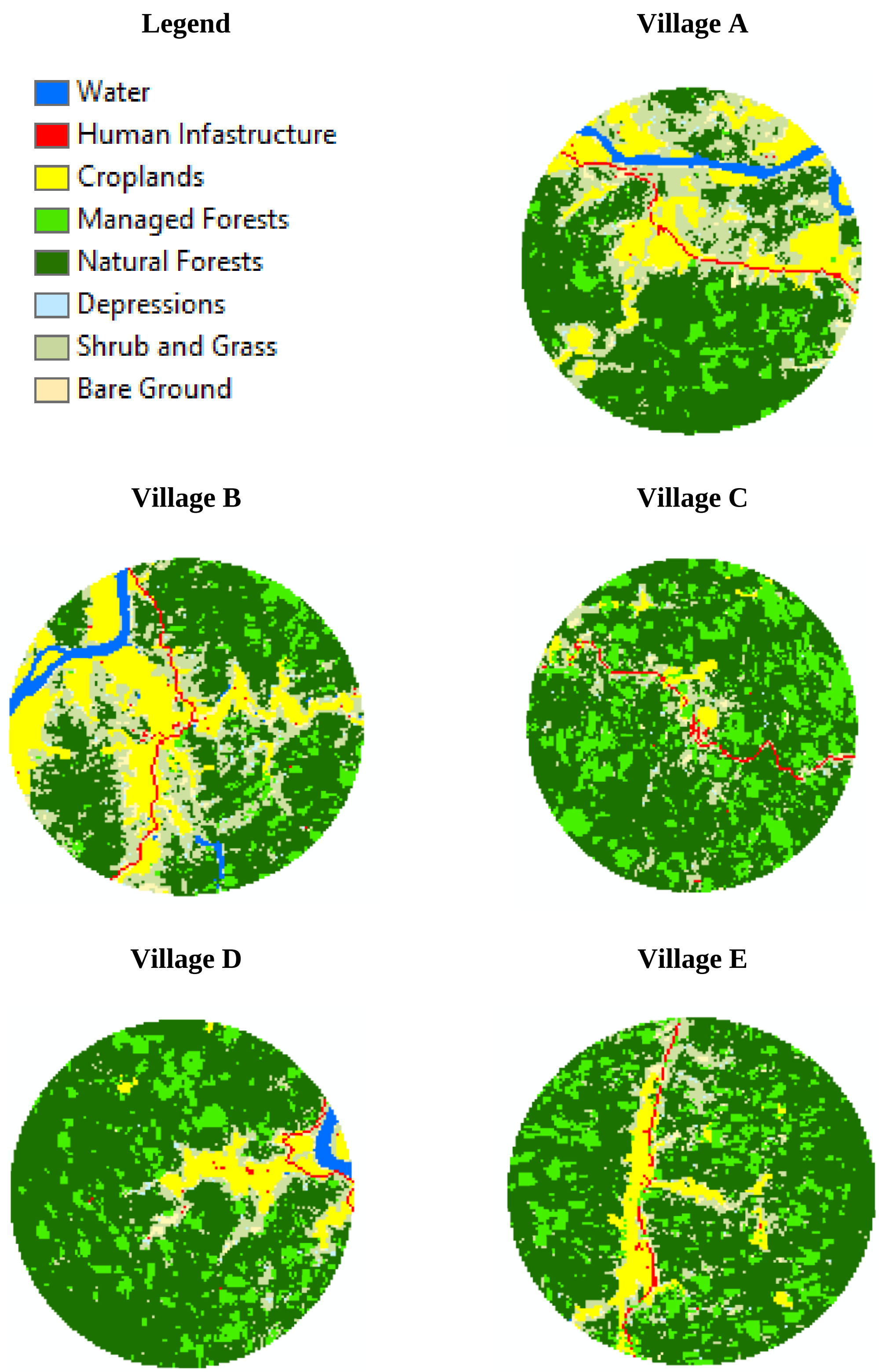


Figure 4-13: Land cover maps of the five surveyed villages. Exact locations not displayed for anonymity.

Following the findings of Chapter 3, I sought to investigate if the relationship between natural forest cover and malaria prevalence discovered there held for these newly surveyed villages. Because the village sampling scheme did not allow for an unbiased measurement of overall village prevalence, I conducted a logistic regression analysis at the individual case level. The regression model was adjusted for age, age-squared, sex, seasonal occupation, the season of data collection, and the use of insecticide-treated bednet the night before the survey. Area of natural forest within a 2 km radius of a respondent's home village was found to be associated with increased malaria risk (OR: 1.35, 95% CI: 1.08 – 1.72).

However, this result was not reinforced by the sensitivity analysis, which only analyzed participants who did not report engaging in forest-based chores. A demographic comparison between the general sample population and the sensitivity analysis sub-sample is provided in Table 4-3. I did not find a significant association between natural forest cover and malaria for this subgroup of respondents (OR: 1.48, 95% CI: 0.91 – 2.47).

Table 4-3: Differences between the sampled population for the primary and sensitivity analysis for forest cover and forest cover loss analysis.

Village	Primary Analysis	Sensitivity Analysis I (No Forest Engagement)
Population Sampled, n	1000	516
Season of Data Collection: n (% of sampled population)		
Rainy	481 (48.1%)	252 (48.8%)
Dry	519 (51.9%)	264 (51.2%)
Sex: n (% of sampled population)		
Female	528 (52.8%)	267 (51.7%)

Male	472 (47.2%)	249 (48.3%)
Age: n (% of sampled population)		
0 – 14	357 (35.7%)	274 (53.1%)
15 – 24	154 (15.4%)	73 (14.2%)
25 – 54	373 (37.3%)	108 (20.9%)
55+	116 (11.6%)	61 (11.8%)
Pregnancy Status: n (% of sampled female population)		
Pregnant	9 (1.7%)	3 (1.1%)
Not Pregnant (excludes males)	519 (98.3%)	264 (98.9%)
Residency Status: n (% of sampled population) "Have you lived in the village for > 6 months?"		
Yes	994 (99.4%)	511 (99.0%)
No	6 (0.6%)	5 (1.0%)
Occupation Seasonality: n (% of sampled population)		
Seasonal	271 (27.1%)	47 (9.1%)
Not Seasonal	729 (72.9%)	469 (90.9%)
Bednet Usage: n (% of sampled population)		
Ordinary Net	669 (66.9%)	327 (63.4%)
Long Lasting Insecticide Net (LLIN)	932 (93.2%)	476 (92.3%)
Impregnated with Insecticide (ITN)	2 (0.0%)	2 (0.4%)
Slept Under any type of Bednet the Night Before Survey	811 (81.1%)	417 (80.8%)
Slept Under an LLIN the Night Before Survey	773 (77.3%)	397 (76.9%)
Occupation Type: n (% of sampled population)		
Indoor	526 (52.6%)	397 (76.9%)
Outdoor	474 (47.4%)	119 (23.1%)
Primary Occupation: n (% of sampled population)		
Dependent	240 (24.0%)	192 (37.2%)
Student	258 (25.8%)	186 (36.1%)
Farmer	141 (14.1%)	34 (6.6%)
Forest-Based Occupation	288 (28.8%)	76 (14.7%)
Other	73 (7.3%)	28 (5.4%)
Land Use		
Attending to Crops/Farming: n (% of sampled population)		
Yes	362 (36.2%)	96 (18.6%)

No	638 (63.8%)	420 (81.4%)
Frequency: n (% of village respondents who said “Yes” to Attending to Crops/Farming)		
Rarely	19 (5.2%)	10 (10.4%)
Usually	152 (42.0%)	42 (43.8%)
Often	191 (52.8%)	44 (45.8%)
Duration: n (% of village respondents who said “Yes” to Attending to Crops/Farming)		
Less than 1 hour	25 (6.9%)	11 (11.5%)
Several hours	284 (78.5%)	74 (77.1%)
All-day	53 (14.6%)	11 (11.5%)
Time of day: n (% not provided because participants could choose multiple options)		
Before Sunrise	76	28
Morning	349	88
Day-time	327	79
After dark	38	7
Working on a Plantation: n (% of sampled population)		
Yes	391 (39.1%)	103 (20.0%)
No	609 (60.9%)	413 (80.0%)
Frequency: n (% of village respondents who said “Yes” to Working on a Plantation)		
Rarely	12 (3.1%)	4 (3.9%)
Usually	183 (46.8%)	39 (37.9%)
Often	196 (50.1%)	60 (58.3%)
Duration: n (% of village respondents who said “Yes” to Working on a Plantation)		
Less than 1 hour	5 (1.3%)	3 (2.9%)
Several hours	339 (86.7%)	88 (85.4%)
All-day	47 (12.0%)	12 (11.7%)
Time of day: n (% not provided because participants could choose multiple options)		
Before Sunrise	87	34
Morning	383	98
Day-time	341	80
After dark	31	11
Conduct household chores that involve trips to water: n (% of sampled population)		
Yes	863 (86.3%)	406 (78.7%)
No	137 (13.7%)	110 (21.3%)
Frequency: n (% of village respondents who said “Yes” to conducting chores that involve trips to the water)		
Rarely	4 (0.5%)	3 (0.7%)
Usually	40 (4.6%)	25 (6.2%)
Often	819 (94.9%)	378 (93.1%)
Duration: n (% of village respondents who said “Yes” to conducting chores that involve trips to the water)		
Less than 1 hour	833 (96.5%)	393 (96.8%)
Several hours	30 (7.4%)	13 (3.2%)
All-day	0	0
Time of day: n (% not provided because participants could choose multiple options)		
Before Sunrise	46	16
Morning	735	346
Day-time	804	369
After dark	34	13
Conduct household chores that involve trips to the forest: n (% of sampled population)		
Yes	484 (48.4%)	0
No	516 (51.6%)	0

