

**Robust Adaptive Pathways for Long-Term Flood Control in Delta
Cities: Addressing Pluvial Flood Risks under Future Deep
Uncertainty**

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Abstract:

Delta cities are increasingly vulnerable to flood risks due to the uncertainties
surrounding climate change and socioeconomic development. Decision-makers face
significant challenges in determining whether to invest ~~in high level flood defenses for~~
~~long term planning~~. Adaptation solutions should ~~be given considerable~~
~~attention~~ consider not only to robustness but also to adaptiveness in case ~~if~~ the future

unfolds ~~not as expectation~~other than as expected. To support decision-making and meet long-term multi-objective targets, we propose a synthesized framework that integrates robustness analysis, adaptiveness analysis, and pathway generation. This framework was applied to evaluate alternative solutions for managing pluvial flood risk in central Shanghai. The results ~~show~~demonstrate that ~~using—relying on a~~ single-objective decision-making approach (focused only on robustness) ~~tends to yield~~can lead to biased ~~options~~outcomes. By examining the ~~valid period~~effectiveness period and flexibility of candidate solutions, we assessed ~~whether alternative solutions could~~their potential to meet long-term flood control targets. The analysis reveals that a combined option—incorporating increased green areas, an improved drainage system, and a deep tunnel with a 30% runoff absorption capacity (D+G+Tun30)—~~is emerged as one of~~ the most robust and adaptive pathways, based on multi-objective trade-off analysis. This study highlights the importance of considering effectiveness period ~~valid period~~ within predefined control targets and retaining flexibility to avoid path-dependency and minimize long-term regrets. The proposed framework is broadly applicable and can ~~be applied to other delta cities to~~ guide adaptive responses to future flood risks in other delta cities.

Keywords: decision-making under deep uncertainty; flood risk reduction; multi-objective trade-off; robust adaptive pathway; Shanghai

1 Introduction

Flood risk is increasing in low-lying delta cities due to rapid urbanization and climate change (Yang et al., 2023), hindering the capacity of urban development. Delta

cities such as Shanghai (Yin et al., 2020), Ho Chi Minh City (Scussolini et al., 2017), and London (Dottori et al., 2023) are facing the combined challenges from extreme rainstorms, sea level rise and urbanization-induced land subsidence with regard to flooding risk reduction (Ward et al., 2017). It is anticipated that as a result of changing climate patterns, the frequency and severity of extreme flood events will increase in urban areas, thereby increasing the flood risk, particularly in ~~increasing-rapidly~~ developing delta cities (Sun et al., 2021).

Delta cities are urged to examine potential climate adaptation options (Han and Mozumder, 2021;) and test their cost-effectiveness in designed ~~socio-economic~~ and climate scenarios to address ~~the~~-rising flood risks (Lin et al., 2020). Dottori et al. (2023) proposed ~~economically-attractive~~ strategies for European cities to deal with increasing river flood risk ~~from cost-effective point of view~~. However, ~~if~~ these strategies or options will remain effective within a fixed timeframe under the uncertainties of climate change, land use change or political change is questionable; in addition, how ~~flexible~~ these strategies can be up-scaled to meet the future needs is ~~also~~ rarely discussed. This ~~comes-to-is~~ a pressing concern for decision makers in long-term planning. In the field of ~~Decision-decision Making-making~~ under ~~D~~deep ~~U~~ncertainty (DMDU), various approaches have ~~been-emerged, such as Robust Decision-Making (RDM)~~. Robust Decision Making (RDM) is effective at identifying strategies that perform well across a wide range of future scenarios through vulnerability analysis and stress-testing, but it lacks explicit guidance on how to sequence actions over time (Lempert et al., 2013; Workman et al., 2021).⁵ Dynamic Adaptive Policy Pathway

(DAPP) by contrast, excels at planning flexible adaptation pathways to avoid lock-in,
but is relatively weaker in quantitatively evaluating robustness across uncertainties
(Haasnoot et al., 2013; Dias et al., 2020) ~~and Real Options Analysis (ROA) (Buurman~~
~~and Babovic, 2016; Kim et al., 2018; Xu et al., 2023).~~

These DMDU approaches have been continuously improved and optimized, the
boundaries between methods have become increasingly blurred, and fusion thinking is
progressively adopted (Haasnoot et al., 2020). As pointed out by Lempert et al. (2003),
RDM provides systematic procedures that emphasize the iterative analysis process of
scenario exploration, which can help decision-makers discover situations where options
may fail, and understand the trade-off among all the adaptation options (Lempert et al.,
2013). Kasprzyk et al. (2013) proposed the Multi-Objective Robust Decision Making
(MORDM) approach by the combination concept of both multi-objective evolutionary
optimizations and RDM (Bartholomew and Kwakkel, 2020; Yang et al., 2021).
Kwakkel et al. (2019) pointed out that the RDM approach usually pays less attention to
the dynamic planning of pathways on long-term scales of climate change. On the other
hand, DAPP, which consist of the strengths of both Adaptive Policymaking (Walker et
al., 2001) and Adaptation pathway (Haasnoot et al., 2012; Ranger et al., 2010), focuses
on generating alternative dynamic pathway to achieve flexibility and avoid lock-in
effects while it lacks quantitative robustness evaluation metrics (e.g., regret-based
criteria or satisficing thresholds) ~~robustness metrics (i.e. satisficing and regret)~~ as well
as a thorough ~~and~~ vulnerability analysis to quantify potential failures (Haasnoot et al.,
2013).

