



Prioritising resilience policies to reduce welfare losses from natural disasters: A case study for coastal Bangladesh

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ABSTRACT

Quantified flood risk assessments focus on asset losses, neglecting longer-term impacts to household welfare via income and consumption losses. The extent of welfare losses depends upon resilience – the ability to anticipate, resist, cope, recover and learn from a shock. Here, we use a novel welfare loss modelling framework and perform a high-resolution spatial analysis in coastal Bangladesh to quantify welfare losses from a tropical cyclone under present and future climatic and socio-economic conditions. We further test various adaptation options that are intended to enhance resilience. Results show that poor households experience, on average, 7% of the asset losses, but 42% of the welfare losses. Combining dike heightening, post-disaster support and stronger housing can reduce welfare losses by up to 70%, and foster sustainable development by benefitting the poor, increasing resilience and demonstrating robustness under socio-economic and climatic uncertainties. Thus, a welfare-orientated perspective helps to identify adaptation options that enhance resilience and leave no-one behind.

1. Introduction

Floods impose a heavy burden on society, causing billions of dollars in damages annually, with a rising trend observed over the last years (Bouwer, 2011; Hallegatte, 2012; Jongman et al., 2012). Future projections show an increasing risk of flooding due to climate change, socio-economic development and land-use changes (Dottori et al., 2018; Hinkel et al., 2014; Mendelsohn et al., 2012), in particular in rapidly urbanising coastal deltas (Neumann et al., 2015; Tessler et al., 2015). Therefore, there is an urgent need to develop robust disaster risk reduction (DRR) strategies to reduce climate-related risks and build more resilient communities.

The UN Sendai Framework for Disaster Risk Reduction 2015–2030 (UNISDR, 2015) calls for increasing attention to the disproportional impacts of floods, the need to consider non-structural solutions to ensure effective recovery and rehabilitation, and the intersection of DRR with sustainable development policies. Others have also emphasized the need for a further mainstreaming of DRR and resilience concepts with the wider sustainable development agenda (Béné et al., 2014; Linkov et al., 2014; Schipper et al., 2016; Zhenmin and Espinosa, 2019). Traditional risk assessments use asset losses to quantify risk, track the progress of DRR policies over time and assess the benefits of adaptation options

(Aerts et al., 2014; Hallegatte et al., 2013). However, using asset losses as a metric of risk has several shortcomings to meet the call to link DRR to sustainable development. First of all, asset losses measure the direct physical impacts to assets and are inherently biased towards richer households, as they have by definition more assets to lose (Hallegatte and Rozenberg, 2017). Consequently, the benefits derived from adaptation options may also be biased towards richer households (Brouwer et al., 2007; Kind et al., 2017). Moreover, impacts from natural disasters extend beyond asset losses. Floods can result in income losses, affect educational and health services, and decrease consumption, all reducing overall welfare (Markhvida et al., 2020; Meyer et al., 2013; Noy, 2016). The poor often lack the resources and financial instruments to smooth income shocks, rebuild their livelihood and maintain pre-disaster consumption (De Alwis and Noy, 2019). Therefore, welfare losses can be long-lasting, and may push or trap households into poverty (Borgomeo et al., 2017; Carter et al., 2007; Dadson et al., 2017; Jakobsen, 2012). In addition, it is a challenge to quantify the benefits of non-structural measures, like insurance and post-disasters support, in conventional risk assessments, as they do not directly reduce asset losses. Altogether, using asset losses as a proxy for disaster risk may obscure the distributional impacts of disasters and fails to capture the wider welfare losses from natural disasters.

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Well-established tools exist to quantify the asset losses from flood events (Aerts et al., 2014; Ward et al., 2017, 2015). On the contrary, little work so far has been done to develop models to quantify welfare losses or provide a base of empirical evidence (Hallegatte and Vogt-schilb, 2016; Noy, 2016; Noy and DuPont, 2018). Hallegatte and Vogt-Schilb (2016) developed a theoretical framework to quantify welfare losses from natural disasters on a global scale. Their work links the extent of welfare losses experienced from disaster impact to the resilience of households, defined as “the ability of society to minimise the resulting welfare losses from a disaster shock” (ibid). The modelling framework assesses how asset losses translate into longer term welfare losses suffered by households, which depends, apart from losses to assets, on the resources and instruments to smooth the resulting shock and rebuild livelihoods. Their global approach allows an intra-country comparison of resilience, but fails to capture spatial variation in risk and vulnerability, which can vary significantly within countries (Narloch and Bangalore, 2018). A global analysis that uses the output of global physical hazard models and global exposure maps may fail to adequately estimate risk in areas with complex geomorphologies (Lewis et al., 2013) and areas prone to disasters like tropical cyclones that need high resolution models to resolve physical processes (Bloemendaal et al., 2019). More spatially explicit assessment would also be more useful for the prioritisation of DRR-interventions within a country. Recent work, therefore, has downscaled previous global analysis to a regional scale, namely for a simulated earthquake in the San Francisco Bay Area (Markhvida et al., 2020) and flooding from a tropical cyclone in the Philippines (Walsh and Hallegatte, 2020; Yonson and Noy, 2018).

Considerable scope exists to extend previous analysis to improve the assessment of welfare losses, and the evaluation of adaptation options, on a high-resolution scale. Previous studies that quantify welfare losses (Hallegatte and Vogt-schilb, 2016; Markhvida et al., 2020; Walsh and Hallegatte, 2020; Yonson and Noy, 2018) have not yet focused on future changes and uncertainties in welfare losses due to climate change and socio-economic growth. In addition, previous work has only considered evaluating the benefit of one policy option, whereas modern DRR portfolios consist of a combination of multiple structural and non-

structural interventions (Hall and Solomatine, 2008; Jongman, 2018). Moreover, the link between DRR and the wider sustainable development goals have not yet been explicitly considered, including potential synergies and trade-offs.

Here, we fill in the abovementioned gaps and use a novel theoretical framework that links disaster impacts to household resilience, which we apply to a high resolution (sub-district/district) scale in coastal Bangladesh. Using Tropical Cyclone Sidr (2007) as a case study, we quantify welfare losses under present and future socio-economic conditions. Moreover, we test a set of 20 adaptation portfolios consisting of three policy interventions (combining structural and non-structural options) and evaluate their effectiveness in reducing welfare losses, improving resilience, being robust against future changes and being pro-poor. This allows us to assess the potential synergies and trade-offs between different policy objectives that contribute to sustainable development. The article is structured as follows: Section 2 introduces the case study. Section 3 explains the methodological framework and data sources used. Section 4 provides the results of the current and future welfare losses, including the evaluation of the portfolios of policy interventions. In Section 5, we discuss the results including the policy implications and relate them to previous work. Section 6 provides a conclusion of the work.

