UNRAVELLING THE SIKASSO PARADOX: AGRICULTURAL CHANGE, COTTON AND MALNUTRITION IN SOUTHERN MALI

Matthew Cooper

A thesis submitted to the faculty at the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Master of Arts in the Department of Geography.

Chapel Hill
2015

Approved By:

Lauren Persha

Colin West

Conghe Song

ABSTRACT

Matthew Cooper: Unravelling the Sikasso Paradox: Agricultural Change, Cotton and Malnutrition in Southern Mali
(Under the direction of Lauren Persha)

The cash crop cotton has been suggested as a cause of the unexpectedly high malnutrition rates in the Sikasso region of Mali. This paper tests that hypothesis as well as two of the proposed pathways by which cotton has been suggested to cause malnutrition: through worsening diets and though reduced ecosystem services from soil degradation and agricultural extensification. Both household surveys and region scale satellite imagery combined with Demographic and Health Surveys suggest that there is an association between cotton cultivation and malnutrition. However, there was no evidence that cotton cultivation is related to worsened diets or malnutrition at a household level. Rather, cotton cultivation, reduced biodiversity and malnutrition are all associated at a village level, indicating that the environmental effects of cotton cultivation may be causing associated malnutrition through reduced ecosystem services.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AASG	Automatic Adaptive Signature Generalization – a method for classifying satellite images taken at different times in the same area.
AIC	Akaike Information Criterion - a measure of the relative quality of statistical models for a given set of data.
ANOVA	Analysis of Variance
CMDT	*Le Companie Malienne pour le Developpement des Fibres Textiles* – A parastatal company that runs cotton production in Mali
DBH	Diameter at Breast Height – an often used measure of tree size
DEM	Digital Elevation Model
DHS	Demographic and Health Survey – surveys conducted by MEASURE and USAID providing health and demographic data for developing countries.
MANOVA	Multivariate Analysis of Variance
MICS	Multiple Indicator Cluster Survey
MUAC	Mid Upper Arm Circumference – a common biometric in assessing child health and malnutrition
LULCC	Land Use and Land Cover Change
NDVI	Normalized Difference Vegetation Index
NTFP	Non-Timber Forest Products
RCT	Randomized Controlled Trial
RDO	Rural Development Organization
SOM	Soil Organic Matter
WHO	World Health Organization

INTRODUCTION

A generation ago, all of southern Mali grew mainly sorghum and millet with organic fertilizer using swidden agriculture, by clearing fields and then leaving them to return to a forested state after a few seasons of farming (Laris, Foltz and Voorhees 2015, Kidron, Karnieli and Benenson 2010). Today, it is increasingly common for farmers to use synthetic fertilizer to grow cotton and maize on fields permanently dedicated to these crops (Moseley and Gray 2008, Laris et al. 2015). This agricultural change has been accompanied by changes in land cover and land use throughout the region: forestlands have been degraded and reduced, while farmland has expanded (Ruelland, Levavasseur and Tribotté 2010).

Accompanying this change in land use and agricultural practices has been a phenomenon known as the "Sikasso Paradox" or "Paradoxe de Sikasso" which is known to both academics (Guillou and Matheron 2014) and development practitioners (Swinkels, Eozenou and Madani 2013, Delarue 2009), and is often framed in relation to cotton (Mesplé-Somps et al. 2008). Of all the regions of Mali, the southernmost region of Sikasso has the most rainfall and therefore the most food diversity, the most productive crops, and, crucially, the greatest access to monetary income via the cash crop cotton. Paradoxically, the region also has the highest rates of malnutrition and child mortality in Mali (Swinkels et al. 2013, Dury and Bocoum 2012).

This study seeks to explore if there is significant correlation between type of agricultural systems and rates of malnutrition. In this case, the type of agricultural system is measured by rates of swidden vs permanent cultivation and percentage of households' total hectarage as cotton, while childhood malnutrition is measured by both DHS (Demographic and Health Surveys) variables and child heath variables measured in household surveys conducted across three study villages. In the DHS surveys, child health outcomes were height for age percentile, weight for age percentile and anemia level. In the household surveys, child health outcomes are child mortality rate by household and the Z-score by age of the child's mid-upper arm circumference (MUAC) using reference data from the WHO (De Onis, Yip and Mei 1997). The study furthermore seeks to examine possible mechanisms generating this observed correlation, such as changes in the availability of ecosystem services or variable diets. This is explored through household surveys and forest surveys conducted in three study villages.

The first question is examined using classified Landsat imagery and DHS data. A regression was run linking different measures of malnutrition and rates of swidden vs permanent agriculture. This regression demonstrated a significant positive correlation between percent of agriculture practiced as swidden and children's weight percentile.

The second part of the study consisted of household and forest surveys in three villages in the different parts of southern Mali. These villages had varying rates of modern vs traditional agricultural practices. Household surveys were conducted asking about a variety of land use and livelihood practices, as well as swidden fields and cotton production. Forest and land cover surveys were conducted in order to examine the extent of forest cover and forest diversity, as well as to conduct ground-truthing on the Landsat classification conducted. The purpose of this part of the study was to better understand, at both a household level and a village level, the different possible drivers connecting permanent cropping and cotton production with observed rates of malnutrition. The household surveys were also intended to see the extent to which local farmers recognize and are aware of trends of malnutrition, agricultural change and land use change.

Theoretical Framework

The central hypothesis of this thesis is that changing agricultural practices from swidden fields growing traditional crops to permanent fields growing cotton and maize can lead to increased childhood malnutrition via decreased ecosystem services or worsened diets or both. This thesis therefore draws on literature concerning cash cropping, agricultural transitions, ecosystem services, diet and nutrition, as well as how each of these factors can be measured.

Ecosystem Services

Ecosystem services are goods provided by natural ecosystems that benefit humanity (Raudsepp-Hearne, Peterson and Bennett 2010). They are numerous and various, and are often grouped into the three categories of regulating services, provisioning services, and cultural/aesthetic services (Wallace 2007). Regulating services include processes that maintain soil fertility, atmospheric composition and climate stability, and water cleanliness. Provisioning services, on the other hand, offer humans a tangible object such as fruits, nuts and grains for food; fibers and other materials for clothing; wood and charcoal for fuel; or plants and fungi for medicine. Finally, cultural and aesthetic services provide intangible but important value to people by providing significance and meaning and fulfilling humanity's spiritual and philosophical needs (Wallace 2007).

Both regulating and provisioning services play a clear and significant role in nutrition in southern Mali. Provisioning services are food products themselves, and thus nearly everything eaten by people in southern Mali is a product of the local environment, from mangoes, to leaves for sauces to sorghum. These provisioning services are in turn supported by regulating services like pollinators, fertile soil, and rainfall.

Often, there are tradeoffs between multiple ecosystem services both within a land cover class and between land cover classes. For example, there can be a tradeoff between crop yield and soil quality, where both the harvested crops and the soil fertility are ecosystem services (González-Esquivel et al. 2015). Low-input traditional swidden farming practices are much better for the soil than input-intensive modern practices, yet have low yields. Modern farming strategies, on the other hand, can be high yielding, but at the cost of strong negative effects on soil quality, water quality and biodiversity (González-Esquivel et al. 2015).

Farmers are quite aware of these tradeoffs, and will manage their landscape in ways that optimize the availability of ecosystem services that will suit their needs.

It has been demonstrated that although ecosystem services with financial benefits are the most broadly preferred, preferences for ecosystem services can vary by social-cultural conditions such as age, income and cultural background (Tadesse et al. 2014). This could explain why different parts of Mali have seen different approaches to transitioning from swidden agriculture to permanent cropping.

Land Use and Land Cover Change

A broad literature exists concerning land use and land cover change (LULCC). The drivers of land use change are complex, and are in many ways a manifestation of people responding to economic incentives, as mediated by institutions (Lambin et al. 2001). Policies around land use in one country can affect economic conditions in another, and this policy “leakage” is often unanticipated (Meyfroidt et al. 2013). Thus, determining the precise cause of observed changes in landscape-scale land use or predicting future changes in land use is a challenging process.

While determining the ultimate cause of land use changes is problematic, land use and land cover can be salient indicators of environmental variables such as forest cover, sequestered carbon, or water availability. Land use can even be an indicator of ecosystem services. Many ecosystem services come in “bundles” associated with one land cover type (Raudsepp-Hearne et al. 2010). Thus, some ecosystem service tradeoffs are made at that land use level: the tradeoff between forestland and cropland, for example, is isomorphic to the tradeoff between timber and agricultural products. While this is not true for all ecosystem services, some critical services are provided by only one land cover class. This is especially true for provisioning services, such as forest products or agricultural grains, for which there is usually a tradeoff with other ecosystem service types (Raudsepp-Hearne et al. 2010).

Land Use and Ecosystem Services

In the Sudanian eco-region of southern Mali, there are two broad classes of land cover types that provide ecosystem services: agricultural areas and wilderness areas. Agricultural areas are those places under direct cultivation, where annual grains, garden crops, perennial fruit or timber trees are grown. They are usually owned by one household, and the provisioning ecosystem services that they provide are claimed by that household. Wilderness areas, on the other hand, can vary from open grasslands to dense forests, and often consist agricultural areas that have recently been left fallow. In rural Mali, they are regarded as common property, and ecosystem services that they provide, from bushmeat to fertile soil, can be used by anyone. In these wilderness areas, forests and their associated ecosystem services in particular are increasingly recognized as both vital and in decline in Sudanian West Africa and in Africa in general. It has been demonstrated that over two-thirds of Africa's 600 million people obtain a major proportion of their subsistence and some cash income from a large and diverse set of forest products and forest-related activities (Arnold and Townson 1998, Kaimowitz 2003) Forest products like trees often serve as 'famine foods' providing alternative sources of nutrition during times of agricultural failure (Bayala et al. 2010). In addition, wild food plants are a major source of alternative income in West Africa (Assogbadjo et al. 2012), and have played a demonstrated role in poverty reduction (Coulibaly-Lingani et al. 2011). In Mali in particular, it was calculated that non-timber forest products provided up to 40% of household income (Heubes et al. 2012). In the face of an uncertain climatological future, forests and the useful tree species they provide are more necessary than ever, because they contribute very directly to the resilience of communities (Robledo et al. 2012).

However, the future of forests in West Africa is uncertain. A continental survey found that African dry forests and woodlands were "the most threatened and least protected ecosystem on the continent" (Bodart et al. 2013). Another study modeling ecosystem services in particular found a decrease in biodiversity and some associated ecosystem services throughout Ghana and Cote d'Ivoire (Leh et al. 2013), while another survey of deforestation and degradation across West African ecoregions found widespread degradation from closed woodlands to open woodlands in the Sudanian ecoregion (Ruelland et al. 2010). A model of land use change and climate change in Benin predicts that large areas could lose up to 50% of their economic value from Néré, Shea, and Baobab, perhaps the three most important and useful tree species in West Africa (Heubes et al. 2012). One of the largest drivers of these changes in availability of forest resources has been agricultural intensification and expansion. Different farming systems used by communities have been shown to affect tree species diversity (Bayala et al. 2010), and one study of local perspectives found that clearing land for cash crops was viewed as the main cause of tree loss (Paré et al. 2009). Thus, decreasing ecosystem services from forests and wild areas is linked both theoretically and empirically to agricultural change and land use change.

Cash Cropping and Land Use

There is a preponderance of evidence from around world demonstrating how the introduction of cash cropping can lead to land use change in the form of agricultural expansion and deforestation (Su et al. 2014). In the Himalayas, it was found that adopting cash crops led to the abandonment of 25%-85% of traditional crops, along with significant changes in land use (Negi, Maikhuri and Rawat 2012). In Laos, traditional rotational rice-based agriculture is being abandoned in favor of cash crops in certain areas, and this is leading to divergent pathways of land use and deforestation (Vongvisouk et al. 2014). Often an increase in land use devoted to cash cropping leads to a proportional decrease in land use dedicated to local food production and forestland. A study in China found that between 1985 and 2009, cash crop cultivation increased at the expense of forestland and rice paddies. A quantitative study in China found that places with "abundant farmland and forest cover" were more likely to be converted to cash cropping. Additionally, distance to water bodies, provincial roads and market towns were major determinants of areas that came under cash crop cultivation (Xiao et al. 2015).

While conversion of forested areas to agriculture leads to a clear and direct decrease in the available provisioning ecosystem services provided by forests, it is less clear the impact that forest degradation and biodiversity loss has on regulating ecosystem services. In areas where only a few key species provide the majority of forest products, a loss in biodiversity may not represent a significant loss in ecosystem services so long as those key species are still present. However, it is clear that biodiversity is necessary for the long-term functioning of the ecosystem itself (Mertz et al. 2007), because more diverse ecosystems are more resilient. In addition, higher species richness means there is a greater variety of goods to be used, especially medicinal plants (Mertz et al. 2007). Indeed, where a high diversity of plant species are available, they are almost all utilized: a survey from Sudanian savannas of southern Burkina Faso found that 82 unique species of trees provided useful non-timber forest products (Paré et al. 2009).

Ecosystem Services and Human Outcomes

While there is a clear theoretical link between ecosystem services and human outcomes such as health and income, research on these linkages is only beginning. Often detecting clear linkages is difficult. A 2012 study in Mali looked at linkages between land degradation and income, hypothesizing that more degraded areas would see lower levels of household income (Liebenow et al. 2012). However, no significant relationship was found. This was theorized to be because of the complexity of the relationship between ecosystem services and livelihood strategies: communities are creative and adaptive, and often find alternative income sources when traditional ones are no longer available (Liebenow et al. 2012). This study also used rainfall-normalized NDVI as an indicator of degradation, although patterns of changes in NDVI, especially in the semi-arid tropics are not well understood (Bégué et al. 2011).

Researchers are increasingly looking at how losses or changes in those ecosystem services that are necessary for food production can have negative human health and nutrition outcomes. Nevertheless, the relationship between ecosystem services and human nutrition is clear, especially in parts of the world where livelihoods are still largely agrarian and largely based on local resources, such as in sub-Saharan Africa (Agarwala et al. 2014). More than other human outcomes based on ecosystem services, human health and nutrition may be especially dependent on biodiversity, as human health is dependent on diverse array of food sources (DeClerck et al. 2011). There have been many calls for interdisciplinary research into the linkages between environmental health and human health, an emerging field that has been called 'econutrition' (DeClerck et al. 2011, Remans et al. 2012).

Some exploratory work has been done linking various ecosystem services with human nutrition in Africa. A global study with a West African component looked at the role of pollination in micronutrient availability, and found that many crops that rely on pollinators in their life cycle are also among the richest in micronutrients that are essential to human health (Chaplin-Kramer et al. 2014). A recent household based study in Ghana found a negative relationship between intensity of cash crop production and various measures of food security, such as food availability, access and utilization (Anderman et al. 2014). Others have been looking at the nutritional value of wild foods and leafy vegetables that still make up a large portion of people's diets in rural Africa (Uusiku et al. 2010, Mavengahama, McLachlan and de Clercq 2013), while a recent study found that more tree cover predicted better diets on a continental scale (Ickowitz et al. 2014). Nevertheless, there is still a lot of work remaining to be done linking specific ecosystem services to human health outcomes (Myers et al. 2013).

Cotton's Effects on Land Use and Ecosystem Services

In West Africa and throughout the sub-Saharan Africa, cotton has major impacts on land use and biodiversity (Baudron et al. 2009) and subsequently on ecosystem services and human health. In addition to the loss of ecosystem services like timber and forest food products through reduced forestland, cotton cultivation can lessen ecosystem services through other pathways, as cotton farming is one of the most polluting forms of agriculture in the world (Baudron et al. 2009). For example, many insecticides used in cotton cultivation in West Africa are banned in developed countries (Stechert et al. 2014). There have even been cases of farmers' deaths as a direct result of pesticides (Moseley and Gray 2008), because farmers receive no training in how to properly use these noxious chemicals. Aside from direct poisoning, these chemicals have major effects on local ecosystems and the services they provide. A study in Benin found that bats, a significant local pollinator, had been exposed to unhealthy levels of pesticides (Stechert et al. 2014).

Perhaps the most significant impact of cotton, however, is on the soil. Cotton production is input intensive and can quickly exhaust soil in the absence of sound management practices (Moseley and Gray 2008). Yields have declined since the mid-1990s, and many postulate that this is clear evidence of cotton's taxing effect (Benjaminsen, Aune and Sidibé 2010), although this is not entirely clear. One survey of soil health in Mali found no clear trends in soil fertility, and concluded that decreasing yields was due to cotton being expanded to fields that were marginal to begin with (Benjaminsen et al. 2010).

However, another study found that cotton cultivation is leading to decreasing soil fertility as measured by Soil Organic Matter (SOM), and that cotton would no longer be economical in 25-35 years (Kidron et al. 2010). While traditional farming methods are probably better for long-term soil health, they are impractical for cotton cultivation, and cannot continue to feed Mali's rapidly-growing population (Grinblat et al. 2015).

Most significantly for this study, cotton cultivation is associated with and responsible for a widespread transition from swidden agriculture to permanent agriculture (Laris et al. 2015). In southern Mali, industrial fertilizers are almost exclusively available to farmers through the national cotton company, CMDT. This means that unless farmers grow cotton, they must use swidden agricultural techniques to obtain healthy soil (Laris et al. 2015). Only by cultivating cotton, and thus accessing fertilizers, can farmers establish permanent fields, even for cultivating other crops like maize. Laris describes this cotton-induced shift as follows:

> "Access to fertilizer and technology has been the catalyst for a shift from rotational agriculture, based on sorghum and millet, to a more intensive farming system where maize and cotton are grown"

Nutrition

In sub-Saharan Africa, more than 200 million people are malnourished (McMichael et al. 2008). This burden is most impactful on children, 28% of which are underweight in sub-Saharan Africa, and 36% of which are stunted in West Africa (UNICEF 2009). The impacts of systemic childhood malnutrition can be long lasting, and its limiting mental and physical effects can last the rest of an individual's life. Thus, when such large proportions of a generation of children are suffering from chronic malnutrition, this can undermine future economic growth and perpetuate poverty (Eozenou, Madani and Swinkels 2013).

In Mali in particular, the effects of malnutrition are stark: 44% of households have a stunted child, with children in the Sikasso region being particularly vulnerable (Eozenou et al. 2013). Household food security in Mali is particularly vulnerable to draught, with childhood malnutrition expected to rise in some areas as climate change affects rainfall variability (Jankowska et al. 2012). Fluctuating food cereals prices have been shown to decrease food security in households that purchase a significant portion of their food (Eozenou et al. 2013), such as urban households or rural household that have invested heavily in cash cropping.

Perhaps one of the most severe and common forms of malnutrition in sub-Saharan Africa is protein-energy malnutrition (Schonfeldt and Gibson Hall 2012), which can lead to Kwashiorkor, the disease that gives children distended bellies. However, other forms of malnutrition, such as anemia, are also common in rural Africa and are often the result of nutrient deficiencies (Remans et al. 2012). Often, nutrition interventions are made targeting these individual nutrient deficiencies (Bhutta et al. 2013). However, programs designed to supplement one or two specific nutrients are often flawed due to an overly reductionist approach to human nutrition, which is multifaceted and complex. For example, even with adequate nutritional intake, malnutrition can still occur due to poor absorption or excessive loss of nutrients (Remans et al. 2012).

Increasingly, good nutrition in agro-environmental settings is seen as a product of a diversity of dietary sources (Remans et al. 2012). While overall dietary diversity is a good predictor of good nutrition, dietary functional diversity is now recognized is most critical. In this paradigm, foods fall into functional groups. For example, in African farming systems, crops like maize, sorghum, millet are all carbohydrate-rich energy sources; beans and peanuts are protein-rich; and chili and sweet potatoes provide nutrients like vitamin A. Adequate nutrition in these farming systems thus requires food intake from foods that capture a wide swath of functional nutritional diversity (Remans et al. 2012).

