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RESEARCH PAPER

Discounting Disaster: Land Markets and Climate Change in the Indian Sundarbans

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Abstract: Data scarcity has hindered studies on the impacts of climate change on land prices in the coastal regions of developing countries. Focused on the Indian Sundarbans, this paper is at the forefront of such research. Market conditions in the region feature unregulated transactions, unenforced zoning, and a lack of disaster insurance. For many residents with hereditary land ownership, stark poverty eliminates any risk buffer provided by savings or other non-essential liquid assets. Using new household surveys and environmental data, our study hypothesizes that salinization and cyclone strikes have already adversely affected land prices. We quantify such impacts using a georeferenced panel of 342 salinity monitoring stations and a spatial raster database on all cyclonic storm strikes since 1970. Our econometric results reveal highly significant negative impacts for both factors. We use the regression results to predict land prices for the most and least favourable environmental conditions recorded in our database. The results show that these climate change–related conditions account for spatial differentials greater than an order of magnitude in land prices. Such extreme risk differentials suggest high financial and fiscal stakes, underscoring the critical importance of appropriately targeted adjustment policies.

Keywords: Indian Sundarbans; land transactions; environmental variables; tropical cyclones; salinity; coastal erosion

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1. INTRODUCTION

This paper uses 2016–17 household surveys and environmental data to investigate the impact of climate change on land prices in the Indian Sundarbans coastal region. Coastal studies relating land prices to climate factors are plentiful in developed countries, particularly the United States (US). However, until recently, data scarcity has hindered similar research in the coastal regions of developing countries. To our knowledge, this paper represents the first such assessment.

The Sundarbans is a UNESCO heritage mangrove forest that extends across the India–Bangladesh border at the mouth of the Ganga–Brahmaputra–Meghna river basin. The incidence of poverty is strikingly high in the Sundarbans, and poor people in the region rely mostly on natural resources for their livelihoods. Salinization is spreading inland, and tidal surges and cyclones—to which the region is prone—are increasing in number and severity (Dasgupta and Wheeler 2018). The combination of poverty, topography, salinization, and the increasing risk of inundation have created conditions that will become widespread as sea-level rise and climate change continue (Dasgupta *et al.* 2016).

Our study uses household data drawn from a georeferenced survey of land transactors, which include information on plot sizes and prices. We quantify environmental conditions using two data sources: (i) a georeferenced panel of salinity measures drawn from 342 monitoring stations in the Indian Sundarbans region and (ii) a spatial raster database that incorporates information on all cyclonic storms that have struck the region since 1970.

Using these data, we estimate an econometric model that relates land prices to the effects of salinization, cyclonic storm intensity, and inundation risk from proximity to the coastline. In theory, one would expect salinization to reduce land prices through its impact on soil fertility. Land prices should also be lower in areas prone to cyclonic storm damage as well as those susceptible to inundation. We use the regression results to predict land prices for cases where salinization, cyclonic storm intensity, and inundation risk are at their least and most favourable levels in the sample.

Overall, our results suggest that climate change–related conditions account for spatial differentials greater than an order of magnitude in Sundarbans land prices. We believe that these results can help inform a key policy debate on whether to compensate residents in threatened coastal regions for their constantly escalating losses from salinization and inundation risk as the sea level rises. The answer may vary with local conditions. However, the urgency of the debate is affected by the scale of the financial and fiscal stakes, which, as our results suggest, is quite large.

The paper is organized into five sections. Section 2 reviews the relevant literature, while Section 3 introduces our household survey dataset and climate-related databases. Section 4 specifies and estimates our econometric model and uses the results to predict land prices. Finally, Section 5 explores the policy implications and concludes the paper.

2. PREVIOUS RESEARCH

As the sea level rises, flooding increases, and salinity spreads inland, land markets in coastal communities will adjust to the uncertainty surrounding the timing and intensity of future changes. In the US, Nakanishi (2016) has shown that natural disasters make land prices more volatile and increase average property values in safer areas. Other studies, mostly from the US, have found that property values are lower in flood zones (Dubé, AbdelHalim, and Devaux 2021; Bakkensen and Barrage 2021; Kousky *et al.* 2020; Florax, and Rietveld 2009; Bin, Kruse, and Landry 2008; Daniel, Bin and Kruse 2006; Harrison, Smersh, and Schwartz 2001; Donnelly 1989; Shilling *et al.* 1985) or subject to time discounting[1] that depends on the incidence of past floods (Ratnadiwakara and Buvaneshwaran 2020; Beltrán, Maddison, and Elliott 2019; Atreya and Ferreira 2014; Atreya, Ferreira, and Kriesel 2013; Bin and Polasky 2004; Bartosova *et al.* 2000) and the existence of mandatory flood insurance programmes (Frazier, Boyden, and Wood 2020; Atreya and Czajkowski 2019; Speyrer and Ragas 1991). Other studies have shown that, despite disaster risks, a region's high property values may be sustained by its natural environmental advantages (Fu and Nijman 2021; Wu, Chen, and Liou 2021; Beltrán, Maddison, and Elliott 2018; Atreya and Czajkowski 2016; Bin and Kruse 2006; Eves 2004).

Studies based in the coastal areas of developing countries can provide a useful extension of the literature because market conditions differ sharply from those in their Western counterparts. In the Indian Sundarbans, land transactions are virtually unregulated, zoning is not enforced, private and public disaster insurance is non-existent, and for many residents whose land ownership is hereditary, stark poverty eliminates any risk buffer provided by savings or other liquid assets that are not essential for survival. In short, the Sundarbans experience exemplifies unconstrained risk adjustment in land markets under rising environmental stress.

In economic theory, the price of a land parcel is generally assumed to reflect

1 'Time discounting' means the lowering of property prices following a flood event. The duration (or 'time') of the price lowering (or 'discounting') varies due to several factors.

the present value of its expected future rent flow at the prevailing discount rate (Hoover and Giarratani 1999).[2] For the Sundarbans, climate-related factors are expected to be significant in this context. Salinization is hypothesised to reduce land rent through its impact on soil fertility (Dasgupta *et al.* 2017). Land rent is expected to be lower in areas prone to cyclonic storm damage as well as those susceptible to inundation and tidal flux. The impacts of salinization, past storm intensity, and inundation risks will depend on their roles in the formation of transactors' expectations about the severity of future conditions.

To date, empirical work on the land market impact of climate-related risks has focused mainly on coastal areas in the US, where storm damage and inundation risk have been afforded more attention than salinization (Dachary-Bernard *et al.* 2019; McAlpine and Porter 2018; McNamara and Keeler 2013; Lichter and Felsenstein 2012; Bin *et al.* 2010; West *et al.* 2001; Yohe *et al.* 1996).

3. DATA

Our data are drawn from six widely dispersed villages (*mouzas*) in the Gosaba, Kultali, and Sagar community development (CD) blocks of the Indian Sundarbans (Figure 1). As Table 1 shows, the three blocks are roughly comparable in area and population density.

3.1 Land Transactions

Data collection in the Sundarbans presents unique challenges because resident communities are isolated and public records are incomplete. Formally, a land transaction involves the execution of a legal deed by the seller in favour of the buyer. The deed is supposed to be filed at the local public office after the payment of registration charges, which are dependent on the transaction price. In practice, the formal process ratifies transactions by wealthier households while informal transactions prevail among poor landowners who cannot read or understand formal contract measures or are unwilling to register because of the fees involved.