Both the RDM and DAPP approaches are arguably ~~in~~ most widely applied, and the concept of integrating two approaches has been proposed (Kwakkel et al., 2016) and practiced in cases (Tariq et al., 2017). However, as Ramm et al. (2018a) illustrated, integration of RDM and DAPP has not been thoroughly implemented, ~~and future~~ opportunities ~~for a combined RDM-DAPP approach include~~ engaging with ~~participants in a combined RDM and DAPP approach include~~ stakeholders to defining clear adaptation objectives, establish suitable metrics, and determine risk tolerance (Ramm et al., 2018b) ~~as since all~~ these factors ~~are anticipated to largely significantly~~ influence the outcomes of alternative pathways (Ramm et al., 2018b). Robustness emphasizes the ability of a strategy to perform in an effective way in many plausible ~~scenarios~~ futures. How to define robustness and assess whether options are insensitive to deep uncertainty to ensure certain performance across multiple plausible futures have sparked extensive discussions, especially when meeting multi-objective targets (Herman et al., 2015; McPhail et al., 2018).

The selection of indicators for robustness depends on the priorities and preferences by policymakers and it will substantially affect the outcomes of decisions (Giuliani and Castelletti, 2016). For example, the decision-makers who endorse risk aversion may under-estimate adaptation options' performance. To overcome the single objective problem framing, Quinn et al. (2017) optimized operations of the four largest reservoirs under several different multi-objective problem framings in Hanoi city (Vietnam), and highlighted the importance of formulating and evaluating alternative stakeholder objectives.

However, an open question remains: to what extent can a traditional robustness evaluation (especially under risk-averse assumptions) suffice for rational decision-making, versus using a multi-objective trade-off analysis to gain a more comprehensive view?~~there is a need for a discussion on either the robustness evaluation of alternatives concerning policymakers' risk aversion can exclusively underpin rational decision-making or the multi-objective trade-off analysis can offer more comprehensive practical and theoretical support.~~ For example, while one might assume the cost of a climate adaptation option is normally proportional to its benefit (risk reduction ~~rate~~), in practice, ~~Options—options~~ with high performance often entail~~mean~~ higher costs input~~and~~ potentially longer construction periods (Dottori et al., 2023). Focusing on a~~The~~ single-objective (whether maximizing risk reduction or cost-benefit efficiency alone)~~in either performance assessment in reducing the risk or solely considering cost benefit~~ provided limited information for long-term planning, indicating a potential for~~and can lead to~~ lock-in or path dependency issues due to overinvestment or maladaptation over time.

Adaptiveness refers to the ability of a strategy to adapt~~adjust~~ to changing conditionse (Haasnoot et al., 2013; Malekpour et al., 2020). Rather than being in opposition, adaptiveness and robustness are complementary: incorporating flexibility can enhance long-term robustness by avoiding overinvestment and lock-in. In this sense, maintaining high level of robustness compromise high level of adaptiveness of a strategy as conditions change. For example, committing immediately to an extremely high-level (and high-cost) flood defense could lead to path-dependency if future conditions turn out less severe than expected, whereas a strategy that can be

incrementally upgraded retains both flexibility and robust performance over time. ~~high~~
~~cost of effective solution may cause path dependency and fails to adapt to the changing~~
~~circumstances due to its financial commitment and over confidence on the safety from~~
~~societies.~~ Despite its importance, the quantification of ‘adaptiveness’ (e.g., in terms of
 flexibility) remains challenging. Considered as the other side of coins against robustness,
 quantification of adaptiveness is yet clearly addressed (Kind et al., 2018). Adaptation
 Tipping point analysis provided insight into when ~~the an~~ options will no longer meet a
specified performance target might falter, indicating potential failure point concerning
the risk reduction target (Haasnoot et al., 2013), and Patient Rule Induction Method
 (PRIM) offers a quantitative way to identify these tipping points ~~is proven to be~~
~~illuminated to identify the use by date of tipping points in a quantitative way~~ (Ramm et
 al., 2018a; 2018b). Kirshen et al. (2015) ~~raised~~ noted that the preferred urban flood
control strategy may change once additional criteria like no-regret and flexibility are
considered at critical thresholds. Rather than choosing an ‘optimal’ here-and-now
solution that could become suboptimal later, a “wait-and-see” approach (delaying or
staging investments) can preserve flexibility. ~~option of selecting urban flood control~~
~~options may differ if additional criteria of no regret and flexibility were considered,~~
~~when a critical threshold is reached under a climate change scenario. Instead of applying~~
~~optimal here and now options, wait and see decisions allow for flexibility. Within In~~
the ROA paradigm, flexibility is explicitly valued since it allows decision-makers to
defer ~~delaying~~ ~~commit~~ ~~committing~~ ~~ment~~ to large, costly, and irreversible ~~decisions~~
measures while implementing smaller steps ~~either exercising different interventions or~~

