Climate Change, Livelihood Threats and Household Responses in the Bangladesh Sundarbans

Susmita Dasgupta*
Moqbul Hossain
Mainul Huq
David Wheeler

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*Authors' names are in alphabetical order.

The authors are respectively Lead Environmental Economist, Development Research Group, World Bank; Principal Scientific Officer, Soil Research Development Institute, Ministry of Agriculture, Bangladesh; Consultant, Bangladesh; and Senior Fellow, World Resources Institute.

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Abstract

This paper quantifies the impact of market access, inundation risk and salinization on the family structure and economic welfare of coastal households in the Sundarbans region of Bangladesh. These households are already on the "front line" of climate change, so their adaptation presages the future for hundreds of millions of families worldwide who will face similar threats by 2100. Our analysis is based on a household decision model that relates spatial deployment of working-age, migration-capable members to inundation and salinization threats. In the accompanying regression exercise, the critical explanatory variables are soil salinity, tidal inundation risk, elevation, polder protection and market access (which reflects travel times to market centers). We employ a spatially-formatted database assembled from several sources: information on household demographics and economic welfare from the Bangladesh Demographic and Health Surveys (DHS) and a survey of Sundarbans households conducted by the World Bank in 2011; soil salinity measures from the Bangladesh Soil Research Development Institute; market access measures from Blankespoor (2010) and Uchida and Nelson (2008, 2009); and three components of inundation risk: distance from the inundation risk margin, calculated from digital maps provided by the GADM database of global administrative areas; and elevation and polder protection, using high-resolution spatial data provided by the government of Bangladesh.

Using appropriate estimation techniques, including adjustments for spatial autocorrelation, we find that households subject to high inundation and salinization threats have significantly higher out-migration rates for working-age adults (particularly males), dependency ratios, and poverty incidence than their counterparts in non-threatened areas. Our findings indicate that the critical zone for inundation risk lies within 4 km of the coast and tidal rivers, with attenuated impacts for coastal-zone households located at higher elevations and protected by polders. Damaging salinity has diffused across a much broader area. We assess impacts using model-based predictions for sample-bounded values of the regression variables. When salinity, inundation risk and market access are switched from their most favorable to least favorable settings, reallocation of labor to outside earning opportunities leads to 59% and 14% decreases in resident working-age males and females, and a 160% increase in the household dependency ratio -- the ratio of old and young dependents to working-age adults. The poverty impact is even more striking: the probability of poverty (lowest-40% wealth status) increases sevenfold.

In summary, our results paint a sobering picture of life at the coastal margin for Sundarbans households threatened by inundation and salinization, particularly households that are unprotected by polders and relatively isolated from market centers. They respond by "hollowing out", as economic necessity drives more working-age adults to seek outside earnings. And those left behind face a far greater likelihood of poverty than their counterparts in less-threatened areas.

We close the paper with preliminary thoughts about adaptation policy in this context. Our powerful results for polder protection and market access, coupled with our previous findings on salinity and road maintenance (Dagupta et al., 2014d) suggest that infrastructure investment may offer a promising option. At present, isolated settlements in the Sundarbans region face travel times to market centers as high as 14 hours. According to our econometric results for poverty incidence, transport network improvements that significantly reduce travel times can lead to substantial reductions in poverty for low-lying coastal households. In light of these results, we believe that transport improvement may be an attractive option if it also incorporates important ecological concerns.

1. Introduction

The potential impacts of climate change on coastal regions include progressive inundation from sea level rise, heightened storm damage, loss of wetlands, and increased groundwater salinity from saltwater intrusion. Worldwide, about 600 million people currently inhabit low-elevation coastal zones that will be affected by progressive inundation and salinization (Wheeler 2011; CIESIN 2010). Recent research suggests that the sea level may rise by one meter or more in the 21st century, which would increase the vulnerable population to about one billion by 2050 (Hansen and Sato 2011; Vermeer and Rahmstorf 2009; Pfeffer et al. 2008; Rahmstorf 2007; Dasgupta et al. 2009; Brecht et al. 2012).

While most research has focused on inundation and losses from heightened storm surges, increased soil and groundwater salinity may also pose significant threats to livelihoods and public health through their impacts on infrastructure, agriculture, aquaculture, coastal ecosystems, and the availability of fresh water for household and commercial use. Understanding the physical and economic effects of salinity diffusion and planning for appropriate adaptation will be critical for long-term development and poverty alleviation in countries with vulnerable coastal regions (Brecht et al. 2012; Dasgupta, et al. 2014a,b,c,d,e).

The Sundarbans region of Bangladesh provides an excellent setting for investigation of these issues, because it is one of the areas most threatened by sea level rise and saltwater intrusion. Farmers and fishing communities are among the poorest of the poor in Bangladesh; many areas face significant soil and water salinity problems, and areas near the sea are frequently affected by tidal surges and cyclones. As climate change proceeds, the vulnerability of the Sundarbans to flooding, storm surges and salinity will inexorably increase. Climate change thus poses a serious threat to the livelihoods of the poor in Sundarbans – especially since their mobility is limited by their economic circumstances and limited land access.

In the Sundarbans, as elsewhere in coastal Bangladesh, salinity is affected by tidal flooding during the wet season, direct inundation by storm surges, and movement of saline groundwater during the dry season (Haque, 2006). In consequence, the potential impact of salinity has become a major concern for the Government of Bangladesh and affiliated research institutions. Recently, the Bangladesh Climate Change Resilience Fund (BCCRF) Management Committee has highlighted salinity intrusion in coastal Bangladesh as a critical part of adaptation to climate change. Prior research on this issue has been conducted or co-sponsored by the Ministry of Environment and Forests (World Bank 2000) and two affiliated institutions: the Center for Geographic and Environmental Information Services (Hassan and Shah 2006) and the Institute of Water Modeling (IWM 2003; UK DEFR 2007). Additional research has been conducted by the Bangladesh Center for Advanced Studies (World Bank 2000; Khan et al. 2011), the Bangladesh Agricultural Research Council (Karim et al. 1982, 1990), and the Bangladesh Soil Resources Development Institute (SRDI 1998a,b; Petersen and Shireen 2001).

Resources will remain scarce, and mobilizing a cost-effective response will require an integrated spatial analysis of threats from sea level rise and salinity diffusion, their socioeconomic and ecological impacts, and the costs of prevention, adaptation and remediation. The temporal and geographic pattern of appropriate adaptation investments will depend critically on the magnitudes of inundation threats and salinity diffusion in different locations. Understanding household choices will also be critical, since households may respond to localized threats of inundation and salinization by relocating some or all members to areas where expected earnings and survival probabilities are higher. Drawing on previous research (Dasgupta, et al. 2014e), this paper attempts to contribute by developing and quantifying a household decision model that relates spatial deployment of working-age, migration-capable members of Sundarbans households to threats posed by potential inundation and salinization, as well as differential access to urban markets. We also investigate the impacts of inundation risk, salinization and market access on poverty incidence, and use our results to identify possible implications for adaptation policy.

The remainder of the paper is organized as follows. Section 2 develops the household labor allocation model from two foundations: a utility function with earnings and family amenities (principally related to task-sharing) as substitutes, and an agricultural profit function with labor and soil fertility as substitutes. In Section 3, we introduce data from DHS survey clusters in the Sundarbans region that we use for model estimation. Section 4 specifies regression equations and reports results for the labor allocation model, as well as a model that quantifies the associated impact on household poverty. Section 5 introduces data from a survey of households in the Sundarbans conducted by the World Bank (2011). In Section 6, we use these data to estimate additional regressions for labor allocation and poverty impact. Section 7 uses sample-bounded values of the regression variables to explore the implications of our results, while Section 8 provides a summary and conclusions.

2. Household Responses to Salinization and Recurrent Inundation

The Sundarbans region of Bangladesh presages the future for other coastal regions, since its communities have already experienced the widespread inundations and salinization that will accompany sea level rise and increased severity of tropical cyclones. Cyclones struck coastal Bangladesh 154 times during the 118-year period between 1877 and 1995, and five severe cyclones struck between 1995 and 2009. On average, severe cyclones strike Bangladesh every three years, producing storm surges that can reach heights of 10 meters (Dasgupta et al. 2010). Accompanying salinization of coastal lands has been exacerbated by sea level rise, progressive land subsidence, and the rapid growth of coastal saltwater shrimp farming.

Recent econometric research by Dasgupta, et al. (2014b,c,d) has shown that salinization has had significant impacts on agricultural income, public health and transport infrastructure in coastal areas.

One result has been progressive reduction of traditional income-earning opportunities in agriculture for coastal households (Islam 2006). This effect has compounded the risks associated with recurrent inundations in the coastal region, which are generally highest along the coast and tidal river littorals. Expected losses from inundation fall with elevation, since communities on higher ground are more protected from storm surges. Soil and groundwater salinity also fall rapidly with elevation, which protects against inland saline diffusion from the ocean and tidal rivers (Dasgupta, et al. 2014b). In many coastal areas, polders provide additional protection from inundation and saltwater intrusion.

