ESSAYS ON MALARIA, ENVIRONMENT AND SOCIETY

Gordon Carlos McCord

Submitted in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy
in the Graduate School of Arts and Sciences

COLUMBIA UNIVERSITY
2012

Abstract

ESSAYS ON MALARIA, ENVIRONMENT AND SOCIETY

Gordon Carlos McCord

The body of work presented here seeks to illuminate the complex relationship between human society, development, and environment for the case of malaria. While malaria profoundly affects human society and prospects for prosperity, public health measures and anthropogenic environmental change alter the intensity of transmission differentially around the globe. Using global maps of malaria risk, the first chapter finds that the elimination of the disease during the course of the 20th century occurred in places where the strength of transmission was weaker due to suboptimal ecology, and that this result holds even after controlling for income levels. The next chapter employs GIS datasets on population, urbanization, malaria risk, and malaria endemicity to spatially estimate the cost of fully deploying ecology-appropriate anti-malaria interventions in Africa; the cost of curbing malaria is found to be small (around $4 per person at risk per year), especially given its high disease burden and subsequent social and economic costs. I next construct a spatial month-to-month ecological index of malaria transmission strength, and use a climate change model to predict changes in ecological transmission strength of malaria and estimate the implied changes in incidence and mortality given current technology and public health efforts. The final chapter uses the malaria ecology index as an instrumental variable to estimate the effect of child mortality on fertility behavior. The large effect of child mortality indicates that malaria has an indirect effect on society beyond morbidity and mortality: high malaria burdens increase fertility rates, thus slowing the demographic transition. These chapters span the fields of epidemiology, public health systems, climate science, economics and demography in order to holistically model the relationship between malaria and human systems; such understanding of coupled human-natural systems will be vital to policy making for sustainable development.

Contents

List of Figures

List of Tables

Acknowledgements

I could spend too long thanking the positive influences in my life; however I can't go forward without at least mentioning the most important:

First, my parents Vince and Carmen Elena. Thanks to you I have the incredible luxury of doing whatever I want with my life. A million times, thank you.

Next, my mentor Jeff Sachs. If any of my work has value, it's because I'm standing on the shoulders of a giant whose kindness and generosity I cannot appreciate enough.

My teachers, especially Douglas Almond, Walter Baethgen, Scott Barrett, Dalton Conley, Joshua Graff-Zivin, Upmanu Lall, Matthew Neidell, Cristian Pop-Eleches, Bhaven Sampat, Wolfram Schlenker, and Awash Teklehaimanot. Lisa Anderson, John Coatsworth, Mona Khalidi and John Mutter deserve our gratitude for their unwavering support of our doctoral program.

All of my peers in the doctoral program, for their support and ideas, but also for teaching me and inspiring me. For being generous with their time, I would like to mention in particular: Jesse Anttila-Hughes, Chandra Kiran Bangalore Krishnamurthy, Ram Fishman and Solomon Hsiang. Heidi Kleedtke has not only been a wonderful friend but also a miracle-worker in finding time for me to see Jeff.

For their support with the work in Chapter 3: Drs. Simon Hay and Robert Snow for providing the Lysenko and malaria risk maps for our use. In addition, Dr. Yemane Ye-ebiyo Yihdego was enormously helpful in clearing up details in the costing. Dr. Maru Aregawi Weldedawit kindly provided some references in the epidemiology literature. Finally, thanks to Adam Storeygard and Yuri Gorokhovich for answering questions on GIS software.

For helping me construct the time-varying malaria ecology index in Chapter 4, I thank Dr. Anthony Kiszewski.

For their support with the work in Chapter 5, we thank: Samuel Freeman for excellent research assistance, as well as seminar participants at the 2006 NBER Health Economics Summer Institute, the Duke Global Health Seminar, the Watson Institute Colloquium at Brown University, Sociology Department Colloquia at Johns Hopkins University and the University of Florida, the Development Economics Seminar at New York University, the Joint Harvard-MIT Economic Sociology Seminar, the Population Studies Colloquium at Pennsylvania State University, the Sustainable Development Seminar at Columbia University and at the 2010 World Congress of Environmental and Resource Economists for useful comments.

Finally, my family. My siblings Dawn and Derek, my brother-in-law James, Brynne, and my extended family in El Salvador all helped keep my feet on the ground and kept me laughing. My niece Elizabeth reminded me that KerPlunk is more fun than work, but also that her generation will have to solve the toughest problems that humanity has ever faced, and our duty is to set them up to succeed.

Chapter 1

Abstract

Context

Human society exists under local and global ecological constraints that define, together with available technology, the relative ease of undertaking different productive activities. Achieving sustainable development – defined broadly as improving human wellbeing without endangering future generations by compromising the planet's life support systems – requires that we understand both how economic development affects environmental processes and how the environment shapes development prospects. A lot of work, particularly in earth and environmental sciences, has improved our understanding of how human activity has changed some of the fundamental natural processes that we depend on. While natural scientists have illuminated some of the effects in the reverse direction – for example, how pollution affects human health or how soil nutrient depletion affects crop yields – social scientists are only beginning to investigate how the environment shapes our societies and conditions fundamental human endeavors such as economic growth, poverty reduction and improved health.

During recent decades, economists studying growth and development have largely overlooked the role of geography and environment, despite the fact that some countries and regions are clearly more vulnerable than others to being mired in poverty. Some regions need more basic infrastructure than others simply to compensate for a difficult physical environment. Barriers that must be offset by investments include adverse transport conditions (landlocked economies, small island economies far from major markets, inland populations far from coasts and navigable rivers, populations living in mountains, long distances from major world markets, very low population densities); adverse agro-climatic conditions (low and highly variable rainfall, lack of suitable conditions for irrigation, nutrient-poor and nutrient-depleted soils, vulnerability to pests and other post-harvest losses, susceptibility to the effects of climate change); adverse health conditions (high ecological vulnerability to malaria and other tropical diseases, high AIDS prevalence); and other adverse conditions (lack of domestic energy sources, small internal market and lack of regional integration, vulnerability to natural hazards, artificial borders that cut across cultural and ethnic groups, proximity to countries in conflict). These infrastructure needs require resources that might otherwise be invested in productive capital, human capital, or technological

advancement, which means that the adverse geography is slowing the virtuous savings-investment cycle of growth among resource-scarce countries. Adam Smith was acutely aware of the role of geography in hindering economic development. He stressed, in particular, the advantages of proximity to low-cost sea-based trade as critical, noting that remote economies would be the last regions to achieve economic development.[1] More recent studies have found statistical significance of these relationships between geography and economic outcome.[2,3]

The body of work presented here seeks to illuminate the complex relationship between human society, development, and environment for the case of malaria. Malaria exacts a high toll on the poorest part of the human family: the disease is the fourth leading cause of death for children under five in low income countries (after neonatal disorders, diarrhea, and pneumonia) and is responsible for at least one in every five child deaths in sub-Saharan Africa.[4] It kills up to 3 million people a year[5], though in recent years scale up of anti-malaria efforts in Africa may have brought deaths to below 1 million. Malaria's burden on society almost surely has repercussions on the economy: there is ample microeconomic empirical evidence[6,7,8,9,10] indicating that high disease burdens worsen productivity and economic outcomes, and most

---

[1] Smith, Adam, The Wealth of Nations, Book I, Chapter 3, paragraph I.3.8
[2] Gallup, J.L., Sachs, J.D. and Mellinger, A.D. 1999. Geography and economic development. International Regional Science Review 22, 179–232.
[3] Mellinger, A., Sachs, J.D. and Gallup, J. 2000. Climate, coastal proximity, and development. In Oxford Handbook of Economic Geography, ed. G. L. Clark, M. P. Feldman and M.S. Gertler. New York: Oxford University Press.
[4] Black R.E., Morris S.S., and Bryce J. 2003. Where and why are 10 million children dying every year? Lancet, v. 361, pp. 2226-2234.
[5] Breman, JG, MS Alilio and A Mills. Conquering the intolerable burden of malaria: what's new, what's needed: a summary. American Journal of Tropical Medicine and Hygiene. 2004; 71: suppl: 1-15.
[6] See Strauss and Thomas (1998) for a survey of the literature in the 1990s.
[7] Shultz, T. Paul, 2002, "Wage Gains Associated with Height as a Form of Health Human Capital," American Economic Review Papers and Proceedings 92: 349-53.
[8] Bleakley, Hoyt, 2007, "Disease and Development: Evidence from Hookworm Eradication in the American South," Quarterly Journal of Economics 122: 73-117.
[9] Behrman, Jere R. and Mark R. Rosenzweig, 2004, "Returns to Birthweight," Review of Economics and Statistics 86: 586-601.
[10] Miguel, Edward, and Michael Kremer, 2004, "Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities," Econometrica 72: 159-217.

evidence points towards adverse macroeconomic effects[11,12,13,14] (though there is an ongoing debate on the general equilibrium effects[15,16,17,18,19]). Similarly, several micro-level studies have found that malaria has adverse effects on educational outcomes[20,21,22], nutrition[23,24], cognitive function[25,26,27], labor productivity[28,29,30], and income[31], while macro-level studies[32,33] find evidence

---

11 Bhargava, Alok, Dean T. Jamison, Lawrence J. Lau, Christopher J.L. Murray, 2001, "Modeling the effects of health on economic growth," Journal of Health Economics, 20:423-440.
12 Bloom, David E. and David Canning, 2003, "The Health and Poverty of Nations: from theory to practice," Journal of Human Development Vol. 4, No. 1.
13 Weil, David N., 2007, "Accounting for the Effect of Health on Economic Growth," Quarterly Journal of Economics 122:3.
14 Bleakley, Hoyt, 2010, "Health, Human Capital, and Development," Annual Review of Economics 2:283-310.
15 Young, Alwyn, 2005, "The Gift of Dying: The Tragedy of AIDS and the Welfare of Future African Generations," Quarterly Journal of Economics 120: 423-66.
16 Acemoglu, Daron and Simon Johnson, 2007, "Disease and Development: The Effect of Life Expectancy on Economic Growth," Journal of Political Economy Vol. 115, No. 6.
17 Bleakley, Hoyt, 2006, "Disease and Development: Comments on Acemoglu and Johnson (2006)" Remarks delivered at the NBER Summer Institute on Economic Fluctuations and Growth, July 16, 2006.
18 Ashraf, Quamrul H., Ashley Lester, David N. Weil, 2008, "When Does Improving Health Raise GDP?", in NBER Macroeconomics Annual 2008, Daron Acemoglu, Kenneth Rogoff and Michael Woodford, eds., University of Chicago Press.
19 Bloom, David E., David Canning and Günther Fink, 2009, "Disease and Development Revisited," NBER Working Paper 15127, July.
20 Leighton, C. & R. Foster, 1993, "Economic impacts of malaria in Kenya and Nigeria," Major Applied Research Paper No. 6, HFS Project (Abt Associates, Bethesda).
21 Brooker, S. et al., 2000 "Situation analysis of malaria in school-aged children in Kenya: what can be done?" Parasitology Today 16, 183-186.
22 Holding, P.A. and R.W. Snow, 2001, "Impact of Plasmodium falciparum malaria on performance and learning: review of the evidence," American Journal of Tropical Medicine and Hygiene, 64(1,2)S, 68-75.
23 Rowland, M. G., T.J. Cole & R.G. Whitehead, 1977, "A quantitative study into the role of infection in determining nutritional status in Gambian village children," British Journal of Nutrition 37, 441–450.
24 Shiff, C. et al., 1996, "Changes in weight gain and anaemia attributable to malaria in Tanzanian children living under holoendemic conditions," Transactions of the Royal Society of Tropical Medicine and Hygiene, 90, 262–265.
25 Al Serouri, A. W., S.M. Grantham-McGregor, B. Greenwood & A. Costello, 2000, "Impact of asymptomatic malaria parasitaemia on cognitive function and school achievement of schoolchildren in the Yemen Republic," Parasitology 121, 337–345.
26 Brewster, D. R., D. Kwiatkowski, & N.J. White, 1990, "Neurological sequelae of cerebral malaria in children," Lancet 336, 1039–1043.
27 Holding, P. A., J. Stevenson, N. Pershu, & K. Marsh, 1999, "Cognitive sequelae of malaria with impaired consciousness," Transactions of the Royal Society of Tropical Medicine and Hygiene, 93, 529–534.
28 Nur, E., 1993, "The impact of malaria on labour use and efficiency in the Sudan," Society of Science and Medicine, 37, 1115–1119.

for economy-wide effects of malaria through additional channels such as higher fertility rates, decreased savings rates, barriers to internal migration and depressed tourism and trade.

While malaria has affected income levels, humanity and economic development have also affected the epidemiology of malaria. Public health efforts during the 20th century greatly reduced the geographic extent of the disease. As incomes rose, better homes and screen doors kept mosquito vectors out and reduced transmission. The urbanization accompanying economic development reduced exposure to the disease, since the *anopheles* favors a nonurban environment. Development has at times increased transmission too. Expanded irrigation to improve agriculture creates new potential breeding sites. Deforestation is bringing previously unexposed human populations in contact with malaria.[34] In addition, climate change is likely to introduce[35] and re-introduce[36] malaria into areas where it is currently absent, and as I will explain in Chapter 4, it will increase disease burden and complicate further efforts at elimination in areas where it is currently present.

Therefore, while malaria profoundly affects human society and prospects for prosperity, public health measures and anthropogenic environmental change alter the intensity of transmission differentially around the globe. This bidirectional relationship between two complex systems (human society and the epidemiology of malaria) exemplifies sustainable

---

[29] Scholz, B. D., R. Gross, W. Schultink & S. Sastroamidjojo, 1997, "Anaemia is associated with reduced productivity of women workers even in less-physically-strenuous tasks," British Journal of Nutrition. 77, 47–57.

[30] Basta, S., S. Soekirman, D. Karyadi & N.S. Scrimshaw, 1979, "Iron deficiency anemia and the productivity of adult males in Indonesia," American Journal of Clinical Nutrition 32, 916–925.

[31] Bleakley, Hoyt, 2010, "Malaria Eradication in the Americas: A Retrospective Analysis of Childhood Exposure," American Economic Journal: Applied Economics 2(2): 1-45.

[32] Sachs, J.D. and J.L. Gallup. 2001, "The economic burden of malaria," American Journal of Tropical Medicine and Hygiene (supplement) 64, 85–96.

[33] Sachs, Jeffrey and Pia Malaney, 2002, "The economic and social burden of malaria," Nature, Vol. 415, No. 6872.

[34] Vittor, A. Y. et al., 2006, "The effect of deforestation on the human-biting rate of Anopheles darlingi, the primary vector of falciparum malaria," American Journal of Tropical Medicine and Hygiene 74:3-11.

[35] Lindsay S.W. and W.J.M. Martens, 1998, "Malaria in the African highlands: past, present and future," Bulletin of the World Health Organization 76:33-45.

[36] Rogers, David J. and Sarah E. Randolph, 2000, "The Global Spread of Malaria in a Future, Warmer World," Science Vol. 289, No. 5485, pp. 1764-1766.

development inquiry. I hope the coming chapters improve our understanding of the interaction between humanity and malaria, so that we might move towards the broader goal of curbing the disease's direct and indirect effects, even in the face of an expected change in climate that will favor malaria transmission in most of the poorest parts of the world. It is also worth noting that a more abstract goal of this research is to inform the broader debate on the role of geography in the history and future prospects of economic development. Malaria has been used in empirical studies that both support[37,38] and refute[39] the hypothesis that geography continues to have a direct effect on economic development. I will discuss my perspective on this debate as I conclude this work in Chapter 6.

Chapter Summaries

Chapter 2: Malaria is a disease very much tempered by ecology; the elimination of the disease during the course of the 20th century occurred in places where the strength of transmission was weaker due to suboptimal ecology. In this chapter I use global maps of malaria risk at various points in time during the 20th century, and then overlay an ecology-derived index of the transmission strength of malaria. I find that the disease was systematically eliminated in areas where the ecology was least favorable for transmission, and that this result holds even after controlling for income levels and using spatial econometrics to take into account the spatial structure of the data. While some scholars believe that malaria elimination in today's rich counties precludes the possibility that malaria is an impediment to development in Africa, my results highlight the fact that the burden of malaria on society was very different across places like 19th-century New York and modern-day sub-Saharan Africa. A proper understanding of the epidemiology of the disease is critical to modeling the relationship between

---

[37] Sachs, Jeffrey D., 2003, "Institutions Don't Rule: Direct Effects of Geography on per capita Income." NBER Working Paper 9490, February.
[38] Carstensen, Kai and Erich Gundlach, 2006, "The Primacy of Institutions Reconsidered: Direct Income Effects of Malaria Prevalence," The World Bank Economic Review, v. 20, no. 3, pp. 309-339.
[39] Acemoglu, Daron, Simon Johnson and James A. Robinson, 2001, "The Colonial Origins of Comparative Development: an Empirical Investigation," American Economic Review, vol. 91, no. 5, December.

malaria burden, public health efforts, and prospects for economic growth. Local ecology has very much conditioned the human experience with the disease.

Chapter 3: The cost of curbing malaria in sub-Saharan Africa is small, especially given its high disease burden and subsequent social and economic costs. This costing model employs GIS datasets on population, urbanization, malaria risk, and malaria endemicity (roughly describing the proportion of the year during which transmission occurs), in order to calculate the cost of an ecology-appropriate package of malaria interventions for every 30 arc-second grid cell in Africa. We provide a financial profile for ramping up interventions to full coverage within three years, and calculate the necessary average yearly expenditure to be around US$3 billion, or around US$4 per African at risk. The result illustrates the relative ease of drastically decreasing the morbidity and mortality of malaria, even if complete eradication may be financially infeasible[40]. This has proven true in recent years: financing for anti-malaria interventions in Africa has risen, and recent data show sharp drops in mortality from the disease (38% reduction in the last decade[41]). While this analysis is not a comparison of cost and benefit (it does not evaluate the cost effectiveness of these interventions nor the social returns), the resulting low cost is suggestive of high returns to investment given the effectiveness of these interventions in trials. In addition, it is worth noting that the methodology employed in the paper does not use national statistics, and therefore offers GIS and ecology-based analysis as an alternative to survey-based costing. This might be particularly useful for needs assessments and financial planning in countries with weak statistical agencies.

Chapter 4: Climate change will make malaria harder to eliminate, and will worsen the disease burden in patterns that can be predicted using an ecological model of the disease. In this chapter I transform the static malaria ecology index published by Kiszewski et al. in 2004 to a month-by-month dynamic version based on the temperature, precipitation and

---

[40] Sabot, Oliver et al., 2010, "Costs and financial feasibility of malaria elimination," Lancet 376:1604-15.

[41] Roll Back Malaria Partnership, 2011, "A Decade of Partnership and Results," Progress & Impact Series No. 7.

local anopheles vector present in each half-degree grid cell around the world. Given the prevalence of the index in the literature, I offer more details on the index's construction than the original publication, including which anopheles vectors are unstable and are replaced by stable vectors when the preceding month lacks sufficient rainfall. I show that my new version of the index has explanatory power over variation in malaria incidence and mortality. I then calculate the index for the years 2020 and 2090 using temperature and precipitation output from the Hadley General Circulation Model, demonstrating how climate change will increase the ecological strength of transmission in many places. Finally, I use the measured elasticity between malaria ecology and incidence/mortality to estimate how climate change will complicate public health efforts to curb the adverse effects of the disease.

Chapter 5: The direct effects of malaria through morbidity and mortality are compounded by the indirect effect it has on fertility and the subsequent delay of the demographic transition. This paper employs the new time-variant malaria ecology index developed in chapter 4 as an instrument for child mortality, in order to better estimate the effect that child mortality has on fertility behavior. Although theory strongly suggests that child mortality affects fertility rates, empirical demography has struggled to estimate the magnitude of the effect because causality probably runs in both directions (parents have more children when child mortality is high, but mortality is more likely as the number of children rises due to low birth spacing and low health investments per child). The results indicate that child mortality is a powerfully robust driver of fertility behavior. Meeting the Millennium Development Goal of reducing 1990 child mortality rates by 66% in sub-Saharan Africa would translate into a reduction of total fertility rates from around 6.3 in 1990 to 3.3, more than halfway towards achieving replacement fertility levels of 2.1. An added point is that malaria clearly has an indirect effect on society beyond morbidity and mortality: high malaria burdens increase fertility rates, thus slowing the demographic transition. This brings the work from the last chapters back to the broader issues of sustainable development. Experience tells us that the demographic transition is a part of the structural change that societies undergo in the process of development. Moreover, achieving the demographic transition in today's high-fertility countries will surely be

necessary for environmental sustainability. Providing energy for the fast-growing developing economies, reducing CO_2 emissions, solving water crises around the world, and ensuring a sufficient global food supply will be hard enough if the human population stabilizes at 9 or 10 billion. It may be outright impossible if the population increases beyond that.

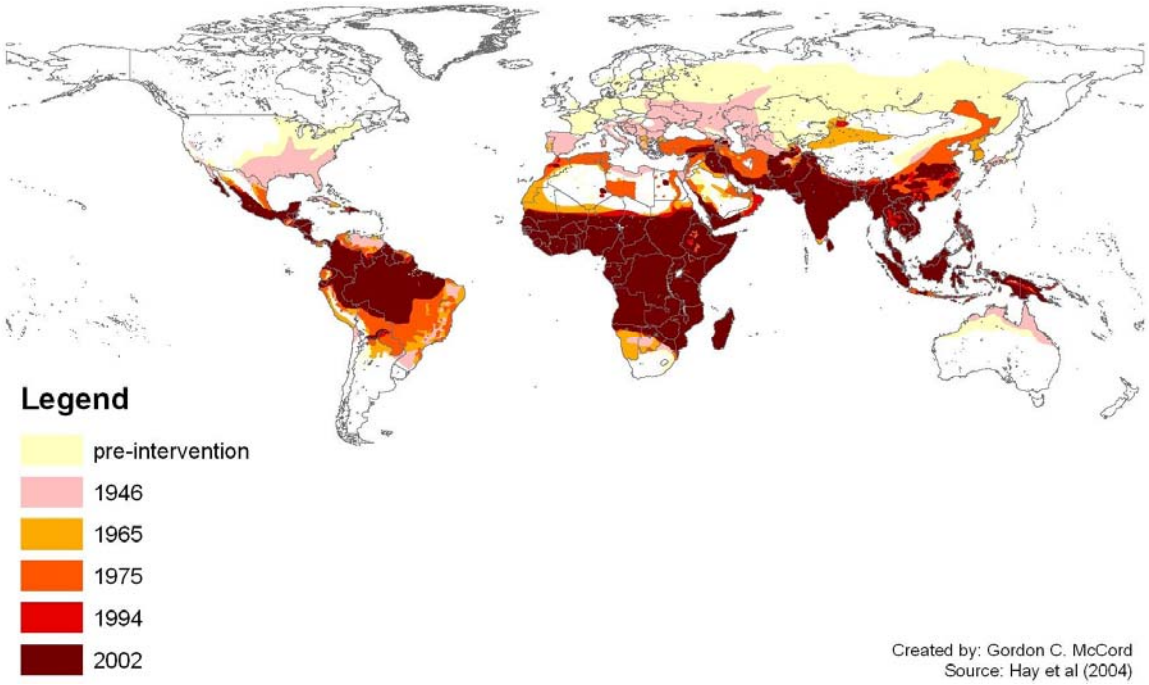
Chapter 2

A Spatial Analysis of Malaria Elimination

Gordon C. McCord

Malaria has afflicted human society for over 2 million years[1], and remains one of the great killer diseases today. The disease is the fourth leading cause of death for children under five in low income countries (after neonatal disorders, diarrhea, and pneumonia) and is responsible for at least one in every five child deaths in sub-Saharan Africa.[2] It kills up to 3 million people a year[3], though in recent years scale up of anti-malaria efforts in Africa may have brought deaths to below 1 million. The probable greatest geographic extent of malaria in history ranged from 64 degrees north latitude to 32 degrees south. During the 20th century, human intervention has significantly reduced the geographic extent of malaria risk, as documented by the WHO and shown on the map below[4].

Figure 2-1: Evolution of the Geographic Extent of Malaria



[1] Ricklefs, Robert E. and Diana C. Outlaw. A Molecular Clock for Malaria Parasites. Science 329, 9 July 2010.
[2] Black R.E., Morris S.S., and Bryce J. 2003. Where and why are 10 million children dying every year? Lancet, v. 361, pp. 2226-2234.
[3] Breman, JG, MS Alilio and A Mills. Conquering the intolerable burden of malaria: what's new, what's needed: a summary. American Journal of Tropical Medicine and Hygiene. 2004; 71: suppl: 1-15.
[4] Hay SI, Guerra CA, Tatem AJ, Noor AM, Snow RW, 2004. The global distribution and population at risk of malaria: past, present and future. The Lancet: Infectious Diseases. Vol. 4 (June), 327-336.

This paper uses GIS (Geographic Information Systems) to explore this documented decrease in geographic extent of malaria. Several estimation strategies explore the extent to which local malaria elimination has been driven tempered by local ecology as opposed to human activity.

The study is motivated by an ongoing debate in the economics literature regarding the drivers of economic growth. While several recent papers have pushed forward the idea that countries' level of economic development today are explained solely by the quality of institutions in the country[5,6,7], other papers have proposed that geographic and ecological variables are also important drivers of countries' economic performance[8,9,10]. Both camps have used the percentage of a country's population at risk of malaria in their papers, arguing that it is an example of geography's effect on human society, and including it in regressions looking to test its effect on income level after controlling for institutions. However, some of the papers reflect little understanding of what the receding extent of malaria means. One argument is that malaria is a symptom but not a cause of poverty, and is eliminated as economic growth occurs (richer countries can afford public health and environmental interventions to combat the disease). The extreme of the argument claims that malaria historically affected the U.S. and Europe, and it didn't stop economic growth there, so it is likely not an important deterrent of growth in Africa. On the other hand, the epidemiology of malaria teaches us that the strength of transmission varies with ecology. This would suggest that malaria was always more severe in some places than others, and perhaps elimination happened not where economic growth happened, but where the ecology allowed easier elimination.

---

[5] Acemoglu, Daron, Simon Johnson and James A. Robinson, 2001, "The Colonial Origins of Comparative Development: an Empirical Investigation," American Economic Review, vol. 91, no. 5, December.

[6] Easterly, William and Ross Levine, 2003, "Tropics, germs, and crops: how endowments influence economic development," Journal of Monetary Economics 50:3-39.

[7] Rodrik, Dani, Arvind Subramanian and Francesco Trebbi, 2004, "Institutions Rule: The Primacy of Institutions Over Geography and Integration in Economic Development," Journal of Economic Growth 9:131-165.

[8] Mellinger, A., J.D. Sachs and J.L. Gallup, 2000, "Climate, coastal proximity, and development," in Oxford Handbook of Economic Geography, G. L. Clark, M. P. Feldman and M.S. Gertler, eds., New York: Oxford University Press.

[9] Gallup, J.L and J.D. Sachs, 2001, "The economic burden of malaria," American Journal of Tropical Medicine and Hygiene (supplement) 64, 85–96.

[10] Sachs, Jeffrey and Pia Malaney, 2002, "The economic and social burden of malaria," Nature, Vol. 415, No. 6872.

This paper does not look to resolve the debate about the drivers of economic growth, but only to illuminate the dynamics of malaria elimination and thus improve understanding of the malaria variable being used in the papers mentioned above. I use GIS to explore the documented decrease in geographic extent of malaria risk, looking to disentagle four factors which I hypothesize will affect whether a place achieves local malaria elimination. The first three factors are income level, technological improvements in combating the disease, and the suitability of the local ecology for malaria transmission. The fourth factor is whether neighboring areas have malaria (since the disease is contagious, and since public health efforts are usually conducted at national level, one can expect that there is significant correlation between the disease outcome of one grid cell on the map and the outcomes in neighboring cells).

The starting hypothesis can be described as follows: while technologies (such as DDT) exist to curb malaria transmission, only some sub-tropical regions *could* use DDT to eliminate transmission – the ones that had low baseline rates of transmission to begin with. Most tropical regions, and especially sub-Saharan Africa, could not break malaria transmission through the application of existing technologies, since baseline rates of transmission were too high to be eliminated by these technologies. In epidemiological terms, the question is whether the suite of intervention tools is enough to drive the basic reproduction number (R_0) of malaria to below 1. R_0 is the expected number of secondary infections produced by each infected individual during her infectious period, in a population which is entirely susceptible. When $R_0 < 1$, each infected individual infects less than one individual on average, and the infection is expected to die out in the population. If $R_0 > 1$, the infection is expected to thrive in the population.[11] Whether a given intervention can drive R_0 to below one depends very much on the pre-intervention R_0. When the pre-intervention number is close to 1, elimination of transmission is feasible. When it is much greater than 1 (and sometimes over 3000 in rural Africa[12]), then elimination of

[11] Heffernan, J.M., R. J. Smith and L.M. Wahl. "Perspectives on the basic reproductive ratio." Journal of the Royal Society Interface. 2, 2005, pp. 281-293.
[12] Smith, DL, McKenzie FE, Snow RW, Hay SI, 2007, "Revisiting the basic reproductive number for malaria and its implications for malaria control," *PLOS Biology* 5(3).

transmission with the same set of technologies is not feasible.[13] Thus income will affect malaria transmission in that it allows a society to employ existing technologies to reduce morbidity/mortality and to break transmission. However, income will not completely explain the geographic extent of malaria risk, since even full use of available interventions would be unable to eliminate the disease where the basic reproductive number is very high.

The next section of the paper describes the model and estimation strategies. I then present the data and how it was prepared for analysis, and then present results.

Model

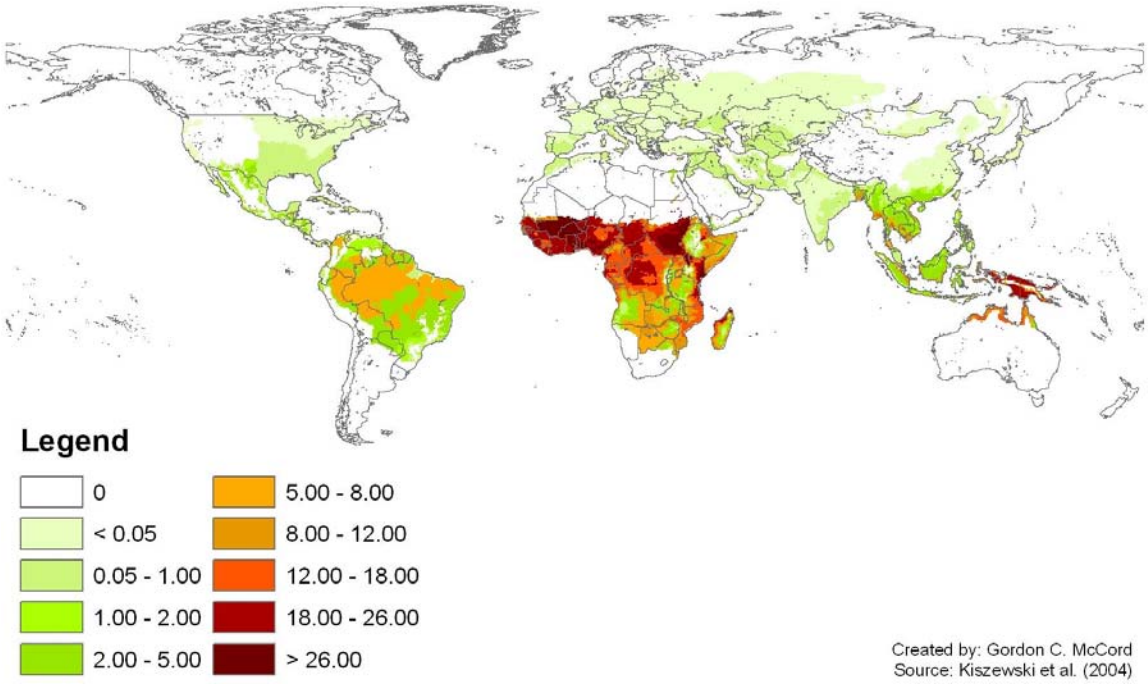
We are interested in what determines whether a particular grid cell on the world map experiences malaria incidence at a given point in time, and looking to measure the role of both the natural drivers of the disease and human efforts to stem it. Several of the variables in nature which determine the strength of malaria transmission have been usefully combined into an index by Kiszewski et al. (2004), which I refer to as the "Malaria Ecology Index". Human efforts would best be captured by coverage rates of anti-malarial interventions such as medicine, indoor residual spraying of insecticide, environmental management (larvacide use on mosquito breeding sites or drainage of swamps) and insecticide-treated bednets. However, these data are not available as a comprehensive global time series, and so I proxy for human effort using both local and national per-capita income (the intuition, again, is that richer countries can afford better public health). The other important covariates in the model are a global time dummy (to capture global technological improvements in fighting the disease) and a control for spatial dependence (since we are interested in knowing the effect of neighboring cells' malaria status on malaria risk).