~~incrementally implementing interventions with long construction times~~ until more information is available (Erfani et al., 2018). ~~In this paper, we define ‘robustness’ as the ability of a strategy to maintain acceptable performance across a wide range of plausible futures, and ‘adaptiveness’ as the ability to adjust or augment the strategy over time in response to how the future unfolds. Therefore, in our framework we incorporate both the timing of adaptations (the tipping point, termed the ‘effectiveness period’ in this paper) and the flexibility to adjust, as key characteristics of adaptiveness that support better long-term planning, incorporating both the tipping point (specify as valid period later in this paper) and flexibility reflect the key characteristics of adaptiveness and thus better assists in a long-term planning~~

In this study, we aim to propose a decision-making synthesized framework ~~which incorporates that integrates~~ both robustness and adaptiveness to formulate a robust adaptive pathway for long-term climate adaptation planning under deep uncertainties. This framework ~~can be utilized is intended~~ to guide decision-makers in prioritizing and sequencing adaptation options – a pressing challenge in urban climate action planning ~~decision-making on the prioritization and sequencing of climate adaptation alternatives, which nowadays remains as a pressing question for urban practitioners on climate action planning. To~~ We demonstrate the novel synthesized framework, it was applied by applying it to examine various climate adaptation alternatives to address the increasing pluvial flood risk in a delta city – (Shanghai), to evaluate a range of flood adaptation alternatives under plausible mid-21st-century scenarios (combining extreme rainfall and deteriorating drainage capacity by the 2070s), based on future (uncertain)

~~scenarios of a combination of extreme rainstorm and the deteriorating drainage capacity by the time of 2050s, to support the decision making.~~

The remainder of this article is organized as follows: Section 2 presents the proposed comprehensive framework and methodology. Section 3 introduces the background of the case study area and the preprocessing procedures. Section 4 presents the results, where a multi-objective trade-off is applied to evaluate the potential pathways for generating a robust adaptive pathway. This analysis combines metrics such as the average risk reduction rate (ARRR), benefit-cost ratio (BCR), ~~valid period~~effectiveness period, and flexibility of all options. Section 5 discusses the key findings related to pluvial flood risk management in coastal cities, the implications of multi-objective trade-off considering both robustness and adaptiveness, how the synthesized framework can inform long-term adaptive policy formulation, and provides recommendations for future work. Finally, Section 6 concludes with a summary.

2 MethodologiesMethodology

2.1 Framework development

Having ~~established~~outlined the challenges of pluvial flood risks ~~posed by future~~under deep uncertainties, ~~this study~~we now presents a robust adaptive pathway framework ~~designed to support for~~ long-term planning. ~~To~~We build ~~built this robust adaptive pathway framework,~~we by extending ~~ing~~ed the taxonomy of DMDU approaches proposed by Kwakkel et al. (2019), ~~which categorizes existing DMDU approaches into five dimensions of decision frameworks, and in incorporating recent advancements in robustness and adaptation methods to the taxonomy in the robustness~~

framework (Herman et al., 2015). Figure 1 provides an overview of our framework's eight sequential steps. We summarize these steps below, then detail each component of the methodology. Building on recent advancements in DMDU approaches, we further refined the framework into the following procedures:



Figure1 Integrated framework of robust adaptive pathways for long-term flood control

1) **Research framing.** Define the long-term flood management objectives and a dynamic policy structure. Unlike a static, short-term plan, the proposed policy structure is dynamic and adaptive, providing a continuous pathway toward achieving long-term flood control goals while retaining flexibility to adjust as future conditions evolve. In our framework, introducing “adaptive” measures alongside traditional approaches enhances overall robustness by reducing the risk of over-investment or lock-in. In contrast to the short term implementation of baseline standards, the policy structure proposed in this work is designed to be dynamic and adaptive. It provides a continuous

pathway toward achieving long-term flood control goals while maintaining the flexibility to adjust to an uncertain future. As a result, the 'adaptive' options enhance the robustness of the solutions and reduce the risk of over-investment.

2) Scenario generation. Develop a set of plausible future scenarios capturing key uncertainties (meteorological, hydrological, socio-economic, etc.). The ranges for uncertain factors can be derived from expert judgments, policy targets, or climate projections (Lempert et al., 2013). We employed a Latin Hypercube Sampling approach (Workman et al., 2021) to efficiently generate diverse futures. In our case study, for instance, futures were defined by varying extreme rainfall intensities and drainage capacity degradation by 2050, based on climate model outputs and local planning assumptions. The process of scenario generation applies multiple (uncertain) factors of meteorological, hydrological, or social-economic. The range of uncertain factors may either according to expert's opinion, policy guideline or climate projections (Lempert et al., 2013). Plausible futures can be generated via scenario sampling algorithms as of Latin Hyper-Cube Sampling (Workman et al., 2021).

3) Alternative generation. Identify and develop a portfolio of adaptation options. In our study, we used stakeholder workshops and policy document analysis to formulate viable flood control measures (both structural and non-structural). The current flood management strategy (status quo) serves as a baseline option, and a range of new adaptation alternatives (e.g., green infrastructure, drainage upgrades, tunnels, and their combinations) were assembled for evaluation. Climate adaptation alternatives were developed through focus-group discussions during a workshop and an analysis of policy

documents. The workshop included key stakeholders such as flood experts, policymakers, and residents. As a result, the existing flood options serve as the baseline scenario, compared to the generated climate adaptation alternatives which are set to be evaluated using flood modelling.