2.1 Household Labor Allocation Decisions

Given the inflexibility of land tenure conditions in the Sundarbans, households in the most threatened areas seldom have the option of moving further inland or uphill. For most, the only recourse is repatriation of outside earnings by working-age family members. To model the household labor allocation decision, we posit a standard diminishing-returns utility function in income and family amenity, which includes both psychic benefits from cohabitation and task-sharing for household upkeep and dependent care. Expected urban earnings are given for each working-age household member. Expected rural earnings are determined by expected profit in local agriculture, which we posit to be a function of a fixed product price net of transport cost to market, soil salinity and inundation risk. To reach household migratory equilibrium, working-age members are sent to outside employment until expected outside earnings for the marginal potential migrant (less urban living expenses) are just equal to expected rural earnings, plus incremental amenity losses. Given the conditions specified above (standard utility function in income and task-sharing amenity; fixed output price, fixed urban wage) the optimal share of working-age members retained in the household is given by:

(1) $\eta^* = f(c,s,r)$

where η = Optimal share of working-age members who are household residents
c = Cost of access to urban markets
s = Soil salinity
r = Inundation risk

$f'(c) < 0$; $f`(r) < 0$

In this specification, two components of expected agricultural revenue -- market access cost and inundation risk -- are exogenous and unaffected by workers' migratory decisions. An increase in either factor unambiguously reduces expected revenue (and earnings), increases out-migration and reduces η, the share of resident working-age household members. The effect of increased soil salinity, on the other hand, is ambiguous because salinity and labor may be complements in production (i.e. increased labor intensity may compensate for increased salinity).[1] The effect on migratory equilibrium depends on the magnitude of labor-salinity complementarity and the impact on net earnings.

2.2 Household Welfare

Increased salinization or inundation risk unambiguously reduces household welfare, although the nature of the welfare reduction will depend on three factors in our model: the magnitude of labor-salinity complementarity, the substitutability of income and amenity, and the proportionality of income-sharing between household members who work outside and those who remain resident. Given the previously-noted assumptions about welfare and agricultural profit functions, we would expect increased salinization or inundation risk to produce a new interior solution in which total family income and family amenity are both reduced. We are agnostic about family income-sharing arrangements, so we have no prior expectation about the magnitude of economic welfare reduction for remaining household

[1] The econometric findings of Dasgupta, et al. (2014b) are ambiguous on the size and significance of the relationship between salinity and labor in high-yield rice production.

residents. However, our expectations about marginal effects on the economic welfare of household residents are unambiguous:

(2) W = w(c,s,r)

where W = Economic welfare of household residents
c = Cost of access to urban markets
s = Soil salinity
r = Inundation risk

w`(c) < 0; w`(s) < 0; w`(r) < 0

3. Data

We estimate equations derived from our household decision model using data from several sources.

3.1 DHS Information on Household Labor and Economic Status

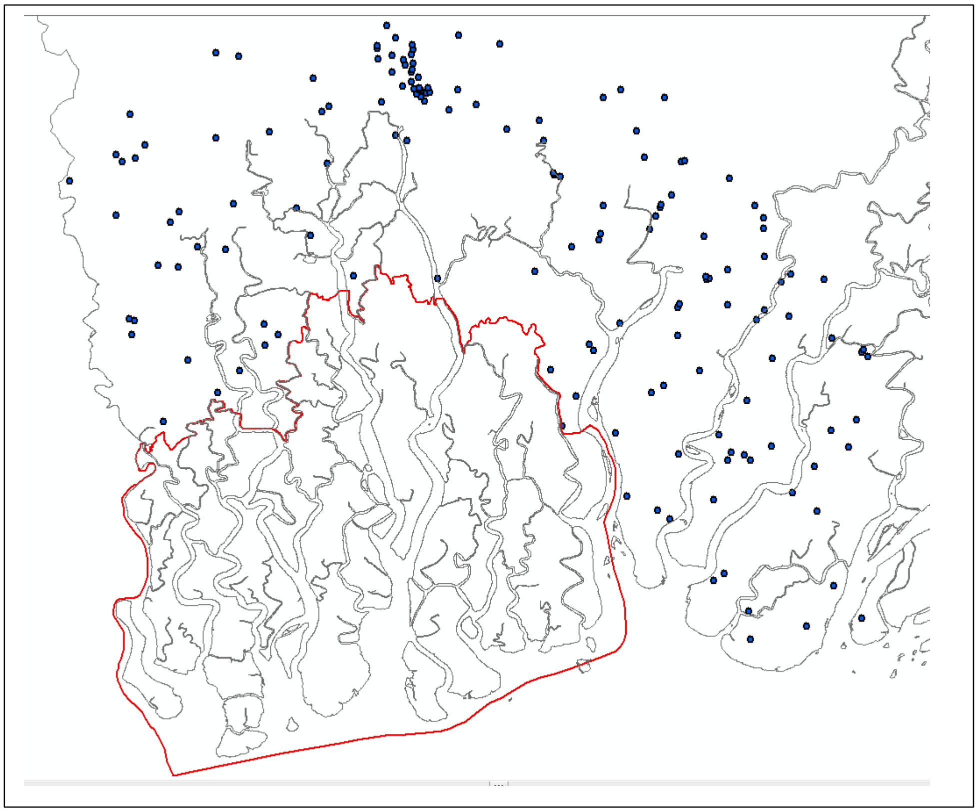
We obtain information on household membership and economic status in the Sundarbans from the Bangladesh Demographic and Health Surveys (NIPORT 2001, 2005, 2009, 2013). Figure 1 displays the 156 sample clusters within 50 km of the core Sundarbans region[2] which participated in DHS surveys during 2000, 2004, 2007 and 2011.[3] Many surveyed clusters lie on or near the coast and tidal river littorals, where they have been exposed to frequent inundations, while others are further inland.

From our 156 clusters, we select households for analysis using a strict residence criterion. The DHS reports whether each surveyed person is a household member, and whether that person slept in the household residence on the previous night. This information allows for a distinction between guests and household members, as well as removal of ambiguity about whether people are physically resident. To

[2] Residence is prohibited in the core region, which is outlined in red in Figure 1,

[3] The indicated locations are cluster centroids supplied by the DHS, which randomly displaces GPS latitude/longitude positions to ensure confidentiality for respondents. DHS-supplied urban centroids are within 2 km of actual centroids; 99% of rural cluster centroids are within 5 kilometers of actual centroids and 1% are within 10 km.

Figure 1: DHS sample survey clusters in the Sundarbans (core region outlined in red)



ensure consistency with our modeling approach, we select only households where all recorded individuals are members who slept there on the night prior to the survey.[4]

For selected households in the cluster samples, we use demographic data on individuals to construct three measures: separate totals for working-age and migration-capable males and females, age 18-60, and a composite total for dependent males and females age 0-17 and 61+. We also extract the DHS wealth index, the best available measure of household economic welfare, which is derived from a principal components analysis that incorporates a household's ownership of selected, easy-to-observe assets such as televisions, bicycles, housing construction materials, and types of water access and sanitation facilities.

[4] We recognize that a few of the surveyed household members who slept there on the previous night may have been visiting from distant areas of employment. We cannot quantify this error factor, but we believe that it must be small.

3.2 Inundation Risk Factors

Inundation risk depends on distance from the surge water inundation margin, which includes the coast and the littorals of tidal rivers (henceforth "the coast" for brevity). Inundation risk also depends on elevation and whether protection is provided by Bangladesh's extensive coastal polder system. For each cluster, we calculate its centroid distance from the coast using the boundary file provided by the GADM database of global administrative areas.[5] We determine centroid elevations and polder-protected clusters using high-resolution digital maps provided by the government of Bangladesh.

3.3 Salinity Measures

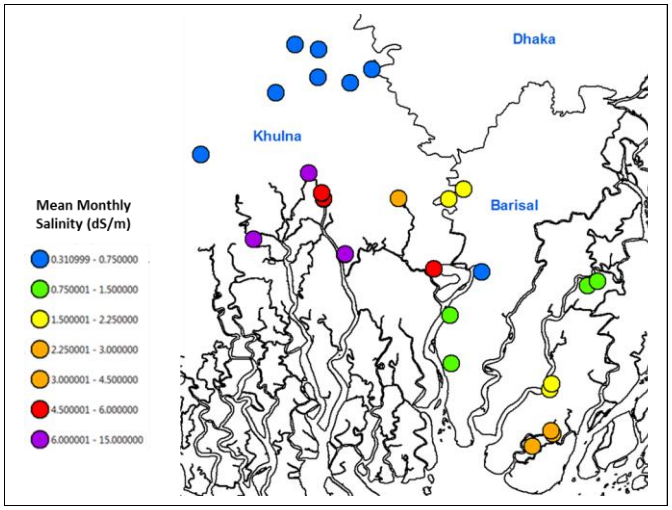
For this study, the Bangladesh Soil Research Development Institute has provided soil salinity monitoring measures for the period 2001-2009. In Dasgupta, et al. (2014b), we extend these measures using projections of river salinization, temperature and rainfall through 2050. Our results (Figure 2) depict current high-salinity areas in the Sundarbans, as well as areas that will have significant increases in soil salinity during the coming decades. Monitoring stations are color-coded using standardized ranges for soil salinity in 2001, 2009 and 2050:[6] Blue (0-0.75 dS/m); Green (0.75-1.50); Yellow (1.50-2.25); Orange (2.25-4.50); Red(4.50-6.00) and Purple (6.00+).

