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The unequal distribution of water risks and adaptation benefits in coastal Bangladesh

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Abstract

Increasing flood risk, salinization and waterlogging threaten the lives and livelihoods of more than 35 million people in Bangladesh's coastal zone. While planning models have long been used to inform investments in water infrastructure, they frequently overlook interacting risks, impacts on the poor, and local context. We address this gap by developing and applying a stochastic-optimisation model to simulate the impact of flood embankment investments on the distribution of agricultural incomes across income groups for six diverse polders (embanked areas) in coastal Bangladesh. Results show that increasing salinity and waterlogging negate the benefits of embankment rehabilitation in improving agricultural production, whilst improved drainage can alleviate these impacts. Outcomes vary across income groups, with risks of crop loss being greatest for the poor. We discuss the need for planning models to consider the interacting benefits and risks of infrastructure investments within a local political economy to better inform coastal adaptation decisions.

Understanding the effectiveness and equity implications of large adaptation infrastructure investment is currently paramount in Bangladesh's coastal region. As one of the world's most vulnerable and biophysically dynamic regions, coastal Bangladesh faces multiple water-related hazards including cyclones, tidal and river flooding, salinization, and waterlogging. With the potential for multiple coinciding hazards to increase in the future, the impact of hydroclimatic risks is likely to be magnified [1,2].

Flood protection embankments and drainage infrastructure were constructed to create polders (embanked areas separated from the surrounding river system) and improve agricultural production as part of the South Asia 'Green Revolution' in the 1960s to 1980s. Initial success in improving flood mitigation and food security [3,4] has been undermined by inadequate maintenance, as well as appropriation by local elites and government actors for alternative production systems such as aquaculture [5,6]. Embankments have been weakened by shrimp farmers who are supported by these elites, drilling holes to bring in saline water [7].

Flood protection goals have consequently become compromised by power imbalances and conflict, contributing to high salinity, waterlogging, wealth disparity, loss of livelihoods, and the displacement of poor and vulnerable people [7-9].

These outcomes are symptomatic of a global pattern of adoption of large water infrastructure projects in response to hydroclimatic risk [10-12], despite it being known that they do not always deliver expected outcomes [13,14]. Traditional water infrastructure planning has largely ignored distributional equity [15,16], resulting in long-term chronic environmental and social impacts [17,18]. Large-scale infrastructure projects are too often subject to control by local elites, thereby reinforcing unequal power structures [19]. Infrastructure effectiveness and the distribution of benefits are a consequence of interactions between the construction, use and operation of built infrastructure and the environmental, social and political context [16,20]. In an era of re-emerging emphasis on large infrastructure [21] combined with increasing evidence of these impacts [22,23], it is imperative for planning models to better account for who benefits and who incurs residual risks [12,24].

Whilst a number of methods exist to support the planning and management of water and flood risk infrastructure considering future uncertainty [25,26], the complex dynamics of the socio-ecological systems into which this infrastructure is introduced remains under-represented in research and practice [19]. Here, we take a novel approach linking quantitative modelling with insights from political economy literature to consider unequal socio-economic status within and across communities, and their inter-relationship with spatial variation in biophysical systems. As with any exploratory model of complex systems, its strength lies in the ability to investigate interacting dynamics to gain new insights that are not possible with sectoral-focused, detailed models. Nonetheless, there are inevitable limitations in precision compared with more detailed process-based models.

We build on earlier work [27,28] to explore the distributional effects of flood protection rehabilitation investments on flood mitigation and agricultural production in six diverse polders across coastal Bangladesh (Figure 1). First, we investigate the interrelationship between embankments, flooding, salinity, waterlogging, and agriculture in determining risk at different spatial scales both within and between polders. We use a risk-based stochastic optimisation model over a sixty-year planning horizon, drawing on contextual information from political economy literature. Second, we explore variability in sequencing and effectiveness of embankment rehabilitation investment decisions in improving crop production across the polders. We assess the role of waterlogging and salinity in limiting embankment rehabilitation effectiveness, and compare it with investment in drainage infrastructure. Third, we examine implications for agricultural income across different socio-economic groups.

We use a novel combination of datasets considering intra- and inter- polder variability in elevation, flood risk, erosion rate, salinity, cropping pattern, distribution of different land holding types, as well as investment cost (Figure 2).

Modelling impacts of water risk on farmer livelihoods

Agriculture is the most important economic activity within the region [33], supporting the livelihoods of a variety of rural classes including day labourers, sharecroppers, as well as small to large landholders. It consequently continues to play the most significant role in sustaining an economically diverse region, despite the expansion of alternative livelihoods such as aquaculture and manufacturing. Tensions in water and land management exist between agriculture and saline aquaculture, the latter of which primarily supports wealthier landholders and elites who reside outside of rural communities

[7]. Aquaculture is less labour-intensive, reducing employment opportunities and thus driving out-migration [9,34]. These tensions influence the construction, use, and operation of flood protection infrastructure.

We examine variations in crop loss within and between six polders (Figure 1) for two types of agricultural groups: subsistence farmers (land holdings of ≤ 0.04 acres); and farm holdings (small, medium, and large, 0.05 to >7.5 acres) [35] (Supplementary Table 4). The six polders are selected using published literature and a scoping visit to represent varying levels of water security risk and poverty; embankment and drainage infrastructure deterioration; institutional arrangements and effectiveness; and involvement in previous, current, or future development projects [36,37].

Flooding is a major cause of crop loss in coastal Bangladesh, resulting from the interaction of different drivers including storm surges, elevated river levels exacerbated by riverbed siltation and polder subsidence, high precipitation, embankment deterioration, poor drainage, and land use management. The relative contribution of these drivers has been examined in previous empirical studies of observed floods, which have shown the ongoing devastating impact of surge-induced flooding caused by cyclones, non-cyclonic storms, and fluvio-tidal events [37,38]. We extend this work to examine long-term risk beyond the observed record by constructing a stochastic model of extreme tidal, fluvial, and cyclonic flood events, embankment condition, and polder elevation (Figure 2).

Of our six polders, flooding is greatest in Polders 32 and 29 based on previous analysis [38], which is reflected in our model (Figure 3a,c; Supplementary Figures 1 and 6). We consider variability in flooding across the region by varying flood magnitude depending on polder location, recognising that a damaging flood event impacts the region on average just over every two years [38]. Polder embankments are damaged during flood events, whilst also being subject to ongoing deterioration due to erosion. We consequently incorporate modelled storm damage and use observed erosion data [39] to model variations in embankment deterioration, with a higher deterioration for Polder 54 in the South-Central region (Figure 3b).

Variations in flooding within each polder are modelled at the scale of the lowest administrative unit (mauza), averaging approximately 280 ha for our study area (ranging from ~11 to over 2,000 ha) [32]. Within each mauza, we estimate flood impacts on crop production comparing subsistence farmers with small to large farm holdings. Agricultural census data [40] is used to identify the number of each holding type for each mauza.

Both flooding and embankment construction influence increasing soil salinity and waterlogging. Soil salinity is influenced by inundation, saline intrusion from reduced upstream freshwater flows, application of saline irrigation water, and influx from areas under saltwater shrimp aquaculture. Salt is flushed from polders during the monsoon season through percolation [41,42]. Embankments can consequently mitigate salinity through reducing tidal and storm-surge inundation of saline water, whilst also contributing to increasing salinity due to increased waterlogging from river siltation and polder subsidence.

Salinity has become sufficiently severe to significantly impact crop production, and can disproportionately affect poorer and marginal farmers [9,43]. Increasing salinity has influenced and been influenced by transitions to saline shrimp aquaculture dominated by large-scale enterprises at the exclusion of local farmers [9]. It is thereby implicated in changing land-use, livelihoods, and local power dynamics [9].

Observed data shows soil salinity to be highest in Polders 32 and 33 within our case study area, with high river salinity levels assumed to affect four of the six polders (30, 32, 33 and 43/1) [31]. Given the pressures of sea level rise, embankment deterioration, subsidence, and drainage deterioration, we project that without action to tackle these issues salinity will exceed 16 dS/m in four of the six polders during the sixty-year simulation period, the level of salinity above which most crops cannot grow [31] (Figure 3d). A reduction in crop yields has been shown at much lower concentrations of <4 dS/m [31,41].

Waterlogging has also become widespread across the coastal zone, with areas that are inundated during intense rainfall or fluvial flooding failing to drain for prolonged periods. We predict that waterlogging will increase over time due to polder subsidence and deteriorating internal polder drainage, exacerbated by deliberate inundation for aquaculture [8,44]. We model waterlogging as a function of elevation difference between the polder and river, and drainage condition (representing infrastructure condition and sedimentation). Using river level elevations [32] enables us to capture seasonal variations, with waterlogging being greatest during the monsoon when rainfall is greatest and river levels are elevated. Modelled waterlogging is most extensive in Polder 32 (followed by Polders 33 and 30), having the lowest elevation of the six polders [30] (Figure 3e and Figure 1).

Impacts upon agricultural production vary between different socio-economic groups. Subsistence farmers primarily grow vegetables (in our model we use representative crops: water gourd and winter and summer pumpkin), whilst farm holdings primarily grow rice [40] (Supplementary Table 6). Whilst those who own less than 0.04 acres of land have been referred to as effectively landless [45], we assume here that it is of sufficient size to produce garden crops. We assume this land is evenly split between gourd, winter, and summer pumpkin across all polders in the absence of further information. We model spatial variation in cropping patterns for farm holdings using Upazila-scale (the second-lowest administrative unit) data, focusing on major crops (local, hybrid and high-yield varieties of rice as well as jute) [40].

The combined effect of flooding, salinity, waterlogging, and crop type are predicted to have a significant impact on crop production, with variations within polders, between polders, and between socio-economic groups. Crop production loss is predicted to be highest in Polders 32 (70%) and 29 (60%) (averaged over the single sixty-year simulation period shown in Figure 3f), with Polder 32 having frequent flooding as well as high salinity and waterlogging. Whilst Polder 29 has a high total crop yield due to a greater proportion of high-yield crops such as hybrid and high-yield (HYV) Boro (spring rice) [40] (Supplementary Figure 7), it also has a much lower proportion of local Aman (monsoon rice) which is grown when salinity is lower.