4) Model simulation. Evaluate each option (and combinations of options) under all futures using an appropriate flood simulation model. The framework can accommodate models of varying complexity: for instance, high-fidelity 1D/2D hydrodynamic models (e.g., SOBEK, MIKE 1D2D; Wang et al., 2018) could be used for detailed analysis at the cost of more computation, whereas simpler conceptual models allow faster simulation of many scenarios. In our case study, we employed a simplified hydrological model based on the SCS-CN method to simulate runoff and flooding, which kept computational demands manageable given the thousands of plausible futures simulations, although the framework could integrate more complex models if needed. Flood inundation models such as SOBEK1D2D, Mike1D2D (Wang et al., 2018) and Info Works can be used to simulate flood routing process and produce maximum inundation maps, which further can be used for flood risk assessment when incorporating the geospatial statistics.

5) Robustness analysis. Assess each option's performance across all futures using robustness criteria, which used to be depicted as $f(a, w_j)$ meaning the performance of option a under scenario w_j . In this study, we assume all scenarios are equally likely (an application of Laplace's principle of insufficient reason) and compute performance indicators for each option under each scenario. Key indicators include the average risk

reduction rate (ARRR), percentage reduction in expected damages compared to baseline, averaged over scenarios, and the benefit cost ratio (BCR), ratio of total avoided damage to total cost. Using these, we evaluate how “robust” each option is, for instance, how well it performs on average and whether it consistently meets acceptable thresholds across scenarios. ~~To evaluate the robustness of all options that have the highest utility under a certain threshold, robustness metrics (e.g. Laplace’s principle of insufficient reason) were used as the decision-making criterion. The calculation of indicators such as the average risk reduction rate (ARRR) and benefit cost ratio (BCR) for each alternative option was performed for each scenario, with an assumption of equal probability for their occurrence. Subsequently, the performance of each option and its combination was evaluated by quantitative comparison and ranking stability (McPhail et al., 2018).~~

6) Adaptiveness analysis. ~~Valid period~~ Determine how long each option remains effective and how easily it can be adjusted. For each single or combined alternatives, we identify its effectiveness period – the duration or range of conditions over which it meets the flood risk target – by finding the point at which its performance falls below the acceptable threshold. We used the PRIM algorithm to analyze scenario results and pinpoint these tipping points; in doing so, we optimized PRIM’s coverage (the proportion of scenarios captured by a tipping point condition) and density (the success rate within those scenarios) to balance generality and precision to balance generality and precision. We refer to the conditions triggering failure as signposts, which are observable indicators that an adaptation or policy change will soon be needed.

Furthermore, we quantify each option's and combination's flexibility in our framework by the number of measures it contains. In other words, a multi-component strategy planned with, say, three measures have a higher planned flexibility score than a single-measure strategy, since it inherently includes more future actions. This flexibility metric reflects only the strategy's planned adaptability, not an absolute limit – even a one-measure strategy could be expanded later. ~~of the alternative options were determined based on the conditions of the successful scenarios under each (individual or combined) option, in conjunction with a specific flood control objective. Optimizing the value of coverage and density of subspace in the PRIM (Patient Rule Induction Method) algorithm help to identify signposts in the adaptation pathway which is in line with the idea of the tipping point in DAPP. Flexibility is evaluated by the ability of convertibility.~~

7) Multi-objective trade-off. Evaluate each alternative across multiple metrics to understand trade-offs. We consider both robustness metrics (e.g., risk reduction, benefit cost ratio, regret-based measures) and adaptiveness metrics (effectiveness period and flexibility) for every strategy. For comparison, all metric values are normalized and, in our analysis, treated with equal importance. This allows us to compute an overall performance score for each alternative. Options that achieve a good balance across all criteria are deemed the most promising candidates for robust and adaptive planning. We did not run a computational multi-objective optimizer which would be typical if there were hundreds of options. Instead, we effectively enumerated and evaluated a small set of candidate solutions manually or with simple search, given the case study's scope.

~~Multi-objective trade-off was implemented using robustness and adaptiveness metrics to evaluate the candidate alternatives. All the metrics are given equal weight and are compared based on their normalized values. The alternative options with highest score to satisfy all the objectives are regarded most promising.~~

8) Robust adaptive pathway. Formulate and select robust adaptive pathways. Using the information on each option's effectiveness period and flexibility, we identify sequences of actions that extend flood protection over time. We generate an adaptation roadmap by considering how the system could transition under transient scenarios. From the set of possible pathways, we then select a robust adaptive pathway that best satisfies the flood control objectives in the long term based on the multi-objective analysis from step 7. Along this pathway, we define key signposts – measurable indicators (e.g., a threshold of rainfall intensity or drainage failure rate) that signal when it's time to shift to the next action. Monitoring these signposts will support future decision-making and adjustments to the plan.~~In light of the adaptability of the valid period (tipping point) and flexibility of transitions in each alternative portfolio, potential pathways were identified, and generated a roadmap based on transient scenarios. A robust adaptive pathway was selected in multi-objective to satisfy the flood control criteria for long term planning. The signposts can be monitored to support future decisions.~~