In 2001, Khulna has the greater variance of the two regions displayed, with northern stations uniformly Blue and central stations heavily Red and Purple. Stations in Barisal vary from Blue to Orange. By 2009, a general pattern of salinity increase is apparent: All stations in northern Khulna have increased from Blue to Green; nearly all stations in Barisal (one exception) are Yellow or Orange. The shift continues through 2050, with some stations in north Khulna changing to Yellow; most stations becoming Purple in central Khulna, and most stations in Barisal becoming Orange (and one changing to Red).

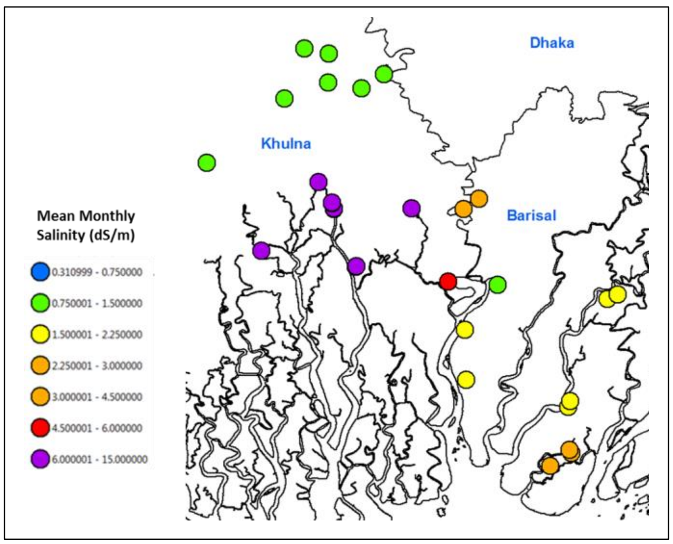
[5] Country boundary shapefiles are available from gadm.org at http://gadm.org/country.
[6] The standard sample-based measure for soil salinity is electrical conductivity (in dS/m -- deciSiemens per meter).

Figure 2: Observed and projected soil salinity measures near the Sundarbans: 2001, 2009, 2050

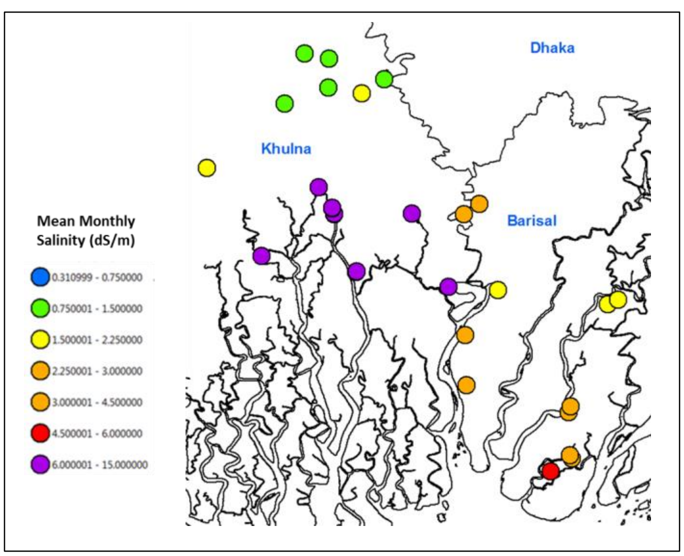
2001



2009



2050



For this paper, we extrapolate slightly from actual 2009 monitor readings to 2011 using the projected path to 2050 for each monitoring station. To derive salinity measures for clusters, we spatially interpolate salinity measures from the soil salinity monitors.[7] We compute the interpolated salinity measure for each month at the geographic centroid of each cluster. Then we calculate the annual salinity means for matching with the other cluster-level variables.

3.4 Market Accessibility

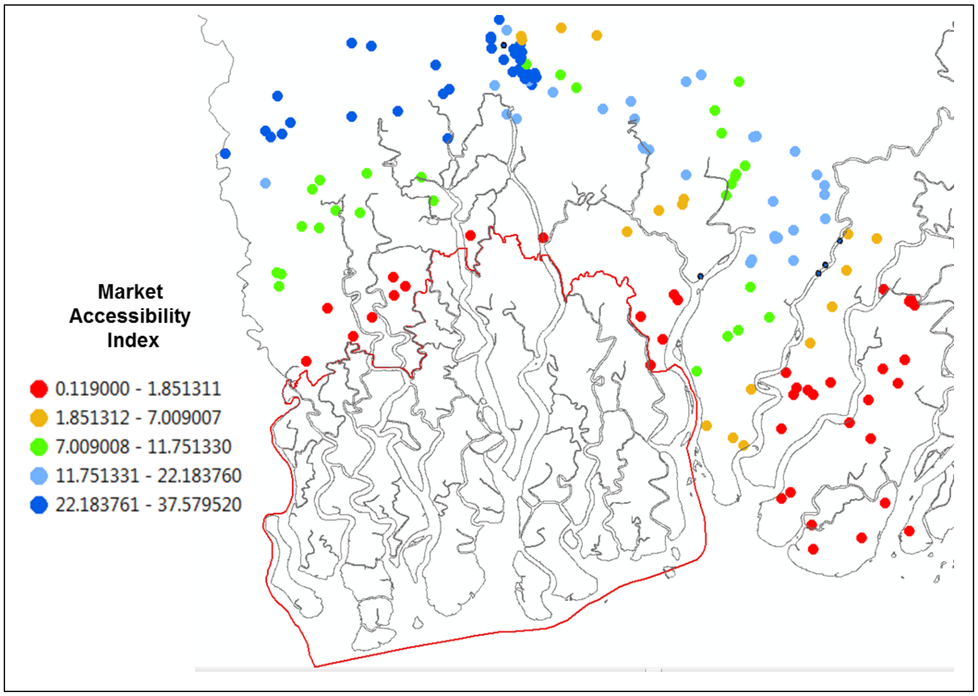
We use a measure of market accessibility developed by Blankespoor (2010), which builds on previous studies by Nelson (2008) and Deichmann (1997, 2005). These studies develop methods for estimating travel times to urban markets, using travel speed assumptions based on GIS-based information about road infrastructure, terrain features, and land use. Deichmann (1997, 2005) defines the accessibility index of a point as the weighted sum of populations for proximate urban centers, where the population of each center is weighted inversely by travel time from the point to the center along the primary road network. Blankespoor (2010) extends the Deichmann methodology for Bangladesh by incorporating extensive network transportation data from the Roads and Highways Department, the Bangladesh Inland Water Transport Authority, and the Bangladesh Center for Environmental and Geographic Information Services. The Blankespoor index also includes the ferry transportation network, along with road network topography. It calculates distance-weighted access for each point, using 2001 census data for 202 cities with populations from approximately 15,000 to 6,500,000. The weights are negative exponentials for distances from the point to each city.

Figure 3 presents the Blankespoor accessibility scores of the Sundarbans DHS clusters. In the figure, accessibility is color-coded from red (least accessible), through orange and green to blue (most accessible). The figure reveals a rough concentric pattern: The lowest accessibility scores are assigned

[7] Our spatial interpolation method employs the geonear package in Stata. Salinity at each point on the surface is a weighted combination of monitor measures; weights decline with the square of the distance from the point to each monitor.

to DHS clusters closest to the Sundarbans core region, along with coastal clusters immediately to the east. Conversely, the inland clusters furthest from the core region have the highest scores.

Figure 3: Market accessibility of DHS Sundarbans sample survey clusters within 50 km of the core region (outlined in red)



4. Model Specification and Estimation

4.1 Household Labor Allocation

Our regression model for household labor allocation relates the household percent of resident working-age individuals to the Blankespoor accessibility index, soil salinity and three components of inundation risk: distance from the coast, elevation and polder protection.[8] We test gender differences by fitting separate regressions for working-age males and females.

[8] Polder protection should also reduce soil salinity in tidal inundation zones, although differences in polder management may affect salinization. We are indebted to our colleague Istiak Sobhan for the latter point.

From the household decision model summarized in equation (1) above, we expect the household percent of working-age individuals to be lower in clusters that have lower market accessibility scores. The expected effect of salinity is ambiguous because rural earnings depend on the degree of complementarity between salinity and labor in agricultural production. The working-age percent should fall with inundation risk, which is lower for clusters that are further from the coast, protected by polders, and at higher elevations.[9] Beyond some distance margin, we would not expect perceived inundation risk to affect household decisions. In the same vein, we would not expect elevation to have differential effects beyond the critical margin. We have determined this margin empirically in preliminary regression work, by introducing dummy variables for unit distances from 1 to 10 km and interacting those dummies with the log of elevation (we use the log form to ensure a lower bound of zero for the elevation effect). We find highly significant distance and elevation effects for the first four kilometers, but no effects beyond 4 km. In addition, we find no statistically-significant difference between the measured impacts for the four included distance dummies and no significant differences for the interactions of these dummies with log elevation. Accordingly, we consolidate the distance and elevation factors into single variables.

