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Author

Garg, Teevrat

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Ecosystems and Human Health: The Local Benefits of Forest Cover in Indonesia

Teevrat Garg*

Abstract

This paper documents the effect of primary forest cover loss on increased incidence of malaria. The evidence is consistent with an ecological response and land use change, anti-malarial programs or migration cannot explain the effect of forest cover loss on increased malarial incidence. The effect is specific to malaria, with forest cover having no discernible effect on other diseases with a disease ecology different from that of malaria. Back of the envelope calculations indicate that the morbidity-related malaria-reducing local benefits of primary forests are at least $1-$2 per hectare.

JEL Codes: Q53, O13, Q56, Q57, Q20

*Email: teevrat@ucsd.edu. School of Global Policy and Strategy, University of California, San Diego. I thank Ben Olken, Matt Hansen, Indra Surbakti and Samuel Bazzi for sharing Indonesian data. The paper has benefited from comments on earlier drafts by Chris Barrett, Ed Barbier, Marc Bellemare, Ariel Ben-Yishay, Julia Berazneva, Jim Berry, Prashant Bharadwaj, Nancy Chau, Chris Golden, Josh Graff Zivin, Gordon Hanson, Jake Hochard, Joel Landry, Shanjun Li, Adrienne Lucas, Gordon McCord, Craig McIntosh, Matt Neidell, Evan Plous, Marc Rockmore, Kevin Roth, Paulo Santos, Russell Toth, and Jeff Vincent. Funding is acknowledged from the Policy Design and Evaluation Laboratory at the University of California - San Diego, Cornell Population Center, the Atkinson Center for a Sustainable Future, the Mario Einaudi Center for International Studies, the Stephen B. and Janice G. Ashley professorship and the South East Asia Program of Cornell University. An earlier draft of this paper was circulated under the title "Public Health Effects of Ecosystem Degradation: Evidence from Deforestation in Indonesia". All errors are my own.

1 Introduction

The conservation of critical ecosystems has become a definitive policy priority of sustainable development goals in the 21st century (United Nations, 2015). Particularly in settings with weak enforcement, typically developing countries, there has been a growing interest in understanding the local effects of ecosystem declines (Bauch et al., 2015; Myers et al., 2013; Prüss-Üstün and Corvalán, 2007). Does the decline in such ecosystems generate adverse health outcomes for local populations? In this paper, I document the malaria burden of increased forest cover loss in Indonesia, which has one of the highest rates of deforestation in the world.

I report two principal findings. First, primary forest cover loss is associated with the increased incidence of malaria; a 1% decline in forest cover increases malarial incidence by 1.85 percentage points or 10%. The effect is strongest in villages close to the forest but persists to a lesser extent in villages away from the forest. Conservative calculations (shown in appendix A.1) suggest that the malaria-related morbidity-reducing benefits of primary forest cover are \$1-\$2 per hectare.

Second, the type of forest matters; loss in primary forests, that are rich in biodiversity, increases incidence of malaria while loss of secondary forests, which are designated for the purposes of logging, has no impact on incidence of malaria, suggesting an underlying ecological response. Consistent with this hypothesis, I find that the effect of primary forest cover loss is specific to malaria with no discernible impact on other diseases, inconsistent with alternative, non-ecological mechanisms that could explain the relationship between forest cover loss and malaria. I further demonstrate that the effect of forest cover loss on incidence of malaria cannot be explained by agricultural land use, anti-malarial programs or migration.

In theory, forest cover loss can affect malaria through several channels. First, forests are often cleared for agricultural activity. When such agricultural activity involves standing water (e.g., paddy cultivation) and other complimentary conditions favorable for malaria-carrying vectors, forest cover loss can indirectly lead to increased incidence of malaria. Second, forest clearing is often correlated with migratory behavior either due to laborintensive deforestation that requires migrant labor or because of plantation and other commercial activities that attract migrants. Migrants can act as latent hosts of malaria since they typically have lower incomes and less access to medical facilities than native populations. Third, changes in forest cover can alter the disease ecology of malaria; forest cover loss results in a reduction in biodiversity and higher order species that would otherwise feed on anopheles mosquitoes, resulting in increased malarial incidence (Pattanayak and Pfaff, 2009).

To address potential endogeneity, I follow a two-pronged approach. First, I use district-level annual satellite data on forest cover and a rich biennial village census data on disease outbreaks, allowing me to employ a fixed-effects approach to control for time-invariant district-level geographic, climatic and demographic factors that could be correlated with both forest cover and disease incidence. I include controls for health care access, poverty measures, distance from cities, sanitation facilities, population density, government sponsored health interventions, precipitation and primary sector of employment. Second, I exploit the epidemiological differences across diseases, in particular the mode of disease transmission, to perform falsification tests on other diseases whose disease ecology differs from that of malaria and show that the effect of forest cover loss is specific to malaria. I include a number of additional robustness checks.

While I rely on an important and long-standing literature linking forest loss to malaria (Myers et al., 2013; Pattanayak and Yasuoka, 2012; Keesing et al., 2010; Pongsiri et al., 2009; Pattanayak and Pfaff, 2009; Patz et al., 2000; Walsh, Molyneux and Birley, 1993), this paper makes two important contributions to existing work. First, this paper employs a fixed-effects approach using panel data to estimate the effect of forest cover loss on incidence of malaria.[1] Previous work has relied on random-effects (Bauch et al., 2015), cross-sectional analysis (e.g., Pattanayak et al. (2010); Yasuoka and Levins (2007); see Bauhoff and Busch (2018) for a detailed review) or simulations (Laporta et al., 2013; Pattanayak et al., 2009). The use of panel data allows for the inclusion of fixed-effects which removes time-invariant characteristics that could confound estimates. Second, the paper makes use of data from

[1] Two concurrent studies, both of which cite earlier versions of this paper, use a fixed-effects approach to estimate the effect of deforestation on malaria in Africa (Bauhoff and Busch, 2018) and specifically Nigeria (Berazneva and Byker, 2017). Relatedly Carrillo et al. (2019) examine the impact of reductions in deforestation on infant mortality but remain agnostic to the mechanism. For other local benefits of forest cover, see Masuda et al. (2019).

administrative heads to provide estimates for an entire country; previous work, with notable exceptions (Bauhoff and Busch, 2018) has relied on a subset of geographic areas within a country, making it difficult to generate nation-wide estimates that can be directly taken to policy discussions.

