WPS7148

Policy Research Working Paper 7148

Facing the Hungry Tide

Climate Change, Livelihood Threats, and Household Responses in Coastal Bangladesh

Susmita Dasgupta
Md. Moqbul Hossain
Mainul Huq
David Wheeler

WORLD BANK GROUP
Development Research Group
Environment and Energy Team
December 2014

Policy Research Working Paper 7148

Abstract

This paper quantifies the impact of inundation risk and salinization on the family structure and economic welfare of coastal households in 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. The analysis is based on a household decision model that relates spatial deployment of working-age, migration-capable members to inundation and salinization threats. The analysis uses appropriate estimation techniques, including adjustments for spatial autocorrelation, and finds 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. The findings indicate that the critical zone for inundation risk lies within four kilometers of the coast, with attenuated impacts for coastal-zone households at higher elevations. The results paint a sobering picture of life at the coastal margin for Bangladeshi households threatened by inundation and salinization, particularly households that are relatively isolated from market centers. They respond by "hollowing out," as economic necessity drives more working-age adults to seek outside earnings. Those left behind face a far greater likelihood of extreme poverty than their counterparts in less-threatened areas. The powerful results for market access, coupled with previous findings on salinity and road maintenance, suggest that infrastructure investment may offer a promising option. Road improvements that reduce travel times for isolated settlements compensate them for an increase in salinity. Thus, road improvement may warrant particular attention as an attractive adaptation investment in coastal Bangladesh.

This paper is a product of the Environment and Energy Team, Development Research Group. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at Sdasgupta@worldbank.org.

Facing the Hungry Tide: Climate Change, Livelihood Threats, and Household Responses in Coastal Bangladesh*

Susmita Dasgupta[1], Md. Moqbul Hossain[2], Mainul Huq[3], David Wheeler[4]

Keywords: Poverty, Climate Change, Salinity, Inundation, Migration, Bangladesh, Coastal Areas

JEL Classification: Q54, I30

Part of our title refers to The Hungry Tide, a novel by Amitav Ghosh that portrays the suffering and resilience of families in the Sundarbans coastal region of India and Bangladesh.

Authors' names are in alphabetical order.

This research was funded by the Knowledge for Change Program

We would like to extend our special thanks to Dr. Zahirul Huque Khan for the river salinity data in coastal Bangladesh. We are also thankful to Dr. Michael Toman for his comments and suggestions.

---

[1] Lead Environmental Economist, Development Research Group, World Bank
[2] Principal Scientific Officer, Soil Research Development Institute, Ministry of Agriculture, Bangladesh
[3] Consultant, World Bank
[4] Senior Fellow, World Resources Institute

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).

Bangladesh provides an excellent setting for investigation of these issues, because it is one of the countries most threatened by sea level rise and saltwater intrusion. In Bangladesh, about 30% of the cultivable land is in coastal areas where 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 from 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., 2014a,b,c,d), this paper attempts to contribute by developing and quantifying a household decision model that relates spatial deployment of working-age, migration-capable members to threats posed by potential inundation and salinization. We also investigate the impacts of inundation risk and salinization 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 the data used 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 uses sample-bounded values of the regression variables to explore the implications of our results, while Section 6 provides a summary and conclusions.

2. Household Responses to Salinization and Recurrent Inundation

Coastal 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 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 in areas directly abutting the coast. 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).

2.1 Household Labor Allocation Decisions

Given the inflexibility of land tenure conditions in coastal Bangladesh, 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) $\eta^* = f(t,s,r)$

where η = Optimal share of working-age members who are household residents
t = Travel time to nearest market center
s = Soil salinity
r = Inundation risk

$f'(t) < 0$; $f'(r) < 0$

In this specification, two components of expected agricultural revenue -- travel time to market 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).[5] The effect on migratory equilibrium depends on the magnitude of labor-salinity complementarity and the impact on net earnings.

[5] 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.

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

(2) $W = w(t,s,r)$

where W = Economic welfare of household residents
t = Travel time to nearest market center
s = Soil salinity
r = Inundation risk

$w`(t) < 0$; $w`(s) < 0$; $w`(r) < 0$

3. Data

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

3.1 Household Labor and Economic Status

We obtain information on household membership in the coastal region from the most recent Bangladesh Demographic and Health Survey (NIPORT 2011). Figure 1 displays our 178 sample clusters, which are drawn from the areas where soil salinity data are available (see the following subsection). [6] Many surveyed clusters lie on or near the coastal margin and have been exposed to frequent inundations, while others are much further inland.

