TIES Power Calculations

Treatment allocation

Table 1 shows the proposed treatment allocation.

Table 1: Treatment Allocation

Condition	Number of Communities
Control	70
PES	60
PES-Plus	60
Total:	190

Outcome variable distribution

Our primary outcome is *community-level forest cover loss in hectares (HA)* measured through remote sensing. This is similar to the outcome measure used in Jayachandran et al. (2017), although not exactly the same. Jayachandran et al. used forest cover *change* in HA, which allows for both gains and losses. However, since our interest is in the preservation of old-growth ("high bush") forest cover, short-term gains in forest cover are not relevant, and we focus attention on loss.

We constructed a preliminary version of forest cover and forest cover loss variables for the years 2021 and 2022 in our study area of Lofa and Gbarpolu counties using the remote-sensed *Global Forest Change* data provided through Google Earth Engine. These data are based on the methods first described in Hansen et al. (2013).[1] Panels (1) and (2) in Figure 1 show the distributions of these variables. While these data provide a useful starting point, they are produced using spatial and temporal interpolation and therefore may understate variability.

Thus, we consider the possibility of using the outcome distributions from Jayachandran et al. as a starting point for our power analysis. This is motivated by the similarities in

[1] Updated data are available at https://glad.earthengine.app/view/global-forest-change.

the contexts of our study communities in Liberia and Jayachandran et al.'s communities in Uganda. Moreover, the effects estimated by Jayachandran et al. provide a useful benchmark for assessing the cost effectiveness of our proposed PES+ intervention. Figure 1 displays distributions for outcome data from Jayachandran et al. (2017) in panels (3), (4), and (5). The Jayachandran et al. data measure forest cover change and loss over two years (panel 4). Our data focus on one-year change, and so we divide the measures in Jayachandran et al. by 2 to make the scales comparable. Then, to construct a forest cover *loss* variable from Jayachandran et al.'s data, we top code the forest cover change distribution at zero (panel 5). Table 2 compares summary statistics of forest loss as measured for our study sites and for Jayachandran et al.'s treatment and control groups.

The comparisons reveal that the distributions are similar across the Liberia and Uganda communities. Mean forest cover loss is somewhat larger in magnitude in the Uganda communities, although the median values are very similar. The Uganda community loss values have substantially larger standard deviations, which is likely because the Liberia data involve more interpolation than the Uganda data. Sampling from the Uganda distribution would provide for a more conservative power analysis than sampling from the distribution that we constructed using the Google Earth Engine data. These comparisons motivate our use of the Jayachandran et al. outcome variable distributions for our power analysis.

Estimation

Our primary hypothesis is that PES-Plus results in more high bush forest cover being left intact than regular PES. To test this hypothesis, we can fit the following regression to the sample of 60 PES and 60 PES-Plus communities:

$$\text{Forest loss in HA}_c = \beta_0 + \beta_1 \text{PES-Plus}_c + \phi_{b[c]} + X_c'\gamma + \epsilon_c,$$

where $\phi_{b[c]}$ are block fixed effects, where $b[c]$ indexes community c's randomization block, and X_c are (mean-centered) covariates, along with interactions, per Lin (2013), to enhance efficiency. We want to test $\beta_1 > 0$. Given the individual-village-level treatment assignment, inference is based on heteroskedasticity robust standard errors. Secondary analyses will estimate (i) the same regression using the sample of 70 control and 60 PES-Plus communities, to obtain estimates relative to a no-intervention counterfactual, and then (ii) a specification that uses PES as the treatment on the sample of 70 control and 60 PES communities, so as to establish what PES accomplishes without the governance condition.

Power analysis

Above we established that the 1-yr. forest loss measure based on Jayachandran et al.'s data could serve as a reasonable approximation to our target outcome distribution., Table 3 presents a re-analysis of Jayachandran et al.'s main results using the 1-yr. forest loss measure.

The p values are a bit larger than what Jayachandran et al. present based on their 2-yr. forest change outcome, presumably due to the top coding. Nonetheless, the sample size is nearly identical to our design in terms of sample size and the control strategy. Using the estimated standard errors, we can constrcct minimum detectable effects as per Bloom (1995). For a two-sided test with 90% confidence (equivalent to a one-sided test with 95% confidence), our design would have 80% power to detect a difference of about 2.485*1.180 = 2.932 HA in the performance of PES-Plus versus standard PES, representing a 0.413 SD effect size relative to the control group standard deviation (7.093) and a 0.375 SD effect size relative to the pooled standard deviation (7.817). For a two-sided test with 95% confidence, our design would have 80% power to detect a difference of about 2.800*1.180 = 3.304 HA in the performance of PES-Plus versus standard PES, representing a 0.466 SD effect size relative to the control group standard deviation and a 0.423 SD effect size relative to the pooled standard deviation. The same calculation would apply for minimum detectable effects for our secondary comparisons of PES-Plus to control and PES to control. In their meta-analysis of five PES programs in Latin America and Africa, Snilsveit et al. (2019) compute a mean effect size on forest cover of 0.32 SD (relative to pooled standard deviations), which is the closest thing to which we can compare our estimate.[2] This implies that the effect we could detect would have to be slightly larger than the average found across PES programs.