Nutrition and Ecosystem Services

There are two pathways by which ecosystem services affect human nutrition. Most directly, human nutrition is dependent on provisioning services that humans gather and eat directly from forests and wild areas, such as bushmeat, fish, wild fruits, and wild roots and leaves. In sub-Saharan Africa, these wild food species are an important source of both micronutrients and macronutrients (Myers et al. 2013), and there is an increasing awareness that the disappearance of these species will pose a nutritional challenge for people who cannot easily replace these food sources (Myers et al. 2013). One study illustrated this clearly by showing that households in Madagascar that were unable to harvest bushmeat had children with a 30% higher risk of iron deficiency and anemia (Golden et al. 2011). Often it is the poorest members of communities who are most likely to be affected by the loss of these ecosystem services (Agarwala et al. 2014).

Aside from provisioning ecosystem services, regulating ecosystem services also affect human nutrition by creating the conditions necessary for productive agriculture. Healthy forests “contribute to the recycling of nutrients, suppression of agricultural pests, detoxification of noxious chemicals, control of hydrological processes and genetic resources for future adaptation to climate change” (Parrotta et al. 2015). In particular, healthy, diverse forests help soil by building up soil organic matter (SOM) when fields are fallow (Remans et al. 2012), and by protecting against erosion.

Thus, diverse forests affect human nutrition through both provisioning and regulating ecosystem services. However, agricultural expansion and extensification has been shown to directly affect this diversity (Laliberte et al. 2010). Decreased forest diversity means a decreased diversity of edible provisioning ecosystem services and therefore a reduction in the dietary diversity that is foundational to human nutrition. Additionally, forest fragmentation "can result in changes in ecosystem functions that can alter the supply and distribution of [regulating] ecosystem services vital for agriculture" (Parrotta et al. 2015). Finally, in addition to the edible provisioning and regulating ecosystem services provided by forests, non-edible provisioning services such as clean water and fuelwood for cooking are also essential to human nutrition and should not be overlooked (Remans et al. 2012).

Swidden Agriculture and Agricultural Transitions

A burgeoning literature is appearing around the practice of swidden agriculture by farmers around the word, and the various ways this traditional form of cultivation is being affected by globalization and the modern world. Academics and policymakers have historically neglected swidden agriculture. Because of its opportunistic and dynamic nature, swidden agriculture can be difficult to classify and detect, using either remote sensing or field survey methods (Van Vliet et al. 2013). Often it is lumped into categories of 'other' or as 'degraded' land cover types. Policymakers usually see swidden agriculture as a threat to local forests, and implement strategies to minimize its prevalence (Van Vliet et al. 2013).

Nevertheless, swidden landscapes can be quite diverse, because fallow fields can go through several phases of recovery and reforestation. In some cases, an increase in swidden agriculture has led to increases in forest cover as well (Robichaud et al. 2001). In addition, some researchers have found severe declines in biodiversity when swidden agriculture is replaced with permanent cropping (Rerkasem et al. 2009). Swidden agriculture is most often practiced in marginal or frontier landscapes (Van Vliet et al. 2013), and the demise of swidden agriculture is often associated with agricultural expansion and intensification (Feintrenie, Schwarze and Levang 2010). In the semi-arid tropics, fields left fallow by swidden agriculture will become forested again faster than other areas (Laris 2008).

The transition away from swidden agriculture has real impacts on people and communities. Swidden landscapes are naturally quite diverse, and provide a wide array of livelihood strategies and ecosystem services (Rerkasem et al. 2009). Leaving this farming system leads to a less diverse and heterogeneous landscape, and therefore a decrease in the diversity of available livelihood opportunities (Castella et al. 2012). Thus, the transition away from swidden agriculture can create new marginalized and vulnerable communities (Cramb et al. 2009). Just as cotton cultivation is perhaps the largest driver of the transition away from swidden agriculture in southern Mali, several studies worldwide have found cash crops to be a driver of similar agricultural transitions (Van Vliet et al. 2013). Still, swidden agriculture persists in the modern world, often in new forms and combined with other land uses (Schmook et al. 2013).

History of the Region

Ecological Context

The study region is based in southern Mali, and the landscape has been variously described as a savanna (Laris and Dembele 2012), a parkland (Bayala et al. 2010), and forest-savanna mosaic. Defining the eco-region can be difficult, as there is a slow decrease in rainfall from south to north in West Africa, leaving no clear ecosystem boundaries based on species composition (Linder et al. 2012). Nevertheless, the area of the study is often characterized as Sudanian savanna with significant presence of *Isoberlinia* trees, between the Sudano-Sahelian grasslands farther north and Guineo-Sudanian savannas to the south. In this ecoregion, open forests and grasslands coexist across the heterogeneous landscape, with closed canopy forest occurring in more mesic areas. The unstable boundary between forest and grasslands shifts based on both natural and human impacts. Humans are well aware of how to control whether an area is forested or grassy, and they use a variety of mechanisms, such as encouraging or suppressing fire, to produce preferred land cover types and encourage biodiversity (Laris 2002, Fairhead and Leach 1996). They also recognize that abandoned agricultural fields and settlements leads to forest, and can even estimate how long ago an area was farmed based on the development of the forest in that area (Laris 2008).

Pre-Colonial Agriculture and History

While the entire study region is somewhat culturally homogenous, speaking mutually-intelligible varieties of Manding languages and practicing an Africanized form of Islam, different areas have distinct cultural histories. The eastern part of the study region is inhabited by Bambaraized Fulani in a cultural region known as Wassoulou, while people who were historically Senufo in the cultural regions of Yorobugula and Ganadougou inhabit the western part of the study area. Much of the linguistic and religious homogeneity of the area is a result of the entire region being conquered by Samori Touré in the late 19th century. Samori Touré imposed Islam and harshly punished the use of non-Manding languages within his empire before it eventually fell to the French.

Communities in the area have traditionally grown sorghum, millet and fonio as field crops, supplemented with garden plants and root crops such as yams, cassava and sweet potatoes. These crops were grown in swidden systems, with plots of forest cleared and farmed for a few years, and then abandoned. Often organic compost fertilizer was applied to increase soil fertility, but farming on one plot couldn't be sustained indefinitely. Thus, after several growing seasons, fields were left to return to a forested state. By 1991, this swidden method was still the most widely practiced form of agriculture (Bationo and Mokwunye 1991) and is still widely practiced to this day (Kidron et al. 2010).

Cotton and Colonialism

Before colonialism, families would grow a few cotton plants for the local production of blankets, ropes and clothes (Lacy 2008). However, during colonialism, administrators began encouraging intensive field cropping of cotton. This was to feed an insatiable demand for cotton in European mills, and was particularly encouraged by the worldwide 'textile famine' caused by the American Civil War (Moseley and Gray 2008). Cotton production remained a major priority of colonial administrators in Mali, to the point that they were spending 70% of their resources on cotton intensification in 1950 (Lacy 2008). From the beginning of commercial cotton cultivation in Mali, clear tradeoffs were recognized between food production and cotton production. One farmer is recorded as saying: "Before the arrival of cotton cultivation, my harvest was sufficient to nourish my family, but with cotton, I don't have time. I want to earn everywhere, and I no longer produce the quantity of cereals I need" (Koenig 2008).

After independence, Rural Development Organizations (RDOs) were formed to encourage cotton production and support farmers in modernizing (Moseley and Gray 2008). Many farmers received their first plows through these RDOs (Lacy 2008), and were motivated to grow cotton so they could access equipment and inputs (Koenig 2008). They then began to use new farming equipment like plows on other crops (Koenig 2008). It can be said that cotton in Mali has led to the uptake of plowed farming using animal labor, as well as abandonment of intercropping and minimum tillage practices (Moseley and Gray 2008).

Cotton Cultivation Today

Today, cotton in Mali is run by a parastatal company known as the *Companie Malienne pour le Developpement des Fibres Textiles* or CMDT. CMDT grew out of the original postcolonial RDOs (Koenig 2008). Originally CMDT signed contracts with entire villages: loans for inputs like fertilizer and sugarcane were taken out on a village level, as well as the risk of debt from crop failure and the fiscal payoff at the end of the season (Lacy 2008). However, in 2003, CMDT allowed sub-village organizations to form, giving individual farmers greater control over the risks and payoffs of cotton cultivation (Lacy 2008).

In spite of declining cotton prices and yields per area since the 1990’s, cotton production is still increasing in Mali (Koenig 2008). Today, cotton is the second-most important cash crop produced in Africa (Moseley and Gray 2008). However, the average wealth of African cotton farmers is less than those that focus on other cash crops (Moseley and Gray 2008). It is still very controversial whether cotton cultivation leads to poverty reduction or poverty production. Many say that the loans farmers must take out to buy cottonseed and cotton inputs are predatory, while others argue that as a primarily smallholder-grown crop, cotton can bring income to a broad swath of African farmers.

METHODS AND DATA

In examining possible relationships between cotton cultivation and malnutrition, two broad approaches were taken to get at the same question. One involved classifying satellite imagery over multiple years and deriving variables from these classified images. These variables were then related to Demographic and Health Survey (DHS) data on anemia levels, height for age percentile (stunting), and weight for age percentile (wasting) in children across 37 DHS sites from 2006 and 2012.

The second approach involved data collected on the ground in three villages in the study region. Household surveys were given to collect data on cultivation of cotton and other crops, wealth, literacy rates, household size, diet and nutrition, as well as data on children's mid-upper arm circumference (MUAC) and child mortality rate at a household level. In addition to the household surveys, forest surveys were conducted to look at tree species richness on a village level. These variables were collected to look at overall relationships between malnutrition and cotton as well as two causal pathways by which cotton cultivation could be leading to malnutrition: through reduced ecosystem services at a village level or through poorer diets on a household level.

Land Cover

The aim of the remote sensing portion of this thesis is to identify areas in southern Mali that are under swidden cultivation, areas that are under permanent cultivation and areas that are not under cultivation. These areas were combined with DHS (Demographic and Health Survey) data from 2006 and 2012 to determine if there is a significant empirical relationship between agricultural practices and malnutrition.

The study area covers 4 different Landsat scenes: path 199 and 198, and rows 53 and 52. Theoretically, the best time to detect agricultural land cover in Sudanian West Africa is after the rainy season, around December, because crops have been harvested yet forests and savannas are not fully senesced. This means that the two land cover types are quite distinct, both spectrally and to the naked eye. This was confirmed by a recent study conducted in the same ecoregion in Burkina Faso, which found the greatest classification accuracy for images taken in the month of December (Liu et al. 2015). Landsat images were obtained approximately every 7 years because most farmers who practice shifting agriculture in Mali abandon their fields after 5 to 7 years. The years, dates and satellites of the images used are given in the following table:

Path	Row	Year	Date	Satellite
198	52	1990	December 28th	Landsat 4 MMS
198	53	1990	December 28th	Landsat 4 MMS
199	52	1991	January 4th	Landsat 4 MMS
199	53	1991	January 4th	Landsat 4 MMS
198	52	1999	December 5th	Landsat 7 ETM+
198	53	1999	December 21st	Landsat 7 ETM+
199	52	1999	December 12th	Landsat 7 ETM+
199	53	1999	December 12th	Landsat 7 ETM+
198	52	2006	December 16th	Landsat 5 TM
198	53	2006	December 16th	Landsat 5 TM
199	52	2006	December 23rd	Landsat 5 TM
199	53	2006	December 23rd	Landsat 5 TM
198	52	2014	December 22nd	Landsat 8 OLI
198	53	2014	December 22nd	Landsat 8 OLI
199	52	2014	December 29th	Landsat 8 OLI
199	53	2014	December 29th	Landsat 8 OLI

Table 1: Summary of Landsat images used in analysis

Images in the same path were then mosaicked, taking the average of the values for the few pixels that overlapped. This was done for all images in the same path except for those in path 198 from 1999, because two images from the same day could not be found. For these images from 1999, each image was classified separately and the images were mosaicked after classification. To extract pixels in the areas of interest, the political areas in which the DHS sites would be analyzed were acquired in shapefile form. This shapefile was then buffered by 25 kilometers, and the Landsat images clipped to the buffered area. The 2014 images were classified according to 11 different land cover categories, and then the classification was generalized to the previous years' images using an updated version of Automatic Adaptive Signature Generalization or AASG (Gray and Song 2013).

The images from 2014 were classified according to 11 land cover types: (1) hilltop grasslands, or *kurukan fuga*, (2) forest plantations, mostly consisting of Cashew (*Anacardium occidentale*), or *yiri turunen* (3) burned savanna or *kungo jeninen*, (4) rivers and shallow water bodies, or *kow ani baw*, (5) mesic grasslands or *folo*, (6) agriculture or *foro*, (7) abandoned agricultural fields or *gwenye*, (8) rural residential areas or *duguw*, (9) bare ground from mines or unpaved roads or *cencen*, (10) unburned savanna and forest or *kungo ani tufin*, and, (11) for the images in Yanfolila, the deep waters of Selingué Lake. Although the analysis was not done across eleven distinct categories, the images were initially classified across all of these categories, as this was how many natural groups there were in the images.

In addition to 6 spectral bands as predictors, altitude from a Digital Elevation Model (DEM) and latitude were also used to aid image classification. The later was used because there was a significant gradient of senescence from the northernmost part of the study region to the southernmost part. Because of this, areas of the same land cover category would have quite different spectral signatures across the images. Thus, adding latitude as one of the classification features in addition to elevation and six spectral bands significantly improved the classification.

Using training data from visual evaluation on the screen, a random forest classifier was created in R and used to classify every pixel in the 2014 images. This classification was then generalized to the 2006, 1999 and 1991 images using an adapted version of the AASG method (Gray and Song 2013). This adapted method used the same technique as Gray and Song to select training data for previous years, but a random forest classifier was used in this study instead of the maximum-likelihood classifier used by Gray and Song. According to this method, pixels in the Near Infra-Red band were differenced between the already-classified 2014 image and the image to be classified. Then, pixels within a 6th of a standard deviation of the median difference were selected. Assuming that the majority of the land cover classes have not changed between 2014 and the year of the image being classified, these selected pixels are very likely to be of the same land cover class. Thus, those pixels were used to train the image to be classified based on the land cover class that was already determined for 2014.

Once the images were classified, images from the same year were all mosaicked together, to create one large classified image for each year in the study. These large rasters were then reclassified twice; once to determine areas with swidden agriculture and areas with permanent agriculture, and once to determine areas with natural land cover types offering public ecosystem services.

For the analysis of land cover types offering ecosystem services, a binary raster was created of all areas offering non-agricultural ecosystem services versus areas offering only agricultural ecosystem services or those offering effectively no ecosystem services (such as bare ground). This was done for the years 2006 and 2014. Hilltop grasslands, burned savanna, rivers, mesic grasslands and unburned savannas were counted as areas offering non-agricultural ecosystem services, while all other areas were excluded.

For the analysis of swidden agriculture vs permanent agriculture, these images were reclassified with planted trees, currently agricultural areas, recently abandoned agriculture and rural residential areas classified as 'agricultural areas' and all other categories classified as 'non-agriculture'. Rural residential areas were classified as agriculture because occasionally pixels that were clearly agricultural were misclassified as rural residential in the rural areas where the analysis would take place. Major urban centers such as Bougouni, Kolondieba and Yanfolila were far enough from the rural DHS clusters that they wouldn't be included in the actual analysis, and thus classifying their urban pixels as 'agriculture' was of no consequence. This time-series approach to detecting swidden agriculture has been used before in southeast Asia (Chowdary, Yasuyuki and Tateishi 2012, Hurni et al. 2012) and is a methodology that Li, in a review of swidden agriculture detection techniques, calls the Landscape Ecology based approach (Li et al. 2014).

Because ground-truthing points were collected in the field in September and October 2014, a confusion matrix can be constructed for this year. Furthermore, because the images from previous years were classified from the 2014 classification using AASG, it is likely that the accuracy of the 2014 image reflects the accuracy of the previous images.

The ground truthing points were collected by walking 3-km transects from the center of each study village, and recording the land over class every 200 meters. Thus, the sampling method was not stratified by land cover class. The confusion matrix for the binary agriculture vs non-agricultural classification is as follows:

		Reference	
		Non-Agriculture	Agriculture
Prediction	Non-Agriculture	190	9
	Agriculture	9	82

Table 2: Classification matrix for agricultural and non-agricultural pixels

The classification had an overall accuracy of 93.8%, and a kappa score of 0.8559. Of the 199 non-agricultural control points collected, 190 were accurately classified and 9 were misclassified as agriculture. For the 91 agricultural control points collected, 82 were classified accurately and 9 were misclassified as non-agriculture.

The binary rasters for each year were then overlaid to determine which areas were practicing permanent agriculture, which were practicing shifting agriculture, and which were consistently some form of non-agricultural land use type. The classified images for 1991, 1999 and 2006 were combined to determine agricultural systems in 2006, and the images for 1999, 2006 and 2014 were combined to determine agricultural systems in 2012. A visual illustration of using multi-temporal classified images to determine areas practicing swidden vs permanent agriculture is illustrated in Figure 1:

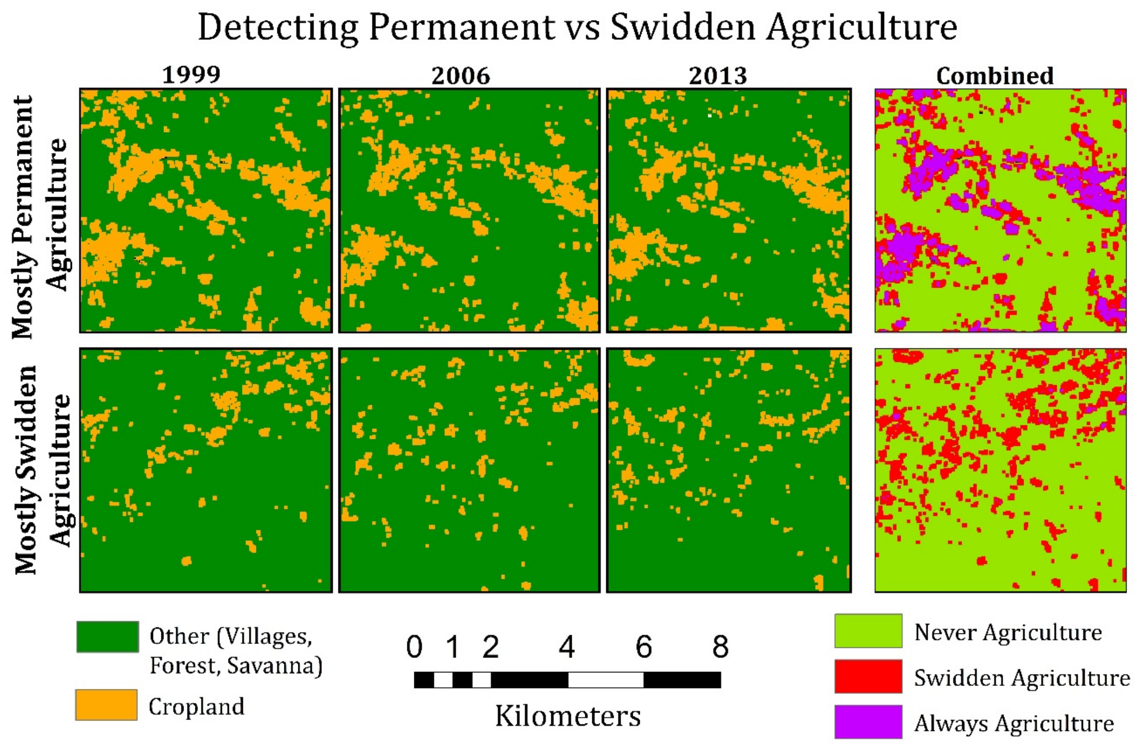

Figure 1: Detecting permanent vs swidden agriculture

Combining DHS Data with Land Cover Data

Demographic and Health Survey (DHS) sites were selected for rural areas in the Circles of Yanfolila, Kolondieba and Bougouni for the years 2006 and 2012. These points were buffered by 5 kilometers, 11 kilometers and 25 kilometers. For both the ecosystem services data and the agricultural type data, data was extracted for DHS points at every buffer and then summarized. For available ecosystem services, the percentage of total land area as a land cover type offering public ecosystem services was calculated. For looking at swidden versus permanent agriculture, pixels that were classified as agriculture two years in a row were counted as permanent. Pixels that had been agriculture and then were later classified as savanna were counted as swidden. Pixels that were only classified as agriculture in the most recent image were discarded. Then, the percentage of pixels classified as swidden out of those classified as either swidden or permanent was calculated.

