Mangroves Help Reduce the Impact of Climate-induced Cyclones in India

Kunxin Zhu,[*,1] Daniela A. Miteva[1], Sathya Gopalakrishnan,[1]

* Corresponding author: zhu.2906@buckeyemail.osu.edu

1. Department of Agricultural, Environmental and Development Economics, The Ohio State University, Columbus, OH

Selected Paper prepared for presentation at the 2023 Agricultural & Applied Economics Association Annual Meeting, Washington DC; July 23-25, 2023

Abstract

Mangroves shelter coastal economic activities during natural hazards like cyclones. However, despite consistent emphasis on such hazard mitigation benefits in mangrove preservation and restoration projects, there is insufficient information about economic value of such benefits, especially in India. Using night light data from 2010 to 2019, we find that cyclones have short-term impacts on rural villages and presence of mangroves can mitigate around 50% of such damage. Moreover, our results reveal that such benefits majorly result from dense mangrove forests. Focusing on the heterogeneity of these results, we identify that mangrove in economically disadvantaged areas with higher cyclone exposures conveys larger hazard mitigation benefits.

1.Introduction

Climate change is projected to increase the frequency of intense tropical cyclones, aligning with the observed rise in the frequency of category 4 or higher cyclones along the east coast of India (Bacmeister et al., 2018). Moreover, the frequency of cyclones increases by around 50% on India west coast since the beginning of the 21st century. This region, which historically experience minimal cyclone impact, is now witnessing an elevated frequency of these extreme weather events (Balaji et al., 2018; Deshpande et al., 2021). As climate change intensifies and coastal population continues to grow (Maul & Duedall, 2019), safeguarding coastal communities and infrastructure in India has become an urgent priority.

While engineering approaches such as sea walls can be used to protect the coastal areas, they can be costly and have negative impacts on the environment (Temmerman et al., 2013). Thus, Indian governments favor nature-based solutions through investments in natural capital like mangroves, which are a specific kind of carbon-rich coastal forests in tropical regions, as an alternative strategy to mitigate cyclone impacts on the coast. In the aftermath of the 2004 Asian tsunami, mangroves gained recognition as “bioshields” due to notable differences in impact between regions with and without existing mangroves (Barbier et al., 2008; Danielsen et al., 2005). Subsequent research find that mangroves can decrease wave actions (Loder et al., 2009) and wind speed (Das & Crépin, 2013), indicating their potential to mitigate impacts from cyclones and storms. On the other hand, there is continuous public interest in mangrove restoration projects. World Bank included mangrove regeneration as one of the objectives in the Tamil Nadu reconstruction programs (Sekhsaria, 2021). Other mangrove restoration and preservation programs are widespread in West Bengal, Odisha, Tamil Nadu, and Gujarat (Dubey et al., 2019; Shah & Ramesh, 2022).

Surprisingly, contrary to the consistent emphasis on mangrove mitigation in mangrove preservation and restoration projects (Shah & Ramesh, 2022), few studies have estimated the economic value of this mitigation service in India. Das and Vincent (2009) find that mangroves can save human lives during cyclone events and provide a lower bound of economic benefits. However, the estimate ignores other mitigation benefits and only represents benefits of such effects in Odisha state. Other studies generally estimate mitigation effects from mangroves and wetlands at larger scales (Hochard et al., 2019, 2021), which ignores the potential heterogeneity across and within countries. Thus, their results might not be representative in India, especially considering the significant differences in cyclone, mangrove, and population distributions within India (Deshpande et al., 2021; Kandasamy, 2017). It is therefore important to have a spatially explicit evaluation of the benefits of mangroves in mitigating hazards to inform better mangrove investment decisions in India.

