Ocean Salinity, Early-Life Health, and Adaptation

Abstract

We study the effects of *in utero* exposure to climate change induced high ocean salinity levels on children's anthropometric outcomes. Leveraging six geo-referenced waves of the Bangladesh Demographic and Health Surveys merged with gridded data on ocean salinity, ocean chemistry and weather indicators (temperature, rainfall and humidity) from 1993 to 2018, we find that a one standard deviation increase in *in utero* salinity exposure leads to a 0.11 standard deviation decline in height-for-age. Effects on weight-for-height and weight-for-age for a similar magnitude increase in salinity are 0.13 and 0.15 standard deviations, respectively. Analyses of parental investments and health-seeking behaviors demonstrate that compensating actions along these dimensions to attenuate the detrimental effects of salinity are few and restricted to poorer households. Using satellite-sourced datasets on agriculture and land-use, we find that increasing salinity constrains farmers' land use choices, restricting cultivation in the more profitable seasons which leads to lower agricultural potential. In particular, the effects of salinity on child health originate in areas with lower agricultural intensity caused by the progressive salinization of productive lands. These results highlight the climate change related costs of environmental insults on early-life health outcomes in vulnerable populations.

Key Words: Ocean salinity, early-life health, climate change, height-for-age, weight-for-height, weight-for-age, children, adaptation, Bangladesh

JEL Codes: Q54, Q15, Q56, I15, O13, J13

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1. Introduction

40% of the world's population lives within 100 km of the coast, and 10% lives in coastal areas less than 10 meters above sea level (United Nations, 2017). Due to anthropogenic climate change, coastal areas around the world are increasingly threatened by changing oceanic conditions such as coastal and tidal flooding, shoreline recession, and progressive salination of coastal land and water. Vulnerable coastal communities in the developing world, especially women and children, are particularly at risk due to the lack of adequate resources to adapt and to build resilience against these changes.

While there is growing evidence that climate change brings persistent negative impacts in the developing world on mortality (Banerjee and Maharaj 2020, Burgess et al. 2017, Deschenes 2014), human capital (Fishman et al. 2019, Maccini and Yang 2009), and nutrition (Blom et al. 2022, Randell et al. 2020), most studies from that literature focus on climate-induced temperature and precipitation extremes. A smaller literature has focused on the effect of equally important climate-induced changes such as coastal flooding (Bakkensen and Barrage 2022, Bernstein 2019, Diaz 2016, Gopalakrishnan et al. 2016,) and ocean acidification (Armand and Taveras 2022). With global communities facing increasing threats from climate change, there is an urgent need for accurate assessments of how oceanic change embodied in features such as rising salinization, generates disproportionately heavier burdens for resource-constrained women and children in the developing world. In this study, we address this research gap by analyzing the early-life health impacts of *in utero* exposure to heightened salinity in coastal communities of Bangladesh. We document two key insights. First, *in utero* exposure to salinity significantly worsens health in early-life. Second, the mechanism that explains this is that an increase in salinity reduces agricultural potential; more specifically, cultivation during the more profitable *Boro* dry-season that requires the use of irrigation (as compared to the rainfed *Aman* season) becomes difficult when the saline content of water for irrigation rises.

We focus on the coastal belt of Bangladesh, a low-lying area home to over 10 million poor people residing in one of the most severely impacted regions of the world in terms of saltwater intrusion. Bangladesh already faces significant challenges related to food security and malnutrition, with over 30% of children under the age of five classified as being stunted in 2018.[1] In recent decades, climate change has caused increasingly rapid salination in coastal Bangladesh up to 100 kms inland (Rahman and Bhattacharya 2006), affecting local agricultural practices and ecosystems. Such impacts are likely to have further exacerbated poor health in early childhood.

To study how exposure to elevated salinity levels during pregnancy shapes early-life health, we construct a novel dataset linking gridded data on salinity, weather, ocean chemistry, and child health outcomes. We obtain geo-referenced monthly data on sea water salinity and other variables at a resolution of 0.083^0 x 0.083^0 (approximately 9 km × 9 km), from January 1993 to December 2019, from the Copernicus Marine Environment Monitoring Service (CMEMS). We then combine this data with children's standardized anthropometric measures (height-for-age, weight-for-height, and weight-for-age z-scores) from six geo-referenced waves of the Bangladesh Demographic and Health Surveys (BDHS) to match monthly local variation in salinity levels to birth histories ranging over almost a quarter of a century.

We leverage a saturated model that controls for unobserved heterogeneity including location-specific seasonality and regional trends, while conditioning on a host of child, mother, and household controls. We exploit exogenous variation in average salinity levels 9 months preceding the child's month of birth, measured as deviations from long-run monthly and yearly

[1] World Bank data series: Prevalence of stunting, Bangladesh. https://data.worldbank.org/indicator/SH.STA.STNT.ZS?locations=BD. Accessed 6/3/2023.

trends, to identify impacts on child health outcomes. The identification rests on comparing very young children that were exposed in the *in utero* period to different levels of exogenous variation in average salinity levels, net of regional (district-level), annual, and seasonal trends, as well as local seasonal and local annual patterns. That is, we facilitate causal interpretation by estimating the impact of exogenous deviations in ocean salinity over local long-run trends, similar to Dell et al. (2012).

We find that exogenous deviations in *in utero* salinity exposure leads to measurable negative effects on child health in early-life. A one standard deviation increase in *in utero* salinity leads to a 0.11 standard deviation decline in the child's height-for-age z-score as of age five, while also increasing the prevalence of stunting and severe stunting by 3.1 and 5.7 percentage points, respectively. Increased salinity adversely impacts weight-for-height and weight-for-age as well. Hence, exposure during pregnancy has scarring effects that result in children being relatively shorter and lighter as of age 5. These results withstand a battery of robustness checks using alternative measures of exposure, nonlinear specifications, and additional ocean chemistry controls. We ensure that our results are not driven by selective fertility or migration.

We then undertake a careful exploration of possible mechanisms to gain insights into the channels through which salinity affects early-life outcomes. While we are unable to directly assess the physiological impacts of maternal sodium intake given data, we note that the average Bangladeshi does not consume more sodium than the world average (Khan et al. 2014, Powles et al. 2013). In light of this, we focus on income and examine whether agricultural production is significantly impacted by salinity. We also consider whether there are compensatory healthcare investments by parents. We find that increasing salinity constrains farmers' land use choices, reducing acreage for dry season irrigated cropland and increasing acreage for monsoon season rainfed cropland (consistent with Shelly et al. 2016). While this switch helps to cope with salty irrigation water that is harmful to crops, it reduces overall yield and profitability. We find that the negative effects of salinity on child health primarily originate in the sample of children resident in clusters experiencing lower agricultural intensity (reduced pasture area, grazing area, rice area, and total rainfed area) due to the progressive salinization of lands.

We next use information on parental investments and health-seeking behavior to evaluate whether such investments react to salinity exposure. In this we are guided by the literature on how parental investments may respond to early-life shocks (Adhvaryu and Nyshadham 2016, Almond and Mazumder 2013), and the fact that the effects of prenatal shocks may be confounded by parental actions (Almond and Currie 2011, Barker 1995). We find that there are few corresponding compensating behaviors to attenuate the detrimental effects of salinity in prenatal and antenatal care including vaccinations, number of antenatal visits, iron supplementation during pregnancy, skilled prenatal care, skilled attendance at birth, and institutional delivery. A closer examination reveals that among poorer households, salinity significantly detracts actions along several of these dimensions, which we hypothesize may be due to the increasing opportunity cost of maternal time.

Our study makes several contributions. First, we contribute to the literature on quantifying the social impact of climate change, especially its impacts on vulnerable communities in the developing world. While extensive evidence has been provided on the effect of temperature and rainfall, for example on agriculture (Moore et al. 2017, Schlenker and Roberts 2009), mortality (Barreca 2012, Burgess et al. 2017, Deschenes and Greenstone 2011), or labor productivity (Liu et al. 2023, Park et al. 2020, Zhang et al. 2018), a relatively small literature has focused on estimating ocean-related hazards. Within this space, the focus has been on estimating the physical implications of sea-level rise including shoreline erosion and coastal flooding (Bernstein et al.

2019, Bosello et al. 2007, Depsky et al. 2022, Diaz 2016, Gopalakrishnan et al. 2016). To the best of our knowledge, Armand and Taveras (2022) is the only other study that offers insights on the effects of climate-induced oceanic alterations on human development. That study analyzed the effect of ocean acidification in a cross-country setting and showed, among other things, that ocean acidification reduces the abundance of nature's wealth (fish species) which leads to increased neonatal mortality in coastal areas. We complement this literature by quantifying the impact of another important oceanic-induced change, salt intrusion, its persistent scarring effect throughout early childhood, and we systematically analyze the various social and behavioral mechanisms through which salinity affects early-life health outcomes. More specifically, after demonstrating that salinity exerts harmful effects on early-life child health (conditional on ocean acidification and other measures of ocean chemistry), we leverage satellite-sourced datasets on agriculture and land-use to document that increased salinity hurts agricultural productivity, thereby highlighting potential income pathways and adaptation strategies at play. In exploring parental and health-seeking investments, we reveal changes in behaviors, particularly among poorer households, where higher salinity exposure leads to decreased early childhood investments. Our analyses also allow us to pin-point the timing of exposure that has the largest impacts, and how those impacts persist over the medium run. Anecdotally, given accelerated sea level rise due to changing climate, increasing salinity is the key issue of concern affecting large numbers of people across many low-lying countries in the world.

Second, we contribute to the body of work that considers the effects of *in utero* shocks on early-life health outcomes, (Almond 2006, Almond and Currie 2011, Almond and Mazumder 2011, Banerjee et al. 2010, Barker 1995, Bleakley 2007), and specifically the effects of environmental shocks (Adhvaryu et al. 2019, DeCicca and Malak 2020, Rocha and Soares 2015, Wilde et al. 2017) and how these, in turn, shape development outcomes (Dell et al. 2012, Maccini and Yang 2009). We contribute by evaluating a previously under-documented, yet extremely important environmental insult that is expected to further intensify due to climate change, and that affects millions of poor people resident in coastal communities globally. The strength of our paper lies in the use of a novel database that provides scope to understand the impacts of climate change on early-life health, while providing the richness of information required to disentangle parental, agricultural, and selection effects in the context of a developing country.

Third, we contribute to the literature on understanding the public health implications of salinity and sodium intake, especially on maternal and early child health impacts. While the effect of sodium intake on adult health has been extensively studied (Hunter et al. 2022), few studies have considered its effects on children's health. In this realm, studies have found that exposure to salinity increases pregnancy-related complications (Khan et al. 2011, Khan et al. 2014, Thompson et al. 2022) as well as infant mortality and morbidity (Dasgupta et al. 2016, Naser et al. 2020). A majority of this literature focuses on either only during or shortly after pregnancy. We contribute in this area by documenting a persistent link between salinity and later-life development beyond prenatal and neonatal periods, while simultaneously evaluating the socio-economic and agricultural mechanisms that underlie the linkage as manifested through changes in land use and healthcare investments.

While our study focuses on Bangladesh to ensure that we account for the multifaceted factors that correlate with ground-truth realities and distinctive attributes of this population, our findings have global significance that extend far beyond the confines of just this country. Due to climate change, vulnerable populations in coastal and low-lying regions across many continents are exposed to escalating saltwater intrusion. Hence, the pressing need to address harmful consequences of sea-level rise is a common thread across numerous countries. For instance, salinization has destroyed several self-sufficient farming communities in Senegal, transforming them into dependent food importers, while also disrupting and threatening habitats with concomitant effects on livelihoods of farmers and fishermen. Similar challenges face the Niger Delta region in Nigeria, the Mekong River Delta in south Vietnam (which has witnessed destruction of coconut groves, rice paddies, and other agricultural resources), and the Bengal Delta region in India; these are a few selected examples from an extensive list of countries combatting coastal erosion and heightened salinity. These examples underline that while our focus is the detrimental effects of salinity in Bangladesh, the findings hold lessons for populations more globally.

Experts agree that the deleterious effects of climate change will exacerbate preexisting vulnerabilities and inequalities, and that there is an urgent need for meaningful action to circumvent the coming challenges (Stern 2022). The results of our study on the scarring effects of salinization on fetal health further emphasize these facts. Understanding how climate change related shocks impair child health is important given that we know that shocks in childhood have long-lasting consequences that resonate long into the future (Currie and Vogl 2013, Edwards 2017), and in order to focus attention on engineering effective coping strategies in environments with low resources and restricted adaptive capacities.[2]

2. Background

2.1 Salination in coastal Bangladesh

Bangladesh, a low-lying deltaic country with a flat topography, is home to one of the largest populations vulnerable to climate change. Criss-crossed by the Brahmaputra, the Ganges, and the

[2] We outline some of the coping strategies that are already in place in the last section of our study.

Meghna rivers, and located at the tip of the Bay of Bengal, the country is continuously subject to sea level rise, tidal surges, shoreline recession, strong cyclones, and riverbank erosion (Rahman et al. 2014). Coastal areas along the Bay of Bengal covering about 3.22 million hectares (Rahman et al. 2011), more than 30% of the country's cultivable land (Rasel et al. 2013) and home to around 11.80 million poor people located across 19 districts (Dasgupta et al. 2018), are particularly susceptible to seawater intrusion and increased salinity levels.

The southwest coastal region, lying about 1.5 meters above mean sea-level, is most threatened by increases in water salinity (Hossain et al. 2018). Annual mean sea-level data for the period 1983-2003 from the Permanent Service for Mean Sea Level (PSMSL) shows that sea-level in the southwest coastal region has increased by 122 mm between 1983 and 2003, with a yearly average increase of roughly twice the global average of 3 mm per year over this 20-year period.[3] As a result, salt intrusion is rapidly increasing in coastal areas. A report from the Soil Resource Development Institute (SRDI, 2010) from the Ministry of Agriculture shows that the amount of salt-affected area during four decades (1973-2009) in coastal areas has increased by 26.70%. Storm surges, the flow of saline groundwater during the dry season coupled with insufficient rainfall to lower saline concentrations, warmer temperatures that increase evaporation, and tidal inundation in the wet season, all affect salinity (Baten et al. 2015, Dasgupta et al. 2016). Rising sea level advances salty ocean water further inland, reaching up to several miles upstream. In addition, tidal effects and upstream freshwater flows cause sea water to travel many miles inland, aggravating the buildup of salt in major rivers. Ground water and surface water connected to these major rivers through water inlets and estuaries also experience increased average salinity concentrations as a consequence (Alam et al. 2017). These are some of the ways in which offshore saline

[3] The data used is for station ID 1451 (Hiron Point, Bangladesh). More information can be obtained from psmsl.org. The data authority for this source is the Bangladesh Inland Water Department of Hydrography, Transport Authority.

concentrations can have large effects on salinity many miles inland, and which, in turn, affect quality of livelihoods, agricultural yields, cropping intensity, biodiversity, and health (Mahmuduzzaman et al. 2014).

Higher salinity levels distort normal cropping patterns and impede agricultural productivity and economic development.[4] Heavy reliance on the agricultural sector implies that saltwater intrusion has significant ecological and socioeconomic implications, with possible spillover effects for the rest of the economy. Hossain et al. (2018) identifies the main coastal communities affected by salt intrusion. Crop farmers, Sundarbans (mangroves) – dependent communities, and landless agricultural laborers are amongst the most vulnerable. Increased salinization causes drinking water shortages, food insecurity, degradation of soil quality, unemployment, and reduction in tree coverage, posing serious threats to public health and primary production (Dasgupta et al. 2015).

2.2 The physiological impact of excessive sodium

The physiological link between sodium intake and health has been studied extensively by the medical science literature.[5] Sodium intake increases the risk of diseases mainly through renal and vascular functions (Ando and Fujita, 2012; Rodriguez-Iturbe et al. 2007). The medical literature has concluded that excessive salt intake is a significant contributor to high blood pressure via both observational studies (Mente et al. 2014) and randomized control trials (Huang et al. 2020). The link has also been established, with less confidence, between excessive sodium intake and cardiovascular diseases (Mente et al. 2018; Taylor et al. 2011; Welsh et al. 2019). Excessive sodium intake can also lead to a number of other health conditions, most of them in later life,

[4] The agricultural sector (agriculture, forestry, and fishing, value added) contributed 12.7 percent of Bangladesh's GDP in 2019, and employed 38.3 percent of the labor force (WDI, World Bank 2021).

[5] The rest of the mineral ingredients in seawater-induced salinity, including calcium, magnesium, and potassium, have mostly positive health impacts: calcium strengthens bone structure; magnesium decreases the risk of a series of diseases, including hypertension, cardiovascular diseases, and diabetes; potassium reduces the negative health impact of sodium intake on blood pressure and heart diseases.

including hypertension, stomach cancer, obesity, and urinary and kidney diseases (Hunter et al. 2022, World Health Organization, 2012).

A smaller public health literature focuses specifically on the impact of sodium intake on maternal and neonatal health outcomes. Through observational studies, sodium has been linked to hypertension, preeclampsia, and low-birth weight, which can impact stunting and underweight (Khan et al. 2011, 2014, Pizzi et al. 2014, Thompson et al. 2022). No study, to the best of our knowledge, has probed the link between maternal sodium exposure and children's outcomes beyond the neonatal stage.

It is important to emphasize in this context that even though many coastal communities in Bangladesh are exposed to salt, on average, intake is not excessively high. Powles et al. (2013) found that the average Bangladeshi adult consumes 9 grams of salt per day. While this exceeds the World Health Organization recommended level of 5 grams per day (World Health Organization, 2012), average sodium intake in Bangladesh is slightly below the global average sodium intake of 10 grams per day, and far below other coastal Asian countries like China, Korea, Myanmar, and Thailand. This suggests that the physiological mechanism tied to sodium would be unlikely to explain the bulk of stunting and/or underweight status in Bangladesh.

2.3 The socio-economic impact of salinity exposure

In parallel, social scientists and researchers have probed the link between salinity exposure and a wide range of public health outcomes. Dasgupta et al. (2016) documents the association between mother's salinity exposure in the last month of pregnancy and infant mortality. Nahian et al. (2018) investigates the correlation between water salinity and health care crises in coastal Bangladesh, while Naser et al. (2020) finds a U-shaped association between drinking water salinity and infant and neonatal mortality in Bangladesh. Chakraborty et al. (2019), using a cross-sectional study in three coastal sub-districts, finds that excess drinking water salinity is associated with increased hospital visits for cardio-vascular diseases, diarrhea, and abdominal pain. Akter (2019) finds that exposure to excessive drinking water salinity in southwest coastal districts decreases the grade advancement of 7 to 12-year-old children, with poverty exacerbating effects.

Beyond direct health impacts, studies have also documented salinity affecting agricultural production and aquaculture. The shortage of grazing land and fodder crops leads to lower milk production, less cattle-rearing, reduced stock of freshwater fish species, and other agro-biodiversity changes that affect households' diet (Alam et al. 2017). Baten et al. (2015) explains that irrigated water demand is affected by saltwater intrusion in surface water, while Rahman et al. (2011) considers the impact of salinity on agro-biodiversity to find that the use of brackish water for irrigation limits the cultivation of rice and vegetables in the dry season. Ziaul Haider et al. (2013) studies the impact of salinity on farmers' livelihood strategies. The study finds that while salinity motivates adaptations such as shrimp cultivation, detrimental effects on agricultural income and employment opportunities still result leading to lower living standards. Anik et al. (2018) investigates the impact of salinity stress on livelihood choices of rural households in southwestern Bangladesh to conclude that households highly dependent on agriculture suffer major crop losses due to high salinity levels. Chen et al. (2022) documents that salt intrusion leads to a decline in cultivating high-yield, salt intolerant rice varieties, leading to a decrease in economic activities in impacted regions. Our results confirm that reduced agricultural productivity is an important mechanism that underlies the negative consequences of salinity on early-life health.

3. Data

3.1 Children's health outcomes

We use 6 rounds of geo-referenced Demographic and Health Surveys (BDHS) for Bangladesh from 1999, 2004, 2007, 2011, 2014, and 2017. The BDHS is a stratified two-stage nationally representative sample. In the first stage, enumeration areas (EAs) are randomly chosen from the Population and Housing Census of Bangladesh and are used as the sampling frame, with stratification by region.[6] In the second stage, within the selected EAs (or clusters), a number of households are randomly selected to be surveyed. We use anthropometric measures (height-for-age z-score (HAZ), weight-for-height z-score (WAH), and weight-for-age z-score (WAZ)) for all children aged 0-5, collected in households within which women of reproductive age (15-49 years) were interviewed. We create indicator variables for stunting, wasting, and undernutrition using these measures. We complement the early childhood outcomes with additional child and household characteristics and other health-related measures. We use the geographic location of each surveyed cluster over rounds to match children by month and year of birth to geo-coded salinity and weather data at the month and year level. [7,8]

To identify the BDHS clusters that are most likely to be affected by rising seawater salinity, we use a measure of proximity to the ocean's shore. For each cluster, we calculate the minimum distance between the cluster's location and the closest shoreline, using the Global Self-Consistent, High Resolution Geography Dataset (GSHHG) (Wessel and Smith 1996). Following the literature, we define coastal communities as those living within 100 km from the ocean, and classify

[6] Bangladesh has 8 administrative divisions: Barisal, Chattogram, Dhaka, Khulna, Mymensingh, Rajshahi, Rangpur, and Sylhet. Each division is further divided into *zilas*, and *zilas* in turn contain *upazilas.*

[7] We use cluster locations obtained by recording the GPS coordinates of each cluster's center during the survey's fieldwork or listing stage. Since DHS surveys contain sensitive information, the locations are altered through a process known as displacement or geo-masking to safeguard the privacy of survey participants. Urban clusters and rural clusters are displaced up to 2 and 10 km, respectively. However, the displacement procedure ensures that the clusters remain within the same administrative units so that the data can be analyzed appropriately within administrative frameworks. For more details, please see Burgert et al. (2013).

