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Welfare and Climate Risks in Coastal Bangladesh

The Impacts of Climatic Extremes on Multidimensional Poverty and the Wider Benefits of Climate Adaptation

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Abstract

It is widely recognized that climate hazards impact the poor disproportionately. However, quantifying these disproportionate hazard impacts on a large scale is difficult given limited information on households' location and socioeconomic characteristics, and incomplete quantitative frameworks to assess welfare impacts on households. This paper constructs a household-level multidimensional poverty index using a synthetic household dataset of 43 million people residing in the coastal zone of Bangladesh. Households are spatially linked to the critical infrastructure networks they depend on, including housing; water, sanitation, and hygiene; electricity; education; and health services. Combined with detailed cyclone hazard data, the paper first quantifies risks to households, agriculture, and infrastructure. It then presents a novel framework for translating critical infrastructure impacts into the temporary incidence of service deprivations, which can contribute to temporary deprivations and hence multidimensional poverty. The paper uses this framework to evaluate the benefits of various adaptation options. The findings show that asset risk due to flooding is US$483 million per year at present, increasing to US$750 million per year in 2050 under climate change. Households face an average infrastructure service disruption of two days per year, which is expected to increase to 4.6 days per year in 2050. This, in turn, would incur a temporary increase in multidimensional poverty (7.2 percent of people are multidimensionally poor at the baseline) of up to 94 percent (2.9 million people) 30 days after an extreme cyclone event (a 1-in-100 years event) at present and 153.9 percent (4.8 million people) in the future. The paper quantifies the large welfare benefits of upgrading embankments, showing how apart from significant risk reduction, these interventions reduce service disruptions by up to 70 percent in some areas and can help up to 1.6 million (0.23 million under current and proposed programs) people from experiencing some form of temporary poverty. Overall, the paper identifies poor households exposed to climate impacts, as well as those prone to falling into poverty temporarily, both of which could help to mainstream equity considerations in new adaptation programs.

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Welfare and Climate Risk in Coastal Bangladesh: The Impacts of Climatic Extremes on Multidimensional Poverty and the Wider Benefits of Climate Adaptation

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1 Introduction

Natural disasters impose large impacts on society, causing damages and affecting millions of people every year (Winsemius et al., 2016; Hallegatte et al., 2019; Dullaart et al., 2021). The adverse impacts of natural disasters extend beyond physical damages alone. Income and consumption losses, and disruptions to essential services (e.g. electricity, water), can have implications for food security, education and health, further diminishing the wellbeing of affected people (Hallegatte et al., 2019). The poor and most marginalized often experience the largest relative welfare losses, as they live close to subsistence levels, have a more vulnerable asset base (e.g. less diversification), and lack the resources to smooth income shocks, maintain pre-disaster consumption and quickly recover from shocks (Hallegatte and Rozenberg, 2017; Hallegatte et al., 2020).

Most disaster risk analyses, however, focus solely on direct damages to assets, neglecting the wider welfare impacts to households, including identifying those disproportionately hit (Markhvida et al., 2020). As a result, these methods cannot be used to measure the benefits of adaptation options that do not reduce asset damages, such as emergency preparedness (although assets can be moved to higher ground), cash-transfers, and humanitarian relief efforts. More importantly, as asset damages obscure the impacts to the poor, adaptation options are often prioritized in asset rich areas, potentially reducing the level of protection offered to poorer areas. Therefore, accounting for the welfare impacts of disasters can help identify communities that will benefit most from DRR measures for their wider wellbeing (Verschuur et al., 2020).

A growing number of studies have analyzed the *ex-post* implications of disasters to income, expenditure, malnutrition, health and education, often using (longitudinal) survey data and econometrics (Noy, 2016; Noy and DuPont, 2018). However, studies modeling the welfare implications *ex-ante*, which would allow them to be embedded in traditional risk assessments, are scarce. As part of the World Bank's *Unbreakable* report, Hallegatte et al. (2016) (henceforth H2016) developed a modeling framework to evaluate the impacts of disasters to households' welfare on a national scale, which over the years has been applied to more detailed case studies in the Philippines (Walsh and Hallegatte, 2019), the San Francisco Bay Area (Markhvida et al., 2020) and Bangladesh (Verschuur et al., 2020). Apart from quantifying the welfare impacts, showing that every 1 USD dollar in asset loss translates into a welfare loss equivalent to 1.6 USD in consumption, the model allows evaluating the wider benefits of both hard (e.g., increased protection) and soft (e.g., cash transfer, access to finance) adaptation options, helping to better target portfolios of interventions to those that benefit most from them in welfare terms.

However, several limitations are inherent to the H2016 modeling framework. First, the use of national survey data, with limited representativeness on a local or regional scale, restricts a more granular analysis of hotspots of welfare impacts within countries. Second, the limited spatial representation of the model prevents us from investigating the drivers of disproportionate welfare impacts. For example, this could be driven by poorer households being relatively more exposed to flooding (e.g., exposure bias) or being dependent on a more vulnerable asset base. Moreover, spatially quantifying the exposure of vulnerable households can help identify suitable regions for pro-poor adaptation measures, as well as other policies that require accurate information on the location of poor households (*e.g.* cash transfers). The third, and most important, concern relates to their conceptualization and quantification of welfare impacts. H2016 only model a single channel through which shocks affect welfare, which is damage to assets resulting in income and consumption losses, assuming that income and consumption are suitable metrics to contrast the disproportionate welfare impacts.

A growing body of literature has emphasized that income and consumption are imperfect metrics of poverty. For example, the global Multidimensional Poverty Index (MDP), developed by the Oxford Poverty and Human Development Initiative (OPHI), captures the acute deprivations in health, education and living standards household face. Such multidimensional poverty measures better capture a households' ability to achieve worthwhile goals ((Stiglitz et al., 2009; Alkire and Foster, 2011), and are therefore aligned with Amartya Sen's idea of capabilities (Sen, 1989) and directly related to the UN's Sustainable Development Goals. The data required for such a framework are also generally available at a more granular level allowing more detailed analyses of the affected households' characteristics. Hence, specifying a modeling framework that can capture alternative channels of disasters impacting household welfare (in this case MDP) can help complement existing disaster risk modeling studies. Moreover, it allows decision-makers to evaluate the wider benefits of adaptation options in terms of asset risk reduction, reduce the time that people face additional deprivations that can negatively affect wellbeing, and prevent people from falling temporarily into poverty.

In this study, we extend the H2016 model and aim to construct a new spatial risk framework to quantify the welfare implications of present-day and future climate extremes to households. The methodology is applied to a case study in the coastal zone of Bangladesh, an area inhabited by around 43 million people and considered to be among the most climate vulnerable regions globally. Using a recently developed synthetic household survey dataset that contains the location and socio-economic characteristics of all households, and linking each household to the critical infrastructures they depend on, we map the baseline level of multidimensional poverty (MDP) in coastal Bangladesh. The MDP index is a combined metric made up of nine indicators based on the global MDP (developed by OPHI). We quantify how cyclone-induced flooding at-present and in the future (2050) can temporarily increase MDP in this region. Moreover, we evaluate the benefits of adaptation, in particular the wider economic benefits of hard infrastructure interventions by upgrading coastal embankments.

Research questions

Several research questions are set to achieve this aim:

- What is the spatial distribution of MDP in Bangladesh's coastal zone, and how does it compare to other poverty metrics?
- What is the cyclone-induced risk in terms of asset damages, population exposed and infrastructure services provision, and how will this change in the future?
- Are poor households disproportionally exposed to cyclone-induced flooding?

- How can cyclone-induced flooding temporarily increase MDP through infrastructure service disruptions?
- How can various adaptation options help protect people and assets and prevent households from falling into temporary poverty?

By answering these questions, this research intends to contribute to improving resilience in coastal Bangladesh. In particular, the methodology and results of this research can be used to provide a better picture of the benefits of existing and future coastal interventions, which can be embedded within the decision-making process.

We start by providing a concise literature background (Section 2), after which we describe the methodology (Section 3 and the results (Section 4). This is followed by a brief conclusion and discussion (Section 5).

2 Background

2.1 Impacts of natural disasters on households

The direct impact of a disaster (e.g. floods) materializes as a consequence of the hazard impacting exposed assets or people combined with the vulnerability of these assets and people to this event. Damages to assets (i.e. physical damages), such as houses, roads, material properties, and agricultural land are the direct manifestation of hazardous impacts, alongside the mortality and displacement of people (Noy, 2016). Direct damages to households and publicly and privately owned assets, and the number of people who die or are affected, are often reported after a disaster and the most commonly used metrics in disaster risk assessment (Markhvida et al., 2020).

However, the impacts of natural disasters go beyond the direct damages and mortality, since disaster impacts to people and assets can translate into longer-term welfare impacts (i.e. sometimes called indirect damages in the literature) by affecting income streams (by increasing unemployment or business interruptions) and disrupting schools, health facilities and the drinking water supply, all contributing to a reduction in overall well-being (Datar et al., 2013; Arouri et al., 2015; Noy, 2016; Nguyen and Minh Pham, 2018; Noy and DuPont, 2018; Leppold et al., 2022). Hence, broadly speaking, one can classify the welfare impacts as those directly affecting households' consumption decisions (Noy and Yonson, 2018), those affecting income (employment lost and business interruptions) (Hallegatte et al., 2019), and those resulting in households temporarily experiencing other deprivations impacting, for example, health, education or living standards.

A large number of studies across geographies have quantified the link between disaster impacts and (short-term) household welfare. For instance, evidence from rural Vietnam over the period 2004 to 2010 showed that floods and droughts respectively caused a 5.9% and 5.2% decrease in per capita income and a 4.4% and 3.5% decrease in per capita expenditure (Arouri et al., 2015). In Bangladesh, the 2004 river flood decreased average household expenditure by 20% among affected households (Brouwer et al., 2007). Others have shown that natural disasters impact school enrollment and attainment in Ethiopia, India, and Vietnam (Nguyen and Minh Pham, 2018), and have various public health implications (e.g. mental, physical) (Leppold et al., 2022). On top of that, studies have linked the incidence of disasters to malnutrition among children. A case study in rural India (Jagatsinghpur district) found, for instance, that children in flood exposed households were 70% more likely to be stunted and 60% more likely to be underweight (Rodriguez-Llanes et al., 2011), while another study across rural India found that exposure to disasters increased the likelihood of being stunted or underweight by 7% (Datar et al., 2013).

Less evidence is available on the disproportionate welfare impacts of disasters, that is, who is most likely to experience welfare impacts. This critically depends on the household's exposure, vulnerability and resilience, the latter capturing the resources available to cope with and recover from a disruptive event (Akter and Mallick, 2013). For instance, those already living in a state of malnutrition are more prone to experience health implications due to disasters. Similarly, households with lower income or savings often lack the ability to smooth consumption shocks, rebuild their houses, keep their children in school or buy alternative sources of water (Hallegatte et al., 2020). For instance, across households affected from Hurricane Mitch in Honduras (1998), poorer households lost a greater percentage of the productive wealth (31%) compared to wealthier households (8%), and took longer to recover from this shock (Carter et al., 2007). After the Mumbai floods of 2005, poor households experienced a relative income loss that was 2.5 times larger than non-poor households (Patankar and Patwardhan, 2016), an observation similar to those made in a number of studies in Bangladesh (Brouwer et al., 2007; Akter and Mallick, 2013; Rabbani et al., 2013) and Pakistan (Kurosaki et al., 2012). Households in Indonesia that experienced an earthquake between 2002 and 2007 were almost 4% more likely to fall into poverty (Dartanto, 2022).

Hence, those already living in poverty are more likely to face disproportionate impacts of disasters, while those living close to the poverty line might be pushed temporarily or chronically into poverty (Hallegatte et al., 2020). However, while it is generally accepted that the poor and most vulnerable experience disproportionate welfare impacts, what the driving factor of this is remains inconclusive or context-specific. More specifically, disparities in impacts across socioeconomic groups could be attributed to the fact that poor households live in areas that are more hazard-prone (*e.g.* exposure bias), poor households experience larger relative losses (*e.g.* lower asset quality, undiversified asset base), or a lack the capacity to cope with the shock (*e.g.* financial resources).

2.2 Quantifying the welfare impacts of disasters

As discussed in the previous section, there is a plethora of *ex-post* analysis of the impacts of natural disasters on human welfare, such as on education, income, health, and inequality, primarily based on longitudinal household surveys and econometric methods. However, quantifying the welfare impacts of natural disasters *ex-ante*, using a risk modeling framework, has received considerably less attention. As such, most risk assessment of natural disasters or climate extremes use asset damages as their main metric of impact, obscuring how the poor might experience disproportionate impacts beyond asset damages (Markhvida et al., 2020; Verschuur et al., 2020).

A number of studies have quantified the exposure of poor households to disasters on a national or global scale (Bangalore et al., 2016; Winsemius et al., 2018). Less information is available on the vulnerability and resilience of poor households exposed to disaster. The extent of vulnerability is often related to the assets that households own, the employment they are engaged in, the type of infrastructure they depend on, and the health and socio-economic characteristics of households. A number of studies have developed regional or national-scale social vulnerability indices of hazard-prone areas using survey data (using subnational statistics), providing insights where the most social vulnerable regions are exposed to hazards (Marzi et al., 2019; Lee et al., 2021). However, these social vulnerability indices are difficult to construct on an individual household level while covering a large spatial scale. The resilience of households captures their ability to smooth shocks to their income or consumption and recover quickly, and is more difficult to infer from survey data. As part of the World Bank's *Unbreakable* report (Hallegatte et al., 2017), Hallegatte *et al.* (2016) (H2016) developed a model that quantifies how disaster impact can result in income and consumption losses, which, consequently, lead to households experiencing welfare losses (using a utility function). This model, which was initially applied on an international scale across 117 countries, has been refined and used in additional detailed case studies, including in the Philippines, San Francisco, and Bangladesh (Walsh and Hallegatte, 2019; Markhvida et al., 2020; Verschuur et al., 2020).

The original H2016 model has several assumptions and limitations inherent to the modeling framework. First, the only disruptive channel resulting in households experiencing income losses is via asset losses, which assumes that households derive income from the assets in their vicinity. The vulnerability of a household to such asset losses is based on a proxy of household vulnerability (e.g. housing type), with households living in lower quality housing experiencing a disproportionately higher income shock given damages to assets, as it is assumed that their asset-base is more hazard-prone. While necessary to make the step from asset damages to income losses, it remains a coarse assumption ignoring which assets are affected, and how households may depend on these assets. Similarly, poor or non-poor households are determined based on their income, assuming that the only way wellbeing is affected is by experiencing a drop in household income. However, using income or consumption as a metric of poverty has its limitations (see next section), especially in low-income countries, and ignores the multidimensional aspects (*e.g.* health, education, living conditions) that result in people living in a state of deprivation. Third, the H2016 operates using national household survey data, which is generally not available on a sufficiently granular level to provide insights into the spatial distribution of welfare losses on a subnational scale, nor the impacts to individual households. Although this has been partly resolved in the follow-up case studies (Philippines, San Francisco, Bangladesh), where regional household survey data was used and the impacts to individual households was evaluated, the survey data generally only includes a small subset of the population.

Hence the H2016 model and its extensions could be supplemented with a complementary analysis that (1) includes a larger representative sample of households on a local scale, (2) models how disasters affect specific assets, services and employment that households depend upon, and (3) quantifies the resulting impacts to the wider development potential of poor or otherwise vulnerable households. Such a model also allows evaluating, and better targeting, adaptation options. While the H2016 made a significant contribution in the sense that it allowed evaluating both hard (e.g. preventive measures) and soft (e.g. cash transfers) interventions in a single modeling framework, it did not allow the evaluation of spatial targeting of these interventions, nor of implementing interventions that make critical infrastructure more climate-resilient.

2.3 Poverty and welfare

Poverty is often measured in monetary terms, such as the international poverty line of $1.90 a day. Monetary poverty captures a household's ability to purchase goods and services, with the poverty line set to reflect a `minimum needs standard' for existence. Monetary poverty is broadly used and has several advantages: it is straightforward to design and track, can easily be interpreted, can be compared across time and regions, and can be easily aggregated over numerous households. However, it only captures one dimension of poverty – a household's consumption or income – and ignores other relevant development outcomes.

As a response, other metrics of poverty have been developed, such as the global MDP developed by the Oxford Poverty and Human Development Initiative (OPHI) (Alkire and Foster, 2011). It was developed to capture a broader picture of poverty based on widely available survey data, coinciding with wider recognition that poverty is a complex concept which cannot be captured using income or consumption alone (Stiglitz et al., 2009). The MDP considers individuals to face poverty if they cannot meet the basic needs deemed necessary for their existence, for example access to sufficient food and clean drinking water, access to education and other basic services, and social empowerment. In other words, the MDP intends to directly capture the households' ability to meet these basic needs, and is thus outcome focused. This is more in line with Amartya Sen's idea of capabilities, which reflect how individuals can convert income into achievements that improve human wellbeing (Sen, 1989). Moreover, the MDP is closely aligned with several of the UN's Sustainable Development Goals. The other benefit of any MDP measure is that it directly captures deprivations households face and allows policies to prioritize specific deprivations. However, it is more difficult to interpret and compare across space as multiple deprivations are aggregated into one number, and the choice of what measures to include and their weight is a normative decision subject to significant debate. As such, monetary poverty is often used in practice, as it precludes one from having to make normative decisions on the type and weight of different indicators.

