

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

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## 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.

**Keywords:** keyword1, keyword2

**JEL:** code1, code2

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## I. Introduction

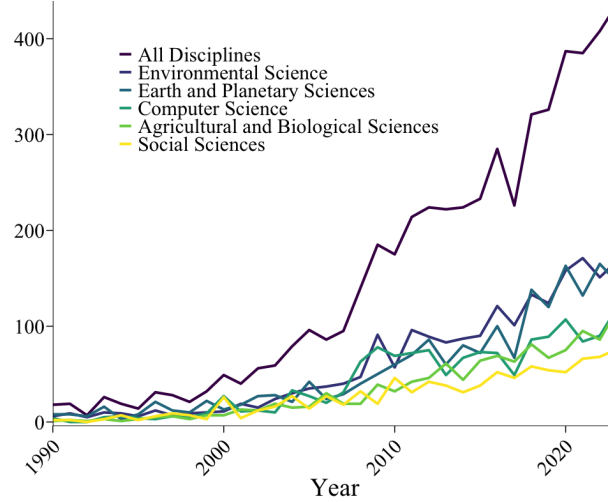
Earth observation (EO) data has become an important tool across a wide range of scientific disciplines over the past two decades. In applied economics research, EO has found ample use to fill in gaps in traditional survey data for areas of the world where ground data is scarce (Overman, 2018). In development 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<sup>1</sup> 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.

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<sup>1</sup>For the similarities, differences and connections between the land use and land cover concepts see (Comber 2008).

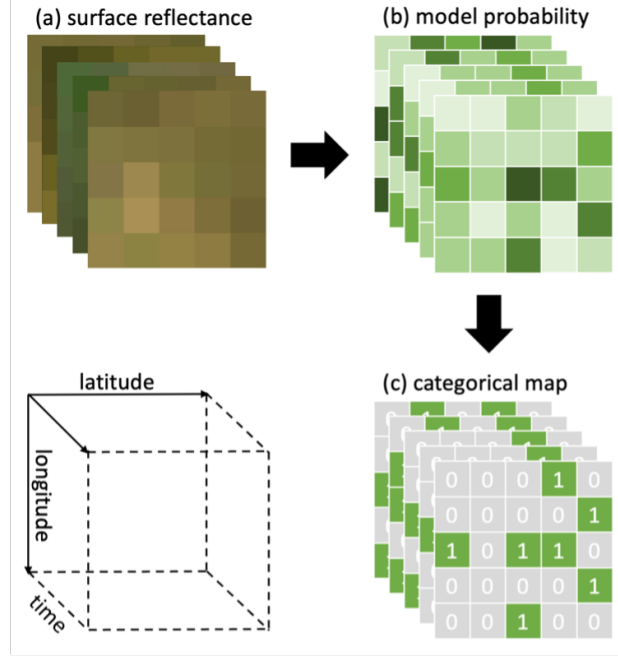


**Figure 1:** Number of publications whose title, abstract, or key words jointly include one or more of "deforestation", "forest loss", and one or more of "GIS", "spatial data", "earth observation", or "remote sense" (data source: SCOPUS).

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.<sup>2</sup> 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.

<sup>2</sup>They are listed in Table ?? 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).

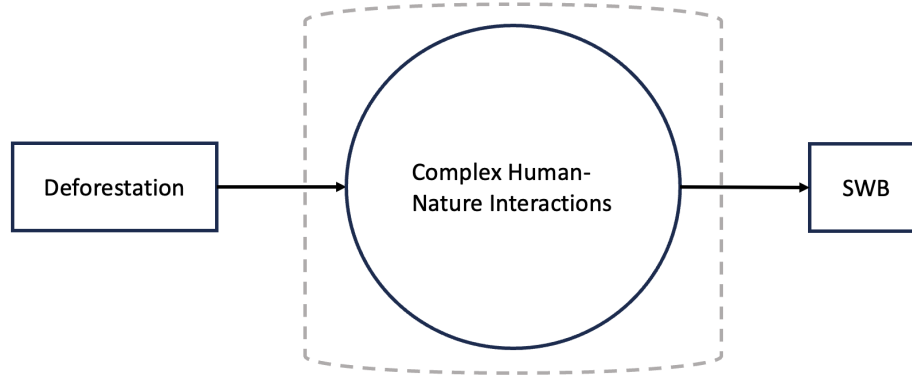
To induce variability, we categorise the probability band into different FNF maps using a locally centred probability threshold with varying offset values. Additionally, we vary the length of the before and after periods as well as the radius of the circular buffers around the survey locations, which 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 with their provision and heightens risk exposure on multiple domains (Lapola et al. 2023).



**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 modelled implicitly.

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.<sup>3</sup>

## 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

<sup>3</sup>We do not include fixed effects to avoid the incidental parameter problem which arises in non-linear panel data models (e.g., Greene 2012).