Malaria Ecology – Malaria Ecology is an ecologically-based spatial index of the stability of malaria transmission based on the interaction of climate with the properties of anopheline vectors of

[13] Note, however, that even with continuing transmission, control of illness and mortality is possible. Thus, maps of malaria transmission may not change while the burden of illness and death could change markedly. Indeed, this has been happening in continental Africa during the last decade.

malaria that determine vectorial capacity.[14] The basic formula for Malaria Ecology combines climatic factors, the presence of different mosquito vector types and the human biting rate of the different mosquito vectors. The index expresses the factors that most powerfully and perennially influence the intensity of malaria transmission. It uses, therefore, a subset of the vectorial capacity equation without terms for mosquito abundance, vector competence, or recovery rate for infected people; that is, it is a subset of the equation that determines the basic reproductive number R_0 of the malaria in a given grid cell. Without interventions, places with a high malaria ecology index will have a high R_0. Because it is built upon climatological and vector characteristics on a cell-by-cell basis, the Malaria Ecology Index is exogenous to public health interventions and economic conditions. Chapter 4 explains the Malaria Ecology Index and its construction in more detail.

Figure 2-2: Malaria Ecology Index



[14] Kiszewski, Anthony, et al., 2004, "A Global Index Representing the Stability of Malaria Transmission," American Journal of Tropical Medicine and Hygiene, 70(5): 486—498.

The Malaria Ecology Index seems very much correlated to malaria incidence[15], especially in the absence of public health interventions. Even a cursory comparison of the maps of the Geographic Extent of Malaria Risk and Malaria Ecology show a clear association: the high latitudes of the northern hemisphere are both where malaria was eliminated first, and also where the malaria ecology index is lowest without being zero. Figure 3 below shows the average Malaria Ecology Index within areas of the Malaria Risk Map. Clearly, areas where malaria was eliminated later have higher mean levels of the Malaria Ecology index.

Figure 2-3: Malaria Ecology by Zones of Malaria Elimination

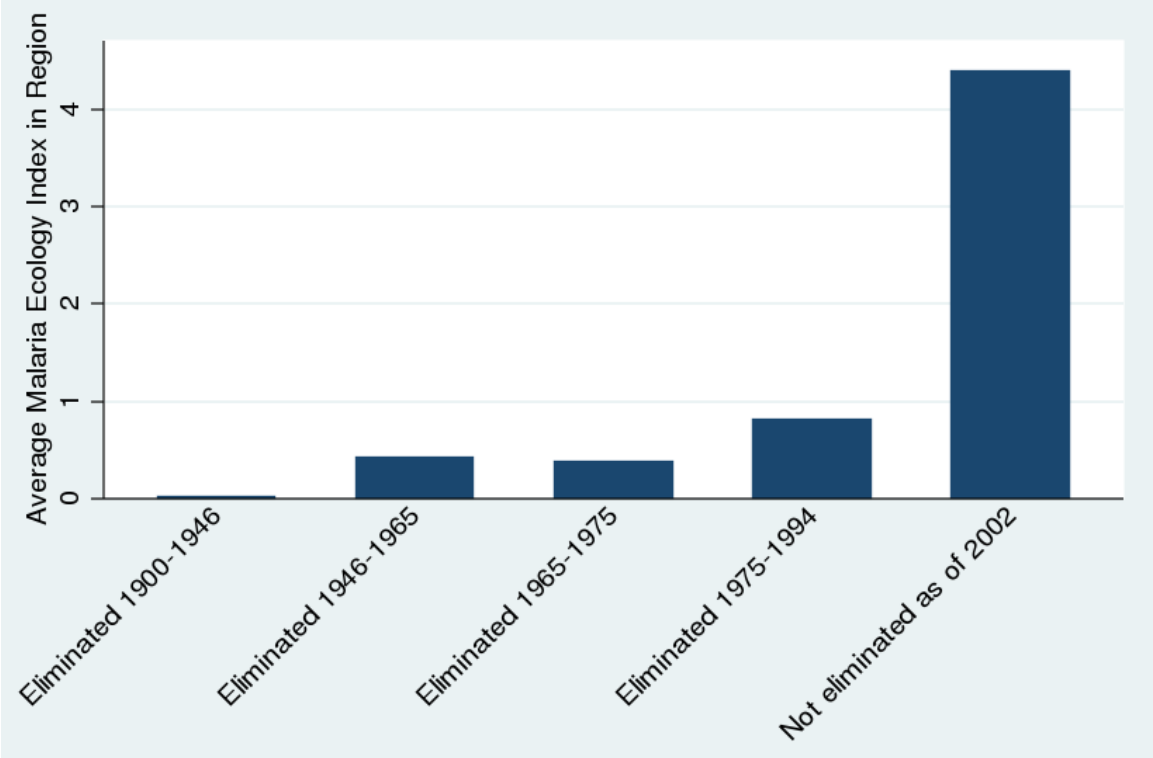
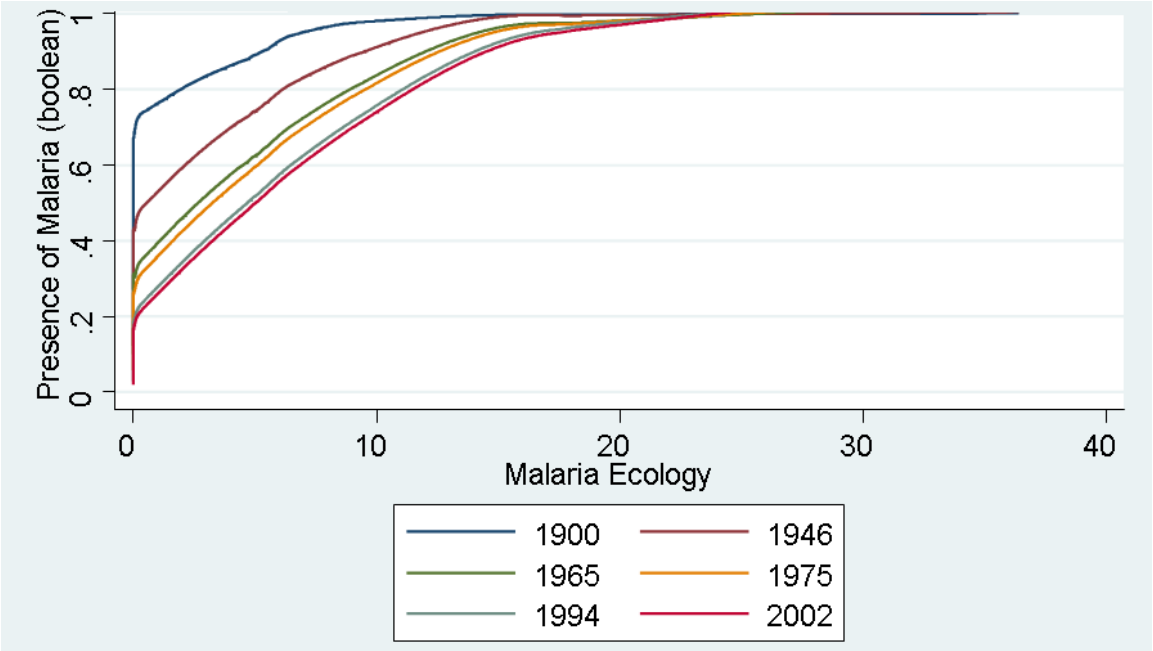


Figure 4 illustrates a similar concept: for each time period, it regresses the likelihood of having malaria present in the grid cell in on the cell's Malaria Ecology Index using local regression methods to see the shape of the relationship. Indeed, higher MEI values make it more likely that a cell has malaria, but what is noteworthy is that as time goes on, the the curve moves to the right indicating that cells with malaria have progressively higher Malaria Ecology

[15] This is further explored in Chapter 4, using a new time-variant version of the index.

Index values. The point where the curves hit the top can be interpreted as the "threshold MEI" value above which all cells have malaria; note how the threshold value is increasing over time as public health measures and new technologies successfully eliminate the disease at higher and higher MEI values.

Figure 2-4: Malaria Risk and Malaria Ecology (Local Regression Estimates)



Technological Advance – During the last 100 years, important advances have been made which aided the control of malaria. The most important is probably the discovery of DDT (Dichlorodiphenyl trichloroethylene), which could be sprayed on the walls of a house and kill insects (including malaria vectors) that rested on that wall. It virtually has no toxic effects on humans at the low levels when used for indoor residual spraying, and is very cheap to manufacture. DDT was first synthesized in 1874, but its insecticide properties were not discovered until 1939, and patented in 1940[16]. Use of DDT led to rapid elimination of malaria in places such as Taiwan, much of the Caribbean, and the Balkans. A second important global change in malaria control is the creation of the World Health Organization (WHO), which

[16] Alilio, Martin S., Ib C. Bygbjerg, and Joel G. Breman, 2004, "Are Multilateral Malaria Research and Controls Programs the Most Successful? Lessons from the Past 100 years in Africa," American Journal of Tropical Medicine and Hygiene, 71 (Supplement 2), 268-278.

greatly improved poor countries' access to medical and public health technology. Starting in the 1950s, the WHO (together with UNICEF) was an important driving force behind anti-malaria compaigns in the developing world. I control for technological advance only very crudely – using time dummies in the panel estimation – but hope at least to flexibly remove global trends in the data which might otherwise bias the other coefficients.

I employ several strategies to shed light on the dynamics of local malaria elimination, keeping in mind that the hypothesis is that whether elimination occurs at any given point in time depends on how favorable the ecology is, the technology available to fight the disease, the ability of the country to invest in public health, and whether the neighboring area (grid cells) have malaria. The last of these factors – resulting from the fact that malaria is a transmittable disease and that public health efforts can occur for contiguous cells within a country at the same time – leads the econometrician to worry about spatial autocorrelation (and perhaps dependence) across grid cells. Since the nature of this disease and control means that malaria outcomes of two neighboring grid cells are correlated, OLS will undersestimate standard erros. We can test statistically whether spatial autocorrelation is present using Moran's Index, which looks to quantify the degree to which spatial autocorrelation is present in the data as follows:

$$\text{Moran's I: } I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} b_{ij}\cdot\left(y_i-\bar{y}\right)\cdot\left(y_j-\bar{y}\right) / \sum_{i=1}^{n}\sum_{j=1}^{n} b_{ij}}{\sum_{i=1}^{n}\left(y_i-\bar{y}\right)^2 / n}$$

n - number of cells
i,j - any two cells
y - value of attribute cell
b - adjacency (0 or 1)

An index value greater than zero indicates that the data exhibits clustering; an index near zero indicates data uncorrelated spatially; an index below zero indicates dissimilar ("checkerboard") data. The map of the geographic extent of malaria risk is "flattened" (that is, the different year-layers of the extent of malaria risk are transformed into a single layer where each color of the map takes a different value, in order to compare the spatial autocorrelation of

the most recent year of malaria transmission in each cell). Moran's statistic was computed for this map, and indicates that there is less than 1% likelihood that the clustering on the map is random (an index z-score of 4.2 with $p < 0.01$). Spatial autocorrelation is therefore present and the econometric stategy must control for it.

Having determined the presence of spatial autocorrelation, we proceed to estimate its extent. One way to deal with spatial autocorrelation is to include the neighbors' malaria risk as controls. The question then becomes which neighbors are relevant. A method to determine the extent of the spatial relationship is to construct a spatial autocorrelation function, based on Conley and Topa (2002) and used in Robalino and Pfaff (2005). The logic is as follows: let our vector of data be X_s (in the "flattened" map employed for the study of spatial autocorrelation, the X_s's are the year when the malaria was last observed in that grid cell). If we assume that the covariance of malaria risk elimination in two grid cells X_{si} and X_{sj} is a function of the distance between them:

$$\text{cov}(X_{s_i}, X_{s_j}) = f\left(\|s_i - s_j\|\right)$$

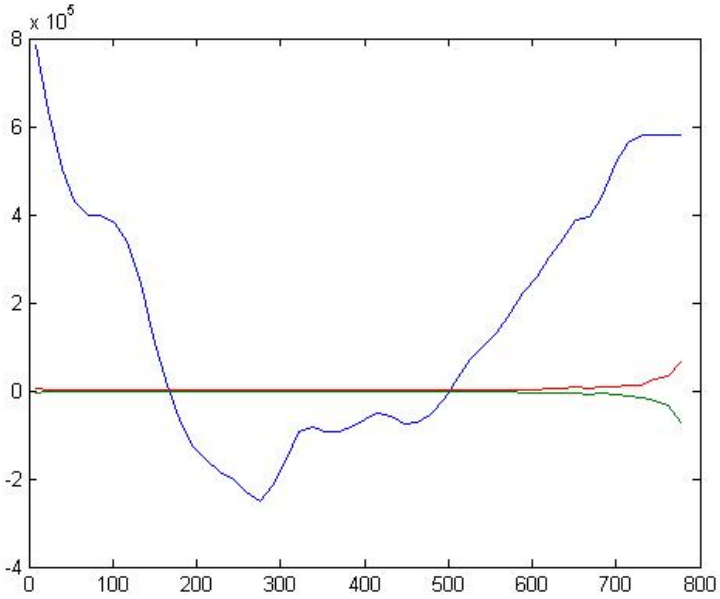
Conley and Topa use a non-parametric estimator of the spatial autocovariance function, estimating the autocovariance at distance δ by a local average of cross-products of demeaned observations that are close to δ units apart. Letting D_{ij} be the distance between X_{si} and X_{sj}, then $f(\delta)$ is estimated as follows:

$$\hat{f}(\delta) = \sum_{i=1}^{N}\sum_{j=1}^{N} W_N\left[|\delta - D_{ij}|\right]\left(X_{s_i} - \overline{X}\right)\left(X_{s_j} - \overline{X}\right)$$

Here, $\overline{X}$ is the sample mean of X, and W_N is a weight function normalized to sum to one. This is, in effect, a kernel regression of $\left(X_{s_i} - \overline{X}\right)\left(X_{s_j} - \overline{X}\right)$ on D_{ij}.

I use a version of the function programmed into Matlab and applying it to the flattened version of the data (as I did above for Global Moran's Index). However, the computational demands prohibit using the entire dataset (85,672 grids cell on land) to estimate $f(\delta)$. The algorithm therefore choses 10,000 points at random from the dataset and plots $f(\delta)$ as follows:

Figure 2-5: Spatial Autocorrelation Function for Malaria Risk



The procedure was repeated several times with different draws, and the function did not change. The plot of *f(δ)* above included not only the function, but 95% confidence bounds; thus we can interpret the graph as follows: when the function *f(δ)* is beyond the bounds, we can reject with 95% confidence the null hypothesis that spatial autocorrelation is absent. In the graph above, *f(δ)* is above the bounds for the first 170 cells, indicating the presence of spatial autocorrelation among cells within 170 cells apart. We cannot control for these many cells in the specifications chosen for our estimations below, so we opt instead for more crude controls for spatial autocorrelation: first, second and third degree neighbors.[17]

Since the dependent variable (whether the cell is at risk of malaria in a given year) is binary, we use a probit estimation model. In order to account for the fact that there could be lack of independence of observations within countries (national public health efforts, for example), I correct standard errors using White's robust covariance matrix clustering by country.

[17] Note that the best method would probably be a spatially explicit estimation with a distance-decay function controlling for spatial dependence, and allowing for spatial structure in the errors. These "spatial econometric" methods are gaining traction in the literature, especially following the work of LeSage (1999) in providing Matlab code to estimate these models. However, these models are hard to employ in a panel framework, and even more so with limited dependent variables (such as our probit models here). The memory requirements for such models make them infeasible for the present work.

I begin with a battery of cross sections for every year in the sample, and then use the entire panel. As a robustness check, the specifications are all repeated with country dummies, thus exploiting only within-country variation. Finally, I employ a difference equation, looking at the determinants of changes in malaria risk between two given years.

Data and Data Preparation

Three sets of GIS data are used in the paper. The first is the map of the geographic extent of malaria risk, shown above. The map represents malaria risk from one or more of the four species of the *Plasmodium* parasite that causes malaria. Data come in GIS format as polygons and each layer (pre-intervention, 1946, 1965, 1975, 1994, and 2002). It is worth noting that these data are extremely coarse; it is likely that in several countries these polygons did not benefit from ground-truthing (particularly in the earlier years) and most likely the polygons follow ecological zone boundaries. Since malaria incidence is the dependent variable, then the results would be unbiased if the measurement error is randomly distributed (though standard errors will be inflated by the measurement error). If, on the other hand, the measurement error is correlated to the independent variables (malaria ecology and income), then point estimates will be biased.

The layers were each rasterized to create grid cells for regression analysis; the cell size was set at 0.5 degrees to be equal to the cell size of the malaria ecology raster map. The malaria ecology data are from Kiszewski (2004) and already come in raster format. Finally, the country boundary map is used from ESRI, and similarly rasterized using the same cell size.

Data on country income come from Maddison (available from 1950-1999) and from the World Bank's World Development Indicators (available from 1960-2003). In both cases we use constant dollar GDP per capita, adjusted for purchasing power parity (these data are therefore comparable over time and across countries). Since using the former forces us to drop the last observation of malaria risk (2002), and the latter forces us to drop the first observation (1946), I run the analysis with each income data source and compare results. I also employ 1-degree-grid-

level income data provided by Yale's G-Econ project (for 1990, in purchasing power parity) in order to estimate the effect of local versus national income levels. The "Gross Cell Product" measure omits income from the mining and hydrocarbon sectors, since these lead to anomalously high per-capita incomes that do not reflect people's well-being on the ground.

Results

The tables below show results for the cross section probit regressions (Table 1), the panel probit regressions (Table 2), and the probit regressions on changes in malaria risk (Table 3). Note that all tables report marginal effects of the independent variables at their mean values. These results are easier to interpret than the probit coefficients.

Table 1 reports the following model, by year:

$$Pr(mal_i = 1) = \beta_0 + \beta_1 \cdot ME_i + \beta_2 \cdot Income\ per\ capita + \beta_3 \cdot mal_{i-1} + \varepsilon_i$$

Note that I will test both national and grid-level income per capita (hence the lack of a subscript in the equation). Also, note that the spatial lag term is the average of the eight neighboring grid cells. Regressions (i) and (ii) report estimates without the spatial lag. Regressions (i), (iii), (viii) and (x) use the World Bank's income measure, while the regressions (v)-(vii) and (ix) use Maddison (keep in mind that the two data sources span different periods). Regressions (ii) and (iv) replace the national income per capita measure with G-Econ grid-level income per capita. Finally, regression (xi) adds country fixed effects to explain within-country variation in malaria outcomes; note that only G-Econ income data can be used in that case since national income levels are washed away by the country fixed effect.

Table 2-1: Cross Section Analysis of Malaria Risk

Dependent Variable:	(i) malaria risk	(ii) malaria risk	(iii) malaria risk	(iv) malaria risk	(v) malaria risk	(vi) malaria risk	(vii) malaria risk	(viii) malaria risk	(ix) malaria risk	(x) malaria risk	(xi) malaria risk
Independent Variables											
Malaria Ecology	0.065***	0.061***	0.006**	0.006**	0.006	0.018**	0.016**	0.021***	0.005*	0.006***	.017**
	(4.41)	(5.28)	(2.35)	(2.44)	(0.61)	(2.12)	(1.96)	(2.59)	(1.70)	(2.87)	(2.38)
log GDP per capita (WDI)	-0.21***		0.005					-0.044*		-0.002	
	(-4.94)		(0.60)					(-1.88)		(-0.18)	
log GDP per capita (Maddison)					-0.020	-0.056*	-0.037*		-0.006		
					(-0.66)	(-1.93)	(-1.82)		(-0.83)		
log non-mineral Gross Cell Product per capita (G-Econ)		-.16***		0.000							0.032
		(-4.39)		(-0.05)							(0.71)
Average of surrounding cells			0.715***	0.79***	2.64***	2.19***	1.817***	1.79***	.702***	0.794***	2.650
			(18.95)	(19.47)	(20.25)	(15.03)	(20.31)	(19.76)	(18.25)	(18.27)	(17.75)
Year in Sample	2002	2002	2002	2002	1950	1965	1975	1975	1994	1994	2002
N =	56736	56485	56681	56428	41903	41525	41525	39371	56151	56880	22211
Pseudo R-squared =	0.52	0.53	0.95	0.95	0.92	0.91	0.90	0.90	0.94	0.94	0.92

z-statistics in parentheses, *** indicates p < 0.01, ** indicates p < 0.05, * indicates p < 0.10

All regressions report marginal effects at the mean of the independent variables

All regressions cluster standard errors by country (White's robust covariance matrix)

Regression (xi) includes country dummies

The first thing to note is that the magnitude of the coefficient on malaria ecology is reduced by an order of magnitude when controlling for neighbors' malaria outcomes (the point estimate ranges from 0.005-0.021 with a spatial lag term, and goes up to 0.061-0.065 in a naïve model). This illustrates the bias that results when ignoring the spatial structure of the data. The results do not change when two and three spatial lags are added to the estimation (these would be controls for the malaria outcomes for twice- and thrice-removed neighbors). The point estimates and significance of malaria and income do not change (results available upon request). This is encouraging, since the potential bias from too simple a spatial structure in the estimation model (only controlling for neighbors' malaria) does not seem to be present.

Malaria ecology is significant throughout – for every year, and for both measures of income – with one exception. The magnitude of the point estimate (when including a spatial lag term) ranges from .005-.021. Using regression (vii) since it gives an estimate in the middle of the range (0.016), we interpret by first calculating the mean malaria ecology in the data sample included in the regression (the mean is 2.3, which is around the national average malaria ecology of Malaysia). Next, we interpret as follows: changing a cell's malaria ecology from the average ME of Malaysia (2.3) to the average of Nicaragua (1.3) would reduce the likelihood of malaria by 1.6%. This may seem small, but moving from the average of Ghana (25.5) to Italy (.07) would reduce likelihood of malaria by 40.7% assuming that the point estimate holds at those parts of the malaria ecology distribution.

In contrast to the robustness of malaria ecology, national income per capita is significant to the 90% level in only half of the eight regressions where it is included. Local (grid-level) income per capita is only significant when not controlling for a spatial lag. This is a first indication that malaria ecology has explanatory power as a determinant of where malaria is present in the world even after controlling for income levels. The association between malaria presence and adverse malaria ecology continues to hold over time after controlling for national income per capita (which would to some extent capture national capacity in public health investments), local income per capita (which would capture household's ability to invest in

malaria prevention), and country fixed effects (which means that the association between malaria ecology and the presence of malaria hold within countries as well as across countries).

It is noticeable, also, that the coefficient on the malaria ecology variable becomes smaller in later years (ignoring (i) and (ii) which didn't include a spatial lag). This is probably due to the threshold nature of the probit model, and the fact that as malaria extent decreases, the cells that still have malaria today are those with highest malaria ecology. Therefore, for later years, the observations around the sample mean of malaria ecology include more and more malaria-free cells, and a slight increase in the malaria ecology will do less to increase the chances of malaria risk. What is important, then, is not the magnitude of the coefficient but the fact that it is significant; malaria ecology does indeed have important explanatory power over which cells are at risk of malaria. One just has to keep in mind that this is a threshold model; variations in malaria ecology below some threshold do little to affect risk, yet once that threshold is passed, malaria risk becomes much more likely.

Table 2 employs a panel framework. All available data are included (notice the different years corresponding to the different time spans of the two income data sources), and as before I control for immediate neighbors' outcomes (results are robust to controlling for twice- and thrice-removed neighbors). All regressions allow for flexible global trends (for example, to capture technological advances) and they cluster standard errors by country-year blocks to correct for contemporaneous country-wide omitted variables (such as public health efforts not adequately captured by income measures). Regressions (i) and (ii) are pooled cross sections using time dummies and the two income data sources. Regressions (iii) and (iv) lag the income per capita variable by one period, to assuage concerns of misspecification due to two-way causality between income and malaria. Just as higher incomes allow societies to invest in public health interventions, malaria's burden on society almost surely has repercussions on the economy: there is ample microeconomic empirical evidence[18,19,20,21,22] indicating that high disease

[18] See Strauss and Thomas (1998) for a survey of the literature in the 1990s.
[19] Shultz, T. Paul, 2002, "Wage Gains Associated with Height as a Form of Health Human Capital," American Economic Review Papers and Proceedings 92: 349-53.

burdens worsen productivity and economic outcomes, and most evidence points towards adverse macroeconomic effects[23,24,25,26] (though there is an ongoing debate on the general equilibrium effects[27,28,29,30,31]). Several micro-level studies have found that malaria has adverse effects on educational outcomes[32,33,34], nutrition[35,36], cognitive function[37,38,39], labor

---

[20] Bleakley, Hoyt, 2007, "Disease and Development: Evidence from Hookworm Eradication in the American South," Quarterly Journal of Economics 122: 73-117.
[21] Behrman, Jere R. and Mark R. Rosenzweig, 2004, "Returns to Birthweight," Review of Economics and Statistics 86: 586-601.
[22] Miguel, Edward, and Michael Kremer, 2004, "Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities," Econometrica 72: 159-217.
[23] Bhargava, Alok, Dean T. Jamison, Lawrence J. Lau, Christopher J.L. Murray, 2001, "Modeling the effects of health on economic growth," Journal of Health Economics, 20:423-440.
[24] Bloom, David E. and David Canning, 2003, "The Health and Poverty of Nations: from theory to practice," Journal of Human Development Vol. 4, No. 1.
[25] Weil, David N., 2007, "Accounting for the Effect of Health on Economic Growth," Quarterly Journal of Economics 122:3.
[26] Bleakley, Hoyt, 2010, "Health, Human Capital, and Development," Annual Review of Economics 2:283-310.
[27] Young, Alwyn, 2005, "The Gift of Dying: The Tragedy of AIDS and the Welfare of Future African Generations," Quarterly Journal of Economics 120: 423-66.
[28] Acemoglu, Daron and Simon Johnson, 2007, "Disease and Development: The Effect of Life Expectancy on Economic Growth," Journal of Political Economy Vol. 115, No. 6.
[29] Bleakley, Hoyt, 2006, "Disease and Development: Comments on Acemoglu and Johnson (2006)" Remarks delivered at the NBER Summer Institute on Economic Fluctuations and Growth, July 16, 2006.
[30] Ashraf, Quamrul H., Ashley Lester, David N. Weil, 2008, "When Does Improving Health Raise GDP?", in NBER Macroeconomics Annual 2008, Daron Acemoglu, Kenneth Rogoff and Michael Woodford, eds., University of Chicago Press.
[31] Bloom, David E., David Canning and Günther Fink, 2009, "Disease and Development Revisited," NBER Working Paper 15127, July.
[32] Leighton, C. & R. Foster, 1993, "Economic impacts of malaria in Kenya and Nigeria," Major Applied Research Paper No. 6, HFS Project (Abt Associates, Bethesda).
[33] Brooker, S. et al., 2000 "Situation analysis of malaria in school-aged children in Kenya: what can be done?" Parasitology Today 16, 183-186.
[34] Holding, P.A. and R.W. Snow, 2001, "Impact of Plasmodium falciparum malaria on performance and learning: review of the evidence," American Journal of Tropical Medicine and Hygiene, 64(1,2)S, 68-75.
[35] Rowland, M. G., T.J. Cole & R.G. Whitehead, 1977, "A quantitative study into the role of infection in determining nutritional status in Gambian village children," British Journal of Nutrition 37, 441–450.
[36] Shiff, C. et al., 1996, "Changes in weight gain and anaemia attributable to malaria in Tanzanian children living under holoendemic conditions," Transactions of the Royal Society of Tropical Medicine and Hygiene, 90, 262–265.
[37] Al Serouri, A. W., S.M. Grantham-McGregor, B. Greenwood & A. Costello, 2000, "Impact of asymptomatic malaria parasitaemia on cognitive function and school achievement of schoolchildren in the Yemen Republic," Parasitology 121, 337–345.
[38] Brewster, D. R., D. Kwiatkowski, & N.J. White, 1990, "Neurological sequelae of cerebral malaria in children," Lancet 336, 1039–1043.

productivity[40,41,42], and income[43], while macro-level studies[44,45] find evidence for economy-wide effects of malaria through additional channels such as higher fertility rates, decreased savings rates, barriers to internal migration and depressed tourism and trade. Columns (v) and (vi) add country fixed effects to the model, which absorb time invariant country-wide omitted variables that may be biasing estimation.

The robustness of the malaria ecology variable continues to hold in a panel framework; the significance is robust to different time spans and income data sources, using lagged instead of contemporaneous income per capita, and to including country fixed effects. Malaria ecology is significant in all but one regression, and ranges from .007-.011. As before, adding spatial lags as controls do not change the magnitude of the coefficient on malaria ecology (results not shown). The income variable is significant in both contemporaneous and lagged form when using Maddison's data and only under fixed effects when using World Bank data. Both malaria ecology and income clearly seem important determinants of whether a cell is at risk of malaria, and there is no indication that the income variable trumps the malaria ecology variable.

---

[39] Holding, P. A., J. Stevenson, N. Pershu, & K. Marsh, 1999, "Cognitive sequelae of malaria with impaired consciousness," Transactions of the Royal Society of Tropical Medicine and Hygiene, 93, 529–534.
[40] Nur, E., 1993, "The impact of malaria on labour use and efficiency in the Sudan," Society of Science and Medicine, 37, 1115–1119.
[41] Scholz, B. D., R. Gross, W. Schultink & S. Sastroamidjojo, 1997, "Anaemia is associated with reduced productivity of women workers even in less-physically-strenuous tasks," British Journal of Nutrition. 77, 47–57.
[42] Basta, S., S. Soekirman, D. Karyadi & N.S. Scrimshaw, 1979, "Iron deficiency anemia and the productivity of adult males in Indonesia," American Journal of Clinical Nutrition 32, 916–925.
[43] Bleakley, Hoyt, 2010, "Malaria Eradication in the Americas: A Retrospective Analysis of Childhood Exposure," American Economic Journal: Applied Economics 2(2): 1-45.
[44] Sachs, J.D. and J.L. Gallup. 2001, "The economic burden of malaria," American Journal of Tropical Medicine and Hygiene (supplement) 64, 85–96.
[45] Sachs, Jeffrey and Pia Malaney, 2002, "The economic and social burden of malaria," Nature, Vol. 415, No. 6872.

Table 2-2: Panel Analysis of Malaria Risk

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Dependent Variable:	malaria risk	malaria risk	malaria risk	malaria risk	malaria risk	malaria risk
Independent Variables						
Malaria Ecology	0.01**	0.009***	0.011***	0.007***	0.004	0.011***
	(2.34)	(4.45)	(3.76)	(3.24)	(1.50)	(2.99)
log GDP per capita (WDI)		-0.012				-0.030***
		(-1.53)				(-2.63)
log GDP per capita (Maddison)	-0.029**				-0.055***	
	(-2.55)				(-2.72)	
Lagged (log GDPpc WDI)				-0.007		
				(-0.76)		
Lagged (log GDPpc Maddison)			-.03***			
			(-3.21)			
Average of surrounding cells	1.83***	1.01***	1.44***	0.92***	2.33***	2.40***
	(34.44)	(30.80)	(33.51)	(24.45)	(30.81)	(31.12)
Year Dummies	*	*	*	*	*	*
Country Dummies					*	*
Years in Sample	1950-1994	1975-2002	1950-1994	1975-2002	1950-1994	1975-2002
N =	181104	152932	181104	96251	124668	64866
# of cells =	56151	113569	56151	113569	56151	113569

z-statistics in parentheses, *** indicates p < 0.01, ** indicates p < 0.05, * indicates p < 0.10
All regressions include a constant (not reported)

Finally, Table 3 looks at what has determined where elimination has happened between different combinations of years (1950-2002, 1965-2002, 1975-2002), using a difference equation and limiting the sample to areas that had malaria in the base year (note, then, that I disregard cells where malaria resurgence has occurred). I control for the income effect using income in the base year, to reduce concerns about endogeneity between malaria outcomes and income (studies cited above argue for an effect of malaria on income, which would create reverse causality in these specifications and lead to biased estimates). Note that malaria ecology comes out as being significant in all four specifications, while the base-period income variable is only significant in two of the four. The point estimate for malaria ecology ranges from -.034 to -.052, meaning that the average Nicaraguan cell (with an average malaria ecology of 1.3) is 3.4%-5.2% more likely than the average Malaysian cell (with an average malaria ecology of 2.3). The results are more striking when comparing Ghana and Italy; assuming the same point estimate, an average Ghanaian cell is 86% less likely to eliminate malaria after controlling for income! These results indicate that malaria ecology has been robustly associated with where malaria elimination occurs; for any given time period, malaria elimination occurred in places where it was easier to

do so from an epidemiological point of view, even when controlling for income. Income, which almost certainly plays a role, does not negate the effect of the local ecology.