In this paper, we use a two-way fixed effects model to estimate the economic benefits of mangroves in cyclone mitigation by analyzing 20 cyclone events in India east coast from 2010 to 2019. We first estimate the overall impacts of cyclones in rural villages. Second, we analyze the mangrove mitigation effects in intensive and extensive margins. Then, we explore heterogeneous effects of cyclones to inform better mangrove restoration and investment decisions in vulnerable regions. Specifically, we find that a category-4 equivalent cyclone can decrease local economic activities, which is measured by night light intensities, by 19.4% for average villages. Such effects are larger in villages with higher poverty rates. However, mangroves can mitigate around 50% of the damage from cyclones.

Our work is related to a large empirical literature testing the economic impact of cyclones. Multiple studies have tried to estimate the short- and long-term impacts of cyclones on economic outcomes across and within countries (see Botzen et al. (2019) and Dell et al. (2014) for detailed reviews). Within this literature, there is a growing trend to use exogeneous wind damage data approximated by local wind field instead of indicators such as reported damage or event counts to accurately represent local cyclone impact (del Valle et al., 2020; Hsiang & Jina, 2014; Noy & Strobl, 2023; Pelli et al., 2023). However, most existing literature use two-way fixed effects models and event study methods, which are subject to bias due to negative weights, especially because of the potential heterogeneous effects of cyclones across time (Goodman-Bacon, 2021; Sun & Abraham, 2021). In this study, we adopt a staggered difference-in-difference estimator developed by de Chaisemartin & D'Haultfoeuille (2022) and combine it with cyclone damage index developed based on local wind. Our result provides suggestive evidence that there are limited long-term effects from the cyclone in the India rural setting. Moreover, while some researchers indicate that countries that have higher social-economic status experience lower damage from cyclones (Kahn, 2005; Noy, 2009), limited studies try to unpack such heterogeneity within country, especially in rural areas. Our result suggests that such mechanisms remain in India rural setting, as cyclones disproportionately affect economically disadvantaged villages.

Our work also contributes to the literature estimating the value of ecosystem services from mangroves and wetlands. Many studies have estimated the benefit of mangroves in natural hazards mitigation (Barbier et al., 2008; Das & Vincent, 2009; del Valle et al., 2020; Hochard et al., 2019), carbon sequestration(Jakovac et al., 2020; Miteva et al., 2015; Siikamäki et al., 2012), and fishery production (Yamamoto, 2023). Particularly, the mitigation effects from mangroves and wetlands are estimated in India (Das, 2012; Das & Vincent, 2009), Indonesia (Laso Bayas et al., 2011), Thailand (Barbier, 2008), central America (del Valle et al., 2020), and USA (Sun & Carson, 2020). However, most of the estimates in Southeast Asia are derived from case studies and are not representative for general cyclones since most of the research are conducted before when the night light intensities are widely used in economics research. To the best of our knowledge, our study is the first study that provides spatially explicit benefits of mangroves in cyclone mitigation effects in India.

2. Data

We construct an annual panel dataset with all east coast villages in India from 2010 to 2019. Specifically, we define east coast villages as villages within 7 miles from the shoreline in West Bengal, Odisha, Andhra Pradesh, and Tamil Nadu. We choose 2019 as the end of our study period because COVID affect India after 2020. During the study period, 20 cyclones events happen in India during study periods, including major cyclones (categories 3 or higher). Since only two of the major cyclones affect places with mangrove and minor cyclones can also affect the rural area, we include all cyclone events in our estimation. Among 20 cyclone events in our study periods, 12 cyclone events affect areas with mangroves, which gives us enough spatial variation to estimate the hazard mitigation effects of mangroves.