[8] Michler et al. (2022) indicates that on average, commonly employed privacy protection techniques do not significantly impact regression estimates.

households living in clusters within 40 km from the ocean as being the most vulnerable. Figure 1 depicts the location of all clusters in our sample. There are 1000 unique clusters among coastal communities, and 630 unique clusters in the sample of vulnerable coastal communities.

3.2 Ocean salinity and chemistry

Our ocean salinity and chemistry data come from the Copernicus Marine Environment Monitoring Service (CMEMS), which is drawn from both satellite Earth Observation and *in-situ* (non-space) data.[9] The gridded dataset has a spatial resolution of 0.083° x 0.083° (approximately 9 km $\times$ 9 km), for the period January 1993 to December 2019.[10] We obtain monthly measures on seawater salinity, seawater temperature, sea surface height (surface value), eastward and northward wind velocity, and the ocean's pH levels over these years.[11] Specifically, our salinity metric measures the amount of dissolved salt in parts per thousand and is commonly reported in practical salinity units (psu).

Following the environmental economics literature, (Deschenes and Greenstone 2011, Zhang et al. 2017), we use inverse-distance matching to obtain measures of local climate at the cluster level. For each cluster, we calculate the weighted average of oceanic chemistry metrics from the 5 closest grid points, weighting each point by the inverse of the squared distance from the cluster's location so that each grid point has a local influence that diminishes with distance.[12]

[9] We use the global ocean 1/12° physical reanalysis (*GLORYS12V1*) product: "global ocean eddy-resolving reanalysis covering the altimetry".
[10] The "*Global_Reanalysis_PHY_001_030*" product contains three datasets (the 3D daily mean fields, monthly mean fields, and monthly climatology mean fields). We use the dataset containing monthly mean fields. For more information on the validation methodology and series of diagnostics used for the dataset, see Drevillon (2018).
[11] The original file format is the Network Common Data Form (NetCDF) and NetCDF-4. We process these files in Python to obtain month-year level data from January 1993 onwards. All variables considered here are on the same regular grid points.
[12] Let c denote a DHS cluster, i a station, and n_c is the number of stations that relate to cluster c (we choose $n_c = 5$). Let d_{ic}^2 be the squared distance between cluster c and station i. We thus define the weight W_{ic} as follows:

3.3 Weather data

Since other features of weather are likely to be correlated with both children's health and salinity levels, we include a series of climatic variables in our analyses.[13] We obtain weather data from the Bangladesh Meteorological Department (BMD) which maintains records of all meteorological events and archives weather and climate data. We obtain station-month-year level data for all 35 stations across Bangladesh from 1970 to 2019, including data on minimum and maximum temperature, rainfall, and humidity.[14] Weather data is interpolated into cluster-level measures using inverse distance weighting of 5 closest neighbors, and then 9-month average values (preceding the child's time of birth) are merged with the child's month and year of birth in the BDHS data, consistent with the approach for the ocean chemistry variables.

3.4 Summary statistics

Table 1 provides summary statistics for the sample that is most vulnerable, that is, within 40 kms of the coastline. The outcomes of interest are continuous for HAZ, WAH, and WAZ. The binary variables *stunted* and *severely stunted* equal one if child HAZ falls below -2 and -3 standard

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$$W_{ic} = \frac{\frac{1}{d_{ic}^2}}{\sum_{k=1}^{n_c} \frac{1}{d_{kc}^2}} \quad for\ d_{ic} \geq o, and\ for\ any\ i, c$$

Thus, temperature $\bar{T}_c$ at cluster c equals to:

$$\bar{T}_c = \sum_{i=1}^{n_c} W_{ic} T_{ic}, \qquad \text{with} \sum_{i=1}^{n_c} W_{ic} = 1$$

where T_{ic} is the temperature at station *i* related to cluster *c*. Simply, T_{ic} is weighted by the inverse of the squared distance given the mean temperature at station *i* (see De Mesnard (2013) for more details on the use of the IDW method in models estimating pollution impact, for instance).

[13] The literature posits that climate change affects the distribution of several climatic variables, and that any model that attempts to evaluate the distributional effects of climate change will likely produce biased results if other climatic variables are omitted. Barreca (2012) for instance finds that humidity, like temperature, is an important determinant of mortality. Zhang et al. (2017) finds that omitting humidity tends to over-predict the cost of climate change (as manifested in temperature and rainfall) on crop yields.

[14] Auffhammer et al. (2013) and Zhang et al. (2017) highlight the importance of having a continuous weather record (and thus few missing observations) when averaging station-data across space to ensure relatively lower loss of weather variation when fixed-effects are used in the empirical model. Although these data do not have a lot of missing values, we complete the series for the relatively few missing observations by using IDW spatial interpolation methods.

deviations, respectively. Similarly, *wasted* and *severely wasted* are binary variables that equal one if child WAH falls below -2 and -3 standard deviations, respectively. *Underweight* and *severely underweight* are constructed from WAZ in a similar fashion. In Panel A, the mean HAZ is -1.80, and approximately 45% and 19% of children aged 0-5 years are stunted and severely stunted, respectively. The mean for WAH and WAZ is -0.91 and -1.67, respectively, and almost 15% and 39% of children in this sample are wasted or underweight, respectively.[15]

In Panel B, the average salinity level during the 9 months preceding the child's month of birth is 12.59 psu, with a standard deviation of 4.40 psu.[16] Ocean's pH averages 8.20. Panel C reports the summary statistics for weather-related variables used as controls in the regressions. Panel D provides information on the characteristics of children, mothers and fathers in our sample. Half of the children are male, and the average child is 29.31 months old. The average birth order is 2.69, and mean mother's age at first birth is 17.95 years. Estimates reveal that 24% and 26% of mothers and fathers in our sample had no education, respectively. In 87% of observations, the head of the household is male.

3.5 The distribution and seasonality of ocean salinity

To visualize climate-induced change in ocean salinity over time, Figure 2 provides kernel densities plots for average salinity levels.[17] Panel A considers the kernel densities for salinity levels associated with clusters within 100 km of the ocean for two periods: 1995-2002 and 2011-2018.

[15] Figure A1 shows that there is substantial heterogeneity in the nutritional status of children across sub-districts in Bangladesh.

[16] The WHO recommends no more than 5 grams of salt per day but there is no clear translation between this metric and recommended salinity exposure in practical salinity units. Nasrin et al. (2020) notes various categories for salinity levels based on optimal conditions for crop growth and soil quality: low saline (0.5 to 5 psu), moderate saline (5 to 18 psu) and high saline (18 to 30 psu). An average of 12.59 psu thus falls in the moderate category.

[17] In addition to examining the temporal progression of salinity in Figures 2 and 3, we also plotted a pair of heatmaps in Figure A2 to visualize the spatial distribution of ocean salinity.

Panel B includes salinity for the vulnerable coastal clusters living within 40 km of the ocean for the same two periods. In both panels, there is a right-ward shift in the distribution over time.

Ocean salinity varies with the onset and end of the monsoon period. Panel A of Figure 3 shows the seasonal variation in salinity (monthly average over years) for ocean points matched to coastal clusters. We observe differences in salinity levels over the pre-and post-monsoon seasons; in particular, salinity increases in the post-monsoon period (October) through the pre-monsoon month of May, after which it declines. Surface salinity in coastal waters is higher in the dry season due to lower rainfall and river discharge, which allows saline water to travel further upstream in major rivers through tidal effects and stronger estuarine exchange flows (Baten 2015, Dasgupta et al. 2015, Shammi et al. 2019). In addition to the monsoons, increases in ice melt in the Himalayas during May through October generates a higher upstream flow of freshwater and river water discharge, thus reducing salinity in coastal areas (Mahmuduzzaman et al. 2014). Our empirical methodology outlined below is cognizant of these seasonal changes. Panel B of Figure 3 shows the distribution of ocean salinity for ocean points matched to sampled coastal clusters. The distribution is mostly skewed to the right, but there is also variation in levels across clusters, revealing that the identifying variation stems from the majority of clusters and not just from a few outliers. Taken together, the two panels of Figure 3 illustrate that ocean salinity exhibits considerable variation across months and clusters.[18]

4. Empirical strategy

To test for the effects of variation in *in utero* salinity on early-life health, we employ the following specification:

$$y_{icdmt} = \beta salinity_{cdmt} + X'_{icdmt}\gamma + \eta_{mt} + \theta_{dm} + \Phi_{dt} + \epsilon_{icdmt} \qquad (1)$$

[18] We control for river salinity with our measures of land cover specific to brackish water and tree cover flooded with saline water (please see Figure A3).

y_{icdmt} is the health outcome for child *i*, born in month *m* in year *t*, whose mother was surveyed in cluster c in district d.[19] We consider the effects of salinity exposure in the 9 month *in utero* phase, and construct $salinity_{cdmt}$ as the average value of ocean salinity (constructed from the 5 closest stations, as described above) in the 9 months preceding the child's month of birth in cluster c.[20] The coefficient of interest is β, and is expected to be negative for HAZ, WAH and WAZ, and positive when the binary indicators for stunting, wasting, and underweight are evaluated.

X_{icdmt} is a vector of variables including child, mother, and household characteristics, and time-varying weather and other ocean chemistry controls that could potentially be correlated with salinity while also determining variation in early-life health. More specifically, we include child's age, gender, and birth order, mother's age at first birth, a dummy variable that equals one if the mother is uneducated, a dummy variable that equals one if the father is uneducated, mother's height, and the gender of the household head.[21] In terms of other weather measures, we include time-varying minimum and maximum temperature, rainfall, the interaction between minimum/maximum temperature and rainfall, and humidity. Other ocean controls include those

[19] As we note above, there are more than 1000 unique clusters when we consider all coastal communities, and 630 unique clusters in the vulnerable coastal communities. Using cluster fixed-effects absorbs a large proportion of the underlying variation as we discuss below.

[20] In modeling salinity as exposure in the *in utero* time period, we follow an established literature which documents that this is the key period of interest in understanding the effect of shocks (Barker 1995, Almond 2006, Almond and Currie 2011, Almond and Mazumder 2011, Almond and Mazumder 2013, Edwards 2017). Alternatives we considered was exposure in the previous growing season(s) or using direct measures of crop yields from previous seasons. However, growing seasons themselves have changed because of weather uncertainties as documented in Shelley et al. (2016) and Chen et al. (2012). Hence by considering growing seasons instead of a pre-determined gestational length of time, our results may reflect reverse causality. We also do not have a direct measure of crop yields unfortunately, since household level crop-yield data is not present in the DHS, and because proxy cluster-level crop yield using Normalized Difference Vegetation Index (NDVI) requires us to know exactly which variety of crop is grown at that scale. Further, our land use data only allows us to distinguish between irrigated vs. dryland agriculture vs. brackish water, with no additional direct details on crop types. In tests below, in order to proxy for previous growing seasons, we include average salinity 6 months prior to conception and average salinity 12 months prior to conception, separately, in our baseline model that includes average salinity in the 9 month *in utero* period. Results reveal that average salinity in the *in utero* time period is of most importance.

[21] We run extensive heterogeneity checks with wealth measures below. In the baseline model, parents' (especially father's) educational level proxies for household wealth.

for ocean acidity (pH value) which is always included, and seawater temperature, sea surface height, and ocean wind velocity which are additionally included in robustness checks.

Equation (1) includes a series of temporal and spatial fixed-effects to control for unobserved heterogeneity in seasonality and in regional trends. Year by month fixed-effects (η_{mt}) are included to control for idiosyncratic changes common across clusters. We also include district fixed-effects interacted with month of birth (θ_{dm}) to control for local seasonal variation, and Φ_{dt} which are district-year of birth fixed-effects to control for district-specific trends in cohort nutritional status, and thus for any local annual patterns in health outcomes.[22] The presence of these fixed-effects implies that we estimate the impact of deviations in ocean salinity over long-run month and year trends, facilitating causal interpretation (Dell et al. 2014). The error term is ϵ_{icdmt}. Following DHS guidance, regressions are weighted so estimates may be interpreted as representative, and we report standard errors clustered at the cluster level (Abadie et al. 2022). The identifying assumption is that there are no omitted variables that are correlated with both the salinity measure and with child health outcomes, so that exposure to salinity levels *in utero*, conditional on the other variables in the models, is unanticipated and as good as random.

Since oceanic variables are correlated, we employ a double-lasso variable strategy to guide our selection of climatic and oceanic variables. The double-lasso strategy works in two steps: the first step regresses the treatment variable (in our case ocean salinity) on the full set of control variables in a lasso regression; the second step regresses the outcome variable on the treatment variable and the selected set of variables from the first step. The double-lasso strategy provides a robust model selection framework (Belloni et al. 2014).

[22] We have nineteen districts in our sample.

We implement the double-lasso estimator on the within-40km-to-ocean sample with all 9 outcome variables using three different selection methods: full cross-validation, adaptive selection, and plugin-adaptive selection. All variables in our main model are included in the double-lasso selection, demeaned with the same set of saturated fixed-effects.[23] We force household controls and salinity to remain in the model, leaving oceanic and weather variables to be selected. Table A1 presents results from running the double-lasso algorithm on 27 candidate models and specifications (3 selection methods for each of the 9 outcome variables), which we use as a guide for the estimations that follow.[24, 25]

5. Results

5.1 The effects of *in utero* salinity exposure

In Table 2, we present results from the regression in equation (1). In Panel A, we restrict the sample to vulnerable coastal areas (DHS clusters within 40 km of the ocean), and in Panel B, we restrict the sample to all DHS clusters in coastal areas, that is those within 100 km of the ocean. Focusing on the coefficients in Panel A, we see consistently negative effects of *in utero* exposure to ocean salinity on children's anthropometric indicators.[26] In column (1), a one standard deviation (SD) increase in *in utero* salinity leads to a 0.11 SD decline in the child's HAZ.[27] In columns (2) and (3), the results are in accordance with our expectations – *in utero* salinity exposure has

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[23] Demeaning is accomplished by extracting the residuals from the regression y = 1 + fixed-effects. As recommended in Luo et al. (2017), we check the residuals obtained from the demeaning regression to find that the within-group means are minimal.
[24] Since sea surface temperature and height are both correlated with ocean salinity, we use non-linear versions of these variables in the robustness checks, as we discuss below.
[25] Sea surface height is a significant predictor of storm surges, which affect coastal communities. We matched reconstructed storm surge levels from GSSR (http://gssr.info/) with existing sea surface height data from CMES and predicted tidal gauge measured storm surges using sea surface height. As we note below, above/below median sea surface height is the best predictor that explains about 40% of the variations.
[26] We assume a gestation period of 9 months but have checked sensitivity when we extend to 10 months (see Panel E of Table A2).
[27] The coefficient on salinity exposure in column (1) of Table 2 is -0.025. We multiply this coefficient by the standard deviation of salinity (4.40) in order to obtain the 0.11 SD decline.

significant effects on the probability that the child is stunted and severely stunted. A one SD increase in salinity increases the prevalence of stunting and severe stunting by 3.1 and 5.7 percentage points, respectively. When the sample is restricted to all coastal communities in Panel B, while the coefficients are of smaller magnitudes, the negative impacts of salinity exposure are still mostly evident.

In columns (4) through (6), we consider WAH and binary variables for wasted and severely wasted. Column (4) of Panel A indicates that the effect of a one SD increase *in utero* salinity leads to a 0.13 SD decrease in WAH, with significant effects evident for wasting and severe wasting. As above, corresponding estimates in Panel B are consistent.

In columns (7) to (9), the dependent variables relate to WAZ. The results again support the hypothesis that *in utero* exposure to salinity exerts detrimental effects on children's health. Higher *in utero* salinity levels are associated with lower WAZ; one SD increase in salinity decreases WAZ by 0.15 SD (representing 13.4 % of the total variations in WAZ). Salinity exposure also leads to children being underweight and severely underweight, signaling nutritional deficiencies in these early years.

5.2 Robustness checks for the main results

5.2.1 Alternative specifications of *in utero* salinity exposure

We construct alternative measures of *in utero* exposure to underline the robustness of our main results (Adhvaryu et al. 2019). We focus on the results for vulnerable coastal areas (within 40 km of the ocean) henceforth. Please see Section A.1 for a detailed description of these results. Overall, our main results hold.

5.2.2 Effects by trimester

Please see Section A.2 for a description of these results.

5.2.3 Timing of exposure: Controlling for salinity before conception and after birth

As a falsification test, we check that impact of salinity matters only in the *in utero* period (Molina and Saldarriaga 2017). In Figure 4, we present results estimating the effects of salinity during the pregnancy period including average salinity levels 1-2 months before conception (10-11 months before birth), 3-4 months before conception (12-13 months before birth), in the month of birth, and 1 trimester after birth. We note that exposure before or after pregnancy does not have significant effects for most outcomes.[28]

5.2.4 Spatial spillover effects

To quantify the spatial spillovers of salinity impacts on children's outcomes, we augment our baseline regression and generate dummy variables for each cluster indicating its distance to the coast in 10 km distance bands. We then replace the single salinity metric in equation (1) with interaction terms between these distance bands and salinity exposure.

Results are presented in Figure 5. We find that the effects of salinity on children's health are larger in clusters closer to the ocean. For instance, the impact of salinity on both WAH and WAZ are negative and significant in most clusters that are within 50 kms of the coast, and insignificant beyond 50 kms. For severe stunting and severe wasting, the effect is significant within 70 kms of the coast. Across the board, the magnitude of the effect decreases over distance, which aligns with expectations. Figure 5 is also the visual representation of the commonly used "donut" regression method to ascertain robustness given displacement of DHS clusters (as noted above Burgert et al. 2013 and Michler et al. 2022 confirm that this displacement does not significantly influence estimates). If we were to exclude a "donut" area of 10 km consistent with displacement in rural areas of the Bangladesh DHS, Figure 5 demonstrates that impacts of salinity still hold.

[28] These results also give us confidence that there is little serial correlation in salinity measures.

5.2.5 The persistence of salinity impacts

We document the persistence of *in utero* salinity exposure. To do so, we augment equation (1) with dummy variables indicating the child's age band, from 0-6 months to 54-60 months, and interact them with the salinity exposure variable. Figure 6 presents the result. We find suggestive evidence that salinity impacts on HAZ and stunted status of infants is small during the first year, increase in the second year peaking at 18-24 months, and then subside thereafter. The effects are mostly insignificant beyond age 4. This is consistent with evidence in Heady et al. (2018) that up to 23 months is when stunting is most likely to manifest itself. Similar patterns exist for WAZ and WAH where the magnitude of the effect peaks at 12-24 months and then declines.

5.3 Comparing our findings to related studies

We place our results in the context of the literature on early-life exposure to environmental shocks and child health. Our work is in line with the empirical evidence that climate shocks affect child nutrition (Dimitrova 2021, Randell et al. 2020, Thiede and Gray 2020, van der Merwe et al. 2022). Further, the size of our main estimate is consistent with the 0.12 SD decrease in HAZ caused by a one SD change in mean PM 2.5 exposure in Singh et al. (2019).[29] Le and Nguyen (2022a) study *in utero* exposure to the outbreak of desert locust swarms in Africa and Asia, and find that compared to unexposed children, those exposed prenatally to the outbreak have lower HAZ, WAH, and WAZ (by 0.16, 0.15 and 0.16 SD, respectively). These results are consistent with our findings using nonlinear specifications (Panels A and B in Table A3). They are also similar to the decline in HAZ, WAH, and WAZ caused by *in utero* exposure to droughts in Bangladesh (Le and Nguyen 2022b).

[29] Note that these are the 2SLS (see for instance, Rosales-Rueda and Triyana (2019) who find that children exposed to fires *in utero* in Indonesia are on average 0.3 standard deviations shorter than unexposed children; and Rangel and Vogl (2019) for the impact of *in utero* exposure to agricultural fires in Brazil on health at birth).

Focusing on the impact of heat exposure on children aged 3-36 months for five West African countries, Blom et al. (2022) finds that for each 100 hours of lifetime exposure to temperatures above 35^0C relative to exposure to temperatures below 25^0C, HAZ falls by 0.17-0.30 SD, while the prevalence of stunting increases by 5.9 percentage points. The effects we document are similar. We conclude that our results are generally in line with previous studies that investigate the impact of early-life environmental shocks on anthropometric measures, and consistent with studies that demonstrate that income shocks in the first thousand days of life have lasting consequences (Baird et al. 2019, Barham et al. 2013).

6. Heterogeneity, mechanisms, and adaptation

6.1 Heterogeneous effects of salinity exposure

We explore heterogeneity in the impacts of *in utero* exposure on health by child, maternal, and locational characteristics. Please see Section A.3 for a description of these results.

6.2 Agricultural and biodiversity-related losses

Significant reductions in agricultural yields, accompanied with ground water and soil quality degradation have profound impacts on livelihoods (Dasgupta et al. 2015, Khanom 2016).[30] We examine agricultural and bio-diversity related adaptation mechanisms, guided by the intuition that salinization of agricultural lands may have cascading effects on health via impacts on crop systems, aquaculture, livestock, homestead agro-forestry, and land use (Costinot et al. 2016, Waldinger 2022). We use two complementary data sources that provide gridded agricultural/land-use variables in order to undertake this exercise. The first is the annual land cover classifications for the period 1993-2019 provided by the Copernicus Land Monitoring Service (CLMS) with a

[30] This has caused aquaculture to boom over the past few decades as coastal communities adapt to increased salinity by relying more on shrimp cultivation. This in turn worsens the soil salinity problem further as brackish water invades surrounding areas, and leads to a fall in the number of indigenous rice varieties (Rahman et al. 2011).

spatial resolution of 300 m (0.003^0). These are consistent with the annual land cover maps from 1992-2015 produced by the ESA-CCI LC project (Defourny et al. 2017). Using the coordinates of each DHS cluster, we create multiple buffer zones of varying distances and count the total number of each land-use class within each buffer zone to track land-use pattern changes over space and time.[31] As noted above, Figure A3 presents an example of the procedure for the 1999 clusters. The geolocation of clusters is then used to match birth histories with land-use patterns.