[2]As in the Jayachandran et al. (2017) study, which is included in the meta-analysis, avoided deforestation dominates these forest cover change outcome measures. Snilsveit et al. (2019) also compute a mean effect for the deforestation rate, but that is on a difference scale (0-1 scale) than our forest loss measure, which is measured in terms of HA.

Figure 1: Comparing Distributions for Outcome Variables in Liberia and Uganda Samples

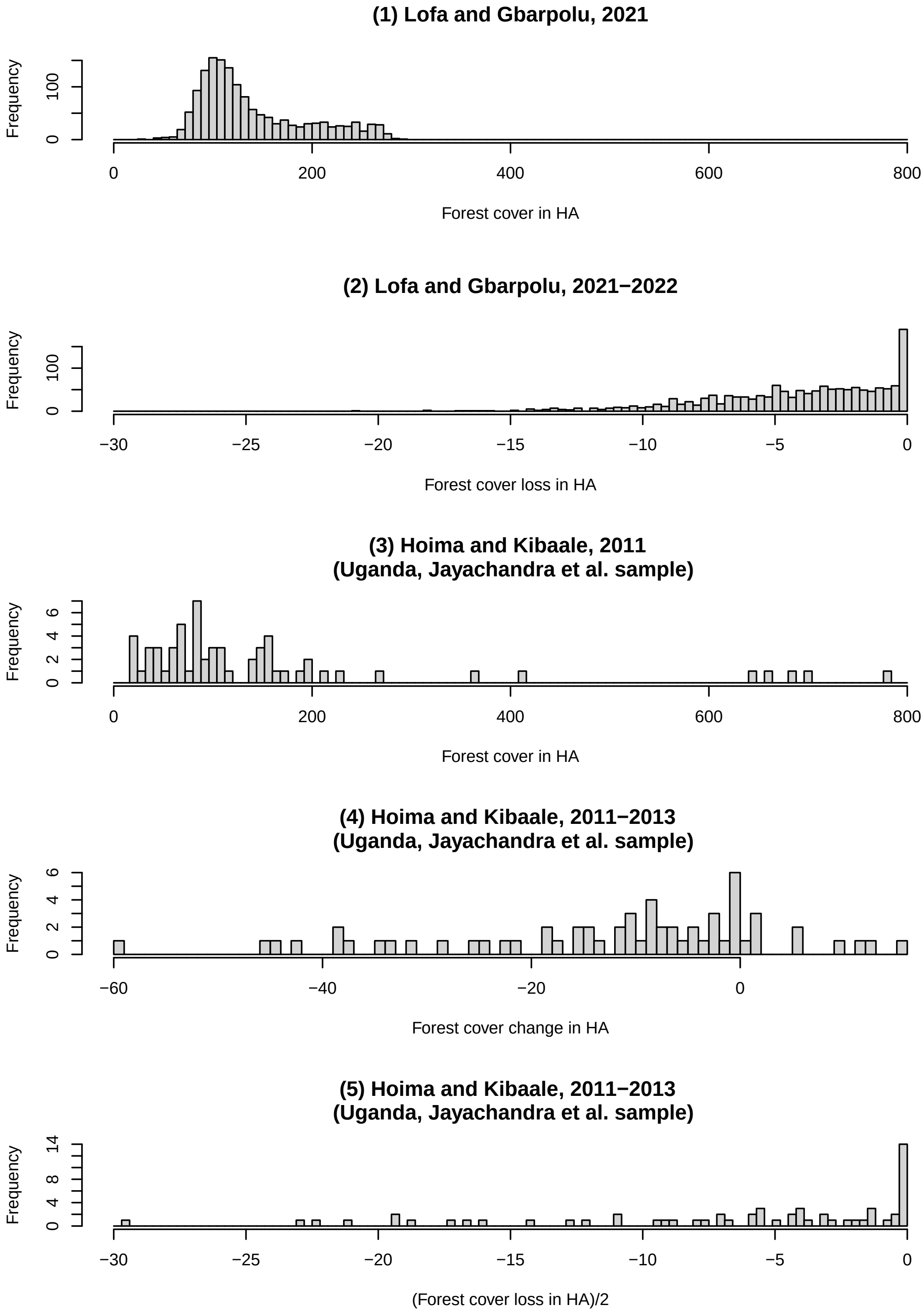

Table 2: Comparing Summary Statistics Across Liberia and Uganda Samples

	Mean	SD	Median
Liberia communities (1 yr. ch. in HA)	-4.138	3.442	-3.482
Uganda control communities (est. 1 yr. ch. in HA)	-7.003	7.093	-4.222
Uganda treated communities (est. 1 yr. ch. in HA)	-5.605	8.530	-2.750
Uganda all communities (est. 1 yr. ch. in HA)	-6.323	7.817	-3.818

Table 3: Reanalysis for Jayachandran et al. main results, using estimated 1-yr. forest loss outcome

	(1)	(2)
Treated	2.125	1.965*
	[1.314]	[1.180]
Control group mean†	-7.003	-7.003
Control variables	No	Yes
Observations	121	121

† Estimates are computed using the analytical weights and control specifications as per Jayachandran et al. (2017).

References

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