2.1. Cyclone

Following Hsiang & Jina (2014) and Pelli et al. (2023), we develop a village-level cyclone damage index from interpolated local wind speed using the International Best Track Archive for Climate Stewardship dataset (Knapp et al., 2018). The dataset contains cyclone tracks and windspeed in 3-hour intervals. In this analysis, we restrict our sample to all cyclones with above 33 knots wind speed that affect India from 2010 to 2020. We start by interpolating each cyclone track into waypoints that represent cyclone eye location and corresponding wind speed in 30-minute intervals. Then, following Pelli et al (2023), we compute the village-level local wind speed using the following wind field model:

$$w_{pv} = e_p \left(\frac{D_{pv}}{26.9978}\right)\ if\ D_{pv} \leq 26.9978$$

$$w_{pv} = e_p \left(\frac{D_{pv}}{26.9978}\right)^{-0.5}\ \ if\ D_{pv} > 26.9978$$

where w_{pv} is the local wind speed in village v because of waypoint p, e_p is the wind speed for each way point p and D_{pv} is the distance between way point and villages in miles. The formula suggests that the wind speed increase linearly to the maximum at the distance cutoff and then slowly decreases with higher distances. This pattern correspond to the idea that cyclones have relative calm inner ring and wind speed reach the maximum at certain radiuses (Deppermann, 1947).

Following Pelli et al (2023), we assume that physical damage is a quadratic term of difference between local wind speed and the 33 knots threshold. We choose 33 knots as the threshold instead of 50 knots (Emanuel, 2011; Jerch et al., 2023; Noy & Strobl, 2023) since poor infrastructure and worse building materials are vulnerable to minor cyclones in developing countries[1]. As a result, we generate the normalized cyclone damage index C_{vt}

$$C_{vt} = \sum_{p \in T} \frac{(w_{pv} - 33)^2}{(150 - 33)^2}\ if\ w_{pv} > 33$$

by summing all way points p within each year t. Specifically, we normalize the wind damage at the category-4 equivalent cyclone level. Thus, our cyclone damage index should be interpreted as the number of hours for category-4 equivalent cyclone damage.

2.2. mangrove

To capture the spatial and temporal distribution of mangroves on India east coast, we assemble annual active mangrove data at 30m resolution (Vancutsem et al., 2021). Since cyclones can damage mangroves and only active mangroves can help to mitigate the wave and wind impacts, it is critical to measure the active mangrove with temporal distribution. The dataset provides (i) a fixed spatial distribution of mangroves and (ii) the temporal change of mangrove cover including degradation and regrowth. We define active mangroves as undisturbed and regrowth mangrove areas, which can capture both increases and decreases in the mangrove areas[2]. For each village, we calculate the width of the mangrove forest between the centroid of each village and shorelines to approximate the protective effects of mangroves (Das & Vincent, 2009; Laso Bayas et al., 2011).

2.3. Night light

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[1] In robustness tests, we change the threshold to 0, 50, and 64 knots. We also use a cubed damage function since the density of cyclone energy is the cubic term of local wind speed (Hsiang, 2010). Our results are robust to all different wind field models.

[2] We find that one hour more category-4 equivalent cyclone damage can decrease active mangrove by around 1% and such effects can sustain for more than 7 years using our active mangrove measure (Appendix Table 1), which provides suggestive evidence that our mangrove definition can represent the temporal change of local mangrove. Moreover, our mangrove measures can also explain the deforestation and restoration of the mangrove area due to anthropogenic effects.

We use nightlight intensity data from the Visible Infrared Imaging Radiometer Suite (VIIRS) as a proxy for village-level economic development (Elvidge et al., 2017). The intensity of night light is reported at 15 arc (500 m) resolution, which is representative at the village level. The data is filtered by background noise, solar and lunar contamination, cloud cover, and features unrelated to electricity lightning such as fires and flares. As a result, the night light data can serve as a good proxy for local electrification as well as development, especially in rural areas (Chanda & Kabiraj, 2020; Dugoua et al., 2018; Mirza et al., 2021; Singhal et al., 2020). Moreover, with finer spatial and temporal distribution, changes in night light data are also useful for the detection of damages and power outages caused by cyclones and flood events (Zhao et al., 2018).