In what follows, I describe the background and data (Section 2), empirical strategy (Section 3), and results (Section 4). In Section 5, I conclude with implications of this research.

2 Background and Data

2.1 Disease Ecology of Malaria

Malaria is spread only through the *Anopheles* mosquito and transmission occurs when the mosquito was previously infected through a blood meal taken from an infected person[2]. The anopheles takes up the sexually differentiated forms of the Plasmodium parasite, which then undergo reproduction in the mosquito's gut, after which the resulting sporozoite forms travel to the salivary glands and are injected into a potential host during the mosquito's next blood meal. The typical lifespan of the female *Anopheles* is 2 weeks and they can travel distances as far as 2 kilometers. In Indonesia, malaria is widespread with 44% of the population, or over 130 million people, at risk of contraction (Elyazar, Hay and Baird, 2011). In any given year, 18.5% of Indonesian villages report having an outbreak of malaria.

Pattanayak and Pfaff (2009) review potential mechanisms through which forest loss can impact the incidence of malaria. First, post-deforestation land use change in the form of urbanization, construction and agricultural production has been associated with increased incidence of malaria (Petney, 2001). Second, forest loss could be correlated with migration, which often increases the incidence of malaria for two reasons - migrants act as latent hosts for infectious diseases, serving as transport from an infected area to a non-infected area (Texier et al., 2013) and migrants tend to have limited access to medical facilities. These

[2]See: `http://www.cdc.gov/malaria/about/faqs.html`

are socio-economic factors behind the link between deforestation and malaria but there is also an ecological link. Forest loss also alters the disease ecology of malaria. This occurs in two ways. First, cleared lands receive more sunlight and are more susceptible to the formation of puddles with a more neutral pH that favors anopheline larvae development. Second, deforestation adversely affects biodiversity of the region and increases malaria incidence by reducing or eliminating species that prey on anopheline larvae and anopheles mosquitoes (Laporta et al., 2013; Yasuoka and Levins, 2007).

2.2 Data

Disease Data: The Indonesian statistical agency, *Badan Pusat Statistik* (BPS) conducts a village census *Podes* every 2-3 years that documents a range of village characteristics and events including the incidence of disease outbreaks for malaria, measles, respiratory infections, dengue fever and diarrheal diseases. The survey includes all of Indonesia's over 68,000 villages. During the period of study, *Podes* was conducted in 2003, 2006, and 2008. Village heads report on whether or not there had been an outbreak of each of these diseases in their village in a given year, and if there were an outbreak how many people died. For 2003 and 2006, no information was collected on the number of people who were infected with malaria. Starting in 2008, the survey also requested information on the number of people infected with malaria distinct from the mortality associated with malaria. Therefore, there is panel variation in the binary indicator of whether or not there was outbreak of a disease in a given village in a given year. In 2008, on average, 14-15 people were infected with malaria in a village that reported an outbreak of malaria.[3] This translated to just over 15 infected persons per thousand persons with a standard deviation of 26 infected persons per 1000 persons. Descriptive statistics on disease data are provided in Appendix Tables A.1.

Other Variables: *Podes* also contains information on the availability of medical facilities including hospitals, integrated health centers, village medicine posts and drug stores in a

[3]The data is collected through oral recall from village heads and is then verified at the sub-district office. The village head makes a subjective decision on whether or not there was an outbreak in a given year. Appendix Figure A.1 shows the distribution of this variable in 2008. The health data has been previously validated in Garg et al. (2018).

given village. When such a medical facility is not present in the village, the survey documents the distance to the nearest facility (in kilometers) and how easy it is to access such a facility on a scale of 1-4. These rich data also contains information on population, area of the village, area under rice cultivation in the village, number of families receiving health cards or poor cards, distance to nearest district office or city, elevation of the village, dominant source of income in the village and whether or not a village is inside, near or outside the forest or located by a river. In addition, I use monthly NOAA/GPCP district-level rainfall data mapped into annual means and standard deviations (Bazzi, 2017). Descriptive statistics of these variables are provided in Appendix Table A.2.

Forest Cover Data: I use forest cover data from 2001-2008 based on satellite imagery (MODIS - 250mX250m) from Burgess et al. (2012) in each district in a given year. I limit the analysis to the islands of Sumatra, Kalimantan, Sulawesi and Papua. The remaining islands are excluded since they had negligible forest cover in the baseline year of the study (2001). The forest cover data are then classified by the zone and district of the forest estate into primary and secondary forests. The resulting variable is $ForestCover_{zdt}$ which measures forest cover in forest zone z, in district d at time t. The advantage of using these data over higher resolution (for example, village level) data is the classification of primary v. secondary forests. Appendix Figure A.2 shows the decline in percentage of land area under primary and secondary forests in a district over time.

3 Estimation Strategy

The primary dependent variable of interest is a binary indicator for malaria incidence in the previous year. I use a linear probability model in the baseline specification.[4] The primary specification is,

$$\begin{aligned} Pr[disease_{vdt} = 1] =& \beta_0 + \beta_1 \operatorname{arcsinh}(ForestCover_{dt}) \\ & + \beta_2 X_{vdt} + \mu_d + \eta_{it} + \gamma_p t + \epsilon_{vdt} \end{aligned} \tag{1}$$

[4] In Appendix Table A.3, I show that my results are robust to choice of various non-linear estimators.

The dependent variable $disease_{vdt}$ denotes whether or not there was a disease outbreak in village v in district d at time t and $\text{arcsinh}(ForestCover_{dt)}$ is the inverse hyperbolic sine transformation of total primary forest cover in district d at time t. X_{vdt} is a vector of controls including log of population, distance to cities, rainfall, dominant occupation in village allowed to vary flexibly across provinces and time, and the inverse hyperbolic sine transformation of non-forested area.[5] μ_d is the district-level fixed effect, η_{it} is the island - year fixed effect, $\gamma_p t$ is the province-specific linear time trend, and ϵ_{vdt} is the regression residual. Standard errors are clustered at the district level to allow for arbitrary correlation within a district and over time accounting for spatial autocorrelation and serial correlation within district over time.