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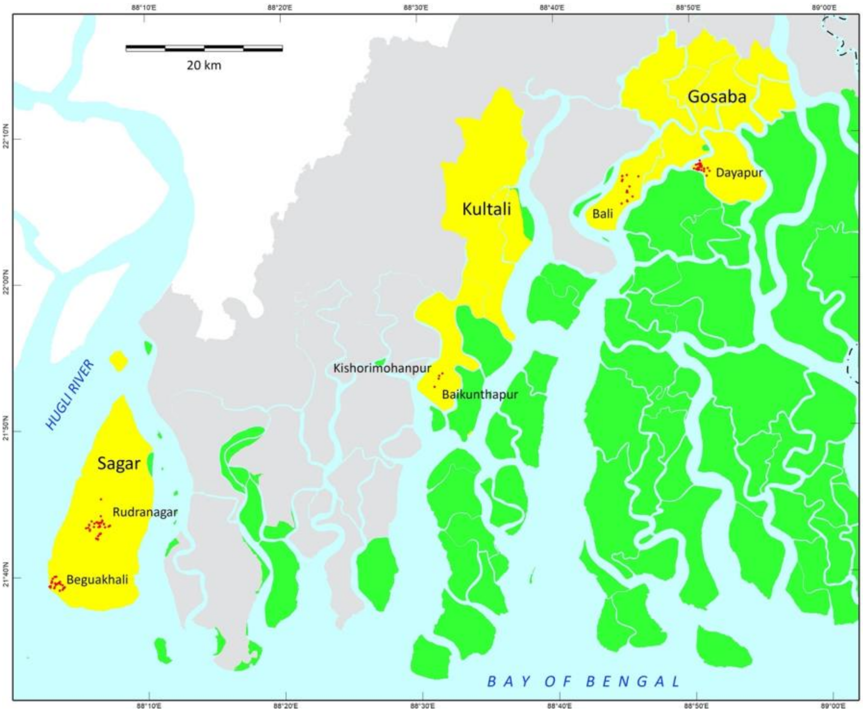
[2] This prevailing view abstracts from numerous potentially qualifying factors, including regulations, local customs, and speculation. For additional discussion, see Buurman (2001).

Figure 1: Locations of Transacting Households, Indian Sundarbans



Note: Red points denote sampled households with village (mouza) names. Study area blocks are shown in yellow. Green and grey /yellow colours denote forested and reclaimed Sundarbans, respectively.
Source: Field Survey using the Global Positioning System. Base map prepared from Resourcesat-2 images for 2015.

The household survey for this research was conducted in the Sundarbans from 1 October 2016 to 15 January 2017, with additional visits to verify and clean the data from March to May 2017. The six sampled villages all have populations near 10,000, according to 2018 estimates, based on the 2001–2011 growth rate. In each village, the survey team identified land transactions that had taken place between 2006 and 2016 (inclusive) with the help of the village elders and village surveyors (*amins*). Initial conversations with the village elders identified families who had made transactions.[3] All identified households were surveyed and additional

[3] Each transaction involves a buyer and a seller, but the final dataset incorporates only one observation per transaction to avoid duplicated measures for model variables. The survey team used data for the first transactor identified, so the database includes both buyers and sellers.

households were identified as transactors over the course of the survey. Cross-checks were performed with the village amins to validate plot sizes, locations, and ownership. We tested and modified the household survey instrument in a pilot study, and the full survey was then conducted for the 456 identified transacting households (Figure 2).

Table 1: Statistics of the Studied Community Development Block, Indian Sundarban

Block	Households (Number)	Population (Number)	Area (km²)	Population Density (Persons/km²)
Gosaba	58,197	246,598	296.7	831.1
Kultali	45,099	229,053	306.2	748.1
Sagar	43,716	212,037	282.1	751.6

Source: *Census of India* (2011)

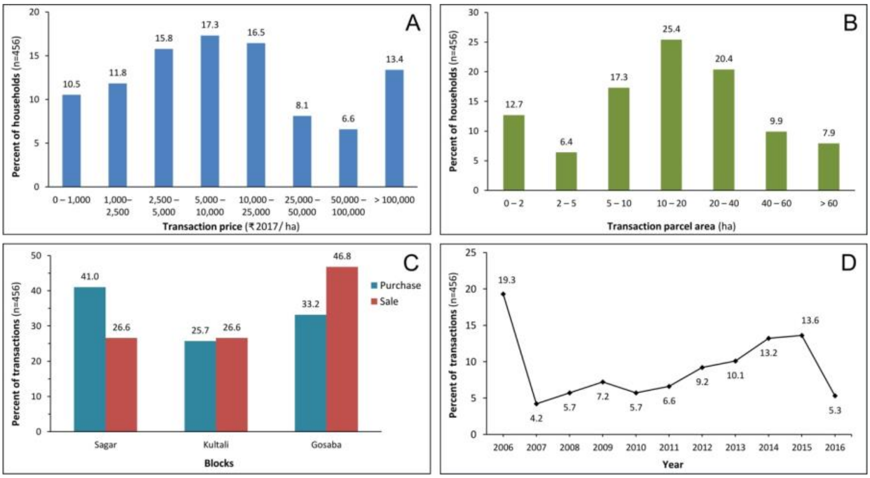
Among the 456 land parcels identified by the survey, 78% are solely used for cultivation, 15% are partly occupied by housing, and 7% are commercial properties. Figure 2 provides summary information on prices, parcel areas, and timing. Real unit land prices are calculated at ₹2,017 per hectare, using the World Bank's annual gross domestic product (GDP) deflator.[4] The sample yields a roughly balanced representation for eight price categories, from prices below ₹1,000 per hectare (10.5% of transactions) to prices above ₹100,000 per hectare (13.4% of transactions). Similarly, transaction parcels are distributed in an approximately balanced manner across seven ranges, from parcels below 2 hectares (12.7%) to those above 60 hectares (7.9%). The transaction timing is widely spaced.

3.2 Climate-related Variables

In this section, we use two variables – cyclone strikes (frequency and intensity) and salinity – to attempt an econometric analysis, where salinity is used as a cross-sectional variable.

[4] The World Bank's GDP deflator for India is the annual price index for goods and services. We have used it to adjust the year-to-year comparison of land market values for price inflation.

Figure 2: Transaction Characteristics of the Sampled Households, Indian Sundarbans — Land Prices (A), Parcel Areas (B), Transactions by Block (C), and Transactions by Year (D)



Source: Primary survey, 2016-17

3.2.1 Cyclone Strikes

Cyclonic storms regularly strike the coastal region of the Sundarbans from May to December. In the northern Bay of Bengal, recent research has found significant increase in the intensity of cyclones with the acceleration of global warming (Bandyopadhyay *et al.* 2021; Mishra 2014; Krishna 2009). Considering the coastlines of Odisha, West Bengal, and Bangladesh during 1877–2016, Bandyopadhyay *et al.* (2021) reported a notable increase in storm landfalls in the Sundarbans region between 1961 and 2016. This implies that the impact of cyclone strikes on land prices must have increased in recent years. This section incorporates the increased frequency and intensity of Sundarbans cyclone strikes into a spatial index for the econometric analysis, which assigns the greatest weight to recent strikes.