Frequency: n (% of village respondents who said "Yes" to conducting chores that involve trips to the forest)		
Rarely	52 (10.7%)	0
Usually	335 (69.2%)	0
Often	97 (20.0%)	0
Duration: n (% of village respondents who said "Yes" to conducting chores that involve trips to the forest)		
Less than 1 hour	68 (14.1%)	0
Several hours	406 (83.9%)	0
All-day	10 (2.1%)	0
Time of day: n (% not provided because participants could choose multiple options)		
Before Sunrise	55	0
Morning	461	0
Day-time	436	0
After dark	9	0
Land-Use Index		
Max	21	13
Mean (sd)	4.4 (3.8)	2.1 (2.4)
Minimum	0	0
Malaria Prevalence: n (% of sampled population)		
***P. falciparum* mono**	38 (3.8%)	9 (1.7%)
***P. vivax* mono**	51 (5.1%)	20 (3.9%)
Mixed *P. falciparum* & *P. vivax*	7 (0.7%)	1 (0.2%)
Any malaria	96 (9.6%)	30 (5.8%)

Fully-adjusted models were also created to assess the relationship between forest loss and malaria. Despite marked differences in the amount of forest loss across villages (Table 4-1), the only metric tested which showed an association with malaria was Forest Loss in 2018 (sq km), which was found to be protective (i.e., the more forest removed in 2018 within 2 km of a participants village, the lower the risk of malaria to that participant) (Table 4-4).

Table 4-4: Model results expressing the risk of Plasmodium presence in the blood as a function of forest loss. Blue cells indicate protective associations; red cells indicate risk associations; white cells indicate non-significant associations.

Variable	Odds Ratio (95% Confidence Interval)
Forest Loss 2017 within 2km radius of village (sq km)	1.01 (0.40 – 2.53)
Forest Loss 2018 within 2km radius of village (sq km)	0.01 (0.00 – 0.82)
Total Forest Loss 2014 – 2018 within 2km radius of village (sq km)	0.96 (0.75 – 1.21)
Average Forest Loss Per Year 2014 – 2018 within 2km radius of the village (sq km per year)	0.82 (0.24 – 2.61)

4.3.4 Land Use & Occupation Relationship to Malaria Exposure

In addition to adjusting for all of the confounders outlined in Section 4.3.2, because I had observed an association between natural forest cover and malaria (notwithstanding the sensitivity analysis), I chose to adjust for natural forest cover in the models used to assess individual land use habits and practices (Table 4-5). Additionally, there were many observed differences in the land use habits of youth as compared to 15+ aged participants, therefore two sensitivity analyses were conducted to more fully explain the relationships found. A demographic comparison of the Primary Analysis, Sensitivity Analysis II, and Sensitivity Analysis III is provided in Table 4-5. Very few participants in the youth subsample reported primary occupations that were not Dependent or Student (1.2%, Table 4-5). While slightly higher percentages among the youth category did report engaging in different land use activities (17.9%, 12.0%, and 23.3% for Farming, Plantation Work, and Forest Chores, respectively), it was still a much lower percentage than for the 15+ population (46.3%, 54.1%, and 62.4% for Farming, Plantation Work, and Forest Chores, respectively) (Table 4-5).

Table 4-5: Differences between the sampled population for the primary and sensitivity analyses for land use activities analysis.

Village	Primary Analysis	Sensitivity Analysis II (0-14)	Sensitivity Analysis III (15+)
Population Sampled, n	1000	357	643
Season of Data Collection: n (% of sampled population)			
Rainy	481 (48.1%)	147 (41.2%)	334 (51.9%)
Dry	519 (51.9%)	210 (58.8%)	309 (48.1%)
Sex: n (% of sampled population)			
Female	528 (52.8%)	168 (47.1%)	360 (56.0%)
Male	472 (47.2%)	189 (52.9%)	283 (44.0%)
Age: n (% of sampled population)			
0 – 14	357 (35.7%)	357 (100%)	0
15 – 24	154 (15.4%)	0	154 (24.0%)
25 – 54	373 (37.3%)	0	373 (58.0%)
55+	116 (11.6%)	0	116 (18.0%)
Pregnancy Status: n (% of sampled female population)			
Pregnant	9 (1.7%)	0 (0%)	9 (2.5%)
Not Pregnant (excludes males)	519 (98.3%)	168 (100%)	351 (97.5%)
Residency Status: n (% of sampled population) “Have you lived in the village for > 6 months?”			
Yes	994 (99.4%)	355 (99.4%)	639 (99.4%)
No	6 (0.6%)	2 (0.6%)	4 (0.6%)
Occupation Seasonality: n (% of sampled population)			
Seasonal	271 (27.1%)	5 (1.4%)	266 (41.4%)
Not Seasonal	729 (72.9%)	352 (98.6%)	377 (58.6%)
Bednet Usage: n (% of sampled population)			
Ordinary Net	669 (66.9%)	225 (63.0%)	444 (69.1%)
Long Lasting Insecticide Net (LLIN)	932 (93.2%)	329 (92.2%)	603 (93.8%)
Impregnated with Insecticide (ITN)	2 (0.0%)	0	2 (0.3%)

Slept Under any type of Bednet the Night Before Survey	811 (81.1%)	280 (78.4%)	531 (82.6%)
Slept Under an LLIN the Night Before Survey	773 (77.3%)	267 (74.8%)	506 (78.7%)
Occupation Type: n (% of sampled population)			
Indoor	526 (52.6%)	352 (98.6%)	174 (27.1%)
Outdoor	474 (47.4%)	5 (1.4%)	469 (72.9%)
Primary Occupation: n (% of sampled population)			
Dependent	240 (24.0%)	104 (29.1%)	136 (21.2%)
Student	258 (25.8%)	248 (69.5%)	10 (1.6%)
Farmer	141 (14.1%)	2 (0.6%)	139 (21.6%)
Forest-Based Occupation	288 (28.8%)	1 (0.3%)	287 (44.6%)
Other	73 (7.3%)	1 (0.3%)	62 (9.6%)
Land Use			
Attending to Crops/Farming			
Yes	362 (36.2%)	64 (17.9%)	298 (46.3%)
No	638 (63.8%)	293 (82.1%)	345 (53.7%)
Frequency: n (% of village respondents who said "Yes" to Attending to Crops/Farming)			
Rarely	19 (5.2%)	10 (2.8%)	9 (1.4%)
Usually	152 (42.0%)	12 (3.4%)	179 (27.8%)
Often	191 (52.8%)	42 (11.8%)	110 (17.1%)
Duration: n (% of village respondents who said "Yes" to Attending to Crops/Farming)			
Less than 1 hour	25 (6.9%)	13 (3.6%)	12 (1.9%)
Several hours	284 (78.5%)	43 (12.0%)	241 (37.5%)
All-day	53 (14.6%)	8 (2.2%)	45 (7.0%)
Time of day: n (% not provided because participants could choose multiple options)			
Before Sunrise	76	17	59
Morning	349	57	292
Day-time	327	55	272
After dark	38	7	31
Working on a Plantation			
Yes	391 (39.1%)	43 (12.0%)	348 (54.1%)
No	609 (60.9%)	314 (88.0%)	295 (45.9%)
Frequency: n (% of village respondents who said "Yes" to Working on a Plantation)			
Rarely	12 (3.1%)	3 (7.0%)	9 (2.6%)
Usually	183 (46.8%)	9 (20.9%)	187 (53.7%)
Often	196 (50.1%)	31 (72.1%)	152 (43.7%)
Duration: n (% of village respondents who said "Yes" to Working on a Plantation)			
Less than 1 hour	5 (1.3%)	2 (4.7%)	3 (0.9%)
Several hours	339 (86.7%)	29 (67.4%)	310 (89.1%)
All-day	47 (12.0%)	12 (27.9%)	35 (10.1%)