2. Case study: Coastal Bangladesh

We use the Western and Central Bangladesh Coastal Zone (WCBCZ) as a case study (20,000 km²), consisting of nine districts (Zila), as depicted in Fig. 1. The nine districts considered here are similar to the regions included in the ESPA Delta project (Hutton et al., 2018; Nicholls et al., 2016). Population density ranges from 288 people/km² in Bagerhat to 1047 people/km² in Barisal, with a large share of the population living in rural areas (BBS, 2016). Poverty incidence ranges from 16% in Bhola to 37% in Patuakhali, with six out of nine districts having higher poverty levels than the country-wide average of 24.3% (BBS, 2016). The WCBCZ is a primarily agriculture-based regional economy with 85% of the inhabitants depending on agriculture for their

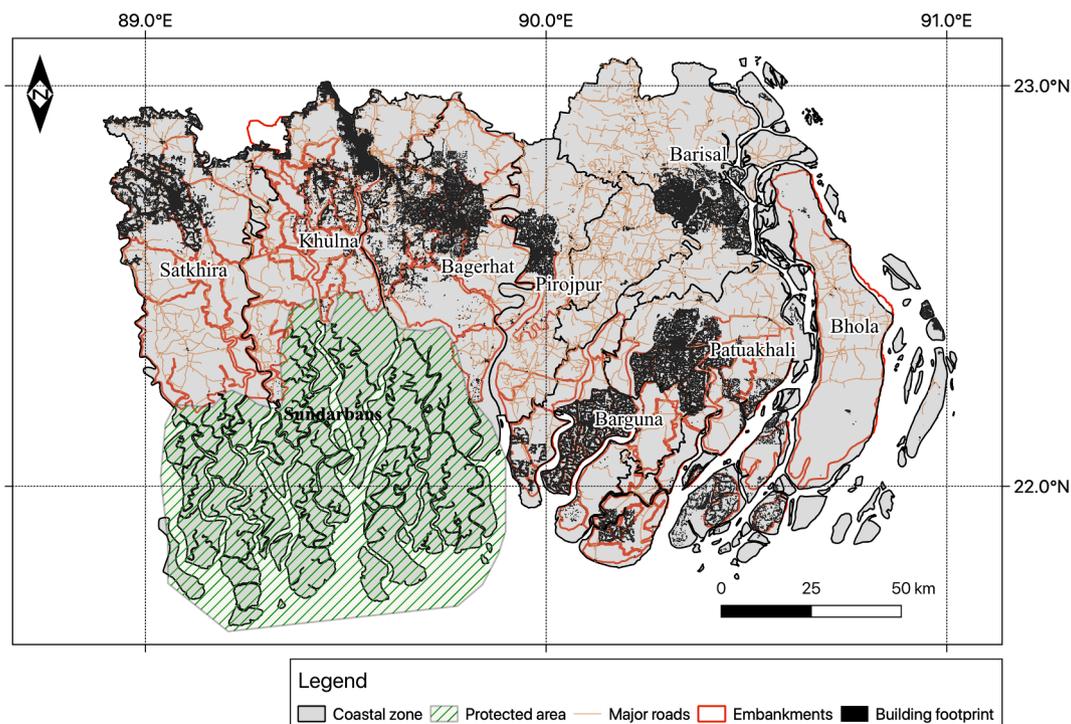


Fig. 1. Overview map of the Western and Central Bangladesh Coastal Zone with the location of the nine districts. The housing and infrastructure (major roads and embankments) are indicated.

livelihood (Lázár et al., 2015). To accommodate a growing agricultural sector and prevent against flooding and saline intrusion, an extensive system of coastal embankments (dikes) were constructed in the 1960 s (Dasgupta et al., 2010), as can be observed from Fig. 1.

Tropical cyclones (TCs) are the most destructive disasters in the WCBCZ (Dasgupta et al., 2010). The Bay of Bengal is prone to TC formation and roughly every three years a destructive TC reaches coastal Bangladesh (Alam et al., 2003; Balaguru et al., 2014). TC Sidr, in 2007, was one of the most devastating cyclone in history, generating a six meter storm surge that inundated large parts of the WBCZ, impacting 2.3 million households (GoB, 2008).

3. Methodology and data sources

A modelling framework is adopted to quantify welfare losses and measure resilience on a district-scale in Bangladesh. Moreover, a range of adaptation options are evaluated under multiple policy objectives. The definition of resilience as defined by Hallegatte et al. (2016) is adopted throughout, linking resilience to welfare losses:

$$Resilience = \frac{Asset\ losses}{Welfare\ losses}$$

in which resilience is the “ability of households to minimise welfare losses from a disaster.” This may be regarded as a rather narrow version of resilience, as it does not contain wider concepts of the capacity of societies to learn and transform (Béné et al., 2014; Cutter et al., 2008; Schipper and Langston, 2015), but nonetheless is a significant step towards consistent quantification of resilience in a form that can be used to compare different places and adaptation interventions.

To construct a modelling framework that can quantify welfare losses and hence measure resilience, a number of components are needed, with an overview provided in Fig. 2. In short, we perform an analysis of the asset losses from TC 2007 using the output of a hydrodynamic model

(Haque et al., 2018), together with a future scenario for 2050 that includes sea-level rise (SLR). A model that calculates welfare losses is adopted from Hallegatte and Vogt-schilb (2016), after which some model modifications are made. We analyse changing socio-economic characteristics of households by creating a future household emulator that samples many plausible future pathways based on regional socio-economic narratives (Hunt, 2018; Lázár et al., 2018). Thereafter, 20 portfolios of three policy interventions are implemented in the modelling framework and their benefits evaluated against multiple policy objectives. It should be noted that the application here is to illustrate and describe the methodology, using TC Sidr as a case study, as different TCs would potentially yield different results.

3.1. Flood modelling

TC Sidr caused extensive flooding in the eastern part of the WBCZ and was estimated to have a return period of approximately 35 years (Adnan et al., 2019). Storm surge inundation extent for TC Sidr is taken from Haque et al. (2018), who used the 3D hydrodynamic model Delft-3D to simulate the extreme water levels from observed wind fields and storm track. The model description and validation are described by Al Azad et al. (2018). To account for future climate change in 2050, a +0.61 m SLR scenario (compared to 2000) is added to the TC simulation to model future inundation extent. This scenario (which includes subsidence) is considered a high-end scenario of SLR (in line with Kopp et al. 2017, see Supplementary Information) that is more informative for coastal management purposes (Hinkel et al., 2015; Kopp et al., 2017). Embankments are incorporated in the model using known data on design heights (Al Azad et al., 2018; Haque et al., 2018). The results of both simulations are shown in Supplementary Fig. 1.