Adopting a monetary poverty index versus an MDP index may highlight a different number and spatial distribution of poor households. Examining this at an aggregate level, Evans *et al.* found that they are comparable at the country level – a country in monetary poverty is likely to face significant MDP and vice versa. At the individual level however, these authors instead find a significant discrepancy between monetary poverty and MDP, with limited overlap between the set of households in monetary poverty and in MDP. The 2019 Global MDP covering 100 countries showed that two-thirds of the multidimensionally poor (886 million people) live in middle-income countries (UNDP, 2019), showing that there is a misalignment between monetary poverty and MDP.

In practice, both monetary and MDP measures of poverty can be used to construct an aggregate measure of welfare, *i.e.*, individuals' well-being. Monetary poverty can be used to construct a welfare measure by aggregating a convex function of individual income or consumption; it is a measure of economic *advantage* and continuously increases with economic growth. A welfare measure based on MDP is instead a measure of economic *disadvantage* – once no households face a deprivation, this measure goes to zero and becomes obsolete. It could thus be argued that

MDP is relatively more suitable to identify the poorest households, whereas monetary measures are more suitable to measure economic progress more broadly.

2.4 Cyclone risk in coastal Bangladesh

The coastal zone of Bangladesh is the case study area in our analysis. The coastal zone of Bangladesh is comprised of 19 districts (second administrative units in Bangladesh) covering 47,200 km^2, which was home to approximately 37.3 million people in 2011 (Bangladesh Bureau of Statistics, 2012), which has increased to almost 43.8 million people in 2021 (preliminary 2021 Census data). While significant progress has been made to improve wellbeing in the coastal zone, as illustrated by the decreasing (infant) mortality rate, poverty reduction, education enrollment, and access to water and sanitation (Hossain et al., 2016), the coastal population is lacking in terms of development compared to the country as a whole. For instance, 60 percent of the coastal Upazilas (third administrative units in Bangladesh) have an above average poverty incidence (which was 24.3 percent in 2016) (Bangladesh Bureau of Statistics, 2016).

The coastal zone is low-lying, with almost two-thirds of the coastal land being located less than three meters above mean sea level (MSL). The large amount of low-lying land, combined with the high population density (~1000 people per km^2) and the Bay of Bengal being prone to frequent tropical cyclones, make the coastal regions (in particular exterior coastal upazilas) vulnerable to the impacts of cyclone-induced wind and storm surges, as well as monsoon flooding (interior coastal upazilas). On average, a tropical storm (winds >63 km per hour) hits Bangladesh every year, while a Category I cyclone or higher (winds >118 km per hour) hits the coast every three years (Islam and Peterson, 2009; Dasgupta et al., 2014). Storm surges generated by cyclones can be very large (3 to 5 meters for a severe cyclone), which is attributed to the re-curvature of the cyclones in the Bay of Bengal and the shallow, funnel-shaped, coastal shelf that amplifies surges (Islam and Peterson, 2009; Dasgupta et al., 2010). As a result, storm surges can travel far inland along the tidal river branches and cause high water levels at embankments hundreds of kilometers from the coast. It has been estimated that tropical cyclones alone cause average annual losses (both damages and losses for all sectors) of almost 1 billion USD, while past events have recorded losses of up to 3.8 billion USD (TC Sidr in 2007) and 3.0 billion USD (TC Gorky in 1991) (Ozaki, 2016).

The cyclone-induced risk, in terms of physical asset damages, is expected to change in the future in coastal Bangladesh. First, climate change may change the frequency and magnitude (e.g. wind speed) of cyclones in the region. Second, sea-level rise increases the height of storm surges, resulting in more widespread inundation. Third, human-induced and natural subsidence, leads to a large relative sea-level rise, which can more than double the expected increase in water levels (Nicholls et al., 2021). Fourth, future economic development and population growth may increase the number of exposed assets in the coastal zone, which can contribute to changing risk, though population projections are highly dependent on the expected migration rates in the region (Chen and Mueller, 2018). Altogether, adaptation is required to prevent risk from increasing and prevent climate migration from the coastal zone.

Apart from cyclone-induced damages and losses to infrastructure assets, cyclones cause human mortality and impacts to human welfare. For instance, Cyclone Amphan (2020), making landfall in the districts of Khulna and Barisal, left over 250,000 people homeless (IFRC, 2021). Cyclone Sidr (2007), the most damaging event of the 21st century in Bangladesh, destroyed 10% of water sources in affected areas, hit 2.2 million farming families by reducing crop production, damaged 8,000 km of roads, and destroyed 2,500 educational facilities (Government of Bangladesh, 2008). Less information is available on the welfare implications to households as a result of extreme wind and flooding, such as losing access to water and sanitation, health facilities, or being pushed into poverty. Some case-studies of communities affected by cyclone Sidr (2007) and Aila (2009) have highlighted the wider impacts to household welfare. For instance, after Cyclone Sidr (2007), food insecurity increased across affected districts, with poorer households that are net food buyers disproportionally affected (as the event caused a food price spike) (Akter and Basher, 2014). Akter and Mallick (2013) showed that after TC Aila (2009), poverty incidence increased from 41% to 63%, unemployment rose from 11% to 60%, while access to sanitation, clean water and electricity all decreased by 10% to 25% across affected communities in Satkhira district. Similarly, TC Aila (2009) increased the salinity levels beyond a tolerable threshold for agriculture in Satkhira, resulting in widespread crop failure for the year following the cyclone, and low yields the years after that. Affected farming households lost on average 45% (non-poor) up to 75% (poor) of their household income, and had to reduce household expenditure and change eating habits (Rabbani et al., 2013). On top of that, across Satkhira and Khulna districts, 32% of all household pit latrines were partially or fully damaged, alongside a 50% decrease in water supply coverage due to damaged tube wells and pond-sand filters (Chakraborty et al., 2016).

Although there is some evidence that the poor and marginalized households are disproportionately affected by disasters in Bangladesh, it is unclear what is driving this. For instance, this could be attributed to the fact that poor households are disproportionally exposed to floods, as has been shown (Akter and Mallick, 2013), or suffer disproportionally large impacts. In particular, the presence of an exposure bias has long been debated and conflicting evidence has been brought forward over the years (Hallegatte et al., 2020). This calls for a highly granular, spatially explicit approach to disentangling the effects of exposure and vulnerability on risk to develop evidence-based ‘pro-poor’ adaptation strategies.

3 Data and methods

We set out a methodology to extend the conventional asset risk framework to a welfare risk framework, using an MDP index as a proxy of household welfare. The methodology consists of five components: (1) household MDP analysis, (2) risk analysis and quantification, (3) service accessibility analysis, (4) poverty impact analysis and (5) cost-benefit analysis of adaptation options.

The workflow of the analysis (components 2 to 4) is schematized in Figure 1.

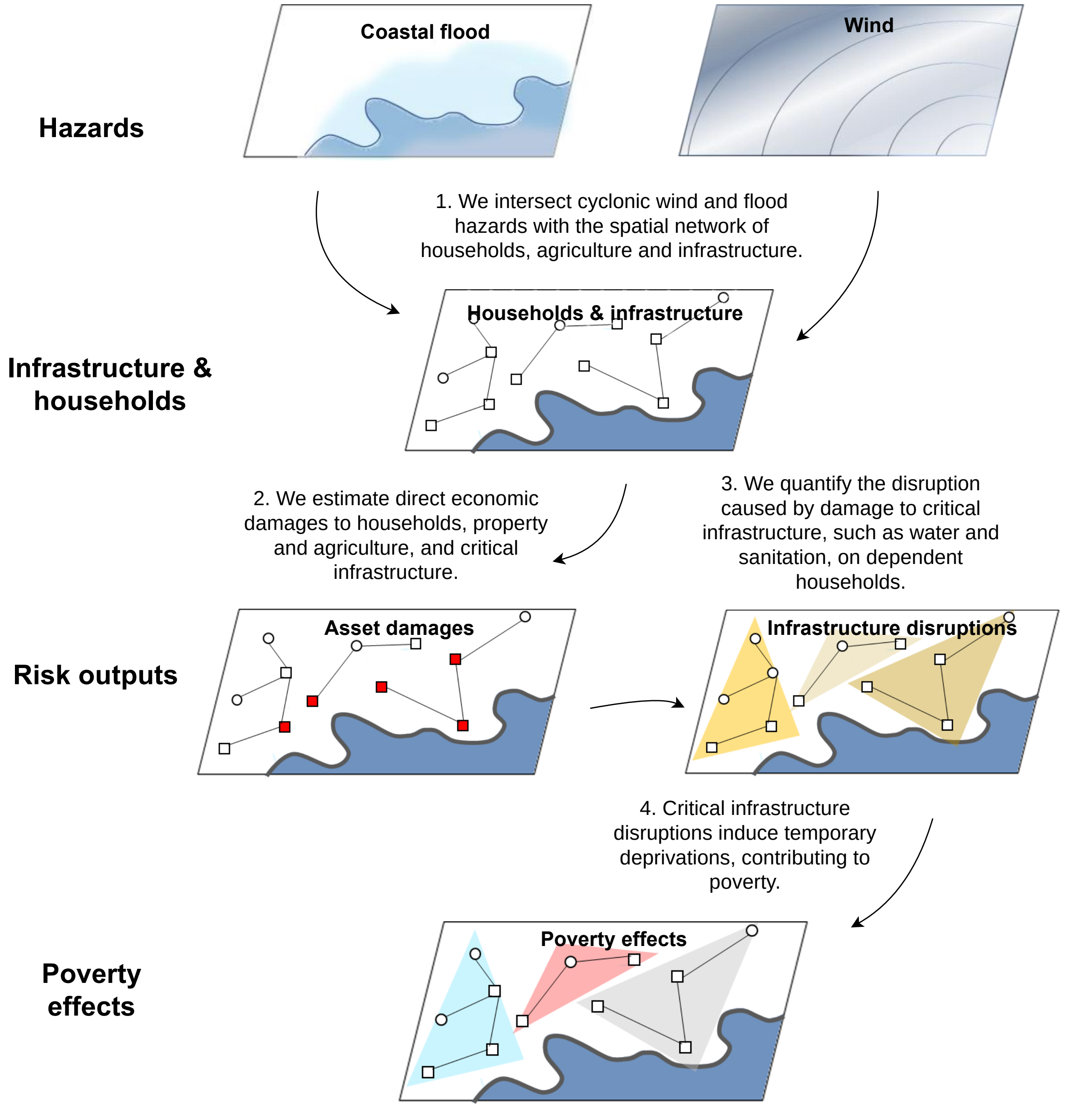

Figure 1. Overview of the risk methodology developed in this study, in which hazard and infrastructure data is used to evaluate both the asset damages and household infrastructure service disruptions, and their effect on temporary poverty for affected households.

3.1 Multidimensional poverty

We create a multidimensional poverty (MDP) index inspired by the OPHI MDP based on a synthetic household survey dataset (SHSD) supplemented by three other variables (see below).

3.1.1 Synthetic household survey data

Recently, a synthetic household survey dataset (SHSD), representing the location (latitude/longitude) and socioeconomic characteristics of almost 43 million people (10.25 million households) across 19 districts and 150 Upazilas in the coastal zone, was developed using both detailed Census data, household survey microdata and spatial microsimulation techniques (Rubinyi et al., 2022). The SHSD provides the best source of information on the deprivations that Bangladeshi households face on a high spatial resolution, and includes information on housing types, access to water, energy and sanitation, and educational data. The details on the SHSD are included in Appendix A; here we only describe how we have constructed the MDP indicators that we use throughout our work. The original SHSD is based on Census 2011 data, which are projected to 2020 to take into consideration that the population has grown and households have experienced improved living standards over this 10-years period, and hence, face lower MDP.

3.1.2 Multidimensional poverty indicators

We construct a new MDP index for the coastal zone of Bangladesh based on nine indicators (see Table 1). The MDP combines variables across the different dimensions that contribute to a households' wellbeing. These variables are grouped into 3 categories (Education, Living standards, Health) in line with the OPHI MDP. Six of the variables from the MDP can be generated from the SHSD. However, the SHSD still captures only a limited number of dimensions of poverty, for example it does not provide information on health indicators. As such, two additional variables are derived from the accessibility analysis (Section 3.4), access to hospital and health facilities, and another measure, child stunting, is derived from the 'Multiple Indicators Cluster Surveys' (MICS) survey dataset using a small area estimation (SAE). SAE uses a regression formulation to distribute aggregated household information to a higher spatial resolution (e.g. from a national to a regional level), either within a survey data (using both aggregated and microdata) or across different surveys (Elbers et al., 2003). Here, we use a regression formulation using overlapping household information in the MICS data and the synthetic household data to construct one variable that is captured in the MICS data (child stunting) but not in the synthetic data (see Appendix B for details). We acknowledge that these variables covering household health status are an incomplete measure of health. We end up with nine variables to construct the MDP index as shown in Table 1.

In line with the OPHI MDP formulation, we also apply a weighting factor to the different variables, such that the three groups contribute equally to the MDP. In the end, the household's MDP score is the weighted sum of the individual deprivations, which scales between 0 and 1.

Based on the index created, we define two levels of MDP:

- ***Moderate MDP:*** *a household has an MDP of 1/3 or higher*
- ***Extreme MDP:*** *a household has an MDP of 1/2 or higher*

Table 1. Overview of the variables used to construct the MDP used in this study.

Group	Deprivation	Criteria	Weight	SDG	Source
Education	Years of Schooling	No eligible household member has completed six years of schooling.	2/12	4	SHSD
Education	School attendance	Any child under 12 is not attending school.	2/12	4	SHSD
Living standards	Sanitation	The household has unimproved or no sanitation facility.	1/12	6	SHSD
Living standards	Drinking Water	The household does not have access to tube well or tap water.	1/12	6	SHSD
Living standards	Electricity	The household does not have access to electricity.	1/12	7	SHSD
Living standards	Housing	The household lives in jhupri or kutcha housing.	1/12	11	SHSD
Health	Hospital	Hospital further than 20km away.	1/12	3	Own analysis
Health	Health	Health center further than 20km away.	1/12	3	Own analysis
Health	Stunted	Child under 5 died in the past 5-years.	2/12	3	MICS

3.2 Risk analysis and quantification

We perform a risk analysis, evaluating damages to housing, infrastructure assets and agricultural land. A risk analysis combines data on the spatial extent of the hazard with the location of exposed assets and land-use, after which the resulting damages are evaluated using specific vulnerability curves and reconstruction costs (Meyer et al., 2013). For the vulnerability curves and reconstruction costs, we have used country-specific data where possible, supplemented by data from countries with comparable characteristics as Bangladesh in terms of asset vulnerability (*e.g.* engineering standards, building types). A brief overview with more details is included in Appendix D.

3.2.1 Hazard data

We consider two types of hazards; cyclone-induced coastal flooding and extreme wind. For coastal flooding, we utilize modeled flood water levels from the Institute of Water Modelling (IWM) in Bangladesh (IWM, 2018). They developed a hydrodynamic model to simulate how extreme storm surges of different magnitudes propagate through the tidal channels in the coastal zone. The modeled flood water levels are then overlayed with a digital elevation model, assuming a complete inundation of unprotected areas and inundation of embanked areas (see below) above their design standards. This approach is known to be simplistic, in particular in terms of the inundation dynamics of the polders and the probability of polders breaching before design conditions are reached. However, given a lack of more refined data to include this failure mechanism, this is not considered here. Future flood simulations for 2050 were performed by adding 0.5m of relative sea-level rise to the model and increasing the wind speed by 8% (henceforth called 'climate change scenario'). This scenario is based on the RCP8.5 sea-level rise scenario and applying a background subsidence rate, and should be seen as an upper bound for 2050 (though sea-level rise rates across climate scenarios do not differ much for 2050). The model output consists of four flood maps (10, 25, 50, 100 return years) for the present and climate change scenario. Figure D1 shows the present and future flood inundation for a 25 and 100-year return period without polders.

The coastal zone of Bangladesh is protected by around 6,000 km of embankments across 139 polders. At the baseline, we assume that polders prevent against a 10-year present-day flood event, which is considered an upper bound as most polders are not well maintained or will flood (due to overtopping or breaching) under a less severe flood event. The locations of all polders are shown in Figure 2, some of which are part of a recently finished program of upgrades (CEIP-I, ten polders) and others proposed to be upgraded in the feasibility study (FS) of a new investment project (FS-NEW, twenty polders). The details of these programs are discussed in Section 3.5.

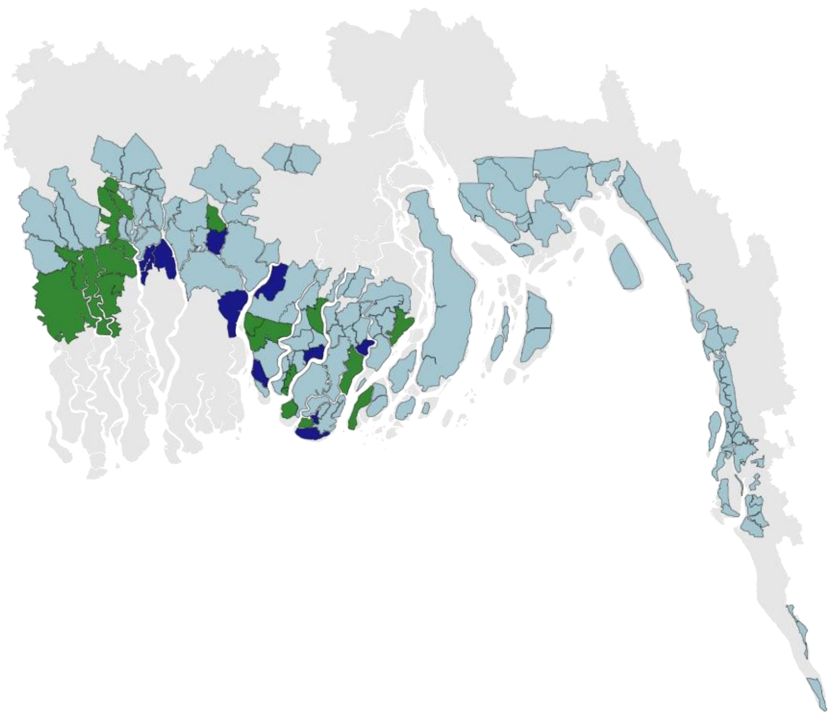

Figure 2. The location of the 139 polders, including those upgraded under CEIP-I (dark blue) and those selected to be upgraded under the feasibility study of FS-NEW (green). The other polders (light blue) are not part of any large-scale program.

