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THE ASSOCIATION OF DEFORESTATION AND OTHER ENVIRONMENTAL FACTORS WITH CHILD HEALTH AND MORTALITY

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The Association of Deforestation and Other Environmental Factors with Child Health and Mortality

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PREFACE

The Demographic and Health Surveys (DHS) Program is one of the principal sources of international data on fertility, family planning, maternal and child health, nutrition, mortality, environmental health, HIV/AIDS, malaria, and provision of health services.

One of the objectives of The DHS Program is to analyze DHS data and provide findings that will be useful to policymakers and program managers in low- and middle-income countries. DHS Analytical Studies serve this objective by providing in-depth research on a wide range of topics, typically including several countries, and applying multivariate statistical tools and models. These reports are also intended to illustrate research methods and applications of DHS data that may build the capacity of other researchers.

The topics in the DHS Analytical Studies series are selected by The DHS Program in consultation with the U.S. Agency for International Development.

It is hoped that the DHS Analytical Studies will be useful to researchers, policymakers, and survey specialists, particularly those engaged in work in low- and middle-income countries.

Sunita Kishor
Director, The DHS Program

ABSTRACT

This report uses data from the Demographic and Health Surveys (DHS) conducted in 12 countries in sub-Saharan Africa, Asia, and Latin America and the Caribbean to study the associations between environmental variables and child health outcomes, including child mortality. The environmental variables include forest cover, deforestation, vegetation index, proximity to protected area, and proximity to water. These variables were extracted from external sources and linked to DHS data at the cluster level. Unadjusted and adjusted regression models were fit between each environmental variable and each child health outcome—malaria, dietary diversity, stunting, underweight, anemia, diarrhea, and mortality. The results were mixed and showed few significant findings; however, stunting and underweight had more significant findings than other outcomes. Some countries (Chad, Guatemala, and Nepal) exhibited more significant findings than others (for instance, Haiti, Cambodia, and the Dominican Republic). A further analysis was performed on three countries—Malawi, Uganda, and Nepal—by pooling three successive DHS surveys for each country. This analysis also showed mixed results. The main limitation of the analysis was its use of cross-sectional data, which do not allow for inferring causality between the environmental variables and the outcomes. The mixed findings call for further studies, preferably using longitudinal data over long periods of time.

KEY WORDS: forest cover, deforestation, vegetation index, proximity to protected area, proximity to water, spatial covariates, child health, child nutrition, child mortality

1 BACKGROUND

1.1 Deforestation and Forest Cover

Numerous environmental gains have been made over the years across sectors, such as increasing access to improved sources of water and phasing out nearly 100 ozone-depleting substances (UNEP 2016). According to the United Nations Environment Program, however, an estimated 12.6 million deaths worldwide in 2012 were attributable to the environment, including 26% of deaths among children under age 5 (UNEP 2016). The causes include a growing human ecological footprint altering land cover, rivers, and oceans (Foley et al. 2005; Myers, Chase, et al. 2013).

One of the main drivers of environmental degradation is deforestation (Zambrano-Monserrate et al. 2018)—that is, the disappearance of natural forest cover (Bauhoff and Busch 2018). While the world's forests cover 4 billion hectares, making up approximately 31% of the land's surface (Berazneva and Byker 2017), around 7.3 million hectares of forests are lost annually (Margono et al. 2014). Deforestation rates are variable across and within regions. One study found that the tropics experienced both the greatest forest losses and also the greatest gains through regrowth and plantation, but with forest losses exceeding gains (Hansen et al. 2013).

Deforestation affects the structure and functioning of natural ecosystems, and is overwhelmingly associated with overall biodiversity loss. Deforestation is also associated with increases in CO_2 emissions, since trees and forests store large amounts of carbon. Deforestation is the second largest anthropogenic source of carbon dioxide in the atmosphere (Zambrano-Monserrate et al. 2018). Through its impacts on biodiversity, deforestation affects the provision and sustainability of ecosystem services—the economic and non-economic benefits humans derive from nature. Globally, around 1.5 billion people rely on forests for their livelihoods (Berazneva and Byker 2017), and the loss of forest cover directly threatens these livelihoods.

1.2 Effects of Deforestation and Other Environmental Variables on Health

Deforestation and other forms of environmental degradation have important consequences for human health. However, the relationship between environmental conditions and health outcomes is often complex and nonlinear. The studies discussed below highlight linkages between changes in land use and people's health, as well as findings on the association of forest cover and deforestation with child health outcomes such as diarrhea, malaria, and nutrition.

Diarrhea is the second leading cause of death among children under age 5 (Bryce et al. 2005; Liu et al. 2012). Using data from the Malawi Demographic and Health Surveys, one study found that net gain in forest cover over a 10-year period was associated with a 34% decrease in the odds of children experiencing diarrhea; moreover, since forests help improve the quality of drinking water, deforestation was associated with an increased risk of childhood diarrhea (Johnson, Jacob, and Brown 2013). Similarly, another study using DHS data in Cambodia found that deforestation was associated with an increased incidence of diarrhea, but no significant association was found between deforestation and dietary diversity, acute respiratory infection, and malaria (Pienkowski et al. 2017). An additional analysis found that residents who lived downstream from protected forested watersheds were less likely to experience diarrhea than those who lived downstream from watersheds that had experienced forest loss (Pattanayak et al. 2017). A study of 35 developing countries found that upstream tree cover is associated with a lower probability of diarrheal disease, especially in rural households where access to piped water supplies is scarcer (Herrera et al. 2017)—signaling the importance of tree cover in rural areas. In contrast, and highlighting that the relationship between deforestation and health is unlikely to be consistent across regions, a study using data from the Nigeria DHS surveys (2008-2013) showed no impact of deforestation on diarrhea (Berazneva and Byker 2017).

Another major cause of child mortality is malaria (Abubakar, Tillmann, and Banerjee 2015; Bryce et al. 2005; Liu et al. 2012). Roughly a third of the world's population (2 billion people) live in areas with high malaria rates (Pattanayak et al. 2017). Children under age 5 are hit the hardest; 70% of all malaria deaths occur in this age group (WHO 2017a). In Nigeria, 40% of under-five deaths were due to malaria (WHO 2017b). One study in Kenya found that temperature was the best predictor for malaria incidence among children under age 5 (Akachi, Goodman, and Parker 2009). Since deforestation can create hotter micro-climates, there is evidence of its association with increases in mosquito vectors' rates of reproduction and changes in species' behavior, which in turn increase human exposure (Pienkowski et al. 2017). Moreover, the mosquito species that spread malaria were found to be more plentiful in landscapes altered by human activities, where the biting rate is eight times higher in areas of high deforestation compared with areas with low deforestation, suggesting that deforestation promotes malaria risk patterns along the frontier (Olson et al. 2010). Such human alteration of the environment through deforestation creates favorable conditions for increased larval presence and breeding (Vittor et al. 2009). The study in Nigeria cited above found that forest loss significantly increased malaria incidence in the first and second years after loss, and then returned to previous levels in the year after loss (Berazneva and Byker 2017).

The relationship between deforestation and malaria, however, is not uniform. A study that combined satellite data on forest loss with individual-level survey data on more than 60,000 children in 17 African countries found no association between deforestation and increased prevalence of malaria (Bauhoff and Busch 2018). The authors of this study suggest that variations in how deforestation takes place in different regions can account for the divergent observations of malaria incidence. Specifically, Bauhoff et al. (2018) has indicated that deforestation in Africa is largely driven by a slow expansion of smallholder agriculture by long-time residents, as opposed to the rapid clearing for agricultural exports seen in other regions. A recent systematic literature review of 47 studies examining whether deforestation promotes or inhibits malaria transmission in the Amazon concluded that deforestation can either increase or decrease incidence of malaria, depending on context and the specifics of the study (Lima et al. 2017).

While empirical evidence linking forests and broad nutritional outcomes remains limited (Pienkowski et al. 2018), some studies have examined deforestation's short- and long-term impacts on nutrition, and whether it contributes to child morbidity and mortality. Johnson et al. (2013) found that loss of forest cover in Malawi was associated with a 19% reduction in the likelihood of children having a diverse diet, as well as a 29% reduction in the likelihood of consuming foods rich in vitamin A, compared with children living in areas with no net change in forest cover. Similarly, two other analyses of the association between deforestation and diet diversity among children in 15 counties of sub-Saharan Africa found that deforestation was associated with lower diet diversity (Galway, Acharya, and Jones 2018; Jones, Acharya, and Galway 2017). Moreover, an analysis of 21 African countries found a positive relationship between tree cover and dietary diversity, concluding that children living in areas with more tree cover consume more nutritious diets (Ickowitz et al. 2014).

Still, in the same vein as the relationship between deforestation and malaria incidence described above, the study by Ickowitz et al. (2014) found that the relationship between deforestation and nutritional outcomes was nonlinear, and instead followed an inverted U curve. It is unclear what drives the relationship between deforestation and nutritional outcomes, with varying effects on different populations. For example, an analysis of DHS data from nine African countries found that forest cover is associated with worse nutritional outcomes in rural areas, and with better outcomes in urban areas; additionally, there is a frontier effect in forest loss that is associated with worse nutrition in the short term, followed by potential improvements (Pienkowski et al. 2018). In this case, it is possible that forest loss negatively affects nutrition and food security by limiting or eliminating access to wild foods; if, however, the previously forested lands were converted to uses that increased incomes and/or access to crops, the effects of nutritional outcomes could be beneficial. This finding suggests that the deforestation rate may have limited predictive power over nutritional and other outcomes. The time since the deforestation event may also shape the relationship. We can expect that multiple factors simultaneously affect nutritional and health outcomes. For instance, nutrition and disease are associated in that malnutrition predisposes people to disease and vice versa (Akachi, Goodman, and Parker 2009). In summary, deforestation may or may not be a significant driver of a nutritional outcome at a given place and time.

Forest loss can have divergent effects on nutritional outcomes. To feed the world's population we need agriculture, and the loss of forest cover has increased over the centuries in response to population growth and needs for food security. Conversely, when populations depend on wild foods as a safety net in times of food shortage or crop failure, the loss of forests can lower nutritional diversity. For example, in several regions of Africa, people are less able to incorporate leafy greens, bush meat, and wild fruits into their diet when their forests disappear (Ickowitz et al. 2014).

1.3 Links to Child Mortality

Many child deaths in developing countries due to diarrhea, malaria, and malnutrition, among other preventable causes, can be attributed to unsafe water, sanitation, and hygiene, which account for the majority of environmentally related deaths (Liu et al. 2012; Murray and Lopez 1997; Prüss-Ustün et al. 2014). Previous studies that explore how deforestation is linked to health outcomes have largely used DHS or other survey data, and these studies are limited to a cross-sectional rather than longitudinal study design (Bauhoff and Busch 2018; Berazneva and Byker 2017; Golding et al. 2017; Herrera et al. 2017; Olson et al. 2010; Pienkowski et al. 2017). Research examining the relationship between deforestation and child mortality is scarce. However, given that deforestation has been shown to influence child health outcomes that lead to mortality, deforestation could affect child mortality rates.

As previously discussed, deforestation and other forms of environmental change cannot be understood as driving negative health outcomes at all spatial or temporal scales. In places as far apart as the Tennessee Valley and Nigeria, swamps that served as homes for mosquito vectors were drained, which successfully reduced malaria (Myers, Gaffikin, et al. 2013). Similarly, in Cambodia national health outcomes have improved due to the use and exploitation of natural resources during a time of economic development and deforestation (Pienkowski et al. 2017). Therefore, we argue that some level of environmental change is necessary to sustain the health of growing human populations. Agriculture, health infrastructure, roads, industrialization, and global trade can all improve health and increase material standards of living (Myers, Gaffikin, et al. 2013), as well as reduce the abundance of pathogens and their vectors. Nonetheless, while there may be short-term advantages of deforestation and other environmental degradation, their impacts of human activity also have direct and indirect adverse health effects, posing a threat to achieving sustainability and making progress in reducing hunger and poverty (Stephens and Athias 2015).

This report uses DHS data to examine the associations between environmental variables such as forest cover and forest loss and child health outcomes and mortality. Given the cross-sectional nature of the data, only associations are examined, and the study cannot determine if there is a causal link. The report covers three regions of sub-Saharan Africa, Asia, and Latin America and the Caribbean, with four countries from each region. The hypothesis of the analysis is that better environmental conditions, measured here by higher forest cover, low levels of forest loss, high vegetation index, and short distance to a protected area or to water, would be associated with better child health outcomes and lower mortality, after controlling for sociodemographic factors. Due to the country-specific nature of the environmental variables, results are described for each country and presented in alphabetical order within each region. A summary that displays evidence of statistical association between the environmental variables and the outcomes is provided at the end of the Results section.

2 DATA AND METHODS

2.1 Data

As Table 1 shows, the analysis uses data from 12 countries with DHS data, with four countries each from Africa (Chad, Ethiopia, Malawi, Uganda), Asia (Bangladesh, Cambodia, Myanmar, Nepal), and Latin America and the Caribbean (Dominican Republic, Guatemala, Haiti, Honduras). The surveys were selected based on having the highest percentage of rural population (World Bank 2014) from each region with available DHS surveys and GPS data after 2010. A further analysis was performed on three countries that each have three DHS surveys completed near or after 2005—Malawi, Uganda, and Nepal.

Table 1 Countries used in the analysis with the percent rural population

Region	Country	Survey year	% rural (2016)[1]
Sub-Saharan Africa	Chad	2014-15	77
Sub-Saharan Africa	Ethiopia	2016	80
Sub-Saharan Africa	Malawi	2015-16	84
Sub-Saharan Africa	Malawi	2010	-
Sub-Saharan Africa	Malawi	2004	-
Sub-Saharan Africa	Uganda	2016	84
Sub-Saharan Africa	Uganda	2011	-
Sub-Saharan Africa	Uganda	2006	-
Asia	Bangladesh	2014	65
Asia	Cambodia	2014	79
Asia	Myanmar	2015-16	65
Asia	Nepal	2016	81
Asia	Nepal	2011	-
Asia	Nepal	2006	-
Latin America and the Caribbean	Dominican Republic	2013	20
Latin America and the Caribbean	Guatemala	2014-15	48
Latin America and the Caribbean	Honduras	2011-12	45
Latin America and the Caribbean	Haiti	2012	40

[1] Source: World Bank 2014.

2.2 Outcome Variables

The analysis used a total of seven outcomes. Five child health outcomes among children living in the household were estimated from the DHS datasets according to the operational definitions below. The prevalence of malaria, another outcome of interest, was extracted from the Malaria Atlas Project (MAP) and linked to the DHS data at the cluster level (Malaria Atlas Project 2015). MAP uses several indicators to predict malaria prevalence. Some of these indicators are extracted from the DHS surveys, such as rapid diagnostic test (RDT) results from Malaria Indicator Surveys (MIS), percentage of fevers accessing an antimalarial medication, and insect-treated-net (ITN) use. Other indicators used by the MAP project to predict malaria include nighttime lights, vegetation index, land surface temperature, population, and precipitation; however, these indicators were not used in the malaria models in this analysis.

The final outcome is child mortality in the 10 years before the survey. This outcome was coded as a binary variable for any child that was not alive in the last 10 years before the interview date. The mortality outcome can be thought of as a measure of the cumulative effect of the environmental variables on the six health outcomes below.

Inadequate dietary diversity: The proportion of the youngest children age 6 to 23 months living with their mother that consumed less than four food groups in the day or night before the survey. The food groups are: 1. infant formula, milk other than breast milk, cheese or yogurt, or other milk products; 2. foods made from grains, roots, and tubers, including porridge and fortified baby food from grains; 3. vitamin A-rich fruits and vegetables; 4. other fruits and vegetables; 5. eggs; 6. meat, poultry, fish, and shellfish (and organ meats); 7. legumes and nuts. Questions on food consumption were not asked in the Malawi 2004 survey.

Stunting: The proportion of de facto children under age 5 with a height-for-age z-score below the median of the World Health Organization (WHO) 2007 reference population by more than two standard deviations.

Underweight: The proportion of de facto children under age 5 with a weight-for-age z-score below the median of the WHO 2007 reference population by more than two standard deviations.

Any anemia: The proportion of de facto children age 6-59 months with a hemoglobin level less than 11 grams per deciliter. Hemoglobin levels are adjusted for altitude. Among the surveys in Table 1, the DHS surveys completed in Bangladesh in 2014, in Chad in 2014-15, and in the Dominican Republic in 2013 did not perform anemia testing.

Diarrhea: The proportion of children under age 5 who had symptoms of diarrhea in the two weeks before the survey.

2.2 Independent Variables

2.2.1 Environmental variables

Five main environmental variables were examined in relation to the outcomes. These were forest cover, forest loss in the 10 years before the survey (or forest decadal loss), vegetation index, proximity to protected areas, and proximity to water. The extraction procedure of these variables except for the forest cover and forest loss is described in detail in Appendix A. The definition of these variables and the procedure for the extraction of the forest cover and forest loss variables are described below.

Forest-related variables were taken from the Hansen et al. (2013) dataset, which contains data on forest cover since 2000. Due to the lack of data before 2000, the analysis for models that included the decadal forest loss variable was restricted to surveys that occurred after 2010.

The tree canopy cover for year 2000 dataset in the Hansen et al. (2013) data shows the percentage of canopy closure for vegetation taller than five meters within the 1 arc-second, about 30 meters at the equator. For this analysis, we defined a pixel as forested if it had 30% or more canopy closure. This is how the forest cover variable was defined. To control for forest loss, we removed all cells that experienced deforestation in years before the survey year. To streamline the extraction for each year, the data was recoded into a binary variable where 1 was forested and 0 was not. This allowed us to use the sum of the pixels in the radius as the count of forested cells. The forested variable used in this analysis is the proportion of cells that are forested within a 10-kilometer radius of the displaced point.

The Hansen et al. (2013) dataset was also used to compute the decadal forest cover variable. In the dataset, the year of gross forest cover loss event shows the year that a particular cell within the tree cover dataset experienced deforestation. To simplify the extraction for each year, the data was recoded into a binary variable where 1 signified experienced forest loss within the past 10 years and 0 signified did not. The forest-loss variables used in the analysis were computed by calculating the proportion of cells within a 10-kilometer radius of the displaced point that experienced deforestation within the previous 10 years.

A forest cover squared variable was also generated to examine whether a nonlinear relationship exists between forest cover and the outcomes.

The vegetation index variable measures the density of green leaves for each cluster (Didan and Barreto 2016). Values can range from zero (no vegetation) to 10,000 (maximum vegetation). Several measures are prepared as part of the larger dataset; we used the average Enhanced Vegetation Index (EV2) variable for this analysis. The data is available for every five years from 1985 to 2015. The index represents all vegetation in an area, including crops and grassland, not just tree cover. For our analysis the vegetation index was outputted for the years 2005, 2010, and 2015, and the data was matched with survey with the nearest corresponding survey year.

Proximity to protected area is a variable that measures in meters the geodesic distance to the nearest protected area, such as parks and protected forest land, using data from the United Nations Environment World Conservation Monitoring Centre (UNEP-WCMC and IUCN 2017). All protected areas in the dataset were included in the analysis regardless of the level of protection. Proximity to water measures in meters the distance to the nearest water body. We used the Wessel and Smith (2017) definition of a lake (L2) at full resolution as well as their shoreline definition (L1), also at full resolution.

Any missing values for these environmental variables were replaced by the median value of the environmental variable at the strata level (i.e., the combination of region and urban or rural place of residence). All of the environmental variables were standardized before they were used in the analysis. Standardization would not have an effect on the significance result or the direction of the associations in the regression analyses, but would change the magnitude of coefficient values.

2.2.2 Control variables

Several control variables used in all the regression models, including child's age, child's sex, mother's education level (none, primary, secondary, or more), household crowding (number of household members who slept in the household last night divided by the number of rooms used for sleeping), the DHS Wealth Index, nighttime lights, and month of interview. Month of interview was used as a proxy to control for seasonality, as many of the child health outcomes in the analysis vary by season (Handa and Mlay 2006). The nighttime lights variable was extracted from the Earth Observations Group at the National Oceanic and Atmospheric Administration (National Centers for Environmental Information 2015). This variable is considered to be a good measure of urbanization and is based on observations of the average radiance composite images, eliminating stray light, lightning, lunar illuminations, and cloud-cover. Any missing values for nighttime lights were replaced by the median value for the combination of region and place of residence.

Outcome-specific control variables were also included in the models. For the diarrhea outcome, it was important to control for the indicators of improved water and sanitation (Arnold and Colford Jr. 2007; Iijima et al. 2001; Jalan and Ravallion 2003; Raina et al. 1999). For stunting and underweight, the perceived size of the child at birth (small, average, large) was included in the models. This was used instead of recall of exact birth weight, as birth weight has many missing values. Perceived size at birth has been shown to be a good proxy and an important indicator for stunting and underweight (Assaf, Kothari, and Pullum 2015).

2.3 Analysis

2.3.1 Maps

The maps used in the results sections were created in ESRI ArcMap 10.6 software. For the forest cover maps, the publicly available cluster locations were layered on top of the United States State Department's Small-Scale International Boundaries (SSIBs), major lakes and rivers (Wessel and Smith 2017), and a version of the Hansen et al. (2013) tree cover data. The tree cover data show in green the areas that had more than 30% canopy coverage in the year 2000. The cluster locations were symbolized by displaying in blue the clusters that experienced 10% or more deforestation, with the rest shown in dark gray. The country being studied is outlined in red.

For the vegetation index maps, the publicly available cluster locations were layered on top of the SSIBs, major lakes and rivers (Wessel and Smith 2017), and the vegetation index. The Enhanced Vegetation Index from 2015 (Didan and Barreto 2016) was symbolized using a brown to green color ramp. All of the clusters are shown in dark gray, and the country being studied is outlined in red.

2.3.2 Regression analysis for the most recent survey

Separate models, one unadjusted and one adjusted, were fit for each of the five environmental variables—forest cover, decadal forest loss, vegetation index, proximity to protected area, and proximity to water—and the seven child health outcomes. In addition, a separate model was fit for forest cover squared to assess whether a nonlinear relationship was found between forest cover and the health outcomes. The overall hypothesis being tested was that an association exists between the environmental variables and the child health outcomes found in the most recent survey. For deforestation, the hypothesis was that the deforestation in the last 10 years had an effect on the child health outcomes measured in the most recent survey.

The adjusted models include child's age, child's sex, mother's education level, household crowding, wealth quintile, month of interview, and nighttime lights. Some outcome-specific variables were also included in the adjusted models—for the diarrhea outcome, access to improved water and improved sanitation were included; and for the stunting and underweight outcomes, the child's perceived size at birth was included.

Multilevel logistic models were fit for the six outcomes of no dietary diversity, diarrhea, stunting, underweight, anemia, and mortality. This included a random intercept for the cluster to account for spatial dependency. To fit the multilevel model and account for the survey sample design, a weight must be supplied at each level. For confidentiality reasons, the DHS only supplies one weight, which is the combination of the household and cluster weight. This weight was used for the second level. For the individual-level weight, an assumption was made that all persons in the household have an equal weight, and therefore this was used to supply a weight for the first level.

The malaria outcome was the proportion of malaria at the cluster level, and therefore the individual data was collapsed to the cluster level so that the unit of analysis is the cluster, not the child as for the remaining outcomes. The malaria models were fit using a generalized linear model with a binomial family and a logit link function. The adjusted model included cluster-level variables for the proportion of households in the cluster that are in the lowest wealth quintile, the proportion of mothers in the cluster with above-primary level of education, and the mean household crowding in each cluster. These variables were constructed by aggregating data from the individual level to the cluster level. For the malaria outcome, the analysis did not include ITN coverage, vegetation index, and nighttime lights in the models, since these were used in the models to produce the malaria prevalence estimates by the Malaria Atlas Project (Bhatt et al. 2015; Malaria Atlas Project 2015).

For the models that include the forest decadal loss variable, the forest cover in the year 2000 for each country was also included in the model. This was in order to control for the initial forest levels in the country for the unadjusted and the adjusted models for forest loss.

2.3.3 Regression analysis for combined surveys

For three countries—Malawi, Nepal, and Uganda—three surveys from each country were combined to examine more closely the effect of forest cover on the outcomes. The surveys were approximately five years apart, as shown in Table 1. A survey variable was generated with 1 being the earliest survey and 3 the most recent. For this analysis, forest cover was categorized as low (0-9.9% cover), medium (10-29.9% cover), and high (30% and above cover). An interaction term was then generated between the categorical forest cover variable and the survey number. This generated a variable with nine categories (low, medium, and high for each of the three surveys). The model would examine whether changes in forest cover have an effect on the outcome. Including the survey variable in the model would also control for the change in the outcome. Three models were fit for this analysis: the first model uses the low cover in survey 1 as the reference category, the second model uses low cover in survey 2 as the reference, and the third model uses low cover in survey 3 as the reference. This helps indicate whether the change in the forest cover is causing the effect on the outcome versus the change in the survey. To illustrate this further, the Akaike Information Criterion (AIC) of the model with the interaction term was compared with a model with the survey variable not including forest cover. A small change in the AIC would indicate that adding forest cover to the model did not contribute much to the explanation of the outcome, and therefore that most of the effect is due to the change in the outcome over the years and not due to changes in the level of forest cover.

As with the regressions for the most recent survey, multilevel logistic models were fit for all outcomes except malaria. For malaria, a generalized linear model with a binomial family and a logit link function was fit. The same control variables for each outcome that were used for the analysis of the most recent survey were also used in these models.

3 RESULTS

3.1 Description of Outcomes and Environmental Variables

3.1.1 Outcomes

Figure 1 shows the percentage of youngest children age 6-23 months living with their mother that consumed less than four food groups in the day or night before the survey, and the percentage of de facto children age 6-59 months with anemia. Across regions, sub-Saharan Africa had the highest percentages of children age 6-23 months lacking dietary diversity—as high as 90% in Chad, followed closely by Uganda, at 87%—and lowest in Honduras, at 32%. The pattern for anemia is less salient. In sub-Saharan Africa, the percentage of de facto children age 6-59 months with anemia ranged from 49% in the 2011 Uganda survey to 73% in the 2006 Uganda survey. In the Asia region, the percentage of young children with anemia ranged from 46% in Nepal to 58% in Myanmar. In the three countries in Latin America and the Caribbean with data on childhood anemia, prevalence was about two-thirds in Haiti compared with about one-third in Guatemala and Honduras.

Figure 1 Percentage of youngest children age 6-23 months living with their mother that consumed less than four food groups in the day or night before the survey and percentage of de facto children age 6-59 months with anemia

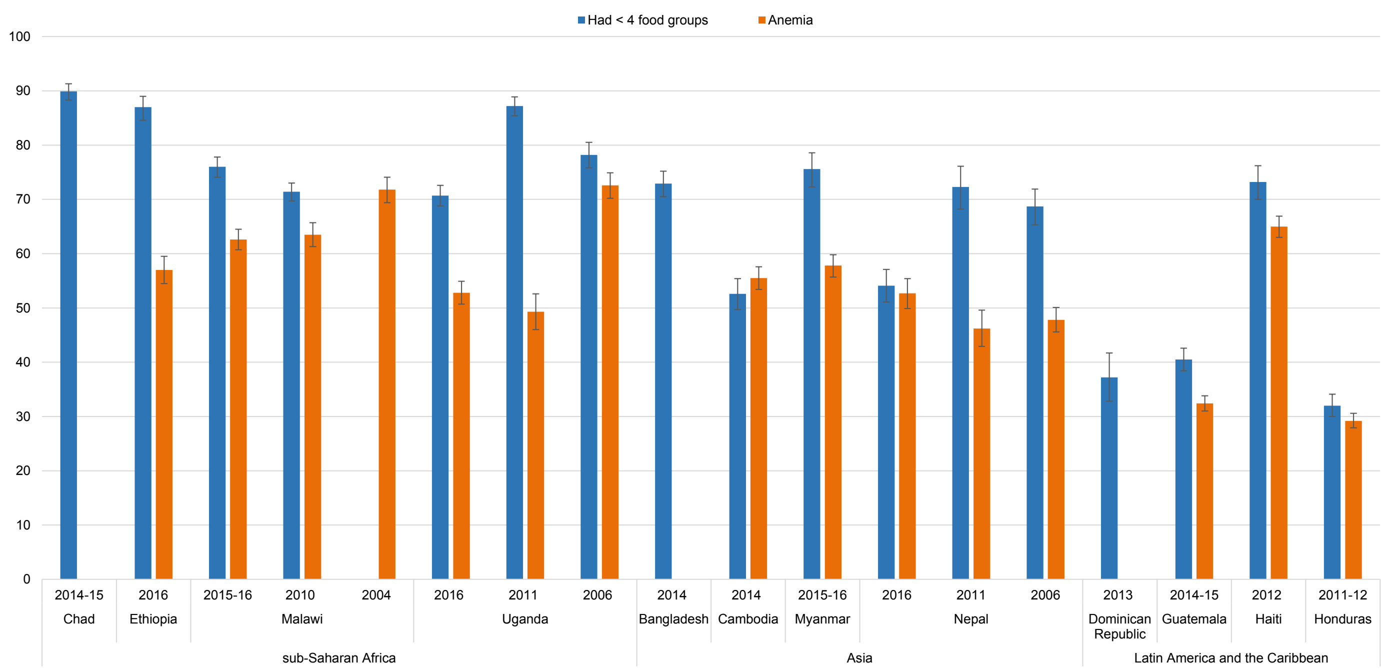
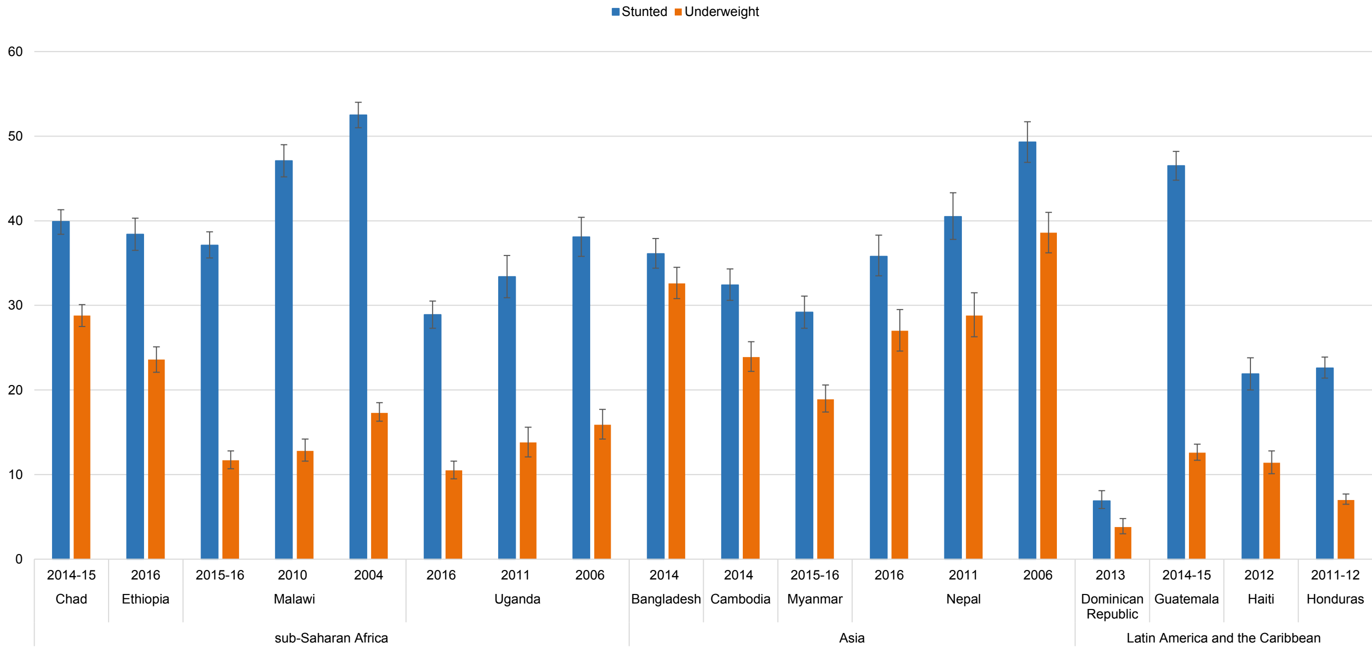


Figure 2 displays the percentage of de facto children under age 5 stunted or underweight. Among countries in the analysis, stunting was most prevalent in Malawi, at 53% of children under age 5, and least prevalent in the Dominican Republic, at 7%. For underweight, Nepal had the highest percentage, at 39%, compared with just 4% in the Dominican Republic. In sub-Saharan Africa, prevalence of underweight was highest in Chad, at 29%. In the Asia region, Nepal had the highest prevalence, at 39%, followed Bangladesh, at 33%. In Latin America and the Caribbean, underweight prevalence was lower, reaching just 13% in Guatemala.