Table 2-3: Determinants of Changes in Malaria Risk

	(i)	(ii)	(iii)	(iv)
Dependent Variable:	-(mal2002-mal1950)	-(mal2002-mal1965)	-(mal2002-mal1975)	-(mal2002-mal1975)
Independent Variables				
Malaria Ecology	-0.052***	-0.05***	-0.034***	-0.036***
	(-3.41)	(-4.76)	(-4.16)	(-4.50)
Base Year log GDP per capita (WDI)			0.032	
			(0.98)	
Base year log GDP per capita (Maddison)	0.235***	0.076		0.062**
	(3.00)	(1.58)		(2.15)
Average elimination in surrounding cells	0.24**	0.389***	0.27***	0.25***
	(2.18)	(4.76)	(3.14)	(3.34)
N =	16353	15854	13605	13957
Pseudo R-squared =	0.30	0.25	0.23	0.24

0.01, ** indicates p < 0.05, * indicates p < 0.10
All regressions report marginal effects at the mean of the independent variables
All regressions cluster standard errors by country

Conclusion and Future Research

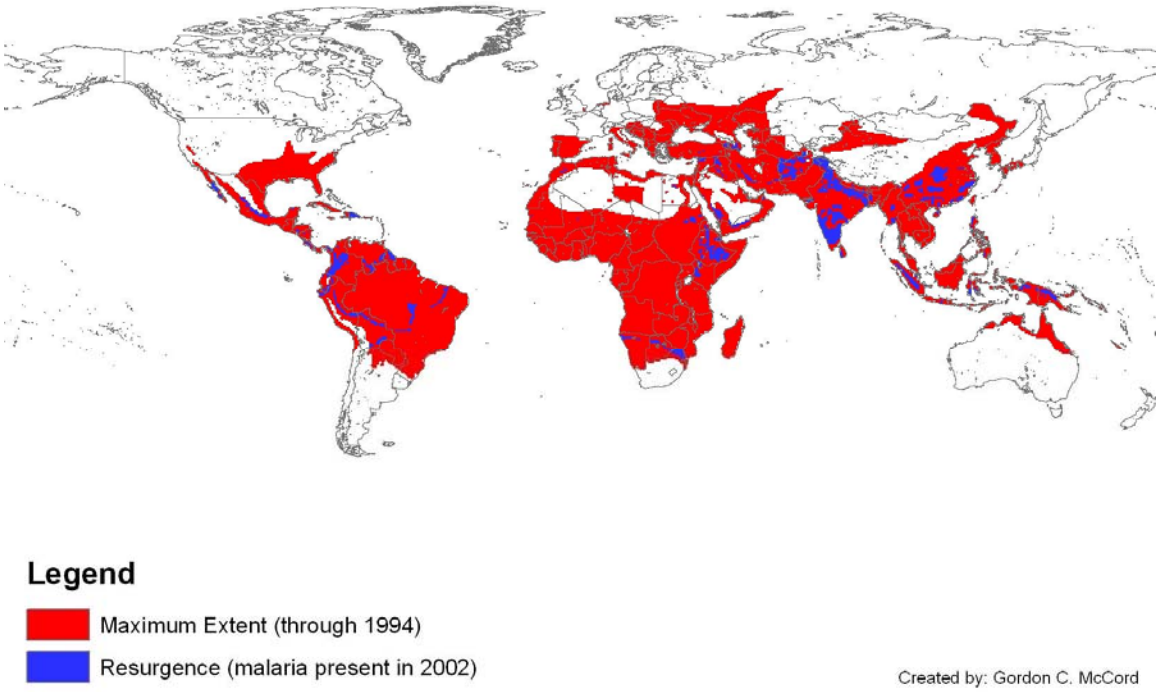
The results from the data analysis support the initial hypothesis: the degree to which the local ecology supports malaria transmission plays an important role in determining which places successfully eliminated malaria. Higher income levels surely make elimination more likely, as countries can afford to employ technologies to curb the disease. However, in places where the malaria ecology leads to a very high basic reproductive number, then even having income cannot lead to elimination if existing technologies are incapable of eliminating the disease.

The implications of this result are relevant more broadly, as it lends support to policies that look to aid poor countries with high disease burdens using outside financing. A high disease burden in very poor areas can lead to poverty traps and low-level equilibria, perhaps until a threshold is passed and the disease is curbed enough to allow the economy to grow (as Chapter 5 explains, mechanism could be that a smaller disease burden decreases mortality rates, which decreases fertility rates, permits the demographic transition and thus allows for more saving, investment and growth). If the ability of a place to control disease is not determined exclusively by the place's socioeconomic characteristics, or choice of policies, or level of income, but instead it is tempered importantly by the underlying ecology, then it there is an argument for helping poor countries invest in health to get them past the threshold mentioned above. The argument,

then, that malaria cannot be a hindrance to growth because it was present in the United States and was eliminated as the country grew wealthier is missing a fundamental point: that malaria's foothold on the human population is not uniform across the world. The U.S. had a basic reproductive number that was much closer to 1, so simple public health interventions (screen doors, swamp drainage, and indoor spraying of DDT in the case of the American south) was enough to bring the number below 1 and break transmission. In Africa, screen doors would clearly not be enough when the reproductive number is so high. In order to reduce malaria burden, sub-Saharan African countries need to employ many more interventions (for example, extensive coverage of malaria treatment, bednets, indoor residual spraying, rapid diagnostics, larvicide and environmental management) and many areas would probably still be unable to completely eliminate the disease. The problem, of course, is that they cannot afford these investments, and their populations still suffer from the burden of this debilitating – and often fatal – disease.

There are several extensions to this work that should be pursued. First, the data are clearly coarse, and ground-truthing these results with country-level studies where malaria incidence data is better would help validation. Secondly, extending the methodology beyond this probit setup may be useful. One issue is that in order to explicitly look at where elimination has occurred (as we did in Table 3 above), we ignored the areas where resurgence has occurred in order to limit the dependent variable to a binary (zero for continued malaria, one for elimination). However, Figure 6 below shows that there are quite a few places where resurgence has occurred at some point. The map shows the maximum extent of malaria (combining 1946-1994) and then in blue shows places that have malaria in 2002 and didn't have it at least once in the past). Some important parts of the world have experienced significant resurgence (parts of India, China, and Ethiopia, most notably), and it would further illuminate the dynamics of malaria elimination if we also tried to understand where malaria resurgence occurred. A case study in one of those countries would explore whether this resurgence is documented or whether it is an artifact of the data, and shed light on what has driven the resurgence.

Figure 2-6: Malaria Resurgence in 2002



Another methodological improvement would be to explicitly model the threshold behavior of the ecological system. Table 4 below shows the percentage of cells with malaria risk by different categories of malaria ecology, over time. For any given year, there seems to be significant decline of malaria risk in a group of categories, and almost zero decline in the categories with higher malaria ecology. This suggests the existence of thresholds: for any point in time with given technology and public health effort, there seems to be decreasing malaria up to some maximum "threshold" level of malaria ecology, above which whatever interventions happened during the preceding period had no effect. A threshold makes sense within the framework of the basic reproductive number, as was discussed above. The most important characteristic about R_0 is that it is a system with a threshold; when R_0 is decreased to below 1, the disease will die out within the population, whereas if R_0 is at 1 or higher, the disease will remain endemic. In terms of estimation, therefore, the effect of malaria ecology on disease is highest when $R_0 \approx 1$; and small changes in ecology (through temperature or precipitation changes, for example) could dramatically change disease outcomes. While the probit model is a

probabilistic model, perhaps a model more explicitly modeling the threshold would better capture some of the dynamics of malaria elimination.

Table 2-4: Percent of Cells with Malaria, by year, by Malaria Ecology Index

Malaria Ecology value	% of cells in sample	1946	1965	1975	1994	2002
0	69.26%	3.86%	6.03%	3.97%	2.38%	2.05%
< .005	7.63%	25.31%	15.67%	14.40%	4.41%	5.60%
< .01	0.87%	38.90%	15.07%	12.52%	2.69%	2.42%
< .1	5.77%	63.88%	32.97%	27.63%	28.26%	27.99%
< .5	2.38%	92.21%	55.44%	53.77%	41.77%	41.38%
< 1	0.39%	81.38%	73.87%	60.06%	52.85%	53.76%
< 5	4.91%	96.15%	87.40%	81.11%	59.86%	60.81%
< 10	3.81%	98.25%	92.94%	89.97%	81.53%	83.62%
< 15	1.57%	96.14%	86.70%	88.71%	87.22%	86.18%
< 20	1.35%	95.32%	98.53%	98.96%	98.27%	98.10%
20 +	2.07%	89.17%	99.27%	99.32%	98.48%	99.21%

A final dimension of interest for future research is to focus on the neighborhood effects ubiquitous in the dynamics of malaria elimination. Given that this is a contagious disease carried by a mosquito vector, there are important neighborhood effects of intervention. For example, one of the most well-known interventions against the mosquito is the use of insecticide-treated bednets, which has been shown to have a neighborhood effect (one household's use of the nets has effects on decreasing the risk of neighboring households[46]). This positive externality is one of the strongest arguments for having universal coverage of bednets in communities at risk. Given this spatial dynamic, then understanding the neighborhood effects of elimination is important. One could imagine, for example, a "frontier of elimination," where malaria risk is decreasing several kilometers ahead of places receiving intervention. While the statistical models above control for neighboring cells, it is only a crude approach and could be enhanced in future research to further illuminate the spatial dynamics of malaria elimination. As mentioned previously, maximum likelihood techniques in spatial econometrics allow estimation of general probit models with spatial dependence and spatial autocorrelation of error terms, however they do not support panel data well, and having tens of thousands of observations render these models unusable due to computational requirements.

[46] Hawley WA, et al., 2003, "Community-wide effects of permethrin-treated bednets on child mortality and malaria morbidity in western Kenya," American Journal of Tropical Medicine and Hygiene 68 (suppl): 121–27.

Chapter 3

Scaling Up Malaria Control in Africa: An Economic and Epidemiological Assessment

Awash Teklehaimanot, Gordon C. McCord, and Jeffrey D. Sachs[1]

[1] This chapter was published in the American Journal of Tropical Medicine and Hygiene in December 2007.

Abstract

This paper estimates the number of people at risk of contracting malaria in Africa using GIS methods and the disease's epidemiologic characteristics. It then estimates yearly costs of covering the population at risk with the package of interventions (differing by level of malaria endemicity and differing for rural and urban populations) for malaria as recommended by the UN Millennium Project. These projected costs are calculated assuming a ramp-up of coverage to full coverage by 2008, and then projected out through 2015 to give a year-by-year cost of meeting the Millennium Development Goal for reducing the burden of malaria by 75% We conclude that the cost of comprehensive malaria control for Africa is US$3.0 billion per year on average, or around US$4.02 per African at risk.

Introduction

The burden of malaria in Africa continues to be extremely high, despite the existence of effective interventions to curb the mortality and morbidity of the disease. Every year, up to three million people die from malaria on the continent.[2] The Millennium Development Goals set in 2000 recognize that malaria must be controlled if Africa is to escape from the cycle of extreme poverty and disease. The MDG on malaria is to "Have halted by 2015 and begun to reverse the incidence of malaria," which has been made more specific by the UN Millennium Project's working group on malaria as "Reduce malaria morbidity and mortality by 75 percent by 2015 from the 2005 baseline level." In January 2005, the working group on malaria recommended that countries where malaria is rife should use an integrated package of preventive and treatment methods to achieve this goal.[3] The project also recommended that insecticide treated mosquito bed nets and effective malaria drugs be given away free of charge, a move endorsed by UN Secretary-General Kofi Annan in March, and by heads of state at the UN World Summit in September 2005.

There are existing, effective methods to control malaria: prevent people from being bitten by mosquitoes — using insecticide treated bed nets and insecticide spray applications — treat those who get infected with effective drugs such as artemisinin-based combination therapies (ACTs), promote health education and communication, and conduct monitoring and evaluation. This paper estimates the number of people at risk of contracting malaria in Africa using GIS methods, and then estimates the yearly costs of covering the population at risk with the package of interventions recommended by the UN Millennium Project.

Derivation of Population at Risk

Due to lack of adequate data collection in Africa's health system, there is incomplete information on the morbidity and mortality associated with malaria.[4] The WHO Global Burden

---

[2] Breman JG, Alilio MS, Mills A, 2004. Conquering the intolerable burden of malaria: what's new, what's needed: a summary. Am J Trop Med Hyg 71: suppl:1--15.

[3] UN Millennium Project, 2005. Coming to Grips with Malaria in the New Millennium. Task Force on HIV/AIDS, Malaria, TB and Access to Essential Medicines, Working Group on Malaria. Sterling, VA: Earthscan.

[4] WHO, 1996. World Malaria Situation in 1993. Weekly Epidemiological Record. 19 January. No. 1, pp. 17--22.

of Disease program estimates burden in Africa through "active" case-detection studies of populations living under different transmission intensity risks, which is subject to under-detection. Several alternative studies have estimated population at risk using other methods, including estimates based on national surveys,[5] estimates based on climate suitability for malaria transmission,[6,7] and estimates based on maps of the geographic extent of malaria in a Geographic Information System (GIS).[8]

We follow the GIS-based strategy by overlaying the following maps: a high-resolution (30 arc-seconds) map of 2005 human population;[9] a map of country boundaries, the most recent (2002) map of the extent malaria of risk[10] (Figure 1 below); a map of malaria endemicity levels constructed in 1968[11] (Figure 2 below); and a map of the extent of urban areas.[8] The latter four maps were rasterized to the same 30 arc-second cell size.

---

[5] Snow RW, Eckert E, Teklehaimanot A, 2003. Estimating the needs for artesunate-based combination therapy for malaria case-management in Africa. Trends Parasitol, Vol. 19, No. 8 August, 363--369.

[6] Craig MH, Snow RW, le Sueur D, 1999. A climate-based distribution model of malaria transmission in sub-Saharan Africa. Parasitol Today 15, 105--111.

[7] Snow RW, Craig M, Deichmann U, Marsh K, 1999. Estimating mortality, morbidity and disability due to malaria among Africa's non-pregnant population. Bull World Health Organ. 77, 624--640.

[8] Snow RW, Guerra CA, Noor AM, Myint HY, Hay SI, 2005. The global distribution of clinical episodes of Plasmodium falciparum malaria. Nature. Mar 10; 434(7030):214--217.

[9] Center for International Earth Science Information Network (CIESIN), Columbia University; International Food Policy Research Institute (IPFRI); the World Bank; and Centro Internacional de Agricultura Tropical (CIAT); 2004. Global Rural-Urban Mapping Project (GRUMP): Urban/Rural Extents. Palisades, NY: CIESIN, Columbia University. Available at http://sedac.ciesin.columbia.edu/gpw. Downloaded March 2006.

[10] Hay SI, Guerra CA, Tatem AJ, Noor AM, Snow RW, 2004. The global distribution and population at risk of malaria: past, present and future. Lancet Infect Dis. Vol. 4 (June), 327--336.

[11] Lysenko AJ, Semashko IN, 1968. Geography of malaria. A medico-geographic profile of an ancient disease. In: Lebedew AW, ed. Itogi Nauki: Medicinskaja Geografija. Moscow, USSR: Academy of Sciences, 25--146.

Figure 3-1: Extent of Malaria Risk in Africa, 2002

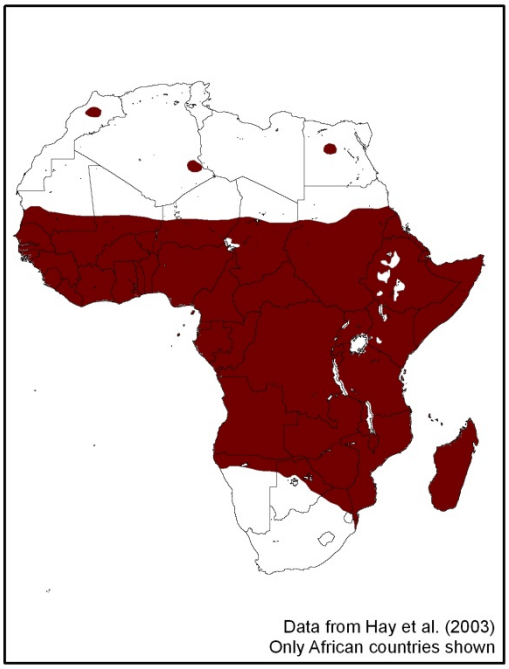
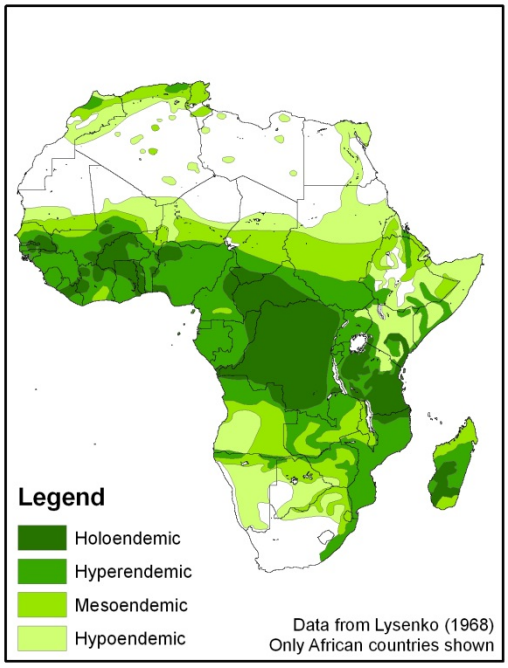


Figure 3-2: Endemicity Levels in Africa



Population sums were then calculated by country for the following categories: total population within the malaria risk zone, population within a malaria risk zone *and* within an urban zone, population within a malaria risk zone *and* within a zone of unstable malaria transmission (either hypoendemic or mesoendemic zones in the endemicity map), and population within a malaria risk zone, an urban zone, and a zone of unstable transmission. (Note that areas showing up on the 1968 endemicity map but are outside the area of 2002 malaria risk are considered to no longer have malaria and are ignored). The resulting estimate for population at risk of malaria in Africa in 2006 is 672 million people, of which 485 million are in rural areas (see Table 1 below). Finally, we used the UN Population Division's median forecast of projected population to calculate a population growth rate for each country, and used it to estimate the population in each country in the above categories for every year between 2006 and 2015. This now allows us to calculate the cost of each intervention, by country and by year, based on the urban and rural population at risk, in stable and unstable malaria transmission areas.

Table 3-1: Population at Risk in 2006 (millions)

				By endemicity level							
				Intensive (holoendemic +				Unstable (mesoendemic +			
				By age group				By age group			
	Total	Urba	Rural	0-4	5-9	10-14	14+	0-4	5-9	10-14	14+
Algeria	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Angola	15.60	4.87	10.73	1.23	0.97	0.86	3.54	1.68	1.32	1.17	4.83
Benin	7.58	2.92	4.66	1.29	1.09	0.95	4.25	0.00	0.00	0.00	0.00
Botswana	0.70	0.25	0.45	0.00	0.00	0.00	0.02	0.08	0.08	0.09	0.42
Burkina Faso	13.88	1.75	12.13	2.57	2.12	1.84	7.36	0.00	0.00	0.00	0.00
Burundi	6.55	0.45	6.09	1.16	0.92	0.84	3.63	0.00	0.00	0.00	0.00
Cameroon	16.54	7.09	9.45	2.42	2.18	2.06	9.64	0.04	0.03	0.03	0.14
Central African Republic	4.00	1.51	2.49	0.62	0.56	0.51	2.26	0.01	0.01	0.01	0.03
Chad	9.14	1.85	7.30	1.25	0.99	0.84	3.42	0.51	0.40	0.34	1.40
Comoros	0.62	0.15	0.47	0.10	0.09	0.07	0.36	0.00	0.00	0.00	0.00
Congo	3.70	2.36	1.33	0.69	0.57	0.48	1.95	0.00	0.00	0.00	0.00
Congo, Dem. Rep.	60.13	17.66	42.48	11.76	9.11	7.60	31.66	0.00	0.00	0.00	0.00
Côte d'Ivoire	17.17	6.91	10.26	2.01	1.81	1.70	7.77	0.59	0.53	0.50	2.27
Djibouti	0.59	0.40	0.19	0.00	0.00	0.00	0.00	0.09	0.08	0.07	0.35
Egypt	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Equatorial Guinea	0.50	0.19	0.31	0.09	0.07	0.06	0.28	0.00	0.00	0.00	0.00
Eritrea	4.70	0.60	4.10	0.06	0.05	0.05	0.20	0.74	0.64	0.55	2.40
Ethiopia	57.86	7.57	50.29	3.98	3.45	3.09	13.26	5.70	4.94	4.43	19.01
Gabon	1.32	0.94	0.37	0.18	0.17	0.17	0.80	0.00	0.00	0.00	0.00
Gambia, The	1.44	0.76	0.69	0.22	0.19	0.17	0.87	0.00	0.00	0.00	0.00
Ghana	21.80	7.64	14.16	3.02	2.76	2.63	13.39	0.00	0.00	0.00	0.00
Guinea	9.18	2.83	6.36	1.54	1.30	1.16	5.18	0.00	0.00	0.00	0.00
Guinea-Bissau	1.37	0.40	0.97	0.27	0.21	0.17	0.72	0.00	0.00	0.00	0.00
Kenya	33.03	6.78	26.25	4.31	3.52	3.08	14.60	1.27	1.04	0.91	4.30
Liberia	3.15	1.15	1.99	0.61	0.48	0.40	1.66	0.00	0.00	0.00	0.00
Libya	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Madagascar	18.70	3.57	15.13	2.38	2.13	1.82	8.12	0.70	0.63	0.54	2.39
Malawi	12.72	2.15	10.57	0.53	0.47	0.40	1.56	1.75	1.56	1.31	5.14
Mali	13.40	3.15	10.25	2.38	1.96	1.65	6.45	0.18	0.15	0.13	0.50
Mauritania	1.30	0.34	0.96	0.00	0.00	0.00	0.01	0.22	0.18	0.15	0.73
Morocco	2.53	0.91	1.62	0.05	0.04	0.04	0.31	0.22	0.21	0.21	1.45
Mozambique	20.25	5.82	14.43	3.20	2.80	2.51	10.90	0.14	0.12	0.11	0.47
Namibia	1.10	0.24	0.87	0.09	0.09	0.09	0.39	0.06	0.06	0.06	0.26
Niger	13.01	2.17	10.85	1.27	1.00	0.80	3.18	1.37	1.08	0.86	3.45
Nigeria	128.2	44.66	83.63	21.51	18.42	16.48	71.76	0.02	0.02	0.02	0.07
Rwanda	8.77	0.59	8.17	1.46	1.22	1.10	4.99	0.00	0.00	0.00	0.00
Sao Tome and Principe	0.15	0.06	0.09	0.02	0.02	0.02	0.09	0.00	0.00	0.00	0.00
Senegal	10.64	4.59	6.06	0.82	0.72	0.66	3.01	0.85	0.75	0.69	3.14
Sierra Leone	5.41	1.69	3.71	0.94	0.74	0.64	3.09	0.00	0.00	0.00	0.00
Somalia	10.38	2.36	8.02	0.86	0.71	0.56	2.68	1.00	0.82	0.65	3.11
South Africa	6.15	1.49	4.67	0.02	0.02	0.02	0.13	0.65	0.64	0.64	4.03
Sudan	33.48	10.21	23.27	0.68	0.62	0.56	2.91	4.08	3.73	3.38	17.53
Swaziland	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tanzania, United	37.17	11.68	25.49	5.33	4.79	4.35	19.77	0.46	0.41	0.37	1.69
Togo	5.28	1.69	3.60	0.86	0.75	0.67	3.00	0.00	0.00	0.00	0.00
Uganda	27.83	3.51	24.32	5.65	4.44	3.63	13.45	0.14	0.11	0.09	0.33
Zambia	11.59	4.12	7.47	1.09	0.95	0.86	3.45	0.90	0.78	0.71	2.85
Zimbabwe	13.05	4.84	8.21	0.61	0.59	0.60	2.77	1.13	1.09	1.12	5.13
All Africa	**671.7**	**186.8**	**484.**	**89.13**	**75.11**	**66.17**	**288.82**	**24.58**	**21.44**	**19.12**	**87.42**

Description of Comprehensive Interventions

The interventions included in this costing exercise encompass most of the key interventions recommended by the UN Millennium Project, and many details of the costing follow those of the report of the Working Group on Malaria.[3] For prevention of disease, they include long-lasting insecticidal bed nets (LLINs), indoor residual spraying (IRS) in unstable transmission areas, training of community health workers, and cost of an information, education, and communication program. For enhanced diagnosis and treatment, they include microscopy, rapid diagnostic tests, effective drugs such as artemisinin-combination therapies (ACTs) for uncomplicated malaria, and treatment of severe malaria. Finally, the costing includes resources for monitoring and evaluation, and for the overhead costs of a global push on malaria control. Below are the assumptions made for each intervention:

- **Long-Lasting Insecticidal Nets (LLINs)**: Following the UN Millennium Project's recommendation, we calculate the cost of complete coverage of LLINs for the population at risk by the end of 2008, with a ramp-up of coverage during 2006, 2007, and 2008. Note that this is a more ambitious target than other costing exercises; the efficacy of LLINs and the mass action effect implies that the entire population, and not just children and pregnant women, should be targeted by LLIN distribution programs.[12] We assume that one net is needed for every two people at risk. The cost of LLINs is around $5, with an additional $2 estimated cost of storage and distribution, and the net needs to be replaced after 5 years (as is the case with Olyset nets).[13] Note that long-lasting nets do not need to be re-impregnated with insecticide during their 5-year lifespan.

[12] Curtis C, Maxwell C, Lemnge M, Kilama WL, Steketee RW, Hawley WA, Bergevin Y, Campbell C, Sachs J, Teklehaimanot A, Ochola S, Guyatt H, Snow RW, 2003. Scaling-up coverage with insecticide-treated nets against malaria in Africa: who should pay? Lancet Infect Dis. Vol 3, May, 304--307.

[13] WHO/RBM/UNICEF/PSI/MSH, 2004. Sources and Prices of Selected Products for the Prevention, Diagnosis and Treatment of Malaria. France, WHO.

- **Indoor Residual Spraying (IRS)**: Selective vector control (including IRS) was part of the WHO's Global Strategy for Malaria Control which was adopted by the Ministerial Conference in 1992 and subsequently endorsed by the World Health Assembly (WHA) and the UN General Assembly. The Global Strategy was also taken up by the RBM partnership for the use of selective control in appropriate epidemiological settings. Recently, the U.S.'s President's Malaria Initiative (PMI) has also emphasized the benefits of IRS. We have estimated the average annual cost of using IRS against malaria in unstable transmission areas at $206 million. However, the cost of blanket spraying all malaria transmission areas is $1.1 billion or up to $2 billion considering intense transmission areas require more than one round of spraying per year. Thus blanket coverage with IRS seems prohibitively expensive, especially since intense transmission areas will be scaling up LLIN coverage, and LLINs are easier to distribute, last for up to five years, face less complex logistic challenges than IRS, and require fewer human resources. We therefore include costs for IRS in unstable transmission areas only, since these areas higher risks of mortality (note that there are some stable transmission areas of special economic consideration, such as resorts or mining operations, where private sector budgets will cover the high per capita costs of IRS). We assume that Lysenko's map of endemicity in Africa continues to represent relative transmission strength in Africa today, since unlike other parts of the world, the continent has benefited from few anti-malaria interventions. We consider the areas of the 2002 extent of malaria risk which are hypoendemic and mesoendemic in Lysenko's map to be low- and moderate-transmission and thus recommended for IRS. (This area, encompassing much of eastern African, part of southern Africa and the Sahel countries is roughly the area experts describe as having unstable transmission[14]). By overlaying this area with the population map, we estimate that 149 million people lived in low- and moderate-transmission areas in Africa in 2005. We follow the costing methodology of the UN Millennium Project Working Group on Malaria. Since costs are at the household level, we assume an average of 5 people per household, that each household has about 300 m^2 of surface that needs

[14] Kiszewski AE, Teklehaimanot A, 2004. A Review of the Clinincal and Epidemiologic Burdens of Epidemic Malaria. Am J Trop Med Hyg 71(Suppl 2), 128--135.

to be sprayed, that each square meter requires 2.67 grams of insecticide (DDT, the insecticide of choice), add a ten percent margin of insecticide, and use a cost of US$4.3 per kilogram of insecticide (this cost corresponds to DDT). In addition, we cost labor requirements for IRS. We divide number of households by 360 person-days to get the number of spray persons needed. We assume 5 spray persons for each squad, 5 squads for each team and for each technician, and 1 supervisor for 5 teams. Wages were set at US$10 per day for the spray persons (for 40 days of work plus 6 training days), US$15 per day for squad chiefs and technicians (both also for 46 days), and US$20 per day for supervisors (for 18 person-days of work). For field equipment, we include a tent (US$2000) for each team and each supervisor, and add $100 per person for all personnel for coveralls, handgloves, goggles, buckets, soaps, etc., and US$0.06 in forms and stationary for each household sprayed. For the first year (2006) we include the cost of the spray pump and spare parts (US$500) for each spray person. Finally, we recognize the costs of other logistics, including vehicles to transport equipment and personnel, spare parts and maintenance, fuel and lubricant, and insurance for the spraying team and vehicles. Since the UN Millennium Project Working Group on Malaria estimated costs for these items in Ethiopia based on number of districts, we cannot replicate the costing in this exercise (since we are only working with population at risk in each country). We therefore totaled these costs (for every year) in the Working Group's exercise and found them to be 30% of the other costs of IRS (which we do model). We therefore added 30% of total IRS costs as an estimate of the cost of logistics.

- **Training Community Health Workers (CHW)**: An RBM survey indicated that between 70% and 90% of febrile children are treated at home.[2] There is therefore an urgent need to treat uncomplicated malaria at the community level, especially given evidence of decreased child mortality among those who see a community health worker (CHW).[15] A number of countries are seeking to improve coverage by extending health

[15] Alemayehu T, Ghebreyesus TA, Witten KH, Bosman A, Teklehaimanot A, 1998. Community-based malaria control programme in Tigray Region, Northern Ethiopia: Results of a mortality survey of rural under-five children. Ethiopian Journal of Health Development. 12(3): 203--211.

services using CHWs for malaria diagnosis and treatment services. We assume that one CHW is needed per 500 population, and that training for malaria control lasts 8 days and costs $10 per day.

- **Human Resource Development:** Note that there are other needs in human resource development; the Malaria Working Group indicates that besides CHWs, training of nurses, physicians, entomologists and malariologists will be needed to guide and implement the program activities. However, these costs are estimated based on the size of the formal health sector (number of hospitals, etc.), and are not estimated based on the size of the population at risk. We approximate the costs based on the methodology of the Working Group on Malaria as follows: we consider the total cost of leadership training for program managers and topping up salary for medical officers, epidemiologists, entomologists, biologists, health officers, nurses, environmental health workers, and malaria technicians. The estimated costs total $704 million for Ethiopia from 2005--2015. Using our estimate of population at risk, we find that this number of human resource development needs translates into around $1.00 per person at risk per year, and use the same assumption for all countries in Africa based on population at risk.

- **Microscopy:** We expect that health facilities such as health centers, rural hospitals, and all hospitals in urban areas will use microscopic examination of stained thick and thin blood smears, the gold standard for malaria diagnosis. The Working Group on Malaria estimates the cost of microscopy using the numbers of hospitals and other health centers in a country, which cannot be duplicated in this paper. We therefore estimate the cost of microscopy as we did for topping-up of salaries. The Working Group on Malaria estimated that the total cost of microscopy for Ethiopia from 2005--2015 to be around $29 million. Using our estimates of population at risk, we find that this number is equivalent to around $0.04 per person at risk per year, and use this number to estimate microscopy costs for all the countries. Note that microscopes can be used for other purposes (TB, other parasitic and bacterial diseases).

- **Rapid Diagnostic Testing (RDT)**: Given that peripheral levels of the health system – particularly rural areas – often cannot meet the laboratory requirements for microscopy, a variety of simple and rapid diagnostic tests have been developed for accurate and reliable malaria diagnosis by community health workers and health facilities. We assume that RDT should be used only in unstable transmission areas, for all age groups.

  In areas of intense transmission, where severe disease and mortality are largely concentrated in children under five years of age, malaria should be treated on the basis of clinical suspicion of malaria and not on confirmed diagnosis by RDTs. People older than 5 years of age have a well developed level of immunity, are at lesser risk of developing severe malaria and a significant proportion are asymptomatic in the presence of malaria parasites. This group (above 5 years old living in intense transmission areas) constitutes the bulk of the febrile cases in Africa (we estimate around 218 million fever episodes) and at the moment will be too expensive to subject every one of them to RDT examination. They should therefore be treated clinically on the basis of seasonality and clinical manifestation of the disease.

  We use the UN Population Division's World Population Prospects' demographic breakdown for every year between 2006 and 2015 to divide our population at risk into groups aged 0--4, 5--9, 10--14, and 14+. Following WHO guidelines, the first age group does not require RDT, since in patients below age 5 every fever episode immediately receives malaria treatment due to the possibility of misdiagnosis.[16] Following similar assumptions to the costing done by the UN Millennium Project Working Group on Malaria, the 5--9 and 10--14 age groups are assumed to experience one fever episode per year and the age 14+ group experiences 0.5 fever episodes per year (these are taken as the average number of fevers from all causes, across all endemicity levels). One RDT kit is needed for each of these fever episodes (again, we restrict ourselves to unstable

[16] WHO, 2005. The role of laboratory diagnosis to support malaria disease management: Focus on the use of RDTs in areas of high transmission. Report of informal consultation (25--26 October 2004). Geneva: WHO (pre-publication copy). Available at http://www.who.int/malaria/docs/ReportLABdiagnosis-web.pdf. Accessed December 30, 2006.

transmission areas), and costs at US$0.61 per kit. Note, that we have built into the model a decrease in fever episodes as LLIN coverage increases: we assume that the proportion of the population covered by LLINs has a 50% reduction in fever episodes (measured reduction in morbidity has ranged from 44%--75%[17,18,19,20]). This decreases the need for RDT as LLIN coverage increases. Moreover, we have assumed that the number of fever episodes for populations living in urban areas is 25% smaller, since transmission tends to be lower in urban areas.