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<sup>4</sup> 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 likert-type ordinal scale from 0 to 10, where higher values indicate higher life satisfaction.<sup>5</sup>

**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:

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

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.<sup>6</sup> 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 pixels-segments that intersect with the circular buffer around each location. The result is a locally centred indicator of PSU’s exposure to deforestation as a function of radius  $r$ , recall length  $d$ , and probability offset  $c$ .

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<sup>4</sup>They are water, trees, grass, flooded vegetation, crops, shrub and scrub, built, bare ground, and snow and ice.

<sup>5</sup>For country-level summary statistics, see Table ?? in the appendix.

<sup>6</sup>At 10m resolution, this operationalises the FAO (2000) definition of forests as covering at least five hectares.

**Other variables** In addition to the SWB score, we obtain a few control variables at the individual, household and PSU levels from GWP. These include the respondents' age, sex, log-income, and immigration status as well as the urbanicity of the interview location . Constructing the deforestation variable involves choosing three parameters. To induce variation, we vary them along the following ranges.

- Radius of circular buffer:  $r_{pat} \in \{5, 10, \dots, 45, 50 \text{ km}\}$
- 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 ( $N = 4,090$ ).

The 3D scatter plot in Figure 4 plots how the 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. The deforestation metric 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.

#### D. Empirical strategy

**Variation in deforestation metrics** To formally test the implications of choosing any given parameter combination, we estimate the following model via OLS:

$$l_{pat} = \beta_1 r_{pat} + \beta_2 c_{pat} + \beta_3 d_{pat} + \omega_p + \zeta_t + \varepsilon_{pat}. \quad (2)$$

Here,  $l_{pat}$  denotes deforestation around PSU  $p$  in area  $a$  at time  $t$ .  $\omega_p$  and  $\zeta_t$  capture year and PSU fixed effects, and  $\varepsilon_{pat}$  an error term, clustered at the PSU level. Thus, we estimate how variation in the parameters changes the deforestation measures for the same PSU.

**Impact on subjective well-being** Next, to investigate the aggregate (local) effect of deforestation on subjective well-being, we estimate the following linear mixed model following Liang and Zeger (1986):

$$y_{ipat} = l_{pat}\beta + \mathbf{x}'_{ipat}\gamma + \omega_p + \zeta_t + \varepsilon_{pat}, \quad (3)$$

where  $y$  is the SWB score,  $\beta$  contains the coefficients of interest, namely the impact of increased deforestation on SWB, and  $\mathbf{x}_{ipat}$  holds the control variables described above. Standard errors are clustered at the admin-1 level since our independent variable does not vary 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.

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*** (0.00)	-0.00*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)
$c$	-26.31*** (3.36)	-0.48*** (0.09)	-11.59*** (1.76)	-29.11*** (3.15)	-61.49*** (7.16)
$r = \dots$					
10 km	-0.07 (0.042)	-0.01 (0.007)	0.00 (0.042)	-0.06 (0.084)	-0.25 (0.14)
15 km	-0.09 (0.07)	-0.01 (0.01)	-0.02 (0.05)	-0.12 (0.10)	-0.38* (0.17)
20 km	-0.09 (0.09)	-0.03** (0.01)	-0.05 (0.06)	-0.12 (0.10)	-0.49* (0.22)
25 km	-0.09 (0.11)	-0.02* (0.01)	-0.04 (0.06)	-0.17 (0.12)	-0.56* (0.26)
30 km	-0.17 (0.11)	-0.03** (0.01)	-0.14 (0.08)	-0.29** (0.10)	-0.70* (0.27)
35 km	-0.16 (0.14)	-0.03** (0.01)	-0.13 (0.07)	-0.35** (0.12)	-0.72** (0.26)
40 km	-0.19 (0.15)	-0.03** (0.01)	-0.16* (0.07)	-0.43*** (0.13)	-0.77** (0.26)
45 km	-0.20 (0.15)	-0.02** (0.01)	-0.18** (0.07)	-0.48*** (0.12)	-0.75** (0.25)
50 km	-0.25 (0.16)	-0.02* (0.01)	-0.23** (0.07)	-0.48*** (0.12)	-0.94** (0.30)
adm1	-0.83*** (0.11)	-0.04** (0.01)	-0.39*** (0.10)	-0.86*** (0.19)	-1.40*** (0.26)
adm2	-0.42*** (0.07)	-0.02* (0.01)	-0.15* (0.07)	-0.23* (0.11)	-0.88** (0.27)
N	313,684	74,877	77,299	80,676	80,832
FEs	Year-PSU	Year-PSU	Year-PSU	Year-PSU	Year-PSU

Notes: Standard errors clustered at adm2 level in parentheses. Other control variables: decimal degree distance to boarder, month of interview, probability midpoint a. \* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$ .