Figure 2 Percentage of de facto children under age 5 stunted or underweight



As Figure 3 shows, the percentage of children under age 5 with symptoms of diarrhea in the two weeks before the survey ranged from a high of 27% in Uganda to just 6% in Bangladesh. Among regions, sub-Saharan Africa had the highest levels of diarrheal symptoms among young children, followed by Latin America and the Caribbean. Across the three DHS surveys studied in Uganda, the percentage of children with symptoms of diarrhea in the two weeks before the survey declined by 6 percentage points between 2006 and 2016.

Figure 3 Percentage of children under age 5 with symptoms of diarrhea in the 2 weeks before the survey

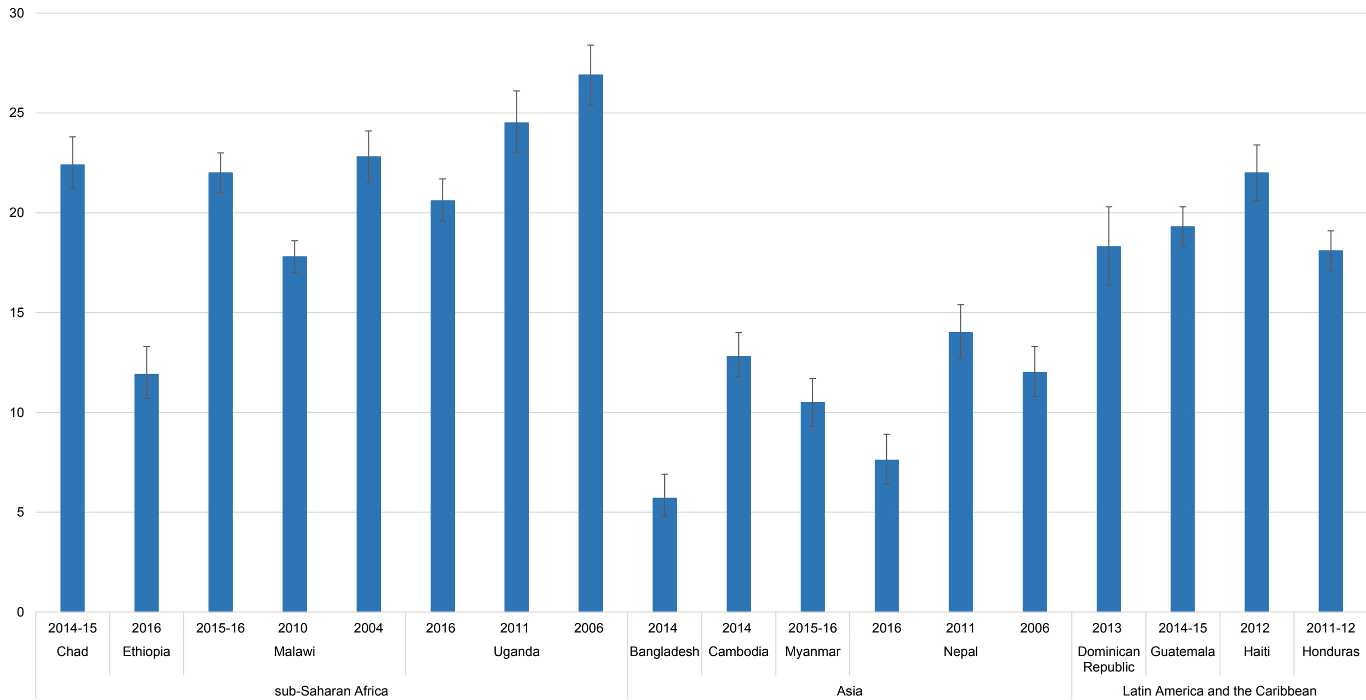


Figure 4 displays estimated malaria rates, which were only available for the sub-Saharan African countries in our study. These data were imported from the MAP project, which provides predicted malaria prevalence at the cluster level, while data for all other outcomes were from the DHS surveys. Ethiopia had the lowest malaria rates, at 0.69% in 2008, while Uganda had the highest, at 47% in 2006. In Uganda, malaria rates were more than cut in half over a decade, to just over a fifth in 2016.

Figure 4 Estimated malaria rates

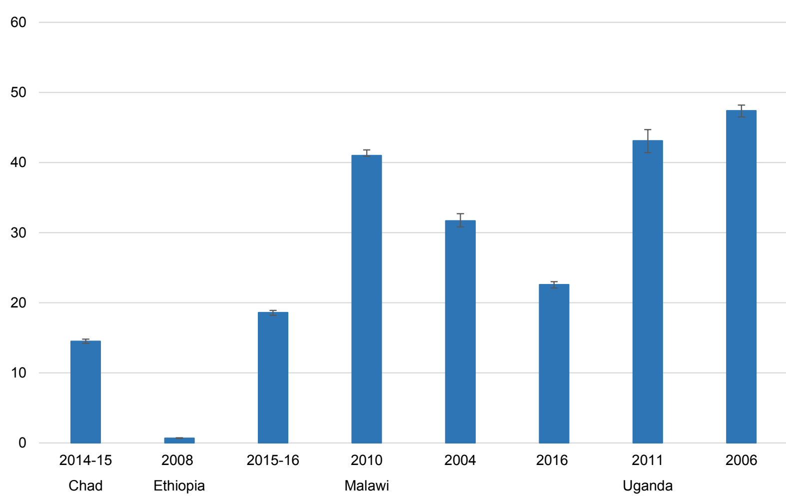
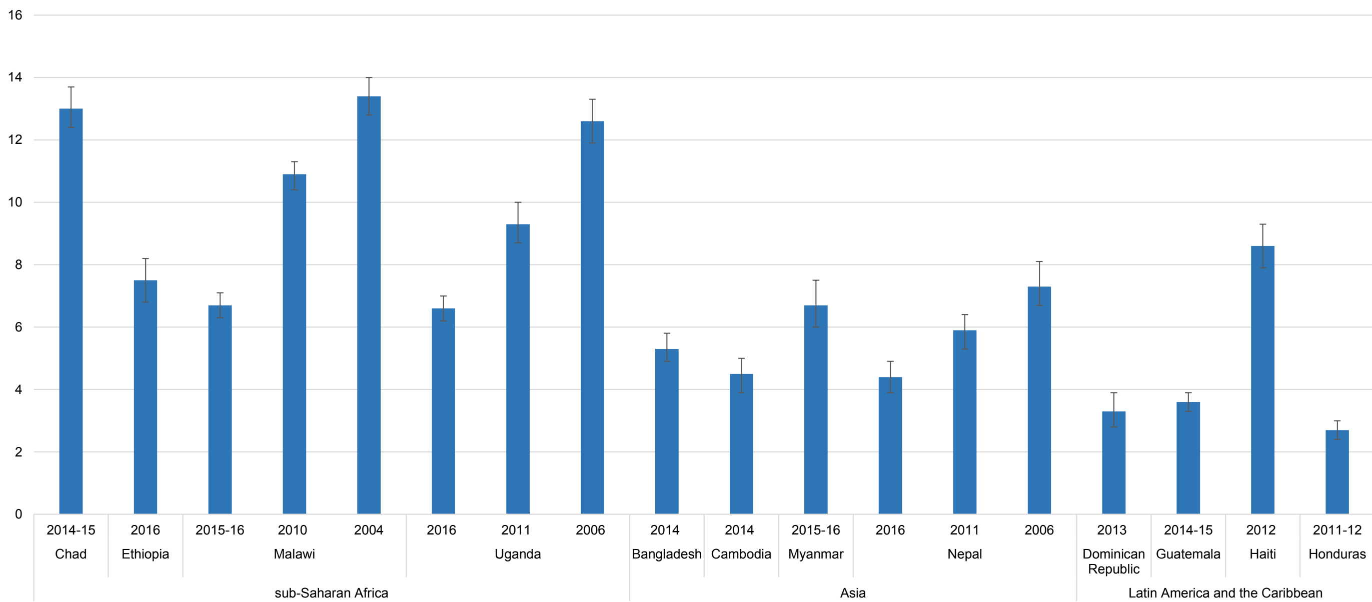


Figure 5 shows the percentage of children who died in the 10 years before the survey. The highest percentages were in sub-Saharan Africa, followed by Latin America and the Caribbean; the Asia region experienced the lowest percentage of child deaths compared with the other regions. Child mortality rates were highest in Malawi in 2004, at 13%, but decreased over the survey years. Mortality rates were lowest in the 2011-12 Honduras survey, at 3%. The percentage of children who died in the 10 years before the survey decreased in all the three countries with multiple surveys. In addition to Malawi, the percentage of child deaths decreased by 6 percentage points in Uganda between the 2006 and 2016 surveys, and Nepal experienced a decreased of nearly 3 percentage points.

Figure 5 Percentage of children who died in the 10 years before the survey



3.1.2 Environmental variables

Table 2 shows the environmental variables included in the analysis in the 12 countries. These environmental variables are forest cover, forest loss in the last 10 years, forest loss in the last five years for three countries, vegetation index, proximity to protected area, and proximity to water. These variables are represented at the cluster level, and the mean as well as the minimum and maximum values are displaced in Table 2.

In sub-Saharan Africa, mean percent forest cover ranged from 0.7% in Chad—which also exhibited the lowest mean percent forest cover in all 12 countries—to 35% in Uganda in the most recent survey. In Asia, Bangladesh had the lowest mean percent forest cover in the region, at 6%, while Nepal had 28% mean percent forest cover. In Latin America and the Caribbean, the mean percent forest cover range is higher compared with Asia and sub-Saharan Africa, ranging from 28% in the Dominican Republic to 54% in Guatemala. For the three countries with three survey years—Malawi, Uganda, and Nepal—where we could observe the change in forest cover over time, forest cover increased in both Malawi and Uganda. In Nepal, however, there was a slight increase in forest cover from 2006 to 2011 and then a decrease from 2011 to 2016.

Forest loss was included in the analysis in the form of two variables at different temporal points of analysis: mean percent forest loss in the 10 years before the survey, and mean percent forest loss in the five years before the survey. In sub-Saharan Africa, Uganda exhibited the highest mean percent forest loss in the last 10 years, at 2.4%, compared with 1.2% in Malawi, and 0.5% in Ethiopia. In the Asia region, Cambodia exhibited the highest mean percent forest loss, at 3.5% compared with 0.3% in Nepal, and 0.2% in Bangladesh. In Latin America and the Caribbean, Guatemala showed the highest mean forest loss (4.8%), while the lowest regional mean forest loss was seen in Haiti (0.7%). For Malawi, Uganda, and Nepal, we performed a further analysis to observe trends, computing the forest loss in the last five years. For Malawi and Uganda, forest loss in the last five years increased across the surveys—for Malawi from 0.2% in 2005 to 0.7% in 2015, and for Uganda from 0.5% in 2005 to 1.6% in 2015. Note that these years do not correspond exactly with the year of the survey, but rather the nearest year with available data. In Nepal, forest loss increased from 0.1% in 2005 to 0.3% in 2010, but decreased again to 0.1% in 2015.

Other environmental variables used in the analysis include vegetation index, proximity to protected area, and proximity to water. Among all countries, Chad had the lowest mean vegetation index, and Honduras had the highest. In regard to proximity to a protected area, Honduras had the lowest mean distance to a protected area in kilometers (km), and Ethiopia had the highest mean distance. In terms of proximity to water, Nepal exhibited the highest mean distance in km to water, followed by Chad, while Haiti had the lowest.

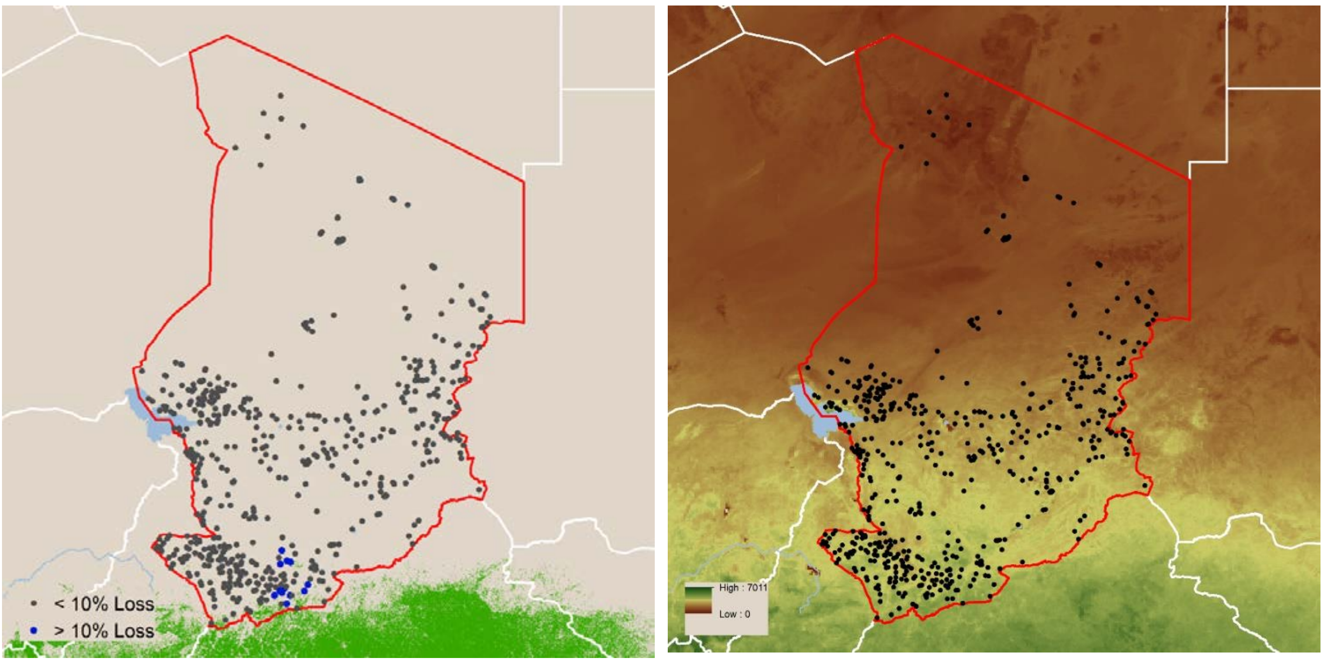
Table 2 Summary of the environmental variables used in the analysis

Region	Country	Survey year	Mean percent forest cover (min, max)	Mean percent forest loss in the 10 years before the survey (min, max)	Mean percent forest lost in the 5 years before the survey (min, max)	Mean vegetation index (min, max)	Mean km distance to protected area (min, max)	Mean km distance to water (min, max)
Sub-Saharan Africa	Chad	2014-15	0.7 (0,50.2)	1.3 (0,18.8)	-	2299 (464,3536)	91 (0,512)	185 (0,959)
Sub-Saharan Africa	Ethiopia	2016	13.4 (0,97.5)	0.5 (0,5.2)	-	2963 (511,5355)	108 (0,657)	107 (0,499)
Sub-Saharan Africa	Malawi	2015-16	7.3 (0,73.7)	1.2 (0,12.8)	0.7 (0,10.0)	2938 (415,4348)	50 (0,132)	53 (0,167)
Sub-Saharan Africa	Malawi	2010	7.9 (0,80.0)	-	0.5 (0,6.0)	3040 (2114, 4412)	46 (0,128)	51 (0,162)
Sub-Saharan Africa	Malawi	2004	8.3 (0,75.8)	-	0.2 (0,3.6)	3013 (1248,4975)	48 (0,125)	53 (0,162)
Sub-Saharan Africa	Uganda	2016	34.7 (0,95.5)	2.4 (0,26.5)	1.6 (0,18.7)	3935 (1600,5572)	68 (0,193)	44 (0,212)
Sub-Saharan Africa	Uganda	2011	36.3 (0,95.6)		1.1 (0,14.8)	3904 (1781,5486)	68 (0,194)	42 (0,230)
Sub-Saharan Africa	Uganda	2006	37.0 (0,97.4)		0.5 (0,3.7)	4033 (2009,5391)	63 (0,191)	48 (0,207)
Asia	Bangladesh	2014	5.8 (0,73.6)	0.2 (0,4.6)	-	2799 (79,4736)	50 (0,130)	58 (0,265)
Asia	Cambodia	2014	10.0 (0,98.8)	3.5 (0,66.1)	-	2933 (1150,5081)	53 (0,109)	40 (0,226)
Asia	Myanmar	2015-16	16.9 (0,95.8)	1.8 (0,27.9)	-	3058 (239,5212)	82 (0,288)	111 (0,438)
Asia	Nepal	2016	27.9 (0,84.0)	0.3 (0,4.2)	0.1 (0,0.6)	3213 (779,4433)	42 (0,128)	238 (81,342)
Asia	Nepal	2011	32.4 (0,82.6)	-	0.3 (0,3.1)	3234 (1620,4229)	41 (0,123)	238 (95,342)
Asia	Nepal	2006	32.2 (0,78.8)	-	0.1 (0,1.1)	3253 (529,4212)	34 (0,105)	175 (74,275)
Latin America and the Caribbean	Dominican Republic	2013	28.1 (2.4,92.7)	2.6 (0.1,10.9)	-	3897 (807,6093)	11 (0,34)	22 (0,93)
Latin America and the Caribbean	Guatemala	2014-15	53.7 (4.1,93.5)	4.8 (0.2,44.2)	-	3942 (1593,5660)	21 (0,101)	47 (0,140)
Latin America and the Caribbean	Honduras	2011-12	51.3 (3.4,95.8)	2.7 (0,20.2)	-	4002 (51,5809)	19 (0,78)	62 (0,214)
Latin America and the Caribbean	Haiti	2012	23.8 (0.4,82.5)	0.7 (0,3.9)	-	3269 (1109,5620)	64 (2,151)	11 (0,57)

3.2 Chad

The maps in Figure 6 show the level of forest cover and deforestation as well as the vegetation index levels. Chad is a landlocked country with very little forest cover and almost no major water source except for Lake Chad, on the western border. Clusters with more than 10% forest loss were found in the south. The vegetation index increases as you move from north to south of the country.

Figure 6 Chad maps: The first map shows the forest cover and forest loss in the last 10 years (blue dots are clusters with more than 10% loss). The second map shows the vegetation index from low (red) to high (green). In both maps the dark dots are the DHS cluster locations.

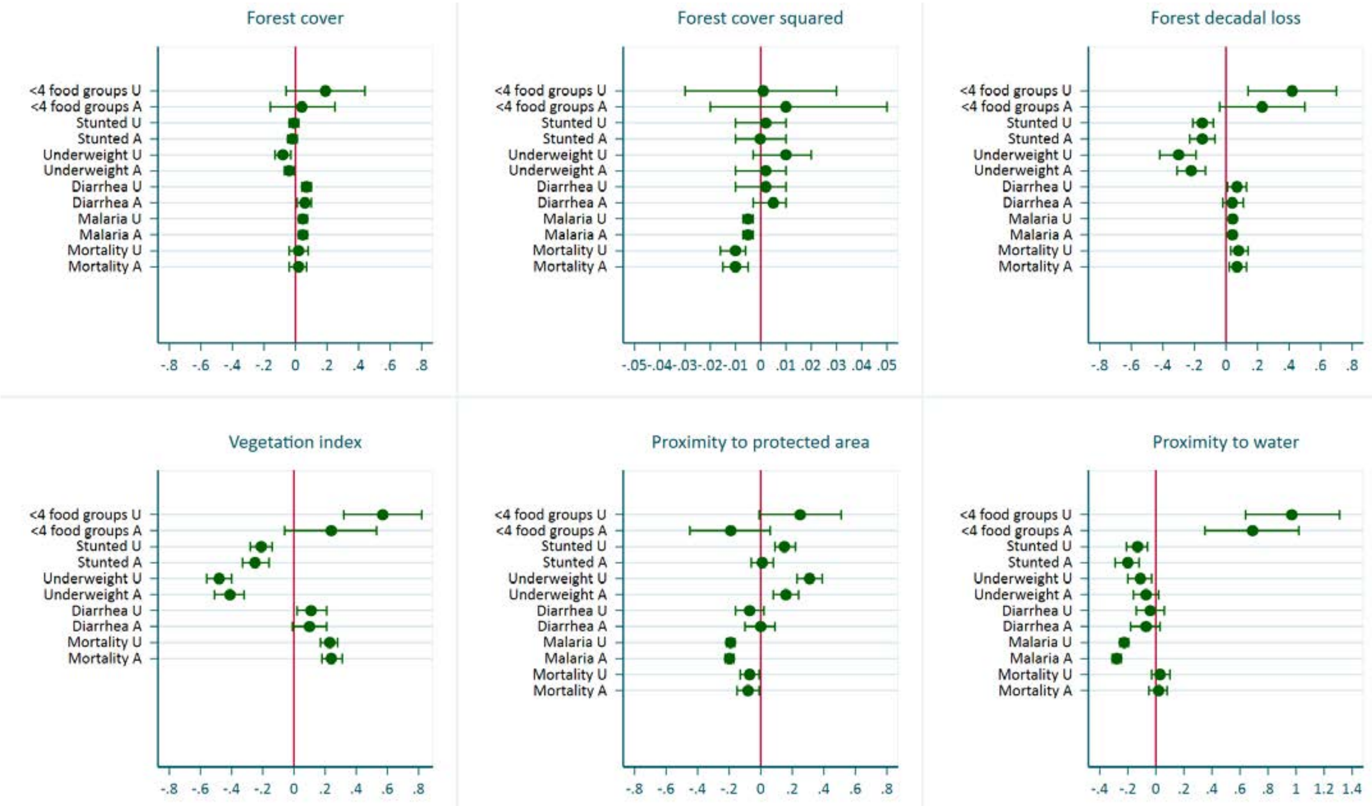


Regression results for the most recent survey

Figure 7 summarizes the results from the regressions of all the environmental variables with the child health outcomes in Chad, including child mortality. It shows both the unadjusted (U) and adjusted (A) coefficients for the environmental variables and the outcomes. Anemia testing was not performed for Chad, and therefore this outcome is not available for analysis. The estimates are also found in Appendix Tables B.2-B.8.

A significant negative association was found between forest cover and underweight, indicating that the higher the forest cover, the less likely children are to be underweight. For diarrhea, the association was positive, with higher forest cover indicating higher likelihood of diarrhea. Malaria also showed a positive association; however, there was a significant negative association between forest cover squared and malaria. This indicates a nonlinear relationship between forest cover and malaria, and thus the positive association observed between malaria and forest cover could be reversed at certain values of forest cover. The same nonlinear relationship was found between forest cover and child mortality.

Figure 7 **Unadjusted (U) and adjusted (A) coefficients from the regressions of each environmental variable with all child health outcomes in Chad 2014-15 DHS survey**



Higher forest loss in the last 10 years was significantly associated with lower likelihood of stunting and underweight in both the adjusted and unadjusted models. However, forest loss was significantly associated with higher likelihood of malaria and mortality—indicating that the more forest loss, the higher the likelihood of malaria and mortality among children in Chad.

Significantly lower likelihood of stunting and underweight was found with higher levels of the vegetation index in both the adjusted and unadjusted models. This was also significant in the unadjusted model for inadequate dietary diversity, but the significance was lost after controlling for other variables. Higher vegetation index was significantly associated with higher levels of child mortality.

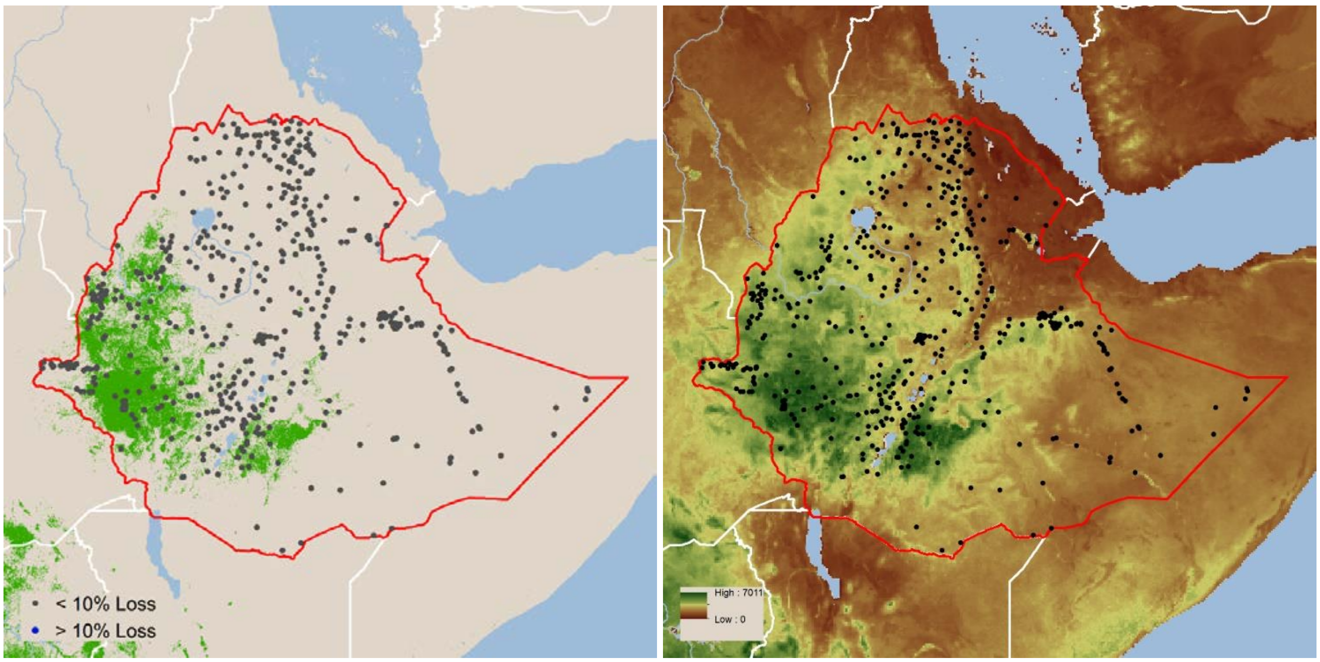
The greater the distance to a protected area, the higher the likelihood of children being underweight in both the adjusted and unadjusted models. Greater distance to a protected area was associated with lower likelihood of malaria and mortality. The greater the distance to water, the higher the likelihood of a child having inadequate dietary diversity. However, greater distance to water was associated with significantly less stunting and malaria among children. As Figure 6 shows, the only major body of water in Chad is Lake Chad.

Proximity to water was the only environmental variable found to be significantly associated with inadequate dietary diversity in children in the adjusted model. With the exception of forest cover, no other environmental variable was significantly associated with diarrhea symptoms among children in Chad.

3.3 Ethiopia

The maps in Figure 8 show the forest cover and vegetation index in Ethiopia. The first map shows that most of the forest cover is concentrated in one area in the west of the country. There were no DHS clusters detected that had more than 10% forest loss. The maximum forest loss in the last 10 years was 5.2% (Table 2).

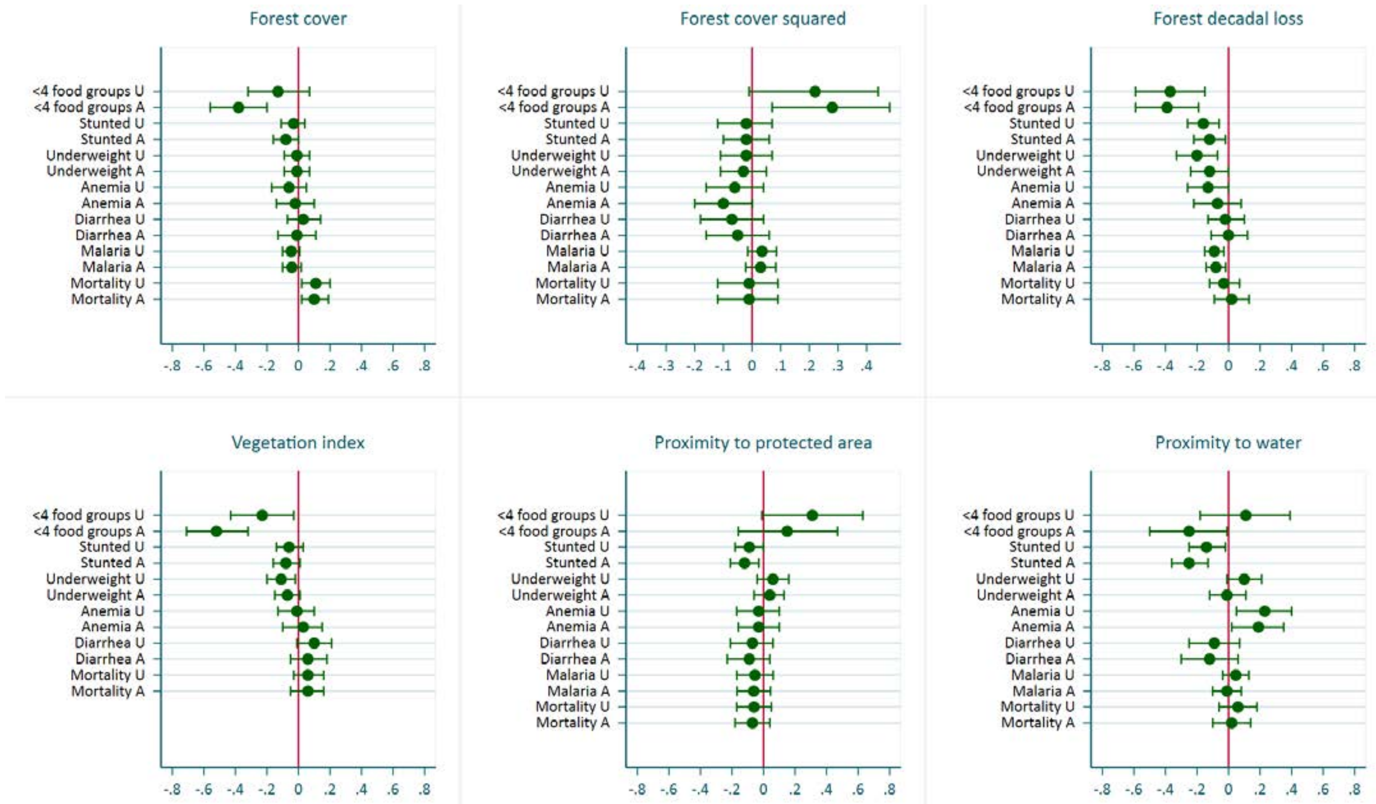
Figure 8 Ethiopia maps: The first map shows the forest cover and forest loss in the last 10 years. The second map shows the vegetation index from low (red) to high (green). In both maps the dark dots are the DHS cluster locations.



Regression results for the most recent survey

Figure 9 summarizes the results from the regressions of all the environmental variables with the child health outcomes in Ethiopia, including child mortality. The figure shows the unadjusted (U) and adjusted (A) coefficients for all the environmental variables and the outcomes in Ethiopia. The estimates are also found in Appendix Tables B.2-B.8.

