Exposure to deforestation: is statistical inference robust to choices in land cover modelling?*

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November 5, 2024

Abstract

Earth observation data has greatly enriched social science research, especially in contexts where data is otherwise scarce or likely to suffer from measurement error. However, social scientists may not have a good enough understanding of remote sensing techniques to avoid unforeseen side effects when using this type of data in novel ways. Economists, for example, often combine gridded land cover data with survey data by reducing the former to a locally centred summary statistic at the interview locations provided by the latter. The decisions taken in this reduction process can affect the resulting exposure metric and subsequent statistical inference. Using interview locations in eleven African countries from a large international survey, we calculate respondents' exposure to deforestation in 90 slightly different ways. To illustrate how this can affect inference, we model respondents' subjective well-being scores on the different versions of their exposure to deforestation in a multi-level, linear mixed model. We variably find significant negative and insignificant effects. Social scientists should be exceedingly careful when using land cover data.

JEL: I31, Q23, Q51, Q56, Q57
Keywords: exposure metrics, spatial data, GIS, earth observation, land cover, bias, inference, measurement error, deforestation, subjective well-being

*We would like to thank Lukas Vashold, Ulrich Wohak, Francesco Scarazzato, and the attendees of the special session "Tropical Deforestation – Measurement, Economic Drivers, and Human Consequences" at the 36th ERSA conference for their valuable input. MW acknowledges funding from Climate Compatible Growth for the final stages of this research.

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I. Introduction

Earth observation (EO) data has become an important tool across a wide range of scientific disciplines over the past two decades. In applied economics research, EO has found ample use to fill in gaps in traditional survey data for areas of the world where ground data is scarce (Overman, 2018). In development economics, data on night time lights and land cover (changes) have been used as proxies for economic activity (Chen et al. 2021; Gibson, Olivia, and Boe-Gibson 2020; Henderson, Storeygard, and Weil 2012; Keola, Andersson, and O. Hall 2015; Sutton and Costanza 2002). In environmental economics, the availability of gridded weather data has enabled a growing body of research dedicated to estimating the past and potential impacts of climate change on socioeconomic outcomes (see, e.g., Baylis 2020; Burke, González, et al. 2018; Burke and Tanutama 2019; Carleton and Hsiang 2016; Deryugina and Hsiang 2017). The new spatial dimension of data has also resulted in new econometric methods for (causal) inference (e.g., Butts 2023b; Butts 2023a; Delgado and Florax 2015; Deryugina and Hsiang 2017), as well as new use cases for existing ones (Druckenmiller and Hsiang 2019; Wuepper and Finger 2023).

Typically, EO data is transformed from its original form (spectral bands, e.g. infrared) into data products like categorical land use and land cover (LULC) maps[1] to analyse the social and economic effects of land cover characteristics and changes therein (García-Álvarez et al. 2022). Typical applications include modelling agricultural crop yields (D'Agostino and Schlenker 2016; Leng and J. W. Hall 2020; Schlenker and Lobell 2010; Schlenker and Roberts 2009), exposure to flood (Becher et al. 2024; Fox et al. 2024; Pople et al. 2024), drought (Anderson et al. 2021; Staal et al. 2020; Tabari and Willems 2023), or wildfires (Baylis and Boomhower 2023; Burke, Heft-Neal, et al. 2022; Wen et al. 2023), and monitoring the health of natural ecosystems more generally.

Deforestation is another classic application for land cover monitoring. As Figure 1 shows, the use of spatial data to study deforestation has grown exponentially since the early 2000s. Data on forest cover change is typically computed using a timeseries (or "raster stack") of forest-non-forest (FNF) maps. Changes at the pixel-level are computed by differencing individual maps or, more often, composites of appropriately lagged before and after periods. Due to the binary nature of the FNF maps, pixels on the resulting difference maps can only take one of three values: -1 (deforestation), 0 (no change), or 1 (reforestation or afforestation). However, the binary FNF maps underlying these simple computations are typically produced using rather complex machine learning algorithms that attach tree cover probability values to pixels, based on their reflective characteristics in a spectral analysis of raw satellite imagery (Fuentes et al. 2024; Ye, Zhu, and Suh 2024). The assignment of 0 or 1 to a pixel is then determined by whether the modelled probability value falls below or above a threshold which effectively defines what constitutes tree cover. These thresholds are often subject to offsets to avoid classification mistakes close to the boundary. Typically, they are neighbourhood specific too, since reflective characteristics vary across different forest ecosystems (Lin et al. 2024; Reiche et al. 2018). Figure 2 schematically depicts how land cover maps are created from surface reflectance images.

[1] For the similarities, differences and connections between the land use and land cover concepts see (Comber 2008).

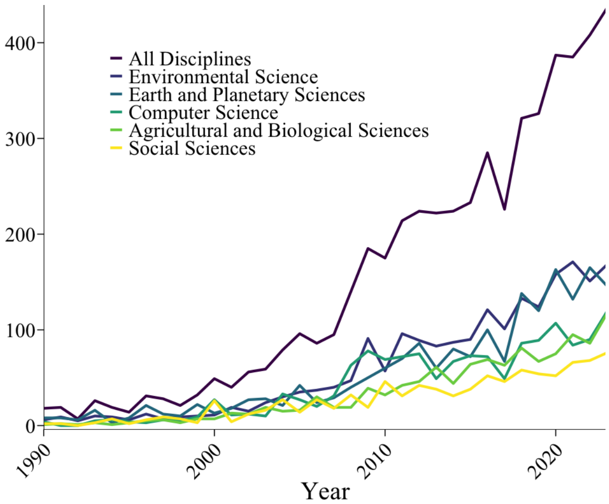

Figure 1: Number of publications whose title, abstract, or key words jointly include one or more of ″deforestation″, ″forest loss″, and one or more of ″GIS″, ″spatial data″, ″earth observation″, or ″remote sense″ (data source: SCOPUS).

Practitioners from fields that have only recently adopted GIS as part of their toolkit may not be aware of these technical details, or able to weigh their effect on the outcomes of interest (Jain 2020; Josephson et al. 2024). When processed gridded categorical data are used to supplement a more traditional, tabular data source with additional covariates, the subtleties underlying the spatial data component are rarely discussed (Foody 2015). Since this is a rather typical use case in economics and other social science disciplines, it poses the following question: How robust are estimates of socioeconomic relationships involving such covariates to changes in the key parameters used to construct them? Put differently, does the categorisation process that underlies land cover maps affect statistical inference of social phenomena? And how important are researchers' choices when aggregating (reducing) gridded data to points, relative to these differences?

To answer these questions, we emulate a typical research scenario from environmental economics. We combine survey data with a gridded land cover data product to model the effects of deforestation on survey respondents' subjective well-being across eleven East African countries.[2] In addition to a categorical landcover map (Figure 2c) we also have access to the pixel-level model probabilities (Figure 2b) underlying it – both at 10 by 10 meter resolution.

[2]They are listed in Table A2 in the appendix.

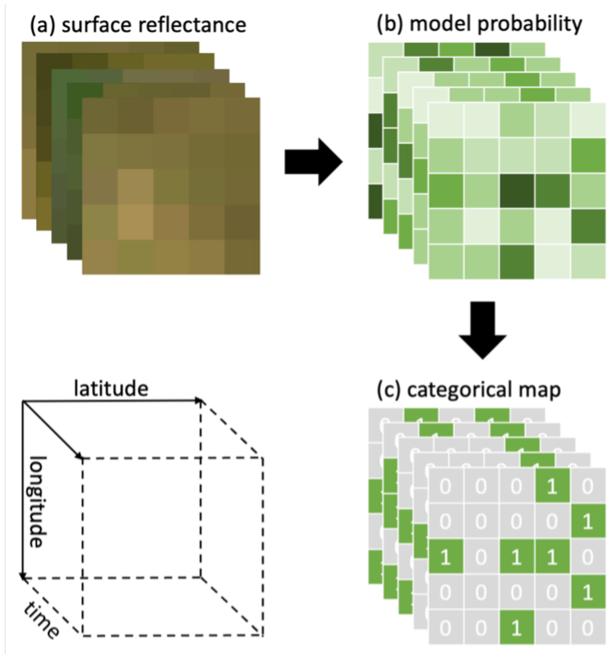

Figure 2: From raw satellite imagery to categorical landcover maps. Surface reflectance (a) enters a statistical model that computes the probability of each pixel belonging to a landcover type (b). By some threshold or benchmark, high (low) probabilities are coded 1 (0) yielding a categorical landcover map (c). In this example the resulting map is a binary FNF map (1 = tree cover, 0 = not).