Time of day: n (% not provided because participants could choose multiple options)			
Before Sunrise	87	19	68
Morning	383	43	340
Day-time	341	36	305
After dark	31	12	19
Conduct household chores that involve trips to water			
Yes	863 (86.3%)	309 (86.6%)	554 (86.2%)
No	137 (13.7%)	48 (13.4%)	89 (13.8%)
Frequency: n (% of village respondents who said "Yes" to conducting chores that involve trips to the water)			
Rarely	4 (0.5%)	2 (0.7%)	2 (0.4%)
Usually	40 (4.6%)	6 (1.9%)	34 (6.1%)
Often	819 (94.9%)	301 (97.4%)	518 (93.5%)
Duration: n (% of village respondents who said "Yes" to conducting chores that involve trips to the water)			
Less than 1 hour	833 (96.5%)	305 (85.4%)	528 (82.12%)
Several hours	30 (7.4%)	4 (1.12%)	26 (4.04%)
All-day	0	0	0
Time of day: n (% not provided because participants could choose multiple options)			
Before Sunrise	46	20	26
Morning	735	269	466
Day-time	804	285	519
After dark	34	10	24
Conduct household chores that involve trips to the forest			
Yes	484 (48.4%)	83 (23.3%)	401 (62.4%)
No	516 (51.6%)	274 (76.7%)	242 (37.6%)
Frequency: n (% of village respondents who said "Yes" to conducting chores that involve trips to the forest)			
Rarely	52 (10.7%)	23 (27.7%)	29 (7.2%)
Usually	335 (69.2%)	53 (63.9%)	282 (70.3%)
Often	97 (20.0%)	7 (8.4%)	90 (22.4%)
Duration: n (% of village respondents who said "Yes" to conducting chores that involve trips to the forest)			
Less than 1 hour	68 (14.1%)	15 (18.1%)	53 (13.2%)
Several hours	406 (83.9%)	68 (81.9%)	338 (84.3%)
All-day	10 (2.1%)	0	10 (2.5%)
Time of day: n (% not provided because participants could choose multiple options)			
Before Sunrise	55	10	45
Morning	461	81	380
Day-time	436	73	363
After dark	9	0	9
Land-Use Index			
Max	21	11.5	21
Mean (sd)	4.4 (3.8)	2.0 (2.4)	5.8 (3.8)
Minimum	0	0	0
Malaria Prevalence: n (% of sampled population)			
***P. falciparum* mono**	38 (3.8%)	8 (2.2%)	30 (4.7%)

***P. vivax* mono**	51 (5.1%)	15 (4.2%)	36 (5.6%)
Mixed *P. falciparum* & *P. vivax*	7 (0.7%)	5 (1.4%)	2 (0.3%)
Any malaria	96 (9.6%)	28 (7.8%)	68 (10.6%)

The modeling results indicate that the exposure metrics which increase the likelihood of having malaria are different for youth as compared to 15+ aged participants. The only significant relationship that was discovered which was consistent across the Primary Analysis, and Sensitivity Analyses II and III was between the Land Use Index and malaria, which is expanded upon in Section 4.3.5. However, many relationships were discovered which were confirmed by the 15+ age Sensitivity Analysis III. For example, working in an outdoor occupation is strongly associated with malaria (OR: 2.22, 95% CI: 1.10 – 4.65). In terms of reported primary occupation, a protective relationship was found for dependents (OR: 0.25, 95% CI: 0.09 – 0.57), while a strong association was found between malaria and forest-based occupations (i.e., Loggers and Plantation Workers) (OR: 1.87, 95% CI: 1.12 – 3.16). Primary occupations of Student, Farmer, or Other were not found to be associated with malaria (Table 4-6).

Primary occupation fails to capture the range of land use activities that Ann residents engage in, especially when the seasonal nature of most jobs is considered. For example, 55 respondents who claimed Farmer as their primary occupation, also indicated that they participate in Plantation Work. Fully-adjusted (including natural forest cover) models were created for each of the land use options (Table 4-6), except for mining, for which the number of respondents was too low (n = 2) for valid analysis. Despite the relationship observed between forest-based primary occupations, reported engagement with plantation work was not found to be associated with malaria (OR: 1.58, 95% CI:

0.95 – 2.64), except for the working-age cohort (Sensitivity Analysis III, OR: 1.92, 95% CI: 1.05 – 3.61). Engaging in forest chores (OR: 2.13, 95% CI: 1.27 – 3.66) was found to be strongly associated with malaria risk for the Primary Analysis, but not the Working-Age Sensitivity Analysis III. However, forest chores were the only significant risk relationship found for the youth cohort (Sensitivity Analysis II, OR: 2.67, 95% CI: 1.10 – 6.52). No significant association was found between farming/attending crops or engaging in water chores (Table 4-5).

The majority of the time of day metrics for land use activities did not have a relationship with malaria, except for farming after dark (OR: 3.25, 95% CI: 1.11 – 8.91, not observed in Sensitivity Analyses) and conducting water chores in the morning (OR: 2.47, 95% CI: 1.11 – 6.57, also observed in working-age Sensitivity Analysis). Frequency and duration metrics were also not found to be associated with malaria when modeled in isolation (Table 4-6) and were instead then combined to create the Land-Use Index (Section 4.3.4), with the exception of reporting conducting forest chores for several hours, which was found to have a protective relationship (OR: 0.41, 95% CI: 0.22 – 0.79, also observed in working-age Sensitivity Analysis).

Table 4-6: Model results expressing the risk of Plasmodium presence in the blood as a function of occupation and land use. Blue cells indicate protective associations; red cells indicate risk associations; white cells indicate non-significant associations. Cells labeled NA did not have high enough responses to allow for the assumptions of the statistical test to be met.

Variable	Odds Ratio (95% Confidence Interval)	Odds Ratio for Sensitivity Analysis II: Youth (0-14)	Odds Ratio for Sensitivity Analysis II: Working-Age (15+)
Occupation Type			
Indoor	1.00	1.00	1.00
Outdoor	2.21 (1.10 – 4.65)	2.96 (0.11 – 33.79)	4.08 (1.60 – 12.70)

Primary Occupation			
Dependent	0.25 (0.09 – 0.57)	0.72 (0.12 – 2.84)	0.21 (0.05 – 0.65)
Student	1.87 (0.91 – 4.04)	1.12 (0.32 – 5.09)	NA
Farmer	0.86 (0.43 – 1.62)	NA	0.88 (0.45 – 1.67)
Forest-Based Occupation	1.87 (1.12 – 3.16)	NA	2.06 (1.18 – 3.65)
Other	0.81 (0.32 – 1.78)	NA	0.93 (0.36 – 2.07)
Land Use			
Attending to Crops/Farming			
Yes	0.77 (0.45 – 1.28)	0.75 (0.20 – 2.20)	0.78 (0.43 – 1.40)
No	1.00	1.00	1.00
Frequency			
Rarely	NA	NA	NA
Usually	0.62 (0.28 – 1.31)	NA	0.76 (0.33 – 1.69)
Often	2.07 (0.96 – 4.66)	NA	1.47 (0.67 – 3.41)
Duration			
Less than 1 hour	0.51 (0.03 – 2.75)	NA	NA
Several hours	0.50 (0.22 – 1.21)	NA	0.85 (0.32 – 2.52)
All-day	2.69 (1.06 – 6.44)	NA	1.65 (0.54 – 4.50)
Time of day			
Before Sunrise	1.60 (0.62 – 3.88)	NA	1.09 (0.33 – 3.08)
Morning	NA	NA	NA
Day-time	1.41 (0.38 – 9.16)	NA	1.06 (0.27 – 7.05)
After dark	3.25 (1.11 – 8.91)	NA	1.81 (0.45 – 6.17)
Working on a Plantation			
Yes	1.58 (0.95 – 2.64)	1.32 (0.35 – 4.05)	1.92 (1.05 – 3.61)
No	1.00	1.00	1.00
Frequency			
Rarely	1.36 (0.20 – 5.60)	NA	0.75 (0.04 – 4.31)
Usually	0.91 (0.49 – 1.69)	NA	0.99 (0.51 – 1.90)
Often	1.05 (0.57 – 1.95)	NA	1.04 (0.55 – 1.99)
Duration			
Less than 1 hour	NA	NA	NA
Several hours	0.77 (0.34 – 1.90)	NA	1.10 (0.45 – 3.39)
All-day	1.48 (0.60 – 3.30)	NA	1.00 (0.33 – 2.56)
Time of day			
Before Sunrise	0.93 (0.39 – 2.05)	NA	0.68 (0.25 – 1.66)
Morning	1.13 (0.19 – 21.55)	NA	1.14 (0.19 – 21.82)
Day-time	1.68 (0.61 – 5.90)	NA	1.48 (0.53 – 5.32)
After dark	1.48 (0.45 – 4.22)	NA	0.65 (0.10 – 2.58)
Conduct household chores that involve trips to the water			
Yes	1.74 (0.81 - 4.30)	0.56 (0.18 – 2.19)	2.84 (0.98 – 12.05)
No	1.00	1.00	1.00
Frequency			
Rarely	3.26 (0.15 - 27.75)	NA	NA