Figure 9 **Unadjusted (U) and adjusted (A) coefficients from the regressions of each environmental variable with all child health outcomes in Ethiopia 2016 DHS survey**



In the first plot we see that there is a negative association between forest cover and inadequate dietary diversity, indicating that the higher the forest cover, the lower the likelihood of consuming less than four food groups net of other factors. However, the significant quadratic term of forest cover with dietary diversity indicates that a nonlinear relationship exists and that the negative association found between forest cover and inadequate dietary diversity could be reversed for certain values of forest cover. Forest cover was marginally significant with mortality in both the unadjusted and adjusted models. The direction of the relationship indicates that the higher the forest cover, the higher the level of child mortality.

While there was very little forest loss found in Ethiopia, forest loss in the last 10 years was negatively associated with inadequate dietary diversity, stunting, underweight, and malaria. This indicates that the higher the forest loss, the lower the likelihood of these outcomes. Higher values of the vegetation index were significantly associated with lower likelihood of inadequate dietary diversity. This was also the case for the unadjusted underweight model, but the significance was lost in the adjusted model.

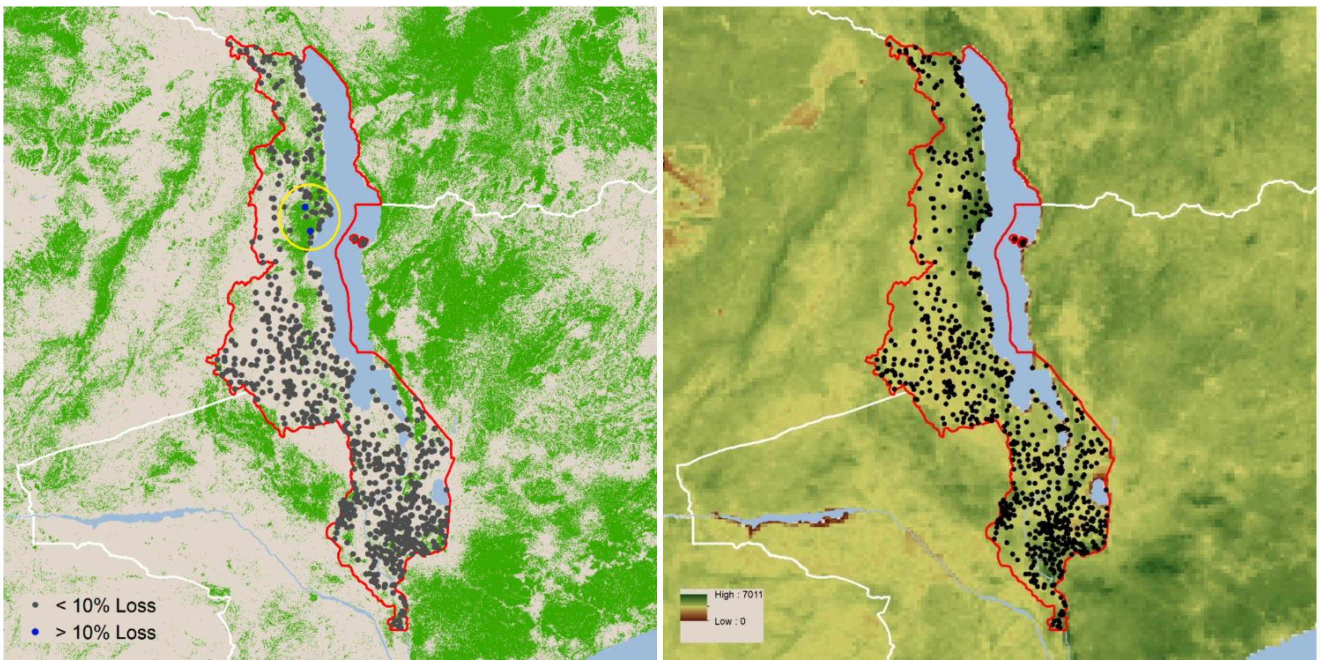
Proximity to protected area in Ethiopia was significantly associated only with stunting. Greater distance to a protected area indicated lower likelihood of stunting. This was also the case for distance to water associated with stunting and inadequate dietary diversity. However, greater distance to water was significantly associated with higher likelihood of anemia. The maps show that the areas with the greatest distance to water are the more rural areas with forest cover, which could explain these findings. Proximity to water was the only environmental variable significant for the anemia outcome in Ethiopia.

No significance was detected between any of the environmental variables and diarrhea. Malaria was only marginally significantly associated with forest loss. Higher forest loss was associated with lower likelihood of malaria. Mortality was only marginally significant with forest cover in the positive direction.

3.4 Malawi

The maps for Malawi in Figure 10 show a very large lake (Lake Malawi) that covers a large area of the country from north to south. Only two DHS clusters were detected that had more than 10% forest loss in the northern part of the country (indicated by the yellow circle in the first map). The vegetation index shown in the second map is mainly from medium to high throughout the country.

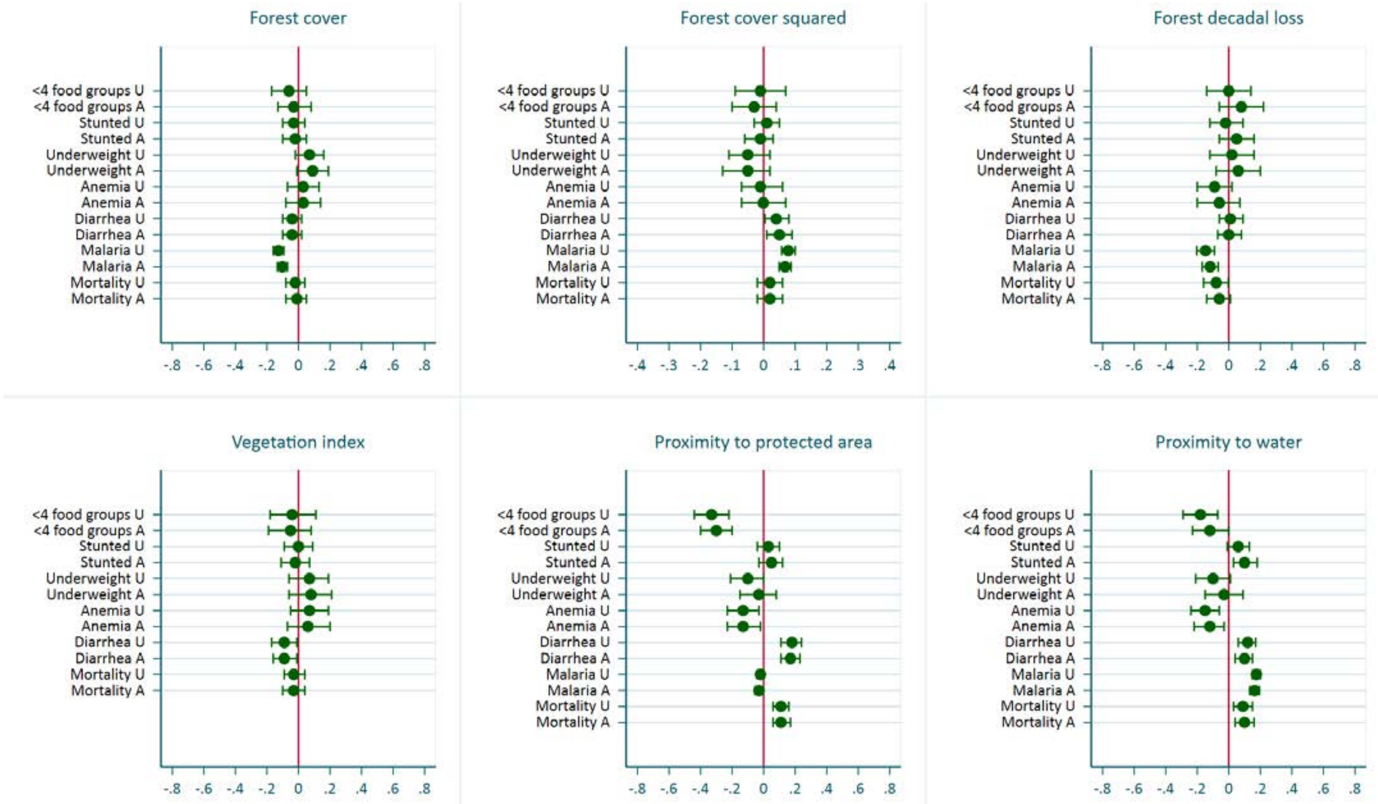
Figure 10 Malawi maps: The first map shows the forest cover and forest loss in the last 10 years. The second map shows the vegetation index from low (red) to high (green). In both maps the dark dots are the DHS cluster locations.



Regression results for the most recent survey

The results from the regressions of all the environmental variables with the child health outcomes in Malawi, including child mortality, are summarized in Figure 11. The figure shows unadjusted (U) and adjusted (A) coefficients for all the environmental variables and the outcomes in the most recent survey. The estimates are also found in Appendix Tables B.2-B.8.

Figure 11 **Unadjusted (U) and adjusted (A) coefficients from the regressions of each environmental variable with all child health outcomes in Malawi 2015-2016 DHS survey**



In the first plot of the figure, we see that forest cover was only significantly associated with malaria. Higher forest cover is associated with a significantly lower likelihood of malaria, but the significant quadratic term for forest cover and malaria indicates that this relationship is not always linear. Forest loss was negatively associated with malaria in Malawi. The higher the forest loss, the lower the likelihood of malaria. A significant nonlinear relationship was also found between forest cover and diarrhea, as shown in the second plot of the figure.

The vegetation index was only significantly associated with diarrhea, with higher levels of the vegetation index indicating lower likelihood of diarrhea.

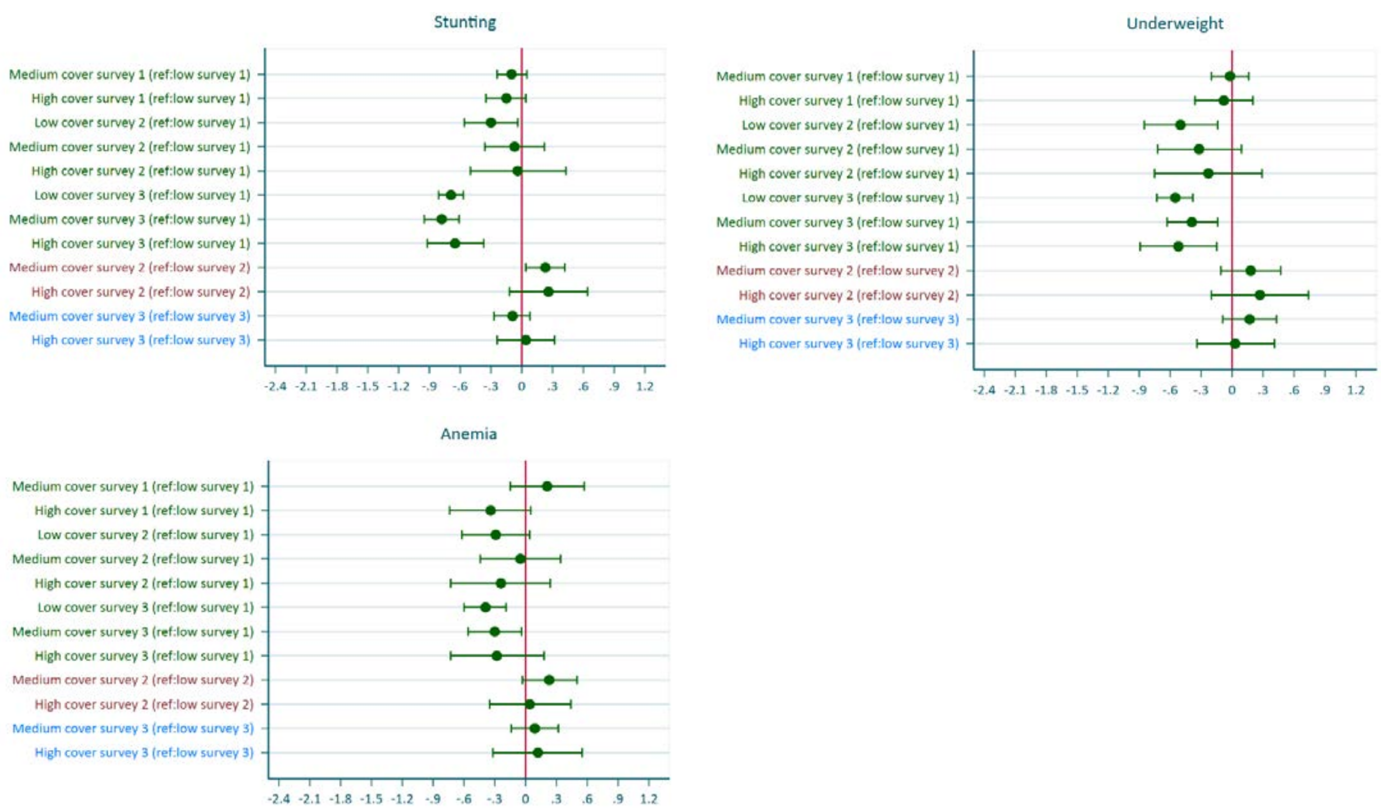
The results for proximity to protected area varied by outcome. It was positively associated with diarrhea and mortality, indicating higher likelihood of these outcomes with increased distance to protected area. It was negatively associated with inadequate dietary diversity, anemia, and malaria, indicating lower likelihood of these outcomes with increased distance. Dietary diversity and anemia were also negatively associated with proximity to water, with longer distances to water associated with lower likelihood of these outcomes. Longer distances to water were significantly associated with higher likelihood of stunting, diarrhea, malaria, and mortality. This may be due to more rural and less developed areas that are further away from Lake Malawi.

Results for combined Malawi data from three surveys

The results from the regressions from three appended Malawi DHS surveys are summarized in Figures 12-15 and Appendix Table B.9. These regressions show the adjusted coefficients for the interaction term between forest cover and each survey (1-3) with the child health outcomes, including child mortality.

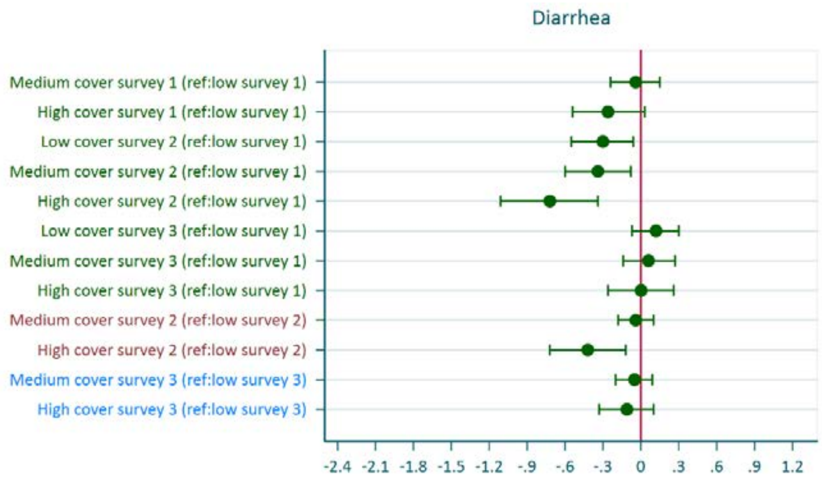
Figure 12 summarizes the regression results for the nutrition outcomes. Questions required to construct the dietary diversity outcome were not included in the Malawi 2004 survey, and therefore regressions were not fit for this outcome. As Figure 12 shows for stunting, the level of forest cover was not significant within the surveys (except for a marginal significance for low cover in survey 2 compared with low cover in survey 1, and for medium cover in survey 2 compared with low cover in survey 2. In survey 3, however, all levels of forest cover were significantly associated with lower likelihood of stunting compared with low level of forest cover in survey 1. When we examine the AIC values in Appendix Table B.9, we see that the difference in AIC is minimal between the model that includes the survey variable and the model that includes the interaction term between survey and forest cover. In addition, the magnitude of the coefficients is similar for all three levels of forest cover in survey 3 compared with low cover in survey 1. Therefore, it appears that the change we see in the forest cover categories in survey 3 compared with low cover in survey 1 is not due to the forest cover, but to the change in the outcome over time that may be attributed to other factors. Similar results were observed for the underweight and anemia outcomes, which can also be seen in Figure 12.

Figure 12 Adjusted coefficients from the regression of an interaction term between forest cover and survey number with the nutrition outcomes in Malawi



In Figure 13 for the diarrhea outcome, we see that forest cover in survey 2 was significantly associated with lower diarrhea compared with low forest cover in survey 1. When we compare the forest cover categories within survey 2, we find that high cover in survey 2 was significantly associated with lower diarrhea compared with low cover in survey 2. Therefore, it appears that it was not only the change in the outcome but also the change in the level of forest cover that had an effect on diarrhea in Malawi in survey 2. However, the effect of forest cover was not strong, as can be seen in the difference in the AIC values reported in Appendix Table B.9. The effect of forest cover found in survey 2 was not found for survey 3.

Figure 13 Adjusted coefficients from the regression of an interaction term between forest cover and survey number for diarrhea in Malawi



The malaria outcome shown in Figure 14 had several significant findings. Within all three surveys, medium and high forest cover was associated with significantly lower odds of malaria compared with low cover. Between the surveys, it appeared that there was no difference between survey 3 and survey 1, but there was a significant difference between survey 2 and survey 1. All categories of forest cover in survey 2 were associated with significantly greater likelihood of malaria compared with low cover in survey 1. However, this could be the effect of the change in the outcome over time between survey 2 and survey 1. In fact, the AIC difference shows that forest cover was not an important factor in the malaria model.

Figure 14 Adjusted coefficients from the regression of an interaction term between forest cover and survey number for malaria in Malawi

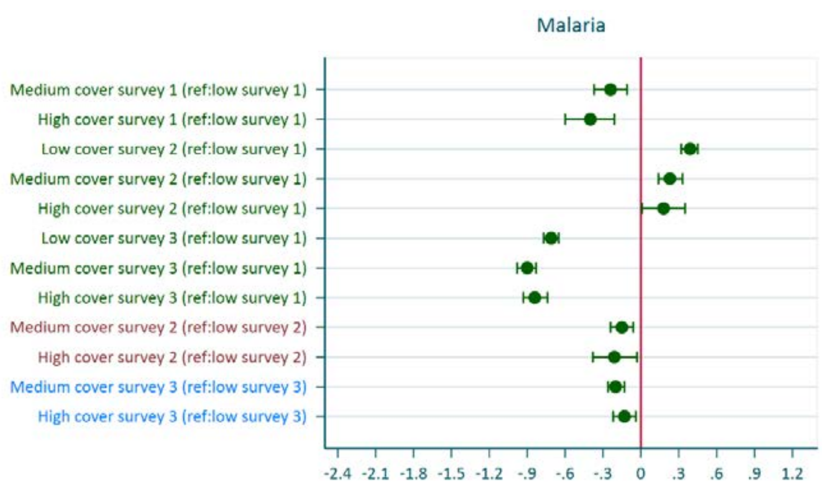
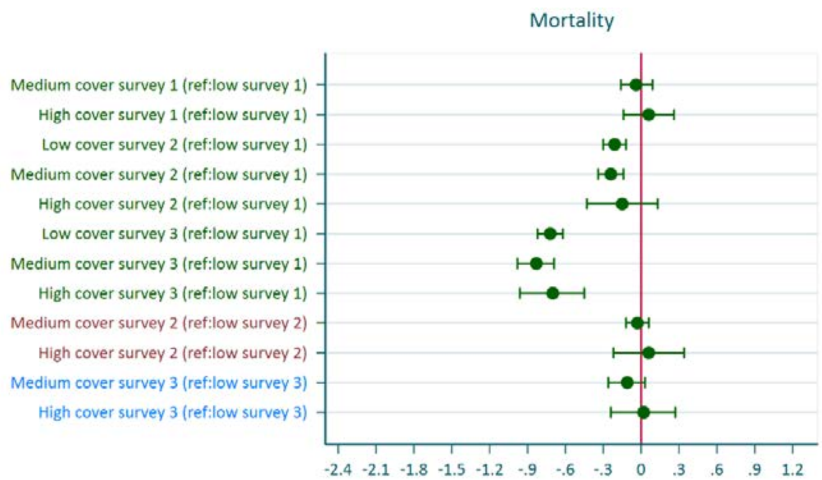


Figure 15 shows the estimates for child mortality in the 10 years before the survey. The results were similar to those for the nutrition outcomes. Here we also see that there is no significant difference in mortality with the level of forest cover within each survey. The significant finding we see in survey 2 and survey 3 is mainly due to the change in the outcome over time and not the level of forest cover. This can also be verified by the similar coefficients of the different forest cover levels within survey 2 and survey 3 when compared with survey 1, as well as the minimal change in the AIC value shown in Appendix Table B.9.

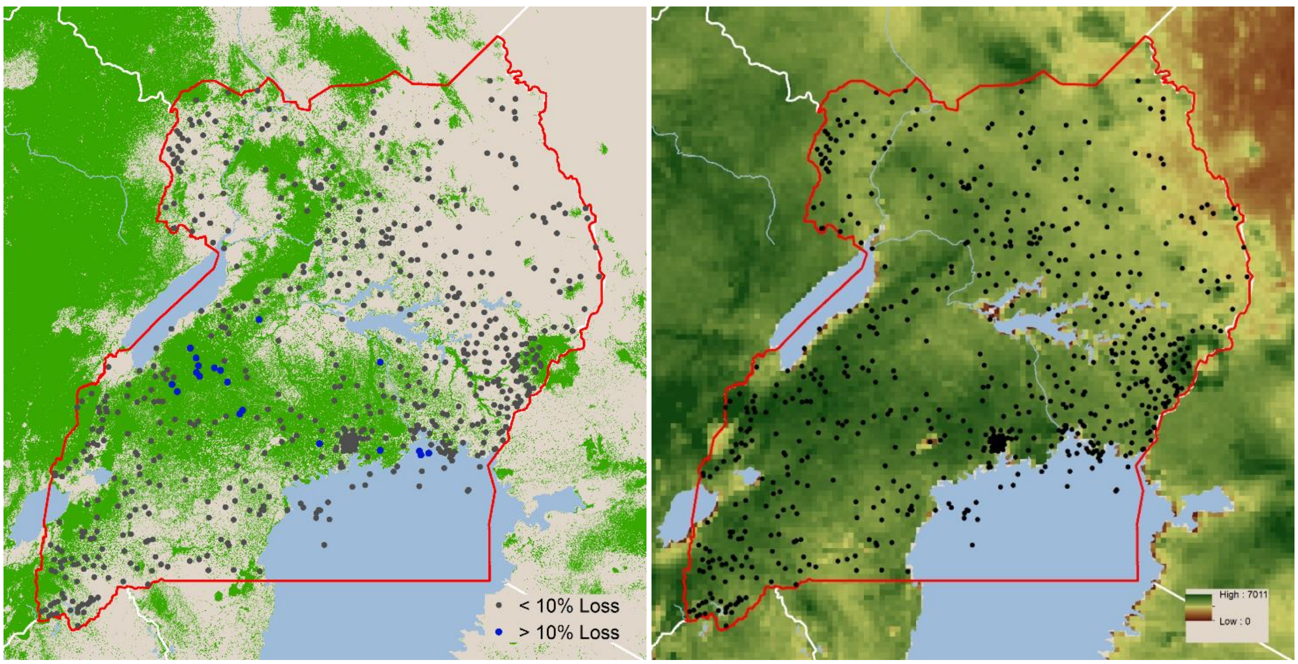
Figure 15 Adjusted coefficients from the regression of an interaction term between forest cover and survey number for mortality in Malawi



3.5 Uganda

Uganda's borders include parts of two lakes—Lake Albert in the northwest and Lake Victoria in the southeast. As the maps in Figure 16 illustrate, there is considerable forest cover in most of the country, and also a number of DHS clusters that experienced more than 10% forest loss. In fact, Uganda had the most forest loss among the four sub-Saharan African countries included in the analysis, with a maximum of 27% loss in one of the clusters (Table 2). The vegetation index map shows a relatively high level of vegetation throughout the country except for low levels in the northeast.

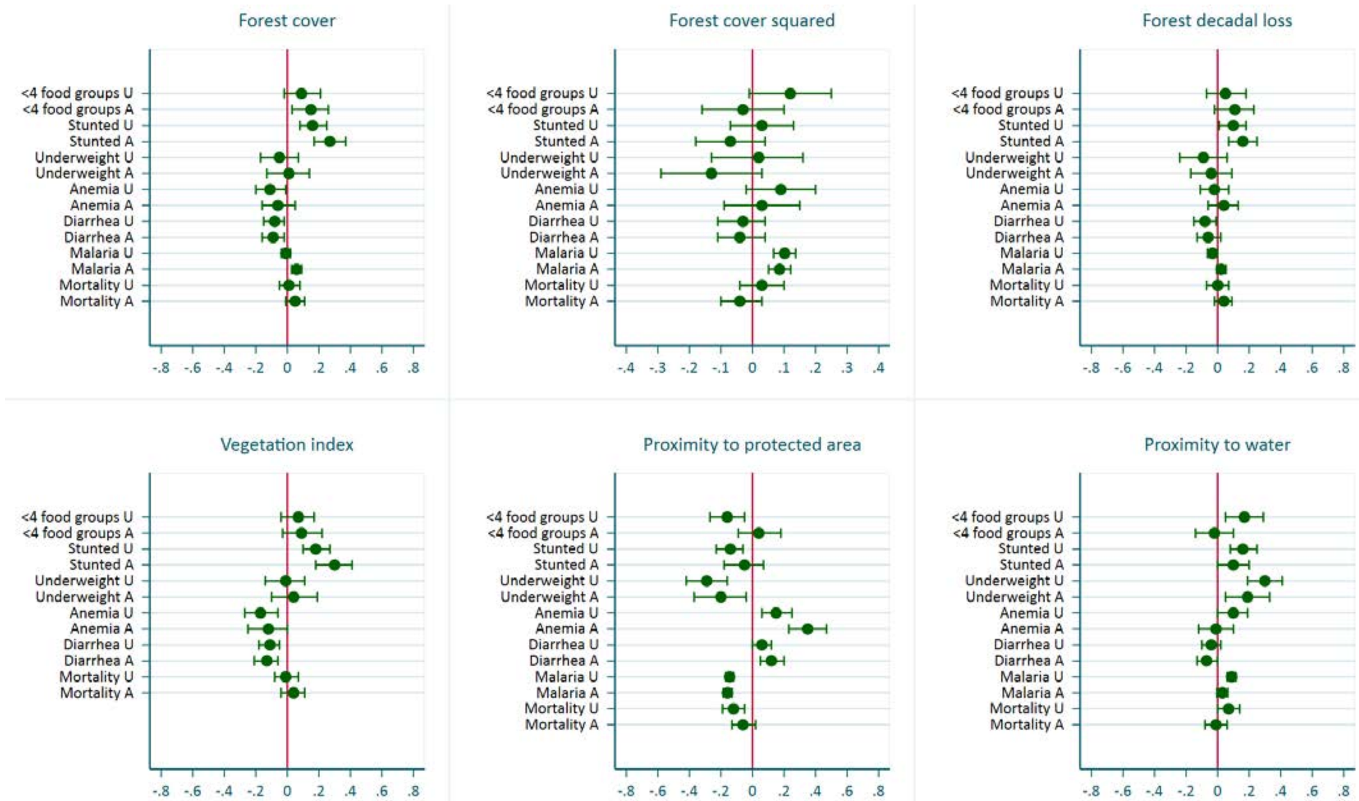
Figure 16 Uganda maps: The first map shows the forest cover and forest loss in the last 10 years (blue dots are clusters with more than 10% loss). The second map shows the vegetation index from low (red) to high (green). In both maps the dark dots are the DHS cluster locations.



Regression results for the most recent survey

Figure 17 presents a summary of results from the regressions of all the environmental variables with the child health outcomes in Uganda, including child mortality. The figure shows the unadjusted (U) and adjusted (A) coefficients for all the environmental variables and the outcomes in the most recent survey. The estimates are also found in Appendix Tables B.2-B.8.

Figure 17 Unadjusted (U) and adjusted (A) coefficients from the regressions of each environmental variable with all child health outcomes in the Uganda 2016 DHS survey



As the first plot in Figure 17 shows, forest cover was positively associated with consuming less than four food groups, stunting, and malaria. The higher the forest cover, the greater the likelihood of these outcomes. For malaria, however, the relationship with forest cover was not linear, since we observe a significant association between malaria and forest cover squared. Forest cover was negatively associated with diarrhea, with higher forest cover associated with lower likelihood of diarrhea. Forest loss in the last 10 years was significantly associated with greater likelihood of stunting. As with forest cover, higher vegetation index was associated with greater likelihood of stunting, but with lower likelihood of diarrhea.

In Uganda, the greater the distance to a protected area, the lower the likelihood of a child being underweight or having malaria. In contrast, the greater the distance to a protected area. the higher the likelihood of being anemic or having diarrhea. Proximity to water was significantly associated only with underweight in the adjusted model. The greater the distance to water, the higher the likelihood of underweight among children.

Results for combined Uganda data from three surveys

Figures 18-21 and Appendix Table B.10 summarize the results from the regressions from three successive Uganda DHS surveys. These regressions show the adjusted coefficients for the interaction term between forest cover and survey number with the child health outcomes, including child mortality.

Figure 18 shows the results of the forest cover interaction term and the nutrition outcomes. For the dietary diversity outcome, there was no difference between the forest cover categories within survey 1 and survey 2, and only a marginal significance in survey 3, which showed an increased likelihood of the outcome for medium and high cover compared with low cover. Between the surveys, it appeared there was no difference between survey 3 and survey 1 except for the low category in survey 3 compared with the low category in survey 1, but there was a significant difference between survey 2 and survey 1. All categories of forest cover in survey 2 were associated with significantly greater likelihood of consuming less than four food groups compared with low cover in survey 1. However, this could be the effect of the change in the outcome between survey 2 and survey 1 (see Appendix Table B.1, which shows that inadequate dietary diversity increased between 2006 and 2011). The AIC difference shows that forest cover was not an important factor for the dietary diversity outcome.

For stunting, high forest cover in survey 2 and survey 3 was associated with greater likelihood of stunting compared with low cover. There was no difference between high and low cover in survey 1 and only a marginal significance in survey 2. There was a strong significance between low forest cover in survey 3 compared with low cover in survey 1 in the negative direction (i.e., less likelihood of stunting). Medium cover in survey 3 compared with low cover in survey 1 was also significant in the negative direction. The AIC for the model that includes forest cover was considerably less (difference of 30) than the model without forest cover (see Appendix Table B.10). This indicates that forest cover is an important factor for the association with stunting in Uganda. Note that forest cover in Uganda decreased over the survey period (Table 2).

No significance was detected between the forest cover interaction term and underweight in Uganda. The AIC difference shown in Appendix Table B.10 is also minimal. This indicates that forest cover is not an important factor for the underweight outcome.

In contrast, several highly significant findings were found between the forest cover interaction term and anemia. In survey 1, medium and high forest cover was associated with significantly less anemia in children. In survey 2, the same effect was only found between high cover and low cover but not medium cover, and in survey 3 there were no significant differences between the forest cover categories. Across the surveys, we find that all forest cover categories in survey 2 and survey 3 were significantly associated with lower likelihood of anemia compared with low cover in survey 1. However, the coefficients in survey 3 and the medium and high categories in survey 2 were very similar, indicating that this change is more likely due to the change in the outcome and not due to changes in forest cover across the surveys. The AIC value in Appendix Table B.10 also showed little difference between the models that include or exclude forest cover.