Household Surveys

Household surveys were conducted in three different villages in order to better understand (1) if there was an association between cotton cultivation and different indicators of childhood malnutrition; (2) whether such an association takes place on a household scale, a village scale, or both; and (3) different causal pathways by which cotton cultivation could be leading to malnutrition.

Of the study villages, two are in the Cercle of Yanfolila, and one is in the Cercle of Kolondieba. The village of Kissa, in Kolondieba Cercle was where the author lived during the Peace Corps and had many local connections to assist with beginning and conducting fieldwork. The other two villages were recommended by the Mayor of the circle of Yanfolila based on criteria such as practicing cotton cultivation, distance from markets and hospitals, population density, and receptivity to the presence of researchers.

In each village, a list of cotton cultivating households was obtained from local cotton growers associations, of which there were two in each village. Additionally, a list of households that did not grow cotton was obtained by either attaining tax documents, or by asking the village chief and other prominent members of the community about such households. All three of the study villages were small enough that all households knew each other well, and so village chiefs could easily name households not present on the list of cotton growers. The list of households was then randomized by drawing names from a hat and recording the order in which they were drawn, until all households had been selected. The surveys were then conducted by visiting households one at a time through the list. Households that did not wish to conduct surveys were to be skipped, although this never happened in practice. Those that were unavailable were returned to at a later time.

Usually surveys took about an hour and a half, and about four were conducted a day. In the end, 114 households were surveyed across three villages.

The content and format of the surveys were modeled off of various microdata surveys collated by the World Bank, such as the 2006 Multiple Indicator Cluster Survey (MICS) used in Cote d'Ivoire and the 2010-2011 Integrated Household Survey in Malawi. The actual survey instruments used are available in Appendix 2. The surveys were designed to collect data on a variety of variables related to cotton production, land cover, wealth, diet and health. In addition, the mid-upper arms of each child between six month and five years of age were measured. Mid-upper arm circumference adjusted by age is a commonly used proxy for malnutrition, as it correlates closely with body mass index and it can be easily measured in the field (Jeyakumar, Ghugre and Gadhave 2013, De Onis et al. 1997). The surveys were conducted with the help of a research assistant from each village, who organized meetings with the household heads. Surveys were conducted in the local language of Bambara and were answered by the household head or by another knowledgeable household member. The survey number was recorded on the datasheets, but not the name of the household, to protect informant anonymity.

Forest Surveys

For this study, to empirically test whether or not biodiversity and ecosystem service levels could associated with malnutrition, tree diversity data was collected from 36 different plots in the study region. During the land cover surveys, when forestland was encountered, several other data points were recorded. A plot center point was designated as the exact point that the GPS signaled that it was 200 meters from the previous land cover center point. Then, all trees within 10 meters of the plot were identified with their species in the local name, their diameter at breast height (DBH) and their height. A tree was defined as any woody plant greater than 2 inches at breast height. A local hunter from each village was paid to act as a research assistant and assist in tree identification. For each unknown tree species, photos were taken, and the local name recorded. These photos were used in conjunction with the book *Arbres, Arbustes et Lianes du Pays Seches de Afrique L'Ouest*, the premier tree identification guide for West Africa. While not all trees could be identified, because the same hunter for each village gave them in their local name, it is possible to assess forest diversity for each village, although the overall diversity between all villages will be impossible to estimate perfectly. This was done to assess the forest diversity and health of the areas within 3 kilometers of a village.

ANALYTIC APPROACH

In investigating the relationship between cotton cultivation and malnutrition, my study approached these factors at two different scales: at a landscape scale using DHS data and satellite imagery as well as at a village/household scale. Looking at data at a village and household scale allowed me to determine exactly how much cotton a given household or village cultivated rather than using just a proxy variable as I had to do at the Landscape scale. It also allowed me to collect data on household diet, forest resource availability and forest species richness, to determine if these variables could help to explain causal pathways generating the observed co-association between cotton cultivation and malnutrition. Looking at the same data at a landscape scale allowed me to show that my findings across the three study villages are generalizable and characteristic of the study region.

Collecting household survey data and analyzing it using statistical models is a common practice in research around development economics, agriculture, livelihoods and international public health. While the most robust findings from such methods are from studies conducted with a randomized controlled trial (RCT) framework, significant correlation between different observed variables can be evidence of a causal relationship and indicate that further research is justified. Some examples of works cited in this paper that this analytic approach is based off of are: Vongvisouk, who used household surveys to demonstrate that cash cropping households have more agricultural land that non cash cropping households in Laos (Vongvisouk et al. 2014) and Huebes, who combined household surveys on non-timber forest product (NTFP) usage with forest surveys to predict future NTFP availability (Heubes et al. 2012).

There is also a well-developed literature around environmental effects on public health, and many studies have combined satellite-derived areal data at multiple scales with point data. Many authors have looked at how environmental variables affects incidences of disease by combining point data with remotely sensed variables, such as Emch, who looked at environmental variables' effect on cholera incidence in South Asia (Emch et al. 2008) or Dambach, who looked at malaria incidence in relation to environmental variables in West Africa (Dambach et al. 2012). This study also owes much to a very similar study of ecosystem services in Mali, which combined household surveys with environmental variables to look at land degradation, ecosystem services and household income (Liebenow et al. 2012)

This study seeks to see if there is indeed a relationship between cotton cultivation and malnutrition as well as to explore possible mechanisms creating this relationship at the household and village level. In doing so, several variables were often used as a proxy for one phenomenon. For example, the variables mid-upper arm circumference, household infant mortality rate, height for age, weight for age and anemia level are all use as indicators of malnutrition. Using multiple variables as an indicator of one broad phenomenon is partially due to that fact that different datasets were used at different scales, and partially necessitated by the breadth of the phenomena under study. Diet, ecosystem services and malnutrition can all be measured across multiple indicator variables that are not all necessarily always present: just because children are underweight does not mean that they will have stunted heights, and just because one forest resource is bountiful does not necessarily mean that an area has high levels of ecosystem services overall. So, this study used multiple variables and sometimes multiple models to explore statistical relationships between broad phenomena. To ensure that variables were not "cherry-picked," the results of all models run are reported here, not just the statistically significant models.

RESULTS

Verifying the Sikasso Paradox

One of the premises upon which the hypothesis was based was that childhood malnutrition is surprisingly worse in the Sikasso region of Mali. To demonstrate empirically that this Sikasso paradox actually exists, child health indicators were aggregated and compared for both DHS surveys, and Welch's t-tests were done to show that children's height for age, weight for age and hemoglobin levels were worse in the study area (n=871) compared to the average for all rural areas in Mali (n=16646). A Welch's t-test was used instead of a student's t-test because the former is more reliable when the two sample populations have unequal sample size. In tabulating region means and country means, sample weights provided by DHS were used.

	Height per Age Percentile	Weight per Age Percentile	Hemoglobin Levels Adjusted for Altitude (g/dL)
All of Mali (mean)	25.1% (*n = 16646, stdev = 31.7%*)	20.6% (*n = 16646, stdev = 27.2%*)	94.12 (*n = 8908, stdev = 18.4*)
Study Region (mean)	21.7% (*n = 871, stdev = 30.2%*)	18.1% (*n = 871, stdev = 25.1%*)	89.54 (*n = 511, stdev = 18.5*)
Welch's T-Test p-value	3.187e-06 ***	0.0003128 ***	1.011e-09 ***

Table 3: Difference between Sikasso region and study area across multiple child malnutrition indicators

These summary statistics show that levels of height per age percentile, weight per age percentile and anemia are significantly worse in the DHS clusters from the Sikasso region of Mali.

Households Models

In addition to searching for region-scale patterns of cotton-driven agricultural change and malnutrition across 37 village clusters, household surveys were conducted in three villages to test two hypothesized causal pathways by which cotton cultivation could be affecting child health; by effecting changes in diet and by effecting changes in ecosystem services.

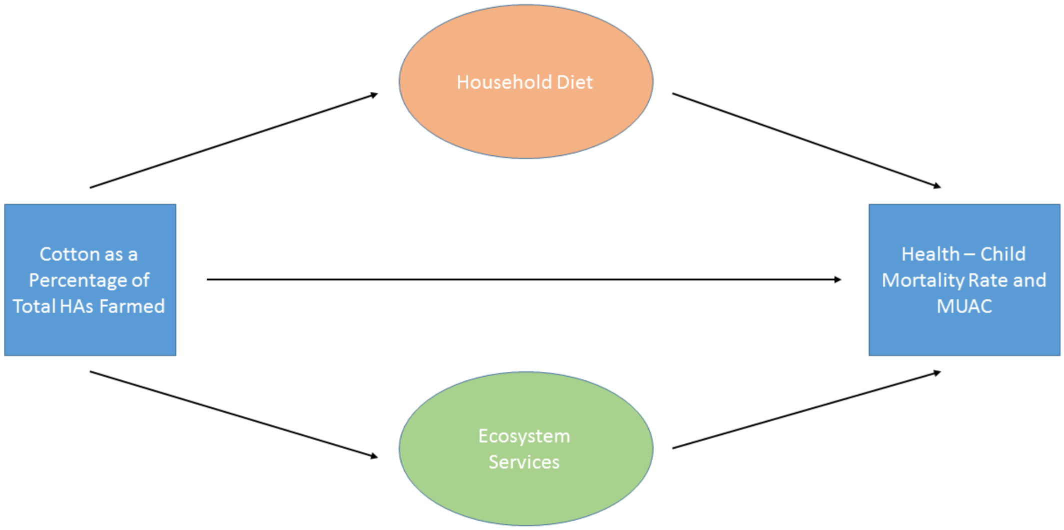

Figure 2: Hypothesized causal pathways linking cotton and health. Every black arrow represents a hypothesized association that was tested.

Cotton and Diet

A common narrative concerning the Sikasso paradox is that cotton-producing households eat worse food in both quality and quantity than those that only grow food crops. This is because there are necessarily tradeoffs between investment in food crops and cotton in terms of time, land area and agricultural inputs. Thus, it was hypothesized that households that dedicate a significant proportion of their farmland to cotton production would have significantly different diets from those that do not invest in cotton production. Specifically, it was hypothesized that they would eat less nutritious, protein dense and investment-intensive foodstuffs like meat, beans, fresh fish, dairy and eggs, which play a more critical role in nutrition (FAO 1997, Schonfeldt and Gibson Hall 2012, Remans et al. 2012).

Major proteinaceous foods measured in this study were meat, bushmeat, beans, peanuts, dry fish, dairy and eggs. Other foods measured were starchy foods rich in carbohydrates, like fonio, toh, rice and couscous. Informants were asked how often they ate each food on a weekly or monthly basis. Some foods were reported to be eaten very regularly across all households and villages - 94.7% of households said they ate toh twice a day, and 95.1% said they ate peanuts at least once a day. However, high-value proteinaceous foods eaten with wide levels of variance across study households were aggregated to determine the number of times a month each household in the study had a significant protein source.

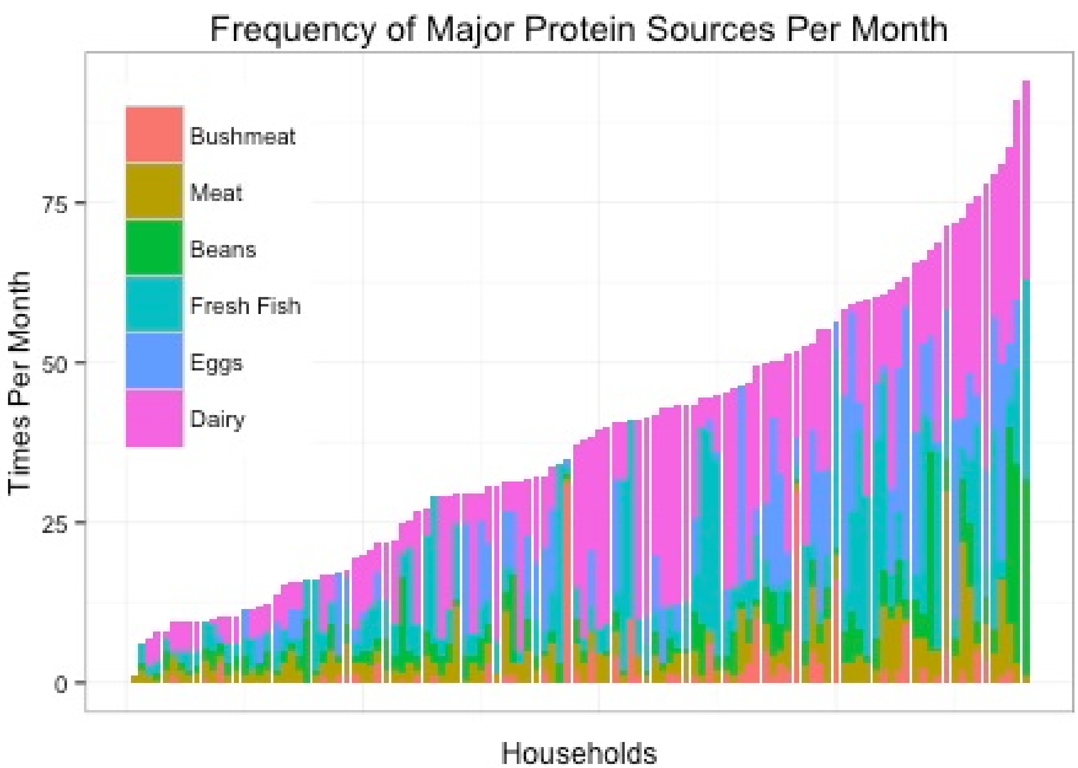

Figure 3: Frequency of major protein sources per month, by household

Although an ANOVA test showed that the three study villages have significantly different levels of cotton cultivation with a p-value of 1.85e-07, the villages did not have significantly different diets for most food items, especially those that were high in protein such as dairy, beans or meat, or even all protein sources combined. To account for village level fixed effects in exploring the relationship between diet and cotton cultivation, village dummy variables were added to the model.

A multiple linear regression run for all households between percentage of total farming area devoted to cotton and frequency of consumption of various food items showed that there was no relationship between cotton cultivation and frequency of consumption of high-value proteinaceous foods. To validate this model, a correlation matrix was created, showing that there was no significant multicollinearity between the predictor variables (see Appendix 1). Furthermore, the residuals were found to be normally distributed.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	4.257e-01	4.781e-02	8.906	1.86e-14 ***
MEAT	-3.037e-03	4.429e-03	-0.686	0.4944
BUSHMEAT	-5.067e-03	3.692e-03	-1.373	0.1728
BEANS	-2.431e-03	2.846e-03	-0.854	0.3951
FISHWET	-3.138e-05	1.740e-03	-0.018	0.9856
FISHDRY	-1.162e-04	1.506e-03	-0.077	0.9386
DAIRY	5.306e-05	6.299e-03	0.008	0.9933
EGGS	5.745e-03	9.460e-03	0.607	0.5450
VILLAGEKISSA	-9.975e-02	4.171e-02	-2.391	0.0186 *
VILLAGEWASADA	-2.299e-01	5.223e-02	-4.401	2.61e-05 ***

Table 4: Relationship between high value food items (IV) and cotton as a percent of households' total production (DV), with village dummy variables.

While there was no significant relationship between cotton farming and frequency of consumption of major proteinaceous foods, it should be noted that there was a very significant relationship between total hectares of cotton farmed and total hectares of maize farmed (p= 7.67e-07) yet no relationship between total hectares of cotton farmed and total hectares of sorghum or millet farmed. This is very unsurprising, as much has already been said about how cotton cultivation is accompanied by increasing maize cultivation (Laris et al. 2015). However, changing from one field grain to another does not have major nutritional import (Remans et al. 2012). Furthermore, overall, households were not found to have significant differences in consumption rates of major proteinaceous foods relative to cotton as a percentage of total crops farmed.

Thus, although it has been suggested that cultivating cotton means households are unable to grow enough food and their children go hungry, this is not borne out by this data. Either houses that cultivate cotton do manage to grow the same amount of food crops as houses that do not invest heavily in cotton, or they use their cotton income to purchase the food that they were not able to cultivate. In either case, whether households invest heavily in cotton or not at all, they do not have significantly different diets.

Diet and Health

Although cotton cultivation was not found to be related to diet, some foods were found to predict child health, especially child mortality. The child health variables surveyed were mid upper arm circumference (MUAC) adjusted for age, and number of child deaths in the last five years adjusted by the household size. Confounding variables tested were the household's overall wealth, the number of literate people in the household, and the amount of childcare provided by the household. The latter variable consisted of an index from 0 to 2 calculated as the number of children who had received vaccines only available at a hospital, plus the number of children who had received oral anti-parasitic medicines, divided by the total number of children. This was because households are variable in the amount of time and money they choose to invest in childcare: some poorer households may invest more into childcare and therefore have healthier children than their income or diet may reflect. This variable was meant to explain such variability.

As was mentioned, a MANOVA test showed that there was no inter-village variation in diet. Separate ANOVA tests of the two major health outcome variables showed that there was also no inter-village trend in the number of deaths in the past five years, but there was a major inter-village trend in MUAC (p= 0.000335), so dummy variables were included in the MUAC model to account for village-level effects.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	8.72E-01	2.55E-01	3.421	0.000701 ***
MEAT	1.67E-02	1.68E-02	0.996	0.31999
BUSHMEAT	1.15E-01	1.55E-02	7.396	1.11e-12 ***
BEANS	3.57E-03	1.19E-02	0.299	0.765069
FISHWET	1.41E-02	6.25E-03	2.262	0.024344 *
DAIRY	-5.49E-02	2.52E-02	-2.176	0.030261 *
EGGS	-1.09E-01	3.22E-02	-3.396	0.000766 ***
CHILDCARE	-4.43E-02	1.30E-01	-0.341	0.733048
WEALTH	6.01E-08	2.68E-08	2.244	0.025469 *
LITERACYPERCAP	-9.17E-01	4.36E-01	-2.104	0.036112 *

Table 5: Relationship between consumption of high-value food items and household child mortality rate

Two multivariate linear regressions were run with frequencies of high-value food sources and possible confounders as the independent variables, and with child MUAC as the dependent variable for one and child mortality as the dependent variable for the other. The child mortality model included all of the possible covariates, but the MUAC model only included literacy rates and childcare, because this model had the best scoring Akaike Information Criterion (AIC). For both models, correlation matrices were created to verify that there was no significant multicollinearity between the predictor variables. Furthermore, tests of normality on the residuals for the models showed that the MUAC model, which had significant results, also had residuals that were normally distributed. These models showed no correlation between consumption of high-value foods and MUAC. However, increasing the frequency of consuming milk and eggs significantly ($p < 0.01$)

reduced the infant mortality rate within a household. Surprisingly, high rates of bushmeat consumption was associated with worse infant mortality rates, suggesting that this is a last resort of households that are already marginalized.

While diet has a significant effect on child mortality rates, cotton cultivation was not found to have any sort of significant relationship with diet. Thus, if cotton cultivation is an explanation for worse-than-expected child health statistics in this part of Mali, it is not because cotton cultivating households have significantly worse diets.

Cotton and Forest Resources

Aside from affecting diets at the household level, cotton is also said to impact local environments and reduce ecosystems services. Thus, it was hypothesized that cotton production would be inversely correlated with different indicators of forest resource availability. Three variables were used to measure the availability of forest resources: the average distance households reported travelling to gather various resources; a binary variable for whether or not households reported a resource decreasing in availability; and the average number of unique tree species found per forest plot near a village. A model was fit for each variable, to see if cotton cultivation was a significant predictor of the variable. Because the population density of an area can greatly affect that area's biodiversity and availability of forest resources, this variable was included in these forest resource models.