During a cyclone's passage, the damage caused by a few hours of battering by waves, winds, and storm surges can equal many years' worth of fair-weather depreciation. The damage inflicted on the region is well-documented (ADB-GoO-WB 2013; EM-DAT 2019; NIDM 2014; Khalil 1993). To illustrate, Cyclone Sidr struck the Sundarbans region of Bangladesh in November 2007, causing 3,406 deaths and economic losses of US$ 1.68 billion (GoB 2008). Cyclone Aila struck the Indian Sundarbans in May 2009, causing 100 deaths and losses above US$ 1.05 billion (IMD 2013; Mallick *et al.* 2011; GoWB 2009; IAA 2009). In the wake of such destruction, Dasgupta and Wheeler (2018) find large coastal population displacement effects.

As noted in Section 1, damage from cyclone strikes may play a significant role in the determination of land prices in the Sundarbans. Introducing this variable into the econometric work requires constructing a damage measure based on the historical record. In this paper, we incorporate the impact of cyclone strikes using a georeferenced panel database of past cyclonic storms (Bandyopadhyay *et al.* 2021) and the methodologies of Dasgupta and Wheeler (2018) and Dasgupta *et al.* (2022), which compute cyclonic storm intensities in a multi-stage exercise.

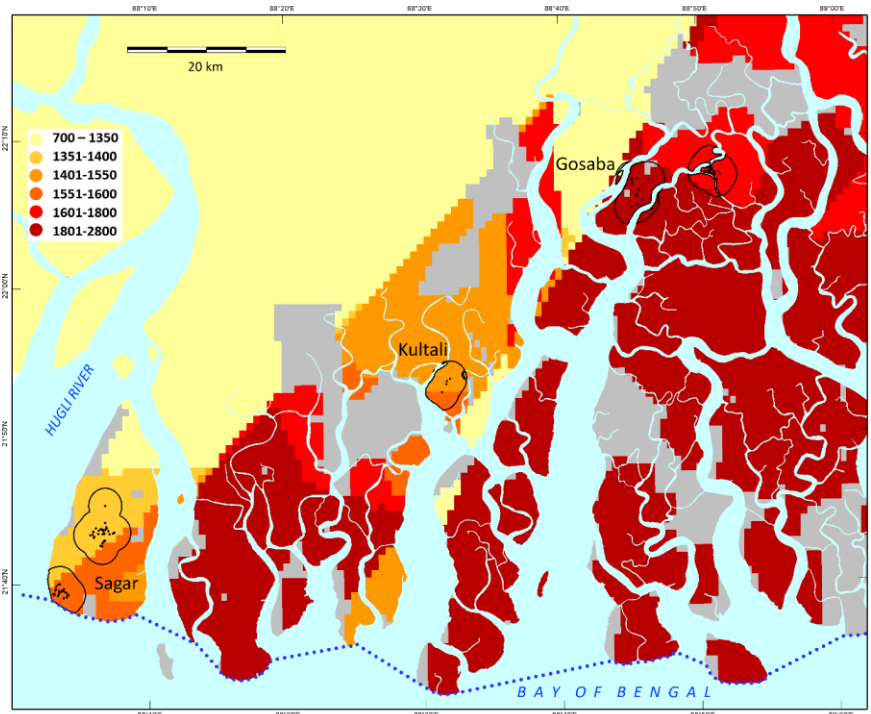
First, we assemble complete georeferenced records for cyclonic storms in the studied region. For the period from 1970 to 2016, we use track data of storms above the wind speed of 33 knots (62 km per hour), available from the International Best Track Archive for Climate Stewardship (IBTrACS, version 3.9). This data source is maintained by the Global Data Center for Meteorology, operated by the United States National Oceanic and Atmospheric Administration (NOAA, 2018). To check for missing data, we also employ georeferenced storm track information from the India Meteorological Department (IMD). We exclude all storms rated as tropical depressions because their maximum wind speeds fall below 34 knots, which limits their potential for causing serious damage. Winds above 33 knots reach gale force and a Beaufort Scale value of 9, when trees start to break off and walking become difficult. The analysis uses two commonly available measures of cyclonic storm strength: (i) maximum wind speed, measured in knots, and (ii) primary impact zone, measured by the radial distance between a storm's centre and the outer boundary of its maximum wind speed zone.

For each storm, we compute the primary impact zone along its track (Bandyopadhyay *et al.* 2021). Using a methodology from the United States National Hurricane Center (USNHC 2018), we compute wind speed at each point after landfall as a function of wind speed at landfall and elapsed time after landfall.[5] We derive wind damage potential using a standard exponential formulation (HRC-AOML 2018).[6]

[5] In the USNHC model, the ratio (wind speed to wind speed at landfall) decays exponentially with time after landfall. The absolute value of the exponential parameter is a positive function of wind speed at landfall (i.e., the rate of decay is greater for storms with higher initial wind speeds).

[6] In our computation, wind damage potential is proportional to the square of wind speed, which is measured in knots (kt). Wind damage potential is therefore expressed in kt^2.

Figure 3: Cyclone Intensity Indices (CII), Indian Sundarbans



Note: CII are dimensioned in kt². The coastline is indicated by the dotted blue line; unclassified land areas are shown in grey; and black boundaries depict the study areas of Sagar, Kultali, and Gosaba.

Source: IBTrACS data from NOAA (2018)

Next, we compute historical storm damage potentials using high-resolution spatial population data from the CIESIN (2019) Gridded Population of the World (GPW, version 4). These data have resolutions of 30 arc seconds (approximately 1 km at the equator). Using a geographic information system (GIS), we overlay each GPW point with all historical cyclone impact zones to identify the cyclones that have affected the point. Thus, for each GPW point, we generate a time series of cyclones, with impact years and estimated wind damage potentials (dimensioned in kt²).

Finally, we divide the historical storm data into three 15-year periods: 1970–1984, 1985–1999, and 2000–2014. For each period, we compute the mean wind damage potential for each GPW point. Then, we combine the mean wind damage potentials for the three periods into an overall storm intensity index (dimensioned in kt²) using weights computed by Dasgupta and Wheeler (2018) and Dasgupta *et al.* (2022) from regression analyses of historical impacts on population displacement in the region.[7] Figure 3 maps the cross-sectional cyclone intensity index (CII) that we use for the econometric analysis in this paper.

3.2.2 Salinity

Water salinity in the Indian Sundarbans is rising as climate change affects river flows and the sea level. Salinity is already near marine levels in southern areas, with measures of 30 parts per thousand (ppt) or higher. By 2050, regional salinity will intensify considerably, with many northern areas also surpassing 30 ppt (Dasgupta *et al.* 2022; Mukhopadhyay *et al.* 2019; Dasgupta *et al.* 2017). These changes are expected to reduce the value of agricultural land in the affected areas. Figure 4 overlays Figure 1 with local enlargements that display marine and riverine encroachments in two study areas during the past century. These changes have brought the shoreline much closer to many households, with direct salinization effects in Beguakhali (Sagar) and longer-term effects from rising riverine salinity in Dayapur (Gosaba).[8]

Our database for econometric estimation includes land transactions in the years 2006–2016. However, water salinity monitoring data are only available for 2012–2015. Matching the two datasets by year would limit our econometric database to 4 of the 11 years in our land transaction sample. Accordingly, we incorporate salinity as a cross-sectional variable based on monitoring data for the same period. Since the salinity observations are incomplete, we perform interpolations on a spatial panel database of readings for 342 monitoring stations in the Indian Sundarbans provided by WWF International (2019) (Figure 5). This is an unbalanced panel, with many time-series observations from some monitoring locations and sparse observations from others. Table 2 displays the available observations by month and year.[9]