From our 178 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 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.[7]

For selected households in the cluster sample, 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 constructions materials, and types of water access and sanitation facilities.

3.2 Inundation Risk Factors

Inundation risk depends on distance from the coast and elevation. For each cluster, we calculate its centroid distance from the coast using the boundary file provided by the GADM database of global administrative areas.[8] We calculate centroid elevations using SRTM data at 90 m resolution provided by Jarvis et al. (2008).

[6] 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.

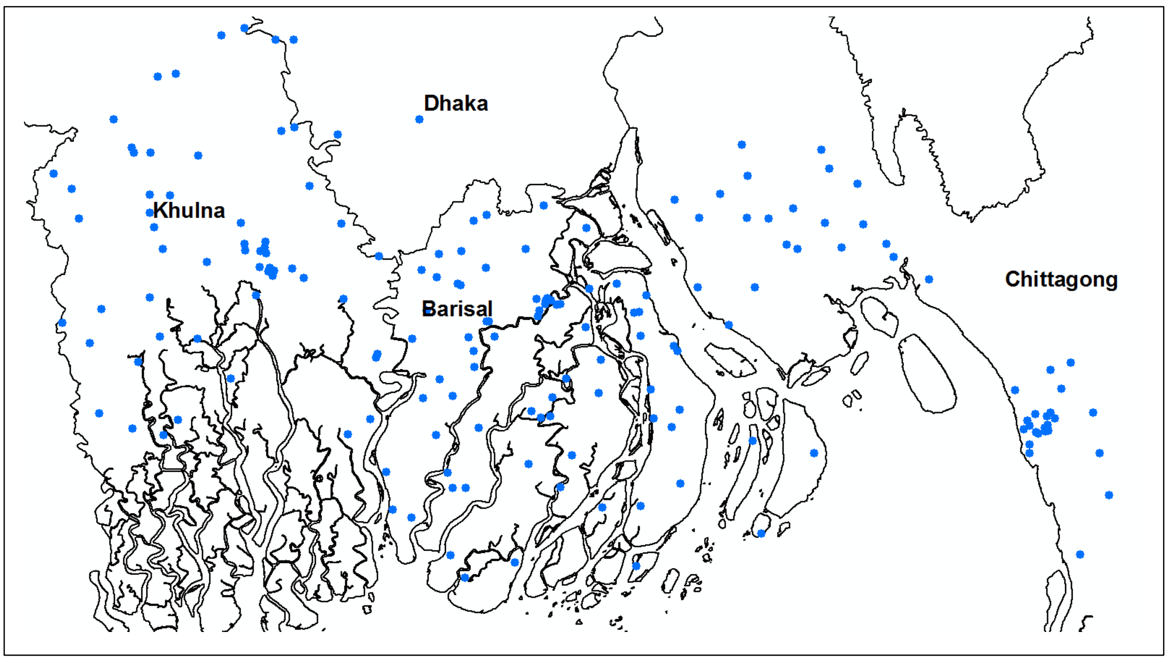
[7] We recognize that a few of the surveyed household members who slept there on the previous night may have been visiting from distant areas of employment. We cannot quantify this error factor, but we believe that it must be small.

[8] Country boundary shapefiles are available from gadm.org at http://gadm.org/country.

3.3 Salinity Measures

For this study, the Bangladesh Soil Research Development Institute has provided measures from 41 soil salinity monitoring stations 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 coastal region of Bangladesh, as well as areas that will have significant increases in soil salinity during the coming decades. Monitoring stations are

Figure 1: Sample survey clusters from DHS 2011



color-coded using standardized ranges for soil salinity in 2001, 2009 and 2050:[9] 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 greatest variance among the four regions, with northern stations uniformly Blue and central stations heavily Red and Purple. Stations in Barisal vary from Blue to Orange, while stations in Chittagong vary from Green to Red.

[9] The standard sample-based measure for soil salinity is electrical conductivity (in dS/m -- deciSiemens per meter).