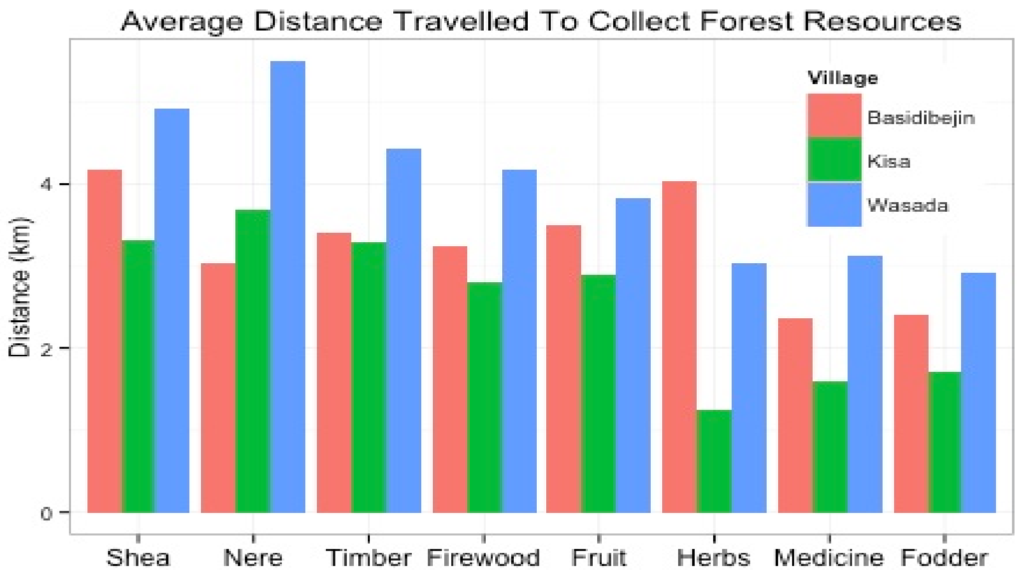

Figure 4: Average distance traveled to collect forest resources, by resource

For average distance to gather forest resources, a multilevel linear regression was run. This was because one of the predictor variables, population density, was measured at the village level and would therefore be linearly dependent on village dummy variables and invalidating their use. So, to account village-level effects without using dummy variables, a multilevel model was selected. In this model, no relationship was found between cotton cultivation and distance to gather forest resources at the household level, and the model's residuals were found to be normally distributed. This was also the case for the logit regression run on resource scarcity: cultivating cotton in no way predicted a change in the log-odds that a household would report resource scarcity. However, cotton cultivation was found to have a significantly negative relationship (p= 0.000456) with tree species richness, even when taking population density into account in a multiple regression run with cotton cultivation and population density predicting biodiversity levels. In validating the model, however, it was found that residuals were not normally distributed. This is almost certainly because the outcome variable, biodiversity, was only one of three possible values. So, while the findings were significant, the validity of the model was somewhat tempered by the fact that only three villages overall could be measured for biodiversity levels, and thus the residuals were not normally distributed.

Overall, these models offer preliminary evidence that cotton cultivation may have a neighborhood effect in reducing the biodiversity of the forest areas surrounding a village, possibly through effects like degrading soil (Benjaminsen et al. 2010), reducing forest connectivity (Parrotta et al. 2015), or harming pollinators (Stechert et al. 2014). Biodiversity is a major indicator of available ecosystem services (Mertz et al. 2007).

Forest Resources and Health

In examining the relationship between forest resources and health outcomes, separate models were made for two child health outcomes with the predictor variables biodiversity, average distance to gather forest resources and whether scarcity was reported for a forest resource. One model was run with the dependent variable as children's MUAC, and one model was run with the dependent variable as the household child mortality rate. Because an ANOVA showed significant inter-village variation for MUAC, a multilevel linear model was used to account for village-level effects, although this was not necessary for the household child mortality rate as there was not significant inter-village variation in this variable. For each model, the possible confounding variables of population density, number of literate members in the household, household wealth status, household size and childcare investment were included. These confounding variables were removed one-by-one and tested against AIC to determine whether they improved the model. In the end, childcare investment remained in the model that had MUAC as the outcome variable, and population density and literate household members remained in the model that had childhood mortality rate as the outcome variable.

In validating these models, no multicollinearity was found between predictor variables. For the MUAC model with significant findings (shown in table 6), a Lilliefors test showed that the residuals are probably not normally distributed, although they may be (p = 0.017, see Appendix 1), and they have a mean of 0 and are not bimodal. The borderline p-value on the Lilliefors test may be an artifact of the somewhat small sample size (n=114).

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-2.87238	0.42211	-6.805	4.66e-11 ***
BIODIVERSITY	0.39583	0.14104	2.807	0.0053 **
DISTANCE	-0.01389	0.03239	-0.429	0.6683
SCARCITY	-0.04767	0.09476	-0.503	0.6153
CHILDCARE	0.14396	0.10644	1.352	0.1771

Table 6: Relationship between indicators of forest health and child MUAC

It was found that increases in biodiversity significantly predicted higher MUACs for children (p= 0.0053), probably though a greater availability of provisioning and regulating ecosystem services. However, no effect was found for reported distance to gather resources or whether a scarcity was reported. Additionally, no relationship was found between forest resource availability variables and child mortality rate. Nevertheless, a significant association between biodiversity as measured by tree species richness and MUAC is very interesting given that a relationship was also found between cotton cultivation and tree species richness.

Summary: Cotton and Health

After examining pathways by which cotton cultivation has been theorized to affect child health, a final model was run for both child health variables, to determine if a direct statistical relationship could be found between cotton as a percent of total farmed area and child health outcomes.

Again, confounding variables were added to the models and removed serially to see if their removal improved the AIC. For the model that had MUAC as an outcome variable, the only confounding variable to improve the model was childcare, whereas for the model with child mortality rate as an outcome, several confounding variables were included. Both models were run with village dummy variables and without village dummy variables.

In validating these models, it was confirmed that there was no multicollinearity among predictor variables. Furthermore, residuals were tested for normality. Although the residuals of the regressions with childhood mortality rate as the outcome variable were not normally distributed, the regressions with MUAC as the outcome variable were found to be normally distributed. These were the models for which statistically significant relationships were found, and from which conclusions were drawn.

While there was no significant relationship between cotton cultivation and household infant mortality rate, there was a significant relationship between MUAC and cotton cultivation. This significant relationship went away, however, when controlling for village-level effects by adding village dummy variables. The fact that the effect went away when controlling for village level dummy variables suggests that if cotton cultivation is a driver of malnutrition, it is more likely to be a driver at a village level than at as household level.

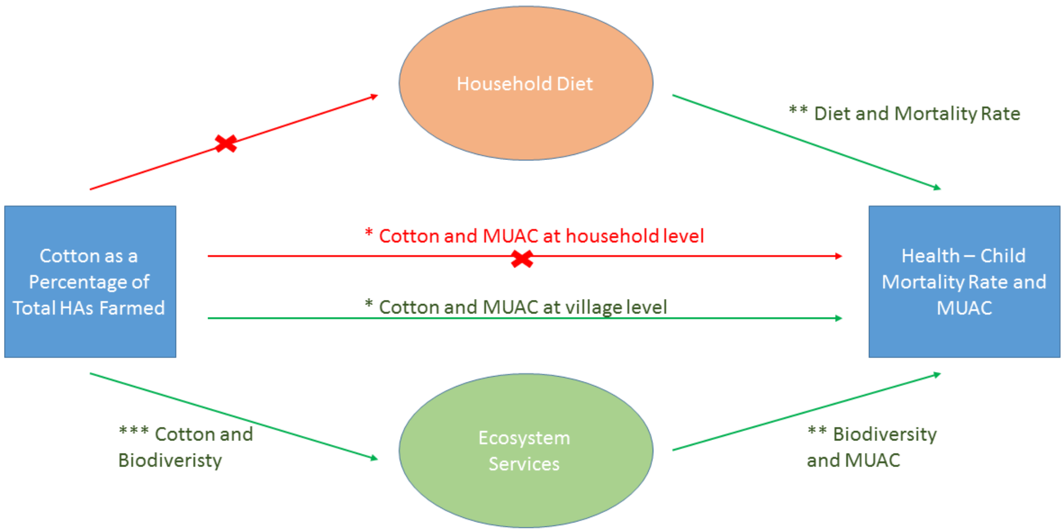

Figure 5: Hypothesized linkages that were proved or disproved, and the degree of significance by which the linkage was demonstrated.

Region Scale Model

To see if the findings of the household surveys are generalizable across the entire region, an analysis was conducted using region-scale data. Separate models were constructed for the outcome variables of weight for age percentile, height for age percentile and for anemia, as measured by hemoglobin levels in grams per deciliter and adjusted for altitude. The predictor variables were cotton cultivation and available ecosystem services. Cotton cultivation was measured by the percentage of agricultural areas within a certain distance of a DHS cluster that were classified as swidden, and available public ecosystem services were measured as the percentage of areas within the same distance of a DHS cluster classified as hilltop grasslands (*kurukan fuga*), burned savanna (*kungo jeninen*), rivers and shallow water bodies, (*kow ani baw*), mesic grasslands (*folo*), or unburned savanna (*kungo ani tufin*). Although land cover types like tree plantations and agricultural fields can offer regulating ecosystem services that benefit all, they mostly provide provisioning services that belong to only one household. When looking at what this paper calls public ecosystem services, this study is looking at land cover types that offer regulating ecosystem services, such as pollinators, watershed protection, or soil rejuvenation; as well as provisioning ecosystem services that are publicly available, such as bushmeat, forest foods, firewood, medicine, etc.

In addition to cotton cultivation and available public ecosystem services, the models also included confounding variables. These were: wealth, a categorical variable supplied by the DHS data; household size; population density at the level of the commune, the smallest administrative unit above the village; the network distance to a market, defined as a town with over 20,000 people; the absolute distance to a *Centre de la Santé Communitaire*, a low-level hospital; and the absolute distance to a *Centre de la Santé Référence*, a higher level hospital. Finally, all of the variables were grouped at the household level or the village level, with the exception of the outcome variables, which measured health effects at the individual level.

The data extracted from buffers around the DHS sites were extracted at multiples scales, and models were constructed for each scale. This was done to determine whether the effects of cotton cultivation on malnutrition occurred at local scales, via pathways like household diet patterns, or whether the effects were more present at larger neighborhood scales. The ecosystem processes affected by cotton cultivation, such as decreased game because of deforestation, were hypothesized to create a neighborhood effect of malnutrition. Additionally, the scale at which landscape drivers of malnutrition can be detected is affected by that fact the coordinates given for the DHS points have been offset by up to 5 kilometers. Examining possible land cover effects at multiple scales was one way to get around this issue.

Because the independent variables are at the village level and the outcome variables are at the individual level, and because the data came from multiple years, the models used were multilevel linear models, with grouping variables as the household level (n=184), the village level (n=37), and the year level (n=2). Because it was not theorized that the relationship between cotton cultivation and malnutrition would vary between different groups at a level, but only that child health outcomes would already be variable between different groups, a random intercept/fixed effects model was used, where intercepts can vary but slopes are held constant. To estimate the p-values of the coefficients, the Satterthwaite approximation of the degrees of freedom is used. In the given tables, PERSWID is the percent of agriculture practiced as swidden, COMMONS is the percent of surrounded areas providing communal ecosystem services, POPDENS is the population density, MARKET, CSCOM and CSREF is the distance to a market, minor hospital or major hospital, WEALTH is the households animal wealth in West African Francs, and HHSIZE is the size of the household. Weight and Height are given in percent*100 and Anemia is altitude-adjusted hemoglobin level in g/dl with one implied decimal.

5 Kilometer Neighborhood

5 kilometers is the smallest reasonable neighborhood to look at landscape effects on DHS clusters, because that is the maximum distance that their GPS coordinates are jittered. Most famers only establish fields within 5 kilometers of their villages, although

the distance can vary with population density. Pathways by which cotton cultivation could affect health at this scale would be dietary as well as ecological.

	Weight	**Height**	**Anemia**
(Intercept)	-2916.936	-2837.932	8.362e+01
	(0.0343*)	(0.29293)	(1.74e-05**)
PERSWID	3193.641	3325.954	-6.823e+00
	(0.0397*)	(0.27208)	(0.641)
COMMONS	-43.358	-15.927	1.213e-01
	(0.9069)	(0.97124)	(0.966)
POPDENS	30.724	30.112	5.221e-02
	(8.50e-05**)	(0.03796*)	(0.433)
MARKET	72.610	187.151	-1.880e-01
	(0.5666)	(0.47622)	(0.879)
CSCOM	-12.485	-61.601	1.086e-01
	(0.6961)	(0.35749)	(0.730)
CSREF	16.700	23.918	5.571e-02
	(0.0749.)	(0.20908)	(0.532)
WEALTH	130.192	130.734	1.610e+00
	(2.71e-11**)	(2.01e-08**)	(1.86e-10**)
HHSIZE	35.592	20.601	5.597e-01
	(1.03e-09**)	(0.00301**)	(7.22e-13**)

Table 7: Coefficients for predictor variables for outcome variables weight, height and anemia, with significance in parenthesis for a 5 km buffer.

Of the villages sampled, the lowest percent of swidden agriculture within 5 km of a village was 47%, whereas the highest rate of swidden agriculture was 98%, with an average of 80% of agriculture being swidden. There was also a slight but clear temporal trend away from swidden agriculture: the average percentage of agriculture classified as swidden practiced by a village in 2006 was 85%, whereas this had decreased to only 72% by 2012. Thus, while permanent cropping is increasing, swidden agriculture is still the dominant form practiced in the region.

The percentage of land cover within 5 km of a DHS site offering ecosystem services varied from only 41% to 97%, with an average of 82%. Again, there is a temporal aspect: just as the percentage of agriculture practiced as permanent cropping has increased, the average percent of land cover offering public ecosystem services has decreased from 87% to 75%. Both of these trends reflect what is called agricultural extensification (Laris et al. 2015). Nevertheless, the high levels of land cover surrounding villages providing public ecosystem services shows how most agricultural fields are patches in a diverse and heterogeneous landscape.

There was a slightly significant (p= 0.039) relationship between percent of agriculture as swidden and children's weight for percentile. An increase of one percent in swidden agriculture predicts an increase of 3.1 percentile points for children's weight. However, no significant relationship was found between the independent variables of rates of swidden agriculture and available ecosystems services and the dependent variables of height by percentile or anemia. The covariates of population density, distance to a city over 20,000 people, distance to a major hospital, distance to a community hospital, household size and household wealth were included in the models. For child weight by percentile, population density and distance to a major hospital were very significant predictors, with increases in distance to a hospital and increases in population density predicting increases in children's weight. Child height by percentile had the same significant confounding variables that were significant in the same way. Additionally, household wealth was a significant predictor of increased child heights. No variables out of percent swidden agriculture and the confounding variables were found to be significant predictors of child anemia.

11 Kilometer Neighborhood

An 11 kilometer area around a village is farther than most farmers go to cultivate fields. Most forest resources are collected within 11 kilometers of a village, and an 11 kilometer buffer was selected because this was the maximum distance that respondents reported travelling to collect forest resources in the household surveys. Sometimes farmers will have fields this far out and they will build houses (*buguda*) to stay in while they are farming. Neighboring villages are can be within 11 kilometer of a village, and their farming practices can affect ecosystem health and the availability of forest resources.

	Weight	Height	Anemia
(Intercept)	-2506.889	-2191.123	8.195e+01
	(0.08829.)	(0.44331)	(0.000109**)
PERSWID	2721.455	2569.043	-4.880e+00
	(0.11244)	(0.43913)	(0.759841)
COMMONS	-23.317	-5.662	9.009e-02
	(0.94985)	(0.98977)	(0.975106)
POPDENS	28.199	26.980	5.849e-02
	(0.00021**)	(0.05387.)	(0.361651)
MARKET	80.866	192.291	-1.928e-01
	(0.54083)	(0.47316)	(0.877729)
CSCOM	-8.340	-55.070	9.753e-02
	(0.80089)	(0.41584)	(0.758026)
CSREF	15.294	22.479	5.794e-02
	(0.11299)	(0.24254)	(0.517835)
WEALTH	130.242	130.813	1.609e+00
	(2.68e-11**)	(1.98e-08**)	(1.88e-10**)
HHSIZE	35.479	20.559	5.600e-01
	(1.16e-09**)	(0.00307**)	(7.15e-13**)

Table 8: Coefficients for predictor variables for outcome variables weight, height and anemia, with significance in parenthesis for an 11 km buffer.

Although the area examined increased by a factor of nearly 5, the variables extracted at this scale were very similar. The variation in percentage of agriculture as swidden ranged from 49% to 98%, with a mean of 81%. Again, there was a trend of decreasing swidden agriculture over time. The distribution of available ecosystem services changed somewhat across all of the study villages. The minimum percentage of land cover within an 11 km buffer providing public ecosystem services was somewhat higher: even the most agriculturalized village has 55% of its land cover providing public ecosystem services. At an 11 kilometer scale, the relationship found between percent of agriculture as swidden and child weight is no longer very significant, but the coefficient is about the same. The regressions for child height and anemia have similar coefficients as they did at the 5 kilometer scale.

25 Kilometer Neighborhood

The largest neighborhood examined was all areas within 25 kilometers of a village. This creates an area 50 kilometer in diameter, so these models are testing for effects at fairly large spatial scales. There are often several neighboring villages within an area this size. This is about the farthest farmers will go to look for pasture for cows. Traditionally, hunters would travel 25 kilometers and farther to look for game, although this is less common today. If there are significant water bodies within this distance, people from multiple villages may travel up to 25 kilometer to fish. Because Bamanan society is patrilocal, women will usually be from villages within 25 kilometers of their husbands' village, and thus extended family networks exist at about this scale. So, there are many social-ecological processes existing at this scale that could affect child health outcomes.

At 25 kilometers, the standard deviations for percentage of agriculture as swidden and percentage of land cover providing public ecosystem services have decreased, meaning that values are beginning to converge on the overall value for the region. Interestingly, the percent of agriculture practiced as swidden is once again significantly related to children’s weight, with an increase in 1 percent in the percent of agriculture practiced as swidden within a 25 kilometer radius circle around a village predicting an increase in 3.8 percentile points in a child's weight for age. Again, household wealth and household size are both significant predictors of positive health outcomes.

	Weight	Height	Anemia
(Intercept)	-3456.923	-4027.367	8.295e+01
	(0.03775*)	(0.21139)	(0.000554**)
PERSWID	3851.622	4813.100	-5.944e+00
	(0.04710*)	(0.19906)	(0.747805)
COMMONS	-20.010	-12.275	6.155e-02
	(0.95683)	(0.97781)	(0.982960)
POPDENS	26.473	26.127	6.270e-02
	(0.00017**)	(0.04463*)	(0.301647)
MARKET	136.191	274.453	-2.717e-01
	(0.31434)	(0.31942)	(0.835797)
CSCOM	-4.340	-55.457	8.296e-02
	(0.88955)	(0.38851)	(0.786540)
CSREF	13.052	19.232	6.192e-02
	(0.16838)	(0.31253)	(0.495332)
WEALTH	129.719	130.543	1.611e+00
	(3.21e-11**)	(2.11e-08**)	(1.83e-10**)
HHSIZE	35.427	20.530	5.602e-01
	(1.23e-09**)	(0.00311**)	(7.08e-13**)

Table 9: Coefficients for predictor variables for outcome variables weight, height and anemia, with significance in parenthesis for a 25 kilometer buffer.

Validating Models

These hierarchical models were validated by checking the distribution of the conditional residuals and the marginal residuals, assuring that the means of both types of residuals were 0 and that distributions were either normally distributed or at least not bimodal. Furthermore, the random effects and conditional residuals were tested to make sure there was no collinearity at any level. The raw results of these tests can be seen in Appendix 1.

Neither the conditional nor the marginal residuals for these models were perfectly normally distributed according to Lilliefors tests. They often had kurtosis on the right side of the distribution, suggesting that the relationship between the predictor variables and the outcome variable is non-linear, and therefore a non-linear statistical model might better fit these data. However, all of the residuals had a mean of 0, indicating that the models were fit as best as they could be given that they were linear models. There was also no collinearity between the random effects and the residuals for any of the models, suggesting that the model sufficiently accounted for random effects for each group at every level. Overall, the models were well fit given that they were linear models. However, better models would have captured some of the non-linearities possibly present in the data. Therefore, the limits of these models should be taken into account when interpreting their results.

DISCUSSION

Diet Pathway from Household Surveys

A very common narrative in the discussion of the impacts of cotton cultivation is that cotton farmers cannot invest as much in food production, and therefore have worse diets compared to before they took up cotton production, or compared to their neighbors who do not grow cotton (Koenig 2008, Mesplé-Somps et al. 2008, Dury and Bocoum 2012).