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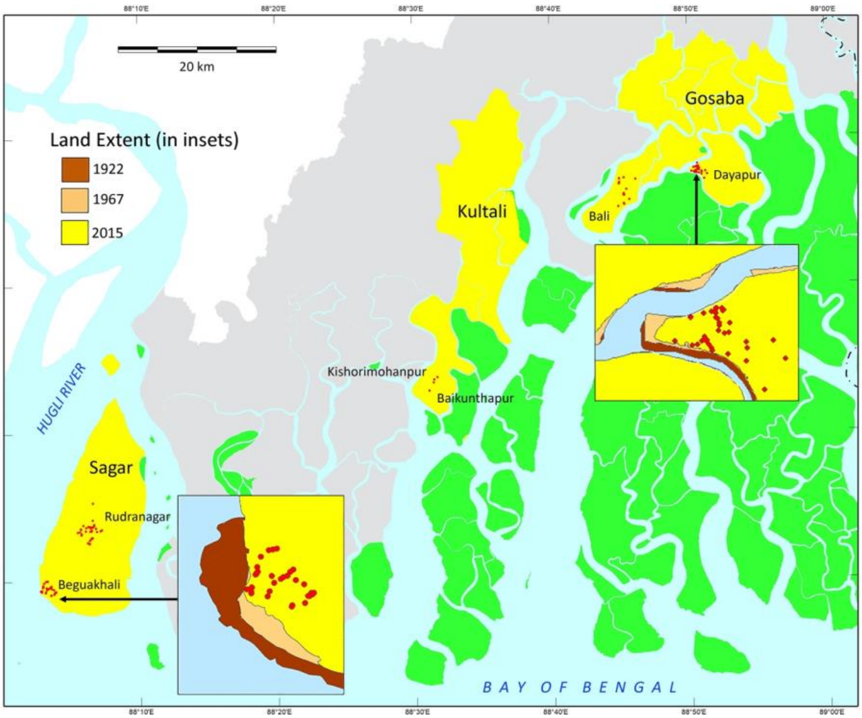
[7] We use storm intensities for previous periods because the results in Dasgupta and Wheeler (2018) indicate that expectations about cyclone strikes in an area adjust to the historical pattern with long lags.

[8] Prawn cultivation in saline water for export may have increased land salinity and depressed land values near prawn farms in the Sundarbans sampled households (Ghoshal *et al.* 2019). However, none of the land clusters used for the present analysis is located close to an aquaculture or prawn farm whose saline operations could influence land prices. In general, prawn farming is conducted only on the outer sides of main embankments in creek-adjacent areas of sections in the southern Indian Sundarbans. Farmlands are usually not converted for aquaculture.

[9] As Table 2 shows, monitoring stations have operated with different frequencies during the sample period. These differences are mainly related to operations and maintenance problems

Figure 4: Coastal and Riverine Encroachment on Two Study Villages, Indian Sundarbans



Note: Red points denote sampled households with village (mouza) names. Study area blocks are shown in yellow. Green and grey /yellow colours denote forested and reclaimed Sundarbans, respectively.

Source: Field Survey using the Global Positioning System. Land extents extracted from 1922 Survey of India topographical maps, 1967 Corona space photos, and 2015 Resourcesat-2 satellite images.

To fill in the panel, we estimate an interpolation model that incorporates fixed effects (FE) for time (by month and year) and location (by monitoring station). The model controls for average differences in salinity at different monitoring stations while incorporating the annual trend and seasonal fluctuations that affect all stations concurrently. The model is specified as follows:

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under typical conditions in the Sundarbans. Observations in the database have been recorded for cases where monitors met the required technical specifications during the periods of operation.

$$\ln S_{it} = \beta_0 + \sum_{j=1}^{N} \beta_j DS_j + \sum_{k=2}^{12} \gamma_k DM_k + \delta y + \varepsilon_{it}$$

(1)

where S_{it} equals salinity (ppt) at monitoring location i in period t; DS_j represents the monitoring dummy variable (1 for monitoring location j and 0 otherwise), DM_k equals the month dummy variable, y stands for the year (2012, …, 2015), and ε_{it} is the stochastic error term.

Table 2: Salinity Monitoring Observations by Month and Year, Indian Sundarbans

Month	2012	2013	2014	2015
January	-	-	64	64
February	40	58	158	64
March	-	132	72	48
April	-	122	72	48
May	2	58	144	60
June	10	52	64	76
July	8	52	56	68
August	-	52	56	44
September	2	46	40	62
October	8	52	64	56
November	36	56	64	56
December	150	96	64	56

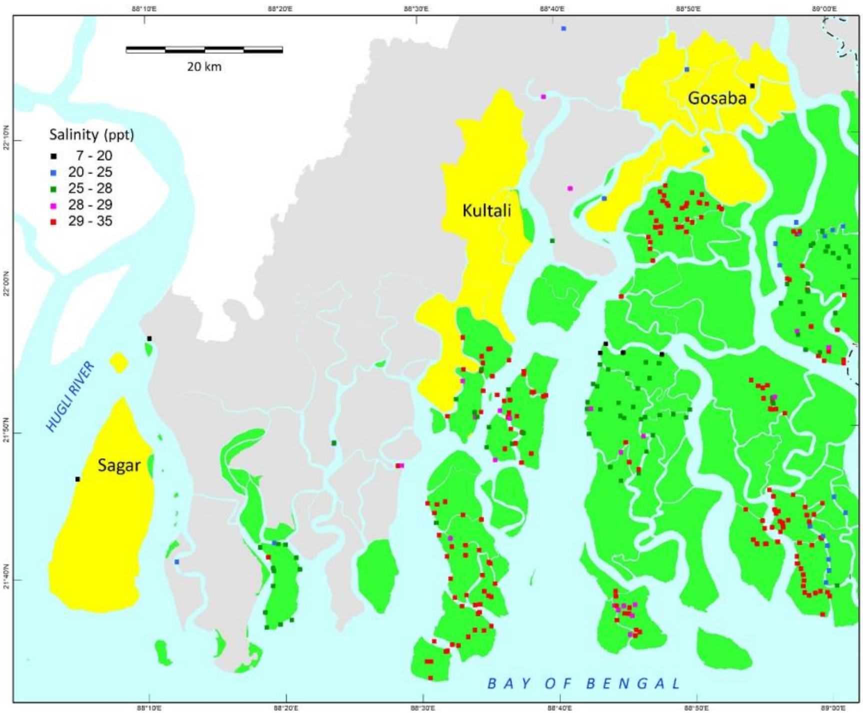
Source: WWF International (2019)

We use regression predictions to fill in the missing observations for the 342 monitoring stations in all 12 months for the years 2012–2015. Using actual and interpolated observations for 2015, we choose the peak month of May for our cross-sectional salinity index.