- **Artemisinin-based Combination Therapies (ACTs)**: We again calculated fever episodes for each of the four age groups mentioned above (including the 0--4 age group, which we assume experience 2 fever episodes per year). We assume that RDT in unstable transmission areas will reveal that around 40% of the fevers are due to malaria and require ACTs (as was assumed by the UN Millennium Project Working Group on Malaria). In intense transmission areas, on the other hand, we assume that 20% of the fever episodes will be examined by microscopy, and these will have a slide positivity rate of 40% (Ethiopia's current slide positivity rate). The 80% of fevers not examined by microscopy all require ACTs. Our total number of fever episodes requiring malaria treatment in 2006 is 395 million, which is within the range of other published estimates.[21] We assume that each treatment course can be treated with either artemether-lumefantrine or artesunate-amodiaquine. Artemether-lumefantrine is assumed to cost US$0.45 for the 0--4 age group, US$0.90 for the 5--9 age group, US$1.35 for the 10--14

[17] Lengeler C, 2004. Insecticide-treated bed nets and curtains for preventing malaria. Cochrane Database Syst Rev.
[18] WHO/UNICEF, 2003. Africa Malaria Report 2003. Available at http://www.who.int/malaria/amd2003/amr2003/pdf/amr2003.pdf. Accessed December 30, 2006.
[19] Maxwell CA, Msuya E, Sudi M, Njunwa KJ, Carneiro IA, Curtis CF, 2002. Effect of community-wide use of insecticide-treated nets for 3--4 years on malarial morbidity in Tanzania. Trop Med Int Health 7(12), Dec: 1003--1008.
[20] Nevill CG, Some ES, Mung'ala VO, Mutemi W, New L, Marsh K, Lengeler C, Snow RW, 1996. Insecticide-treated bednets reduce mortality and severe morbidity from malaria among children on the Kenyan coast. Trop Med Int Health Apr; 1(2): 139--146.
[21] The World Malaria Report 2005 (RBM/WHO/UNICEF) estimates between 210--300 million clinical cases in Africa. Snow RW et al. (2003) estimate 1.7 billion fever episodes in Africa per year, and find cost of treating 60% of these fevers with ACTs. Snow RW et al. (2005), meanwhile, estimate 365 million clinical cases in 2002.

age group, and US$1.80 for the 14+ age group.[22,23] Artesunate-amodiaquine is estimated to cost US$0.23 for the children under 1, $0.45 for the 1--6 age group, US$0.80 for the 7--13 age group, and $1.48 for the 13+ age group (we use RBM's recommended dosages[24] and averages of prices from Sanofi-Aventis, Ipca, and Cipla,[25] and adjust to match age groups in our analysis). We use the average of the cost of artemether-lumefantrine and artesunate-amodiaquine. As above, we assume a 50% reduction in fever episodes for the population covered by LLINs, and 25% fewer fever episodes among urban populations. For intense transmission areas, this is a 50% reduction in all fevers; for unstable transmission areas, it is a 50% reduction of fevers that needs ACTs, that is, a 50% reduction of the original 40% of total fevers. ACT production is a bottleneck, as discussed below; we assume that enough ACTs will be produced to meet need starting in 2008, but for 2006 and 2007 there will be a shortage. We include a US$0.10 cost of using other drugs (sulfadoxine-pyrimethamine (SP)-amodiaquine combination or SP-chloroquine combination) to treat the fevers that will not be treated with ACTs in 2006 and 2007. It is expected that in a year's time, ACTs such as dihydroartemisinin piperaquine will become available, resulting in overall increased production and cost reduction.

- **Management of Severe Malaria**: We include a rough approximation of management of severe malaria, using the median cost of $29.50 for managing a severe malaria case as

[22] Novartis, 2006. "Media Release (September 29, 2006): Novartis announces initiative to improve access to state-of-the-art anti-malarial treatment Coartem." Available at www.novartis.com. Accessed January 31, 2007.
[23] Correspondence with WHO.
[24] WHO, 2006. Guidelines for the Treatment of Malaria. Switzerland: WHO.
[25] RBM, 2006. ACTs Procured by WHO and UNICEF. Available at: http://www.rbm.who.int/docs/mmss/actSourcesPrices_catalogue.pdf. Accessed December 30, 2006.

derived by WHO/AFRO.[26] We assume that about 1% of the malaria episodes would progress to severe malaria.[27]

- **Information, Education and Communication**: A program to educate communities and promote behavioral change is an important element in successful malaria reduction. The program should produce information, education, and communication materials targeting health workers, community leaders, and communities; it should use radio spots, television, drama and other educational media to increase treatment-seeking behavior, compliance, and use of LLINs, target IRS; and organize sensitization and advocacy meetings at district, regional, and national levels. The Working Group on Malaria estimated that the cost of IEC for Ethiopia $614,000 per year. Using our estimates of population at risk, we find that this number is equivalent to around $0.011 per person at risk per year, and use this number to estimate IEC costs for all the countries.

- **Monitoring and Evaluation**: Monitoring and evaluation are essential components of malaria control programs to track effectiveness of the interventions over time. Activities involve assessment of routine health services data and periodic community and household surveys in order to develop process indicators for implementation, and outcome indicators for case management, prevention, and program impact.[28] In addition, the effectiveness of antimalarials and insecticides must be monitored. Following the standard practice in programs funded by the Global Fund to fight AIDS, TB and Malaria, we add 7% of costs as monitoring and evaluation.

---

[26] WHO/AFRO, 2002. Clinical, Behavioural and Socioeconomic Factors Related to Severe Malaria: a Multicentre Study in the African Region. Available at http://www.who.int/malaria/cmc_upload/0/000/016/330/multicenter.pdf. Accessed December 30, 2006.

[27] Greenwood B, Marsh K, Snow R, 1992. Why do some African children develop severe malaria? Parasitol Today. Nov; 8(11): 381-383.

[28] Bryce J, Roungou JB, Nguyen-Dinh P, Naimoli JF, Breman JH. Evaluation of national malaria control programmes in Africa. 1994. Bull World Health Organ (72: 371--381).

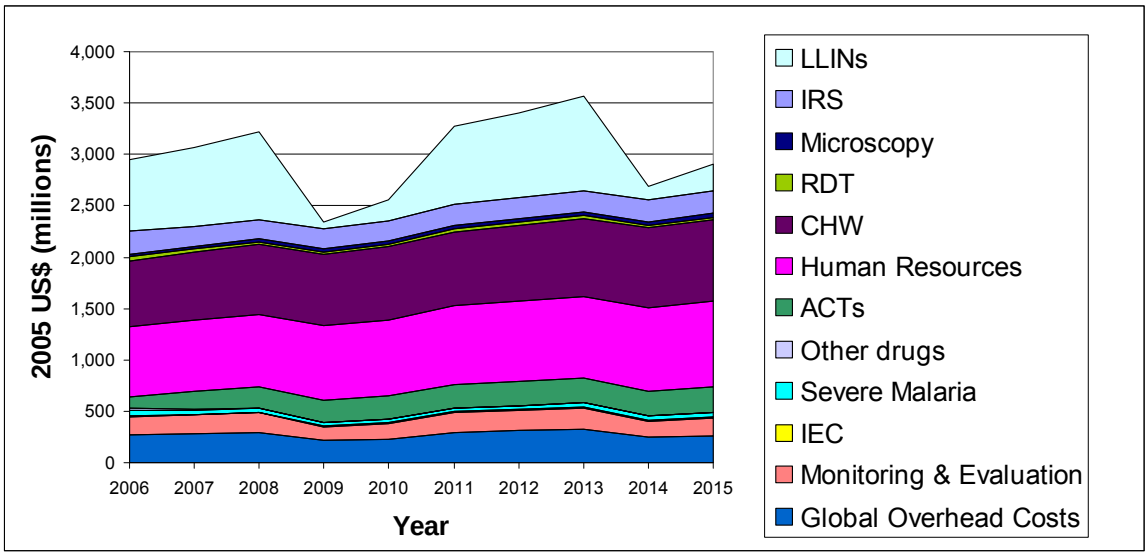
- **Overhead Costs**: Finally, we add 10% of the cost to account for the overhead costs in a global effort to reach full coverage of these malaria interventions by 2008.

Using our estimated population at risk and the costing assumptions above, we arrive at the projected total yearly costs for all of Africa shown in Table 3-2 and graphed below in Figure 3-3:

Table 3-2: Cost Estimates

Totals (millions of US$)	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Average
LLINs	700	770	854	58	199	760	831	916	121	263	547
IRS	223	187	191	195	200	204	209	213	218	222	206
CHW	645	660	676	692	708	724	741	758	776	793	717
Microscopy	28	28	29	30	30	31	32	33	33	34	31
Human Resources	677	693	709	726	743	760	778	796	814	832	753
RDT	40	33	25	26	26	27	27	28	29	29	29
ACTs	109	168	212	217	222	227	232	238	243	249	212
Other drugs	26	13	0	0	0	0	0	0	0	0	4
Severe Malaria	54	45	34	35	36	36	37	38	39	40	39
IEC	7	7	7	8	8	8	8	8	9	9	8
Monitoring & Evaluation	176	182	192	139	152	194	203	212	160	173	178
Global Overhead Costs	268	279	293	212	232	297	310	324	244	264	272
Total	**2,953**	**3,065**	**3,222**	**2,337**	**2,556**	**3,270**	**3,408**	**3,564**	**2,684**	**2,908**	**2,997**
Total per total population (dollars)	$3.24	$3.29	$3.39	$2.41	$2.58	$3.23	$3.30	$3.38	$2.49	$2.65	$3.00
Total per person at risk (dollars)	$4.40	$4.46	$4.58	$3.24	$3.47	$4.33	$4.41	$4.51	$3.32	$3.52	$4.02

Figure 3-3: Malaria Intervention Costs (all Africa)



The most striking fact from these numbers is their modest magnitude. Given that we are talking about a disease that kills around two million African children every year, the fact that full coverage of LLINs and ACTs (plus the other interventions) costs only $3.00 per African (or $4.02 per person at risk of malaria) is astounding and encouraging.

We examined these numbers in comparison with earlier studies. The UN Millennium Project Working Group on Malaria performed a detailed costing of interventions for Ethiopia, and arrived at an average of US$238 million per year, which comes to around US$2.70 per capita per year (compared to $3.00 in our results above; note that unlike the working group, we include salaries for CHWs, without which our per capita cost is $2.29). Another costing estimate (Kiszewski A and others, unpublished) of malaria interventions for Africa results in $1.7 billion, an equivalent of around US$2.10 per person at risk per year. It is heartening that our GIS-based approach and different costing assumptions produce similar results and corroborate the magnitude of the per capita cost of these interventions.

Scaling up to Full Coverage in 2008

Given that our model assumes full coverage of LLINs by the end of 2008, it is instructive to look at costs before 2008 carefully. In order to reach full coverage of all interventions by 2008, the international community needs to begin planning ahead to guarantee sufficient production of LLINs and ACT treatment courses. Full coverage in 2008 means that around 352 million nets must be distributed in Africa by the end of that year. Around 20 million nets have been distributed in 2005 (the Global Fund to fight AIDS, TB and Malaria – the largest provider of resources for malaria control in Africa – has approved purchases of around 22--31 million LLINs between 2005 and 2007, and we looked at the GFATM disbursement reports and found that roughly 20 million nets had been distributed in 2005). Our costing model above includes a ramping up of distribution to 100 million new nets in 2006, 110 million new nets in 2007, and 122 million new nets in 2008. Since production of LLINs by the two producing companies (Sumitomo and Vestergaard) in 2006 is currently planned for around 80 million nets, the donor countries should commit as soon as possible to funding a scale up of production in 2007 and 2008 so that full coverage can be reached by 2008. Two other LLIN products from other manufacturers are also expected to be in the market soon, which would alleviate the production capacity constraint.

With regard to treatment, the current estimate for production of ACTs in 2006 is 130 million treatment doses, which is insufficient to meet the estimated 395 million treatments needed. In 2006 and 2007, our costing model assumes that fevers that cannot be treated with ACTs will be treated with either SP-amodiaquine combination or SP-chloroquine combination, which both cost about US$0.10. By 2008, we assume that enough ACTs will be produced to meet the need, which our projections show to be around 251 million treatment courses. This implies a doubling of ACT production between now and 2008. For our model, we use the estimated 130 million treatment courses for 2006 production, and in order to ramp up to 251 million by 2008, we use 200 million as the number of ACT treatments produced in 2007. Again, since ACTs are produced by private companies, this increase in production can only happen if donors agree in advance to purchase the required treatment courses.

Note that this costing exercise was carried out in early 2006; since scale up in 2006 has been slower than expected, this implies a faster scale up will be needed in 2007 and 2008, and full coverage could perhaps be reached by early 2009. The important point, however, is that full coverage can be reached within approximately three years, and average annual costs between now and 2015 are not high.

Conclusion

We have employed a GIS-based method to estimate the population in Africa at risk of contracting malaria, and proceeded to calculate the cost of providing this population a comprehensive set of interventions to reduce malaria incidence and mortality. The interventions in our model are adjusted for urban areas and for unstable transmission areas. Although these estimates are rough and cannot replace country-specific malaria planning and cost estimates, the exercise shows that a GIS-based costing strategy comes up with comparable results to methods that estimate population at risk using survey methods. In areas where survey methods may severely underestimate population at risk, GIS-based estimates provide a useful alternative method. Ideally, maps of malaria risk and intensity will be updated frequently in the future to provide up-to-date estimates given the impact of interventions. Our results make it evident that

the costs of comprehensive malaria interventions are very low on a per-capita or per-patient basis. Nevertheless, full coverage is beyond the reach of African government budgets. Given that the disease kills millions, is readily preventable and curable, and has been shown to hamper economic development, the international community should seize the opportunity to reduce massively this human disease burden at such a low cost. Other public health efforts, such as measles and polio campaigns currently underway, present an opportunity to synergize by also delivering malaria interventions, especially bed nets.[29,30]

[29] Grabowsky M, Nobiya T, Ahun M, Donna R, Lengor M, Zimmerman D, Ladd H, Hoekstra E, Bello A, Baffoe-Wilmot A, Amofah G, 2003. Linking ITN distribution to measles campaigns achieves high and rapid coverage at low cost. Proceedings of the annual meeting of the American Society of Tropical Medicine and Hygiene. Philadelphia, 4 Dec, Abstract 1230.

[30] American Red Cross and CORE, 2004. "Malaria Case Study Partnerships in Action: An Integrated Approach to Combining a Measles Campaign with a Bed Net, Vitamin A and Mebendazole Campaign in Zambia," July. (available online at http://pdf.dec.org/pdf_docs/PNADB968.pdf).

Chapter 4

Malaria Ecology and Climate Change

Gordon C. McCord

Malaria has afflicted human society for over 2 million years[1], and remains one of the great killer diseases today. The disease is the fourth leading cause of death for children under five in low income countries (after neonatal disorders, diarrhea, and pneumonia) and is responsible for at least one in every five child deaths in sub-Saharan Africa.[2] It kills up to 3 million people a year[3], though in recent years scale up of anti-malaria efforts in Africa may have brought deaths to below 1 million. Malaria is highly conditioned by ecology, because of which climate change is likely to change the local dynamics of the disease through changes in ambient temperature and precipitation. To assess the potential implications of climate change for the malaria burden, this paper employs a Malaria Ecology Index from the epidemiology literature, relates it to malaria incidence and mortality using 20th century data, and then draws implications for 2020 and 2090 by extrapolating the index using general circulation model (GCM) predictions of temperature and precipitation.

The paper is organized as follows: the first section describes the role of climate in the epidemiology of malaria. It then describes the construction of the Malaria Ecology Index (MEI), including the contribution of calculating it on a year-to-year basis. The paper then turns to show how malaria ecology helps explain the timing of local malaria elimination around the globe in the 20th century. Next are statistical tests of whether the MEI has explanatory power over within-country year-to-year variation in malaria incidence and mortality rates. The paper uses output from a climate model (the Hadley GCM) to illustrate how malaria ecology would evolve under a set of climate change assumptions. Finally, it discusses implications of this change for the malaria burden, and concludes.

Climate and the Epidemiology of Malaria

Malaria is a disease strongly regulated by climatic conditions for several reasons. First, a key part of the life cycle of the *Plasmodium* parasite depends on a high ambient temperature. Higher ambient temperatures increase the metabolic rate of the *Plasmodium*, resulting in a shorter

---

[1] Ricklefs, Robert E. and Diana C. Outlaw. A Molecular Clock for Malaria Parasites. Science 329, 9 July 2010.

[2] Black R.E., Morris S.S., and Bryce J. 2003. Where and why are 10 million children dying every year? Lancet, v. 361, pp. 2226-2234.

[3] Breman, JG, MS Alilio and A Mills. Conquering the intolerable burden of malaria: what's new, what's needed: a summary. American Journal of Tropical Medicine and Hygiene. 2004; 71: suppl: 1-15.

sporogony period inside the *Anopheles*, and thus in an increased likelihood that the *Plasmodium* will successfully undergo reproduction and make the mosquito infective before the end of the mosquito's life-span. Second, precipitation must be adequate to create breeding sites (in Africa, for example, most *Anopheles* vectors breed in rain puddles although some like brackish standing water). Additionally, the intensity of malaria transmission depends on the specific mosquito species that is present and its relative preference to biting humans versus animals. These three factors – temperature, precipitation, and the human biting preference of the local *Anopheles* vector – are therefore key inputs into the general expression for the basic reproduction number of malaria[4]:

$$R_0 = \frac{ma^2bce^{-gn}}{r(-\ln p)}$$

m - ratio of mosquitoes to humnas
a - human feeding rate
1/g - average mosquito life-span
n - incubation period
c - human-to-mosquito transmission efficiency
b - mosquito-to-human transmission efficiency
1/r - human infectious period
1/-ln(p) - daily mosquito survival probability

In epidemiological terms, the basic reproduction number (R_0) is the expected number of secondary infections produced by each infected individual in its infectious period, in a population which is entirely susceptible. When $R_0 < 1$, each infected individual infects less than one individual on average, and the infection is expected to die out in the population. If $R_0 > 1$, the infection is expected to thrive in the population. Whether a given intervention can drive R_0 to below one depends strongly on the pre-intervention R_0. When the pre-intervention number is close to the threshold of 1, elimination of transmission is feasible. When it is much greater than 1 (numbers higher than 100 are not uncommon in rural sub-Saharan Africa, and have been

[4] Smith, David L and F Ellis McKenzie. 2004. Statics and dynamics of malaria infection in Anopheles mosquitoes. Malaria Journal 3:13.

measured above 3000[5]), then elimination of transmission with the same set of technologies is not feasible.[6]

The value of R_0 directly affects whether local elimination is feasible. Interventions that curb the rates of transmission and therefore reduce R_0, such as indoor residual spraying of DDT, are only successful in locally eliminating the disease if they reduce R_0 below the threshold of 1. Thus, the effectiveness of existing technologies strongly depends on the baseline R_0: if it is relatively close to unity, the intervention can help push it below the threshold. But in those locations where the baseline value is very high, these same interventions may be ineffective. This explains why many temperate regions eliminated malaria with interventions that would have little effect in sub-Saharan Africa.

Construction of the Malaria Ecology Index

The Malaria Ecology Index uses models of the disease's epidemiological dynamics (based on the interaction of climate with the dominant properties of anopheline vectors that determine vectorial capacity) to construct an ecologically-based spatial index of the stability of malaria transmission.[7] I follow Kiszewski et al (2004) in measuring the effects of ambient temperature on the force of transmission of malaria, as expressed through the length of the extrinsic incubation period, and therefore the proportion of the vector population able to survive long enough to become infectious. However, whereas Kiszewski et al averaged 1901-1990 monthly temperature and precipitation to generate a single cross-section value of the index, I instead construct a time-varying annual index for every year from 1900 to 2006. The index is constructed on a 0.5 degree spatial grid to derive the climatic characteristics of individual months, and then averaged over a 12-month period.

---

[5] Smith, DL, McKenzie FE, Snow RW, Hay SI, 2007, "Revisiting the basic reproductive number for malaria and its implications for malaria control," *PLOS Biology* 5(3).

[6] Note, however, that even with continuing transmission, control of illness and mortality is possible. Thus, maps of malaria transmission may not change, while the burden of illness and death could change markedly.

[7] Kiszewski, Anthony, Andrew Mellinger, Andrew Spielman, Pia Malaney, Sonia Ehrlich Sachs and Jeffrey Sachs. "A Global Index Representing the Stability of Malaria Transmission." American Journal of Tropical Medicine and Hygiene. 70(5), 2004, pp 486—498.

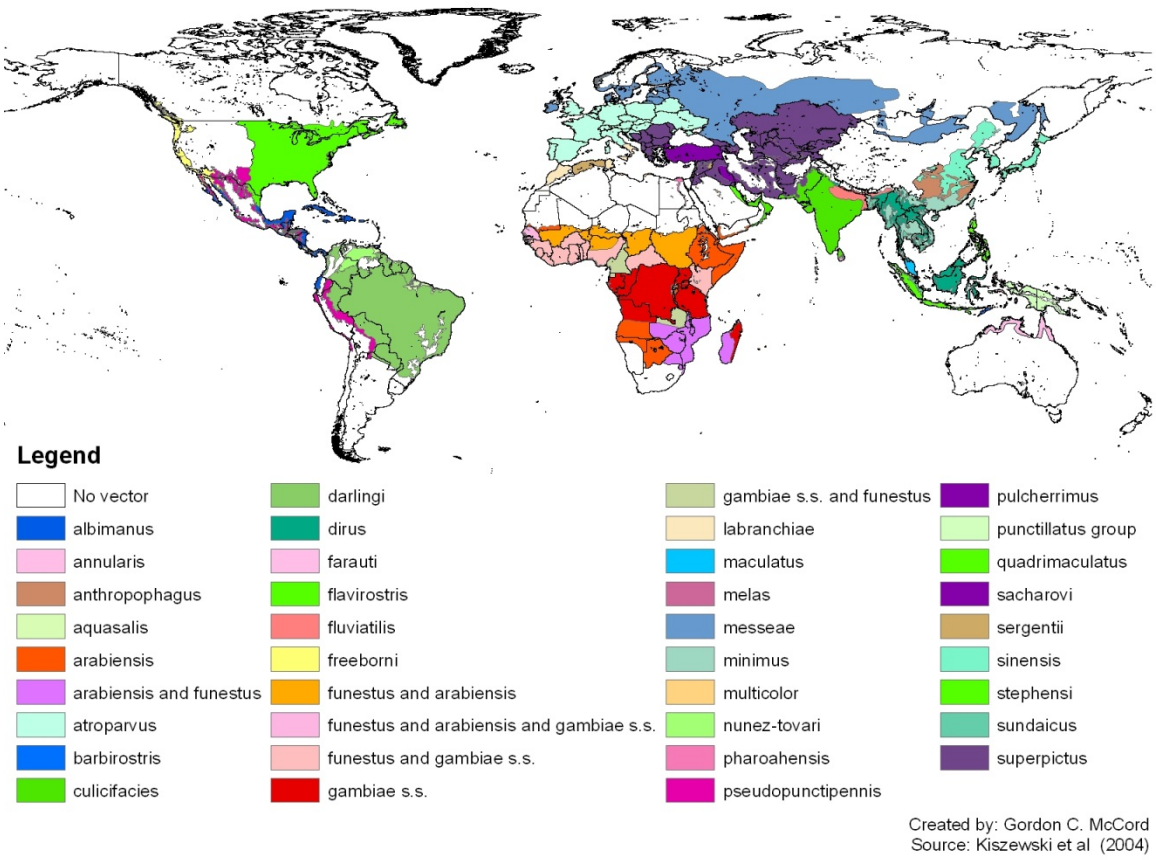
I begin with Kiszewski et al.'s identification of the distribution of anopheline species across the world using observation records and satellite-based vegetation maps to identify likely habitats where observations have not been recorded. A dominant species thus is identified for each spatial zone, and for each month (in cases where there is a seasonal pattern to the dominant species). Following Kiszewski et al., an ecological screen was created for the presence or absence of a vector during particular months. (For those vectors that breed mainly in temporary water, a minimum precipitation threshold of 10mm per month, lagged one month, is used to judge when the vector would be present in the site during a given month. Vectors that mainly exploit permanent or semi-permanent bodies of water were considered to be independent of seasonal fluctuations in rainfall unless empirical evidence indicated otherwise. In temperate or altitudinous regions, temperature thresholds are used to determine whether parasites can develop in mosquito vectors in a particular month, assuming that malaria parasites cannot develop when the mean monthly temperature remains below 15°C). Table 1 lists the vectors, and highlights unstable vectors which are removed when the previous month has below 10 mm of precipitation, and replaced with a stable vector if one is present on that grid cell.

Table 4-1: Stability of Vectors

Species	median hbi	Habitat Stability & Characteristics	Response to Rainfall Condition		
			Deficient	Normal	Excess
albimanus	0.1015	mostly temporary, heliophilic	negative	positive	positive
anthropophagus	0.01	mostly permanent	stable	stable	stable
aquasalis	0.109	brackish, permanent	stable	stable	stable
arabiensis	0.871	mostly temporary	negative	positive	positive
atroparvus	0.245	brackish, permanent, heliophilic	stable	stable	stable
barbirostris	0.127	mostly permanent, vegetated	stable	stable	stable
culicifacies	0.0515	mostly temporary	negative	positive	positive
darlingi	0.4575	mostly permanent	stable	stable	stable
dirus	0.355	mostly permanent, heliophilic	stable	stable	stable
farauti	0.658	variable			
flavirostris	0.3	mostly permanent, flowing	stable	stable	stable
fluviatilis	0.034	mostly permanent, flowing, heliophilic	stable	stable	stable
freeborni	0.0192	mostly permanent, heliophilic	stable	stable	stable
funestus	0.98	mostly permanent	stable	stable	stable
gambiae s.s.	0.939	mostly temporary	negative	positive	positive
koliensis	0.922	mostly temporary, heliophilic	negative	positive	positive
labranchiae	0.151	mostly brackish, coastal	stable	stable	stable
maculatus	0.155	mostly permanent	stable	stable	stable
marajoara					
melas	0.69	mostly brackish, coastal	negative	stable	stable
messeae	0.172	mostly permanent	stable	stable	stable
minimus	0.425	mostly flowing	negative	positive	
multicolor	0.08	variable			
nuneztovari	0.222	mostly temporary	negative	positive	positive
pharoahensis	0.52	mostly permanent	stable	stable	stable
pseudopunctipennis	0.477	mostly temporary, heliophilic	negative	positive	positive
pulcherrimus	0.0615	mostly permanent	stable	stable	stable
punctulatus group	0.861	variable			
quadrimaculatus	0.111	mostly permanent	stable	stable	stable
sacharovi	0.087	mostly brackish, inland or coastal	stable	stable	stable
sergentii	0.1	mostly temporary	negative	positive	positive
sinensis	0.018	mostly permanent, heliophilic	stable	stable	stable
stephensi	0.023	wells, cisterns, peridomestic	stable	stable	stable
superpictus	0.0925	mostly permantny, flowing	stable	stable	stable
sundaicus	0.611	brackish, coastal	stable	stable	stable

Note that the mosquito screen is ecology-based and not affected by human activity; indeed, it is worth keeping in mind that public health interventions against malaria serve to break the transmission cycle, but do not eliminate the presence of the vector itself (even until today, *Anopheles* mosquitoes capable of transmitting malaria can be found throughout the US and Europe, places where malaria has been largely eradicated). A map of the dominant species in the presence of adequate rainfall is shown in Figure 1.

Figure 4-1: Dominant Vector of the Anopheles Genus



The basic formula for Malaria Ecology combines climatic factors, the presence of different mosquito vector types and the human biting rate of the different mosquito vectors. The index expresses the factors that most powerfully and perennially influence the intensity of malaria transmission. It uses, therefore, a subset of the vectorial capacity equation described in the previous section without terms for mosquito abundance, vector competence, or recovery rate for infected people. To calculate the duration of the extrinsic incubation period "E," the index (1) was calculated for each month, and biting activity was designated based on the average monthly temperature and Moshkovsky's degree-day-based formulae (2).

$$(1)\ \sum_{m=1}^{12} \frac{a_{i,m}^2 p_{i,m}^E}{-\ln p_{i,m}}$$

Where:

m = month (1-12)

i = identity of dominant vector

a = proportion biting people (0-1)

p = daily survival rate (0-1)

E = length of extrinsic incubation period in days, where T is the mean monthly temperature:

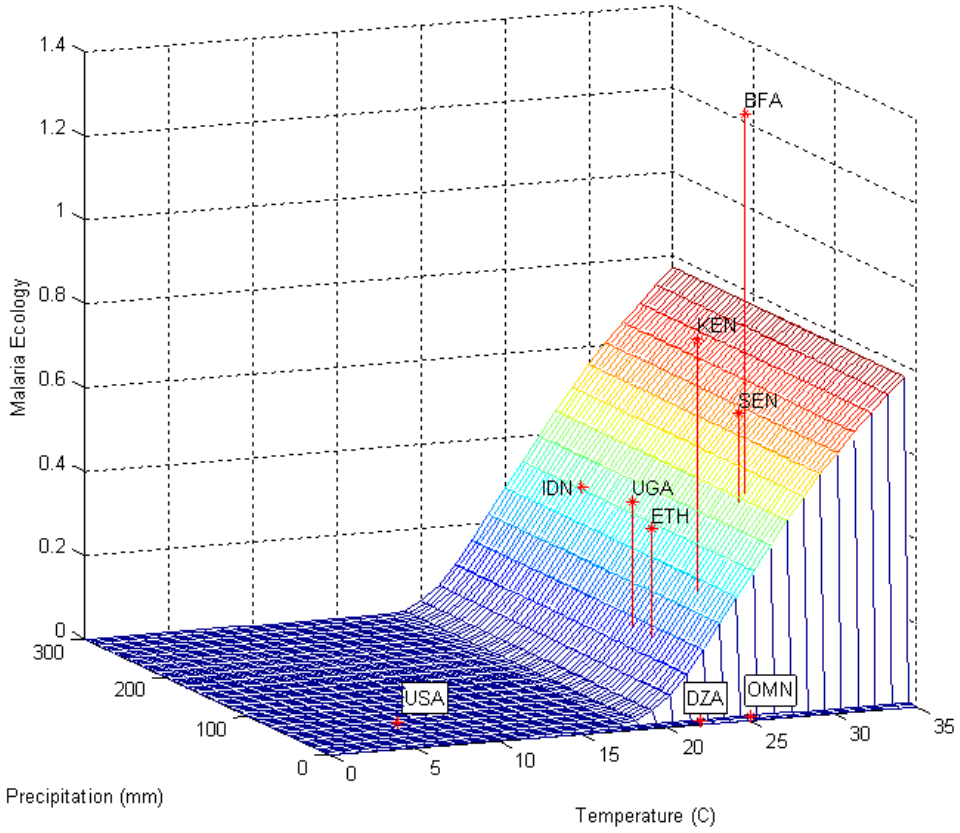
(2) $E = 111 / (T-16)$ for Plasmodium falciparum

Because it is built upon climatological and vector characteristics, the Malaria Ecology Index is exogenous to public health interventions and economic conditions, and thus can serve as an exogenous instrument for malaria risk.[8,9] Moreover, its particular functional form means that it is likely capturing a dynamic that will be relatively uncorrelated to other temperature- and precipitation-determined processes (like agricultural yields, for example). Figure 2 below illustrates graphically how the index varies with temperature and precipitation for a given human biting index of 0.5:

[8] Sachs, Jeffrey D. "Institutions Don't Rule: Direct Effects of Geography on per capita Income." NBER Working Paper 9490, February 2003.

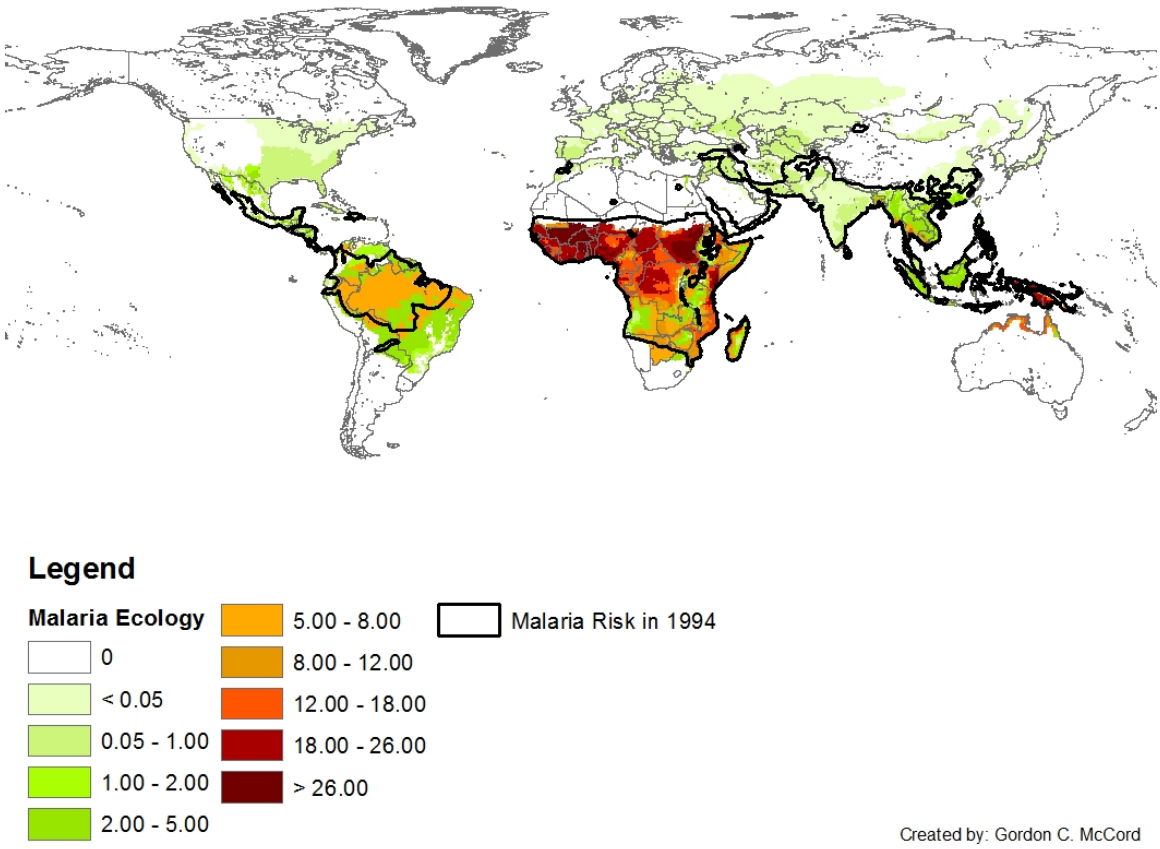
[9] Carstensen, Kai and Gundlach, Erich. 2006. The Primacy of Institutions Reconsidered: Direct Income Effects of Malaria Prevalence. The World Bank Economic Review, v. 20, no. 3, pp. 309-339.