While it is said but not demonstrated that cotton farmers grow less food, it is very clear and empirically evident that they grow different grains. Increasing cultivation of cotton and permanent cropping is highly associated with the cultivation of maize (Laris et al. 2015). Researchers have written much about this phenomenon already and it is borne out by my own data. This is because many of the higher-impact tools and inputs necessary for cotton cultivation, such as ox-drawn plows and artificial fertilizers, produce much greater gains for maize production than they do for the production of more traditional crops, like sorghum or millet (Laris et al. 2015). Thus, while toh is still the staple food of all households, consumed twice daily by 94.7% of surveyed households, cotton farming households are eating more toh from maize flour and non-cotton farming households are eating more toh from millet or sorghum flour.

Nevertheless, the nutritional differences between maize and traditional grains are marginal. All of these crops provide mostly carbohydrate energy, some protein and some minerals (FAO 1997), and would not be said to be significantly different functionally (Remans et al. 2012). Thus, cultivating and consuming these crops at different rates would have little impact on childhood health. What really matters for child health is protein rich foods: meat, fish, beans, peanuts, dairy, and eggs (FAO 1997, Remans et al. 2012).

The household surveys that were conducted support these findings from the childhood health literature. Frequency of dairy and egg consumption in particular predicted fewer child deaths within a household in the past five years, even when taking into account a household's total livestock wealth, literacy rates, and how much the household has invested in childcare. It is somewhat surprising that frequency of consumption of other proteinaceous foods did not predict better health statistics. This could be because the household surveys were based on informant recall and not direct observation. For every proteinaceous food except eggs and diary, informants were asked to tell how many times in the past month they ate it, and they usually had difficulty assigning a precise number to the frequency. For milk and eggs, however, they were asked to give the frequency in the past week, and it was these two dietary items in particular that had a significant relationship with a child health outcome. The exact relationship between health and other proteinaceous foods might have been better illuminated if the household survey questions had been framed differently.

Interestingly, higher rates of bushmeat consumption predicted increases in child mortality rates. This is probably indicative that bushmeat is a major resource of poorer households that would not otherwise have any meat or protein sources, especially because bushmeat is one of the least nutritious and least desirable forms of meat available. In the past, larger animals were more common, and bushmeat consisted of animals like antelope (*sigi*). Today, bushmeat consists of smaller animals like lizards (*kooro*), bush rats (*joro*) and even small birds: hardly ample sources of protein or nutrition. This is a result of deforestation and agricultural extensification, and a clear illustration of how diminished ecosystem services associated with cotton cultivation could have a neighborhood effect leading to worse child health outcomes, especially for households that were already poorer and more dependent on forest resources.

Overall, however, for the households in the villages from this study, proteinaceous foods were found to be eaten by cotton farming and non-cotton farming households with the same frequency, with no major variation between villages and no major relationship with cotton cultivation. This is true for all proteinaceous foods surveyed as well as for those that were asked across shorter recall windows and therefore reflect more accurate responses. So, since there is no relationship between cotton cultivation and consumption of these high-value proteinaceous foods, diet is might not be a pathway by which cotton cultivation is leading to worse child health outcomes.

Ecosystem Services Pathway From Household Surveys

Based on the evidence from this study, it seems that village level effects of cotton cultivation could be a driver of unexpectedly poor health statistics in the Sikasso region of Mali. Cotton cultivation was found to be associated with lower tree species richness, and lower tree species richness was in turn a predictor of smaller mid upper arm circumference (MUAC) of children between six months and five years old.

Three different metrics were used to look at forest resources: average distance households reported travelling to gather resources, whether or not households reported scarcity of a resource, and overall tree species richness of the forests around a village, in terms of average number of unique tree species in a 30 foot radius forest plot. There was no relationship between the percentage of a household's crops that were cotton and the distance households travelled to collect resources or whether houses reported scarcity. This is probably because resource scarcity and the distance households must travel to gather resources are based on agricultural and resources harvesting practices at the entire village level, not on a household-by-household level. It is even possible that households that cultivate less cotton have less income from cotton, and therefore must base more of their livelihood on forest resources. These households would be more likely to notice scarcity, and may have to travel farther to gather resources, as they are more dependent on them. So, while growing more cotton would theoretically lead to fewer resources at the village level, growing more cotton may not accurately represent this at the household level based on the indicators used.

However, there was a relationship between village-level biodiversity and household cotton production. While the indicator of biodiversity used was average number of trees per sample plot, this is indicative of much more. Greater tree diversity can mean more vegetation for grazing animals. More vegetation for grazing animals in turn means greater production of eggs and milk, which were demonstrated to be linked to child health. Higher levels of biodiversity is also indicative healthier soils, which means that crops will be more productive if that patch of forest has been cleared. Biodiversity is often proportional to of the availability of ecosystem services that directly affect human health, especially in developing countries (Mertz et al. 2007).

Much work has been done on how natural regimes supplant fallow fields in swidden systems, even in southern Mali. Laris has demonstrated how abandoned fields can quickly lead to dense and healthy wooded areas, *but only when they are farmed in traditional, low-impact ways* (Laris 2008). Practices like using ox-drawn plows instead of hand-tilling the soil; farming soil-depleting crops like cotton instead of nitrogen-fixing legumes; and using synthetic fertilizer instead of organic fertilizer can all lead to fallow fields that are slow to return to a forested state, and remain marginal or degraded for a long time. Thus, it is clear how cotton farming and the new agricultural methods that come with it could reduce biodiversity.

It is undeniable that ecosystem services are foundational to human health and well-being. This is especially true in places like rural Mali, where almost the entirety of peoples' livelihoods come from their immediately surrounding environments. Although even rural Malians are getting increasingly more of their material possessions from markets and cash purchases, their diets are still overwhelmingly locally sourced. Nevertheless, ecosystems services can be difficult to measure and quantify. Sometimes ecosystem services are the direct quantity of a good, such as shea fruits. However, some of the most vitally important ecosystem services, such as pollinators or healthy soil, cannot be easily reduced to one measure. Researchers must therefore use somewhat indirect measures, like biodiversity. So, there are theoretical reasons why more unique tree species in an area are correlated with children's arm sizes may seem specious.

Landscape Scale and Household Surveys

Child health is multifaceted and complex. This study had to use many different indicators of child health to get at possible effects cotton cultivation could have on children's health overall. Anemia levels, child mortality rates, and various biometrics like weight percentile, height percentile and mid upper arm circumference are usually but not necessarily correlated. While the consumption of certain foods was found to be correlated with lower child mortality rates, the majority of the findings showed that cotton cultivation was associated with biometrics, like MUAC and weight percentile, and almost no relationship was found between anemia and cotton cultivation, diet or forest resources.

Although diet predicted lower child mortality rates, this variable was not correlated with any forest resource indicators or with cotton production overall. This could be because there are other drivers of child mortality rates than just malnutrition. Non-nutritional diseases and households' abilities to prevent and treat these diseases could be greater drivers of child mortality rates than nutrition alone. There could also be more uncertainty behind mortality statistics than biometric statistics because deaths are an overall rare occurrence. The true probability of a child dying can be hard to gauge without a large sample size, whereas wasting or stunting can be relatively directly assessed using biometrics. So, biometrics are more reliable indicators of child malnutrition and this is probably why they were the more often found to be statistically significant than anemia levels or child mortality rates.

The household surveys showed that cotton cultivation affects local ecosystem services and forest biodiversity, and the landscape scale surveys showed that this effect does not go beyond the immediate vicinity of a village. Both surveys showed that cotton cultivation may affect child health through a neighborhood effect, and but there was no evidence of a direct effect within a household. This suggests that the effect may be ecological. Cotton cultivation and the agricultural changes that come with it have been shown to affect the myriad ecosystem services upon which human well-being depends (Benjaminsen et al. 2010, Stechert et al. 2014, Kidron et al. 2010), and human nutrition in turn has been shown to be very much dependent on ecosystem services (Remans et al. 2012, DeClerck et al. 2011, Golden et al. 2011). This study offers some evidence in this vein, showing that cotton cultivation is associated with lowered biodiversity and malnutrition.

Issues

One major issue that this study faces was with the independent variables in the landscape scale analysis. The study used classified Landsat imagery over time to detect areas practicing swidden agriculture in comparison to those practicing permanent agriculture, and used that statistic to approximate the prevalence and intensity of cotton cultivation. There is significant evidence that permanent cropping is increasingly common due to the fertilizers and agricultural inputs that are only available to cotton farmers (Laris et al. 2015), and many researchers have written about how agricultural change, specifically in relation to swidden agriculture, is a direct result of cotton cultivation (Koenig 2008).

Nevertheless, farmers do leave old cotton fields fallow, especially when empty forest abounds for starting new fields. Thus, while it very likely that areas with permanently farmed fields are growing cotton somewhere, it is not certain that those permanent fields themselves are growing cotton. It could be that nearby swidden fields are being used for cotton production, while the permanent fields are actually used for growing maize or other crops. So, while the percentage of agriculture classified as swidden is a useful measure for understanding the prevalence of cotton cultivation and the use of modern agricultural methods, it is not a direct measure. Further research around the role of cash crops in the transition towards permanent cropping should focus on quantifying this change.

Another major issue with the methodology utilized was that agricultural areas that only appeared in the last satellite image in the series could not be classified. In order for a field to be classified as permanent or swidden agriculture, it had appear twice, either as agriculture both times (permanent) or agriculture the first time and savanna at a later time (swidden). So, when looking at the relationship between malnutrition and swidden agriculture rates, one is actually looking at the relationship between malnutrition and rates of swidden agriculture a few years prior.

The findings presented in this paper certainly suggest that cotton may play a role in the unexpectedly poor child health statistics in the Sikasso region of Mali. Nevertheless, the region scale examination of agricultural change and child health outcomes from 2006 and 2012 conducted here found an only slight affect. Thus, it is likely that there are other drivers of child malnutrition and anemia beyond simply agricultural change. Two frequently significant confounding variables in the models run were population density and distance to a major hospital. Thus, these demographic and infrastructural factors seem to be playing a role in child health statistics. Further analysis should also look more at farmers' income and debt in relation to health and cotton farming.

CONCLUSION

This study gives empirical evidence that high cotton-cultivating areas have worse nutrition compared to those with less cultivation during the same year. It investigated this relationship using both in-depth surveys from three villages and at the landscape scale from 37 villages. These findings suggest that this effect may be because of environmental degradation and not because cotton producing households have worse diets than their neighbors that produce less or no cotton. This study is meant to contribute to the debate around the problems and benefits of cotton and cash crops in general for subsistence farmers.

While cotton production is associated with worse nutrition in one year, over time there has been a trend of increasing cotton production as well as major gains in child health outcomes. Both of these trends are the result of complex processes involved in globalization, and it is impossible to say that the gains over time in diminishing malnutrition would have happened without increasing production of cotton. Furthermore, most farmers in southern Mali are enthusiastic about cotton production, as well as the agricultural technologies it makes available to them and the cash income they can earn from it. So, rather than demonizing the crop itself, efforts to reduce rates of malnutrition should aim to lessen cotton's impact on ecosystem services or to supplant these services that have been lost.

APPENDIX 1: SUMMARY STATISTICS OF ALL MODELS

Village-scale Models:

***Variable Summaries*:**

COTTON: Percentage of agricultural hectarage cultivated devoted to Cotton in 2013 (n=114, household level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
 0.0000  0.1818  0.2857  0.2841  0.3933  0.8889 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.1119, p-value = 0.001307
```

MEAT: Number of times in a normal month that a household eats meat from livestock animals (n=114, household level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   1.500   2.750   3.658   4.000  25.000 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.2455, p-value < 2.2e-16
```

BUSHMEAT: Number of times in a normal month that a household eats meat from animals hunted or trapped in public areas (forests, grasslands, rivers) (n=114, household level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   0.000   0.000   1.753   1.500  31.000 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.3503, p-value < 2.2e-16
```

BEANS: Number of times in a normal month that a household eats beans (n=114, household level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   1.000   2.250   4.033   4.000  31.000 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.2678, p-value < 2.2e-16
```

FISHWET: Number of times in a normal month that a household eats fresh fish (n=114, household level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   3.000   4.500   8.447   7.000  31.000 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.3276, p-value < 2.2e-16
```

FISHDRY: Number of times in a normal month that a household eats dried fish (n=114, household level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
   0.00    6.25   31.00   22.60   31.00   31.00 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.4197, p-value < 2.2e-16
```

DAIRY: Number of times in a normal month that a household eats dairy products (n=114, household level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   1.000   2.250   3.149   5.375  10.000 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.1878, p-value = 1.211e-10
```

EGGS: Number of times in a normal month that a household eats eggs (n=114, household level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
   0.00    0.00    0.50    1.44    2.00    9.00 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.245, p-value < 2.2e-16
```

DEATHS: Number of children under five years old who died in the past five years, divided by the total number of people in the house (n=108, household level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
0.00000 0.00000 0.00000 0.05413 0.07095 0.66670 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.3081, p-value < 2.2e-16
```

MUAC: The Z-score of the Mid-Upper Arm Circumference of Children between 6 months and 5 years in the household. The Z-score of the circumference was calculated for the age based on WHO reference data (n=364, individual level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
 -5.124  -1.912  -1.304  -1.334  -0.804   2.414 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.0356, p-value = 0.3167
```

DISTANCE: Average distance reported travelling to gather the forest resources shea, néré, timber, firewood, fruits, medicine and sauce-leaves (n=104, household level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
 0.8438  2.0710  2.7680  3.2920  4.2500 10.2500 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.136, p-value = 6.407e-05
```

SCARCITY: A binary variable, reporting whether or not a forest resource was perceived as increasing in scarcity. Resources were shea, néré, timber, firewood, fruits, medicine and sauce-leaves (n=104, household level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
 0.0000  0.0000  1.0000  0.5962  1.0000  1.0000 
```

BIODIVERSITY: Average number of individual tree species on forest plots around a village. While this is an indicator of biodiversity, a more accurate descriptor would be 'species richness' (n=3, village level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  2.938   2.938   3.444   3.389   3.818   3.818 
```

LITERACYPERCAP: Percentage of individuals in a household who were reported as being literate, in French or Bambara (n=114, household level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
0.00000 0.09022 0.22140 0.20930 0.29790 1.00000 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.0994, p-value = 0.007526
```

WEALTH: Total livestock wealth of a household, in West African Francs, based on local market rates for livestock.

```
   Min.  1st Qu.   Median     Mean  3rd Qu.     Max. 
      0   400000   882500  1565000  1838000 12300000 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.2289, p-value = 3.656e-16
```

POPDENS: People per square kilometer at each commune, from the 2006 national census. (n=3, village level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  7.073   7.073  31.390  24.990  32.540  32.540 
```

CHILDCARE: An index of how much effort the household has put into caring for the child's health. The number of children who have received vaccinations, plus the number of children who have received antiparasitic medicine divided by the total number of children (n=106, household level)

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   1.500   2.000   1.693   2.000   2.000 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.3995, p-value < 2.2e-16
```

VILLAGE: The village a given record is from. Can be a grouping variable in multilevel models or a categorical/dummy variable in simple linear regression.

***Model Summaries*:**

Cotton and Diet - Multiple regression:

```
Call:
lm(formula = COTTON ~ MEAT + BUSHMEAT + BEANS + FISHWET + FISHDRY + 
    DAIRY + EGGS + VILLAGE, data = survey)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.40865 -0.12082 -0.00207  0.10143  0.47696 
```

```
Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)    4.257e-01  4.781e-02   8.906 1.86e-14 ***
MEAT          -3.037e-03  4.429e-03  -0.686   0.4944    
BUSHMEAT      -5.067e-03  3.692e-03  -1.373   0.1728    
BEANS         -2.431e-03  2.846e-03  -0.854   0.3951    
FISHWET       -3.138e-05  1.740e-03  -0.018   0.9856    
FISHDRY       -1.162e-04  1.506e-03  -0.077   0.9386    
DAIRY          5.306e-05  6.299e-03   0.008   0.9933    
EGGS           5.745e-03  9.460e-03   0.607   0.5450    
VILLAGEKISSA  -9.975e-02  4.171e-02  -2.391   0.0186 *  
VILLAGEWASADA -2.299e-01  5.223e-02  -4.401 2.61e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1663 on 104 degrees of freedom
Multiple R-squared:  0.266,	Adjusted R-squared:  0.2025 
F-statistic: 4.188 on 9 and 104 DF,  p-value: 0.0001227

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.0494, p-value = 0.7072

Correlation Matrix of Predictor Variables:
           MEAT BUSHMEAT  BEANS FISHWET  DAIRY   EGGS
MEAT      1.000   -0.034  0.123  -0.031  0.234  0.328
BUSHMEAT -0.034    1.000 -0.104   0.043 -0.089  0.050
BEANS     0.123   -0.104  1.000   0.108  0.195  0.153
FISHWET  -0.031    0.043  0.108   1.000  0.010 -0.115
DAIRY     0.234   -0.089  0.195   0.010  1.000  0.090
EGGS      0.328    0.050  0.153  -0.115  0.090  1.000
```

Diet and Health - Multiple regression with DEATHS as outcome:

```
Call:
lm(formula = DEATHS ~ MEAT + BUSHMEAT + BEANS + FISHWET + DAIRY + 
    EGGS + CHILDCARE + WEALTH + LITERACYPERCAP, data = health)

Residuals:
    Min      1Q  Median      3Q     Max 
-2.3907 -0.6859 -0.2909  0.4412  3.0658 

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
(Intercept)     8.723e-01  2.550e-01   3.421 0.000701 ***
MEAT            1.672e-02  1.678e-02   0.996 0.319990    
BUSHMEAT        1.148e-01  1.552e-02   7.396 1.11e-12 ***
BEANS           3.569e-03  1.193e-02   0.299 0.765069    
FISHWET         1.413e-02  6.247e-03   2.262 0.024344 *  
DAIRY          -5.491e-02  2.524e-02  -2.176 0.030261 *  
EGGS           -1.093e-01  3.218e-02  -3.396 0.000766 ***
CHILDCARE      -4.430e-02  1.298e-01  -0.341 0.733048    
WEALTH          6.005e-08  2.676e-08   2.244 0.025469 *  
LITERACYPERCAP -9.166e-01  4.356e-01  -2.104 0.036112 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 1.032 on 339 degrees of freedom
  (15 observations deleted due to missingness)
Multiple R-squared:  0.234,      Adjusted R-squared:  0.2137
F-statistic: 11.51 on 9 and 339 DF,  p-value: 8.983e-16

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.1263, p-value = 1.172e-14

Correlation Matrix of Predictor Variables:
             MEAT BUSHMEAT  BEANS FISHWET  DAIRY   EGGS CHILDCARE WEALTH LITERACY
MEAT        1.000   -0.032  0.114  -0.037  0.224  0.348     0.062  0.330   -0.019
BUSHMEAT   -0.032    1.000 -0.096   0.046 -0.096  0.072     0.031 -0.103   -0.154
BEANS       0.114   -0.096  1.000   0.113  0.227  0.150    -0.164 -0.057   -0.141
FISHWET    -0.037    0.046  0.113   1.000  0.020 -0.136     0.094 -0.024    0.153
DAIRY       0.224   -0.096  0.227   0.020  1.000  0.106     0.032  0.425    0.104
EGGS        0.348    0.072  0.150  -0.136  0.106  1.000     0.030  0.182   -0.063
CHILDCARE   0.062    0.031 -0.164   0.094  0.032  0.030     1.000  0.110    0.193
WEALTH      0.330   -0.103 -0.057  -0.024  0.425  0.182     0.110  1.000    0.068
LITERACY   -0.019   -0.154 -0.141   0.153  0.104 -0.063     0.193  0.068    1.000
```