4. RESULTS AND DISCUSSION

Our econometric model includes FE for the three CD blocks in order to incorporate the impact of unobserved factors such as attractiveness for tourism and differential soil fertility. We include FE for the observation years as well as interaction terms that allow for land price dynamics in the different blocks. We estimate a log-linear model since the distribution of land prices is highly skewed but approximately log-normal. This approach minimizes outlier effects while preserving the information in extreme observations.[10] We control for plot size since extensive research has documented a significant negative relationship between plot size and land price.[11]

Figure 5: Salinity Estimates in the Indian Sundarbans, May 2015



Note: Salinity values are in parts per thousand (ppt)
Source: WWF International (2019)

We specify the following estimation model:[12]

$$\ln X_{it} = \alpha_0 + \alpha_1 D_i + \alpha_2 C_i + \alpha_3 S_i + \alpha_4 N_i + \sum_{j=1}^{3} \delta_j B_j + \sum_{j=1}^{3} \delta_j B_j y_t + \sum_{k=2006}^{2016} B_k DY_k + \varepsilon_{it}$$

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[10] We believe that this approach is superior to truncating highly skewed distributions to eliminate arbitrarily identified outliers. For further discussion, see Tukey (1977).

[11] For a summary of past research, see Lin and Evans (2000).

[12] We have also experimented with a measure of local land erosion risk, proxied by the change in the distance to the nearest riverine shoreline from 1967 to 2015. This measure has positive and negative values for accretion and erosion, respectively. Because it proved insignificant in all estimates, we excluded it from the final specification of the estimation model (2).

Expectations: $\alpha_1 > 0$; α_2, α_3, and $\alpha_4 < 0$

(2)

For household *i* and period *t*, $ln\ X_{it}$ equals the log land transaction price; D_i represents the distance from the coastline (see Figure 3); C_i indicates past and expected future wind damage from cyclonic storms; S_i represents salinity of the nearest monitoring location; N_i indicates the size of the transacted plot; B_j equals the CD block dummy variables for Gosaba (1), Kultali (2), and Sagar (3); y_t stands for the observation year; DY_k equals the dummy variables for years (2006, …, 2016); and ε_{it} is the stochastic error, subject to spatial and temporal autocorrelation.

Land transactions are recorded by year from 2006 to 2016; we convert prices per hectare to ₹2,017 using the India GDP deflator in the World Bank's World Development Indicators. For D_i, we compute the distance from each household location to the nearest point on a coastal polyline constructed by the authors. As shown in Figure 3, the polyline follows the outer coastlines of the southernmost Sundarbans islands, with direct linear segments between islands. C_i for a household is the nearest point in the spatial raster of past storm severity indicators described in Section 3.2.1 (Figure 3). S_i for a household is the estimated reading for May 2015 from the nearest water salinity monitor described in Section 3.2.2 (Figure 5). We use this as our proxy variable, following the finding of Dasgupta *et al.* (2017) that land salinity in this coastal region is strongly predicted by proximate water salinity. The size of each transacted plot is drawn from our survey data.

Table 3 reports our results for land prices in recorded transactions. To test for robustness, we use alternative estimators that incorporate different assumptions about the structure of the stochastic error term (ε_{it}) in the model. These techniques produce the same point estimates for model parameters, but their differing estimates of standard errors (and the accompanying *t* statistics) may lead to very different inferences about the statistical significance of model variables. We replicate the point estimates in columns 1–3 to aid the interpretation of the *t* statistics. In this case, we find that our model is robust to the changes. We include results for ordinary least squares (OLS), standard errors adjusted for 71 clusters of household groups (hamlets), and a spatial heteroscedasticity and autocorrelation consistent (HAC) estimator that incorporates both spatial and temporal autocorrelation (Hsiang 2010, 2020).

Table 3: Regression Results: Land Price Versus Climate-related Variables

Independent Variables	**(1) OLS**	**(2) Cluster SE**	**(3) Spatial HAC**
Salinity	−0.238 (4.36)**	−0.238 (2.09)*	−0.238 (3.49)**
Cyclone strike intensity	−0.004 (2.58)*	−0.004 (3.50)**	−0.004 (3.23)**
Plot area	−0.023 (9.39)**	−0.023 (5.65)**	−0.023 (4.80)**
D (Kultali)	−327.206 (2.22)*	−327.206 −1.93	−327.206 (2.67)**
D (Kultali) × year	0.163 (2.21)*	0.163 −1.93	0.163 (2.67)**
D (Sagar)	−356.766 (2.58)*	−356.766 (2.85)**	−356.766 (2.50)*
D (Sagar) × year	0.176 (2.56)*	0.176 (2.84)**	0.176 (2.49)*
Constant	23.975 (6.39)**	23.975 (5.63)**	23.975 (7.16)**
Observations R squared R-squared	456 0.3	456 0.3	456

Notes: Dependent variable: log land price
The absolute value of *t* statistics are in parentheses.
* = 5% significance level and ** = 1% significance level.
[a] Dummy variable results for 2007–2016 are excluded.
OLS: ordinary least squares; HAC: heteroscedasticity and autocorrelation consistent; D: Distance from shoreline

4.1 Fixed Effects and Collinearity

Preliminary estimates show that collinearity between the CD block FE and D_i, our measure of distance from the coastline, is too great for independent parameter estimation. We choose to retain the block FE since it may absorb the effects of factors other than distance from the coastline. We exclude the dummy variable for the Gosaba block to avoid total collinearity, so the two blocks' results should be interpreted as deviations from the result for Gosaba. The FE estimates for Kultali and Sagar are both negative and significant, with a somewhat larger estimated effect for Sagar. Since the

Sagar block is closer to the ocean, this may partly reflect the distance from the coastline. However, other factors may also be involved. To cite one possibility, Figure 5 shows that salinity measures for the Sagar region are both sparse and low. These may not adequately represent salinity for Sagar, particularly in Beguakhali village (Figure 1), because it is close to the open ocean. Part of the negative result for Sagar may represent an adjustment for this factor.

The positive, significant interactions of the two block dummy variables with observation years suggest that exogenous trends have reduced the FE differences from Gosaba during the sample period. We incorporate the full set of yearly dummy variables in all regressions, but the results are trendless and insignificant. We therefore exclude them to make Table 3 easier to read.

4.2 Results for Environmental Risks and Plot Size

We find the expected signs and high significance in all cases: land transaction price decreases with salinity and cyclone intensity index (CII). Despite the sample correlation of salinity and CII, their independent covariation with land price is sufficient to yield consistently high significance for OLS, cluster standard errors (SE), and spatial HAC. We find that land price falls significantly with plot size, as reported in most of the empirical literature on land price determination in developed countries.

While we incorporate adjustments for spatial and temporal autocorrelation, our estimates only reflect land values revealed by transactions. An extensive body of literature has studied the problem of estimation bias when samples are truncated because some potential transactions are excluded due to mismatches between buyers and sellers (Bishop *et al.* 2020; Gatzlaff and Haurin 1997, 1998; Gatzlaff and Ling 1994; Munneke and Slade 2000). In our case, the most likely source of truncation bias is inherited land with very high salinity and/or cyclone risk, for which non-market factors may create a reservation price that exceeds very low offers from buyers. Our area controls for salinity and cyclone risk are the best available, but their spatial resolution may not capture the full range of local variations, including extremely low values. Where those occur, buyer/seller mismatches may preclude any transactions. If our survey database excludes properties with the lowest valuation in high-risk areas, our sample transactions will overstate market valuations in those areas. By implication, our estimates may be downwardly biased, understating the marginal impact of salinity and cyclone strike risk on land prices. Our estimated parameter values should therefore be regarded as conservative.