Figure 18 Adjusted coefficients from the regression of an interaction term between forest cover and survey number with the nutrition outcomes in Uganda

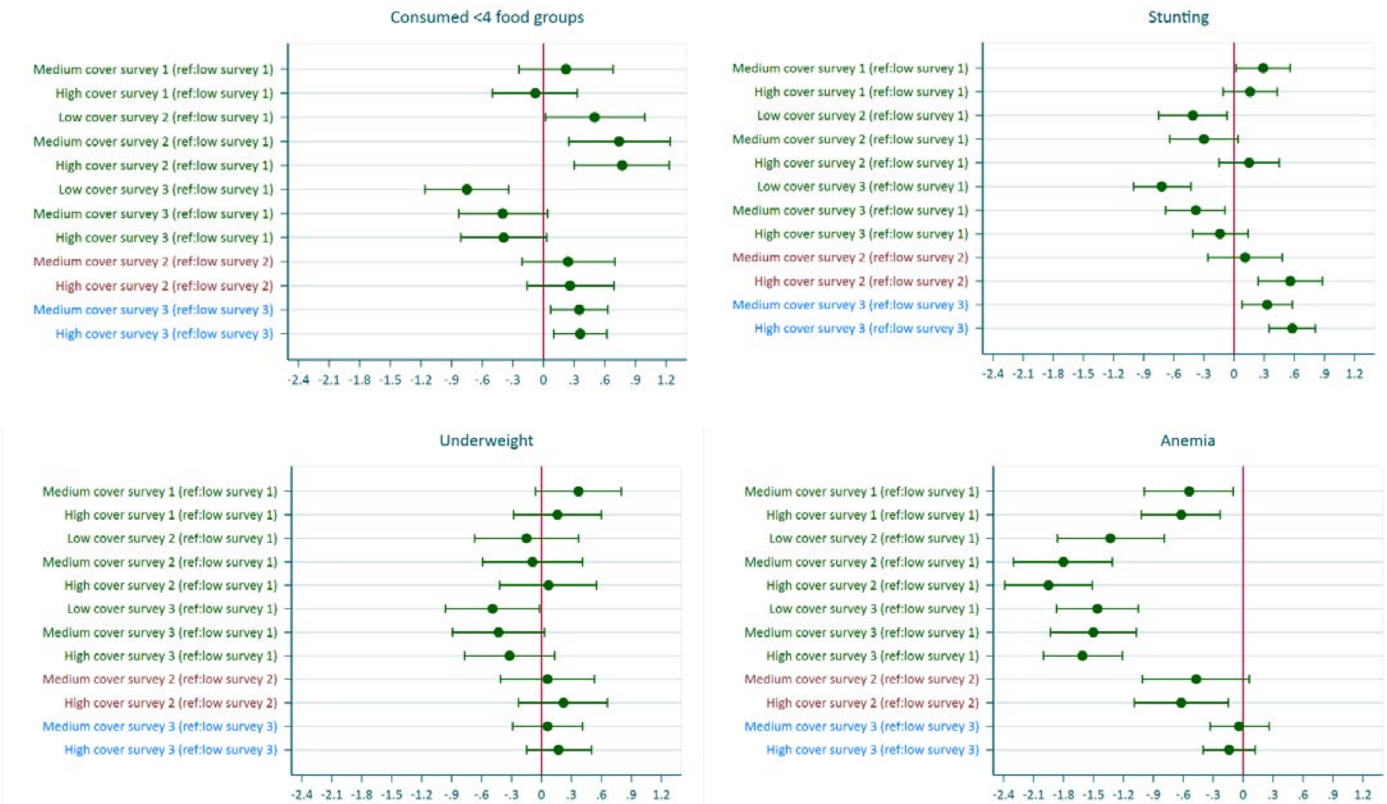
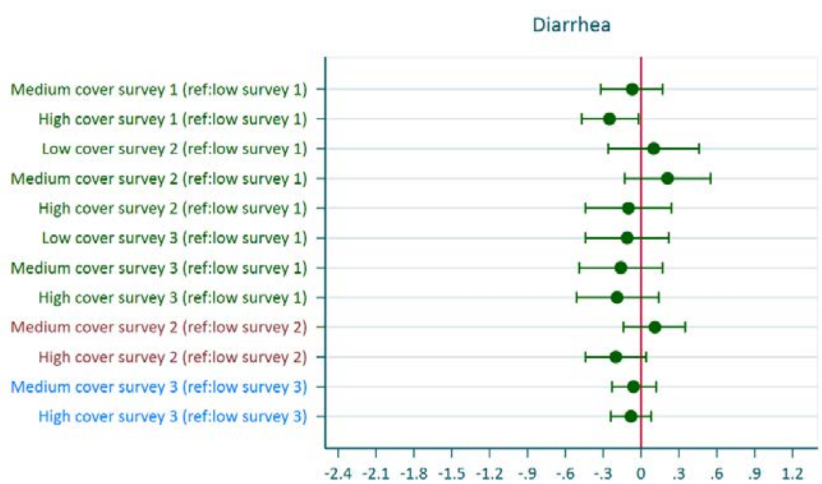


Figure 19 shows that no significance was detected between the forest cover interaction term and diarrhea. The AIC difference shown in Appendix Table B.10 is also minimal. This indicates that forest cover is not an important factor for the diarrhea outcome in Uganda.

Figure 19 Adjusted coefficients from the regression of an interaction term between forest cover and survey number for diarrhea in Uganda.



For the malaria outcome, Figure 20 shows that high forest cover in survey 1 was significantly associated with increased likelihood of malaria compared with low forest cover. However, in surveys 2 and 3 only medium forest cover was associated with significantly lower likelihood of malaria compared with low cover within each survey; in survey 3 the significance of this association was marginal. Across the surveys, we see highly significantly coefficients for all the categories of forest cover in survey 3 compared with survey 1. However, these coefficients were all similar in magnitude, and this result, coupled with the low difference in the AIC, implies that the significance we see is due to the change in the outcome and not the forest cover.

In Figure 21, we see that in all three surveys the association between medium and high forest cover and mortality was not significantly different compared with low forest cover. All the forest cover categories in survey 2 and survey 3 were associated with significantly lower mortality compared with low cover in survey 1. However, the coefficients for all the forest cover categories in survey 2 and the categories in survey 3 were similar. The AIC difference was also low. These findings indicate that the forest cover was not an important predictor of mortality and the changes observed in the interaction term are due to changes in the outcome.

Figure 20 Adjusted coefficients from the regression of an interaction term between forest cover and survey number for malaria in Uganda

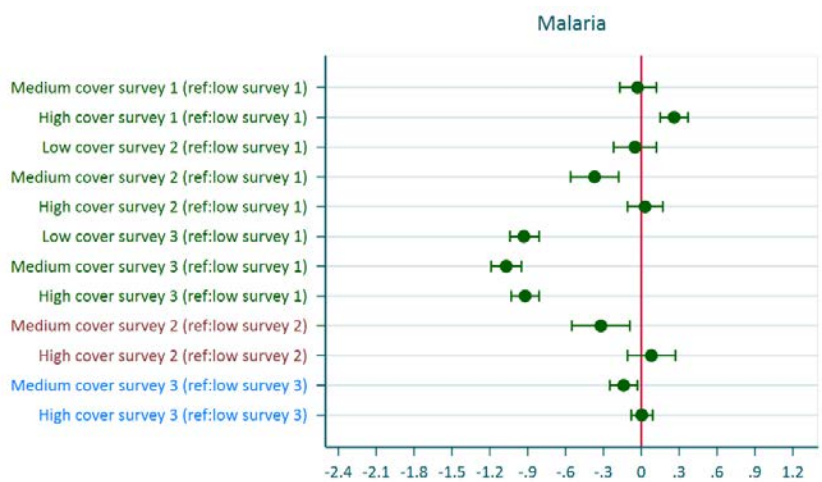
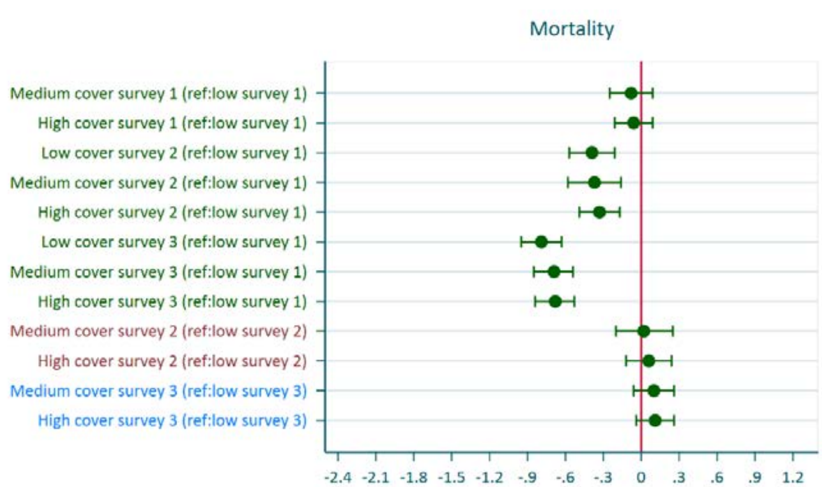


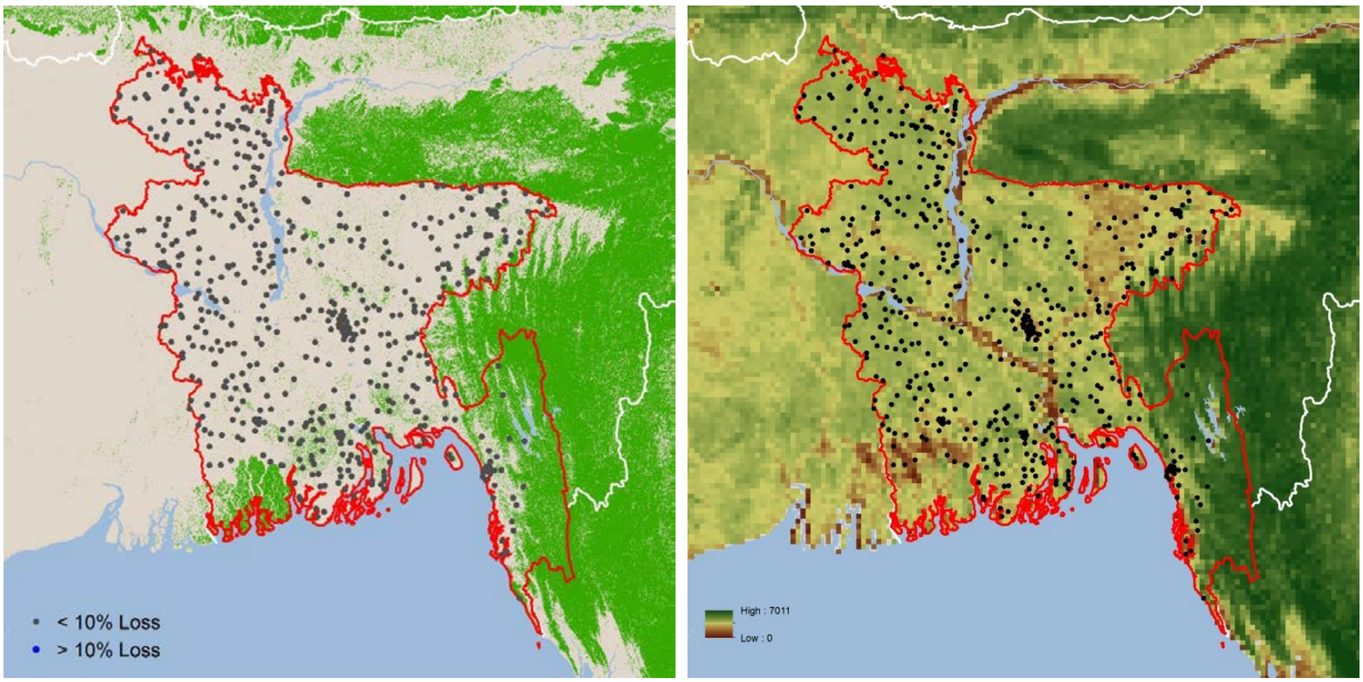
Figure 21 Adjusted coefficients from the regression of an interaction term between forest cover and survey number for mortality in Uganda



3.6 Bangladesh

As the maps in Figure 22 show, Bangladesh possesses very little forest cover except in a few locations in the south of the country. No DHS clusters had more than 10% forest loss. The maximum forest loss was 4.6% (Table 2). However, a medium level of the vegetation index was found throughout Bangladesh, and high vegetation in the southeast corner of the country.

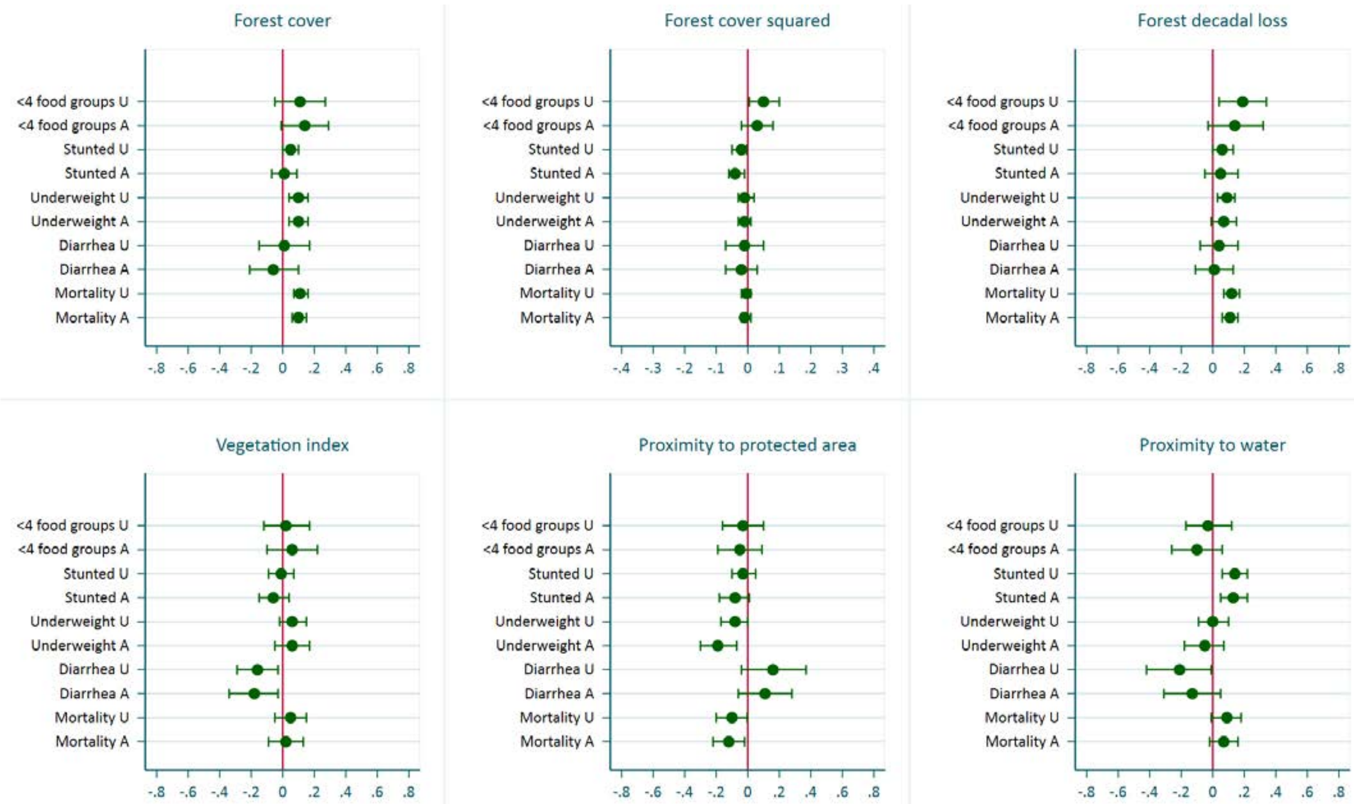
Figure 22 Bangladesh maps: The first map shows the forest cover and forest loss in the last 10 years. The second map shows the vegetation index from low (red) to high (green). In both maps the dark dots are the DHS cluster locations.



Regression results for the most recent survey

Figure 23 summarizes the results from the regressions of all the environmental variables with the child health outcomes in Bangladesh, including child mortality. The figure shows unadjusted (U) and adjusted (A) coefficients for all the environmental variables and the outcomes in the most recent survey. The estimates are also found in Appendix Tables B.2-B.8.

Figure 23 **Unadjusted (U) and adjusted (A) coefficients from the regressions of each environmental variable with all child health outcomes in the Bangladesh 2014 DHS survey**



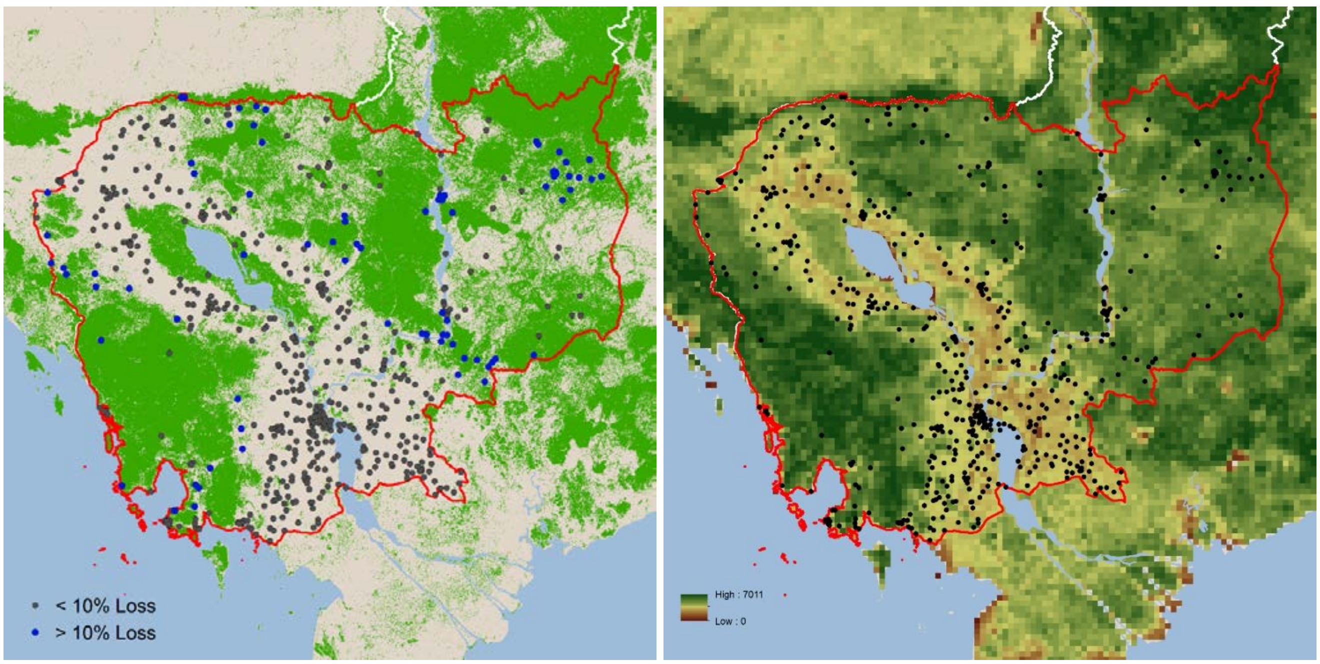
The first plot in Figure 23 shows that higher forest cover in Bangladesh was associated with greater likelihood of underweight and mortality among children. A nonlinear significant relationship was found between forest cover and stunting. While forest loss was not significant for any of the child health outcomes, greater forest loss in the last 10 years was significantly associated with higher child mortality. Diarrhea was the only health outcome significantly associated with vegetation index—the higher the vegetation index, the lower the likelihood of a child having diarrhea.

Proximity to protected area was only significantly associated with underweight and mortality, both in the negative direction. For these outcomes the greater the distance to a protected area, the lower the likelihood of the outcome. Proximity to water was only significantly associated with stunting. As the final plot in Figure 23 shows, the greater the distance to water, the higher the prevalence of stunting.

3.7 Cambodia

Cambodia has considerable forest cover, as the maps in Figure 24 show. There were also several DHS clusters with identified forest loss, scattered throughout the country. Cambodia had the highest forest loss among the Asian countries included in the analysis (Table 2). One cluster had a forest loss of 66% over the last 10 years. The vegetation index ranged from medium to high, with medium levels found in the middle of the country. Cambodia also has several lakes and rivers, indicating that distance to water would be small for most clusters.

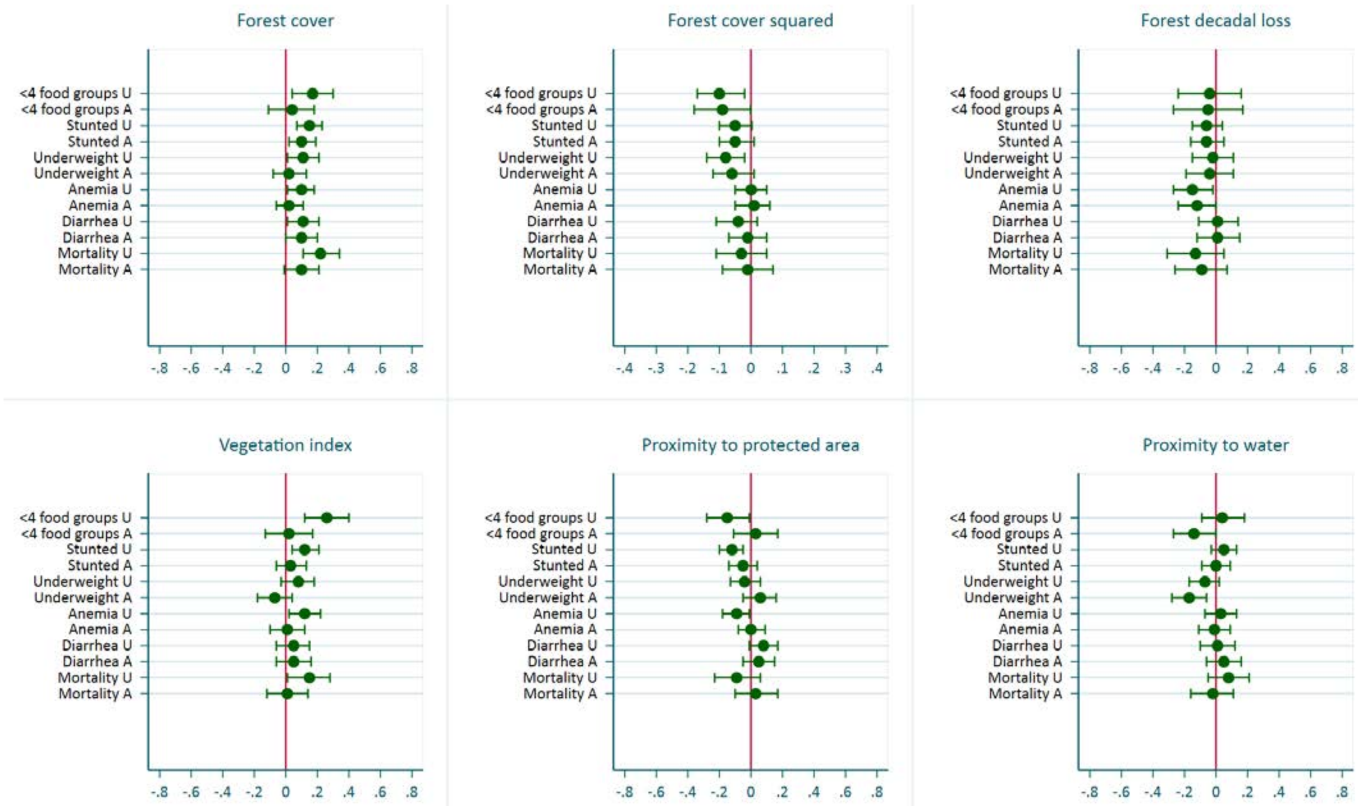
Figure 24 **Cambodia maps: The first map shows the forest cover and forest loss in the last 10 years (blue dots are clusters with more than 10% loss). The second map shows the vegetation index from low (red) to high (green). In both maps the dark dots are the DHS cluster locations.**



Regression results for the most recent survey

Figure 25 summarizes the results from the regressions of all the environmental variables with the child health outcomes in Cambodia, including child mortality. The unadjusted (U) and adjusted (A) coefficients are shown for all the environmental variables and the outcomes in the most recent survey. The estimates are also found in Appendix Tables B.2-B.8.

Figure 25 **Unadjusted (U) and adjusted (A) coefficients from the regressions of each environmental variable with all child health outcomes in the Cambodia 2014 DHS survey**

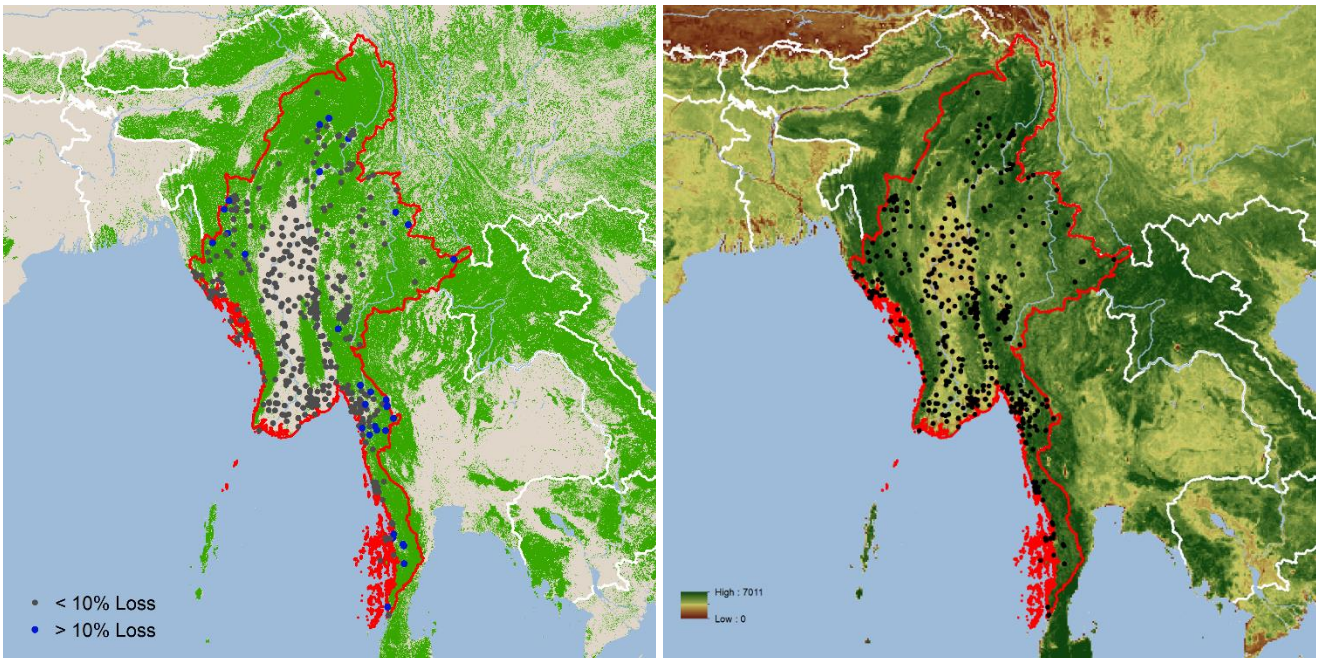


As Figure 25 shows, while forest cover was significantly associated with several outcomes in the unadjusted models, it was significantly associated only with stunting in the adjusted models. The greater the forest cover, the greater the likelihood of stunting. No nonlinear relationship was detected between forest cover and the child health outcomes. Forest loss in the last 10 years had a marginally significant association with anemia in the adjusted model, with higher forest loss associated with lower likelihood of anemia. No outcome was significantly associated with the vegetation index or with proximity to protected area in the adjusted models. Only underweight was significantly associated with proximity to water, with greater distance to water associated with lower likelihood of underweight among children.

3.8 Myanmar

Myanmar is a coastal country that has considerable forest cover throughout, with only one area in the center of the country having low forest cover, as the maps in Figure 26 show. Many areas of the country experienced forest loss in the last 10 years. The vegetation index ranged from medium to high, with medium levels concentrated mainly in the center of the country.

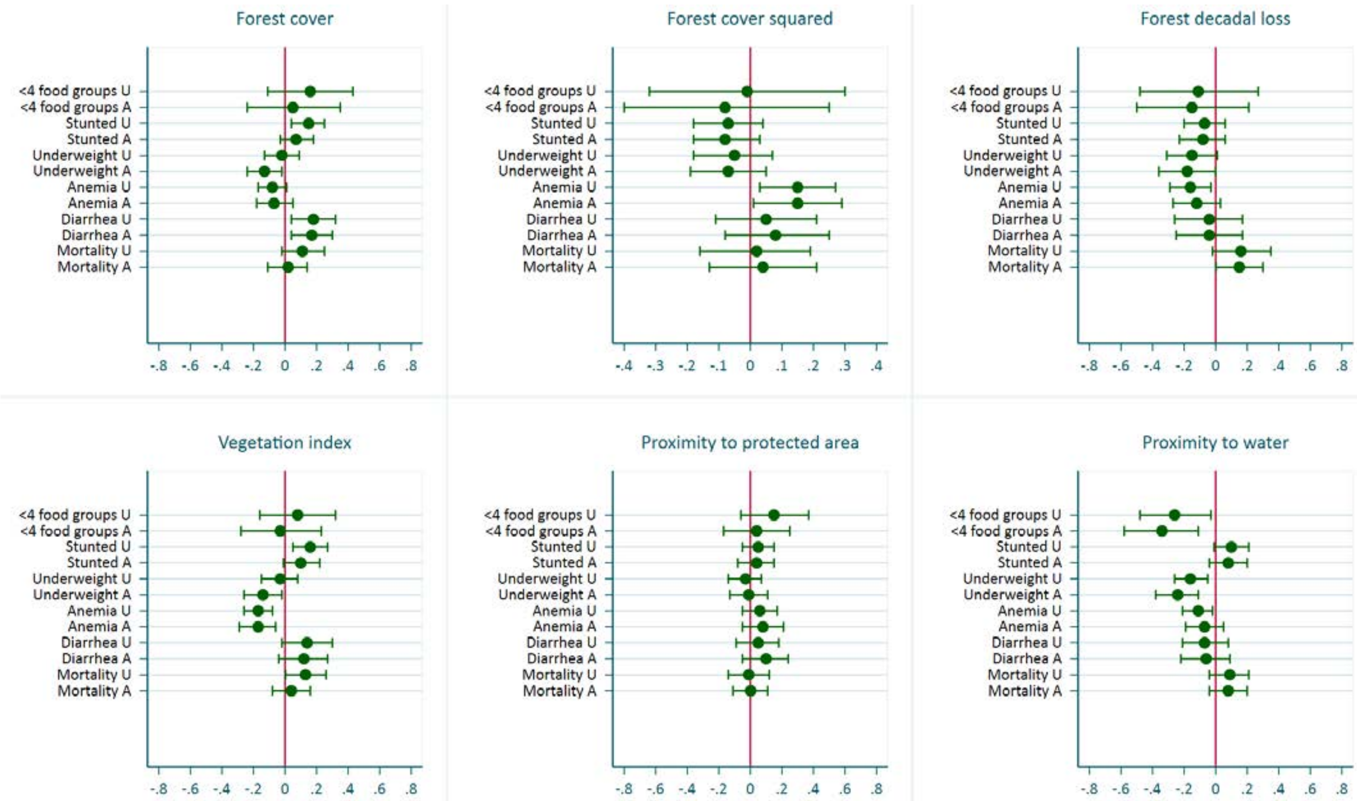
Figure 26 Myanmar maps: The first map shows the forest cover and forest loss in the last 10 years (blue dots are clusters with more than 10% loss). The second map shows the vegetation index from low (red) to high (green). In both maps the dark dots are the DHS cluster locations.



Regression results for the most recent survey

Figure 27 summarizes the results from the regressions of all the environmental variables with the child health outcomes in Myanmar, including child mortality. Unadjusted (U) and adjusted (A) coefficients are shown for all the environmental variables and the outcomes in the most recent survey. The estimates are also found in Appendix Tables B.2-B.8.

Figure 27 Unadjusted (U) and adjusted (A) coefficients from the regressions of each environmental variable with all child health outcomes in the Myanmar 2015-2016 DHS survey



As shown in Figure 27, forest cover was significantly but marginally associated with underweight. Higher forest cover was associated with lower likelihood of being underweight. Forest cover was also significantly associated with diarrhea but in the positive direction, indicating that more forest cover was associated with higher likelihood of diarrhea. In the second plot, we see a marginally significant nonlinear association between forest cover and anemia. Forest loss in the last 10 years was only significantly associated with mortality—the greater the forest loss, the greater the likelihood of mortality. But the level of significance was marginal.