Diet and Health - Multiple regression with MUAC as outcome:

```
Call:
lm(formula = MUAC ~ MEAT + BUSHMEAT + BEANS + FISHWET + DAIRY + 
    EGGS + LITERACYPERCAP + CHILDCARE, data = health)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.4256 -0.5775 -0.0433  0.5168  3.6865 

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)    
(Intercept)    -1.7381678  0.2019949  -8.605 2.62e-16 ***
MEAT           -0.0280220  0.0129439  -2.165   0.0311 *  
BUSHMEAT       -0.0152665  0.0123557  -1.236   0.2174    
BEANS           0.0004231  0.0093016   0.045   0.9637    
FISHWET         0.0035944  0.0048826   0.736   0.4621    
DAIRY          -0.0007839  0.0183167  -0.043   0.9659    
EGGS            0.0113395  0.0257676   0.440   0.6602    
LITERACYPERCAP  0.2386307  0.3469212   0.688   0.4920    
CHILDCARE       0.2530507  0.1021841   2.476   0.0137 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8358 on 350 degrees of freedom
  (5 observations deleted due to missingness)
Multiple R-squared:  0.04323,    Adjusted R-squared:  0.02136
F-statistic: 1.977 on 8 and 350 DF,  p-value: 0.0485

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.0377, p-value = 0.2462

Correlation Matrix of Predictor Variables:
            MEAT BUSHMEAT  BEANS FISHWET  DAIRY   EGGS CHILDCARE   LITERACY
MEAT       1.000    0.016  0.157   0.009  0.229  0.376    -0.023     -0.028
BUSHMEAT   0.016    1.000 -0.059   0.204 -0.143  0.088     0.073     -0.149
BEANS      0.157   -0.059  1.000   0.078  0.206  0.169    -0.287     -0.145
FISHWET    0.009    0.204  0.078   1.000 -0.054 -0.169     0.097      0.117
DAIRY      0.229   -0.143  0.206  -0.054  1.000  0.076    -0.047      0.079
```

```
EGGS        0.376    0.088  0.169  -0.169  0.076  1.000    -0.045     -0.083
CHILDCARE  -0.023    0.073 -0.287   0.097 -0.047 -0.045     1.000      0.222
LITERACY   -0.028   -0.149 -0.145   0.117  0.079 -0.083     0.222      1.000
```

Cotton and Forest Resources – Multilevel regression with DISTANCE as outcome:

```
Linear mixed model fit by REML t-tests use Satterthwaite approximations to
degrees of freedom [
merModLmerTest]
Formula: DISTANCE ~ COTTON + POPDENS + (1 | VILLAGE)
   Data: survey

REML criterion at convergence: 396.6

Scaled residuals:
    Min      1Q  Median      3Q     Max
-1.8784 -0.7303 -0.0603  0.4703  3.9414

Random effects:
 Groups   Name        Variance Std.Dev.
 VILLAGE  (Intercept) 1.045    1.022
 Residual             2.492    1.578
Number of obs: 104, groups: VILLAGE, 3

Fixed effects:
             Estimate Std. Error        df t value Pr(>|t|)
(Intercept) 3.309e+00  1.454e+00 1.260e+00   2.275    0.221
COTTON      7.272e-03  1.025e+00 1.010e+02   0.007    0.994
POPDENS     1.055e-04  5.267e-02 1.060e+00   0.002    0.999

Correlation of Fixed Effects:
        (Intr) COTTON
COTTON  -0.291
POPDENS -0.886  0.107

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.0884, p-value = 0.04386
```

Cotton and Forest Resources – Logit regression with SCARCITY as outcome:

```
Call:
glm(formula = SCARCITY ~ COTTON + VILLAGE, family = "binomial",
    data = survey)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5895  -1.1543   0.8356   0.9455   1.2515

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)     0.7433     0.6771   1.098    0.272
COTTON          0.3836     1.3559   0.283    0.777
VILLAGEKISSA   -0.2689     0.5632  -0.478    0.633
VILLAGEWASADA  -0.9159     0.6162  -1.486    0.137

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 140.30  on 103  degrees of freedom
Residual deviance: 136.22  on 100  degrees of freedom
```

```
  (10 observations deleted due to missingness)
AIC: 144.22

Number of Fisher Scoring iterations: 4

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.3352, p-value < 2.2e-16
```

Cotton and Forest Resources – Simple regression with BIODIVERSITY as outcome:

```
Call:
lm(formula = BIODIVERSITY ~ COTTON + POPDENS, data = survey)

Residuals:
     Min       1Q   Median       3Q      Max
-0.58302 -0.33728 -0.03567  0.28713  0.60134

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.818385   0.119539  31.943  < 2e-16 ***
COTTON      -0.706975   0.195657  -3.613 0.000456 ***
POPDENS     -0.009153   0.003238  -2.827 0.005582 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3561 on 111 degrees of freedom
Multiple R-squared:  0.1218,     Adjusted R-squared:  0.106
F-statistic: 7.696 on 2 and 111 DF,  p-value: 0.0007414

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.1517, p-value = 8.717e-07
```

Forest Resources and Health – Multilevel regression with DEATHS as outcome:

```
Linear mixed model fit by REML t-tests use Satterthwaite approximations to
degrees of freedom [
merModLmerTest]
Formula: DEATHS ~ BIODIVERSITY + DISTANCE + SCARCITY + POPDENS +
LITERACYPERCAP +      (1 | VILLAGE)
   Data: survey

REML criterion at convergence: -121.2

Scaled residuals:
    Min      1Q  Median      3Q     Max
-0.7745 -0.5582 -0.2888  0.0886  5.4458

Random effects:
 Groups   Name        Variance  Std.Dev.
 VILLAGE  (Intercept) 1.369e-06 0.00117
 Residual             1.242e-02 0.11143
Number of obs: 101, groups: VILLAGE, 3

Fixed effects:
                 Estimate Std. Error         df t value Pr(>|t|)
(Intercept)    -0.0100597  0.1147252  0.0000000  -0.088    1.000
BIODIVERSITY    0.0133250  0.0331437  0.0000000   0.402    1.000
DISTANCE       -0.0037664  0.0072583 95.0000000  -0.519    0.605
```

```
SCARCITY       -0.0003843  0.0232469 95.0000000  -0.017    0.987
POPDENS         0.0018679  0.0011357  0.0000000   1.645    1.000
LITERACYPERCAP -0.0746754  0.0722611 95.0000000  -1.033    0.304

Correlation of Fixed Effects:
            (Intr) BIODIV DISTAN SCARCI POPDEN
BIODIVERSIT -0.920
DISTANCE     0.143 -0.377
SCARCITY    -0.293  0.124  0.106
POPDENS     -0.451  0.201 -0.026  0.148
LITERACYPER  0.236 -0.337  0.075 -0.075 -0.173

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.2317, p-value = 1.239e-14
```

Forest Resources and Health – Multilevel regression with MUAC as outcome:

```
Linear mixed model fit by REML t-tests use Satterthwaite approximations to
degrees of freedom [
merModLmerTest]
Formula: MUAC ~ BIODIVERSITY + DISTANCE + SCARCITY + CHILDCARE + (1 |
VILLAGE)
   Data: health

REML criterion at convergence: 861.8

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.3280 -0.6486 -0.0133  0.5976  4.6619

Random effects:
 Groups   Name        Variance  Std.Dev.
 VILLAGE  (Intercept) 9.534e-15 9.764e-08
 Residual             7.069e-01 8.408e-01
Number of obs: 341, groups: VILLAGE, 3

Fixed effects:
              Estimate Std. Error        df t value Pr(>|t|)
(Intercept)   -2.87238    0.42211 336.00000  -6.805 4.66e-11 ***
BIODIVERSITY   0.39583    0.14104 336.00000   2.807   0.0053 **
DISTANCE      -0.01389    0.03239 336.00000  -0.429   0.6683
SCARCITY      -0.04767    0.09476 336.00000  -0.503   0.6153
CHILDCARE      0.14396    0.10644 336.00000   1.352   0.1771
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
            (Intr) BIODIV DISTAN SCARCI
BIODIVERSIT -0.866
DISTANCE     0.132 -0.419
SCARCITY    -0.179  0.023  0.159
CHILDCARE   -0.010 -0.404  0.163 -0.053

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.0542, p-value = 0.01743
```

Cotton and Health – Simple linear regression with DEATHS as outcome:

```
Call:
lm(formula = DEATHS ~ COTTON + LITERACYPERCAP + POPDENS, data = survey)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.08731 -0.06215 -0.02853  0.01038  0.61447 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)  
(Intercept)     0.026686   0.041787   0.639   0.5245  
COTTON         -0.021939   0.065954  -0.333   0.7401  
LITERACYPERCAP -0.070726   0.066407  -1.065   0.2893  
POPDENS         0.001863   0.001023   1.822   0.0714 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1071 on 104 degrees of freedom
  (6 observations deleted due to missingness)
Multiple R-squared:  0.04454,	Adjusted R-squared:  0.01698 
F-statistic: 1.616 on 3 and 104 DF,  p-value: 0.1902

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.239, p-value < 2.2e-16
```

Cotton and Health – Simple linear regression with MUAC as outcome:

```
Call:
lm(formula = MUAC ~ COTTON + CHILDCARE, data = health)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.4502 -0.5540  0.0224  0.5030  3.6566 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -1.55921    0.19799  -7.875 4.15e-14 ***
COTTON      -0.64979    0.26982  -2.408   0.0165 *  
CHILDCARE    0.23694    0.09572   2.475   0.0138 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8313 on 356 degrees of freedom
  (5 observations deleted due to missingness)
Multiple R-squared:  0.03742,	Adjusted R-squared:  0.03201 
F-statistic: 6.919 on 2 and 356 DF,  p-value: 0.001127

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.0296, p-value = 0.6207
```

Cotton and Health – Simple linear regression with VILLAGE dummy variable:

```
Call:
lm(formula = MUAC ~ COTTON + CHILDCARE + VILLAGE, data = health)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.5632 -0.5186  0.0082  0.4883  3.8428 
```

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)    -1.5147     0.2308  -6.564 1.87e-10 ***
COTTON         -0.3731     0.3179  -1.174    0.241
CHILDCARE       0.1559     0.1011   1.542    0.124
VILLAGEKISSA   -0.1357     0.1199  -1.131    0.259
VILLAGEWASADA   0.1466     0.1308   1.121    0.263
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.827 on 354 degrees of freedom
  (5 observations deleted due to missingness)
Multiple R-squared:  0.05267,    Adjusted R-squared:  0.04197
F-statistic: 4.921 on 4 and 354 DF,  p-value: 0.0007148

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.039, p-value = 0.2038
```

Landscape-scale Models:

***Variable Summaries*:**

WEIGHT: Weight for Age percentile * 100 (n=21775, individual level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
      0      75     568    1787    2622    9980

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.2385, p-value < 2.2e-16
```

HEIGHT: Height for Age percentile * 100 (n=21775, individual level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
      0      24     413    2069    2937    9980

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.2512, p-value < 2.2e-16
```

ANEMIA: Anemia level of individual in grams per deciliter, adjusted for altitude (n=12775, individual level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  24.00   80.00   91.00   89.54  101.00  178.00

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.064, p-value < 2.2e-16
```

PERSWID: Percent of agricultural pixels within a given buffer of a village that were classified as swidden (n=37, village level).

5-km

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.4101  0.7706  0.8298  0.8191  0.8989  0.9977

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.1204, p-value < 2.2e-16
```

11-km

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.4988  0.7204  0.8290  0.8119  0.9194  0.9821

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.0972, p-value < 2.2e-16
```

25-km

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.4737  0.7650  0.8232  0.8083  0.8782  0.9838

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.1105, p-value < 2.2e-16
```

COMMONS: Percent of pixels within a given buffer of a village that were classified as neither agriculture nor village land cover types (ie, land cover types providing public ecosystem services) (n=37, village level).

5-km

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.3434  0.7733  0.8470  0.8291  0.8938  0.9911

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.0881, p-value < 2.2e-16
```

11-km

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.3434  0.7733  0.8470  0.8291  0.8938  0.9911

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.0881, p-value < 2.2e-16
```

25-km

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 0.3434  0.7733  0.8470  0.8291  0.8938  0.9911

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.0881, p-value < 2.2e-16
```

POPDENS: People per square kilometer at each commune, from the 2006 national census. (n=37, village level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  6.216  18.500  21.530  25.600  31.390 201.600

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.2391, p-value < 2.2e-16
```

MARKET: Network distance in kilometers to a city with over 20,000 people, from a Harvest Choice dataset (n=37, village level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  1.336   2.631   3.221   3.347   3.731   8.848

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.1562, p-value < 2.2e-16
```

CSCOM: Absolute distance in km to a Centre de la Santé Communitaire - a lower level hospital (n=37, village level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  2.613   5.399   8.754  10.020  14.020  35.780 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.1221, p-value < 2.2e-16
```

CSREF: Absolute distance in km to a Centre de la Santé Référence - a higher level hospital (n=37, village level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  4.015  24.450  40.320  43.740  50.680 110.000 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.1486, p-value < 2.2e-16
```

WEALTH: Ordinal Categorical variable index of household wealth, from the DHS surveys: 1 Poorest; 2 Poorer; 3 Middle; 4 Richer; 5 Richest. (n=186, household level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  1.000   1.000   2.000   2.296   3.000   5.000 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.2002, p-value < 2.2e-16
```

HHSIZE: Number of people living in the household, from the DHS surveys (n=186, household level).

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  2.000   5.000   7.000   7.694  10.000  22.000 

Lilliefors (Kolmogorov-Smirnov) normality test:
D = 0.128, p-value < 2.2e-16
```

HOUSEHOLD: Grouping variable (n=186).

VILLAGE: Grouping variable (n=37).

YEAR: Grouping variable, to capture year level fixed effects between the 2006 and 2012 DHS surveys (n=2).

Model Summaries:

5-km Buffer with WEIGHT as outcome variable:

```
Linear mixed model fit by REML
t-tests use  Satterthwaite approximations to degrees of freedom
['merModLmerTest']
Formula: WEIGHT ~ PERSWID + COMMONS + POPDENS + MARKET + CSCOM + CSREF + 
WEALTH + HHSIZE + (1 | HOUSEHOLD) + (1 | VILLAGE) + (1 | 
    YEAR)
   Data: landscape[landscape$BUFFER == 5000, ]
```

```
REML criterion at convergence: 395999.6

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.2741 -0.6440 -0.1794  0.2807  3.8675

Random effects:
 Groups    Name        Variance Std.Dev.
 HOUSEHOLD (Intercept) 4287753  2071
 VILLAGE   (Intercept)  889319   943
 YEAR      (Intercept)       0     0
 Residual              4462460  2112
Number of obs: 21775, groups: HOUSEHOLD, 184; VILLAGE, 37; YEAR, 2

Fixed effects:
             Estimate Std. Error        df t value Pr(>|t|)
(Intercept) -2916.936   1322.303    34.000  -2.206   0.0343 *
PERSWID      3193.641   1494.433    35.000   2.137   0.0397 *
COMMONS       -43.358    370.594 20767.000  -0.117   0.9069
POPDENS        30.724      6.742    29.000   4.557 8.50e-05 ***
MARKET         72.610    125.212    28.000   0.580   0.5666
CSCOM         -12.485     31.628    27.000  -0.395   0.6961
CSREF          16.700      9.035    29.000   1.848   0.0749 .
WEALTH        130.192     19.533 21527.000   6.665 2.71e-11 ***
HHSIZE         35.592      5.827 21644.000   6.108 1.03e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
        (Intr) PERSWI SAVANN POPDEN MARKET CSCOM  CSREF  WEALTH
PERSWID -0.873
COMMONS -0.127 -0.112
POPDENS -0.597  0.442  0.026
MARKET  -0.286  0.100 -0.005 -0.031
CSCOM    0.164 -0.297 -0.017 -0.188  0.050
CSREF   -0.147  0.015  0.012  0.378 -0.429 -0.391
WEALTH  -0.034 -0.002  0.000 -0.020  0.011  0.006 -0.012
HHSIZE  -0.046  0.001 -0.001  0.009  0.015  0.006  0.002  0.133

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.167, p-value < 2.2e-16

The correlation coefficient between conditional residuals and level 1 random
effects: 0.0273727756415379

The correlation coefficient between conditional residuals and level 2 random
effects: 0.00227826458322065
```

5-km Buffer with HEIGHT as outcome variable

```
Linear mixed model fit by REML
t-tests use  Satterthwaite approximations to degrees of freedom
['merModLmerTest']
Formula: HEIGHT ~ PERSWID + COMMONS + POPDENS + MARKET + CSCOM + CSREF +
WEALTH + HHSIZE + (1 | HOUSEHOLD) + (1 | VILLAGE) + (1 |
    YEAR)
   Data: landscape[landscape$BUFFER == 5000, ]
```

```
REML criterion at convergence: 403601.4

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.1757 -0.6084 -0.1347  0.2745  3.4941

Random effects:
 Groups    Name        Variance Std.Dev.
 HOUSEHOLD (Intercept) 8622239  2936
 VILLAGE   (Intercept) 3926871  1982
 YEAR      (Intercept)       0     0
 Residual              6300154  2510
Number of obs: 21775, groups: HOUSEHOLD, 184; VILLAGE, 37; YEAR, 2

Fixed effects:
             Estimate Std. Error        df t value Pr(>|t|)
(Intercept) -2837.932   2653.874    32.000  -1.069  0.29293
PERSWID      3325.954   2977.987    33.000   1.117  0.27208
COMMONS       -15.927    441.756 21526.000  -0.036  0.97124
POPDENS        30.112     13.845    29.000   2.175  0.03796 *
MARKET        187.151    259.221    28.000   0.722  0.47622
CSCOM         -61.601     65.843    28.000  -0.936  0.35749
CSREF          23.918     18.618    29.000   1.285  0.20908
WEALTH        130.734     23.292 21754.000   5.613 2.01e-08 ***
HHSIZE         20.601      6.944 21743.000   2.967  0.00301 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
        (Intr) PERSWI SAVANN POPDEN MARKET CSCOM  CSREF  WEALTH
PERSWID -0.891
COMMONS -0.074 -0.070
POPDENS -0.607  0.455  0.015
MARKET  -0.292  0.101 -0.003 -0.035
CSCOM    0.172 -0.316 -0.010 -0.193  0.049
CSREF   -0.160  0.031  0.008  0.381 -0.432 -0.389
WEALTH  -0.019 -0.003  0.000 -0.012  0.007  0.004 -0.008
HHSIZE  -0.028  0.001  0.000  0.006  0.009  0.003  0.002  0.134

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.167, p-value < 2.2e-16

The correlation coefficient between conditional residuals and level 1 random
effects: -0.0206892588768401

The correlation coefficient between conditional residuals and level 2 random
effects: 0.00397709107311646
```

5-km Buffer with ANEMIA as outcome variable

```
Linear mixed model fit by REML
t-tests use  Satterthwaite approximations to degrees of freedom
['merModLmerTest']
Formula: ANEMIA ~ PERSWID + COMMONS + POPDENS + MARKET + CSCOM + CSREF +
WEALTH + HHSIZE + (1 | HOUSEHOLD) + (1 | VILLAGE) + (1 |
    YEAR)
```

```
   Data: landscape[landscape$BUFFER == 5000, ]

REML criterion at convergence: 104467.5

Scaled residuals: 
    Min      1Q  Median      3Q     Max 
-4.2225 -0.4986 -0.0026  0.5429  6.1745 

Random effects:
 Groups    Name        Variance Std.Dev.
 HOUSEHOLD (Intercept) 216.818  14.725  
 VILLAGE   (Intercept)  87.441   9.351  
 YEAR      (Intercept)   1.481   1.217  
 Residual              194.514  13.947  
Number of obs: 12775, groups: HOUSEHOLD, 185; VILLAGE, 37; YEAR, 2

Fixed effects:
              Estimate Std. Error         df t value Pr(>|t|)    
(Intercept)  8.362e+01  1.288e+01  1.300e+01   6.493 1.74e-05 ***
PERSWID     -6.823e+00  1.440e+01  1.800e+01  -0.474    0.641    
COMMONS      1.213e-01  2.887e+00  1.250e+04   0.042    0.966    
POPDENS      5.221e-02  6.569e-02  3.100e+01   0.795    0.433    
MARKET      -1.880e-01  1.229e+00  3.000e+01  -0.153    0.879    
CSCOM        1.086e-01  3.123e-01  3.000e+01   0.348    0.730    
CSREF        5.571e-02  8.823e-02  3.100e+01   0.631    0.532    
WEALTH       1.610e+00  2.524e-01  1.165e+04   6.378 1.86e-10 ***
HHSIZE       5.597e-01  7.791e-02  1.091e+04   7.184 7.22e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
        (Intr) PERSWI SAVANN POPDEN MARKET CSCOM  CSREF  WEALTH
PERSWID -0.882                                                 
COMMONS -0.101 -0.093                                          
POPDENS -0.598  0.451  0.021                                   
MARKET  -0.289  0.103 -0.004 -0.034                            
CSCOM    0.166 -0.307 -0.013 -0.192  0.048                     
CSREF   -0.152  0.026  0.011  0.380 -0.432 -0.388              
WEALTH  -0.047 -0.002  0.000 -0.023  0.005 -0.010 -0.003       
HHSIZE  -0.050 -0.010  0.000  0.003  0.007  0.014  0.001  0.217

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.0712, p-value < 2.2e-16

The correlation coefficient between conditional residuals and level 1 random
effects: -0.00722941685425745

The correlation coefficient between conditional residuals and level 2 random
effects: 0.00403526720101505
```