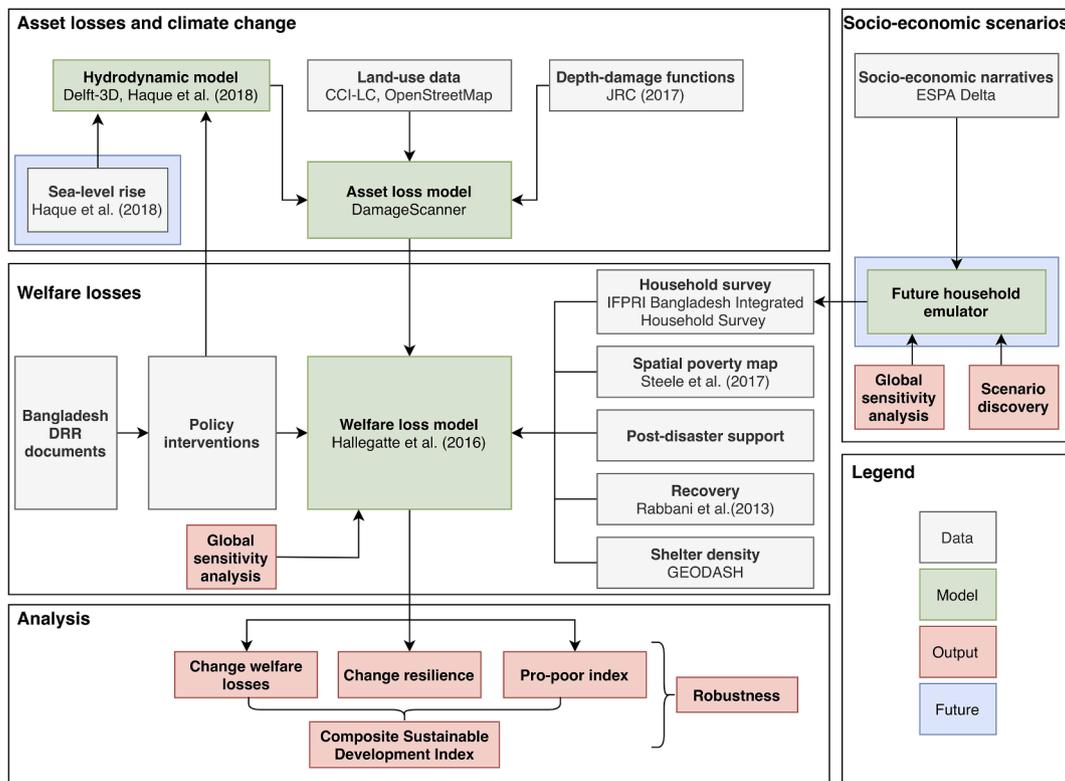


Fig. 2. Overview of models, data sources and outcomes. The welfare model combines the damage assessment and the socio-economic scenarios derived from the survey/household emulator. Policy interventions are implemented in the welfare model and the hydrodynamic model. Outputs are the benefits of the interventions under different policy objectives together with robustness analysis.

3.2. Asset losses

We calculate asset losses using a traditional approach in the flood risk community that superimposes inundation maps on land-use maps, translating the exposed assets to damages using depth-damage curves (Meyer et al., 2013; Winsemius et al., 2016). Five land-use classes are considered; agriculture, residential, infrastructure, commercial and industrial. Agricultural land-use is obtained by filtering out the five agricultural land cover classes from the 300-m resolution global land-use map provided by the ESA CCI Land Cover project. For infrastructure, only road infrastructure is considered. Road infrastructure is derived from OpenStreetMap (OSM), which contains an almost complete set of roads worldwide (Koks et al., 2019; Meijer et al., 2018). Individual building footprints are extracted from OSM, from which 'residential', 'industrial' and 'commercial' building types are filtered out. Asian-specific depth-damage curves and maximum potential damages values per land-use type are used (Huizinga et al., 2017). Total damages are then calculated by multiplying the inundation depth with the land-use specific depth-damages curve and damages value per grid cell ($\sim 30 \times 30$ m), which are then aggregated to a district-level.

3.3. Welfare losses

Welfare losses are estimated by an earlier developed model (Hallegatte et al., 2016; Hallegatte and Vogt-schilb, 2016) that simulates how asset losses impact the income sources of exposed households after accounting for financial mechanisms (both private and public) to smooth income shocks. Impacts are calculated for two representative household groups, a poor and non-poor group, in order to assess the distributional impact between both. We make a number of model modifications to make it suitable for a district-wide analysis and to refine some modelling assumptions. The Supplement includes all technical details of the model, whereas here we only focus on the general ideas and model modifications.

Our welfare analysis is based on changes in consumption (Mechler, 2009; Noy and Yonson, 2018). Expenditure for consumption is derived from various income sources: (1) income derived from labour, which is produced locally and vulnerable to disaster impacts, and (2) income from non-labour (e.g. social safety nets, remittances), which is assumed to be unaffected by the local disaster shock. Labour income is a function of the assets used to generate income and the productivity of these assets. Therefore, asset losses generate a shock to those assets used to generate income, either publicly owned (e.g. infrastructure, natural capital) or privately owned (e.g. tractor, loom). Reconstructing affected assets to their pre-disaster state takes a number of years, following an exponentially decaying function. By definition, poor households own fewer private assets to derive income from and are more dependent on publicly provided assets. The type of housing is used as a proxy for total asset vulnerability (e.g. those living in weaker housing generate income from more vulnerable assets, such as weaker roads and materials), with housing shown to be a good indicator of disaster vulnerability in Bangladesh (Dasgupta et al., 2010; Hossain, 2015). Moreover, the model accounts for the fact that poor households may be disproportionately exposed (exposure bias) (Narloch and Bangalore, 2018; Winsemius et al., 2018). Non-labour income sources (social protection and remittances) and savings can be used to smooth income fluctuations, as these are not affected by the disaster, thereby reducing the potential consumption losses. The model further assumes that part of the losses are prevented by the presence of an early warning system that allows households to take steps to limit their losses, and affected households receive post-disaster support (PDS) from the central government (e.g. cash transfers) to reduce income losses. The income losses, after accounting for all mechanisms to absorb income fluctuations, result in households foregoing consumption, thereby affecting their welfare. Welfare losses are calculated by applying a classical welfare function (or utility function) with a positive marginal elasticity value that relates

changing consumption to changing welfare. The marginal elasticity value can be interpreted as a distributional weight factor that accounts for the fact that a 1 dollar consumption loss has a relatively greater effect on a poor household's welfare than a non-poor household's welfare. This parameter is controversial in literature (Kind et al., 2017), and has been set equal to 1.5 similar as in Hallegatte et al. (2016). The asset losses are then divided by the resulting welfare losses to find the resilience of poor and non-poor households per district.

