The impact of malaria on education: Evidence from Ethiopia*

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Abstract

Estimates of the benefits of malaria reduction derived from countries that eradicated the disease are not necessarily applicable to sub-Saharan Africa, where malaria incidence and mortality is high and all eradication attempts were unsuccessful. This paper estimates the effects of malaria on schooling using geographic and survey data from Ethiopia. I show that self-reported malaria is highly correlated with village topographical characteristics. Using these environmental conditions as predictors of the disease, I estimate that moving from a village with no malaria to one with average malaria reduces schooling in children and adults by 0.30-0.60 years.

JEL Classification: O15, I15, I25

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1 Introduction

Tropical diseases, especially malaria, have been shown to reduce schooling achievement. For instance, some recent papers comparing cohorts born before and after eradication attempts in several countries show significant increases in schooling achievement post-eradication (Lucas, 2010, Percoco 2011), in contrast to evidence from India that does not show such benefits from eradication (Cutler et al, 2010). These papers complement other, recent work on the effects of eradication on wages (Bleakely, 2010), GDP growth (Gallup and Sachs, 2001).

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There are at least two reasons to provide additional estimates on the impact of malaria on education. First, existing estimates are based on countries that successfully eradicated malaria, at least for a time. None of these are in Africa, where the disease is most prevalent and where an estimated 90% of child deaths from malaria are thought to occur (Cook and Zumla, 2008). The list of places with successful eradication programs excludes Africa not for want of trying: there were large-scale eradication attempts in several sub-Saharan countries, including the Garki province in Nigeria, the Pare-Taveta region of Tanzania/Kenya, and Cameroon (Breman et al, 2004). Such attempts failed not necessarily due to flaws in the eradication design, but because the disease ecology in Africa is unusually complex, ensuring the failure of any eradication campaign. Successful eradication in Africa would require dealing with all four types of malaria parasite (*P. falciparum, ovalae, vivax, malariae*) and dozens of mosquito species, some of which are considered extraordinarily effective in transmitting disease and avoiding the standard methods of mosquito control interventions (D'Antonio and Spielman, 2001). By comparison, in places where large-scale, broadly successful eradication took place—Southern Europe, the American South, and parts of Latin America—malaria was less entrenched and the mosquito vectors easier to be dispensed with. These differences in environment between eradication countries and countries with heavy disease burden suggest the need to be cautious in applying estimates from one to the other.

A second reason for the need for additional estimation strategies is that the spillover effects from malaria eradication might differ from those arising from malaria reduction, and they might be a poor proxy when evaluating initiatives aimed at reducing the burden of the disease (without outright eradication). This is important since current malaria interventions (such as indoor residual spraying or insecticide-resistant bed net distributions) mostly reduce the frequency of malaria infections. In contrast, existing research focuses either on partial equilibrium effects of childhood exposure, or general equilibrium effects of childhood exposure.[1]

[1] One reason to believe that eradication could overestimate the impact of malaria reduction on schooling is that frequent and intense biting from infected mosquitoes confers a degree of acquired immunity that shields the victim from severe sickness and mortality. This immunity disappears if infection becomes less frequent, and might therefore lead to an increased chance of severe morbidity or death when infection does happen. Whether

This paper attempts to address these issues by studying differences in malaria risk in an African country, Ethiopia, using arguably exogenous drivers of local malaria transmission. Ethiopia is a particularly suitable country to examine because Ethiopian villages vary considerably in their exposure to malaria, and perhaps like nowhere else, even villages in close proximity to one another can have starkly different malaria incidence profiles. The main explanation for this is the complex topography of this mountainous country, and the sensitivity of malaria transmission to local differences in elevation and slope. Here, I use differences in the *interaction* between elevation and slope as exogenous shifters of a self-reported measure of malaria prevalence, and use instrumental variable techniques to obtain a measure of the impact on schooling outcomes. I do this by matching a large-scale household survey (the 2004 Ethiopia Welfare Monitoring Survey) with satellite-derived weather and topographic maps. The implied "causal" effect of malaria on education, when village topographic characteristics are used as instruments, is in the range of 0.3-0.6 years for a village going from no malaria to a village with average malaria incidence.

The identification strategy used has many advantages and some drawbacks. First, I find that the interaction between elevation and slope captures malaria rates quite well. That is because malaria is sensitive to elevation differences in places (flatlands) where the habitat is suitable for mosquito breeding, and is not sensitive to elevation in unsuitable areas (steep lands). Second, the variation in topographic characteristics is large enough that it is possible to estimate differences in malaria prevalence across villages located within the same province (*wareda*), the smallest administrative unit in Ethiopia after the village. Since most administrative units, local markets, and school administration are centralized at the provincial level, the within-estimator eliminates a large source of heterogeneity in health and education. Moreover, within province estimates largely eliminate unobserved variation in weather, disease patterns, agricultural practices, and cultural traditions. Third, and most importantly, the approach allows me to estimate the impact of malaria across all incidence intensities, thanks to the great

these negative effects of malaria reduction in fact affect educational attainment remains an open question.

variation in morbidity that spans hyperendemic, hypoendemic, and malaria free villages.

The main drawback of this approach is that testing the exclusion restriction is not simple. A causal interpretation requires topography to be uncorrelated with other possible factors that may affect children's education. Indeed, it is likely that elevation and slope are correlated with many factors other than disease, including agricultural production, households wealth, and the returns from education. It is less clear whether the *interaction* between elevation and slope should be correlated with those same factors, after controlling for the direct effect. To the extent that these factors are observable and can be controlled for, I find that they have a small impact on my estimates. To gain a better sense of which factors might be important confounders, I also explicitly study the relationship between topography and a number of village variables, including asset, land and livestock ownership, exposure to agricultural shocks and distances to major services like schools. I do find that land ownership declines in areas with lower predicted malaria incidence, suggesting perhaps differences in land pressure. Since land pressure differences might come from malaria pushing uplands those individuals with higher propensity for education, the estimates presented in this paper possibly include the indirect impact of malaria prevalence on (past) migratory patterns, such that there are unobservable differences in ability across topographic characteristics.[2]

Since it is impossible to test all possible pathways between topography and education with the available data, I present two more pieces of evidence that suggest that malaria is the most likely pathway. First, I show that the correlation between elevation and education disappears in villages located in malaria-free areas. Second, I run a falsification test using data from Nepal. Like Ethiopia, Nepal is a developing country whose environment is shaped by differences in elevation and whose climate varies from sub-tropical lowlands to alpine highlands. Unlike Ethiopia, Nepal (a malaria-endemic country) had a malaria eradication campaign in the fifties, and as a consequence the disease is now rare. Using data from the Nepal Demographic

[2]Note that there is some evidence that malaria has an impact on land relocation choice: see Zhang, Castro and Canning (2011) for an example from Brazil. Ethiopia has a history of internal migration, mostly associated with civil wars and state-sponsored violence. I will show in section 6.1 that there are no significant differences in length of land tenure, excluding *recent* migration to the lowlands as a channel.

Health Surveys from the 2001 and 2006 rounds, I find that there is no correlation between elevation and sickness, or between elevation and education.

The estimates found in this paper are comparable with findings from the literature on malaria. Lucas (2010) estimates the causal effect of a 10% reduction in malaria in Paraguay and Sri Lanka to be 0.1 years of schooling, which is significantly less than what I find here. Barreca (2010) used variation in rainfall and temperature in the 1920s American South to estimate that a standard deviation increase in exposure to *in-utero* and postnatal malaria reduced education by 0.23 years.[3] My estimates are somewhat larger than what has found previously, suggesting that the gains for malaria reduction are larger in non-eradication countries.

Aside from contributing to the literature on the effects of tropical disease on human capital accumulation, my paper provides a better understanding on the opportunities—and shortfalls—presented by the use of satellite derived data in the study of malaria. In the last two decades, a lot of resources have been placed in using these data to construct maps that predict malaria incidence (see, for instance, the maps of predicted malaria from the MARA/ARMA project in figure 3), but up to now it has been unclear whether these can be used as instrumental variables. By matching topographical predictors of malaria with detailed household information, this paper shows that slope/elevation interactions can function as instruments with some possible caveats.

The rest of the paper is structured as follows: the next section provides background information on Ethiopia and malaria. Section 3 presents the data. Section 4 discusses the methodology. Section 5 include the main results from the paper, with section 6 exploring the validity of the exclusion restrictions. The conclusion follows.

[3] Barreca's methodology of using weather variation captures one particular channel through which malaria affects education that does not depend on eradication, although it does not shed light on other important pathways, including the role of expectation of future morbidity.