While the night light data are suitable for studying local economic development in developing countries with limited high-quality data, several concerns remain. First, while night light data is correlated with multiple economic indicators (e.g. population, employment, consumption, electricity usage), it is hard to determine which exact indicators are measured (Asher et al., 2021). As a result, we prefer to interpret our result as the damage of cyclones on local economic activities[3]. Second, the night light data might not be consistent for both urban and rural areas. In this study, we restrict our sample to rural areas. Several other common critiques for night light data include inconsistency because of different satellites and limited data range. However, such issues do not apply to VIIRS data.

2.4. other data

We supplement the dataset with geological and socio-economic characteristics. The full list of covariates and the source is shown in Table 1.

3. Result

We begin with estimating the local economic impacts of cyclones. Our main empirical specification is a two-way fixed effects model. For village v in year t, we estimate the cyclone impacts on local night light intensities:

$$\ln NL_{vt} = \alpha + \beta\, C_{vt} + \gamma X_{vt} + \delta_{sd} + \eta_t + \epsilon_{vt}$$

where $\ln NL_{vt}$ is the mean light intensity in village v and year t. The right-hand side includes cyclone damage index we generate, precipitation level in monsoon season for each village v and year t, and village-level socio-economic indicators from 2001 census. We include subdistrict level spatial fixed effect and year fixed effect so that we can estimate mangrove mitigation effects from spatial variation of average mangrove coverage within subdistricts. In our preferred model, we use robust standard errors because our sample covers all the villages on India east coast and cyclones can be viewed as random conditional on each village (Abadie et al., 2022). As robustness tests, we re-estimate our models with different clustered standard error methods and different fixed effects.

As shown in Table 2, following cyclone exposure, villages on India east coast darken in the year that cyclones hit. While smaller, the effect is also present after we control for the village fixed effects and subdistrict specific time trends. Following general recommendations about the interpretation of the

[3] Since it is hard to distinguish between short-term power outages and displacement due to building damage by cyclones, we are cautious about interpreting the magnitude of our results. However, the mangrove mitigation effects can still be interpreted as mitigation effects for overall cyclone impacts.

night light change in natural hazards context (del Valle et al., 2020; Henderson et al., 2012; Kocornik-Mina et al., 2020), we interpret our results as the reduction of local economic activity captured by night light change. Specifically, we find standard category-4 cyclones[4] can decrease rural economic activities by 19.4% (Table 2 Column 2).

To address potential bias from heterogeneous treatment effects across time, we adopt a staggered difference-in-difference estimator developed by de Chaisemartin & D'Haultfoeuille (2022), which can estimate the treatment effects for continuous treatment (Table 3). Because the estimator requires discrete treatment, we use the number of hours each village experience local wind speeds exceeding 130 knots, which can represent the number of hours that village is affected by categories 4 or higher cyclones. The coefficient is similar to those we estimated based on the TWFE models, suggesting that even the largest cyclones have limited effects on rural night light after one years.

We next investigate whether mangroves can help to mitigate the cyclone impact by

$$\ln NL_{vt} = \alpha + \beta_0\, C_{vt} + \beta_1 C_{vt} S_v + \beta_1 C_{vt} Mangrove_{vt} + \gamma X_{vt} + \delta_{sd} + \eta_t + \epsilon_{vt}$$

where S_v is the distance to shorelines and $Mangrove_{vt}$ represents different mangrove indicators. In this model, we use cyclone index with threshold 0 similar to (Hsiang, 2010) to include more minor cyclones into our cyclone index, which results in a lower overall effect (Table 3 Column 4) Since mangroves mitigate more cyclone impacts from weaker cyclones (Sun & Carson, 2020), we believe this estimate might be more representative for mangrove mitigation effects. We include interactions between the distance to shorelines and cyclone index since storm surge and wind can have lower effects on inland regions, regardless of presence of mangroves.