4.3 Assessing Impact Magnitudes

Our econometric results suggest that salinization and cyclonic storm damage play significant roles in determining land prices in the Indian Sundarbans. However, their empirical importance hinges on actual impact magnitudes. As noted earlier, the Sundarbans case differs markedly from previously studied Western cases because transactions are unregulated, zoning is not enforced, private and public disaster insurance does not exist, and poverty eliminates any financial risk buffer for many households. To assess impact magnitudes, we use our regression results to predict land prices for the most and least favourable environmental conditions recorded in our database.

Table 4 shows that the Sagar block exhibits the most favourable environmental conditions in terms of salinity (17.8 ppt) and CII (1,365), while the Gosaba block has the least favourable conditions (salinity of 29.3 ppt and CII of 1,876). We use our econometric results to predict the associated land prices in 2016, with dummy variable controls for Sagar and Gosaba.[13] Our results show that the environmental variables have very large effects under the prevailing market conditions in the Sundarbans. Point estimates for land prices under the most and least favourable conditions are ₹86,622 and ₹3,997, respectively. We augment the comparison with lower- and upper-bound predictions using a forecast SE, which shows that the two ranges are far from overlapping.

Summing up, within our Sundarbans sample, the point prediction for land price under the most favourable environmental conditions is nearly 22 times the point prediction under the least favourable conditions. By implication, land prices in areas that are currently least affected will fall sharply as continued sea-level rise and storm intensification drive those areas toward the current worst-case values.

[13] Here, it is useful to recall the interpretation of block dummy variables with the Gosaba dummy excluded. The results for Sagar and Kultali are differences from the FE for Gosaba. To predict for Sagar, its dummy variable is set at 1 while the dummy for Kultali is set at 0. To predict for Gosaba, the dummies for both Sagar and Kultali are set at 0. We also include the interactions of block dummy variables with observation years in the predictions.

Table 4: Predicted Land Prices Under the Most and Least Favourable Environmental Conditions, Indian Sundarbans

<table>
<tr><th colspan="2" rowspan="2">Environmental Conditions</th><th rowspan="2">Value</th><th rowspan="2">Block</th><th colspan="3">Predicted Land Price (₹2,017)</th></tr>
<tr><th>Point</th><th>−1.96 SE</th><th>+1.96 SE</th></tr>
<tr><td rowspan="2">Most favourable</td><td>Salinity (ppt)</td><td>17.8</td><td>Sagar</td><td rowspan="2">6,622</td><td rowspan="2">2,550</td><td rowspan="2">230,519</td></tr>
<tr><td>Cyclone intensity index (CII)</td><td>1,365</td><td>Sagar</td></tr>
<tr><td rowspan="2">Least favourable</td><td>Salinity (ppt)</td><td>29.3</td><td>Gosaba</td><td rowspan="2">3,997</td><td rowspan="2">1,389</td><td rowspan="2">11,502</td></tr>
<tr><td>Cyclone intensity index (CII)</td><td>1,876</td><td>Gosaba</td></tr>
</table>

Note: ppt stands for parts per thousand
Source: Compiled from NOAA (2018), WWF International (2019), and primary surveys

5. POLICY IMPLICATIONS AND CONCLUSION

We believe that these results can help address an important policy question for threatened coastal regions: should residents be compensated for the ever-increasing losses from salinization and inundation risk as the sea level rises? For wealthier households or businesses whose acquisition of coastal land has already benefited from deep risk discounts, there is no apparent rationale for additional compensation. However, our results suggest that poorer residents with inherited coastal land will face steep depreciation of their primary asset as ocean encroachment continues.

Some form of means-tested compensation may be warranted, but its form will be critical. For example, periodic compensation payments in situ would inevitably rise until they become fiscally unsustainable. In contrast, one-time compensation could be affected by public land purchases from poorer households at above-market prices, followed by the proscription of settlement or auction resale at a loss under the condition of caveat emptor. Whatever measures are considered, the risk differentials revealed by our results indicate that the financial and fiscal stakes are quite high.

This econometric exercise for the Indian Sundarbans has afforded the opportunity to study unconstrained risk adjustment in land markets under rising environmental stress. The extreme risk-based price differentials highlight the critical importance of appropriately targeted adjustment policies for this climate-vulnerable coastal region as well as those of other developing countries.

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REFERENCES

ADB-GoO-WB. 2013. "Cyclone Phailin in Odisha, October 2013: Rapid Damage and Needs Assessment Report: 60." Asian Development Bank, Government of Odisha, World Bank. http://hdl.handle.net/10986/17608

Atreya, Ajita, and Jeffery Czajkowski. 2019. "Graduated Flood Risks and Property Prices in Galveston County." *Real Estate Economics* 47 (3): 807–44. https://doi.org/10.1111/1540-6229.12163.

Atreya, Ajita, and Susana Ferreira. 2014. "Seeing is Believing? Evidence from Property Prices in Inundated Areas." *Risk Analysis* 35 (5): 828–48. https://doi.org/10.1111/risa.12307.

Atreya, Ajita, Susana Ferreira, and Warren Kriesel. 2013. "Forgetting the Flood? An Analysis of the Flood Risk Discount Over Time." *Land Economics* 89 (4): 577–96. https://doi.org/10.3368/le.89.4.577.

Bakkensen, Laura, and Lint Barrage. 2021. "Going Underwater? Flood Risk Belief Heterogeneity and Coastal Home Price Dynamics." *The Review of Financial Studies*. https://doi.org/10.1093/rfs/hhab122.

Bandyopadhyay, Sunando, Susmita Dasgupta, Zahirul Huque Khan, and David Wheeler. 2021. "Spatiotemporal Analysis of Tropical Cyclone Landfalls in Northern Bay of Bengal, India and Bangladesh." *Asia Pacific Journal of Atmospheric Sciences* 57 (4): 799–815. https://doi.org/10.1007/s13143-021-00227-4.

Bartosova Alena, David E Clark, Vladimir Novotny, and Kyra S Taylor. 2000. "Using GIS to Evaluate the Effects of Flood Risk on Residential Property Values." *Economics Faculty Research and Publications* 131. https://epublications.marquette.edu/econ_fac/131.

Beltrán, Allen, David Maddison, and Robert JR Elliott. 2018. "Is Flood Risk Capitalised into Property Values?" *Ecological Economics* 146 (C): 668–85. https://doi.org/10.1016/j.ecolecon.2017.12.015.

Beltrán, Allen, David Maddison, and Robert Elliott. 2019. "The Impact of

Flooding on Property Prices: A Repeat-sales Approach." *Journal of Environmental Economics and Management* 95 (C): 62–86. https://doi.org/10.1016/j.jeem.2019.02.006.

Bin, Okmyung, and Jamie Brown Kruse. 2006. "Real Estate Market Response to Coastal Flood Hazards." *Natural Hazards Review* 7 (4): 137–44. https://doi.org/10.1061/(ASCE)1527-6988(2006)7:4(137).

Bin, Okmyung, and Stephen Polasky. 2004. "Effects of Flood Hazards on Property Values: Evidence Before and After Hurricane Floyd." *Land Economics* 80 (4): 490–500. https://doi.org/10.2307/3655805.