Figure 4-2: Malaria Ecology for HBI = 0.5



The figure also indicates the average value of the index for nine countries (note that they are mostly off the surface because the average human biting index in those countries is not 0.5). Note the very particular functional form, with significant nonlinearities at 16 degrees Celsius and 10 mm of precipitation. The average Malaria Ecology Index for 1994-2002 is mapped in Figure 3 below, together with an outline of malarious areas of the world in 1994:

Figure 4-3: Average Malaria Ecology from 1994-2002

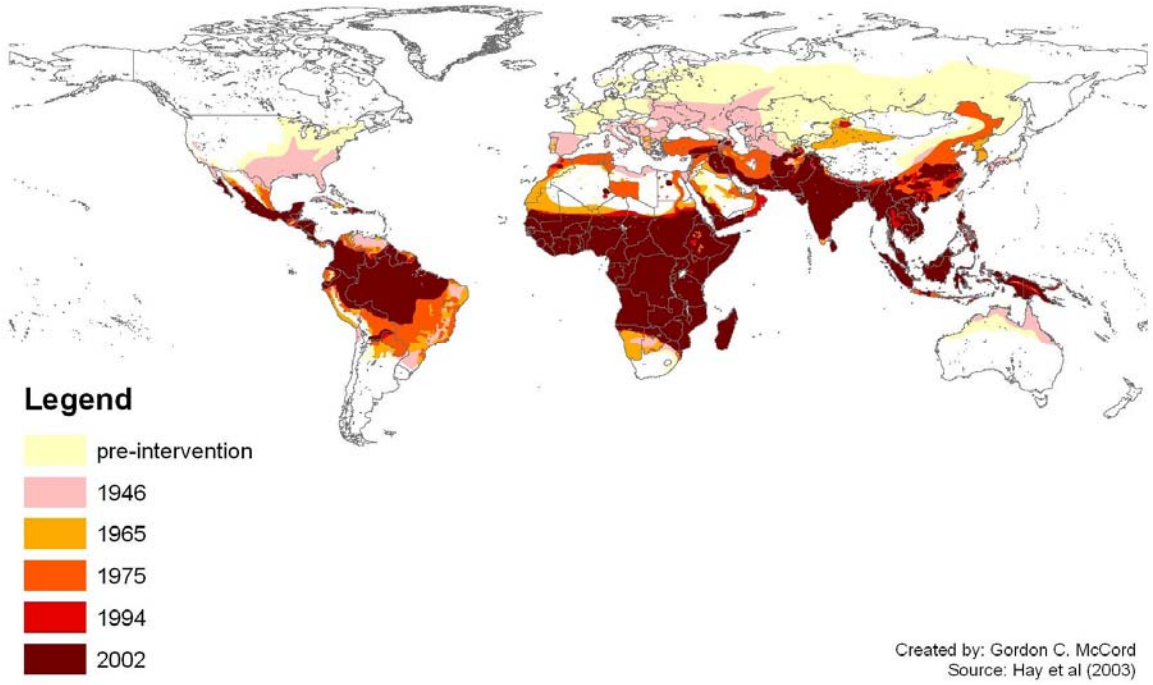


Malaria Ecology and Malaria Elimination

Given that the Malaria Ecology Index represents a part of the basic reproduction number of the disease, places with a lower MEI will have proportionately lower R_0 holding the non-MEI factors constant. Since the effect of successful public health campaigns in eliminating a disease is to decrease R_0 below 1, then places with a lower MEI will have a lower pre-intervention R_0. This means, in turn, that public health interventions (such as screen doors) will be more likely to break disease transmission in places with a lower MEI. The relationship between MEI and historical malaria elimination can be verified directly by looking at data on the geographic extent of malaria over the last century.

The probable greatest geographic extent of malaria in history ranged from 64 degrees north latitude to 32 degrees south (Figure 4).[10] During the 20th century, human intervention has significantly reduced the geographic extent of malaria risk, as documented by the WHO and as shown on the map below. Figure 4 represents malaria risk from one or more of the four species of the *plasmodium* parasite that causes malaria. Data come in GIS format as polygons and each layer (pre-intervention, 1946, 1965, 1975, 1994, and 2002). The layers were each rasterized to create grid cells for regression analysis; the cell size was set at 0.5 degrees to be equal to the cell size of the malaria ecology raster map.

Figure 4-4: Evolution of Geographic Extent of Malaria

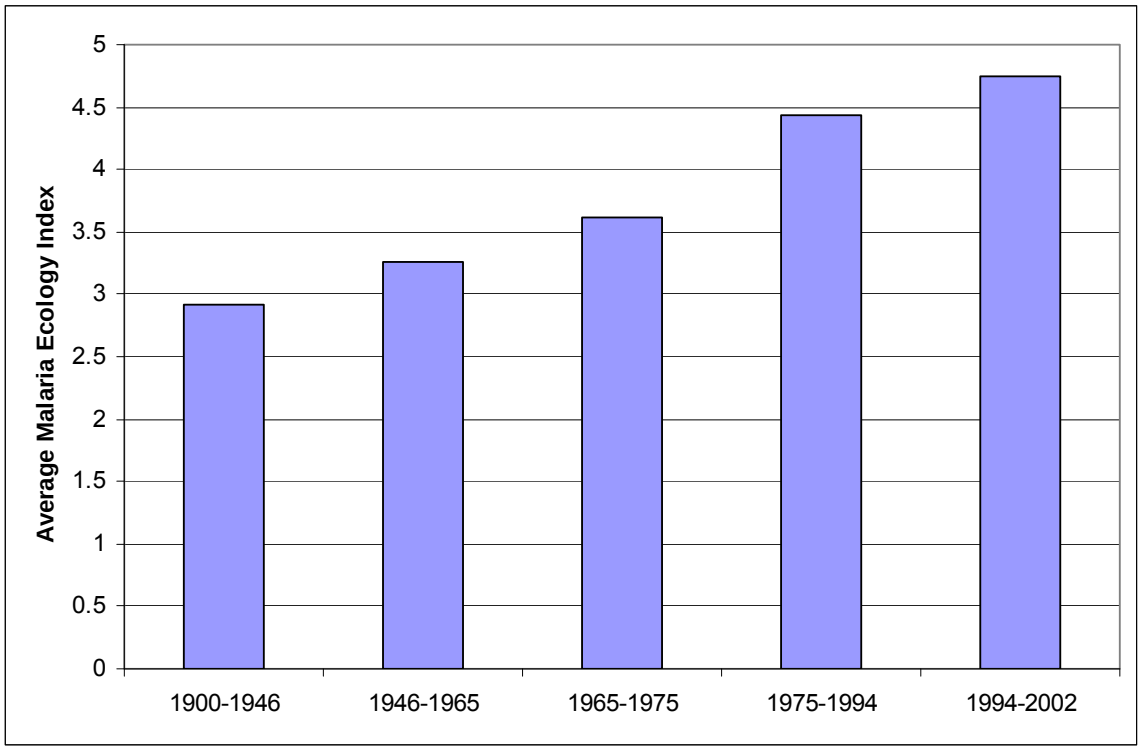


Even a cursory comparison of the maps of the Geographic Extent of Malaria Risk and Malaria Ecology reveals that the high latitudes of the northern hemisphere are both where malaria was eliminated first, and also the malaria ecology index is lowest without being zero. The bar graph below shows the different means of the Malaria Ecology Index within areas of the

[10] Hay SI, Guerra CA, Tatem AJ, Noor AM, Snow RW, 2004. The global distribution and population at risk of malaria: past, present and future. The Lancet: Infectious Diseases. Vol. 4 (June), 327-336.

Malaria Risk map. As explained in Chapter 2, areas where malaria was eliminated later have higher mean levels of the Malaria Ecology index, with the highest average MEI value in the burgundy-colored area where malaria is still transmitted today.

Figure 4-5: Malaria Ecology in Malarious Zones, per year



Malaria Ecology and Malaria Incidence & Mortality

As a test for the performance of the Malaria Ecology Index, I averaged the index within each country's national boundaries to create a national version of the index, and test its relationship to yearly national-level malaria incidence and mortality data as reported by WHO.[11] The evolution of malaria ecology and malaria incidence (in cases per thousand people) is shown below for two very different countries: Colombia and Burundi. Upon visual inspection the index does seem strongly correlated to incidence both in Colombia (a middle-income country where malaria mortality is lower since the *Plasmodium vivax* is rarely lethal) and in Burundi (a low-income country where *Plasmodium falciparum* dominates, resulting in many more fatalities).

[11] World Health Organization. 2008. World Malaria Report 2008. Geneva.

Figure 4-6: Malaria Incidence and Ecology in Colombia

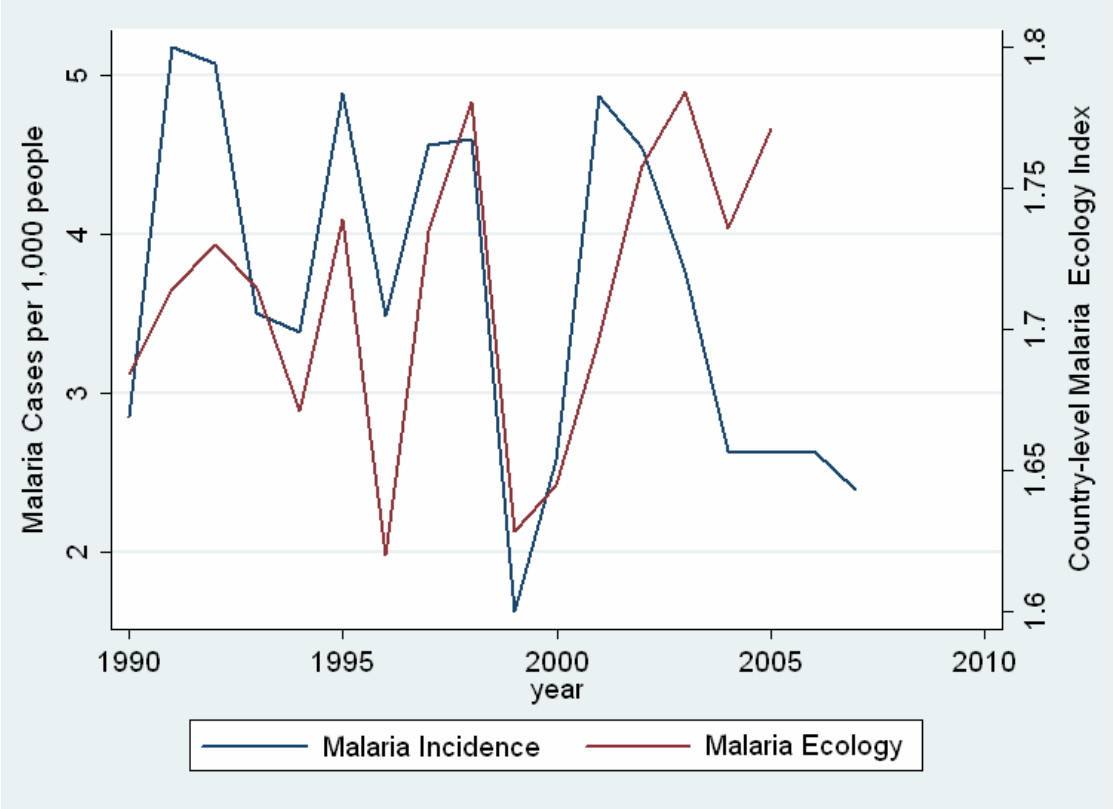
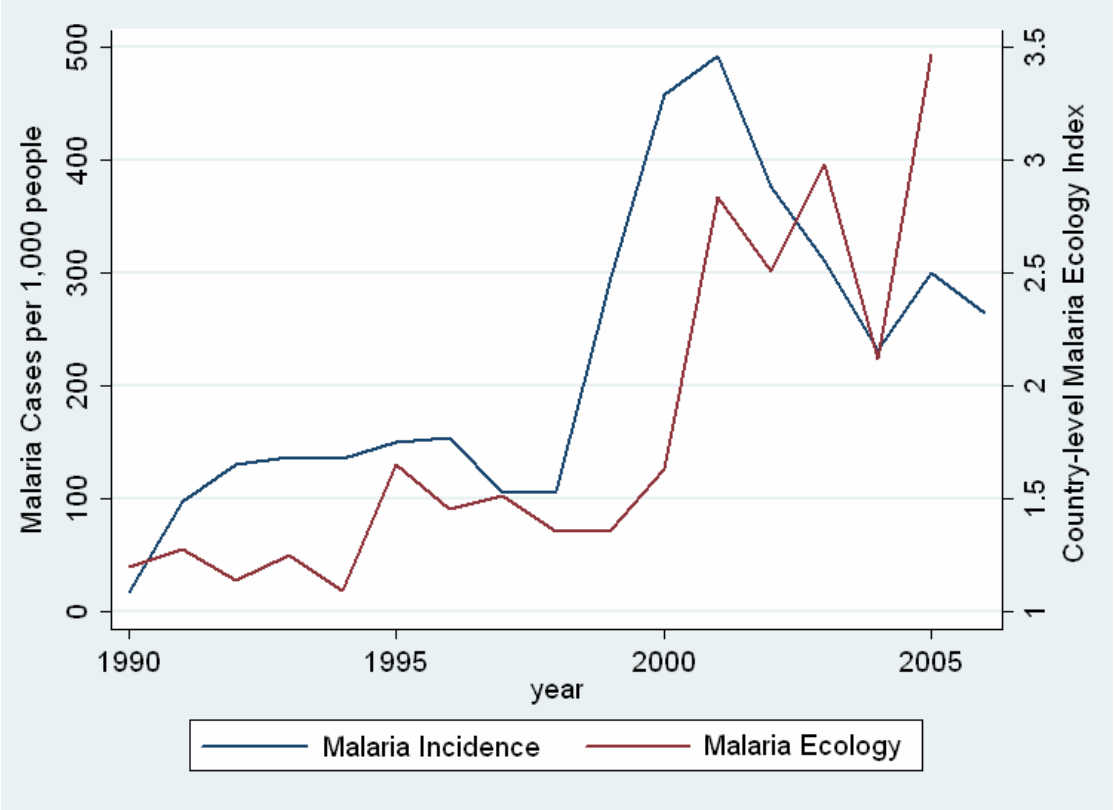


Figure 4-7: Malaria Incidence and Ecology in Burundi



To test the statistical strength of these relationships, I run country-level regressions of the annual incidence (in cases per thousand population) and mortality (in deaths per thousand population) on the malaria ecology for that year, using country dummies and controlling flexibly for global trends by using year dummies. The results are in Table 2 below, and indicate that higher values for the index are associated with higher malaria incidence and mortality after including country and year dummies.

Table 4-2: Malaria Ecology, Incidence and Mortality from 1990-2005

Dependent Variable:	(i) ln(Malaria cases per 1,000 population)	(ii) ln(Malaria deaths per 1,000 population)
Independent Variables		
Malaria Ecology	0.23**	0.37**
	(2.20)	(2.56)
N =	1187	534
Countries =	85	72
Years =	1990-2005	1990-2005
Within R-squared =	0.02	0.20

t-statistic in parentheses, ** indicates significant to 95% confidence.
Sample includes Latin America & Caribbean, Sub-Saharan Africa, East Asia & Pacific and South Asia
Regressions include country and year dummies and a constant (not reported)
Regressions report robust standard errors clustered by country
Regressions w eigh observations by population

These results are quite telling: since the fixed-effects approach allows us to control for all unobserved time-invariant heterogeneity across countries, and since we are using year-to-year variation in the ecological index, we can be quite confident that the effect of the Malaria Ecology Index on incidence and mortality is well-identified in the estimation above. The Appendix explores these relationships separately by region, and finds that malaria ecology is most tightly associated to incidence in sub-Saharan Africa and Latin America, though the lack of power in regressions and the likely measurement error in incidence data weakens results. Similarly, the low R-squared in regression (i) is likely due to very noisy national incidence data; assuming that this measurement error in the dependent variable is randomly distributed around the true

incidence, then the point estimates are unbiased but the standard errors are larger and R-squared is smaller.

The Kiszewski et al. (2004) version of the index only allows for cross-sectional analysis, which would fail to control for many time-static unobserved variables that might bias the estimation. The results in table 2 suggest that an increase of the Malaria Ecology Index by one unit would result in a 23% increase in malaria cases, and a 37% increase in malaria mortality. Figures 8 & 9 below show graphically the how higher values of the malaria ecology index are associated with higher incidence after partialling out country and year dummies in the model. The dotted line shows local regression estimates, while the solid line represents the linear approximation. The densities are provided to indicate that the positive relationship is weakened only where the data is very sparse. Note that the relationship is especially robust across the domain of the malaria ecology residuals in the sub-Saharan Africa data, which is where most of the world's malaria burden is concentrated.

Figure 4-8: Malaria Incidence and Ecology, full sample, 1990-2005

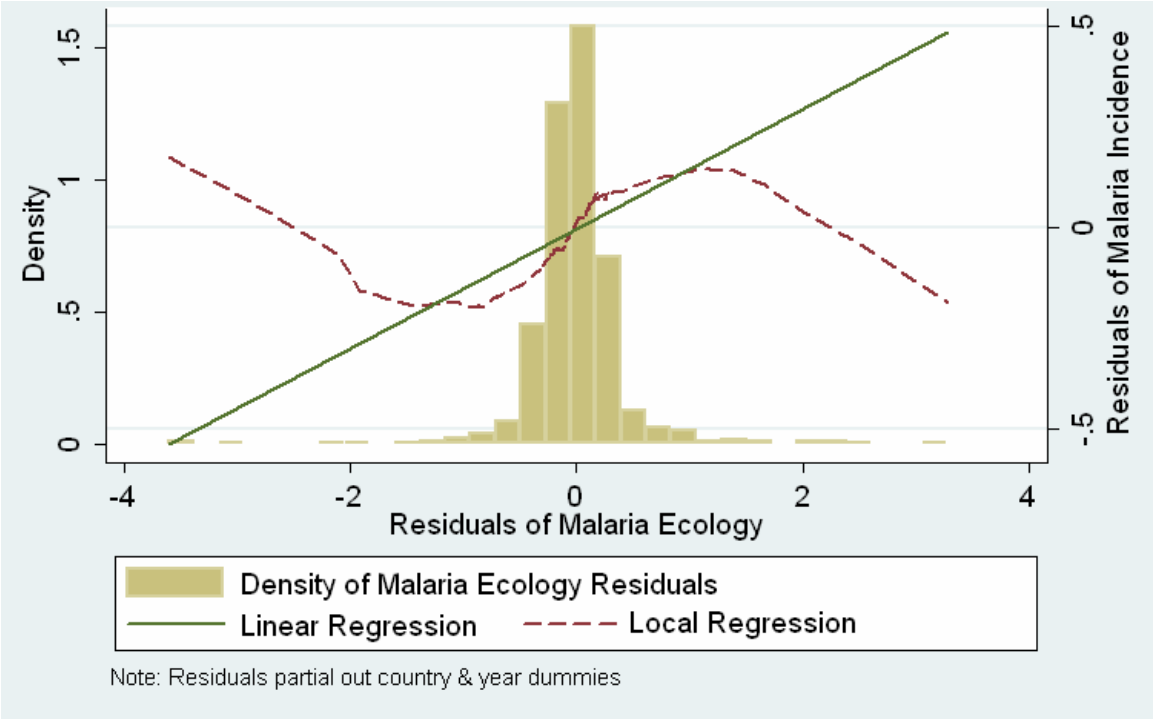
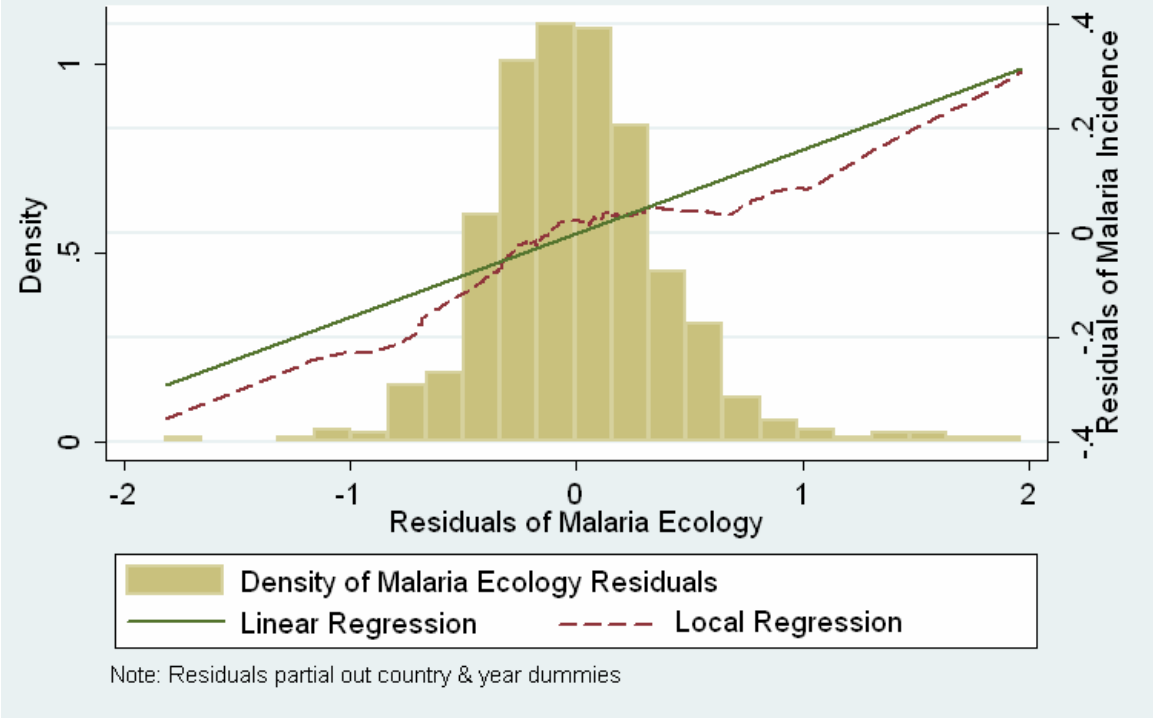


Figure 4-9: Malaria Incidence and Ecology, only sub-Saharan Africa, 1990-2005



Malaria Ecology under Climate Change

The paper has thus far explained the role that ecology plays in the transmission of malaria and constructed a year-to-year ecology-based index proportional to the strength of the disease transmission. I then showed that, as expected, places where malaria elimination occurred during the twentieth century are those where the Malaria Ecology Index (and therefore the pre-public health intervention R_0) was lowest. Finally, the index was shown to have explanatory power over year-to-year variation in both malaria incidence and mortality during 1990-2005. The next step, then, is to use results from a General Circulation Model (GCM) of the global climate to calculate the Malaria Ecology Index under a scenario of climate change later in the 21st century. Here, I use the output from the A1B scenario of the widely-used Hadley 3 GCM of the UK Met Office's Hadley Centre.[12] The A1B scenario assumes a future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and rapid introduction of new and more efficient technologies. I use the Hadley model's projection of

[12] Data can be downloaded from the IPCC at http://www.mad.zmaw.de/IPCC_DDC/html/SRES_AR4/index.html

average monthly temperature and precipitation between 2011-2030 and 2080-2099 to create two maps of the Malaria Ecology Index under a climate change scenario. Note that the maps use the same color ranges as the map above for 1994-2002, so that colors can be directly compared across maps.

Figure 4-10: Malaria Ecology Index in 2020

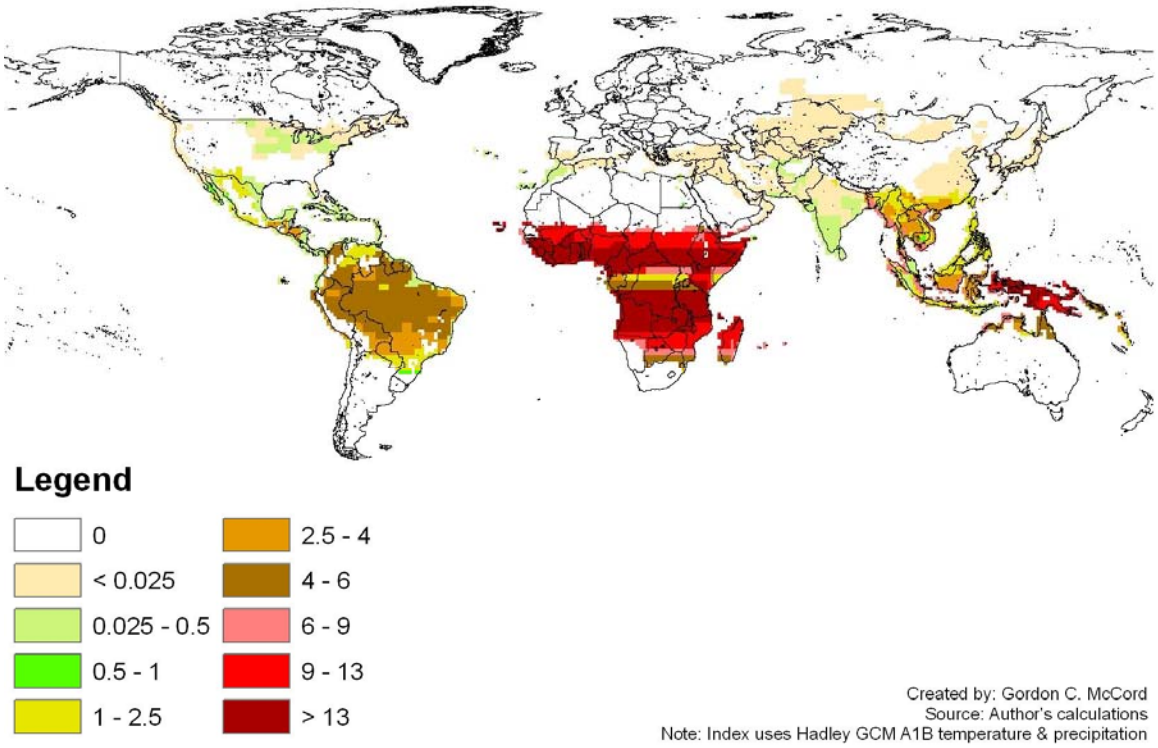
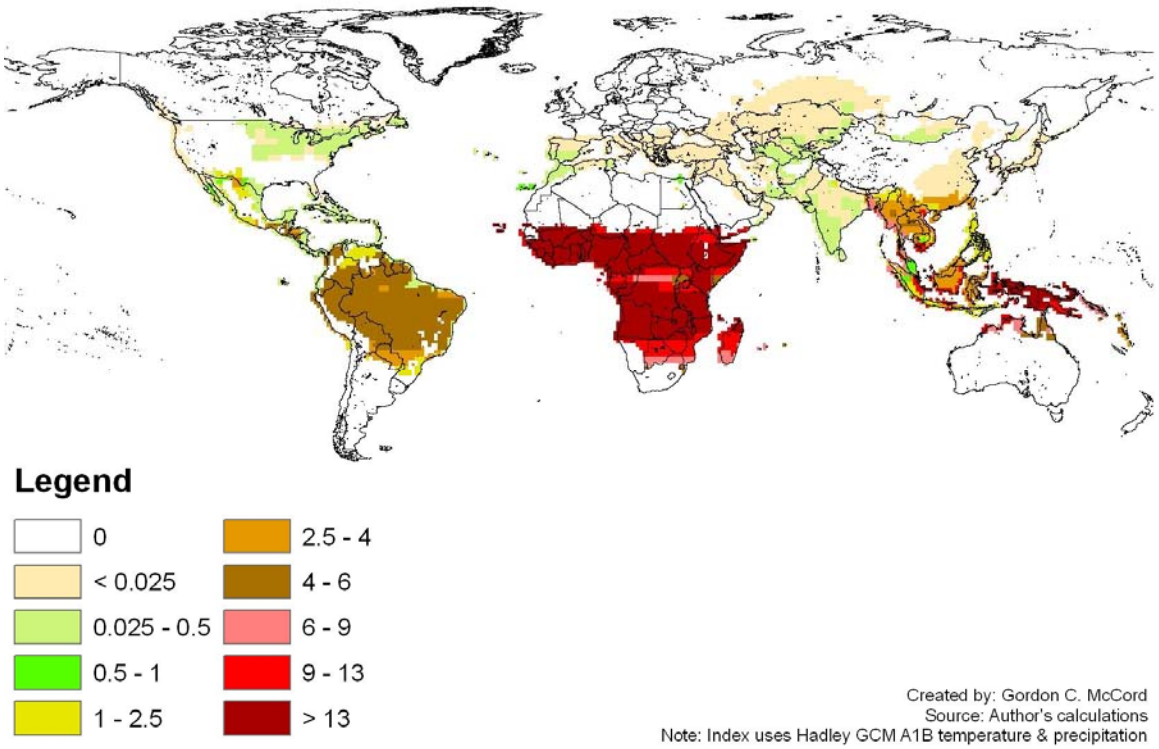


Figure 4-11: Malaria Ecology Index in 2090



The maps of the 2020 and 2090 Malaria Ecology Index clearly show a worsening of malaria conditions for most of the world relative to the 1994-2002 map above. With few exceptions (such as the US southeast, where the MEI drops to zero, and Central Asia, where it decreases), the Malaria Ecology Index increases markedly. If we limit the scope *only* to locations that were malarious in 2002, the average MEI between 1994 and 2002 was 4.74 (as shown on the bar graph above). These same regions are projected to have an average MEI of 6.37 in 2020, and 8.01 in 2090, which would imply an R_0 that is 50-100% higher, and thus complicate the ability of public health efforts to reduce R_0 to below the threshold value of 1.

Implications and Conclusion

The implications of climate change for malaria have been the subject of several studies[13]. This paper adds to this literature by constructing a year-to-year Malaria Ecology Index based solely on ecological factors exogenous to human intervention, and demonstrates the predictive power of the index over the historical record of elimination and over within-country year-to-year fluctuations in malaria morbidity and mortality. Since the MEI represents a part of the basic reproduction number (R_0) equation, and given that public health measures successfully curb a disease when they push the R_0 below 1, then results predicting significant increases in MEI (up to a doubling of the mean MEI by 2090) have profound implications for malaria control. In places of the world where policy choices, resource allocation, and current technologies have struggled to reduce R_0 to below 1 (not coincidentally those places where R_0 is highest), a doubling of R_0 due to climate change would mean that bringing the disease under control will be a much more challenging prospect. Finally, the relationship between the Malaria Ecology Index and malaria incidence and mortality suggest that a doubling of the MEI (a four-point increase from 4 to 8) would lead to a 92% (0.23*4) increase in malaria incidence, and a 148% (0.37*4) increase in mortality rates given calibration using 1990-2005 data. Considering that malaria accounts for over 300 million clinical cases today, and kills between 1-3 million people, such large increases in incidence and mortality rates represent significant burdens on the human population. Since malaria has been showed to exact a measurable economic burden[14,15] and to hinder the demographic transition[16], a worsening of the malaria situation would further push many of the poorest societies away from thresholds they need to reach in order to break their poverty trap.

Improvements in future work will push forward in two directions. First, the Malaria Ecology Index can be calculated for more than one GCM's scenario, or for an ensemble of

---

[13] For example, Lindsay and Martens (1998), Hay et al. (2002), Bouma (2003).
[14]Gallup, John Luke and Jeffrey D. Sachs. "The Economic Burden of Malaria," The Supplement to The American Journal of Tropical Medicine & Hygiene. Vol. 64, no. 1, 2, January/February 2001.
[15] Sachs, Jeffrey D. and Pia Malaney. "The Economic and Social Burden of Malaria." Nature Insight, Vol. 415, no. 6872, Feb. 7, 2002.
[16] McCord, Gordon C., Dalton Conley and Jeffrey D. Sachs. "Improving Empirical Estimation of Demographic Drivers: Fertility, Child Mortality & Malaria Ecology." Social Science Research Network Working Paper. July 2010.

scenarios. In addition, a robustness check would be to construct the MEI for the 20th century using GCM output for the 20th century instead of actual weather data, in order to make sure that differences in past and future MEI are not just due to the difference between actual weather data and a GCM model's output. Secondly, the discussion above of long-term impacts of changes in malaria ecology assumes that no new technologies become available to fight the disease and that countries continue using available technologies at the present rate. In fact, however, economic growth and technological change between now, 2030 and 2090 will likely mitigate some of the effect of a worsening of malaria ecology. While my estimation of malaria ecology's effect on incidence and mortality did include a flexible global time trend to capture some of the increases in public health investments over the period, a more complete model might attempt to jointly estimate malaria ecology and the role of public health spending directly. This would allow calculating the effect of climate change on malaria using the GCM's predicted temperature and precipitation *as well as* the assumptions made in the GCM concerning income levels in 2030 and 2090. I leave such an exercise for future work.