2 Background

2.1 Malaria

2.1.1 Malaria transmission and schooling

Malaria affects approximately 250 million people and is responsible for one million deaths annually (WHO, 2009). This disease is transmitted to humans through bites of female *anophelae* mosquitoes. Once infected, a person can develop chills, very high fevers, anemia, and—especially in children less than 5 years of age—brain damage, coma, and death. The seriousness of symptoms depends, to a great extent, on the degree of parasitaemia, itself a function of the number of infected bites suffered by the patient (the inoculation rate). In general, the higher the inoculation rate, the higher the chance of severe symptoms or permanent damage. However, a partial immunity to the disease can be acquired if a person survives infection and is continuously reinfected. Acquired immunity allows individuals to tolerate very high parasitaemia while suffering limited or no discomfort.[4] In areas of year-round high malaria incidence, then, morbidity and mortality for children 0-5 years old tends to be very high, declining with age after that point. In areas where malaria transmission is low or seasonal, early life malaria morbidity and mortality is generally much lower, with morbidity and mortality declining with age but less steeply, because there is no acquired immunity.[5]

2.1.2 Transmission: slope and temperature

Malaria transmission is affected by land slope and temperature. Mosquito larvae need stagnant water pools to survive, and these pools are less likely to form in sloped areas. Moreover, larvae developing in water pools in sloped areas are more likely to be washed away during downpours. Thus, sloped areas make for poor mosquito breeding ground, reducing the threat of malaria

[4] Acquired immunity is quickly lost after a short period of time if the person is not reinfected, making the individual susceptible to feeling sick again in case of eventual reinfection. This was widely observed during several malaria eradication attempts in sub-Saharan Africa, which interrupted malaria transmission for one to three years and caused local resistance to the disease to lapse, causing significant morbidity and mortality.

[5] See Cook and Zumla (2008) for additional and comprehensive information on malaria.

transmission.

Increases in temperature increase malaria transmission because they increase the survival rate of mosquito larvae and reduce the length of sporogony—the time it takes for a mosquito which has ingested infected blood to be able to transmit the disease (Cook and Zumla, 2008). Below a certain temperature threshold (corresponding to approximately 18 degrees Celsius), sporogony is sufficiently slow that it cannot be completed before the mosquito dies, making malaria transmission impossible. The relationship between temperature and sporogony is represented in figure 1, boxes a. and c. (Craig, Snow and le Sueur, 1999).

In Ethiopia, air temperature is largely determined by elevation. Figure 2 shows the relationship between elevation and the average daily temperature in the warmest month for Ethiopia. Above 2,500 meters of elevation, temperatures are consistently below the no-malaria threshold, making villages located there malaria-free.[6]

To be sure, malaria is not the only vector borne tropical disease that might be influenced by temperature and terrain. Dengue fever (transmitted by mosquitoes) is generally concentrated in urban areas and is found sporadically in Ethiopia (Aseffa, 1993); Yellow fever and Chikungunya (also transmitted by mosquitoes) are rare in the country;[7] Sleeping sickness (transmitted by tze-tze flies) is also found sporadically (Fevre et al, 2006) as is Rift Valley fever (which, in any case, has severe morbidity and mortality rates in less than 1% of patients [WHO, 2010a]). Ethiopia is considered at a high risk of meningitis epidemics (Cuevas et al, 2007), and while there is some association between environmental factors (rainfall, forest cover, dust levels, human population density) and the spread of the disease, the relationship between meningits and either elevation or slope is not understood.[8] Other diseases, like diarrheal dis-

[6]In this paper, I focus on elevation as opposed to temperature because the entomological literature is unclear about how to take into consideration daily and seasonal variations in temperature. Nonetheless, all results in this paper are very similar when using measures of average daily temperature, with results available upon request.

[7]Aseffa [1993] reports no cases in Ethiopia from 1966, and the WHO in 1995 reported no cases between 2000 and 2004. In 2004, there were a total of 128 suspected yellow fever cases in sub-Saharan Africa.

[8]Meningococcal bacteria is spread person to person through cough droplets, so there is not a direct connection with topographical factors. The most recent epidemic prior to the study period was in 2001-2002, where a total of 1,332 cases and 85 fatalities were identified (WHO, 2002).

eases or influenza, might be affected by land slope or temperature, but they are unlikely to be affected by the interaction of the two.

2.2 Malaria in Ethiopia

In Ethiopia, the estimated incidence rate for malaria (i.e., the estimated probability of contracting the disease in a year) is 15%, which is low relative to the rest of sub-Saharan Africa (where the average incidence rate is 0.33), but higher than any other country outside of sub-Saharan Africa bar Panama, Laos, Myanmar, and the Solomon Islands (Korenromp, 2005). Despite the somewhat low incidence rate, this country is an appealing place to do a study on malaria for at least two reasons. First, malaria is still a very important public health problem: Ethiopia is thought to experience some 10 million cases per year, the fourth highest case number in sub-Saharan Africa (behind Nigeria, the DRC, Tanzania, and Uganda [Korenromp, 2005]). According to an Ethiopian report, clinical malaria accounts for 10 - 40% of all outpatient consultations, 13 - 26% of inpatient admissions at various health facilities, and is responsible for 15-17% of case fatalities in health facilities (WHO, 2006).

A second reason for considering malaria in Ethiopia is that, unlike most other African countries, there is extensive local variation in malaria incidence. Figure 3A and 3B make this clear. The figures show the predicted malaria incidence across the continent, according to the MARA/ARMA model (MARA, 2011). For most countries, malaria incidence has extremely high spacial autocorrelation. Ethiopia, on the other hand, has a very low degree of spacial autocorrelation; malaria in Ethiopia is a localized disease. Studies indicate the presence of spatial autocorrelation in malaria rates for villages located within 5 to 10 kilometers, dropping rapidly after that (Yeshiwondim et al, 2009). This feature permits the estimation of the impact of malaria incidence by comparing villages in close proximity to one another.

3 Data

The Welfare Monitoring Survey (WMS) was conducted by the Ethiopian Statistical Agency between June 24 and July 3 of 2004, and it involved over 2,000 villages across all states in the Ethiopian Federation. It covers basic individual and household characteristics, as well as access to several services. Crucially, it includes information on both schooling and individual level health conditions (including self-reported malaria spells) in the preceding two months. These health outcomes refer to the months May and June, corresponding to the end of the short rains (known as the "*belg*") and of the short malaria season (which generally runs from mid-March to June).[9]In particular, for each member of the household, the survey asks whether the individual faced a health problem in the prior two months and, if so, what was the reason for this sickness. The questionnaire provides six different reasons, including malaria. Using this information, I constructed a measure of self-reported recent malaria incidence at a village level as the fraction of the surveyed population who was reported as suffering from malaria. Since this measure of malaria incidence comes from self-reported diagnoses, they might well be wrong: those reporting malaria might simply be suffering from fevers or pain from other types of infections or diseases. The treatment of this measurement error is considered in section **??**.

I integrated the information from the WMS with village temperature and elevation derived from the use of two additional datasets. The first database is an electronic map developed by the Ethiopian Development Research Institute (EDRI), in collaboration with the International Food Programme Research Institute (IFPRI). Researchers at these institutes transferred paper maps of all Ethiopian administrative units into digital form. These digital maps spatially divide the country into its administrative units, from largest (states) to smallest (villages). Using the EDRI/IFPRI electronic maps, I matched the names of the villages in the electronic map with the names of the WMS villages (see figure 4). I was unable to find a few villages within regions that were fully mapped, mostly due to discrepancies in the name in the WMS and in

[9]The peak malaria season in Ethiopia is September to November, after the long rains (*meher*). The timing of rains varies from region to region.

the EDRI/IFPRI maps. Furthermore, I dropped a few regions that remained unmapped at the time. In total, around 35% of villages in the three regions were dropped. Unfortunately, it appears that dropped villages are different from mapped villages along several different dimensions. They appear more rural and a little poorer and less educated. Thus, the sample used here is not representative of Ethiopian villages.

Elevation, temperature, rainfall and slope for the entire country of Ethiopia come from remote sensing data collected by NASA satellites and elaborated by scientists at the Livermore National Laboratory in California. This data shows, for any coordinate point in Ethiopia, its elevation, slope, average rainfall, and minimum, maximum and average daily temperatures for each month of the year. I transferred the remote sensing data to the EDRI/IFPRI map by averaging elevation and temperature over the entire surface of each village.

Table 1 provides summary statistics of the study villages. Around a quarter of individuals were sick in the prior two months. A quarter of sick respondents reported suffering from malaria, half did not report a specific disease, and the rest were evenly divided among the other diseases. The dependent variables of the paper (years of schooling for children aged between 7 and 19 and adults) are presented next. At the time of the survey, children who were currently in school were in between grades due to the summer break. Since many are still enrolled, average schooling for children is somewhat different from adults, who have largely completed formal education. On average, both the children sample and the adult sample report having one year of schooling, although the sample of children has significantly more variation in schooling outcomes than the adults.