To induce variability, we categorise the probability band into different FNF maps using a locally centred probability threshold with varying offset values. Additionally, we vary the length of the before and after periods as well as the radius of the circular buffers around the survey locations, which we use to extract point values from the grid. Varying these parameters one at a time, we obtain 90 combinations to calculate different versions of our deforestation metric. We then relate respondents' subjective well-being scores to these exposure metrics in a multi-level linear mixed model to test how the metric variability we induced affects statistical inference in terms of coefficient size and statistical significance.

The rest of the paper is structured as follows. Section II outlines the conceptual framework behind our analysis, introduces and summarises our data sources, describes the deforestation exposure metric's construction, and discusses the econometric strategy used to estimate deforestation impacts on subjective well-being. Results of this exercise and robustness checks are provided in Section III. Section IV discusses our findings and concludes.

II. Data and methods

A. *Conceptual framework*

Tree-based ecosystems provide services that are essential to the social and economic systems we live in and rely on – see Table A1 in the appendix. Deforestation, in turn, interferes

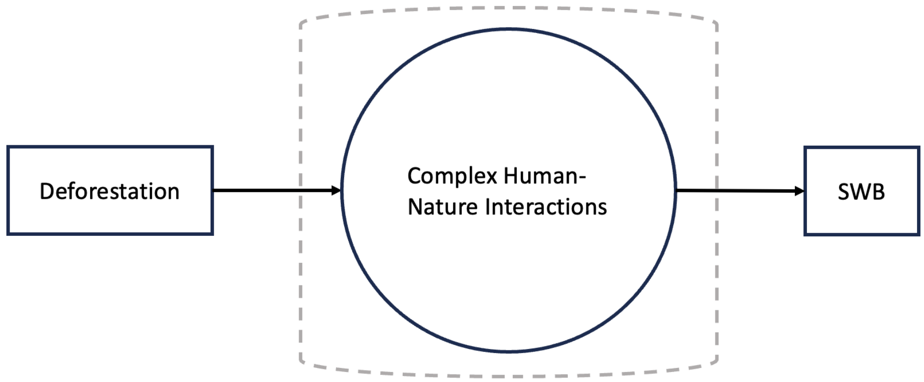

Figure 3: Simplified directed acyclic graph. Subjective well-being captures the local aggregate effects of complex human nature interactions affected by deforestation. Everything inside the dashed border is unobserved and only modeled implicitly.

with their provision and heightens risk exposure on multiple domains (Lapola et al. 2023). Outcomes that are sensitive to deforestation may also be linked to one another and nested in a complex system that spans local, regional and global human-nature interactions. Because of the non-linearities involved, statistical inference on one specific impact domain is inherently difficult.

An alternative to estimating each of the potential effects of deforestation separately is to measure an outcome that can, at least in part, proxy for the aggregate effect of deforestation on people's well-being. The life satisfaction approach to environmental valuation uses subjective well-being scores for this purpose (Ferreira and Moro 2010; Frey, Luechinger, and Stutzer 2010; Maddison, Rehdanz, and Welsch 2020; OECD 2018; Welsch and Kühling 2009). The reasoning behind this method is summarised in the directed acyclic graph (DAG) in Figure 3.

The complex human-nature interactions affected by deforestation are only considered implicitly through their effect on subjective well-being (SWB). A regression of SWB on deforestation can identify their local net effect, conditional on appropriate control variables to avoid confounding and a range of fixed and random effects to account for unobserved heterogeneity across space and time.

B. Data sources

The Gallup World Poll (GWP) is an international household survey that provides yearly repeated cross-sections of residents in more than 140 countries since 2005 (Gallup, 2021). It is composed of randomly selected, nationally representative samples of approximately 1000 individuals per country per year. We use the years 2016-2019 for which precise location data is available at the primary sampling unit (PSU) level; this is approximately equivalent to the village level.

Location data are often distorted to preserve privacy, which can lead to measurement error at a highly localised scale (Michler et al. 2022). GWP, however, reports undistorted central points within interview clusters rather than individual locations, thus relieving this concern. Measurement concerns based on systematic differences in the distance between true location and the reported PSU-centroid (Carter and Munos 2021) do not arise at the spatial scale of interest (>5km).

We construct our deforestation exposure metrics from Google's Dynamic World (DW) dataset (Brown et al., 2022). DW is a near real-time global LULC mapping product that includes nine distinct land cover classes at daily frequency from 2015. At 10m resolution, DW captures more localised variation in forest cover than other open access maps (García-Álvarez et al. 2022). Its nine LULC classes[3] are globally coherent and comparable and it provides the class probabilities which underly the classification, enabling us to adjust the confidence levels upwards (downwards) by applying a higher (lower) probability threshold.

C. *Variable construction*

Outcome Our dependent variable is respondents' SWB. It is measured on a Cantrill Self-Anchoring striving instrument[4] which yields a Likert-type ordinal scale ranging in integers from 0 to 10, where higher values indicate higher life satisfaction.[5]

Exposure First, we link the spatial data with the survey data by drawing a circular buffer with radius r around each PSU location p. Next, we isolate the tree cover probability band within each location's buffer for the d days previous to the interview as well as for the period of the same length one year prior; we call d the recall length. Take each period's respective mean, denoting by P^B the average probability before, and by P^A the one after. We also use the tree label band (the FNF map provided by DW) and compute the average probability of tree cover in pixels labelled trees over the preceding year. This yields a locally centred probability threshold a. We classify pixels as forest loss according to the following simple rule:

$$D_p = \begin{cases} 1, \text{ if } P_p^B \geq a_p + c \text{ and } P_p^A \leq a_p - c, \\ 0, \text{otherwise} \end{cases} \tag{1}$$

In addition, we only consider pixels as forested in the before period if their probability is above the threshold plus the offset and if they are 4-connected in a contiguous patch of 49 other pixels that meet the same criterion.[6] This step prevents us from counting trees outside forests.

The last step is to reduce the gridded deforestation metric to the points corresponding to the PSU locations. This is done by taking the area-weighted mean of all pixel-segments

[3]They are water, trees, grass, flooded vegetation, crops, shrub and scrub, built, bare ground, and snow and ice.

[4]The exact question used to elicit SWB reads: "Please imagine a ladder with steps numbered from zero at the bottom to 10 at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time?" (Gallup 2021).

[5]For country-level summary statistics constructed from our baseline parameter combination ($d = 90$, $r = 35$, $c = 0.1$), see Table A2 in the appendix.

[6]At 10m resolution, this operationalises the FAO (2000) definition of forests as covering at least five hectares.

that intersect with the circular buffer around each location. The result is a locally centred indicator of each PSU's exposure to deforestation as a function of radius r, recall length d, and probability offset c. In the main analysis we consider relative deforestation metric where a value of 1 indicates a complete loss of local forest coverage. Constructing the deforestation variable involves choosing three parameters. To induce variation, we vary them along the following ranges.

- Radius of circular buffer: $r_{pat} \in \{5, 10, \ldots, 45, 50 \text{ km}\}$
- Recall length: $d_{pat} \in \{90, 180, 360 \text{ days}\}$
- Probability offset: $c_{pat} \in \{0.1, 0.2, 0.3\}$

Taking all combinations of parameter values, we obtain 90 different sets of deforestation values matched with the survey data at the PSU level ($N = 4,090$).