We modified the model to better reflect the context of coastal Bangladesh. First, a location-specific recovery period was estimated based on evidence from TC Aila (2009) in Bangladesh (Rabbani et al., 2013), after which recovery duration was estimated to be 3 years for non-poor households and 6 years for poor households. Second, the exposure bias is estimated per district using high resolution spatial poverty maps (Steele et al., 2017), after which we compare the poverty levels in inundated areas compared to the district-wide average. Exposure bias derived from this dataset is negligible, which can be attributed to the definition of poverty adopted in this work (which is based on household income of \$2.50 per day, which is different from the 'Cost of Basic Needs' approach used for deriving official poverty numbers) and the random nature of TCs. This does not preclude the existence of an exposure bias, as derived from empirical data in Bangladesh (Brouwer et al., 2007). Third, the model accounts for the presence of an early warning system which enables people to reduce asset losses. Per district, we use the cyclone shelter density (extracted from GeoDASH) as an indicator of households taken precautionary measures, which is supported by previous empirical evidence (Roy et al., 2015; Saha and James, 2017). Fourth, the Government of Bangladesh has a well-established Post-Disaster Recovery (PDS) and relief programme to assist affected households after disasters (Mahmud and Prowse, 2012). Based on payment data after TC Sidr (GoB, 2008), we estimate that the PDS covered approximately 20% of an average poor household's asset losses (targeted to both poor and non-poor households). Finally, we incorporate the effect that savings can have on buffering welfare losses. Savings data were obtained from our household survey (see next paragraph), both formal (bank/NGO) and informal savings (relatives). To account for this additional buffer to reduce welfare losses, we implement a simple savings withdrawal scheme that scales with the extent of the income shock (see Supplement for implementation).

District-level household data on labour income, non-labour income, housing type and savings are all taken from the 2015 Bangladesh Integrated Household Survey from IFPRI (Ahmed et al., 2013). Total monthly income is aggregated to the household level resulting in a household income distribution per district. In the Supplement, we compare the results from the IFPRI to another regional survey (Adams et al., 2016), which show good agreement. To split the household data into the two representative groups, we use poverty incidence rates from the 2016 Household Income and Expenditure Survey (BBS, 2016), and assume that poverty incidence scales with household income similar to Hallegatte et al. (2016). The poverty incidence rate thus corresponds to a poverty household income threshold that is used to split the households into poor and non-poor groups. All household characteristics are then averaged per group to end up at representative household characteristics per income group. Supplementary Table 6 and 7 provide descriptive data on the main modelling parameters per district.

3.4. Future household emulator

The future economic developments in Bangladesh are highly uncertain and many plausible socio-economic pathways exist. The current trends in coastal Bangladesh are a decreasing income from agriculture and shrimp farming, decreasing poverty rate and rising income from non-ecosystem dependent sources like manufacturing (Hossain et al., 2016; Lázár et al., 2018). A household emulator is designed to sample future scenarios of potential pathways of households' wellbeing in 2050. Assumptions are made on future wealth trends for sectoral income

(agriculture, fisheries, wage, manufacturing, services, livestock, poultry), population, employment, remittances, access to savings, social safety nets and housing (type of wall and roof). The wealth drivers are sampled within a range of possible future values, which are inspired by the socio-economic narratives included in the ESPA Delta project and described into more detail in [Hunt \(2018\)](#) and [Lázár et al. \(2018\)](#). For the ESPA Delta project, three socio-economic pathways were considered (central: Business as Usual, lower: Less Sustainable, upper: More Sustainable), which were made coherent with national economic projections, proposed policy initiatives and global shared socio-economic pathways ([Hunt, 2018](#)). The Supplement describes the scenarios and sample range per wealth driver.

The emulator samples a future socio-economic scenario, using the assumptions on wealth drivers, after which the existing household data is modified. By re-calculating household income, and assuming similar poverty thresholds per districts, one can model how households move in or out of poverty. In total, 1000 futures with household characteristics are sampled, which are fed back into the welfare model to re-calculate the welfare and resilience per district. The new socio-economic situation will also influence the effectiveness of policy interventions ([Section 3.5](#)), and re-evaluating the analysis for the future conditions provides insights into the robustness of policy interventions under a range of different futures.

3.5. Policy interventions

Twenty portfolios of three policy interventions are implemented in the modelling framework to evaluate their benefits in achieving the different policy objectives ([Section 3.6](#)). These portfolios combine structural, nature-based and soft measures, aiming to enhance production, reduce vulnerability, or increase the ability to cope and recover from shocks. All combinations, with keys, are summarised in [Table 1](#). Details about the implementation are included in [Supplement S5](#).

3.5.1. Policy interventions to enhance protection

The protection interventions include a dike elevation measure and a nature-based solution. In 2015, the World Bank started the Coastal Embankment Improvement Project (CEIP) to rehabilitate and improve the coastal embankments ([Adnan et al., 2019](#); [Brown and Nicholls, 2015](#)). In line with this, the dike intervention consist of a 1 m heightening of the embankments that are incorporated in the hydrodynamic model (after which the cyclone simulation is run again). The nature

Table 1

Overview of the 20 portfolios that combine measures that enhance protection, decrease vulnerability and improve the coping and recovery ability. The keys summarise the combinations and will be further used throughout this work.

Protection	Vulnerability	Coping and Recovery	Key
Dike (D)	Housing (H)	Rebuild fast (R)	D-H-R
		Access to savings poor (SP)	D-H-SP
		Access to savings non-poor (SP)	D-H-SNP
		Social safety net (SN)	D-H-SN
		Post-disaster support (PS)	D-H-PS
	Preparedness (P)	Rebuild fast (R)	D-P-R
		Access to savings poor (SP)	D-P-SP
		Access to savings non-poor (SP)	D-P-SNP
		Social safety net (SN)	D-P-SN
		Post-disaster support (PS)	D-P-PS
Nature (N)	Housing (H)	Rebuild fast (R)	N-H-R
		Access to savings poor (SP)	N-H-SP
		Access to savings non-poor (SP)	N-H-SNP
		Social safety net (SN)	N-H-SN
		Post-disaster support (PS)	N-H-PS
	Preparedness (P)	Rebuild fast (R)	N-P-R
		Access to savings poor (SP)	N-P-SP
		Access to savings non-poor (SP)	N-P-SNP
		Social safety net (SN)	N-P-SN
		Post-disaster support (PS)	N-P-PS

intervention includes a 1 km wide reforestation stretch in the coastal zone of Barguna, Bhola and Patuakhali (see [Supplement Fig. 6](#)), which is included in the hydrodynamic model by changing the roughness of the land surface.