The rest of the table describes some of the key controls used in this study. Since I exclude urban and peri-urban household and focus entirely on rural villages[10], the vast majority (92%) of households are farming families, with 4% declaring having no land ownership. The survey includes information on a number of assets, which I summarize into a unique vector of wealth (not included in the table). The households interviewed are generally quite poor, reporting

[10] I was given access to rural data only

generally few assets. 23% of households are female headed. Ethiopians are livestock-rich (almost five units of either sheep, goats, donkeys or cows per household), and most households own at least one ox, which is used to till the land and is a significant determinant of productivity. I also report exposure of households to shocks, as measured by the number of times the household suffered a given problem in the prior 5 years. Droughts and livestock losses are frequently reported, as are deaths in the family (an average of 0.28 deaths in the past 5 years). Finally, the data includes information on distance of the household to several types of facilities, including schools and clinics. Primary schools are relatively close, on average 45 minutes on foot. Health facilities (as well as secondary schools, hospitals, and other services reported in the survey but not on this table) are far, averaging well over 2 hours walking. In general, such services are often located in the district town, a few miles away from most villages.

4 Methodology

The objective of this paper is to estimate α_1^c from the following village level regressions v in province p:

$$y_{vp}^c = \alpha_0^c + \alpha_1^c malaria\_risk_{vp} + T_{vp}\gamma_T^c + \bar{X}_{vp}^c\gamma_x^c + \rho_p + \epsilon_{vp}^c, \tag{1}$$

where the main outcome y^c of interest is the average years of schooling for village cohort group c. The main regressor of interest is $malaria\_risk$, the incidence rate of the disease in a village. Cohorts are defined over age (school aged children with less than 19 years of age, and adults with more than 19 years of age) and gender. I include two sets of controls. T includes average village rainfall, average village slope or quintile of slope, and elevation (in some cases which will be discussed later in the section). It thus controls for environmental characteristics that affect incomes as well as malaria incidence. $\bar{X}^c$ controls for other determinants of education and includes village averages of: cohort age and sex, education of household heads, spouses, ownership of oxen and livestock, household asset ownership, distance to primary schools and health centers, and the fraction of households with a female household head. Since many of these variables are determined by the completed education of adults, the control set $\bar{X}^c$ for adult cohorts include only cohort age and distance to facilities.[11] Finally, all regressions include province fixed effects ρ_p, so the effects of malaria incidence on education comes from differences in malaria within the same province. Since sickness and education are likely correlated at the village and province level, I obtain conservative standard errors by running regressions at the village level, and by clustering errors at the province level.

The objective of the study is to provide an estimate of α_1^c–the impact of malaria risk on schooling. While malaria rates vary over time, depending on weather and other time-variant factors, *malaria_risk* should be time-invariant. That is, the observed malaria incidence rate over a period of time t is related to malaria risk through the following:

$$village\_malaria_{vp,t} = malaria\_risk_{vp} + \xi_{vp,t}.$$

In the WMS sample, the underlying malaria risk is unobservable, and the only measure of malaria risk available is $village\_malaria_{vp,2004}$, the percentage of individuals who were reported as suffering from malaria. The presence of unobserved shifters of malaria in 2004, $\xi_{vp,2004}$, biases the coefficient towards the null.[12] Moreover, the self-reported nature of *village_malaria* creates a series of additional problems. For instance, more informed households (which presumably have a higher demand for education) might also be more likely to report disease spells, providing a further bias towards the null hypothesis. And even if malaria incidence were measured with no bias or error, villages with higher investments in education might also value higher investments in malaria prevention and lower malaria rates, thus biasing estimates upward.[13]

I address these shortcomings by using a two stage least squares approach that instruments recent self-reported village malaria using village topographical characteristics. That is,

[11]Results presented here are robust to changes in the controls, including the addition of distances to other facilities and services and average exposure to shocks.

[12]Malaria in the highlands fluctuates from year to year and seasonally. Fortunately, the survey was taken between June 24 and July 3, a period that generally follows the peak of the minor transmission season (March-June). Thus the survey covers a period of malaria transmission.

[13]At the time of the survey, mosquito nets were quite rare in rural Ethiopia. However, malaria incidence is sensitive to environmental management, which might occur in wealthier villages.

I first run the regression,

$$village\_malaria_{vp} = Z_{vp}\beta + T_{vp}\gamma_T + \bar{X}_{vp}\gamma_x + \rho_p + \omega_{vp}, \tag{2}$$

where the instrument set Z includes one of the following:

1. Elevation, on the subset of villages in malaria-prone areas (below 2,500 meters of altitude);
2. Elevation, a dummy for villages located above 2,500 meters, and their interaction, on the entire set of villages located at all elevations;
3. Full interactions between village elevation, quintiles of village slope, and a dummy for villages located above 2,500 meters. This regression controls for the direct effect of elevation and quintiles of village slope in the second stage.

The use of elevation as a sole instrument requires that the exclusion restriction holds. That is, the within-province variation in village elevation has no other way to affect schooling other than through its impact on malaria. This may be hard to justify in light of the potentially important environmental differences across elevation zones. For instance, crop choice in Ethiopia varies by elevation, so the exclusion restriction is violated if crop choice impacts education (say, through labor demand or farm income). This remains true also in the second instrument set. The exclusion restriction for the third set is different, because elevation and slope appear directly in the second stage as controls. For this instrument set to be plausible, it is necessary to believe that whatever impact elevation or slope have on schooling, it does not work through the *interaction* between the two. Since this assumption is much more stringent and realistic, estimates from the first two instrument sets are shown for comparison purposes, and those from the third instrument set are preferred.

5 Results

5.1 Malaria and topography

I document the relationship between the disease environment and topography in figure 5 and table 2. Figure 5 plots the non-parametric estimate of the measure of self-reported malaria on village elevation. As altitudes increase, the proportion of the villagers reporting it decreases. The proportion of villages suffering from malaria remains flat and close to zero for elevations above 2,500 meters, as expected. The trend below 2,500 meters is roughly linear, so in this paper I present results based on a linear trend (and results do not change if a more flexible relationship is used).

Table 2A reports coefficient estimates from regressions of disease prevalence on village elevation, slope, and covariates (including average rainfall and province fixed effects). I consider two specifications, one that excludes villages above the 2,500 meter line, and one that includes all villages and tests for the presence of the 2,500 meter spline. Columns 1 and 2 confirm that higher elevation villages are healthier: on average, each 100 meters of elevation gain reduces sickness by 0.8%, or approximately 3% of the average level of village sickness. Moreover, this correlation disappears above the 2,500 meter line, something that would be expected if the correlation is driven by malaria. Land slope is negatively correlated with sickness, but the coefficient is marginally insignificant with a p-value of 0.11 (0.14 for column 2). In columns 3 and 4, I consider only those who reported malaria, and I find a similar pattern. The coefficient on altitude indicates that just 100 meters gain in elevation is sufficient to reduce malaria by 0.5%, or 7.4% of mean malaria—a very high rate. Slope is now strongly significant, indicating that more sloped villages have lower reporting of malaria. The rest of the table show that topography does not explain any other type of sickness (columns 5 and 6) and have some (statistically not significant) effects on mortality (table 7 and 8).[14]

Since malaria falls with elevation and slope, it is natural to ask whether the incidence

[14]The measure used here (number of deaths in the household in the past 5 years) include all types of deaths for all age groups.

of malaria is more sensitive to elevation gains in flatlands than in steep-lands. In other words, whether the interaction between elevation and slope can be used to predict malaria reporting. In table 2b, I show that this is indeed the case by regressing malaria on elevation, quintiles of slope, and their interactions for villages located below the 2,500 meter threshold. Elevation predicts malaria in villages located in the bottom four quintiles of land slope—but not in the steepest villages, which have low incidence rates everywhere. Moreover, the interaction coefficients are jointly significant: the p-value on the F-statistic of joint significance is 0.047.

In column 2 and 3, I repeat the exercise for other diseases and overall sickness. The interaction terms have the opposite signs, suggesting declining health problems with elevation in steep villages. Taken individually, diseases such as diarrhea, tuberculosis, ear, nose and throat problems, and other types of injuries are sometimes correlated with elevation at higher slopes only (not shown). Thus, the pattern of high correlation with elevation in flatlands is specific to malaria. Finally, mortality (column 4) follows a similar pattern as malaria, with strong correlation between elevation and deaths in flatlands and no correlation in steeper lands. This is suggestive that severe sickness and mortality is driven by malaria, and not by (possibly less severe) diseases.

Finally, I consider a regression of malaria on elevation, slope quintiles dummies, above 2,500 meter dummy, and all interactions for the full sample. Controlling for elevation and slope quintile dummies, the various interaction terms are also predictors of malaria. Since the patterns of malaria and topography are similar to those already reported, the results are reported in the appendix. The p-value of the F-statistic associated with these terms is 0.001. These will be used in the following section as excluded instruments.

5.2 Schooling and malaria

Having established that recently reported malaria is correlated to topography in a specific way, the next task is to show that schooling is similarly correlated. In table 3, I regress the average years of schooling for children and adults on elevation, slope, and covariates, first focusing on elevations below the 2,500 meter threshold (columns 1 and 2) and then on all villages (columns 3 and 4).[15] Children and adults living at higher elevations have higher educational attainment. Conversely, the higher the slope of the village, the lower the educational attainment. Moreover, when slope dummies are interacted with elevation (column 5 through 7), regressions show that there are gains in education from elevation in flat areas, but the higher the slope, the lower the gain: 100 meters of elevation gain correspond to an additional 0.095 years of schooling for children and 0.078 years for adults for those living in flat areas. The gain in schooling declines as slope increases, and there are no gains for those living in the steepest areas. This pattern is what could be expected if malaria were driving educational attainment.[16] The inclusion of covariates reduces somewhat the relationship between topography and education: when covariates are excluded, coefficients are more significant, perhaps suggesting that part of the impact of malaria on schooling is mediated through the long-term villages' accumulation of wealth.