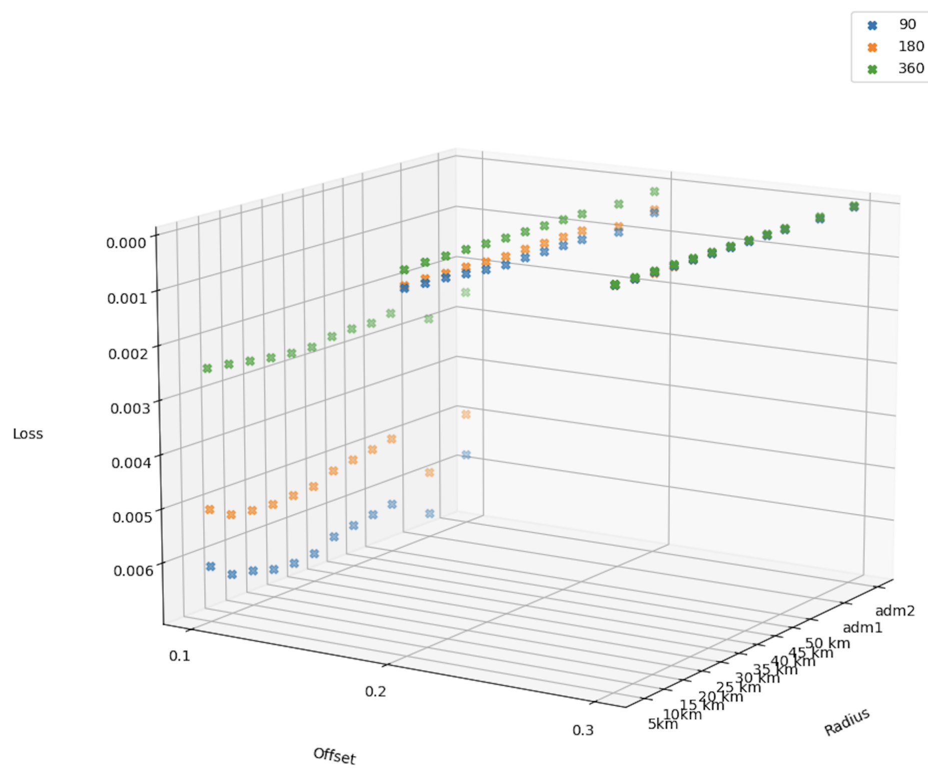

Figure 4: Figure 4: Variation in the mean deforestation as a function of offset, radius and recall length.

The 3D scatter plot in Figure 4 plots how the mean deforestation metric varies in the probability offset, the buffer radius, and the recall length. Offsets above 0.1 lead to over-rejection such that hardly any deforestation is captured. Mean deforestation also seemingly decreases with recall length while the trend from varying the radius is less clear. There is a distinct jump in the deforestation metric between a radius of 50 km or less and larger administrative units.

Other variables In addition to the SWB score, we obtain a number of control variables at the individual, household, PSU, and Admin-1 levels from GWP. These include the respondents' gender, age, and immigration status as well as the urbanicity of the interview location, month of the interview, Admin-1 areas, and distance to the closest (international) border.

D. *Empirical strategy*

Variation in deforestation metrics To formally test the implications of choosing any given parameter combination, we estimate how variation in the parameters changes the deforestation metrics for the same PSU. Thus, we estimate the following model via OLS:

$$l_{pat} = \beta_1 r_{pat} + \beta_2 c_{pat} + \beta_3 d_{pat} + \omega_a + \zeta_t + \varepsilon_{pat}. \tag{2}$$

Here, l_{pat} denotes deforestation around PSU p in area a at time t. ω_a and ζ_t capture year and Admin-1 fixed effects, and ε_{pat} an error term, clustered at the PSU level.

Impact on subjective well-being Next, we investigate the aggregate (local) effect of deforestation on subjective well-being. As respondents are nested within PSUs, we use a hierarchical model with random PSU-Year level intercepts. In our preferred specification, we include a set of time and region fixed effects and a range of respondent control variables besides the deforestation metric:

$$y_{ipat} = l_{pat}\beta + \mathbf{x}'_{ipat}\gamma + \omega_a + \zeta_t + u_p + \varepsilon_{pat}, \tag{3}$$

where y_{pat} is the SWB score of respondent i located in PSU p, nested in admin-1 area a, in year t. β contains the coefficients of interest, namely the impact of increased deforestation on SWB. Year and Admin-1 fixed effects are denoted by ζ_t and ω_a respectively, while the random PSU-level intercepts are captured by u_p. $\mathbf{x}_{ipat}$ holds the control variables described above. Standard errors are clustered at the admin-1 level since our independent variable is measured at the PSU level (Abadie et al. 2023).

III. Results

A. *Deforestation exposure*

In Table 1, the first column shows the results estimated from the entire sample of PSU locations. Columns 2-5 are estimated on subsamples along percentiles of forest cover in the before period to control whether the initial extent of forest cover affects the impact of parameter variation on the deforestation metric.

Across all model specifications, deforestation as a percentage of previous forest cover decreases in recall length as well as in the probability cutoff. In fact, increasing recall length by a single day decreases the deforestation metric by 0.01 percentage points and this effect is relatively stable and highly statistically significant, regardless of initial forest cover.

Table 1: Regression output from Equation 2.

	(1)	(2)	(3)	(4)	(5)
$l(\%)$	full sample	25th perc.	50th perc.	75th perc.	100th perc.
d	-0.01***	-0.00***	-0.00***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
c	-26.31***	-0.48***	-11.59***	-29.11***	-61.49***
	(3.36)	(0.09)	(1.76)	(3.15)	(7.16)
$r =$					
10 km	-0.07	-0.01	0.00	-0.06	-0.25
	(0.042)	(0.007)	(0.042)	(0.084)	(0.14)
15 km	-0.09	-0.01	-0.02	-0.12	-0.38*
	(0.07)	(0.01)	(0.05)	(0.10)	(0.17)
20 km	-0.09	-0.03**	-0.05	-0.12	-0.49*
	(0.09)	(0.01)	(0.06)	(0.10)	(0.22)
25 km	-0.09	-0.02*	-0.04	-0.17	-0.56*
	(0.11)	(0.01)	(0.06)	(0.12)	(0.26)
30 km	-0.17	-0.03**	-0.14	-0.29**	-0.70*
	(0.11)	(0.01)	(0.08)	(0.10)	(0.27)
35 km	-0.16	-0.03**	-0.13	-0.35**	-0.72**
	(0.14)	(0.01)	(0.07)	(0.12)	(0.26)
40 km	-0.19	-0.03**	-0.16*	-0.43***	-0.77**
	(0.15)	(0.01)	(0.07)	(0.13)	(0.26)
45 km	-0.20	-0.02**	-0.18**	-0.48***	-0.75**
	(0.15)	(0.01)	(0.07)	(0.12)	(0.25)
50 km	-0.25	-0.02*	-0.23**	-0.48***	-0.94**
	(0.16)	(0.01)	(0.07)	(0.12)	(0.30)
ADM1	-0.83***	-0.04**	-0.39***	-0.86***	-1.40***
	(0.11)	(0.01)	(0.10)	(0.19)	(0.26)
ADM2	-0.42***	-0.02*	-0.15*	-0.23*	-0.88**
	(0.07)	(0.01)	(0.07)	(0.11)	(0.27)
N	313,684	74,877	77,299	80,676	80,832
Year FE	yes	yes	yes	yes	yes
ADM1 FE	yes	yes	yes	yes	yes

Notes: Standard errors clustered at Adm1 level in parentheses. Other control variables: decimal degree distance to international border, month of interview, tree cover probability midpoint a. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

As for the probability offset, increasing it by ten percentage points decreases deforestation by about 26 percent, but this effect is much stronger in heavily forested areas. For observations above the 75th percentile of forest cover, the same change in c is associated with a 62 percent decrease in deforestation while it decreases deforestation by a mere half percent for observations below the 25th percentile.

Relative to the smallest radius (5km), a larger radius is associated with decreases in the deforestation metric. However, this effect is insignificant in the full sample. Extracting the deforestation metric across the entire admin-1 or admin-2 area has a statistically significant negative effect across all model specifications, indicating that important local variation is being lost at these levels of spatial aggregation.

B. Impact on statistical inference

We start by showing OLS estimates of Equation 3 for the date generated with parameter values $c = 0.1$, $d = 90$ days, and $r = 35$ km in Table 2. Our preferred specification controls for respondents' sex and age, whether they were born abreoad, and whether they live in one of three increasingly urban settings, relative to rural dwellers. We also include both year and ADM1 fixed effects. Column 1 shows estimates for the full sample, while columns 2-5 split the sample in quartiles of initial average tree cover within the 35km circular buffers surrounding the observations' PSU locations.