Obtaining a consistent estimate of β_1 relies on the identifying assumption that there are no time varying omitted variables correlated with both forest cover and malarial incidence. In theory, this assumption may be suspect. For instance, local institutional quality could affect both forest cover loss and disease incidence through low provision of medical facilities. Absent randomization and a context-preserving natural experiment (for instance, forest fires are an unsuitable natural experiment since they eliminate most biological life, making it impossible to uncover an underlying ecological mechanism), I rely on panel methods and a rich set of controls and set up two falsification tests to validate the identifying assumption.

First, I test whether primary forest loss explains the incidence of four other diseases: dengue, diarrhea, measles and respiratory infections, each of whose disease ecology differs from that of malaria. If there are unobserved variables correlated with both local human health and forest cover, then forest cover would also likely have an impact on diseases other than malaria. An absence of any discernible effect on other diseases would be consistent with the forest cover and human health relationship being specific to malaria, reducing the threat to identification from omitted variables correlated with forest cover and health in general. As a corollary, I test whether socio-economic variables such as poverty status are correlated with each of the disease outcomes. Finding a relationship between

[5]Our estimates are insensitive to the correction of inverse hyperbolic sine transformation proposed by Bellemare and Wichman (2019).

all disease outcomes and poverty, but only malaria (and no other disease) and primary forest loss would be consistent with a causal effect of primary forest loss on malaria.

Second, I exploit differences in the type of forests - primary and secondary. If there are omitted variables generically relating deforestation activity with malarial incidence, then ex-ante, the effects should be similar across forest types. However, if the effects of forest loss on malarial incidence are specific to primary forests, then the evidence would be consistent with an ecological response driving the relationship between forest cover and malaria.[6]

4 Results

The principal finding of this paper is that one percent decline in forest cover increases the likelihood of malarial outbreak by 2.01 percentage points (Table 1, Column 1), and that the underlying mechanism is likely an ecological as opposed to socio-economic response. Using the sample average of the probability of malarial outbreak of 0.185, a 1% decline in forest cover in a district increases the probability of malarial outbreak in *each* village in that district by 10.8%. I treat this as the baseline result and it is robust to the inclusion of a large set of controls (Table 1, Column 2), and trends (Table 1, Column 3) . Back of the envelope calculations (Appendix A.1) suggest that morbidity associated health benefits of primary forest cover in the range of $1 - $2 per hectare.

4.1 Falsification Tests

In order to validate the research design, I perform two falsification tests exploiting differences in disease ecology (testing effects of primary forest cover loss on other diseases) and forest ecology (testing the effects of non-primary forests on malaria).

Other Diseases: Different diseases have different disease ecologies and as such different mechanisms of transmission. For instance, measles is an airborne disease, while diarrhea

[6]It is worth noting that there may also be reverse feedback loop where deforestation induced malaria reduces labor supply for future deforestation. To the extent that such a feedback loop exists, it would downward bias these estimates making them a lower bound.

is a water-borne disease. I use incidence data on other diseases to show that the relationship between forest cover and malaria is specific to the disease ecology of malaria and not generically to health by considering similar measures of measles, diarrhea, respiratory infections and dengue. As shown in Table 2, there is no statistically significant effect of forest cover change on the incidence of the other diseases. Conversely, as expected, there is a strong correlation between the number of poor people in a village and the incidence of all diseases (Table 3). The presence of a correlation between poverty and all diseases combined with the absence of any observable effect of forest loss on diseases other than malaria is consistent with primary forest cover loss increasing the incidence of malaria through an ecological mechanism.[7]

Types of Forests: Primary forests are designated as biodiversity reserves whereas secondary forests are demarcated for purposes of logging and land conversion for agriculture and palm oil. However, illegal deforestation occurs in both types of forests (Burgess et al., 2012). In Table 4, I exploit these differences and show that only primary forest loss is associated with increased malarial incidence. This effect is statistically different from the effect of secondary forests (opposite sign) at the 5% level, consistent with an ecological mechanism.

4.2 Alternative Explanations

In this section, I consider three alternative explanations, other than an ecological response, that could, in theory, explain a statistical association between primary forest loss and malaria. In each case, I find evidence inconsistent with these hypothesis.

Social Programs: I address the possibility of spurious correlation between anti-malaria or other social programs and forest cover (e.g. less remote places with low baseline forest cover and therefore lower forest loss could be more likely to receive anti-malarial services

[7]The lack of a discernible effect of forest cover on dengue may appear inconsistent with the core result since dengue is also spread via disease carrying vectors, particularly the *Aedes Aegypti* and *Aedes Albopictus* mosquitoes. However, this remains a valid falsification test since the disease ecologies of malaria and dengue differ considerably. The *Aedes Aegypti* and *Aedes Albopictus* mosquitoes, unlike the female *Anopheles* mosquito that carries malaria are almost stationary and prevalent mostly in urban areas. Since most urban areas have negligible forest cover, we should not expect to see an effect of forest cover on incidence of dengue.

and programs) in two ways. First, I show that forest cover, conditional on observables and fixed effects, has no effect on the number of beneficiaries of the health and anti-poverty pro-social programs (Table 5). As such it doesn't appear that there is any systematic relationship between primary forest cover loss and the take-up of social programs. Second, I disaggregate results by proximity of villages to the forest (Appendix Table A.4).[8] When considering only the set of villages inside or near forests, the effects of primary forest loss are almost twice as large in magnitude (Appendix Table A.4, Column 1) than in villages away from forests (Appendix Table A.4, Column 2), although this difference is not statistically significant at conventional levels.[9]

Migration: A threat to internal validity would be if increased migration correlated with deforestation leads to higher incidence of malaria because migrants can potentially act as latent hosts of malaria (Texier et al., 2013).[10] I find two pieces of evidence inconsistent with this hypothesis. First, I show that decreases in primary and secondary forest cover are not associated with increases in overall population (Appendix Table A.5).[11] If anything, forest cover loss is associated with a decrease in population and this effect is similar across primary and secondary forests but the effect of forest cover loss on malaria is specific to primary forests (Table 4). Second, the placebo tests demonstrate that the effect is specific to malaria; migrants working in forestry sector would have to be carrying malaria and no other disease. This would be in contrast to work in public health documenting several instances where migratory behavior has been associated with the outbreak of other diseases such as diarrhea and dengue in addition to malaria (Eisenberg et al., 2006).