By 2009, a general pattern of salinity increase is already apparent: All stations in northern Khulna have increased from Blue to Green; nearly all stations in Barisal (one exception) are Yellow or Orange; and stations in Chittagong have become heavily Orange as well. The shift continues through 2050, with some stations in north Khulna changing to Yellow; most stations becoming Purple in central Khulna, most stations in Barisal becoming Orange (and one changing to Red), and the sole Green station in Chittagong becoming Yellow.[10]

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 41 soil salinity monitors.[11] We compute the interpolated salinity measure for each month of 2011 at the geographic centroid of each cluster. Then we calculate the annual salinity mean for matching with the other cluster-level variables.

3.4 Travel Time to Market Centers

We use high-resolution spatial estimates of travel time to the nearest urban area with 50,000+ population, developed by Uchida and Nelson (2009). Our centroid estimate for each DHS cluster is the nearest measure in our Uchida-Nelson point file, which has a resolution of .00083 decimal degrees or .92 km. We believe the nearest-neighbor approach is appropriate in this context, since the median distance from the closest Nelson-Uchida point is .36 km in our sample. In contrast, the DHS introduces much larger random variations into cluster centroid locations to ensure respondents' confidentiality: within 2 km of the actual centroid for urban clusters and 5 km for most rural clusters.

[10] We have excluded one geographically-isolated station from Figure 2 to make the clustered icons easier to view. This station, Patenga, is further south on the coast of Chittagong. It is Yellow in 2001 and 2009, and changes to Orange in 2050.

[11] 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.

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 travel time to the nearest urban center, soil salinity and two components of inundation risk: distance from the coast and elevation. We test gender differences by fitting separate regressions for working-age males and females.

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 are further from urban centers. 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, and at higher elevations.

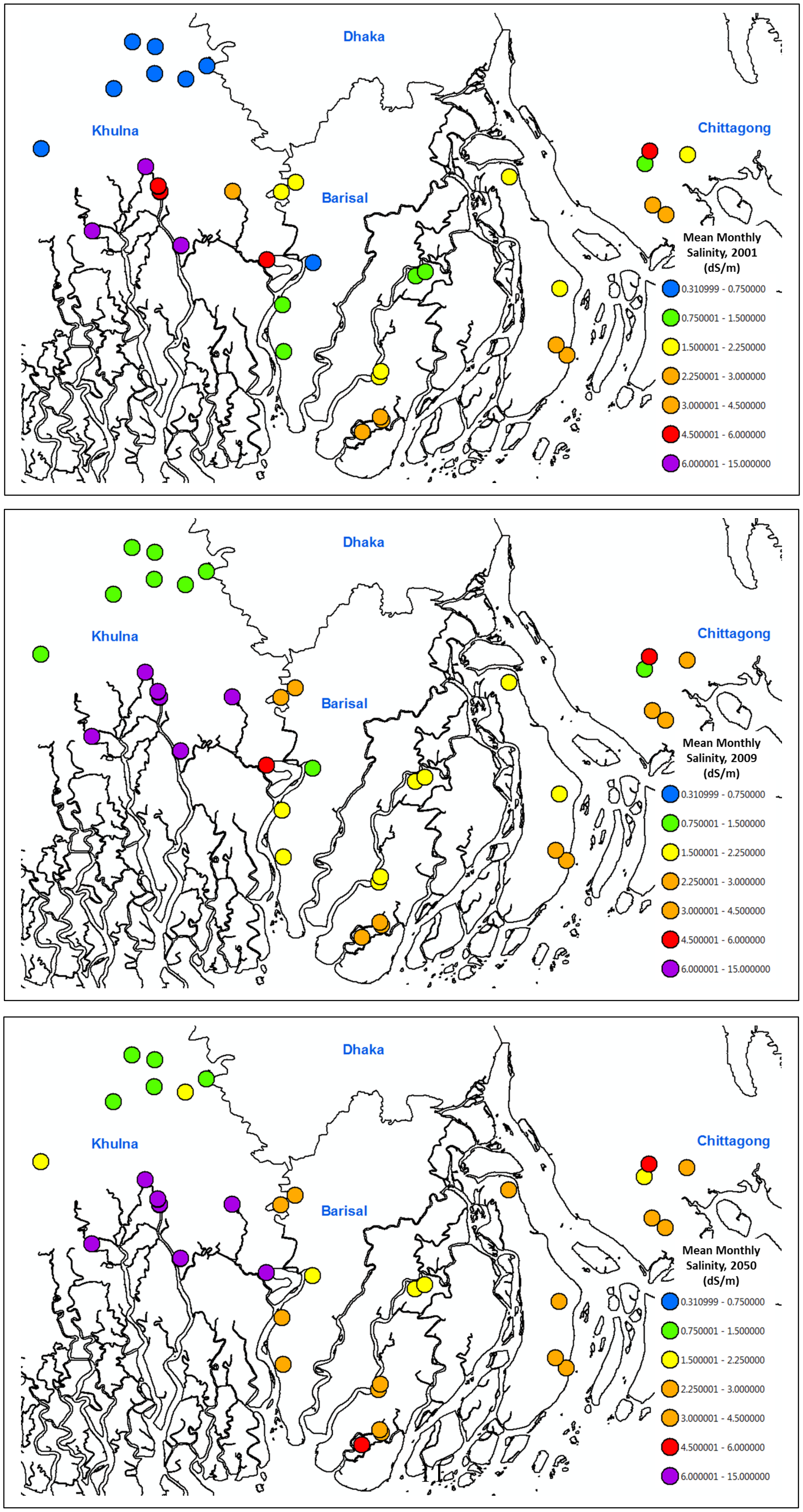
Beyond some distance margin, we would not expect perceived inundation risk to affect household decisions. In the same vein, we would not expect elevation to have differential effects beyond the critical margin. We have determined this margin empirically in preliminary regression work, by introducing 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.