On the full sample, a one percentage loss of tree cover is associated with a 0.005 decrease in SWB rating, albeit this association is only weakly significant ($p < 0.05$). We find slightly larger effect sizes of 0.017 and 0.008 for the second and fourth quartile ($p < 0.05$) and insignificant positive associations for the first and third quartiles. The effects of sex are insignificant across the board. Age decreases people's SWB in all specifications ($p < 0.001$). Lastly, urban dwellers report significantly higher levels of SWB compared to rural dwellers. This effect is most pronounced for those living in suburbs, whose SWB score is on average 0.302 points higher than that of rural respondents.The same qualitative results persist when using absolute forest loss (output available upon request).

Finally, we rerun the model for all 90 parameter combinations of r_{pt}, d_{pt}, and c_{pt}. Since the estimated coefficients are too numerous to be presented in tabular form, we plot them in Figure 5. 14 of the 90 estimates are statistically significant and negative. Seven of them occur with offset c = 0.1, four with c = 0.2, and three with c = 0.3. Ten of the statistically significant coefficients come from the models with 90 days recall, while 180 and 360 days yield three and one significant estimate, respectively. The non-zero effects we find are relatively equally distributed across radii. There is, nonetheless, ample evidence that changing the parameters underlying the deforestation metric's construction affects the outcome of statistical inference.

Table 2: Regression output from Equation 3.

SWB	(1) full sample	(2) 25th perc.	(3) 50th perc.	(4) 75th perc.	(5) 100th perc.
$l(\%)$	-0.005*	0.033	-0.017*	-0.000	-0.008*
	(0.002)	(0.037)	(0.008)	(0.006)	(0.003)
Sex (female)	0.051	0.107	0.089	0.030	-0.006
	(0.032)	(0.061)	(0.066)	(0.066)	(0.063)
Age	-0.056***	-0.057***	-0.056***	-0.065***	-0.048***
	(0.005)	(0.009)	(0.010)	(0.009)	(0.009)
Foreign born	0.359**	0.407	0.169	0.350	0.528
	(0.127)	(0.252)	(0.214)	(0.264)	(0.314)
Small town	0.152**	0.057	0.390***	0.166	0.064
	(0.049)	(0.092)	(0.102)	(0.100)	(0.096)
Large city	0.256***	0.129	0.382**	0.289	0.550*
	(0.073)	(0.130)	(0.143)	(0.173)	(0.235)
Suburb of City	0.302***	0.113	0.381**	0.327*	0.504**
	(0.070)	(0.170)	(0.145)	(0.146)	(0.155)
N	30,132	7,504	7,559	7,521	7,548
Year FE	yes	yes	yes	yes	yes
ADM1 FE	yes	yes	yes	yes	yes

Notes: Standard errors clustered at ADM1 level in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

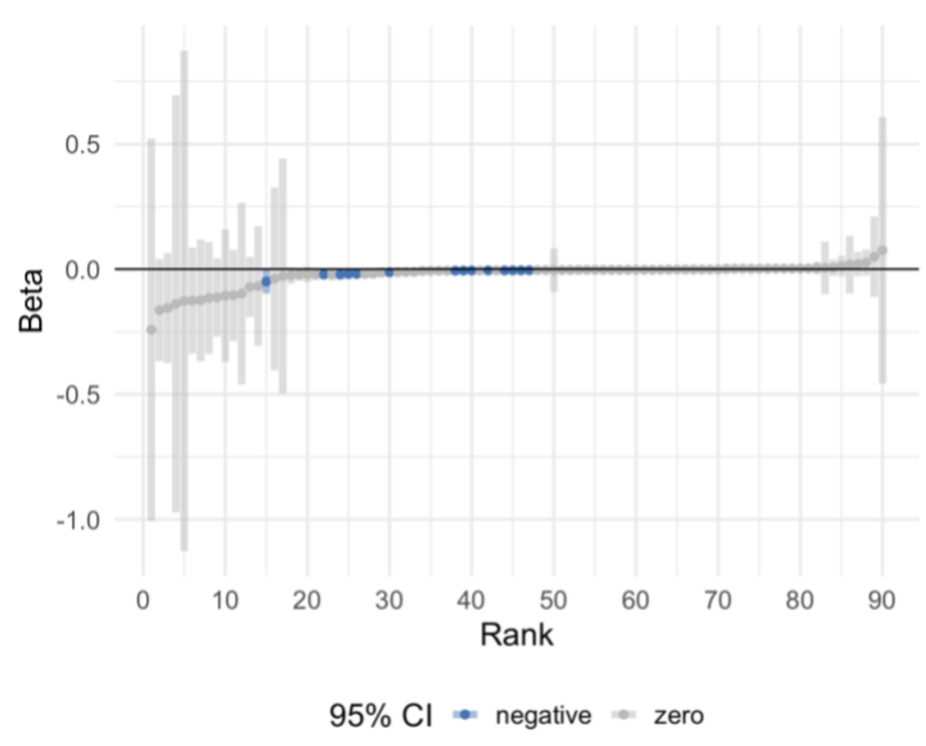

Figure 5: Estimates of the SWB response to a 1 percent increase in forest loss from 90 different model specifications.

C. Robustness

SWB is ordinal rather than continuous; a detail which we have not explicitly modelled thus far to keep with the literature (Praag and Ferrer-i-Carbonell 2008; Ferrer-i-Carbonell and Frijters 2004). However, to ensure that this potential misspecification (using an LLM for inference on a non-Gaussian response variable) does not alter our results (Schröder and Yitzhaki 2017), we re-estimate the baseline specification in a generalised linear mixed model (GLMM) with a probit link-function and random effects.[7] Moreover, we estimate the model separately for each of the eleven countries in our sample to test for heterogeneity between them. Neither of these robustness tests alters the qualitative results presented above. At baseline, we variably find small significant effects and null effects (output available upon request).

IV. Conclusion

This paper emulated a typical empirical setting from environmental economics by combining geocoded tabular survey data with point-reductions of gridded landcover maps. Where most studies tend to use landcover maps directly "off the shelf", we show that decisions underlying the construction of such categorical landcover data matter. Our analysis demonstrates how choices about the spatial and temporal extent of reduction (in our case the radius r and recall d) and about precision (the probability threshold offset c) can meaningfully change the resulting spatial data points, and then carry over into statistical inference whenever point-reduced variables are used as covariates in statistical analysis. The 90 combinations of our key parameters yield a range of estimates that differ in terms of their sign and significance, with the probability offset inducing the largest changes in inference. Overall there is, at best, weak evidence of small negative changes in SWB as a result of deforestation

The choice of probability offset can be avoided, in some applications, by using time series methods for break detection in the tree cover probability rather than the simple differencing approach used here.[8] The choices related to point reduction cannot be avoided as easily, however, if the goal is to link spatial data with tabular data through point coordinates. Choosing the circular buffer radius or some other user-definition of an area of interest around a survey location should, where possible, be informed by existing evidence on the effect decay distance of the phenomenon in question. Similarly, effect persistence through time (i.e. the temporal equivalent to spatial effect decay distance) should inform the choice of recall length. For example, it has been shown that subjective well-being tends to revert to its long-term average rather quickly following temperature shocks (see, e.g.,

[7]We do not include fixed effects to avoid the incidental parameter problem which arises in non-linear panel data models (e.g., Greene 2012).

[8]These methods are generally much more computationally expensive, which limits their use for national-level or regional comparative studies with moderate resolution data in practice. Popular break detection algorithms include BFAST (Mashhadi and Alganci 2022; Masiliūnas et al. 2021; Verbesselt, Masiliunas, and Zeileis 2022), CCDC (Bullock, Healey, et al. 2022; Friedl et al. 2022; Pasquarella et al. 2022), AVOCADO (Decuyper et al. 2022) or combined ensemble suites of multiple algorithms (Arévalo et al. 2020; Bullock, Woodcock, and Holden 2020).

Dietrich and Nichols 2023). This may explain why we find less significant effects when using longer recalls.

Whenever they are available, model probabilities should be used in lieux of binary labels to either determine change statistics through break detection or, barring that, control whether results are robust to a change in the probability threshold plus any offset thereon. As our paper demonstrates, empirical relationships can be highly sensitive to alterations of these parameters, and thus researchers and policy makers should conduct these robustness checks thoroughly before drawing any policy-relevant conclusions.