2.2 Methods of robust adaptive pathway procedures

Robustness analysis

Deciding on a robustness criterion is essentially a meta-decision problem. The choice of robustness option is the meta-problem of how to decide (Herman et al., 2015). In our context, robustness of a strategy refers to its satisfactory performance across a range of uncertain future states. The performance of a system is frequently described by robustness option when dealing with a decision-making process, including significant uncertainty. Various robustness metrics can be used to quantify robustness under uncertainty, including Maximax, Maximin, Mean-variance, Starr's domain criterion, Laplace's principle of insufficient reason, etc. Each metric embodies a different risk preference, so the choice of metric can influence which option appears most favorable are used to evaluate a system's performance in various scenarios (state of the worlds). Different robustness metrics represent distinctive risk preferences, and the selection of robustness indicators influences the choice of alternative options (Giuliani and Castelletti, 2016). In this study, we adopted For the risk aversion metric, the neutral risk aversion of Laplace's principle of insufficient reason as one robustness measure: in the absence of known scenario probabilities, we assign equal weight to all scenarios and identify solutions that perform best on average. s widely documented to help identify the solution that performs best in neutral risk aversion. Furthermore, it suggests that in the absents of knowledge of the probabilities associated with the different scenarios, the decision could be taken by assigning equal probability to all scenarios. The performance of option or combination a_i is depicted as Equation (1).

$$a^* = \arg \max_{a \in A} \left(\frac{1}{N} \sum_{j=1}^N f(a, w_j) \right)$$

$$\arg \max_a \left(\frac{1}{N} \sum_{i=1}^m \sum_{j=1}^n f(a_i, w_j) \right) \quad (1)$$

where a^* denotes the optimal option or combination, A is the set of all options or combinations (listed in table 2), N is the total number of futures. And $f(a, w_j)$ is the performance of option or combination a under future w_j , which represents the expected flood risk associated with adaptation option or combination a under future w_j , as generated from the flood-damage simulation model. This risk value forms the basis for evaluating robustness through indicators such as the ARRR.

Where a_i is option i of alternative options set (a) (listed in table 2), and w_j is in the scenario set w . $f(a_i, w_j)$ represents the option performance value of scenario j , a_p is the selection of option p with best performance.

In many robust decision-making frameworks, criteria related to satisficing and regret are used as performance measures. Satisfaction and regret are frequent indications of robustness options in RDM decision-making procedures (Herman et al., 2015). Regret is broadly the opportunity loss incurred by not choosing the optimal action in a given scenario – essentially, how much worse a strategy performs compared to the best possible outcome in that scenario. Satisfaction can be viewed as a measure of how well a strategy meets a predefined target (combining effectiveness and efficiency). In our evaluation, we compute these metrics relative to a baseline scenario or option. Broadly, regret quantifies the cost (not necessarily monetary) of choosing incorrectly. It can be defined as the cost of a single solution, associated with the deviation from its baseline performance. On the other hand, satisfaction can be defined as the amalgamation of effectiveness and efficiency. Equation (2) illustrates how we calculate regret-based performance for the alternatives. In this situation, the evaluation of candidate options'

performance is presented as the deviation from the baseline performance, see Equation (2).

$$P_i = \frac{1}{N} \sum_{j=1}^N \frac{|f(a, w_j) - f(a_0, w_j)|}{f(a_0, w_j)}$$

$$P_i = \frac{1}{n} \sum_{i=1}^m \sum_{j=1}^n \frac{|f(a_i, w_j) - f(a_0, w_j)|}{f(a_0, w_j)} \quad (2)$$

Where P_i is the average performance value of average risk reduction rate (ARRR) of alternative options or combinations in all plausible futures N , $f(a_i, w_j)$ represents the performance value of pluvial flood risk of option a in scenario future w_j , and $f(a_0, w_j)$ is the performance value of pluvial flood risk of the baseline option a_0 of in scenario future w_j .

Decision-makers also examine whether any given strategy has vulnerable scenarios – situations in which it fails to meet minimum acceptable performance – that whether the scenario sets of alternative options contain an unacceptable possibility. The A threshold can be set to define what constitutes intolerable performance for vulnerable scenarios defines whether there is an intolerable risk control level. Metrics like the domain criterion quantify the fraction of the uncertainty space (subsets of all futures) in which a solution meets all performance requirements. The domain criterion quantifies the volume of the uncertain factor space in which a solution meets the decision makers' performance requirements. Such considerations align with policy risk indicators often used in practice (e.g., minimum safety standards or environmental protection criteria) to ensure options avoid unacceptable outcomes. Indicators of risk control policy are frequently included in the research, such as local environmental protection legislation, urban drainage planning, and other documents. They can also

~~provide appropriate reference opinions determined by local governments or relevant decision makers and experts.~~ Based on the elicitation of local requirements, we define the P_i^* as the ~~average~~ performance of average risk reduction rate(ARRR) which satisfies the minimum threshold of the given flood control target ($F_0, F_0=0.7$ in this case), as depicted in Equation (3).

$$P_i^* = \frac{1}{s} \sum_{j=1}^s \frac{|f(a, w_j) - f(a_0, w_j)|}{f(a_0, w_j)} \geq F_0 \quad \text{---} \quad P_i^* = \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^n f(a_i, w_j) \geq F_0 \quad (3)$$

Where P_i^* represents the ~~average~~ performance value of ARRR of the option or combination a_i in all subsets s of all plausible scenario futures N that meets the given flood control target F_0 . PRIM is applied to identify clusters of successful cases by searching across the full set of futures N for each option or combination. Specifically, for each option or combination a , we select the subset of future s that leads to the most successful outcome by balancing coverage and density with given flood control target.