Appendix

The table below presents the region-by-region analysis of the association between malaria ecology and malaria incidence. Sub-Saharan Africa shows the tightest correlation between the two variables. However, adding the other regions increases the strength of the association, indicating that regressing within regions might be resulting in a lack of power, thus explaining the lack of significance.

Table 4-3: Region-by-Region Analysis of Malaria Ecology and Incidence

Independent Variable	Sample	ln(Malaria cases per 1,000 population)	N	countries	within R-squared
Malaria Ecology	Sub-Saharan Africa	0.16*	568	45	0.06
		(1.68)			
	South Asia	1.94	95	6	0.14
		(1.57)			
	East Asia & Pacific	0.05	211	14	0.14
		(0.09)			
	Latin America & Caribbean	-0.13	313	20	0.10
		(-0.14)			
	Middle East & North Africa	0.08	149	10	0.08
		(1.50)			
	All	0.15	1336	95	0.02
		(1.17)			
	All except Middle East & North Africa	0.23**	1187	85	0.02
		(2.20)			

t-statistic in parentheses, * indicates α = 0.10, ** α = 0.05

Regressions include country and year dummies and a constant (not reported)

Regressions report robust standard errors clustered by country

Within R-squared computed without clustering

One reason for why the malaria ecology index performs less well in Latin America is that while the index is calibrated for Plasmodium falciparum, malaria in Latin America is predominantly caused by Plasmodium vivax, which has a slightly different functional form in its temperature-dependent incubation period function. It is worth noting that the index predicts incidence better than mortality, and the likely reason is that malaria mortality data is notoriously poor: data are available for fewer countries than for incidence, and malaria-related death is frequently attributed to other factors. The paucity of good data is especially acute in sub-Saharan Africa, where many countries lack capacity for accurate national data collection. The insignificant results in some of the region-by-region estimates are likely due to insufficient power after year and country fixed effects reduce degrees of freedom, and secondly due to inflated standard errors resulting from measurement error in the dependent variable.

Chapter 5

Improving Empirical Estimation of Demographic Drivers: Fertility, Child Mortality & Malaria Ecology

Gordon C. McCord, Dalton Conley, and Jeffrey D. Sachs[1]

[1] Received "Revise & Resubmit" at the Journal of Development Economics.

Abstract

Much of Africa has yet to go through a demographic transition; this Malthusian crisis of high mortality, high fertility, rapid population growth and chronic extreme poverty has been attributed to factors including the status of women, pro-natalist policies, and poverty itself. Large uncertainty exists among demographers as to the relative importance of these factors, mostly since econometric estimation is complicated by the endogeneity of fertility to other variables of interest. We attempt to improve estimation of the effect of the child mortality variable on fertility by deploying exogenous variation in the ecology of malaria transmission. Results show that child mortality is a powerfully robust driver of fertility behavior. Meeting the Millennium Development Goal of reducing 1990 child mortality rates by 66% in sub-Saharan Africa would translate into a reduction of total fertility rates from around 6.3 in 1990 to 3.3, more than halfway towards achieving replacement fertility levels of 2.1.

Introduction

The broad categories of determinants of fertility are generally thought to be reasonably well identified by demographers, sociologists and economists, though the detailed quantitative determinants of fertility levels and changes are much less understood. The relationships between fertility, on the one hand, and economic development, the status of women, access to family planning, pro-natalist or pro-planning policies of government, and mortality (both adult and child), on the other hand, have been elegantly theorized and extensively studied. Likewise, many researchers have gone before us in empirically modeling these relationships in both cross-country and within-country analyses, some of which explicitly tackle endogeneity problems in estimation using instrumental variables.[2]

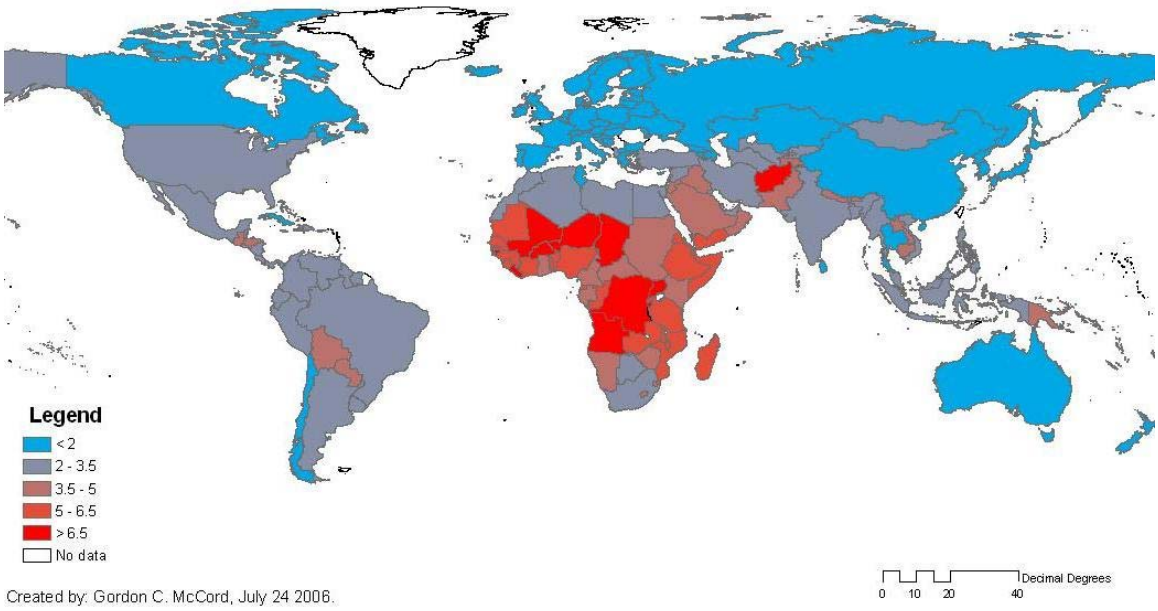
In quantitative terms, however, we still lack a good understanding of why some countries have experienced significant reductions of fertility rates, while those in Africa remain with very high fertility rates—on average difference of almost three births between Sub-Saharan Africa and the rest of the developing world. (See Figure 1, below, for the distribution of total fertility rates in the developing world.) To what extent are Africa's high fertility rates the result of illiteracy, poverty, high child mortality, or lack of access of the poor to contraception? If the region experiences a mortality decline, what would the effect on fertility be? This paper seeks to contribute towards a quantitative assessment of these questions. We acknowledge from the start, however, that many of the potential explanatory variables are only imperfect proxies for the household and community-level drivers of fertility and fertility change. Bongaarts et al.[3] posits that fertility is regulated directly by proximate determinants (e.g., contraception, age at marriage, abortion), while socioeconomic variables (income, education, mortality) affect fertility only indirectly by modifying the proximate determinants. Thus, we can aim only to get a rough quantitative assessment of the role of key categories of determinants, rather than precise point estimates of how specific policy changes would affect fertility rates.

---

[2] The most relevant to this paper are attempts to instrument child mortality: Schultz (1997), Benefo and Schultz (1996), Dreze and Murthi (2001), and Kalemli-Ozcan (2006).

[3] J. Bongaarts, O. Frank, R. Lesthaeghe, The proximate determinants of fertility in sub-Saharan Africa. Population and Development Review, v. 10, no. 3 (Sept), pp. 511-537. 1984

Figure 5-1: Total Fertility Rates (in 2000)



Most theories of the demographic transition have put great stress, and we believe rightly so, on the causal link from high child mortality to high desired fertility. Simply put, when parents do not know whether their children will survive, they respond by having large families. In a high mortality context, cultural patterns – age of marriage, social norms in childrearing, community support structures – also favor high natality. The original model of the demographic transition, indeed, was driven almost solely by child mortality rates. Exogenous changes to child mortality (e.g., the advent of public health, safe drinking water, immunizations, improved nutrition) were seen as the primary precursor to reduced fertility rates—albeit with a lag of one or more generations. This putative lag reflected two things according to the standard analysis: first, the lag in perception of households that mortality rates had indeed come down persistently and reliably; and second, the lag in cultural norms surrounding marriage age, birth spacing, family size, and so forth, all needed to promote the transition from high to low fertility. Many studies found, indeed, that the fertility transition is strongly conditioned by a preceding child mortality transition. That said, recent experience suggests that the lag may be waning and that demographic transitions are happening with increased rapidity once "triggered": whereas Western Europe's transitions took over a century (1800-1930 for Britain), more recent large declines in fertility have happened in as little as twenty or fewer years, such as in Bangladesh,

Mauritius, and Iran (see Marandi et al[4] for a discussion of Iran). Most research attributes these declines to changes in access to family planning (Cleland et al.[5] in the case of the Matlab experiment in Bangladesh or Aghajanian[6] in the case of Iran), although some scholars emphasize female education and child mortality (Raftery et al[7] in the case of Iran). Others suggest that with the advent of mass media, cultural changes—such as those related to fertility behavior—spread more rapidly than they once did. These temporal (and other) challenges of identification leave open questions as to the relative magnitude of the role of child mortality reduction in the context of 20th century fertility declines.

One issue that continues to plague this basic line of research—and therefore which may be relevant to the African question—is the question of causal directionality between child mortality and fertility choice. There is a direct biological effect of high fertility on child survival: short birth intervals can prevent mothers' nutrient repletion in low-income settings, thus compromising the mother's ability to provide nutrients to the fetus during pregnancy.[8] Moreover, several scholars have shown that reduced family size affects human capital investment (Conley and Glauber[9]; Joshi and Schultz[10]; Mogstad and Wiswall[11]) on the micro level as well as

[4] S. A. Marandi, A. Mehryar, M. J. Abbasi-Shavazi, Z. Majdfar, M. H. Shamsian. 2006. "Iran: From Family Sizes of Six to Replacement Levels in 15 Years," in Tobias, Michael, Bob Gillespie, Elizabeth Hughes, and Jane Gray Morrison. No Vacancy: Global Responses to the Human Population Explosion. Pasadena, CA: Hope Publishing House.

[5] J. Cleland, J. F. Phillips, S. Amin, and G.M. Kamal. "The Determinants of Reproductive Change in Bangladesh: Success in a Challenging Environment." World Bank: Washington DC, 1994.

[6] A. Aghajanian. 1991. "Population Changes in Iran, 1966-86: A Stalled Demographic Transition?" Population and Development Review. Vol. 17, No. 4, pp. 703-15.

[7] A. E. Raftery, S. M. Lewis and A. Aghajanian. 1995. "Demand or Ideation? Evidence from the Iranian Marital Fertility Decline." Demography Vol. 32, No. 2, pp. 159-82.

[8] C. Ronsmans, 1996, "Birth spacing and child survival in Senegal," International Journal of Epidemiology (25)5: 989-997.

[9] D. Conley and R. Glauber. 2006. "Parental Educational Investment and Children's Academic Risk: Estimates of the Impact of Sibship Size and Birth Order from Exogenous Variation in Fertility." Journal of Human Resources.

[10] S. Joshi and T. P. Schultz. 2007. "Family Planning as an Investment in Development: Evaluation of a Programs' Consequences in Matlab, Bangladesh." Economic Growth Center Discussion Paper 951. Yale University, New Haven, Connecticut.

[11] M. Mogstad and M. Wiswall. 2009. Family Size and Children's Education: How Linear Models Can Mask a Non-Linear Relationship. NYU Economics Working Paper.

economic growth at the macro level (Hazan and Berdugo[12]; Moav[13]). Likewise, the argument can be made that at least some of the powerful correlation of child mortality and fertility represents increased child mortality because of higher fertility due to increased strain on household caloric resources and decreased parental care and supervision with the addition of more children. With these concerns in mind, in this paper we pursue a strategy of deploying exogenous variation in ecological conditions to derive estimates of the causal impact of child mortality on fertility. We then discuss the implications of these findings for the lagging demographic transition in Africa.

Mortality and Fertility

Chowdhury[14] identifies three possible relationships between fertility and mortality: a lagged causal relationship from mortality to fertility (the theory of demographic transition and choice theory) whether through child "hoarding" (as a precautionary insurance mechanism to guarantee surviving heirs) (Heer and Smith[15]) or direct replacement (for a discussion see, e.g., Cleland[16]); a causal relationship from fertility to mortality (the Ricardian theory); and an interdependent relationship between mortality and fertility (the modern economic theory of population). Note that the causal pathway from high fertility to child mortality works through biological and human capital channels, as mentioned in the previous section. Perhaps the most influential recent model of fertility choice among economists is the economic theory of fertility offered by Becker and Barro[17]. Assuming stable wage rates and interest rates, falling child mortality lowers the costs average cost of raising surviving children since a greater proportion of the total investment in childrearing costs realizes a benefit (assuming little or no benefits from

---

[12] M. Hazan and B. Berdugo. 2002. Child Labour, Fertility, and Economic Growth. The Economic Journal, v. 112, pp. 810-828.
[13] O. Moav. 2005. Cheap Children and the Persistence of Poverty. The Economic Journal, v. 115, pp. 88-110.
[14] A. Chowdhury. 1988. The Infant Mortality-Fertility Debate: Some International Evidence. Southern Economic Journal, v. 54, no. 3, pp. 666-674.
[15] D. M. Heer. and D. O. Smith. 1968. Mortality Level, Desired Family Size, and Population Increase. Demography, v. 5, no. 1, pp. 104-121.
[16] J. Cleland. 2001. "The Effects of Improved Survival on Fertility: A Reassessment." Population and Development Review, Vol. 27, Supplement: Global Fertility Transition, pp. 60-92.
[17] G. Becker. and R. Barro. 1988. A Reformulation of the Economic Theory of Fertility. The Quarterly Journal of Economics, v. CIII, no. 1, pp. 1-25.

non-surviving children). Therefore, the authors argue that fertility rates will initially rise as child mortality declines (and cite evidence to this effect). However, if there is no accompanying change in the parents' interest or wage rates, they argue that there is no cumulative effect. Thus, in the Becker-Barro model, any reduction in fertility resulting from a decline in child mortality would have to work indirectly through wage or interest rates.

Many have attempted to elaborate on the Barro and Becker model theoretically as well as empirically. For example, Doepke[18] seeks to understand whether "stochastic outcomes and fertility choice are quantitatively important." (p. 337) He differentiates between total fertility rate and net fertility rate, the latter being the average number of children per woman surviving to age five. Doepke concludes that child mortality is causally related to declining fertility rates, but that other factors are responsible for declines in net fertility. With *replacement* as the mechanism, each family has a target number of children. The death of one child induces the family to replace that child and, as a result, mortality directly affects total fertility rate. However, for mortality to affect the net fertility rate, the *hoarding* motive would have to take place. Parents would preemptively increase their fertility to protect against potential loss. If this mechanism is present, then a decline in mortality would result in a decline in net fertility. Doepke tests three models. He reports that "all three models are consistent with declining total fertility rates (i.e. number of births) in response to falling mortality. However, we are left without a clear-cut prediction for the relationship of child mortality to net fertility (i.e. the number of survivors)." (p. 344)

In his attempts to test for causality, Chowdhury[13] finds no consistent results across his thirty-five country sample. Fourteen of his cases support the hypothesis that infant mortality causally impacts fertility, while only two cases support the opposite hypothesis. The remaining cases indicate feedback between the two variables, or the absence of a relationship between fertility and mortality. His results provide stronger support for the hypothesis that mortality effects fertility, but they are notably (and admittedly) inconclusive. Meanwhile, Zakir and

[18] M. Doepke. 2005. Child mortality and fertility decline: Does the Barro-Becker model fit the facts? Journal of Population Economics, v. 18, pp. 337-366.

Wunnava[19] found that fertility rates impact mortality rates, and not vice-versa. Their model employs GLS regression on cross-sectional data and fails to acknowledge the endogeneity of fertility and mortality, leading to a model that is notably mis-specified.

Seeking to better address the endogeneity of child mortality and fertility, Schultz[20] instruments mortality using calorie availability. However, the validity of his instrument is open to question, as one can imagine a direct, negative causal impact of calorie availability on fertility. Moreover, the instrumented child mortality variable is significant only in cross section and not after including country dummies. In another attempt to deal with endogeneity concerns, Benefo and Schultz[21] instrument child mortality using variables for community health services and environment, including distance to a market, distance to a clinic, amount of rainfall and malaria/measles. However, the authors discover that child mortality is only statistically significant if treated as an exogenous variable, but when instrumented by community health services and environment, mortality is not a statistically significant determinant of fertility. Likewise, Dreze and Murthi[22] instrument mortality using access to safe drinking water, claiming that the latter variable should be unrelated to fertility except through its effect on mortality—again a questionable estimation assumption since safe drinking water is correlated to economic development, which should have an independent effect on fertility. Finally, Kalemli-Ozcan[23] examines the impact of AIDS mortality on halting the demographic transition in Sub-Saharan Africa by using circumcision prevalence as an instrument for AIDS risk. She finds that the AIDS mortality crisis has indeed led to high fertility rates and less human capital investment in

---

[19] M. Zakir and P. Wunnava. 1999. Factors affecting infant mortality rates: evidence from cross-sectional data. Applied Economics Letters, v. 6, pp. 271-273.
[20] Schultz, T. Paul. 1997. Demand for Children in Low Income Countries. in Rosenzweig, M. R. and Stark, O. (eds.) Handbook of Population and Family Economics.
[21] Benefo, Kofi and Schultz, T. Paul. 1996. Fertility and Child Mortality in Cote d'Ivoire and Ghana. The World Bank Economic Review, v. 10, no. 1, pp. 123-158.
[22] Dreze, Jean and Murthi, Mamta. 2001. Fertility, Education, and Development: Evidence from India. Population and Development Review, v. 27, no. 1, pp. 33-63.
[23] Kalemli-Ozcan, Sebnem. 2006. "Aids, 'Reversal' of the Demographic Transition and Economic Development: Evidence from Africa." NBER Working Paper Series, w12181,

offspring (the effects of HIV on fertility are debated, however, as Fortson[24] has found very little effect of HIV prevalence on fertility).

It is worth noting that all of these studies find a relatively small elasticity of child mortality to fertility. If we convert their coefficients to percentages using sample means, Benefo and Schultz [20] find an elasticity of 0.02-0.03, and admit that, "…we estimate that four to fifteen fewer child deaths are associated with a reduction of only one birth. We have no good explanation for the small size of this estimate of the fertility response to child mortality." (p.152) Similarly, Kalemli-Ozcan (2006) finds an elasticity of 0.02 (after converting to percentages), while Dreze and Murthi (2001) find an elasticity of 0.11 in the specification using IV, although the instrument's validity might be open to question. Finally, Schultz (1997) finds an elasticity of .64 (converted to percentages) when instrumenting child mortality with caloric intake, but only achieves significance in cross-section and is thus open to more omitted variable bias.

Malaria Ecology

To preview our empirical approach, we argue that the strength of malaria transmission as a function of ecological factors is exogenous to fertility, and use it as an instrument for child mortality. Malaria is currently the fourth leading cause of death (after neonatal disorders, diarrhea, and pneumonia) for children under five in low income countries (see Black et al.[25]) and is responsible for at least one in every five child deaths in sub-Saharan Africa.[26] Estimates of malaria mortality in Africa range from one million to three million deaths per year. Malaria mortality, in turn, is highly sensitive to ecological conditions, as explained below. Employing malaria ecology as an instrument does not imply, of course, that malaria is the only disease

[24] Fortson, Jane, 2009, "HIV/AIDS and Fertility," American Economic Journal: Applied Econometrics 1:3, 170-194.

[25] Black R.E., Morris S.S., and Bryce J. 2003. Where and why are 10 million children dying every year? Lancet, v. 361, pp. 2226-2234.

[26] Since infection with malaria leaves an individual more vulnerable to morbidity and mortality from other infections, malaria is an indirect as well as a direct killer. It is very likely implicated in more than one fifth of all deaths. In some malaria control trials, the reduction of malaria has reduced all-cause under-5 mortality by as much as 40 percent.

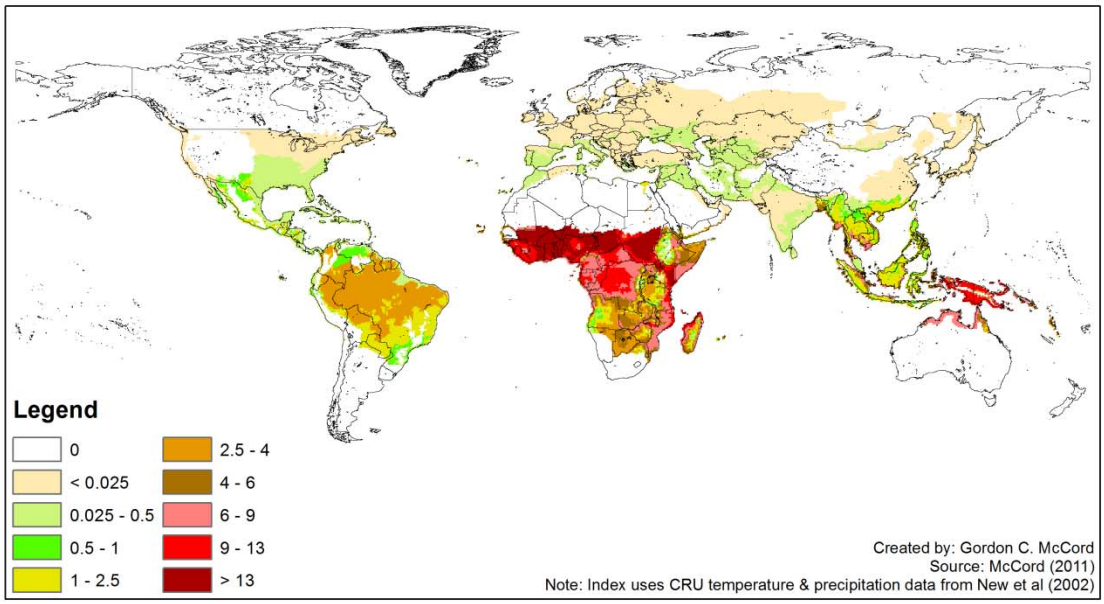
affecting child mortality. However, its strong link to ecology allows us to exploit it in order to remove the endogenous part of child mortality rates and isolate its causal effect on fertility.

Specifically, we deploy an ecological index of malaria transmission (used elsewhere as well; see, e.g., Sachs[27]; Carstensen and Gundlach[28] for the use of a time-static version, and McCord[29] for the time-varying version). The index combines ecological factors—rainfall and temperature—with biological ones such as the human biting preference of the mosquito species that serves as the vector for the transmission of malaria (see the Appendix for more details on the construction of the index). It is worth highlighting that the index does not include any information on human population nor on mosquito abundance; both variables affect actual malaria outcomes but are endogenous to fertility and public health efforts and are excluded from the index construction. The 1960-2005 average distribution of this malaria ecology index is mapped in Figure 2, below. While the underlying factors determining malaria transmission may be endogenous to human population movements over the course of thousands of years (through co-evolution with mosquito species), we assert that from the point of view of the current demographic transition in recent decades the biophysical ecology of malaria transmission is exogenous. Moreover, we expand over Conley et al.[30] by employing the time-varying version of malaria ecology: this allows us to pursue a longitudinal strategy within countries over time, which, in turn allows for a fixed-effects approach to factor out time-invariant country-specific determinants of fertility. The index varies month to month only with changes in temperature and changes in the dominant anopheles vector due to seasonality or varying precipitation. Each anopheles vector has a different human biting preference, which affects the index. More detailed information on the index construction is available in the appendix and in Chapter 4.

---

[27] Sachs, J.D. 2003. Institutions Don't Rule: Direct Effects of Geography on Economic Development. NBER Working Paper 9490.
[28] Carstensen, Kai and Gundlach, Erich. 2006. The Primacy of Institutions Reconsidered: Direct Income Effects of Malaria Prevalence. The World Bank Economic Review, v. 20, no. 3, pp. 309-339.
[29] See Chapter 4 of this dissertation.
[30] Conley, D., McCord, G.C., and Sachs, J.D. "Africa's Lagging Demographic Transition: Evidence from Exogenous Impacts of Malaria Ecology and Agricultural Techonology." National Bureau of Economics Research Working Paper No. 12892. February 2007.

Figure 5-2: Malaria Ecology Index (averaged over 1960-2005)



It is important to note that this malaria ecology index does not include the number of malaria cases or deaths, but only the potential strength of transmission, which we argue should be exogenous to fertility. However, another concern might be the exclusion restriction that malaria ecology might affect total fertility rates through another channel besides child mortality. A review of the medical literature shows that malaria may have a direct effect on fertility through malaria-related severe anemia, as well as through increased incidence of hypertensive diseases of pregnancy and spontaneous abortion.[31,32,33,34,35] Since these prevent a live birth, and since TFR counts only live births, then this effect should work in the opposite direction of our putative causal model, thereby biasing any net effect of child mortality on fertility toward zero. Likewise,

---

[31] Etard, J.F., Kodia, B. and Ronsmans, C. 2003. Seasonal Variation in Direct Obstetric Mortality in Rural Senegal: Role of Malaria? American Journal of Tropical Medicine and Hygiene, v. 68, no. 4, pp. 503-504.

[32] Maubert, Bertrand, Fievet, Nadine, Tami, Germaine, Cot, Michel, Boudin, Christian, and Deloron, Philippe. 1999. Development of Antibodies against Chondroitin Sulfate A-Adherent Plasmodium falciparum in Pregnant Women. Infection and Immunity, v. 67, n. 10, pp. 5367-5371.

[33] Sartelet, H., Rogier, C., Milko-Sartelet, I., Angel, G., and Michel, G. Malaria associated pre-eclempsia in Senegal. 1996. Lancet, v. 347, n. 9008, p. 1121.

[34] Guyatt, H.L., and Snow, R.W. 2001. Malaria in pregnancy as an indirect cause of infant mortality in sub-Saharan Africa. Transactions of the Royal Society of Tropical Medicine and Hygiene, v. 95, n. 6, pp. 569-576.

[35] See also http://www.rbm.who.int/cmc_upload/0/000/015/369/RBMInfosheet_4.htm for overview information on malaria in pregnancy.

maternal malaria during pregnancy is also associated with low birth weight and increased neonatal and infant mortality—which is in line with our models. That said, there is some evidence that malaria may reduce lactation period (Bates et al.[36]), which might increase fertility through decreased child spacing. Malaria might also increase maternal mortality, however this does not affect the calculation of total fertility rates; TFR is calculated as the average number of children a hypothetical woman would have at the end of her reproductive period if she were subject during her life to the fertility rates of a given period. Finally, Lorentzen, McMillan, and Wacziarg[37] have argued that adult mortality should have an independent effect on fertility (and child human capital investment) by changing the discount rate of mothers and fathers. However, we note that although malaria can kill adults, most malaria mortality occurs among children.

As an added motivation for the adequacy of the malaria ecology instrument, we tested its relationship to national level malaria incidence and mortality data from 1990-2005 as reported by WHO[38]. The evolution of malaria ecology and malaria incidence (in cases per thousand people) is shown in Figure 3 below for Colombia and Ethiopia. Note that the lack of monotonicity in the index and lack of country-level trends assuage concerns that later results are due to common trends in fertility, malaria ecology, and an unobserved determinant of fertility. We run country-level regressions of the annual incidence (cases per thousand people) on the malaria ecology for that year, using country dummies, country-specific time trends, and weighing observations by population. The results are in Table 1 below, and show that higher values for the index are associated with higher malaria incidence and mortality after including country and period dummies and country-specific time trends.

---

[36] Bates I, Fenton C, Gruber J, Lalloo D, Medina Lara A, Squire SB, Theobald S, Thomson R, Tolhurst R. 2004. Vulnerability to malaria, tuberculosis, and HIV/AIDS infection and disease. Part 1: determinants operating at individual and household level. Lancet Infectious Disease, May; 4(5): 267-77.

[37] P. Lorentzen, J. McMillan, and R. Wacziarg. 2005. "Death and Development." NBER Working Paper No. 11620.

[38] World Health Organization. 2008. World Malaria Report 2008. Geneva.

Figure 5-3: Malaria Incidence & Ecology in Colombia & Ethiopia

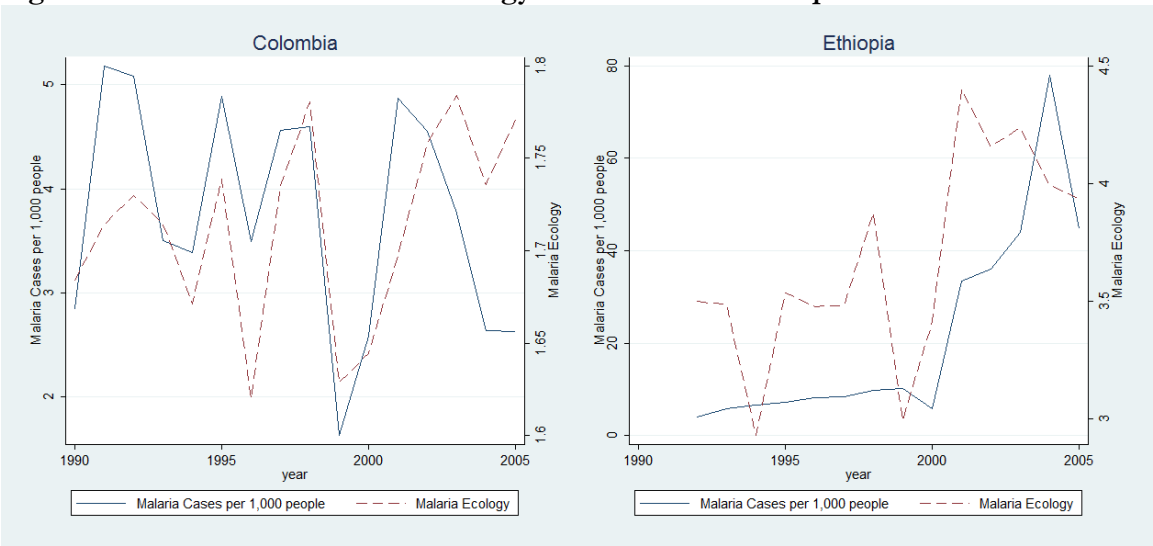


Table 5-1: Malaria Ecology and Malaria Incidence & Mortality

Dependent Variable:	(i) ln(Malaria cases per 1,000 population)	(ii) ln(Malaria deaths per 1,000 population)
Independent Variables		
Malaria Ecology	0.23**	0.37**
	(2.20)	(2.56)
N =	1187	534
Countries =	85	72
Years =	1990-2005	1990-2005
Within R-squared =	0.02	0.20

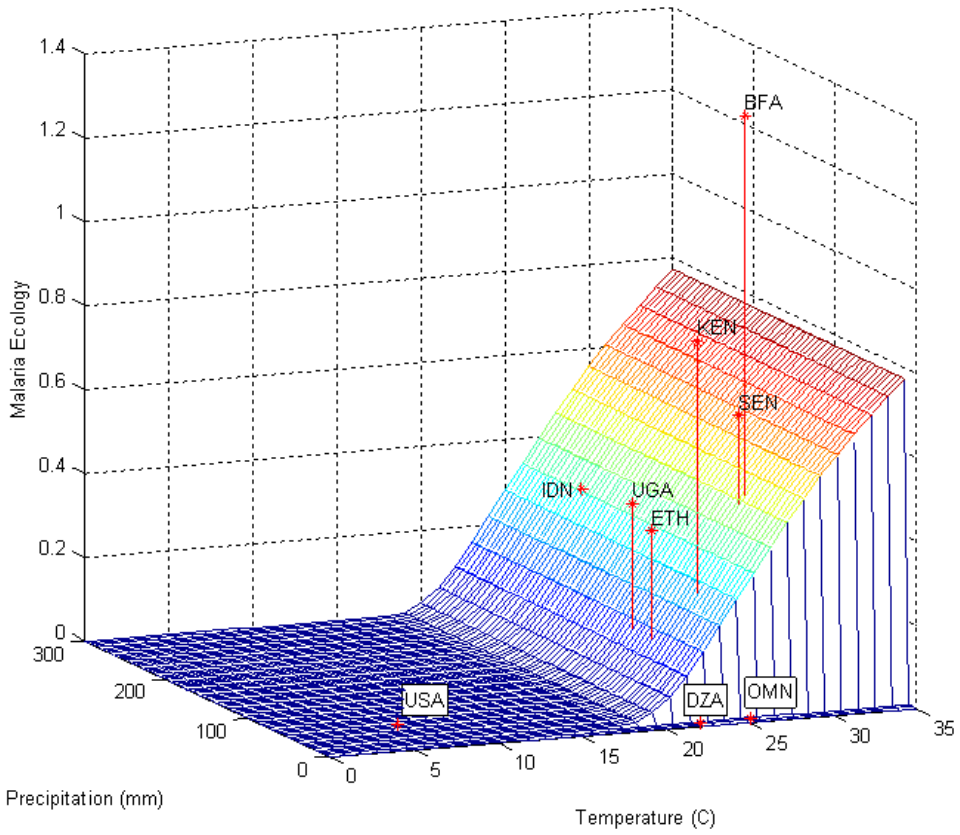
t-statistic in parentheses, ** indicates significant to 95% confidence.
Sample includes Latin America & Caribbean, Sub-Saharan Africa, East Asia & Pacific and South Asia
Regressions include country and year dummies and a constant (not reported)
Regressions report robust standard errors clustered by country
Regressions w eigh observations by population

In order for the malaria ecology instrument to be valid, it is important that the instrument affect fertility only through child mortality. As mentioned earlier, malaria ecology might have direct effects on fertility largely through spontaneous abortion, but this would result in attenuation bias. One may also be concerned that temperature and precipitation are components of the index and they could affect fertility through other channels (such as

agricultural production as in Jones and Olken[39], and thus the return to children's labor on the field). However, note that the climatic variables enter the index in a specific nonlinear form emerging from the epidemiological dynamics and so unlikely to be strongly correlated to agriculture or other non-epidemiological systems. Figure 4 below plots the malaria ecology index against temperature and precipitation to illustrate the nonlinearity. Since the human biting rate of the local dominant anopheles vector also goes into the index, the figure shows the value of the function at all levels of precipitation and temperature for a given HBI of 0.5, as well as the actual value of several countries on an average month (these countries are not on the surface because they have HBI different from 0.5). Correlation between the index and agricultural yields is -.35, and malaria ecology has no effect on yields after controlling for temperature, precipitation, and country-specific time trends (this table is available upon request). Moreover the analysis below will demonstrate that the estimation of the child mortality effect is robust to including temperature and precipitation as controls, as well as agricultural yield.