References

1. **Abadie, A. et al.** (Feb. 2023). When Should You Adjust Standard Errors for Clustering?*. *The Quarterly Journal of Economics* **138**.1, 1–35. ISSN: 0033-5533. DOI: 10.1093/qje/qjac038. (Visited on 02/25/2023).

2. **Agrawal, A. et al.** (June 2018). Editorial Overview: Forest Governance Interventions for Sustainability through Information, Incentives, and Institutions. *Current Opinion in Environmental Sustainability*. Environmental Change Issues 2018 **32**, A1–A7. ISSN: 1877-3435. DOI: 10.1016/j.cosust.2018.08.002. (Visited on 12/17/2022).

3. **Alves de Oliveira, B. F. et al.** (Oct. 2021). Deforestation and Climate Change Are Projected to Increase Heat Stress Risk in the Brazilian Amazon. *Communications Earth & Environment* **2**.1, 1–8. ISSN: 2662-4435. DOI: 10.1038/s43247-021-00275-8. (Visited on 07/08/2023).

4. **Anderson, W. et al.** (Aug. 2021). Violent Conflict Exacerbated Drought-Related Food Insecurity between 2009 and 2019 in Sub-Saharan Africa. *Nature Food* **2**.8, 603–615. ISSN: 2662-1355. DOI: 10.1038/s43016-021-00327-4. (Visited on 01/06/2024).

5. **Arévalo, P. et al.** (2020). A Suite of Tools for Continuous Land Change Monitoring in Google Earth Engine. *Frontiers in Climate* **2**. ISSN: 2624-9553. (Visited on 08/01/2023).

6. **Bamwesigye, D. et al.** (Feb. 2019). *Deforestation, Climate Change and Food Security Nexus in Sub-Sahara Africa: Content Analysis*. DOI: 10.20944/preprints201902.0154.v1. Preprints: 2019020154. (Visited on 05/26/2023).

7. **Bastin, J.-F. et al.** (July 2019). The Global Tree Restoration Potential. *Science* **365**.6448, 76–79. DOI: 10.1126/science.aax0848. (Visited on 05/25/2023).

8. **Baylis, P.** (Apr. 2020). Temperature and Temperament: Evidence from Twitter. *Journal of Public Economics* **184**, 104161. ISSN: 00472727. DOI: 10.1016/j.jpubeco.2020.104161. (Visited on 11/30/2020).

9. **Baylis, P. and J. Boomhower** (Jan. 2023). The Economic Incidence of Wildfire Suppression in the United States. *American Economic Journal: Applied Economics* **15**.1, 442–473. ISSN: 1945-7782. DOI: 10.1257/app.20200662. (Visited on 09/02/2024).

10. **Becher, O. et al.** (Feb. 2024). Prioritising Climate Adaptation Options to Minimise Financial and Distributional Impacts of Water Supply Disruptions. *Environmental Research: Infrastructure and Sustainability* **4**.1, 015007. ISSN: 2634-4505. DOI: 10.1088/2634-4505/ad0ff0. (Visited on 10/16/2024).

11. **Blöschl, G.** (Oct. 2022). Three Hypotheses on Changing River Flood Hazards. *Hydrology and Earth System Sciences* **26**.19, 5015–5033. ISSN: 1027-5606. DOI: 10.5194/hess-26-5015-2022. (Visited on 08/12/2024).

12. **Bochow, N. and N. Boers** (Oct. 2023). The South American Monsoon Approaches a Critical Transition in Response to Deforestation. *Science Advances* **9**.40, eadd9973. DOI: 10.1126/sciadv.add9973. (Visited on 08/12/2024).

13. **Bolton, A. V., D. Montag, and V. Gallo** (May 2022). Global Forestry Areas, Deforestation and Mental Health: A Worldwide Ecological Study. *The Journal of Climate Change and Health* **6**, 100109. ISSN: 26672782. DOI: 10.1016/j.joclim.2021.100109. (Visited on 02/22/2023).

14. **Bullock, E. L., S. P. Healey, et al.** (July 2022). Timeliness in Forest Change Monitoring: A New Assessment Framework Demonstrated Using Sentinel-1 and a Continuous Change Detection Algorithm. *Remote Sensing of Environment* **276**, 113043. ISSN: 0034-4257. DOI: 10.1016/j.rse.2022.113043. (Visited on 08/01/2023).

15. **Bullock, E. L., C. E. Woodcock, and C. E. Holden** (Mar. 2020). Improved Change Monitoring Using an Ensemble of Time Series Algorithms. *Remote Sensing of Environment*. Time Series Analysis with High Spatial Resolution Imagery **238**, 111165. ISSN: 0034-4257. DOI: 10.1016/j.rse.2019.04.018. (Visited on 08/01/2023).

16. **Burke, M., F. González, et al.** (July 2018). Higher Temperatures Increase Suicide Rates in the United States and Mexico. *Nature Climate Change* **8**, 723–729. (Visited on 12/10/2020).

17. **Burke, M., S. Heft-Neal, et al.** (Oct. 2022). Exposures and Behavioural Responses to Wildfire Smoke. *Nature Human Behaviour* **6**.10, 1351–1361. ISSN: 2397-3374. DOI: 10.1038/s41562-022-01396-6. (Visited on 09/02/2024).

18. **Burke, M. and V. Tanutama** (2019). *Climatic Constraints on Aggregate Economic Output*. NBER Working Paper 25779. Cambridge, MA: National Bureau of Economic Research. (Visited on 12/10/2020).

19. **Butts, K.** (Mar. 2023a). Geographic Difference-in-Discontinuities. *Applied Economics Letters* **30**.5, 615–619. ISSN: 1350-4851. DOI: 10.1080/13504851.2021.2005236. (Visited on 09/02/2024).

20. — (Jan. 2023b). JUE Insight: Difference-in-differences with Geocoded Microdata. *Journal of Urban Economics*. Special Issue: JUE Insight Shorter Papers **133**, 103493. ISSN: 0094-1190. DOI: 10.1016/j.jue.2022.103493. (Visited on 09/02/2024).

21. **Carleton, T. A. and S. M. Hsiang** (Sept. 2016). Social and Economic Impacts of Climate. *Sience* **353**.6304, 1112–1127. ISSN: 0036-8075. DOI: 10.1126/science.aad9837. (Visited on 12/09/2020).

22. **Carter, E. D. and M. K. Munos** (Aug. 2021). Impact of Imprecise Household Location on Effective Coverage Estimates Generated through Linking Household and Health Provider Data by Geographic Proximity: A Simulation Study. *International Journal of Health Geographics* **20**.1, 38. ISSN: 1476-072X. DOI: 10.1186/s12942-021-00292-y. (Visited on 10/15/2024).

23. **Chen, S. et al.** (Nov. 2021). Monitoring Temperate Forest Degradation on Google Earth Engine Using Landsat Time Series Analysis. *Remote Sensing of Environment* **265**, 112648. ISSN: 0034-4257. DOI: 10.1016/j.rse.2021.112648. (Visited on 08/01/2023).

24. **Cheng, S. H. et al.** (Jan. 2019). A Systematic Map of Evidence on the Contribution of Forests to Poverty Alleviation. *Environmental Evidence* **8**.1, 3. ISSN: 2047-2382. DOI: 10.1186/s13750-019-0148-4. (Visited on 12/07/2022).

25. **Comber, A. J.** (Nov. 2008). Land Use or Land Cover? *Journal of Land Use Science* **3**.4, 199–201. ISSN: 1747-423X, 1747-4248. DOI: 10.1080/17474230802465140. (Visited on 09/05/2024).

26. **D'Agostino, A. L. and W. Schlenker** (Nov. 2016). Recent Weather Fluctuations and Agricultural Yields: Implications for Climate Change. *Agricultural Economics* **47**.S1, 159–171. DOI: 10.1111/agec.12315. (Visited on 11/20/2020).

27. **Decuyper, M. et al.** (Feb. 2022). Continuous Monitoring of Forest Change Dynamics with Satellite Time Series. *Remote Sensing of Environment* **269**, 112829. ISSN: 0034-4257. DOI: 10.1016/j.rse.2021.112829. (Visited on 08/27/2024).