Bin, Okmyung, Ben Poulter, Christopher F Dumas, and John C Whitehead. 2011. "Measuring the Impact of Sea-level Rise on Coastal Real Estate: A Hedonic Property Model Approach." *Journal of Regional Science* 51 (4): 751–67. https://doi.org/10.1111/j.1467-9787.2010.00706.x.

Bin, Okmyung, Jamie Brown Kruse, and Craig E Landry. 2008. "Flood Hazards, Insurance Rates, and Amenities: Evidence from the Coastal Housing Market." *Journal of Risk and Insurance* 75 (1): 63–82. https://doi.org/10.1111/j.1539-6975.2007.00248.x.

Bishop, Kelly C, Nicolai V Kuminoff, H Spencer Banzhaf, Kevin J Boyle, Kathrine von Gravenitz, Jaren C Pope, V Kerry Smith, and Christopher D Timmins. 2020. "Best Practices for Using Hedonic Property Value Models to Measure Willingness to Pay for Environmental Quality." *Review of Environmental Economics and Policy* 14 (2): 260–81. https://doi.org/10.1093/reep/reaa001.

Buurman, J. 2001. "Land Markets and Land Prices: A Review of the Theory." Unpublished paper, Department of Spatial Economics, Free University, Amsterdam.

Census of India. 2011. Population Data of Blocks in South Twenty-Four Parganas District, West Bengal. https://www.census2011.co.in/data/district/17-south-twenty-four-parganas-west-bengal.html

Dachary-Bernard, Jeanne, H Rey-Valette, and Et Bénédicte Rulleau. 2019. "Preferences among Coastal and Inland Residents Relating to Managed Retreat: Influence of Risk Perception in Acceptability of Relocation Strategies." *Journal of Environmental Management* 232: 772–80. https://doi.org/10.1016/j.jenvman.2018.11.104.

Daniel, Vanessa E, Raymond Florax, and Piet Rietveld. 2009. "Flooding Risk and Housing Values: An Economic Assessment of Environmental Hazard." *Ecological Economics* 69 (2): 355–65. https://doi.org/10.1016/j.ecolecon.2009.08.018.

Dasgupta, Susmita, and David Wheeler. 2018. "The Cyclone's Shadow: Historical Storm Impacts and Population Displacement in Bangladesh, West Bengal and Odisha." *World Bank Policy Research Working Paper*.

Dasgupta, Susmita, David Wheeler, and Santadas Ghosh. 2022. "Fishing in Salty Waters: Poverty, Occupational Saline Exposure, and Women's Health in the Indian Sundarbans." *Journal of Management and Sustainability* 12 (1). https://doi.org/10.5539/jms.v12n1p1.

Dasgupta, Susmita, David Wheeler, Sunando Bandyopadhyay, Santadas Ghosh, and Utpal Roy. 2022. "Coastal Dilemma: Climate Change, Public Assistance, and Population Displacement." *World Development* 150: 105707. https://doi.org/10.1016/j.worlddev.2021.105707.

Dasgupta, Susmita, Mainul Huq, Md Golam Mustafa, Istiak Sobhan, and David Wheeler. 2017. "The Impact of Aquatic Salinization on Fish Habitats and Poor Communities in a Changing Climate: Evidence from Southwest Coastal Bangladesh." *Ecological Economics* 139: 128–39. https://doi.org/10.1016/j.ecolecon.2017.04.009.

Dasgupta, Susmita, Md Moqbul Hossain, Mainul Huq, and David Wheeler. 2016. "Facing the Hungry Tide: Climate Change, Livelihood Threats, and Household Responses in Coastal Bangladesh." *Climate Change Economics* 7 (3): 1650007. https://doi.org/10.1142/S201000781650007X.

Dasgupta, Susmita, Md. Moqbul Hossain, Mainul Huq, and David Wheeler. 2018. "Climate Change, Salinization and High-yield Rice Production in Coastal Bangladesh." Agricultural and Resource Economics Review 47 (1): 66–89. https://doi.org/10.1017/age.2017.14.

Donnelly, William A. 1989. "Hedonic Price Analysis of the Effect of a Floodplain on Property Values." *Journal of the American Water Resources Association* 25 (3): 581–86. https://doi.org/10.1111/j.1752-1688.1989.tb03095.x.

Dubé, Jean, Maha AbdelHalim, and Nicolas Devaux. 2021. "Evaluating the Impact of Floods on Housing Price Using a Spatial Matching Difference-in-differences (SM-DID) Approach." *Sustainability* 13 (2): 804. https://doi.org/10.3390/su13020804.

EM-DAT. 2019. "The International Disaster Database." Centre for Research on the Epidemiology of Disasters. Accessed 25 June 2019 http://www.emdat.be/database.

Eves, Chris. 2004. "The Impact of Flooding on Residential Property Buyer Behaviour: an England and Australian Comparison of Flood Affected Property." *Structural Survey* 22 (2): 84–94. https://doi.org/10.1108/02630800410538613.

Frazier, Tim, Elizabeth E Boyden, and Erik Wood. 2020. "Socioeconomic Implications of National Flood Insurance Policy Reform and Flood Insurance Rate Map Revisions." *Natural Hazards* 103: 329–46. https://doi.org/10.1007/s11069-020-03990-1.

Fu, Xinyu, and Jan Nijman. 2021. "Sea Level Rise, Homeownership, and Residential Real Estate Markets in South Florida." *The Professional Geographer* 73 (1): 62–71. https://doi.org/10.1080/00330124.2020.1818586.

Gatzlaff, Dean H, and David C Ling. 1994. "Measuring Changes in Local House Prices: An Empirical Investigation of Alternative Methodologies." *Journal of Urban Economics* 35 (2): 221–44. https://doi.org/10.1006/juec.1994.1014.

Gatzlaff, Dean H, and Donald R Haurin. 1997. "Sample Selection Bias and Repeat-sales Index Estimates." The Journal of Real Estate Finance and Economics 14 (1): 33–50. https://doi.org/10.1023/A:1007763816289.

Gatzlaff, Dean H, and Donald R Haurin. 1998. "Sample Selection and Biases in Local House Value Indices." *Journal of Urban Economics* 43 (2): 199–222. https://doi.org/10.1006/juec.1997.2045.

Ghoshal, TK., Debasis De, G Biswas, Prem Kumar, and KK Vijayan. 2019. "Brackish Water Aquaculture: Opportunities and Challenges for Meeting Livelihood Demand in Indian Sundarbans." In *The Sundarbans: A Disaster-Prone Eco-Region*, edited by H Sen, 321–49. Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-030-00680-8_11.

GoB. 2008. "Cyclone Sidr in Bangladesh: Damage, Loss and Needs Assessment for Disaster Recovery and Reconstruction." Government of Bangladesh. https://www.gfdrr.org/sites/default/files/2275_CycloneSidrinBangladeshExecutiveSummary.pdf.

GoWB. 2009. "Flood Management: Aila." Irrigation and Waterways Department, Government of West Bengal. https://wbiwd.gov.in/index.php/applications/aila.

CIESIN. 2019. "Gridded Population of the World (GPW)." Center for International Earth Science Information Network. Accessed 30 December 2019. https://sedac.ciesin.columbia.edu/data/collection/gpw-v4.

Harrison, David, Greg T Smersh, and Arthur Schwartz. 2001. "Environmental Determinants of Housing Prices: The Impact of Flood Zone Status." *Journal of Real Estate Research* 21 (1–2): 3–20. https://doi.org/10.1080/10835547.2001.12091045.