For TC wind, we use data from Steptoe and Economou (2021), who reconstructed the wind speed profiles of 12 historical cyclones making landfall in Bangladesh using a numerical wind model (Met Office Unified Model). To estimate the risk across the coastal zone, we used cyclone wind maps for six return periods (2, 5, 10, 20, 50, 100-years), which were created by fitting an extreme value distribution to modeled wind speeds per grid (Steptoe and Economou, 2021). Examples of the cyclone maps are shown in Figure D2. Future wind speed maps are derived by adding an 8% increase in the maximum wind speed to the return period maps, making them consistent with the coastal flood scenario.

3.2.2 Exposure, vulnerability and risk

The exposed assets and land-use we include in our analysis are housing, roads, educational facilities, health facilities, hospitals, electricity substations, wells, latrines and agricultural land. Commercial and industrial land-use are not considered in this study, given the lack of data. However, evidence from Cyclone Sidr (2007) suggests that damages to commercial and industrial assets only contributed 3% to the total disaster damages and are thus small.

The location and type of housing (e.*g.*, jhupris, kutcha, semi-pucca, pucca) per household are taken from SHSD derived for the coastal zone of Bangladesh. For critical infrastructure assets (roads, schools, health facilities, hospitals, electricity substations), we collected various geospatial layers of the different asset types, with an overview of the data sources included in Table D1. For tube wells and latrines, we do not have asset data on the location of wells and latrines. However, we do know the number households that are dependent on tube wells and pit latrines using the SHSD. Hence, we use the exposure of those households that use tube wells and pit latrines as an indicator of the location of assets. The rationale for this is that pit latrines are commonly located on the household premises at a distance of 10 meters or less from the house (personal communication DPHE, 2022), while tube wells are generally co-located with housing within a relatively small radius (*e.g.*, tube wells serve a surface area of an around 150-meter radius according to the Bangladesh National Strategy for Water Supply and Sanitation). While pit latrines often serve a single household, tube wells serve on average ten households (personal communication DPHE, 2022).

To model damages, both vulnerability curves (per hazard) and reconstruction costs are required. In Tables D2 and D3, we present an overview of the vulnerability curves and reconstruction costs per asset type, which were obtained from various reports, personal communication with responsible government agencies, and from the literature.

For agricultural land, we look at spatial crop maps derived from satellite data (Singha et al., 2019), which includes the location of agricultural fields used for rice production in the different cropping seasons (Aman, Boro, Aus). We merge rice yield per hectare and rice price per district from the 2019 Agricultural Production report to create a map of crop value exposed. We use a district-specific correction factor such that the agricultural land per district corresponds with the amount of rice produced (*e.g.*, to take into consideration that not all agricultural land is used for cultivation). We ignore the timing of the cyclone events with respect to the cropping season. In general, cyclones strike during the months March – July and September – December, which corresponds to the sowing of Aus (March-May) and Aman (June-July) rice, the harvest of Boro rice (April – May), and the harvest of Aman (November – December). Hence, it is likely that the occurrence of a cyclone affects one or multiple rice crops. Without adequate information on the timing of the event, we assume that if a crop field gets flooded and the crop field is fully damaged (see Table D2 for fragility curve), the entire production within a grid cell is lost (either single, double, or tripped cropped), which is considered an upper bound.

By overlaying the hazard maps with the exposed assets and land-use and combining this with the vulnerability curves and reconstruction costs, we model the damages to the assets and agricultural fields. To estimate risk, we adopt the trapezoidal rule, which is common practice to estimate the risk given a discrete number of return periods.

3.3 Service accessibility analysis

Apart from direct damages to assets, service disruptions can occur if the assets that provide essential services to dependent households are damaged and are out of service for a given amount of time. In this study, we link these service disruptions to the MDP constructed. As such, we consider households' access to schools (for rural households having a child below 12),[1] health centers (*i.e.*, family welfare centers), hospitals, energy (for those urban household having electricity[2]), latrines (for those households using latrines) and water (for those households using tube wells). Moreover, we consider housing as an infrastructure service, with direct damages to housing considered a 'loss of service'. We briefly describe the methodology below and a summary of the methodology in Table 2. Supporting information is included in Appendix E.

Table 2. Overview of the methodology to connect geolocated households to infrastructure services.

Infrastructure type	Household connected	Method accessibility
Schools	Rural households with child below 12	Connected via road network to closest school.
Health centers	All households	Connected via road network to closest school.
Hospitals	All households	Connected via road network to closest school.
Energy (substations)	All urban households having an energy connection	Connect to substation in closest proximity.
Sanitation	All households using pit latrines	Assumed co-located with household location
Water	All households using tube wells	Assumed co-located with household location

[1] The database on educational facilities from LGED only includes educational facilities in rural areas. As a result, we limited ourselves to the accessibility of rural households with respect to schools.

[2] The synthetic household survey does not distinguish the type of electricity access (e.g. grid or off-grid solution). We hereby assume that only households in urban settlements with electricity are connected to the main electricity grid, while rural settlement have alternative energy provision, such as solar systems through the Bangladesh Solar Home Systems (SHS) Program, the largest national off-grid electrification program in the world.

Housing	All households	Assumed co-located with household location

3.3.1 Accessibility analysis

The accessibility of certain infrastructure services (education, hospitals, and health facilities) is modeled by connecting all households via the road network to the closest infrastructure asset. This is done by first creating a topologically correct road network using the road infrastructure data. Second, based on the road type (*e.g.*, highways or zila road) and paving (*e.g.* pucca or katcha), we assign a speed to the road segment. The processed road map with allocated speeds is shown in Figure E1. Third, we assign every household location in the synthetic household survey to the closest road and every infrastructure asset to the closest road. Then, for every household, we find the closest asset that this household can reach and derive the time and distance it takes to access these assets. Based on this, we find the total number of households that are using each individual asset and the road segments that are used to reach this asset.

For electricity services, we connect the urban households with electricity access to the closest substation, assuming that they will be connected to the substation via a local distribution network. We assume that rural households are not connected to the main grid, but instead use rural community electricity services, such as solar panels. As described in Section 3.2, we assume that tube wells and pit latrines are co-located with households, and the infrastructure service provision is directly modeled using the location of households in the SHSD data.

3.3.2 Infrastructure services

Using the accessibility analysis, we can derive the system of infrastructure services across the coastal zone. Across the coastal zone, 71% of the urban households have access to electricity. Moreover, 88% of the rural households and 75% of the urban households are using dug wells for accessing drinking water, which, given a total of around 0.5 million functioning tube wells located in the coastal zone (based on DPHE data), equates to around 18 households per well. Moreover, 97% and 98% of the rural and urban households, respectively, have access to some form of sanitation, with 71% and 78% of rural and urban households having improved sanitation facilities.

An overview of the household allocation to assets and the roads per infrastructure type is shown in Figure 3, showing clear size differences in the service areas of different infrastructure assets. One can observe that access to educational facilities is very decentralized (median of 173 households per asset) given the large number of assets, while access to hospitals is very centralized (median 52,787 households per asset) with a relatively small number of main roads used to access these hospitals. Access to health facilities (median 8,619 households per asset) shows a more regional infrastructure services provision with each facility serving a relatively equal sized regional service area. The median number of households per electricity substation is 7,400 households, concentrated in the urban areas.

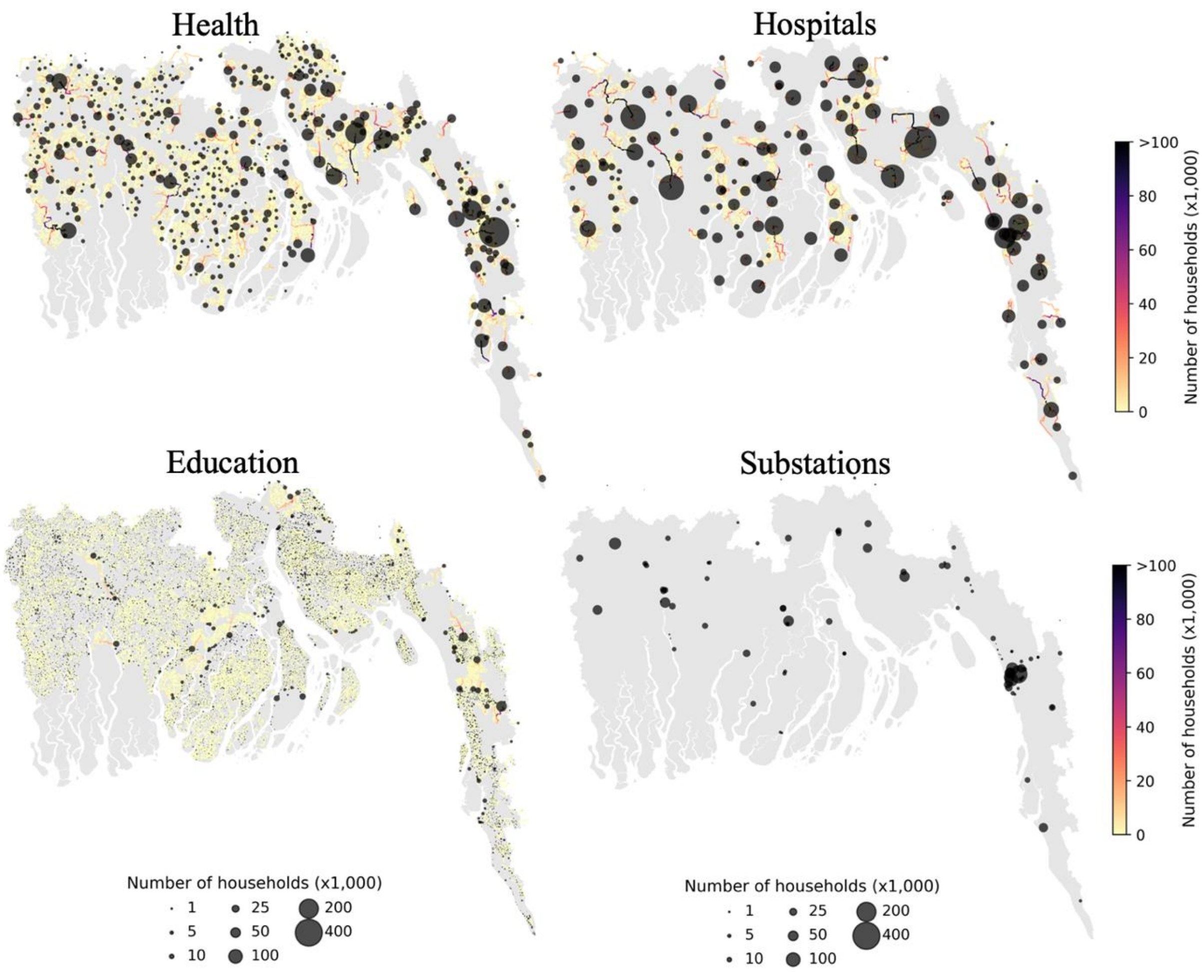

Figure 3. The location of infrastructure assets alongside the number of households using these assets (marker size), and the roads used to access these infrastructure assets.

3.3.3 Service disruption

The extent of an infrastructure service disruption is related to the number of households that use a particular asset and the time it takes to repair or reconstruct the affected assets. The repair and reconstruction duration of the assets depends on several factors, including the level of damage it has endured, the type of asset (*e.g.*, some assets might be easier to restore than others), the geographical location of the assets (*e.g.*, assets in rural assets are less accessible) and the severity of the disaster event (*e.g.*, during larger disasters, it might take longer to mobilize labor and financial and material resources to repair and reconstruct the assets).

Given that data on the repair and reconstruction duration is hard to collect, we adopt a practical approach and estimate the repair and reconstruction duration for three levels of infrastructure damage; (1) limited damage, which need repairs only (0 – 30% damage), (2) moderate damage, which need repairs and partly reconstruction (30 – 80% damage), and (3) large damage, which requires full reconstruction (80 – 100% damage). The duration refers to the average time to reconstruct damaged assets after a large-scale disaster event, and hence not just the repair or reconstruction cost of a single asset (that is, it may only take a couple of hours to repair a damaged tube well but requires multiple days to restore water services in an affected area). We collate disruption duration values per infrastructure type based on existing evidence and consultancy with some key experts (*e.g.*, the World Bank team and country experts). We model the disruption duration as a linear interpolation between the three values, as is shown in Figure E2. We can thereby link the amount of damage an asset endured (Section 3.2) to the time needed to restore infrastructure services. We ignore that in some cases, temporary or emergency measures are taken to provide essential services while assets are being repaired or reconstructed (*e.g.*, emergency health, education or latrines provision).

Taken together, we estimate the *disruption risk* per asset, expressed in the terms of average expected number of days per year an asset cannot provide services. By multiplying this disruption risk output by the number of dependent households, we provide the *service disruption risk*, expressed in units of Household Disruption Days (HDD) per year.

Apart from the aggregate service disruption risk, we can also model the service disruption risk to every individual household. That is, we can approximate for every individual household whether it loses access to water, sanitation, electricity (if connected in the first place), schools, health facilities and hospitals. We will utilize this in Section 3.5 to model who loses access to (some of these) essential services, which will ultimately affect their level of MDP poverty during the time it takes to restore infrastructure services.

3.4 Impacts on multidimensional poverty

To estimate the welfare impacts to disaster-affected households, we look at the relationship between disaster impact and MDP in two ways.

1) Exposure of multidimensionally poor households: by overlaying the flood maps with the location of households that are considered multidimensionally poor, we can estimate the exposure of multidimensionally poor households. We define exposed households as those experiencing at least 0.5 meter of flood depth at their house. In general, households that are multidimensionally poor are considered to have a higher socio-economic vulnerability, and hence may suffer disproportionally.
2) Temporary incidence of MDP: by modeling the disruptions to infrastructure services and the households that depend upon them, we can evaluate which households temporarily face additional deprivations, and whether this pushes them into moderate or extreme MDP.

These two metrics are complementary since some regions might have a low baseline incidence of MDP but have a high potential for seeing an increase in MDP after a shock. Similarly, some areas have a high baseline of MDP but a relatively small number of households that are prone to falling into MDP. Moreover, it is necessary to consider both aspects, since those already facing MDP cannot experience further deprivations beyond the extreme MDP threshold.

Note that we only look at the impacts caused by flooding, since several of the infrastructure assets are considered unaffected by extreme wind. In theory, one would need to evaluate the joint probability of flooding and wind speed to derive the service disruptions of assets due to cyclones, which is beyond the scope of this study.

3.4.1 Exposure of multidimensional poverty households

Households that are in MDP are considered to be more vulnerable than those not in MDP. For instance, households that are in MDP might find it harder to access health facilities or hospitals as they are located further away or have lower baseline health (e.g. as indicated by child stunting indicator). Moreover, flooding in areas with a higher fraction of households having unimproved sanitation facilities or drinking water sources can result in disease outbreaks or other health implications.

We can capture the relative ***exposure bias*** of Upazila in terms of MDP exposure; the percentage differences between the fraction of households exposed that are multidimensionally poor relatively to the baseline MDP level across the coastal zone. This metric helps to identify the largest disproportionate exposure of multidimensionally poor households in relative terms.

3.4.2 Temporary incidence of MDP

Even if households do not face MDP at the baseline, they may be prone to falling into MDP if they face additional deprivations during cyclones, such as losing access to clean water, adequate sanitation, or electricity. However, as infrastructure is being repaired or reconstructed, people gradually gain access to their baseline level of services again. Here, we evaluate the temporary increase in moderate and extreme MDP levels for a given number of days after the shock. We hereby assume that within the timeframe between the incidence of the shock and the maximum duration to restore infrastructure service, households gradually gain access again to infrastructure in a linear fashion. That is, if it takes 100 days to restore education across an affected region, and 1,000 households depend on the affected schools, 500 households gain access again after 50 days and 750 households have access again after 75 days. The ‘Child stunting’ and ‘Years of schooling’ indicators of the MDP are considered unaffected by disaster impact.

3.5 Evaluating the wider benefits of adaptation

The Government of Bangladesh, supported by the various international organizations (*e.g.*, World Bank), have implemented a large variety of climate adaptation options since independence. The most notable investment was the construction of 139 polders across the coastal zone that protect the low-lying areas from flooding and boost agricultural productivity by reducing the salinity levels inside the polder boundaries. In recent years, a number of polders are being rehabilitated and/or upgraded to improve the protection levels and their structural integrity, especially for those polders exposed to erosion. Similarly, other types of structural adaptation have been implemented, such as flood-proofing of critical infrastructure and improved emergency response.