Usually	0.87 (0.25 - 2.32)	NA	1.02 (0.29 – 2.85)
Often	0.97 (0.39 - 2.93)	0.53 (0.08 – 10.73)	1.05 (0.38 – 3.72)
Duration			
Less than 1 hour	0.47 (0.20 - 1.24)	0.19 (0.02 – 4.19)	0.53 (0.21 – 1.54)
Several hours	2.14 (0.81 - 5.04)	5.31 (0.02 – 51.67)	1.89 (0.65 – 4.78)
All-day	NA	NA	NA
Time of day			
Before Sunrise	0.21 (0.01 - 1.04)	NA	0.31 (0.02 – 1.58)
Morning	2.47 (1.11 - 6.57)	1.21 (0.30 – 8.12)	2.99 (1.15 – 10.23)
Day-time	0.64 (0.30 - 1.53)	0.82 (0.20 – 5.55)	0.61 (0.25 – 1.72)
After dark	0.93 (0.21 - 2.83)	NA	1.18 (0.26 – 3.83)
Conduct household chores that involve trips to the forest			
Yes	2.13 (1.27 - 3.66)	2.67 (1.10 – 6.52)	1.82 (0.97 – 3.59)
No	1.00	1.00	1.00
Frequency			
Rarely	0.61 (0.20 - 1.51)	0.12 (0.00 – 0.74)	1.02 (0.28 – 2.89)
Usually	0.92 (0.53 - 1.65)	12.42 (2.08 – 241.79)	0.65 (0.35 – 1.22)
Often	1.44 (0.74 - 2.68)	NA	1.67 (0.84 – 3.22)
Duration			
Less than 1 hour	2.15 (1.05 - 4.26)	2.56 (0.52 – 11.79)	2.13 (0.91 – 4.75)
Several hours	0.41 (0.22 - 0.79)	0.39 (0.08 – 1.91)	0.42 (0.21 – 0.88)
All-day	3.65 (0.85 - 14.38)	NA	3.06 (0.70 – 12.29)
Time of day			
Before Sunrise	1.12 (0.43 - 2.60)	0.62 (0.03 – 4.71)	1.19 (0.71 – 3.02)
Morning	1.55 (0.42 - 10.13)	NA	1.26 (0.33 – 8.39)
Day-time	1.54 (0.58 - 5.34)	1.54 (0.20 – 32.04)	1.44 (0.47 – 6.29)
After dark	2.65 (0.51 - 11.31)	NA	2.18 (0.41 – 9.54)

4.3.5 Land Use Index

High levels of diversity were observed in regards to reported land use activities. For example, 162 respondents (16.2%) indicated that they participated in farming/attending crops, working on a plantation, engaging in forest-based chores, and engaging in water chores all within the three months before the survey. On the other end of the spectrum, only seven respondents (0.7%) indicated that they only participate in farming/attending crops, answering no to every other land use question. With so many villagers reporting high interactions with many different land use activities, it is vital to allow for quantifying differing levels of interaction within this analysis, which was accomplished by introducing LUI.

Equation 4-1 quantified LUIs ranging from 0 to 21, with a median of 3.5 and a mean of 4.4 (Figure 4-14). The majority of the respondents' LUI score was less than 3, with 85 respondents (8.5%) having an LUI of 0. An LUI score of 0 indicates that the respondent did not report engaging in any of the land use activities investigated in this study (farming, plantation work, water chores, mining work, or forest chores), while an LUI score of 3 implies the respondent is engaged in 1-2 land use activities (usually water chores and farming, or water chores and forest chores), with one land use being practiced more frequently than the other. For example, a common theme among respondents who scored a 3 was to rate their frequency of water chores as “Often (almost every day),” with their other land use rated as “Usually (at least once a month).” LUI scores of 6 or more indicate participation in 3 or more activities with moderate to high frequency or duration. In comparison, LUI scores above 9 generally imply participation in at least four land use activities with both high frequency or duration. The maximum LUI of 21 was reported by a single participant who reported to engaged in both Farming and Plantation Work often (nearly every day), all-day. This participant also reported a seasonal occupation which could explain the high LUI score.

The average LUI for women was 4.25, while the average for men was slightly higher at 4.66. A t-test revealed that the LUI average for women was statistically lower than that for men ($p = 0.044$), indicating that men participate in a higher diversity of land use activities. Working-aged people also reported engaging in the highest diversity of land use activities. The LUI averages for the age groupings, 0-14, 15-24, 25-54, and 55+ were 2.02, 4.51, 6.67, and 4.67, respectively. Malaria prevalence was found to be higher among respondents with higher LUI scores (Table 4-7). A fully-adjusted logistic model found that the LUI score was significantly associated with malaria (OR: 1.09, 95% CI: 1.02 – 1.17). This relationship was also confirmed by Sensitivity Analysis II (0 – 14 participants, OR: 1.19, 95% CI: 1.01 – 1.40) and Sensitivity Analysis III (15+ participants, OR: 1.09, 95% CI: 1.01 – 1.17).

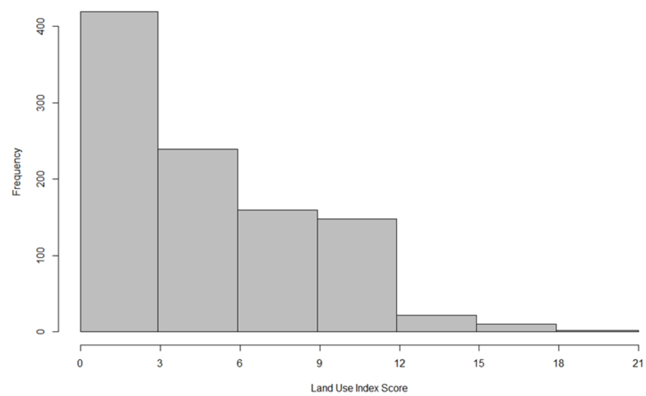


Figure 4-14: Histogram of participants' Land Use Index scores.

Table 4-7: Malaria prevalence amongst participants with different Land Use Index scores.

Land Use Index Score	Malaria Prevalence	N
0-3	5.01%	419
3-6	10.04%	239
6-9	15.00%	160
9+	14.84%	182

4.4 Discussion

This study greatly enhances our understanding of the land use practices of the people of Ann Township. In general, conducting water chores was the most common land use observed between genders and age groups, but beyond conducting water chores in the morning hours, water chores were not associated with malaria risk. For the other primary land use activities (farming, plantation work, forest chores), however, engagement varied by gender and age. Men, particularly those aged 25 – 54, were the most likely to engage in plantation work. Women reported working on plantations in high numbers until the 55+ age group, where women were more likely to drop out of plantation work compared to men. Youth aged 0 – 14 reported the lowest levels of engagements with all land use activities, with less than 25% reporting engagement with farming, plantation work, or forest chores. Typically, youth remained students until reaching 14 – 15 years of age, with few exceptions.

The majority of people reported engaging in the four main land use activities during the morning and day-time. While farming after-dark was found to increase the risk of malaria, the data does not support that many people are conducting any sort of land use after dark in general. Conducting water chores in the morning was also found to be associated with higher malaria risk – however, 73.5% of our sample population reported conducting water chores in the morning.

A major finding of this work, however, is the wide diversity of land use activities undertaken by village residents, which is not fully represented by their primary occupation title. Malaria intervention strategies that target people based solely on their primary occupation should not be the standard. For example, a strategy that targets Loggers for prophylactic measures due to their high level of interaction with the forest would miss the opportunity to prevent malaria in Students aged 0 – 14 that also experience a high level of interaction with the forest through conducting forest chores.

A good example of the complexity of land use practices in Ann can be observed within the small cohort (n=12) of respondents aged 0-14 that responded that they usually (at least once a month) or often (nearly every day) spent all-day at a plantation. Of the 12 respondents, two claimed that their primary occupation was dependent (aged 3 and 5), 9 were students, and 1 was a Plantation Worker. This reinforces that primary occupation is not a suitable proxy for land use habits, while also bringing in an interesting dynamic – bringing dependents to work. While I am unable to test this theory due to de-identified data, it is likely true that the two dependents from this sample are not necessarily engaging in plantation work, but are accompanying parents who are.

While some single factors were found to be associated with increased malaria occurrence (for example, conducting forest chores), the observed diversity in land use activities necessitated quantification. I did this through a simple Land-Use Index, which revealed a 1.11 increase in malaria odds for every 1 unit increase in LUI score. The Land Use Index was the only factor found to be significantly associated with malaria for both youth aged 0 – 14 and older participants, 15+. Livelihood diversification is generally seen as a positive way to decrease a person's economic vulnerability (Hahn et al., 2009). However, the results indicate that engaging in several different land use activities (not necessarily equivalent to livelihoods) may contribute to their exposure to infection, especially vector-borne diseases like malaria.

Malaria prevalence in Ann Township remains low; however, the overall prevalence in this study (9.6%) is very similar to the overall prevalence (9.4%) found in a similar population collected in 2016 (Chapter 3). Both studies surveyed 1000 participants, though the village locations differed between studies. While direct comparison is impossible due to differences in the season of data collection, land cover, village environmental settings, and land use activities between, it is reasonable to assume that malaria prevalence in Ann has not declined from 2016 – 2019. The vast majority of cases in both studies were also subclinical, which may explain the lack of progress in malaria elimination. Moreover, these results indicate that the currently deployed strategy for malaria elimination in these settings is not sufficiently effective to warrant Myanmar's and WHO's goal of malaria elimination by 2030. Thus, new targets interventions that can identify and treat most likely carriers of subclinical malaria are of crucial importance to sustain the progress in malaria elimination achieved to date.