4.2 Specification: Household Labor Allocation

We specify our final estimation model for labor allocation as follows:

(3) $\eta_{ij} = \beta_0 + \beta_1 M_j + \beta_2 S_j + \beta_{31} C_j + \beta_{32} P_j C_j + \beta_{41} C_j logE_j + \beta_{42} P_j C_j logE_j + \varepsilon_{ij}$

Expected signs: $\beta_1 > 0$, $\beta_{32} < 0$, $\beta_{32} > 0$; $\beta_{41} > 0$, $\beta_{42} < 0$

where, for household i in cluster j

η_{ij} = Household percent of resident working-age individuals (male or female)
M_j = Market accessibility index
S_i = Average cluster soil salinity (dS/m)

[9] Proximity to the coast may also affect labor migration through another channel: conversion of some coastal agricultural areas to shrimp farming since the 1970's, which has displaced many agricultural laborers. We are indebted to our colleague Istiak Sobhan for this observation.

C_j = Coastal proximity dummy variable (1 if cluster is within 4 km; 0 otherwise)
E_j = Elevation of the cluster centroid (m)
P_j = Polder protection (1 if protected; 0 otherwise)
ε_{it} = Random error term

In this specification, we expect the household percent of resident working-age individuals to be higher for clusters with higher market accessibility and lower for clusters within 4 km of the coast. However, the latter effect should be reduced by polder protection. Within the 4 km coastal zone, we expect the household percent of working-age individuals to be higher at higher elevations (where inundation risk is lower). Again, we expect this effect to be reduced by polder protection. As we have noted in Section 2, the expected sign of salinity is ambiguous because the degree of complementarity between salinity and labor in agriculture is unknown.

4.3 Estimation and Results: Household Labor Allocation

After application of our strict residential reporting rule for household selection, we have sufficient observations on all variables for an estimation sample of 2,762 households distributed across 156 sample clusters. We have tested the full model in equation (3) for all specifications and both genders. In all cases, results for all inundation risk variables (C, PC, ClogE, PClogE) are statistically insignificant. However, deletion of the polder interactions yields frequent significance for coastal zone location (C) and its interaction with elevation (ClogE). We conclude that multicollinearity precludes any inferences about polder effects in this case, and we exclude polder interactions from our final regressions.[10] We re-introduce these variables for our wealth regressions in the following section.

Tables 1 and 2 report our results for working-age males and females, respectively. The natural estimator for our regression model is tobit since the dependent variable, household percent of resident working-age individuals, is left-truncated at zero. Accordingly, the first three columns report estimates

[10] The impact of multicollinearity on classical significance tests depends on the relative size of correlations among independent variables and the partial correlations between the dependent variable (household prime-age worker percent in this case) and the independent variables.

for standard tobit, GLS tobit (which allows for differences in error variances for our 156 sample clusters) and tobit with robust standard errors.

Spatial autocorrelation may also be an issue, but the DHS assignment of identical centroid coordinates to households in each cluster makes it impossible to use the standard estimators. Because distances are significantly larger between than within clusters, we test for order-of magnitude spatial autocorrelation effects by randomly varying household coordinates within .01 decimal degree (approximately one kilometer) of cluster centroid values. This enables us to incorporate spatial autocorrelation into the results reported in the seventh columns of Tables 1 and 2.[11] These are estimates for a linear model, since an appropriate spatial tobit estimator was not available to us. For comparison, we also include linear estimates for OLS, GLS and Robust regressions in columns four, five and six of the two tables.

Table 1 presents results for working-age male household residents, which are strongly consistent with our prior expectations in all seven specifications. [12] The impact of market accessibility is positive and highly significant. Location within 4 km of the coast has a negative, highly-significant impact, while its interaction with elevation is positive and highly significant.[13] Our results for salinity are positive and highly significant, suggesting a strong role for labor-salinity complementarity in the determination of local earnings.

Our results for working-age female residents in Table 2 provide an instructive counterpoint to the estimates for males in Table 1. We find equally-significant positive results for market accessibility, a traditional poverty determinant that is not related to coastal inundation risk. However, the estimated effect of market accessibility on female residency is lower than the effect for males. The same is true

[11] We use the Stata routine spreg with an inverse-distance matrix to obtain these estimates,

[12] We use log salinity because prior experimentation has shown that it performs better in all regressions.

[13] The interaction term adjusts the coastal zone coefficient for elevation. In this case, the positive result indicates that the negative impact of coastal zone location on prime-age male residence is reduced as elevation increases.

for salinity and inundation risk: The signed effects are the same, but the estimated impacts are so small that their 95% confidence intervals include zero effects in all cases. We conclude that coastal risk

Table 1: Household deployment of working-age males in the Sundarbans region

Dependent variable: Working-age male percent of resident household members

	Tobit	Tobit GLS	Tobit Robust	OLS	GLS	Robust	Spatial Autocorrelation
Market accessibility index	0.155	0.155	0.155	0.136	0.136	0.136	0.164
	(3.93)**	(3.32)**	(3.96)**	(3.92)**	(3.37)**	(3.96)**	(3.67)**
Log salinity	1.858	1.858	1.858	1.626	1.626	1.626	2.141
	(3.40)**	(3.05)**	(3.40)**	(3.41)**	(3.11)**	(3.43)**	(3.30)**
Coastal zone	-38.01	-38.01	-38.01	-32.35	-32.35	-32.35	-39.83
(within 4 km)	(2.24)*	(1.86)	(2.31)*	(2.19)*	(1.88)	(2.37)*	(2.17)*
Coastal zone	6.981	6.981	6.981	5.963	5.963	5.963	7.312
x Log elevation	(2.12)*	(1.79)	(2.19)*	(2.08)*	(1.82)	(2.25)*	(2.06)*
Constant	20.815	20.815	20.815	22.349	22.349	22.349	31.73
	(20.13)**	(16.42)**	(20.16)**	(24.73)**	(20.72)**	(24.89)**	(11.54)**
Observations	2,762	2,762	2,762	2,762	2,762	2,762	2,762
R-squared				0.03	0.03	0.03	

Absolute value of t statistics in parentheses
*** significant at 5%; ** significant at 1%**

Table 2: Household deployment of working-age females in the Sundarbans region

Dependent variable: Working-age female percent of resident household members

	Tobit	Tobit GLS	Tobit Robust	OLS	GLS	Robust	Spatial Autocorrelation
Market accessibility index	0.099	0.099	0.099	0.094	0.094	0.094	0.12
	(3.00)**	(2.96)**	(2.89)**	(2.96)**	(2.93)**	(2.85)**	(2.93)**
Log salinity	0.127	0.127	0.127	0.152	0.152	0.152	0.498
	(0.28)	(0.29)	(0.27)	(0.35)	(0.36)	(0.33)	(0.84)
Coastal zone	-2.482	-2.482	-2.482	-3.256	-3.256	-3.256	-5.258
(within 4 km)	(0.18)	(0.17)	(0.18)	(0.24)	(0.24)	(0.25)	(0.31)
Coastal zone	0.599	0.599	0.599	0.748	0.748	0.748	1.195
x Log elevation	(0.22)	(0.22)	(0.22)	(0.29)	(0.29)	(0.29)	(0.37)
Constant	26.709	26.709	26.709	27.01	27.01	27.01	39.336
	(31.02)**	(32.31)**	(30.93)**	(32.74)**	(34.06)**	(32.66)**	(14.01)**
Observations	2,762	2,762	2,762	2,762	2,762	2,762	2,762
R-squared				0.00	0.00	0.00	

Absolute value of t statistics in parentheses
*** significant at 5%; ** significant at 1%**

factors are important for household labor allocation decisions, but principally through their impact on working-age males.[14]

4.4 Specification: Household Economic Welfare

Our estimation exercise for household economic welfare is more general than the exercise for working-age residents, since it incorporates all direct and indirect effects of salinization and inundation risk. We are particularly interested in the impact of coastal risk variables on poverty, so we have adopted a different estimation strategy in this case. First, we translate households' DHS wealth indices into percentile measures and identify households in the bottom two quintiles (the lowest 20% and 40%) of the national DHS distribution. Then we specify and estimate the following model:[15]

$$(4)\quad p(Q)_{ij} = \beta_0 + \beta_1 M_j + \beta_2 S_j + \beta_{31} C_j + \beta_{32} P_j C_j + \beta_{41} C_j logE_j + \beta_{42} P_j C_j logE_j + \varepsilon_{ij}$$

Expected signs: $\beta_1 < 0$; $\beta_2 > 0$; $\beta_{31} > 0$, $\beta_{32} < 0$; $\beta_{41} < 0$, $\beta_{42} > 0$

where, for household i in cluster j

$p(Q)_{ij}$	=	Probability of being in the lowest 20% or 40% by wealth status
M_j	=	Market accessibility index
S_i	=	Average cluster soil salinity in (dS/m)
C_j	=	Coastal proximity dummy variables (1 if cluster is within 4 km; 0 otherwise)
E_j	=	Elevation of the cluster centroid (m)
P_j	=	Polder protection (1 if protected; 0 otherwise)
ε_{it}	=	Random error term

As previously noted, all three locational factors should have significant effects on household economic welfare. We expect the incidence of household poverty to decrease with market access and increase with salinization. Poverty should increase with proximity to the coast, but this affect should be reduced by polder protection. Conversely, poverty should decrease as elevation rises in the coastal zone,

[14] The gender difference may well reflect traditional task divisions, in which females focus on dependent care and household upkeep while males engage in agricultural labor and other activities outside the household.