Banking on adaptation infrastructure

Rehabilitation of Bangladesh's embankments and drainage system has been a focus of adaptation investment since the 1990's, costing in excess of $600 million USD (details provided in Supplementary Table 7). Though risks of waterlogging and salinity were recognised, the relative impacts and benefits of adapting to these threats have not been systematically quantified. To explore these interactions, we optimize an embankment investment sequence by considering flood risk reduction and investment costs, which is the economic rationale that is conventionally applied to adaptation investments [46] (optimisation parameters are described in Supplementary Table 8). We assume that during rehabilitation, embankments are returned to their as-built condition. We subsequently investigate the role of waterlogging and salinity, and compare the effectiveness of embankment rehabilitation with investment in drainage infrastructure.

We consider a maximum of three potential investments per polder over the first forty years of the sixty-year simulation period (estimated to cost over $600 million USD [47] for all polders), with investments allowed at 5-year time intervals. We use multi-objective optimisation to explore embankment investment priorities, timing, and impacts under three conditions: (1) minimise expected crop income loss with no investment cost constraint; (2) minimise expected crop income loss with an investment cost constraint of $200 million USD; and (3) minimise both crop loss and investment cost. Expected crop income loss, $\mathrm{E}(L)$, is calculated as a percentage reduction from the maximum potential crop income, $\bar{I}$, based on maximum potential yields (provided in Supplementary Table 6): $\mathrm{E}(L) = \left(\bar{I} - \mathrm{E}(I)\right) / \bar{I}$, where $\mathrm{E}(I)$ is the expected crop income calculated as an average of 100 stochastic iterations.

Under all three conditions, embankment investment is largely driven by flood risk reduction potential (Supplementary Figures 8 to 10). When costs are constrained, the greatest investment is in Polder 32 (Supplementary Figure 9 and 10). Crop income loss remains significant across polders even with all three embankment rehabilitations permitted per polder under the first condition with no cost constraint. For Polder 32, income loss with maximum investment is estimated to be 60% for small to large farm holdings and 90% for subsistence farmers, compared with 70% (farm holdings) and 90% (subsistence farmers) with no investment (averaged over 1,000 stochastic flood simulations, Figure 4). Embankment investment is found to be more effective in reducing crop loss for small to large farm holdings with little benefit for subsistence farmers. These findings are broadly consistent with observed losses from an extreme flood in 1998, noting variations in study area [48]. Observed losses are found to exceed 90% for some rice varieties.

Investment is also influenced by variation in embankment deterioration, driven by differences in erosion rates which are higher adjacent to Polder 54 [39]. As such, a greater reduction in crop loss for small to large farm holders is found with investment in Polder 54 relative to Polder 29, despite Polder 29 having a higher flood risk and greater crop loss.

Whilst embankment investment results in a substantial reduction in flooding (Supplementary Figure 6), the direct risk from large floods is relatively small in the majority of polders when compared to the impacts of waterlogging and salinity on crop production (Figure 4).

To further examine the relative impacts of waterlogging and salinity on crop production, we firstly conduct three sensitivity tests, and secondly explore an alternative intervention targeting improved drainage. We use 1,000 stochastic flood simulations to compare expected crop loss between scenarios. For the sensitivity tests, we alternately set (1) waterlogging and then (2) salinity to zero in the model, which results in a significant reduction in modelled crop loss (Figure 4). Variations are found between polders and farm holdings as to which has the biggest impact. Under a combined zero salinity and waterlogging scenario with no embankment investment, the total expected agricultural income per year for the six polders increases by >100% for small to large farm holdings, as opposed to <10% for embankment investment. This difference is even greater for subsistence farmers, where the increase in income is >200% compared with <5% for embankment investment.

Our third sensitivity test explores the influence of sediment deposition in reducing waterlogging and salinity (through increased elevation and consequently reducing flood events bringing in saline water). Sediment deposition has gained increasing attention in Bangladesh through Tidal River Management (TRM) projects with varying degrees of success [49,50]. Whilst the focus of TRM is on deposition during smaller, regular floods, we use our model of large flood events to test the sensitivity to deposition. Elevation is increased in flooded mauzas by a maximum of 37 cm [51] and scaled based on the size of each flood. This is a conservative estimate based on reported average deposition [51], which was observed to be as high as 60-70 cm in some locations.

Given that sediment deposition only occurs during large floods within our model, the overall impact is negligible with only a small improvement in Polder 32. We note that other studies have shown sediment deposition to have greater potential when considering more regular inundation events under TRM [50], and it has been adopted as a mitigation strategy in the Bangladesh Delta Plan 2100 [52]. It remains a debated topic, with studies highlighting the context-specific biophysical and socio-political setting required for its success (such as seasonality, magnitude of tidal flow, spatial distribution of sediment concentration, river salinity, and availability of land that can be inundated) [49,50].

As an alternative intervention to embankment rehabilitation, we then examine the effectiveness of investing in polder drainage by assuming no deterioration in drainage condition occurs during the simulation, thereby reducing waterlogging. Poor interior polder drainage is caused by siltation, blockages, as well as inadequate maintenance and operation, and has been reported as being a cause of waterlogging and consequently crop damage by household surveys [44]. We find a no-drainage deterioration scenario to have a greater influence in reducing crop loss for all polders relative to embankment rehabilitation, with the exception of subsistence farmers in Polder 32. The expected crop income increases by ~30% for small to large farm holdings and ~40% for subsistence farmers. Whilst our representation of drainage condition is necessarily simple due to the spatial scale of our model and hence the exact values should be treated with caution, our findings are consistent with other studies that have found drainage congestion and poor operation to be an important contributor to waterlogging and hence crop loss [44].

Within polders, variations in modelled crop income between mauzas are significant, and are greatest in Polder 29 under a no-investment (190 – 390 USD/ha) and embankment investment scenario (220 – 420 USD/ha) (Figure 5). Under an embankment investment scenario with no waterlogging or salinity, the greatest variation is in Polder 43/1 (350 – 440 USD/ha). Comparing a no-investment with an embankment investment scenario, increases in area averaged income varied most in Polder 32 (30% - 50%). Whilst observed data was not available to verify these differences, these results highlight the significance of intra-polder spatial variations in investment impacts which has too often been overlooked in adaptation assessments.

Winners and losers of infrastructure investment

We compare differences in modelled crop income loss for subsistence farmers (vegetables) and small to large farm holdings (rice and jute) and find average crop income loss to be higher by up to 90% for subsistence farmers across all polders for our two interventions (Figure 4). Differences between subsistence farmers and small to large farm holdings are greatest for Polder 33, which has high salinity minimal flooding. The higher loss for subsistence farmers is primarily due to salinity having a greater impact on vegetable growth compared with other crops.

These results are consistent with empirical data for areas adjacent to the Meghna River [53], where floodplain residents below the poverty line (defined in this case as below US$105/capita/year) reported on average 42% flood damage (proportion of household income) as opposed to 17% for those above. However, this included multiple sources of damage, for which crop damage was the highest (27%) along with house property damage. In contrast, an analysis [48] of the 1998 flood for seven Upazilas (including Khulna) did not show higher production loss for smaller land holdings, although it did find a higher percentage loss of assets as well as significant impact on labour opportunities.

In our analysis, small to large farm holdings had similar crop income loss due to consistency in cropping patterns, despite variations in the number of holding types per mauza (with different susceptibility to flooding).

Distributional variations in adaptation costs and benefits also have an important gender-dimension, being influenced by access to labour and socio-economic status. We are unable to represent this in our analysis as census data does not capture the complex intra-household gender implications of agricultural income or adaptation investment. Available data does show that all farm types have a higher proportion of male-headed holdings, yet subsistence farmers have more female-headed holdings (5%) compared with small-large farm holdings (2%) (at an Upazila-scale) [40] (Supplementary Table 5). We recommend further work is undertaken to better understand the gendered implications of investment decisions.

Toward equitable flood infrastructure investment

Our findings provide important insights for the current and future management of Bangladesh's coastal zone. The region is central to the Government of Bangladesh's development goals, with plans including the development of a transportation hub, tourism, and additional industry [52,54]. Rehabilitation of coastal embankments is a key component of these goals, with ongoing investment through programs such as the $400 million USD Coastal Embankment Improvement Project [55].

We show that the benefits of investment in flood embankment rehabilitation can be overwhelmed by increasing salinity and waterlogging, and that these cannot be examined or mitigated in isolation. Furthermore, we show that investments in drainage rehabilitation have a greater overall influence on reducing crop loss for all polders relative to embankment rehabilitation, leading to crop income increases of ~30% for small to large farm holdings and ~40% for subsistence farmers. We demonstrate the feasibility and value of modelling distributional impacts ex-ante, supporting empirical evidence that challenges commonly held assumptions on the effectiveness of embankments.

The physically dynamic nature of the system combined with vulnerability to natural hazards, high poverty, and weakness of local institutions presents a critical need for exploratory planning tools that can accommodate multiple interacting risks and their spatial variation, limited and diverse data, and can be applied to understanding of the local political economy. Such tools provide an opportunity to further develop our capacity to represent such systems, and how they can be used to complement more detailed analyses on subsets of processes with greater accuracy and precision. Understanding these interactions can assist in identifying the right problem (or set of problems), and who defines what 'right' is. It can support the identification of how, where and when to invest to target areas with the highest vulnerability, which may be missed when focusing on investments with the greatest return or ease of implementation.

Larger-scale adaptations, including embankments and drainage infrastructure, continue to attract large sums of finance and development assistance. Smaller-scale adaptations, which include financial assistance such as direct cash payments after disasters, hazard forecasting and shelters, and strengthening of homes, can also help to mitigate the damage of climate-related disasters [56]. These can complement large-scale infrastructure, and can target the most vulnerable provided there is adequate geospatial poverty data.

