Does Forest Loss Increase Human Disease? Evidence from Nigeria

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It is estimated that about one quarter of the global disease burden in terms of healthy life years lost and about one quarter of all premature deaths can be attributed to modifiable environmental factors (Pruss-Ustun and Corvalan 2006). Three infectious diseases – diarrhea, respiratory infections, and malaria – account for the largest absolute burden in developing countries with children facing the greatest impacts. There is a growing body of evidence demonstrating the health burden of air and water pollution, as well as important productivity and income effects (see, for example, reviews of the literature in Pattanayak and Pfaff (2009) and Greenstone and Jack (2016)). Studies that focus on the impacts of natural resource degradation are fewer. A recent paper by Garg (2016), for example, examines the public health effects of ecosystem degradation in Indonesia.

In this paper, we extend this new literature on the health impacts of environmental degradation by estimating the causal impact of forest loss on infectious disease incidence in young children using temporal and spatial variation in the last two decades in Nigeria. Our estimation strategy involves geolinking a new high-resolution dataset of global forest change to child-level health data from the Nigeria Demographic and Health Surveys from 2008 and 2013. We find that forest loss significantly increases the incidence of malaria, though it does not affect the incidence of diarrhea and respiratory diseases. The impact of forest loss on malaria is large (one standard deviation of forest loss increases malaria incidence by more than 5 percent in children under five) and the dynamic pattern of the impact suggests a temporary ecological disturbance consistent with findings in the tropical medicine literature.

I. Deforestation and disease burden in Nigeria

The world's forests cover almost four billion hectares or about 31 percent of the land surface. They are a source of timber and food, provide habitat for numerous species, and supply essential ecosystem services such as climate regulation, filtration of water, and protection of soils. While the annual rate of global deforestation has slowed since its highest of 16 million hectares in the 1990s, it is still high in many regions. Nigeria has experienced one of the greatest net losses in Sub-Saharan Africa. Between 1990 and 2015, Nigeria lost over 17 million hectares of forest and other wooded land area, with an average annual loss of 3.5 percent for forests and 5 percent for wooded land areas, due to agricultural encroachment, infrastructure development, excessive official and unofficial logging, firewood collection, and urbanization (FAO 2015). Uncoordinated land use policy, weak enforcement and inadequate funding of existing conservation policies and programs, as well as poor data quality (the last national forest inventory dates back to 1997) remain the major impediments to forest conservation (Usman and Adefalu 2010). Figure 1 presents our estimates of tree loss in Nigeria between 2000 and 2012.

At the same time, Nigeria is home to one-fifth of Africa's population with some of the highest disease burdens on the continent. Despite significant progress in health outcomes since the 1990s, in 2013 the under-five mortality rate remained at 117 deaths per 1,000 live births and there were 560 maternal deaths per 100,000 live births (WHO 2015). Among children under five, 21 percent of deaths are attributed to malaria, 15 percent to acute respiratory infections, and 10 percent to diarrhea.

The direction of the impact of environmental degradation such as tree loss on the incidence and severity of infectious diseases is not clear *a priori*. Forests and wooded areas are a source of fuel for more than 50 percent of Nigeria's population that relies on solid biomass for cooking. Forests regulate temperature and rainfall that affect the breeding and survivorship of malariacarrying mosquitoes and filter water for the rural and urban population, 70 percent of which still lacks access to improved drinking-water sources. While the biological mechanisms linking forest cover and disease are complex, and potentially nonrandom location of deforestation and confounding trends in the economy make it difficult to tease out the effects of tree loss on health outcomes, we believe our identification strategy provides new and useful evidence. This evidence motivates further investigation of underlying mechanisms and long-term economic consequences (on educational attainment, productivity, and income, for example) of environmental degradation (as called for in Greenstone and Jack (2015)).