[15] The DHS surveys also include measures of education and health that are traditionally associated with higher incomes. However, we believe that health and education are jointly determined with income in a fully-specified model. We restrict model variables to the set specified in (4) because we have insufficient identifying information to include endogenous education and health measures as separate factors.

but this effect should also be reduced by polder protection. Polders also reduce salinity by preventing tidal flooding. This may well reduce the estimated impact of our direct salinity measure, which represents a projection from sometimes-distant salinity monitors that does not control for polder protection.

4.5 Estimation and Results: Household Economic Welfare

Our economic welfare regressions do not include household residence data for demographic groups, so we do not need to limit the sample by applying our strict residential reporting rule. This expands the estimation sample to 4.234 households distributed across 156 sample clusters. Tables 3 and 4 report our results. The natural estimator for our regression model is probit, since the dependent variable is dichotomous: 1 for households in the lowest 40% (Table 3) or 20% (Table 4) of the DHS household wealth index and 0 otherwise. Accordingly, the first three columns report estimates for standard probit, GLS probit (which allows for differences in error variances for our 156 sample clusters) and probit with robust standard errors.

Spatial autocorrelation may also be an issue but, as we previously noted, the DHS assignment of identical centroid coordinates to households in each cluster makes it impossible to use the standard estimators. Again, we incorporate order-of-magnitude spatial autocorrelation effects by randomly varying household coordinates within .01 decimal degree (approximately one kilometer) of cluster centroid values. We report our spatial autocorrelation results in the seventh column of Table 3.[16] These are estimates for a linear probability model, since an appropriate spatial probit estimator was not available to us. For comparison, we also include linear probability estimates for OLS, GLS and Robust regressions in columns four, five and six of the table.

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[16] Again, we use the Stata routine spreg with an inverse-distance matrix to obtain these estimates,

Table 3 reports our results for the probability of lowest-40% status. Our results are strongly consistent with prior expectations, including the estimator that adjusts for spatial autocorrelation. Market accessibility has a negative, highly significant impact on the probability that a household is in

Table 3: Household poverty in the Sundarbans region (lowest 40%)

Dependent variable: Household DHS wealth indicator status (1 if lowest national 40%; 0 otherwise)

	Probit	Probit GLS	Probit Robust	OLS	GLS	Robust	Spatial Autocorrelation
Market accessibility index	-0.026	-0.026	-0.026	-0.009	-0.009	-0.009	-0.004
	(10.40)**	(5.37)**	(10.29)**	(10.45)**	(5.35)**	(10.46)**	(5.85)**
Log salinity	-0.024	-0.024	-0.024	-0.006	-0.006	-0.006	0.005
	(0.72)	(0.33)	(0.73)	(0.54)	(0.24)	(0.53)	(0.59)
Coastal zone (within 4 km)	15.071	15.071	15.071	5.27	5.27	5.27	3.644
	(5.42)**	(2.50)*	(5.04)**	(5.64)**	(2.63)**	(5.44)**	(4.73)**
Coastal zone x Polder protection	-11.05	-11.05	-11.05	-3.823	-3.823	-3.823	-2.692
	(3.64)**	(1.72)	(3.43)**	(3.70)**	(1.75)	(3.56)**	(3.20)**
Coastal zone x Log elevation	-2.868	-2.868	-2.868	-1.002	-1.002	-1.002	-0.693
	(5.38)**	(2.49)*	(5.00)**	(5.61)**	(2.62)**	(5.43)**	(4.71)**
Coastal zone x Log elevation x Polder protection	2.177	2.177	2.177	0.756	0.756	0.756	0.529
	(3.74)**	(1.77)	(3.52)**	(3.82)**	(1.81)	(3.69)**	(3.28)**
Constant	-0.173	-0.173	-0.173	0.425	0.425	0.425	0.132
	(2.89)**	(1.19)	(2.88)**	(20.33)**	(8.06)**	(19.66)**	(5.31)**
Observations	4,234	4,234	4,234	4,234	4,234	4,234	4,234
R-squared				0.11	0.11	0.11	

Absolute value of t statistics in parentheses
*** significant at 5%; ** significant at 1%**

Table 4: Household poverty in the Sundarbans region (lowest 20%)

Dependent variable: Household DHS wealth indicator status (1 if lowest national 20%; 0 otherwise)

	Probit	Probit GLS	Probit Robust	OLS	GLS	Robust	Spatial Autocorrelation
Market accessibility index	-0.021	-0.021	-0.021	-0.004	-0.004	-0.004	-0.002
	(6.98)**	(3.76)**	(6.75)**	(6.91)**	(3.76)**	(6.94)**	(4.56)**
Log salinity	0.06	0.06	0.06	0.016	0.016	0.016	0.012
	(1.48)	(0.99)	(1.59)	(1.76)	(1.11)	(1.90)	(1.74)
Coastal zone (within 4 km)	4.525	4.525	4.525	0.942	0.942	0.942	0.576
	(1.37)	(0.98)	(1.50)	(1.30)	(0.97)	(1.51)	(0.98)
Coastal zone x Polder protection	0.213	0.213	0.213	0.614	0.614	0.614	0.483
	(0.06)	(0.04)	(0.06)	(0.76)	(0.54)	(0.83)	(0.74)
Coastal zone x Log elevation	-0.853	-0.853	-0.853	-0.179	-0.179	-0.179	-0.109
	(1.35)	(0.96)	(1.48)	(1.29)	(0.96)	(1.50)	(0.97)
Coastal zone x Log elevation x Polder protection	0.03	0.03	0.03	-0.097	-0.097	-0.097	-0.08
	(0.04)	(0.03)	(0.05)	(0.63)	(0.45)	(0.69)	(0.64)
Constant	-1.05	-1.05	-1.05	0.152	0.152	0.152	0.053
	(14.31)**	(8.08)**	(14.52)**	(9.37)**	(5.41)**	(9.87)**	(3.56)**
Observations	4,234	4,234	4,234	4,234	4,234	4,234	4,234
R-squared				0.07	0.07	0.07	

Absolute value of t statistics in parentheses
*** significant at 5%; ** significant at 1%**

the lowest 40% of the DHS national wealth index distribution. The results also match our prior expectations about the effects of the inundation risk factors: coastal zone location, elevation and polder protection. As we suspected, however, our direct salinity estimate is not sufficiently robust for independent significance once we account for coastal location and polder protection.

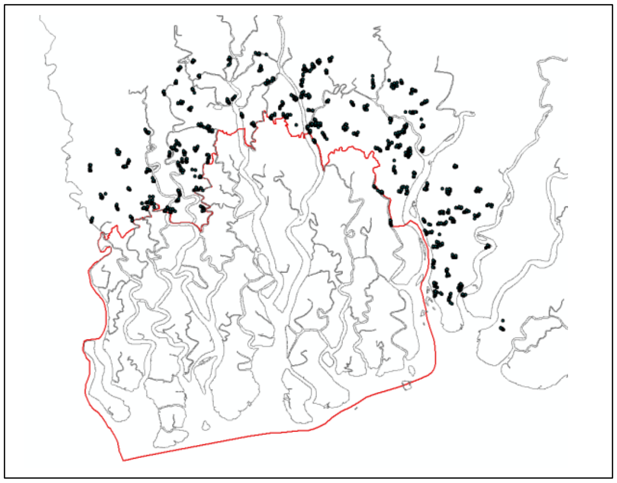
Our results for lowest-20% status (Table 4) strongly corroborate the significance of market accessibility, but they are uniformly weak otherwise. This is particularly surprising in light of our consistent 20% and 40% results for the World Bank's Sundarbans Household Survey, which we report in Section 6.

5. Sundarbans Household Survey Data

We extend our analysis using information from a survey of 2,144 Sundarbans households conducted by the World Bank (2011).[17] The survey data have several attractive features in this context. First, in contrast to the DHS, the World Bank survey provides exact location coordinates for each household. This is particularly useful for obtaining precise information on elevation, polder protection and distance from the coast. Second, the survey provides a complete accounting of the migration status of household members by age and sex. This permits direct analysis of household spatial labor allocation within prime-age male and female cohorts. In contrast, the lack of precise migrant information in the DHS surveys only permits indirect inferences about the impacts of market access, salinity and inundation risk on migration.

[17] Elimination of households with problematic location data yields 2,127 observations for the analysis.

Figure 4: Households surveyed by the World Bank (2011) in the Sundarbans (core region outlined in red)



Finally, the World Bank survey includes local salinity measures. In contrast, as Figure 2 shows, many of the monitors used for our salinity estimates in the previous section are relatively far from the Sundarbans.

At the same time, the World Bank survey has one significant disadvantage for our study. The Blankespoor sub-regional market accessibility index only provides a small sample of observations in this case, because World Bank survey households are clustered in relatively few administrative sub-regions. Accordingly, we proxy market access using Uchida-Nelson travel time estimates. These are high-resolution spatial estimates of travel time to the nearest urban area with 50,000+ population, developed by Uchida and Nelson (2008, 2009). The locational coordinates of the World Bank survey households enable us to generate high-resolution travel time estimates for households by using the nearest Uchida-Nelson points (which have a resolution of .00083 decimal degrees, or about 92 meters).