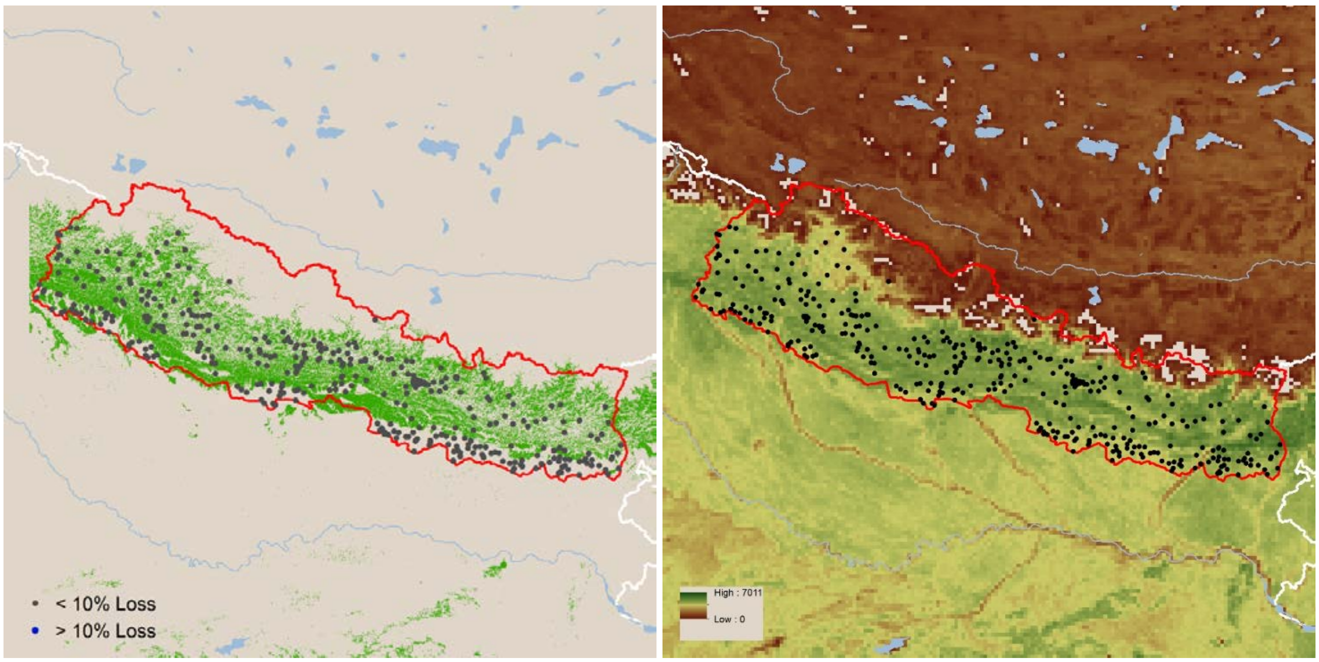
The vegetation index was only significantly associated with underweight and anemia in the adjusted models. For both outcomes, the higher the vegetation index, the lower the likelihood of the outcome.

Proximity to protected area was not significantly associated with any of the child health outcomes. Proximity to water was significantly associated with consuming less than four food groups and underweight in children, both in the negative direction—the greater the distance to water, the lower the likelihood of the outcome.

3.9 Nepal

Nepal is a landlocked country, with no major bodies of water. Figure 28 shows that most forest cover in Nepal is in the south, and there were no DHS clusters that experienced more than a 10% loss in forest cover. The maximum forest loss was 4.2% (Table 2). The vegetation index was medium to high for most of the country, with low levels found in the north, where the Himalayan Mountains are.

Figure 28 Nepal maps: The first map shows the forest cover and forest loss in the last 10 years. The second map shows the vegetation index from low (red) to high (green). In both maps the dark dots are the DHS cluster locations.



Regression results for the most recent survey

Figure 29 shows the results from the regressions of all the environmental variables with the child health outcomes in Nepal, including child mortality. Unadjusted (U) and adjusted (A) coefficients are shown for all the environmental variables and the outcomes in the most recent survey. The estimates are also found in Appendix Tables B.2-B.8.

Figure 29 Unadjusted (U) and adjusted (A) coefficients from the regressions of each environmental variable with all child health outcomes in the Nepal 2016 DHS survey

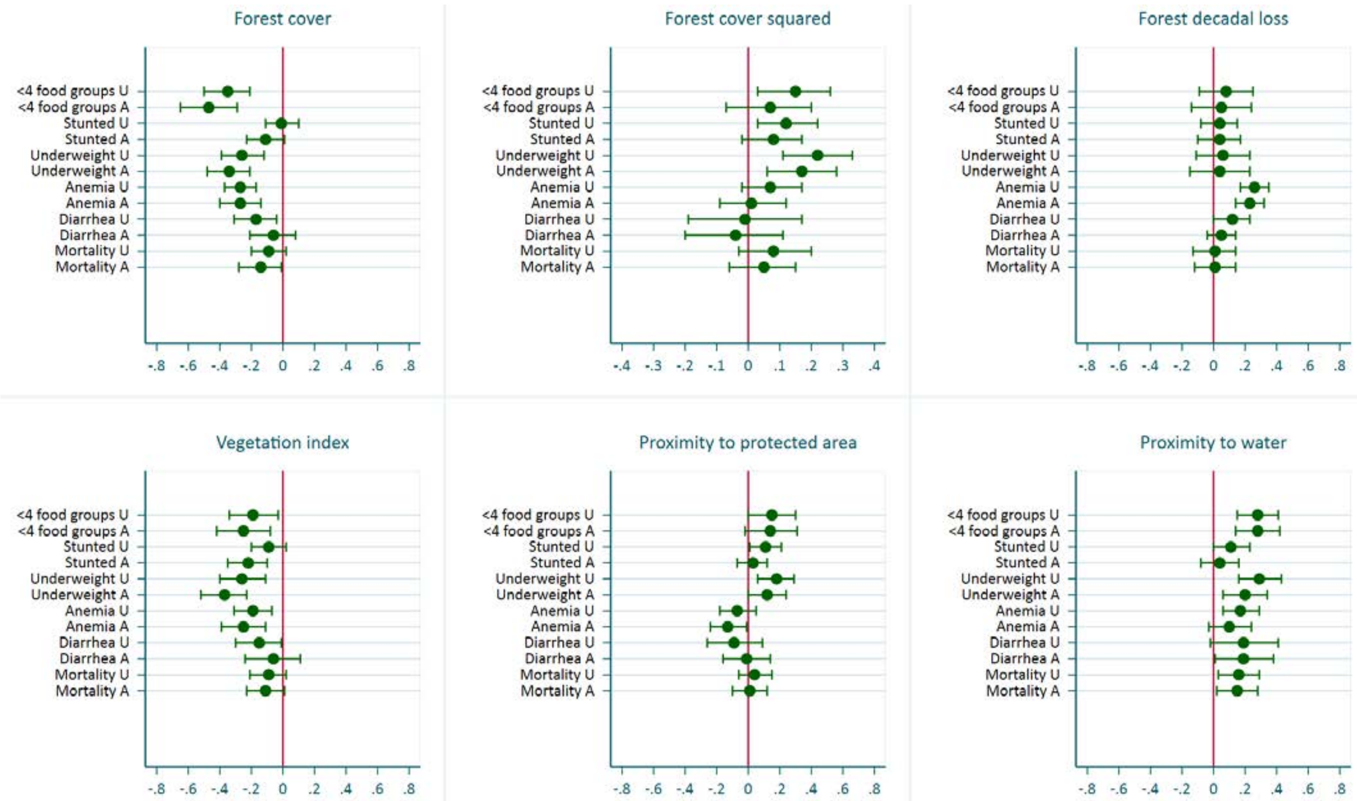


Figure 29 shows that several health outcomes were significantly associated with forest cover in Nepal. Higher forest cover was significantly associated with lower likelihood of consuming less than four food groups, underweight, anemia and marginally lower likelihood for mortality. The significant quadratic term between forest cover and underweight, shown in the second plot, indicates that the negative association between forest cover and underweight is nonlinear and the relationship could be reversed for certain values of forest cover. Forest loss in the last 10 years was only significantly associated with greater likelihood of anemia.

Similar to forest cover, the vegetation index also had several significant associations with the health outcomes. Higher vegetation index was significantly associated with lower likelihood of consuming less than four food groups, stunting, underweight, and anemia—that is, all the nutrition outcomes.

Marginal significance was found between proximity to protected area and underweight and anemia in children. The greater the distance to a protected area, the higher the likelihood of underweight. For anemia, the association was in the negative direction—the greater the distance to a protected area, the lower the likelihood of anemia. Proximity to water was significantly associated with consuming less than four food groups, underweight, and mortality, all in the positive direction. For these outcomes, the greater the distance to water, the more likely the outcome.

Results for combined Nepal data from three surveys

The results from the regressions from three combined Nepal DHS are summarized in Figures 30-32 and in Appendix Table B.11. These regressions show the adjusted coefficients for the interaction term between forest cover and the order of the survey (1-3) with the child health outcomes, including child mortality.

Figure 30 shows the results of the forest cover interaction term and the nutrition outcomes. For all nutrition outcomes except stunting (that is, for consumed less than four food groups, underweight, and anemia), higher forest cover within each survey was associated with lower likelihood of the outcome compared with low cover. Across the surveys for these outcomes, higher forest cover also was associated with lower likelihood of the outcomes compared with low cover in survey 1, except for consumed less than four food groups in survey 2. The AIC difference for these outcomes was also substantial. Therefore, for these outcomes it appears that forest cover is an important factor, with higher forest cover associated with lower likelihood of the outcomes. These results were not found for the stunting outcome. For stunting, there were no significant differences between the forest cover categories within each of the three surveys. Only medium and high forest cover in survey 3 was highly significant in the negative direction with stunting. However, the coefficients were of similar magnitude and the AIC difference was low, implying that forest cover was not an important factor for stunting in Nepal.

Figure 30 Adjusted coefficients from the regression of an interaction term between forest cover and survey number with the nutrition outcomes in Nepal.

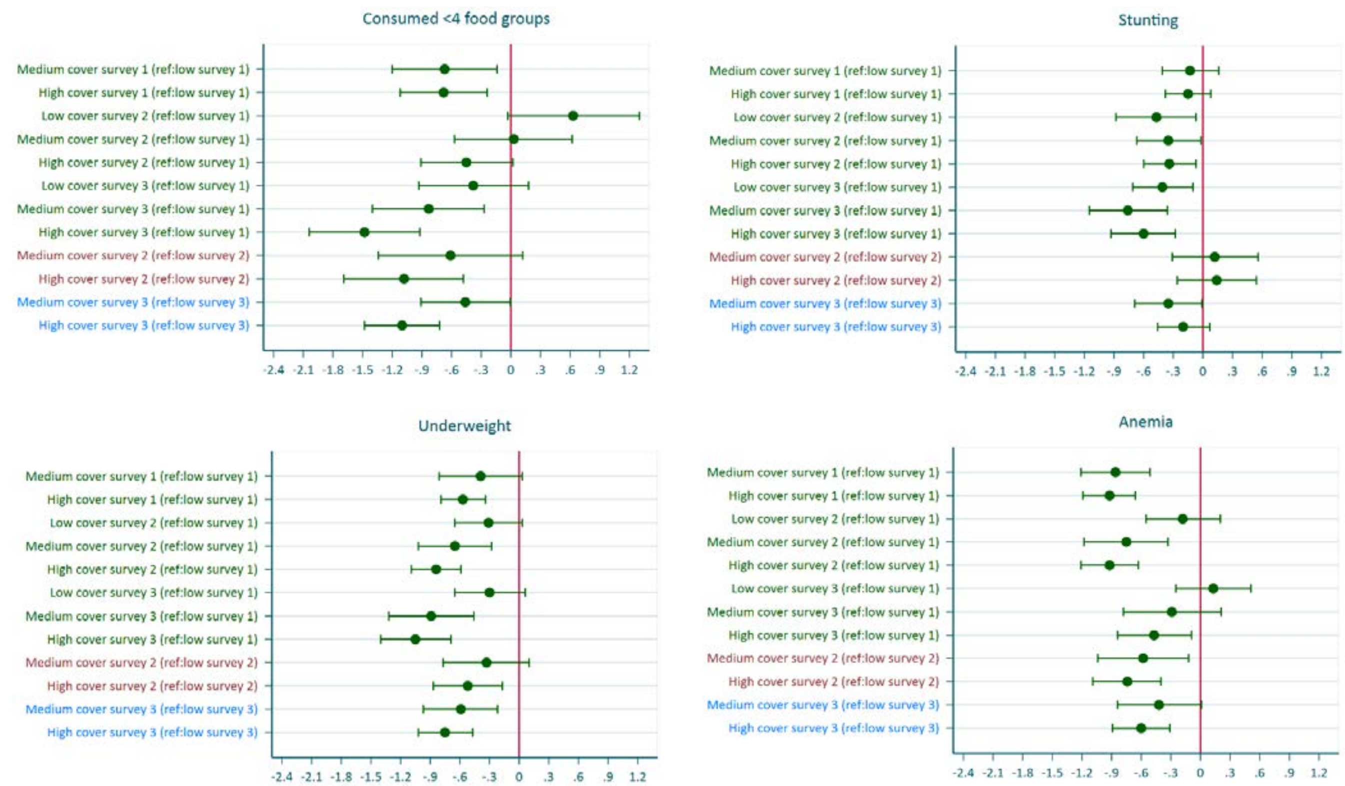


Figure 31 for the diarrhea outcome shows that high forest cover was associated with lower likelihood of diarrhea only in survey 2, and only marginally associated for high cover in survey 3. There were no other significant findings except for a higher likelihood of diarrhea for low forest cover in survey 2 compared with low cover in survey 1. The AIC difference indicates that forest cover is not an important indicator for diarrhea in Nepal.

Figure 31 Adjusted coefficients from the regression of an interaction term between forest cover and survey number for diarrhea in Nepal

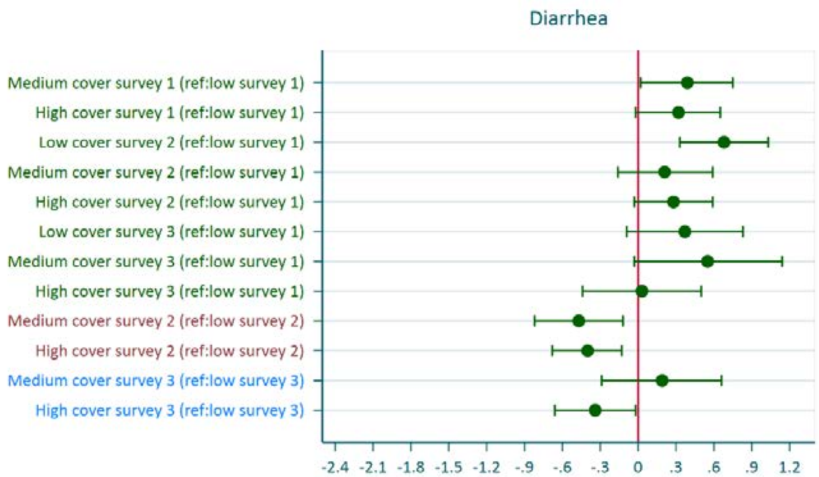
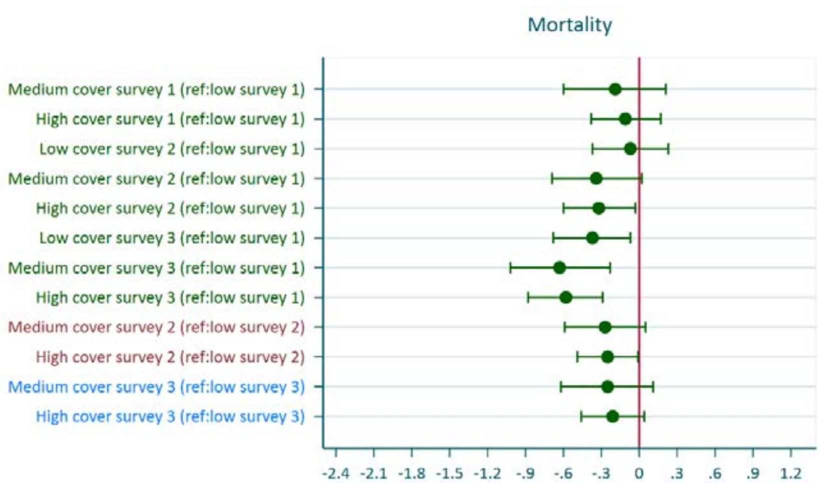


Figure 32 shows few significant findings between the forest cover interaction term and mortality. Within each survey there were no significant differences between the forest cover categories and child mortality except for a marginal significance between high cover and low cover in survey 2. The highly significant findings for medium and high forest cover in survey 3 compared with low cover in survey 1 are similar in magnitude and most likely are due to changes in the outcome. This is confirmed by the small difference in the AIC between the model that includes forest cover and the model that does not.

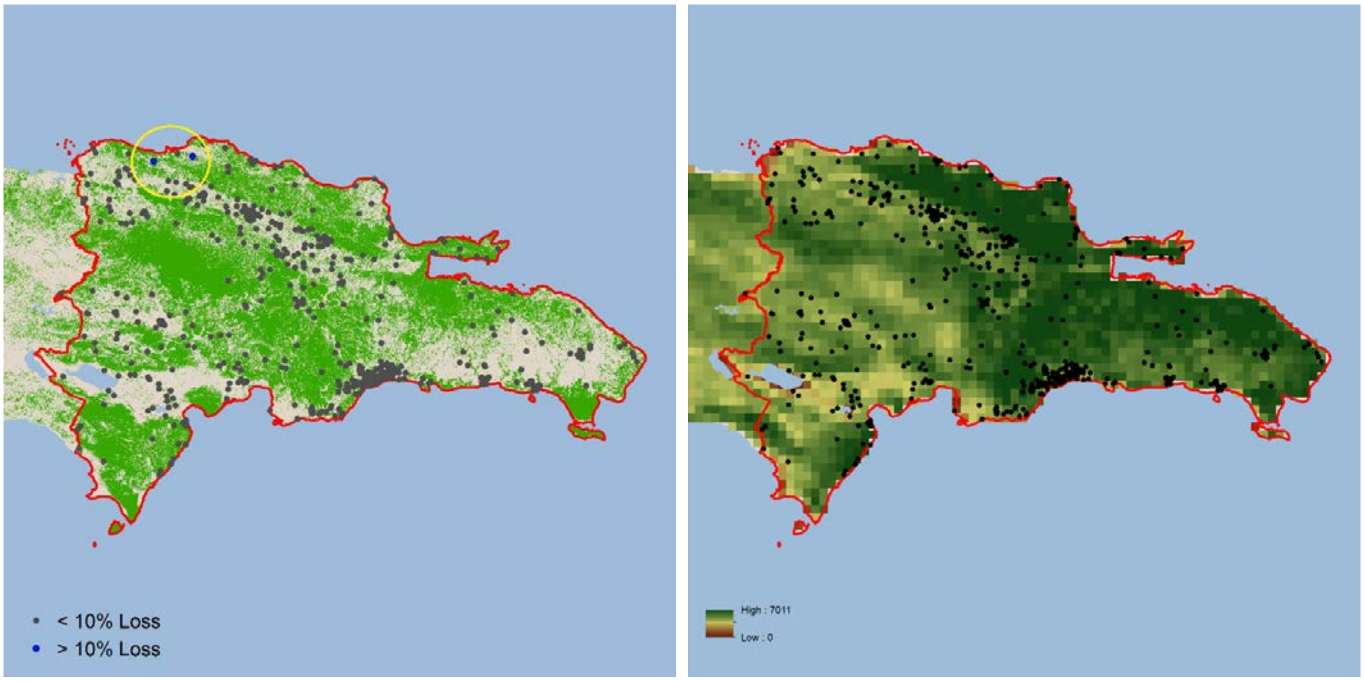
Figure 32 Adjusted coefficients from the regression of an interaction term between forest cover and survey number for mortality in Nepal



3.10 Dominican Republic

The Dominican Republic covers part of an island in the Caribbean, with Haiti covering the other part. The maps in Figure 33 show very high levels of forest cover and vegetation throughout the country. Only two DHS clusters, indicated by the yellow circle in the first map, had more than 10% loss of forest cover in the last 10 years. The maximum forest loss was 11% (Table 2).

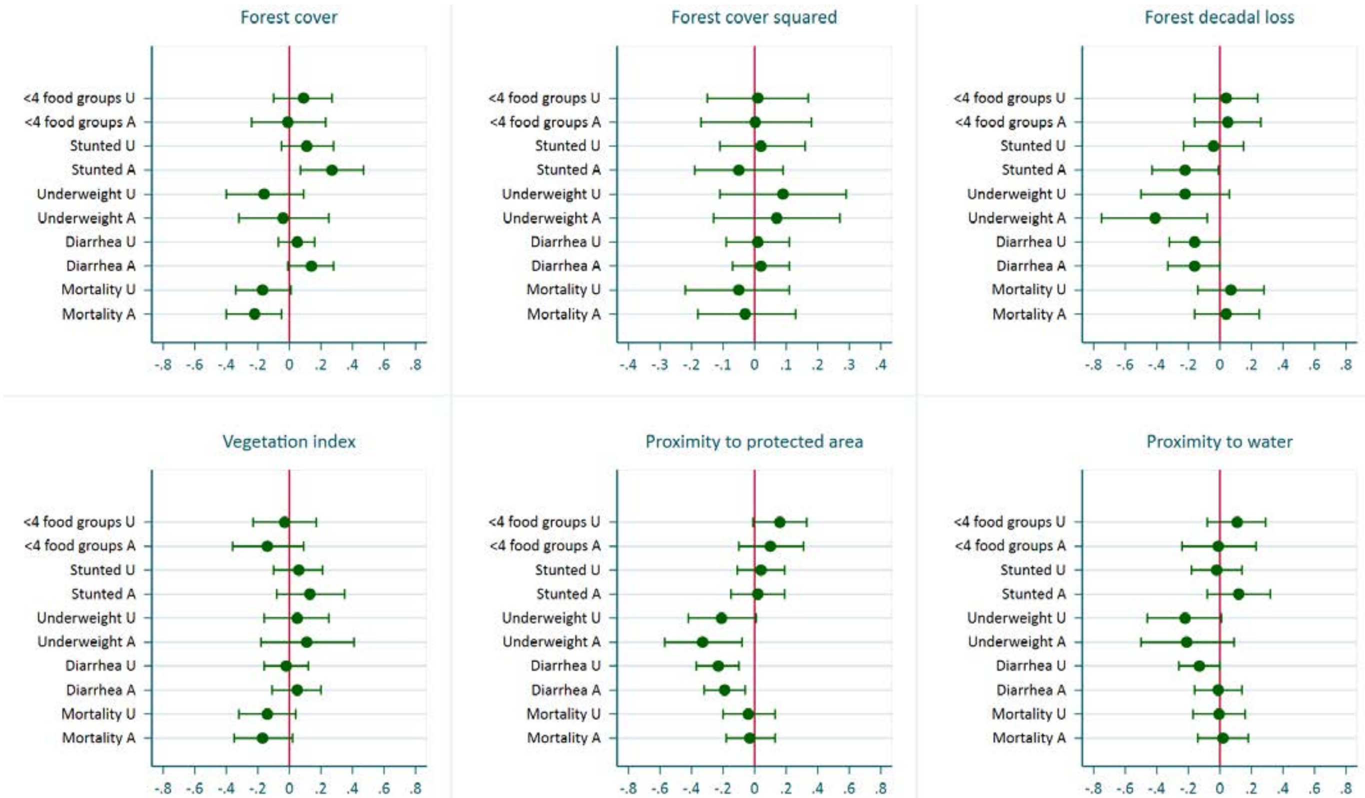
Figure 33 Dominican Republic maps: The first map shows the forest cover and forest loss in the last 10 years (blue dots are clusters with more than 10% loss). The second map shows the vegetation index from low (red) to high (green). In both maps the dark dots are the DHS cluster locations.



Regression results for the most recent survey

Figure 34 shows the results from the regressions of all the environmental variables with the child health outcomes in the Dominican Republic, including child mortality. The figure shows unadjusted (U) and adjusted (A) coefficients for all the environmental variables and the outcomes in the most recent survey. The estimates are also found in Appendix Tables B.2-B.8.

Figure 34 **Unadjusted (U) and adjusted (A) coefficients from the regressions of each environmental variable with all child health outcomes in the Dominican Republic 2013 DHS survey**



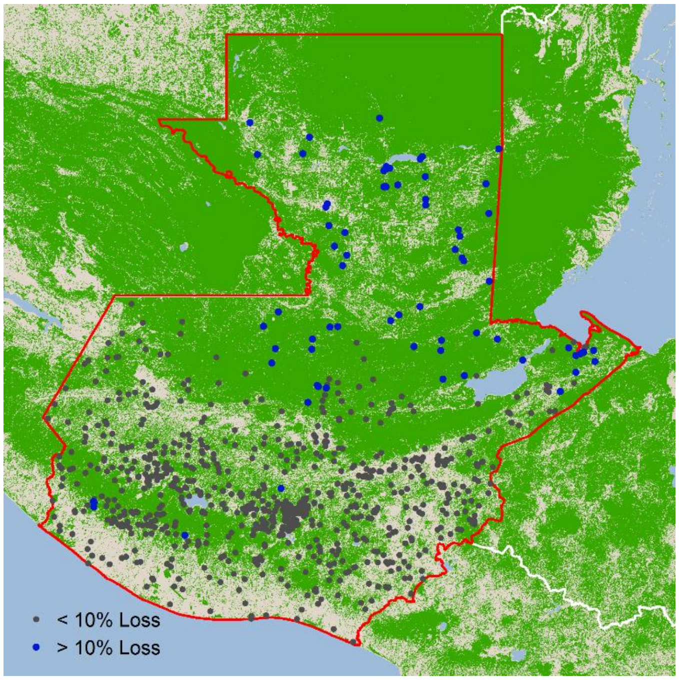
In the first plot of Figure 34 we see that higher forest cover was significantly associated with greater likelihood of stunting among children, but lower likelihood of mortality. There were no significant associations between forest cover squared and the health outcomes, indicating that the significant associations found with stunting and mortality are linear. A marginal significance was found between forest loss and stunting and underweight. For these two outcomes, greater forest loss was associated with lower likelihood of the outcome. There were also no significant associations between the vegetation index and any of the outcomes in the adjusted models.

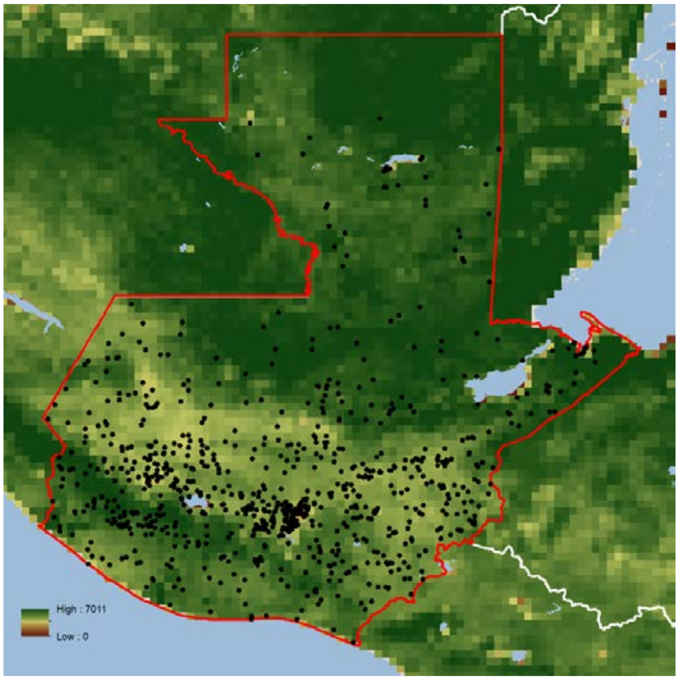
Proximity to protected area was significantly associated with underweight and diarrhea in the negative direction—that is, greater distance to a protected area was significantly associated with lower likelihood of underweight and diarrhea in children. However, proximity to water was not significantly associated with any of the outcomes.

3.11 Guatemala

Guatemala is a coastal country with very high forest cover and vegetation, as the maps in Figure 35 show. There were a number of DHS clusters that had more than 10% forest loss, with most of the loss concentrated in the north. Guatemala experienced the most loss among the four countries in Latin America and the Caribbean included in the analysis, reaching 44% (Table 2).

Figure 35 Guatemala maps: The first map shows the forest cover and forest loss in the last 10 years (blue dots are clusters with more than 10% loss). The second map shows the vegetation index from low (red) to high (green). In both maps the dark dots are the DHS cluster locations.

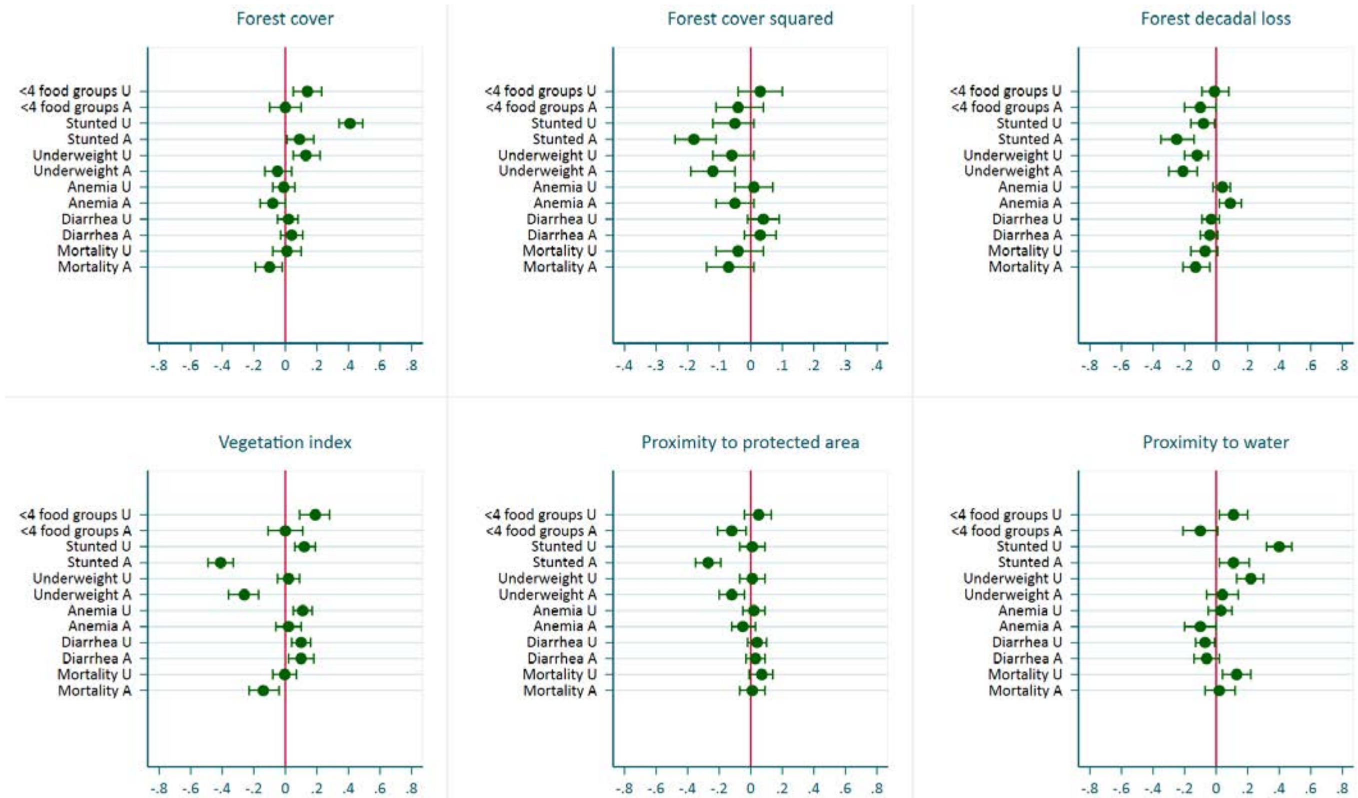




Regression results for the most recent survey

The results from the regressions of all the environmental variables with the child health outcomes in Guatemala, including child mortality, are summarized in Figure 36. The figure shows unadjusted (U) and adjusted (A) coefficients for all the environmental variables and the outcomes in the most recent survey. The estimates are also found in Appendix Tables B.2-B.8.