We then examine how salinity exposure may drive land use decisions, aiming to shed light on the agricultural mechanism. To do so, we explain annual land use patterns from 1993-2019 for each 30 km buffer from the cluster's center with ocean salinity, pH, average weather conditions, and a set of fixed-effects (including district FE, year FE, and district-year FE). Table 3 presents the results. We find that higher salinity levels are associated with less land used for irrigated crops and more for rainfed crops. This is in line with evidence in Shelley et al. (2016) and Chen et al. (2022), where coastal farmers fallow for the winter dry season (*boro*) and plant rainfed agriculture in the wetter monsoon (*Aman*) season to cope with seasonal salinity exposure. The transition from winter irrigated to monsoon rainfed agriculture is often coupled with using salinity-resistant traditional rice varieties which have significantly lower yields (Shelley et al. 2016, Chen et al. 2022). We also find significant land use responses moving from forests to shrubland when facing higher salinity levels. Taken together, increasing salinity constrains farmers' land use choices and

[31] We create buffer zones of 5 km, 10 km, 20 km and 30 km, but report results only for 30 km given space constraints. Further, to proxy for agricultural cultivated area, we use the IPCC classes representing rainfed cropland and irrigated cropland. To proxy for forestry area, we aggregate the IPCC classes representing tree cover (broad-leaved, needle-leaved, evergreen and deciduous). We also focus on the tree cover flooded with saline water, and on other land-use classes for shrub land, grassland, sparse vegetation, other bare areas, and water. For further details, see the correspondence between the IPCC land categories used for the change detection and the LCCS legend used in the land cover classes provided by the Land Cover Climate Change Initiative - Product User Guide v2. Issue 2.0.

deters the planting of profitable crops such as irrigated rice.[32] The repercussions of higher salinity, such as making cultivation less feasible in the more profitable *Boro* dry-season and requiring a shift back to the *Aman* season, restricts farmers' choices and potentially affects child health through impacts on earnings.[33]

We augment equation (1) with additional land use mediators, including the share of land within a given buffer for rainfed crops, irrigated crops, forests, saline flooded forests (mangroves), wetland, shrubland, and urban settlement. Table 4 presents the results. There is a decrease in the magnitude of the salinity coefficient on HAZ after conditioning on land use patterns by 84% (the coefficient becomes insignificant). This suggests that land use is an important mediating factor for salinity's effects on children's health.

To substantiate the above with more evidence that the agricultural channel is a plausible one explaining the salinity-child health nexus, we use the *History Database of the Global Environment – HYDE 3.2* (Goldewijk et al. 2017) to build indicator variables to proxy for the intensity of agricultural activities. The database provides gridded time series of population and land use from 10,000 B.C to 2017 A.D. The data is available for time intervals 100 years apart until 1700, then 10 years apart till 2000, and in 1-year intervals from 2000-2017. We use the available data from 2000 to 2017 and process the geospatial files for the gridded land use data (available at the 0.083^0 by 0.083^0 degree resolution, or approximately 9 km $\times$ 9 km). We thus

[32] Rice cultivation is pivotal in Bangladesh, accounting for nearly half of rural employment (Islam et al. 2020). It is grown across three seasons: *Aus*, *Aman*, and *Boro*, where the latter two seasons are relatively the more important. *Boro* is characterized by its need for irrigation, as it occurs during the dry period. Due to advanced irrigation methods (shallow and deep tube wells) and high-yielding varieties, *Boro* rice tends to surpass *Aman* rice in yield and profitability (Shelley et al. 2016). Consequently, *Boro* rice cultivation has seen substantial growth in recent decades (Shelley et al. 2016).

[33] It is possible that there is amplified risk from drought for instance, when farmers are forced to rely on rainfed wet season farming. Thus, one climate-induced factor (salinity) forces cultivators to be more exposed to another climate-induced factor (droughts/rainfall uncertainty). We test whether *in utero* exposure to drought has additional significant impacts on child health in the presence of salinity. We find little evidence for this in our study sample.

obtain annual data for total land used for grazing, for pasture, for total rainfed agricultural area, total rainfed agricultural area devoted to the production of rice, and total rainfed agricultural area for other crops (except rice), all measured in square km per grid cell.[34] We then consider the heterogeneous effect of salinity on child health by the intensity of these agricultural activities. Figure 7 reports the coefficients on salinity exposure when different sub-samples are used based on indicator variables for below or above median values for pasture area, grazing area, rice, and rainfed cultivated area.[35] These results provide suggestive evidence that children born in clusters experiencing lower agricultural activities (below median) face more pronounced negative health effects. We note in Figure 7 that the extent and intensity of rainfed agricultural land devoted to rice production and to other crops clearly drive the effects of salinity on child health, as coefficients on salinity exposure for *"rice area"* and *"total rainfed area"* are significant when the samples are restricted to children born in clusters experiencing below median agricultural activities in their year of birth. We conclude that the agricultural mechanism is important in explaining the harmful effects of salinity.

6.3 Early childhood health investments

We test whether the effect of salinity on child health is intensified or mitigated by compensating behaviors of parents (Almond and Mazumder 2011). In Panel A of Table 5 we examine the impact of salinity on post-birth vaccinations. The coefficients are negative suggesting that increased exposure reduces early childhood investments. In results discussed below, we find that these negative impacts originate mainly in the relatively poorer households, which is

[34] Note that this reduces the sample size since we cannot match the data for children in the BDHS who were born between 1994-1999 as annual data are only available from 2000 onwards.

[35] Figure 7 provides illustrative evidence since these categories are themselves likely to reflect changes in land use patterns as a consequence of increased salinity and are thus not exogenous. But we have no clear "before" period in our sample since some level of salinity is likely to have been always present.

suggestive of an income channel. Water and soil salinization lead to crop failure, destroying employment opportunities and resulting in lower agricultural incomes. This could hinder health-related investments in both the prenatal and postnatal stages. Increased opportunity cost of maternal time (Bhalotra et al. 2010, Bharadwaj et al. 2020) due to livelihood losses could also explain the fall in vaccination rates.[36]

In Panel B of Table 5, we consider effects on the number of antenatal visits, prenatal care, medical assistance during delivery, and institutional delivery. In columns (1) and (2), we find that higher salinity reduces the number of antenatal visits and lowers the likelihood of receiving iron tablets during pregnancy. In columns (3) to (6), the dependent variable equals one if prenatal care and medical assistance at birth came from either a doctor or a nurse, respectively. Again, effects are negative. In column (7), *"Delivery: at home"* equals one if the mother reports that she gave birth at home. Greater salinity raises the likelihood of home birth. As we note below, these results mainly arise among the relatively poorer households (similar to Banerjee and Maharaj 2020).

Differences in parental investments in prenatal and postnatal healthcare drive part of the negative effects of *in utero* salinity exposure. In Table A7, we re-estimate the impact of salinity presented in Table 2, conditioning on these variables. We find that receiving antenatal checkups and prenatal assistance from doctors significantly improves children's outcomes, and the effects of salinity become smaller and insignificant.

Drawing on insights from Baird et al. (2011) regarding the significance of gender and birth order, we explore if the effects of salinity on health-seeking behavior differ along these

[36] The literature provides mixed evidence on health shocks, compensating behaviors, and parental investments. Molina and Saldarriaga (2017) finds negative effects of heat shocks on medical assistance at birth in the Andean region. Armand and Taveras (2022) does not observe any significant effect of ocean pH on antenatal and delivery investments. Adhvaryu et al. (2019) finds that health investments reduce the effects of *in utero* dust exposure in West Africa.

dimensions. The results are reported in Table A8. We find that there are little differential impacts in Panel A. In Panel B, it is mostly the sub-sample of non-first-born children who are affected.

6.4 Higher incidence of diseases

Please see Section A.4 for a description of these results.

6.5 Wealth

We analyze the influence of wealth in mediating the impacts of salinity. The BDHS data has a wealth indicator that classifies households in quintiles of the wealth distribution across rounds, constructed using information on assets owned. Since agricultural losses in particular are likely to be concentrated among those who own land (the relatively richer households), we create a binary variable that equals one for households in the top two quintiles of wealth, zero otherwise (the alternate land use measure in BDHS has too many missing values). This indicator thus distinguishes the richest households in the distribution. We begin by investigating the effect of salinity exposure on these households and results are presented in Table A10. These show that salinity reduces the likelihood that households are in the richest quintiles of the wealth distribution.

Given the strong effect of salinity on wealth, we expect that conditioning on the household wealth indicator in the main results of Table 2 will reduce the impact of salinity on outcomes. Results presented in Table A11 confirm this to be the case. Whereas the salinity coefficient was significant in eight of the nine outcomes in Table 2, it is significant in five outcomes in Table A11. Additionally, the household wealth indicator has strong impacts across all columns.

To obtain better insights into the strength of the wealth mechanism, we apply sequential g-estimation and use a two-step method as outlined in Acharya et al. (2016). Our aim is to compare the average treatment effect (ATE) of higher *in utero* salinity exposure with the average controlled direct effect (ACDE).[37] We use the non-linear specification in Panel A of Table A3 to implement this given ease of interpretation. The ACDE indicates what the effect of higher *in utero* levels would be had this mediator not changed, that is, we can obtain the main effect on child outcomes after "de-mediating" the effect of wealth.[38]

The ACDEs of *in utero* salinity net of wealth as a mediator are negative and significant (albeit of lower statistical significance when the outcome is HAZ), indicating that higher levels of salinity would still negatively impact child health outcomes even if there had been no change in wealth. Referring specifically to the difference between the ATEs and the ACDEs of *in utero* salinity, we find that approximately 23.5%, 12.6%, and 17.2% of the total effects are mediated by wealth when the outcomes of interest are HAZ, WAH, and WAZ, respectively.

Finally, we analyze variations in parental investments, health-seeking behavior and prenatal care by wealth status. That is, we differentiate results presented in Table 5 by wealth. These results are shown in Table A12 and reveal that many of the significant results in Table 5 arise among the poorer households.

7. Selective fertility and migration

We address potential selection issues related to fertility, birth, and migration. We start by testing whether exposure to salinity induces gender imbalance. Studies have documented the long-term effects of early-life shocks involving boys' culling and girls' scarring (Catalano and Bruckner 2006, Liu et al. 2014), and that the vulnerability of male fetuses leads to excess male mortality in

[37] The key assumption to identify the ACDE is sequential unconfoundedness (Acharya et al. 2016). In our case, this implies that there should be no omitted variables for the effect of *in utero* salinity exposure on child health outcomes, conditional on the pre-treatment covariates. There should also be no omitted variables for the effect of wealth on the outcomes, conditional on salinity levels, pre-treatment controls, and intermediate confounders.

[38] In the first stage, we regress the child health outcomes on *in utero* salinity exposure (measured as a dummy variable for above median exposure), the mediator, the pre-treatment controls, and the other covariates used as intermediate confounders. In the second stage, we regress a de-mediated version of the predicted child outcome on the treatment, and the pre-treatment covariates. The coefficient on salinity from this second stage regression is the estimated ACDE.

response to negative health shocks (Sanders and Stoecker 2015). In Table A13, we test whether salinity exposure affects the probability that the child is male conditional on the set of controls in equation (1). In column (1) we consider whether *in utero* salinity exposure alone predicts the child's gender. In column (2) we consider the impact of salinity while controlling for the salinity level in the month of conception. In column (3) we consider average exposure in the 2-9 months period during gestation, and in column (4) we include both salinity in the month of conception and in months 2-9 of gestation. In column (5) we consider a nonlinear specification that includes quartiles of salinity levels. None of the estimated coefficients are significant.

Next, we consider survival bias. In this context we note that weaker children are more likely to die, indicating that those children who survive in our sample are positively selected (Dancer et al. 2008). This leads to a conservative bias in our results, that is, our estimates would be even larger in the absence of such positive selection.

We next consider selection on parental characteristics. We demonstrate in Panels A and B of Table A14 that these characteristics do not correlate with salinity exposure (these tests are motivated by Buckles and Hungerman (2013) and Wilde et al. (2017)). In Panel A, the maternal characteristics considered are mother's education (6 and 12 years or less of education) in columns (1) and (2), height in column (3), a dummy variable that equals one if she is currently working in column (4), and mother's age. In Panel B, we consider mother's age at the time of first delivery, the age difference with the household's head, the gender and age of the household head, and father's education (12 years or less of education). There are mostly no effects except in the case of mother's height and father's education which we control for in all models.

Finally, we check whether migration impacts our estimates. In the DHS, we observe how long mothers have been resident in the cluster (community). We employ two checks related to this information. First, we check whether the estimated salinity impact varies by length of residence. We do so by restricting the sample to children whose mothers have lived in the current place of residence for more than 3, 5, 10, 15, and 20 years.[39] The results are presented in Panel A of Figure A6 and show that as compared to the main results in Table 2, the salinity impact is somewhat larger in samples who have been resident in the same location for longer lengths of time. But the fact that even households who have been resident in the area for relatively short time periods are affected suggests that selective out-migration (perhaps by richer households) overtime cannot explain all our findings. We do lose precision beyond 15 years, likely due to small sample size.

Second, we check whether the estimated effect varies by the relative timing between conception and the mother's move to the current community. Children whose mother moved to the current community after conception (5.3% of the sample) may not receive the full length of *in utero* period salinity exposure corresponding to the current community, potentially attenuating our estimates.[40] Panel B of Figure A6 presents these results. We find slightly larger effects for women who have lived in the community since before conception compared to the baseline estimate, although the difference is not statistically significant.

8. Conclusion

This study evaluates the harmful consequences of ocean salinity on the health of very young children in coastal Bangladesh and finds that *in utero* exposure to salinity significantly worsens health in early-life. The main reason for this is because rising salinity reduces agricultural potential – cultivation during the relatively more profitable *Boro* dry-season that requires irrigation

[39] The sample sizes are 4,292, 3,586, 2,295, 1,449 and 919, if we restrict our sample to children whose mothers have lived in the current cluster for more than 3, 5, 10, 15, and 20 years, respectively.

[40] 3.4% of the sample moved to the current community during pregnancy. 1.9% of the sample moved to the current community after birth. These are relatively small proportions and so we do not remove them from our baseline regression.

(as compared to the rainfed *Aman* season) becomes more challenging given the increasing salt content of water used for irrigation. We employ geo-referenced data on ocean salinity merged with child health outcomes from 6 waves of the Bangladesh Demographic Health Surveys to analyze how variations in *in utero* salinity exposure affects children anthropometrics. Our strategy leverages exogenous variations in salinity over time and space (deviations from long run district-specific means), while controlling for the effects of district-specific seasonality and local trends. Our main results indicate that a one standard deviation increase in *in utero* salinity exposure decreases HAZ scores by 0.11 standard deviation (7.7% of the sample mean), while increasing the prevalence of stunting and severe stunting. Similar effects are obtained for WAH and WAZ. We underline the validity of our results with numerous robustness and specification checks.

We demonstrate that higher salinity levels are associated with lower early childhood investments in prenatal and post-birth stages, mostly among poorer households. The absence of compensating behaviors suggests that parental investments in early-life are not mitigation strategies. Where we do find evidence for adaptation is in our analysis of agricultural land use using satellite-sourced information. Here we document suggestive evidence that salinity affects the scale and intensity of agricultural activities, with possible deleterious consequences on incomes, food security, and nutritional intake.

By leveraging exogenous variation in deviations of ocean salinity from long-run trends, our estimates essentially provide a short-run impact assessment. Long-run adjustments over elevated salinity levels could include migration, changing production technology and practices, or labor reallocation. Unfortunately, data constraints prevent us from directly quantifying long-run adaptation to salt intrusion using long differences or other panel data techniques (e.g. Burke and Emerick 2016; Cui 2020; Merel and Gammans 2021; Liu et al. 2023). In the case of migration in particular, to the extent that our data allow, our study shows that at least in the medium run (10-15 years), salinity impacts do not differ between families who stayed and families who recently migrated in.

Our findings have important implications for coastal communities in Bangladesh and in other low-lying countries across the world as climate change induced increases in salinity generate irreversible environmental changes. A clear policy implication is that additional investment in the development of salinity-resistant crop varieties as well as small-scale desalination technologies to provide more livelihood options to farmers.[41] Further, providing health services to women closer to their places of residence and work may help to curtail some of the health costs to very young children that arise due to the increasing opportunity cost of mother's time. Our results highlight that a comprehensive assessment of the effects of salinity is essential to increase resilience and to minimize catastrophic fallouts on human health, income, and well-being.

[41] To overcome salinity challenges, communities have adopted strategies such as seasonal water storage, desalination, rainwater harvesting, crop rotation, and transitioning from rice cultivation to alternative crops or marine aquaculture. Hossain et al. (2018) suggests mechanisms for recharging groundwater resources, and emphasizes the need for coastal land zoning to strike a balance between shrimp farming and crop-agriculture. Khanom (2016) stresses the value of educating farmers on the adoption of salt-tolerant crops, and diversification. Dasgupta et al. (2018) spotlights government efforts in promoting salt-resistant rice varieties, underscoring farmer education on cultivation techniques and the importance of farmer adaptability. Mazumder and Kabir (2022) advocate for Climate-Smart Agriculture (CSA) techniques, and collaborative initiatives among governmental agricultural services, NGOs, and rural advisories. Several recent reports highlight the urgency for Bangladesh to strengthen its protective polders in coastal areas (World Bank 2022). The Coastal Embankment Improvement Project (CEIP) stands out as a crucial effort to bolster the resilience of coastal regions against tidal floods, storm surges, and salinity intrusion. CEIP encourages community participation and involves strengthening embankments and developing hydraulic infrastructures. The $400 million project, funded jointly by the World Bank and other sources, was approved in 2013 with a projected completion date of December 2023. As a result of this important initiative, over 400,000 people, half of them women, have been protected against tidal flooding and storm surges. By December 2021, the project had strengthened 249 km of embankments, constructed over 100 hydraulic structures, and cleared several kilometers of drainage channels. This has significantly increased agricultural productivity in the project areas.

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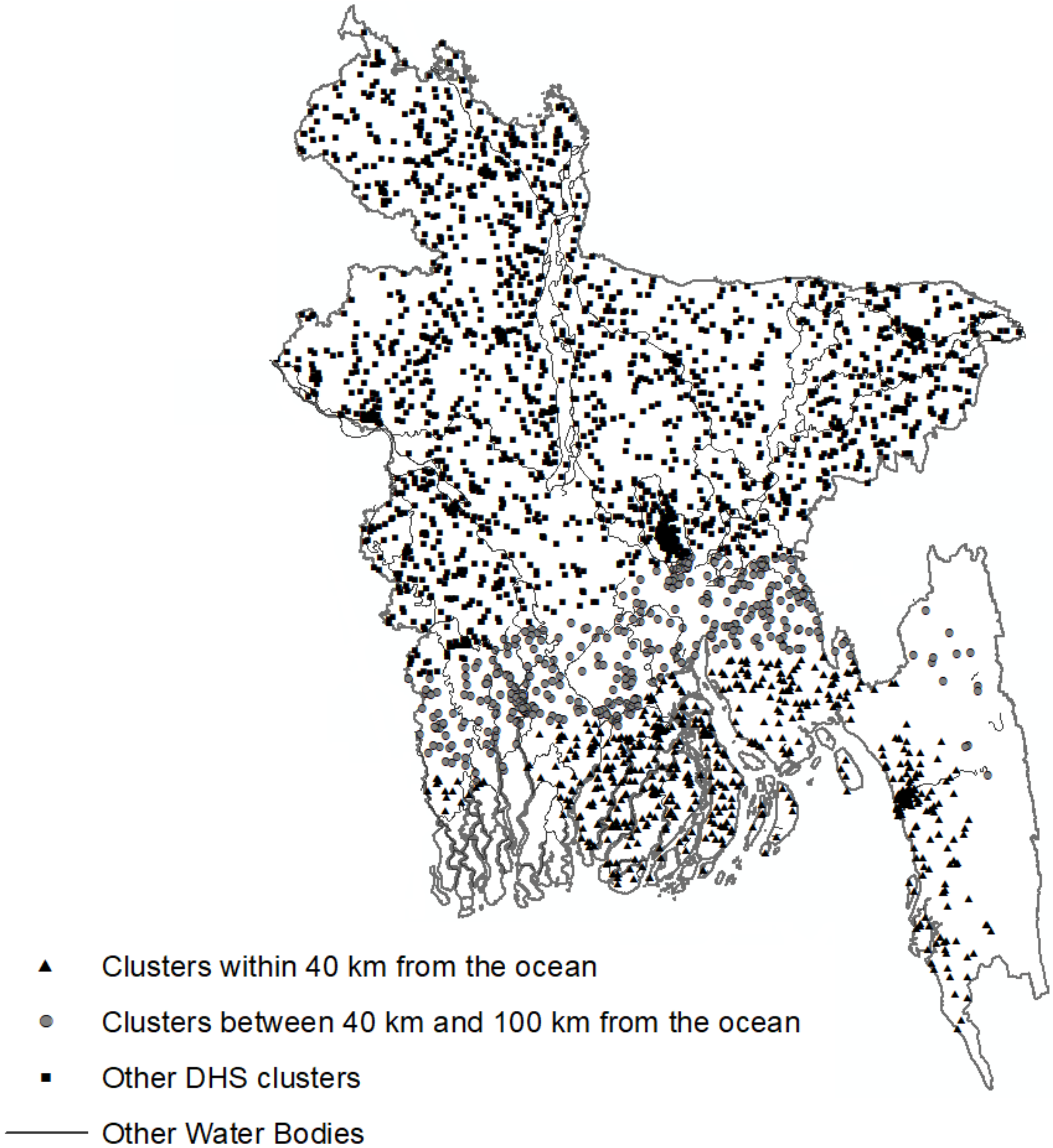
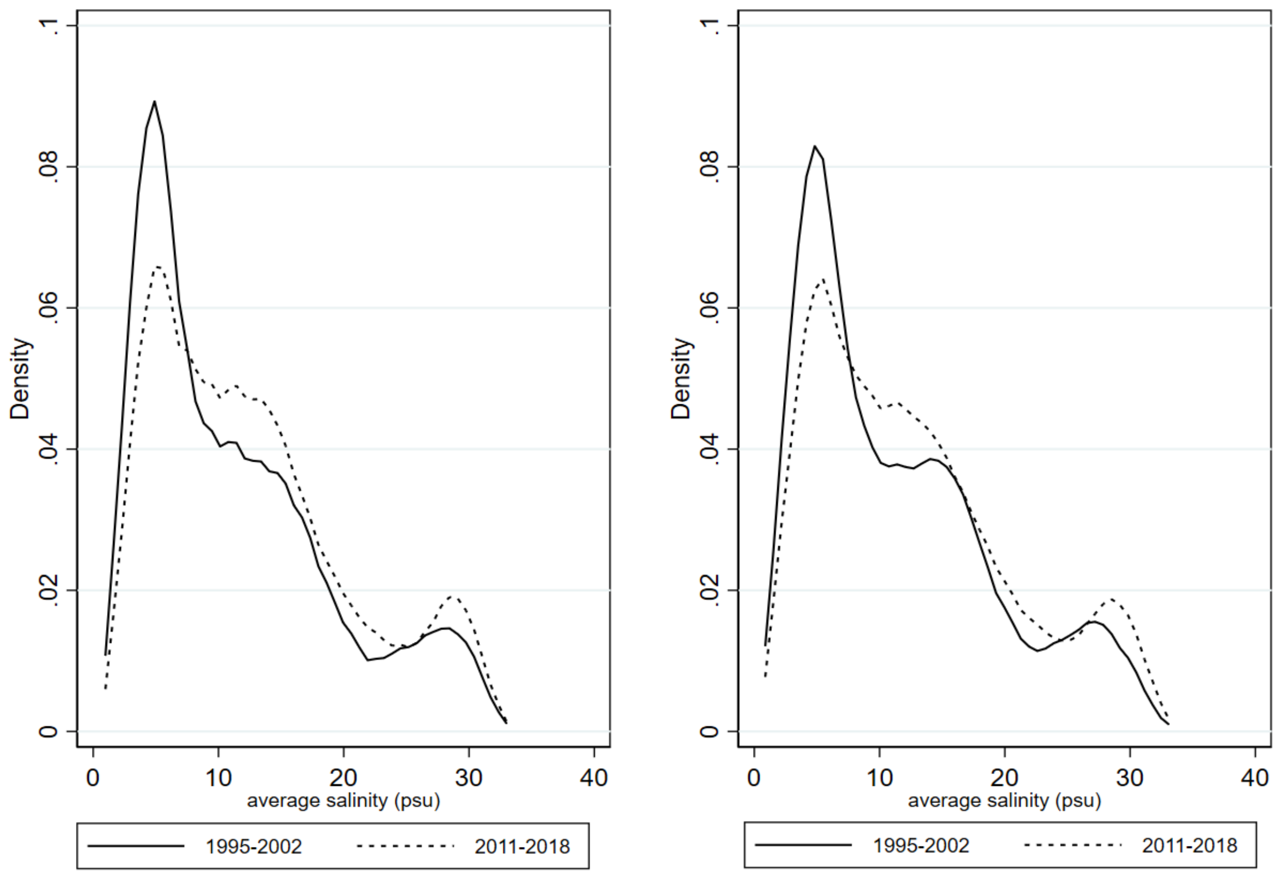
Figure 1: BDHS coastal communities