6. Econometric Results for Sundarbans Households

The previous discussion highlights several measurement issues that bear on our reported results for the Sundarbans households. First, the results for prime-age workers are of particular interest because they reflect more precise information about migrant status than the DHS results. Second, our measure of travel time for this exercise is less complete than the market access measure used for the DHS regressions. Third, the measure of household wealth status in the Sundarbans survey is effectively identical to the previously-described measure employed by the DHS surveys.

Tables 5 and 6 report our results for prime-age males and females, respectively. We find highly-significant results for market access, indexed by travel time in this case. For both males and females, the proportion who are permanent out-migrants increases with travel time to the nearest market center. As in the DHS case, the estimated response coefficients are larger for males. However, our results for salinity differ sharply from the DHS results. With a more precise measure of migrant status in this case, we find that the effect of salinity on out-migration by prime-age males is positive and significant. We find sign reversal for female out-migrants, but the result is not statistically significant. The contrasting salinity results from the DHS and World Bank surveys introduce a note of ambiguity that will have to be resolved by future research.

Our results for coastal zone location and polder protection are uniformly weak for male and female migrants. Problems with multicollinearity dictated exclusion of interactions with elevation.

For household poverty (Tables 7 and 8), our market access results strongly corroborate the DHS results: Travel time to market has a positive, significant impact on the probability that the wealth status of a Sundarbans household is in the lowest 20% or 40%. Our results for salinity are uniformly insignificant for the Sundarbans. However, our results have the expected signs and high significance for coastal zone location and its interaction with polder protection. Coastal zone location significantly increases the probability that a household is in the lowest 20% or 40%, but this effect is significantly reduced for households with polder protection.

Table 5: Sundarbans survey household deployment of working-age males

Dependent variable: Permanent migrant percent of working age males

	Tobit	Tobit Robust	OLS	Robust	Spatial Autocorrelation
Uchida-Nelson travel time	11.966	11.966	1.148	1.148	0.532
	(5.00)**	(5.36)**	(5.33)**	(4.45)**	(2.55)*
Salinity[18]	153.32	153.32	13.822	13.822	8.122
	(3.02)**	(3.51)**	(2.85)**	(2.82)**	(1.82)
Coastal zone	-9.824	-9.824	-1.463	-1.463	-1.106
	(0.65)	(0.65)	(1.16)	(1.26)	(0.95)
Coastal zone x Polder protection	20.594	20.594	1.968	1.968	1.669
	(1.56)	(1.57)	(1.82)	(2.12)*	(1.63)
Constant	-226.3	-226.3	0.572	0.572	-1.473
	(10.58)**	(14.11)**	(0.48)	(0.47)	(1.36)
Observations	2,127	2,127	2,127	2,127	2,127
R-squared			0.02	0.02	

[18] We use salinity rather than log salinity in these regressions because many area salinity measures are zero in the World Bank survey.

Table 6: Sundarbans survey household deployment of working-age females

Dependent variable: Permanent migrant percent of working age females

	Tobit	Tobit Robust	OLS	Robust	Spatial Autocorrelation
Uchida-Nelson travel time	4.445	4.445	0.807	0.807	0.5
	(3.26)**	(3.38)**	(3.58)**	(3.38)**	(2.68)**
Salinity	-12.77	-12.77	-3.778	-3.778	-3.574
	(0.41)	(0.42)	(0.74)	(0.80)	(0.85)
Coastal zone	-15.14	-15.14	-2.05	-2.05	-1.663
	(1.83)	(1.82)	(1.55)	(1.53)	(1.44)
Coastal zone x Polder protection	7.149	7.149	0.864	0.864	0.741
	(0.99)	(0.98)	(0.77)	(0.79)	(0.72)
Constant	-90.3	-90.3	6.675	6.675	1.743
	(9.89)**	(10.66)**	(5.36)**	(5.24)**	(1.20)
Observations	2,127	2,127	2,127	2,127	2,127
R-squared			0.01	0.01	

Table 7: World Bank survey: household poverty in the Sundarbans region: lowest 40%

Dependent variable: Sundarbans survey household wealth indicator status (1 if lowest 40%; 0 otherwise)

	Probit	Probit Robust	OLS	Robust	Spatial Autocorrelation
Uchica-Nelson travel time	0.077	0.077	0.03	0.03	0.012
	(5.36)**	(5.36)**	(5.43)**	(5.39)**	(2.21)*
Salinity	0.468	0.468	0.181	0.181	0.128
	(1.45)	(1.46)	(1.45)	(1.44)	(1.07)
Coastal zone	0.259	0.259	0.1	0.1	0.082
	(3.06)**	(3.08)**	(3.07)**	(3.09)**	(2.62)**
Coastal zone x Polder protection	-0.169	-0.169	-0.066	-0.066	-0.058
	(2.35)*	(2.35)*	(2.37)*	(2.35)*	(2.17)*
Constant	-0.597	-0.597	0.267	0.267	-0.039
	(7.43)**	(7.46)**	(8.74)**	(8.94)**	-0.91
Observations	2,127	2,127	2,127	2,127	2,127
R-squared			0.02	0.02	

Table 8: World Bank survey: household poverty in the Sundarbans region: lowest 20%

Dependent variable: Sundarbans survey household wealth indicator status (1 if lowest 20%; 0 otherwise)

	Probit	Probit Robust	OLS	Robust	Spatial Autocorrelation
Uchica-Nelson travel time	0.11	0.11	0.034	0.034	0.015
	(7.08)**	(6.93)**	(7.38)**	(6.71)**	(3.09)**
Salinity	0.431	0.431	0.121	0.121	0.099
	(1.21)	(1.23)	(1.18)	(1.14)	(1.00)
Coastal zone	0.344	0.344	0.098	0.098	0.08
	(3.64)**	(3.69)**	(3.66)**	(3.60)**	(3.09)**
Coastal zone x Polder protection	-0.225	-0.225	-0.068	-0.068	-0.057
	(2.87)**	(2.88)**	(2.99)**	(2.84)**	(2.56)*
Constant	-1.357	-1.357	0.055	0.055	-0.057
	(14.44)**	(14.41)**	(2.19)*	(2.34)*	(1.93)
Observations	2127	2127	2127	2127	2127
R-squared			0.03	0.03	

Table 9: Sample-based values for impact exploration

Sample-Based Values	Salinity (dS/m)	Accessibility Index	Distance from Coast (km)	Elevation (m)
Low	1	1	1	0.8
High	13	35	20	3

7. Implications of the Results

7.1 DHS Results

Our DHS results are generally consistent with prior expectations about signs and significance, but they do not provide easily-interpreted evidence about impact magnitudes. We explore this issue in two exercises: The first analyzes the labor allocation results using a matrix of sample low and high values for accessibility, salinity, distance from the coast and elevation. The second incorporates polder protection in an exploration of poverty impacts.

Household Composition

Using all combinations of the values in Table 9, we employ the tobit estimates[19] in Tables 1 and 2 to predict corresponding household residence percents of working-age males and females. For each household we add the two predicted percents, subtract the total from 100 to determine dependent percents[20], and calculate dependency ratios (percent dependents/percent working-age adults). Table 10 presents our results, ordered by dependency ratio.

Our results indicate powerful impacts for market accessibility, salinity and inundation risk. At one extreme, households with high values for salinity and market access (rows 1,2,3) have residence percents of working-age adults around 62% and dependency ratios around 0.60. At the other extreme (rows 15-16), households in low-lying coastal zones with low market accessibility have much lower

[19] The standard, GLS and Robust tobit parameter estimates are identical; only the estimated standard errors differ.
[20] This approach ensures additivity to 100%. We have also estimated a third equation for the dependent percent, generated predictions for the variables in Table 9, and totaled percents for dependents, working-age males and working-age females. This unconstrained approach generates total predicted shares above 95% in all cases.

Table 10: Impact results for resident family structure

	Salinity (dS/m)	Accessibility Index	Distance from Coast (km)	Elevation (m)	Percent Males 18-60	Percent Female 18-60	Percent Adults 18-60	Percent Dependents (0-17,61+)	Female/Male Ratio, Adults 18-60	Dependency Ratio
1	13	35	1	3	32.81	31.42	64.23	35.77	0.96	0.56
2	13	35	20	0.80	31.01	30.49	61.50	38.50	0.98	0.63
3	13	35	20	3	31.01	30.49	61.50	38.50	0.98	0.63
4	1	35	1	3	28.05	31.09	59.14	40.86	1.11	0.69
5	1	35	20	3	26.25	30.16	56.41	43.59	1.15	0.77
6	1	35	20	0.80	26.25	30.16	56.41	43.59	1.15	0.77
7	13	1	1	3	27.54	28.07	55.61	44.39	1.02	0.80
8	13	35	1	0.80	23.59	30.63	54.22	45.78	1.30	0.84
9	13	1	20	0.80	25.74	27.13	52.87	47.13	1.05	0.89
10	13	1	20	3	25.74	27.13	52.87	47.13	1.05	0.89
11	1	1	1	3	22.77	27.74	50.52	49.48	1.22	0.98
12	1	35	1	0.80	18.82	30.30	49.12	50.88	1.61	1.04
13	1	1	20	0.80	20.97	26.81	47.78	52.22	1.28	1.09
14	1	1	20	3	20.97	26.81	47.78	52.22	1.28	1.09
15	13	1	1	0.80	18.31	27.28	45.59	54.41	1.49	1.19
16	1	1	1	0.80	13.55	26.95	40.50	59.50	1.99	1.47

working-age adult percents and dependency ratios that are at least two times higher. Intermediate cases illustrate the effects of changes in model variables on dependency ratios via their impact on working-age male and female percents. As our econometric results indicate, the relative impacts are greater for working-age males: From row 1 to row 16, their percent household representation falls by 58.7% (from 32.81% to 13.55%). For females, the corresponding decrease is 14.2% (from 31.42% to 26.95%).