I turn to instrumental variable estimates in table 4, panels A and B. Here, I assume that village topographical characteristics are valid instruments for malaria incidence, and look directly at the impact of recent self-reported village malaria on average years of schooling for children and adults, with results disaggregated by gender. In the first column, I report OLS results. In column 2, I use instrument set 1 on villages that lie below the 2,500 meter threshold. In column 3, I include all villages, and use instrument set 2. Finally, in column 4 I report the preferred specification, which controls for elevation and slope quintiles, and uses instrument set 3. Since the latter two regressions include multiple instruments, I report the results from a limited information maximum likelihood estimation (LIML), which reduces any biases in the IV estimates originating from having many instruments, small sample size, or weak instruments.

[15]Coefficients on covariates are not shown but move in the expected direction: parental wealth and education increase childrens schooling and distance to schools decreases it. Livestock ownership is associated with more schooling, suggesting that the income effect from livestock trump substitution effects arising from the fact that animal husbandry is an important labor activity of Ethiopian children.

[16]As a further check, regressions on the entire sample with a triple interaction term between elevation, slope quintiles and a dummy for above 2,500 meters lead to very similar results on the interaction terms: significant and declining interaction terms for those below the threshold, insignificant if above the threshold.

Looking at the first column of the table, the coefficient on malaria is small and statistically insignificant for all OLS regressions, as expected if measurement error is the most important problem. When turning to the IV specification in column 2, however, the coefficient on malaria becomes negative, large, and statistically significant for children, and marginally insignificant for adults (p-value for the adult regression: 0.10). Coefficients for women are slightly larger but within the standard error of those for men for both adults and children. Coefficients are very similar when the instrument set includes elevation splined at 2,500 meters (columns 3), although they are smaller for adults. Finally, column 4 shows that, even after controlling for the direct effect of elevation on schooling, instrumented malaria remains strongly and negatively associated with lower schooling levels, with higher point estimates but also larger variance. Point estimates are higher for males than females, which is consistent with epidemiological evidence showing that Ethiopian males are more exposed to the disease (Yeshiwondim et al, 2009).[17] Overall, considering all estimated coefficients, the regressions indicate that moving from a no malaria village to one with average malaria (where the average is 5.7% for all villages, and 6.7% for those located below 2,500 meters) reduces education by 0.34-0.49 years for children, and 0.33-0.63 years for adults.

The regressions provided in panels A and B pass a number of tests. F-statistics of joint significance for the first stage are large for all instrument types. The underidentification rejects the null of underidentification with a 99% confidence. Instruments are found to be mildly weak: the Kleibergen-Paap Wald rk F statistic varies from 2.76 to 3.0, which is a rejection at slightly above the 10% level.

5.3 Other outcomes

There are several ways in which a higher incidence of malaria could drive down education attainment. Aside from the effects of exposure at birth, contemporaneous malaria could lead to

[17]Boys and adult men spend more time in the fields than girls, who spend a larger fraction of their time at home. Since sleeping outside to protect the field is quite common, farm workers are more exposed to mosquito bites.

school absenteeism, higher dropout rates, and —when a parent is sick— substitution between adult and child labor. Moreover, expectations about future sickness could also lead to lower education levels. For instance, if severe malaria morbidity and mortality declines with child age, higher incidence of malaria could lead to delayed school entry, or no entry at all.

The data used in this paper is not suitable to explore these channels in great detail. In the last panel of table 4, I report OLS and IV results on three outcomes which relate to these channels: the proportion of children over the age of 10 engaged in work, the fraction with no schooling, and the average age of those with no schooling. The coefficient of malaria incidence on child labor is positive, but statistically insignificant. That is not too surprising, given that work is measured only for the prior seven days and is therefore quite noisy. The following set of results indicate that the fraction of children unschooled increases with predicted malaria incidence, suggesting that one reason for the lower average education outcomes found in panel A and B come from a larger fraction of children not having any schooling at all. Finally, the last set of regressions consider the average age of those with no education. If children in places with more malaria enter school later, the average age of children with no schooling should be higher, after controlling for age and proportion of children never enrolled in school. This is not something consistently found in the malaria regressions: the coefficient on malaria is positive (as expected) when elevation is the sole instrument, but it is not statistically significant and turns negative in column 4.

6 Testing the exclusion restriction

The IV results in table 4 originate from the positive correlation between topography (the interaction of elevation and slope) and education. In order for these measures to take a casual sense, it is necessary that the within-province variation in topography has no other way of affecting schooling other than through its impact on malaria. It is important to emphasize that many factors could be involved. For instance, elevation alone could affect farm productivity, exposure to weather shocks, income, or demand for child labor. Higher elevation villages might have closer access to schools, services, or labor markets where returns to education are higher. Finally, differences in elevation might correlate with differences in preferences, migratory patterns, and other unobservable characteristics. Whether these differences vary across slopes is, however, the relevant question. In this section, I present partial evidence in support of the method used: I show the relationship between other education determinants and the topography instruments, in search of patterns that are consistent with the reduced form findings of table 3. Obviously, this approach will provide only partial evidence, since villages might be very different along a variety of ways unobserved in the data.

6.1 Topography and other village differences

I explore the relationship between other factors that affect education and elevation by running the following set of regressions on village-level averages:

$$y_{vp} = Z_{vp}\beta + T_{vp}\gamma_T + \bar{X}_{vp}\gamma_x + \rho_p + \omega_{vp}, \tag{3}$$

where y_v are characteristics of a village that could affect either the demand or supply of education, Z_{vp} is the instrument set 3, and X_{vp} and T_{vp} include the regressors in equation (2). For simplicity, I only report the β estimates from the sample to villages located below the 2,500 meter threshold in table 5.

The first concern with the exclusion restriction is that differences in the natural environment across elevations and slopes affect agricultural production. To address the first concern, and lacking direct information on farm productivity and household earnings, I make use of the information about household exposure to possibly exogenous production shocks in the survey. Households were asked how many times they suffered drought, floods, livestock deaths, or other shocks in the prior five years. I report columns 1-4, I regress elevation on the average number of reported instances.

Second, I assess the possibility that the instruments are correlated with village endowments as measured by three variables: the asset ownership index (which I refer as wealth), the size of landholdings, and the number of livestock owned.

Third, topographical differences in population density and market structure (say, arising from highland planes being more densely populated or economically diverse) could be a threat to identification if these lead children to seek employment outside of farming–where schooling may be important.[18] In columns 8 and 9, I consider two proxies: fraction of household that are landless, and fraction of household heads employed in non-farm sectors.

Fourth, topography might be correlated with migration. Unfortunately, the data does not include information on in- or out-migration. As a partial and admittedly unsatisfying check, I show in column 10 that length of land tenure does not vary by elevation interacted with slope. If flat, low elevation areas are at the receiving end of *recent* migratory flows (from landless people in flat, higher elevation areas), we could expect that average land tenure is lower.

Finally, it is possible that steep-lands in high elevation areas have, for historical or political reasons, a more developed infrastructure. Since the exact location of each village relative to the surrounding major towns or cities is unobserved, I make use of household-specific distances to locations or facilities. Column 11 considers the special case of distance to elementary schools.[19]

Table 5 largely shows that the observed variables do not correlate with slope in a way that threatens identification–that is, they are not more correlated with elevation in flat areas than in steep areas. For instance, other shocks, livestock ownership, and distance to school and other facilities are all correlated with elevation in steep areas, but not in flat areas, shocks to livestock has significant correlation only in quintile 2 and 4, and average tenure, floods, wealth and non farm employment are all uncorrelated with the instruments. Possible candidates

[18]It should be noted that any land scarcity in flat highlands could work against educational attainment if the smaller plots impact the ability of households to pay for schooling.

[19]School distance is a convenient proxy to distance to other services, since distances to other services (like health centers, markets, roads, sources of farm goods, and so on) behave in a similar pattern (regressions not shown).

for alternative explanations are landlessness (which is correlated with elevation only for slope quintile 2), landholding size (correlated with elevation at all slopes), and droughts (correlated only in quintile 1). The result on landlessness and landholding size could suggest that population pressure is more sensitive to elevation in flatter areas. However, not one alternative explanation fits precisely the pattern observed for the malaria and schooling regression: strong correlation with elevation in the flat lands, declining correlation at higher slopes, and no correlation at all in the steepest quintile. Therefore, controlling for droughts, land sizes, and landlessness neither change magnitude or significance of the estimated malaria impact on schooling, nor are statistically significant explanatory variables in the education equation.