11-km Buffer with WEIGHT as outcome variable

```
Linear mixed model fit by REML
t-tests use  Satterthwaite approximations to degrees of freedom
['merModLmerTest']
```

```
Formula: WEIGHT ~ PERSWID + COMMONS + POPDENS + MARKET + CSCOM + CSREF +
WEALTH + HHSIZE + (1 | HOUSEHOLD) + (1 | VILLAGE) + (1 |      YEAR)
   Data: landscape[landscape$BUFFER == 11000, ]

REML criterion at convergence: 396001.1

Scaled residuals: 
    Min      1Q  Median      3Q     Max 
-2.2697 -0.6434 -0.1796  0.2809  3.8668 

Random effects:
 Groups    Name        Variance Std.Dev.
 HOUSEHOLD (Intercept) 4289484  2071.1  
 VILLAGE   (Intercept)  954275   976.9  
 YEAR      (Intercept)       0     0.0  
 Residual              4462380  2112.4  
Number of obs: 21775, groups: HOUSEHOLD, 184; VILLAGE, 37; YEAR, 2

Fixed effects:
             Estimate Std. Error        df t value Pr(>|t|)    
(Intercept) -2506.889   1427.060    33.000  -1.757  0.08829 .  
PERSWID      2721.455   1670.117    34.000   1.629  0.11244    
COMMONS       -23.317    370.719 21007.000  -0.063  0.94985    
POPDENS        28.199      6.683    30.000   4.219  0.00021 ***
MARKET         80.866    130.634    28.000   0.619  0.54083    
CSCOM          -8.340     32.751    28.000  -0.255  0.80089    
CSREF          15.294      9.362    29.000   1.634  0.11299    
WEALTH        130.242     19.536 21557.000   6.667 2.68e-11 ***
HHSIZE         35.479      5.828 21648.000   6.088 1.16e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
        (Intr) PERSWI SAVANN POPDEN MARKET CSCOM  CSREF  WEALTH
PERSWID -0.886                                                 
COMMONS -0.112 -0.110                                          
POPDENS -0.525  0.356  0.038                                   
MARKET  -0.333  0.164 -0.012 -0.020                            
CSCOM    0.174 -0.300 -0.016 -0.165  0.030                     
CSREF   -0.066 -0.070  0.021  0.361 -0.438 -0.364              
WEALTH  -0.034  0.001 -0.001 -0.019  0.011  0.004 -0.012       
HHSIZE  -0.035 -0.008  0.001  0.006  0.013  0.009  0.002  0.133

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.1662, p-value < 2.2e-16

The correlation coefficient between conditional residuals and level 1 random
effects: -0.0199824878154021

The correlation coefficient between conditional residuals and level 2 random
effects: 0.00384584462043112
```

11-km Buffer with HEIGHT as outcome variable

```
Linear mixed model fit by REML
```

```
t-tests use  Satterthwaite approximations to degrees of freedom
['merModLmerTest']
Formula: HEIGHT ~ PERSWID + COMMONS + POPDENS + MARKET + CSCOM + CSREF +
WEALTH + HHSIZE + (1 | HOUSEHOLD) + (1 | VILLAGE) + (1 |      YEAR)
   Data: landscape[landscape$BUFFER == 11000, ]

REML criterion at convergence: 403601.8

Scaled residuals: 
    Min      1Q  Median      3Q     Max 
-2.1757 -0.6082 -0.1345  0.2753  3.4939 

Random effects:
 Groups    Name        Variance Std.Dev.
 HOUSEHOLD (Intercept) 8628952  2938   
 VILLAGE   (Intercept) 4018929  2005   
 YEAR      (Intercept)       0     0   
 Residual              6300092  2510   
Number of obs: 21775, groups: HOUSEHOLD, 184; VILLAGE, 37; YEAR, 2

Fixed effects:
             Estimate Std. Error        df t value Pr(>|t|)    
(Intercept) -2191.123   2822.513    32.000  -0.776  0.44331    
PERSWID      2569.043   3280.457    33.000   0.783  0.43913    
COMMONS        -5.662    441.760 21535.000  -0.013  0.98977    
POPDENS        26.980     13.427    29.000   2.009  0.05387 .  
MARKET        192.291    264.503    29.000   0.727  0.47316    
CSCOM         -55.070     66.684    28.000  -0.826  0.41584    
CSREF          22.479     18.846    29.000   1.193  0.24254    
WEALTH        130.813     23.292 21754.000   5.616 1.98e-08 ***
HHSIZE         20.559      6.944 21743.000   2.961  0.00307 ** 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
        (Intr) PERSWI SAVANN POPDEN MARKET CSCOM  CSREF  WEALTH
PERSWID -0.902                                                 
COMMONS -0.066 -0.069                                          
POPDENS -0.534  0.372  0.023                                   
MARKET  -0.340  0.166 -0.008 -0.022                            
CSCOM    0.184 -0.320 -0.010 -0.170  0.027                     
CSREF   -0.077 -0.053  0.014  0.362 -0.439 -0.361              
WEALTH  -0.020  0.000  0.000 -0.011  0.007  0.003 -0.008       
HHSIZE  -0.021 -0.005  0.000  0.004  0.008  0.005  0.002  0.134

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.167, p-value < 2.2e-16

The correlation coefficient between conditional residuals and level 1 random
effects: 0.0278275918670557

The correlation coefficient between conditional residuals and level 2 random
effects: 0.00226070338740844
```

11-km Buffer with ANEMIA as outcome variable

```
Linear mixed model fit by REML
```

```
t-tests use  Satterthwaite approximations to degrees of freedom
['merModLmerTest']
Formula: ANEMIA ~ PERSWID + COMMONS + POPDENS + MARKET + CSCOM + CSREF +
WEALTH + HHSIZE + (1 | HOUSEHOLD) + (1 | VILLAGE) + (1 |      YEAR)
   Data: landscape[landscape$BUFFER == 11000, ]

REML criterion at convergence: 104467.5

Scaled residuals: 
    Min      1Q  Median      3Q     Max 
-4.2226 -0.4985 -0.0025  0.5428  6.1743 

Random effects:
 Groups    Name        Variance Std.Dev.
 HOUSEHOLD (Intercept) 216.6702 14.7197 
 VILLAGE   (Intercept)  87.9671  9.3791 
 YEAR      (Intercept)   0.6177  0.7859 
 Residual              194.5154 13.9469 
Number of obs: 12775, groups: HOUSEHOLD, 185; VILLAGE, 37; YEAR, 2

Fixed effects:
              Estimate Std. Error         df t value Pr(>|t|)    
(Intercept)  8.195e+01  1.346e+01  1.000e+01   6.090 0.000109 ***
PERSWID     -4.880e+00  1.564e+01  1.300e+01  -0.312 0.759841    
COMMONS      9.009e-02  2.887e+00  1.252e+04   0.031 0.975106    
POPDENS      5.849e-02  6.317e-02  3.100e+01   0.926 0.361651    
MARKET      -1.928e-01  1.243e+00  3.000e+01  -0.155 0.877729    
CSCOM        9.753e-02  3.137e-01  3.000e+01   0.311 0.758026    
CSREF        5.794e-02  8.858e-02  3.100e+01   0.654 0.517835    
WEALTH       1.609e+00  2.524e-01  1.165e+04   6.376 1.88e-10 ***
HHSIZE       5.600e-01  7.794e-02  1.092e+04   7.185 7.15e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
        (Intr) PERSWI SAVANN POPDEN MARKET CSCOM  CSREF  WEALTH
PERSWID -0.894                                                 
COMMONS -0.091 -0.093                                          
POPDENS -0.529  0.367  0.031                                   
MARKET  -0.337  0.167 -0.010 -0.022                            
CSCOM    0.182 -0.315 -0.013 -0.169  0.026                     
CSREF   -0.074 -0.057  0.019  0.362 -0.440 -0.361              
WEALTH  -0.048  0.002  0.000 -0.022  0.006 -0.011 -0.003       
HHSIZE  -0.032 -0.028  0.001 -0.003  0.003  0.020  0.003  0.217

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.0712, p-value < 2.2e-16

The correlation coefficient between conditional residuals and level 1 random
effects: -0.00716815990409958

The correlation coefficient between conditional residuals and level 2 random
effects: 0.00403649976282376
```

25-km Buffer with WEIGHT as outcome variable

```
Linear mixed model fit by REML
```

```
t-tests use  Satterthwaite approximations to degrees of freedom
['merModLmerTest']
Formula: WEIGHT ~ PERSWID + COMMONS + POPDENS + MARKET + CSCOM + CSREF +
WEALTH + HHSIZE + (1 | HOUSEHOLD) + (1 | VILLAGE) + (1 |      YEAR)
   Data: landscape[landscape$BUFFER == 25000, ]

REML criterion at convergence: 395999.4

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.2715 -0.6440 -0.1803  0.2812  3.8664

Random effects:
 Groups    Name        Variance Std.Dev.
 HOUSEHOLD (Intercept) 4287715  2070.7
 VILLAGE   (Intercept)  902773   950.1
 YEAR      (Intercept)       0     0.0
 Residual              4462429  2112.4
Number of obs: 21775, groups: HOUSEHOLD, 184; VILLAGE, 37; YEAR, 2

Fixed effects:
             Estimate Std. Error        df t value Pr(>|t|)
(Intercept) -3456.923   1599.233    34.000  -2.162  0.03775 *
PERSWID      3851.622   1872.190    35.000   2.057  0.04710 *
COMMONS       -20.010    369.651 19807.000  -0.054  0.95683
POPDENS        26.473      6.175    30.000   4.287  0.00017 ***
MARKET        136.191    132.954    28.000   1.024  0.31434
CSCOM          -4.340     30.969    28.000  -0.140  0.88955
CSREF          13.052      9.242    29.000   1.412  0.16838
WEALTH        129.719     19.535 21552.000   6.640 3.21e-11 ***
HHSIZE         35.427      5.828 21648.000   6.079 1.23e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
        (Intr) PERSWI SAVANN POPDEN MARKET CSCOM  CSREF  WEALTH
PERSWID -0.914
COMMONS -0.108 -0.086
POPDENS -0.346  0.168  0.069
MARKET  -0.459  0.331 -0.023 -0.024
CSCOM    0.090 -0.187 -0.035 -0.095  0.016
CSREF    0.051 -0.176  0.028  0.372 -0.460 -0.358
WEALTH  -0.017 -0.014  0.001 -0.023  0.006  0.008 -0.009
HHSIZE  -0.026 -0.012  0.001  0.007  0.010  0.009  0.004  0.133

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.166, p-value < 2.2e-16

The correlation coefficient between conditional residuals and level 1 random
effects: -0.0195293469814163

The correlation coefficient between conditional residuals and level 2 random
effects: 0.00383163240007301
```

25-km Buffer with HEIGHT as outcome variable

```
Linear mixed model fit by REML
```

```
t-tests use  Satterthwaite approximations to degrees of freedom
['merModLmerTest']
Formula: HEIGHT ~ PERSWID + COMMONS + POPDENS + MARKET + CSCOM + CSREF +
WEALTH + HHSIZE + (1 | HOUSEHOLD) + (1 | VILLAGE) + (1 |      YEAR)
   Data: landscape[landscape$BUFFER == 25000, ]

REML criterion at convergence: 403600.5

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.1756 -0.6081 -0.1348  0.2747  3.4937

Random effects:
 Groups    Name        Variance Std.Dev.
 HOUSEHOLD (Intercept) 8619289  2936
 VILLAGE   (Intercept) 3862116  1965
 YEAR      (Intercept)       0     0
 Residual              6300186  2510
Number of obs: 21775, groups: HOUSEHOLD, 184; VILLAGE, 37; YEAR, 2

Fixed effects:
             Estimate Std. Error        df t value Pr(>|t|)
(Intercept) -4027.367   3159.557    33.000  -1.275  0.21139
PERSWID      4813.100   3674.864    34.000   1.310  0.19906
COMMONS       -12.275    441.291 21407.000  -0.028  0.97781
POPDENS        26.127     12.448    29.000   2.099  0.04463 *
MARKET        274.453    270.852    29.000   1.013  0.31942
CSCOM         -55.457     63.322    28.000  -0.876  0.38851
CSREF          19.232     18.714    29.000   1.028  0.31253
WEALTH        130.543     23.292 21755.000   5.605 2.11e-08 ***
HHSIZE         20.530      6.944 21743.000   2.957  0.00311 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
        (Intr) PERSWI SAVANN POPDEN MARKET CSCOM  CSREF  WEALTH
PERSWID -0.926
COMMONS -0.065 -0.054
POPDENS -0.358  0.188  0.042
MARKET  -0.464  0.329 -0.014 -0.023
CSCOM    0.097 -0.207 -0.022 -0.094  0.011
CSREF    0.044 -0.165  0.019  0.368 -0.461 -0.352
WEALTH  -0.010 -0.008  0.000 -0.014  0.004  0.005 -0.006
HHSIZE  -0.016 -0.007  0.000  0.005  0.006  0.005  0.003  0.134

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.167, p-value < 2.2e-16

The correlation coefficient between conditional residuals and level 1 random
effects: 0.027801953390623

The correlation coefficient between conditional residuals and level 2 random
effects: 0.00226198261061631
```

25-km Buffer with ANEMIA as outcome variable

```
Linear mixed model fit by REML
```

```
t-tests use  Satterthwaite approximations to degrees of freedom
['merModLmerTest']
Formula: ANEMIA ~ PERSWID + COMMONS + POPDENS + MARKET + CSCOM + CSREF +
WEALTH + HHSIZE + (1 | HOUSEHOLD) + (1 | VILLAGE) + (1 |      YEAR)
   Data: landscape[landscape$BUFFER == 25000, ]

REML criterion at convergence: 104467.2

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.2228 -0.4986 -0.0025  0.5429  6.1740

Random effects:
 Groups    Name        Variance Std.Dev.
 HOUSEHOLD (Intercept) 216.710  14.721
 VILLAGE   (Intercept)  87.815   9.371
 YEAR      (Intercept)   1.436   1.198
 Residual              194.515  13.947
Number of obs: 12775, groups: HOUSEHOLD, 185; VILLAGE, 37; YEAR, 2

Fixed effects:
              Estimate Std. Error         df t value Pr(>|t|)
(Intercept)  8.295e+01  1.551e+01  9.000e+00   5.347 0.000554 ***
PERSWID     -5.944e+00  1.801e+01  1.100e+01  -0.330 0.747805
COMMONS      6.155e-02  2.882e+00  1.232e+04   0.021 0.982960
POPDENS      6.270e-02  5.970e-02  3.100e+01   1.050 0.301647
MARKET      -2.717e-01  1.300e+00  3.100e+01  -0.209 0.835797
CSCOM        8.296e-02  3.036e-01  3.000e+01   0.273 0.786540
CSREF        6.192e-02  8.976e-02  3.200e+01   0.690 0.495332
WEALTH       1.611e+00  2.524e-01  1.166e+04   6.381 1.83e-10 ***
HHSIZE       5.602e-01  7.795e-02  1.092e+04   7.187 7.08e-13 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
        (Intr) PERSWI SAVANN POPDEN MARKET CSCOM  CSREF  WEALTH
PERSWID -0.920
COMMONS -0.088 -0.070
POPDENS -0.347  0.177  0.057
MARKET  -0.464  0.335 -0.018 -0.025
CSCOM    0.089 -0.195 -0.030 -0.095  0.012
CSREF    0.054 -0.174  0.025  0.369 -0.464 -0.352
WEALTH  -0.027 -0.014  0.001 -0.027  0.001 -0.008  0.000
HHSIZE  -0.019 -0.032  0.001  0.002 -0.004  0.018  0.007  0.218

Lilliefors (Kolmogorov-Smirnov) normality test of residuals:
D = 0.0712, p-value < 2.2e-16

The correlation coefficient between conditional residuals and level 1 random
effects: -0.00708978711959713

The correlation coefficient between conditional residuals and level 2 random
effects: 0.0040442759067882
```

APPENDIX 2: SURVEY INSTRUMENT

Date: ________________ **Circle one: Yanfolila Kolondieba** **Household number:** ________________

Cultural Consensus Questions

1	I could not feed my family without cotton	1	2	3	4	5
2	I choose to grow crops if they taste good	1	2	3	4	5
3	I choose to grow crops if it's what my people grow	1	2	3	4	5
4	I choose to grow crops if it is nutritious	1	2	3	4	5
5	I choose to grow crops if it makes financial sense	1	2	3	4	5
6	We do not have to worry about conserving resources because Allah will provide for us	1	2	3	4	5
7	The land is changing quickly from how it used to be	1	2	3	4	5
8	There is not as much forest as there used to be	1	2	3	4	5
9	We should have more chances to grow cash crops	1	2	3	4	5
10	Malnutrition is a problem here	1	2	3	4	5
11	Lack of money is a problem here	1	2	3	4	5
12	Forests are important and should be conserved	1	2	3	4	5
13	It is bad to give children eggs	1	2	3	4	5
14	Modern (toubabou) farming techniques are better	1	2	3	4	5
15	Traditional (Bamanan) farming techniques are better	1	2	3	4	5
16	It is necessary to go hunting to feed my household	1	2	3	4	5
17	We must respect the rules of forest resource use	1	2	3	4	5
18	Synthetic fertilizer is better than organic fertilizer	1	2	3	4	5
19	Organic fertilizer is better than synthetic fertilizer	1	2	3	4	5
20	There is too much garbage in the village.	1	2	3	4	5
21	Trees have spirits/souls	1	2	3	4	5
22	There are demons and spirits in the forest.	1	2	3	4	5

Date: ________________ **Circle one: Yanfolila Kolondieba** **Household number:** ________________

Forest Resources

	How often do you collect it when it is in season?	Is this product increasing, decreasing, or stable in abundance?	Do you do anything to encourage this product?	How far into the forest do you have to go to find this?
Shea				
Nere				
Timber				
Firewood				
Fruits				
Nabulu				
Medicine				
Animal Fodder				

Livestock

For each:	How many do you own?
Goats	
Sheep	
Cows	
Horse	
Chicken	
Kami	
Donkey	
Duck	

Date: ________________ **Circle one: Yanfolila Kolondieba** **Household number:** ________________

Farming

	In 2013:	In 2014:
For each crop:	How many hectares did you plant?	Haw many hectares have you planted?
Maize		
Sorghum		
Pearl Millet		
Rice		
Peanuts		
Beans (Cowpeas)		
Bambara Groundnuts		
Sesame		
Fonio		
Da		

For each field that you own: List here farmers' description of location.	How big is it (ha)?	How many years (incl. this one) have you been farming it?	How long has it been since it was cleared?	Do you plan to leave it fallow? If so, in how many years? (not incl. this one)

Agroforestry

Do you grow the following trees?	
Mangoes	
Lemons	
Oranges	
Eucalyptus	
Gmelinia	
Teak	
Moringa	
Papayas	
Bananas	
Cashews	

Date: ________________ **Circle one: Yanfolila Kolondieba** **Household number: ________________**

Cotton

Is CMDT present here? If so, in 2013:				If not:	
How many hectares of cotton did you grow?	How many kilos did you harvest?	How much did you get per kilo?	How much of your cotton money did you use to buy food? (As percentage)	Where is the nearest CMDT office?	Why isn't CMDT here?