Hoover, Edgar M, and F Giarratani. 1999. *An Introduction to Regional Economics. Web Book of Regional Science*, 4. New York, US: Alfred A Knopf. https://researchrepository.wvu.edu/rri-web-book/4.

HRC-AOML. 2018. "Hurricane Damage as a Function of Wind Speed." Miami, FL: Hurricane Research Division, Atlantic Oceanographic and Meteorological Laboratory, US National Oceanic and Atmospheric Administration. http://www.aoml.noaa.gov/hrd/tcfaq/D5.html.

Hsiang, Solomon M. 2010. "Temperatures and Cyclones Strongly Associated with Economic Production in the Caribbean and Central America." *PNAS* 107 (35). https://www.pnas.org/doi/10.1073/pnas.1009510107.

Hsiang, Solomon M. 2020. "Standard Error Adjustment (OLS) for Spatial Correlation and Serial Correlation in Panel Data in (Stata and Matlab)." *Fight Entropy*. http://www.fight-entropy.com/2010/06/standard-error-adjustment-ols-for.html.

IAA. 2009. "In-depth Recovery Needs Assessment of Cyclone Aila Affected Areas, Bangladesh: 36." International Aid Agencies. https://reliefweb.int/sites/reliefweb.int/files/resources/F6603B7EF22A16B4C125768D004B1190-Full_Report.pdf.

IMD. 2013. "Severe Cyclonic Storm Aila: A Preliminary Report." New Delhi: Regional Specialised Meteorological Centre, India Meteorological Department.

Khalil, Gazi M. 1993. "The Catastrophic Cyclone of April 1991: Its Impact on the Economy of Bangladesh." *Natural Hazards* 8 (3): 263–81. https://doi.org/10.1007/BF00690911.

Kousky, C, H Kunreuther, M LaCour-Little, and S Wachter. 2020. "Flood Risk and the Housing Market." *Journal of Housing Research* 29: S3–S24. https://doi.org/10.1080/10527001.2020.1836915.

Krishna, K Muni. 2009. "Intensifying Tropical Cyclones over the North Indian Ocean during Summer Monsoon—Global Warming." *Global and Planetary Change* 65 (1–2): 12–16. https://doi.org/10.1016/j.gloplacha.2008.10.007.

Lichter, Michal, and Daniel Felsenstein. 2012. "Assessing the Costs of Sea-level Rise and Extreme Flooding at the Local Level: A GIS-based Approach." *Ocean and Coastal Management* 59: 47–62. https://doi.org/10.1016/j.ocecoaman.2011.12.020.

Lin, Tzu-Chin, and Alan W Evans. 2000. "The Relationship between the Price of Land and Size of Plot when Plots are Small." *Land Economics* 76 (3): 386–94. https://doi.org/10.2307/3147036.

Mallick, Bishwajit, Khan Rubayet Rahaman, and Joachim Vogt. 2011. "Coastal Livelihood and Physical Infrastructure in Bangladesh after Cyclone Aila." *Mitigation and Adaptation Strategies for Global Change* 16 (6): 629–48. https://doi.org/10.1007/s11027-011-9285-y.

McAlpine, Steven A, and Jeremy R Porter. 2018. "Estimating Recent Local Impacts of Sea-level Rise on Current Real-estate Losses: A Housing Market Case Study in Miami-Dade Florida." *Population Research and Policy Review* 37 (6): 871–95. https://doi.org/10.1007/s11113-018-9473-5.

McNamara, Dylan E and Andrew Keeler. 2013. "A Coupled Physical and Economic Model of the Response of Coastal Real Estate to Climate Risk." *Nature Climate Change* 3 (6): 559–62. https://doi.org/10.1038/nclimate1826.

Mishra, Ashutosh. 2014. "Temperature Rise and Trend of Cyclones over the Eastern Coastal Region of India." *Journal of Earth Science & Climate Change* 5 (9): 227. https://doi.org/10.4172/2157-7617.1000227.

Mukhopadhyay, Anirban, David Wheeler, Susmita Dasgupta, Ajanta Dey, and Istiak Sobhan. 2019. "Mangrove Spatial Distribution in the Indian Sundarbans: Predicting Salinity-induced Migration." *Journal of Management and Sustainability* 9 (1): 1–15. https://doi.org/10.5539/jms.v9n1p1.

Munneke, Henry J, and Barrett A Slade. 2000. "An Empirical Study of Sample-selection Bias in Indices of Commercial Real Estate." *The Journal of Real Estate Finance and Economics* 21 (1): 45–64. https://doi.org/10.1023/A:1007861303058.

Nakanishi, Hayato. 2016. "How the Change of Risk Announcement on Catastrophic Disaster Affects Property Prices?" In *The Economics of the Global Environment*, edited by Graciela Chichilnisky and Armon Rezai, 577–95. Cham, Switzerland: Springer. https://doi.org/10.1007/978-3-319-31943-8_25.

NIDM. 2014. "Proceedings, National Workshop on Phailin Cyclone 2013: Lessons Learnt." New Delhi, India: Ministry of Home Affairs, Government of India. https://doi.org/10.13140/RG.2.2.21903.59043.

NOAA. 2018. International Best Track Archive for Climate Stewardship (IBTrACS), National Oceanic and Atmospheric Administration. https://www.ncdc.noaa.gov/ibtracsRatnadiwakara, Dimuthu, and Buvaneshwaran

Venugopal. 2020. "Do Areas Affected by Flood Disasters Attract Lower-income and Less Creditworthy Homeowners?" *Journal of Housing Research* 29 (1): S121–S143. https://doi.org/10.1080/10527001.2020.1840246.

Shilling, James D, John D Benjamin, and CF Sirmans. 1985. "Adjusting Comparable Sales for Floodplain Location." *The Appraisal Journal* 53 (3): 429–37.

Speyrer, Janet Furman, and Wade R Ragas. 1991. "Housing Prices and Flood Risk: An Examination using Spline Regression." *The Journal of Real Estate Finance and Economics* 4 (4): 395–407. https://doi.org/10.1007/BF00219506.

Tukey, John W. 1977. *Exploratory Data Analysis*. Reading, Massachusetts: Addison-Wesley Pub. Co.

USNHC. 2018. "Hurricane Decay: Demise of a Hurricane." United States National Hurricane Center. http://www.hurricanescience.org/science/science/hurricanedecay.

West, J Jason, Mitchell J Small, and Hadi Dowlatabadi. 2001. "Storms, Investor Decisions, and the Economic Impacts of Sea Level Rise." *Climatic Change* 48 (2): 317–42. https://doi.org/10.1023/A:1010772132755.

Wu, Pei-Ing, Yi Chen, and Je-Liang Liou. 2021. "Housing Property along Riverbanks in Taipei, Taiwan: A Spatial Quantile Modelling of Landscape Benefits and Flooding Losses." *Environment, Development and Sustainability* 23: 2404–38. https://doi.org/10.1007/s10668-020-00680-7.

WWF. 2019. "Sundarbans Salinity Monitoring Database." World Wide Fund for Nature International.

Yohe, Gary, James Neumann, Patrick Marshall, and Holly Ameden. 1996. "The Economic Cost of Greenhouse-induced Sea-level Rise for Developed Property in the United States." *Climatic Change* 32 (4): 387–410. https://doi.org/10.1007/BF00140353.