Measuring Social Effects of Deforestation Exposure

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Abstract: A large literature documents the positive relationship between forest ecosystem services and socioeconomic well-being in forest-proximate communities, in particular in lower income contexts. How deforestation affects these synergies, however, is less well understood. While aggregate forest loss metrics over any given administrative subdivision or area are widely used in social science research, measuring exposure to deforestation from an individual's or household's perspective is not commonplace. We combine geo-referenced data from a nationally representative survey in 34 sub-Saharan African countries with spatially explicit land use and land cover data at 10 by 10-meter resolution. For every survey location in our sample, we compose locally centered metrics of forest cover change. For robustness, we vary the detection sensitivity, circle radius, and recall period length of our exposure metrics to test how each of these parameters influence the final product, and we compare our local exposure metrics to traditional deforestation metrics. We conclude by envisioning applications for which localized exposure metrics might prove relevant in future research.

JEL Codes: I31, Q23, Q51, Q56, Q57

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Introduction

Forests cover 31% of the earth's land area. Roughly a quarter of the human population live within 5 km of a forest (Newton et al., 2020). However, many of these forests are in danger of being destroyed. The planet has lost 12% of its forests since 2001. Most of this deforestation is occurring in low income countries, where people rely on it the most as a source of food, water, and income (*The State of the World's Forests 2020*, 2020).

The following paper sets out new guidelines for studying the socioeconomic impacts of this global phenomenon. The destruction of forests is a concern across the developing world, but its effects have not been captured in a systematic way because forests have a number of benefits that are difficult to quantify, and because deforestation metrics are not reported in relation to human populations centers. Rather most deforestation metrics are designed to provide researchers about wildlife, biodiversity, and carbon sequestration.

In Economics applications, on the other hand, the host of design choices that are needed for deforestation indicators is rarely discussed. This paper sheds light on the sensitivity of local socio-economic damage estimates to deforestation definitions. Thus, in this paper we seek to answer two separate but related questions:

- First, how does deforestation relate to key socio-economic and wellbeing metrics of nearby communities in low-income countries?
- Second, how do these relationships change when using deforestation metrics based on different levels of geographic granularity?

To answer these questions we combine socioeconomic data with deforestation data across different spatial and temporal dimensions. We utilize a geolocated nationally representative household survey that covers 34 countries in Sub-Saharan Africa, and spans 4 years. Using spatial analysis, we combine this survey data with deforestation metrics we generate from 10m by 10m resolution land use data. This provides us very flexible deforestation variables, which we set up to provide information on different sized areal units, at varying distances of proximity to each household, and cover different temporal units. This enables us to test how much socioeconomic indicators relate to deforestation that occurs within a range of distances from a community, and within the administrative area boundaries to which a community belongs.

In addition to creating our own customized deforestation measurements, we also compare deforestation metrics generated by other institutions whose metrics are commonly relied upon by other researchers and policy makers in the field. This provides us a more robust analysis, helps us validate our deforestation metrics, and allows us to measure how useful commonly used deforestation data is at understanding what happens to communities when nearby forests are lost.

Roughly a quarter of the human population live within 5 km of a forest (Newton et al., 2020). However, many of these forests are in danger of being destroyed. The planet has lost 12% of its forests since 2001. Most of this deforestation is occurring in low income countries, where people rely on it the most as a source of food, water, and income (The State of the World's Forests 2020, 2020). variables. These variables, such as life evaluation questions, enable survey respondents to take into account a wide array of factors affecting their life, including both economic and non-economic considerations. This Life Evaluation metric provides a comprehensive measure of one's quality of life, making it more likely we capture effects of deforestation. Accordingly, we also use this variable when comparing localized and non-localized deforestation metrics.

We do rely solely on this variable. We also investigate what types of social and economic variables are most associated with deforestation, and in which context. Ultimately we believe this analysis provides researchers and policy makers a better understanding of the human-forest relationship, and what metrics are most important to monitor this moving forward.

Data

The following section describes the data and variable construction. First, we explain our dependent variable – the SWB metric called Life Evaluation, which we obtain from the Gallup World Poll. Second, we detail the forest cover and forest attrition distance variables.

Subjective Well Being

Our SWB data comes from the first question on the Gallup World Poll (GWP). The GWP is an annual survey, conducted each year since 2006, representing 95% of the world's population each year. Each country has a sample of N=1,000, except a handful of high population countries that have larger samples, and a few small population countries which have samples of 500.

Each country is surveyed through probability-based survey methods, administering surveys through face-to-face interviews in three-fourths of the countries and phone interviews in the other quarter. All data used in our analysis comes from face-to-face interviews. In these countries, nationally representative sampling frames are used, which are stratified by urbanity and region. Countries are sampled according to probability proportional to size sampling, and cities are not oversampled. Base weights and post-stratification weights are usually based on the most recent census, but sometimes rely on other sources when countries have no up-to-date census. Post-stratification weights are constructed using gender, age, and education.

World Poll surveys are typically administered between March and October of each year. Seasonality is an important issue, which is taken into account during the interpretation of the results. Countries tend to be interviewed the same month every year, helping to ensure strong repeated cross-sectional data, but there are a few exceptions to this as well. To account for these exceptions, we control for deviations from the usual month of interview in a country. At the sub-national level, interviews are conducted in a quasi-random order throughout the region.