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

2001

2009

2050



4.2 Specification: Household Labor Allocation

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

(3) $\eta_{ij} = \beta_0 + \beta_1 T_j + \beta_2 S_j + \beta_3 C_j + \beta_4 C_j log E_j + \varepsilon_{ij}$

Expected signs: β_1, $\beta_3 < 0$; , $\beta_4 > 0$

where, for household i in cluster j

η_{ij} = Household percent of resident working-age individuals (male or female)
T_j = Travel time to nearest urban center from cluster centroid (hundreds of minutes)
S_i = Average cluster soil salinity in 2011 (dS/m)
C_j = Coastal proximity dummy variable (1 if cluster is within 4 km; 0 otherwise)
E_j = Elevation of the cluster centroid (m)
ε_{it} = Random error term

In this specification, we expect the household percent of resident working-age individuals to be lower for clusters that are further from urban centers and within 4 km of the coast. 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). 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 3,367 households distributed across 178 sample clusters.

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 for standard tobit, GLS tobit (which allows for differences in error variances for our 178 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.[12] 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. The impact of travel time to the nearest urban center is negative and highly significant. For the two inundation risk factors, both highly significant, location within 4 km of the coast has a negative impact, while its interaction with elevation is positive. 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 in Table 1. We find equally-significant negative results for travel time to the nearest urban center, a traditional poverty determinant that is not related to coastal inundation risk. However, the estimated effect of travel time on female residency is substantially lower than the effect for males. The same is true for salinization 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 but one case. We conclude that coastal risk factors are important for household labor allocation decisions, but principally through their impact on working-age males.

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

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 quintile of the national DHS distribution. Then we specify and estimate the following model:[13]

(4) $p(Q)_{ij} = \beta_0 + \beta_1 T_j + \beta_2 S_j + \beta_3 C_j + \beta_4 C_j log E_j + \varepsilon_{ij}$

Expected signs: β_1, β_2, $\beta_3 > 0$; , $\beta_4 < 0$

where, for household i in cluster j

$p(Q)_{ij}$	=	Probability that houshold i in cluster j is in the lowest national wealth quintile
T_j	=	Travel time to nearest market center from cluster centroid (hundreds of minutes)
S_i	=	Average cluster soil salinity in 2011 (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)
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 increase with distance from the nearest urban center, salinization and proximity to the coast. The latter effect should be attenuated by elevation.

[13] 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.