[39] Jones, Benjamin F. and Benjamin A. Olken. 2010. "Climate Shocks and Exports." American Economic Review: Papers & Proceedings 100:454-459.

Figure 5-4: Malaria Ecology & Temperature, Precipitation (for HBI = 0.5)



Data

We compiled a national-level, cross-country dataset covering the period 1960-2005. The demographic data (fertility, infant mortality and child mortality) come from the U.N. Population Division[40]. All other data sources are described below.

A note on the time series: the time series data we use in this dataset is divided into quinquennia, beginning in 1960 and ending in 2005. This is determined largely by the fact that the U.N. Population Division, our main source for demographic data, uses five year averages for several of the key demographic variables considered in our analysis, such as TFR and child

[40] United Nations Population Division. 2004. World Population Prospects: the 2004 Revision.

mortality. Whenever we have used yearly time series data, we compute five year averages for the appropriate quinquennia.[41]

The variables used in the analysis are the following:

TFR: Total fertility rate, or number of children per woman of reproductive age. Data from the U.N. Population Division reported as 5 year averages.

Under-5 Mortality Rate: Data from the U.N. Population Division on the mortality rate in children under the age of 5, collected in averages over 5 year periods. Note that we use the natural logarithm of both total fertility and child mortality; the natural limits to a childbearing during a woman's reproductive lifetime suggest a nonlinear relationship which calls for a log-log approach. Figures 5 & 6 show the bivariate relationship between fertility and child mortality with and without logarithms; evidently the log-log form is more appropriate in the linear regression context.

[41] The quinquennia are the following: 1960 through 1964; 1965 through 1969; 1970 through 1974; 1975 through 1979; 1980 through 1984; 1985 through 1989; 1990 through 1994; 1994 through 1999; 2000 through 2004.

Figure 5-5: Total Fertility Rate & Under-5 Mortality

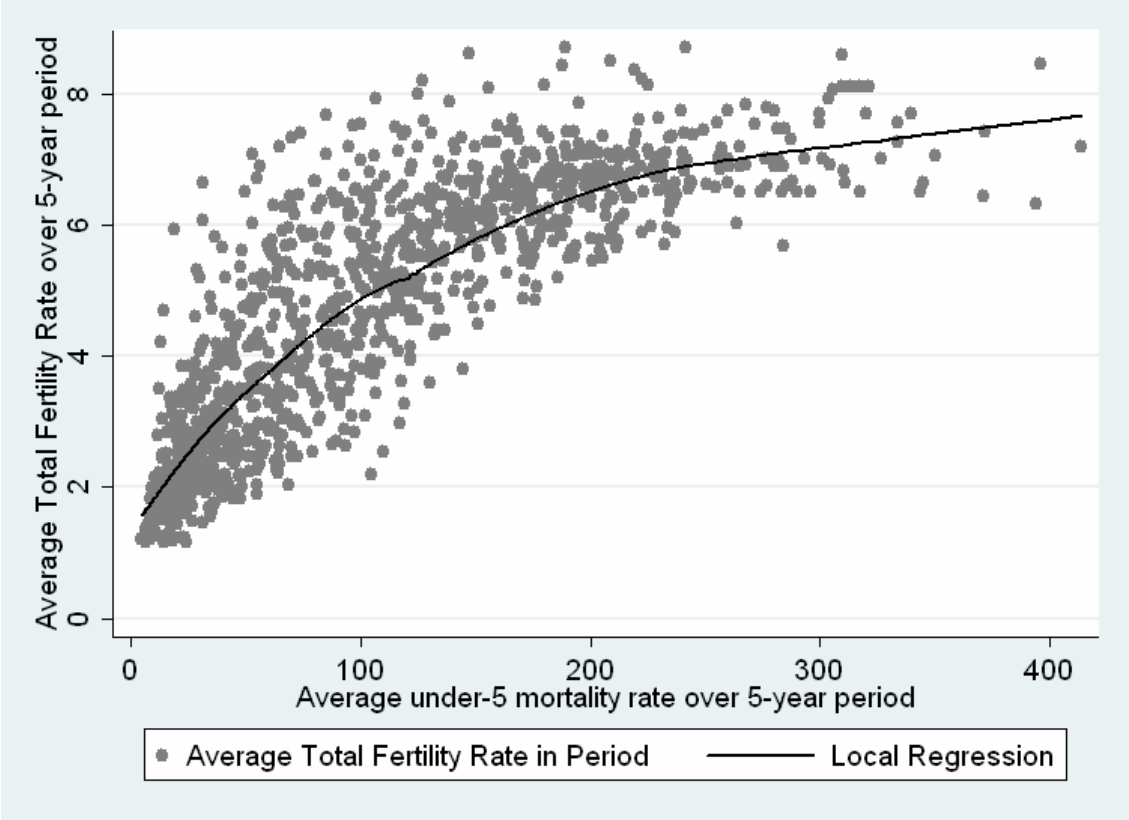
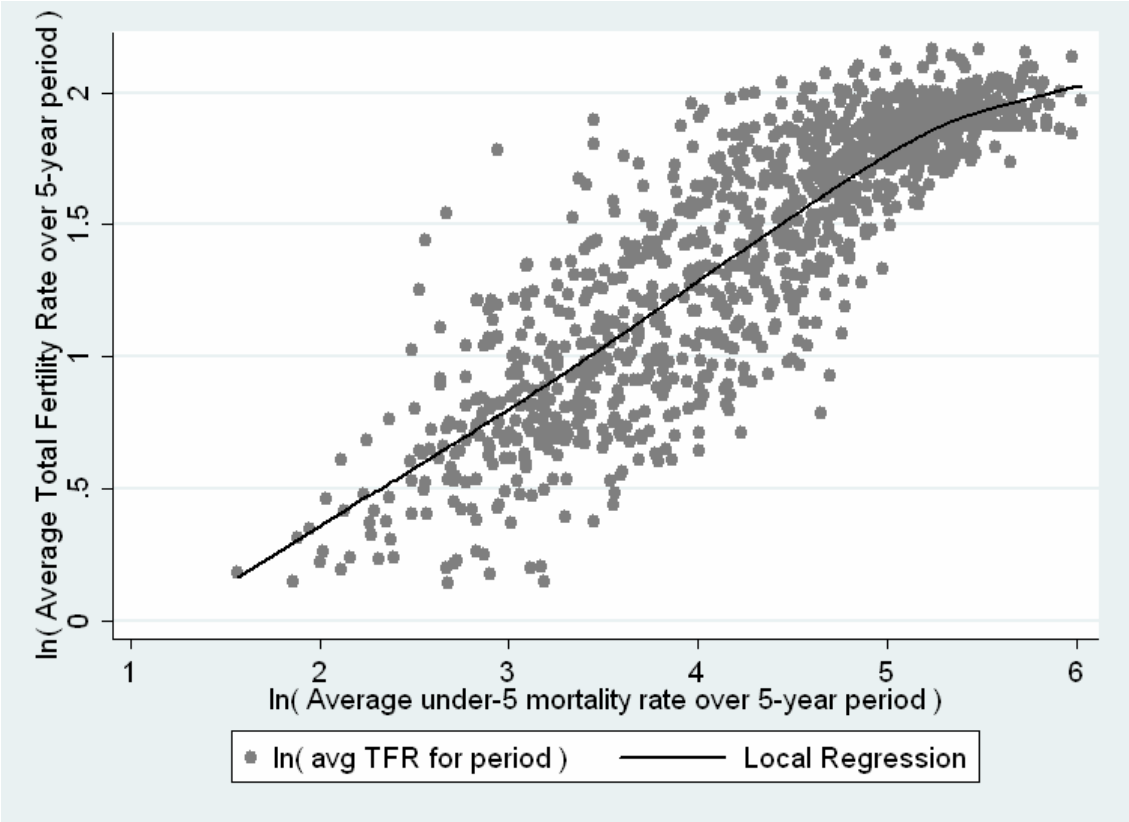


Figure 5-6: Total Fertility Rate & Under-5 Mortality (ln-ln transformation)



Index of malaria ecology. Malaria Ecology is an ecologically-based spatial index of the stability of malaria transmission based on the interaction of climate with the dominant properties of anopheline vectors of malaria that determine vectorial capacity (Kiszewski et al.[42]). The index is constructed on a 0.5 degree spatial grid to derive the climatic characteristics of individual months, and then averaged over a 12-month period for every year (McCord, 2011). For a complete description of the ME variable see the appendix. Note that the index does not rely on disease incidence or human mortality or morbidity, but instead only on biophysical factors, and therefore provides a variable that is ideally exogenous to human intervention.

[42] Kiszewski, Anthony, Mellinger, Andrew, Spielman, Andrew, Malaney, Pia, Sachs, Sonia Ehrlich, and Sachs, Jeffrey. 2004. A Global Index Representing the Stability of Malaria Transmission. American Journal of Tropical Medicine and Hygiene, v. 70, no. 5, pp. 486-498.

Temperature and Precipitation. The Malaria Ecology variable is constructed using temperature and precipitation data from the Climate Research Unit in East Anglia, described in New et al[43]. The data is available monthly at the 0.5 degree grid cell level from 1901-2006; we use data from 1960-2006.

Log of GDP per capita, measure at purchasing-power-parity, in 2000 international dollars. Yearly data are taken from the World Bank's World Development Indicators database[44]. We calculate our own averages for each 5 year period.

Average years of females' secondary schooling: Data are from Barro and Lee[45]. We calculate our own averages for each five-year period. We chose this age band to measure educational attainment since it was presumed that post-puberty adolescence and young adulthood were the critical time periods during which "fertility engines" would ignite (Wu and Martin[46]) and thus the correct population to measure.

Region: We use the World Bank regional classifications, with a dummy variable for Sub-Saharan African countries. Please see the World Bank's *World Development Indicators 2009* for more information regarding how specific countries are classified.

Population: Total population by country. Five year averages calculated from U.N. Population Division yearly data. Given that the sample includes large and small countries, we use weighted least squares and weigh observations by country population in expectation that variance is likely higher in smaller countries. (Results are unchanged if no weights are used).

---

[43] New, M. Lister, D., Hulme, M. and Makin, I. 2002. A high-resolution data set of surface climate over global land areas. Climate Research 21.
[44] World Bank. 2009. World Development Indicators. Accessed from http://publications.worldbank.org/WDI/
[45] Barro, Robert J and Jong-Wha Lee. A New Data Set of Educational Attainment in the World, 1950-2010. NBER Working Paper 15902. April 2010.
[46] Wu, Lawrence and Stephen Martin. 2002. "Is There an Engine of Nonmarital Fertility?" University of Wisconsin, CDE Working Paper No. 2002-14.

Cereal Yields per Hectare: Kilograms per hectare of harvested land of wheat, rice, maize, barley, oats, rye, millet, sorghum, buckwheat, and mixed grains (World Bank, 2009).

Means and standard deviations for the sample of country-years are presented in Table 2, below. We present un-weighted values, as well as values obtained using weights by population size. Weighting by population size diminishes mean TFR in our sample by less than 1 child per woman (4.71 to 3.84), and reduces the mean child mortality rate by around 15 deaths per 1,000 live births.

Table 5-2: Means and Standard Deviations of Variables in Sample

	Mean		Standard Deviation	
	Un-weighted	Population weighted	Un-weighted	Population weighted
Variable				
Total Fertility Rate	4.71	3.84	1.93	1.70
Under 5 mortality rate (per 1,000)	108.8	93.64	80.3	62.98
Malaria Ecology Index	2.73	1.49	3.97	3.01
Average Temperature (°C)	20.4	17.38	7.36	9.2
Average Precipitation (mm)	101.5	86.27	70.0	56.7
GDP per capita, PPP, constant $	4,224	2,942	3,838	2,985
Females' Years of Secondary Schooling	1.11	1.01	1.10	0.84
Average Population (millions)	28.9	475	114	472
Cereal Yields per Hectare (kg/ha)	1,682	2,459	1,054	1,293
Year	1986.5	1988.9	12.5	12.0

Methods and Findings

In order to evaluate the effects of child mortality on fertility we employ several statistical models on our panel. We first use reduced form OLS, then OLS with fixed effects, and then test which of those two models is preferred. We then move to an instrumental variable framework (instrumenting for child mortality) using malaria ecology. We test for the endogeneity of the child mortality variable and the strength of the malaria ecology instrument in the first stage.

Table 5-3: OLS and Fixed-Effects Regression of Total Fertility Rates

	(i)	(ii)	(iii)	(iv)	(v)
Dependent Variable:	ln(TFR)	ln(TFR)	ln(TFR)	ln(TFR)	ln(TFR)
Independent Variables					
Sub-Saharan Africa dummy	0.66***	0.21***	0.46***	0.71***	
	(6.41)	(4.18)	(5.23)	(3.95)	
ln(under-5 Mortality Rate)		0.46***			0.1*
		(8.30)			(1.82)
Females' Years of Secondary Schooling			-0.27***		-0.07
			(-7.38)		(-1.54)
ln(GDP per capita, in PPP prices & constant $)				-0.06	0.07**
				(-0.73)	(2.28)
N =	1255	1142	896	735	536
R-squared =	0.50	0.81	0.64	0.48	0.83

t-statistics in parentheses; *** indicates significant to 99% confidence, ** to 95%, and * to 90%.
All regressions include year dummies and a constant, which are not reported.
All regressions weigh observations by population and report robust standard errors clustered by country
Regression (v) includes country dummies
All regressions exclude high-income countries
R-squared for (v) is within R-squared, calculated by running regression without weights or clustering

We begin the reduced form OLS analysis looking simply at regional deviations from a baseline time trend (regression (i) in Table 3). Since we are interested primarily in sub-Saharan Africa, we collapse the other World Bank regions into the suppressed category in order to interpret the difference between sub-Saharan Africa and the rest of the developing world. Note that high-income countries are excluded, since they have completed the demographic transition and intertemporal variation in fertility is likely to be following very different dynamics. From regression (i) we see that sub-Saharan Africa has a TFR that is roughly 90% higher ($e^{.66}$) than the rest of the developing world. Regression (ii) then looks at child mortality, the variable of interest. The regression surely suffers from endogeneity (we have discussed above how high fertility can impact child mortality, and how previous studies have found child mortality to be endogenous after formal tests), so while it is not a perfect model and does not allow us to deduce causality or interpret coefficients, it documents the strength of the correlations between these variables and fertility. Regressions (iii) – (iv) add other variables which we will use as controls in the analysis (income and women's education). In this simplified framework, all of the variables come out as significant and with predicted signs (high child mortality is associated with higher fertility, while increasing income and increasing women's education are associated with lower fertility). Note that there are several observations for every country in the sample, so we

estimate Huber-White standard errors robust to clustering within countries in regressions (i) – (iv). Regression (v) is estimated using fixed-effects. All variables maintain their significance and sign. Note that the sub-Saharan Africa dummy with the controls in these "naïve" models comes down from .56 in every case, and as low as 0.21 when child mortality is included. Although this equation is mis-specified, the result motivates a careful examination of child mortality in explaining Africa's high fertility rates. When the control variables are all included in this naïve regression, the variables are all significant, but the coefficient on income switches sign, owing most probably to the multicollinearity between the variables. Regression (v) moves to a fixed-effects framework by inserting country dummies (this now discards all cross-country variation and uses the controls to explain within-country variation in TFR). All the variables are now significant when included jointly. A Hausman test to compare the two specifications (an OLS and fixed-effects version of regression (v)) rejected the null that the OLS model is valid, leaving us with the fixed effects specifications as preferred.

We tested the robustness of the FE regression (v) by omitting the income variable, since the purported endogeneity of income might be biasing other coefficients. Both the child mortality and female education variables remain significant and of comparable magnitude.

We then move to the instrumental variables framework, where the time-varying malaria ecology variable instruments for child mortality. All regressions include country dummies to reduce omitted variable problems, all include global period dummies to flexibly control for global trends, and all weight the observations by population. Note that following Bertrand et al[47], the serial correlation in our dependent variable (fertility) calls for clustering by country in all regressions. Regression (i) is the first stage of the basic regression, showing that the exogenous malaria ecology is leading to increases in child mortality. The second stage is (ii), where the instrumented child mortality variable

[47] Bertrand, Marianne, Esther Duflo and Sendhil Mullainathan. 2004. "How Much Should We Trust Differences-in-Differences Estimates?" Quarterly Journal of Economics. Vol. 119, No.1, pp. 249-75.

Table 5-4: Instrumenting for Child Mortality using Malaria Ecology

Dependent Variable:	(i) ln(u5MR)	(ii) ln(TFR)	(iii) ln(u5MR)	(iv) ln(TFR)	(v) ln(u5MR)	(vi) ln(TFR)	(vii) ln(u5MR)	(viii) ln(TFR)	(ix) ln(u5MR)	(x) ln(TFR)
Independent Variables										
Malaria Ecology	**0.31**		**0.32**		**0.28**		**0.21**		**0.23**	
	(9.84)		**(10.06)**		**(8.11)**		**(4.98)**		**(6.13)**	
ln(under-5 Mortality Rate)		**0.77**		**0.85**		**0.60**		**0.68**		**0.67**
		(6.59)		**(6.27)**		**(4.96)**		**(3.48)**		**(3.18)**
Females' Years of Secondary Schooling							**0.11**	-0.02		
							(-3.73)	(-0.27)		
ln(GDP per capita, in PPP prices & constant $)									0.04	0.02
									(1.60)	(0.45)
Average temperature over period			**-0.07**	-0.14						
			(-2.44)	(-2.09)						
Average precipitation over period			-0.002	0.001						
			(-1.58)	(0.37)						
ln(Cereal Yield per Hectare)					**-0.22**	-0.23				
					(-4.26)	(-1.44)				
N =	1134	1134	1134	1134	1001	1001	857	857	717	717
Countries =	142	142	142	142	136	136	100	100	134	134
F-test on instrument =	16.46		19.14		12.7		4.6		10.34	
Cragg-Donald Statistic =	96.76		101.11		65.72		24.77		37.58	
Within R-squared =	0.77	0.74	0.77	0.73	0.78	0.74	0.80	0.81	0.71	0.72

t-statistics in parentheses; *** indicates significant to 99% confidence, ** to 95%, and * to 90%.
All regressions include country dummies, time period dummies and a constant (not reported).
Regressions (i), (iii), (v), (vii), and (ix) are first stage for (ii), (iv), (vi), (viii), and (x) respectively.
All regressions weigh observations by population
All regressions exclude high-income countries.
All regressions reports robust standard errors clustered by country
Within R-squared computed without clustering or analytical weights

has a coefficient of 0.77 (larger than the estimates in Table 3).

Evaluating the lag structure of child mortality's effect on fertility is nontrivial in an instrumental variables framework. We ran regression (ii) and its first stage using the contemporary and one of 5-year, 10-year, 15-year, and 20-year lagged values of child mortality instrumented by the lagged malaria ecology (these results are not reported in the table). Only with the 10-year lag did the child mortality coefficient remain significant, and the magnitude of the contemporary and lagged coefficients were about equal and half of the coefficient in regression (ii). As a test for reverse causation from fertility to mortality, we included different leads to the regression with a 10-year lag, and in all cases the lead was not significant. Regression (iv) and its first stage (iii) add temperature and precipitation to show that the malaria ecology instrument and the estimate for child mortality are robust to those controls (the first stage coefficient hardly changes, and the coefficient on child mortality increases to 0.85), and in fact malaria ecology is capturing the nonlinear relationship between climate and disease transmission. To further assuage concerns that the malaria ecology instrument might be affecting fertility through a channel other than child mortality, we control for cereal yields per hectare in regression (vi) and find that instrument is still significant in the first stage and the coefficient on child mortality drops to 0.60. Adding females' years of secondary schooling in (viii) reduces the child mortality coefficient to 0.68 (though the education variable itself isn't significant in the second stage). Including income in (x) reduces the child mortality coefficient to 0.67.

Table 5 limits the sample to low-income countries. The results are qualitatively the same as using both middle- and low-income countries, but low-income countries have a slightly higher elasticity of fertility to child mortality (between .69-1.03 in these estimates). This is evidence of the fact that poor countries are higher mortality environments, where the replacement response to child mortality is prevalent and thus fertility responds contemporaneously to variations in mortality. We limit discussion below to results using the entire sample because sub-Saharan Africa's demographic transition will likely go hand-in-hand with rising incomes, and looking at the average (and more conservative) estimated elasticity across low and middle income countries seems warranted.

Figure 5-7: Low-Income Country Sample

Dependent Variable:	(i) ln(u5MR)	(ii) ln(TFR)	(iii) ln(u5MR)	(iv) ln(TFR)	(v) ln(u5MR)	(vi) ln(TFR)	(vii) ln(u5MR)	(viii) ln(TFR)	(ix) ln(u5MR)	(x) ln(TFR)
Independent Variables										
Malaria Ecology	**0.22**		**0.24**		**0.16**		**0.21**		**0.10**	
	(10.36)		**(8.98)**		**(6.75)**		**(8.12)**		**(3.33)**	
ln(under-5 Mortality Rate)		**0.86**		**1.03**		**0.89**		**0.69**		**0.96**
		(6.51)		**(4.87)**		**(4.28)**		**(4.12)**		**(2.55)**
Females' Years of Secondary Schooling							-0.01	0.0006		
							(-0.35)	(0.01)		
ln(GDP per capita, in PPP prices & constant $)									**-0.22**	0.08
									(-5.46)	(0.65)
Average temperature over period			-0.04	-0.13						
			(-0.83)	(-1.20)						
Average precipitation over period			0.001	-0.002						
			(0.86)	(-0.78)						
ln(Cereal Yield per Hectare)					**-0.28**	0.05				
					(-6.43)	(0.38)				
N =	477	477	477	477	453	453	352	352	296	296
Countries =	58	58	58	58	58	58	41	41	54	54
F-test on instrument =										
Cragg-Donald Statistic =										
Within R-squared =	0.74	0.52	0.48	0.48	0.73	0.57	0.77	0.75	0.66	0.70

t-statistics in parentheses; *** indicates significant to 99% confidence, ** to 95%, and * to 90%.
All regressions include country dummies, time period dummies and a constant (not reported).
Regressions (i), (iii), (v), (vii), and (ix) are first stage for (ii), (iv), (vi), (viii), and (x) respectively.
All regressions weigh observations by population
All regressions include only low-income countries
All regressions reports robust standard errors clustered by country
Within R-squared computed without clustering or analytical weights

We proceed to run some tests on the malaria ecology instrument. First we test the endogeneity of the child mortality variable (the null of exogeneity can be rejected at a one percent alpha level) and for the strength of the instrument (the F-tests for the instrument in the first stage are reported in the table; most are above Staiger and Stock's[48] rule of thumb value of F=10, so we can conclude that the instrument is strong). To further dispel concerns of a weak

[48] Staiger, Douglas and James H. Stock. 1997. "Instrument Variables with Weak Instruments." Econometrica 65(3): 557-86.

instrument, we follow Stock and Yogo[49] and compute the Cragg-Donald statistic, which tests underidentification by examining the smaller eigenvalue of the F-statistic matrix of the first stage regression. In all cases, the statistic exceeds the critical value of 16.38, suggesting that bias and significance test distortions due to a weak instrument are not a concern here. Next, we run all specifications with a limited information maximum likelihood estimator (Fuller[50]) with a modification parameter of $\alpha = 1$, which is robust than 2SLS with a weak instrument (Hahn, Hausman, and Kuersteiner[51], Hausman, Stock and Yogo[52]). In all cases, the coefficient on child mortality remained significant and of the same magnitude (within 0.01 of the 2SLS estimates).

All regressions were re-estimated without the population weights; results were qualitatively unchanged (the coefficient on mortality ranges between 0.39-0.57 and is always significant; in addition, the female education variable is significant in the second stage without the population weights). Another robustness test was to add a dummy for China after 1980, since its fertility rate was to some extent artificially lowered by the one-child policy put in place in 1979. Given that we are weighting observations by population, then China's large weight might be driving results. Adding the dummy, however, did not affect results. Finally, we dispense with clustering and analytical weights in order to estimate the basic model in (i) and (ii) using first differences instead of fixed effects. The results are qualitatively similar: the child mortality coefficient drops from 0.54 under FE to 0.4 under FD. The coefficient on the serial correlation of errors is 0.25, which does not strongly warrant one model above the other. We opt to report FE results throughout so that population weights and clustering of standard errors can be employed.

---

[49] Stock, James H. and Motohiro Yogo. 2002. "Testing for Weak Instruments in Linear IV Regressions." NBER Technical Working Paper. No. 284. National Bureau of Economics Research. Cambridge, MA.

[50] Fuller, Wayne A. 1977. "Some Properties of a Modification of the Limited Information Estimator." Econometrica 45(4): 9395-54.

[51] Hahn, Jinyong, Jerry Hausman and Guido Kuertsteiner. 2004. "Estimation with Weak Instruments: Accuracy of Higher-Order Bias and MSE Approximations." Econometrics Journal 7(1):272-306.

[52] Hausman, Jerry, James H. Stock, and Motohiro Yogo. 2005. "Asymptotic Properties of the Hahn-Hausman Test for Weak Instruments." Economics Letters 89(3):333-342.

The effect of child mortality on fertility is overwhelmingly robust across specifications. The income and education variables are less robust: after child mortality is instrumented, they are not robust to clustering by country. We do not focus on interpreting their coefficients due to the potential endogeneity problems (fertility might affect these control variables), but they serve to give a range of plausible estimates on the child mortality variable given potential omitted variable bias. The coefficients on child mortality have ranged between 0.10 in the non-IV fixed-effects specification to 0.85 in the IV fixed-effects specification (and up to 1.03 for low-income countries).

The preferred specifications are the IV regressions with country dummies, population-weighted observations, and clustering by country, which gave a range of 0.60 – 0.85. This range corresponds to having a decrease of TFR of 40% - 56% (or a decrease of 2.5 – 3.5 births from the 1990 level of 6.3) if child mortality were to decrease by 66% from its 1990 value in sub-Saharan Africa (the Millennium Development Goal for child mortality). Even the smallest coefficient in the IV specification yields a powerful effect: a TFR reduction of 2.3 if child mortality is reduced by 66%. This points to the fact that child mortality still plays a powerful role in fertility choice in the 20th century, an order of magnitude larger than the effect identified in some less well-identified studies mentioned previously.

Before concluding, it is worth pausing to discuss the generalizability of the child mortality coefficient estimated through IV. Some authors have expressed concern with interpreting coefficients from IV too generally: the coefficient from IV only is the local average treatment effect for the sub-population for which the instrument is well-correlated to the endogenous variable. In order to make sure that we can draw policy implications for sub-Saharan Africa, we check the first stage regression of under-5 mortality on malaria ecology using only sub-Saharan African observations. We find that the coefficient on malaria ecology is positive and significant, indicating that sub-Saharan Africa is a "complier" in the sense that the sub-sample exhibits a strong first stage. In the second stage, the estimated coefficient on child mortality rises to 1.11 (and is marginally insignificant, probably due to sample size). We opt for focusing on a coefficient identified from the larger sample not only to be conservative but because it is

likely that the responsiveness of fertility to changes child mortality is likely to go down as the demographic transition progresses. Therefore, to think about the average elasticity of child mortality across the whole transition and not just in pre-transition countries, we report estimates using the entire developing world.

A second concern is that our child mortality coefficient might only be valid for children dying due to malaria. However, there is nothing in the demography literature or theory that identifies a differentiated fertility response to a child death depending on the cause of death (though one might imagine different fertility responses between health-related deaths and conflict-related deaths, for example). Nonetheless, whether there is a differentiated fertility response depending on cause of child death is beyond the scope of this paper, but in the absence of such evidence we maintain that the child mortality coefficient that we have estimated is a step forward in the quantitative study of fertility dynamics.

Conclusion

We are only the latest in a long research tradition to test the link between child mortality and fertility. We add to this literature through the deployment of a novel instrument: malaria ecology. Instrumenting child mortality in this way yields a result that appears robust across a number of models that include or exclude various control variables, time and country fixed effects and with or without population weights. In all our models, we find that child survival is a quantitatively important and robust driver of fertility. This is where the theory of the demographic transition started: save children and families will choose to have fewer children. The finding is consistent with the fact that the demographic transition has proceeded in the widest range of social settings: rural and urban, male-dominated and gender equal, impoverished and middle-class[16]. Since the child mortality transition has also proceeded in a wide range of settings, it is plausible that fertility has been driven largely by changes child mortality.

This is not to say, however, that child mortality is the only important driver of a demographic transition. As explained in Bongaarts et al (1984), family planning through contraception, sexual behavior and abortion, are proximate determinants of fertility which are affected by socioeconomic variables such as income, education, and health. If socioeconomic and policy variables are to successfully trigger a transition, then the change in desired fertility must be allowed to translate into a change of actual fertility through the proximate variables (especially contraception use). Though we have focused on better quantifying the role of reducing child mortality, the importance of other variables affecting fertility such as female education or access to family planning should not be understated.

If this conclusion is correct, it heralds the possibility of a rapid fertility transition in Africa. Child survival can be dramatically improved in a short period of time (UN Millennium Project[53]). It is indeed possible, even in a very low income setting and within a five-year period, to reduce the child mortality rate from 150 per 1,000 or above, to well below 100 per 1,000. Similarly, other determinants of fertility, such as increases in agricultural yields and public policies in support of family planning, may change in just a few years, in contrast with many socioeconomic variables. Sub-Saharan Africa's TFR in 1990 was 6.3, and in 2007 it was 5.1 (World Bank, 2009). If the Millennium Development Goals are achieved and child mortality is decreased by two-thirds compared to 1990, our results would predict a decrease in TFR of around 3 babies to 3.3, or more than half of the reduction necessary to reach replacement fertility of 2.1. If in addition female education is increased, access to family planning is improved, and farm yields increased, the resulting fertility reductions would correspond to a new TFR in sub-Saharan Africa of around 2.1. While these predictions are very crude, nevertheless the prospect for a rapid, policy-supported transition to lower fertility in Africa, say a TFR of less than 3.0 within a decade, looks reasonable. The results also point to the continued importance of child mortality in fertility declines: while other variables emphasized in research and policy (such as family planning or female education) are important contributors to decline in fertility,

[53] United Nations Millennium Project. Investing in Development: A Practical Plan to Achieve the Millennium Development Goals. Earthscan: New York, 2005.

child mortality declines seem to account for around half of the fertility decline and its importance in demographic dynamics should not be ignored.

More research is needed to continue exploring the causes of rapid fertility transitions seen in some countries in the last few decades. In particular, our models do not attempt to solve the endogeneity issues with the control variables, nor attempt to understand the lag structure in changes to the independent variables (though, as mentioned above, changes in child mortality are found to have lagged effects on fertility). Future work could look intensively at case studies of rapid fertility declines and attempt to better model lagged effects of the determinants of TFR. In the meantime, however, this paper provides a more reliable range of estimates for how changes in child mortality causally translate into changes in fertility behavior. To our knowledge, no paper has employed a time-varying exogenous instrument to solve the endogeneity problem between fertility and child mortality. The results are also encouraging: whereas previous estimates of the elasticity of fertility to child mortality using IV have failed to find statistical significance or have found perplexingly small magnitudes, our result finds that child mortality is likely to account for over half of the fertility reduction during the demographic transition.