To illustrate on intermediate case, consider households in low-elevation, high-salinity areas that have low market access (rows 9,15). Reducing their coastal distance from 20 km to 1 km reduces their working-age male percents from 25.74% to 18.31%, with negligible impacts on female percents. As a consequence the household dependency ratio increases by 33.7%, from 0.89 to 1.19.

To summarize, our results suggest that all location variables have large impacts on household composition, principally via their effects on household decisions about departure of working-age males for outside earning opportunities.

Household Economic Welfare

The results in Table 3 show that polder protection has a highly-significant impact on economic welfare, while our direct measure of salinity is insignificant.[21] Using the values in Table 11, we explore welfare impacts using probit estimates that exclude salinity.[22]

Table 11: Sample-based values for impact exploration

Sample-Based Values	Polder Protection	Accessibility Index	Distance from Coast (km)	Elevation (m)
Low	**0**	**1**	**1**	**0.8**
High	**1**	**35**	**20**	**3**

The summary results in Table 12 provide striking evidence that our results are significant for poverty status as well as family structure. For low-lying clusters (.8 m elevation), we focus on the

[21] As we noted previously, salinity effects undoubtedly explain part of the estimated impact of coastal location, elevation and polder protection.
[22] The standard, GLS and Robust probit parameter estimates are identical; only the estimated standard errors differ.

impacts of polder protection, market accessibility and distance from the coast.[23] Coastal households with low market access and no polder protection have a 99.1% probability of lowest-40% wealth status. This falls to 92.7% if market access is increased to a high level and 76.7% if polder protection is added. Changing both variables reduces the lowest-40% probability to 43.5%.

Table 12: Impact results for household wealth status

	Polder Protection	**Market Accessibility Index**	**Distance from Coast (km)**	**Probability of Lowest-40% Status**
1	0	1	1	99.1
2	0	35	1	92.7
3	1	1	1	76.7
4	1	35	1	43.5
5		1	20	41.1
6		35	20	13.2

Rows 5 and 6 highlight the advantage of inland location. Households 20 km from the coast with low market access have a lowest-40% probability of 41.1%, while similarly-distant households with high market access have a probability of 13.2%.[24]

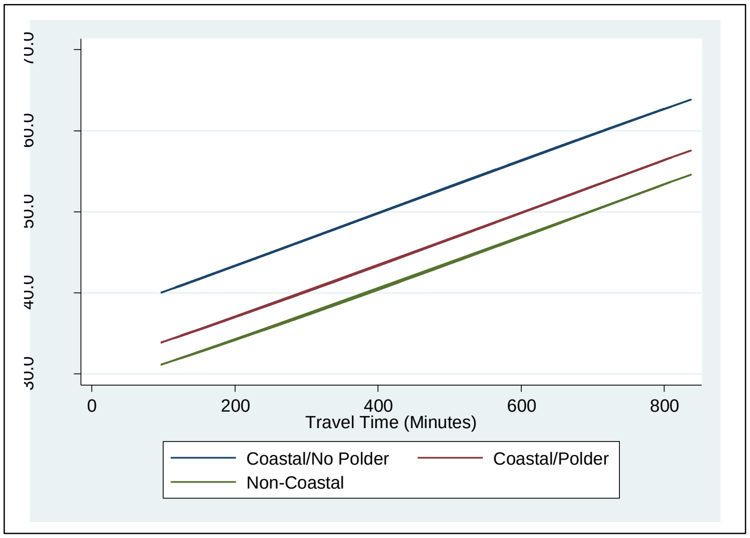
7.2 Sundarbans Household Survey Results

Since poverty impacts are of particular interest, we focus our Sundarbans analysis on the relationship between travel time and the probability of lowest-40% wealth status. We re-estimate our probit model without salinity, since it is insignificant in our results. Figure 5 plots predicted lowest-40% probability vs. travel time for three cases: (1) Coastal households without polder protection, (2) coastal households with polder protection, and (3) non-coastal households. Travel times vary from 97 minutes to 837 minutes in the dataset. For the lowest travel time, lowest-40% probabilities in the three cases are 40%, 33.9% and 31.2%, respectively. For the highest travel time, they are 63.8%, 67.6% and 54.6%.

[23] Here it is important to recall that we use "the coast" as an abbreviation for the coast and tidal river littorals.
[24] The coastal zone dummy variable is zero for households 20 km from the coast. Since polder protection interacts with the coastal dummy, it does not affect the impact of market access on households outside the coastal zone.

These results clearly highlight the relative importance of market access as a poverty determinant in the Sundarbans.

Figure 5: Sundarbans survey households: travel time and lowest 40 % status



7.3 Policy Implications

Our comparative location results may have significant implications for adaptation investments, which are intended to compensate households that are differentially affected by climate change. To illustrate, we use the DHS results to compare poverty risks. A household at low elevation (0.8 m) with low market access (1) has a 99.1% chance of wealth status in the lowest 40% if it has no polder protection and lies within 1 km of the coast. In contrast, a household with the same elevation and market access that is 20 km from the coast has a 41.1% chance of lowest-40% wealth status -- 58%% lower than its coastal counterpart. Part of this differential is due to direct inundation risks, and part to the salinization that inevitably accompanies inundation. As we have noted, the monitors that provide our salinity measures are too widely scattered to permit reliable separation of poverty impacts for salinity and inundation risk at the household level. In either case, one possible approach to adaptation policy is direct assistance to bolster coastal inundation defenses and promote the adoption of saline-resistant crops.

Another potentially-attractive option is highlighted by our market access results for the DHS and Sundarbans survey households. To continue the previous illustration, consider the impact of improving market access for a low-elevation coastal household from the lowest level (1) to the highest (35), with and without polder protection. For households without polder protection, the result is a predicted reduction in lowest-40% wealth status probability from 99.1% to 92.7%. With polder protection, improving market access reduces the poverty probability from 76.7% to 43.5%.[25] In light of these results, we believe that travel time reductions via transport network improvements may also contribute significantly to adaptation in some cases.[26]

8. Summary and Conclusions

This paper has quantified the impact of market access, inundation risk and salinization on the family structure and economic welfare of households in the Sundarbans region of Bangladesh. These families are already on the "front line" of climate change, so their adaptation presages future decisions by hundreds of millions of families worldwide who will face similar threats by 2100. Their behavior may also provide useful insights for adaptation investment planners.

Our exercise builds on a household decision model that relates spatial deployment of working-age, migration-capable members to threats posed by potential inundation and salinization in the coastal region. Our spatially-formatted data come from several sources: information on household demographics and economic welfare from the Bangladesh Demographic and Health Surveys (DHS) and a Sundarbans household survey conducted by the World Bank (2011); soil salinity measures from the Bangladesh Soil Research Development Institute; market access measures from Blankespoor (2010) and Uchida and Nelson (2008, 2009); and three components of inundation risk: distance from the coast,

[25] As we note in Section 3.4, our measure of market accessibility has two components: distance to urban markets and the size of those markets (proxied by population). By implication, market accessibility for a Sundarbans settlement can be increased by measures that expand the size of nearby urban markets, as well as improvement of transport infrastructure.
[26] We should emphasize that transport network improvements should incorporate ecological concerns, since such improvements can also catalyze deforestation and land degradation.

calculated from digital maps provided by the GADM database of global administrative areas; and elevation and polder protection, using high resolution data provided by the government of Bangladesh.

We specify and estimate regression models that quantify the impacts of market access, inundation risk and salinization on household composition, along with the impact on household economic welfare. In the latter case, we focus on the probability that households are in the lowest 40% of the wealth distribution. We use appropriate estimation models -- tobit for the household composition analysis, probit for the poverty assessment -- and incorporate adjustments for spatial autocorrelation.

For the DHS survey data, our results are highly significant and strikingly consistent across estimators. Our findings indicate that the critical zone for inundation risk lies within 4 km of the coast, with attenuated impacts for coastal-zone households located at higher elevations or in polder-protected areas. We assess the impact of these variables using model-based predictions for sample-bounded values of the regression variables. From most to least favorable conditions, we find that reallocation of labor to outside earning opportunities leads to 58.7% and 14.2% decreases in resident working-age males and females, and a 160% increase in the dependency ratio -- the ratio of old and young dependents to working-age adults. The poverty impact is also striking: From most to least favorable conditions, we find that the probability of lowest-40% economic status increases more than sevenfold, from 13.2% to 99.1%. Our results from the Sundarbans survey data also paint a striking picture, with changes from best to worst conditions associated with an increase in poverty probability from 31.2% to 63.8%.