Our result indicates that around 50% of cyclone impact can be mitigated in villages with mangrove protection (Table 4 Column 2). The mitigation effects mainly come from mangroves in Odisha and West Bengal. The coefficient for mangroves in Tamil Nadu also has a positive sign while it is not statistically significant at 10% (Table 4 Column 5). In the intensive margin, we find that wider mangrove protection belt has larger protection effects (Table 4 Column 3). Around 1.2 miles of mangrove protection belt can fully mitigate the cyclone impact, which aligns with the finding that places with higher mangrove coverage share more benefit from mangrove mitigation effects. Since mangrove deforestation is often correlated with the expansion of agricultural land and increasing fishery production (Suresh & Sahu, 2015; Yamamoto, 2023), mangrove width can be endogenous. Thus, we use mangrove width outside of the village territory as an instrumental variable for mangrove width and find higher mitigation benefits from mangroves (Table 4 Column 4).

We next consider the heterogeneity of cyclone effects. Specifically, we are interested in the differential effect of cyclones by wealth level. We test this by interacting the cyclone damage index with multiple wealth indicators from DHS data and census.

$$\ln NL_{vt} = \alpha + \beta_0\, C_{vt} + \beta_1 C_{vt} S_v + \beta_1 C_{vt} Wealth_v + \gamma X_{vt} + \delta_{sd} + \eta_t + \epsilon_{vt}$$

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[4] Based on our wind field model, villages around eyes of category 4 cyclones on average experience 4-hour equivalent damage.

$Wealth_v$ is cross-sectional wealth indicator from 2001 population census and DHS survey in 2016. We still control for interaction between distance to shorelines and cyclone index since inland villages tend to be poorer than coastal villages.

The interaction term of the cyclone index and wealth indicators capture the change of cyclone impacts conditional on baseline levels. In general, we find that cyclones have lower effects in wealthier villages, whether it is indicated by the percentage of households above 60 percentiles, poverty rate, or owned agricultural land (Table 5 Column 3,4, and 5). We also find that if percentage agricultural workers is higher, lower cyclone impacts can be captured by nightlight. However, such effects are small compared to overall cyclone effects (Table 5 Column 2).

4. Discussion

In this paper, we find that cyclones have negative short-run impacts in rural India, as is captured by night light intensity. We further show that the presence of mangroves can mitigate these negative effects by approximately 50%. Wider mangroves can significantly mitigate damage from cyclones. As a result, West Bengal and Odisha are states where mangrove mitigation effects are most obvious. Similar to across-country analysis that find cyclones have less effects in wealthier countries, we find that cyclones also have less impact in wealthy rural villages in India. Collectively, our results suggest that investment in mangrove preservation and plantation programs conveys greater natural hazard mitigation benefits in economically disadvantaged regions with higher cyclone exposure. Specifically, since mangroves are more likely to be degraded in poorer regions for short-term gains in agriculture and fishery sectors (Suresh & Sahu, 2015), policymakers need to be cautious about the long-term trade-off and justice implications of related decisions.

Our results also imply that coast front mangroves can have far reaching cyclone mitigation benefits for inland regions 7 miles away from the mangroves. Thus, local economic decisions weighing the benefit and the cost of mangroves are likely to result in the underinvestment of mangroves (Samuelson, 1954). Policymakers should be cautious about the externality provided by mangrove when making investment decisions.

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Table 2. Effects of cyclones on night light

	(1)	(2)	(3)	(4)	(5)
	log nightlight	log nightlight	log nightlight	log nightlight	log nightlight
Cyclone index 33 2	-0.0538***	-0.0538***	-0.0470***	-0.0366***	-0.0308***
	(0.00338)	(0.00575)	(0.00587)	(0.00295)	(0.00293)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Sd fixed effect	Yes	Yes	Yes	No	No
Sd specific time trends	No	No	Yes	No	Yes
Village fixed effect	No	No	No	Yes	Yes
Other control	Yes	Yes	Yes	Yes	Yes
Observations	69263	69263	69263	69263	69263
Adjusted R-squared	0.678	0.678	0.682	0.911	0.917

∗∗∗ p<0.01, ∗∗ p<0.05, ∗ p<0.1

The robust standard errors are clustered at village levels in column 1 and robust standard errors without clustering are reported in other columns.