The political economy of infrastructure management and maintenance following its initial construction can also transform impacts with significant implications to the distribution of benefits[20], and yet is frequently overlooked. Maintenance and use of embankments and drainage infrastructure influence the degree of saline water influx, sediment influx, drainage of excess ponded water, as well as vulnerability and exposure to flood risk. These environmental factors in turn influence and are influenced by land management, access to labour, access to decision making power, and ultimately capacity to build resilience against environmental risk and social poverty. Challenges in managing this political economy and chronic risks are exacerbated by donor preferences for large capital investments with insufficient attention to subsequent management and maintenance [6].

The dynamics and challenges described are by no means specific to coastal Bangladesh. Globally, the growing environmental and social impacts of existing infrastructure projects continue to motivate debate on alternative means of managing flood risk [57]. We have developed an approach that provides insights into the complex dynamics between hydroclimatic risk and social systems, and demonstrate the importance of a multi-disciplinary, systems-approach in designing adaptation strategies. We believe that such approaches are needed to provide actionable insights for effective adaptation in vulnerable coastal regions.

Methods

We develop a risk-based model that extends the work of Borgomeo et al. [27] to focus on distributional impacts considering different socio-economic groups; within and between polder heterogeneity parameterised using high resolution datasets; as well as more explicit representation of drivers influencing crop yield. We also draw on the work of Lázár et al. [33], Nicholls et al. [58], and Payo et al. [59], who integrate flood and salinity impacts on crop production for different households in coastal Bangladesh. Here, we focus instead on implications for embankment rehabilitation investment decisions.

The model uses crop yield as a metric for evaluating flood embankment investments given the key role it places in supporting livelihoods across coastal Bangladesh. Crop yield (Y) is calculated as a function of salinity (s_F) and waterlogging (w) for unflooded areas using a monthly time step (t), by proportionally reducing the maximum potential yield ($\bar{Y}$): $Y(t) = \bar{Y}(t) - \bar{Y}(t)\left[\min\left(\frac{s_F(t)+w(t)}{2}\right),1\right]$. The spatial unit of analysis is a mauza although the spatial resolution of datasets varies. Mauzas are estimated to be either completely flooded or not flooded based on their elevation using Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) data [30]. The frequency and magnitude of flood events are calibrated to observed data from 1988 to 2012 [38] for each of the six polders, and is described further in the Supplementary Information (Supplementary Figure 2 and Supplementary Table 1).

Within-polder flooding is influenced by embankment condition, modelled as a value between 0 and 1 with a starting condition of 0.6 (60% of the maximum condition) to represent initial deterioration across all polders (in the absence of further information). Condition is assumed to deteriorate at a constant rate over time due to erosion, with additional deterioration during a flood event proportional to the magnitude of the event (further described in the Supplementary Information under Embankment reliability). We model embankments as a single entity which spans the entire periphery of each polder given the lack of available information on variability within individual polders.

Soil salinity (s_L) is calculated as a combination of chronic increases (s_c) and short-term influxes (s_F) by taking the maximum of the two mechanisms for any given mauza (m) each month. Concentrations are normalised to a value between 0 and 1 using an upper limit of 16 dS/m above which there is a significant impact on crops, noting that impacts on more sensitive crops can occur at much lower concentrations [31,41]: $s_L(t,m) = \min\left(\frac{\max\left(s_c(t), s_F(t,m)\right)}{16}, 1\right)$. Mauza-scale salinity is used to reduce crop yield for each mauza, and is then summed for the entire polder.

Chronic salinity is assumed to increase at a constant rate of 0.09 dS/m per year based on average historical data [31] (Supplementary Figure 4), with the initial salinity in each polder varying between 8 and 14 dS/m (estimated using area weighted average salinity for 2009 [31], Supplementary Figure 3 and Supplementary Table 2). A monthly soil salinity profile [33] is used to represent seasonal variations at a polder scale (p): $s_c(t,p) = \left[s_c(t-1,p) + s_I\right] \cdot s_p(t)$.

During a flood event, the salinity influx for flooded mauzas is assumed to equal that of the river (s_R), and consequently varies spatially across the six polders (between 2 and 28 dS/m) [31] (Supplementary Table 3). Salinity concentrations are assumed (in the absence of available observed data) to decline over time with a ~50% reduction over a period of two years: $s_F(t,m) = s_R(p)e^{-bt'}$ (where -b controls the rate of decline, set 0.03 to reduce salinity by ~50% in two years; and t' is the time since the last flood event).

Waterlogging is assumed to be a function of drainage infrastructure condition (d), and elevation inside the polder [30] (e_L) relative to the river (e_w) (estimated from three observed gauges [32]):

$$w(t,m) = \begin{cases} 0.5 \cdot \left(e_w(t)/e_L(t,m)\right) + 0.5 \cdot (1 - d(t)) & \text{if } e_w < e_L \\ 1 & \text{otherwise} \end{cases}$$

Drainage condition is modelled as $d(t) = d(t-1) - ad(t-1)$ where a=0.005 (a decline of 50% in just over 10 years for a starting condition of 0.8).

Susceptibility to waterlogging is modelled through analysis of elevation differences between the polder and river, where drainage from the polder is restricted (precipitation also predominantly occurs during the monsoon when river levels are elevated). Land elevation is averaged over a mauza (m), and is assumed to decline over time due to subsidence (s) (caused by lack of sediment deposition due to polderisation and accelerated compaction) at a rate of 2 cm/yr [51]: $e_L(t,m) = e_L(t-1,m) - s + d_s \cdot F_F \text{ for } F > 0$ (where d_s is the sediment deposition, set to zero for all model runs except the deposition scenario where it is set to 37cm; F_F is the fraction flooded between 0 and 1, and represents the magnitude of the flood event outside the polder; and F is the start of a flood, set to 1 and at other times 0). The adopted subsidence rate is based on published literature comparing average differences in elevation between natural and poldered areas over a 50-year period [51]. There is substantial variation in published estimates of subsidence, largely due to a lack of existing understanding of subsidence processes in deltas [60]. The value we have adopted here is at the higher end of published estimates, enabling us to explore the sensitivity to changes in elevation.

Drainage infrastructure is assumed to only influence waterlogging when the polder is at a higher elevation than the river, and is assumed to influence only a proportion of runoff given percolation can occur.

Embankment rehabilitation investment timing and sequencing is evaluated using multi-objective optimisation, with the model run over a sixty-year simulation period with an initial forty-year investment period followed by a twenty-year no-investment period. A one-year spin-up period is used. The model is evaluated firstly using a single objective to minimise expected crop income loss (E(L)); secondly to minimise E(L) with an investment cost constraint of $200 million USD (half that of the Coastal Embankment Improvement Project currently being implemented); and thirdly to minimise both E(L) and total investment cost.

Embankment rehabilitation costs are estimated using existing rehabilitation project cost estimates and embankment lengths (further details are provided in Supplementary Table 7). We estimate these to sum to $204 million US for a single upgrade of the embankment in each polder, or $621 million USD for three in each.

Sensitivity to the number of Monte-Carlo simulations, optimisation results, and optimisation epsilon values (which influence the precision considered to be significant to distinguish between objective function values, Supplementary Figures 8 to 10) are evaluated. Comparing 100, 200 and 500 stochastic iterations during optimisation, it is found that objective function values vary by a similar order of magnitude between optimisation simulations as between different number of stochastic iterations. Given the model run-time constraints, 100 stochastic simulations are adopted for optimisation, noting that the stochastic generation of flood events are found to have limited impact overall on embankment investment decisions. Repeating optimisation runs influence the timing and sequencing of investments, likely to be a combined effect of lack of sensitivity to flood incidence (and hence investments) and convergence of optimisation solutions. Impact on overall crop income loss values are insignificant. Varying epsilon values did not have a significant impact on results.

Evaluation of model performance (described in the Supplementary Information and shown in Supplementary Figure 5) is constrained by the paucity of data and complexity of interactions represented. We acknowledge there is a significant level of uncertainty in the results presented, and emphasize the role of the analysis as providing insights and recommendations for improving systems-thinking in infrastructure modelling and planning. For this analysis, the most significant implication of uncertainty in system conceptualisation, representation, and input data is where any of the drivers of crop loss play a greater impact than shown here. In addition, we recognise there are both drivers and impacts not represented – such as changing land use, crop disease, access to employment, access to financial support such as loans and subsidies, or impacts to lives or property resulting from floods and storms.

We use R to generate Figure 3 and 4 using the libraries ggplot2, reshape, ggpubr, and egg.

Data Availability

The data generated for this study are available within the paper and Supplementary Information. Data analysed from third party sources are available, but restrictions may apply to the availability of some of these data which were accessed under specific agreements associated with the current study.

Code Availability

Code used to undertake our analysis can be found at https://github.com/EmilyWaterModelling/CoastalRisk

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Author contributions

EJB & JWH designed the study. EJB and JWH conducted most of the analysis, with input from MSGA. EJB wrote most of the manuscript, with input from all authors who helped shape the overall narrative, contributed text, provided references, and produced or contributed to figures.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information is available for this paper.

Figure Captions

Figure 1. Variation in elevation, poverty, and salinity across six case study polders in Bangladesh's coastal zone. The percent poverty shown is based on the 'upper poverty level', defined as those who are moderately poor using 2010 Bangladesh Poverty Maps[29]. Elevation is derived from digital elevation data[30], whilst soil salinity is estimated using observed data from 2009[31]. Spatial boundaries were provided by WARPO[32]. The base map was created using ArcGIS software by Esri. ArcGIS and ArcMap™ are the intellectual property rights of Esri and are used herein under licence. Copyright © Esri. All rights reserved. Source: Esri, Garmin, GEBCO, NOAA NGDC, and other contributors.

Figure 2. Interacting flood hazard, vulnerability, and infrastructure interventions influence the distribution of climate impacts. We consider variations in flood risk, erosion, salinity, waterlogging, elevation, and cropping patterns across different polders, simulating impacts on different farm

holding types representing different socio-economic groups (adapted from Figure 1 in Borgomeo et al, 2018 with permission from Taylor & Francis Ltd).