Notes: Figure 1 shows the location of all BDHS clusters in our sample. The black triangles represent coastal clusters that are within 40 km from the ocean. The gray circles represent coastal clusters that are between 40 km and 100 km from the ocean. The black squares represent all the other DHS clusters. Data citation: Wessel, P., and Smith, W. 1996. A Global Self-consistent, Hierarchical, High-resolution Shoreline Database, *Journal of Geophysical Research*, 101, 8741-8743.

Figure 2: Kernel densities of salinity 1995-2018

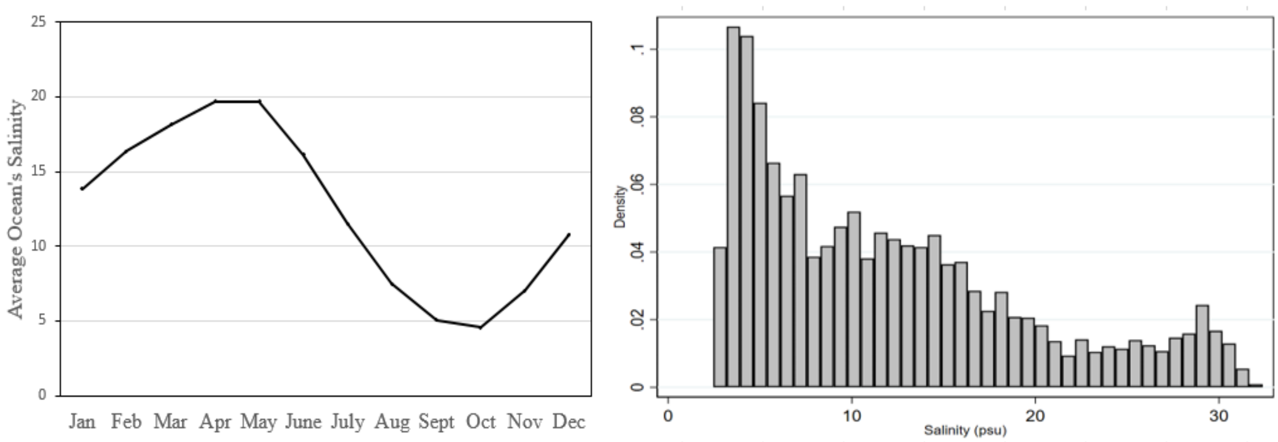
Panel A: All Coastal Communities **Panel B: Vulnerable Coastal Communities**



Notes: Authors' calculations using the Copernicus Marine Environment Monitoring Service (CMEMS) for two periods. Panel A shows the kernel density for ocean's salinity for clusters within 100 km of the ocean (coastal communities). Panel B shows the kernel density for ocean's salinity for clusters within 40 km of the ocean (vulnerable coastal communities). To match the gridded salinity data to the cluster level, we use the IDW method as explained in the text.

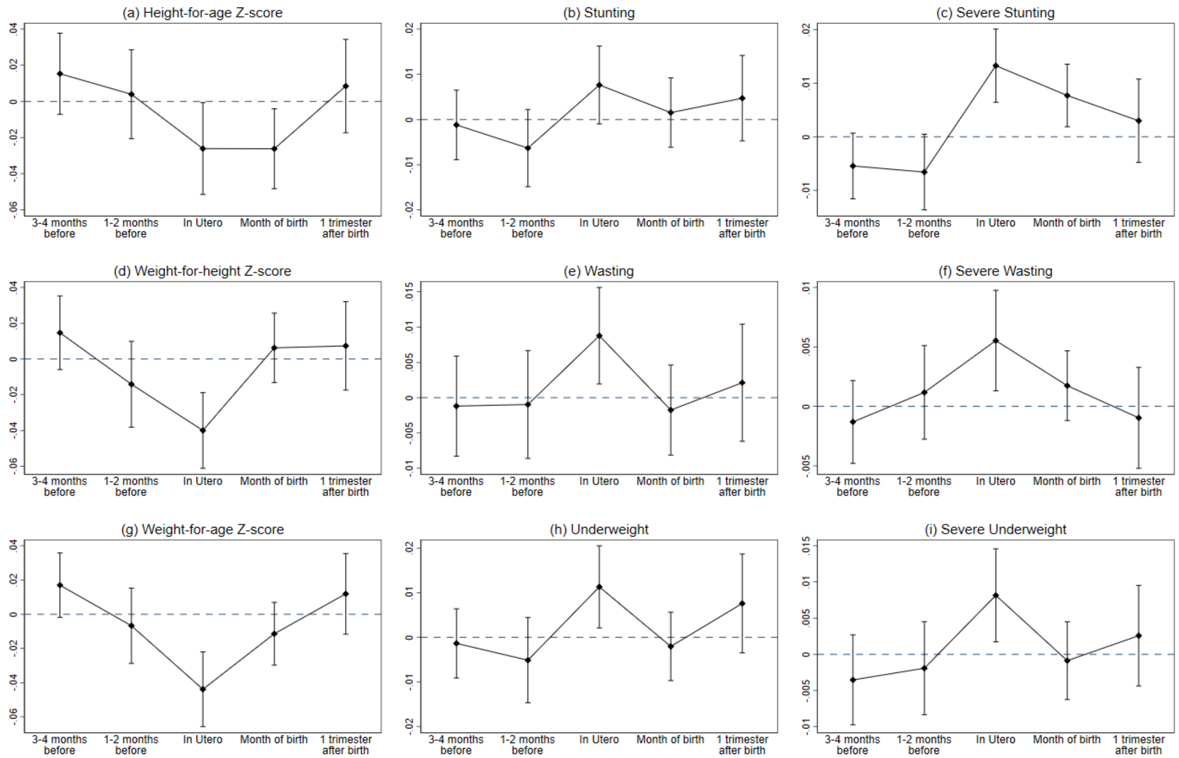
Figure 3: The seasonality and distribution of salinity in coastal communities

Panel A: The Seasonality of Salinity **Panel B: The Distribution of Salinity**



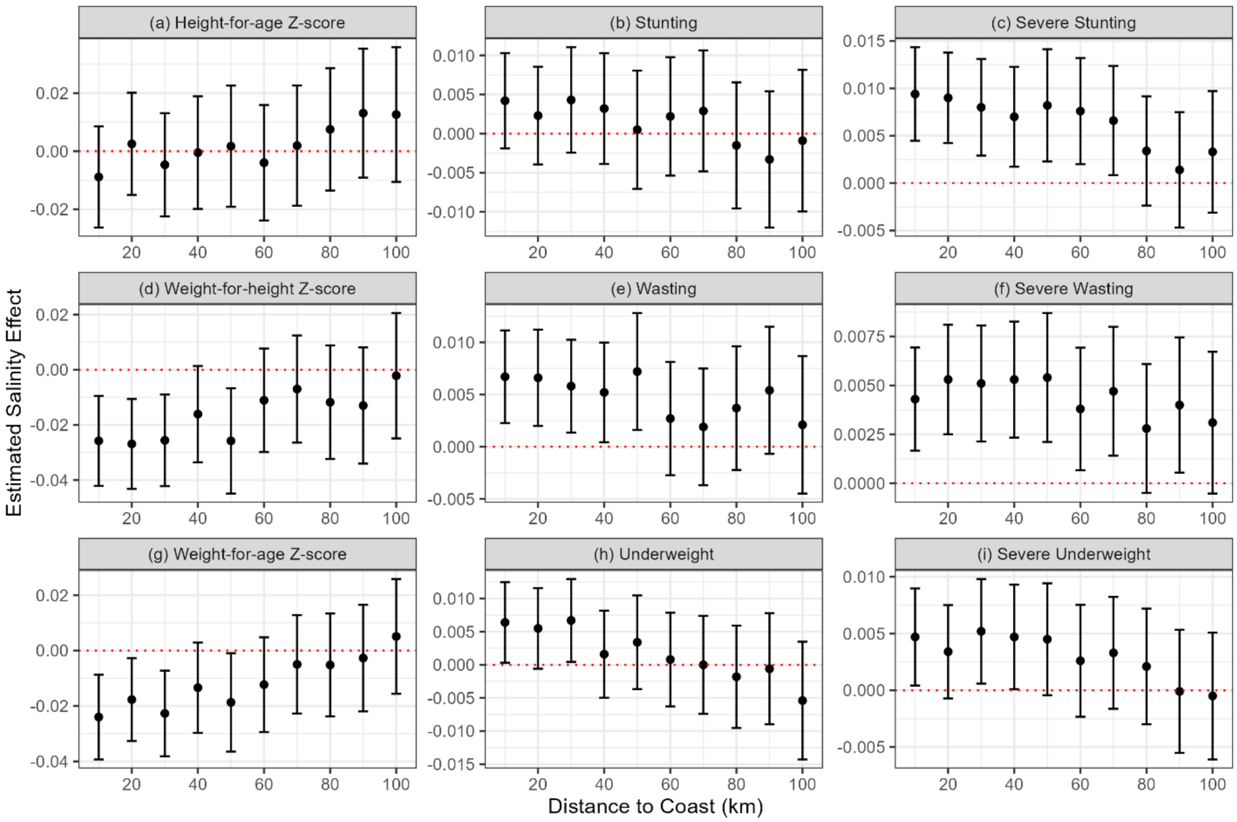
Notes: Authors' calculations using the Copernicus Marine Environment Monitoring Service (CMEMS). Panel A shows the seasonality of salinity (average salinity for each month over all the years) for all coastal communities in our data (ocean points matched to clusters in all coastal communities). Panel B shows the distribution of salinity in the data for all coastal communities. To match the gridded salinity data to the cluster level, we use the IDW method as explained in the text.

Figure 4: The effects of salinity on child health, controlling for salinity levels before conception and after birth



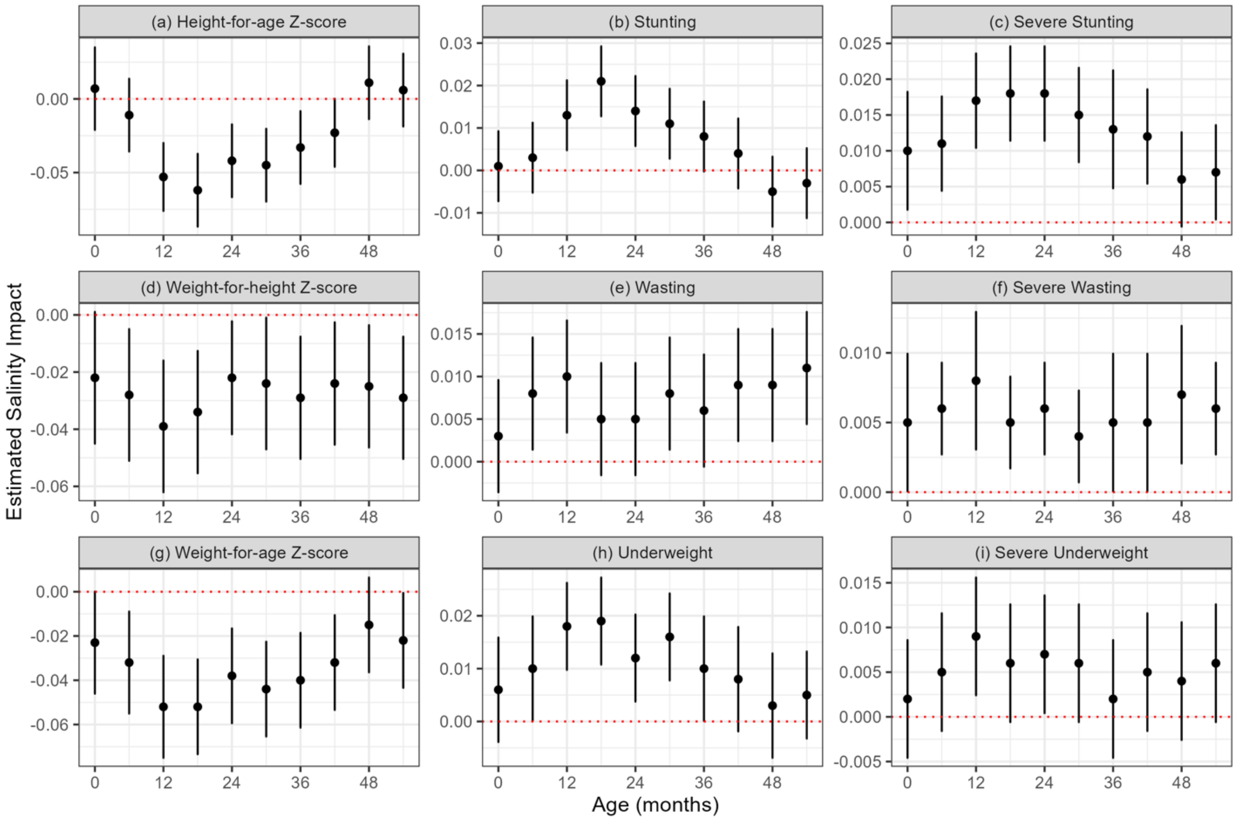
Notes: The data shows the coefficients of salinity exposure (at different times in the baseline specification). We augment equation (1) with controls for the average salinity levels 1-2 months before conception, 3-4 months before conception, in the month of birth, and one trimester after birth. The sample is restricted to DHS clusters that are within 40 km from the ocean. We use the same set of controls, spatial and temporal fixed-effects as reported in Table 2. Confidence intervals are reported at 90% level. The timing of exposure is shown on the horizontal axis, and corresponding point estimates are shown on the vertical axis. This falsification test is similar to Molina and Saldarriaga (2017) and Armand and Taveras (2022).

Figure 5: Spatial spillovers of salinity exposure on child health



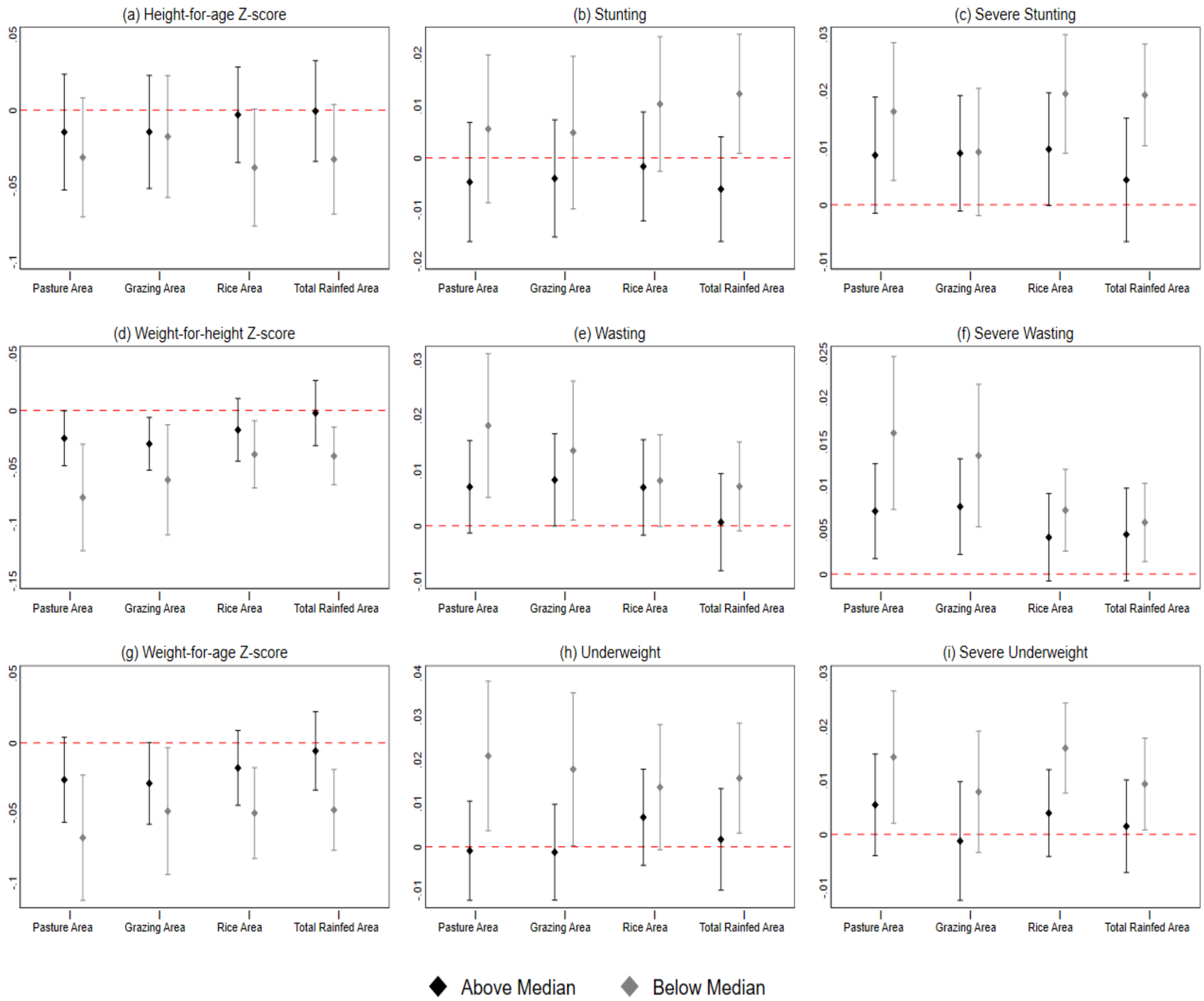
Notes: The panel shows the spatial spillover of *in utero* salinity impact on health outcomes by distance to the coastline. Each sub-panel represents one regression model, which include the interaction between salinity and distance bands indicating the distance between the cluster and the coastline. All regressions include child, mother, household, and weather controls, and ocean's pH levels used in the main regression analysis. The same set of spatial and temporal fixed-effects are used. Please see Table 1 for details on dependent variables and controls. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. Error bar represents 90% confidence interval.

Figure 6: Persistence of salinity exposure through early childhood



Notes: The panel shows the persistence *in utero* salinity impact on health outcomes by age of children. Each sub-panel represents one regression model, which include the interaction between salinity and age bands indicating the age of the child at the time of the survey, from 0-6 months to 54-60 months. All regressions include child, mother, household, and weather controls, and ocean's pH levels used in the main regression analysis. The same set of spatial and temporal fixed-effects are used. Please see Table 1 for details on dependent variables and controls. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. Error bar represents 90% confidence interval.