Since 2008, the day that the interview was conducted has been recorded. Since 2016, the GPS coordinates of the interview have been recorded. GPS was recorded at the primary sampling unit level, meaning the GPS accuracy is within one kilometer of the interview.

Subjective well-being, as measured by Cantril-type scales (Cantril, 1966) can be interpreted as a censored, ordinal transform of an underlying (latent) utility function. For any individual respondent, economists generally hypothesise that "there is a continuously varying strength of preferences that underlies the rating they submit" (Greene, 2018; Hole & Ratcliffe, 2021; Kaiser & Vendrik, 2020; Schröder & Yitzhaki, 2017; Sofer et al., 2016; Yamauchi, 2020). To see this more formally, denote utility as ranging over the entire real line:

$$-\infty < U_i < +\infty$$

where i indicates the individual. A Cantril scale with K ordered response categories maps onto the utility as follows:

$$Y_i = k \; if \; \mu_k < U_i \leq \mu_{k+1}, k = 1, \ldots, K$$

Thus, we observe a response category when the latent utility falls within the range defined by the two threshold parameters k and $k + 1$, which are assumed to be strictly increasing in k, such that

$$\mu_k < \mu_{k+1} \forall k. \text{ with } \mu_1 = -\infty \text{ and } \mu_{K+1} = \infty$$

1.1. Forest Cover Metrics

The analysis uses the share of an area's surface covered by forests (Forest Cover, FC) to capture forest dynamics. They are first computed for each pixel on a grid and then aggregated through circular buffers with radius r around each interview location. To measure change in a forest's structure over time, "before" and "after" periods are defined relative to each interview date d_i. The "after" period starts $d\sim$ days before d_i and ends on d_i. The "before" period is set to precede the "after" period by a year, thus stretching from $d_i - 365 - d\sim$ to $d_i - 365$. The timing is depicted graphically in Figure 2, along a line signifying a discrete date count $-\infty \leq d \leq \infty$.

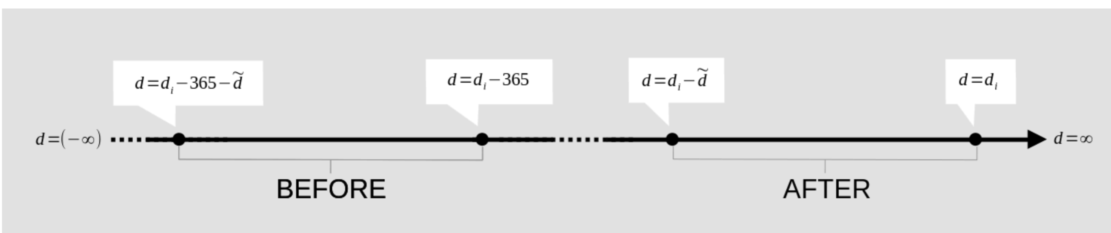

Figure 2: Before and After periods are defined relative to the interview date.

First, we process the "trees" band of Dynamic World, which provides the probability $P(T_{pd} = 1)$ that a given pixel p is entirely covered by trees at date d, by taking its mean over the "before" and "after" periods, respectively. Next, we construct binary maps that categorize each pixel as either tree-covered (1) or not (0), based on whether its mean value lies above or below a threshold $0 \leq \tau \leq 1$.

According to the FAO (2000) definition, only clusters of trees that cover an area larger than or equal to 5 hectares are considered forests. We apply this definition by requiring that every tree-covered pixel's 4-connected neighborhood include at least 49 other tree-covered pixels. At Dynamic World's 10×10 meter resolution, these neighborhoods of 50 pixels equate to an area of 5 hectares. A 4-connected (or Von Neumann) neighborhood consists of pixels that touch one another at one of their edges and, therefore, its pixels are connected horizontally and vertically. We do not consider as neighbors those pixels that touch at their corners and connect diagonally, as in 8-connected (or Moore) neighborhoods.

Tree-covered pixels outside large enough neighborhoods are recoded as zero to transform our binary tree-cover map into a forest/non-forest map.

Next, we derive our forest change metrics on the grid (i.e. by pixel) before aggregating them via a circular buffer. To derive forest cover loss, we compare the “before” and “after” periods’ forest status in each pixel. Pixels that moved from forest to non-forest status are coded 1, while all other pixels receive a zero, thus yielding a loss/non-loss map. These statistics are finally aggregated to each interview’s location by computing their mean within a circular buffer with a radius of around the interview location, weighted by each pixel’s area share within the buffer.

To perform the calculations outlined above, we use Google Earth Engine (GEE), a cloud-based platform that enables users to access a petabyte-scale archive of remote sensing data and conduct geospatial analysis on Google’s infrastructure, in combination with the R statistical programming language. Specifically, the rgee package (Aybar et al., 2020) provides us with a interface between the two, which allows us to compile geospatial calculations on GEE, download the result to a local machine, merge with the interview data, and proceed to the data cleaning and analysis phases in R. A script written to compile the forest change variables in GEE and transform them into a format that can be used for analysis in R runs successfully in about ninety minutes for all of Gallup’s interview locations in Uganda between 2016 and 2019.