Figure 3. A typical simulation of future climate hazards and impacts on crop production for six different polders assuming no embankment rehabilitation investment. Modelled variations in flood magnitude calibrated to observed events (a) are used in combination with spatial variations in elevation and embankment condition (b) to estimate the agricultural area flooded within polders (c). Flooding combined with modelled soil salinity (d) and waterlogging (e) are used to estimate crop production, shown as a fraction of the maximum potential production (f). Both salinity and waterlogging are scaled to a range of 0 to 1, where 1 represents total crop loss. Shown here is a single simulated future time series from the ensemble of 1000 stochastic model runs, which are used to estimate future risk and associated uncertainties. P29, P30, P32, P33, P43/1 and P54 are the six different polders analysed in this study (see Figure 1 for locations).

Figure 4. Differences in average crop income loss between socio-economic groups across scenarios and polders. Expected yearly crop income loss across 1000 stochastic simulations differs significantly between subsistence and small to large farm holdings in aggregate (results for small to large holdings are largely identical), as well as across polders. The role of different drivers of income loss (flood, salinity and waterlogging) as well as the effectiveness of interventions varies across both polders and socio-economic groups. Spatial boundaries were provided by WARPO[32].

Figure 5. Spatial variations in the effectiveness of embankment investment and removing waterlogging and salinity on crop income. Crop income is the area averaged income (USD/ha), averaged over the 60-year simulation period and 1,000 stochastic simulations. Left to right: no investment; embankment investment; embankment investment with no waterlogging or salinity. Spatial boundaries were provided by WARPO[32].

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The unequal distribution of water risks and adaptation benefits in coastal Bangladesh

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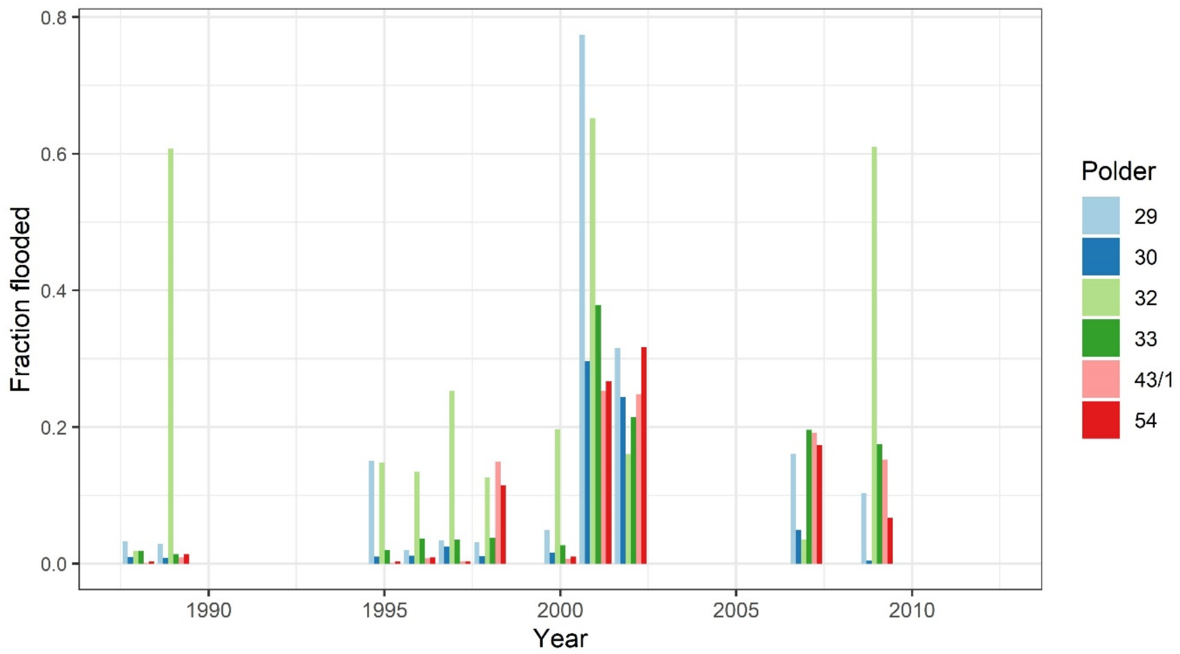
Supplementary Information

This document provides a summary of the main model components. Building on the conceptual model described in Borgomeo et al. [1], we represent the following main processes: flooding, embankment reliability, salinity, waterlogging, farm holdings and crop yield. A summary of model performance and optimisation results is also provided. Figures were generated using R with the following libraries: ggplot2, reshape, ggpubr, egg, and readx1.

Flooding

Flood frequency and magnitude are estimated using Landsat satellite images from 1988 to 2012. Flood events are filtered using regional averaged river and surge level data, to include only those caused by fluvial-tidal or storm surge flooding (as opposed to pluvial flooding caused by monsoon precipitation) (Supplementary Figure 1). Storm surge floods include those caused by Cyclone Sidr in 2007, Cyclone Aila in 2009, and non-cyclonic storms from monsoon depressions [2]. Methods for estimating the size and timing of events are described in Adnan et al. [2], and are applied here specifically for the six case study polders. Estimates are likely to be an underestimation, as they are based on pre- and post-monsoon satellite imagery due to cloud obscuring the images during the monsoon. However, they provide the best available evidence of the frequency and magnitude of events across the case study polders.



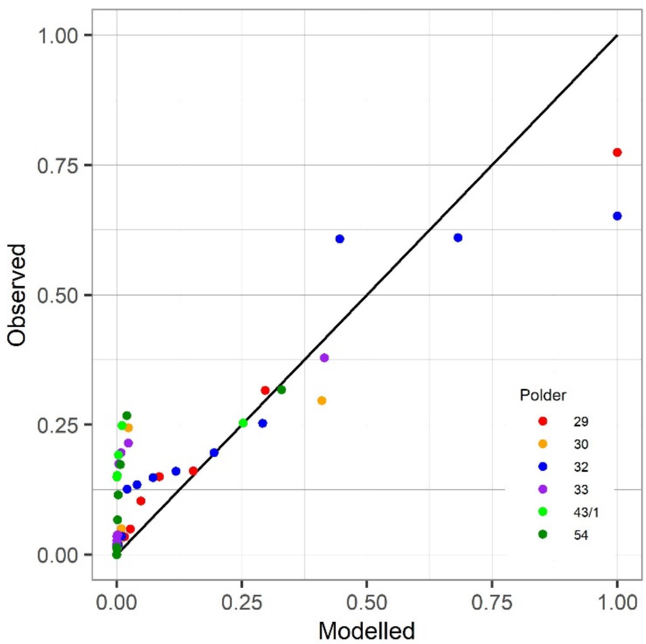
Supplementary Figure 1. Observed fraction flooded for the six polders between 1988 and 2012 based on fluvial-tidal and/or storm surge events.

Water level data at Dumuria, Chalna and Mongla were also analysed, along with observed cyclone events. However, there was no clear relationship with observed area flooded. This points to complex mechanisms influencing flood inundation inside the polders, with flooding often due to a combination of elevated water levels, storm events, and deteriorated embankments resulting in breaching [2,3]. Breaching is reported to be the more frequent cause of inundation compared with overtopping, hence may not necessarily coincide with the highest water levels. Spatial resolution and uncertainty in observed data also contributes to difficulty in attributing observed flooding to specific driving mechanisms.

This combination of drivers paired with lack of data on embankment breaching limits the capacity to calibrate modelled and observed flood events. Here, we calibrate flood magnitude and frequency by comparing modelled and observed fraction flooded. We note that the fraction flooded is dependent on embankment condition, which was not included in the calibration due to lack of information.

Using observed data, flood frequency was defined using a Poisson distribution with $\lambda=1/27$ (one event in just over two years, with 27 being months), whilst flood magnitude was calibrated to give the following values for the *a* and *b* parameters of the beta distribution (see Borgomeo et al. [1] for details regarding these distributions): (1) *a* parameter: 0.9, 0.8, 1.0, 0.8, 0.5, and 0.7; and (2) *b* parameter: 2.9, 8.4, 1.8, 8.3, 7.8 and 8.0 for polders 29, 30, 32, 33, 43/1 and 54 respectively.

A Quantile-Quantile plot comparing modelled with observed events run using 10,000 years of model simulation is shown in Supplementary Figure 2. There is a poor fit for small to medium events with the model underestimating observations. The fit is poorer for polders with fewer flood events, and is also biased toward fitting larger events based on the calibration objective function. This is expected given only 11 observed events were available for calibration. The calibration assumed a constant embankment condition of 0.6 for all polders. Not surprisingly, the calibration was highly sensitive to this assumption for lower condition values given the condition directly influences frequency and magnitude of inundation.



Supplementary Figure 2. Quantile-Quantile plot comparing modelled and observed fraction flooded for the six polders (red=Polder 29, orange=Polder 30, blue=Polder 32, purple=Polder 33, light green=Polder 43/1, and dark green=Polder 54) using calibrated beta and lambda values. Simulations are run for 10,000 years.

The stochastic generation of flood events does not account for seasonality. Whilst this is significant in Bangladesh given most fluvial-tidal events occur during the monsoon, the observed flood events between 1988 and 2012 occurred throughout the year (May, July, August, September, October and November, Supplementary Figure 1). Major cyclones SIDR and Aila occurred in November and May respectively.

The analysis is focussed upon a baseline condition, which includes endogenous changes to the system, for example due to embankment deterioration, but does not yet incorporate exogenous changes in future flooding due to factors such as climate change, sea level rise, or changed sediment supply to the delta. Analysing the system's sensitivity to these factors will be the subject of future research. We do consider increases in flooding due to embankment deterioration, being our main focus of analysis and the main cause of increased flooding [2,4,5].

Having generated a series of flood events for each polder, we then calculate the fraction flooded within the polder, which is subsequently used to identify which mauzas, the smallest administrative unit, (if any) are considered to be flooded based on elevation. The fraction flooded (F_F) for polder p at time t is calculated in a manner similar to that used by Borogmeo et al. [1] (we exclude an additional damage parameter used in Borgomeo et al.):

$$F_F(p,t) = \begin{cases} \dfrac{1}{e_R(p,t)} \cdot f^3(p,\tau) & \text{if } t = \tau \\ \left(\dfrac{1}{e_R(p,t)} \cdot f^3(p,\tau)\right) \cdot e^{-\frac{\tau - t}{5}} & \text{if } \tau < t < \tau + 5 \end{cases}$$

Fraction flooded is a function of the embankment reliability e_R and size of the flood event external to the polder (f) and starts at time $\tau = t$. It is then assumed that the flood recession follows an exponential decay over six months.