3.5.2. Policy interventions to reduce vulnerability

Recent analysis showed that most people affected by TCs live in so-called semi-pukka, kacha and jhupri houses ([Akter and Mallick, 2013](#); [Dasgupta et al., 2010](#); [Hossain, 2015](#)). As mentioned before, the asset vulnerability of households is based on the type of housing. The housing intervention upgrades households living in a jhupri house to a semi-pukka house. The preparedness intervention assumes that the emergency response of the districts will be improved, in line with the recent Multipurpose Disaster Shelter Project, which increases the prevented damages with 50%.

3.5.3. Policy interventions to enhance coping and recovery

The coping and recovery measures that are implemented range from responses on a household level to Central Government action. The ‘Rebuild fast’ intervention is assumed to reduce the recovery duration by 1 year, by faster recovery of public infrastructure. The ‘Access to savings non-poor’ intervention simulates universal access to savings for non-poor households. In contrast, the ‘Access to savings poor’ solution provides the poor households with universal access to finance. The latter is in line with recent developments of extending micro-level finance to poor households in order to build-up savings for investments and recovery ([Mallick et al., 2017](#); [Parvin and Shaw, 2013](#)). The social safety net (SSN) intervention is implemented by increasing payments by 30% for those receiving SSNs, increasing their income diversification. Finally, the ‘Post-disaster support’ solution extends the existing emergency relief and rehabilitation fund of the Central Government. This is incorporated by increasing the lump-sum cash transfer to affected households by an additional 20% of the poor households’ asset losses.

3.6. Policy objectives

After performing a review of disaster risk related policies in Bangladesh (see [Supplementary Information](#)), the overarching objective of the country is to promote economic growth, targeting poor and vulnerable households, and building resilience against climate change risks, by coupling DRR efforts to the wider sustainable development objectives. We have set out four objectives in line with this rationale. The main objective is to reduce disaster losses, here using welfare losses as a proxy. We compare the losses with interventions to the baseline case without. The second objective is to become more resilient by improving the coping and recovery ability of households in general, with resilience values again compared before and after implementing the policy interventions. The third objective is to promote pro-poor solutions. We have constructed a pro-poor index (PPI) that measures how policy interventions reduce the welfare losses for the poor households compared to the non-poor households, with a higher score if poor households benefit disproportionately. We combine these policy objectives into an overarching composite index, called the ‘Composite Sustainable Development Index’ (CSDI), with is simply the Euclidean distance in 3D space with the three objectives on the main axis. Here, equal weights are assigned in the CSDI, whereas different weights could be assigned based on political preferences for achieving the different objectives.

At last, it is assessed how robust, referring to the ability to maintain performance under a wide range of scenarios ([Lempert and Collins, 2007](#)), the policy interventions are against future socio-economic and climatic conditions. We use a minimax regret metric ([Savage, 1951](#)), which seeks to minimise the worst-case regret under a wide range of scenarios (opposite to maximising the benefits). We refer to other papers ([Lempert and Collins, 2007](#)) and a general textbook ([Marchau et al., 2019](#)) on decision making under deep uncertainty for further reference. We normalise the robustness values on a scale from 0 to 1, with 1 being

the most robust options.

3.7. Uncertainty analysis

A range of uncertainties are present that accrue throughout the modelling chain, including model uncertainties, assumptions made about the implementation of policy interventions, and the range of potential future socio-economic changes. Therefore, we have performed various uncertainty analysis, including a Method of Morris global sensitivity analysis (Campolongo et al., 2007) and a scenario discovery analysis using the Patient Rule Induction Method (PRIM) (Bryant and Lempert, 2010; Kwakkel and Jaxa-Rozen, 2016). For brevity, we will not discuss this analysis here, but refer to the Supplement for further information and results.

3.8. Downscaling approach

As mentioned, we use the district level as our spatial scale given the data availability on this level. However, within districts, there may be a stark contrast between urban and rural areas. Therefore, we have developed a downscaling approach to downscale the district-level resilience estimates to an Upazila (sub-district) level using 2011 Census data on housing type (see Supplement). This to illustrate that a further disaggregation is desired to better understand the relative impacts between urban and rural households.

4. Results

4.1. Asset losses

Affected areas from TC Sidr were mainly the unembanked parts of the coastal zone. Towards the future, SLR will worsen the situation in these parts, thereby mainly affecting Barisal, Jhalokati, Patuakhali and Pirojpur. The total asset losses are estimated to be 10.7 billion BDT (US \$150.7 million) with SLR increasing this number to 14.1 billion BDT (US \$198.0 million). We further estimate that the asset losses directly affect the welfare of 57,600 households now and potentially up to 84,150 in 2050 due to SLR alone, which, given an average 4.5 person per households, equals ~260,000 and ~380,000 people, respectively. Asset losses expressed as a percentage of the district-wide total assets value range from small losses (0.11% in Bhola) up to 5.35% of all assets (Barisal). Moreover, asset losses are expected to increase dramatically as a result of SLR in Jhalokati (102%), Patuakhali (73%), Barisal (60%) and Pirojpur (54%), whereas SLR will not affect Bhola (1.7%), Bagerhat (4.3%) and Sathkira (0.9%) much.

4.2. Welfare losses

Table 2 shows the reconstructed and future welfare losses expressed as a fraction of the Aggregate Household Income (AHI: number households × household income). In line with the asset losses, welfare losses

are highest in the most severely affected districts Barisal, Khulna and Patuakhali, equal to 3–6.6% of AHI. Although poor households only experience 2–12% of capital losses, they suffer 31.8–50.1% of the welfare losses. Moreover, Table 2 shows the increase in capital and welfare losses, including uncertainty, caused by the changing socio-economic characteristics and SLR. The strongest rise is observed in Pirojpur, Patuakhali, Jhalokati and Barisal due to SLR, reinforced by a growing socio-economic exposure, with increasing losses up to 140–184%. Bagerhat and Khulna will experience only a marginal increase (13–32.8%) and some scenarios project decreasing welfare losses due to improved resilience (Section 4.3). Sathkira has a mean decrease of welfare losses (–3.6%). Barguna and Bhola experience strong socio-economic growth, but negligible SLR influence, resulting in increased welfare losses (60.8–69.7%) that outpace improvements in resilience.

4.3. Resilience

Fig. 3 shows the current resilience estimates per Upazila, and the future resilience estimated using the household emulator. On a district-level, resilience varies from 63% to 77% (Fig. 31a), which, within the definition of resilience adopted, means that every BDT 1 asset loss equals a BDT 1.30–1.59 loss in terms of welfare. The regional variations in resilience can for instance be attributed to a factor four difference in access to financial products for poor households or a factor three difference in the income diversification of the poor (Supplementary Table 6). However, the downscaled results suggest that resilience varies between 54.8% in Dacope (Khulna district) up to 77–78% in some Upazilas in Khulna and Pirojpur districts. Large inequalities exist, and the poor households have, on average, 13 times lower resilience than non-poor households, with large inter-district differences ranging from ~7 times in Bagerhat, Khulna and Patuakhali, up to ~37 times in Jhalokati.