Table 1: Household deployment of working-age males in coastal Bangladesh

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

	Tobit	Tobit GLS	Tobit Robust	OLS	GLS	Robust	Spatial Autocorrelation
Travel time to urban center	**-1.409**	**-1.409**	**-1.409**	**-1.179**	**-1.179**	**-1.179**	**-0.838**
	(5.28)**	**(4.51)****	**(5.26)****	**(5.23)****	**(4.52)****	**(5.37)****	**(4.13)****
Salinity	**0.475**	**0.475**	**0.475**	**0.409**	**0.409**	**0.409**	**0.297**
	(4.04)**	**(3.13)****	**(4.07)****	**(4.08)****	**(3.12)****	**(4.01)****	**(3.44)****
Coastal zone (within 4 km)	**-5.704**	**-5.704**	**-5.704**	**-4.680**	**-4.680**	**-4.680**	**-3.498**
	(3.55)**	**(3.63)****	**(3.76)****	**(3.46)****	**(3.61)****	**(3.86)****	**(2.93)****
Coastal zone x Log elevation	**2.653**	**2.653**	**2.653**	**2.118**	**2.118**	**2.118**	**1.605**
	(3.22)**	**(3.66)****	**(3.58)****	**(3.04)****	**(3.48)****	**(3.58)****	**(2.62)****
Constant	**23.910**	**23.910**	**23.910**	**25.294**	**25.294**	**25.294**	**15.004**
	(35.81)**	**(25.22)****	**(35.38)****	**(44.70)****	**(31.28)****	**(44.00)****	**(6.72)****
Observations	**3,367**	**3,367**	**3,367**	**3,367**	**3,367**	**3,367**	**3,367**
R-squared				**0.02**	**0.02**	**0.02**	

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

Table 2: Household deployment of working-age females in coastal Bangladesh

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

	Tobit	Tobit GLS	Tobit Robust	OLS	GLS	Robust	Spatial Autocorrelation
Travel time to urban center	-0.728	-0.728	-0.728	-0.708	-0.708	-0.708	-0.644
	(3.48)**	(3.53)**	(3.60)**	(3.51)**	(3.58)**	(3.66)**	(3.02)**
Salinity	0.141	0.141	0.141	0.134	0.134	0.134	0.122
	(1.52)	(1.32)	(1.47)	(1.49)	(1.30)	(1.44)	(1.44)
Coastal zone (within 4 km)	-2.421	-2.421	-2.421	-2.120	-2.120	-2.120	-1.959
	(1.92)	(1.34)	(1.82)	(1.75)	(1.25)	(1.68)	(1.68)
Coastal zone x log Elevation	1.350	1.350	1.350	1.215	1.215	1.215	1.125
	(2.09)*	(1.42)	(2.00)*	(1.95)	(1.36)	(1.89)	(1.86)
Constant	29.691	29.691	29.691	29.888	29.888	29.888	25.803
	(56.53)**	(55.78)**	(55.84)**	(59.03)**	(58.49)**	(58.18)**	(3.95)**
Observations	3,367	3,367	3,367	3,367	3,367	3,367	3,367
R-squared				0.01	0.01	0.01	

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

4.5 Estimation and Results: Household Economic Welfare

This exercise does not use 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 5,513 households distributed across 178 sample clusters.

Table 3 reports our results. The natural estimator for our regression model is probit, since the dependent variable is dichotomous: 1 for households in the lowest national DHS wealth index quintile and 0 otherwise. Accordingly, the first three columns report estimates for standard probit, GLS probit (which allows for differences in error variances for our 178 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.[14] 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.

Our results are strongly consistent with prior expectations in all cases, including the estimator that adjusts for spatial autocorrelation. Travel time to the nearest urban center, salinity and coastal zone location all have positive, highly significant impacts on the probability that a household is in the lowest

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

Table 3: Household poverty in coastal Bangladesh

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

	Probit	Probit GLS	Probit Robust	OLS	GLS	Robust	Spatial Autocorrelation
Travel time to urban center	0.165	0.165	0.165	0.044	0.044	0.044	0.022
	(10.14)**	(5.22)**	(10.47)**	(10.79)**	(4.95)**	(9.61)**	(7.06)**
Salinity	0.022	0.022	0.022	0.006	0.006	0.006	0.003
	(2.90)**	(1.62)	(2.93)**	(3.07)**	(1.64)	(2.91)**	(2.28)*
Coastal zone (within 4 km)	0.794	0.794	0.794	0.223	0.223	0.223	0.123
	(8.53)**	(4.59)**	(8.68)**	(9.04)**	(4.16)**	(7.51)**	(6.63)**
Coastal zone x log Elevation	-0.271	-0.271	-0.271	-0.079	-0.079	-0.079	-0.045
	(5.52)**	(3.10)**	(5.76)**	(6.22)**	(3.06)**	(5.40)**	(4.71)**
Constant	-1.429	-1.429	-1.429	0.058	0.058	0.058	-0.000
	(31.41)**	(16.93)**	(31.30)**	(5.65)**	(3.25)**	(5.83)**	(0.02)
Observations	5,113	5,113	5,113	5,113	5,113	5,113	5,113
R-squared				0.06	0.06	0.06	

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

quintile of the DHS national wealth index distribution.[15] As expected, the impact of coastal zone residence is attenuated by elevation.