Internationally, the net present value of benefits (PVB) and the net present value of costs (PVC) are commonly used to represent benefits and costs, respectively (Liao et al., 2014). In this study, PVB is selected as the pluvial flood risk reduction rate (RRR) before and after the implementation of the options, rather than as the pluvial flood risk reduction value. It is important to note that the goal of this study is not to calculate the direct risk of extreme pluvial flooding in the future, as the absolute value of the risk would be too large for meaningful comparison. Therefore, the benefit-cost ratio (BCR) is presented simply as the ratio of PVB to PVC.

Adaptiveness analysis

PRIM is an interactive statistical clustering algorithm that generates a series of subspaces by peeling away layers of the uncertainty space, where the coverage and density of points of interest in each box are greater than in the surrounding space (Matrosov, 2013). As a visualized tool for exploratory analysis, PRIM is widely used in many works to investigate either key factors causing system failure or vulnerable scenarios that might cause alternative options' failure. Parameters of coverage, density, and interpretability characterize the subspaces. These three metrics are usually correlated, with increasing density resulting in decreasing coverage and interpretability. It turns out that an analyst needs to trade-off in selecting the potential coverage, density, and interpretability to achieve the best combination. The subspaces describe the conditions beyond which coastal inundation impacts are unacceptable signifying adaptation tipping points are reached (Ramm et al., 2018a). Key factors along with the tipping point of options are evaluated in associated timeframes which need not be exact. Identifying an indicative period at which conditions describing adaptation tipping points indicate a ~~valid period~~effectiveness period (or use-by year) (Haasnoot et al., 2013). The results of PRIM can assist decision-makers in identifying sensitive ranges of uncertain factors or combinations, and factors with little influence can be safely disregarded.

Following a decision initially, flexibility in decision theory is related to the remaining choices available in the following period. The larger this set, the more flexibility the decision maker retains. This idea can be generalized to staged choices

over multiple periods. For example, Erfani et al. (2018) proved that flexibility is valuable in providing decision nodes in multistage scenarios (planning periods in every 5 years) for least-cost water supply intervention scheduling. One way of deriving the value of flexibility is thus by comparing costs and benefits of a flexible investment strategy with those of a less flexible, that is, a more robust strategy (Kind et al., 2018). However, flexibility is not treated as delayed option value as other ROA work calculated, instead, we consider the convertibility of options that is still in line with the idea of wait-and-see yet is more straight-forward. It is important to note that a strategy initially implemented as a single measure does not preclude future augmentation if conditions worsen. In our framework, however, such augmentations were not pre-planned in single-measure scenarios. Therefore, our ‘flexibility’ metric should be interpreted as the degree of planned adaptability, rather than an absolute limit on a strategy’s potential to adapt.

Multi-objective trade-off

The cost and benefit of investment in adaption options may lead to a static decision-making perspective. Therefore, an important question was raised for robust decision-making of how to avoid failure scenarios regarding factors including risk reduction rates over time, cost of option, and economic benefit ratio. On this basis, making robust decisions needs to include other factors beyond cost and benefit, such as ~~valid-period~~effectiveness period and flexibility, for a comprehensive evaluation in the long-term (Erfani et al. 2018)

The optimization of options’ combinations can be identified via the trade-off

process by Equation (4).

$$\max_{l \in L} F(l) = [y_1(l), y_2(l), y_3(l), y_4(l)]$$

$$Maximize F(l_{p,r}) = (\gamma_{flexibility}, \gamma_{valid\ period}, \gamma_{cost-benefit}, \gamma_{performance}) \quad (4)$$

Where $l_{p,r} = [p, r]$ $\forall p \in P; \forall r \in R$

Where $l \in L$ is a candidate adaptation pathway from the set of feasible pathways

L ; $y_1(l)$: Flexibility — number of successful alternatives reachable from pathway l ;

$y_2(l)$: Effectiveness period — duration before performance drops below threshold; $y_3(l)$:

Benefit-Cost Ratio (BCR) — economic efficiency of pathway l ; $y_4(l)$: Average Risk

Reduction Rate (ARRR) — robustness of flood risk performance. Where $l_{p,r}$ represents

the pathway scheme, r is any of the robustness metric set R . $\gamma_{flexibility}$, $\gamma_{valid\ period}$,

$\gamma_{cost-benefit}$ and $\gamma_{performance}$ are the values of indicators from different dimensional

objects.