Appendix: Time-Varying Malaria Ecology Index

The time-varying malaria ecology index used in this paper was developed in chapter 4 as an extension of the Malaria Ecology index developed by Kiszewski et al. (2004). Malaria Ecology is an ecologically-based spatial index of the stability of malaria transmission based on the interaction of climate with the dominant properties of anopheline vectors of malaria that determine vectorial capacity. Malaria is a disease of climate because a key part of the life cycle of the parasites (sporogony) depends on a high ambient temperature and because vectors require sufficient rainfall to provide breeding sites. Additionally, the intensity of malaria transmission depends on the specific mosquito species that are present and their relative attraction to humans versus animals. The Malaria Ecology variable published by Kiseweski et al. measures the effects of ambient temperature (using a monthly average from 1901-1990) on the force of transmission of malaria, as expressed through the length of the incubation period of the parasite in the

mosquito's gut, and therefore the proportion of the vector population able to survive long enough to become infectious. The index is constructed on a 0.5 degree spatial grid to derive the climatic characteristics of individual months, and then averaged over a 12-month period. The first step is to identify the distribution of anopheline species across the world using observation records and satellite-based vegetation maps to identify likely habitats where observations have not been recorded.

A dominant species is identified for each spatial zone, and for each month (in cases where there is a seasonal pattern to the dominant species). An ecological screen was created for the presence or absence of a vector during particular months. (For those vectors that breed mainly in temporary water, a minimum precipitation threshold of 10mm per month, lagged one month, is used to judge when the vector would be present in the site during a given month. Vectors that mainly exploit permanent or semi-permanent bodies of water were considered to be independent of seasonal fluctuations in rainfall unless empiric evidence indicated otherwise. In temperate or altitudinous regions, temperature thresholds are used to determine whether parasites can develop in mosquito vectors in a particular month, assuming that malaria parasites cannot develop when the mean monthly temperature remains below 15°C). Note that the mosquito presence screen is ecology-based and not affected by human activity; indeed, it is worth keeping in mind that public health interventions against malaria serve to break the transmission cycle, but do not eliminate the presence of the vector itself (even until today, Anopheles mosquitoes capable of transmitting malaria can be found throughout the US and Europe, places where malaria has been largely eradicated).

The basic formula for Malaria Ecology combines climatic factors, the presence of different mosquito vector types and the human biting preference of the different mosquito vectors. The index expresses the factors that most powerfully and perennially influence the intensity of malaria transmission. It uses, therefore, a subset of the vectorial capacity equation without terms for mosquito abundance, vector competence, or recovery rate for infected people. To calculate the duration of the extrinsic incubation period "E," the index was

calculated for each month, and biting activity was designated based on the average monthly temperature and Moshkovsky's degree-day-based formulae:

$$Malaria\ Ecology_{i,year} = \left(\sum_{m=1}^{12} a_{i,m}^{2} \cdot p_{i,m}^{E} \Big/ -\ln(p_{i,m}) \right)_{year}$$

Where:
m = month (1-12)
i = identity of dominant vector
a = proportion biting people (0-1)
p = daily survival rate (0-1)
E = length of extrinsic incubation period (in days) = $111/(temperature - 16)$

Because it is built upon climatological and vector characteristics on a cell-by-cell basis, Malaria Ecology is exogenous to public health interventions and economic conditions. The Malaria Ecology index correlates strongly to malaria incidence, especially in the absence of public health interventions. Even a cursory comparison of the map of the geographic extent of malaria risk and Malaria Ecology show clear similarities: the high latitudes of the northern hemisphere are both where malaria was eliminated first, and also the malaria ecology index is lowest without being zero.

Chapter 4 re-calculates the index month-by-month using the same methodology using monthly data for temperature and precipitation. The index is aggregated to the country level without weighting by population to prevent potential endogeneity if humans can migrate internally to adapt to malaria prevalence.

Chapter 6

Implications and Future Work

The chapters above explore the relationship between malaria, the natural environment and society, illustrating how an epidemiological grounding in malaria modeling yields insights on why humanity has succeeded in eliminating the disease in some places and not others (Chapter 2), how much it would cost to curb the burden of malaria in areas where it is still transmitted (Chapter 3), and how the burden is likely to evolve under climate change (Chapter 4). In addition, the ecological model allowed us to quantify one of the important indirect effects of the disease: the consequences of malaria for fertility rates and the demographic transition (Chapter 5). This finding is relevant beyond the malaria community, since it contributes to a broader question in empirical social science: the degree to which child mortality reductions result in declines in fertility.

Malaria Control

The work here takes steps towards recognizing that heterogeneity in malaria ecology is an important determinant of the history of malaria elimination, of the cost of curbing the disease in a particular location, and of the increases or decreases of malaria burden under climate change. An important lesson for empirical malaria modeling revolves around the construction of a nonlinear index well-grounded in epidemiology as opposed to curve-fitting with separable terms for precipitation and temperature, as many studies employ. The Malaria Ecology Index created by Kiszewski et al. (2004) and extended in Chapter 5 does well in predicting malaria incidence because it captures thresholds and drastic nonlinearities in how temperature, precipitation and vector switching affect transmission strength. Moreover, the studies here are notable for the limited amount of information used for successful prediction; whereas many studies of malaria transmission and ecology are much more localized and employ much more data (for example, modeling the effect of land cover, breeding sites, or how humans spend their time), the results here are easily generalizable given that they use only temperature and precipitation to give us insight on prospects for elimination, costs of intervention packages, and likely effects of climate change for malaria. Future work along these lines would refine these models as global coverage of relevant data on anti-malaria interventions becomes available. For example, spatial datasets of bednet coverage or anti-malarial treatments would allow me to augment the index and recalibrate

its effect on incidence while still preserving global coverage. This would be of particular use to global modeling of malaria under climate change with different assumptions about public health expenditure. Much more research is needed to properly model future malaria burden in a fashion that integrates ecology, public health investments, parasite resistance to antimalarials, vector resistance to insecticides, and human migration within and across nations.

Economic Development

The chapters above do not directly analyze determinants of economic growth. However, the fact that malaria places such a heavy burden on some of the world's poorest societies and ample literature has shown that poor health compromises individual outcomes and broader economic development, suggest that the low cost of curbing the disease ($4.02 per African per year) calculated in Chapter 2 makes anti-malaria investments highly efficient from a social cost-benefit perspective.

A second point related to economic development regards the ongoing academic debate on the role of geography and institutions for economic growth. The results in the chapters above indicate that the burden of malaria is highly conditioned by ecology, and that malaria's effect on child mortality has broader implications by affecting fertility rates and the demographic transition. To the extent that malaria ecology affects the demographic transition as well as mortality rates, the observed high settler mortality rates used by Acemoglu, Johnson, and Robinson (2001) as an instrumental variable for current economic institutions would not be appropriate. The high mortality rates would be correlated with an underlying disease ecology which in turn is a direct contributor to economic performance through its depressing effect on the demographic transition. In short, settler mortality is correlated with ecological variables that have a direct reach into modern economic development, so that settler mortality cannot be deemed to be an appropriate instrument. More research is needed to quantifying the many channels through which geography directly affects prospects for development, and how technology conditions those relationships. For example, places once limited by high transport costs to global markets might experience bursts of growth when information technology

obviates the need for transporting products. Or, societies once hampered by high disease burdens might unlock growth potential when given access to appropriate public health measures. The way forward in research, then, is to move beyond a fear of geographic determinism and instead work to understand how geography and technology interact to help define growth potential.

Sustainable Development

The results from chapters 4 & 5 contribute to the growing sustainable development literature in two ways. First, insofar as the burden that human society places on global environmental systems is a function of the size of the human population, then Chapter 5's link between public health and total sustainability is nontrivial. Public health interventions that are shown to facilitate the demographic transition need to be seriously considered as policy options to promote sustainable development locally and globally.

Secondly, as a contribution to coupled climate-society models, Chapters 4 & 5 highlight an important feedback that has received little attention: increased temperatures might have consequences for child mortality through enhanced malaria transmission, which may in turn delay demographic transitions in poor countries. This results in a larger global human population in the long run, which *ceteris paribus* increases greenhouse gas emissions and exacerbates climate change. A recent study has found that slowing population growth could account for 16-29% of emissions reductions required to avert serious climate change.[1] In future research I hope to connect the public health-demography link to the demography-climate change link in order to formally evaluate public health interventions against other interventions and policies designed to reduce greenhouse gas emissions. A model such as this would allow converting a child's life saved to carbon-equivalent units, and the cost of the life-saving public health intervention might be compared against the price of carbon credits, for example. These

[1] O'Neill, Brian C. et al., 2010, "Global demographic trends and future carbon emissions," Proceedings of the National Academies of Science.

exercises would add to the accepted benefits of decreasing child mortality, and affect social cost-benefit analyses evaluating public health interventions around the world.

Finally, it is worth noting that the research undertaken here strengthens the case for sustainable development as a separate academic discipline bridging the social and natural sciences for the purpose of studying and solving specific challenges. As we move forward in thinking about ecology and infectious disease, or about public health and climate change, or public health and demography, economists and demographers cannot afford to be agnostic about the links of disease to ecology, nor can climate scientists ignore feedback effects through public health and demography in their coupled models. The interdisciplinary links in the challenges of sustainable development are not second order curiosities; appropriate modeling of the complexity, even if it requires multi-disciplinary modeling, is necessary before we can have any confidence that we understand these coupled human-natural systems on a first order.

Bibliography

Acemoglu, Daron and Simon Johnson. 2007. "Disease and Development: The Effect of Life Expectancy on Economic Growth." *Journal of Political Economy* Vol. 115, No. 6.

Acemoglu, Daron, Simon Johnson and James A. Robinson. 2001. "The Colonial Origins of Comparative Development: an Empirical Investigation." *American Economic Review*, vol. 91, no. 5, December.

Aghajanian, A. 1991. "Population Changes in Iran, 1966-86: A Stalled Demographic Transition?" *Population and Development Review*. Vol. 17, No. 4, pp. 703-15.

Al Serouri, A. W., S.M. Grantham-McGregor, B. Greenwood & A. Costello, 2000, "Impact of asymptomatic malaria parasitaemia on cognitive function and school achievement of schoolchildren in the Yemen Republic," *Parasitology* 121, 337–345.

Alemayehu T, Ghebreyesus TA, Witten KH, Bosman A, Teklehaimanot A, 1998. Community-based malaria control programme in Tigray Region, Northern Ethiopia: Results of a mortality survey of rural under-five children. *Ethiopian Journal of Health Development.* 12(3): 203--211.

Alilio, Martin S., Ib C. Bygbjerg, and Joel G. Breman (2004) "Are Multilateral Malaria Research and Controls Programs the Most Successful? Lessons from the Past 100 years in Africa," *American Journal of Tropical Medicine and Hygiene*, 71 (Supplement 2), 268-278.

American Red Cross and CORE, 2004. "Malaria Case Study Partnerships in Action: An Integrated Approach to Combining a Measles Campaign with a Bed Net, Vitamin A and Mebendazole Campaign in Zambia," July. (available online at http://pdf.dec.org/pdf_docs/PNADB968.pdf).

Ashraf, Quamrul H., Ashley Lester, David N. Weil. 2008. "When Does Improving Health Raise GDP?" in *NBER Macroeconomics Annual 2008*, Daron Acemoglu, Kenneth Rogoff and Michael Woodford, eds., University of Chicago Press.

Barro, Robert J and Jong-Wha Lee. A New Data Set of Educational Attainment in the World, 1950-2010. NBER Working Paper 15902. April 2010.

Basta, S., S. Soekirman, D. Karyadi & N.S. Scrimshaw. 1979. "Iron deficiency anemia and the productivity of adult males in Indonesia." *American Journal of Clinical Nutrition* **32,** 916–925.

Bates I, Fenton C, Gruber J, Lalloo D, Medina Lara A, Squire SB, Theobald S, Thomson R, Tolhurst R. 2004. Vulnerability to malaria, tuberculosis, and HIV/AIDS infection and disease. Part 1: determinants operating at individual and household level. *Lancet Infectious Disease,* May; 4(5): 267-77.

Becker, G. and R. Barro. 1988. A Reformulation of the Economic Theory of Fertility. *The Quarterly Journal of Economics*, v. CIII, no. 1, pp. 1-25.

Behrman, Jere R. and Mark R. Rosenzweig. 2004. "Returns to Birthweight." *Review of Economics and Statistics* 86: 586-601.

Benefo, Kofi and Schultz, T. Paul. 1996. Fertility and Child Mortality in Cote d'Ivoire and Ghana. *The World Bank Economic Review*, v. 10, no. 1, pp. 123-158.

Bertrand, Marianne, Esther Duflo and Sendhil Mullainathan. 2004. "How Much Should We Trust Differences-in-Differences Estimates?" *Quarterly Journal of Economics*. Vol. 119, No.1, pp. 249-75.

Bhargava, Alok, Dean T. Jamison, Lawrence J. Lau, Christopher J.L. Murray. 2001. "Modeling the effects of health on economic growth." *Journal of Health Economics*, 20:423-440.

Black R.E., Morris S.S., and Bryce J. 2003. Where and why are 10 million children dying every year? *Lancet*, v. 361, pp. 2226-2234.

Bleakley, Hoyt. 2006. "Disease and Development: Comments on Acemoglu and Johnson (2006)." Remarks delivered at the NBER Summer Institute on Economic Fluctuations and Growth, July 16, 2006.

Bleakley, Hoyt. 2007. "Disease and Development: Evidence from Hookworm Eradication in the American South." *Quarterly Journal of Economics* 122: 73-117.

Bleakley, Hoyt. 2010. "Health, Human Capital, and Development." *Annual Review of Economics* 2:283-310.

Bleakley, Hoyt. 2010. "Malaria Eradication in the Americas: A Retrospective Analysis of Childhood Exposure." *American Economic Journal: Applied Economics* 2(2): 1-45.

Bloom, David E. and David Canning. 2003. "The Health and Poverty of Nations: from theory to practice." *Journal of Human Development* Vol. 4, No. 1.

Bloom, David E., David Canning and Günther Fink. 2009. "Disease and Development Revisited." *NBER Working Paper* 15127, July.

Bongaarts, J., O. Frank, R. Lesthaeghe, The proximate determinants of fertility in sub-Saharan Africa. *Population and Development Review*, v. 10, no. 3 (Sept), pp. 511-537. 1984.

Bouma, Menno Jan. 2003. Methodological problems and amendments to demonstrate effects of temperature on the epidemiology of malaria. A new perspective on the highland epidemics in Madagascar, 1972-89. *Transactions of the Royal Society of Tropical Medicine and Hygiene* 97:133-139.

Breman, JG, MS Alilio and A Mills. Conquering the intolerable burden of malaria: what's new, what's needed: a summary. *American Journal of Tropical Medicine and Hygiene*. 2004; 71: suppl: 1-15.

Brewster, D. R., D. Kwiatkowski, & N.J. White. 1990. "Neurological sequelae of cerebral malaria in children." *Lancet* 336, 1039–1043.

Brooker, S. et al. 2000. "Situation analysis of malaria in school-aged children in Kenya: what can be done?" *Parasitology Today* 16, 183-186.

Bryce J, Roungou JB, Nguyen-Dinh P, Naimoli JF, Breman JH. Evaluation of national malaria control programmes in Africa. 1994. *Bull World Health Organ* (72: 371--381).

Carstensen, Kai and Gundlach, Erich. 2006. The Primacy of Institutions Reconsidered: Direct Income Effects of Malaria Prevalence. *The World Bank Economic Review*, v. 20, no. 3, pp. 309-339.

Center for International Earth Science Information Network (CIESIN), Columbia University; International Food Policy Research Institute (IPFRI); the World Bank; and Centro Internacional de Agricultura Tropical (CIAT); 2004. Global Rural-Urban Mapping Project (GRUMP): Urban/Rural Extents. Palisades, NY: CIESIN, Columbia University. Available at http://sedac.ciesin.columbia.edu/gpw. Downloaded March 2006.

Chowdhury, A. 1988. The Infant Mortality-Fertility Debate: Some International Evidence. *Southern Economic Journal*, v. 54, no. 3, pp. 666-674.

Cleland, J. 2001. "The Effects of Improved Survival on Fertility: A Reassessment." *Population and Development Review*, Vol. 27, Supplement: Global Fertility Transition, pp. 60-92.

Cleland, J., J. F. Phillips, S. Amin, and G.M. Kamal. "The Determinants of Reproductive Change in Bangladesh: Success in a Challenging Environment." World Bank: Washington DC, 1994.

Conley, D. and R. Glauber. 2006. "Parental Educational Investment and Children's Academic Risk: Estimates of the Impact of Sibship Size and Birth Order from Exogenous Variation in Fertility." *Journal of Human Resources*.

Conley, D., G.C. McCord and J.D. Sachs. "Africa's Lagging Demographic Transition: Evidence from Exogenous Impacts of Malaria Ecology and Agricultural Techonology." *National Bureau of Economics Research Working Paper No. 12892*. February 2007.

Conley, Timothy G. and Giorgio Topa. "Socio-economic Distance and Spatial Patterns in Unemployment." *Journal of Applied Econometrics*. 17: 303-327. Jul/Aug 2002.

Craig MH, Snow RW, le Sueur D, 1999. A climate-based distribution model of malaria transmission in sub-Saharan Africa. *Parasitol Today 15*, 105--111.

Curtis C, Maxwell C, Lemnge M, Kilama WL, Steketee RW, Hawley WA, Bergevin Y, Campbell C, Sachs J, Teklehaimanot A, Ochola S, Guyatt H, Snow RW, 2003. Scaling-up coverage with insecticide-treated nets against malaria in Africa: who should pay? *Lancet Infect Dis.* Vol 3, May, 304--307.

Doepke, M. 2005. Child mortality and fertility decline: Does the Barro-Becker model fit the facts? *Journal of Population Economics*, v. 18, pp. 337-366.

Dreze, Jean and Murthi, Mamta. 2001. Fertility, Education, and Development: Evidence from India. *Population and Development Review*, v. 27, no. 1, pp. 33-63.

Easterly, William and Ross Levine. 2003. "Tropics, germs, and crops: how endowments influence economic development." *Journal of Monetary Economics* 50:3-39.

Etard, J.F., Kodia, B. and Ronsmans, C. 2003. Seasonal Variation in Direct Obstetric Mortality in Rural Senegal: Role of Malaria? *American Journal of Tropical Medicine and Hygiene*, v. 68, no. 4, pp. 503-504.

Fortson, Jane. 2009. "HIV/AIDS and Fertility." *American Economic Journal: Applied Econometrics* 1:3, 170-194.

Fuller, Wayne A. 1977. "Some Properties of a Modification of the Limited Information Estimator." *Econometrica* 45(4): 9395-54.

Gallup, John Luke and Jeffrey D. Sachs. 2001. "The Economic Burden of Malaria," The Supplement to *The American Journal of Tropical Medicine & Hygiene*. Vol. 64, no. 1, 2, January/February.

Gallup, J.L., J.D. Sachs, and A.D. Mellinger. 1999. "Geography and economic development." *International Regional Science Review* 22, 179–232.

Grabowsky M, Nobiya T, Ahun M, Donna R, Lengor M, Zimmerman D, Ladd H, Hoekstra E, Bello A, Baffoe-Wilmot A, Amofah G, 2003. Linking ITN distribution to measles campaigns achieves high and rapid coverage at low cost. *Proceedings of the annual meeting of the American Society of Tropical Medicine and Hygiene*. Philadelphia, 4 Dec, Abstract 1230.

Greenwood B, Marsh K, Snow R, 1992. Why do some African children develop severe malaria? *Parasitol Today*. Nov; 8(11): 381-383.

Guyatt, H.L., and Snow, R.W. 2001. Malaria in pregnancy as an indirect cause of infant mortality in sub-Saharan Africa. *Transactions of the Royal Society of Tropical Medicine and Hygiene*, v. 95, n. 6, pp. 569-576.

Hahn, Jinyong, Jerry Hausman and Guido Kuertsteiner. 2004. "Estimation with Weak Instruments: Accuracy of Higher-Order Bias and MSE Approximations." *Econometrics Journal* 7(1):272-306.

Hausman, Jerry, James H. Stock, and Motohiro Yogo. 2005. "Asymptotic Properties of the Hahn-Hausman Test for Weak Instruments." *Economics Letters* 89(3):333-342.

Hawley WA, et al. 2003. "Community-wide effects of permethrin-treated bednets on child mortality and malaria morbidity in western Kenya." *American Journal of Tropical Medicine and Hygiene* 68 (suppl): 121–27.

Hay SI, Guerra CA, Tatem AJ, Noor AM, Snow RW, 2004. The global distribution and population at risk of malaria: past, present and future. *The Lancet: Infectious Diseases*. Vol. 4 (June), 327-336.

Hay SI, Rogers DJ, Randolph SE, Stern DI, Cox J, Shanks GD, Snow RW. 2002. Hot topic or hot air? Climate change and malaria resurgence in East African highlands. *TRENDS in Parasitology*. Vol. 18, No. 12.

Hazan, M. and B. Berdugo. 2002. Child Labour, Fertility, and Economic Growth. *The Economic Journal*, v. 112, pp. 810-828.

Heer, D.M. and D. O. Smith. 1968. Mortality Level, Desired Family Size, and Population Increase. *Demography*, v. 5, no. 1, pp. 104-121.

Heffernan, J.M., R. J. Smith and L.M. Wahl. "Perspectives on the basic reproductive ratio." *Journal of the Royal Society Interface*. 2, 2005, pp. 281-293.

Holding, P.A. and R.W. Snow. 2001. "Impact of Plasmodium falciparum malaria on performance and learning: review of the evidence." *American Journal of Tropical Medicine and Hygiene*, 64(1,2)S, 68-75.

Holding, P. A., J. Stevenson, N. Pershu, & K. Marsh. 1999. "Cognitive sequelae of malaria with impaired consciousness." *Transactions of the Royal Society of Tropical Medicine and Hygiene,* 93, 529–534.

Jones, Benjamin F. and Benjamin A. Olken. 2010. "Climate Shocks and Exports." American Economic Review: Papers & Proceedings 100:454-459.

Joshi, S. and T. P. Schultz. 2007. "Family Planning as an Investment in Development: Evaluation of a Programs' Consequences in Matlab, Bangladesh." Economic Growth Center Discussion Paper 951. Yale University, New Haven, Connecticut.

Kalemli-Ozcan, Sebnem. 2006. "Aids, 'Reversal' of the Demographic Transition and Economic Development: Evidence from Africa." NBER Working Paper Series, w12181.

Kiszewski A.E. and A. Teklehaimanot. 2004. A Review of the Clinical and Epidemiologic Burdens of Epidemic Malaria. *Am J Trop Med Hyg 71*(Suppl 2), 128--135.

Kiszewski, Anthony, Andrew Mellinger, Andrew Spielman, Pia Malaney, Sonia Ehrlich Sachs and Jeffrey Sachs. "A Global Index Representing the Stability of Malaria Transmission." *American Journal of Tropical Medicine and Hygiene*. 70(5), 2004, pp 486—498.

Leighton, C. & R. Foster. 1993. "Economic impacts of malaria in Kenya and Nigeria." *Major Applied Research Paper* No. 6, HFS Project (Abt Associates, Bethesda).

Lengeler, C. 2004. Insecticide-treated bed nets and curtains for preventing malaria. Cochrane Database Syst Rev.

Lindsay, S.W. and W.J.M. Martens. 1998. Malaria in the African highlands: past, present and future. *Bulletin of the World Health Organization* 76:33-45.

Lorentzen, P., J. McMillan, and R. Wacziarg. 2005. "Death and Development." NBER Working Paper No. 11620.

Lysenko AJ, Semashko IN, 1968. Geography of malaria. A medico-geographic profile of an ancient disease. In: Lebedew AW, ed. Itogi Nauki: Medicinskaja Geografija. Moscow, USSR: Academy of Sciences, 25--146.

Marandi, S.A., A. Mehryar, M. J. Abbasi-Shavazi, Z. Majdfar, M. H. Shamsian. 2006. "Iran: From Family Sizes of Six to Replacement Levels in 15 Years," in Tobias, Michael, Bob Gillespie, Elizabeth Hughes, and Jane Gray Morrison. No Vacancy: Global Responses to the Human Population Explosion. Pasadena, CA: Hope Publishing House.

Maubert, Bertrand, Fievet, Nadine, Tami, Germaine, Cot, Michel, Boudin, Christian, and Deloron, Philippe. 1999. Development of Antibodies against Chondroitin Sulfate A-Adherent *Plasmodium falciparum* in Pregnant Women. *Infection and Immunity*, v. 67, n. 10, pp. 5367-5371.

Maxwell CA, Msuya E, Sudi M, Njunwa KJ, Carneiro IA, Curtis CF, 2002. Effect of community-wide use of insecticide-treated nets for 3--4 years on malarial morbidity in Tanzania. *Trop Med Int Health* 7(12), Dec: 1003--1008.

McCord, Gordon C., Dalton Conley and Jeffrey D. Sachs. "Improving Empirical Estimation of Demographic Drivers: Fertility, Child Mortality & Malaria Ecology." *Social Science Research Network Working Paper*. July 2010.

Mellinger, A., Sachs, J.D. and Gallup, J. 2000. "Climate, coastal proximity, and development." in *Oxford Handbook of Economic Geography*, ed. G. L. Clark, M. P. Feldman and M.S. Gertler. New York: Oxford University Press.

Miguel, Edward, and Michael Kremer. 2004. "Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities." Econometrica 72: 159-217.

Moav, O. 2005. Cheap Children and the Persistence of Poverty. *The Economic Journal*, v. 115, pp. 88-110.

Mogstad, M. and M. Wiswall. 2009. Family Size and Children's Education: How Linear Models Can Mask a Non-Linear Relationship. NYU Economics Working Paper.

Nevill CG, Some ES, Mung'ala VO, Mutemi W, New L, Marsh K, Lengeler C, Snow RW, 1996. Insecticide-treated bednets reduce mortality and severe morbidity from malaria among children on the Kenyan coast. *Trop Med Int Health* Apr; 1(2): 139--146.

New, M. Lister, D., Hulme, M. and Makin, I. 2002. A high-resolution data set of surface climate over global land areas. *Climate Research* 21.

Novartis, 2006. "Media Release (September 29, 2006): Novartis announces initiative to improve access to state-of-the-art anti-malarial treatment Coartem." Available at www.novartis.com. Accessed January 31, 2007.

Nur, E. 1993. "The impact of malaria on labour use and efficiency in the Sudan." *Society of Science and Medicine,* 37, 1115–1119.

O'Neill, Brian C. et al. 2010. "Global demographic trends and future carbon emissions." *Proceedings of the National Academies of Science.*

RBM, 2006. ACTs Procured by WHO and UNICEF. Available at: http://www.rbm.who.int/docs/mmss/actSourcesPrices_catalogue.pdf. Accessed December 30, 2006.

Raftery, A.E., S. M. Lewis and A. Aghajanian. 1995. "Demand or Ideation? Evidence from the Iranian Marital Fertility Decline." *Demography* Vol. 32, No. 2, pp. 159-82.

Ricklefs, Robert E. and Diana C. Outlaw. A Molecular Clock for Malaria Parasites. *Science* 329, 9 July 2010.

Robalino, Juan A. and Alexander Pfaff. "Contagious Development: Neighbor's Interactions in Deforestation." November 2005, unpublished.

Rodrik, Dani, Arvind Subramanian and Francesco Trebbi. 2004. "Institutions Rule: The Primacy of Institutions Over Geography and Integration in Economic Development." *Journal of Economic Growth* 9:131-165.

Rogers, David J. and Sarah E. Randolph. 2000. "The Global Spread of Malaria in a Future, Warmer World." *Science* Vol. 289, No. 5485, pp. 1764-1766.

Ronsmans, C. 1996. "Birth spacing and child survival in Senegal." *International Journal of Epidemiology* 25(5): 989-997.

Rowland, M. G., T.J. Cole & R.G. Whitehead. 1977. "A quantitative study into the role of infection in determining nutritional status in Gambian village children." *British Journal of Nutrition* 37, 441–450.

Sabot, Oliver et al. 2010. "Costs and financial feasibility of malaria elimination," *Lancet* 376:1604-15.

Sachs, Jeffrey D. 2003. "Institutions Don't Rule: Direct Effects of Geography on per capita Income." NBER Working Paper 9490, February.

Sachs, J.D. and Gallup, J.L. 2001. "The economic burden of malaria." *American Journal of Tropical Medicine and Hygiene* (supplement) 64, 85–96.

Sachs, Jeffrey D. and Pia Malaney. 2002. "The Economic and Social Burden of Malaria." *Nature Insight*, Vol. 415, no. 6872, Feb. 7.

Sartelet, H., Rogier, C., Milko-Sartelet, I., Angel, G., and Michel, G. Malaria associated pre-eclempsia in Senegal. 1996. *Lancet*, v. 347, n. 9008, p. 1121.

Scholz, B. D., R. Gross, W. Schultink & S. Sastroamidjojo. 1997. "Anaemia is associated with reduced productivity of women workers even in less-physically-strenuous tasks." *British Journal of Nutrition.* **77,** 47–57.

Schultz, T. Paul. 1997. Demand for Children in Low Income Countries. in Rosenzweig, M. R. and Stark, O. (eds.) Handbook of Population and Family Economics.

Shultz, T. Paul. 2002. "Wage Gains Associated with Height as a Form of Health Human Capital." *American Economic Review Papers and Proceedings* 92: 349-53.

Shiff, C. et al. 1996. "Changes in weight gain and anaemia attributable to malaria in Tanzanian children living under holoendemic conditions." *Transactions of the Royal Society of Tropical Medicine and Hygiene*, 90, 262–265.

Smith, Adam. 1776. The Wealth of Nations. Edwin Cannan, ed., 1904, London: Methuen and Co., Ltd.

Smith, David L and F Ellis McKenzie. 2004. Statics and dynamics of malaria infection in Anopheles mosquitoes. *Malaria Journal* 3:13.

Smith, DL, McKenzie FE, Snow RW, Hay SI. 2007. Revisiting the basic reproductive number for malaria and its implications for malaria control. *PLOS Biology* 5(3).

Snow RW, Craig M, Deichmann U, Marsh K, 1999. Estimating mortality, morbidity and disability due to malaria among Africa's non-pregnant population. *Bull World Health Organ. 77*, 624--640.

Snow RW, Eckert E, Teklehaimanot A, 2003. Estimating the needs for artesunate-based combination therapy for malaria case-management in Africa. *Trends Parasitol*, Vol. 19, No. 8 August, 363--369.

Snow RW, Guerra CA, Noor AM, Myint HY, Hay SI, 2005. The global distribution of clinical episodes of Plasmodium falciparum malaria. *Nature*. Mar 10; 434(7030):214--217.

Staiger, Douglas and James H. Stock. 1997. "Instrument Variables with Weak Instruments." *Econometrica* 65(3): 557-86.

Stock, James H. and Motohiro Yogo. 2002. "Testing for Weak Instruments in Linear IV Regressions." *NBER Technical Working Paper*. No. 284. National Bureau of Economics Research. Cambridge, MA.

Strauss, John and Duncan Thomas. 1998. "Health, Nutrition, and Economic Development." *Journal of Economic Literature* 36: 766-817.

UN Millennium Project, 2005. Coming to Grips with Malaria in the New Millennium. Task Force on HIV/AIDS, Malaria, TB and Access to Essential Medicines, Working Group on Malaria. Sterling, VA: Earthscan.

United Nations Population Division. 2004. *World Population Prospects: the 2004 Revision*.

Vittor, A. Y. et al. 2006. "The effect of deforestation on the human-biting rate of Anopheles darlingi, the primary vector of falciparum malaria." *American Journal of Tropical Medicine and Hygiene* 74:3-11.

Weil, David N., 2007, "Accounting for the Effect of Health on Economic Growth," *Quarterly Journal of Economics* 122:3.

WHO, 1996. World Malaria Situation in 1993. *Weekly Epidemiological Record*. 19 January. No. 1, pp. 17--22.

WHO, 2005. The role of laboratory diagnosis to support malaria disease management: Focus on the use of RDTs in areas of high transmission. Report of informal consultation (25--26 October 2004). Geneva: WHO (pre-publication copy). Available at http://www.who.int/malaria/docs/ReportLABdiagnosis-web.pdf. Accessed December 30, 2006.

WHO. 2006. Guidelines for the Treatment of Malaria. Switzerland: WHO.

WHO. 2008. *World Malaria Report 2008*. Geneva.

WHO/AFRO. 2002. Clinical, Behavioural and Socioeconomic Factors Related to Severe Malaria: a Multicentre Study in the African Region. Available at http://www.who.int/malaria/cmc_upload/0/000/016/330/multicenter.pdf. Accessed December 30, 2006.

WHO/RBM/UNICEF/PSI/MSH. 2004. Sources and Prices of Selected Products for the Prevention, Diagnosis and Treatment of Malaria. France, WHO.

WHO/UNICEF. 2003. Africa Malaria Report 2003. Available at http://www.who.int/malaria/amd2003/amr2003/pdf/amr2003.pdf. Accessed December 30, 2006.

World Bank. 2009. *World Development Indicators.* Accessed from http://publications.worldbank.org/WDI/

Wu, Lawrence and Stephen Martin. 2002. "Is There an Engine of Nonmarital Fertility?" University of Wisconsin, CDE Working Paper No. 2002-14.

Young, Alwyn. 2005. "The Gift of Dying: The Tragedy of AIDS and the Welfare of Future African Generations." *Quarterly Journal of Economics* 120: 423-66.

Zakir, M., and P. Wunnava. 1999. Factors affecting infant mortality rates: evidence from cross-sectional data. Applied Economics Letters, v. 6, pp. 271-273.