5. Implications of the Results

Our results are consistent with prior expectations about signs and significance, but they do not provide easily-interpreted evidence about impact magnitudes. We explore this issue using a matrix of sample low and high values for the relevant variables in our model:

Table 4: Sample-based values for impact exploration

Sample-Based Values	Salinity (dS/m)	Time to Urban Center (minutes)	Distance from Coast (km)	Elevation (m)
Low	1	0	0	1
High	13	300	30	10

5.1 Implications for Household Composition

Using all combinations of the values in Table 4, we employ the tobit estimates[16] 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[17], and calculate dependency ratios (percent dependents/percent working-age adults). Table 5 presents our results, ordered by dependency ratio.

Our results indicate a powerful impact for all three location variables -- distance from the nearest urban center, salinity and inundation risk. At one extreme, households in high-salinity areas that are very near urban centers (rows 1,2,3) have the highest residence percents of working-age adults and dependency ratios around 0.60. At the other extreme (row 16), households in low salinity, low-elevation

[15] The sole exceptions are the GLS results for the probit and linear probability models, which fail to reach the standard for classical significance.
[16] The standard, GLS and Robust tobit parameter estimates are identical; only the estimated standard errors differ.
[17] This approach ensures additivity to 100%. We have also estimated a third equation for the dependent percent, generated predictions for the variables in Table 4, and totaled percents for dependents, working-age males and working-age females. This unconstrained approach generates total predicted shares above 95% in all cases.

areas that are far from an urban center and close to the coast have much lower working-age adult percents and dependency ratios that are 2.5 times higher (1.52). Intermediate cases in Table 5 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 52.6% (from 30.49% to 14.46%). For females, the corresponding decrease is 21.7% (from 32.22% to 25.23%).

To illustrate on intermediate case, consider households in low-elevation, high-salinity areas that are far from an urban center (rows 6,14). Reducing their coastal distance from 30 km to 1 km reduces their working-age male and female percents from 25.86% and 29.34% to 20.16% and 26.92%, respectively. As a consequence the household dependency ratio increases by 38.3%, from 0.81 to 1.12.

To summarize, our results suggest that all three 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.

5.2 Implications for Household Economic Welfare

Using all combinations of the values in Table 4, we use the probit estimates[18] in Table 3 to predict corresponding wealth quintile status. Table 6 presents our results, ordered by the probability that a household is in the lowest quintile of the DHS national household wealth distribution.

[18] The standard, GLS and Robust probit parameter estimates are identical; only the estimated standard errors differ.

Table 5: Impact results for resident family structure

	Salinity (dS/m)	Time to Urban Center (minutes)	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	0	1	10	30.49	32.22	62.71	37.29	1.06	0.59
2	13	0	30	1	30.09	31.53	61.62	38.38	1.05	0.62
3	13	0	30	10	30.09	31.53	61.62	38.38	1.05	0.62
4	13	300	1	10	26.27	30.03	56.3	43.7	1.14	0.78
5	1	0	1	10	24.79	30.52	55.31	44.69	1.23	0.81
6	13	300	30	1	25.86	29.34	55.21	44.79	1.13	0.81
7	13	300	30	10	25.86	29.34	55.21	44.79	1.13	0.81
8	1	0	30	1	24.39	29.83	54.22	45.78	1.22	0.84
9	1	0	30	10	24.39	29.83	54.22	45.78	1.22	0.84
10	13	0	1	1	24.38	29.11	53.49	46.51	1.19	0.87
11	1	300	1	10	20.56	28.34	48.9	51.1	1.38	1.04
12	1	300	30	10	20.16	27.65	47.81	52.19	1.37	1.09
13	1	300	30	1	20.16	27.65	47.81	52.19	1.37	1.09
14	13	300	1	1	20.16	26.92	47.08	52.92	1.34	1.12
15	1	0	1	1	18.68	27.41	46.09	53.91	1.47	1.17
16	1	300	1	1	14.46	25.23	39.68	60.32	1.75	1.52