Most future scenarios show an increase in resilience (up to 90%), due to improved access to financial services, decreased unemployment and improved housing. Some future scenarios, however, show a decrease in resilience (down to 61%), for instance due to decreasing income from agriculture and fisheries (environmental degradation). Fig. 3b shows future resilience values for the mean socio-economic scenario. On average, district-wide resilience changes with 4.3% (50th percentile), up to 7–11% (Khulna, Pirojpur) and as low as –0.6% (Patuakhali).

4.4. Effectiveness of policy interventions

The heatmaps in Fig. 4a–d illustrate the benefits of the portfolios of policy interventions included for the three policy objectives and the CSDI index. The 90% uncertainty range is included in Supplementary Fig. 8. The three different objectives all have different patterns, indicating that the performance of interventions differ per objective. Moreover, using the heatmaps, one can quickly assess if interventions are district-specific or work well across all districts. Mean welfare loss reduction is up to 70% (interventions 1–5), with lowest mean loss reduction of around 2%. The pattern in welfare loss reduction is mostly

Table 2

Summary of the present and future (2050) welfare losses. The first two columns show the capital and welfare losses as a function of AHI. 'Impact poor' shows the distribution of losses for poor households and the last four columns indicate the future increase in capital and welfare losses, including 90% uncertainty.

District	Fraction of AHI (%)		Impact poor (%)		Change capital losses (%)		Change welfare losses (%)	
	Capital	Welfare	Capital	Welfare	Mean	90%	Mean	90%
Barisal	4.67	6.61	5.6	43.7	190.7	95.6–313.9	184.2	88.0–306.6
Patuakhali	2.53	3.60	12.2	50.1	142.0	68.6–236.0	140.6	71.0–233.5
Khulna	2.14	3.25	11.1	49.0	42.2	–5.3–106.8	32.8	–13.7–95.0
Barguna	0.95	1.38	6.6	40.6	71.8	16.4–142.1	69.7	16.1–140.9
Jhalokati	0.79	1.23	2.0	43.4	158.7	84.8–252.9	143.6	72.4–235.0
Sathkira	1.01	1.44	5.3	32.1	1.6	–34.5–52.6	–3.6	–38.4–46.8
Pirojpur	0.54	0.70	6.5	42.1	174.2	83.1–288.7	166.9	73.4–291.0
Bagerhat	0.18	0.26	11.5	48.8	20.1	–14.3–67.7	13.0	21.1–58.7
Bhola	0.09	0.13	3.3	31.8	68.3	14.3–139.9	60.8	8.1–128.7

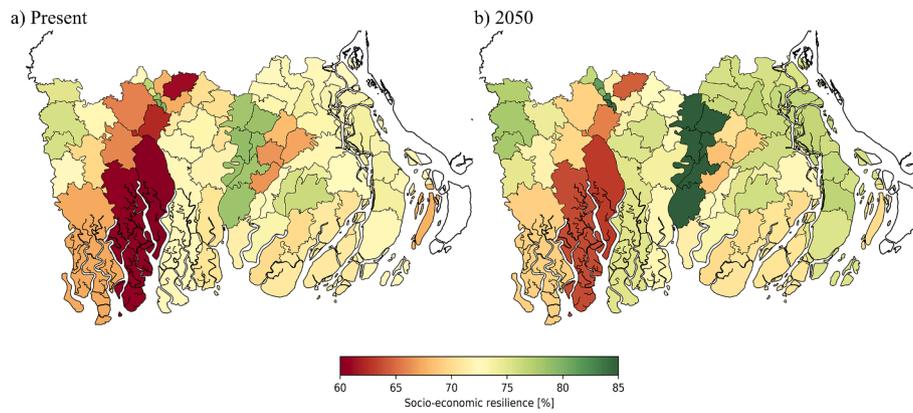


Fig. 3. (a) Downscaled Upazila-level resilience estimates for the present conditions. (b) Downscaled Upazila-level resilience for the mean socio-economic scenario for 2050.