Here, we analyze the benefits of historical and potential climate adaptation options, which we compare to the situation without the intervention. We consider three investment programs to upgrade coastal embankments (e.g. improve their flood protection standards by elevating them), which are an example of a type of adaptation intervention for protecting an area's physical infrastructure. We evaluate the wider benefits of adaptation in terms of:

- **Asset risk reduction**: A reduction in the direct damages to infrastructure, housing, and agriculture. For those interventions for which we have cost estimates as well, we can consider the benefit-cost ratio (BCR).
- **Service disruption risk reduction**: We can consider the benefits in terms of the reduced number of households-days of service disruptions. This is done in percentage points. Benefits are taken for the region that is protected by the embankments.
- **Reduced incidence of MDP**: We can consider the reduction in the number of people that face temporary MDP after a shock.

Upgrading coastal embankments are considered as most relevant options as major programs are currently being implemented or are proposed, data on their costs are available, and the benefits of hard infrastructure are often solely expressed in terms of asset risk reduction only, and not their wider welfare benefits. Note that we have also tested implementing two other adaptation options, notably flood proofing of WASH infrastructure and more rapid recovery efforts. These complementary interventions are described in Appendix G. We have excluded these from the main text as the costs, and hence BCR, is difficult to establish for these interventions.

Details on upgrading coastal protection infrastructure

Under the Coastal Embankment Improvement Project Phase 1 (CEIP-I), which started in 2013, ten polders across the coastal zone have been upgraded to withstand a storm surge level with a frequency of occurrence of once in 25-years in the future (2050, which includes sea-level rise) (see dark blue polders in Figure 2). By incorporating these protection levels in the model and comparing the results to the counterfactual situation before project implementation (i.e. protection against present-day one in 10-year event), the benefits of the polder upgrades can be re-evaluated. The costs are taken from the reported costs to upgrade the embankments under CEIP-I, which cover the construction costs of the embankments and the slope protection constructed for parts of the embankments (excluding construction and upgrades of water infrastructure).

Under a new proposed investment program, for which the feasibility study (FS) has been performed (FS-NEW), a new set of 20 polders are potentially selected for further upgrades (see green polders in Figure 2). Similarly as for CEIP-I, we evaluate the benefits for the selected polders compared to the situation without them. The costs are scaled based on the CEIP-1 costs (*i.e.*, scaled by the length of embankments).

Third, we also evaluate a hypothetical scenario in which all polders (ALL-POLDERS) in the coastal zone are upgraded. This includes the CEIP-I polders, the FS-NEW polders and all other polders not yet considered as part of an investment scheme (light blue polders in Figure 2).

4 Results

4.1 Baseline multidimensional poverty

Figure 4 shows the baseline moderate and extreme MDP for coastal Bangladesh on an Upazila level. Across the coastal zone, 28.1% of people live in moderate MDP, whereas 7.2% of the people living in extreme MDP. The highest incidence is in the Cox's Bazar region, the Meghna Estuary region (Bhola, Patuakhali, Lakshmipur, Noakhali), and the Upazilas bordering the Sundarbans. The largest contribution to the MDP are deprivations faced by households in terms of housing (67.6%) followed by electricity (40.2%), hospital access (29.3%), sanitation (25.9%), health access (18.2%), school attendance (13.8%), child stunting (10.5%), years of schooling (8.4%) and access to water (7.4%).

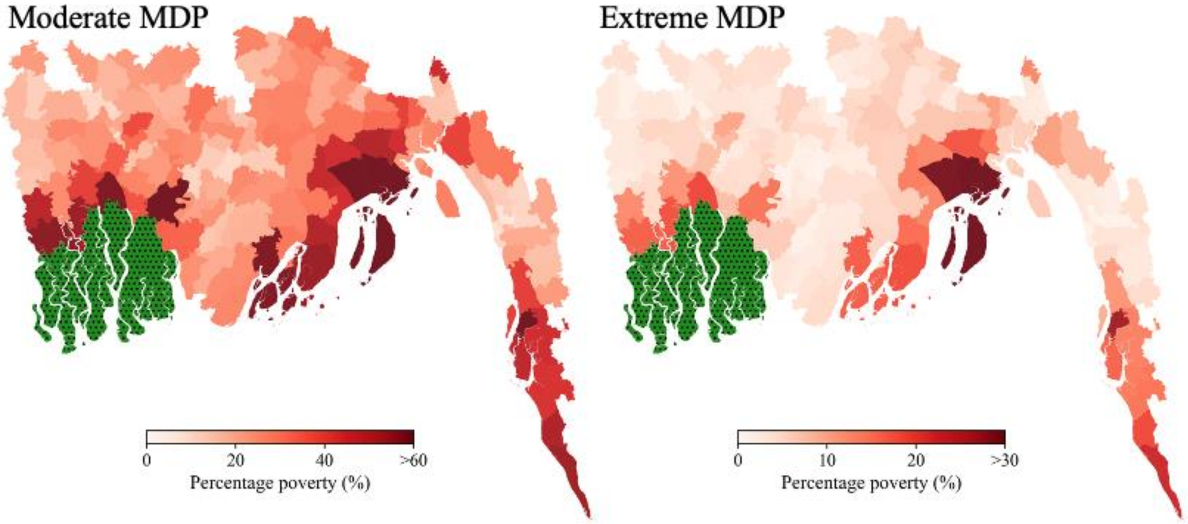

Figure 4. Moderate (left) and extreme (right) MDP on an Upazila level. The green area covers the Sundarbans and are excluded from the analysis.

Since our MDP metric is a complementary poverty metric, we also compare the spatial distribution to other poverty metrics available in Bangladesh, such as household consumption, which is based on the 2017 Household Income and Expenditure Survey (HIES), the official poverty metric (based on a 'Cost of Basic Needs' approach), and a MDP metric constructed on a district level (using MICS survey). These alternative poverty proxies are shown in Appendix C, showing that regional differences between poverty proxies exist, but also considerable regional overlap. For instance, we identify pockets of high MDP close to the Sundarbans, the Meghna Estuary region and in Cox's Bazar. This is in line with the official poverty metric, which shows high poverty incidence in the Meghna Estuary region, close to the Sundarbans, and the southern top of Cox's Bazar. However, consumption estimates show a clearer East-West divide, in some places not well aligned with the MDP index and official poverty index. However, average consumption values are often skewed by a small number of richer households. The district-wide MDP index is well aligned with our more spatially detailed MDP index, although the areas just north of the Sundarbans do not show up here given the high level of spatial aggregation.

This indicates that no poverty index is perfect and a combination of poverty metrics is required to understand the complex nature of poverty in developing country contexts. Moreover, it shows that aggregating the poverty data can hide high poverty incidence on a more granular level.

4.2 Asset risk analysis

4.2.1 Flood risk

At present, the Expected Annual Damages (EAD) to households and infrastructure are estimated to be 349.4 and 10.4 USD million per year, respectively, while the present day agricultural losses are estimated to be 124.2 USD million per year. Figure 5 shows the Upazila-level aggregates, with a large risk in the Chattogram region and the western part of the coastal zone, as well as some hotspots along the central coastal zone.

Climate change can elevate the risk to housing and infrastructure to 585.1 USD million per year, a 63% increase, while the agricultural losses increase to 164.1 USD million per year, a 32% increase. Together, the total asset risk increases from 483 USD million to 749 USD million per year (55% increase). Figure 5 shows the future risk estimates per Upazila, clearly showing how central coastal Upazilas will experience a clear increase in risk.

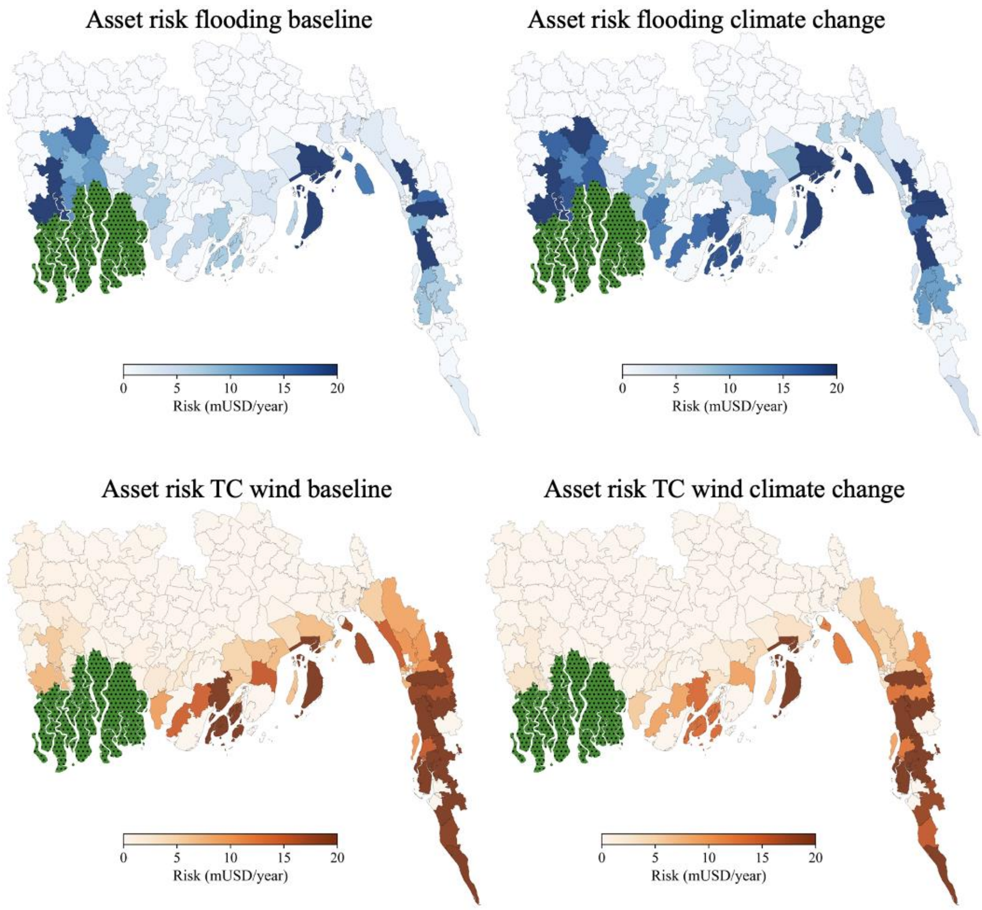

Figure 5. Asset risk as a result of flooding (top) and tropical cyclone wind (bottom) at present (left) and in 2050 under climate change. The green area covers the Sundarbans and are excluded from the analysis.

4.2.2 Extreme wind risk

On top of the flood-induced asset risk, the occurrence of extreme winds can cause asset damages worth 413.7 USD million per year, roughly the same amount as flood asset damages. Climate change can increase this number by 53%, underlining the strong non-linearity of the vulnerability of assets; given that extreme winds increase with 8% in the climate change scenario, damages have a marginal increase of over 6 times the change in wind (53% divided by 8%). The largest asset damages are found in the urbanized eastern part of the coastal zone with high density of residential properties, as well as in some of the central coastal Upazilas, such as Bhola island, with lower population density but a higher fraction of lower quality housing.

4.3 Service disruption risk analysis

4.3.1 Asset service disruption risk

The aggregate service disruption risk to assets can be expressed as the asset disruption risk (days per year) times the number of households dependent on these assets. We call this the household disruption days per year, or HDD per year. In this way, we can identify the most at-risk assets from a service disruption perspective. For instance, a HDD of 10 million per year is equivalent to 500,000 households not having access to education for 20 days per year, or 1 million households do not have access to water for 10 days per year.

Under the present-day flood risk scenario, the largest service disruption is to hospitals (11.5 million HDD per year), followed by health facilities (11,1 million HDD per year), educational facilities (6.4 million HDD per year), and electricity substations (0.3 million HDD per year). The geographical distribution of the service disruptions is shown in Figure 6, showing large risk to hospitals, health facilities and schools in hazard-prone areas in the east of the coastal zone, given the large population density. As a result of climate change, the service disruption risk will increase by 157 – 188%, depending on the type of infrastructure asset, with the largest increase expected for educational facilities, in particular in the western part of the coastal zone.

In terms of the risk to the roads needed to access the infrastructure assets, large differences between infrastructure types are observed. While the risk to roads accessing educational facilities is low compared to asset service disruption risk (1.9 million HDD per year), the risk to roads accessing health facilities (25.7 million HDD per year) and hospitals (15.1 million HDD per year) is higher than asset service disruption risk. The latter is due to the high concentration of households using roads exposed to flooding, in particular in the western part of coastal zone (Figure 6). As a result of climate change, the level of service disruption risk to the road network is growing considerably, by 290 – 470%, given more frequent and more severe transport disruptions, in particular to roads initially not exposed to flooding.

In terms of household facilities (housing and WASH infrastructure), the present-day service disruption risk to tube wells is 9.3 million HDD per year, which will more than double because of climate change to 22.7 million HDD per year. The risk of disruptions to sanitation facilities is 13.9 million household days per year at present, which can increase to 33.4 million HDD per year in 2050. Housing disruptions increase from 21.0 million HDD per year to 34.6 million HDD per year in 2050.

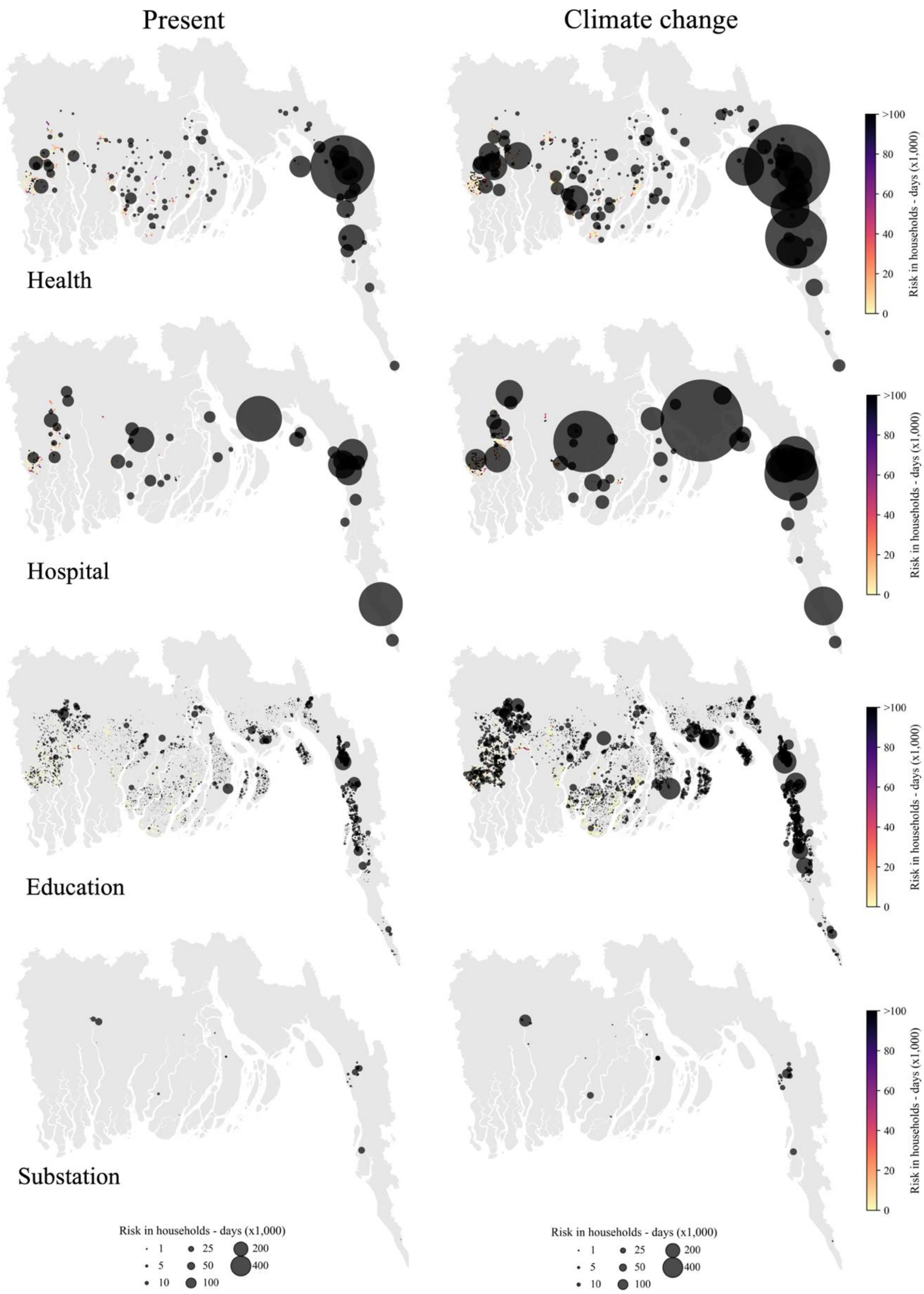

Figure 6. Service disruption risk to assets at present (left) and in the 2050 under climate change (right). The markers indicate the risk to assets in HDD per year, while the color shows the same risk but to the road network used to access the infrastructure assets.

4.3.2 Household service disruption risk

A large share of the households in the coastal zone are exposed (that is, risk larger than zero) to one or multiple service disruptions each year as a result of cyclone-induced flooding. In fact, of all households, 13.1% (19.9%) face water service disruptions, 15.2% (23.0%) face sanitation disruptions, 5.8% (7.6%) face electricity disruptions, 16.6% (19.8%), face education disruptions, 24.0% (34.9%) face disruptions due to inoperable health facilities, 29.3% (40.7%) face disruptions as a result of operable hospitals, and 27.3 (35.0%) face disruptions to their housing under the present-day (future) scenario.