Figure 36 **Unadjusted (U) and adjusted (A) coefficients from the regressions of each environmental variable with all child health outcomes in the Guatemala 2014-2015 DHS survey**



Forest cover was highly significant in association with stunting in the unadjusted model. After adjusting for other variables, however, the association with stunting became marginally significant. Higher forest cover was significantly associated with higher likelihood of stunting, but forest cover squared was also significantly associated with stunting, indicating that the relationship between stunting and forest cover is not linear. A significant nonlinear relationship was also found between forest cover and underweight, as shown in the second plot. Higher forest cover was significantly associated with lower likelihood of anemia and mortality in children but with a marginal significance, as shown in the first plot. For these two outcomes, higher forest cover was significantly associated with lower likelihood of the outcome.

Forest loss in the last 10 years was marginally significant with inadequate dietary diversity, with greater forest loss associated with lower likelihood of consuming less than four food groups. It was also significant in the negative direction for stunting, underweight, and mortality—greater forest loss was associated with lower likelihood of these outcomes. However, it was marginally significant with anemia in the positive direction, indicating that greater forest loss was associated with higher likelihood of anemia in Guatemala.

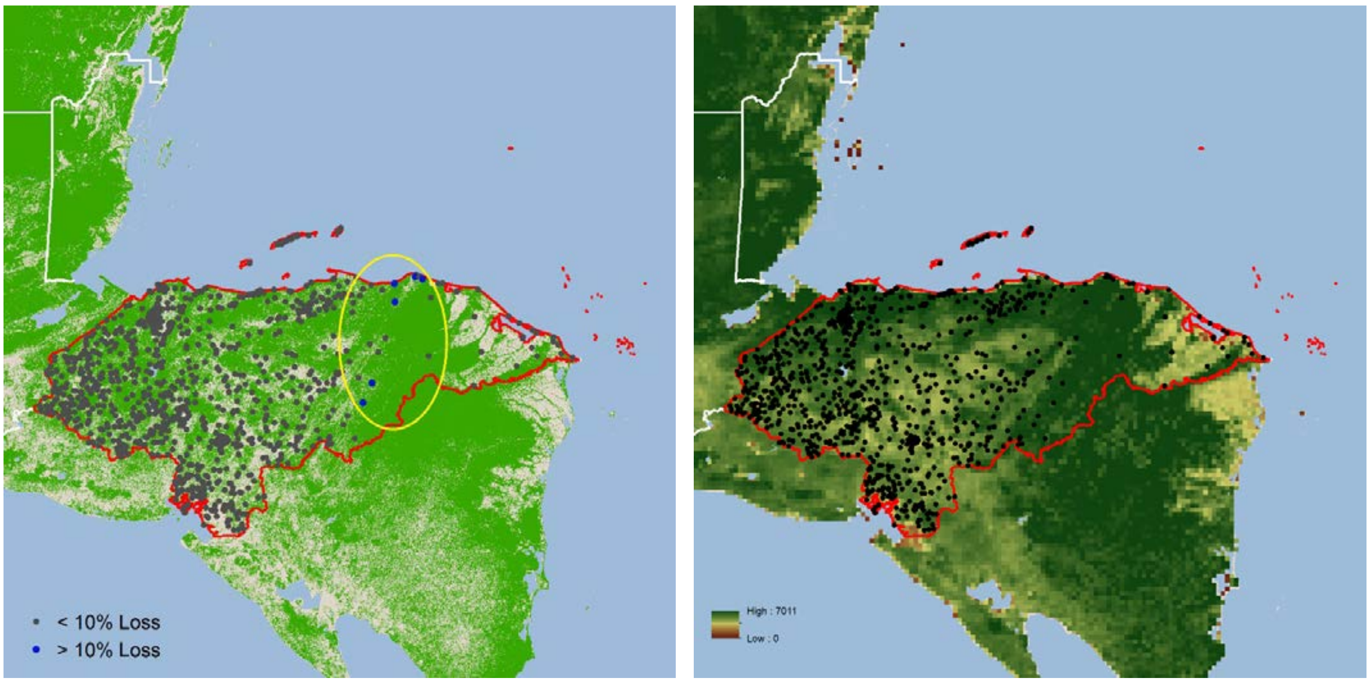
Higher levels of the vegetation index were associated with lower likelihood of stunting, underweight, and mortality in children. However, it was positively associated with diarrhea—indicating greater likelihood of diarrhea in children at higher levels of the vegetation index.

Proximity to protected area was negatively associated with consuming less than four food groups, stunting, and underweight. For these outcomes, the greater the distance to a protected area, the lower the likelihood of the outcome. However, greater distance to water was significantly associated with greater likelihood of stunting and marginally lower likelihood of anemia.

3.12 Honduras

Honduras is a Caribbean country with high forest cover and vegetation throughout the country, as the maps in Figure 37 show. Few clusters, indicated by the yellow circle in the first map, were found to have experienced more than 10% forest loss in the last 10 years.

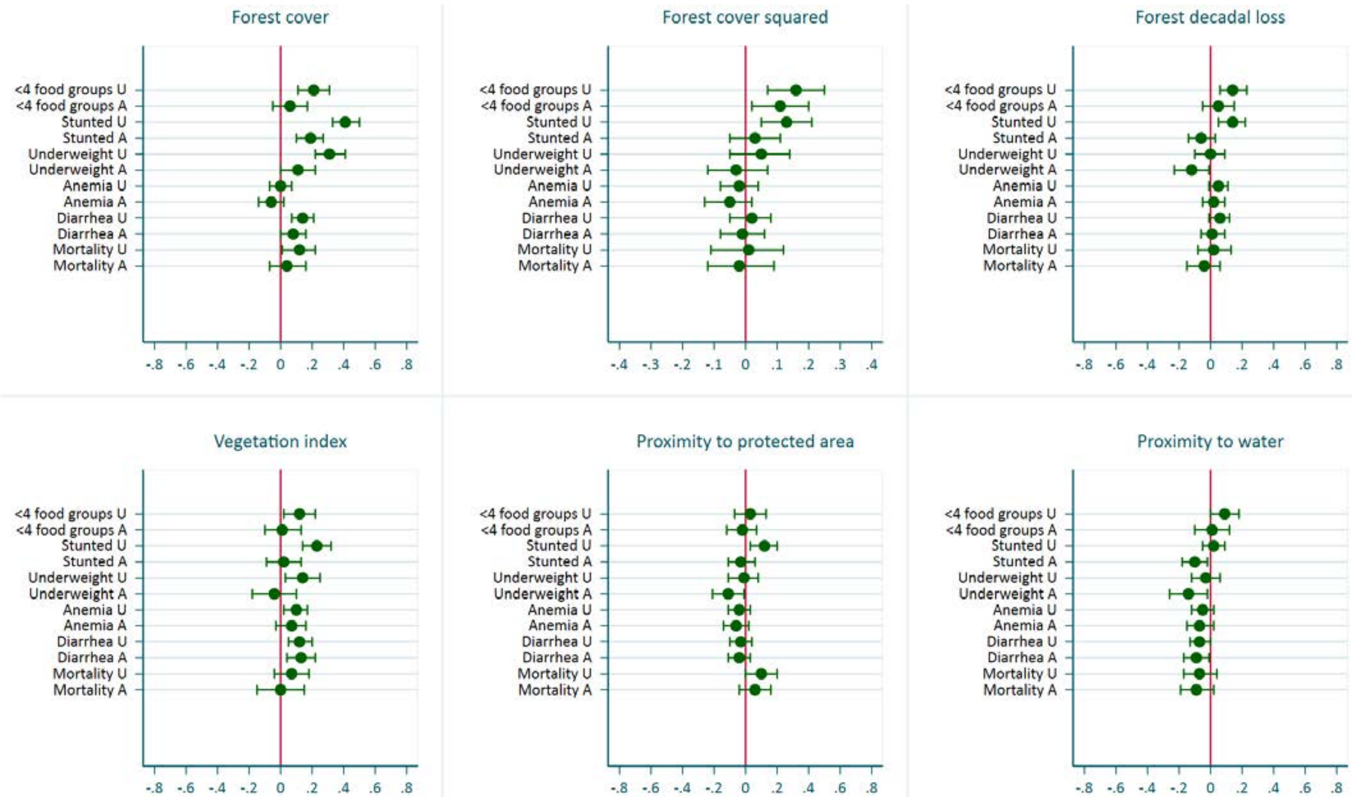
Figure 37 Honduras maps: The first map shows the forest cover and forest loss in the last 10 years (blue dots are clusters with more than 10% loss). The second map shows the vegetation index from low (red) to high (green). In both maps the dark dots are the DHS cluster locations.



Regression results for the most recent survey

Figure 38 shows the results from the regressions of all the environmental variables with the child health outcomes in Honduras, including child mortality. The unadjusted (U) and adjusted (A) coefficients are shown for all the environmental variables and the outcomes in the most recent survey. The estimates are also found in Appendix Tables B.2-B.8.

Figure 38 Unadjusted (U) and adjusted (A) coefficients from the regressions of each environmental variable with all child health outcomes in the Honduras 2011-2012 DHS survey



Higher forest cover in Honduras was significantly associated with higher likelihood of stunting and diarrhea, but for diarrhea the significance was marginal. There was a significant nonlinear association between forest cover and inadequate dietary diversity, as shown in the second plot. There was a marginal but significant association between forest loss in the last 10 years and underweight, with higher forest loss associated with lower likelihood of underweight in children.

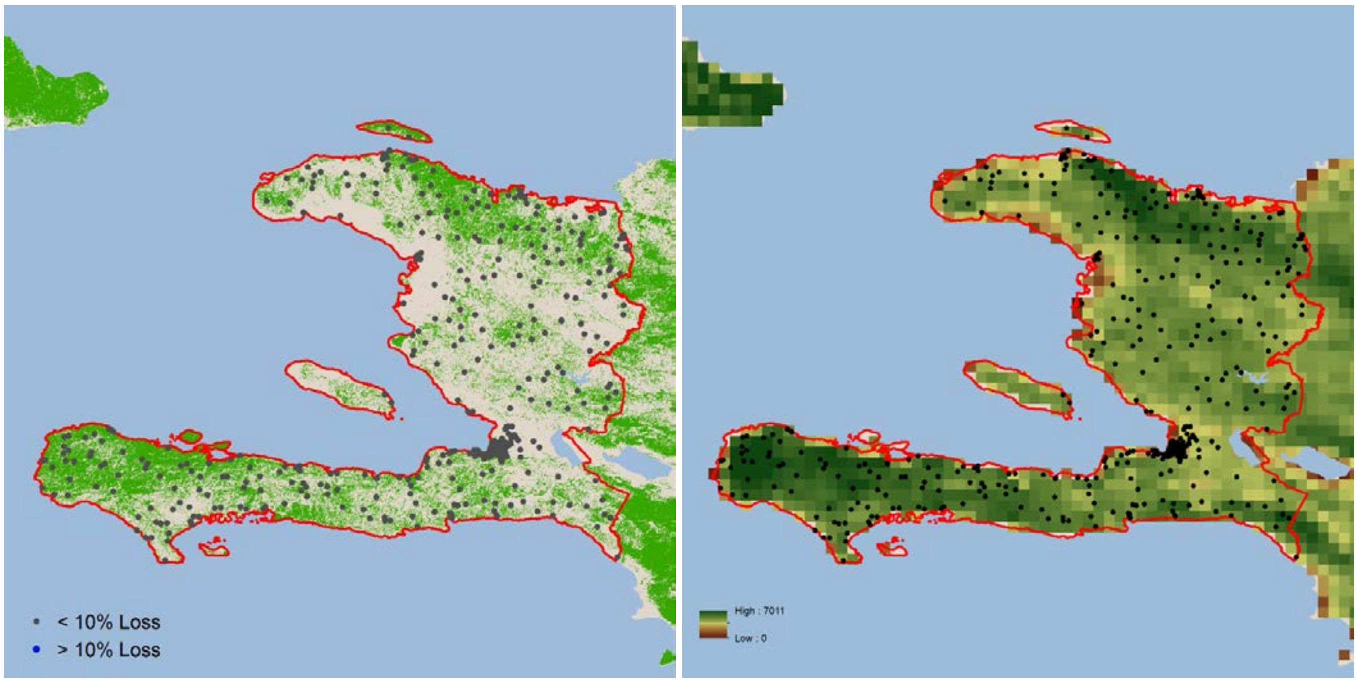
Only diarrhea was significantly associated with the vegetation index in the adjusted models. For this outcome, the higher the vegetation index, the greater the likelihood of diarrhea in children.

Proximity to protected area was only marginally significant with underweight. Greater distance to a protected area was significantly associated with lower likelihood of underweight. This result was also found between proximity to water and underweight, with greater distance to water associated with lower likelihood of underweight, but with a marginal significance. A marginal significance in the negative direction was also found between proximity to water and stunting and diarrhea. For these two outcomes, the greater the distance to water, the lower the likelihood of the outcome.

3.13 Haiti

Haiti is located on the western part of the Caribbean island that has the Dominican Republic to the east. Figure 39 shows forest cover scattered throughout Haiti and very high vegetation in most parts of the country. There were no DHS clusters that exhibited more than 10% forest loss in the last 10 years. The maximum forest loss was 4% (Table 2), the lowest level of forest loss among the four Latin American and Caribbean countries in the analysis.

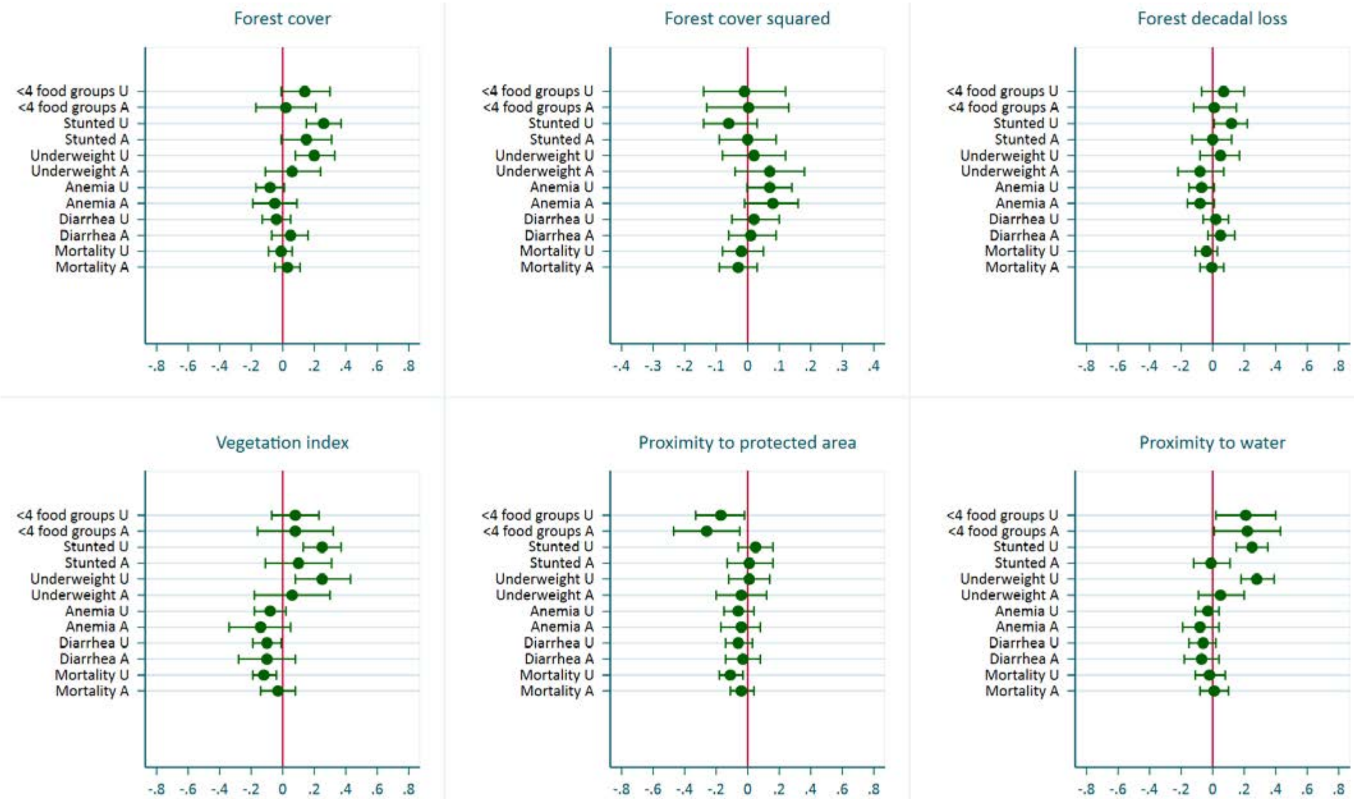
Figure 39 Haiti maps: The first map shows the forest cover and forest loss in the last 10 years. The second map shows the vegetation index from low (red) to high (green). In both maps the dark dots are the DHS cluster locations.



Regression results for the most recent survey

The results from the regressions of all the environmental variables with the child health outcomes in Haiti, including child mortality, are summarized in Figure 40. The figure shows unadjusted (U) and adjusted (A) coefficients for all the environmental variables and the outcomes in the most recent survey. The estimates are also found in Appendix Tables B.2-B.8.

Figure 40 Unadjusted (U) and adjusted (A) coefficients from the regressions of each environmental variable with all child health outcomes in the Haiti 2012 DHS survey



With the exception of a marginal significance found between inadequate dietary diversity and the two proximity variables, no significance was detected in the adjusted models between the outcomes and the environmental variables. Greater distance to a protected area was significantly associated with lower likelihood of consuming less than four food groups. Greater distance to water was significantly associated with higher likelihood of consuming less than four food groups. The lack of significant findings in Haiti may be explained by the relatively uniform distribution of the vegetation index, as the maps show, and no forest loss more than 10%. In addition, most of the country is surrounded by water, so proximity to water is also relatively uniform throughout the country.

3.14 Summary of Findings

Table 3 provides a summary of the significant findings from the regression analysis shown in the forest plots and Appendix Tables B.2-B.8. The table indicates whether the association found between each environmental variable and each health outcome was negative or positive, as well as its level of significance. A negative association indicates that the higher the value of the environmental variable, the lower the likelihood of the outcome. Since all the outcomes are constructed to be negative—that is, poor health outcomes—a negative association with the environmental variable would indicate a better health outcome. A positive association would indicate the opposite—the higher the value of the environmental value, the greater the likelihood of an adverse health outcome.

Except for the anemia and malaria outcomes, the analysis was performed for 12 countries with recent DHS surveys—four each in sub-Saharan Africa, Asia, and Latin America and the Caribbean. Overall, as the summary table shows, few significant findings were found and many of the significant findings were of marginal significance ($p<0.05$). It is also important to note that the coefficients were small in magnitude, as shown in Appendix Tables B.2-B.8, even after the environmental variables were standardized, which would increase the size of the coefficients. In addition, most of the findings were not consistently in the same direction, but with some exceptions. For instance, a negative association was always found for the forest loss and vegetation index variables with the underweight outcome. A positive association was always found between forest cover and stunting. For the malaria outcome, which was only available for four countries, three of the countries showed a negative association with proximity to protected area. The stunting and underweight outcomes had more significant findings compared with the other outcomes. In terms of forest loss, we would expect that the greater the deforestation, the greater the likelihood of a positive association—that is, an adverse health outcome. However, the results showed that the association was usually negative, especially for the stunting and underweight outcomes. There were no significant findings of association between forest loss and diarrhea.

Some countries had more significant associations than others. Haiti, Cambodia, and the Dominican Republic had the smallest number of significance findings, as shown in Table 3. We need to keep in mind, however, that the anemia and malaria outcomes were not available for all countries. Analysis on the malaria outcome was only performed for the sub-Saharan African countries. Anemia testing was not available in Bangladesh, Chad, and the Dominican Republic. Even after excluding malaria and anemia, however, Chad, Guatemala, and Nepal had the most significant findings.

Table 3 Summary of significant findings from the regression analysis between each environmental variable and each outcome

Environmental variable	Had < 4 food groups	Diarrhea	Stunted	Underweight	Anemia[1]	Malaria[2]	Mortality
Forest cover	Ethiopia --- Nepal --- Uganda +	Uganda - Chad ++ Honduras + Myanmar +	Dominican Rep. ++ Honduras +++ Cambodia + Uganda +++	Chad -- Myanmar - Nepal --- Bangladesh +++	Nepal --- Guatemala +	Malawi --- Chad ++ Uganda +++	Dominican Rep. - Guatemala - Nepal - Bangladesh +++ Ethiopia +
Forest cover squared	Cambodia - Ethiopia ++ Honduras +	Malawi ++	Bangladesh -- Guatemala ---	Guatemala --- Nepal ++	Ethiopia – Myanmar +	Chad --- Malawi +++ Uganda +++	Chad ---
Forest loss 10 years	Ethiopia ---		Chad --- Dominican Rep. - Ethiopia - Guatemala --- Uganda +++	Chad --- Dominican Rep. - Ethiopia - Guatemala --- Honduras - Myanmar -	Cambodia - Guatemala ++ Nepal +++	Ethiopia - Malawi --- Chad +++	Guatemala - Bangladesh +++ Chad + Myanmar +
Vegetation index	Ethiopia --- Nepal --	Bangladesh - Malawi - Uganda --- Honduras ++	Chad --- Guatemala --- Nepal --- Uganda +++	Chad --- Guatemala --- Myanmar - Nepal ---	Myanmar -- Nepal ---	Malawi --- Chad +++ Uganda +++	Guatemala – Chad +++
Proximity to protected area	Guatemala -- Haiti - Malawi ---	Dominican Rep. - Malawi +++ Uganda ++	Ethiopia - Guatemala ---	Bangladesh -- Dominican Rep. -- Guatemala -- Honduras - Uganda - Chad +++	Malawi - Nepal - Uganda +++	Chad --- Malawi - Uganda ---	Bangladesh - Chad - Malawi +++
Proximity to water	Ethiopia - Myanmar -- Malawi - Haiti + Chad +++ Nepal +++	Honduras - Malawi +++ Nepal +	Chad --- Ethiopia --- Honduras - Bangladesh ++ Malawi ++	Honduras - Cambodia -- Myanmar --- Nepal ++ Uganda ++	Guatemala - Malawi - Ethiopia +	Chad --- Malawi +++	Malawi +++ Nepal +

Note: A negative sign indicates a significant negative coefficient (in purple), a positive sign indicates a significant positive coefficient (in blue). The number of signs indicates the level of significance; 1 sign p<0.05; 2 signs p<0.01; 3 signs p<0.001. 1 - Bangladesh, Chad, and Dominican Republic did not have anemia testing; 2 - Malaria outcome is only available for Chad, Ethiopia, Malawi, and Uganda.

4 DISCUSSION

The period since the industrial revolution has been an era of unprecedented environmental alteration. Virtually every ecosystem has shown some measure of human intervention, affecting biodiversity and the quality of the air, water, and soils across many regions. At a global scale, however, indicators of human development, including life expectancy and child mortality rates, have been rapidly and steadily improving. In fact, a global study found that at the country level neither the rate of forest loss nor the percentage of land that human activities had highly disturbed were associated with a negative condition for any of several health indicators analyzed, including life expectancy, infant mortality rate, and low birthweight (Huynen, Martens, and De Groot 2004). We have known for centuries that environmental conditions affect human and animal health, and increasingly recognize the importance, value, and the frequent irreplaceability of the resources that nature provides. Therefore, it is intuitive to infer that environmental degradation should be paralleled by declines in health indicators, at least for indicators that are potentially directly affected by environmental conditions.

The relationship between environmental change and human health outcomes is likely too complex to be ascertained by correlative analyses. Some of the sources of this complexity have been mentioned in this report. The temporal dimension may be important, for example if environmental change leads to improvements in human wellbeing in the short or medium term but is ultimately harmful in the long term (Myers and Patz 2009). The spatial scale of analysis may also be important. Global analyses generally treat each unit of environmental change, such as forest loss, as equal to any other, but we know that damage to some areas (e.g., watersheds, see Herrera et al. 2017) or ecosystems can more immediately affect ecosystem services and health. Additionally, the spatial configuration of environmental change may itself drive its consequences for human health. Specifically, analyzing the total area deforested may obscure whether deforestation progresses in multiple small fronts as opposed to large tracts, which may determine its overall impact on health (Allan, Keesing, and Ostfeld 2003; Suzán et al. 2008). Another critical point is that to a varying extent, societies can mitigate the effects of environmental degradation through infrastructure, governance systems, and/or behavior change (Myers and Patz 2009).

We would expect that the multiple relationships between environmental conditions and health outcomes are nonlinear, and the shape of these relationships can vary across ecological and socioeconomic contexts (Raudsepp-Hearne et al. 2010). In fact, the analysis of the forest cover squared variable showed statistical evidence of nonlinear relationships with child health outcomes in a few countries and for a few outcomes (Table 3). For malaria, a significant nonlinear relationship for forest cover was found in three of the four sub-Saharan African countries that examined this outcome.

It is therefore unsurprising that the results of this analysis show a lack of a singular, geographically consistent association between the environmental and health metrics studied. Few significant results were found in the regression models that included the environmental variables and the health outcomes, and most findings with strong statistical evidence of association were not consistent across countries (Table 3). In addition, almost all the significant coefficients were very small, even after the variables were standardized (Appendix Tables B.2-B.8), indicating that the contribution of these environmental variables to the explanation of the outcome is minimal.

By definition, this analysis was restricted to globally representative datasets of environmental variables that matched DHS data. Among the available environmental datasets, we selected those that could have a plausible effect on human health or nutritional outcomes. For example, previous studies have demonstrated associations between forest cover and nutritional outcomes (Ickowitz et al. 2014), the effects of nature protection on livelihoods and food security (Andam et al. 2010; Lester et al. 2009), and the relationship between deforestation and disease risk (Vittor et al. 2006; Wolfe et al. 2005), among others. In the analysis we included low- and middle-income countries, which have a variety of ecological conditions, baseline forest cover, cultures, and economic development. As expected, we found divergent responses across countries and indicators. It is likely that the significant findings detected are due to the association of these environmental variables with other variables that would provide a direct and stronger link to the outcomes (such as wealth, urbanization, and access to services), and not due to the environmental variables themselves.

An important limitation of this type of analysis is that statistically significant associations can at best indicate correlation, but do not by themselves allow for inferring causality. Ideally, investigation of the effects of deforestation on nutrition and health should be based on longitudinal data collected over large areas and for a long time, and should account for local capacity to mitigate or adapt to environmental change. For example, the effects of forest loss on food security is probably more direct among populations that traditionally have depended on forest products for their diets (Harris et al. 2017; Powell, Hall, and Johns 2011), and when changes in land use do not provide potential for access to other food sources or means of support. Similarly, any effect of deforestation on infectious disease is probably more direct among populations with less access to health care than others with better access, even if their environmental risk is the same. Unfortunately, available datasets generally lack sufficient detail to ascertain or control for these kinds of attributes.

For three countries—Malawi, Nepal, and Uganda—three surveys from each country were combined to examine more closely the temporal relationship between forest cover and the health outcomes. It appeared from this analysis that many changes in the outcomes (mainly improvements) across the surveys were not due to changes in forest cover over time, but rather to changes in the outcome over time that could be attributed to other factors. In some cases, such as the nutrition outcomes of inadequate dietary diversity, underweight, and anemia in Nepal, findings appeared to be due to the changes in forest cover over time. However, it is difficult to make these causal inferences even with the use of pooled data, since we are not following individuals or the same clusters over time; this would require the use of longitudinal data and perhaps examination also over a longer period. From the available data used in the analysis, we can only indicate how these associations changed over time. When we detected a statistically significant relationship between forest cover and the outcome, we were unable to ascertain whether these variables were causally linked or co-varied due to an association with another variable.

In this analysis, even comparisons of neighboring countries failed to uncover a consistent signal indicating an overall health effect of deforestation. Comparing neighboring countries with similar ecosystems could help eliminate the effects of ecological conditions on health outcomes. However, we found that this was not the case. An example is a comparison between the results for Haiti and the Dominican Republic. Although these two countries can be expected to be the most ecologically similar in our sample, since they share a relatively small island, their development pathways as well as their cultural and socioeconomic contexts are vastly dissimilar.

Ecosystems in Haiti are much more degraded than in the Dominican Republic. Overall, local conditions are sufficiently dissimilar across the island that it is difficult to identify a signal in this two-country comparison. In Haiti the analysis found a significant association only for the inadequate dietary diversity outcome and the proximity variables; no other significance was detected for the associations between remaining environmental variables and health outcomes. In the Dominican Republic there were few significant findings, and two marginally significant findings indicated that greater forest loss was associated with lower likelihood of underweight and stunting. For some countries, for example Chad, Guatemala, and Nepal, the analysis found more significant findings than for others, which may imply that environmental factors have stronger effects in these countries; further in-depth studies are required to verify this finding.

The analysis did reveal some interesting patterns. For instance, for some findings, both forest cover and deforestation showed a negative association with the outcomes (i.e., both higher forest cover and higher levels of deforestation were associated with better health outcomes). This occurred in Ethiopia with dietary diversity, Chad and Myanmar with underweight, Malawi with malaria, and Guatemala with mortality (Table 3). This could mean that more deforestation tends to occur in areas with more initial forest cover, and therefore, these variables are correlated. The analysis attempted to correct for this paradox by including the initial forest cover level (forest cover in year 2000) in the models that include deforestation. Another explanation could be the relationship with the vegetation index. For these countries and outcomes, the association with the vegetation index was also in the negative direction. This suggests that deforestation was potentially associated with clearing lands for farms and crops, therefore improving nutrition outcomes and ultimately reducing levels of child mortality. For example, the map of Chad in Figure 6 shows that deforestation occurred in areas with the highest vegetation index.

The negative association between deforestation and the vegetation index (but not forest cover) was found in Chad with stunting, and Guatemala with stunting and underweight. There were also inconsistencies in the findings within the outcomes. For diarrhea, higher forest cover was associated with a higher likelihood of diarrhea in Chad, Honduras, and Myanmar. This pattern is the opposite of what previous studies from Malawi and Cambodia have reported (Johnson, Jacob, and Brown 2013; Pienkowski et al. 2017). However, the results show that higher forest cover was associated with a lower likelihood of diarrhea in Uganda. No countries showed any significant association between diarrhea and deforestation, in line with the findings from a previous study in Nigeria by Berazneva and Byker (2017).