6.2 Falsification tests

An additional way to check the validity of the exclusion restriction is to test whether topography has a direct impact on education in developing countries without malaria. Here I consider the case of Nepal. Due to the presence of the Himalayan mountains, the rural population of this country is dispersed across many different elevations. Moreover, elevations in Nepal span the same ecosystems as Ethiopia, from the sub-tropical environment in the Terai lowlands to alpine environment in the highlands. Finally, while malaria was endemic in Nepal, following an eradication campaign in 1958 and subsequent malaria control program incidence rate of the disease is very low, with less than 3,500 confirmed cases in 2009. (WHO, 2010). Since malaria has been only a minor factor for decades, the effect of elevation on education is driven entirely by other unobservable characteristics that I am unable to capture using the Ethiopian data.

In table 6, I report results of health and education regressions using DHS data collected in rural areas during the 2001 and 2006 rounds, which contain information on health shocks suffered by children in the prior two weeks, educational attainment of all household members, and precise measurements of village elevation. Unfortunately, the data does not include several key variables of interest, including village slope, distance to schools and other facilities, and other household controls like wealth (for the 2001 round), so it is not possible to replicate precisely the results from Ethiopia. I thus regress average education on elevation with a reduced set of controls. As before, since education and health outcomes might be correlated within villages, I run village-level regressions where all left and right hand side variables are averaged at the village level. Normally, errors should also be clustered at the province level to deal with within-province correlation; unfortunately, there are only 13 land divisions in the DHS data, too few to provide consistent results. As an alternative, I report block-bootstrapped standard errors. Finally, since I lack the information required to determine the elevation above which malaria cannot be sustained, I consider several sub-samples of villages located below 2,000 meters, 1,500 meters, and 1,000 meters.

Panel A regresses the fraction of children who are reported suffering from fevers (which can proxy for malaria), diarrhea, and cough on elevation, covariates, and region dummies. In all cases, the coefficient estimates are small and statistically significant, regardless of village sample. This confirms that there is no elevation-health gradient in Ethiopia.

In panel B and C, I test for the presence of an elevation-education gradient. As before, I run separate regressions for children and adults, and by gender. In all cases, coefficient estimates are not statistically different from zero. Children's education is positively correlated with elevation only in the subsample of villages below the 2,000 meters, and in all cases the coefficient estimates are much smaller than those found in Ethiopia. For adults, education is negatively correlated with elevation across all specifications. These results suggest that elevation per se may not be correlated with unobserved determinants of education.

7 Conclusion

This paper presents estimates of the causal impact of malaria on schooling using data from an African country. I find that living in Ethiopian villages that are less prone to malaria increase schooling for adults and children by approximately 0.3-0.6 years, which is a large in a country with very low schooling. These estimates rely on the fact that malaria incidence falls with elevation, but by less in steeply sloped villages where there is little malaria to begin with. I also find that elevation and slope matter for education only in the range of elevations where malaria is likely to occur and cease to matter in places with no malaria. Moreover, I use data from Nepal, a country with significant variation in elevation but no malaria, to show that neither health nor education are correlated with elevation.

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Table 1: Summary Statistics

	All villages		;es below 2,500 m	
	Mean	St. Dev.	Mean	St. Dev.
Recent reported village health problems:				
All sickness (% of village)	0.244	0.128	0.251	0.129
Malaria (% village)	0.057	0.095	0.066	0.100
Years of schooling:				
Children (age 7-19)	0.968	0.730	0.978	0.755
Boys (age 7-19)	1.241	0.932	1.257	0.959
Girls (age 7-19)	0.796	0.841	0.789	0.856
Adults (age >20)	1.033	0.938	1.060	0.959
Male (age >20)	1.662	1.419	1.714	1.448
Women (age >20)	0.473	0.691	0.483	0.705
Household characteristics				
% farming households	0.922	0.110	0.921	0.111
% Landless	0.041	0.066	0.042	0.066
Tenure (years)	10.069	5.608	9.712	5.229
% Female head	0.229	0.131	0.228	0.132
Number of ivestock	4.676	4.097	4.258	3.916
Number of oxen	0.927	0.657	0.913	0.595
Number of shocks (past 5 years)				
Deaths	0.287	0.425	0.292	0.446
flood_5yrs	0.133	0.393	0.136	0.406
drought_5yrs	0.417	0.798	0.434	0.816
livestock~rs	0.386	0.618	0.387	0.619
othershock~s	0.048	0.234	0.049	0.250
Distances to facilities (in hrs)				
School	0.710	0.599	0.715	0.626
Health facilities	5.069	7.185	4.864	6.951
Observations	1000		844	

Table 2a: Relationship between elevation and reported health incidents

VARIABLES	(1) All sickness types	(2)	(3) Malaria	(4)	(5) Other sickness	(6)	(7) Death	(8)
Elevation	-0.008***	-0.008***	-0.005***	-0.005***	-0.003	-0.003	-0.011	-0.010
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.010)	(0.009)
Elevation x 2,500 m		0.009*		0.009***		0.000		0.036**
		(0.005)		(0.002)		(0.005)		(0.012)
Slope	-0.230	-0.174	-0.330***	-0.278***	0.098	0.102	-0.64*	-0.434
	(0.144)	(0.117)	(0.079)	(0.058)	(0.121)	(0.101)	(0.364)	(0.310)
Observations	844	1,000	844	1,000	844	1,000	844	1,000
R-squared	0.056	0.051	0.133	0.139	0.022	0.020	0.018	0.016
Number of provinces	276	295	276	295	276	295	276	295
Average outcome var:	0.251	0.244	0.067	0.057	0.185	0.186	0.293	0.287

Village level regressions on self-reported recent incidence of sickness reported by individuals in the prior two months. Deaths measured as theaverage number of instances suffered by household in past 5 years. Odd columns exclude villages over 2,500m which are malaria-free. Even columns include all villages. Controls: village averages of land size, rainfall, school and health facility distance, female headed household, age of head, wealth quantile, education of household head, education of spouse, livestock and oxen ownership, and province f.e. Errors clustered at the province level reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 2b: Relationship between slope, elevation, and reported sickness

VARIABLES	(1) Malaria	(2) Other sickness	(3) All sickness	(4) Deaths
Elevation	-0.009**	0.002	-0.007	-0.028**
	(0.004)	(0.004)	(0.005)	(0.014)
Elevation x quantile:				
Slope 2	0.001	-0.001	-0.000	0.016
	(0.004)	(0.004)	(0.005)	(0.014)
Slope 3	0.000	-0.004	-0.004	0.001
	(0.004)	(0.004)	(0.005)	(0.012)
Slope 4	0.004	-0.005	-0.001	0.019
	(0.004)	(0.004)	(0.005)	(0.019)
Slope 5	0.008**	-0.008*	-0.000	0.027
	(0.004)	(0.004)	(0.006)	(0.017)
Observations	844	844	844	844
R-squared	0.152	0.034	0.063	0.029
Number of provinces	276	276	276	276
P-values of F-tests:				
Elev., 2nd quantile=0	0.012	0.830	0.123	0.339
Elev., 3rd quantile=0	0.000	0.394	0.005	0.009
Elev., 4th quantile=0	0.057	0.295	0.043	0.611
Elev., 5th quantile=0	0.652	0.056	0.062	0.949

Village level regressions on self-reported recent incidence of sickness.
Controls and error clustering: see table 2A.
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Reduced form effects of village topography on schooling

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep var:	Villages < 2,500 m		All villages		Villages <2,500 m		
Average yrs schooling	Children	Adults	Children	Adults	Children	Adults	All
Elevation	0.031**	0.046**	0.031**	0.036*	0.095***	0.078*	0.075***
	(0.013)	(0.022)	(0.012)	(0.021)	(0.023)	(0.040)	(0.027)
Slope	-1.643**	-2.221**	-1.227*	-2.218**			
	(0.787)	(1.115)	(0.628)	(0.893)			
Above 2,500m			1.158*	0.501			
			(0.669)	(0.725)			
Above 2,500m × Elevation			-0.051**	-0.022			
			(0.025)	(0.027)			
Slope 2					0.751**	-0.244	0.209
					(0.373)	(0.605)	(0.431)
Slope 3					1.130***	-0.184	0.266
					(0.395)	(0.662)	(0.467)
Slope 4					0.918**	0.954	0.700
					(0.447)	(0.721)	(0.513)
Slope 5					1.491***	0.662	0.814
					(0.479)	(0.728)	(0.532)
Elevation × :							
Slope 2					-0.048**	0.001	-0.020
					(0.021)	(0.032)	(0.023)
Slope 3					-0.066***	0.005	-0.017
					(0.021)	(0.034)	(0.024)
Slope 4					-0.056**	-0.056	-0.046*
					(0.024)	(0.038)	(0.026)
Slope 5					-0.089***	-0.054	-0.059**
					(0.025)	(0.038)	(0.027)
Average dep var:	0.976	0.965	1.060	1.033	0.976	0.965	
Observations	844	844	1,000	1,000	844	844	844
R-squared	0.408	0.105	0.412	0.120	0.418	0.130	0.127
Number of provinces	276	276	295	295	276	276	276
P-Value of F-test:							
Elev. 2nd quantile					0.002	0.009	0.011
Elev. 3rd quantile					0.084	0.010	0.014
Elev. 4th quantile					0.020	0.388	0.091
Elev., 5th quantile					0.706	0.335	0.338