Figure 7: Heterogeneous effects of salinity exposure on child health, by intensity of agricultural activities



Notes: The panel shows the heterogeneous effects of salinity while *in utero* on health outcomes by intensity of agricultural activities as proxied by indicator variables for below or above sample median values for pasture area, grazing area, rice, and rainfed cultivated area. Estimates are from equation (1). Each coefficient is computed in separate regressions where the sample is restricted to the corresponding group. All regressions include child, mother, household, and weather controls, and ocean's pH levels used in the main regression analysis. The same set of spatial and temporal fixed-effects are used. Please see Table 1 for details on dependent variables and controls. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. Confidence intervals are reported at 90% level.

Table 1: Summary statistics of selected variables

	Mean	Std. Deviation
	(1)	(2)
Panel A: health outcomes		
Height-for-age z-score (HAZ)	-1.804	1.417
Stunting (HAZ < 2 SD)	0.451	0.498
Severe stunting (HAZ < 3 SD)	0.190	0.392
Weight-for-height z-score (WAH)	-0.910	1.130
Wasting (WAH < 2 SD)	0.146	0.353
Severe wasting (WAH < 3 SD)	0.032	0.177
Weight-for-age z-score (WAZ)	-1.671	1.153
Underweight (WAZ < 2 SD)	0.390	0.488
Severe underweight (WAZ < 3 SD)	0.119	0.323
Panel B: ocean chemistry variables		
Ocean salinity (psu)	12.591	4.396
Ocean's pH level	8.199	0.045
Panel C: weather-related variables		
Minimum temperature (deg. Celcius)	18.691	1.660
Maximum temperature (deg. Celcius)	33.872	0.797
Rainfall (mm, logs)	5.360	0.402
Humidity (%)	81.274	2.466
Panel D: child, mother, household controls		
Child's age (months)	29.307	17.298
Child is male	0.503	0.500
Child birth order	2.691	1.794
Mother's age at first birth	17.950	2.957
Mother's height	150.895	5.328
Mother has no education	0.240	0.420
Father has no education	0.260	0.440
Head of household is male	0.871	0.335

Notes: The data sources include the BDHS 1999, 2004, 2007, 2011, 2014, and 2017, and the Copernicus Marine Environment Monitoring Service (CMEMS). The sample is restricted to coastal communities living within 40 km of the ocean.

Table 2: The effects of salinity exposure on child health

	Dependent Variables:								
	HAZ	Stunted (HAZ < 2 SD)	Severely Stunted (HAZ < 3 SD)	WAH	Wasted (WAH < 2 SD)	Severely Wasted (WAH < 3 SD)	WAZ	Underweight (WAZ < 2 SD)	Severely Underweight (WAZ < 3 SD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Sample of DHS Coastal Clusters Within 40 km									
salinity exposure	-0.025*	0.007*	0.013***	-0.029**	0.007**	0.006***	-0.035***	0.011**	0.005
(in utero)	(0.013)	(0.004)	(0.004)	(0.011)	(0.003)	(0.002)	(0.012)	(0.005)	(0.004)
Observations	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
Mean of dependent variable	-1.804	0.451	0.190	-0.910	0.146	0.033	-1.672	0.39	0.119
R-squared	0.323	0.278	0.227	0.169	0.151	0.162	0.268	0.218	0.182
Panel B: Sample of DHS Coastal Clusters Within 100 km									
salinity exposure	-0.007	0.004	0.009***	-0.026***	0.007**	0.005***	-0.023**	0.007*	0.005*
(in utero)	(0.011)	(0.004)	(0.003)	(0.009)	(0.003)	(0.002)	(0.010)	(0.004)	(0.003)
Observations	12,544	12,544	12,544	12,544	12,544	12,544	12,544	12,544	12,544
Mean of dependent variable	-1.727	0.422	0.167	-0.837	0.134	0.029	-1.574	0.353	0.102
R-squared	0.299	0.255	0.216	0.164	0.131	0.115	0.263	0.204	0.164
Child, mother, household controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ocean chemistry control (pH)	✓	✓	✓	✓	✓	✓	✓	✓	✓
District, year of birth, month of birth FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year of birth x month of birth FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
District x month of birth FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
District x year of birth FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table shows the coefficients of salinity exposure (measured as the average level 9 months prior to birth). The dependent variables in columns (1), (4), and (7) for height-for-age z-score, weight-for-height z-score, and for the weight-for-age z-score, respectively, are continuous. Dependent variables in columns (2), (5), and (8) are binary variables that equal to one if the child is stunted, wasted, and underweight, respectively, while in columns (3), (6), and (9), the binary variables equal to one if the child is severely stunted, severely wasted, and severely underweight, respectively. The child, mother, household controls include the child's age (in months) and gender, child birth order, mother's age at first birth, a dummy variable that equals to one if the mother has no education, a dummy variable that equals to one if the father has no education, mother's height, and the gender of the household head. Weather controls include minimum and maximum temperature, rainfall (in logs), the interaction between minimum and maximum temperature and log of rainfall, and humidity. We also control for the ocean's pH levels. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. Panel A considers the sub-sample of DHS clusters that are within 40 km of the ocean while Panel B considers the sub-sample of DHS clusters that are within 100 km of the ocean. ***p<0.01, **p<0.05, *p<0.1.

Table 3: The effects of salinity exposure on land use

	Dependent Variables: Share of land within a given buffer for:						
	rainfed cropland	irrigated cropland	forest	saline flooded forest	wetland	shrubland	urban settlement
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
annual salinity exposure	0.0071***	-0.0225***	-0.0005	0.0039***	-0.0001***	0.0091***	-0.0013***
	(0.0012)	(0.0030)	(0.0010)	(0.0007)	(0.0000)	(0.0018)	(0.0002)
annual pH exposure	0.4414***	-0.4841	0.2131	0.4562***	0.0188***	1.1418***	-0.2159***
	(0.1191)	(0.3024)	(0.1332)	(0.1147)	(0.0045)	(0.2261)	(0.0272)
annual rainfall	0.0003***	-0.0010***	-0.0000	0.0002***	0.0000	-0.0001	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
annual humidity	-0.0014	0.0154***	-0.0143***	-0.0040***	-0.0005***	-0.0051***	-0.0023***
	(0.0029)	(0.0058)	(0.0025)	(0.0012)	(0.0001)	(0.0014)	(0.0003)
annual max temperature	-0.0182**	0.2034***	0.0481***	-0.0061	0.0018***	0.0196***	-0.0001
	(0.0071)	(0.0190)	(0.0068)	(0.0043)	(0.0003)	(0.0065)	(0.0009)
annual min temperature	-0.0363***	0.2370***	0.0536***	-0.0017	0.0013***	0.0267***	-0.0004
	(0.0089)	(0.0211)	(0.0092)	(0.0055)	(0.0004)	(0.0078)	(0.0012)
annual dry temperature	-0.0109	-0.3456***	-0.1078***	0.0177***	-0.0021***	-0.1200***	0.0029
	(0.0200)	(0.0294)	(0.0206)	(0.0068)	(0.0007)	(0.0168)	(0.0032)
Observations	16,536	16,536	16,536	16,536	16,536	16,536	16,536
R-squared	0.6974	0.7911	0.6459	0.6106	0.6723	0.7830	0.8478

Notes: This table shows the impact of annual oceanic and local weather variables on land use choices. Each observation represents a 30-km buffer zone centered around a cluster that is within 40 km from the ocean. Dependent variables are percentages of land within the 30-km buffer that are devoted to those land use categories. All independent variables are aggregated by calendar year to match with the temporal interval of the dependent variables. All regressions include district-year fixed-effects. Robust standard errors presented in parentheses, clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table 4: The effects of salinity exposure on child health conditioning on land use

	Dependent Variables:								
	HAZ	Stunted	Sev. Stunted	WAH	Wasted	Sev. Wasted	WAZ	Underweight	Sev. Unwt.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sample of DHS Coastal Clusters Within 40 km								
salinity exposure	-0.004	0.001	0.008**	-0.026*	0.008**	0.005**	-0.021	0.006	0.000
(in utero)	(0.014)	(0.005)	(0.004)	(0.014)	(0.004)	(0.002)	(0.013)	(0.005)	(0.003)
rainfed cropland	1.187*	-0.189	-0.213	0.012	-0.093	-0.253***	0.781	-0.226	-0.170
	(0.608)	(0.215)	(0.153)	(0.517)	(0.163)	(0.082)	(0.520)	(0.210)	(0.154)
irrigated cropland	0.350	-0.050	-0.069	-0.234	0.105*	0.019	0.075	0.041	-0.044
	(0.217)	(0.078)	(0.065)	(0.184)	(0.053)	(0.029)	(0.177)	(0.071)	(0.052)
forest	2.394***	-0.521*	-0.688***	0.813	-0.160	-0.375***	2.038***	-0.812***	-0.380*
	(0.710)	(0.273)	(0.212)	(0.653)	(0.186)	(0.096)	(0.592)	(0.251)	(0.199)
saline flooded forest (mangroves)	0.062	0.060	-0.145	0.212	-0.006	-0.095	0.320	-0.133	-0.206*
	(0.655)	(0.240)	(0.158)	(0.529)	(0.160)	(0.066)	(0.495)	(0.199)	(0.123)
wetland	-21.338	4.942	-0.466	16.989	-5.426	0.610	-2.308	-2.362	-2.696
	(16.145)	(6.061)	(4.636)	(14.020)	(4.007)	(2.016)	(13.332)	(5.911)	(3.811)
shrubland	-1.095**	0.399**	0.334**	-0.323	0.094	0.274***	-1.010	0.346*	0.341***
	(0.538)	(0.201)	(0.147)	(0.664)	(0.131)	(0.090)	(0.652)	(0.206)	(0.128)
urban settlement	2.645	-1.168	0.735	1.574	-0.538	0.185	2.273	-1.664	-0.245
	(2.900)	(1.125)	(0.791)	(2.971)	(0.769)	(0.425)	(2.755)	(1.057)	(0.610)
Observations	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.326	0.279	0.232	0.170	0.152	0.168	0.272	0.222	0.186

Notes: This table reports coefficients of salinity exposure (measured as the average level 9 months prior to birth). The dependent variables in columns (1), (4), and (7) for height-for-age z-score, weight-for-height z-score, and for the weight-for-age z-score, respectively, are continuous. Dependent variables in columns (2), (5), and (8) are binary variables that equal one if the child is stunted, wasted, and underweight, respectively, while in columns (3), (6), and (9), the binary variables equal to one if the child is severely stunted, severely wasted, and severely underweight, respectively. The child, mother, household controls include the child's age (in months) and gender, child birth order, mother's age at first birth, a dummy variable that equals if the mother has no education, a dummy variable that equals one if the father has no education, mother's height, and the gender of the household head. Weather controls include min. and max. temp., rainfall (in logs), interactions between min. and max. temp. and log of rainfall, and humidity. We also control for the ocean's pH levels. The land use variables here represent the share of land within a 30 km buffer from each cluster. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. We consider the sub-sample of DHS clusters that are within 40 km of the ocean. ***p<0.01, **p<0.05, *p<0.1.

Table 5: The impact of salinity on parental investments, health-seeking behavior, and prenatal care

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Sample of DHS Coastal Clusters Within 40 km						
	Early Investments in Child Health: Vaccination Received						
	Polio 1	Polio 2	BCG	DPT 1	DPT 2	Measles	Tetanus
salinity exposure	-0.006*	-0.011**	-0.004	-0.005	-0.011**	-0.011**	-0.012*
(in utero)	(0.003)	(0.005)	(0.003)	(0.004)	(0.005)	(0.005)	(0.007)
Observations	7,410	7,389	7,408	7,408	7,408	7,384	4,198
R-squared	0.316	0.377	0.269	0.315	0.371	0.505	0.263
	Panel B: Sample of DHS Coastal Clusters Within 40 km						
	Prenatal Care and At Birth Investments						
	No. of antenatal visits	Received iron tablet	Prenatal care: Doctor	Prenatal care: Nurse	Assistance at birth: Doctor	Assistance at birth: Nurse	Delivery: at home
salinity exposure	-0.139***	-0.017**	-0.017***	-0.006*	-0.008**	-0.013***	0.018***
(in utero)	(0.031)	(0.007)	(0.005)	(0.003)	(0.004)	(0.005)	(0.005)
Observations	5,857	3,672	5,856	5,856	6,845	6,845	6,836
R-squared	0.364	0.339	0.370	0.180	0.283	0.325	0.286
Child, mother, household controls	✓	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓	✓
Ocean chemistry control (pH)	✓	✓	✓	✓	✓	✓	✓
District, year of birth, month of birth FE	✓	✓	✓	✓	✓	✓	✓
Year of birth x month of birth FE	✓	✓	✓	✓	✓	✓	✓
District x month of birth FE	✓	✓	✓	✓	✓	✓	✓
District x year of birth FE	✓	✓	✓	✓	✓	✓	✓

Notes: This table shows the coefficients of salinity exposure (measured as the average level 9 months prior to birth). The child, mother, household controls include the child's age (in months) and gender, child birth order, mother's age at first birth, a dummy variable that equals to one if the mother has no education, a dummy variable that equals to one if the father has no education, mother's height, and the gender of the household head. Weather controls include minimum and maximum temperature, rainfall (in logs), the interaction between minimum and maximum temperature and log of rainfall, and humidity. We also control for the ocean's pH levels. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. Panel A considers the sub-sample of DHS clusters that are within 40 km of the ocean, and the dependent variables are coded as 1 if the child has received the type of vaccination presented in each column. In Panel B, we consider the same sample of coastal communities, and the dependent variable is continuous in column (1) for the number of antenatal visits. The other outcome variables in columns (2) to (7) are binary variables that equal to one if the mother received iron tablet during pregnancy, prenatal care, assistance at birth, and if delivery happened at home, respectively. ***p<0.01, **p<0.05, *p<0.1.

APPENDIX

Section A.1

In Panel A of Table A2 in the Appendix, the results on child health outcomes remain robust when we use the sum of monthly salinity values (in logs) for the 9 months prior to birth as the source of variation. In Panel B, we retain average *in utero* salinity but also control for the number of months in which salinity exceeds the cluster's mean (by at least one standard deviation) as a measure of intensity. The estimates for the main variable of interest are in the same ballpark as those from the main analysis. In Panel C, we use the standard deviation of salinity in the 9 months before birth as the variable of interest. The results show that higher salinity dispersion is also associated with deteriorating child health outcomes. We exclude the southwestern districts from the sample of vulnerable coastal areas in Panel D, given the exceptionally high levels of salinity there. The coefficients remain in the same ballpark. In Panel E, we assume a gestation period of 10 months; our main results mostly do not change. In Panel F, we retain *in utero* exposure as the treatment variable while simultaneously including average salinity in the month and year of birth. We note that the salinity impact from the month and year of birth is not statistically significant by itself, nor does it change the magnitude of the estimated impact of *in utero* salinity exposure significantly.

[1] As a falsification check that salinity intrusion and not differences in rainy/dry seasons drives our results, we restrict our sample to coastal communities living within 50 to 100 km from

[1] There is additional noise added however in the case of two of the three outcomes related to HAZ. But adding up the point estimates for *in utero* and the month and year of birth coefficients yields a total impact of salinity on HAZ that is of a similar magnitude (-0.028) to our main specification (-0.025). This is possible since we cannot control for day of birth, and so some children may be exposed for a relatively longer period of time to levels in their month of birth depending on the point in time when they are born. Furthermore, we considered another specification that conditions on the standardized measure of salinity and other controls where the standardization is with respect to the cluster-level means. However, this method soaks up all between cluster variation within upazilas. We also considered using mother fixed-effects to focus on the temporal variations in *in utero* salinity among children born to the same mother. We are

the coast, hypothesizing that these populations experience comparable rainy seasons to those on the coast but face lower salinity levels. Consistent with expectations, results in Panel G (which align with insights on the spatial spillovers of salinity in Figure 5) are insignificant. In Panel H, we include cluster fixed-effects in our baseline models along with district-month and district-year of birth fixed-effects.[2] We lose significance for two outcomes relative to our main results, likely because the inclusion of cluster fixed-effects in addition to district fixed-effects interacted with time fixed-effects reduces the identifying variation (the estimated effects for WAZ and WAH are also somewhat larger). Panel I demonstrates the robustness of our findings when standard errors are clustered at the district level.[3] We incorporate average temperature for each month of gestation in Panel J, alongside our set of climatic controls to find little difference. In Panel K of Table A2, we augment our baseline specification with additional ocean physics controls including quantiles of sea surface height, median sea surface temperature and ocean wind velocity, to check for robustness.[4] This also serves to control for factors such as storm surges which can impact local livelihoods.[5] In general, results on WAH and WAZ remain

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unable to implement this given the substantial increase in the number of parameters to be estimated (due to the large number of mothers in the sample) relative to sample size, similar to the issue we face in including cluster fixed-effects in this study.

[2] While potentially controlling for issues such as sorting, including more disaggregated levels of fixed-effects in cross-sectional data diminishes identifying variation. Following Balietti et al. (2022), which makes this point, Figure A4 plots the standard deviation for salinity with fixed-effects of different granularities. When cluster fixed-effects are included, the identifying variation drops by about four-fold. Thus, following Balietti (2022), we include regional level fixed-effects (district-level) in the main specification.

[3] This addresses the fact that clustering standard errors at the level of the DHS cluster may create spatial correlation mechanically if nearby clusters are likely matched to the same unit of grid cell data for salinity. Since clustering at the higher level of districts does not change our results appreciably, mechanical spatial correlation is unlikely.

[4] We include dummy variables for the 20^{th}, median, and 80^{th} percentile of sea surface height.

[5] Only 7 tidal gauges across the Bangladeshi coast record storm surge data. The spatial variation is thus insufficient for our purposes. Instead, we proxy storm surge events using sea surface height, as we note above, to find that across different models, predictions at actual tidal gauges measurements are best at the median level of sea surface height (R^2 is highest and equals 0.40 when using median sea surface height to predict 95^{th} tidal gauge readings). We thus use this benchmark value (along with the 20^{th} and 80^{th} percentile values) of sea surface height in these checks.

unaltered. We lose some precision in the case of HAZ, but the sign and magnitude of the coefficient remains about the same.

In Table A3, we replace our variable of interest with binary variables constructed using the sample distribution of salinity to account for non-linearities in effects. In Panel A, we condition on an indicator variable that equals one if salinity is greater or equal to the 50th percentile value (corresponding to a salinity value of 11.3 psu). The results suggest that children exposed to above median *in utero* salinity levels experience worse health. In Panel B, we use quartiles of salinity exposure and include three indicator variables that each equal one if the child experienced *in utero* salinity levels equal to the second, third, or fourth quartile range of values.[6] The results show that relative to the lowest quartile exposure (the omitted category), children in the third and fourth quartiles particularly have lower HAZ, WAH, and WAZ, and higher prevalence of severe stunting, wasting, and underweight. In Panel C, we exclude the southwestern districts from the sample in Panel B to show that results hold.

Section A.2

We disaggregate the exposure variable by trimester to understand whether there are gestational periods in which the effects of salinity are more pronounced. This involves estimating a variant of our baseline model in equation (1) where $\beta Salinity_{cdmt}$ is replaced with three variables for mean salinity exposure in the first, second, and third trimesters. The results are presented in Table A4. Stunting is mainly caused by exposure to salinity in the second trimester: a one SD increase in salinity decreases HAZ by 0.18 SDs, increases the chance of stunting by 5.7 percentage points, and the chance of severe stunting by 7.1 percentage points. Wasting is mainly caused by exposure to salinity in the first trimester (with mild impacts from exposure in the third

[6] For the lowest quartile, salinity ≤ 9.3 psu, second quartile: 9.3-11.3 psu, third quartile: 11.3-15.4 psu, and for the top quartile: salinity ≥ 15.4 psu.

trimester): a one SD increase in salinity exposure in the first trimester decreases WAH by 0.16 SDs. Results for WAZ suggest that second trimester exposure matters. The second trimester is when the fetus is in advanced stages of physical and neurological development while the third trimester is when most of the weight gain occurs. Impacts on HAZ and WAZ are thus consistent with this course of development. However, since exposure across the gestational cycle probably cannot be judged independently, we are reluctant to pinpoint the only trimester that matters significantly for these outcomes.

Section A.3

As we note above, these analyses focus on the most vulnerable households living within 40 km of the ocean. Results are presented in Tables A5 and A6. In Panel A of Table A5, we estimate impacts by gender of the child which we use as a benchmark for several reasons. It could be that there exists gender-biased early childhood health investments by parents (Asadullah et al. 2021, Bharadwaj et al. 2020) in favor of boys (a possibility that we explore below). Or the decline in income caused by progressive salinization could differentially impact prenatal care and health-seeking behavior, affecting girls' health disproportionately (also explored below). It could also be that the relative vulnerability of male fetuses to adverse shocks leads healthier boys to survive to term and then to depict better health outcomes post-birth (Gualtieri and Hicks 1985, Kraemer 2000, Sanders and Stoecker 2015). We investigate below whether this is true in our sample by evaluating the association between salinity exposure and the probability that the child's gender is male. Returning to the results, the estimates using sub-samples restricted to female children point to larger negative effects in many of the outcomes.

In Panel B, we consider heterogeneous effects of salinity across birth order. We see that while salinity has a detrimental impact on all children, in general, children of higher parity are more negatively affected relative to first-born children. This result is likely due to intrafamily resource constraints such that when the number of children in the household increases, parental investments decrease (Becker and Tomes, 1976; Li et al. 2008).[7]

We then use mother's height as an indicator of mother's health in Panel C. We split the sample by median mother's height, and document evidence that children of relatively shorter mothers are more negatively impacted. In Panel D, we run separate regressions for the sample of children whose mothers work outside of the home versus those whose mothers are not engaged in this manner. We measure effects relatively more precisely mostly for children whose mothers do not work. Children of unemployed mothers are potentially more exposed to the health damages of salinity. Working mothers who are likely educated may have access to knowledge on how to protect their children, or have recourse to more effective mitigation strategies.[8]

In Table A6, we consider sub-samples created based on location characteristics where population density and built-up area are used as proxies for the level of urbanization. In Panel A, we find that the response of outcomes to salinity is greater in areas with population density below the sample median. The results in Panel B, where we use total built-up area (measuring the number of towns, cities, and other buildings in squared km per grid cell), lend support to these findings.[9]

In Figure A5, we consider whether children conceived in different times of the year are affected by salinity exposure differentially, given that during the monsoon season, precipitation attenuates salinity impacts. We focus on month of conception since it is usually the case that mothers are unaware of being pregnant, and so we are more confident that adaptive behaviors have

[7] We show that the negative effects of salinity on prenatal care and at birth investments are more pronounced for non-first born children below.