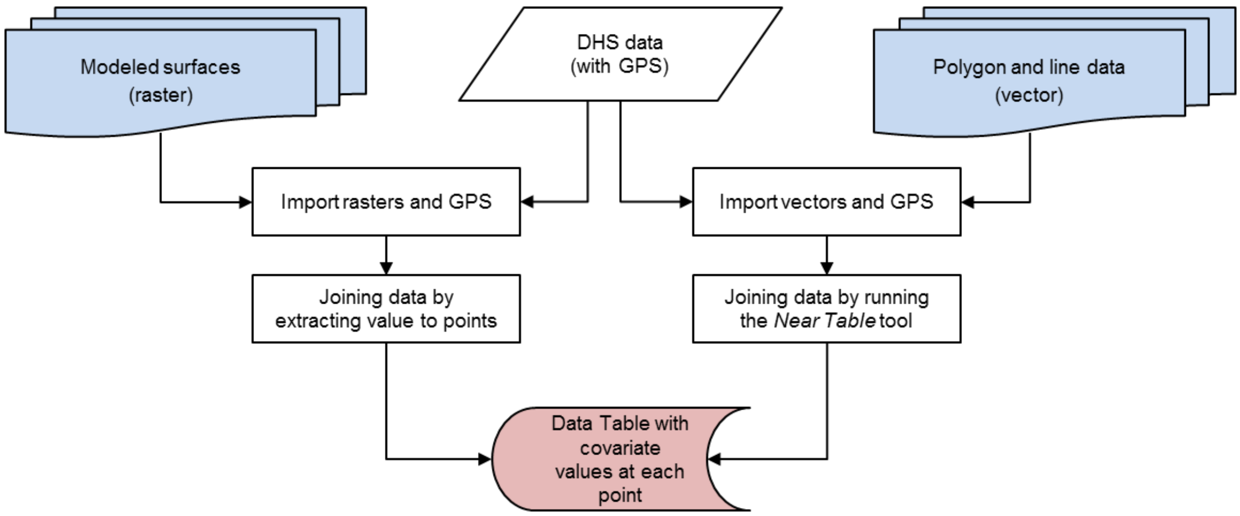
Analysis of the association between the environmental variables and malaria was only performed using data from four countries. However, the analysis still found inconsistencies in the results. For example, forest cover was associated with a higher likelihood of malaria in Chad and Uganda; in contrast, forest cover was associated with a lower likelihood of malaria in Malawi. Deforestation was associated with a higher likelihood of malaria in Chad, but with a lower likelihood of malaria in Ethiopia (although marginal) and in Malawi. The finding that for Chad and Malawi the relationship of forest cover and deforestation with malaria was in the same direction could be explained by the significant association with forest cover squared for these countries, indicating that the relationship between forest cover and malaria is not linear.

The literature also has demonstrated some mixed findings on the association between malaria and forest cover and deforestation. Deforestation was positively associated with malaria in Brazil and Nigeria (Berazneva and Byker 2017; Olson et al. 2010). However, an analysis of 17 African countries did not find an association between deforestation and increased malaria (Bauhoff and Busch 2018), and a systematic review of this link found mixed results (Lima et al. 2017).

The results of this analysis confirm the complexity of investigating linkages between health and the environment, and they underscore the limitations of available global datasets. These results do not imply that deforestation or other forms of environmental degradation have no effects on health outcomes. As mentioned in this report, there is ample evidence of the contributions that functioning ecosystems make to human health and nutrition. USAID policy acknowledges the critical contributions of biodiversity to achieving development goals across sectors (USAID 2014), and the U.S. Government Global Food Security Strategy 2017-2021 recognizes the role of ecosystem functions in supporting food security goals. Over sufficiently large scales, human wellbeing is ultimately dependent on ecosystem resources and functions that cannot all be replaced by infrastructure or technology. The results of this analysis confirm that the linkages are complex, unlikely to be uniform, and often nonlinear, and suggest that there are no simple policy options or interventions to provide multiple benefits across development sectors including health.

APPENDIX A: EXTRACTION PROCEDURE

The environmental variables came from two types of data: raster and vector. Raster data, such as images and modeled surfaces, rely on pixels or cells to convey their data values. On the other hand, vector data, such as points, lines, and polygons, show the discrete location or boundary of a feature. Because of the differences in the data types, the methods to extract meaningful values needed to vary. The following flow chart shows the general process that we used.



If the data were provided as a raster, we used a neighborhood calculation. For data in a vector format, we used a distance measure.

The following table shows the environmental variables that were extracted with the year of the data used, the summary method used, and the extraction methods that were used, with a citation for the dataset.

Appendix Table A.1 Summary of the environmental variables

Dataset	Year	Summary	Method	Citation
Enhanced Vegetation Index	2005, 2010, 2015	Mean	Neighborhood Calculations	Didan and Barreto 2016
Malaria	2005, 2010, 2015	Mean	Neighborhood Calculations	Malaria Atlas Project 2015
Night Lights	2015	Mean	Neighborhood Calculations	National Centers for Environmental Information 2015
Proximity to Protected Places	2017	Distance	Distance Calculations	UNEP-WCMC and IUCN 2017
Proximity to Water	2017	Distance	Distance Calculations	Wessel and Smith 2017

For all of the extractions, we used the publicly available cluster locations published by the DHS Program. Each of the clusters was displaced from the actual location by up to 10 kilometers for rural points and 2 kilometers for urban points. More information about the displacement procedure used can be found in Burgert et al. (2013). The procedures that we used attempted to compensate as much as possible for the uncertainty of the cluster locations, but the uncertainty adds an element of error to all extracted values.

A.1 Neighborhood Calculations using Raster Data

The neighborhood calculations were done using several Python scripts that moved data through the process and did the actual extractions. Instead of writing a zonal statistics algorithm ourselves, we relied on the rasterstats package's version of the algorithm (Perry 2016).

First, a circular buffer was drawn around each point. For all of the environmental characteristics, the buffers had a radius of 10 kilometers for rural points and 2 kilometers for urban points. This was done to compensate for the displacement of points to protect the confidentiality of respondents and to account for the varying pixel size of data sets.

All raster cells with centroids falling within this buffer were used in the raster extraction calculation. Any raster cell whose centroid did not fall within these buffers was not used for the calculations. The zonal statistics algorithm can output a number of summary statistics including sum, count, and mean. If this process failed to return a value, the value of the cell directly underneath the cluster location was used. These steps were performed in sequence for all GPS points in the input DHS dataset.

A.2 Distance Calculations using Vector Data

The distance from DHS points to each of the coasts or lakes and protected areas was measured using the Near Table tool in ArcMap (ESRI 2017). The tool calculates the geodesic distance between each DHS point and the nearest boundary of a selected polygon or line feature class. The distance calculated was appended as an attribute to the DHS points' attribute table, which we then joined with all the data from the raster extraction activity.

APPENDIX B: APPENDIX TABLES B.1-B.11

Appendix Table B.1 **Percentage of children in the household that consumed less than four food groups in the day or night before the survey, had diarrhea in the 2 weeks before the survey, were stunted, underweight, or had any anemia**

		Did not have at least 4 food groups		Diarrhea		Stunted		Underweight		Anemia		Malaria	Mortality	
Country	Year	% [95% C.I.]	N	% [95% C.I.]	N	% [95% C.I.]	N	% [95% C.I.]	N	% [95% C.I.]	N	% [95% C.I.]	% [95% C.I.]	N
Bangladesh	2014	72.9 [70.5,75.2]	2425	5.7 [4.8,6.9]	7625	36.1 [34.4,37.9]	7318	32.6 [30.8,34.5]	7318	NA		NA	5.3 [4.9,5.8]	16970
Chad	2014-15	89.9 [88.3,91.3]	4632	22.4 [21.2,23.8]	16643	39.9 [38.4,41.3]	10854	28.8 [27.5,30.1]	10854	NA		14.5 [14.2,14.8]	13.0 [12.4,13.7]	37905
Dominican Republic	2013	37.2 [32.8,41.7]	1053	18.3 [16.4,20.3]	3391	6.9 [6.0,8.1]	3619	3.8 [3.0,4.8]	3619	NA		NA	3.3 [2.8,3.9]	7006
Ethiopia	2016	87.0 [84.6,89.0]	2990	11.9 [10.7,13.3]	10287	38.4 [36.5,40.3]	10376	23.6 [22.1,25.1]	10552	57.0 [54.5,59.5]	9263	0.69 [0.64,0.74]	7.5 [6.8,8.2]	22755
Guatemala	2014-15	40.5 [38.4,42.6]	3569	19.3 [18.3,20.3]	12229	46.5 [44.8,48.2]	12567	12.6 [11.7,13.6]	12567	32.4 [31.0,33.8]	11161	NA	3.6 [3.3,3.9]	24191
Honduras	2011-12	32.0 [30.0,34.1]	3027	18.1 [17.1,19.1]	9607	22.6 [21.4,23.9]	10167	7.0 [6.5,7.7]	10167	29.2 [27.9,30.6]	8692	NA	2.7 [2.4,3.0]	19629
Haiti	2012	73.2 [70.0,76.2]	1928	22.0 [20.6,23.4]	6010	21.9 [20.0,23.8]	4529	11.4 [10.1,12.8]	4529	65.0 [63.0,66.9]	4049	NA	8.6 [7.9,9.3]	13090
Cambodia	2014	52.6 [49.7,55.4]	2081	12.8 [11.8,14.0]	6752	32.4 [30.6,34.3]	4893	23.9 [22.2,25.7]	4893	55.5 [53.4,57.6]	4456	NA	4.5 [3.9,5.0]	14805
Myanmar	2015-16	75.6 [72.3,78.6]	1235	10.5 [9.3,11.7]	4123	29.2 [27.3,31.1]	4089	18.9 [17.4,20.6]	4100	57.8 [55.7,59.8]	3376	NA	6.7 [6.0,7.5]	8998
Malawi	2015-16	76.0 [74.1,77.8]	4768	22.0 [21.0,23.0]	16009	37.1 [35.6,38.7]	5707	11.7 [10.7,12.8]	5786	62.6 [60.7,64.5]	5245	18.6 [18.2,18.9]	6.7 [6.3,7.1]	34774
Malawi	2010	71.4 [69.7,73.0]	5644	17.8 [17.0,18.6]	17612	47.1 [45.2,49.0]	4849	12.8 [11.6,14.2]	4849	63.5 [61.3,65.7]	4441	41.0 [40.1,41.8]	10.9 [10.4,11.3]	38060
Malawi	2004	NA		22.8 [21.5,24.1]	9436	52.5 [51.0,54.0]	8569	17.3 [16.3,18.5]	8569	71.8 [69.4,74.1]	2174	31.7 [30.8,32.7]	13.4 [12.8,14.0]	19461
Nepal	2016	54.1 [51.1,57.1]	1490	7.6 [6.4,8.9]	4778	35.8 [33.5,38.3]	2421	27.0 [24.6,29.5]	2428	52.7 [49.9,55.4]	2165	NA	4.4 [3.9,4.9]	10187
Nepal	2011	72.3 [68.2,76.1]	1446	14.0 [12.7,15.4]	5086	40.5 [37.8,43.3]	2485	28.8 [26.3,31.5]	2485	46.2 [42.9,49.6]	2207	NA	5.9 [5.3,6.4]	11225
Nepal	2006	68.7 [65.3,71.9]	1438	12.0 [10.8,13.3]	5205	49.3 [46.9,51.7]	5258	38.6 [36.2,41.0]	5258	47.8 [45.6,50.1]	4691	NA	7.3 [6.7,8.1]	11531
Uganda	2016	70.7 [68.8,72.6]	4103	20.6 [19.6,21.7]	13338	28.9 [27.3,30.5]	5117	10.5 [9.5,11.6]	5136	52.8 [50.7,54.9]	4739	22.6 [22.1,23.0]	6.6 [6.2,7.0]	29361
Uganda	2011	87.2 [85.4,88.9]	2122	24.5 [23.0,26.1]	7007	33.4 [30.9,35.9]	2350	13.8 [12.1,15.6]	2350	49.3 [46.0,52.6]	2142	43.1 [41.4,44.7]	9.3 [8.7,10.0]	15478
Uganda	2006	78.2 [75.8,80.5]	2265	26.9 [25.4,28.4]	7276	38.1 [35.8,40.4]	2687	15.9 [14.2,17.7]	2687	72.6 [70.2,74.9]	2466	47.4 [46.5,48.2]	12.6 [11.9,13.3]	15985

Note: For diarrhea, stunted, and underweight, this was among children under age 5 years. For consuming less than 4 food groups, it was for the youngest child age 6-23 months living with the mother, and for anemia, it is for children age 6-59 months. Malaria rates are estimated from the MAP project and total observations are not provided for this outcome. Mortality is estimated as the proportion of deaths in the last 10 years. NA - Data not available for the survey.

Appendix Table B.2 **Unadjusted (U) and adjusted (A) regression coefficients for having consumed less than four food groups (inadequate dietary diversity)**

		Forest cover				Forest cover squared				Forest decadal change			
Country	**Year**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**
Bangladesh	2014	0.11	[-0.05,.27]	0.14	[-0.01,.29]	0.05*	[0.005,0.1]	0.03	[-0.02,.08]	0.19*	[0.04,0.34]	0.14	[-0.03,0.32]
Chad	2014-15	0.19	[-0.06,.44]	0.04	[-0.16,.25]	0.001	[-0.03,.03]	0.01	[-0.02,.05]	0.42**	[0.14,0.7]	0.23	[-0.04,0.50]
Dominican Republic	2013	0.09	[-0.1,0.27]	-0.01	[-0.24,.23]	0.01	[-0.15,0.17]	0.002	[-0.17,.18]	0.04	[-0.16,0.24]	0.05	[-0.16,0.26]
Ethiopia	2016	-0.13	[-0.32,.07]	-0.38***	[-0.56,-0.2]	0.22	[-0.01,0.44]	0.28**	[0.07,0.48]	-0.37***	[-0.59,-0.15]	-0.39***	[-0.59,-0.19]
Guatemala	2014-15	0.14**	[0.05,0.23]	-0.002	[-0.1,0.1]	0.03	[-0.04,0.1]	-0.04	[-0.11,0.04]	-0.01	[-0.09,0.08]	-0.10*	[-0.20,-0.005]
Honduras	2011-12	0.21***	[0.11,.031]	0.06	[-0.05,.17]	0.16***	[0.07,0.25]	0.11*	[0.02,0.2]	0.14**	[0.06,0.23]	0.05	[-0.05,0.15]
Haiti	2012	0.14	[-0.01,0.3]	0.02	[-0.17,.21]	-0.01	[-0.14,0.12]	0.003	[-0.13,0.13]	0.07	[-0.07,0.2]	0.01	[-0.12,0.15]
Cambodia	2014	0.17*	[0.04,0.3]	0.04	[-0.11,.18]	-0.10*	[-0.17,-0.02]	-0.09*	[-0.18,-0.001]	-0.04	[-0.24,.016]	-0.05	[-0.27,0.17]
Myanmar	2015-16	0.16	[-0.11,0.43]	0.05	[-0.24,.35]	-0.01	[-0.32,0.3]	-0.08	[-0.40,.25]	-0.11	[-0.48,0.27]	-0.15	[-0.50,0.21]
Malawi	2015-16	-0.06	[-0.17,.05]	-0.03	[-0.13,.08]	-0.01	[-0.09,0.07]	-0.03	[-0.1,0.04]	0.003	[-0.14,0.14]	0.08	[-0.06,0.22]
Nepal	2016	-0.35***	[-0.5,-0.21]	-0.47***	[-0.65,-0.29]	0.15*	[0.03,0.26]	0.07	[-0.07,0.2]	0.08	[-0.09,0.25]	0.05	[-0.14,0.24]
Uganda	2016	0.09	[-0.02,.21]	0.15*	[.03,.26]	0.12	[-0.01,0.25]	-0.03	[-0.16,0.1]	0.05	[-0.07,0.18]	0.11	[-0.02,0.23]

		Vegetation index				Proximity to protected area				Proximity to water			
Country	**Year**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**
Bangladesh	2014	0.02	[-0.12,0.17]	0.06	[-0.10,0.22]	-0.03	[-0.16,0.10]	-0.05	[-0.19,0.09]	-0.03	[-0.17,0.12]	-0.10	[-0.26,0.06]
Chad	2014-15	0.57***	[0.32,0.82]	0.24	[-0.06,0.53]	0.25	[-0.01,0.51]	-0.19	[-0.45,0.06]	0.97***	[0.64,1.31]	0.69***	[0.35,1.02]
Dominican Republic	2013	-0.03	[-0.23,0.17]	-0.14	[-0.36,0.09]	0.16	[-0.01,0.33]	0.10	[-0.10,0.31]	0.11	[-0.08,0.29]	-0.01	[-0.24,0.23]
Ethiopia	2016	-0.23*	[-0.43,-0.03]	-0.52***	[-0.71,-0.32]	0.31	[-0.01,0.63]	0.15	[-0.16,0.47]	0.11	[-0.18,.39]	-0.25*	[-0.5,-0.01]
Guatemala	2014-15	0.19***	[0.09,0.28]	0.001	[-0.11,0.11]	0.05	[-0.04,0.13]	-0.12**	[-0.21,-0.03]	0.11*	[0.02,0.20]	-0.10	[-0.21,0.01]
Honduras	2011-12	0.12*	[0.02,0.22]	0.01	[-0.10,0.13]	0.03	[-0.07,0.13]	-0.02	[-0.12,0.07]	0.09	[-0.03,0.18]	0.01	[-0.1,0.12]
Haiti	2012	0.08	[-0.07,0.23]	0.08	[-0.16,0.32]	-0.17*	[-0.33,-0.02]	-0.26*	[-0.47,-0.05]	0.21*	[0.02,0.40]	0.22*	[0.01,0.43]
Cambodia	2014	0.26***	[0.12,0.40]	0.02	[-0.13,0.17]	-0.15*	[-0.28,-0.01]	0.03	[-0.11,0.17]	0.04	[-0.09,0.18]	-0.14	[-0.27,0]
Myanmar	2015-16	0.08	[-0.16,0.32]	-0.03	[-0.28,0.23]	0.15	[-0.06,0.37]	0.04	[-0.17,0.25]	-0.26*	[-0.48,-0.03]	-0.34**	[-0.58,-0.11]
Malawi	2015-16	-0.04	[-0.18,0.11]	-0.05	[-0.19,0.08]	-0.33***	[-0.44,-0.22]	-0.30***	[-0.40,-0.20]	-0.18**	[-0.29,-0.07]	-0.12*	[-0.23,-0.03]
Nepal	2016	-0.19*	[-0.34,-0.03]	-0.25**	[-0.42,-0.08]	0.15	[-0.01,0.30]	0.14	[-0.02,0.31]	0.28***	[0.15,0.41]	0.28***	[0.14,.042]
Uganda	2016	0.07	[-0.04,0.17]	0.09	[-0.03,0.22]	-0.16**	[-0.27,-0.05]	0.04	[-0.09,0.18]	0.17**	[0.05,0.29]	-0.02	[-0.14,0.1]

*p<0.05, **p<0.001, ***p<0.0001

Appendix Table B.3 Unadjusted (U) and adjusted (A) regression coefficients for diarrhea

		Forest cover				Forest cover squared				Forest decadal change			
Country	**Year**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**
Bangladesh	2014	0.01	[-0.15,0.17]	-0.06	[-0.21,0.10]	-0.01	[-0.07,0.05]	-0.02	[-0.07,0.03]	0.04	[-0.08,0.16]	0.01	[-0.11,0.13]
Chad	2014-15	0.07***	[0.04,0.10]	0.06**	[0.01,0.10]	0.002	[-0.01,0.01]	0.01	[-0.003,0.01]	0.07*	[0.01,0.13]	0.04	[-0.02,0.11]
Dominican Republic	2013	0.05	[-0.07,0.16]	0.14	[-0.01,0.28]	0.01	[-0.09,0.11]	0.02	[-0.07,0.11]	-0.16*	[-0.32,0]	-0.16	[-0.33,0]
Ethiopia	2016	0.03	[-0.07,0.14]	-0.01	[-0.13,0.11]	-0.07	[-0.18,0.04]	-0.05	[-0.16,0.06]	-0.02	[-0.13,0.1]	0.003	[-0.11,.012]
Guatemala	2014-15	0.02	[-0.05,0.08]	0.04	[-0.03,0.11]	0.04	[-0.01,0.09]	0.03	[-0.02,0.08]	-0.03	[-0.09,0.02]	-0.04	[-0.10,0.01]
Honduras	2011-12	0.14***	[0.07,0.21]	0.08*	[0,0.16]	0.02	[-0.05,0.08]	-0.01	[-0.08,0.06]	0.06	[-0.01,0.12]	0.01	[-0.06,0.09]
Haiti	2012	-0.04	[-0.13,0.05]	0.05	[-0.07,0.16]	0.02	[-0.05,0.10]	0.01	[-0.06,0.09]	0.02	[-0.06,0.1]	0.05	[-0.03,0.14]
Cambodia	2014	0.11*	[0.01,0.21]	0.10	[0,0.20]	-0.04	[-0.11,0.02]	-0.01	[-0.07,0.05]	0.01	[-0.11,0.14]	0.01	[-0.12,0.15]
Myanmar	2015-16	0.18*	[0.04,0.32]	0.17*	[0.04,0.3]	0.05	[-0.11,0.21]	0.08	[-0.08,0.25]	-0.04	[-0.26,0.17]	-0.04	[-0.25,0.17]
Malawi	2015-16	-0.04	[-0.10,0.02]	-0.04	[-0.10,0.02]	0.04*	[0.004,0.08]	0.05**	[0.01,0.09]	0.01	[-0.06,0.09]	0.004	[-0.07,0.08]
Nepal	2016	-0.17*	[-0.31,-0.04]	-0.06	[-0.21,0.08]	-0.01	[-0.19,0.17]	-0.04	[-0.20,0.11]	0.12*	[0,0.23]	0.05	[-0.04,0.14]
Uganda	2016	-0.08*	[-0.15,-0.02]	-0.09**	[-0.16,-0.02]	-0.03	[-0.11,0.04]	-0.04	[-0.11,0.04]	-0.08*	[-0.15,-0.01]	-0.06	[-0.13,0.02]

		Vegetation index				Proximity to protected area				Proximity to water			
Country	**Year**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**
Bangladesh	2014	-0.16*	[-0.29,-0.03]	-0.18*	[-0.34,-0.03]	0.16	[-0.04,0.37]	0.11	[-0.06,0.28]	-0.21*	[-0.42,-0.01]	-0.13	[-0.31,0.05]
Chad	2014-15	0.11*	[0.02,0.21]	0.10	[-0.01,0.21]	-0.07	[-0.16,0.02]	-0.005	[-0.10,0.09]	-0.04	[-0.14,0.06]	-0.07	[-0.18,0.03]
Dominican Republic	2013	-0.02	[-0.16,0.12]	0.05	[-0.11,0.20]	-0.23***	[-0.37,-0.10]	-0.19**	[-0.32,-0.06]	-0.13	[-0.26,0]	-0.01	[-0.16,0.14]
Ethiopia	2016	0.10	[-0.01,0.21]	0.06	[-0.05,0.18]	-0.07	[-0.21,0.06]	-0.09	[-0.23,0.04]	-0.09	[-0.25,0.07]	-0.12	[-0.30,0.06]
Guatemala	2014-15	0.10**	[0.04,0.16]	0.10*	[0.02,0.18]	0.04	[-0.02,0.10]	0.03	[-0.03,0.09]	-0.07*	[-0.13,-0.01]	-0.06	[-0.14,0.02]
Honduras	2011-12	0.12***	[0.05,0.20]	0.13**	[0.04,0.22]	-0.03	[-0.10,0.04]	-0.04	[-0.11,0.03]	-0.07*	[-0.13,0]	-0.09*	[-0.17,-0.01]
Haiti	2012	-0.10*	[-0.19,-0.01]	-0.10	[-0.28,0.08]	-0.06	[-0.14,0.03]	-0.03	[-0.14,0.08]	-0.06	[-0.15,0.02]	-0.07	[-0.18,0.04]
Cambodia	2014	0.05	[-0.06,0.15]	0.05	[-0.06,0.16]	0.08	[-0.01,0.17]	0.05	[-0.05,0.15]	0.01	[-0.10,0.12]	0.05	[-0.06,0.16]
Myanmar	2015-16	0.14	[-0.02,0.30]	0.12	[-0.04,0.27]	0.05	[-0.09,0.18]	0.10	[-0.05,0.24]	-0.07	[-0.21,0.08]	-0.06	[-0.22,0.09]
Malawi	2015-16	-0.09*	[-0.17,-0.01]	-0.09*	[-0.16,-0.01]	0.18***	[0.11,0.24]	0.17***	[0.11,0.23]	0.012***	[0.06,0.17]	0.10***	[0.04,0.15]
Nepal	2016	-0.15*	[-0.30,-0.01]	-0.06	[-0.24,0.11]	-0.09	[-0.26,0.09]	-0.01	[-0.16,0.14]	0.19	[-0.02,0.41]	0.19*	[0.01,0.38]
Uganda	2016	-0.11***	[-0.18,-0.05]	-0.13***	[-0.21,-0.06]	0.06*	[0.001,0.12]	0.12**	[0.05,0.20]	-0.04	[-0.10,0.02]	-0.07	[-0.13,0.0002]

*p<0.05, **p<0.001, ***p<0.0001

Appendix Table B.4 Unadjusted (U) and adjusted (A) regression coefficients for stunting

		Forest cover				Forest cover squared				Forest decadal change			
Country	**Year**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**
Bangladesh	2014	0.05	[0,0.10]	0.01	[-0.07,.09]	-0.02*	[-0.05,-0.004]	-0.04**	[-0.06,-0.01]	0.06	[0,0.13]	0.05	[-0.05,0.16]
Chad	2014-15	-0.01	[-0.04,.02]	-0.02	[-0.05,.01]	0.002	[-0.01,0.01]	-0.004	[-0.01,0.01]	-0.15***	[-0.21,-0.08]	-0.15***	[-0.23,-0.07]
Dominican Republic	2013	0.11	[-0.05,.28]	0.27**	[.07,.47]	0.02	[-0.11,0.16]	-0.05	[-0.19,0.09]	-0.04	[-0.23,0.15]	-0.22*	[-0.43,-0.01]
Ethiopia	2016	-0.03	[-0.11,.04]	-0.08	[-0.16,0]	-0.02	[-0.12,0.07]	-0.02	[-0.10,0.06]	-0.16**	[-0.26,-0.06]	-0.12*	[-0.22,-0.02]
Guatemala	2014-15	0.41***	[.34,.49]	0.09*	[.01,.18]	-0.05	[-0.12,0.01]	-0.18***	[-0.24,-0.11]	-0.08*	[-0.16,-0.01]	-0.25***	[-0.35,-0.14]
Honduras	2011-12	0.41***	[.33,.50]	0.19***	[.1,.27]	0.13**	[0.05,0.21]	0.03	[-0.05,0.11]	0.14**	[0.050,.22]	-0.06	[-0.14,0.03]
Haiti	2012	0.26***	[.15,.37]	0.15	[-0.01,.31]	-0.06	[-0.14,0.03]	0.0001	[-0.09,0.09]	0.12*	[0.01,0.22]	-0.003	[-0.13,0.12]
Cambodia	2014	0.15***	[.07,.23]	0.10*	[.02,.19]	-0.05	[-0.1,0.003]	-0.05	[-0.10,0.01]	-0.06	[-0.15,0.04]	-0.06	[-0.16,0.05]
Myanmar	2015-16	0.15**	[.04,.25]	0.07	[-0.03,.18]	-0.07	[-0.18,.040]	-0.08	[-0.18,0.03]	-0.07	[-0.20,0.06]	-0.08	[-0.23,0.06]
Malawi	2015-16	-0.03	[-0.1,.04]	-0.02	[-0.1,.05]	0.01	[-0.03,0.05]	-0.01	[-0.06,0.03]	-0.02	[-0.12,0.09]	0.05	[-0.06,0.16]
Nepal	2016	-0.01	[-0.11,.10]	-0.11	[-0.23,.01]	0.12*	[0.03,0.22]	0.08	[-0.02,0.17]	0.04	[-0.08,0.15]	0.04	[-0.10,0.17]
Uganda	2016	0.16***	[.08,.25]	0.27***	[.17,.37]	0.03	[-0.07,0.13]	-0.07	[-0.18,0.04]	0.10*	[0.01,0.18]	0.16***	[0.07,0.25]

		Vegetation index				Proximity to protected area				Proximity to water			
Country	**Year**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**
Bangladesh	2014	-0.01	[-0.09,0.07]	-0.06	[-0.15,.04]	-0.03	[-0.10,0.05]	-0.08	[-0.18,.01]	0.14***	[0.06,0.22]	0.13**	[0.05,0.22]
Chad	2014-15	-0.21***	[-0.28,-0.14]	-0.25***	[-0.33,-0.16]	0.15***	[0.09,0.22]	0.01	[-0.06,.08]	-0.13***	[-0.21,-0.06]	-0.20***	[-0.29,-0.12]
Dominican Republic	2013	0.06	[-0.10,0.21]	0.13	[-0.08,.35]	0.04	[-0.11,0.19]	0.02	[-0.15,.19]	-0.02	[-0.18,0.14]	0.12	[-0.08,0.32]
Ethiopia	2016	-0.06	[-0.14,0.03]	-0.08	[-0.16,.01]	-0.09	[-0.18,0]	-0.12*	[-0.21,-0.03]	-0.14*	[-0.25,-0.02]	-0.25***	[-0.36,-0.13]
Guatemala	2014-15	0.12***	[0.06,0.19]	-0.41***	[-0.49,-0.33]	0.01	[-0.07,0.09]	-0.27***	[-0.35,-0.19]	0.40***	[0.32,0.48]	0.11*	[0.02,0.21]
Honduras	2011-12	0.23***	[0.14,0.32]	0.02	[-0.09,.13]	0.12**	[0.03,0.20]	-0.03	[-0.11,.06]	0.02	[-0.05,0.09]	-0.01*	[-0.18,-0.02]
Haiti	2012	0.25***	[0.13,0.37]	0.10	[-0.11,.31]	0.05	[-0.06,0.16]	0.01	[-0.13,.16]	0.25***	[0.15,0.35]	-0.01	[-0.12,0.11]
Cambodia	2014	0.12**	[0.04,0.21]	0.03	[-0.06,.13]	-0.12**	[-0.2,-0.05]	-0.05	[-0.14,.04]	0.05	[-0.03,0.13]	-0.002	[-0.09,0.09]
Myanmar	2015-16	0.16**	[0.05,0.27]	0.10	[-0.01,0.22]	0.05	[-0.05,0.15]	0.04	[-0.08,.15]	0.10	[-0.01,0.21]	0.08	[-0.04,0.20]
Malawi	2015-16	-0.02	[-0.09,0.09]	-0.02	[-0.11,0.07]	0.03	[-0.04,0.10]	0.05	[-0.03,.12]	0.06	[-0.01,0.13]	0.10**	[0.03,.018]
Nepal	2016	-0.09	[-0.20,0.02]	-0.22***	[-0.35,-0.10]	0.11*	[0.01,0.21]	0.03	[-0.07,.12]	0.11	[0,00.23]	0.04	[-0.08,0.16]
Uganda	2016	0.18***	[0.10,0.27]	0.30***	[0.18,0.41]	-0.14***	[-0.23,-0.06]	-0.05	[-0.18,.07]	0.16***	[0.08,0.25]	0.10	[0,0.20]

*p<0.05, **p<0.001, ***p<0.0001

Appendix Table B.5 Unadjusted (U) and adjusted (A) regression coefficients for underweight