In 2013:	How much did you use total?	How much did it cost?	Where did you go to buy it?	How much did you use per hectare?	For what crops?
Synthetic Fertilizer					
Organic Fertilizer					
Pesticides					
Seeds					

Date: ________________ **Circle one: Yanfolila Kolondieba** **Household number:** ________________

Diet Cont

How Many Times is ____ Served per____		Dairy/Week	
		Eggs/Week	
		Fonio/Week	
Meal/Day		Toh/Week	
Meat/Month		Rice/Week	
Bushmeat/Month		Couscous/Week	
Fish/Month		NakoFenw/Week	
Beans/Month		Peanuts/Week	
Fish/Month		Beans/Month	

Gardening

What do you garden?		
Hot peppers		
Tomatoes		
Bitter Eggplant		
Eggplant		
Okra		
Da		

Child Health

For each child that has returned in the past five years:	
How did they return?	How old were they?

For each living child:								
Have they had malaria before?	Have they had vaccines before?	Have they had a pill for worms in the last 6 months?	Have they had diarrhea in the past two weeks?	Have they had a fever in the past two weeks?	Have they been the the hospital in		Mid-Upper Arm Circumference
					Year	5 years	

Date: ________________ **Circle one: Yanfolila Kolondieba** **Household number:** ________________

Household Info

For each person:				
Number	Relation to household head	Age	Education completed	Have they been sick for at least 3 of the last 12 months?
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				
11				
12				
13				
14				
15				
16				

Diet

What plants do you collect for Nabulu?

In the past month, did you buy:		Where?
Sugar		
Flower		
Salt		
Maggi		
Tomatoes		
Yams		
Rice		
Beans		
Potatoes		
Hot Peppers		
Bitter Eggplan		
Eggplant		
Sweet Potatoes		
Cassava		
Oil		

REFERENCES

Agarwala, M., G. Atkinson, B. P. Fry, K. Homewood, S. Mourato, J. M. Rowcliffe, G. Wallace & E. Milner-Gulland (2014) Assessing the Relationship Between Human Well-being and Ecosystem Services: A Review of Frameworks. *Conservation and Society,* 12**,** 437.

Anderman, T. L., R. Remans, S. A. Wood, K. DeRosa & R. S. DeFries (2014) Synergies and tradeoffs between cash crop production and food security: a case study in rural Ghana. *Food Security,* 6**,** 541-554.

Arnold, M. & J. Townson. 1998. *Assessing the potential of forest product activities to contribute to rural incomes in Africa*. Overseas Development Institute London.

Assogbadjo, A. E., R. Glèlè Kakaï, F. G. Vodouhê, C. A. M. S. Djagoun, J. T. C. Codjia & B. Sinsin (2012) Biodiversity and socioeconomic factors supporting farmers' choice of wild edible trees in the agroforestry systems of Benin (West Africa). *Forest Policy and Economics,* 14**,** 41-49.

Bationo, A. & A. Mokwunye. 1991. Role of manures and crop residue in alleviating soil fertility constraints to crop production: With special reference to the Sahelian and Sudanian zones of West Africa. In *Alleviating soil fertility constraints to increased crop production in West Africa*, 217-225. Springer.

Baudron, F., M. Corbeels, F. Monicat & K. E. Giller (2009) Cotton expansion and biodiversity loss in African savannahs, opportunities and challenges for conservation agriculture: a review paper based on two case studies. *Biodiversity and Conservation,* 18**,** 2625-2644.

Bayala, J., R. Kindt, M. Belem & A. Kalinganire (2010) Factors affecting the dynamics of tree diversity in agroforestry parklands of cereal and cotton farming systems in Burkina Faso. *New Forests,* 41**,** 281-296.

Bégué, A., E. Vintrou, D. Ruelland, M. Claden & N. Dessay (2011) Can a 25-year trend in Soudano-Sahelian vegetation dynamics be interpreted in terms of land use change? A remote sensing approach. *Global Environmental Change,* 21**,** 413-420.

Benjaminsen, T. A., J. B. Aune & D. Sidibé (2010) A critical political ecology of cotton and soil fertility in Mali. *Geoforum,* 41**,** 647-656.

Bhutta, Z. A., J. K. Das, A. Rizvi, M. F. Gaffey, N. Walker, S. Horton, P. Webb, A. Lartey, R. E. Black & T. L. N. I. R. Group (2013) Evidence-based interventions for improvement of maternal and child nutrition: what can be done and at what cost? *The Lancet,* 382**,** 452-477.

Bodart, C., A. B. Brink, F. Donnay, A. Lupi, P. Mayaux & F. Achard (2013) Continental estimates of forest cover and forest cover changes in the dry ecosystems of Africa between 1990 and 2000. *J Biogeogr,* 40**,** 1036-1047.

Castella, J.-C., G. Lestrelin, C. Hett, J. Bourgoin, Y. R. Fitriana, A. Heinimann & J.-L. Pfund (2012) Effects of Landscape Segregation on Livelihood Vulnerability: Moving From Extensive Shifting Cultivation to Rotational Agriculture and Natural Forests in Northern Laos. *Human Ecology,* 41**,** 63-76.

Chaplin-Kramer, R., E. Dombeck, J. Gerber, K. A. Knuth, N. D. Mueller, M. Mueller, G. Ziv & A. M. Klein (2014) Global malnutrition overlaps with pollinator-dependent micronutrient production. *Proc Biol Sci,* 281**,** 20141799.

Chowdary, V., K. Yasuyuki & R. Tateishi (2012) Monitoring of Spatio-temporal Land Cover Changes in Part of Oudomxay Province, Northern Mountainous Region of Laos Using Remote Sensing. *Asian Journal of Geoinformatics,* 12.

Coulibaly-Lingani, P., P. Savadogo, M. Tigabu & P.-C. Oden (2011) Factors influencing people's participation in the forest management program in Burkina Faso, West Africa. *Forest Policy and Economics,* 13**,** 292-302.

Cramb, R. A., C. J. P. Colfer, W. Dressler, P. Laungaramsri, Q. T. Le, E. Mulyoutami, N. L. Peluso & R. L. Wadley (2009) Swidden Transformations and Rural Livelihoods in Southeast Asia. *Human Ecology,* 37**,** 323-346.

Dambach, P., V. Machault, J.-P. Lacaux, C. Vignolles, A. Sié & R. Sauerborn (2012) Utilization of combined remote sensing techniques to detect environmental variables influencing malaria vector densities in rural West Africa. *Int J Health Geogr,* 11**,** 10.1186.

De Onis, M., R. Yip & Z. Mei (1997) The development of MUAC-for-age reference data recommended by a WHO Expert Committee. *Bulletin of the World Health Organization,* 75**,** 11.

DeClerck, F. A., J. Fanzo, C. Palm & R. Remans (2011) Ecological approaches to human nutrition. *Food & Nutrition Bulletin,* 32**,** 41S-50S.

Delarue, J., Mesplé-Somps, S., Naudet, J. D., and Robilliard, A. S. (2009) Le paradoxe de Sikasso: coton et pauvreté au Mali. *Développement, Institutions and Analyses*.

Dury, S. & I. Bocoum (2012) Le "paradoxe" de Sikasso (Mali): pourquoi "produire plus" ne suffit-il pas pour bien nourrir les enfants des familles d'agriculteurs? *Cahiers Agricultures*.

Emch, M., C. Feldacker, M. Yunus, P. K. Streatfield, V. DinhThiem & M. Ali (2008) Local environmental predictors of cholera in Bangladesh and Vietnam. *The American journal of tropical medicine and hygiene,* 78**,** 823-832.

Eozenou, P. H.-V., D. Madani & R. Swinkels (2013) Poverty, malnutrition and vulnerability in Mali. *World Bank Policy Research Working Paper*.

Fairhead, J. & M. Leach. 1996. *Misreading the African landscape: society and ecology in a forest-savanna mosaic*. Cambridge University Press.

FAO. 1997. *Agriculture, Food and Nutrition for Africa: A Resource Book for Teachers of Agriculture*. Food & Agriculture Org.

Feintrenie, L., S. Schwarze & P. Levang (2010) Are local people conservationists? Analysis of transition dynamics from agroforests to monoculture plantations in Indonesia.

Golden, C. D., L. C. Fernald, J. S. Brashares, B. R. Rasolofoniaina & C. Kremen (2011) Benefits of wildlife consumption to child nutrition in a biodiversity hotspot. *Proceedings of the National Academy of Sciences,* 108**,** 19653-19656.

González-Esquivel, C. E., M. E. Gavito, M. Astier, M. Cadena-Salgado, E. del-Val, L. Villamil-Echeverri, Y. Merlín-Uribe & P. Balvanera (2015) Ecosystem service trade-offs, perceived drivers, and sustainability in contrasting agroecosystems in central Mexico. *Ecology and Society,* 20.

Gray, J. & C. Song (2013) Consistent classification of image time series with automatic adaptive signature generalization. *Remote Sensing of Environment,* 134**,** 333-341.

Grinblat, Y., G. J. Kidron, A. Karnieli & I. Benenson (2015) Simulating land-use degradation in West Africa with the ALADYN model. *Journal of Arid Environments,* 112**,** 52-63.

Guillou, M. & G. Matheron. 2014. Feeding the World Starts with Fighting Poverty. In *The World's Challenge*, 185-198. Springer.

Heubes, J., K. Heubach, M. Schmidt, R. Wittig, G. Zizka, E.-A. Nuppenau & K. Hahn (2012) Impact of future climate and land use change on non-timber forest product provision in Benin, West Africa: linking niche-based modeling with ecosystem service values. *Economic botany,* 66**,** 383-397.

Hurni, K., C. Hett, A. Heinimann, P. Messerli & U. Wiesmann (2012) Dynamics of Shifting Cultivation Landscapes in Northern Lao PDR Between 2000 and 2009 Based on an Analysis of MODIS Time Series and Landsat Images. *Human Ecology,* 41**,** 21-36.

Ickowitz, A., B. Powell, M. A. Salim & T. C. H. Sunderland (2014) Dietary quality and tree cover in Africa. *Global Environmental Change,* 24**,** 287-294.

Jankowska, M. M., D. Lopez-Carr, C. Funk, G. J. Husak & Z. A. Chafe (2012) Climate change and human health: Spatial modeling of water availability, malnutrition, and livelihoods in Mali, Africa. *Applied Geography,* 33**,** 4-15.

Jeyakumar, A., P. Ghugre & S. Gadhave (2013) Mid-Upper-Arm Circumference (MUAC) as a Simple Measure to Assess the Nutritional Status of Adolescent Girls as Compared With BMI. *ICAN: Infant, Child, & Adolescent Nutrition,* 5**,** 22-25.

Kaimowitz, D. 2003. Not by bread alone… forests and rural livelihoods in sub-Saharan Africa. In *Forests in poverty reduction strategies: capturing the potential. EFI Proceedings*, 45-63.

Kidron, G. J., A. Karnieli & I. Benenson (2010) Degradation of soil fertility following cycles of cotton–cereal cultivation in Mali, West Africa: A first approximation to the problem. *Soil and Tillage Research,* 106**,** 254-262.

Koenig, D. (2008) Rural Development Is More Than Commodity Production. *Hanging by a Thread: Cotton, Globalization, and Poverty in Africa*.

Lacy, S. M. (2008) Cotton Casualties and Cooperatives: Reinventing Farmer Collectives at the Expense of Rural Malian Communities? *Hanging by a Thread: Cotton, Globalization, and Poverty in Africa*.

Laliberte, E., J. A. Wells, F. DeClerck, D. J. Metcalfe, C. P. Catterall, C. Queiroz, I. Aubin, S. P. Bonser, Y. Ding & J. M. Fraterrigo (2010) Land-use intensification reduces functional redundancy and response diversity in plant communities. *Ecology letters,* 13**,** 76-86.

Lambin, E. F., B. L. Turner, H. J. Geist, S. B. Agbola, A. Angelsen, J. W. Bruce, O. T. Coomes, R. Dirzo, G. Fischer & C. Folke (2001) The causes of land-use and land-cover change: moving beyond the myths. *Global environmental change,* 11**,** 261-269.

Laris, P. (2002) Burning the seasonal mosaic: preventative burning strategies in the wooded savanna of southern Mali. *Human Ecology,* 30**,** 155-186.

--- (2008) An Anthropogenic Escape Route from the "Gulliver Syndrome" in the West African Savanna. *Human Ecology,* 36**,** 789-805.

Laris, P. & F. Dembele (2012) Humanizing savanna models: integrating natural factors and anthropogenic disturbance regimes to determine tree–grass dynamics in savannas. *Journal of Land Use Science,* 7**,** 459-482.

Laris, P., J. D. Foltz & B. Voorhees (2015) Taking from cotton to grow maize: The shifting practices of small-holder farmers in the cotton belt of Mali. *Agricultural Systems,* 133**,** 1-13.

Leh, M. D. K., M. D. Matlock, E. C. Cummings & L. L. Nalley (2013) Quantifying and mapping multiple ecosystem services change in West Africa. *Agriculture, Ecosystems & Environment,* 165**,** 6-18.

Li, P., Z. Feng, L. Jiang, C. Liao & J. Zhang (2014) A Review of Swidden Agriculture in Southeast Asia. *Remote Sensing,* 6**,** 1654-1683.

Liebenow, D. K., M. J. Cohen, T. Gumbricht, K. D. Shepherd & G. Shepherd (2012) Do ecosystem services influence household wealth in rural Mali? *Ecological Economics,* 82**,** 33-44.

Linder, H. P., H. M. de Klerk, J. Born, N. D. Burgess, J. Fjeldså & C. Rahbek (2012) The partitioning of Africa: statistically defined biogeographical regions in sub-Saharan Africa. *Journal of Biogeography,* 39**,** 1189-1205.

Liu, J., J. Heiskanen, E. Aynekulu & P. K. E. Pellikka (2015) Seasonal variation of land cover classification accuracy of Landsat 8 images in Burkina Faso. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* XL-7/W3**,** 455-460.

Mavengahama, S., M. McLachlan & W. de Clercq (2013) The role of wild vegetable species in household food security in maize based subsistence cropping systems. *Food Security,* 5**,** 227-233.

McMichael, A. J., S. Friel, A. Nyong & C. Corvalan (2008) Global environmental change and health: impacts, inequalities, and the health sector. *BMJ: British Medical Journal,* 336**,** 191.

Mertz, O., H. M. Ravnborg, G. L. Lövei, I. Nielsen & C. C. Konijnendijk (2007) Ecosystem services and biodiversity in developing countries. *Biodiversity and Conservation,* 16**,** 2729-2737.

Mesplé-Somps, S., D. IRD, P. A.-S. Robilliard & P. J. Gräb (2008) Coton et pauvreté en Afrique de l'Ouest: analyse comparée des conditions de vie des ménages au Mali et au Burkina Faso. *Dial, Paris*.

Meyfroidt, P., E. F. Lambin, K.-H. Erb & T. W. Hertel (2013) Globalization of land use: distant drivers of land change and geographic displacement of land use. *Current Opinion in Environmental Sustainability,* 5**,** 438-444.

Moseley, W. G. & L. C. Gray. 2008. *Hanging by a thread: Cotton, globalization, and poverty in Africa*. Ohio University Press.

Myers, S. S., L. Gaffikin, C. D. Golden, R. S. Ostfeld, K. H. Redford, T. H. Ricketts, W. R. Turner & S. A. Osofsky (2013) Human health impacts of ecosystem alteration. *Proceedings of the National Academy of Sciences,* 110**,** 18753-18760.

Negi, V. S., R. K. Maikhuri & L. S. Rawat (2012) Paradigm and ecological implication of changing agricultural land-use: A case study from Govind Wildlife Sanctuary, Central Himalaya, India. *Journal of Mountain Science,* 9**,** 547-557.

Paré, S., P. Savadogo, M. Tigabu, J. M. Ouadba & P. C. Odén (2009) Consumptive values and local perception of dry forest decline in Burkina Faso, West Africa. *Environment, Development and Sustainability,* 12**,** 277-295.

Parrotta, J., J. de Pryck, B. Obiri, C. Padoch, B. Powell, C. Sandbrook, B. Agarwal, A. Ickowitz, K. Jeary & A. Serban. 2015. The Historical, Environmental and Socio-Economic Context of Forests and Tree-Based Systems for Food Security and Nutrition. International Union of Forest Research Organizations (IUFRO).

Raudsepp-Hearne, C., G. D. Peterson & E. M. Bennett (2010) Ecosystem service bundles for analyzing tradeoffs in diverse landscapes. *Proc Natl Acad Sci U S A,* 107**,** 5242-7.

Remans, R., J. Fanzo, C. A. Palm & F. DeClerck. 2012. Ecology and human nutrition. In *Integrating Ecology and Poverty Reduction*, 53-75. Springer.

Rerkasem, K., D. Lawrence, C. Padoch, D. Schmidt-Vogt, A. D. Ziegler & T. B. Bruun (2009) Consequences of Swidden Transitions for Crop and Fallow Biodiversity in Southeast Asia. *Human Ecology,* 37**,** 347-360.

Robichaud, W. G., A. R. Sinclair, N. Odarkor-Lanquaye & B. Klinkenberg (2001) Stable forest cover under increasing populations of swidden cultivators in central Laos: the roles of intrinsic culture and extrinsic wildlife trade. *analysis,* 1976.

Robledo, C., N. Clot, A. Hammill & B. Riché (2012) The role of forest ecosystems in community-based coping strategies to climate hazards: Three examples from rural areas in Africa. *Forest Policy and Economics,* 24**,** 20-28.

Ruelland, D., F. Levavasseur & A. Tribotté (2010) Patterns and dynamics of land-cover changes since the 1960s over three experimental areas in Mali. *International Journal of Applied Earth Observation and Geoinformation,* 12**,** S11-S17.

Schmook, B., N. van Vliet, C. Radel, M. d. J. Manzón-Che & S. McCandless (2013) Persistence of Swidden Cultivation in the Face of Globalization: A Case Study from Communities in Calakmul, Mexico. *Human Ecology,* 41**,** 93-107.

Schonfeldt, H. C. & N. Gibson Hall (2012) Dietary protein quality and malnutrition in Africa. *British Journal of Nutrition,* 108 Suppl 2**,** S69-76.

Stechert, C., M. Kolb, M. Bahadir, B. A. Djossa & J. Fahr (2014) Insecticide residues in bats along a land use-gradient dominated by cotton cultivation in northern Benin, West Africa. *Environ Sci Pollut Res Int,* 21**,** 8812-21.

Su, S., C. Yang, Y. Hu, F. Luo & Y. Wang (2014) Progressive landscape fragmentation in relation to cash crop cultivation. *Applied Geography,* 53**,** 20-31.

Swinkels, R., P. Eozenou & D. Madani (2013) Poverty, Malnutrition and Vulnerability in Mali. *World Bank Report*.

Tadesse, G., E. Zavaleta, C. Shennan & M. FitzSimmons (2014) Local Ecosystem Service Use and Assessment Vary with Socio-ecological Conditions: A Case of Native Coffee-Forests in Southwestern Ethiopia. *Human Ecology,* 42**,** 873-883.

UNICEF (2009) State of the world's children report. *New York, NY: UNICEF*.

Uusiku, N. P., A. Oelofse, K. G. Duodu, M. J. Bester & M. Faber (2010) Nutritional value of leafy vegetables of sub-Saharan Africa and their potential contribution to human health: A review. *Journal of Food Composition and Analysis,* 23**,** 499-509.

Van Vliet, N., O. Mertz, T. Birch-Thomsen & B. Schmook (2013) Is There a Continuing Rationale for Swidden Cultivation in the 21st Century? *Human Ecology,* 41**,** 1-5.

Vongvisouk, T., O. Mertz, S. Thongmanivong, A. Heinimann & K. Phanvilay (2014) Shifting cultivation stability and change: Contrasting pathways of land use and livelihood change in Laos. *Applied Geography,* 46**,** 1-10.

Wallace, K. J. (2007) Classification of ecosystem services: Problems and solutions. *Biological Conservation,* 139**,** 235-246.

Xiao, R., S. Su, G. Mai, Z. Zhang & C. Yang (2015) Quantifying determinants of cash crop expansion and their relative effects using logistic regression modeling and variance partitioning. *International Journal of Applied Earth Observation and Geoinformation,* 34**,** 258-263.