Agricultural Land Use: Keesing et al. (2010) note that the agricultural use of cleared land could drive the increased incidence of malaria (e.g. paddy cultivation that involves main-

[8] I separate villages that are classified as "inside" and "on the border" of forests from villages classified as being "away" from forests. This characterization of the location of the village relative to the forest is provided by village heads and then verified at the district or sub-district office.

[9] The difference has a p-value of 0.22.

[10] Recent work has shown, for example, the causal link between some road construction activity and deforestation (Asher, Garg and Novosad, 2018).

[11] Population changes, in theory, occur through births, deaths and migration. Unless, forest cover changes are associated with changes in births and deaths through a channel other than malaria, population for the purposes of this test, serves as a reasonable proxy. For instance, see Lucas (2013); McCord, Conley and Sachs (2017) for the effects of malaria on fertility.

taining standing water in fields) rather than the clearing of forests themselves. I test explicitly for paddy cultivation and show that forest cover change has negligible effects on rice cultivation and including this area as a control variable doesn't affect the main results (Appendix Table A.6, Columns 1 and 2 respectively). Second, if agricultural activity correlated with forest cover changes were driving the relationship between forest cover and malarial incidence, we would expect to observe this effect regardless of forest types since the driving factor would be the use of the land post clearing rather than what was cleared; results specific to primary forests (Table 4) are therefore inconsistent with such a mechanism.

5 Conclusion

Ecosystem degradation poses a fundamental threat to lives and livelihoods, especially in the poorest parts of the world. In this paper, I provide evidence on the effect of sustained primary forest cover on reducing malarial incidence in Indonesia. Specifically, a 1% increase in primary forest cover reduces the probability of malarial outbreak by approximately 10%, generating malaria-related morbidity-reducing benefits of at least $1-$2 per hectare of primary forest. The effects are specific to malaria and specific to primary forests implying an ecological mechanism underpinning the relationship between forest cover and malaria.

Importantly, these estimates present the short-run benefits of sustained forest cover. Future work should examine how more permanent and sustained changes in ecosystems affect the incidence of infectious diseases to uncover a key missing ingredient in willingness to pay for natural capital (Fenichel and Abbott, 2014). Together, this body of research should not only inform conservation programs, but also provide new evidence on immediate and localized benefits of ecosystems that have been previously understudied, especially in poor communities where feedback between ecological and economic systems maybe pervasive (Barrett, Garg and McBride, 2016; Frank and Schlenker, 2016).

References

Asher, Sam, Teevrat Garg, and Paul Novosad. 2018. "The ecological footprint of transportation infrastructure."

Barrett, Christopher B, Teevrat Garg, and Linden McBride. 2016. "Well-being dynamics and poverty traps." *Annual Review of Resource Economics*, 8: 303–327.

Bauch, Simone C, Anna M Birkenbach, Subhrendu K Pattanayak, and Erin O Sills. 2015. "Public health impacts of ecosystem change in the Brazilian Amazon." *Proceedings of the National Academy of Sciences*, 112(24): 7414–7419.

Bauhoff, Sebastian, and Jonah Busch. 2018. "Does Deforestation Increase Malaria Prevalence? Evidence from Satellite Data and Health Surveys." *Center for Global Development Working Paper Series*.

Bazzi, Samuel. 2017. "Wealth heterogeneity and the income elasticity of migration." *American Economic Journal: Applied Economics*, 9(2): 219–55.

Bellemare, Marc F, and Casey J Wichman. 2019. "Elasticities and the inverse hyperbolic sine transformation." *Oxford Bulletin of Economics and Statistics*.

Berazneva, Julia, and Tanya S Byker. 2017. "Does forest loss increase human disease? Evidence from Nigeria." *American Economic Review Papers & Proceedings*, 107(5): 516–21.

Burgess, Robin, Matthew Hansen, Benjamin A Olken, Peter Potapov, and Stefanie Sieber. 2012. "The Political Economy of Deforestation in the Tropics." *Quarterly Journal of Economics*, 127(4): 1707–1754.

Carrillo, Bladimir, Danyelle K Branco, Juan C Trujillo, and João E Lima. 2019. "The Externalities of a Deforestation Control Policy in Infant Health: Evidence from Brazil." *Economic Development and Cultural Change*, 67(2): 369–400.

Eisenberg, Joseph NS, William Cevallos, Karina Ponce, Karen Levy, Sarah J Bates, James C Scott, Alan Hubbard, Nadia Vieira, Pablo Endara, Mauricio Espinel, Gabriel Trueba, Lee W. Riley, and James Trostle. 2006. "Environmental change and infectious disease: how new roads affect the transmission of diarrheal pathogens in rural Ecuador." *Proceedings of the National Academy of Sciences*, 103(51): 19460–19465.

Elyazar, Iqbal RF, Simon I Hay, and J Kevin Baird. 2011. "Malaria distribution, prevalence, drug resistance and control in Indonesia." *Advances in Parasitology*, 74: 41.

Fenichel, Eli P, and Joshua K Abbott. 2014. "Natural capital: from metaphor to measurement." *Journal of the Association of Environmental and Resource Economists*, 1(1/2): 1–27.

Frank, Eyal G., and Wolfram Schlenker. 2016. "Balancing economic and ecological goals." *Science*, 353(6300): 651–652.

Garg, Teevrat, Stuart E Hamilton, Jacob P Hochard, Evan Plous Kresch, and John Talbot. 2018. "(Not so) gently down the stream: River pollution and health in Indonesia." *Journal of Environmental Economics and Management*, 92: 35–53.

Keesing, Felicia, Lisa K Belden, Peter Daszak, Andrew Dobson, C Drew Harvell, Robert D Holt, Peter Hudson, Anna Jolles, Kate E Jones, and Charles E Mitchell. 2010. "Impacts of biodiversity on the emergence and transmission of infectious diseases." *Nature*, 468(7324): 647–652.