Country	Year	Forest cover				Forest cover squared				Forest decadal change			
		U	95% C.I.	A	95% C.I.	U	95% C.I.	A	95% C.I.	U	95% C.I.	A	95% C.I.
Bangladesh	2014	0.10***	[0.04,0.16]	0.10***	[0.04,0.16]	-0.01	[-0.03,0.02]	-0.01	[-0.03,0.01]	0.09**	[0.03,0.14]	0.07	[-0.01,0.15]
Chad	2014-15	-0.08**	[-0.13,-0.03]	-0.04**	[-0.07,-0.01]	0.01	[-0.003,0.02]	0.002	[-0.01,0.01]	-0.30***	[-0.42,-0.19]	-0.22***	[-0.31,-0.13]
Dominican Republic	2013	-0.16	[-0.40,0.09]	-0.04	[-0.32,0.25]	0.09	[-0.11,0.29]	0.07	[-0.13,0.27]	-0.22	[-0.50,0.06]	-0.41*	[-0.75,-0.08]
Ethiopia	2016	-0.01	[-0.09,0.07]	-0.01	[-0.09,0.07]	-0.02	[-0.11,0.07]	-0.03	[-0.11,0.05]	-0.20**	[-0.33,-0.07]	-0.12*	[-0.24,0]
Guatemala	2014-15	0.13**	[0.05,0.22]	-0.05	[-0.13,0.04]	-0.06	[-0.12,0.01]	-0.12***	[-0.19,-0.05]	-0.12***	[-0.20,-0.05]	-0.21***	[-0.30,-0.12]
Honduras	2011-12	0.31***	[0.22,0.41]	0.11	[0,0.22]	0.05	[-0.05,0.14]	-0.03	[-0.12,0.07]	-0.004	[-0.10,0.09]	-0.12*	[-0.23,-0.01]
Haiti	2012	0.2**	[0.08,0.33]	0.06	[-0.11,0.24]	0.02	[-0.08,0.12]	0.07	[-0.04,0.18]	0.05	[-0.08,0.17]	-0.08	[-0.22,0.07]
Cambodia	2014	0.11*	[0.01,0.21]	0.02	[-0.08,0.13]	-0.08*	[-0.14,-0.02]	-0.06	[-0.12,0.01]	-0.02	[-0.15,0.11]	-0.04	[-0.19,0.11]
Myanmar	2015-16	-0.02	[-0.13,0.09]	-0.13*	[-0.24,-0.02]	-0.05	[-0.18,0.07]	-0.07	[-0.19,0.05]	-0.15	[-0.31,0.01]	-0.18*	[-0.36,0]
Malawi	2015-16	0.07	[-0.02,0.16]	0.09	[-0.01,0.19]	-0.05	[-0.11,0.02]	-0.05	[-0.13,0.02]	0.02	[-0.12,0.16]	0.06	[-0.08,0.02]
Nepal	2016	-0.26***	[-0.39,-0.12]	-0.34***	[-0.48,-0.21]	0.22***	[0.11,0.33]	0.17**	[0.06,0.28]	0.06	[-0.11,0.23]	0.04	[-0.15,0.23]
Uganda	2016	-0.05	[-0.17,0.07]	0.01	[-0.13,0.14]	0.02	[-0.13,0.16]	-0.13	[-0.29,0.03]	-0.09	[-0.24,0.06]	-0.04	[-0.17,0.09]

Country	Year	Vegetation index				Proximity to protected area				Proximity to water			
		U	95% C.I.	A	95% C.I.	U	95% C.I.	A	95% C.I.	U	95% C.I.	A	95% C.I.
Bangladesh	2014	0.06	[-0.02,0.15]	0.06	[-0.05,0.17]	-0.08	[-0.17,0]	-0.19**	[-0.3,-0.07]	0.004	[-0.09,0.10]	-0.05	[-0.18,0.07]
Chad	2014-15	-0.48***	[-0.56,-0.40]	-0.41***	[-0.51,-0.32]	0.31***	[0.23,0.39]	0.16***	[0.08,0.24]	-0.11**	[-0.2,-0.03]	-0.07	[-0.16,0.02]
Dominican Republic	2013	0.05	[-0.16,0.25]	0.11	[-0.18,0.41]	-0.21	[-0.42,.01]	-0.33**	[-0.57,-0.08]	-0.22	[-0.46,0.01]	-0.21	[-0.5,0.09]
Ethiopia	2016	-0.11*	[-0.20,-0.02]	-0.07	[-0.15,0.01]	0.06	[-0.04,.16]	0.04	[-0.06,0.13]	0.10	[-0.01,0.21]	-0.01	[-0.12,0.11]
Guatemala	2014-15	0.02	[-0.05,0.09]	-0.26***	[-0.36,-0.17]	0.01	[-0.07,.09]	-0.12**	[-0.2,-0.04]	0.22***	[0.13,0.30]	0.04	[-0.06,0.14]
Honduras	2011-12	0.14*	[0.03,0.25]	-0.04	[-0.18,0.10]	-0.01	[-0.11,.08]	-0.11*	[-0.21,-0.01]	-0.03	[-0.12,0.06]	-0.14*	[-0.26,-0.02]
Haiti	2012	0.25**	[0.08,0.43]	0.06	[-0.18,0.30]	0.01	[-0.12,.14]	-0.04	[-0.20,0.12]	0.28***	[0.18,0.39]	0.05	[-0.09,0.20]
Cambodia	2014	0.08	[-0.03,0.18]	-0.07	[-0.18,0.04]	-0.04	[-0.13,.06]	0.06	[-0.05,0.16]	-0.07	[-0.17,0.02]	-0.17**	[-0.28,-0.06]
Myanmar	2015-16	-0.03	[-0.15,0.08]	-0.14*	[-0.26,-0.02]	-0.03	[-0.14,.07]	-0.01	[-0.13,0.11]	-0.16**	[-0.26,-0.05]	-0.24***	[-0.38,-0.11]
Malawi	2015-16	0.07	[-0.06,0.19]	0.08	[-0.06,0.21]	-0.10	[-0.21,0]	-0.03	[-0.15,0.08]	-0.10	[-0.21,0.01]	-0.03	[-0.15,0.09]
Nepal	2016	-0.26***	[-0.40,-0.11]	-0.37***	[-0.52,-0.23]	0.18**	[0.06,0.29]	0.12*	[0,0.24]	0.29***	[0.16,0.43]	0.20**	[0.06,0.34]
Uganda	2016	-0.01	[-0.14,0.11]	0.04	[-0.10,0.19]	-0.29***	[-0.42,-0.16]	-0.20*	[-0.37,-0.04]	0.30***	[0.19,0.41]	0.19**	[0.05,0.33]

*p<0.05, **p<0.001, ***p<0.0001

Appendix Table B.6 **Unadjusted (U) and adjusted (A) regression coefficients for anemia**

		Forest cover				Forest cover squared				Forest decadal change			
Country	**Year**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**
Ethiopia	2016	-0.06	[-0.17,0.05]	-0.02	[-0.14,0.10]	-0.06	[-0.16,0.04]	-0.10*	[-0.20,0]	-0.13*	[-0.26,0]	-0.07	[-0.22,0.08]
Guatemala	2014-15	-0.01	[-0.08,0.06]	-0.08*	[-0.16,0]	0.01	[-0.05,0.07]	-0.05	[-0.11,0.01]	0.04	[-0.02,0.09]	0.09**	[0.02,0.16]
Honduras	2011-12	-0.004	[-0.07,0.07]	-0.06	[-0.14,0.02]	-0.02	[-0.08,0.04]	-0.05	[-0.13,0.02]	0.05	[-0.01,0.11]	0.02	[-0.05,.09]
Haiti	2012	-0.08	[-0.17,0.01]	-0.05	[-0.19,0.09]	0.07	[-0.002,0.14]	0.08	[-0.01,0.16]	-0.07	[-0.15,0.01]	-0.08	[-0.16,0.01]
Cambodia	2014	0.10*	[0.01,0.18]	0.02	[-0.06,0.11]	0	[-0.05,0.05]	0.01	[-0.05,0.06]	-0.15*	[-0.27,-0.02]	-0.12*	[-0.24,0]
Myanmar	2015-16	-0.08	[-0.17,0.01]	-0.07	[-0.18,0.05]	0.15*	[0.03,0.27]	0.15*	[0.01,0.29]	-0.16*	[-0.29,-0.03]	-0.12	[-0.27,0.03]
Malawi	2015-16	0.03	[-0.07,0.13]	0.03	[-0.08,0.14]	-0.01	[-0.07,0.06]	-0.001	[-0.07,0.07]	-0.09	[-0.2,0.02]	-0.06	[-0.2,0.07]
Nepal	2016	-0.27***	[-0.37,-0.17]	-0.27***	[-0.4,-0.14]	0.07	[-0.02,0.17]	0.01	[-0.09,0.12]	0.26***	[0.17,0.35]	0.23***	[0.14,0.32]
Uganda	2016	-0.11*	[-0.20,-0.01]	-0.06	[-0.16,0.05]	0.09	[-0.02,0.20]	0.03	[-0.09,0.15]	-0.02	[-0.11,0.07]	0.04	[-0.06,0.13]

		Vegetation index				Proximity to protected area				Proximity to water			
Country	**Year**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**
Ethiopia	2016	-0.01	[-0.13,0.10]	0.03	[-0.10,0.15]	-0.03	[-0.17,0.10]	-0.03	[-0.16,0.10]	0.23*	[0.05,0.40]	0.19*	[0.02,0.35]
Guatemala	2014-15	0.11***	[0.05,0.17]	0.02	[-0.06,0.10]	0.02	[-0.05,0.09]	-0.05	[-0.12,0.03]	0.03	[-0.05,0.10]	-0.10*	[-0.20,0]
Honduras	2011-12	0.10*	[0.02,0.17]	0.07	[-0.03,0.16]	-0.04	[-0.11,0.03]	-0.06	[-0.14,0.02]	-0.05	[-0.12,0.02]	-0.07	[-0.15,0.02]
Haiti	2012	-0.08	[-0.18,0.02]	-0.14	[-0.34,0.05]	-0.06	[-0.15,0.04]	-0.04	[-0.17,0.08]	-0.03	[-0.11,0.04]	-0.08	[-0.19,0.04]
Cambodia	2014	0.12*	[0.02,0.22]	0.01	[-0.10,0.12]	-0.09*	[-0.18,-0.01]	0.003	[-0.08,0.09]	0.03	[-0.07,0.13]	-0.01	[-0.11,0.09]
Myanmar	2015-16	-0.17***	[-0.26,-0.08]	-0.17**	[-0.29,-0.06]	0.06	[-0.05,0.17]	0.08	[-0.05,0.21]	-0.11*	[-0.21,-0.02]	-0.07	[-0.19,0.05]
Malawi	2015-16	0.07	[-0.05,0.19]	0.06	[-0.07,0.20]	-0.13*	[-0.23,-0.03]	-0.13*	[-0.23,-0.02]	-0.15**	[-0.24,-0.06]	-0.12*	[-0.22,-0.03]
Nepal	2016	-0.19**	[-0.31,-0.07]	-0.25***	[-0.39,-0.11]	-0.07	[-0.18,0.05]	-0.13*	[-0.24,-0.01]	0.17**	[0.06,0.29]	0.10	[-0.03,0.24]
Uganda	2016	-0.17**	[-0.27,-0.06]	-0.12	[-0.25,0]	0.15**	[0.06,0.25]	0.35***	[0.23,0.47]	0.10*	[0,0.19]	-0.01	[-0.12,0.10]

*p<0.05, **p<0.001, ***p<0.0001

Appendix Table B.7 Unadjusted (U) and adjusted (A) regression coefficients for malaria

		Forest cover				Forest cover squared				Forest decadal change			
Country	**Year**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**
Chad	2014-15	0.047***	[0.020,0.075]	0.047**	[0.019,0.075]	-0.005***	[-0.007,-0.003]	-0.005***	[-0.007,-0.003]	0.043***	[0.023,0.062]	0.041***	[0.019,0.063]
Ethiopia	2016	-0.046	[-0.101,0.008]	-0.042	[-0.101,.018]	0.035	[-0.015,.085]	0.030	[-0.022,.083]	-0.090**	[-0.151,-0.03]	-0.080*	[-0.142,-0.018]
Malawi	2015-16	-0.127***	[-0.16,-0.093]	-0.102***	[-0.134,-0.070]	0.078***	[0.057,0.100]	0.068***	[0.049,0.087]	-0.147***	[-0.203,-0.091]	-0.118***	[-0.169,-0.067]
Uganda	2016	-0.009	[-0.0380,0.020]	0.059***	[0.027,0.091]	0.102***	[0.067,0.137]	0.086***	[0.051,0.121]	-0.032	[-0.064,0]	0.023	[-0.006,0.053]

		Vegetation index				Proximity to protected area				Proximity to water			
Country	**Year**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**
Chad	2014-15	0.143***	[0.121,0.166]	0.171***	[0.142,0.200]	-0.191***	[-0.217,-0.165]	-0.198***	[-0.226,-0.170]	-0.226***	[-0.256,-0.195]	-0.279***	[-0.311,-0.247]
Ethiopia	2016	-0.022	[-0.074,.031]	-0.002	[-0.067,0.063]	-0.054	[-0.169,0.061]	-0.0620	[-0.168,0.044]	0.046	[-0.037,0.129]	-0.010	[-0.101,0.081]
Malawi	2015-16	-0.175***	[-0.213,-0.138]	-0.158***	[-0.198,-0.117]	-0.020	[-0.041,0.002]	-0.029*	[-0.055,-0.004]	0.175***	[0.149,0.201]	0.164***	[0.133,0.194]
Uganda	2016	0.064***	[0.031,0.097]	0.153***	[0.118,0.188]	-0.145***	[-0.171,-0.119]	-0.158***	[-0.186,-0.129]	0.089***	[0.060,0.117]	0.030	[-0.005,0.064]

*p<0.05, **p<0.001, ***p<0.0001

Appendix Table B.8 **Unadjusted (U) and adjusted (A) regression coefficients for mortality**

		Forest cover				Forest cover squared				Forest decadal change			
Country	**Year**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**
Bangladesh	2014	0.11***	[0.07,0.16]	0.10***	[0.06,0.15]	-0.005	[-0.02,.010]	-0.01	[-0.02,0.01]	0.12***	[0.07,0.17]	0.11***	[0.06,0.16]
Chad	2014-15	0.02	[-0.04,0.08]	0.02	[-0.04,0.07]	-0.01***	[-0.016,-0.006]	-0.01***	[-0.015,-0.005]	0.08**	[0.03,0.14]	0.07*	[0.02,0.13]
Dominican Republic	2013	-0.17	[-0.34,0.01]	-0.22*	[-0.4,-0.05]	-0.05	[-0.22,0.11]	-0.03	[-0.18,0.13]	0.07	[-0.14,0.28]	0.04	[-0.16,0.25]
Ethiopia	2016	0.11*	[0.02,0.20]	0.10*	[0.02,0.19]	-0.01	[-0.12,0.09]	-0.01	[-0.12,0.09]	-0.03	[-0.12,0.07]	0.02	[-0.09,0.13]
Guatemala	2014-15	0.01	[-0.08,0.10]	-0.10*	[-0.19,-0.02]	-0.04	[-0.11,0.04]	-0.07	[-0.14,0.01]	-0.07	[-0.16,0.01]	-0.13**	[-0.21,-0.04]
Honduras	2011-12	0.12*	[0.01,0.22]	0.04	[-0.07,0.16]	0.01	[-0.11,0.12]	-0.02	[-0.12,0.09]	0.02	[-0.08,0.13]	-0.04	[-0.15,0.06]
Haiti	2012	-0.01	[-0.09,0.06]	0.03	[-0.05,0.11]	-0.02	[-0.08,0.05]	-0.03	[-0.09,0.03]	-0.04	[-0.11,0.03]	-0.005	[-0.08,0.07]
Cambodia	2014	0.22***	[0.11,0.34]	0.10	[-0.01,0.21]	-0.03	[-0.11,0.05]	-0.01	[-0.09,0.07]	-0.13	[-0.31,0.05]	-0.09	[-0.26,0.07]
Myanmar	2015-16	0.11	[-0.02,0.25]	0.02	[-0.11,0.14]	0.02	[-0.16,0.19]	0.04	[-0.13,0.21]	0.16	[-0.02,0.35]	0.15*	[0.002,0.30]
Malawi	2015-16	-0.02	[-0.08,0.04]	-0.01	[-0.08,0.05]	0.02	[-0.02,0.06]	0.02	[-0.02,0.06]	-0.08*	[-0.16,-0.003]	-0.06	[-0.14,0.01]
Nepal	2016	-0.09	[-0.20,0.02]	-0.14*	[-0.28,-0.01]	0.08	[-0.03,0.20]	0.05	[-0.06,0.15]	0.01	[-0.13,0.14]	0.01	[-0.12,0.14]
Uganda	2016	0.01	[-0.05,0.08]	0.05	[-0.01,0.11]	0.03	[-0.04,0.10]	-0.04	[-0.10,0.03]	0.001	[-0.07,0.07]	0.04	[-0.02,0.09]

		Vegetation index				Proximity to protected area				Proximity to water			
Country	**Year**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**	**U**	**95% C.I.**	**A**	**95% C.I.**
Bangladesh	2014	0.05	[-0.05,0.15]	0.02	[-0.09,0.13]	-0.10*	[-0.20,-0.004]	-0.12*	[-0.22,-0.02]	0.09	[-0.01,0.18]	0.07	[-0.02,0.16]
Chad	2014-15	0.23***	[0.17,0.28]	0.24***	[0.18,0.31]	-0.07*	[-0.13,-0.01]	-0.08*	[-0.15,-0.01]	0.03	[-0.03,0.10]	0.02	[-0.05,0.08]
Dominican Republic	2013	-0.14	[-0.32,.04]	-0.17	[-0.35,0.02]	-0.04	[-0.20,0.13]	-0.03	[-0.18,0.13]	-0.01	[-0.17,0.16]	0.02	[-0.14,0.18]
Ethiopia	2016	0.06	[-0.03,.16]	0.06	[-0.05,0.16]	-0.06	[-0.17,0.05]	-0.07	[-0.18,0.04]	0.06	[-0.06,.018]	0.02	[-0.1,0.14]
Guatemala	2014-15	-0.004	[-0.08,.07]	-0.14**	[-0.23,-0.04]	0.07	[-0.01,0.14]	0.01	[-0.07,0.09]	0.13**	[0.04,.022]	0.02	[-0.07,0.12]
Honduras	2011-12	0.07	[-0.04,.18]	-0.00001	[-0.15,0.15]	0.10	[-0.0005,0.20]	0.06	[-0.04,0.16]	-0.07	[-0.17,0.04]	-0.09	[-0.19,0.02]
Haiti	2012	-0.12**	[-0.19,-0.04]	-0.03	[-0.14,0.08]	-0.11**	[-0.18,-0.03]	-0.04	[-0.11,0.04]	-0.02	[-0.11,0.08]	0.01	[-0.08,0.10]
Cambodia	2014	0.15*	[0.01,0.28]	0.01	[-0.12,0.14]	-0.09	[-0.23,0.06]	0.03	[-0.10,0.17]	0.08	[-0.05,0.21]	-0.02	[-0.16,0.11]
Myanmar	2015-16	0.13*	[0.003,.26]	0.04	[-0.08,0.16]	-0.01	[-0.14,0.12]	0.002	[-0.11,0.11]	0.09	[-0.04,0.21]	0.08	[-0.04,0.20]
Malawi	2015-16	-0.03	[-0.09,.04]	-0.03	[-0.10,0.04]	0.11***	[0.06,0.16]	0.11***	[0.06,0.17]	0.09**	[0.03,0.15]	0.10***	[0.04,0.16]
Nepal	2016	-0.09	[-0.21,.02]	-0.11	[-0.23,0.01]	0.04	[-0.06,0.15]	0.01	[-0.10,0.12]	0.16*	[0.03,0.29]	0.15*	[0.02,0.28]
Uganda	2016	-0.01	[-0.08,.07]	0.04	[-0.04,0.11]	-0.12***	[-0.19,-0.05]	-0.06	[-0.13,0.02]	0.07*	[0,0.14]	-0.01	[-0.08,0.06]

*p<0.05, **p<0.001, ***p<0.0001

Appendix Table B.9 Adjusted regression coefficients for the appended Malawi surveys

	Stunting		Underweight		Anemia		Diarrhea		Malaria		Mortality	
	Ceof.	**95% C.I.**	**Ceof.**	**95% C.I.**	**Ceof.**	**95% C.I.**	**Ceof.**	**95% C.I.**	**Ceof.**	**95% C.I.**	**Ceof.**	**95% C.I.**
Low cover survey 1 (Ref.)												
Medium cover survey 1	-0.10	[-0.24,0.05]	-0.02	[-0.20,0.16]	0.21	[-0.15,0.57]	-0.04	[-0.24,0.15]	-0.24***	[-0.37,-0.11]	-0.04	[-0.16,0.09]
High cover survey 1	-0.15	[-0.35,0.04]	-0.08	[-0.36,0.20]	-0.34	[-0.74,0.05]	-0.26	[-0.54,0.03]	-0.40***	[-0.6,-0.21]	0.06	[-0.14,0.26]
Low cover survey 2	-0.30*	[-0.56,-0.04]	-0.50**	[-0.85,-0.14]	-0.29	[-0.62,0.04]	-0.30*	[-0.55,-0.06]	0.39***	[0.32,0.45]	-0.21***	[-0.3,-0.12]
Medium cover survey 2	-0.07	[-0.36,0.22]	-0.32	[-0.72,0.09]	-0.05	[-0.44,0.34]	-0.34*	[-0.6,-0.08]	0.23***	[0.14,0.33]	-0.24***	[-0.34,-0.14]
High cover survey 2	-0.04	[-0.50,0.43]	-0.23	[-0.75,0.29]	-0.24	[-0.73,0.24]	-0.72***	[-01.11,-0.34]	0.18*	[0.01,0.35]	-0.15	[-0.43,0.13]
Low cover survey 3	-0.69***	[-0.81,-0.57]	-0.55***	[-0.73,-0.38]	-0.39***	[-0.6,-0.19]	0.12	[-0.07,0.3]	-0.71***	[-0.77,-0.65]	-0.72***	[-0.82,-0.62]
Medium cover survey 3	-0.78***	[-0.95,-0.61]	-0.39**	[-0.63,-0.14]	-0.30*	[-0.56,-0.04]	0.06	[-0.14,0.27]	-0.90***	[-0.98,-0.83]	-0.83***	[-0.98,-0.69]
High cover survey 3	-0.65***	[-0.92,-0.37]	-0.52**	[-0.89,-0.15]	-0.28	[-0.73,0.18]	0.002	[-0.26,0.26]	-0.84***	[-0.93,-0.74]	-0.70***	[-0.96,-0.45]
Low cover survey 2 (Ref.)												
Medium cover survey 2	0.23*	[0.04,0.42]	0.18	[-0.11,0.47]	0.23	[-0.03,0.50]	-0.04	[-0.18,0.10]	-0.15**	[-0.24,-0.06]	-0.03	[-0.12,0.06]
High cover survey 2	0.26	[-0.12,0.64]	0.27	[-0.2,0.74]	0.04	[-0.35,0.44]	-0.42**	[-0.72,-0.12]	-0.21*	[-0.38,-0.03]	0.06	[-0.22,0.34]
Low cover survey 3 (Ref.)												
Medium cover survey 3	-0.09	[-0.27,0.08]	0.17	[-0.09,0.43]	0.09	[-0.14,0.32]	-0.05	[-0.2,0.09]	-0.20***	[-0.26,-0.13]	-0.11	[-0.26,0.03]
High cover survey 3	0.04	[-0.24,0.32]	0.03	[-0.34,0.41]	0.12	[-0.32,0.55]	-0.11	[-0.33,0.10]	-0.13**	[-0.22,-0.04]	0.02	[-0.24,0.27]
AIC: forest cover and survey	*22157.9*		*13312.8*		*12318.8*		*40671.0*		*1859.4*		*58086.9*	
AIC: only survey variable	*22157.2*		*13305.0*		*12312.8*		*40674.8*		*1851.1*		*58078.5*	
Difference in AIC	*-0.7*		*-7.8*		*-6.0*		*3.8*		*-8.4*		*-8.4*	

*p<0.05, **p<0.001, ***p<0.0001

Appendix Table B.10 Adjusted regression coefficients for the appended Uganda surveys

	Consumed <4 food groups		Stunting		Underweight		Anemia		Diarrhea		Malaria		Mortality	
	Ceof.	95% C.I .	Ceof.	95% C.I.	Ceof.	95% C.I.	Ceof.	95% C.I.	Ceof.	95% C.I.	Ceof.	95% C.I.	Ceof.	95% C.I.
Low cover survey 1 (Ref.)														
Medium cover survey 1	0.22	[-0.24,0.68]	0.29*	[0.02,0.56]	0.37	[-0.06,0.80]	-0.54*	[-0.99,-0.10]	-0.07	[-0.32,0.17]	-0.03	[-0.17,0.12]	-0.08	[-0.25,0.09]
High cover survey 1	-0.08	[-0.50,0.33]	0.16	[-0.11,0.43]	0.16	[-0.28,0.60]	-0.62**	[-1.02,-0.23]	-0.25*	[-0.47,-0.02]	0.26***	[0.15,0.37]	-0.06	[-0.21,0.09]
Low cover survey 2	0.50*	[0.02,0.99]	-0.41*	[-0.75,-0.07]	-0.15	[-0.67,0.37]	-1.33***	[-1.86,-0.79]	0.10	[-0.26,0.46]	-0.05	[-0.22,0.12]	-0.39***	[-0.57,-0.21]
Medium cover survey 2	0.74**	[0.25,1.24]	-0.30	[-0.64,0.04]	-0.09	[-0.59,0.41]	-1.80***	[-2.30,-1.31]	0.21	[-0.13,0.55]	-0.37***	[-0.56,-0.18]	-0.37***	[-0.58,-0.16]
High cover survey 2	0.77**	[0.30,1.23]	0.15	[-0.15,0.45]	0.07	[-0.42,0.55]	-1.95***	[-2.39,-1.51]	-0.10	[-0.44,0.24]	0.03	[-0.11,0.17]	-0.33***	[-0.49,-0.17]
Low cover survey 3	-0.75***	[-01.16,-0.34]	-0.72***	[-01,-0.43]	-0.49*	[-0.96,-0.02]	-1.46***	[-1.87,-1.05]	-0.11	[-0.44,0.22]	-0.93***	[-1.04,-0.81]	-0.79***	[-0.95,-0.63]
Medium cover survey 3	-0.40	[-0.83,0.04]	-0.38**	[-0.68,-0.09]	-0.43	[-0.89,0.03]	-1.50***	[-1.93,-1.07]	-0.16	[-0.49,0.17]	-1.07***	[-1.19,-0.95]	-0.69***	[-0.85,-0.54]
High cover survey 3	-0.39	[-0.81,0.03]	-0.14	[-0.41,0.14]	-0.32	[-0.77,0.13]	-1.61***	[-2.00,-1.21]	-0.19	[-0.51,0.14]	-0.92***	[-1.03,-0.81]	-0.68***	[-0.84,-0.53]
Low cover survey 2 (Ref.)														
Medium cover survey 2	0.24	[-0.21,0.70]	0.11	[-0.26,0.48]	0.06	[-0.41,0.53]	-0.47	[-1.01,.06]	0.11	[-0.14,0.35]	-0.32**	[-0.55,-0.09]	0.02	[-0.20,0.25]
High cover survey 2	0.26	[-0.16,0.69]	0.56***	[0.24,0.88]	0.22	[-0.23,0.66]	-0.62*	[-1.09,-0.15]	-0.20	[-0.44,0.04]	0.08	[-0.11,.27]	0.06	[-0.12,0.24]
Low cover survey 3 (Ref.)														
Medium cover survey 3	0.35*	[0.07,0.63]	0.33**	[0.08,.058]	0.06	[-0.29,0.41]	-0.04	[-0.33,0.26]	-0.06	[-0.23,0.12]	-0.14*	[-0.25,-0.03]	0.10	[-0.06,0.26]
High cover survey 3	0.36**	[0.10,.062]	0.58***	[0.35,.081]	0.17	[-0.15,0.50]	-0.14	[-0.40,0.12]	-0.08	[-0.24,0.08]	0.004	[-0.08,0.09]	0.11	[-0.04,0.26]
AIC: forest cover and survey	*8268.4*		*10013.7*		*5988.6*		*9048.7*		*27543.2*		*1240.1*		*35492.1*	
AIC: only survey variable	*8267.9*		*10043.9*		*5983.0*		*9052.7*		*27546.8*		*1233.4*		*35485.0*	
Difference in AIC	*-0.5*		*30.2*		*-5.6*		*4.0*		*3.6*		*-6.7*		*-7.1*	

*p<0.05, **p<0.001, ***p<0.0001

Appendix Table B.11 Adjusted regression coefficients for the appended Nepal surveys

	Consumed <4 food groups		Stunting		Underweight		Anemia		Diarrhea		Mortality	
	Ceof.	**95% C.I.**	**Ceof.**	**95% C.I.**	**Ceof.**	**95% C.I.**	**Ceof.**	**95% C.I.**	**Ceof.**	**95% C.I.**	**Ceof.**	**95% C.I.**
Low cover survey 1 (Ref.)												
Medium cover survey 1	-0.67*	[-01.2,-0.14]	-0.13	[-0.41,0.16]	-0.39	[-0.81,0.03]	-0.86***	[-1.21,-0.51]	0.39*	[0.02,0.75]	-0.19	[-0.60,0.21]
High cover survey 1	-0.68**	[-1.12,-0.24]	-0.15	[-0.38,0.08]	-0.57***	[-0.79,-0.34]	-0.92***	[-1.19,-0.66]	0.32	[-0.02,0.65]	-0.11	[-0.38,0.17]
Low cover survey 2	0.63	[-0.03,1.30]	-0.47*	[-0.88,-0.07]	-0.31	[-0.65,0.03]	-0.18	[-0.55,0.20]	0.68***	[0.33,1.03]	-0.07	[-0.37,0.23]
Medium cover survey 2	0.03	[-0.57,0.62]	-0.35*	[-0.67,-0.02]	-0.65***	[-1.02,-0.28]	-0.75***	[-1.18,-0.33]	0.21	[-0.16,0.59]	-0.34	[-0.69,0.02]
High cover survey 2	-0.45	[-0.91,0.02]	-0.34*	[-0.6,-0.07]	-0.84***	[-1.09,-0.59]	-0.92***	[-1.21,-0.63]	0.28	[-0.03,0.59]	-0.32*	[-0.60,-0.03]
Low cover survey 3	-0.38	[-0.93,0.18]	-0.41**	[-0.71,-0.10]	-0.30	[-0.65,0.06]	0.13	[-0.25,0.51]	0.37	[-0.09,0.83]	-0.37*	[-0.68,-0.07]
Medium cover survey 3	-0.83**	[-1.4,-0.27]	-0.76***	[-1.15,-0.36]	-0.89***	[-1.32,-0.46]	-0.29	[-0.78,0.21]	0.55	[-0.03,1.14]	-0.63**	[-1.02,-0.23]
High cover survey 3	-1.48***	[-2.04,-0.92]	-0.60***	[-0.93,-0.28]	-1.05***	[-1.40,-0.69]	-0.47*	[-0.84,-0.09]	0.03	[-0.44,0.50]	-0.58***	[-0.88,-0.29]
Low cover survey 2 (Ref.)												
Medium cover survey 2	-0.61	[-1.34,0.12]	.12	[-0.31,0.56]	-0.33	[-0.77,0.10]	-0.58*	[-1.04,-0.12]	-0.47**	[-0.82,-0.12]	-0.27	[-0.59,0.05]
High cover survey 2	-1.08***	[-1.69,-0.48]	.14	[-0.26,0.54]	-0.52**	[-0.87,-0.17]	-0.74***	[-1.09,-0.40]	-0.40**	[-0.68,-0.13]	-0.25*	[-0.49,-0.01]
Low cover survey 3 (Ref.)												
Medium cover survey 3	-0.46*	[-0.91,-0.005]	-0.35*	[-0.69,-0.01]	-0.59**	[-0.97,-0.22]	-0.42	[-0.84,0.01]	0.19	[-0.29,0.66]	-0.25	[-0.62,0.11]
High cover survey 3	-1.10***	[-1.48,-0.72]	-0.20	[-0.46,0.07]	-0.75***	[-1.02,-0.47]	-0.60***	[-0.89,-0.31]	-0.34*	[-0.66,-0.02]	-0.21	[-0.46,0.04]
AIC: forest cover and survey	*4758.0*		*11901.1*		*11064.8*		*10493.4*		*10000.0*		*14459.3*	
AIC: only survey variable	*4814.4*		*11896.6*		*11110.0*		*10556.5*		*10007.5*		*14455.4*	
Difference in AIC	*56.4*		*-4.6*		*45.1*		*63.1*		*7.5*		*-3.8*	

*p<0.05, **p<0.001, ***p<0.0001

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