28. **Delgado, M. S. and R. J. G. M. Florax** (Dec. 2015). Difference-in-Differences Techniques for Spatial Data: Local Autocorrelation and Spatial Interaction. *Economics Letters* **137**, 123–126. ISSN: 0165-1765. DOI: 10.1016/j.econlet.2015.10.035. (Visited on 02/06/2023).

29. **Depicker, A. et al.** (Nov. 2021). Historical Dynamics of Landslide Risk from Population and Forest-Cover Changes in the Kivu Rift. *Nature Sustainability* **4**.11, 965–974. ISSN: 2398-9629. DOI: 10.1038/s41893-021-00757-9. (Visited on 08/12/2024).

30. **Deryugina, T. and S. M. Hsiang** (2017). *The Marginal Product of Climate*. NBER Working Paper 24072. National Bureau of Economic Research. (Visited on 12/10/2020).

31. **Dietrich, S. and S. Nichols** (Feb. 2023). *More than a Feeling: A Global Economic Valuation of Subjective Wellbeing Damages Resulting from Rising Temperatures*. Working Paper. Maastricht. UNU-MERIT Working Papers: 2023-005.

32. **Druckenmiller, H. and S. M. Hsiang** (Oct. 2019). *Accounting for Unobservable Heterogeneity in Cross Section Using Spatial First Differences*. Tech. rep. Cambridge, MA: National Bureau of Economic Research. DOI: 10.3386/w25177. (Visited on 10/11/2020).

33. **Duku, C. and L. Hein** (May 2021). The Impact of Deforestation on Rainfall in Africa: A Data-Driven Assessment. *Environmental Research Letters* **16**.6, 064044. ISSN: 1748-9326. DOI: 10.1088/1748-9326/abfcfb. (Visited on 05/26/2023).

34. **Ellison, D. et al.** (Mar. 2017). Trees, Forests and Water: Cool Insights for a Hot World. *Global Environmental Change* **43**, 51–61. ISSN: 0959-3780. DOI: 10.1016/j.gloenvcha.2017.01.002. (Visited on 02/22/2023).

35. **Estifanos, T. K. et al.** (2024). Impacts of Deforestation on Childhood Malaria Depend on Wealth and Vector Biology. *GeoHealth* **8**.3, e2022GH000764. ISSN: 2471-1403. DOI: 10.1029/2022GH000764. (Visited on 08/12/2024).

36. **Ettinger, A. K. et al.** (Feb. 2024). Street Trees Provide an Opportunity to Mitigate Urban Heat and Reduce Risk of High Heat Exposure. *Scientific Reports* **14**.1, 3266. ISSN: 2045-2322. DOI: 10.1038/s41598-024-51921-y. (Visited on 08/12/2024).

37. **FAO** (Nov. 2000). *On Definitions of Forest and Forest Change*. Working Paper 33. Rome: FAO.

38. **Faust, C. L. et al.** (2018). Pathogen Spillover during Land Conversion. *Ecology Letters* **21**.4, 471–483. ISSN: 1461-0248. DOI: 10.1111/ele.12904. (Visited on 08/12/2024).

39. **Ferreira, S. and M. Moro** (July 2010). On the Use of Subjective Well-Being Data for Environmental Valuation. *Environmental and Resource Economics* **46**.3, 249–273. ISSN: 1573-1502. DOI: 10.1007/s10640-009-9339-8. (Visited on 05/26/2023).

40. **Ferrer-i-Carbonell, A. and P. Frijters** (July 2004). How Important Is Methodology for the Estimates of the Determinants of Happiness? *The Economic Journal* **114**.497, 641–659. ISSN: 0013-0133, 1468-0297. DOI: 10.1111/j.1468-0297.2004.00235.x. (Visited on 05/22/2023).

41. **Foody, G. M.** (Mar. 2015). Valuing Map Validation: The Need for Rigorous Land Cover Map Accuracy Assessment in Economic Valuations of Ecosystem Services. *Ecological Economics* **111**, 23–28. ISSN: 0921-8009. DOI: 10.1016/j.ecolecon.2015.01.003. (Visited on 09/05/2024).

42. **Fox, S. et al.** (Apr. 2024). Integrating Social Vulnerability into High-Resolution Global Flood Risk Mapping. *Nature Communications* **15**.1, 3155. ISSN: 2041-1723. DOI: 10.1038/s41467-024-47394-2. (Visited on 09/02/2024).

43. **Frey, B. S., S. Luechinger, and A. Stutzer** (2010). The Life Satisfaction Approach to Environmental Valuation. *Annual Review of Resource Economics* **2**.1, 139–160. DOI: 10.1146/annurev.resource.012809.103926. (Visited on 02/24/2023).

44. **Friedl, M. A. et al.** (2022). Medium Spatial Resolution Mapping of Global Land Cover and Land Cover Change Across Multiple Decades From Landsat. *Frontiers in Remote Sensing* **3**. ISSN: 2673-6187. (Visited on 08/01/2023).

45. **Fuentes, I. et al.** (Aug. 2024). Is the Change Deforestation? Using Time-Series Analysis of Satellite Data to Disentangle Deforestation from Other Forest Degradation Causes. *Remote Sensing Applications: Society and Environment* **35**, 101210. ISSN: 2352-9385. DOI: 10.1016/j.rsase.2024.101210. (Visited on 09/09/2024).

46. **Gallup** (Oct. 2021). *Gallup Worldwide Research Methodology and Codebook*. Tech. rep. Washington, D.C.: Gallup, Inc.

47. **García-Álvarez, D. et al.** (2022). "Global General Land Use Cover Datasets with a Time Series of Maps". In: *Land Use Cover Datasets and Validation Tools: Validation Practices with QGIS*. Ed. by D. García-Álvarez et al. Cham: Springer International Publishing, pp. 287–311. ISBN: 978-3-030-90998-7. DOI: 10.1007/978-3-030-90998-7_15. (Visited on 08/01/2022).

48. **Garg, T.** (Nov. 2019). Ecosystems and Human Health: The Local Benefits of Forest Cover in Indonesia. *Journal of Environmental Economics and Management* **98**, 102271. ISSN: 00950696. DOI: 10.1016/j.jeem.2019.102271. (Visited on 02/22/2023).

49. **Gauci, V. et al.** (July 2024). Global Atmospheric Methane Uptake by Upland Tree Woody Surfaces. *Nature* **631**.8022, 796–800. ISSN: 1476-4687. DOI: 10.1038/s41586-024-07592-w. (Visited on 08/12/2024).

50. **Gibson, J., S. Olivia, and G. Boe-Gibson** (2020). Night Lights in Economics: Sources and Uses. *Journal of Economic Surveys* **34**.5, 955–980. ISSN: 1467-6419. DOI: 10.1111/joes.12387. (Visited on 09/02/2024).

51. **Greene, W. H.** (2012). *Econometric Analysis*. Pearson. ISBN: 0-273-75356-8. (Visited on 10/20/2019).

52. **Halder, B. et al.** (Jan. 2023). Large-Scale Flood Hazard Monitoring and Impact Assessment on Landscape: Representative Case Study in India. *Sustainability* **15**.14, 11413. ISSN: 2071-1050. DOI: 10.3390/su151411413. (Visited on 08/12/2024).

53. **Henderson, J. V., A. Storeygard, and D. N. Weil** (Apr. 2012). Measuring Economic Growth from Outer Space. *American Economic Review* **102**.2, 994–1028. ISSN: 0002-8282. DOI: 10.1257/aer.102.2.994. (Visited on 11/04/2021).

54. **Herrera, D. et al.** (Oct. 2017). Upstream Watershed Condition Predicts Rural Children's Health across 35 Developing Countries. *Nature Communications* **8**.1, 811. ISSN: 2041-1723. DOI: 10.1038/s41467-017-00775-2. (Visited on 07/08/2023).

55. **Jagger, P. et al.** (July 2022). The Role of Forests and Trees in Poverty Dynamics. *Forest Policy and Economics* **140**, 102750. ISSN: 1389-9341. DOI: 10.1016/j.forpol.2022.102750. (Visited on 08/01/2022).