The average elevation is then estimated for each entire polder (L_P) and that of each mauza (L_M) using the Shuttle Radar Topography Mission (SRTM) digital elevation model [6]. Elevation bands are defined for each polder, and assigned to each mauza (Supplementary Table *1*). During a flood, any mauza where $L_M < L_P$ is assumed to be flooded.

Supplementary Table 1. Elevation bands derived using SRTM

Elevation Band (m)	Polder 29		Polder 30		Polder 32		Polder 33		Polder 43/1		Polder 54	
	Cumul. %	No. Mauza	Cumul. %	No. Mauza	Cumul %	No. Mauza	Cumul. %	No. Mauza	Cumul. %	No. Mauza	Cumul. %	No. Mauza
-8 - 2	23	0	22	0	46	0	15	0	5	0	2	0
2 - 3	51	21	51	5	64	3	46	0	13	0	8	0
3 - 4	73	30	75	22	84	2	75	7	29	0	22	0
4 - 5	83	17	88	9	94	1	90	2	49	1	45	1
5 - 6	89	5	94	0	98	0	96	0	68	25	67	12
6 - 7	94	0	98	0	100	0	99	0	83	10	83	6
7 - 8	97	0	99	0	100	0	100	0	92	2	92	0
8 - 9	99	0	100	0	100	0	100	0	97	2	97	0
9 - 23	100	0	100	0	100	0	100	0	100	1	100	0

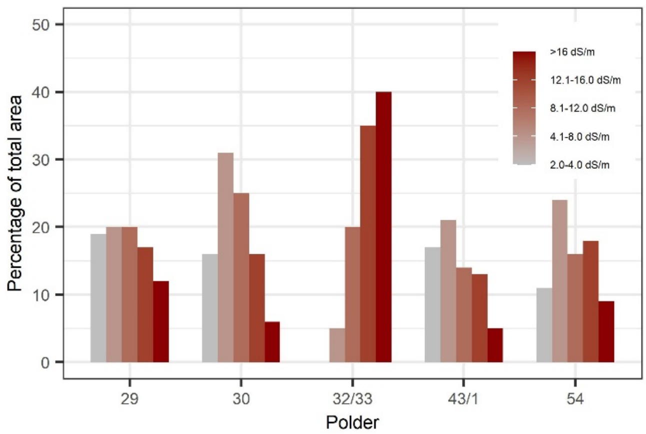
Embankment reliability

Embankment deterioration was modelled as described by Borgomeo et al. [1], with deterioration rates unchanged for Polder 54 (0.005), and halved for the remaining polders (0.0025). The higher deterioration for Polder 54 is based on observed erosion maps showing higher rates in this region [7]. At these rates, the embankment condition deteriorates to 0.1 after 29 years (with a starting condition of 0.6 for all polders in the absence of any rehabilitation or flood events – representative of 60% of the maximum condition). Values are estimated given the absence of actual embankment deterioration. Further analysis of erosion data (unavailable for this study) and impacts on embankments would be needed to improve this estimate.

Salinity

Different initial soil salinity concentrations are used to reflect spatial across the polders. Polder-scale concentrations are estimated using Upazila-scale data [8] using an area weighted average of different salinity categories (Supplementary Figure 3 and Supplementary Table *2*). Historical salinity values are also estimated for 60 years prior to 2009 (from 1949 to 2009) by back-casting using the same historical rate of change, and are used to evaluate model performance. Rate of change is estimated by fitting a linear trend to observed data and averaging across the three Upazilas (Supplementary Figure 4). Assumed river salinity values are shown in Supplementary Table *3*. For both soil and river salinity, time-series data was not available.

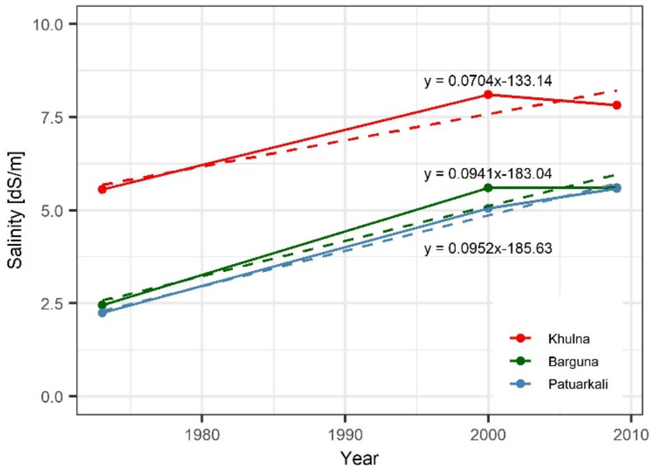
The persistence of elevated salt concentration following a flood event was estimated in the absence of further information to decline by roughly 50% over a period of two years. Clarke et al. [9] found irrigation water at 8 ppt (approximately 10-15 dS/m) to result in the persistence of modelled elevated salt concentrations for 65% of the 118 years of simulation.



Supplementary Figure 3. 2009 soil salinity categories for the case study polders with percentage area for each polder (Source: derived using data from Soil Resources Development Institute, 2010).

Supplementary Table 2. Estimated average soil salinity for current and historical simulations based on data from SRDI [8]

	Polder					
	29	**30**	**32**	**33**	**43/1**	**54**
Average salinity (2009) (dS/m)	9	9	14	14	8	9
Estimated historical salinity	4	3	8	8	3	4



Supplementary Figure 4. Temporal change in salinity with the average estimated as being +0.09 dS/m per year.

Supplementary Table 3. Assumed river salinity for each polder, used to for model parameter s_R (derived from SRDI [8]).

	Polder					
	29	**30**	**32**	**33**	**43/1**	**54**
Station	**Dumuria**	**Batiaghata**	**Dacope**	**Dacope**	**Barguna (Amtali) - Payra river**	**Kalapara**
River salinity (dS/m)	17	28	28	28	2	28

*assume same as for Batiaghata

Waterlogging

River levels used for modelling waterlogging are estimated using average observed water level data for three stations in the South West zone (SW 28 - Dumuria, SW 244 - Mongla, and SW 243 - Chalna) [10]. There is insufficient spatial resolution in available data to show variations between polders. Levels are a monthly average of the maximum monthly high tide value from April 1982 to February 2003.

The rate of deterioration of drainage infrastructure (which influences waterlogging) is set to 0.005 [1]. Using a starting condition of 0.8 (on a scale of 0 to 1 with 1 being completely functional), this results in a deterioration of 50% in approximately 10 years, reaching close to zero (0.02) in approximately 60 years (period of simulation). Similar to embankment deterioration, this is estimated in the absence of observed data. A 1993 Bangladesh Southwest Area Water Resources Management Plan [11] states that the six case study polders had satisfactory polder drainage (with less than 30% of area experiencing congestion) at the time, giving an indicative starting condition.

Farm holdings

The primary livelihoods in the study area are estimated based on a scoping visit of polders 29, 30, 32, 33 and 35/3 [12], and are reported as being: agriculture/aquaculture; day labourers (including temporary migration to urban areas in search of work); fishing (including fish fry collection although this has been restricted through government embargos); some small service oriented business; and professional occupations (such as teachers and NGOs). High levels of unemployment are reported in some areas of Polder 32. Many women work as housewives in non-income generating roles. This is consistent with the livelihood categories for south western and central Bangladesh adopted by Lazar et al. [13]. Whilst the focus of this analysis is on agriculture, it could be extended to consider other livelihood types.

The use of non-farm holdings to represent subsistence farmers is intended to capture the differential impacts on poorer households. It is recognised that there is significant potential to further extend this to consider a greater diversity in income and labour, as well as the landless poor.

A summary of the four categories of income groups is shown in Supplementary Table 4, and is implemented at a mauza scale to enable intra-polder variability in income to be modelled. Small farms dominate the study area. Available information on gender disaggregation based on household head for holdings and population engaged in agricultural work is shown in Supplementary Table 5.

Supplementary Table 4. Farm size characteristics and holdings by polder, estimated using agricultural census data [14].

Type	Area (acre) (average shown in brackets)	Area (ha)	No. Holdings by Polder					
			29	30	32	33	43/1	54
Subsistence (non-farm holding with cultivated area)*	<= 0.04 (0.02)	0.01	910	355	960	1,110	1,678	1,035
Small farms	0.05 – 2.49 (1.27)	0.51	7,502	4,699	3,828	6,798	10,511	4,655
Medium farms	2.5 – 7.49 (5.0)	2.0	1,946	1,568	1,005	1,882	3,382	2,142
Large farms	7.50 – 25+ (16.25)	6.6	215	178	242	299	570	411
Total holdings			***10,573***	***6,800***	***6,035***	***10,089***	***16,141***	***8,243***
Total area (ha)			***9,146***	***6,711***	***5,569***	***9,215***	***15,903***	***9,381***

**Non-farm holdings with cultivated area was estimated using the total non-farm holdings at a mauza scale, and the proportion of non-farm holdings with cultivated area at an Upazila scale (not available at a mauza scale).*

Supplementary Table 5. Gender differences in farm holdings and agricultural work for Upazilas Dumuria (Polder 29), Batiaghata (Polder 30), Dacope (Polders 32 and 33), Amtali (Polder 43/1) and Kala Para (Polder 54) [14].

Holding Type	Farm holding head (%)		Population engaged in agricultural work (%)	
	Male	Female	Male	Female
Subsistence (non-farm holding with cultivated area)	95	5	68	32
Small farms	98	2	71	29
Medium farms	99	1	74	26
Large farms	99	1	77	23

Crop yield

Yearly (y) crop yield is calculated as the monthly minimum yield for each year to account for salinity, waterlogging and flood impacts. Winter crops which span a calendar year are therefore misrepresented, but given yields are averaged over all years and stochastic simulations, this is unlikely to have a significant impact on results. Production per crop and holding type ($P_{x,h}$) is

$$P_{x,h}(y) = \min Y_x(t) \cdot r_x \cdot A_h \cdot N_h \cdot$$

Mauza scale differences in cropping patterns were considered, but have a higher level of uncertainty than Upazila differences given lack of available data and the higher likelihood for them to change over time. Differences between small, medium and large farm holdings are minimal based on data from Khulna Upazila. Cropping patterns for each polder are estimated by selecting the largest Upazila which overlaps.