Controls in adult regression: village averages of land size, rainfall, school and health facility distance.
Controls in the children regression: same as those for adults, plus: female headed household, age of child, education of household head and spouse, wealth quantile, livestock and oxen ownership.
All regressions at the village level and include province f.e.
Errors clustered at the province level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Reported malaria on education in Ethiopia

Reported coeff: village malaria	(1)	(2)	(3)	(4)
Estimation method	OLS	IV	IV-LIML	IV-LIML
Instruments		Elevation	Elevation Elevation ×2,500m	Elevation ×2,500m ×slope quintiles
Sample	Full	< 2,500m	Full	Full
Panel A: Children's education				
All children	-0.075	-5.076**	-5.377**	-8.612*
	(0.298)	(2.425)	(2.382)	(4.471)
R-squared	0.404	0.530	0.480	0.225
Boys	0.284	-5.985*	-4.884*	-9.102*
	(0.422)	(3.204)	(2.549)	(4.847)
R-squared	0.372	0.511	0.530	0.314
Girls	-0.201	-6.107**	-6.906**	-7.046**
	(0.362)	(2.929)	(2.785)	(3.548)
R-squared	0.369	0.485	0.407	0.400
Panel B: Adults' education				
All adults	-0.216	-9.409	-5.142	-5.762*
	(0.366)	(6.107)	(3.618)	(3.310)
R-squared	0.096	0.301	0.509	0.486
Male adults	-0.508	-6.226	-2.608	-10.496
	(0.551)	(6.072)	(4.140)	(7.094)
R-squared	0.094	0.575	0.610	0.460
Female adults	0.116	-8.833*	-5.088*	-3.249
	(0.296)	(5.316)	(2.905)	(2.555)
R-squared	0.069	-0.018	0.338	0.442
Panel C: Other child outcomes				
Child labor	0.082	0.236	0.445	0.288
	(0.059)	(0.464)	(0.337)	(0.342)
R-squared	0.113	0.501	0.452	0.475
Fraction unschooled	0.036	1.275*	1.337**	1.948**
	(0.087)	(0.651)	(0.657)	(0.921)
R-squared	0.359	0.561	0.524	0.390
Average age of unschooled	0.106	8.969	4.281	-12.933
	(0.511)	(5.699)	(5.008)	(19.491)
R-squared	0.401	0.591	0.629	0.505
Observations	1,000	844	1,000	1,000
Province f.e.	295	295	295	295

All regressions at village level with full controls and province fixed effects. Child labor is the fraction of children over 10 years old who reported working in prior 7 days. Fraction unschooled is the fraction of children never enrolled in class. Regressions on the average age of unschooled includesthe fraction of unschooled children as a control. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5: Village characteristics and topography

Column title is dependent var	(1) Floods	(2) Droughts	(4) Livestock loss	(5) Other shocks	(6) Wealth	(7) Land size	(8) Livestock ownership	(9) Nonfarm employment	(10) Landless	(11) Tenure length	(12) School distance
Elevation	-0.010	-0.074**	0.006	-0.001	0.014	-0.038	0.116	0.001	0.003	-0.008	-0.029
	(0.015)	(0.035)	(0.030)	(0.013)	(0.021)	(0.040)	(0.096)	(0.008)	(0.004)	(0.189)	(0.022)
Elevation × :											
Slope 2	0.001	0.049*	0.038	0.008	0.008	-0.049	-0.001	0.005	0.004	0.021	0.014
	(0.013)	(0.029)	(0.027)	(0.017)	(0.020)	(0.040)	(0.096)	(0.006)	(0.004)	(0.183)	(0.022)
Slope 3	0.003	0.048	0.014	0.001	0.002	-0.028	-0.049	0.002	0.001	-0.018	0.016
	(0.015)	(0.030)	(0.030)	(0.012)	(0.021)	(0.033)	(0.099)	(0.008)	(0.004)	(0.169)	(0.020)
Slope 4	0.015	0.057	0.031	0.008	0.005	-0.007	0.073	0.003	-0.001	-0.085	-0.029
	(0.014)	(0.035)	(0.031)	(0.014)	(0.022)	(0.038)	(0.100)	(0.009)	(0.004)	(0.183)	(0.033)
Slope 5	-0.003	0.054	-0.034	-0.008	-0.009	-0.055	0.065	0.004	-0.001	-0.137	-0.022
	(0.018)	(0.034)	(0.038)	(0.013)	(0.022)	(0.037)	(0.100)	(0.010)	(0.004)	(0.197)	(0.034)
Observations	844	844	844	844	844	844	844	844	844	844	844
R-squared	0.010	0.025	0.049	0.018	0.054	0.057	0.079	0.067	0.049	0.077	0.079
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Province f.e.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Mean dep. var	0.132	0.414	0.386	0.048	-0.976	2.886	4.800	0.181	0.049	10.09	0.712
P-value of F-statistic											
Elev., 2nd quintile=0	0.519	0.327	0.064	0.381	0.239	0.005	0.234	0.354	0.006	0.932	0.451
Elev., 3rd quintile=0	0.576	0.284	0.378	0.991	0.403	0.008	0.378	0.616	0.105	0.825	0.467
Elev., 4th quintile=0	0.724	0.564	0.086	0.355	0.170	0.131	0.008	0.500	0.165	0.542	0.053
Elev., 5th quintile=0	0.389	0.458	0.245	0.060	0.728	0.000	0.004	0.346	0.263	0.326	0.067

Column title is dependent variable. Shocks measured as the village average of the number of times a household suffered the shock in the prior 5 years. Wealth: average value of asset index. Tenure length: the number of years in that residence. Errors clustered at the province levels in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Effect of elevation on recent child health and average schooling in Nepal

Reported: coefficient on elevation Dep var: row title	All villages (1)	Villages <2000m (2)	Villages <1500m (3)	Villages<1000m (4)
Panel A: Recent reported sickness				
Fever	-0.002	-0.001	-0.003	0.001
	(0.002)	(0.003)	(0.003)	(0.006)
R-squared	0.118	0.115	0.175	0.202
Diarrhea	-0.001	0.001	0.002	0.004
	(0.002)	(0.003)	(0.002)	(0.007)
R-squared	0.132	0.142	0.151	0.147
Cough	-0.001	-0.000	-0.001	0.008
	(0.001)	(0.002)	(0.004)	(0.006)
R-squared	0.198	0.209	0.229	0.248
Panel B: Children's education				
All children	-0.017	0.002	0.009	0.025
	(0.013)	(0.008)	(0.009)	(0.030)
R-squared	0.731	0.728	0.736	0.730
Boys	-0.019	0.006	0.008	0.029
	(0.012)	(0.006)	(0.011)	(0.029)
R-squared	0.671	0.677	0.672	0.667
Girls	-0.016	-0.001	0.008	0.025
	(0.016)	(0.013)	(0.013)	(0.037)
R-squared	0.706	0.699	0.716	0.712
Panel C: Adult's education				
All Adults	-0.027	-0.011	-0.014	-0.081
	(0.022)	(0.027)	(0.032)	(0.056)
R-squared	0.151	0.154	0.113	0.109
Male adults	-0.040	-0.017	-0.009	-0.114
	(0.026)	(0.033)	(0.043)	(0.075)
R-squared	0.119	0.119	0.075	0.074
Female Adults	-0.021	-0.006	-0.017	-0.040
	(0.016)	(0.020)	(0.022)	(0.044)
R-squared	0.219	0.230	0.204	0.174
Observations	385	356	294	207

Village level observations from DHS 2001 and 2006.
Panel A: dependent variable is sickness types experienced by children age 0-5 in the prior two weeks.
Controls for panel A and B include village agerages of: age of children, sex, education of household head and spouse, fraction of household headed by a woman, and a dummy for the 2001 survey.
Controls for panel C include village average of adult age, sex, and dummy for the 2001 survey.
All regressions include sample domain f.e.Standard errors clustered at the sample domain level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

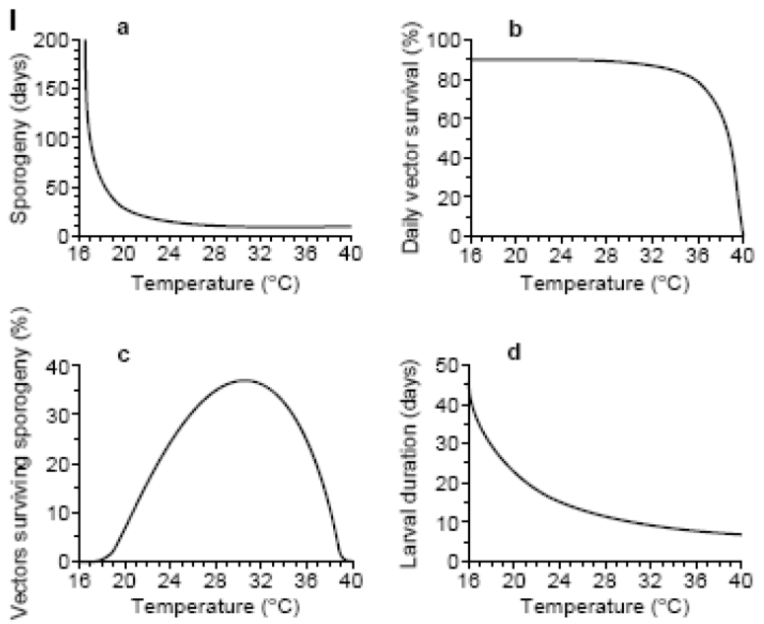
Appendix: Topography, Malaria, and Education
All elevation interactions