Robust adaptive pathway

Adaption tipping points (~~valid-period~~effectiveness periods) are central to

adaptation pathways, the conditions under which an action no longer meets the

specified objectives. The timing of the adaptation points for a given action, its ~~valid~~

~~period~~effectiveness period, is scenario dependent. The DAPP, manually drawn based

on model results or expert judgment, presents an overview of relevant pathways

(Haasnoot et al., 2020). In this study, we first examined the ~~valid-period~~effectiveness

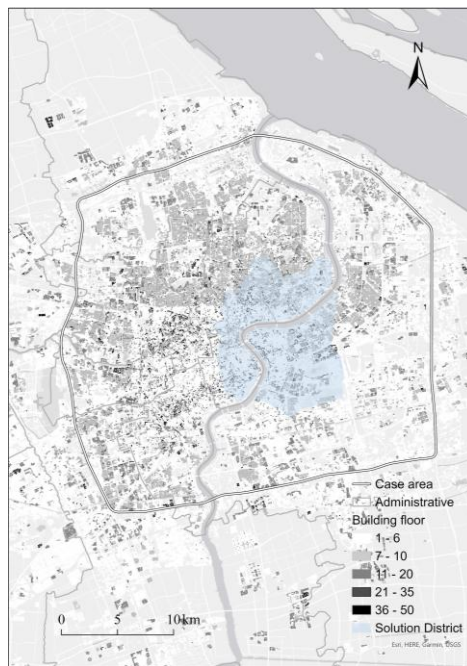
period of alternative options by PRIM analysis to identify acceptably robust adaptation pathway for future flood control. We then identified the combination of candidate pathways in consideration of both ~~valid period~~effectiveness period and flexibility, ensuring the adaptive solutions in incremental stages allow for maintaining flood control levels before committing to larger schemes. Roadmap of candidate's pathways are generated during this procedure. Lastly, the preferred robust pathway is determined by a trade-off analysis of all the criteria.

3 Case study

3.1 Background

Shanghai, with a domain of 6,340 km², provides residences to 24.9 million population with a built-up area of 1237.9km² in 2021. Shanghai has been perhaps the most important economic and financial center in China, and it now aspires to be one of the world's most important economic, financial, shipping, and trade centers (Shanghai Statistic Yearbook, 2021). Shanghai is surrounded by water on three sides: the East China Sea to the east, the Yangtze River Estuary to the north, and Hangzhou Bay to the south. In addition, the Huangpu River, a Yangtze River tributary, flows through the heart of Shanghai. The average yearly precipitation is approximately 1400mm in recent 10 years, with 63% concentrated during the flooding season from May to September (Shanghai Climate Change Research Center, 2022). As a result, the most catastrophic hazard in Shanghai has been floods produced by torrential rainfall, which annually disrupts transportation and other social activities, causes substantial economic losses, and threatens urban safety.

Shanghai has the lowest elevation (with averagely 4m above m.s.l.) and large numbers of old-lane residential buildings in central city, which have fewer floors compared to other districts that is vulnerable to the extreme pluvial flood events see [Figure 4-2](#)). The spatial distribution of rainfall will continue to concentrate in urban areas, and the increasing likelihood of extreme precipitation ([Liang and Ding, 2017](#)), combined with the trends of relative sea-level, will cause stakeholders, includes residents, policymakers, and scientists etc., to be concerned about the rising flooding risk in delta cities of Shanghai ([Du et al., 2020](#)).



[Figure 4-2](#) Case area, administrative, and solution district (blue shade) in center Shanghai, including spatial distribution of building footprints indicating the number of stories (gray shades), the base map was provided by Esri, using ArcGIS Online Services.

3.2 Research Framing

Based on the proposed framework, the dimensions, components, and metrics of this study are organized as shown in Table 1. To ensure urban safety, this study defines an explicit flood control objective of achieving a 70% average risk reduction rate, in alignment with the Shanghai Flood Control and Drainage Plan (2020–2035) (Shanghai Municipal Water Authority, 2020).

Table 1 Dimensions of the research framework

Dimension	Components			Metrics
Research framing	Alternative options to generate robust and adaptive pathway			Definition of flood control objective
Scenarios generation	Increased rainfall	Rain island effect	Drainage decrease	Latin hypercube sampling (LHS)
Alternatives generation	Drainage increased	Increase of green area	Deep tunnel with 30%, 50%, or 70% of runoff absorption	Predefined by local flood control plan
Model simulation	Hydrology	Flood risk	Geospatial statistics	Grid aggregation
Robustness analysis	Performance (ARRR)	Measure Cost (Life cycle cost)	Benefit	Laplace and Domain criterion
Adaptiveness analysis	Signpost	Valid <u>periodEffectiveness period</u>	Flexibility	PRIM
Multi-objective Trade-off	Robustness	Adaptiveness		Metric evaluation
Robust adaptive pathway	Candidate pathway identification, roadmap generation, and monitoring of signposts			Transition scenarios

The robustness analysis serves as the foundation of our methodology, ensuring that the proposed solutions can withstand future uncertainties. Once robustness is assessed, we proceed to the adaptiveness analysis, which allows us to account for flexibility in response to unforeseen challenges. ~~We conduct~~The a trade-off ~~optimization~~analysis in terms of robustness and adaptiveness was of particular significance to providing iterative stress tests over many plausible scenarios using

robustness metrics and identifying ~~valid period~~effectiveness periods and flexibility to generate alternative pathways. Following the structure of robust decision-making pathway framework, Figure 2-3 illustrates the entire procedures for long-term flood control planning in the Shanghai case study.