Figure 3 visually explores the relationship between forest attrition distance – the average distance to the next forest edge – and forest cover. It plots mean FAD against forest cover as a percentage of the buffer area and overlays a third-order polynomial fit. It reveals a nonlinear relationship that suggests monotonic and accelerated attrition as the percentage of land covered by forest decreases. The same trend has been established for the USA by Yang & Mountrakis (2017). Figure 4 plots the change in mean FAD against forest cover loss as a percentage of previously forested area. This graph shows a monotonic positive relation that remains relatively flat at low rates of deforestation and picks up towards the right at higher rates of deforestation.

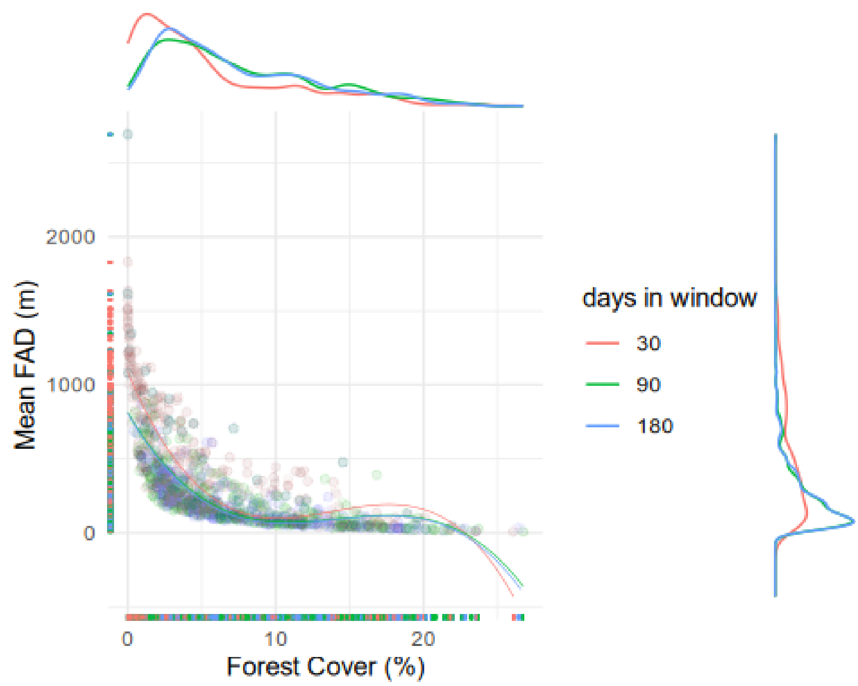

Figure 3: Forest Attrition and Forest Cover (Level)

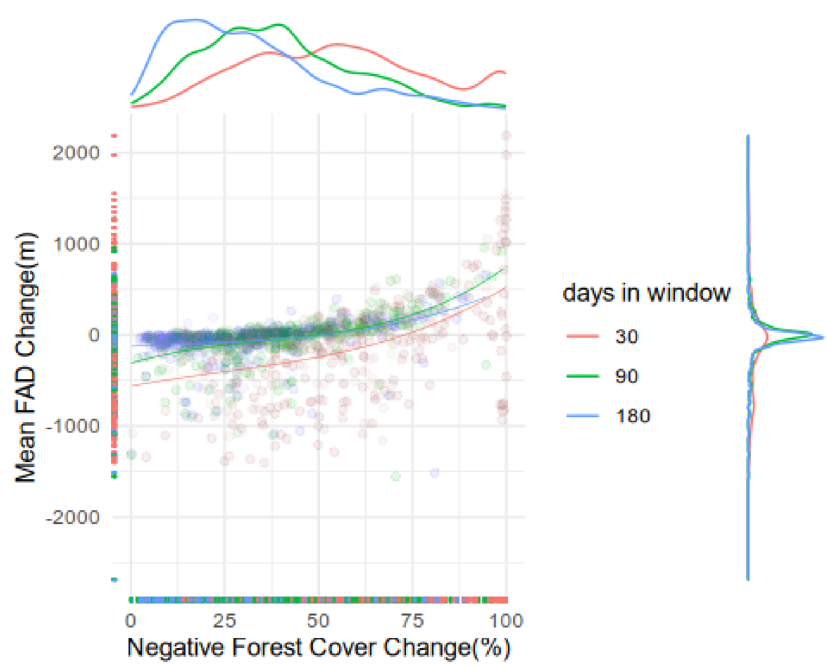

Figure 4: Forest Attrition and Forest Cover (Change)

Further Content

We are currently in the process of compiling the data for a variety of radii, cut-off points, and recall periods to enable our robustness checks. While we have existing regression results from an earlier version of this paper - showing a statistically significant negative effect of deforestation within 10 km on a person's well being - the newfound methodological focus of this paper motivated us not to include them here. Rather, we will present a set of new findings based on regressing deforestation at different distances from a location, over differently sized recall windows, and with varying precision parameters on our deforestation detection algorithm.

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