	(1)	(2)	(3)
Dep var:	Malaria	Children	Adults
Topographical characteristics:			
Below 2,500m:			
Elevation	-0.010***	0.087***	0.030
	(0.003)	(0.021)	(0.033)
Elevation x:			
Slope 2	0.001	-0.038*	0.025
	(0.003)	(0.020)	(0.027)
Slope 3	0.002	-0.033	0.028
	(0.003)	(0.023)	(0.029)
Slope 4	0.005	-0.047**	-0.015
	(0.003)	(0.023)	(0.030)
Slope 5	0.009***	-0.069***	-0.024
	(0.003)	(0.023)	(0.033)
Above 2,500 m:			
Elevation X above 2,500m	0.031***	0.046	-0.157
	(0.009)	(0.204)	(0.322)
Elevation X above 2,500m X:			
Slope 2	-0.019*	-0.153	0.070
	(0.010)	(0.214)	(0.336)
Slope 3	-0.018**	-0.091	0.053
	(0.009)	(0.205)	(0.333)
Slope 4	-0.024**	-0.128	0.080
	(0.010)	(0.208)	(0.323)
Slope 5	-0.028***	-0.116	0.216
	(0.010)	(0.211)	(0.327)
Observations	1,000	1,000	1,000
R-squared	0.156	0.445	0.126
Number of provinces	295	295	295
P-value of F-tests:			
Below 2,500 m:			
Elev., 2nd quintile	0.0025	0.005	0.0312
Elev., 3rd quintile	0.0001	0.0446	0.0271
Elev., 4th quintile	0.0228	0.0285	0.5104
Elev., 5th quintile	0.3986	0.7062	0.3573
Above 2,500 m:			
Elev., 1st quintile	0.0201	0.6625	0.718
Elev., 2nd quintile	0.3727	0.2409	0.7977
Elev., 3rd quintile	0.1532	0.3858	0.2597
Elev., 4th quintile	0.5403	0.2103	0.0998
Elev., 5th quintile	0.7002	0.3245	0.118

First stage and reduced form regressions based on table 2 and table 3.
Topography based on insturment set 3.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure1: Effects of temperature on malaria cycle.

Box 1. Relationships between Temperature and Sporogonic Duration (*n*), Mosquito Survival (*p*) and Larval Duration



Source: Craig et al, 1999

Figure 2: relationship between temperature and altitude

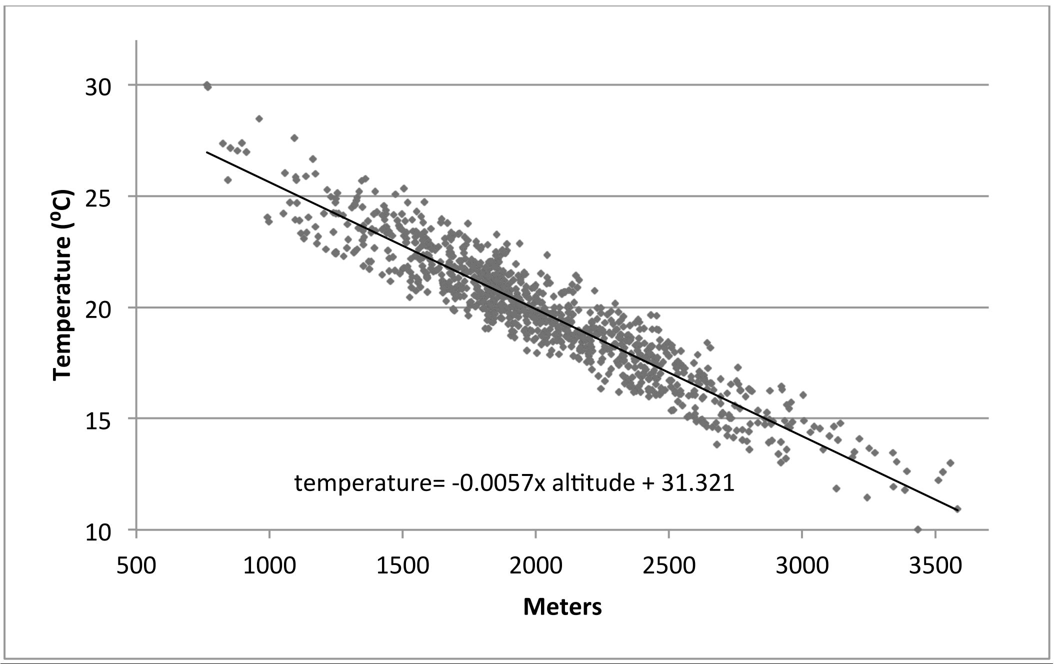
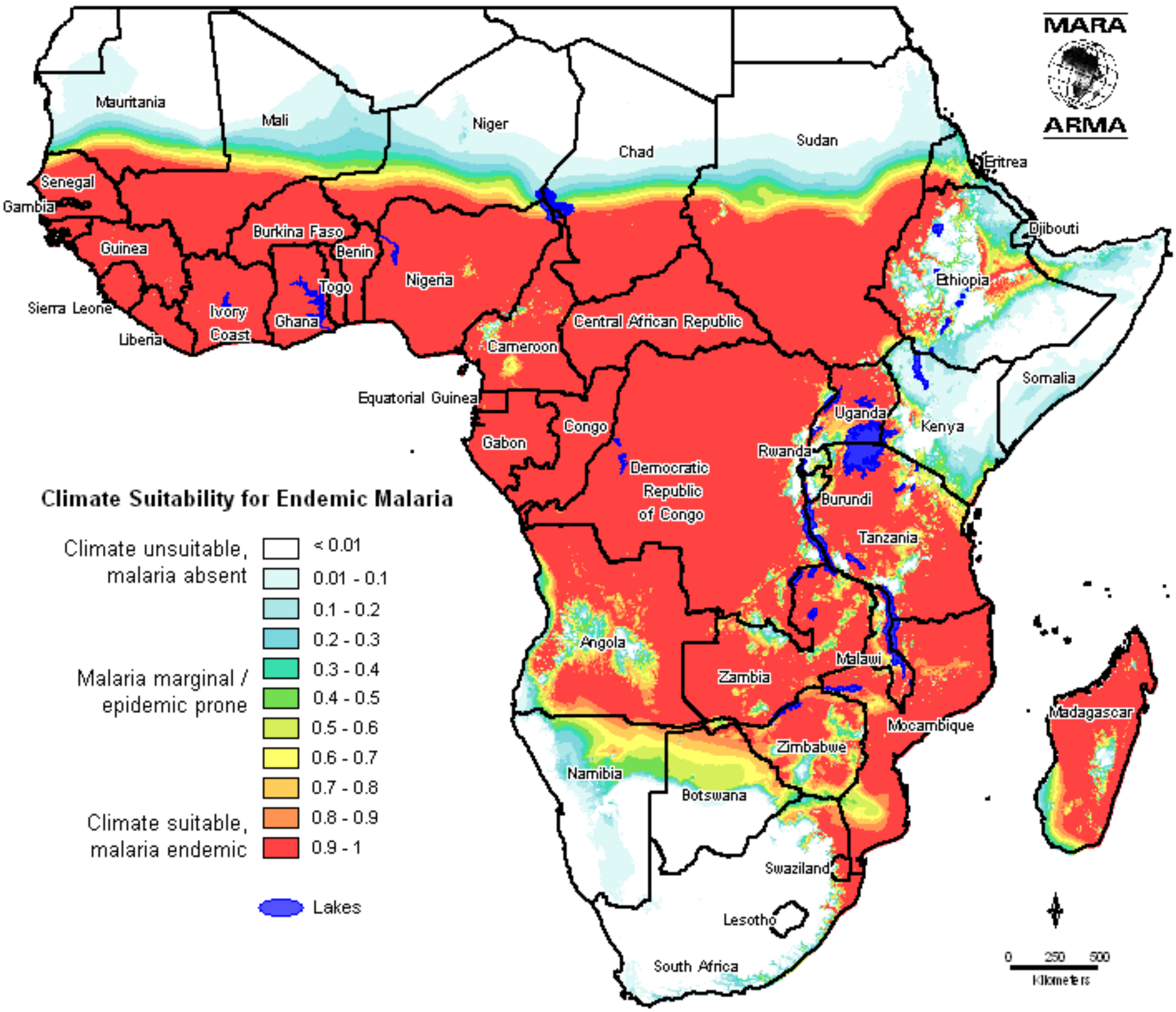