Figure 7 shows the household service disruption risk expressed in terms of the annual expected number of days a year an average household in the coastal zone faces service disruptions due to flooding disaggregated per district. That is, we have divided the HDD per year by the number of households in the coastal zone. At present, the household service disruption risk is equivalent to two days per year, with the highest risk in Bhola, Chittagong, Cox's Bazar and Noakhali districts. In 2050, the risk may increase to 4.5 days per year, an increase of 133%, with the largest absolute risk in Barguna, Chittagong, Cox's Bazar and Noakhali (all above 6 days per household). However, in relative terms, a risk increase of over 200% is found in Barguna, Lakshmipur, and Pirojpur.

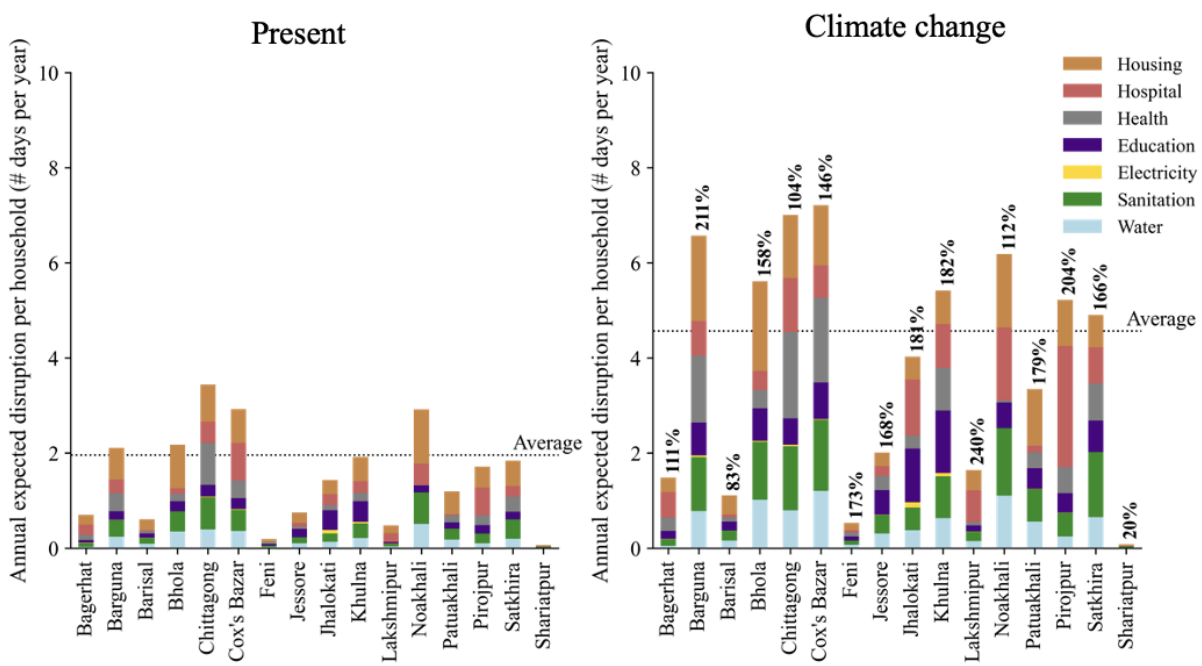

Figure 7. The average expected service disruption (days per year) per household at present (left) and in 2050 (right). The bar plots show the contribution of the different infrastructure types to service disruption risk, with the horizontal line showing the average across the coastal zone. The percentages in the right plot show the relative increase in risk.

In most districts, the infrastructure type that contributes most to service disruption risk is health facilities, while in some districts, educational facilities (Jhalokati, Khulna) and hospitals (Noakhali, Pirojpur) contribute substantially to service disruption risk. In Figure F1, the contribution of the different infrastructure types per return period is shown, which highlight that water, education, sanitation and electricity service disruptions are important for lower return periods but become less dominant for higher return periods. On the other hand, the share of service disruptions associated with hospitals, health facilities and housing are increasingly more important under higher return periods for most districts, in particular in the climate change scenario.

4.4 Household welfare impacts

4.4.1 Exposure of poor households

We analyze whether poor households are disproportionately exposed to flooding (relative to the coastal-wide MDP incidence), and where this relative exposure is highest. The results of the exposure analysis are shown in Table F1.

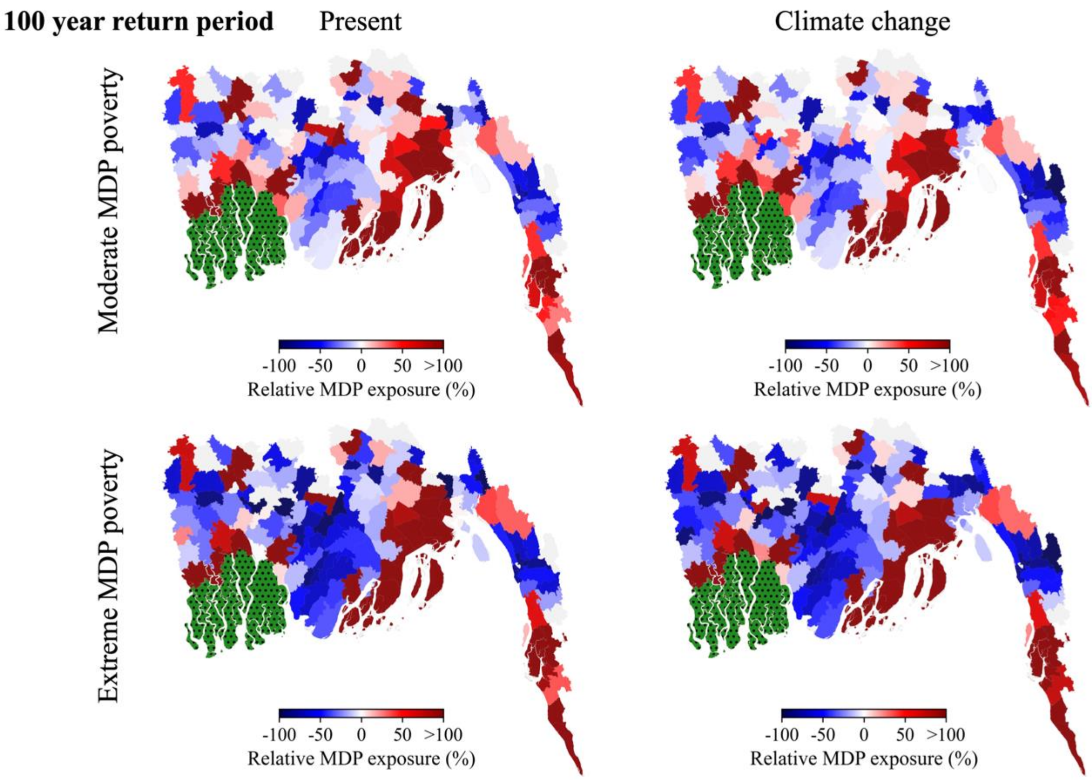

Figure 8. Fraction of exposed multidimensionally poor households relative to the baseline multidimensional poverty incidence across the coastal zone for the 100-year flood return period at present and in the future. The green area covers the Sundarbans and are excluded from the analysis.

Under a 25-year flood return period, 1.1 million households are exposed to flooding at present, increasing to 1.8 million households in the future. 37.0% (35.9%) of exposed households face moderate MDP and 12.2% (11.1%) face extreme MDP at present (in the future), compared to the baseline incidence of 28.2% and 7.2%, resulting in an exposure bias of ~1.3 and ~1.5 – 1.7, respectively. Under a 100-year flood return period, 2.7 million households are exposed to flooding at-present, and up to 3.5 million in 2050. Of these households, 33.9% (33.1%) face moderate MDP and 9.9% (9.4%) face extreme MDP at present (in the future), a lower, but still positive, exposure bias.

These results underline that there is a large exposure bias, particularly for extreme multidimensionally poor households and more frequent floods (10- and 25-year events, see Table F1). If floods get more extreme, in terms of severity or because of climate change (or both), the number of exposed households increase, but the exposure bias decreases as relatively more non-multidimensionally poor households become exposed. In other words, a large share of the most vulnerable households live in the most at-risk areas of the coastal zone.

Areas with high exposure to MDP are indicated in red in Figure 8 for the moderate and extreme MDP levels under the 100-year flood return period. High relative exposure areas, such as in Cox's Bazar district, the Meghna Estuary area, and north of the Sundarbans, are those with high MDP incidence. However, some hotspots further inland are also showing up. These areas have lower baseline risk but multidimensionally poor households are living in hazard-prone areas.

4.4.2 Temporary multidimensional poverty incidence

Apart from direct exposure, households may face a temporary increase in poverty due to flood hazard impacts to households and infrastructure, which result in additional deprivations. Figure 9 shows the temporary incidence of MDP across the coastal zone for the different flood return periods compared to the baseline (horizontal line) as a function of the recovery duration. We consider the 10, 30 and 100 day the short, medium and longer-term timeframe of poverty incidence. Some key results from the figures are summarized in Table F2 per flood return period.

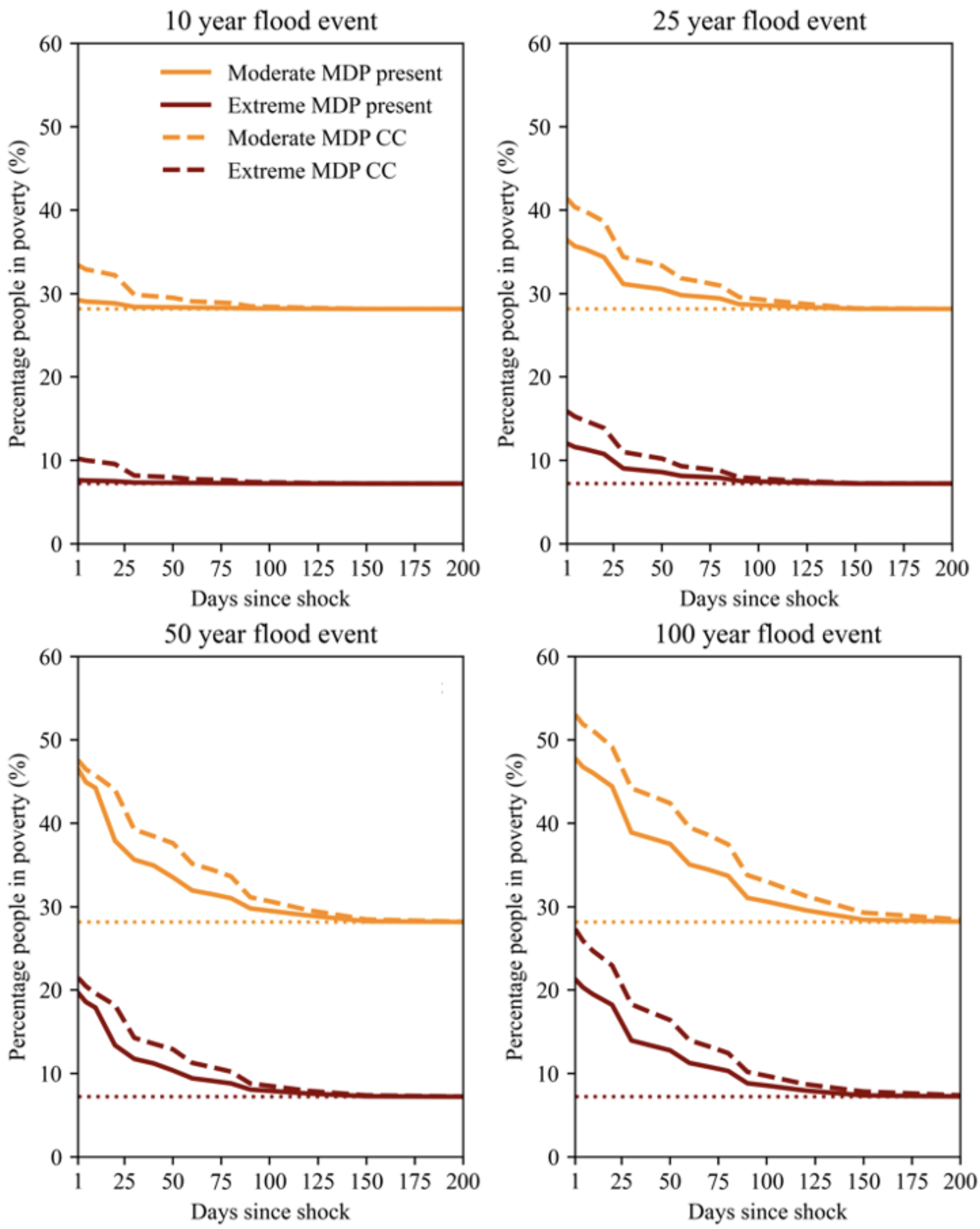

Figure 9. Temporary incidence of multidimensional poverty after a flood event with a given return period at present (solid line) and in the future (dashed line).

Under a 25-year flood event, incidence of extreme MDP would increase by 57.6% (105.3%) after 10 days, 25.5% (52.7%) after 30 days, and 1.9% (4.7%) after 120 days under the present-day (climate change) scenario. For context, the baseline number of people in extreme MDP is 3.1 million people. A 100-year flood event increases the incidence of extreme MDP by 171% (243.3%) after 10 days, 93.8% (153.9%) after 30 days, and 10.4% (20.9%) after 120 days under the present-day (climate change) scenario. As such, climate change alone can double the number of households being pushed temporarily into poverty on various time scales.

As can be seen from Figure 9, the temporary incidence of extreme MDP is higher, in relative terms, than moderate MDP, given the higher exposure bias and lower baseline incidence. Moreover, the severity of the flood event affects both the number of households falling into short-term poverty (line moving up in Figure 9) and the number of households experiencing additional deprivations long-term (line moving towards the right in Figure 9). This is because more households are exposed directly, as shown in the previous section, alongside the fact that infrastructure will endure more severe damages and more assets are affected at the same time, both resulting in longer service disruptions.

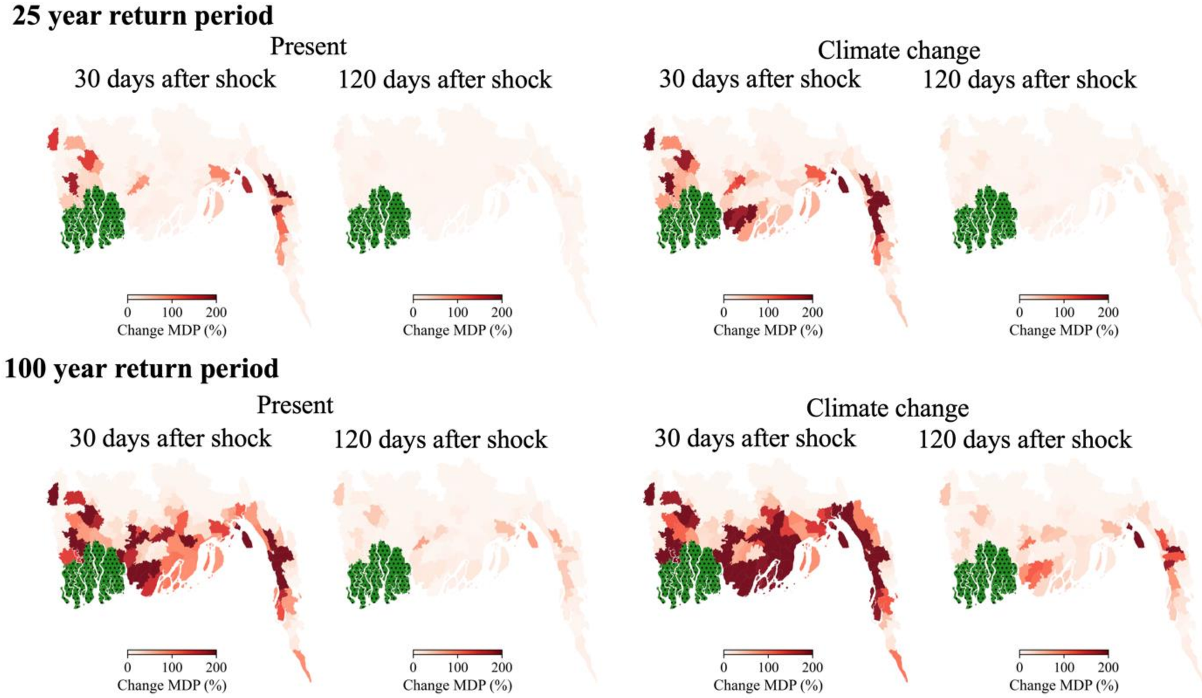

Figure 10. The change in extreme MDP incidence on a medium- and longer-term time scales after a flood event at present (left) and in the future (right). The top panel shows the result for the 25-year flood event while the bottom panels show the results for the 100-year flood event.

Figure 10 shows a selection of the results for the temporary incidence of extreme MDP, for two return periods and two timeframes, on an Upazila level. The same results for moderate MDP are shown in Figure F2. Under the 25-year event, Upazilas in Chattogram and the western coastal zone have a high increase in incidence after 30 days, but for all Upazilas the incidence after 120 days is back to its baseline. Under the 100-year event however, a much large share of the coastal zone faces a temporary MDP spike, with more than 200% increase after 30 days for some Upazilas. In fact, under the climate change scenario, almost the entirety of external coastal zone has a greater than 200% increase after 30 days. Even after 120 days, Upazilas in and surrounding Chattogram still have an increase in MDP incidence, in particular under the climate change scenario. In these areas, making sure infrastructure services are quickly restored, or alternative services are provided, is essential to prevent a spike in long-term poverty incidence.

4.5 Wider benefits of adaptation

The different adaptation programs discussed all results in multiple benefits in terms of asset risk reduction, service disruption risk reduction, and prevented temporary poverty incidence. In Table 3, these different results are summarized.