Previous research has explored the link between forest workers and increased malaria risk (Soe et al., 2017; Zaw et al., 2017). However, to my knowledge, no previous study has controlled for village-level natural forest coverage as I have. I found that for every one sq km increase in natural forest coverage, malaria odds increase by a factor of 1.11. Alongside this, I found evidence of strong associations between forest-based primary occupations and malaria even when the fractional natural forest cover surrounding the village is controlled for, as well as engaging in forest chores and malaria. The group least at risk for malaria were those who claimed to be Dependents, who were also the most likely to report little to no engagement with most of the land use activities (farming, plantation work, forest chores). This points to the efficacy of the current malaria prevention strategy in Myanmar, which focuses on vector control within the home. The World Health Organization has begun to call for prevention outside this domain, stating that "tools are also needed for the protection of people when they are outside of homes protected by core interventions owing to occupational or other reasons" in their Global Technical Strategy for Malaria 2016-2030. However, the two principal vector control measures implemented within the National Plan for Malaria Elimination in Myanmar remain home-focused (NMCP, 2017). Measure 1 includes universal population coverage and usage of long-lasting insecticidal nets (LLINs), while measure 2 (employed to a lesser extent) suggests indoor residual spraying (IRS). The results presented here indicate that these strategies will be insufficient to target the remaining reservoir of exposure, because my results indicate this exposure is occurring outside of the home, particularly in forested landscapes.

Following the high risk of malaria associated with forested landscapes, it seems counter-intuitive that a large body of research has observed a link between the removal of forest (deforestation) and malaria risk. I sought to answer firstly if this relationship between deforestation and malaria is observable in Ann Township, and, if so, is this relationship due to a shift in the ecology of the affected region (i.e., differences in vector preference for a natural vs. cleared forest as has been observed in Vietnam, (Do Manh et al., 2010)), or instead because of activity by individuals within forested areas to clear the land. I did not find any association between the amount of deforested land near a village and malaria, with the notable exception of a strong decrease in risk of malaria for villagers living in an area with high amounts of deforestation within the year of data collection (2018).

These results imply that any ecological shift which occurs in a deforested area may not be responsible for observations of increased malaria. For example, forested landscapes allow for higher malaria exposure than croplands based on my results and previous research (Chapter 3). Therefore, the conversion of forests to croplands could lower the risk of malaria for that area. However, most forest conversion occurring in Ann Township is the clearing of natural forest for conversion to plantation (managed forest). While I found no association between plantation work and an individual's malaria risk, claiming a primary occupation that was forest-based (which was dominated by Plantation Workers) was associated with malaria. This result warrants further exploration, particularly an entomological study which can assess the distribution of mosquitoes across natural forest, managed forests (plantations), croplands, and other land covers. However, based on the results of this study, it does seem that the most likely cause of the relationship observed in other studies between deforestation and malaria prevalence is that the workers conducting the forest clearing are going to engage with forested landscapes more frequently in an area that is experiencing rapid forest conversion. A limitation to the deforestation analysis presented here is that the GFC data used is only available in a yearly format, which does not allow for the investigation of finer temporal scales. For example, while some of the respondent information was collected in early 2018, it is not possible to quantify how much forest loss occurred both before and after data collection.

4.5 Conclusions

A significant finding of this research was the weak relationship between natural forest cover and malaria, and the absence of any relationship between deforestation and malaria. This second finding appears at first to contradict other studies which have observed increased malaria risk alongside increased deforestation, however, when natural forest cover surrounding a village is controlled for, the land use factors that contribute most significantly to increased malaria risk are those which put people in direct contact with forests, including conducting forest chores, having an outdoor job, and having a primary occupation in the logging and/or plantation industry. This suggests that the relationship between deforestation and malaria is related to the increased interaction between people and forested landscapes (i.e., entering a natural forest to clear it), and perhaps not due to an ecological shift in mosquito populations after forest clearing.

While land use practices varied widely within the study population, one theme emerged clearly. The current reservoir of malaria remaining in Ann Township is held by people who are exposed to malaria through their land use behaviors outside of their homes. While preventing exposure in the home may have directly influenced Myanmar’s achievement of low-transmission status, now is the time to shift the strategies away from home. Prevention methods should focus on anyone (official forest-related occupation or no) that engages in land use activities which bring them within proximity of forested landscapes.

Chapter 5: Conclusions

In this dissertation, I have used an interdisciplinary approach to explore and characterize malaria exposure in Ann Township, Myanmar. By pulling from the fields of geography, public health, epidemiology, biomedical science, computer science, and statistics, I have provided context and nuance to the complexities of the population's exposure to malaria in Ann. A significant portion of my dissertation harnesses the cutting-edge capabilities of satellite remote sensing to quantify and assess malaria exposure, which is analyzed here as a component of risk assessment within the framework set forth by the IPCC and altered within the Introduction. Satellite data and methods allow for repeatable and spatially contiguous landscape-scale characterizations of population distribution and reflect well the primary local occupations through land cover and land use mapping. However, public health methodologies were crucial to contextualizing the broad observed patterns of landscape use and linking those to malaria occurrence. While incorporating interdisciplinary techniques was challenging, especially in regards to fusing disparate datasets, which were often mismatched temporally and spatially, it allowed for a better understanding of malaria exposure in Ann Township. This new understanding is likely to contribute to the development of more successful targeted approaches that will aid in the WHO's global malaria elimination agenda.

5.1 Summary of Major Findings

The primary goal of this dissertation, introduced in Chapter 1, was to answer the research question: *"What landscape ecological factors and individual land use activity* *patterns are contributing to the observed differences in malaria presence and prevalence between the villages of Ann Township in Rakhine State, Myanmar?"* To answer this question, I conducted three integrated studies that examined the heterogeneous and complex malaria exposure patterns within Ann Township while also assessing the capabilities and limitations of employing satellite earth observations to quantify and explain that complexity.

In Chapter 2, titled "Mapping Remote Rural Settlements at 30 m Spatial Resolution Using Geospatial Data-Fusion", I answered one of the most basic, but fundamental, questions: where do the people affected live? By harnessing the power of big data analytics, machine learning, and moderate resolution satellite earth observations together with an understanding of place-specific regional variations in human activity, I was able to map the remote and isolated villages of Ann Township with an accuracy of 86.5%. Numerous small settlements not previously mapped by other datasets were identified, revealing that the population of Ann Township is far more dispersed and isolated than shown in all previously-available maps. Two particularly novel findings emerged from this work: 1. For Ann Township specifically, the presence of fire was strongly associated with human activity and greatly improved settlement mapping accuracy. This finding represented a place-specific practice (slash-and-burn agriculture) that points to the key contributions that human geography can make within the field of artificial intelligence population mapping. 2. Through incorporating multiple primarily open-source geospatial data products, I able to overcome the challenges inherent in mapping settlements, which are comprised of structures smaller than that of a single Landsat pixel, which had not previously been attempted. The method I developed was able to successfully utilize moderate resolution data (which was previously considered insufficient for fine-scale population mapping), which was crucial to the algorithm's ability to be adopted by data-poor regions. Moderate resolution satellite data is freely and openly available globally, which allows for the method to be applied to different locations of varying spatial extents to monitor changes in patterns of human population distribution both retrospectively and prospectively.

In Chapter 3, titled "Contextualizing Malaria Exposure in Myanmar by Combining Satellite-Derived Land Cover and Use Observations with Field Surveys," I was able to answer Science Question 2, "*How do village-scale environmental settings impact malaria occurrence in individual villagers?"* To do this, I contextualized land cover and land use metrics to form a cohesive picture of malaria exposure within Ann Township by pairing remotely sensed indices with on-the-ground survey data and laboratory analysis, which were carried out by a team of medical researchers from Duke Global Health Institute and Myanmar's Department of Medical Research. I found that villages with high natural forest cover in their immediate proximity are most likely to house persons with malaria, with the odds of a person having malaria increasing by a factor of 1.96 per 1 square kilometer increase in natural forest cover within a 2 km radius of a village. This finding was true even for villagers who did not claim to visit the forest frequently. In comparison, villages with high areas of croplands were less likely to contain residents with malaria, with the exception of men directly engaged in farm work. Forest loss was also identified to be a potential contributor to malaria risk in the region.

When the findings of Chapters 2 and 3 are considered together, the results point to that malaria prevalence in Ann Township may be significant in the most marginalized and isolated villages. Chapter 2 found that remote settlements in Ann extend well east of those identified by the best available village map created by the Myanmar Information Management Unit (MIMU) (Figure 2-7). Back-of-the-envelope calculations of these newly identified villages, based on the basemap used in Chapter 3, indicate that natural forest could make up to 73% of the land cover immediately surrounding these previously unidentified settlements. Assuming that the relationship between forest cover and malaria extends into the eastern areas of Ann Township, it is likely that significant prevalences may be found among the populations living there. This estimate is particularly concerning given the difficulty inherent in reaching those isolated settlements to provide medical care and preventative measures.