Based on available agricultural census data [14], major crops for the Upazilas covering our case study polders included aus, aman, boro, jute, oil seeds and pulses. We focus here on aus, aman, boro and jute given these are considered major crops (along with potato and wheat) [15]. Wheat was not present in the mauzas for our study area based on available data. Oil seeds and pulses are an aggregate of multiple crops and hence are also not included.

In the absence of additional information, vegetable growing for subsistence farmers is represented using water gourd and pumpkin (winter and summer). The actual yield for subsistence farmers is not known, hence the census data for farm holdings is used as an approximation. The actual yield is therefore likely to be lower than indicated here.

Crop differences in yield sensitivity to salinity is not captured in this model, and could be included in future work.

Crop prices are based on average values from agricultural census data [15], which can differ from local prices. We assume an exchange rate of 1 taka = 0.0116 USD at the time of writing.

Supplementary Table 6. Crop characteristics

Crop	Potential yield (t/ha)[1]	Crop price (taka/kg)[2]	Crop calendar[3]	Subsistence	Small	Medium	Large
Local Aus	2.5	13.4	Apr-Aug		X	X	X
HYV Aus	5.5	13.2	Apr-Aug		X	X	X
Local Aman	2.5	13.7	Aug-Dec		X	X	X
HYV Aman	5.5	15.7	Aug-Dec		X	X	X
Local Boro	2.5	14.3	Nov-May		X	X	X
Hybrid Boro	10	16.2	Jan-May		X	X	X
HYV Boro	7	16.2	Jan-May		X	X	X
Jute **(bales)**[4]	15	8557	May-Sep		X	X	X
Water gourd	28	13.3	Jul-Mar	X			
Pumpkin (winter, Rabi)	35	13.2	Nov-Mar	X			
Pumpkin (summer, kharif)	35	13.2	Mar-Nov	X			

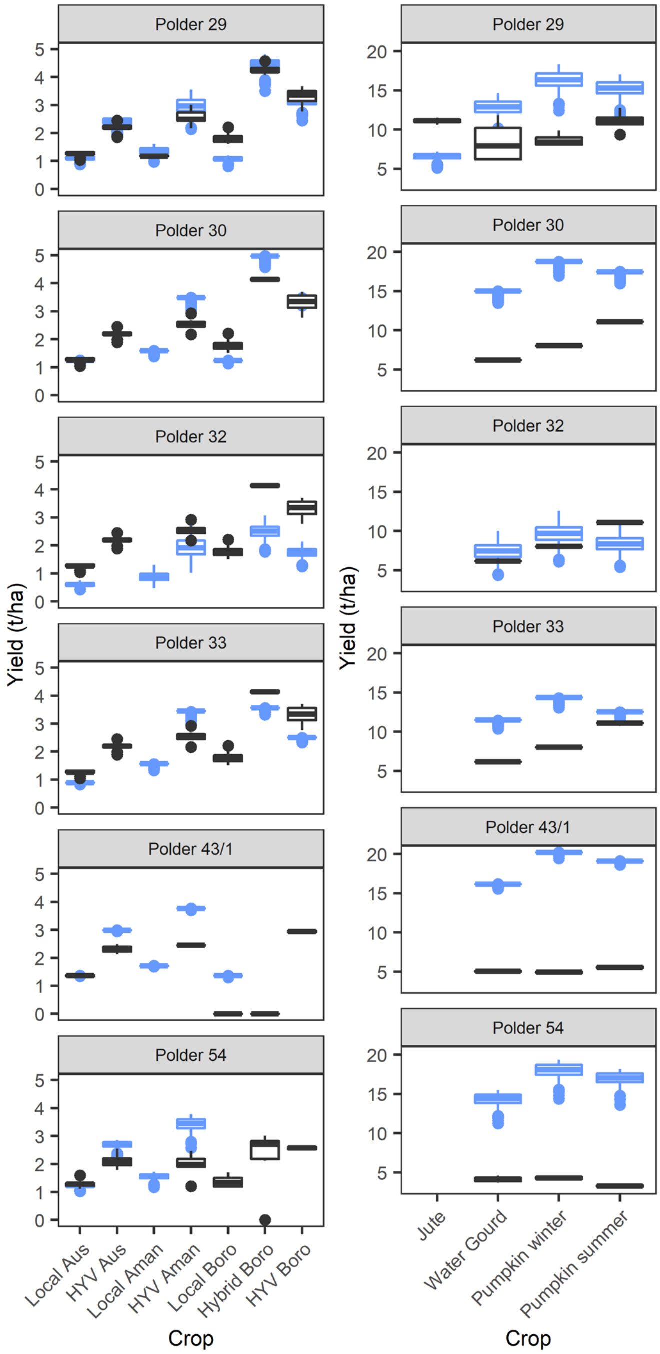
[1]*Values taken from a combination of data and expert knowledge [16]. The value for pumpkin is based on BARI Mistikumra-1, early winter variety [17].*
[2]*From Yearbook of Agricultural Statistics 2016 [15] Table 10.3. Prices quoted as per quintal taka with the assumption that 1 quintal = 100kg. No price was included for hybrid boro hence values for HYV boro were used as an approximation.*
[3] *Crop calendars are given as ranges using information from Yearbook of Agricultural Statistics 2016 [15]. Here, months are taken to be the widest range, whilst in reality the growing season is likely to be shorter. However, given these calculations are focused on the maximum flood area during the season, this is unlikely to have a significant impact. Dates for pumpkin were not given, hence were estimated using data on kharif and rabi seasons.*
[4]*Jute is reported in bales, where 1 bale=180kg. Values are consequently reported for bales/ha and taka/bale.*

Model performance

Model performance is evaluated by comparing against observed District-scale crop yields in Khulna (Polders 29, 30, 32 and 33), Barguna (Polder 43/1) and Patuarkhali (Polder 54) (Supplementary Figure 6). The comparison is limited by differences in the spatial scale of observed data (District) compared with modelled (polder), as well as limitations in comparable dates and crops. We used District-scale observed data for all crops for 2014/2015 and 2015/2016 BBS[15]. We also use observed yields from 2001/2002 to 2009/2010 [18], although the available data only included local and HYV aus, HYV aman, and local and HYV boro for Khulna and Pautarkhali. Modelled results draw on observed Upazila-scale cropping patterns and mauza-scale numbers of farm holdings.

We use a 60-year modelled 'historical scenario' to provide a more realistic comparison with observed historical data. This is configured using higher starting elevations (adding 1m based on observations from Auerbach et al. [5] for unpoldered areas), combined with lower starting soil salinity levels (see salinity section for values) from 1949-2009. 1000 stochastic simulations are used to evaluate variability across different stochastic flood events.

The ranges in modelled and observed data are presented as box plots to reflect both availability and uncertainty in data.



Supplementary Figure 5. Comparison between observed (black) and modelled (blue) crop yields. Observed data from BBS Yearbooks from 2001/2002 to 2009/2010 for local and HYV Aus, HYV Aman, Local and HYV Boro, (Khulna and Patuarkhali); and 2014/2015 and 2015/2016 for all crops except Local Aman (all Upazilas). The modelled data uses the 'historical' scenario with increased elevation and reduced soil salinity across 1000 stochastic simulations. Observed data includes 462 data points in total with variations between years and crops. Box plots include the median, two hinges (first and third quartiles), two whiskers (representing values up to 1.5x the inter-quartile range), and individual outlying points.

There is substantial variation in performance between crops and polders, with the lower yield crops (rice) generally performing better than the higher yield crops (jute, water gourd and pumpkin) with the exception of Polder 32 (Supplementary Figure 6). In some locations, yields are shown as non-zero in the District level observed data, yet are reported as not being grown based on Upazila-scale cropping patterns (such as HYV aus for Polder 30).

For most polders, the modelled yields for vegetables for subsistence farmers are substantially higher than observations (noting that observations are for all farm holdings and not for subsistence farmers), suggesting that crop losses are far greater than for rice. Better agreement is observed in Polders 29 and 32 where there is a higher incidence of flooding. This suggests there may be additional significant factors decreasing crop yield that are either not considered here, for example pests or access to fertiliser. However, without any specific data for local yields on subsistence farms, it is difficult to determine whether our model does over-estimate yields. Should it do so, it is likely that crop income for subsistence farmers is lower still than estimated here.

We note the challenge in both calibrating and evaluating model performance in the representation of complex systems with poor data availability. Despite the mixed performance across crops and polders, we believe the model provides valuable insights into the interaction of water-related risks across a highly heterogeneous region that can assist water infrastructure planning.

Embankment Investment Costs

Major investment projects targeting rehabilitation of the coastal embankment and drainage system are shown in Supplementary Table 7. Our estimated cost of $204 million USD to rehabilitate the six case study polders draws on our own calculations using polder lengths and estimated costs for existing projects [23], and hence should not be taken to reflect actual detailed costings of embankment rehabilitation.

Supplementary Table 7. Embankment rehabilitation project costs

Project	Cost (million USD)
Coastal Embankment Rehabilitation Project	53 [19]
Khulna-Jessore Drainage Rehabilitation Project	45 [20]
Emergency 2007 Cyclone Recovery and Restoration Project	109 [21]
Coastal Embankment Improvement Project	400 [22]

Optimisation

A multi-objective optimisation algorithm eMoga [24] was used to explore trade-offs. eMoga has been previously applied in hydrological applications [25]. The algorithm parameter values used are shown in Supplementary Table 8.