56. **Jain, M.** (Jan. 2020). The Benefits and Pitfalls of Using Satellite Data for Causal Inference. *Review of Environmental Economics and Policy* **14**.1, 157–169. ISSN: 1750-6816. DOI: 10.1093/reep/rez023. (Visited on 10/15/2024).

57. **Josephson, A. et al.** (Sept. 2024). *The Mismeasure of Weather: Using Remotely Sensed Earth Observation Data in Economic Context*. arXiv: 2409.07506 [econ, q-fin]. (Visited on 10/15/2024).

58. **Keola, S., M. Andersson, and O. Hall** (Feb. 2015). Monitoring Economic Development from Space: Using Nighttime Light and Land Cover Data to Measure Economic Growth. *World Development* **66**, 322–334. ISSN: 0305-750X. DOI: 10.1016/j.worlddev.2014.08.017. (Visited on 09/05/2024).

59. **Landrigan, P. J. et al.** (Feb. 2018). The Lancet Commission on Pollution and Health. *The Lancet* **391**.10119, 462–512. ISSN: 01406736. DOI: 10.1016/S0140-6736(17)32345-0. (Visited on 07/08/2023).

60. **Lapola, D. M. et al.** (Jan. 2023). The Drivers and Impacts of Amazon Forest Degradation. *Science* **379**.6630, eabp8622. DOI: 10.1126/science.abp8622. (Visited on 07/12/2023).

61. **Leng, G. and J. W. Hall** (Apr. 2020). Predicting Spatial and Temporal Variability in Crop Yields: An Inter-Comparison of Machine Learning, Regression and Process-Based Models. *Environmental Research Letters* **15**.4, 044027. ISSN: 1748-9326. DOI: 10.1088/1748-9326/ab7b24. (Visited on 10/16/2024).

62. **Li, B. V., C. N. Jenkins, and W. Xu** (Jan. 2022). Strategic Protection of Landslide Vulnerable Mountains for Biodiversity Conservation under Land-Cover and Climate Change Impacts. *Proceedings of the National Academy of Sciences* **119**.2, e2113416118. DOI: 10.1073/pnas.2113416118. (Visited on 08/12/2024).

63. **Lin, F.-C. et al.** (May 2024). A Model for Forest Type Identification and Forest Regeneration Monitoring Based on Deep Learning and Hyperspectral Imagery. *Ecological Informatics* **80**, 102507. ISSN: 1574-9541. DOI: 10.1016/j.ecoinf.2024.102507. (Visited on 09/09/2024).

64. **Maddison, D., K. Rehdanz, and H. Welsch**, eds. (2020). *Handbook on Wellbeing, Happiness, and the Environment*. Cheltenham, UK ; Northampton, MA, USA: Edward Elgar Publishing. ISBN: 978-1-78811-933-7.

65. **Mapulanga, A. M. and H. Naito** (Apr. 2019). Effect of Deforestation on Access to Clean Drinking Water. *Proceedings of the National Academy of Sciences* **116**.17, 8249–8254. DOI: 10.1073/pnas.1814970116. (Visited on 02/17/2023).

66. **Mashhadi, N. and U. Alganci** (Nov. 2022). Evaluating BFASTMonitor Algorithm in Monitoring Deforestation Dynamics in Coniferous and Deciduous Forests with LANDSAT Time Series: A Case Study on Marmara Region, Turkey. *ISPRS International Journal of Geo-Information* **11**.11, 573. ISSN: 2220-9964. DOI: 10.3390/ijgi11110573. (Visited on 03/15/2023).

67. **Masiliūnas, D. et al.** (Jan. 2021). BFAST Lite: A Lightweight Break Detection Method for Time Series Analysis. *Remote Sensing* **13**.16, 3308. ISSN: 2072-4292. DOI: 10.3390/rs13163308. (Visited on 08/27/2024).

68. **Michler, J. D. et al.** (Sept. 2022). Privacy Protection, Measurement Error, and the Integration of Remote Sensing and Socioeconomic Survey Data. *Journal of Development Economics* **158**, 102927. ISSN: 0304-3878. DOI: 10.1016/j.jdeveco.2022.102927. (Visited on 02/22/2023).

69. **Miller, D. C. et al.** (Oct. 2021). Forests, Trees and Poverty Alleviation: Policy Implications of Current Knowledge. *Forest Policy and Economics* **131**, 102566. ISSN: 1389-9341. DOI: 10.1016/j.forpol.2021.102566. (Visited on 08/01/2022).

70. **Morand, S. and C. Lajaunie** (Mar. 2021). Outbreaks of Vector-Borne and Zoonotic Diseases Are Associated With Changes in Forest Cover and Oil Palm Expansion at Global Scale. *Frontiers in Veterinary Science* **8**. ISSN: 2297-1769. DOI: 10.3389/fvets.2021.661063. (Visited on 08/12/2024).

71. **Nabuurs, G.-J. et al.** (2022). "Agriculture, Forestry and Other Land Uses (AFOLU)". In: *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Ed. by P. Shukla et al. Cambridge, UK and New York, NY, USA: Cambridge University Press. Chap. 7. DOI: 10.1017/9781009157926.009.

72. **Nowak, D. J. and M. Van den Bosch** (May 2019). Les Effets Des Arbres et de La Forêt Sur La Qualité de l'air et La Santé Humaine Dans et Autour Des Zones Urbaines: *Santé Publique* **S1**.HS1, 153–161. ISSN: 0995-3914. DOI: 10.3917/spub.190.0153. (Visited on 07/08/2023).

73. **OECD** (June 2018). *Subjective Well-Being Valuation*. Tech. rep. Paris: OECD, pp. 173–194. DOI: 10.1787/9789264085169-10-en. (Visited on 03/29/2023).

74. **Pacheco Quevedo, R. et al.** (May 2023). Land Use and Land Cover as a Conditioning Factor in Landslide Susceptibility: A Literature Review. *Landslides* **20**.5, 967–982. ISSN: 1612-5118. DOI: 10.1007/s10346-022-02020-4. (Visited on 08/12/2024).

75. **Pasquarella, V. J. et al.** (June 2022). Demystifying LandTrendr and CCDC Temporal Segmentation. *International Journal of Applied Earth Observation and Geoinformation* **110**, 102806. ISSN: 1569-8432. DOI: 10.1016/j.jag.2022.102806. (Visited on 08/01/2023).

76. **Pathak, M. et al.** (2022). "Technical Summary". In: *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Ed. by P. Shukla et al. Cambridge, UK and New York, NY, USA: Cambridge University Press. DOI: 10.1017/9781009157926.002.

77. **Pople, A. et al.** (July 2024). *The Importance of Being Early: Anticipatory Cash Transfers for Flood-Affected Households*. CSAE Working Paper WPS/2021-07-02. Oxford: Center for the Study of African Economies.

78. **Praag, B. M. S. van and A. Ferrer-i-Carbonell** (2008). *Happiness Quantified: A Satisfaction Calculus Approach*. Rev. ed. Oxford: Oxford University Press. ISBN: 978-0-19-171859-5.

79. **Rahman, R. A., B. White, and C. Ma** (June 2024). The Effect of Growth, Deforestation, Forest Fires, and Volcanoes on Indonesian Regional Air Quality. *Journal of Cleaner Production* **457**, 142311. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2024.142311. (Visited on 08/12/2024).

80. **Ramadhan, C., R. Dina, and E. Nurjani** (July 2023). Spatial and Temporal Based Deforestation Proclivity Analysis on Flood Events with Applying Watershed Scale (Case Study: Lasolo Watershed in Southeast Sulawesi, Central Sulawesi, and South Sulawesi, Indonesia). *International Journal of Disaster Risk Reduction* **93**, 103745. ISSN: 2212-4209. DOI: 10.1016/j.ijdrr.2023.103745. (Visited on 08/12/2024).

81. **Reddington, C. L. et al.** (Oct. 2015). Air Quality and Human Health Improvements from Reductions in Deforestation-Related Fire in Brazil. *Nature Geoscience* **8**.10, 768–771. ISSN: 1752-0894, 1752-0908. DOI: 10.1038/ngeo2535. (Visited on 07/08/2023).