Building on findings from Chapter 3, in Chapter 4, titled "Malaria Exposure in Ann Township, Myanmar as a Function of Land Use" I was able to answer research Science Question 3, *"When exposure associated with village-scale environmental settings is held constant, what individual level land use activities contribute to increased malaria occurrence?"* A major finding of this research was the weak relationship between natural forest cover and malaria, and the absence of any relationship between forest loss and malaria. This second finding appears at first to contradict the findings of other studies and those reported in Chapter 3, which have observed increased malaria risk alongside increased deforestation. However, when natural forest cover surrounding a village is controlled for, the land use factors that contribute most significantly to increased malaria risk include: conducting forest chores, having an outdoor job, and having a job in the logging or plantation industry, which are all land uses that bring respondents into direct contact with forested areas. This is an important finding because it suggests that for Ann Township, any relationships observed between deforestation and malaria are likely the result of increased human activity within forests (increased number of jobs in logging, plantation work in newly cleared forests, etc.). In essence, this is in opposition to research which claims that the removal of forest cover and subsequent altering of the vector ecology results in increased malaria. While that explanation could hold for areas like South America, it does not seem as plausible an explanation for Ann.

Furthermore, many activities were not associated with an increase in malaria occurrence, including farming, being a student, and conducting chores near the water. Claiming to be a dependent was the only factor that was associated with a lowering of malaria occurrence. Despite differences in land use activities and their relationship to malaria exposure, participating in a diversity of land use activities with high levels of frequency and extended durations did contribute to malaria risk, with a 1.11 increase in malaria odds for everyone 1 unit increase in land use index score. These results have significant relevance for targeted malaria elimination strategies in Myanmar, which is highlighted in Section #5.2.

5.2 Implications for Malaria Interventions in Myanmar

The two principal vector control measures for malaria prevention implemented within the National Plan for Malaria Elimination in Myanmar (NMCP, 2016) focus on prevention from within the home. Measure 1 includes universal population coverage and usage of long-lasting insecticidal nets (LLINs), while measure 2 (employed to a lesser extent) suggests indoor residual spraying (IRS). While these strategies have likely contributed to the large reduction in malaria cases seen in Myanmar, with my research reinforcing that home is the safest place to be (see the risk of malaria for Dependents, Chapter 4), my research also indicates that the malaria exposure paradigm has either shifted or that the home was never the primary exposure location. Despite these home-centric elimination strategies, the prevalence of malaria observed in Ann in 2016 and later in 2018 remained the same, at close to 10% of the population. My results indicate that the exposure pathway responsible for these remaining cases is found outside of the home. The remaining reservoirs of malaria in Ann Township are found primarily in people who are conducting a variety of land use activities, particularly those that bring them close to forests. The paradigm of interventions must quickly shift to interrupt the exposure pathways outside of the home to enable further progress in malaria elimination in Myanmar.

Thankfully, interventions that seek to disrupt this exposure pathway can and should be targeted in such a way to only affect those most at risk. Choosing an appropriate intervention strategy is key to encouraging community acceptance of the intervention, which is more likely to occur for targeted interventions. For example, previous research has shown that Myanmar villages can vary widely in their acceptance of Mass Drug Administration (MDA). In this intervention, an entire population is treated for malaria, regardless of infection status (Cheah and White, 2016). MDA is only recommended by the World Health Organization under very limited and specific circumstances (WHO, 2015c). Critical to the success of MDA is the participation of every single person within the administered region. In a recent study, community engagement with an MDA program in Kayin State ranged from 57% - 88% across villages (Kajeechiwa et al., 2017). Moving away from mass interventions to more targeted interventions should be considered then, particularly given that local knowledge of malaria risk within Ann Township is quite high. For example, local leaders within Ann reported no association between farming and malaria (T. Loboda, personal communication), which was confirmed in the analysis I conducted in Chapter 4. Therefore, based on the findings of Chapters 3 and 4, a strategy targeting forest workers and those conducting chores in the forest, especially if they live in a village with natural forest as the dominating land cover, is recommended.

Another important indicator of the receptiveness of interventions is community cohesion. Kajeechiwa et al. (2016) found that villages along the Thai-Myanmar border with greater cohesion (similar demographic and ethnic backgrounds) were much more likely to accept interventions willingly than villages that were fragmented due to recent conflict or fluxes in short-term residents. Up until this point in time, Ann Township has not experienced the same levels of political and cultural conflict currently occurring in other parts of Rakhine State. This relative stability has likely led to the widespread acceptance of Social Malaria Workers as deployed by the Myanmar Health Assistant Association (www.3MDG.org), which has been reported by local leaders (T. Loboda, personal communication). These reports are promising for the development of targeted interventions – however, recent news reports from within the country point to the possibility of rising tensions in the region. According to local news reports, clashes between the Arakan Rohingya Salvation Army and the Tatmadaw (Myanmar Military) occurred on Christmas Day 2019 within Ann (Frontier, n.d.). This news further emphasizes the need for quick action before more potential conflicts erupt, which may thwart malaria elimination progress.

5.3 Contributions to Remote Sensing for Public Health

In addition to exploring primary thematic content (population distribution, environmental settings, individual land use activities), the three studies also provided methodological advances within the field of satellite remote sensing, in terms of both population mapping and exposure assessment. Satellite remote sensing has been generally accepted as a useful tool for assessing exposure in public health studies (Curran et al., 2000; Hay, 2000; Rochon et al., 2010), particularly in providing quantitative measures of acute exposures like smoke from wildfires (Mirzaei et al., 2018; Yao and Henderson, 2014) or extreme temperature events (Buscail et al., 2012; Johnson et al., 2009), or chronic exposures like air pollution (Kloog et al., 2012; Puett et al., 2019; Yanosky et al., 2018). However, this dissertation proves that remote sensing is an essential tool in even more diverse ways. Not only does satellite remote sensing offer the ability to identify where people are (as proven in Chapter 2), it also allows for the quantification and accurate view of village-level ecological settings (as shown in Chapter 3) and communal land use activity on the landscape (Chapter 3). This is an exciting new possibility that is different but highly complementary to satellite-based mosquito habitat suitability modeling. While satellite earth observation-based studies are well-represented in vector modeling efforts, the ability to intersect mosquito habitat with the human use of the landscape has not well explored previously.

Additionally, a significant finding of this work was the usability of moderate resolution earth observations. Within the remote sensing community, human behavior is typically considered to be something only observable through fine-scale, very high-resolution (VHR) data. Chapters 2 and 3 of this dissertation provide strong evidence to the contrary. This finding is crucial because very high-resolution earth observations remain expensive, temporally infrequent, spatially inconsistent, and computationally challenging to analyze. Many of these challenges can be overcome by instead harnessing the power of moderate resolution data, which are often free, temporally frequent, offer global spatial coverage, and are more readily analyzed. Furthermore, the ability to use globally available moderate resolution data to address these critical exposure questions opens the door for historical analyses, as some moderate resolution datasets (such as Landsat) have been collected for decades and programs (such as Sentinel-2 and Landsat 9) continue to expand.

Satellite earth observations were critical to enhancing the understanding of malaria exposure in Ann, through the ability to map population distribution in a cost-effective and reproducible way, as well as bolstering limited survey data with contextual information that offered critical insights into the relationship between LCLU and malaria exposure. Like many malaria-endemic countries, Myanmar lacks data that could bolster its elimination efforts. Therefore, globally available remotely sensed datasets should be considered a critical and necessary component of informing any targeting strategies in support of malaria elimination

5.4 Future Research Directions

Many of the conclusions found through this research lend themselves to immediate next steps and future research directions. As discussed in Chapters 3 and 4, more research is needed to assess the causal link between forest cover and malaria in Myanmar. As the economy of Myanmar grows, it is likely that the conversion of natural forests to teak, rubber, or other plantations will accelerate. Understanding the relationship between malaria, forest cover, and forest conversion will be critical to eliminating malaria under these rapidly changing socio-economic conditions. While my results point to that any observed link between deforestation and malaria is most likely the result of increased human interaction with forested landscapes, we cannot rule out the possibility of an ecological shift in vector populations due to the land cover preferences of the two dominant mosquito species. Future work should include entomological surveys which could improve our understanding of the relationship between the vector and the landscape. Additionally, differences in the parasitemia present in different species of *Anopheles* could also explain some of the differences observed in *P. falciparum*, *P. vivax*, and mixed infections – though broader sampling is needed to ensure statistical accuracy of any specific parasite research (cases of specific parasite species infections were too low in both surveys for statistically meaningful analysis).