Laporta, Gabriel Zorello, Paulo Inácio Knegt Lopez de Prado, Roberto André Kraenkel, Renato Mendes Coutinho, and Maria Anice Mureb Sallum. 2013. "Biodiversity can help prevent malaria outbreaks in tropical forests." *PLoS Neglected Tropical Diseases*, 7(3): e2139.

Lucas, Adrienne M. 2013. "The impact of malaria eradication on fertility." *Economic Development and Cultural Change*, 61(3): 607–631.

Masuda, Yuta J, Brianna Castro, Ike Aggraeni, Nicholas H Wolff, Kristie Ebi, Teevrat Garg, Edward T Game, Jennifer Krenz, and June Spector. 2019. "How are healthy, working populations affected by increasing temperatures in the tropics? Implications for climate change adaptation policies." *Global Environmental Change*, 56: 29–40.

McCord, Gordon C, Dalton Conley, and Jeffrey D Sachs. 2017. "Malaria ecology, child mortality & fertility." *Economics & Human Biology*, 24: 1–17.

Myers, Samuel S, Lynne Gaffikin, Christopher D Golden, Richard S Ostfeld, Kent H Redford, Taylor H Ricketts, Will R Turner, and Steven A Osofsky. 2013. "Human health impacts of ecosystem alteration." *Proceedings of the National Academy of Sciences*, 110(47): 18753–18760.

Pattanayak, Subhrendu K, and Alexander Pfaff. 2009. "Behavior, environment, and health in developing countries: evaluation and valuation." *Annual Review of Resource Economics*, 1(1): 183–217.

Pattanayak, Subhrendu K, and Junko Yasuoka. 2012. "Deforestation and malaria: Revisiting the human ecology perspective." In *Human Health and Forests*. 219–240. Routledge.

Pattanayak, Subhrendu K, Catherine G Corey, Yewah F Lau, and Randall A Kramer. 2010. "Biodiversity conservation and child malaria: microeconomic evidence from Flores, Indonesia." *Economic Research Initiatives at Duke Working Paper*, 1(85).

Pattanayak, Subhrendu K, Martin T Ross, Brooks M Depro, Simone C Bauch, Christopher Timmins, Kelly J Wendland, and Keith Alger. 2009. "Climate change and conservation in Brazil: CGE evaluation of health and wealth impacts." *The BE Journal of Economic Analysis & Policy*, 9(2).

Patz, Jonathan A, Thaddeus K Graczyk, Nina Geller, and Amy Y Vittor. 2000. "Effects of environmental change on emerging parasitic diseases." *International Journal for Parasitology*, 30(12): 1395–1405.

Petney, Trevor N. 2001. "Environmental, cultural and social changes and their influence on parasite infections." *International Journal for Parasitology*, 31(9): 919–932.

Pongsiri, Montira J, Joe Roman, Vanessa O Ezenwa, Tony L Goldberg, Hillel S Koren, Stephen C Newbold, Richard S Ostfeld, Subhrendu K Pattanayak, and Daniel J Salkeld. 2009. "Biodiversity loss affects global disease ecology." *Bioscience*, 59(11): 945–954.

Prüss-Üstün, Annette, and Carlos Corvalán. 2007. "How much disease burden can be prevented by environmental interventions?" *Epidemiology*, 18(1): 167–178.

Texier, Gaëtan, Vanessa Machault, Meili Barragti, Jean-Paul Boutin, and Christophe Rogier. 2013. "Environmental determinant of malaria cases among travellers." *Malaria Journal*, 12(1): 87.

United Nations. 2015. "Transforming our world: The 2030 agenda for sustainable development."

Walsh, JF, DH Molyneux, and MH Birley. 1993. "Deforestation: effects on vector-borne disease." *Parasitology*, 106(S1): S55–S75.

Yasuoka, Junko, and Richard Levins. 2007. "Impact of deforestation and agricultural development on anopheline ecology and malaria epidemiology." *American Journal of Tropical Medicine and Hygiene*, 76(3): 450–460.

Tables and Figures

Table 1: Forest Cover and Malarial Incidence

Was there an outbreak of malaria?	(1) FE	(2) Add Controls	(3) Quadratic Trends
Forest Cover (IHS)	-0.0201***	-0.0185***	-0.0207***
	(0.00649)	(0.00650)	(0.00683)
Observations	45,104	45,104	45,104
Districts	240	240	240
R-squared	0.128	0.136	0.137
District FE	Yes	Yes	Yes
Island-Year FE	Yes	Yes	Yes
Controls	No	Yes	Yes
Province-Trends	Linear	Linear	Quadratic
Mean Incidence	0.185	0.185	0.185

Standard errors clustered at the district level in parentheses. Statistical significance is denoted as *** p <0.01, ** p <0.05, * p <0.1. Control variables include climate variables, dominant occupation flexibly interacted with year and province fixed effects, distance from nearest capital, and log of population and the inverse hyperbolic sine of non-forested area. The full regression output with coefficients on covariates is provided in Appendix Table A.8.

Table 2: Forest Cover and Outbreak of Different Diseases

Was there an outbreak of disease?	(1) Malaria	(2) Dengue	(3) Diarrhea	(4) Respiratory	(5) Measles
Forest Cover (IHS)	-0.0185***	0.00386	-0.00555	-0.00936	-0.00283
	(0.00650)	(0.00412)	(0.00768)	(0.00607)	(0.00416)
Observations	45,104	45,104	45,104	45,104	45,104
Districts	240	240	240	240	240
R-squared	0.136	0.148	0.080	0.076	0.069
Mean Incidence	0.185	0.064	0.174	0.104	0.075

Standard errors clustered at the district level in parentheses. Statistical significance is denoted as *** p <0.01, ** p <0.05, * p <0.1. Control variables include climate variables, dominant occupation flexibly interacted with year and province fixed effects, distance from nearest capital, and log of population and the inverse hyperbolic since of non-forested area. All specifications control for district fixed effects, island-year fixed effects and province specific linear time trends.