[8] The differences by gender of the child are not statistically significant. However, there is a consistent pattern in which the more vulnerable children (girls, those born later with relatively shorter and potentially uneducated mothers) are especially susceptible. Our reasoning in reporting coefficients by gender follows Rocha and Soares (2015).

[9] The data are available from HYDE 3.2, a data source on which we elaborate below.

not been adopted. Panel A of Figure 3 shows that salinities levels are highest in the second quarter (Apr-Jun) and lower in the third quarter (Jul-Sep) when the monsoons arrive. Correspondingly, we find that for HAZ, stunted, WAZ and underweight in particular, detrimental effects are larger for children conceived in the second quarter relative to those conceived in the third quarter. The estimates for the other outcome measures are noisier.

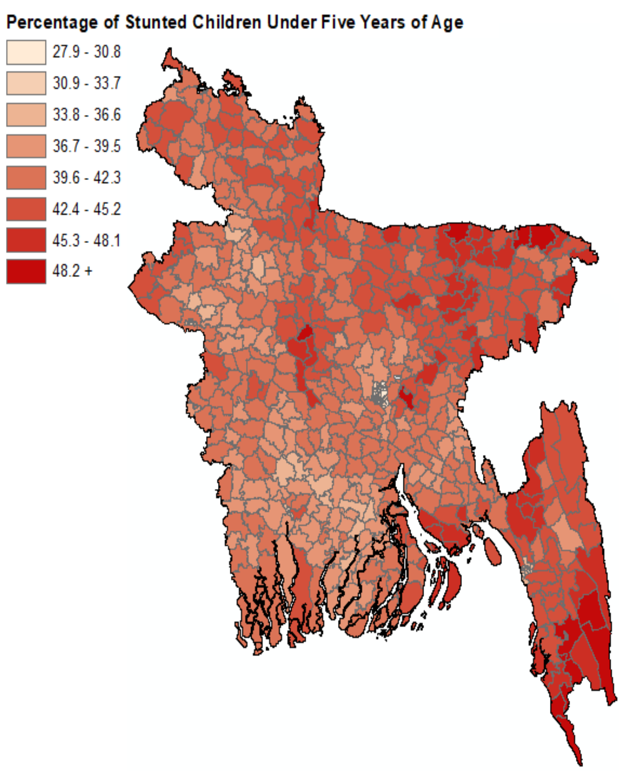
Section A.4

We ascertain whether higher *in utero* salinity exposure affects the incidence of diseases (including fever, cough, and diarrhea). The outcome of interest in this case is a dummy variable that equals one if the child had diarrhea in the previous two weeks. Our focus on this variable is justified based on the evidence that diarrhea is particularly prevalent in children exposed to high salinity levels in coastal Bangladesh (Chakraborty et al. 2019).

Results are reported in Table A9. In columns (1) and (4), we consider all the households in DHS clusters living within 40 km from the ocean. In columns (2) and (5), we restrict the sample to households belonging to the lower wealth quintiles while in columns (3) and (6), we report results for the sample restricted to households in the top two quintiles. The variable of interest (a dummy variable that takes a value of one if the child is exposed to an above median salinity level) is positive but not significant in column (1). It is significant when we restrict our analysis to households in the lower wealth quintiles implying that elevated salinity levels increase the incidence of diarrhea for poorer children. In columns (4) to (6), we introduce an interaction term between salinity exposure and child's age in months to investigate whether the association persists as the child grows older. We find that children exposed to above median salinity levels have a higher likelihood of suffering from diarrhea, with a more pronounced effect again for poorer children. The coefficients on the interaction terms are negative and significant indicating that the association between above median salinity and diarrhea diminishes with age.

Figure A1: The nutritional status of children in Bangladesh

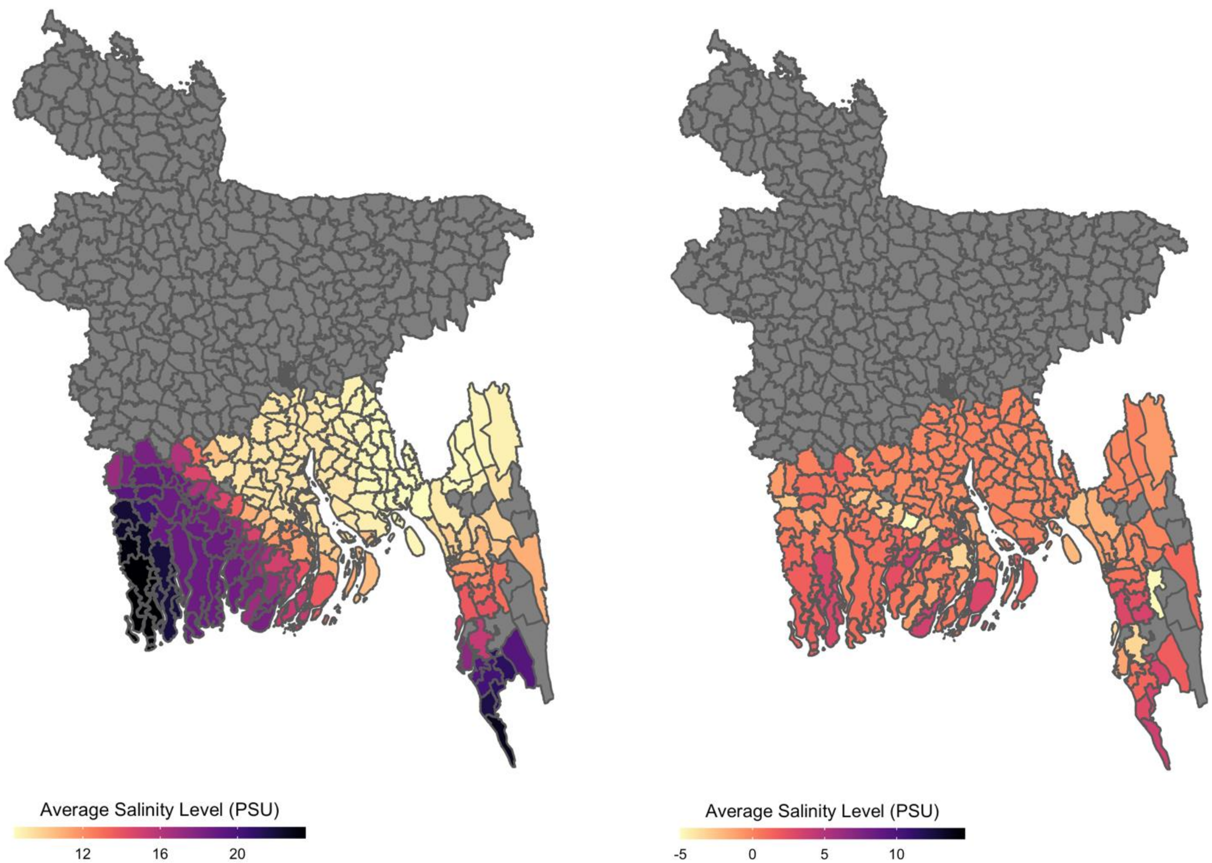
Panel A **Panel B**



Notes: Panel A shows the percentage of stunted children under five years of age at the *upazila* (sub-district) level in 2012 in Bangladesh, while Panel B shows the percentage of underweight children under five years of age at the *upazila* (sub-district) level in 2012. The data is available from the Food and Agriculture Organization (FAO), and uses the 2012 Undernutrition Maps of Bangladesh.

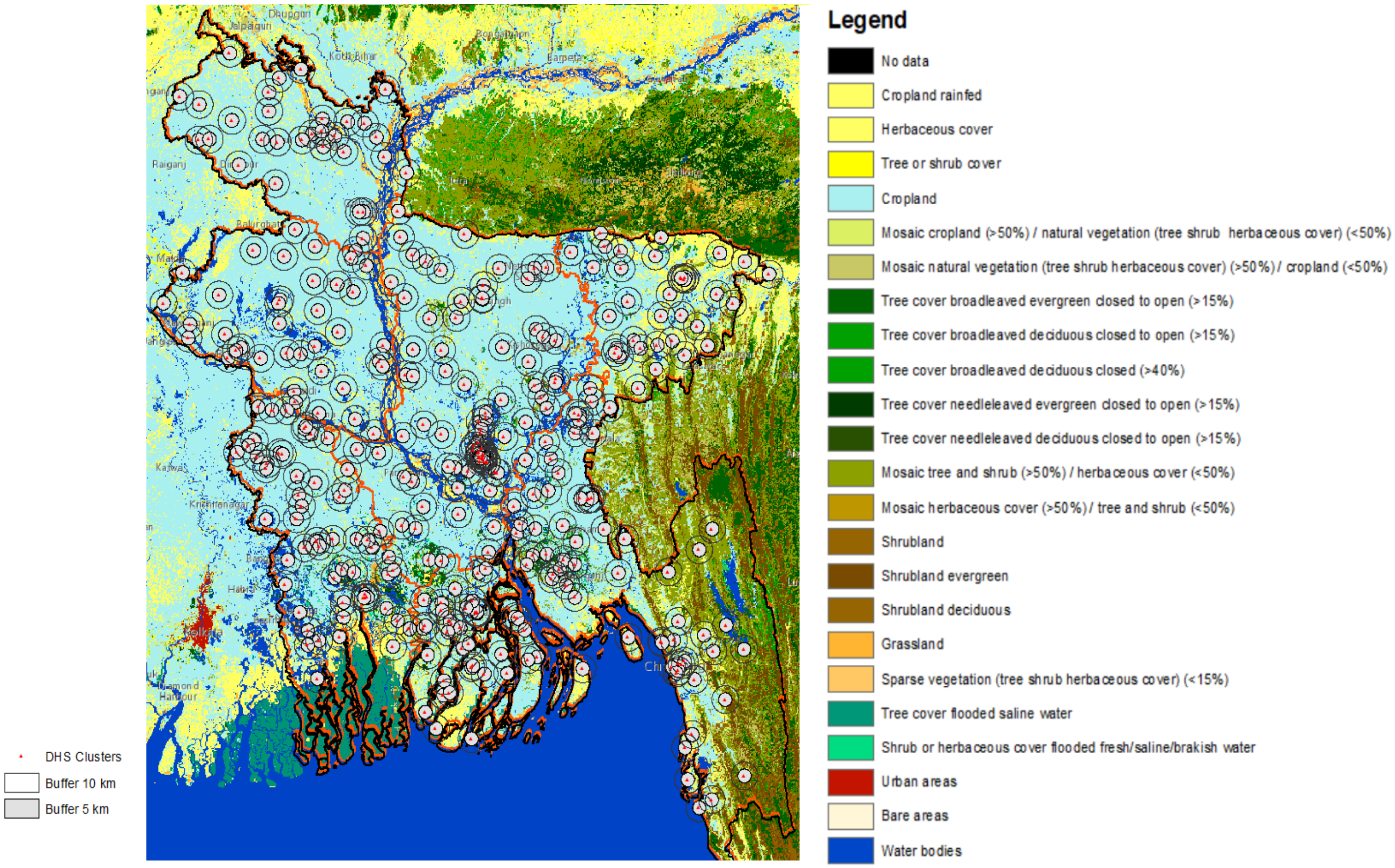
Figure A2: Spatial distribution of ocean salinity exposure 1994-2019

Panel A: Average Salinity Levels **Panel B: Deviation from District Averages**



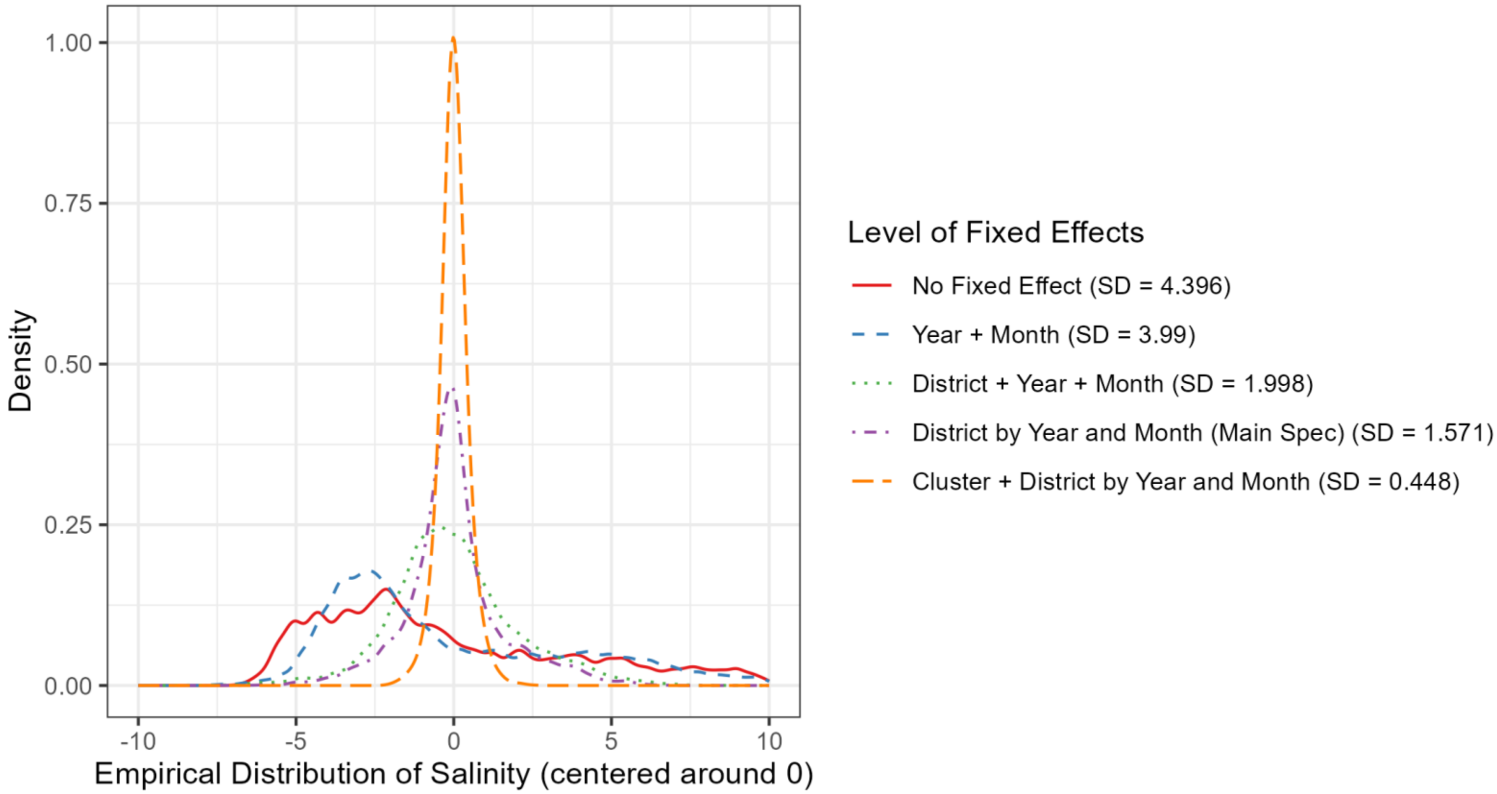
Note: Panel A (left) shows heatmaps of calculated average salinity level (in PSU) for each upazila (subdistrict) within 100 km to the coast over our sample period (1994-2019). Panel B (right) shows heatmaps of upazila-level deviation from the average district-level salinity level. Upazila-level salinity metric is averaged from salinity levels for DHS clusters within each cluster, calculated from inverse distance averaging the five closest oceanic salinity observation to each cluster. Gray areas are upazilas that are either more than 100km away from the coast line or are not sampled by the DHS.

Figure A3: Land-cover classifications



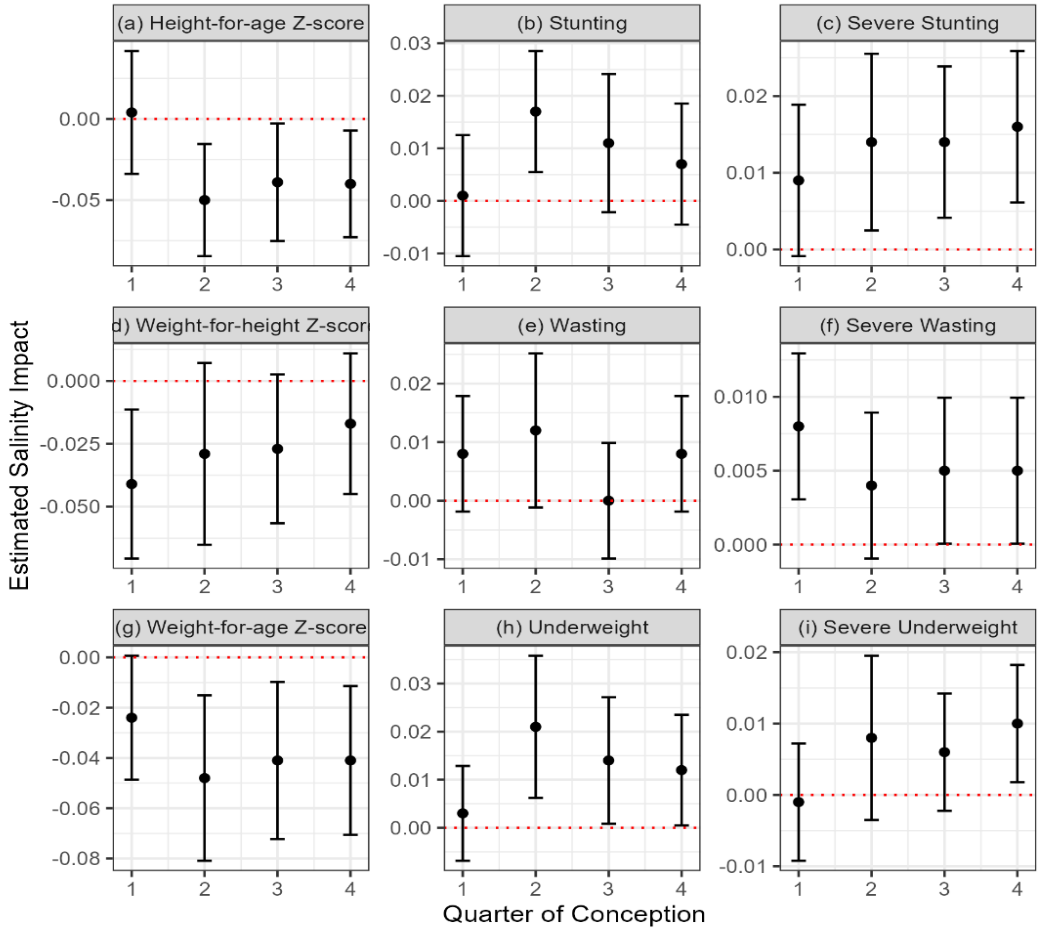
Notes: This shows the land cover map for 1993, and the location of the DHS clusters as of 1999. We also show buffers of 5 km and 10 km drawn around each cluster to obtain an estimate of land cover use. Data citation: Defourny, P., Lamarche, C., Bontemps, S., De Maet, T., Van Bogaert, E., Moreau, I., Brockmann, C., Boettcher, M., Kirches, G., Wevers, J., Santoro, M., Ramoino, F., and Arino, O. (2017). Land Cover Climate Change Initiative - Product User Guide v2. Issue 2.