However, while the vector information will be important, there remain opportunities for further study of the influence of human behavior on malaria exposure. While both of the qualitative datasets analyzed in Chapters 3 and 4 provided crucial insights, they did not answer, “why do these specific groups have higher rates of malaria?” The specific explanatory drivers of increased malaria occurrence in plantation workers are currently only hypothesized but not confirmed. The hypotheses related to increased exposure of these workers to mosquito populations could be explored using entomological surveys. However, other hypotheses point to an increase in local parasite densities through the inflow of migrant populations, which potentially carry *Plasmodium spp*. into the region and boost the local transmission in the plantation settings. Social network analysis may provide valuable insights into the interactions between villagers (the vast majority of our study populations were permanent residents) and seasonally hired migrant workers.

Much of the design of the current study was limited by the available survey data sources, which were designed and carried out for purposes drastically different than the goals of this research. To maximize the capacity for research aimed at assessing individual-level exposure, I would have chosen to implement a cohort study where a group of participants is followed over time to more accurately pinpoint when they were infected with malaria, with follow-ups that can assess if they are infected multiple times. It is particularly challenging to isolate the time that a person was infected with subclinical malaria, especially for *P. vivax,* which can lie dormant in the liver for years (Baird, 2013). A cohort study design would allow for at least a general sense of the temporal nature of malaria infection, while also tracking the changes in conditions which related heavily to malaria prevalence in Chapter 4, namely climatic season of data collection and if a person was employed in a seasonal job.

A cohort study would also allow for more nuanced questioning since the participants would be enrolled for a longer amount of time. For example, in Chapter 4, participating in chores that brought a person into the forest (e.g., hunting, firewood and construction material collection, fruit gathering) was found to be a significant risk factor for malaria. However, the question did not discriminate exactly what the participants were doing in the forest. It also did not capture participants who may spend time in the forest for reasons outside of those listed in the survey, for example, walking through the forest to reach a job site, playing in the forest as a child, etc. While I recognize the challenges of collecting such detailed data, a time diary of each participant in regards to how and where they spend their day would be ideal for teasing out the relationship between land use and malaria exposure. Exciting work is being conducted by Geospatial Scientists to study human mobility patterns and malaria, and I believe that a cohort study like the one I describe could dovetail with geospatial mobility data to create a comprehensive picture of the daily habits of a person at risk for malaria.

All of the above future research ideas rely heavily on an outsider's interpretation of the local people's experiences. Therefore, I would also like to conduct a participatory mapping study in the future. While participatory mapping has been employed successfully to map infrastructure in support of malaria elimination strategies (Dongus et al., 2007; Solís et al., 2018), it has been virtually absent from studies that seek to describe malaria exposure. Based on communications with local leaders in the villages studied, I believe that inviting villagers to map locations within and just outside of their village where they believe themselves to be most at risk of malaria infection may provide new avenues for research that have not yet been explored in existing studies.

Finally, other exciting opportunities exist for future work that increases the synergies between satellite remote sensing and public health. One of the primary goals of Chapter 2 was to develop a methodology for population distribution mapping that could be reproducible elsewhere. The existing algorithm will likely perform well across other remote mountainous regions of Myanmar (e.g., Chin, Kachin, and Shan states), with additional training samples required to represent lowland cropland-dominated landscapes which contextually and spectrally differ from Ann Township. For this first iteration of the algorithm, I collected 3720 sample pixels, which represent just 0.025% of the ~14.5

million pixels that cover Ann when imaged at 30 m resolution. This is promising for limiting the time intensity of training data collection for expansion to larger regions. Also promising is that data availability, in general, is better across the lowland areas of Myanmar than it is for the remote mountainous regions. However, it is those regions, including Ann, which are particularly affected by a lack of precise settlement distribution data. The algorithm without any further modification is likely to make a considerable contribution to the state of settlement mapping for these regions. Indeed, work is currently ongoing to apply the algorithm to the entire country of Myanmar.

The use of Landsat data throughout this dissertation provides exciting opportunities to conduct historical settlement and LCLU pattern analysis, given the long history of Landsat data collection. Perhaps more exciting, though, is the ability to adapt the methodologies employed here to new moderate resolution datasets in the future, including Landsat 9 (launch scheduled for 2020) and Sentinel 2 (2015 – present). The Sentinel 2 mission collects similar spectral bands to the Landsat 8 mission, however, it also includes a higher repeat frequency and, for many bands, a finer spatial resolution (10 m, 20 m, and 60 m). Work is well underway to create a harmonized Landsat and Sentinel 2 (HLS) data product (Claverie et al., 2018). This dataset could increase the likelihood of obtaining cloud-free composites, which would be of particular utility for Ann and other subtropical regions where cloud-free images can be scarce.

5.5 Concluding Remarks

In his classic malaria textbook, L.W. Hackett (1937) wrote, "*Everything about malaria is so moulded [sic] and altered by local conditions that it becomes a thousand* *different diseases and epidemiological puzzles. Like chess, it is played with a few pieces, but is capable of an infinite variety of situations.*" As demonstrated in this dissertation, the role of geography in the epidemiology of malaria cannot be understated. Malaria exposure in Southeast Asia is quantifiably different from exposure in Africa and other malaria-endemic regions. Drilling down further, malaria exposure differs at the village level, and even more so at the individual level. Interventions that work in Africa may not have the same effects in Southeast Asia, and similarly, interventions in one village may not have the same effects in another. Considering the highly heterogeneous and rapidly changing prevalence of asymptomatic malaria, satellite earth observations in conjunction with socio-economic surveys and laboratory analysis are crucial to identifying likely reservoirs of malaria, pinpointing areas of high exposure, and most importantly, developing targeted intervention strategies which will have the highest impact under the specific socio-ecological settings of the target area.

Myanmar is poised to join the ranks of countries that have eliminated malaria. In an ideal world, my findings will be irrelevant ten years from now because Myanmar will have eliminated the last reservoirs of malaria. However, in order to achieve that goal, locally-relevant intervention strategies must continue to be developed, implemented, and assessed for efficacy. The incorporation of interdisciplinary techniques within this dissertation allowed for a better understanding of malaria exposure in Ann Township. Through the results shown here and future interdisciplinary work, nuanced assessments of malaria exposure across the world can be more fully incorporated into the global malaria elimination agenda.

Appendices

Table A-1: Mean Decrease in Accuracy for all 84 variables used in Random Forest model. Table is sorted in order of descending importance for the Settlement class.

	Mean Decrease in Accuracy for Settlement Class	Mean Decrease in Accuracy for Agriculture Class	Mean Decrease in Accuracy for Other Class	Full Model Mean Decrease in Accuracy	Full Model Mean Decrease in Gini
NDWI7 (Dry-Cold Season)	23.290	10.536	16.886	25.827	71.908
Distance to Roads	22.905	26.688	28.638	33.599	74.454
NBR2 (Dry-Cold Season)	22.242	13.025	26.257	30.615	100.733
Distance to Water	22.021	15.724	17.962	27.266	34.584
Elevation	21.332	26.727	16.300	29.240	41.924
Distance to MODIS Active Fire (2013-2014)	18.157	13.652	16.491	23.975	30.704
Distance to VIIRS Active Fire (2013-2014)	18.096	12.135	19.482	22.578	29.334
Landat 8 TIRS Band 10 (Dry-Hot Season)	17.725	13.427	12.892	22.619	31.236
Landat 8 TIRS Band 10 (Dry-Cold Season)	17.701	9.875	14.486	22.953	31.371
Distance to 3rd Order or Greater Waterway	17.450	17.163	19.188	25.650	35.494
Landat 8 TIRS Band 11 (Dry-Hot Season)	17.004	11.673	14.854	22.140	31.328
NBR2 (Dry-Hot Season)	17.002	11.406	20.591	22.346	83.318
NDWI7 (Dry-Hot Season)	15.945	11.589	16.739	23.410	30.513
NDWI6 (Dry-Cold Season)	15.730	11.918	12.252	19.688	27.028
Landsat 8 OLI Band 7 SWIR 2 (Dry-Cold Season)	15.494	11.508	15.926	19.355	76.216
Texture: NIR Occurrence Mean (Dry-Cold Season)	15.364	15.061	14.383	23.333	25.972