Table 6: Impact results for household wealth status

	Salinity (dS/m)	Time to Urban Center (minutes)	Distance from Coast (km)	Elevation (m)	Probability of Lowest-Quintile Status
1	1	0	30	1	0.08
2	1	0	30	10	0.08
3	1	0	1	10	0.11
4	13	0	30	10	0.13
5	13	0	30	1	0.13
6	13	0	1	10	0.16
7	1	300	30	1	0.18
8	1	300	30	10	0.18
9	1	300	1	10	0.23
10	13	300	30	10	0.26
11	13	300	30	1	0.26
12	1	0	1	1	0.27
13	13	300	1	10	0.31
14	13	0	1	1	0.36
15	1	300	1	1	0.45
16	13	300	1	1	0.56

These results provide striking evidence that our results are important for poverty as well as family structure. For households in low-salinity areas that are distant from the coast and proximate to an urban center (rows 1,2), the predicted probability of lowest-quintile wealth status is only 8%. At the other extreme (row 16), households in high-salinity low-elevation areas that are far from an urban center and next to the coast have a predicted lowest-quintile probability of 56%. In intermediate cases, Table 5 illustrates the impacts of changes in location variables. For households in low-elevation areas that are far from an urban center and close to the coast (rows 15,16) increasing salinity from 1 dS/m to 13 dS/m raises the lowest-quintile probability from 45% to 56%. For households in low-salinity areas that are far from an urban area and close to the coast (rows 9,15), reducing elevation from 10 m to 1 m increases the lowest-quintile probability from 23% to 45%. Finally, for households in high salinity, high elevation areas that are close to the coast (rows 6,13), changing travel time to the nearest urban center from 0 to 300 minutes increases the lowest-quintile probability from 16% to 31%.

Our comparative results for salinity and travel time may have significant implications for adaptation investments, which are intended to compensate households that are differentially affected by climate change. To illustrate, we consider the case of coastal households at 1 m elevation that lie within the 4 km coastal margin. Varying travel times from 0 hours to 9 hours (the sample maximum), we find that increasing salinity from 1 dS/m to 13 dS/m increases the probability of lowest-quintile economic status by an average of 10%. Across variations in salinity, we find that decreasing travel time by 1 hour decreases the probability of lowest-quintile economic status by an average of 4%. By implication, road improvements that shorten market access time for a low-lying community at the coastal margin by 2 1/2 hours would be sufficient to offset a poverty-inducing increase in salinity from the sample best case (1 dS/m) to the worst case (13 dS/m).

We recognize that discussions of adaptation to salinization normally focus on *direct* compensation for welfare losses via measures such as diffusion of saline-resistant crops, development of low-salinity drinking water supplies and greater road maintenance expenditures to offset salinity-accelerated depreciation.[19] In the case of road improvement, which includes maintenance, our results have identified an investment target that qualifies from the direct targeting perspective, while also offering powerful leverage for indirect compensation through the poverty-reducing effect of improved market access.

6. Summary and Conclusions

This paper has quantified the impact of inundation risk and salinization on the family structure and economic welfare of coastal households in Bangladesh. These families are already on the “front line” of

[19] For empirical results on these issues, see Dasgupta, et al. (2014b,c,d).

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 five sources: information on household demographics and economic welfare from the Bangladesh Demographic and Health Survey (DHS) for 2011; soil salinity measures from the Bangladesh Soil Research Development Institute; market access measures from Uchida and Nelson (2009); and two components of inundation risk: distance from the coast, calculated from digital maps provided by the GADM database of global administrative areas; and elevation, using SRTM data at 90 m resolution provided by Jarvis et al. (2008).

We specify and estimate regression models that quantify the impacts of 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 quintile of the national wealth distribution. We use appropriate estimation models -- tobit for the household composition analysis, probit for the poverty assessment -- and incorporate adjustments for spatial autocorrelation.

The 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 at higher elevations. Damaging salinity has diffused across a much broader area. 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 53% and 22% 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 even more striking: From most to least favorable conditions, we find that the probability of lowest-quintile economic status rises by nearly 600%, from 8% to 56%.

In summary, our results paint a sobering picture of life at the coastal margin for Bangladeshi 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 Bangladesh 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 powerful 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 coastal region face travel times to market centers as high as nine hours. According to our econometric results for poverty incidence, road improvements that reduce travel times for isolated settlements by 2 1/2 hours would be sufficient to compensate them for an increase in salinity from the best to worst levels in our database. In light of these results, we believe that road improvement may warrant particular attention as an attractive adaptation investment in coastal Bangladesh.

References

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, 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.

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.

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.