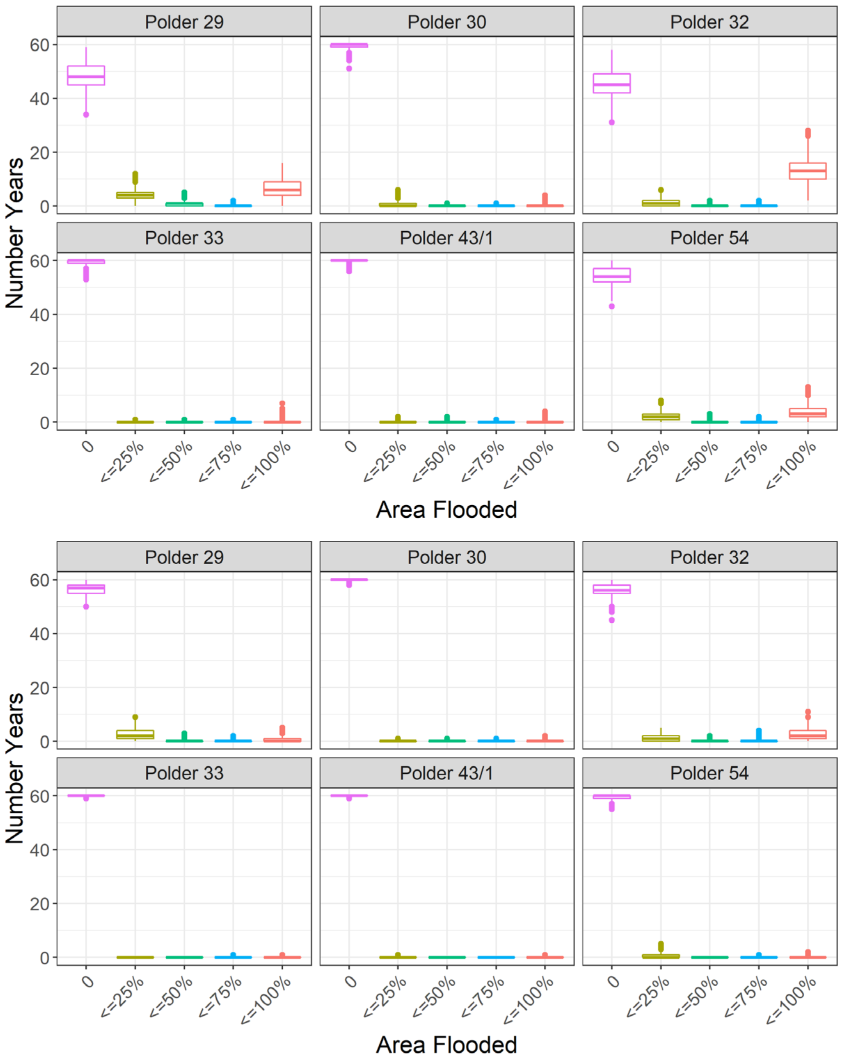
Supplementary Table 8. eMoga parameter values

Parameter	Parameter value
Population	100
Maximum generations	10,000
Probability of crossover	1.0
Probability of mutation	0.003

Supplementary Figures

Polder flooding

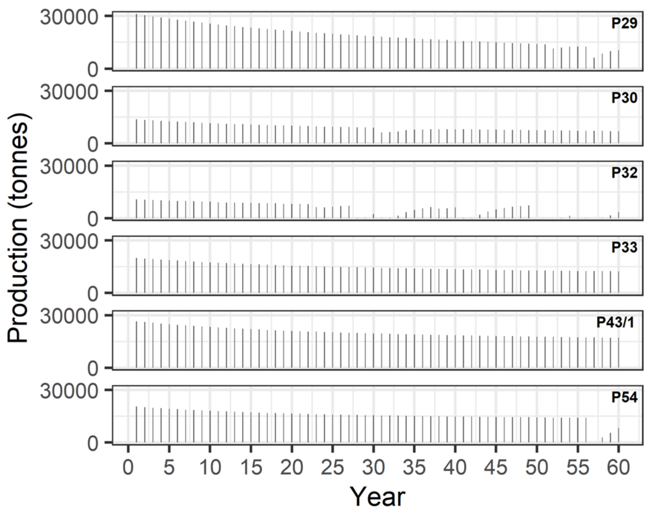
Variations in flood events across the polders for a no embankment investment and high embankment investment scenario (using the single objective optimisation solution to minimise crop income loss) is shown in Supplementary Figure 6. The greatest flooding in Polders 32 and 29 is consistent with observed data reported by Adnan et al. [2]. Using 1000 stochastic simulations, results show variability in the magnitude and frequency of events, yet the overall pattern of flooding between the polders is unchanged. The number of large flood events reduces under a high embankment investment scenario.



Supplementary Figure 6. Number of years during the sixty-year simulation that experience internal flooding of different magnitude, shown as a percentage of the total polder area. A high embankment investment scenario (bottom plot) shows limited improvement in area flooded compared with a no investment scenario (top plot). Box plots show the variation across 1000 stochastic simulations and include the median, two hinges (first and third quartiles), two whiskers (representing values up to 1.5x the inter-quartile range), and individual outlying points.

Crop Production

With no embankment investment for a single model iteration, total crop production is greatest in Polders 29 (with more high yield crop varieties) and 43/1 (with the greatest crop area), and smallest in Polder 32 and 30 (which have the smallest crop area) [14].



Supplementary Figure 7. Total crop production for each polder during the sixty-year simulation assuming no embankment investment.

Optimisation

The following figures show variations in embankment investment timing and frequency for:

1. Single objective optimisation to minimise expected crop income loss, $\min E(L)$;
2. Single objective optimisation to minimise expected crop income loss with a $200 million USD constraint on investment, $\min E(L)$ subject to $TIn = \sum_{p=1}^{P}\sum_{r=1}^{R} In_{p,r} \leq 200 \text{ million USD}$ (where P are the six polders, R is the number of embankment rehabilitation investments over the simulation for each polder, and In is the investment cost); and
3. Multi-objective optimisation to minimise expected crop income loss and total investment cost.

In all cases, loss is calculated for each farm holding type (subsistence, small, medium and large, h) as a sum of crop income over all polders and crops (C), and averaged over the 60 year simulation (T):

$$L_h = \sum_{p=1}^{P} \frac{\sum_{c=1}^{C} \overline{I}_{p,h,c} - \sum_{t=1}^{T}\sum_{c=1}^{C} \frac{I_{p,h,c}}{T}}{\sum_{c=1}^{C} \overline{I}_{p,h,c}}$$

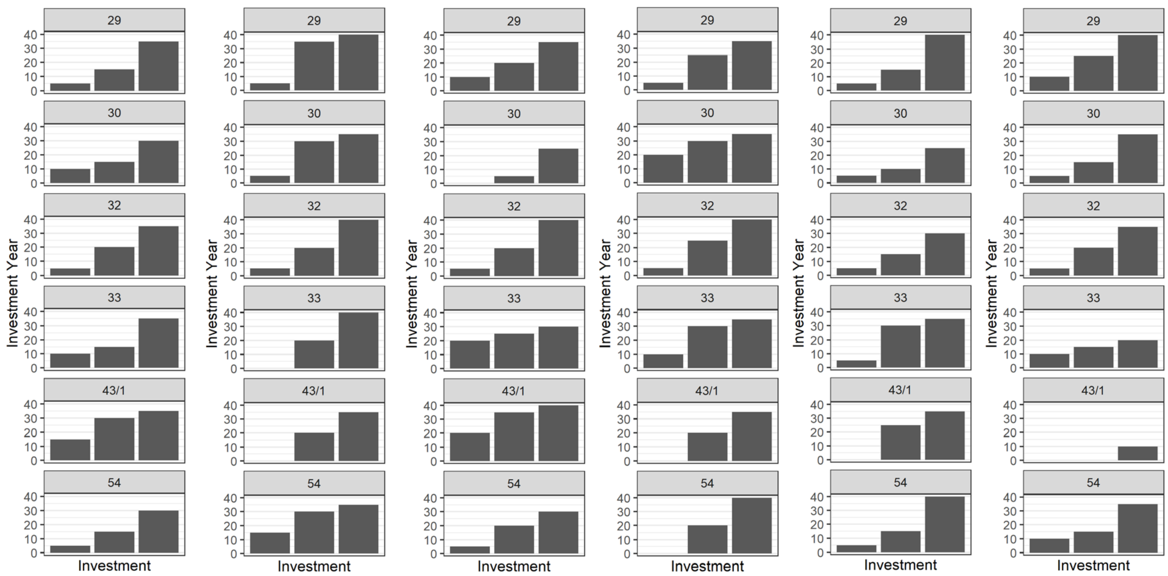
Expected loss is calculated as: $E(L_h) = \sum_{n=1}^{N} \frac{L_h}{N}$ by averaging over the number of stochastic simulations (N=100). Each of the three optimisations above are repeated for all household types in aggregate where $E(L) = \sum_{h=1}^{H} E(L_h)$; or for subsistence farmers only: $E(L) = E(L_{subsistence})$.

1. Minimising expected crop income loss

The sequence of embankment rehabilitation investments allowing the maximum of three for each polder is shown in Supplementary Figure 8. A column shows when an investment is made, with the y-axis showing the year of investment. Investments are spread across the investment period with minimal differences in timing.

Two epsilon values (used to define the resolution of the non-dominated solution space) were tested for the loss objective function, the first being 0.1 and the second being 0.01 to allow greater resolution for archived non-dominated solutions. However, differences in modelled loss were insignificant (0.555 for an epsilon value of 0.1 and 0.556 for an epsilon value of 0.01). A further epsilon value test using 0.001 was used for the no waterlogging/no salinity scenario, and similarly had no significant impact.

Differences between the with and without waterlogging/salinity scenarios, and between optimising for all farm holdings compared with only subsistence farmers had little impact on the investment strategy. Removing waterlogging and salinity significantly reduced the expected crop income loss. Losses for subsistence farmers only are higher than those averaged across all four farm holding types.