Landsat Tree Cover Continuous Fields Product	15.320	11.737	15.823	20.399	34.894
Tasseled Cap Wetness (Dry-Cold Season)	13.952	9.270	10.967	15.675	44.980
Texture: NIR Occurrence Mean (Dry-Hot Season)	13.642	11.446	17.649	23.689	25.481
Seasonal Difference in Tasseled Cap Wetness	13.512	13.307	13.502	20.410	37.381
Slope	13.434	11.526	11.212	18.911	20.550
Texture: NIR CoOccurrence Mean (Dry-Cold Season)	12.753	13.061	11.111	18.074	18.825
Seasonal Difference in Red Band	12.746	10.238	11.603	16.436	23.066
Landsat 8 OLI Band 5 NIR (Dry-Cold Season)	12.741	14.464	14.323	19.377	25.982
NBR (Dry-Cold Season)	12.562	9.566	15.530	17.039	61.630
NDWI6 (Dry-Hot Season)	12.322	10.684	12.713	20.274	17.315
Tasseled Cap Brightness (Dry-Cold Season)	12.275	15.720	11.683	19.117	28.367
Global Bare Ground 2010 Product	12.015	17.125	11.644	19.666	26.947
Texture: NIR Occurrence Range (Dry-Cold Season)	11.884	9.154	8.985	16.749	15.797
Seasonal Difference in Tasseled Cap Brightness	11.863	12.375	10.121	16.462	28.007
Landsat 8 TIRS Band 11 (Dry-Cold Season)	11.680	11.831	12.697	18.493	23.181
Season Difference in NIR	11.174	9.466	10.268	17.515	17.117
Landsat 8 OLI Band 6 SWIR 1 (Dry-Hot Season)	10.955	17.067	13.080	20.552	45.755
Texture: NIR CoOccurrence Mean (Dry-Hot Season)	10.663	9.127	12.092	18.223	13.107
Tasseled Cap Wetness (Dry-Hot Season)	10.571	11.995	12.271	16.012	40.891
Texture: NIR Occurrence Variance (Dry-Hot Season)	10.384	9.440	9.444	15.309	16.284
NDWI (Dry-Hot Season)	10.292	10.363	11.204	14.182	27.124

Texture: NIR Occurrence Variance (Dry-Cold Season)	10.219	10.273	9.264	16.021	15.450
Landsat 8 OLI Band 4 Red (Dry-Cold Season)	10.069	12.148	16.502	17.243	82.425
NDVI (Dry-Hot Season)	9.949	10.949	11.569	14.362	30.943
Tasseled Cap Greenness (Dry-Hot Season)	9.761	11.232	9.878	14.629	17.232
Texture: NIR Occurrence Range (Dry-Hot Season)	9.684	8.873	10.960	15.675	15.851
SAVI (Dry-Hot Season)	9.671	11.532	9.625	14.159	23.530
Landsat 8 OLI Band 5 NIR (Dry-Hot Season)	9.600	11.971	17.208	19.941	28.648
Landsat 8 OLI Band 7 SWIR 2 (Dry-Hot Season)	9.428	11.428	14.354	15.447	55.340
Tasseled Cap Brightness (Dry-Hot Season)	9.272	13.451	12.156	15.617	39.570
Tasseled Cap Greenness (Dry-Cold Season)	9.197	10.369	8.816	14.503	14.907
Texture: NIR CoOccurrence Variance (Dry-Cold Season)	9.126	8.974	6.188	13.404	11.616
NDMI (Dry-Cold Season)	9.048	10.114	9.833	12.104	35.752
Landsat 8 OLI Band 1 Blue (Dry-Hot Season)	9.036	10.155	9.867	14.005	19.911
Landsat 8 OLI Band 3 Red (Dry-Cold Season)	9.008	13.675	10.726	13.599	47.416
Landsat 8 OLI Band 6 SWIR 1 (Dry-Cold Season)	8.972	11.232	9.331	12.808	23.788
MSAVI (Dry-Hot Season)	8.858	8.940	9.752	12.711	22.059
Landsat 8 OLI Band 3 Red (Dry-Hot Season)	8.723	11.416	10.708	12.767	55.531
Landsat 8 OLI Band 1 Blue (Dry-Cold Season)	8.718	7.945	9.361	14.960	17.990
Landsat 8 OLI Band 4 Red (Dry-Hot Season)	8.671	13.665	15.414	16.415	73.126
Texture: NIR CoOccurrence Second Moment (Dry-Cold Season)	8.519	2.858	6.732	11.670	8.263

NDMI (Dry-Hot Season)	8.459	9.873	10.680	15.152	23.436
Texture: NIR CoOccurrence Entropy (Dry-Cold Season)	7.849	5.317	8.750	12.451	9.416
Landsat 8 OLI Band 2 Green (Dry-Hot Season)	7.841	9.981	9.770	12.300	25.974
NDWI (Dry-Cold Season)	7.838	9.341	10.629	13.236	17.276
NBR (Dry-Hot Season)	7.706	8.415	11.140	12.261	29.906
EVI (Dry-Hot Season)	7.676	9.893	11.629	13.628	22.951
Seasonal Difference in Tasseled Cap Greenness	7.674	12.551	12.010	18.525	18.629
NDVI (Dry-Cold Season)	7.419	9.520	12.319	13.625	31.483
MSAVI (Dry-Cold Season)	7.201	9.694	10.519	14.853	14.311
Texture: NIR CoOccurrence Variance (Dry-Hot Season)	6.736	5.605	9.821	13.138	9.582
Landsat 8 OLI Band 2 Green (Dry-Cold Season)	6.654	4.759	8.775	10.288	19.222
SAVI (Dry-Cold Season)	6.597	10.320	9.782	13.757	14.225
Texture: NIR CoOccurrence Contrast (Dry-Cold Season)	5.989	7.129	8.468	12.318	9.016
Texture: NIR CoOccurrence Homogeneity (Dry-Hot Season)	5.644	6.879	8.904	12.567	8.591
Texture: NIR CoOccurrence Homogeneity (Dry-Cold Season)	5.562	6.269	5.545	9.953	9.148
Texture: NIR CoOccurrence Dissimilarity (Dry-Cold Season)	5.538	5.208	6.722	9.863	7.353
EVI (Dry-Cold Season)	5.060	11.651	9.245	13.685	16.868
Texture: NIR CoOccurrence SecondMoment (Dry-Hot Season)	4.998	5.558	8.652	11.030	8.820
Texture: NIR CoOccurrence Entropy (Dry-Hot Season)	4.637	5.127	10.368	12.793	9.131
Texture: NIR CoOccurrence Correlation (Dry-Hot Season)	4.332	9.028	3.912	10.175	12.565
Texture: NIR CoOccurrence Contrast (Dry-Hot Season)	3.248	6.277	9.950	12.518	9.020

Texture: NIR CoOccurrence Dissimilarity (Dry-Hot Season)	3.174	5.490	8.319	10.249	7.024
Texture: NIR CoOccurrence Correlation (Dry-Cold Season)	2.812	3.557	5.392	7.086	10.744
Texture: NIR Occurrence Skewness (Dry-Hot Season)	2.109	1.787	4.599	5.283	5.917
Texture: NIR Occurrence Entropy (Dry-Cold Season)	0.174	-0.761	2.507	1.674	0.783
Texture: NIR Occurrence Entropy (Dry-Hot Season)	-0.046	1.910	1.512	2.073	0.965
Texture: NIR Occurrence Skewness (Dry-Cold Season)	-0.455	3.866	4.167	4.942	3.191

Table A-2: Reference samples, by strata. For Chapter 3, the final number of reference samples was 833. The distribution of samples amongst strata (i.e., LCLU classes) was between proportional allocation and equal allocation. We specified a minimum sample size per class to be 75 samples to ensure adequate sampling for rare classes (e.g., villages). The spatial unit of analysis was a 30-meter by 30-meter pixel, consistent with the spatial unit of the LCLU classification.

Strata	Area (pixels)	Area (proportion)	Number of samples
Perennial water	300875	4.30%	75
Impervious surface	6876	0.10%	75
Villages	5315	0.10%	75
Croplands	246172	3.50%	75
Managed forests	394159	5.70%	75
Natural forests	5669060	81.70%	308
Shrub and grass	262724	3.80%	75
Bare surfaces	53672	0.80%	75
Total	6938853	100.00%	833

Table A-3: The linguistic measurement scale adapted from Woodcock and Gopal (2000) used to assess the accuracy of the LCLU mapping. Four expert interpreters evaluated the 833 samples against the linguistic-measurement scale. The samples were compared with Google Earth imagery and responses were recorded using Microsoft Access.

Rank	Description
5	**Absolutely right:** No double about the match. Perfect.
4	**Good answer:** Would be happy to find this answer given on the map.
3	**Reasonable or acceptable answer:** Maybe not the best possible answer but it is acceptable; this answer does not pose a problem to the user if it is seen on the map.
2	**Understandable but wrong:** Not a good answer. There is something about the site that makes the answer understandable but there is clearly a better answer. This answer is a problem.
1	**Absolutely wrong:** The answer is absolutely unacceptable and completely wrong.

Table A-4: Results of MAX and RIGHT functions (operators developed by Woodcock and Gopal (2000)). "MAX" and "RIGHT", are summarized in Table 9. These metrics provide information on the distribution of errors and also the frequency of errors, where MAX: "Highest rating given to a category for a given site to measure a match and provides a conservation estimate of accuracy" and RIGHT: "Accepts matches using any degree of right, which in the linguistic scale used here is any score greater than or equal to 3"

Map classes	Number of samples	Max (Rank = 5)	RIGHT (Rank ≥ 3)	Area weights (proportion)
Perennial water	75	21	26	0.043
Impervious surface	75	6	36	0.001
Villages	75	44	61	0.001
Croplands	75	51	63	0.035
Managed forests	75	22	36	0.057
Natural forests	308	229	277	0.817
Shrub and grass	75	1	15	0.038
Bare surfaces	75	0	17	0.008
Total	833	374	531	

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