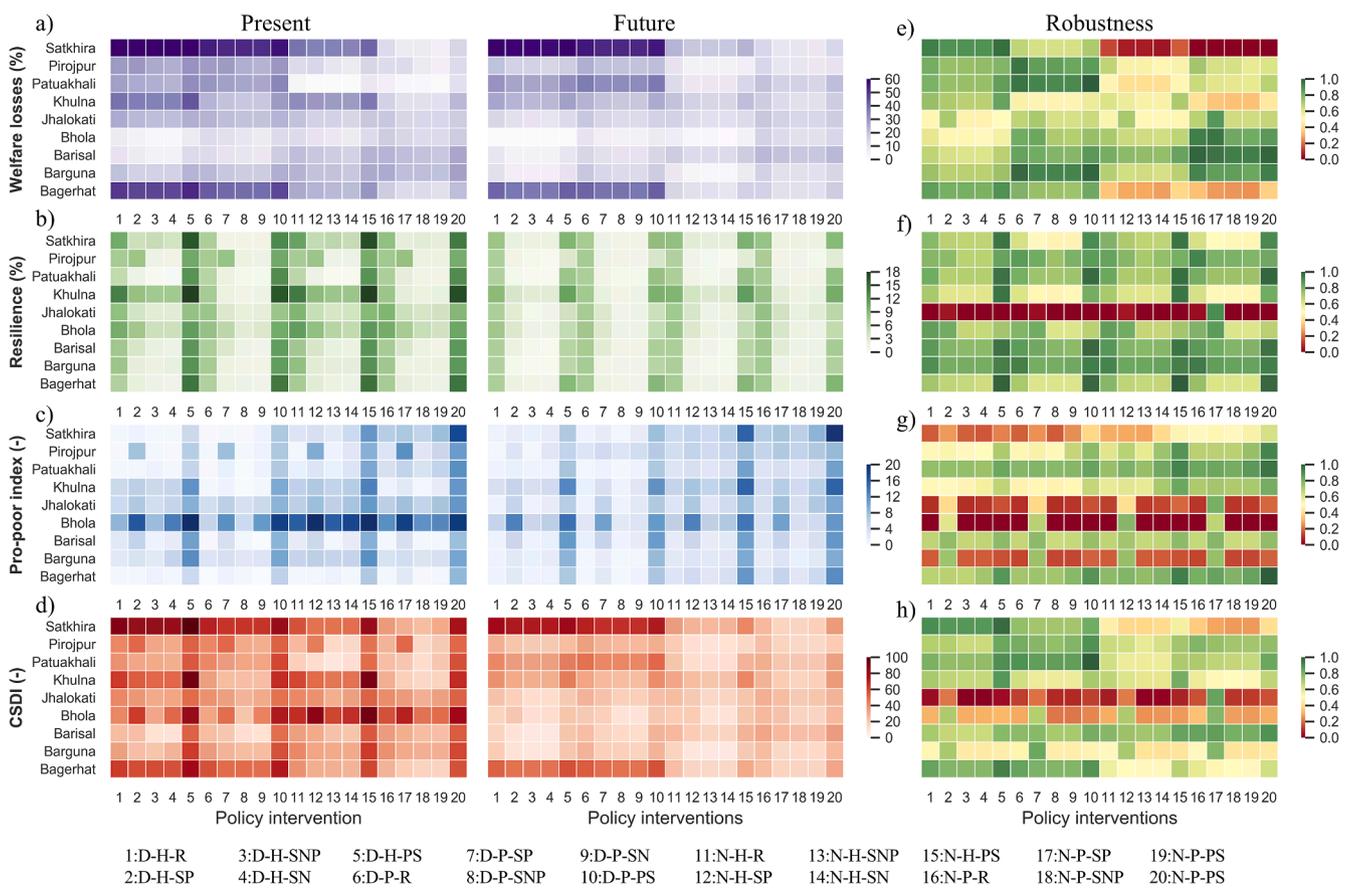


Fig. 4. (a–d) On the left hand side, the heatmaps of the mean effectiveness of policy interventions under present impacts for the different policy objectives. Darker colour indicates larger benefits. On the right hand side, the effectiveness of policy interventions under future impacts from SLR and socioeconomic growth for the different policy objectives. (e–h) the robustness of interventions, with red colour indicating low robustness and green colour large robustness. The keys that correspond to the portfolios are included on the bottom. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

horizontal (Fig. 4a), meaning that measures are specific for a district. The inland districts (e.g. Bagerhat and Satkhira) largely benefit from the dike intervention, whereas the coastal districts (e.g. Barisal and Bhola) benefit primarily from the nature-based solution. Districts with a large percentage of households in unimproved (e.g. jhupri, see Supplementary Table 7) housing (e.g. Khulna, Satkhira) greatly benefit from improved housing as can be seen by the high effectiveness of interventions 1–5 and 11–15. The pattern for resilience and pro-poor are more vertical (Fig. 4b–c), implying that a portfolio does or does not works well across

all districts. For resilience, portfolios that include PDS and faster recovery work well across all districts, improving resilience by up to 22% (highest in Khulna). The lowest resilience increases are found for solution 8, only improving resilience by maximum 2.7%. For districts with relatively low access to finance (e.g. Bhola, see Supplementary Table 6), providing additional access to savings for the poor helps building resilience. The pro-poor index shows again large benefits for PDS and access to savings poor, which can help reduce inequalities if implemented in an equitable way. Some portfolios (5/12/15) help reduce

welfare losses by 28.5–32.4% more for the poor than for the non-poor, which is particularly apparent in Bhola.

The CSDI combines the aforementioned objectives, leading to a more complex picture of effectiveness (Fig. 4d). The largest alignment can be achieved in Sathkira, Bhola, Khulna and Bagerhat. Portfolios with extended PDS work well across all districts (5/10/15/20). Dikes in combination with housing tend to work well in inland districts with large housing inequality (e.g. Khulna and Sathkira), whereas access to savings for the poor in combination with a nature-based solution and either improved housing or early warning system has large overall benefits (12/17 are high) in the coastal districts (e.g. Bhola and Pirojpur). Barisal, despite having the largest absolute losses, has limited opportunity for alignment between objectives for this TC scenario, with PDS in combination with a nature-based solution being the most viable option.

4.5. Effectiveness of policy interventions in the future

Results for the benefits under future climatic and socio-economic conditions are shown in the heatmaps on the right-hand side of Fig. 4a–d per policy objective (Supplementary Fig. 9 for 90% uncertainty). In Bagerhat, Khulna and Sathkira, the mean welfare losses across all interventions and scenarios are close to present day losses (fractions: 0.83, 1.06, 0.61). In the remaining districts, the mean absolute losses with portfolios implemented varies between 1 and 2.5 of the present-day losses, with Barisal and Pirojpur having the highest fractions (2.45, 2.30).

Most portfolios of interventions become less efficient in the future, which is to be expected if overall resilience improves and poverty reduces. Welfare loss reduction decreases slightly, with a maximum of 60% (1–10, Sathkira), but resilience and the pro-poor index decreases more rapidly. Resilience can now be increased by 10–11% in some portfolios (5/15/20), whereas others (8/9) only improve resilience by 1.4–1.5%. Portfolios including PDS are still pro-poor, with up to 20–27% larger benefits to the poor in some districts (e.g. Sathkira, Khulna, Bhola). Fig. 4e–h illustrates the robustness (green colours indicating more robust solutions), with robustness being very specific per district. The nature-based solution is not robust for welfare loss reduction in districts that will experience large SLR, in contrast to dikes (Bagerhat, Sathkira) (see Fig. 4e). Some districts (e.g. Jhalokati) show an overall low robustness for achieving resilience (fifth line Fig. 4f). This is due to the fact that these districts have low resilience now (especially poor households have low resilience) and the effectiveness of interventions depends on changing socio-economic conditions, which show a large uncertainty range. This results in large uncertainties for the effectiveness of interventions in building resilience and being pro-poor, and hence a low robustness. For the pro-poor index (Fig. 4g), most districts (e.g. Barguna and Bhola) show low robustness for most interventions, except portfolios with access to savings for the poor. In districts with large uncertainties in poverty reduction, interventions may work well under low poverty reduction scenarios, but become obsolete under high poverty reduction scenarios. Overall, PDS seems to be robust under future socio-economic change for most districts.

For the CSDI, the potential mean benefits are lower, indicating that the policy objectives become less effective and aligned (Fig. 4d). Portfolios with access to savings for the poor and PDS work well overall, and improved housing seems to be more robust in districts with large shares of unimproved housing (e.g. Sathkira). Portfolios including social safety nets and access to savings for the non-poor have little robustness in most districts.