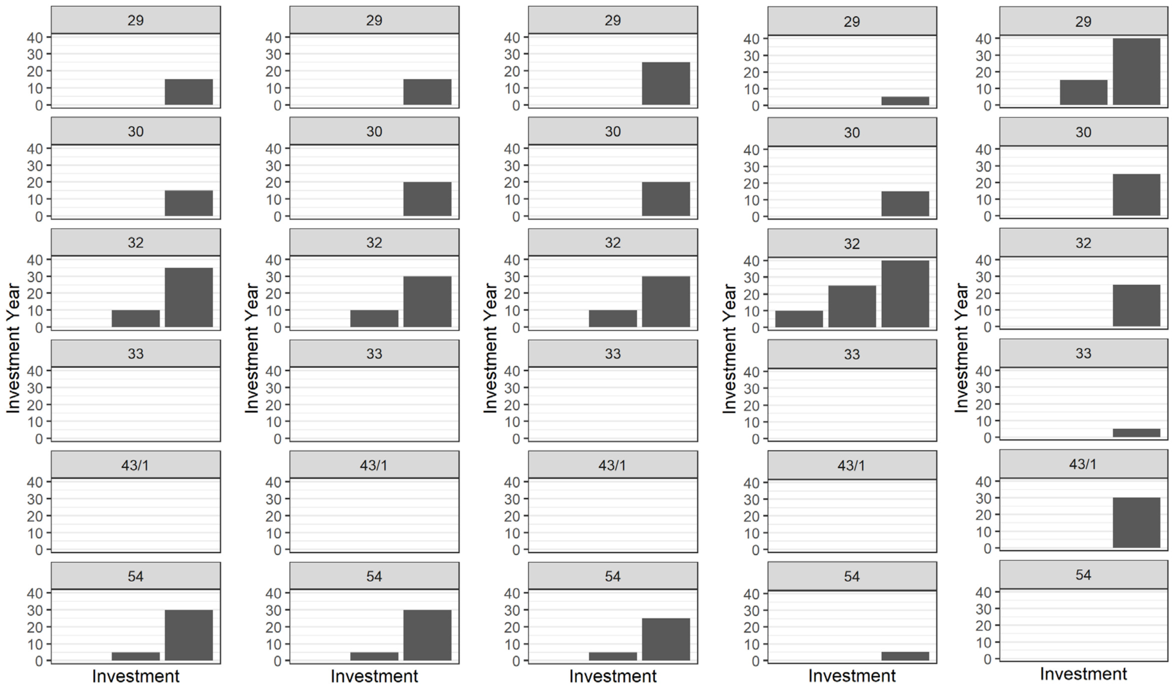


Supplementary Figure 8. Optimisation investments for single objective with no constraint. Left to right: all farm holdings (epsilon value = 0.1); all farm holdings with epsilon value = 0.01; all farm holdings with no salinity or waterlogging and epsilon value of 0.01; all farm holdings with no salinity or waterlogging and epsilon value of 0.001; subsistence only (epsilon of 0.1); subsistence only (epsilon value of 0.01). Average loss L to R: 0.555; 0.556; 0.004; 0.004; 0.699; 0.699.

2. Minimising expected crop income loss with cost constraint

When a cost constraint is introduced, clear differences in investment priority between polders are observed (Supplementary Figure 9). The greatest investment is in Polders 32 and 54 with no investment in Polders 33 and 43/1. The exact timing is found to be sensitive to variations in stochastic events and optimisation performance, tested by repeating the optimisation three times as a sensitivity test.

Removal of waterlogging and salinity did not have a significant impact on investment strategy, with differences between sensitivity runs being similar or greater than differences between the with and without waterlogging/salinity scenarios. Losses are significantly reduced. Similarly, optimising for subsistence farmers only has no observable impact on investment strategy.

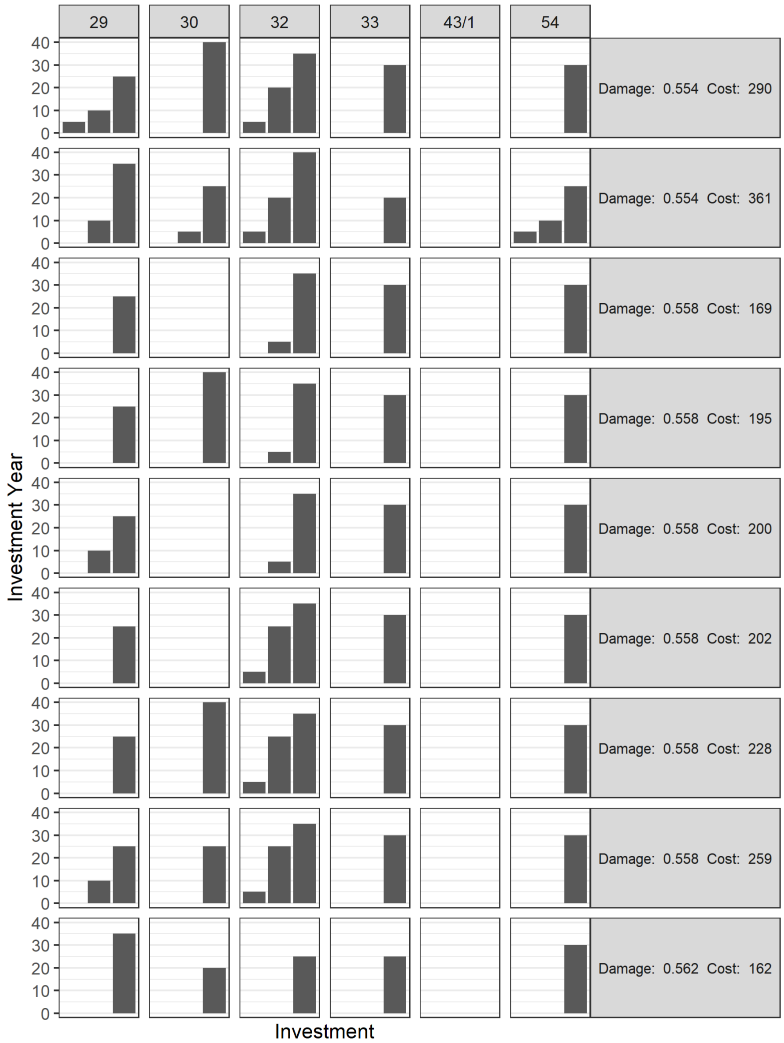


Supplementary Figure 9. Optimisation investments for single objective (all farm holdings) with a $200 USD constraint. Left to right: epsilon value of 0.1; epsilon value of 0.01; sensitivity test 1; sensitivity test 2; sensitivity test 3. All sensitivity tests use and epsilon value of 0.01. Average loss L to R: 0.559; 0.559; 0.559; 0.560; 0.569.

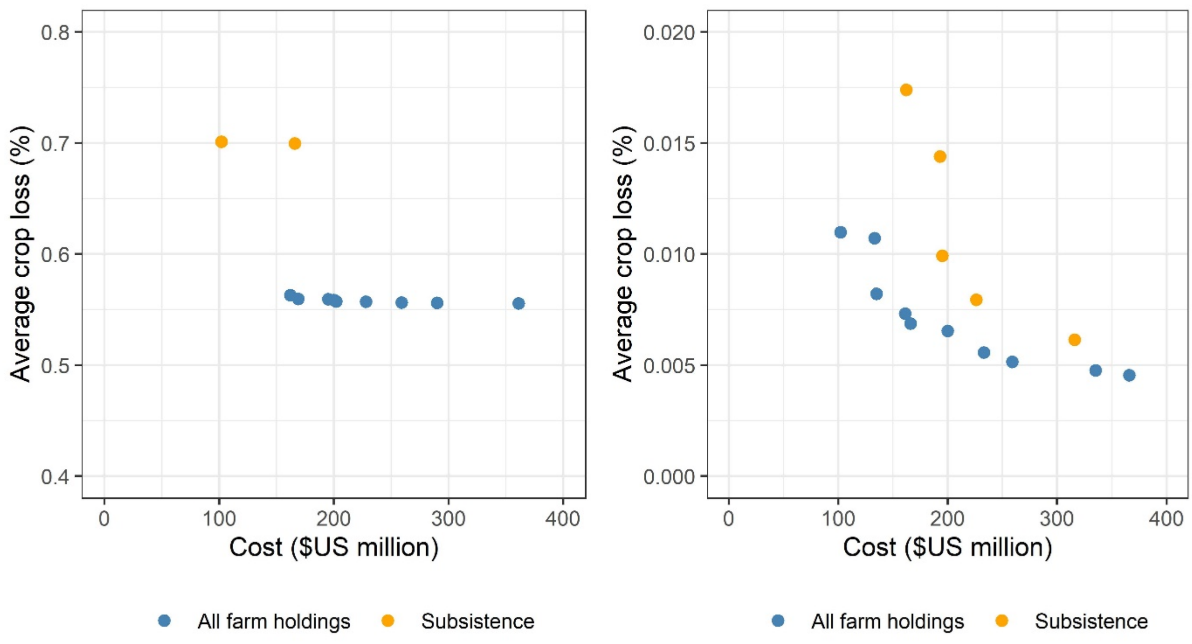
3. Minimising expected crop income losses and investment cost

When both crop income loss and investment cost are minimised using multi-objective optimisation, there is consistently no investment in Polder 43/1 across all non-dominated solutions, with the highest investment in Polder 32 followed by Polder 29 (Supplementary Figure 10). Overall, there are very few non-dominated solutions suggesting a lack of sensitivity of crop loss to embankment investments and consequently flooding (Supplementary Figure 11). This can also be seen from the small change in loss despite changes in the number of investments. The solutions are sensitive to the stochastic simulation of the flood events and the optimisation performance, with a lower loss found using multi-objective optimisation (with 9 investments in total) compared with a single objective (using 16 investments).

Consistent with the single objective optimisation results, removal of waterlogging and salinity as well as optimising for subsistence farmers only has no significant impact on investment strategy, yet changes the resulting expected crop income loss (Supplementary Figure 11).



Supplementary Figure 10. Optimisation investments for two objectives (minimise crop income loss and investment cost) for all farm holdings (epsilon value of 0.01 for loss and 1.0 for investment cost).



Supplementary Figure 11. Non-dominated multi-objective optimisation solutions for all farm holdings and subsistence farmers only with L: salinity and waterlogging included; and R: removed. With salinity and waterlogging, loss is close to 70% for subsistence farmers, as opposed to ~55% averaged across all farm holdings. Without salinity and waterlogging, loss is less than 2%. In both cases, loss is relatively insensitive to investment.

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