The CEIP-I and FS-NEW projects both have substantial benefits in terms of asset risk reduction, together equal to around 55 USD million per year at present and almost 100 USD million per year in the future. Using a standard cost-benefit framework,[3] the discounted benefits derived over its lifetime are 132 – 243 USD million for CEIP-I and 781 to 1383 million USD for FS-NEW. Compared to the cost of the programs (which include mobilization cost, riverbank protection base costs, land acquisition), which are 172 million for CEIP-I and 408 million for FS-NEW, the BCR are 0.8 – 1.4 for CEIP-I and 1.3 – 2.4 for FS-NEW. Similarly, the ALL-POLDERS scenario has benefits worth 149.4 USD million at present and 280.5 USD million in the future, which would result in a BCR of 1.0 – 1.8.

Moreover, as can be observed from Table 3, the embankment upgrades also provide additional benefits in terms of reduced service disruptions and poverty incidence. The service disruptions benefits 34% – 46% of the areas protected by CEIP-1, 41% – 69% for areas protected by FS-NEW and 14% – 36% for all embanked areas. As such, from a service disruption point of view, the existing and proposed embankment upgrades have a large relative benefit compared to the benefits derived across all polders. For a 25 year event, both embankment upgrades prevent around 80,000 people from falling into extreme poverty for 30 days at present and over 100,000 people in the future. This is fraction (10.0% – 13.4%) of the total of 600,000 people at present and 1 million in the future that are could benefit from all polder. What is also clear is that while preventing temporary poverty incidence under a 25-year event (its design level), it does not provide benefits for more extreme events, as polders do not protect against these flood severities. On the other hand, other interventions, such as climate-proofing WASH infrastructure and speeding up recovery efforts have limited benefits in terms of asset risk reduction but do provide complementary welfare benefits beyond the protection level of the embankments (see Appendix G).

[3] We assume a lifetime of 40-years, discount factor of 10%, population growth of 1%, and economic growth of 2% to 6%.

Table 3. Summary of the benefits of different adaptation programs discussed in terms of reduction of asset damages, service disruptions and temporary poverty incidence. *The service disruption benefits are derived for the local area that the embankments protect and not for the coastal region as a whole.

		CEIP-I		FS-NEW		ALL-POLDERS	
Metric	Day	Present	CC	Present	CC	Present	CC
Asset damages (mUSD)		6.9	15.7	47.1	82.6	149.4	280.5
Service disruption (%)*		33.8	46.1	40.6	68.5	14.2	35.9
Temporary MDP (x1,000 people)							
25 year - extreme MDP	10	31	59	165	176	1143	1607
25 year - extreme MDP	30	13	19	67	85	597	1036
25 year - extreme MDP	120	0	0	8	13	53	137
100 year - extreme MDP	10	0	0	0	0	0	0
100 year - extreme MDP	30	0	0	0	0	0	0
100 year - extreme MDP	120	0	0	0	0	0	0

5 Summary and discussion

5.1 Summary

In this working paper, we presented a new quantitative risk assessment framework that evaluates (i) climate-induced asset risk to housing, infrastructure and agriculture, (ii) cascading service disruption risk caused by critical infrastructure failures, (iii) the exposure of households that suffer from multidimensional poverty (MDP) and (iv) the temporary incidence of MDP as a result of critical infrastructure service disruptions. We employ this risk assessment framework to explore the wider benefit of climate adaptation (through embankment improvement programs) in terms of their economic performance, through cost-benefit analysis, and in terms of their contribution towards equity-related objectives, more specifically their effectiveness at alleviating climate-induced MDP. We applied this framework to the highly vulnerable coastal zone of Bangladesh, utilizing a newly developed synthetic household dataset. The framework is designed to be generic and adaptable to other geographies where similar datasets are available.

Asset risk at present as a result of flooding is estimated to be 483 USD million, which is projected to increase up to 750 USD million in 2050 due to climate change alone, not accounting for socioeconomic projections. Extreme winds can add an additional 414 USD million to this risk, which can increase 53% in the future because of climate change. Note that we do not account for non-linear effects (e.g. compound flood-wind events).

As a result of flooding of critical infrastructure assets (which includes hospitals, health and education, electricity substations, WASH infrastructure and housing), households face, on average, a service disruption risk of 2 days per year, which can increase to 4.5 days per year by 2050. In four districts, the future service disruption risk is more than 6 days per year.

At present, 25.8% of the coastal population is exposed to flooding (100-year event), which can increase to 33.2% in 2050. Of the exposed population, 33.1% – 39.5% of households face moderate MDP, while 9.4% – 13.8% faces extreme MDP, depending on the flood severity, which is higher than the baseline MDP incidence of 28.1% (moderate) and 7.2% (extreme), respectively. As such, MDP households are disproportionately exposed, and exposure bias of 1.17 – 1.92, with higher exposure bias for lower flood return periods and more extreme MDP. In other words, the most deprived households live in the most at-risk areas in the coastal zone.

The combination of direct household exposure (that is, households are flooded) and infrastructure exposed (that is, infrastructure households depend on are flooded) can result in temporary poverty incidence. For instance, under a 25-year flood event, the incidence of extreme MDP increases by 25.5% (52.7%) after 30 days and 1.9% (4.7%) after 120 days under the present-day (climate change) scenario, while under a 100-year flood event the incidence of extreme MDP increases by 93.8% (153.9%) after 30 days, and 10.4% (20.9%) after 120 days under the present-day (climate change) scenario. As such, climate change alone can double the number of households being pushed temporarily into poverty on various time scales.

Investing in protective infrastructure can reduce both asset risk and the adverse welfare implications of flooding. The existing CEIP-I program and a new proposed program (FS-NEW), in total providing upgrades to 30 polders, prevent asset damages worth 100 USD million per year in 2050, and have small but positive BCR ratios. Upgrading all polders in the coastal zone (139 in total) can result in risk reduction benefits of 281 USD million per year in 2050, without considering population or socioeconomic growth. However, existing cost-benefit analyses do not include the wider benefits of such adaptation options. The upgraded embankments can reduce the service disruption risk by 36% – 69% in 2050 for the areas they protect. Moreover, the two programs (CEIP-I and FS-NEW) reduce the number of people experiencing some sort of temporary MDP by 230,000 in the future under a 25-year event, which can be up to 1.6 million people if all polders would be upgraded. However, embankment upgrades only protect up to their protection level, making complementary interventions, such as climate-proofing infrastructure or improved emergency response, necessary to reduce welfare losses under more extreme flood events.

5.2 Discussion

Our newly developed methodology underlines our understanding that focusing on asset risk alone does not provide a full picture of the potential welfare implications of climate hazards and climate change. Compared to other quantitative welfare frameworks, such as that presented by H2016, we present an alternative framework to capture multiple risk transmission pathways that impact welfare, providing a more granular perspective on welfare losses than looking at losses in consumption alone. However, these methodologies should not be seen as substitutes, but rather as complementary tools for analyzing welfare impacts, as certain welfare dimensions (such as food insecurity, health implications, or consumption shocks) are not included in our modeling framework. As such, future research endeavors should aim at harmonizing both modeling frameworks to bring them together into one overarching assessment.

As shown in our methodology, when looking at the welfare implications of disasters, it is important to both look at disparities in terms of the exposed population, thereby identifying who is more socially vulnerable or less able to cope and recover from potential adverse impacts, as well as those that are prone to fall below some poverty (or other) threshold. In our case study, some areas have a low poverty baseline, such as the urbanized areas of Chattogram, but a high susceptibility of people falling below the poverty line during cyclone events. On the other hand, some areas, such as Cox's Bazar, have a high baseline poverty incidence but a lower susceptibility of households falling below the poverty line due to shocks. Other areas, such as those close to the Sundarbans, have both high baseline incidence and high susceptibility for temporary poverty incidence. These three regions require different strategies given their contexts; making sure the poor are not exposed versus making sure those prone to falling back into poverty will recover quickly. Our proposed framework provides an initial platform upon which decision-makers can balance climate adaptation and overall development (e.g., poverty alleviation) interventions, and explore potential synergies between the two.

Different types of adaptation options, including hard and soft options, are often hard to compare to one another in a quantitative manner, in particular softer solutions that do not reduce asset risk. Here, we have quantified the wider benefits of hard infrastructure solutions, while our framework also allows complementary interventions such as flood-proofing critical infrastructure and improved disaster recovery efforts. Although not done in this work, putting a dollar value on experienced service disruptions, or temporary MDP incidence, one could include such wider welfare impacts in the CBA, allowing one to compare and contrast different interventions in a more comprehensive way. As such, the framework presented provides the basis for evaluating how portfolios of interventions can reduce both asset risk as well as benefit people in terms of welfare, underlining that a holistic portfolio including hard and certain soft interventions (only those affecting service disruptions, not those related to consumption such as direct payments), is required to achieve both. In this work, we have only evaluated a limited number of interventions, and did not run combinations of interventions. In particular, evaluating the benefits of complementary portfolios of interventions allows looking at the synergies and trade-offs between interventions and is a promising avenue of future research.

The methodological advances presented in this working paper are driven by the recent developments in terms of constructing synthetic population datasets of entire countries, as done for Bangladesh here, including realistic, but synthetic, locations. The entire methodology (except the flood hazard maps) relies on publicly available data sources, making it (in theory) possible to replicate such analysis in other regions globally. However, extending the risk analysis from asset damages alone to the welfare implications of individual households increases the complexity, data requirements, and computational resources considerably. For instance, constructing the synthetic household data relies on detailed Census data, which is not available everywhere, as well as being very computationally intensive for large countries. As such, the quality of the synthetic household output, including which variables can be considered, is dependent on the level of detail of input data, in particular the socioeconomic survey data. We present a method, using a Small Area Estimation technique, to add an additional variable that is not originally in the Census data to the synthetic household data. However, this might not be feasible for other variables or using different survey data. As such, moving forward, less complex versions of the methodology presented could be developed and tested, such that it can be more universally applied.

In future work, the methodology could be enhanced by 1) incorporating socioeconomic projections and associated changes in exposure and vulnerability to enable a more comprehensive future scenario analysis, 2) employing a stress-testing approach to better capture uncertain hazard inputs and cross-correlations and spatial dependence between hazards and infrastructure networks, and (3) test portfolios of interventions to evaluate their synergies and trade-offs, (4) more directly incorporating the health status of households, and (5) incorporating employment and household income as additional household characteristics that could be affected after disaster impact.

Overall, our work demonstrates the added value in terms of improving quantitative estimates of hazard-induced welfare impacts. First, the synthetic household survey data enables an improved understanding of poverty incidence at a high-resolution, which can be useful for targeting interventions to the most vulnerable communities before or after disasters happen. Second, the analysis can help design new adaptation programs and how to best spatially target them to yield both asset risk reduction and welfare benefits. In the end, better aligning disaster risk reduction and climate change adaptation efforts with development objectives can present large synergies, ultimately helping to create a more climate-resilient society.

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Appendix A: Synthetic Household Survey Data

Baseline synthetic population modeling

Synthetic household survey data (SHSD) is constructed using a combination of microsimulation techniques and asymmetric population modeling. Microsimulation modeling refers to algorithms to generate a synthetic population for a target area by extracting data from various sources and constructing an entire new dataset with required household attributes (often on a more spatially granular scale).

Details of the methodology are described in Rubinyi *et al.* (Rubinyi et al., 2022). In short, the SHSD is created using both aggregate tables for population margins (e.g., at a certain administrative level) and microdata that contains variables included in the aggregated tables. For both, data from the 2011 Bangladesh National Census is used, with aggregates tables available at the union level (admin level 4) and microdata available at the Upazila level (admin level 3). The steps to create a synthetic population data can be summarized as follows: (1) calibrate survey weights in the microdata to fit population margins, (2) extrapolate the microdata using alias sampling to generate the synthetic population, (3) set the variables of interest, household or personal variables, based on the microdata and "predict" them for each person in the synthetic population, and (4) use simulated annealing (SA) to calibrate the synthetic population to known population margins.

The synthetic data contains three types of information (see Table A1). 'Basic structural information' (sex, age, relationship to household head, urban/rural, Upazila), which are created for each household and household member, are sampled from the microdata and are kept fixed to generate a realistic base. 'Household-level variables' (housing type, housing structure, tenancy status, water source, electricity, sanitation) are defined on a household level and are modeled and appended to the 'Basic structural variables'. 'Individual-level variables' (years of schooling, literacy, level of education, employment status and industry) are modeled on an individual level and are appended to the 'Basic structural variables; and the 'Household-level variables'.

This synthetic population dataset is then disaggregated to a point layer of population density based on WorldPop data (by converting grids to random points) by randomly assigning modeled households to the sampled point layer. This is done at the union level, implying that a randomization component is added such that households within the union boundaries cannot be identified.

Projecting synthetic populations from 2011 to 2021

The 2011 synthetic dataset is projected to 2021 populations, based on Upazila level regional variables. The data is projected using the evolution of education, fertility, mortality, urbanization and migration. This includes: (1) transitions in education based on age, (2) fertility decline over time, (3) mortality rates (using period life-tables by sex), (4) urbanization within

Upazilas and towards other Upazilas, and (5) international work migration. Applying these projections results in a new synthetic population dataset for 2021 that captures the population dynamics over time.

Table A1. Overview of the different variables in the synthetic dataset, including which variables are used in the calibration process using simulated annealing.

Category	Variable	Options	Simulated annealing
Basic structural variables	Sex	Male, female	yes
	Age	Years	yes
	Relationship to head of household	Head, Spouse/partner, Child, Non-relative, Other relative, Unknown	no
	Urban	Urban, rural	no
	Upazila	Upazila name	no
Household-level variables	Housing type	General, institutional	no
	Housing structure	Pucka, semi-pucka, katcha, jhupri	yes
	Tenancy status	Owner, renting, usufruct	yes
	Water source	Tap, tube well, other	yes
	Electricity	Yes, no	yes
	Sanitation	Sanitary with water seal, sanitary without water seal, non-sanitary, none	yes
Individual-level variables	Years of schooling	Years	no
	Literacy	Yes, no	yes
	Level of education	Less than primary, primary, secondary, university	no
	Employment status	Employed, unemployed, inactive	no
	Industry	Agriculture, industry, services	no

Appendix B: Small Area Estimation using MICS data

To include additional health variables in the multidimensional poverty index used, we use Small Area Estimation (SAE) techniques to infer the probability a household has at least one stunted child under five. This variable is included in line with SDG goals for zero hunger and no poverty, as it also forms a proxy for longer-term household poverty.

Small area estimation predicts the value of a variable (the target variable) that is not available in a more granular dataset (the target dataset) using a more detailed data available in a separate dataset (the using dataset). The using dataset, here the MICS dataset, is used to estimate a predictive model of the target variable, here stunting. By using a set of independent variables that is also available in the target dataset, the value of the target variable can be predicted for all households. This method can be used to gain additional statistical power, but is used here for the more modest aim of better understanding what households are likely to struggle to provide their children with appropriate nutrition.

More technically, we implement Small Area Estimation using the SAE Stata package developed by Ming Cong Nguyen.[4] This package implements the Elbers, Lanjouw and Lanjouw (2003) (ELL) model to implement Generalized Least Squares to create a synthetic variable whether a household has a stunted child based on the information in the MICS survey to supplement the synthetic dataset.

As we observe a synthetic census dataset, we can use an observation weight of one as all households are theoretically observed. For the MICS data, we weight the observation by the household weight to account for the differences in probabilities households will get sampled. We cluster standard errors at the upazila level, and to estimate the model we use the assumptions from ELL with some of the improvements suggested by Nguyen (2018) for estimation.

The following set of overlapping variables across the synthetic dataset and MICS are used for small are estimation, see Table B1.

Table B1 Overview of the different variables used for the Small Area Estimation analysis.

[4] Nguyen, Minh Cong; Corral, Paul; Azevedo, Joao Pedro; Zhao, Qinghua. 2018. SAE - A Stata Package for Unit Level Small Area Estimation. Policy Research Working Paper; No. 8630. World Bank, Washington, DC, https://openknowledge.worldbank.org/handle/10986/30650

Variable	Definition	Data type
Household size	What size is the household?	Continuous
Urban	Does the household live in an urban area?	Binary
Years Schooling	Is the household MDP deprived in terms of education level (1 if the most educated household member has less then 6 years of schooling)?	Binary
School Attendance	Do all children attend school up to class 8?	Binary
Sanitation	What sanitary facilities does the household have access to?	Multinomial
Drinking water	What source of drinking water does the household has access to?	Multinomial
Electricity	Does the household have access to electricity?	Binary
Housing	Does the household have live in Jhupri or Kutcha housing?	Binary
Tenancy	Does the household own their home?	Multinomial
Education household head	What level of education does the household head have?	Multinomial
Age of household head	What age is the household head?	Continuous

Appendix C: Discussion on Household Survey Data in Bangladesh

We compare our newly constructed MDP (Figure C1) with existing indicators of poverty in the coastal zone of Bangladesh.