II. Data

Our health data come from the Nigeria Demographic and Health Surveys (DHS), nationally representative cross-sectional geo-referenced surveys for 2008 and 2013 (NPC and ICF 2009; NPC and ICF 2014). We construct a two-year panel of Nigeria's second smallest administrative units – local government areas (LGAs) – that appear in each of the survey rounds. The data used, however, are at an individual-level: for each child under 5 years of age, we have outcomes for the three main infectious diseases. The prevalence of malaria is estimated by asking mothers whether their child had been ill with a fever during the two weeks preceding the survey. Similarly, acute respiratory infection (ARI) (with pneumonia being the most serious outcome of ARI) and diarrhea are estimated by the incidence of a cough accompanied by short, rapid breathing or diarrhea, respectively, in the two weeks preceding the survey. These data are based on the mother's perception of illnesses. While they are not validated by a medical examination during the survey, the data have been found to serve as good proxies for actual diseases (see, for example, Okiro and Snow (2010)). The resulting sample includes over 35,000 children under five across 409 LGAs. In addition, the DHS data contain other individual- and household-level demographic and socio-economic variables that we use as controls in estimation.[1]

Our regressor of interest, tree loss, comes from a high-resolution dataset of global forest change based on time-series analysis of Landsat images at a spatial resolution of one arc-second (about 30 meters at the equator), with loss allocated annually (Hansen et al. 2013). Forest loss is defined as a change from a forest to non-forest state (or a stand-replacement disturbance), encoded as either 1 (loss) or 0 (no loss). The DHS data sets report longitude and latitude of the primary sampling unit, a cluster, and defined on the basis of census enumeration areas. The locations of clusters are, however, randomly displaced to protect the confidentiality of survey respondents.[2] Following the best practice guidelines outlined in Perez-Haydrich et al. (2013), we create a 5-km buffer zone for each DHS cluster and calculate the share of pixels in the buffer zone with forest loss for the year of and up to seven years preceding the DHS interview.

Two additional spatial data sets are used in the study. Soil fertility indicators (soil organic carbon content, soil pH, and Cation Exchange Capacity for 1-15 cm soil depth) are from the African SoilGrids 250m GeoTiffs data set (Hengl et al. 2015) and the nighttime lights from cities, towns, and other sites with persistent lighting data are from the National Oceanic and Atmospheric Administration-National Geophysical Data Center[3] (US Air Force Weather Agency 2009). The nighttime lights data have been found to be a useful disaggregated proxy for economic activity in regions with low data quality (Chen and Nordhaus 2011).

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[1] The full set of controls and their description are reported in the appendix.

[2] Rural locations are displaced 0-5 kilometers (with one percent displaced 0-10 kilometers) and urban locations are displaced 0-2 kilometers. The displacement is a random direction and random distance process.

[3] We use the Version 4 of the DSMP-OLS Nighttime Lights Time Series, at a resolution of 30 arc-seconds and constructed using the smoothed spatial resolution mode.

III. Estimation strategy

We use several strategies to account for potential nonrandom location of deforestation and confounding trends in the economy that make it difficult to tease out the effects of tree cover loss on health outcomes. First, we include fixed effects at the LGA level and time-region trends to estimate the health effects using only within-LGA variation. We also include controls at the cluster level: soil fertility and altitude to account for deforestation due to clearing of land for agriculture and time-varying annual changes in nighttime lights data to account for urbanization, infrastructure development, and other confounding economic trends. We estimate the following equation:

$$Y_{itc} = \alpha_0 + \sum_{j=0}^{3} \beta_j loss_{tc}^{j} + \boldsymbol{X'_{itc}\gamma} + \boldsymbol{LGA'_{c}\pi} + \mu' month_{itc} + \boldsymbol{DHSyear'_{t}\,\theta}$$
$$+ \sum_{m=1}^{12} \lambda_m month_{tc}^{m}\ x\ Region_c x\ DHSYear_t +\ \epsilon_{itc},$$

where Y_{itc} is a health outcome for child *i* in DHS year *t* in cluster *c* (incidence of malaria, cough, or diarrhea) and β_j provides estimates of the impact of tree loss for a series of lagged years on the incidence of health outcome. LGA_c is a set of LGA-fixed effects, $month_{itc}$ is a month of the interview and $DHSyear_t$ accounts for the round of the DHS survey, $\sum_{m=1}^{12} \lambda_m month_{tc}^{m}\ x\ Region_c x\ DHSYear_t$ provides controls for regional weather and annual variation in seasonality that may influence the prevalence of infectious diseases, and the vector $\boldsymbol{X'_{itc}}$ includes a rich set of individual- and household-level controls, as well as cluster-level soil fertility, altitude, and time-varying nighttime lights data. We cluster standard errors at the LGA level and account for stratification used in the DHS sampling design.