Figure A4: Fixed-effects and Treatment Variation of Ocean Salinity



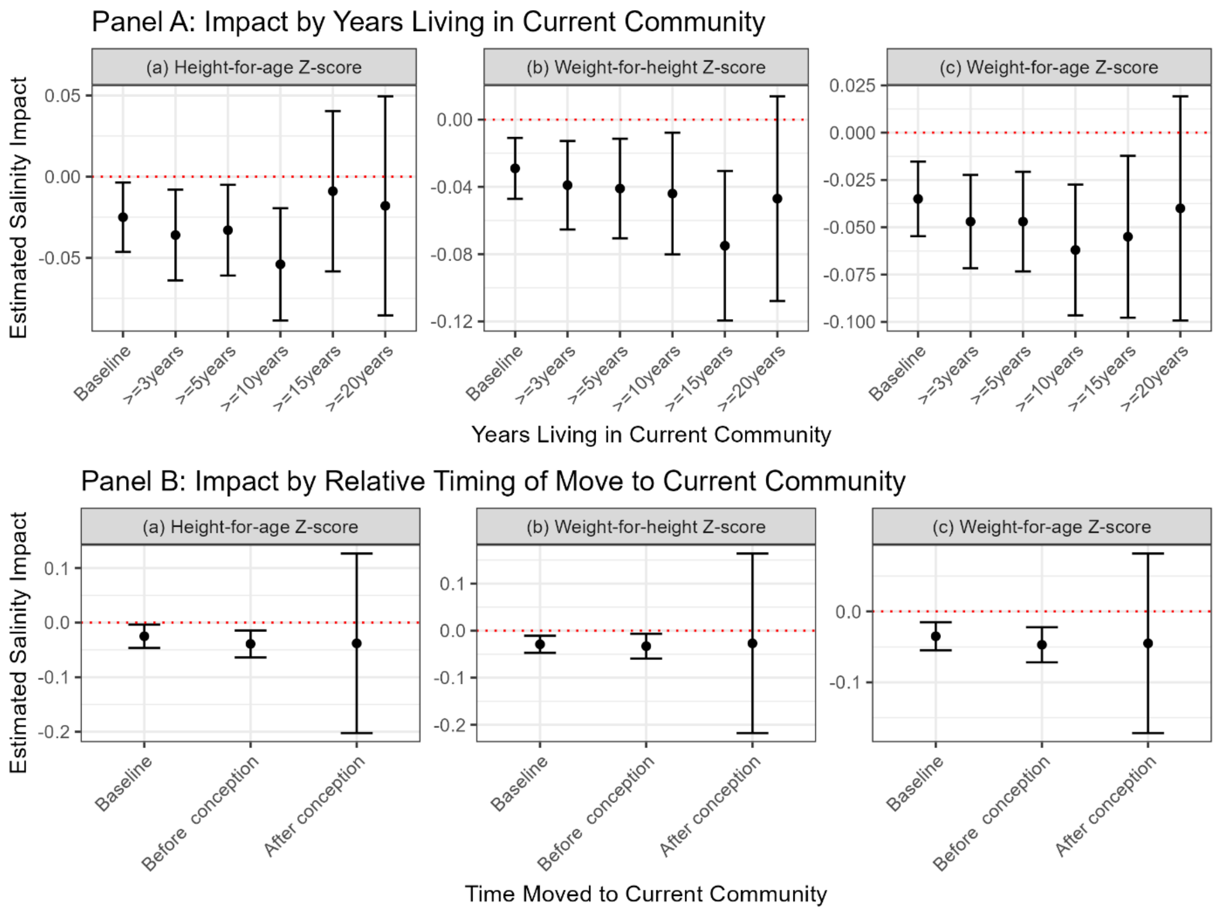
Note: This figure plots the empirical distributions of the salinity variable after including different levels of spatial and temporal fixed-effects. Five nested levels of fixed-effects are presented: No Fixed-effect, Year + Month FEs, District + Year + Month FEs, District by Year and Month FEs (the main specification), and Cluster + District by Year and Month FEs. All distributions are centered around zero. Standard deviation of these distributions are displayed in the legend area.

Figure A5: The impacts of salinity exposure on child health by quarter of conception



Notes: The panel shows the effect of *in utero* salinity on health outcomes by quarter of conception. Each sub-panel represents one regression model, which include the interaction between salinity and the quarter of the child's conception, tracing back 9 months from the child's month of birth. All regressions include child, mother, household, and weather controls, and ocean's pH levels used in the main regression analysis. The same set of spatial and temporal fixed-effects are used. Please see Table 1 for details on dependent variables and controls. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. Error bar represents 90% confidence interval.

Figure A6: The impact of salinity exposure by migration status



Note: Panel A (top) plots salinity impacts by mother's migration status. Each sub-panel include six regression models: the baseline estimate identical to that in Table 2, and five additional models each restricting the sample to include children whose mother have been living in the current community for more than 3, 5, 10, 15, and 20 years. Panel B (bottom) plots salinity impacts by the timing of mother moved to the current community. Each sub-panel include four regression models: the baseline estimate identical to that in Table 2, and three additional models restricting the sample to include children whose mother moved to the current community before that child's conception or after that child's conception. All regressions include child, mother, household, and weather controls, and ocean's pH levels used in the main regression analysis. The same set of spatial and temporal fixed-effects are used. Please see Table 1 for details on dependent variables and controls. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. Error bar represents 90% confidence interval.

Table A1: Double-lasso selection of oceanic and weather controls

Variable	Frequency Selected (1)	Probability Selected (2)	Correlation Coeff w/ salinity (3)
		Ocean Chemistry	
Sea Surface Height	27	100%	-0.92
Sea Surface Temperature	27	100%	0.79
North Wind Velocity	18	67%	-0.05
pH	12	44%	-0.29
		Weather	
Cumulative Rainfall	12	44%	0.23
Average Humidity	6	22%	-0.15
Maximum Temperature	6	22%	-0.04
Minimum Temperature	3	11%	0.33
Minimum Temperature * Cumulative Rainfall	1	4%	0.39

Note: Double-Lasso selection on oceanic and weather variables on the 40km-from-ocean sample. 27 double-Lasso models are estimated on 9 outcome variables (HAZ, stunted, severely stunted, WAH, wasted, severely wasted, WAZ, underweight, and severely underweight) using three different criteria of selection (cross-validated, adaptive, and plugin adaptive). Ocean salinity and household characteristics are always included in the double-lasso model. All variables are demeaned by the same set of saturated fixed-effects through extracting the residual from the regression y = 1 + fixed-effects. Column 1 reports the number of times a variable is included in the double-Lasso selection; Column 2 reports the probability that a variable is selected out of 27 candidate models. Column 3 reports the empirical correlation between the variable and ocean salinity after demeaning.

Table A2: The effects of salinity exposure on child health, using alternative measures of exposure and additional controls

	Dependent Variables:								
	HAZ	Stunted (HAZ < 2 SD)	Severely Stunted (HAZ < 3 SD)	WAH	Wasted (WAH < 2 SD)	Severely Wasted (WAH < 3 SD)	WAZ	Underweight (WAZ < 2 SD)	Severely Underweight (WAZ < 3 SD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log accumulated levels of salinity exposure								
Panel A:	**Sample of DHS Coastal Clusters Within 40 km**								
accumulated salinity levels (logs)	-0.332*	0.089	0.174***	-0.347**	0.097**	0.093***	-0.448***	0.144**	0.082*
(past 9 months)	(0.174)	(0.056)	(0.051)	(0.148)	(0.044)	(0.029)	(0.152)	(0.064)	(0.046)
Observations	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.323	0.278	0.228	0.169	0.151	0.163	0.268	0.219	0.182
	Control for Number of Months Above Cluster Mean Salinity								
Panel B:	**Sample of DHS Coastal Clusters Within 40 km**								
salinity exposure	-0.026*	0.007*	0.013***	-0.027**	0.007*	0.006**	-0.035***	0.011**	0.005
(in utero)	(0.013)	(0.004)	(0.004)	(0.011)	(0.004)	(0.002)	(0.012)	(0.005)	(0.004)
number of months with above	0.015	-0.004	0.002	-0.029	0.017**	0.008	-0.012	0.006	0.013
cluster mean	(0.036)	(0.012)	(0.010)	(0.034)	(0.008)	(0.005)	(0.031)	(0.012)	(0.008)
Observations	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.323	0.278	0.227	0.169	0.151	0.163	0.268	0.219	0.182
	Standard Deviation of Salinity								
Panel C:	**Sample of DHS Coastal Clusters Within 40 km**								
standard deviation of salinity	-0.035*	0.007	0.018***	-0.030*	0.005	0.010***	-0.043**	0.014*	0.012**
(for the 9 months before birth)	(0.021)	(0.007)	(0.006)	(0.018)	(0.006)	(0.004)	(0.018)	(0.007)	(0.005)
Observations	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.323	0.277	0.227	0.168	0.150	0.162	0.267	0.218	0.182
Panel D:	**Sample of DHS Coastal Clusters Within 40 km (excluding southwestern districts)**								
salinity exposure	-0.028*	0.007	0.013***	-0.026**	0.006*	0.007***	-0.035***	0.012**	0.007*
(in utero)	(0.014)	(0.005)	(0.004)	(0.012)	(0.004)	(0.002)	(0.013)	(0.005)	(0.004)
Observations	7,152	7,152	7,152	7,152	7,152	7,152	7,152	7,152	7,152
R-squared	0.328	0.279	0.235	0.171	0.155	0.173	0.274	0.219	0.192
	Assuming 10 Months of Gestation								
Panel E:	**Sample of DHS Coastal Clusters Within 40 km**								
salinity exposure	-0.025*	0.006	0.012***	-0.030***	0.008**	0.006***	-0.036***	0.012**	0.006

(in utero - assume 10 months)	(0.014)	(0.004)	(0.004)	(0.012)	(0.004)	(0.002)	(0.012)	(0.005)	(0.004)
Observations	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.323	0.278	0.227	0.169	0.151	0.162	0.268	0.218	0.182
			Including Salinity at the Month and Year of Birth						
Panel F:			**Sample of DHS Coastal Clusters Within 40 km**						
salinity exposure	-0.017	0.007	0.011***	-0.037***	0.009**	0.005**	-0.036***	0.013**	0.008**
(in utero)	(0.014)	(0.005)	(0.004)	(0.012)	(0.004)	(0.002)	(0.013)	(0.005)	(0.004)
salinity exposure	-0.011	-0.000	0.003	0.012	-0.002	0.001	0.001	-0.002	-0.003
(in month and year of birth)	(0.009)	(0.003)	(0.002)	(0.008)	(0.003)	(0.001)	(0.007)	(0.003)	(0.002)
Observations	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.323	0.278	0.227	0.169	0.151	0.162	0.268	0.219	0.182
Panel G:			**Sample of DHS Clusters Between 50 km and 100 km**						
salinity exposure	0.035	0.001	-0.001	0.015	-0.005	-0.002	0.032	-0.008	0.006
(in utero)	(0.025)	(0.011)	(0.008)	(0.028)	(0.008)	(0.003)	(0.026)	(0.011)	(0.007)
Observations	3,844	3,844	3,844	3,844	3,844	3,844	3,844	3,844	3,844
R-squared	0.369	0.329	0.305	0.261	0.235	0.219	0.343	0.290	0.269
			Including Cluster Fixed-effects						
Panel H:			**Sample of DHS Coastal Clusters Within 40 km**						
salinity exposure	-0.008	0.007	0.011	-0.085***	0.028***	0.009*	-0.066**	0.010	0.024***
(in utero)	(0.034)	(0.012)	(0.009)	(0.028)	(0.010)	(0.005)	(0.029)	(0.012)	(0.008)
Observations	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.406	0.363	0.305	0.263	0.232	0.249	0.359	0.303	0.259
			Standard Error Clustered at the District Level						
Panel I:			**Sample of DHS Coastal Clusters Within 40 km**						
salinity exposure	-0.025	0.007*	0.013*	-0.029**	0.007*	0.006**	-0.035**	0.011*	0.005
(in utero)	(0.019)	(0.004)	(0.006)	(0.013)	(0.004)	(0.003)	(0.014)	(0.005)	(0.004)
Observations	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.323	0.278	0.227	0.169	0.151	0.162	0.268	0.218	0.182
			Including Average Temperature for Each Month of Gestation						
Panel J:			**Sample of DHS Coastal Clusters Within 40 km**						
salinity exposure	-0.021	0.006	0.012***	-0.023**	0.007**	0.005**	-0.029**	0.008*	0.004
(in utero)	(0.013)	(0.004)	(0.004)	(0.011)	(0.003)	(0.002)	(0.012)	(0.005)	(0.004)
Observations	7.920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.324	0.280	0.229	0.172	0.153	0.166	0.271	0.221	0.185
			Controlling for ocean chemistry						

Panel K:				**Sample of DHS Coastal Clusters Within 40 km**					
salinity exposure	-0.019	0.005	0.012***	-0.030**	0.009**	0.006**	-0.033***	0.012**	0.006*
(in utero)	(0.014)	(0.005)	(0.004)	(0.013)	(0.004)	(0.002)	(0.012)	(0.005)	(0.004)
Observations	7.920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.323	0.278	0.227	0.169	0.151	0.163	0.268	0.219	0.182

Notes: All regressions include the controls in the main regression analysis. The same set of spatial and temporal fixed-effects are used. Please see Table 1 for details on dependent variables and controls. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1

Table A3: The effects of salinity exposure on child health using nonlinear specifications

	Dependent Variables:								
	HAZ	Stunted	Severely Stunted	WAH	Wasted	Severely Wasted	WAZ	Underweight	Severely Underweight
		(HAZ < 2 SD)	(HAZ < 3 SD)		(WAH < 2 SD)	(WAH < 3 SD)		(WAZ < 2 SD)	(WAZ < 3SD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Sample of DHS Coastal Clusters Within 40 km (Using below/above median sample value of salinity)									
salinity exposure	-0.145**	0.030	0.036**	-0.149***	0.036**	0.039***	-0.206***	0.069***	0.043***
(in utero) above median	(0.062)	(0.022)	(0.018)	(0.057)	(0.018)	(0.012)	(0.054)	(0.022)	(0.016)
Observations	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.323	0.278	0.226	0.169	0.151	0.164	0.268	0.219	0.183
Panel B: Sample of DHS Coastal Clusters Within 40 km (Using quartiles of salinity)									
salinity exposure	-0.030	0.012	0.046**	-0.013	0.014	0.024**	-0.016	0.002	0.011
(in utero) second quartile	(0.064)	(0.023)	(0.020)	(0.064)	(0.020)	(0.010)	(0.059)	(0.025)	(0.018)
salinity exposure	-0.171*	0.038	0.072***	-0.156**	0.046*	0.059***	-0.217***	0.069**	0.052**
(in utero) third quartile	(0.087)	(0.029)	(0.027)	(0.076)	(0.025)	(0.016)	(0.076)	(0.031)	(0.023)
salinity exposure	-0.159	0.059	0.117***	-0.214**	0.066**	0.058***	-0.246**	0.092**	0.049
(in utero) fourth quartile	(0.111)	(0.038)	(0.033)	(0.100)	(0.032)	(0.020)	(0.100)	(0.042)	(0.033)
Observations	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.323	0.278	0.227	0.169	0.151	0.165	0.268	0.219	0.183

Panel C: Sample of DHS Coastal Clusters Within 40 km

(Using quartiles of salinity and excluding southwestern districts)

salinity exposure	0.008	-0.012	0.019	-0.073	0.018	0.027**	-0.034	0.015	0.003
(in utero) second quartile	(0.071)	(0.025)	(0.022)	(0.067)	(0.020)	(0.011)	(0.064)	(0.026)	(0.019)
salinity exposure	-0.101	0.006	0.056**	-0.154**	0.037	0.050***	-0.172**	0.060**	0.038*
(in utero) third quartile	(0.079)	(0.027)	(0.026)	(0.074)	(0.023)	(0.013)	(0.071)	(0.030)	(0.021)
salinity exposure	-0.214**	0.048	0.077**	-0.240**	0.051*	0.056***	-0.305***	0.111***	0.066**
(in utero) fourth quartile	(0.106)	(0.034)	(0.033)	(0.094)	(0.030)	(0.019)	(0.097)	(0.039)	(0.029)
Observations	7,152	7,152	7,152	7,152	7,152	7,152	7,152	7,152	7,152
R-squared	0.328	0.279	0.234	0.171	0.155	0.174	0.275	0.220	0.193

Notes: All regressions include child, mother, household controls, weather controls, and pH used in the main regression analysis. The same set of spatial and temporal fixed-effects are used too. Please see Table 1 for details on dependent variables and controls. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table A4: The effects of salinity exposure on child health by trimester

	Dependent Variables:								
	HAZ	Stunted (HAZ < 2 SD)	Severely Stunted (HAZ < 3 SD)	WAH	Wasted (WAH < 2 SD)	Severely Wasted (WAH < 3 SD)	WAZ	Underweight (WAZ < 2 SD)	Severely Underweight (WAZ < 3SD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sample of DHS Coastal Clusters Within 40 km								
salinity exposure	0.009	-0.004	-0.001	-0.022**	0.005*	0.003	-0.008	0.003	0.001
(in utero) 1st trimester	(0.010)	(0.004)	(0.003)	(0.010)	(0.003)	(0.002)	(0.009)	(0.004)	(0.003)
salinity exposure	-0.026**	0.008**	0.010***	-0.004	-0.001	-0.001	-0.020**	0.006	0.004
(in utero) 2nd trimester	(0.011)	(0.004)	(0.003)	(0.009)	(0.003)	(0.001)	(0.009)	(0.004)	(0.003)
salinity exposure	-0.006	0.002	0.002	-0.003	0.004	0.004***	-0.006	0.002	0.000
(in utero) 3rd trimester	(0.010)	(0.003)	(0.003)	(0.009)	(0.003)	(0.001)	(0.008)	(0.004)	(0.003)
Observations	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.323	0.278	0.228	0.169	0.151	0.163	0.268	0.219	0.182

Notes: All regressions include child, mother, household controls, weather controls, and pH used in the main regression analysis. The same set of spatial and temporal fixed-effects are used. Please see Table 1 for details on dependent variables and controls. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table A5: The heterogeneous effects of salinity on child health

	Dependent Variables:								
	HAZ	Stunted (HAZ < 2 SD)	Severely Stunted (HAZ < 3 SD)	WAH	Wasted (WAH < 2 SD)	Severely Wasted (WAH < 3 SD)	WAZ	Underweight (WAZ < 2 SD)	Severely Underweight (WAZ < 3 SD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A:	**Sub-Sample: Male Children Only**								
salinity exposure	-0.001	0.004	0.001	-0.040**	0.005	0.005**	-0.027*	0.006	0.006
(in utero)	(0.017)	(0.006)	(0.005)	(0.016)	(0.005)	(0.002)	(0.015)	(0.007)	(0.004)
Observations	3,933	3,933	3,933	3,933	3,933	3,933	3,933	3,933	3,933
	Sub-Sample: Female Children Only								
salinity exposure	-0.033*	0.008	0.022***	-0.024	0.012**	0.008**	-0.040***	0.014**	0.007
(in utero)	(0.018)	(0.006)	(0.005)	(0.016)	(0.005)	(0.003)	(0.015)	(0.007)	(0.005)
Observations	3,904	3,904	3,904	3,904	3,904	3,904	3,904	3,904	3,904
Panel B:	**Sub-Sample: First Born Children Only**								
salinity exposure	-0.026	0.008	0.002	-0.017	0.013*	0.008**	-0.031	0.005	0.002
(in utero)	(0.026)	(0.010)	(0.007)	(0.023)	(0.007)	(0.004)	(0.021)	(0.009)	(0.006)
Observations	2,411	2,411	2,411	2,411	2,411	2,411	2,411	2,411	2,411
	Sub-Sample: Non-First Born Children								
salinity exposure	-0.027*	0.006	0.015***	-0.035***	0.007*	0.007***	-0.041***	0.014**	0.010**
(in utero)	(0.015)	(0.005)	(0.005)	(0.013)	(0.004)	(0.003)	(0.013)	(0.006)	(0.004)
Observations	5,429	5,429	5,429	5,429	5,429	5,429	5,429	5,429	5,429
Panel C:	**Sub-Sample: Mother's height (below median)**								
salinity exposure	-0.012	0.006	0.011**	-0.050***	0.006	0.006**	-0.041***	0.009	0.009**
(in utero)	(0.018)	(0.006)	(0.005)	(0.017)	(0.004)	(0.003)	(0.015)	(0.006)	(0.004)
Observations	3,899	3,899	3,899	3,899	3,899	3,899	3,899	3,899	3,899
	Sub-Sample: Mother's height (above median)								
salinity exposure	-0.028	0.007	0.013**	-0.015	0.009*	0.005*	-0.028	0.011	0.001
(in utero)	(0.019)	(0.006)	(0.006)	(0.016)	(0.005)	(0.003)	(0.017)	(0.008)	(0.006)
Observations	3,940	3,940	3,940	3,940	3,940	3,940	3,940	3,940	3,940

Panel D:					**Sub-Sample: Working Mothers**				
salinity exposure	-0.036	0.023**	0.012	-0.025	0.012	0.010*	-0.038	0.018	-0.001
(in utero)	(0.032)	(0.010)	(0.009)	(0.030)	(0.008)	(0.005)	(0.027)	(0.013)	(0.008)
Observations	1,485	1,485	1,485	1,485	1,485	1,485	1,485	1,485	1,485
					Sub-Sample: Non-Working Mothers				
salinity exposure	-0.028*	0.005	0.014***	-0.022*	0.006	0.005*	-0.033**	0.009	0.006
(in utero)	(0.016)	(0.005)	(0.004)	(0.013)	(0.004)	(0.003)	(0.014)	(0.006)	(0.004)
Observations	6,305	6,305	6,305	6,305	6,305	6,305	6,305	6,305	6,305

Notes: This table shows the coefficients of salinity exposure (measured as the average level 9 months prior to birth) for different sub-samples used in separate regressions. The dependent variables in columns (1), (4), and (7) for height-for-age z-score, weight-for-height z-score, and for the weight-for-age z-score, respectively, are continuous. Dependent variables in columns (2), (5), and (8) are binary variables that equal to one if the child is stunted, wasted, and underweight, respectively, while in columns (3), (6), and (9), the binary variables equal to one if the child is severely stunted, severely wasted, and severely underweight, respectively. The child, mother, household controls include the child's age (in months) and gender, child birth order, mother's age at first birth, a dummy variable that equals to one if the mother has no education, a dummy variable that equals to one if the father has no education, mother's height, and the gender of the household head. Weather controls include minimum and maximum temperature, rainfall (in logs), the interaction between minimum and maximum temperature and log of rainfall, and humidity. We also control for the ocean's pH levels. All regressions are OLS, are weighted, and include the same set of fixed-effects included in equation (1). Robust standard errors are clustered at the DHS cluster level. We consider DHS clusters within 40 km of the ocean. ***p<0.01, **p<0.05, *p<0.1.