Table 3. Alternative cyclone indexes and SDID estimators

	(1) Cyclone index 33 2	(2) Cyclone index 33 3	(3) Cyclone index 64 2	(4) Cyclone index 0 2	(5) Windspeed 130	(6) Windspeed 130
Cyclone index	-0.0538***	-0.0909***	-0.00629***	-0.0237***	-0.136***	-0.13846***
	(0.00575)	(0.0115)	(0.000664)	(0.00281)	(0.0448)	(0.0318)
mangrove width	-0.784***	-0.785***	-0.785***	-0.784***	-0.786***	
	(0.0541)	(0.0541)	(0.0541)	(0.0541)	(0.0541)	
Year fixed effect	Yes	Yes	Yes	Yes	Yes	
sd fixed effect	Yes	Yes	Yes	Yes	Yes	
Other control	Yes	Yes	Yes	Yes	Yes	
Observations	69263	69263	69263	69263	69263	69263
Adjusted R-squared	0.678	0.678	0.678	0.678	0.678	

∗∗∗ p<0.01, ∗∗ p<0.05, ∗ p<0.1

Column 1-5 report results from traditional TWFE models. Column 6 report result using SDID estimator.

Table 4. Mangrove mitigation effects for cyclone

	(1) log nightlight	(2) log nightlight	(3) log nightlight	(4) log nightlight	(5) log nightlight
Cyclone index 0 2	-0.0311***	-0.0315***	-0.0310***	-0.0314***	-0.0319***
	(0.00358)	(0.00358)	(0.00358)	(0.00358)	(0.00360)
Shoreline distance X Cyclone index 0 2	0.00201***	0.00200***	0.00192***	0.00198***	0.00211***
	(0.000531)	(0.000529)	(0.000534)	(0.000532)	(0.000531)
mangrove width	-0.785***	-0.547***	-0.912***	-0.863***	-0.611***
	(0.0540)	(0.0530)	(0.0855)	(0.0847)	(0.0553)
Mangrove X Cyclone index 0 2		0.0160***			
		(0.00327)			
Mangrove		-0.348***			
		(0.0231)			
mangrove width X Cyclone index 0 2			0.0271**	0.0353**	
			(0.0125)	(0.0112)	
West Bengal X Mangrove X Cyclone index 0 2					0.0293***
					(0.00646)
Odisha X Mangrove X Cyclone index 0 2					0.0177***
					(0.00446)
Andhra Pradesh X Mangrove X Cyclone index 0 2					-0.00995
					(0.00647)
Tamil Nadu X Mangrove X Cyclone index 0 2					0.0161
					(0.0126)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
sd fixed effect	Yes	Yes	Yes	Yes	Yes
Other control	Yes	Yes	Yes	Yes	Yes
Mangrove X state	No	No	No	No	Yes
Observations	69263	69263	69263	69263	69263
Adjusted R-squared	0.678	0.680	0.678	0.678	0.681

∗∗∗ p<0.01, ∗∗ p<0.05, ∗ p<0.1

Column 1,2,3, and 5 report results from TWFE models. Column 4 report results from IV estimation. Mangrove is a temporal constant indicating whether the village is protected by any mangrove within the whole study period and we include interaction term between the mangrove indicator and state dummy to control for correlation between mangrove coverage and night light intensity in each state.