IV. Impact of forest loss on infectious diseases

Table 1 presents estimates of the impact of forest loss on malaria, diarrhea, and cough. For each disease we begin by estimating a pooled OLS regression of disease incidence on lags of forest loss and proceed to add LGA and year fixed effects followed by the full set of time-varying controls described above. For all three diseases, the pooled regression indicates a negative correlation between forest loss and disease, with forest loss one year ago associated with large statistically significant decrease in malaria (column 1) and diarrhea (column 4). These initial results indicate that in the aggregate, areas with higher rates of deforestation have better health outcomes. However, there are many omitted factors correlated with both deforestation and health that potentially bias these initial estimates. When we control for time-invariant unobserved differences across the LGAs (along with time-varying individual and cluster controls), the coefficient on malaria remains large, but reverses sign, while for diarrhea the coefficient approaches zero. When we add controls for factors related to the causes of deforestation, such as soil fertility, altitude and changes in nighttime lights data, the coefficient on malaria decreases slightly but remains large and significant at a 1 percent level (column 3), while the estimated impact of forest loss on diarrhea (column 6) and cough (column 9) remains small and insignificant.

The results for malaria in column 3 indicate that a loss of one percent of forest cover in the previous year leads to a 2.5 percentage point increase in malaria incidence. The final row of the table interprets the magnitude of the estimated impact of one standard deviation of forest loss (0.3 percent) in terms of mean levels of disease incidence.

V. Malaria and forest loss

The additional lags of forest loss allow us to investigate the dynamic impact of forest loss on malaria and suggest a temporary ecological disturbance consistent with findings in the tropical medicine literature. Figure 2 shows the cumulative impact of forest loss on the incidence of malaria and diarrhea. The positive (and statistically significant) impact is felt for malaria one and two years since forest loss, after which it declines to zero.

Yasuoka and Levins (2007) and Pattanayak and Pfaff (2009) review potential pathways through which disturbed ecological conditions due to forest loss and land transformation can affect malaria infection and disease transmission. They conclude that both biophysical changes (average temperature and variability, amount and duration of sunlight, humidity, water and soil conditions, and vegetation) and human behavioral changes (increased human contact due to siting of settlements, irrigation systems, migration, etc.) can link forest loss to increased malaria incidence. These changes influence the ecology of the disease – larval and adult survivorship of mosquitos, as well as their reproduction and vectorial capacity. Links between deforestation and the incidence of human malaria have been shown, for example, in Brazil (Olson et al. 2010) and in Malaysia (Fornace et al. 2016). To our knowledge, however, only one paper provides causal evidence. Using district-level variation in deforestation and village-level census data from Indonesia, Garg (2016) reports a statistically significant impact of deforestation on malaria.

VI. Conclusion and next steps

We demonstrate the causal impact of forest loss on infectious disease incidence in young children in 21st century Nigeria. We find that forest loss significantly increases the incidence of malaria, though it does not impact diarrhea and respiratory diseases. Exposure to malaria at young age has been shown to have significant effects on both health and economic outcomes later in life (malaria, for example, has been shown to affect educational attainment and literacy (Lucas 2010)). Our findings, thus, motivate further investigation of long-term consequences of forest loss on economic outcomes in Nigeria and elsewhere on the continent.

TABLE 1. THE IMPACT OF FOREST LOSS ON DISEASE INCIDENCE

Dependent variable	Malaria (Fever)			Diarrhea			Respitory (Cough)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(3)
Forest Loss									
this year	1.158	-0.0232	0.0257	-1.344*	-0.701	-0.571	1.251	-1.551	-1.636
	(0.966)	(1.049)	(1.069)	(0.691)	(0.636)	(0.652)	(1.168)	(1.202)	(1.215)
1 year ago	-3.353**	2.680***	2.549***	-3.474***	0.142	0.0950	-1.912	1.146	0.953
	(1.491)	(0.981)	(0.979)	(1.283)	(0.759)	(0.735)	(1.184)	(0.892)	(0.890)
2 years ago	-0.926	1.614	1.682*	1.076	0.919	0.848	-2.520**	-1.073	-0.924
	(1.468)	(1.037)	(1.013)	(1.700)	(1.134)	(1.095)	(1.119)	(0.919)	(0.896)
3 years ago	-0.181	-3.443	-3.894	-6.215***	0.0529	-0.384	6.617*	0.602	0.596
	(2.620)	(2.938)	(2.969)	(1.390)	(1.228)	(1.298)	(3.467)	(2.413)	(2.433)
LGA fixed effects (409 units)	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Seasonality	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
HH and indiv controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Soil and altitude	No	No	Yes	No	No	Yes	No	No	Yes
Nighttime lights	No	No	Yes	No	No	Yes	No	No	Yes
Observations	35,792	34,456	34,456	35,726	34,390	34,390	35,698	34,365	34,365
R-squared	0.001	0.089	0.090	0.004	0.088	0.088	0.001	0.099	0.099
Mean disease incidence	14.3%			10.4%			11.1%		
Impact of 1sd of forest loss 1 year ago as a percent of mean disease incidence	-7.2%	5.7%	5.4%	-10.2%	not st. sig	not st. sig	not st. sig	not st. sig	not st. sig