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 percent and this effect is relatively stable and highly statistically significant, regardless of initial forest cover.

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*

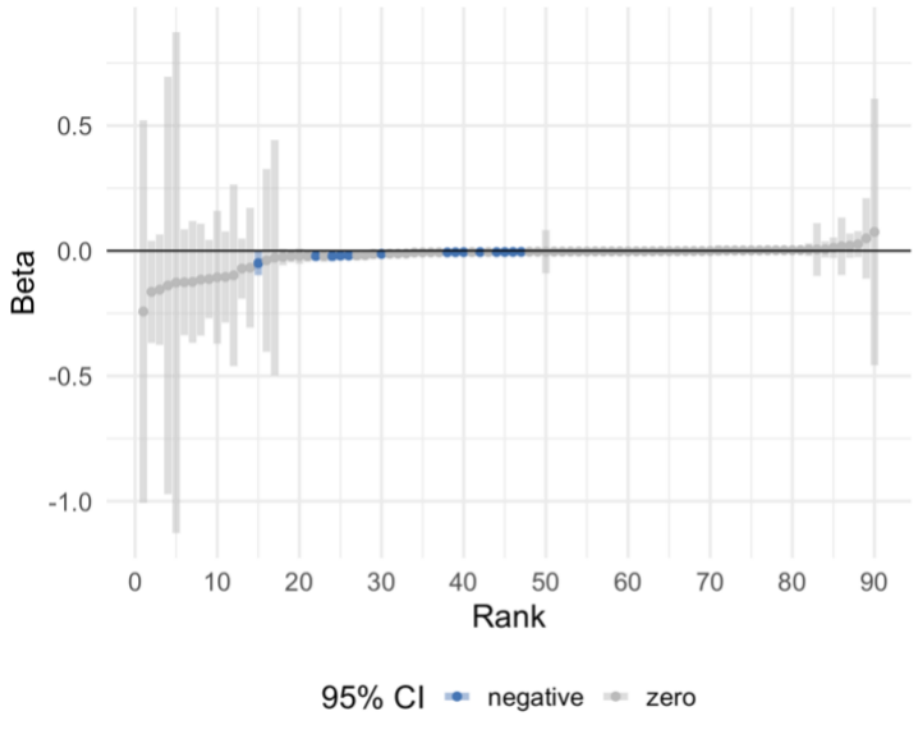
We start by showing OLS estimates of Equation 3 for  $c = 0.1$ ,  $d = 90$ , and  $r = 35km$  in Table 2. Depending on the fixed effects included, the model estimates that deforestation has either very little or no effect on SWB; at most -0.0017 points at the sample mean of forest loss. The effects of sex are insignificant across the board, while people report to be worse off with age, and better off if they are native to the country they live in, or if they live in an urban rather than rural setting. Again, we estimate the model for subsamples along the quartiles of SWB to test for heterogeneous treatment effects. An additional percent of forest loss decreases subjective well-being by 0.017 points in people within the second quartile of SWB and by 0.008 in respondents within the fourth quartile. The same qualitative results persist when using absolute forest loss.

**Table 2:** Regression output from Equation 3.

	(1)	(2)	(3)	(4)	(5)
	full sample	25th perc.	50th perc.	75th perc.	100th perc.
SWB					
$l(\%)$	0.00	0.00	-0.01*	-0.00	-0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sex (1 = F)	0.02	0.02	0.05	0.05	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Age	-0.06***	-0.06***	-0.06***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Native	0.34**	0.34**	0.36**	0.36**	0.34**
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
Suburb	0.14**	0.16**	0.15**	0.15**	0.17***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Small town	0.26***	0.24***	0.26***	0.29***	0.29***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)
Big city	0.23**	0.21**	0.30***	0.31***	0.30***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)
N	30,132	30,132	30,132	30,132	30,132
Year FE	no	yes	yes	yes	yes
Country FE	no	no	yes	no	no
Adm1 FE	no	no	no	no	yes
Country-Year FE	no	no	no	yes	no

Notes: Standard errors clustered at admin1-year level in parentheses. Includes also month of interview FE and PSU random effects.  
 \* $p < 0.05$ , \*\* $p < 0.01$ , \*\*\* $p < 0.001$ .

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.



**Figure 4:** 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, following the literature (Praag and Ferrer-i-Carbonell 2008; Ferrer-i-Carbonell and Frijters 2004), we have not explicitly modelled thus far. To ensure that this potential misspecification of the model does not alter our results (Schröder and Yitzhaki 2017), we re-estimate the baseline specification using ordinal probit with random effects. 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 zero 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  $c$ ) 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.<sup>7</sup> 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., 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 lieu 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.

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<sup>7</sup>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, Masiliūnas, 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).

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## Appendix

**Table A1:** Variables affected by forest ecosystems.

<b>Demonstrated Relationship</b>	<b>Supporting Studies</b>
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)