Table 3: Poverty and Outbreak of Different Diseases

	(1)	(2)	(3)	(4)	(5)
Was there an outbreak of disease?	Malaria	Dengue	Diarrhea	Respiratory	Measles
Log(Number of Poor Cards)	0.0101***	0.0112***	0.00926***	0.00591**	0.00466**
	(0.00319)	(0.00196)	(0.00323)	(0.00272)	(0.00210)
Observations	37,111	37,111	37,111	37,111	37,111
Districts	232	232	232	232	232
R-squared	0.137	0.161	0.084	0.078	0.068
Mean Incidence	0.185	0.064	0.174	0.104	0.075

Standard errors clustered at the district level in parentheses. Statistical significance is denoted as *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Control variables include climate variables, dominant occupation flexibly interacted with year and province fixed effects, distance from nearest capital, and log of population and the inverse hyperbolic since of non-forested area. All specifications control for district fixed effects, island-year fixed effects and province specific linear time trends.

Table 4: Forest Cover and Malaria by Type of Forest

Was there an outbreak of malaria?	(1) Primary Forest	(2) Secondary Forest
Forest Cover (IHS)	-0.0185***	0.00423
	(0.00650)	(0.00884)
Observations	45,104	37,231
Districts	240	233
R-squared	0.136	0.159

Standard errors clustered at the district level in parentheses. Statistical significance is denoted as *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Control variables include climate variables, dominant occupation flexibly interacted with year and province fixed effects, distance from nearest capital, and log of population and the inverse hyperbolic since of non-forested area. All specifications control for district fixed effects, island-year fixed effects and province specific linear time trends.

Table 5: Forest Cover and Log Enrollment in Pro-Social Programs

	(1) Poor Cards	(2) Health Cards
Forest Cover (IHS)	-0.0145	-0.0194
	(0.0263)	(0.0241)
Observations	37,111	31,107
R-squared	0.278	0.469

Standard errors clustered at the district level in parentheses. Statistical significance is denoted as *** p <0.01, ** p <0.05, * p <0.1. Control variables include climate variables, dominant occupation flexibly interacted with year and province fixed effects, distance from nearest capital, and log of population and the inverse hyperbolic since of non-forested area. All specifications control for district fixed effects, island-year fixed effects and province specific linear time trends. "Poor Cards" and "Health Cards" are defined as the log of number of people in the village who have benefited from those social programs.

A Appendix

A.1 Valuing the benefit of forest cover in Indonesia

In this section, I describe the assumptions used in making back of the envelope calculations. First, I derive level estimates of the effect of forest cover on reducing malarial outbreaks. I then make data driven assumptions to translate the increased probability of malarial outbreaks to generate an estimate of the number of malarial infections reduced per unit of forest cover. Next, I use estimates from the literature to compute the number of days of lost work. Finally, I use the minimum wage to compute the dollar value associated with morbidity-reducing malaria-related benefits of local forest cover.

A.1.1 Forest Cover and Malaria (Level Effects)

Below, I re-estimate equation (1) using (1000s of) hectares of forest cover as the independent variable instead of standard deviations. The results here are similar to those in table 1 and allow for more mechanical back of the envelope calculations. I employ the most conservative estimate, in column (1). Against a baseline malarial incidence of 0.185, a 1000 hectares of forest cover reduces malarial incidence by 0.2%.

A.1.2 Probability of Outbreak to Infected Individuals

The above section shows that 1000 hectares of forest cover reduces malarial outbreak by 0.2% in every village in that district. An outbreak, on average, means that 15 individuals are infected. There are 250 villages, on average, in each district. That means 1000 hectares of forest cover results in $0.002x15x250 = 7.5$ reduced infected individuals in each district.

A.1.3 Morbidity Cost of Deforestation based on Per Capita Income

A single bout of malaria results in 10-20 sick days.[12] Therefore, 1000 hectares of primary forest cover saves about 75-150 lost working days in a year per district. The average 2017 minimum wage in Indonesia is USD 252 per month[13] and assuming 20 working days in a month, is USD 12.6 per day. Thus, 1000 hectares of primary forest cover generates USD 945 - USD 1890 in morbidity-related malaria reducing ecosystem services. This is equivalent to estimates of USD 1 - USD 2 per hectare.

[12] See: `http://malaria.jhsph.edu/about_malaria/`

[13] The average minimum wage for Indonesia in 2017 is IDR 3.5 million per month which translates to USD 252 based on exchange rates on January 12, 2017.

A.2 Additional Figures and Tables

Figure A.1: Kernel Density Distribution of Infections conditional on reported outbreak in 2008