5. Discussion

5.1. Synergies and conflicts between policy objectives and robustness

Although the use of only one TC scenario make the results difficult to

extrapolate to other TCs, the results clearly illustrate that the policy interventions that reduce the current risk are not necessarily the ones that work well under future changes, and are not always the most robust options. Therefore, in order to avoid maladaptation, these three perspectives should be coherent. To illustrate this potential (mis) alignment, the top three portfolios for current, future and robust welfare losses are compared. Supplementary Table 9 summarises these findings with most districts having two or three matching portfolios. For instance, Barisal and Bhola show alignment between the objectives by implementing a nature-based solution with improved early-warning system, whereas Barguna and Jhalokati have less internal consistencies, and a trade-off exist between achieving robustness under future uncertainties and minimising current welfare losses. Moreover, for the other districts, multiple combinations of interventions all have high alignment, showing illustrating that there is flexibility in the choosing effective portfolios in line with preferences of decision-makers. A similar exercise is done for the CSDI with results in Supplementary Table 10. This shows, for instance, how dike heightening in combination with PDS support has a high CSDI now, in the future, and with high robustness for Bagerhat, Pirojpur and Patuakhali, whereas Barisal and Bhola have a high CSDI for PDS and a nature-based solution. However, Barguna and Jhalokati have conflicting options. Improved housing and PDS work well to improve the CSDI under present conditions, early-warning and PDS/fast recovery work well for the future, but the most robust options are portfolios that include access to saving for the poor.

5.2. Comparison to previous work and policy implications

Our results show that TC Sidr caused welfare losses of up to 4.7% of AHI. Poor households experienced, on average, 7% of the asset losses, but 42% of the welfare losses. This indicates that a narrow framing of flood damage in terms of asset losses can overlook impacts upon the poorest in society. Therefore, investments to improve DRR based on traditional risk assessments may not reach those who experience the largest welfare impacts of disasters. The finding of disproportional welfare losses borne by the poor are also reported in Walsh and Hallegatte (2020), who found similar ratios for the Philippines.

Similar disproportionalities were found for the resilience values, with values varying between districts and between income groups. This difference gets even higher if one further disaggregates to sub-district scale. Still, resilience values are higher in most districts than those reported in Walsh and Hallegatte (2020) and Yonson and Noy (2018), even though poverty incidence is lower in the Philippines. This provide evidence for the already well-functioning social protection and post-disaster support system in Bangladesh (Karim and Noy, 2015; Peduzzi et al., 2012). Inter-district differences arise because of existing inequalities in income, access to savings and income diversification. For instance, access to financial products for poor households is a factor four higher in the districts Barguna, Pirojpur and Sathkira compared to Bhola. However, differences in resilience tends to be uncorrelated with overall poverty incidence. More generally, we do not find a clear driver of changes in resilience among the model input, illustrating that a complex interplay of socio-economic factors determine the extent of welfare losses. Overall, we find that a higher-resolution spatial analysis is imperative to disentangle the relationship between environmental risks, poverty and resilience (Narloch and Bangalore, 2018).

For the 20 portfolios of policy interventions, we again observe large differences between districts and policy objectives, indicating that trade-offs are unavoidable and that the effectiveness of interventions depends highly on socio-economic context. The great effectiveness of PDS, via lump-sum cash transfers, was also found by Walsh and Hallegatte (2020) in the Philippines, who showed that cash transfers would yield a benefit-cost ratio of 4.9 after TC Yolanda, and Hallegatte et al. (2016) who determined that PDS would have an average benefit-cost value of 2.2 across countries. Access to savings for the poor is another measure that works well across districts, even under changing conditions. This

comment was also made by Brouwer et al. (2007) within a river flood context in Bangladesh, especially if savings and insurance can be targeted to the ultra-poor. This evidence can support the continued financing of soft measures that are often more flexible over time, easier to scale up and can be tailored to the needs of the poor. Most districts have a multitude of portfolios with comparable benefits, allowing flexibility in decision-making in line with development and political preferences.

We note that the composite index used in this study should be interpreted as a guiding metric to evaluate synergies and trade-offs between policy objectives. Any multi-criteria decision-making approach suffers from potential biases in the way objectives and criteria are selected, and weights are assigned (Gamper and Turcanu, 2015). For the CSDI, we have assigned equal weights to all objectives, although different weights could be set according to the preferences of decision-makers. The relationship between indicators, measured by Pearson's correlation coefficient, is moderate (welfare – resilience: 0.26, welfare – pro-poor: –0.26 and resilience – pro-poor: 0.55), and hence we expect some sensitivity to the inclusion of the weights in the result of the CSDI. Therefore, for transparency, we have included the individual policy objectives separately as well, which could allow decision-makers to assess how the CSDI might shift if one policy objective is preferred over the other.

Future work on quantifying welfare losses from natural disasters should integrate lesson learned from empirical findings on the link between welfare losses, poverty and resilience (Aker and Mallick, 2013; Narloch and Bangalore, 2018), and the recent literature on high-resolution social vulnerability indices (H et al., 2020; Kabir et al., 2019; Marzi et al., 2019). Moreover, extending the current analysis to multiple hazards, with different intensities, will help to improve the generalisation and robustness of the spatial optimisation of DRR interventions.

6. Conclusion

Using a district-scale analysis in coastal Bangladesh, this work aimed at quantifying present and future welfare losses from a severe tropical cyclone event. Further, the objective was to better understand the resilience of households and identify potential adaptation options under a multi-objective optimisation framework by coupling risk reduction to the wider sustainable development agenda, including robustness under changing climate and socio-economic conditions.

We find that poor households experienced, on average, 7% of the asset losses, but 42% of the welfare losses. Climate change and socio-economic growth in 2050 may cause welfare losses to grow up to 184%, with future welfare losses modulated by an increase in households' resilience (e.g. improved housing, access to savings). Resilience ranges between 63% and 77% with a median 4.3% increase in 2050 because of socio-economic growth. Using a targeted set of interventions may further reduce future welfare losses. For instance, combining dike heightening, post-disaster support and stronger housing can reduce welfare losses by up to 70%, and foster sustainable development by benefitting the poor, increasing resilience and demonstrating robustness under socio-economic and climatic uncertainties.

Our study concludes that a welfare-based perspective provides a more comprehensive insight into the distributional impacts of disasters that are overlooked when solely considering asset losses. Modelling future socio-economic growth and climate change and linking it to changing resilience is essential to understand the connection between future risks and effectiveness of adaptation options. Resilience is not static but should be seen as something that co-evolves with development. The preferred adaptation option differs widely per socio-economic setting, illustrating the such high-resolution spatial analyses are essential to avoid 'one-size-fits-all' solutions and effectively allocate DRR spending. Results indicate that a portfolio of hard and soft measures can accelerate risk reduction efforts and help achieve wider sustainable

development objectives by enhancing (climate) resilience, demonstrating robustness under changing conditions, and strengthening pro-poor developments efforts.

CRediT authorship contribution statement

J. Verschuur: Conceptualization, Methodology, Validation, Writing - original draft. **E.E. Koks:** Conceptualization, Writing - original draft, Supervision. **A. Haque:** Methodology, Writing - review & editing. **J.W. Hall:** Conceptualization, Writing - original draft, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.gloenvcha.2020.102179>.

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