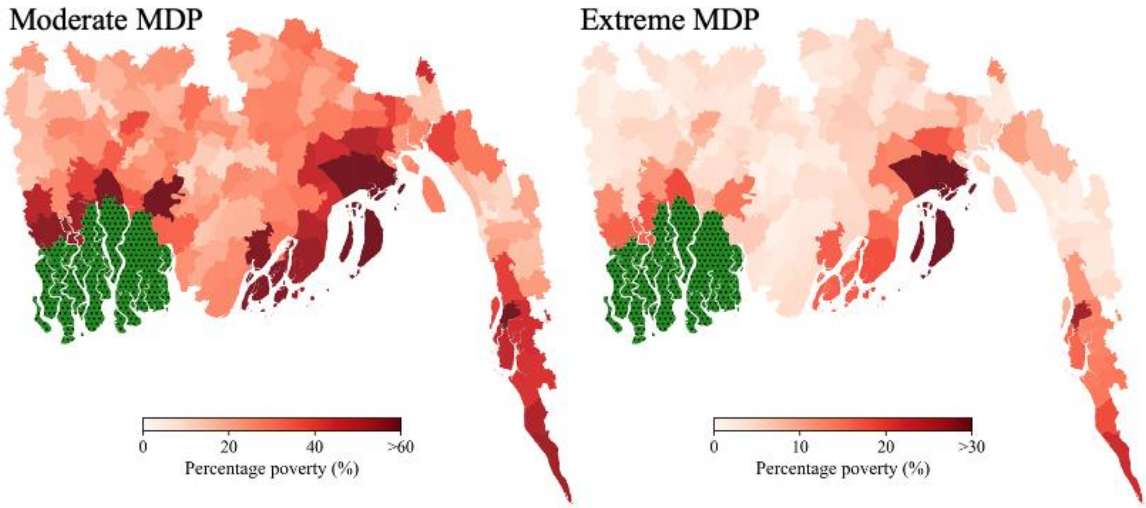

Figure C1. Moderate (left) and extreme (right) multidimensional poverty on an Upazila level.

Figure C2 shows the geographical distribution of household's consumption and poverty incidence on an Upazila level derived from the Bangladesh Household Income and Expenditure (HIES) survey 2017. Figure C2a-b show the Upazila level distribution of household consumption for rural and urban households. One can clearly see a stark East-West divide in rural expenditure, while urban expenditure has a less clear geographical pattern. Moreover, in almost all Upazilas, the urban expenditure is higher than rural expenditure. Figure C2c-d shows the share of people below the higher and lower poverty line. These poverty lines are based on the local cost of consuming 2,112 calories per day and some non-food products.[5] The upper poverty line allows for a larger amount of non-food products than the lower poverty line. These should be interpreted as respectively the lower poverty and upper poverty line. Note that the white color indicates the approximate national-level poverty incidence. The incidence of poverty shows that some of the poorest Upazilas are located along the coast, in particular the Upazilas close to the Sundarbans, the Meghna Estuary and in the Cox's Bazar area.

In addition to the consumption-based poverty metrics, we construct a district-wide MDP based on the HIES data as shown in Figure C2. This indicator follows the same definition as the

[5] We follow the official methodology used to estimate poverty lines. The first non-food allowance is estimated taking the median of the amount spent on non-food items for a reference group of households whose total per capita expenditure was close to the food poverty line. This is used for the lower poverty line. The non-food allowance for the higher poverty line is estimated by taking the median amount spent on non-food items for a similar reference group of households whose per-capita food expenditure was close to the food poverty line. Data on around 50 non-food products is used (Available here: https://catalog.ihsn.org/catalog/7399/related-materials).

official MDP. The highest levels of multidimensional poverty are observed in the Cox's Bazar area as well as the Bhola region.

This comparison shows that the distribution of poverty depends on the poverty metric adopted. Hence, there is no single metric that captures all dimensions of poverty adequately.

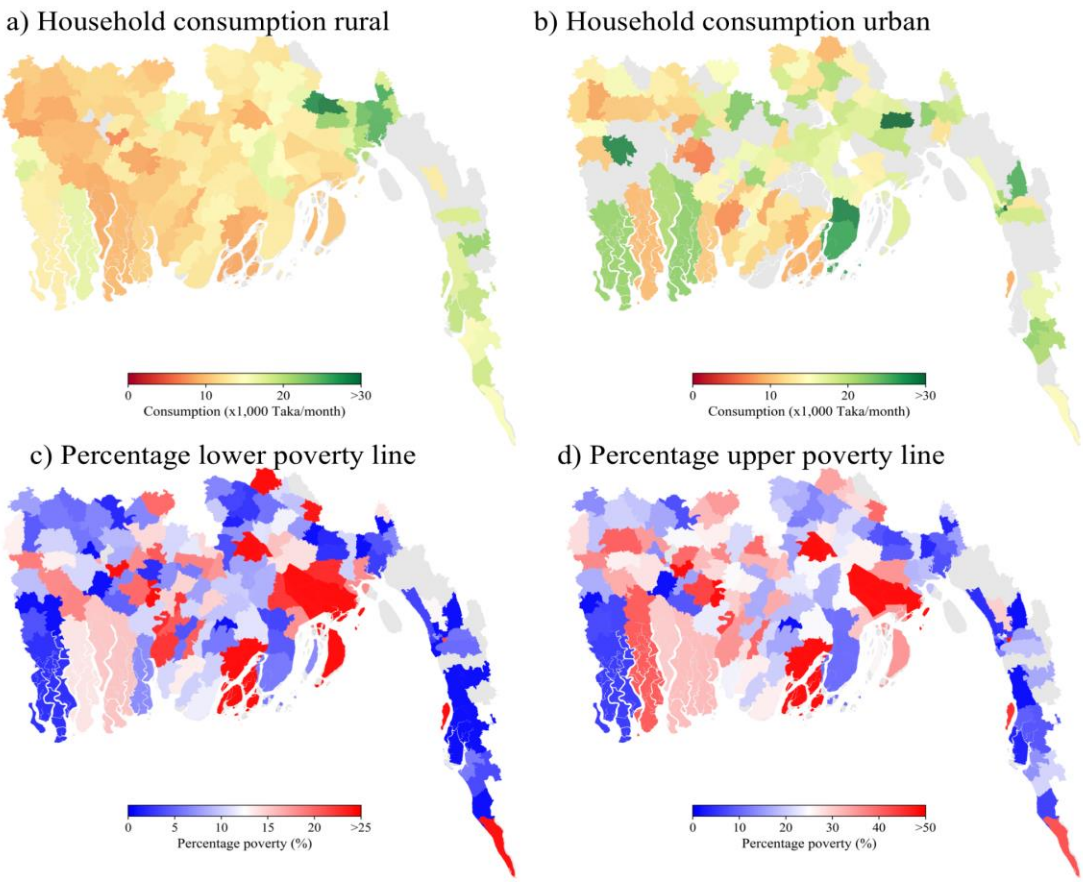

Figure C2. Household rural and urban consumption (Taka per month), as well as the percentage of households in the lower and upper poverty line. All data is based on the HEIS survey data.

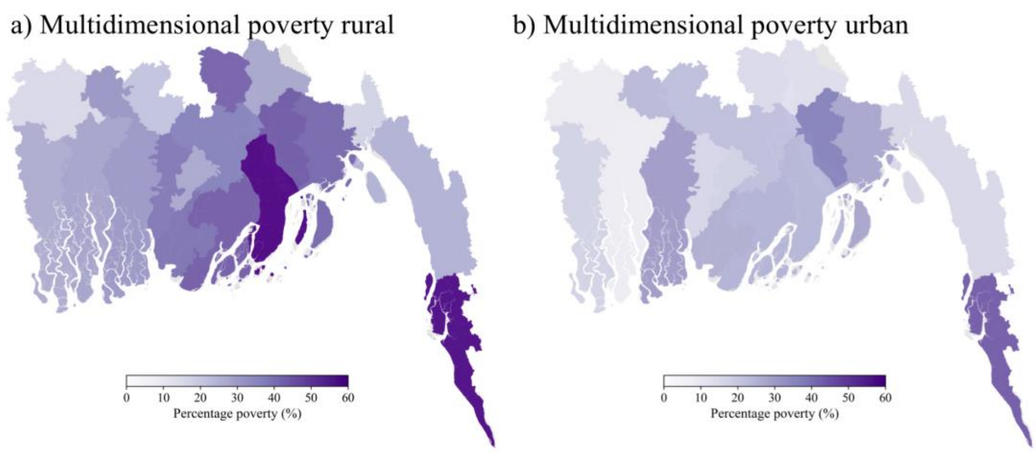

Figure C3. MDP for urban and rural households using MICS survey data.

Appendix D: Additional information on hazard risk modeling

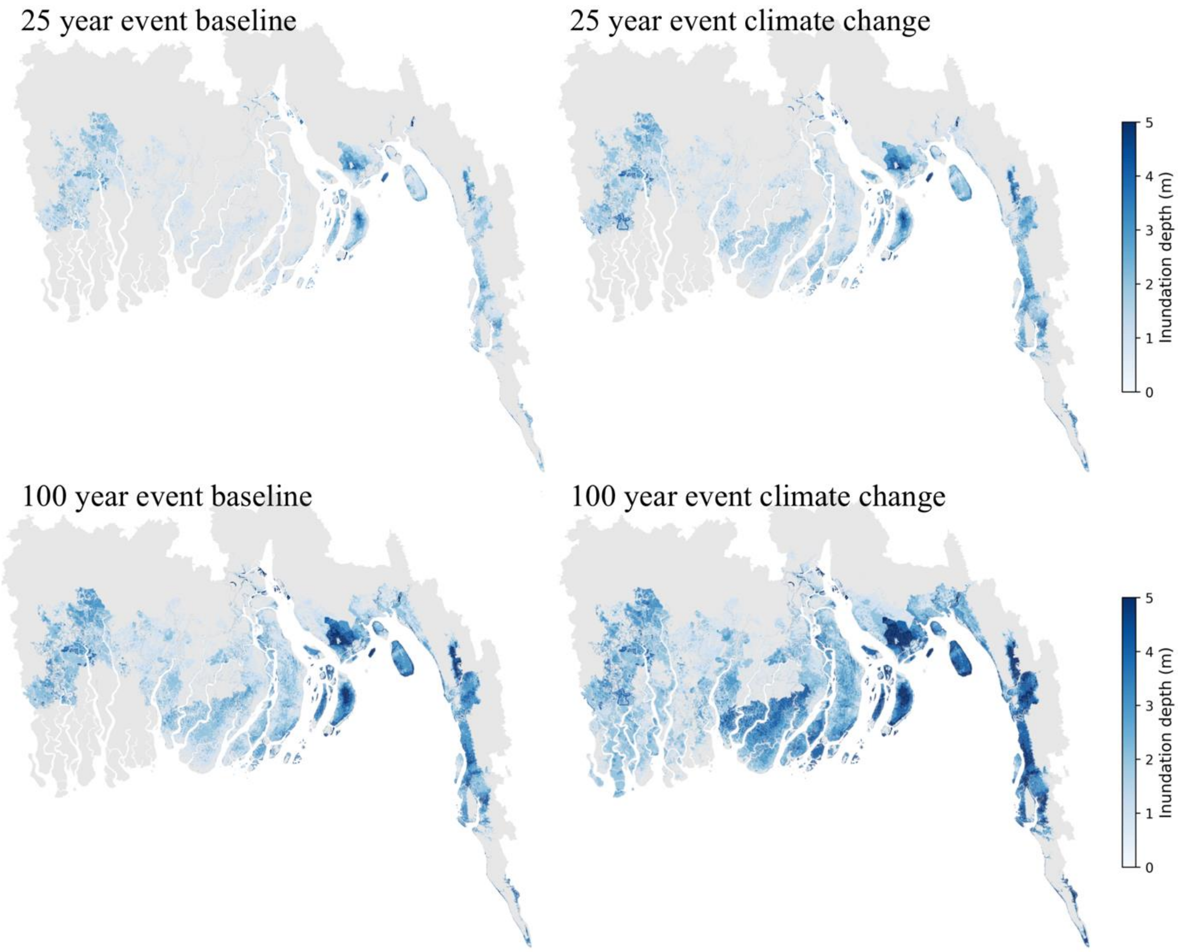

Figure D1. The flood inundation extent and depth for two return periods (25 and 100-years) under the baseline and climate change scenario. The climate change scenarios include a 0.5 meter of sea-level rise and an 8% increase in the cyclone wind speed.

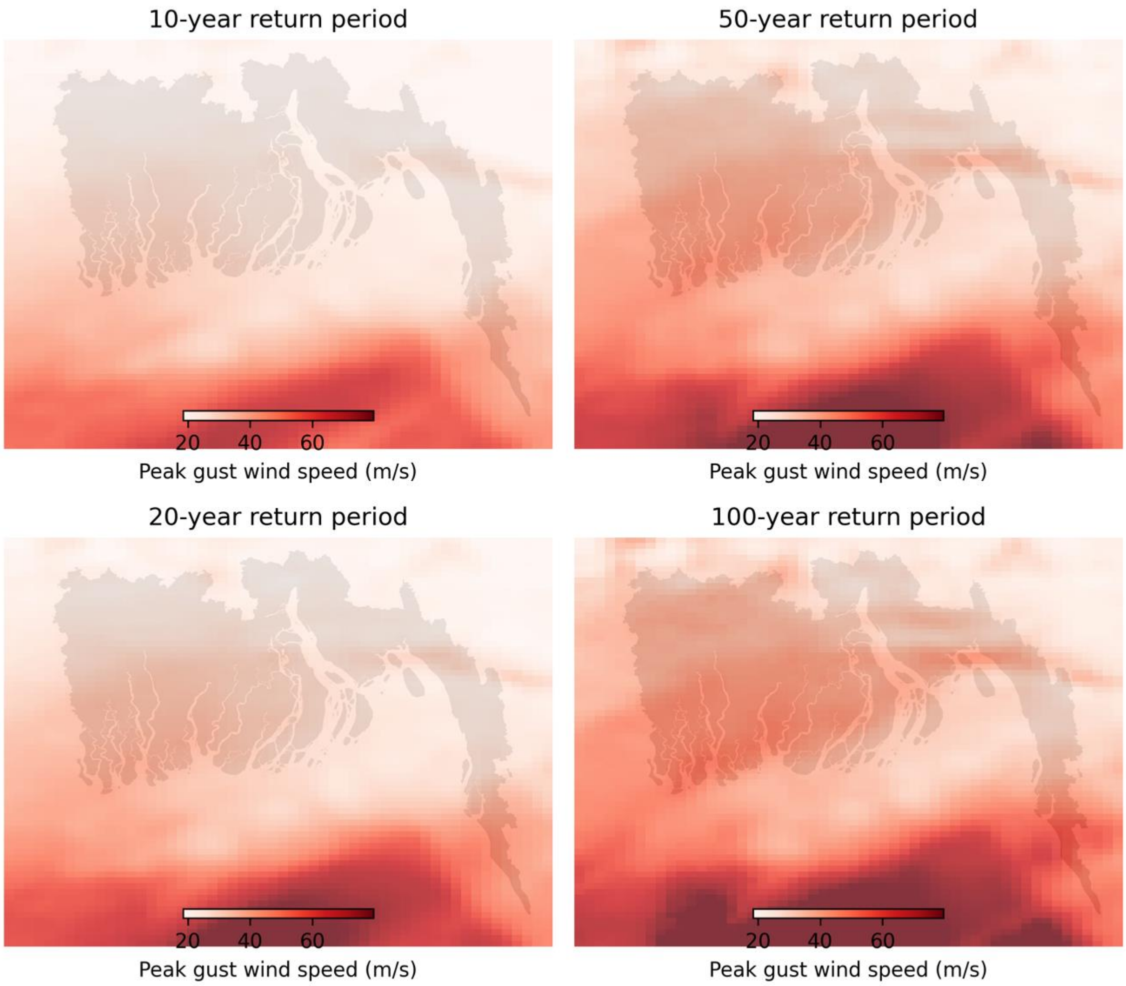

Figure D2: The wind speed maps for four return periods under the baseline conditions.

Table D1 Overview of the different datasets used in the risk and service accessibility analysis

Asset type	Class	Source	Public	Note
Housing	Jhupris, Kutcha, Semi-Pucca, Pucca	Synthetic household data	no	Internal WB data
Road	Road types (e.g. highway, zila, village) and paving (paved/unpaved)	LGED	yes	
Hospitals		LGED	yes	
Health		LGED	yes	
Schools		LGED	yes	
Electricity substation		PGC	no	Internal WB data
Wells		Synthetic household data	no	We assume that wells are located close to households, so when households are exposed, wells are also exposed. Internal WB data
Sanitation		Synthetic household data	no	We assume that pit latrines are located close to households, so when households are exposed, latrines are also exposed. Internal WB data
Crop fields	Boro, Aman and Aus	Singha et al. (2019)	yes	Satellite-derived rice crop maps per rice season

Table D2 Overview of the different asset types and the reconstruction costs (in million Taka or Taka) used in the analysis.

Asset type	**Taka million**	**Source**
Hospital	3	Sidr damage assement
Health center	0.33	Sidr damage assement
Substation	10	AIIB (2019)
School (partly destroyed)	4.5	Sidr damage assement
Roads (paved, per km)	2	Sidr damage assement
Roads (unpaved, per km)	0.4	Sidr damage assement
Asset type	**Taka**	**Source**
Water well	500	Sidr damage assement
Pit latrines	1500	Sidr damage assement
Housing Jhupris property	110,000	Khairul et al. (2022)
Housing Jhupris building	276,000	Khairul et al. (2022)
Housing Kutcha property	110,000	Khairul et al. (2022)
Housing Kutcha building	276,000	Khairul et al. (2022)
Housing Semi-Pucca property	191,000	Khairul et al. (2022)
Housing Semi-Pucca building	865,000	Khairul et al. (2022)
Housing Pucca property	319,000	Khairul et al. (2022)
Housing Pucca building	1,436,000	Khairul et al. (2022)

Table D3 Overview of the different fragility curves adopted.