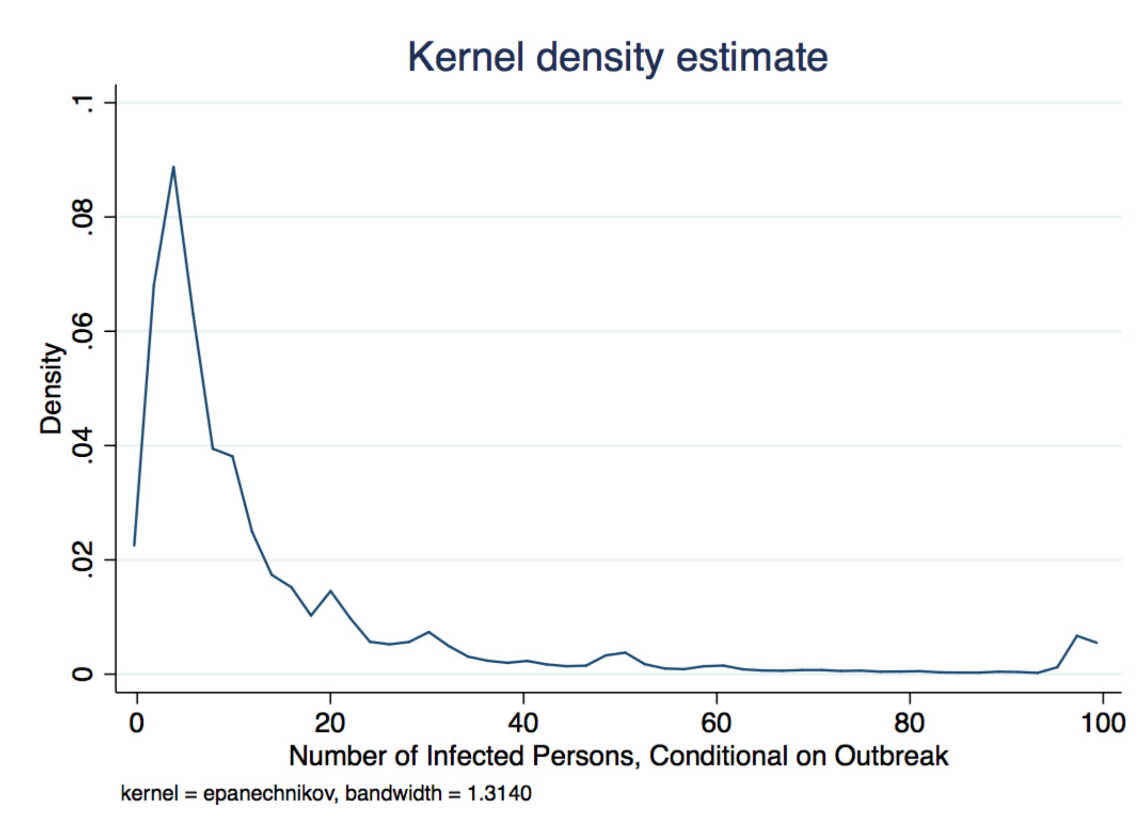

Figure A.2: Percentage Area (District Level) Under Primary and Secondary Forests in Indonesia

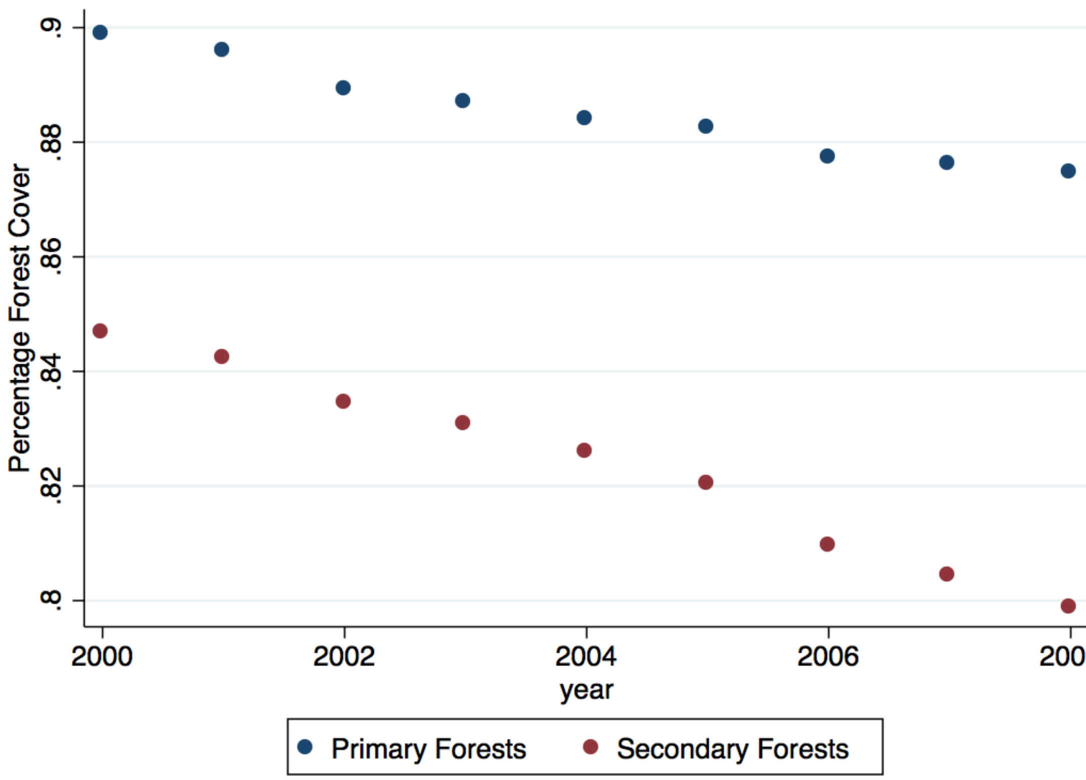

Table A.1: Fraction of Villages with Disease Outbreaks (Village Level)

Was there an outbreak of	(1) Primary Forests	(2) Secondary Forests
Malaria	0.185	0.210
	(0.388)	(0.407)
Dengue	0.0645	0.0553
	(0.246)	(0.229)
Diarrhea	0.174	0.186
	(0.379)	(0.389)
Respiratory	0.104	0.105
	(0.305)	(0.307)
Measles	0.0748	0.0849
	(0.263)	(0.279)
Observations	45,104	37,234

Standard deviations in parentheses. Column 1 shows mean and standard deviation for the sub-sample of villages with primary forests. Column 2 shows mean and standard deviation for the sub-sample of villages with secondary forests.

Table A.2: Key Independent Variables (Village Level)

	(1) Full Sample	(2) Primary Forests	(3) Secondary Forests
100's of Families Receiving Poor Status Papers	0.325	0.313	0.302
	(0.759)	(0.698)	(0.758)
100's of Families Receiving Health Cards	0.774	0.758	0.721
	(1.386)	(1.411)	(1.249)
Hospital (Yes = 1; No = 0)	0.635	0.629	0.649
	(0.928)	(0.926)	(0.934)
Ease of Access to Nearest Hospital[a]	2.590	2.577	2.671
	(0.881)	(0.874)	(0.881)
Population Density	0.00641	0.00454	0.00439
1000's of persons per hectare	(0.0341)	(0.0227)	(0.0207)
Rice Field Area (1000 Ha)	0.251	0.231	0.291
	(1.215)	(1.027)	(1.511)
Is the village by a river? (Yes = 1, No = 0)	0.709	0.706	0.723
	(0.454)	(0.456)	(0.447)
Elevation Above Sea Level (100 meters)	2.120	2.194	2.264
	(4.968)	(5.675)	(4.693)
Mean Annual Rainfall (1000mm)	0.0698	0.0691	0.0706
	(0.0177)	(0.0169)	(0.0186)
Annual Variation in Rainfall (1000mm)	0.0319	0.0313	0.0323
	(0.00987)	(0.00959)	(0.0103)
Observations	100,572	40,938	33,753

Standard deviations in parentheses. Column 2 shows mean and standard deviation for the sub-sample of villages inside or on the border of the forest area. Column 3 shows mean and standard deviation for the sub-sample of villages. These characterizations are made by the village head and verified at the sub-district office.