Table A6: The heterogeneous effects of salinity on child health, based on locational characteristics

	Dependent Variables:								
	HAZ	Stunted (HAZ < 2 SD)	Severely Stunted (HAZ < 3 SD)	WAH	Wasted (WAH < 2 SD)	Severely Wasted (WAH < 3 SD)	WAZ	Underweight (WAZ < 2 SD)	Severely Underweight (WAZ < 3 SD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A	**Sub-Sample: Population Density (Below Median)**								
salinity exposure	-0.026	0.004	0.014**	-0.027*	0.002	0.006*	-0.036**	0.004	0.007
(in utero)	(0.018)	(0.006)	(0.006)	(0.015)	(0.004)	(0.003)	(0.015)	(0.006)	(0.006)
	Sub-Sample: Population Density (Above Median)								
salinity exposure	-0.022	0.009	0.006	-0.031	0.006	0.010**	-0.032	0.017	0.004
(in utero)	(0.026)	(0.010)	(0.007)	(0.028)	(0.008)	(0.005)	(0.027)	(0.011)	(0.006)
Panel B	**Sub-Sample: Built-Up Areas (Below Median)**								
salinity exposure	-0.036*	0.007	0.015**	-0.030*	0.010*	0.008**	-0.045**	0.008	0.008
(in utero)	(0.020)	(0.006)	(0.006)	(0.016)	(0.005)	(0.003)	(0.018)	(0.007)	(0.005)
	Sub-Sample: Built-Up Areas (Above Median)								
salinity exposure	0.027	-0.016*	-0.001	0.000	0.003	0.004	0.019	-0.015	0.002
(in utero)	(0.029)	(0.010)	(0.008)	(0.034)	(0.011)	(0.005)	(0.030)	(0.011)	(0.007)

Notes: This table shows the coefficients of salinity exposure (measured as the average level 9 months prior to birth) for different sub-samples used in separate regressions. The dependent variables in columns (1), (4), and (7) for height-for-age z-score, weight-for-height z-score, and for the weight-for-age z-score, respectively, are continuous. Dependent variables in columns (2), (5), and (8) are binary variables that equal to one if the child is stunted, wasted, and underweight, respectively, while in columns (3), (6), and (9), the binary variables equal to one if the child is severely stunted, severely wasted, and severely underweight, respectively. The child, mother, household controls include the child's age (in months) and gender, child birth order, mother's age at first birth, a dummy variable that equals to one if the mother has no education, a dummy variable that equals to one if the father has no education, mother's height, and the gender of the household head. Weather controls include minimum and maximum temperature, rainfall (in logs), the interaction between minimum and maximum temperature and log of rainfall, and humidity. We also control for the ocean's pH levels. All regressions are OLS, are weighted, and include the same set of fixed-effects included in equation (1). Robust standard errors are clustered at the DHS cluster level. We consider DHS clusters within 40 km of the ocean. ***p<0.01, **p<0.05, *p<0.1.

Table A7: The effects of salinity exposure on child health controlling for prenatal care and at birth investments

	Dependent Variables:								
	HAZ	Stunted (HAZ < 2 SD)	Severely Stunted (HAZ < 3 SD)	WAH	Wasted (WAH < 2 SD)	Severely Wasted (WAH < 3 SD)	WAZ	Underweight (WAZ < 2 SD)	Severely Underweight (WAZ < 3SD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
salinity exposure	-0.017	0.001	0.007	-0.026	0.007	0.004	-0.028*	0.003	0.005
(in utero)	(0.016)	(0.006)	(0.005)	(0.017)	(0.005)	(0.003)	(0.015)	(0.007)	(0.005)
no. of antenatal visits	0.055***	-0.013***	-0.007*	0.034**	-0.003	-0.001	0.057***	-0.013***	-0.005*
	(0.015)	(0.005)	(0.004)	(0.014)	(0.004)	(0.002)	(0.013)	(0.005)	(0.003)
received iron tablet	-0.108*	0.014	0.013	-0.088	0.023	0.014*	-0.115**	0.038*	0.023
	(0.065)	(0.021)	(0.018)	(0.055)	(0.015)	(0.008)	(0.052)	(0.022)	(0.016)
prenatal care: doctor	0.234***	-0.075***	-0.058***	0.063	-0.030*	-0.021**	0.167***	-0.064***	-0.054***
	(0.073)	(0.024)	(0.020)	(0.058)	(0.017)	(0.010)	(0.063)	(0.024)	(0.017)
prenatal care: nurse	0.035	-0.025	-0.003	0.022	-0.012	0.000	0.038	-0.078***	-0.016
	(0.093)	(0.033)	(0.022)	(0.077)	(0.021)	(0.013)	(0.076)	(0.030)	(0.019)
assistance: doctor	0.141	-0.058	0.022	-0.014	0.002	0.001	0.095	0.013	-0.017
	(0.097)	(0.038)	(0.026)	(0.098)	(0.026)	(0.014)	(0.092)	(0.036)	(0.025)
assistance: nurse	0.107	-0.029	-0.033	0.129	-0.000	0.008	0.121	-0.024	0.019
	(0.090)	(0.034)	(0.024)	(0.081)	(0.022)	(0.010)	(0.076)	(0.031)	(0.022)
delivery: at home	0.034	-0.008	0.009	-0.084	0.032	0.003	-0.041	0.061**	0.027
	(0.073)	(0.027)	(0.020)	(0.062)	(0.020)	(0.009)	(0.062)	(0.027)	(0.019)
Observations	3,663	3,663	3,663	3,663	3,663	3,663	3,663	3,663	3,663
R-squared	0.411	0.349	0.297	0.235	0.219	0.175	0.353	0.293	0.240
Child, mother, household controls	✓	✓	✓	✓	✓	✓	✓	✓	✓

Weather controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ocean chemistry control (pH)	✓	✓	✓	✓	✓	✓	✓	✓	✓
District, year of birth, month of birth FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year of birth x month of birth FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
District x month of birth FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
District x year of birth FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table shows the coefficients of salinity exposure (measured as the average level 9 months prior to birth). The dependent variables in columns (1), (4), and (7) for height-for-age z-score, weight-for-height z-score, and for the weight-for-age z-score, respectively, are continuous. Dependent variables in columns (2), (5), and (8) are binary variables that equal to one if the child is stunted, wasted, and underweight, respectively, while in columns (3), (6), and (9), the binary variables equal to one if the child is severely stunted, severely wasted, and severely underweight, respectively. The child, mother, household controls include the child's age (in months) and gender, child birth order, mother's age at first birth, a dummy variable that equals to one if the mother has no education, a dummy variable that equals to one if the father has no education, mother's height, and the gender of the household head. Weather controls include minimum and maximum temperature, rainfall (in logs), the interaction between minimum and maximum temperature and log of rainfall, and humidity. We also control for the ocean's pH levels. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1

Table A8: The impact of salinity on health investments, health-seeking behavior, and prenatal care, by gender and birth order

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Sample of DHS Coastal Clusters Within 40 km						
	Early Investments in Child Health: Vaccination Received						
	Polio 1	Polio 2	BCG	DPT 1	DPT 2	Measles	Tetanus
	Male Children Only						
salinity exposure	-0.007*	-0.012**	-0.004	-0.004	-0.011**	-0.015**	-0.008
(in utero)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)	(0.010)
	Female Children Only						
salinity exposure	-0.006	-0.010*	-0.006	-0.006	-0.011*	-0.006	-0.020**
(in utero)	(0.004)	(0.006)	(0.004)	(0.004)	(0.006)	(0.007)	(0.008)
	First Born Children Only						
salinity exposure	-0.008*	-0.015**	-0.009**	-0.009*	-0.016**	-0.010	-0.004
(in utero)	(0.004)	(0.007)	(0.004)	(0.005)	(0.007)	(0.007)	(0.012)
	Non-First Born Children Only						
salinity exposure	-0.006	-0.009*	-0.003	-0.004	-0.010*	-0.014**	-0.014*
(in utero)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)	(0.007)
	Panel B: Sample of DHS Coastal Clusters Within 40 km						
	Prenatal Care and At Birth Investments						
	No. of antenatal visits	Received iron tablet	Prenatal care: Doctor	Prenatal care: Nurse	Assistance at birth: Doctor	Assistance at birth: Nurse	Delivery: at home
	Male Children Only						
salinity exposure	-0.140***	-0.012	-0.019**	-0.002	-0.009*	-0.017**	0.020***
(in utero)	(0.043)	(0.011)	(0.007)	(0.005)	(0.005)	(0.006)	(0.007)
	Female Children Only						
salinity exposure	-0.150***	-0.025**	-0.017***	-0.009**	-0.006	-0.009	0.015**
(in utero)	(0.039)	(0.011)	(0.007)	(0.005)	(0.005)	(0.006)	(0.007)
	First Born Children Only						
salinity exposure	-0.183***	-0.001	-0.011	-0.005	0.001	-0.012	0.025**
(in utero)	(0.057)	(0.016)	(0.010)	(0.007)	(0.008)	(0.011)	(0.011)
	Non-First Born Children Only						
salinity exposure	-0.146***	-0.022***	-0.021***	-0.006*	-0.010**	-0.014***	0.020***
(in utero)	(0.035)	(0.008)	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)

Notes: This table shows the coefficients of salinity exposure (measured as the average level 9 months prior to birth) for different sub-samples used in separate regressions. The child, mother, household controls include the child's age (in months) and gender, child birth order, mother's age at first birth, a dummy variable that equals to one if the mother has no education, a dummy variable that equals to one if the father has no education, mother's height, and the gender of the household head. Weather controls include minimum and maximum temperature, rainfall (in logs), the interaction between minimum and maximum temperature and log of rainfall, and humidity. We also control for the ocean's pH levels. All regressions are OLS, are weighted, and include the same set of fixed-effects included in equation (1). Robust standard errors are clustered at the DHS cluster level. Panel A considers the sub-sample of DHS clusters that are within 40 km of the ocean, and the dependent variables are coded as 1 if the child has received the type of vaccination presented in each column. In Panel B, we consider the same sample of coastal communities, and the dependent variable is continuous in column (1) for the number of antenatal visits. The other outcome variables in columns (2) to (7) are binary variables that equal to one if the mother received iron tablet during pregnancy, prenatal care, assistance at birth, and if delivery happened at home, respectively. ***p<0.01, **p<0.05, *p<0.1.

Table A9: The Effect of Salinity Exposure During Pregnancy on the Incidence of Diarrhea

	Dependent Variable: Child had diarrhea in the previous 2 weeks					
	All	Lower wealth quintiles	Top two wealth quintiles	All	Lower wealth quintiles	Top two wealth quintiles
	(1)	(2)	(3)	(4)	(5)	(6)
	Sample of DHS Coastal Clusters Within 40 km					
salinity exposure	0.016	0.028*	-0.004	0.040**	0.054**	0.037
(in utero) above median	(0.013)	(0.015)	(0.022)	(0.019)	(0.023)	(0.031)
age of child (months)	-0.001***	-0.000	-0.001***	-0.000	0.000	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
salinity exposure x age of child				-0.001**	-0.001*	-0.001*
				(0.000)	(0.001)	(0.001)
Observations	7,917	4,924	2,930	7,917	4,924	2,930
R-squared	0.138	0.194	0.294	0.139	0.194	0.295
Child, mother, household controls	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓
Ocean chemistry control (pH)	✓	✓	✓	✓	✓	✓
District, year of birth, month of birth FE	✓	✓	✓	✓	✓	✓
Year of birth x month of birth FE	✓	✓	✓	✓	✓	✓
District x month of birth FE	✓	✓	✓	✓	✓	✓
District x year of birth FE	✓	✓	✓	✓	✓	✓

Notes: This table shows the coefficients on a dummy variable that takes a value of one if the child had above median in utero salinity exposure, on the child's age (in months), and on the interaction between these two variables. The dependent variable in all columns is a dummy variable that equals to one if it was reported, at the time of the survey, that the child had diarrhea during the past two weeks. In columns (1) and (4), we consider all households in our sample. In columns (2) and (5), we restrict the sample to households belonging to the lower wealth quintiles while in columns (3) and (6), only households belonging to the top two wealth quintiles are considered. The child, mother, household controls include the child's age (in months) and gender, child birth order, mother's age at first birth, a dummy variable that equals to one if the mother has no education, a dummy variable that equals to one if the father has no education, mother's height, and the gender of the household head. Weather controls include minimum and maximum temperature, rainfall (in logs), the interaction between minimum and maximum temperature and log of rainfall, and humidity. We also control for the ocean's pH levels. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. We consider the sub-sample of DHS clusters that are within 40 km of the ocean. ***p<0.01, **p<0.05, *p<0.1.

Table A10: The effects of salinity exposure on wealth

	Dependent Variable: Top Two Wealth Quintiles (1)
	Sample of DHS Coastal Clusters Within 40 km
salinity exposure	-0.053***
(in utero)	(0.007)
Observations	7,978
R-squared	0.284
Weather controls	✓
Ocean chemistry control (pH)	✓
District, year of birth, month of birth FE	✓
Year of birth x month of birth FE	✓
District x month of birth FE	✓
District x year of birth FE	✓

Notes: This table shows the coefficients of salinity exposure (measured as the average level 9 months prior to birth). The dependent variable in column (1) is a binary variable that equal to one if the household is in the top two wealth quintiles. Weather controls include minimum and maximum temperature, rainfall (in logs), the interaction between minimum and maximum temperature and log of rainfall, and humidity. We also control for the ocean's pH levels. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. We consider the sub-sample of DHS clusters that are within 40 km of the ocean. ***p<0.01, **p<0.05, *p<0.1.

Table A11: The effects of salinity exposure on child health conditional on wealth quintiles

	Dependent Variables:								
	HAZ	Stunted (HAZ < 2 SD)	Severely Stunted (HAZ < 3 SD)	WAH	Wasted (WAH < 2 SD)	Severely Wasted (WAH < 3 SD)	WAZ	Underweight (WAZ < 2 SD)	Severely Underweight (WAZ < 3 SD)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Sample of DHS Coastal Clusters Within 40 km								
salinity exposure	-0.007	0.001	0.009**	-0.023*	0.006*	0.006**	-0.021*	0.006	0.003
(in utero)	(0.013)	(0.004)	(0.004)	(0.012)	(0.004)	(0.002)	(0.012)	(0.005)	(0.004)
top two highest wealth quintiles	0.438***	-0.145***	-0.098***	0.135***	-0.038***	-0.010*	0.348***	-0.121***	-0.056***
	(0.042)	(0.015)	(0.011)	(0.042)	(0.011)	(0.006)	(0.041)	(0.017)	(0.010)
Observations	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920	7,920
R-squared	0.337	0.290	0.237	0.171	0.153	0.163	0.281	0.228	0.186
Child, mother, household controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Ocean chemistry control (pH)	✓	✓	✓	✓	✓	✓	✓	✓	✓
District, year of birth, month of birth FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year of birth x month of birth FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
District x month of birth FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
District x year of birth FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: This table shows the coefficients of salinity exposure (measured as the average level 9 months prior to birth). The dependent variables in columns (1), (4), and (7) for height-for-age z-score, weight-for-height z-score, and for the weight-for-age z-score, respectively, are continuous. Dependent variables in columns (2), (5), and (8) are binary variables that equal to one if the child is stunted, wasted, and underweight, respectively, while in columns (3), (6), and (9), the binary variables equal to one if the child is severely stunted, severely wasted, and severely underweight, respectively. The child, mother, household controls include the child's age (in months) and gender, child birth order, mother's age at first birth, a dummy variable that equals to one if the mother has no education, a dummy variable that equals to one if the father has no education, mother's height, and the gender of the household head. Weather controls include minimum and maximum temperature, rainfall (in logs), the interaction between minimum and maximum temperature and log of rainfall, and humidity. We also control for the ocean's pH levels. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. ***p<0.01, **p<0.05, *p<0.1.

Table A12: The impact of salinity on health investments, health-seeking behavior, and prenatal care, by wealth quintile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Sample of DHS Coastal Clusters Within 40 km						
	Early Investments in Child Health: Vaccination Received						
	Polio 1	Polio 2	BCG	DPT 1	DPT 2	Measles	Tetanus
	Sample: in lower wealth quintiles						
salinity exposure	-0.009**	-0.013**	-0.004	-0.006	-0.013*	-0.018***	-0.016**
(in utero)	(0.004)	(0.006)	(0.004)	(0.005)	(0.006)	(0.006)	(0.008)
	Sample: top two wealth quintiles						
salinity exposure	0.002	-0.000	-0.001	-0.000	-0.002	0.007	0.005
(in utero)	(0.004)	(0.006)	(0.005)	(0.004)	(0.006)	(0.006)	(0.011)
	Panel B: Sample of DHS Coastal Clusters Within 40 km						
	Prenatal Care and At Birth Investments						
	No. of antenatal visits	Received iron tablet	Prenatal care: Doctor	Nurse	Assistance at birth: Doctor	Nurse	Delivery: at home
	Sample: in lower wealth quintiles						
salinity exposure	-0.086***	-0.017*	-0.012*	-0.009**	-0.002	-0.004	0.007
(in utero)	(0.029)	(0.010)	(0.007)	(0.003)	(0.003)	(0.004)	(0.004)
	Sample: top two wealth quintiles						
salinity exposure	-0.170**	-0.002	-0.007	-0.013	0.004	-0.005	0.011
(in utero)	(0.075)	(0.015)	(0.011)	(0.008)	(0.011)	(0.011)	(0.012)

Notes: This table shows the coefficients of salinity exposure (measured as the average level 9 months prior to birth) for different sub-samples used in separate regressions. The child, mother, household controls include the child's age (in months) and gender, child birth order, mother's age at first birth, a dummy variable that equals to one if the mother has no education, a dummy variable that equals to one if the father has no education, mother's height, and the gender of the household head. Weather controls include minimum and maximum temperature, rainfall (in logs), the interaction between minimum and maximum temperature and log of rainfall, and humidity. We also control for the ocean's pH levels. All regressions are OLS, are weighted, and include the same set of fixed-effects included in equation (1). Robust standard errors are clustered at the DHS cluster level. Panel A considers the sub-sample of DHS clusters that are within 40 km of the ocean, and the dependent variables are coded as 1 if the child has received the type of vaccination presented in each column. In Panel B, we consider the same sample of coastal communities, and the dependent variable is continuous in column (1) for the number of antenatal visits. The other outcome variables in columns (2) to (7) are binary variables that equal to one if the mother received iron tablet during pregnancy, prenatal care, assistance at birth, and if delivery happened at home, respectively. ***p<0.01, **p<0.05, *p<0.1.

Table A13: The effects of salinity exposure on child’s gender

	Dependent Variable: Probability that the Child is Male				
	(1)	(2)	(3)	(4)	(5)
	Sample of DHS Coastal Clusters Within 40 km				
salinity exposure *(in utero)*	-0.001 (0.004)	-0.003 (0.006)			
salinity exposure (in month of conception)		0.002 (0.004)		0.002 (0.004)	
salinity exposure (2-9 months during gestation)			-0.001 (0.004)	-0.003 (0.005)	
salinity exposure *(in utero)* second quartile					0.018 (0.028)
salinity exposure *(in utero)* third quartile					0.001 (0.031)
salinity exposure *(in utero)* fourth quartile					-0.024 (0.040)
Observations	7,920	7,920	7,920	7,920	7,920
R-squared	0.131	0.131	0.131	0.131	0.131
Child, mother, household controls	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓
Ocean chemistry control (pH)	✓	✓	✓	✓	✓
District, year of birth, month of birth FE	✓	✓	✓	✓	✓
Year of birth x month of birth FE	✓	✓	✓	✓	✓
District x month of birth FE	✓	✓	✓	✓	✓
District x year of birth FE	✓	✓	✓	✓	✓

Notes: This table shows the impact of salinity on the probability that the child is male. The dependent variable is a dummy variable that equals to one if the child is male. The child, mother, household controls include the child's age (in months), child birth order, mother's age at first birth, a dummy variable that equals to one if the mother has no education, a dummy variable that equals to one if the father has no education, mother's height, and the gender of the household head. Weather controls include minimum and maximum temperature, rainfall (in logs), the interaction between minimum and maximum temperature and log of rainfall, and humidity. We also control for the ocean's pH levels. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. We use the sub-sample of DHS clusters that are within 40 km of the ocean.***p<0.01, **p<0.05, *p<0.1.

Table A14: The Effects of Salinity Exposure on Parental Characteristics

	Dependent Variables:				
	mother's education		mother's height	mother employed	mother's current age
	<= 6 years	<= 12 years			
	(1)	(2)	(3)	(4)	(5)
Panel A	**Sample of DHS Coastal Clusters Within 40 km**				
salinity exposure	0.001	0.001	0.103*	-0.002	0.080
(in utero)	(0.006)	(0.002)	(0.061)	(0.005)	(0.053)
Observations	7,978	7,978	7,933	7,978	7,978
R-squared	0.144	0.100	0.126	0.211	0.148
Panel B	(1)	(2)	(3)	(4)	(5)
	mother 's age at delivery	age difference with head	gender of HH head	age of HH head	father's education (<=12 years)
salinity exposure	0.057	0.028	0.001	0.108	0.005**
(in utero)	(0.049)	(0.159)	(0.004)	(0.150)	(0.002)
Observations	7,978	7,978	7,978	7,978	7,978
R-squared	0.130	0.141	0.170	0.137	0.121
Child, mother, household controls	×	×	×	×	×
Weather controls	✓	✓	✓	✓	✓
Ocean chemistry control (pH)	✓	✓	✓	✓	✓
District, year of birth, month of birth FE	✓	✓	✓	✓	✓
Year of birth x month of birth FE	✓	✓	✓	✓	✓
District x month of birth FE	✓	✓	✓	✓	✓
District x year of birth FE	✓	✓	✓	✓	✓

Notes: This table shows the coefficients of salinity exposure (measured as the average level 9 months prior to birth) on parental characteristics. In Panel A, the dependent variables in columns (1) and (2) are binary variables that equal to one if the mother has 6 and 12 years or less of education, respectively. The dependent variables in columns (3) and (5) are continuous. The dependent variable in column (4) is a binary variable that equals to one if the mother is currently working. In Panel B, the dependent variables in columns (1), (2), and (4) are continuous. In column 3, we use a dummy variable that equals to one if the household head is male, and in column (5), the dependent variable equals to one if the father has 12 years or less of education. Weather controls include minimum and maximum temperature, rainfall (in logs), the interaction between minimum and maximum temperature and log of rainfall, and humidity. We also control for the ocean's pH levels. All regressions are OLS and are weighted. Robust standard errors are clustered at the DHS cluster level. We consider the sub-sample of DHS clusters that are within 40 km of the ocean. ***p<0.01, **p<0.05, *p<0.1.