Table 5. Heterogeneous effects by wealth indicators

	(1)	(2)	(3)	(4)	(5)
	log nightlight	log nightlight	log nightlight	log nightlight	log nightlight
	No	Percentage ag worker	Percentage households above 60 percentile	poverty rate	average owned ag land
Cyclone index 33 2	-0.0729***	-0.0988***	-0.130***	-0.0697***	-0.0966***
	(0.0161)	(0.0215)	(0.0240)	(0.0167)	(0.0169)
Shoreline distance X Cyclone index 33 2	0.00903***	0.00854***	0.0109***	0.0105***	0.00904***
	(0.00323)	(0.00321)	(0.00318)	(0.00321)	(0.00325)
mangrove width	-0.661***	-0.662***	-0.500***	-0.472***	-0.649***
	(0.0532)	(0.0532)	(0.0506)	(0.0481)	(0.0528)
Interaction term X Cyclone index 33 2		0.000480**	0.0878***	-0.0553	0.00138***
		(0.000221)	(0.0294)	(0.0386)	(0.000244)
Interaction term			1.839***	-1.720***	-0.00175***
			(0.0399)	(0.0617)	(0.000256)
Year fixed effect	Yes	Yes	Yes	Yes	Yes
sd fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	40921	40921	40921	40921	40921
Adjusted R-squared	0.700	0.700	0.714	0.707	0.701

∗∗∗ p<0.01, ∗∗ p<0.05, ∗ p<0.1

Number of observations are smaller since we drop villages without DHS information from more than 3 rural clusters.

Appendix

Table A1. Effects of cyclones on mangrove width

	Estimate	SE	LB CI	UB CI	N	Switchers
Effect_0	-0.00679	0.001114	-0.00898	-0.00461	57457	8973
Effect_1	-0.01071	0.001269	-0.0132	-0.00822	53747	8973
Effect_2	-0.01293	0.002299	-0.01744	-0.00842	45697	5766
Effect_3	-0.00909	0.001901	-0.01282	-0.00537	39611	5144
Effect_4	-0.00765	0.002141	-0.01185	-0.00345	36575	5144
Effect_5	-0.01258	0.002281	-0.01705	-0.00811	30247	4902
Effect_6	-0.01679	0.002904	-0.02248	-0.0111	24936	4902
Effect_7	-0.01901	0.003503	-0.02587	-0.01214	21554	4399
Placebo_1	0.000326	0.000706	-0.00106	0.00171	57457	8973
Placebo_2	-6.9E-05	0.000735	-0.00151	0.001373	43262	7041

Table A2. Effects of cyclones on night light

	log nightlight	log nightlight	log nightlight	log nightlight	log nightlight
Cyclone index 33 2	-0.0538***	-0.0538***	-0.0470***	-0.0366***	-0.0308***
	(0.00338)	(0.00575)	(0.00587)	(0.00295)	(0.00293)
mangrove width	-0.784***	-0.784***	-0.783***	-3.565***	-1.486***
	(0.121)	(0.0541)	(0.0541)	(0.411)	(0.409)
Percentage forest	0.0820	0.0820	0.0746	0.913***	1.029***
	(0.348)	(0.138)	(0.144)	(0.205)	(0.258)
Distance to city	-0.850***	-0.850***	-0.847***		
	(0.0542)	(0.0205)	(0.0205)		
Percentage younger than 6	0.0309***	0.0309***	0.0308***		
	(0.00378)	(0.00137)	(0.00136)		
Percentage ag worker	0.0246***	0.0246***	0.0248***		
	(0.00682)	(0.00245)	(0.00244)		
Percentage ag workerXMonsoon precipitation	-0.000870***	-0.000870***	-0.000875***		
	(0.000187)	(0.0000671)	(0.0000669)		
Monsoon precipitation	0.486***	0.486***	0.487***	-0.298***	-0.186***
	(0.0127)	(0.00443)	(0.00442)	(0.0371)	(0.0364)
Average slope	-0.139***	-0.139***	-0.139***		
	(0.0422)	(0.0148)	(0.0148)		
Shoreline distance	0.00268	0.00268	0.00270		
	(0.00563)	(0.00209)	(0.00208)		
Year fixed effect	Yes	Yes	Yes	Yes	Yes
sd fixed effect	Yes	Yes	Yes	No	No
sd specific time trends	No	No	Yes	No	Yes
village fixed effect	No	No	No	Yes	Yes
Observations	69263	69263	69263	69263	69263
Adjusted R-squared	0.678	0.678	0.682	0.911	0.917