Asset	Flood vulnerability	Wind vulnerability
Household · Katcha · Pucka · Semi-pucka · Jhulpris	Khairul et al., 2022 Split mud/brick/concrete	Goyal et al., 2016 Split semi engineered/non engineered
Educational facilities	Brick building (Khairul et al., 2022)	Acosta 2021 - low rise wooden buildings
Health center	Brick building (Khairul et al., 2022)	Semi engineered (Goyal et al., 2016)
Hospitals	JRC (Asia commercial building)	World Bank and CAPRA (2016)
Road • Paved • Unpaved	JRC	NA
Agriculture	Khairul et al., 2022	NA
Electricity substation	Miyamoto international	Miyamoto international
Pit latrines	Assume 1m threshold	NA
Wells	Assume 1m threshold	NA

Appendix E: Additional information service disruption modeling

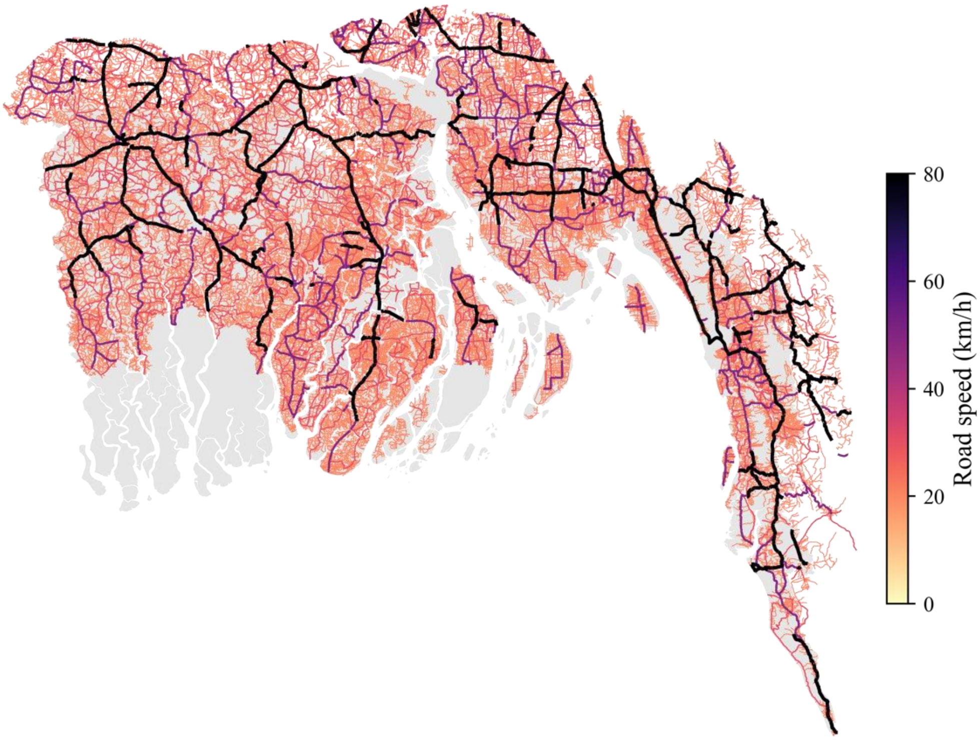

Figure E1. The road infrastructure layer used in this study including the allocated speed per road segment.

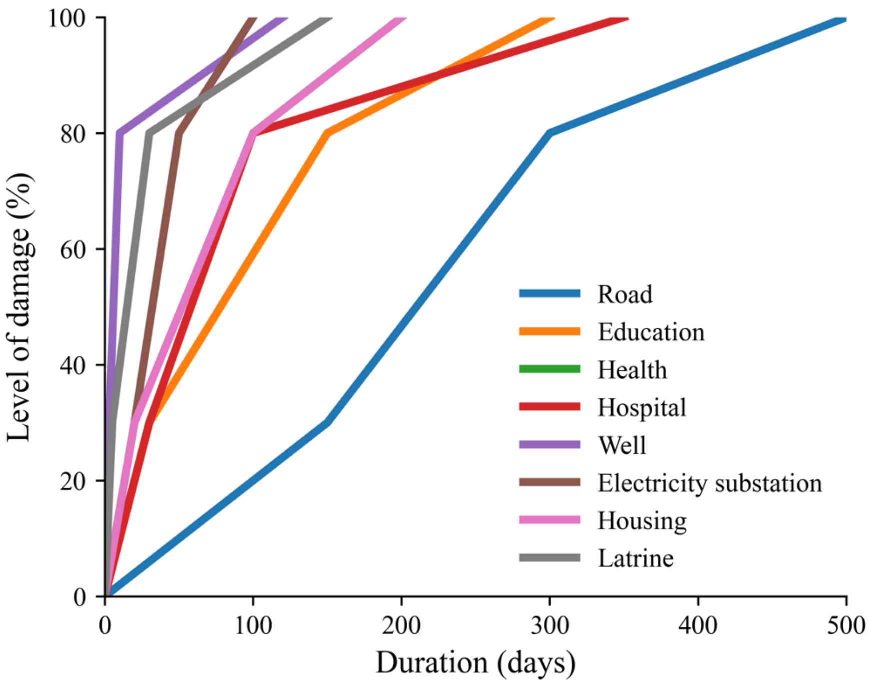

Figure E2. Overview of the disruption duration curves per asset type showing the repair and recovery duration as a function of the level of damage.

Table E1 Overview of the repair and reconstruction time per asset type

Asset type	Repair (0-30% damage)	Repair + partial reconstruction (30-80% damage)	Reconstruction (80%-100% damage)
Road	150	300	500
Education	30	150	300
Health	30	100	200
Hospital	30	100	350
Well	3	10	120
Pit latrines	5	30	150
Electricity substation	20	50	100
Housing	20	100	200

Appendix F: Additional results

Table F1. Results of the exposure analysis and the corresponding exposure bias of MDP households.

	10-year		25-year		50-year		100-year	
	Present	CC	Present	CC	Present	CC	Present	CC
Households exposed								
Absolute exposure (millions)	0.46	0.83	1.11	1.84	1.63	2.75	2.73	3.51
Percentage of households (%)	4.3	7.8	10.5	17.4	15.4	26.0	25.8	33.2
MDP (%)								
Moderate MDP	39.5	38.6	37.0	35.9	35.6	34.2	33.9	33.1
Extreme MDP	13.8	13.0	12.2	11.0	11.2	10.0	9.9	9.4
Exposure bias (-)								
Moderate MDP	1.40	1.37	1.31	1.27	1.26	1.21	1.20	1.17
Extreme MDP	1.92	1.81	1.69	1.53	1.56	1.39	1.38	1.31

Table F2. Summary of temporary poverty incidence on the short (10 days), medium (30 days) and longer term (100 days) after a flood event. The top panel shows the absolute temporary poverty incidence, and the bottom panel the relative increase compared to the baseline poverty incidence.

		10-year		25-year		50-year		100-year	
	Day	Present	CC	Present	CC	Present	CC	Present	CC
Absolute incidence (%)									
Moderate MDP	10	30.0	32.7	35.3	39.9	44.2	45.7	46.1	51.1
	30	28.4	29.9	31.1	34.1	35.6	39.2	38.9	44.2
	120	28.2	28.3	28.4	28.8	28.9	29.6	29.6	31.3
Extreme MDP	10	7.6	9.9	11.4	14.8	17.9	19.6	19.5	24.7
	30	7.3	8.2	9.0	11.0	11.7	14.3	14.0	18.3
	120	7.2	7.3	7.3	7.5	7.6	7.9	8.0	8.7
Relative increase (%)									
	10	6.3	15.9	25.3	41.5	56.9	62.2	63.3	81.3
	30	0.7	5.9	10.5	21.1	26.4	39.2	37.9	56.7
	120	0.0	0.3	0.7	2.3	2.6	4.9	4.9	11.0
	10	4.9	37.1	57.6	105.3	148.4	172.2	171.0	243.3
	30	1.9	13.6	25.5	52.7	63.1	98.2	93.8	153.9
	120	0.2	1.1	1.9	4.7	5.5	9.8	10.4	20.9

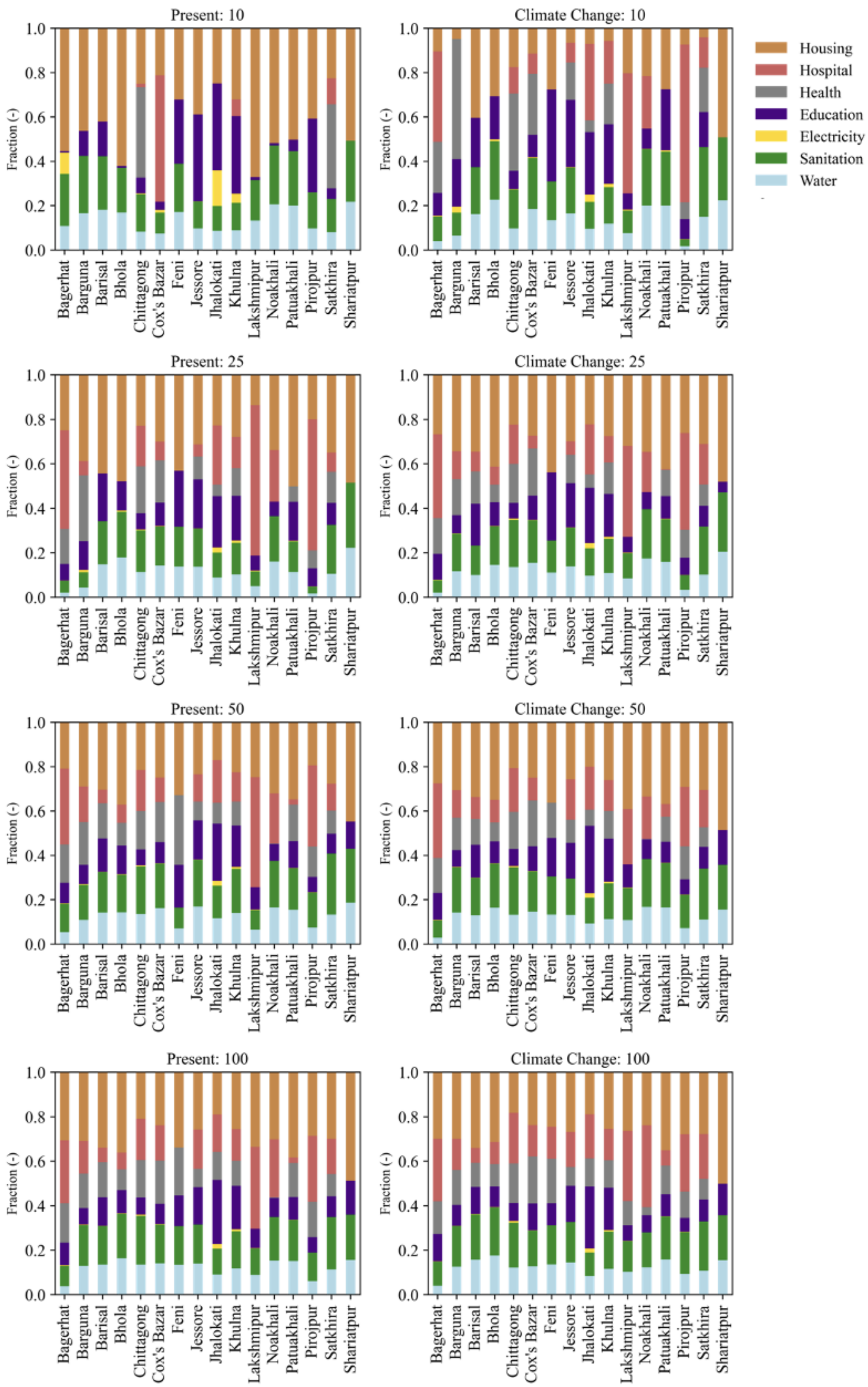

Figure F1. Contribution of different infrastructure services to district-wide household service disruptions per return period.

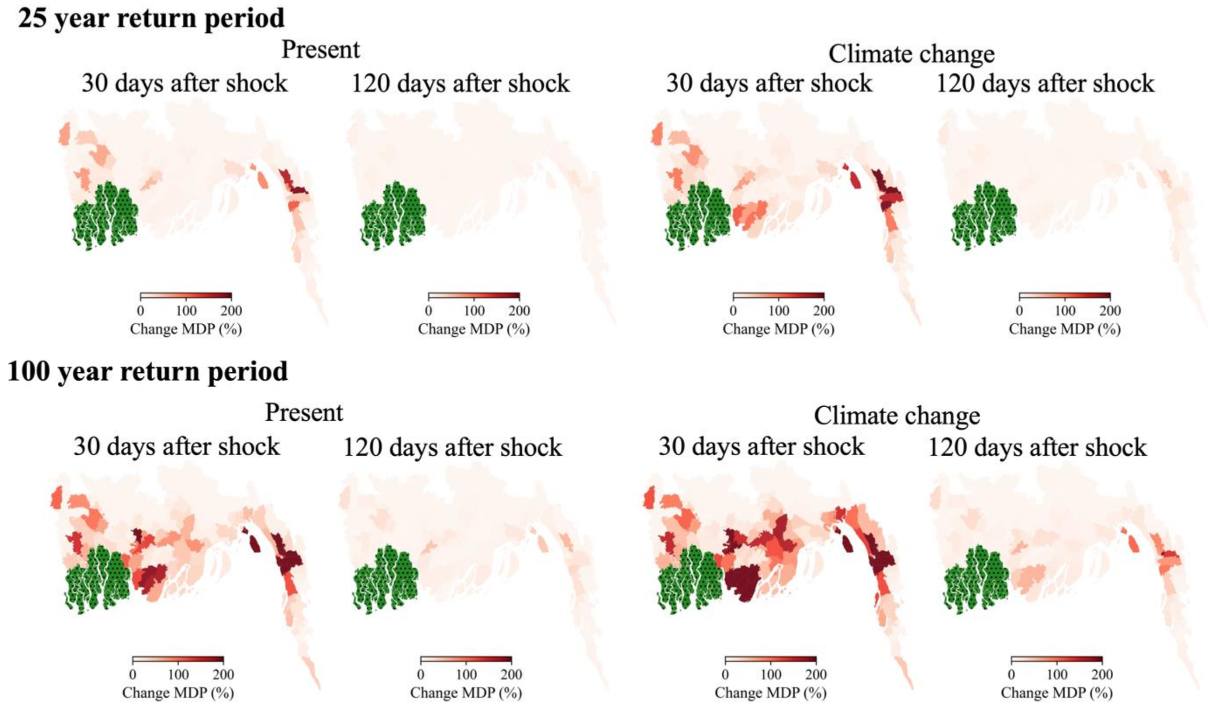

Figure F2. Change in moderate MDP incidence on a medium and longer term time scales after a flood event at present (left) and in the future (right). The top panel shows the result for the 25-year flood event while the bottom panels shows the results for the 100-year flood event.

Appendix G: Additional adaptation options

We describe the results for two additional adaptation options that are considered: flood proofing of WASH infrastructure and more rapid recovery efforts.

Flood proofing of WASH Infrastructure

Many programs are underway, both by NGOs and the responsible government agencies, to flood-proof WASH infrastructure by raising the platform in combination with a soak well (for tube wells). This means that for smaller-scale flood events, WASH infrastructure can still be used by households. However, one can realistically only elevate tubewells to about 5 to 10 feet (150 – 300 cm) to avoid problems with pumping (personal communication, DPHE, 2022). Here, we evaluate the benefits of raising WASH infrastructure such that the flood threshold (the threshold above which tube wells and pit latrines become inoperable) changes from 1 meter to 2.5 meters. We only do this in flood-affected areas. Although costs are hard to estimate, some have estimated that it takes around 200 – 300 USD dollar to raise a tubewell and create a drainage soak well. Similarly, raising pit latrines generally costs around 20% extra (20% of construction costs) (personal communication, DPHE, 2022).

More rapid disaster recovery

Over the years, the Government of Bangladesh has made significant steps in improving the emergency response after large-scale disasters. To evaluate the benefits of this, which is often hard to evaluate in terms of asset damages, we create a hypothetical scenario in which all infrastructure and housing can be rebuilt 20% faster than the baseline scenario. For instance, after Cyclone Sidr, the government implemented the housing assistance program that helped affected households to rebuild their damaged or destroyed houses.

Results

The complementary benefits of flood-proofing WASH infrastructure are clear; while providing little benefits in terms of asset risk reduction, service disruptions are reduced by over 20%, which particularly prevent poverty incidence during more severe flood events. As such, even if the polders do not provide protection during a 100-year event, flood-proofed WASH infrastructure enables continued service provision of water and sanitation, preventing people from experiencing additional deprivations. This is particularly evident during large-scale flood events where most WASH facilities would otherwise be disrupted.

Similarly, the faster recovery adaptation option, through the mobilization of emergency supplies or efforts to speed up service restoration, do not have any benefits in terms of asset risk, but have large benefits in terms of preventing temporary poverty incidence. Compared to the other options, improved recovery efforts prevent households from falling into longer term poverty (120 days), in particular for the most extreme flood events.

Table G1. Summary of the benefits of different adaptation programs discussed in terms of reduction of asset damages, service disruptions and temporary poverty incidence.

		WASH		Recovery	
Metric	Day	Present	CC	Present	CC
Asset damages (mUSD)		1.1	2.5	0.0	0.0
Service disruption (%)		14.2	35.9	20.0	20.0
Temporary MDP (x1,000 people)					
25 year - extreme MDP	10	265	376	31	37
25 year - extreme MDP	30	214	338	67	92
25 year - extreme MDP	120	15	24	57	133
100 year - extreme MDP	10	390	375	38	41
100 year - extreme MDP	30	354	345	110	131
100 year - extreme MDP	120	31	37	252	345