Notes: Table presents estimates of equation (1) where the dependent variable is reported disease incidence for children under the age of 5. Columns 1-3 report results for malaria, columns 4-6 for diarrhea, and columns 7-9 for cough. The full set of individual and household controls are listed in the appendix.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

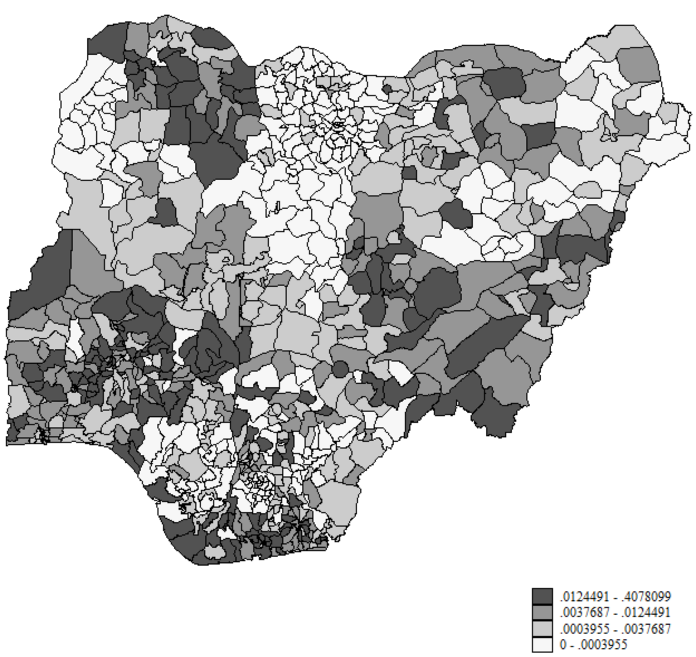

FIGURE 1. GEOGRAPHIC VARIAION OF FOREST LOSS IN NIGERIA BY LGA (2001-2012)

Notes: The map shows the average rate of forest loss from 2001 to 2012 by LGA in the clusters we observe in the 2008 and 2013 Nigerian DHS, where the rate is calculated as the percentage decrease in tree cover in a 5km buffer around the DHS cluster. LGAs not observed in 2008 or 2013 are not shaded. Source: Author’s calculations based on forest loss data from (Hansen et al. 2013).

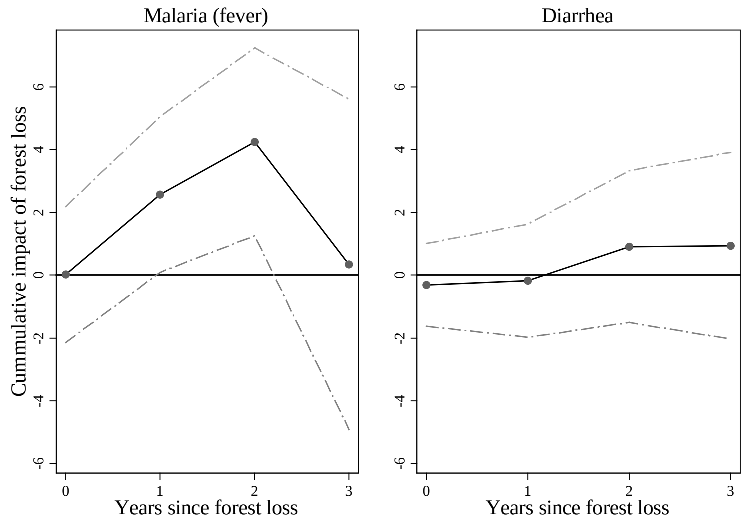

FIGURE 2. CUMULATIVE IMPACT OF FORREST LOSS

Notes: The figure plots the cumulative sum of the forest loss coefficients from Table 1 for malaria (column 3) and diarrhea (column 6). Dotted lines show 95 percent confidence intervals for each sum.

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