Figure 3.A

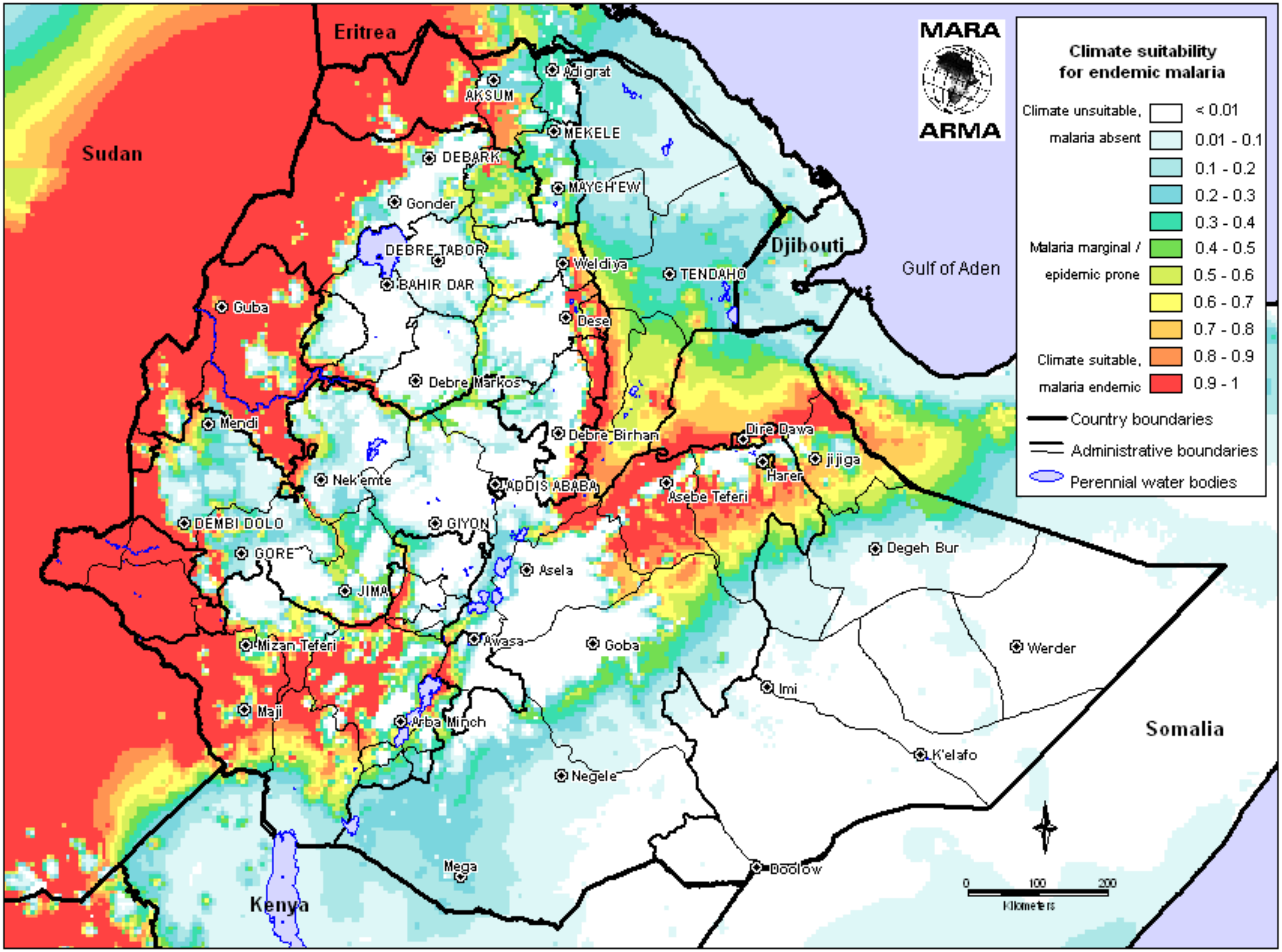
Distribution of Endemic Malaria



This map is a product of the MARA/ARMA collaboration (http://www.mara.org.za). July 2002, Medical Research Council, PO Box 70380, Overport, 4067, Durban, South Africa
CORE FUNDERS of MARA/ARMA: International Development Research Centre, Canada (IDRC); The Wellcome Trust UK; South African Medical Research Council (MRC); Swiss Tropical Institute, Multilateral Initiative on Malaria (MIM) / Special Programme for Research & Training in Tropical Diseases (TDR), Roll Back Malaria (RBM).
Malaria distribution model: Craig, M.H. et al. 1999. Parasitology Today 15: 105-111.
Topographical data: African Data Sampler, WRI, http://www.igc.org/wri/sdis/maps/ads/ads_idx.htm.

Figure 3.B.

Ethiopia: Distribution of Endemic Malaria



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Topographical data: African Data Sampler, WRI, http://www.igc.org/wri/sdis/maps/ads/ads_idx.htm

Figure 4 Selected villages (bottom map); wareda map (top map)

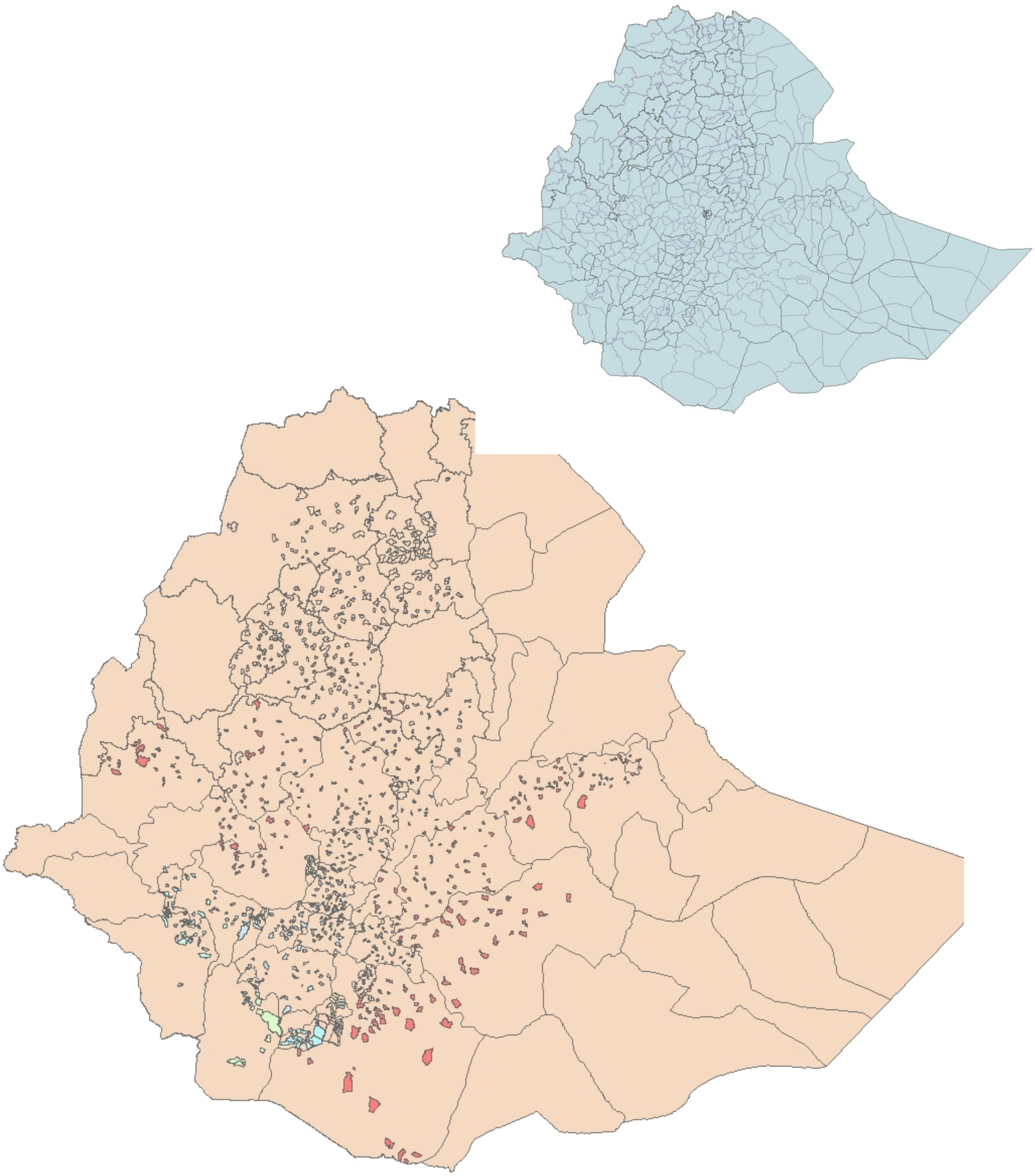

Figure 5: Malaria and elevation (non-parametric estimation)