In summary, our results paint a sobering picture of life at the coastal margin for Sundarbans households threatened by inundation and salinization. Confronted by greater threats, they “hollow out” as economic necessity drives more working-age adults to seek outside earnings. And those left behind suffer impoverishment at far higher levels than their counterparts who are not on the front lines of climate change. This problem seems likely to grow steadily, in the Sundarbans and elsewhere, as the sea moves inexorably inland and salinization precedes its arrival.

In closing, we offer some preliminary thoughts about the implications of our findings for adaptation policy. Our results highlight the importance of polder protection for poverty reduction. In addition, our results for market access, coupled with our previous findings on salinity and road maintenance (Dagupta et al., 2014d), suggest that infrastructure investment may offer a promising option. At present, isolated settlements in the Sundarbans face travel times to market centers as high as 14 hours. Our results suggest that the incidence of poverty in such communities could be lowered substantially by transport network improvements that reduce travel times significantly. In light of these results, we believe that such improvements may warrant particular attention, although they should also incorporate ecological concerns.

References

Blankespoor, Brian. 2010. Market Accessibility in Bangladesh. Development Research Group, World Bank.

Brecht, Henrike, Susmita Dasgupta, Benoit Laplante, Siobhan Murray and David Wheeler. 2012. Sea-Level Rise and Storm Surges: High Stakes for a Small Number of Developing Countries. The Journal of Environment & Development, 21: 120-138.

CIESIN. 2010. Low-Elevation Coastal Zone (LECZ) Rural-Urban Estimates. http://sedac.ciesin.columbia.edu/gpw/lecz.jsp

Dasgupta, Susmita, Mainul Huq, Zahirul Huq Khan, Manjur Murshed Zahid Ahmed, Nandan Mukherjee, Malik Fida Khan and Kiran Pandey. 2010. Vulnerability of Bangladesh to Cyclones in a Changing Climate: Potential Damages and Adaptation Cost. World Bank Policy Research Working Paper No. 5280. April.

Dasgupta, Susmita, Farhana Akhter Kamal, Zahirul Huque Khan, Sharifuzzaman Choudhury and Ainun Nishat. 2014a. River Salinity and Climate Change: Evidence from Coastal Bangladesh. Policy Research Working Paper No. 6817, Development Research Group, World Bank. March

Dasgupta, Susmita, Md. Moqbul Hossain, Mainul Huq and David Wheeler. 2014b. Climate Change, Soil Salinity and the Economics of High-Yield Rice Production in Coastal Bangladesh. Policy Research Working Paper (forthcoming), Development Research Group, World Bank.

Dasgupta, Susmita, Mainul Huq and David Wheeler. 2014c. Drinking Water Salinity and Infant Mortality in Coastal Bangladesh. Policy Research Working Paper (forthcoming), Development Research Group, World Bank.

Dasgupta, Susmita, Mainul Huq and David Wheeler. 2014d. Climate Change, Groundwater Salinization and Road Maintenance Costs in Coastal Bangladesh. Policy Research Working Paper (forthcoming), Development Research Group, World Bank.

Dasgupta, Susmita, Mainul Huq and David Wheeler. 2014e. Facing the Hungry Tide: Climate Change, Livelihood Threats and Household Responses in Coastal Bangladesh. Policy Research Working Paper (forthcoming), Development Research Group, World Bank.

Dasgupta, Susmita, Benoit Laplante, Craig Meisner, David Wheeler and Jianping Yan. 2009. The impact of sea level rise on developing countries: a comparative analysis. Climatic Change, 93(3-4): 379-388.

Deichmann, Uwe. 1997. Accessibility indicators in GIS. United Nations, Statistics Division.

Deichmann, Uwe. 2005. Accessibility index in Bangladesh (unpublished).

GADM. 2012. GADM database of Global Administrative Areas. http://www.gadm.org.

Hansen, J.E., and M. Sato. 2011. Paleoclimate Implications for Human-made Climate Change. NASA Goddard Institute for Space Studies and Columbia University Earth Institute.

Haque, S.A. 2006. Salinity Problems and Crop Production in Coastal Regions of Bangladesh. Pakistan Journal of Botany, 38(5): 1359-1365.

Hassan, A. and Md. A.R. Shah. 2006. Impact of Sea Level Rise on Suitability of Agriculture and Fisheries. Center for Environmental and Geographic Information Services, Dhaka, Bangladesh.

Islam, M. Rafiqul. 2006. Managing Diverse Land Uses in Coastal Bangladesh: Institutional Approaches. Chapter 18 in Chu Thai Hoanh, To Phuc Tuong, John W. Gowing, Bill Hardy, eds., Environment and Livelihoods in Tropical Coastal Zones: Managing Agriculture–Fishery–Aquaculture Conflicts. CAB: Oxon, UK.

IWM. 2003. Sundarban Biodiversity Conservation Project: Surface Water Modeling, Final Report. Institute of Water Modeling, Ministry of Environment and Forests, Government of Bangladesh.

Jarvis A., H.I. Reuter, A. Nelson and E. Guevara. 2008. Hole-filled seamless SRTM data V4, International Centre for Tropical Agriculture (CIAT), available from http://srtm.csi.cgiar.org.

Karim, Z., S.M. Saheed, A.B.M. Salauddin, M.K. Alam and A. Huq. 1982. Coastal saline soils and their management in Bangladesh. Soils publication No. 8, Bangladesh Agricultural Research Council.

Karim, Z., S.G. Hussain and M. Ahmed. 1990. Salinity problems and crop intensification in the coastal regions of Bangladesh. Soils publication No. 33. Bangladesh Agricultural Research Council.

Khan, Aneire, Andrew Ireson, Sari Kovats, Sontosh Kumar Mojumder, Amirul Khusru, Atiq Rahman and Paolo Vineis. 2011. Drinking Water Salinity and Maternal Health in Coastal Bangladesh: Implications of Climate Change. Environmental Health Perspectives, 119(9), September.

National Institute of Population Research and Training (NIPORT), Mitra and Associates, and ICF International. 2013. Bangladesh Demographic and Health Survey. 2011. Dhaka, Bangladesh and Calverton, Maryland, USA: NIPORT, Mitra and Associates, and ICF International.

National Institute of Population Research and Training (NIPORT), Mitra and Associates, and Macro International. 2009. Bangladesh Demographic and Health Survey 2007. Dhaka, Bangladesh and Calverton, Maryland, USA: National Institute of Population Research and Training, Mitra and Associates, and Macro International.

National Institute of Population Research and Training (NIPORT), Mitra and Associates, and ORC Macro. 2005.Bangladesh Demographic and Health Survey 2004. Dhaka, Bangladesh and Calverton, Maryland [USA]: National Institute of Population Research and Training, Mitra and Associates, and ORC Macro.

National Institute of Population Research and Training (NIPORT), Mitra and Associates (MA), and ORC Macro (ORCM). 2001. Bangladesh Demographic and Health Survey 1999-2000. Dhaka, Bangladesh and Calverton, Maryland [USA]: National Institute of Population Research and Training, Mitra and Associates, and ORC Macro.

Nelson, Andrew. 2008. Travel time to major cities: A global map of Accessibility. Global Environment Monitoring Unit --- Joint Research Centre of the European Commission, Ispra Italy. Available at http://gem.jrc.ec.europa.eu/

Petersen, L. and S. Shireen. 2001. Soil and water salinity in the coastal area of Bangladesh. Bangladesh Soil Resource Development Institute.

Pfeffer, W. T., J. T. Harper and S. O'Neel. 2008. Kinematic constraints on glacier contributions to 21st-century sea-level rise. Science, 321: 1340-1343.

Rahmstorf, Stefan. 2007. A semi-empirical approach to projecting future sea-level rise. Science, 315: 368-370.

SRDI. 1998a. Soil salinity map of Bangladesh (1973). Soil Resources Development Institute, Dhaka.

SRDI. 1998b. Soil salinity map of Bangladesh (1997). Soil Resources Development Institute, Dhaka.

SRDI. 2000. Soil salinity in Bangladesh 2000. Soil Resources Development Institute, Dhaka.

SRDI. 2010. Saline Soils of Bangladesh. Soil Resources Development Institute, Dhaka.

Uchida, H. and A. Nelson. 2009. Agglomeration Index: Towards a New Measure of Urban Concentration. Background paper for World Development Report 2009. Washington, DC: World Bank.

UK DEFR (U.K. Department of Environment, Food and Rural Affairs). 2007. Investigating the Impact of Relative Sea-Level Rise on Coastal Communities and Their Livelihoods in Bangladesh. Dhaka:Institute of Water Modelling in Bangladesh and Center for Environment and Geographic Information Services in Bangladesh.

Vermeer, M. and S. Rahmstorf. 2009. Global Sea Level Linked to Global Temperature. Proceedings of the National Academy of Sciences, 106(51): 21527-32.

Wheeler, David. 2011. Quantifying Vulnerability to Climate Change: Implications for Adaptation Assistance. Center for Global Development Working Paper No. 240.

World Bank. 2000. Bangladesh: Climate Change and Sustainable Development. Report No. 21104-BD. Rural Development Unit, South Asia Region. December.

World Bank. 2011. Survey questionnaire: Livelihoods, Biodiversity Conservation, Adaptation to Climate Variability and Socio- economic Development in Sundarbans –Bangladesh. World Bank Human Development Department and South Asia Sustainable Development Department.