82. **Reiche, J. et al.** (Jan. 2018). Improving Near-Real Time Deforestation Monitoring in Tropical Dry Forests by Combining Dense Sentinel-1 Time Series with Landsat and ALOS-2 PALSAR-2. *Remote Sensing of Environment* **204**, 147–161. ISSN: 0034-4257. DOI: 10.1016/j.rse.2017.10.034. (Visited on 09/09/2024).

83. **Schlenker, W. and D. B. Lobell** (2010). Robust Negative Impacts of Climate Change on African Agriculture. *Environmental Research Letters* **5**, 1–8. DOI: 10.1088/1748-9326/5/1/014010. (Visited on 11/20/2020).

84. **Schlenker, W. and M. J. Roberts** (Sept. 2009). Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change. *Proceedings of the National Academy of Sciences* **106**.37, 15594–15598. DOI: 10.1073/pnas.0906865106. (Visited on 10/23/2024).

85. **Schröder, C. and S. Yitzhaki** (Feb. 2017). Revisiting the Evidence for Cardinal Treatment of Ordinal Variables. *European Economic Review* **92**, 337–358. ISSN: 0014-2921. DOI: 10.1016/j.euroecorev.2016.12.011. (Visited on 02/01/2023).

86. **Smith, C., J. C. A. Baker, and D. V. Spracklen** (Mar. 2023). Tropical Deforestation Causes Large Reductions in Observed Precipitation. *Nature* **615**.7951, 270–275. ISSN: 1476-4687. DOI: 10.1038/s41586-022-05690-1. (Visited on 04/03/2024).

87. **Smith, S. et al.** (2024). The State of Carbon Dioxide Removal - 2nd Edition. DOI: 10.17605/OSF.IO/F85QJ. (Visited on 06/06/2024).

88. **Staal, A. et al.** (Apr. 2020). Feedback between Drought and Deforestation in the Amazon. *Environmental Research Letters* **15**.4, 044024. ISSN: 1748-9326. DOI: 10.1088/1748-9326/ab738e. (Visited on 08/12/2024).

89. **Sutton, P. C. and R. Costanza** (June 2002). Global Estimates of Market and Non-Market Values Derived from Nighttime Satellite Imagery, Land Cover, and Ecosystem Service Valuation. *Ecological Economics* **41**.3, 509–527. ISSN: 0921-8009. DOI: 10.1016/S0921-8009(02)00097-6. (Visited on 09/02/2024).

90. **Tabari, H. and P. Willems** (May 2023). Sustainable Development Substantially Reduces the Risk of Future Drought Impacts. *Communications Earth & Environment* **4**.1, 1–10. ISSN: 2662-4435. DOI: 10.1038/s43247-023-00840-3. (Visited on 10/26/2023).

91. **Verbesselt, J., D. Masiliunas, and A. Zeileis** (Oct. 2022). *Package "Bfast"*.

92. **Welsch, H. and J. Kühling** (2009). Using Happiness Data for Environmental Valuation: Issues and Applications. *Journal of Economic Surveys* **23**.2, 385–406. ISSN: 1467-6419. DOI: 10.1111/j.1467-6419.2008.00566.x. (Visited on 02/24/2023).

93. **Wen, J. et al.** (Dec. 2023). Quantifying Fire-Specific Smoke Exposure and Health Impacts. *Proceedings of the National Academy of Sciences* **120**.51, e2309325120. DOI: 10.1073/pnas.2309325120. (Visited on 09/02/2024).

94. **Wigand, M. E. et al.** (Nov. 2022). Climate Change, Pollution, Deforestation, and Mental Health: Research Trends, Gaps, and Ethical Considerations. *GeoHealth* **6**.11. ISSN: 2471-1403, 2471-1403. DOI: 10.1029/2022GH000632. (Visited on 02/22/2023).

95. **Wolff, N. H. et al.** (Sept. 2018). Impacts of Tropical Deforestation on Local Temperature and Human Well-Being Perceptions. *Global Environmental Change* **52**, 181–189. ISSN: 0959-3780. DOI: 10.1016/j.gloenvcha.2018.07.004. (Visited on 02/01/2023).

96. **Wuepper, D. and R. Finger** (Jan. 2023). Regression Discontinuity Designs in Agricultural and Environmental Economics. *European Review of Agricultural Economics* **50**.1, 1–28. ISSN: 0165-1587. DOI: 10.1093/erae/jbac023. (Visited on 09/05/2024).

97. **Ye, S., Z. Zhu, and J. W. Suh** (May 2024). Leveraging Past Information and Machine Learning to Accelerate Land Disturbance Monitoring. *Remote Sensing of Environment* **305**, 114071. ISSN: 0034-4257. DOI: 10.1016/j.rse.2024.114071. (Visited on 09/09/2024).

98. **Zhang, M. and X. Wei** (Mar. 2021). Deforestation, Forestation, and Water Supply. *Science* **371**.6533, 990–991. DOI: 10.1126/science.abe7821. (Visited on 08/12/2024).

Appendix

Table A1: Variables affected by forest ecosystems.

Demostrated Relationship	**Supporting Studies**
Air quality	Landrigan et al. (2018), Nowak and Van den Bosch (2019), Rahman, White, and Ma (2024), and Reddington et al. (2015)
Water quality and access to clean drinking water	Ellison et al. (2017), Herrera et al. (2017), Mapulanga and Naito (2019), and Zhang and Wei (2021)
Exposure to infectious disease	Estifanos et al. (2024), Faust et al. (2018), Garg (2019), and Morand and Lajaunie (2021)
Local temperature regulation	Alves de Oliveira et al. (2021), Ettinger et al. (2024), and Wolff et al. (2018)
Mental health	Bolton, Montag, and Gallo (2022) and Wigand et al. (2022)
Food security	Bamwesigye et al. (2019)
Vulnerability to poverty	Agrawal et al. (2018), Cheng et al. (2019), Jagger et al. (2022), and Miller et al. (2021)
Land slides	Depicker et al. (2021), Li, Jenkins, and Xu (2022), and Pacheco Quevedo et al. (2023)
Floods	Blöschl (2022), Halder et al. (2023), and Ramadhan, Dina, and Nurjani (2023)
Droughts	Bochow and Boers (2023), Duku and Hein (2021), C. Smith, Baker, and Spracklen (2023), and Staal et al. (2020)
Increase in green house gases	Bastin et al. (2019), Gauci et al. (2024), Nabuurs et al. (2022), Pathak et al. (2022), and S. Smith et al. (2024)

Table A2: Baseline summary statistics ($d = 90, r = 35, c = 0.1$) by country.

	Forest cover (before)	SWB	l (%)	l (km^2)
Non-missing obs.	31,246	36,245	31,246	31,246
All countries, N = 37,0511	0.23 (0.11)	4.0 (2.7)	0.006 (0.012)	24 (45)
Burundi, N = 8801	0.26 (0.04)	3.8 (2.9)	0.007 (0.004)	28 (15)
Comoros, N = 2,0001	0.13 (0.03)	4.4 (3.0)	0.000 (0.000)	0 (0)
Ethiopia, N = 5,0621	0.14 (0.10)	4.2 (2.1)	0.002 (0.005)	6 (20)
Kenya, N = 3,7771	0.20 (0.09)	4.6 (2.7)	0.012 (0.016)	47 (60)
Madagascar, N = 3,0001	0.30 (0.12)	4.2 (2.3)	0.008 (0.012)	32 (46)
Malawi, N = 3,9281	0.22 (0.07)	3.6 (3.0)	0.003 (0.003)	11 (13)
Mozambique, N = 2,9281	0.31 (0.13)	4.9 (3.3)	0.007 (0.013)	26 (50)
Rwanda, N = 3,9821	0.20 (0.07)	3.3 (2.2)	0.003 (0.003)	12 (13)
Tanzania, N = 3,9361	0.22 (0.13)	3.4 (2.7)	0.006 (0.015)	22 (59)
Uganda, N = 3,6161	0.27 (0.09)	4.5 (3.0)	0.014 (0.017)	52 (64)
Zimbabwe, N = 3,9421	0.31 (0.07)	3.4 (2.6)	0.008 (0.010)	32 (40)
p-value	<0.001	<0.001	<0.001	<0.001

Notes: Mean values with standard-deviations in parantheses. P-values from Kruskal-Wallis nonparametric rank sum statistic; null-hypothesis is that variables are identically distributed across countries.