[a] Ease of access defined as follows. 0 = hospital in village, 1 = very easy, 2 = easy, 3 = difficult and 4 = very difficult. These delineations are made by the village head and verified at the district/sub-district office.

[b] Rainfall variables calculated over the sample range of 2001-2008.

Table A.3: Comparison of Results from LPM, Logit and Probit

Was there an outbreak of malaria in the previous year?	(1) LPM	(2) Logit	(3) Probit
Forest Cover (IHS)	-0.0201***	-0.0191***	-0.0210***
	(0.00649)	(0.00645)	(0.00693)
Observations	45,104	44,728	44,728

Standard errors clustered at the district level in parentheses. Statistical significance is denoted as *** p <0.01, ** p <0.05, * p <0.1.

Table A.4: Forest Cover and Malaria by Distance from Forest

Was there an outbreak of malaria?	(1) Outside Forest	(2) Inside/Near Forest
Forest Cover (IHS)	-0.0156**	-0.0273***
	(0.00640)	(0.0102)
Observations	32,222	12,882
Districts	234	220
R-squared	0.133	0.180

Standard errors clustered at the district level in parentheses. Statistical significance is denoted as *** p <0.01, ** p <0.05, * p <0.1. Control variables include climate variables, dominant occupation flexibly interacted with year and province fixed effects, distance from nearest capital, and log of population and the inverse hyperbolic since of non-forested area. All specifications control for district fixed effects, island-year fixed effects and province specific linear time trends. The coefficients of Forest Cover (IHS) for Outside Forest and Inside/Near Forest are not statistically different at conventional levels (p-value = 0.22).

Table A.5: Population and Forest Cover by Type of Forest

Dependent Variable: Log (Population)	(1) Primary Forest	(2) Secondary Forest
Forest Cover (IHS)	0.0508**	0.0261***
	(0.0207)	(0.00706)
Observations	45,104	37,231
R-squared	0.585	0.578

Standard errors clustered at the district level in parentheses. Statistical significance is denoted as *** p <0.01, ** p <0.05, * p <0.1. Control variables include climate variables, dominant occupation flexibly interacted with year and province fixed effects, distance from nearest capital, and the inverse hyperbolic since of non-forested area. All specifications control for district fixed effects, island-year fixed effects and province specific linear time trends.

Table A.6: Agricultural Activity, Forest Cover, Malaria

	(1) Rice Area Percentage	(2) Malaria Outbreak
Forest Cover (IHS)	-0.000154	-0.0178***
	(0.000229)	(0.00549)
Rice Field Area (IHS)		0.0321**
		(0.0157)
Observations	41,332	41,332
R-squared	0.275	0.124

Standard errors clustered at the district level in parentheses. Statistical significance is denoted as *** p <0.01, ** p <0.05, * p <0.1. Control variables include climate variables, dominant occupation flexibly interacted with year and province fixed effects, distance from nearest capital, and log of population and the inverse hyperbolic since of non-forested area. All specifications control for district fixed effects, island-year fixed effects and province specific linear time trends.

Table A.7: Forest Cover and Malarial Incidence (Levels)

Was there an outbreak of malaria?	(1) FE	(2) Add Controls	(3) Add Lags
Forest Cover (1000 Ha)	-0.000376***	-0.000386**	-0.0175***
	(0.000143)	(0.000149)	(0.00341)
Forest Cover One Year Before (1000 Ha)			0.0712***
			(0.0202)
Forest Cover Two Years Before (1000 Ha)			-0.0539***
			(0.0179)
Observations	45,104	45,104	45,104
R-squared	0.130	0.137	0.139
District FE	Yes	Yes	Yes
Island-Year FE	Yes	Yes	Yes
Controls	No	Yes	Yes
Lags	No	No	Yes
Mean Incidence	0.185	0.185	0.185

Standard errors clustered at the district level in parentheses. Statistical significance is denoted as *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The full set of controls include geographic variables, climate variables, dominant occupation flexibly interacted with year and province fixed effects, distance from nearest capital, and population density. All specifications control for province specific linear time trends.

Table A.8: Forest Cover and Malarial Incidence (Full Regression Output)

	(1)	(2)	(3)
Was there an outbreak of malaria?	FE	Add Controls	Quadratic Trends
Forest Cover (IHS)	-0.0201***	-0.0185***	-0.0207***
	(0.00649)	(0.00650)	(0.00683)
Village Near Forest		0.0341***	0.0334***
		(0.0100)	(0.0101)
Village Inside Forest		0.0635**	0.0635**
		(0.0301)	(0.0302)
Distance to Kabupaten Office (100Km)		-0.000511	-0.000329
		(0.00921)	(0.00927)
Height Above Sea Level (100 meters)		-0.000442	-0.000523
		(0.00128)	(0.00131)
Mean Annual Rainfall (1000mm)		-0.851	-0.611
		(0.986)	(0.942)
Annual Variation in Rainfall (1000mm)		2.112	2.408
		(1.702)	(1.900)
Log(Population)		0.00677	0.00678
		(0.00721)	(0.00731)
Non-Forest Area (IHS)		0.00386	0.00384
		(0.00255)	(0.00251)
Observations	45,104	45,104	45,104
Districts	240	240	240
R-squared	0.128	0.136	0.137
District FE	Yes	Yes	Yes
Island-Year FE	Yes	Yes	Yes
Controls	No	Yes	Yes
Province-Trends	Linear	Linear	Quadratic
Mean Incidence	0.185	0.185	0.185

Standard errors clustered at the district level in parentheses. Statistical significance is denoted as *** p <0.01, ** p <0.05, * p <0.1. Control variables include climate variables, dominant occupation flexibly interacted with year and province fixed effects, distance from nearest capital, and log of population and the inverse hyperbolic sine of non-forested area.