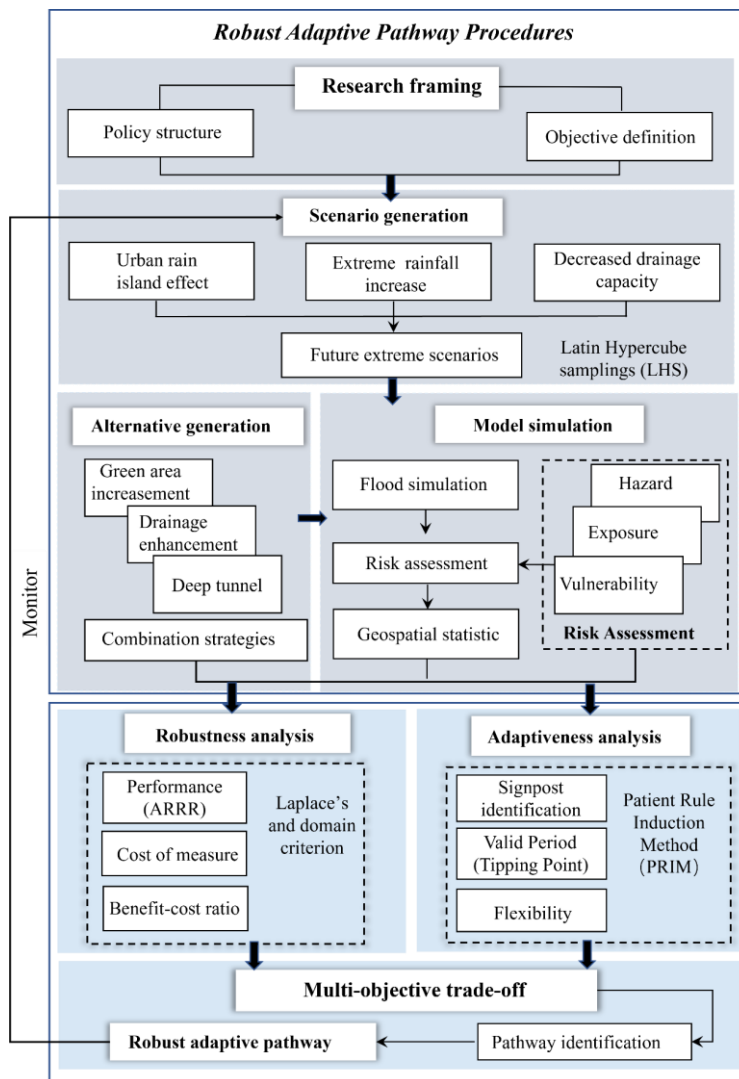


Figure 2-3 Framework of robust adaptive decision-making pathway, which incorporates the

robustness, adaptiveness, multi-objective trade-off, and pathway generation (blue boxes).

3.3 Scenario generation

Precipitation is predicted very likely to increase in the Yangtze River Basin in the 21st century (Hui et al., 2018), and the frequency and intensity of extreme rainstorm events may continue to increase (uncertain factor of the α , future rainfall assumed to increase from 7% to 18%). Shanghai's spatial rainfall patterns reveal a significant "rain island effect" between urban centers and suburbs (Liang and Ding, 2017) (uncertain factor of the β , assumed to increase from 10% to 20% in central region (Xujiahui and Pudong rain gauges), decrease from -0.076% to -0.038% (other 9 rain gauges in Shanghai)). In addition, land subsidence has been a persistent issue due to the groundwater exploitation and construction of high-rise buildings (Yang et al., 2020). By 2050, it is projected that the current river embankment and drainage systems in Shanghai will experience a 20-30% reduction in capacity due to a likely relative rise in sea level of 50 cm (compared to the year of 2010), caused by both sea level rise and land subsidence (Wang et al., 2018). The uncertain factor of the decrease of drainage capacity (γ , assumed to decrease from 0 to 50% due to the anthropogenic land subsidence and sea level rise) is designed to be the degradation effect of restraining the water from the urban drainage system flowing to the river system due to the high river water level caused by the continually rising sea level, land subsidence, and other degradation factors.

This study focused on a record-breaking convective rainfall that occurred on September 13, 2013 and had an intensity record of 140.7mm within 3 hour (at 17-19h).

The variation interval of each uncertainty factors was clarified, and Latin Hyper Cube Sampling (LHS) was used to construct 100 plausible futures ~~scenario cases~~ based on the historic "913" extreme rainfall event in 2013 ([Supplementary materials Text 1](#)).

3.4 Alternative generation

It is acknowledged that the current Shanghai flood control infrastructure is insufficient to protect the city from long-term inundation risk (Shanghai Municipal Water Authority, 2020). Three options, drainage improvement, increase of green area, and construction of deep tunnel, are pre-defined with stakeholders of experts and decision-makers following the Shanghai Flood Control and Drainage Plan (2020-2035). The solution district locates in the core business district (CBD) of Shanghai and is highlighted in [Figure 42](#). We defined the existing structure of flood control measures as the baseline and evaluated alternative measures' performance verse the baseline control level in the flood simulation model ([Table S4](#)).

3.5 Model simulation

Simulations of extreme pluvial flood inundation under climate change scenarios are carried out using the Shanghai Urban Inundation Model (SUIM) ([Supplementary materials Text 2](#)). It was created to couple multiple simulation processes, which consists of the SCS-CN hydrological model, statistical analysis of flooding results, risk assessment, and assessment of adaptation measures. Appropriate socioeconomic indicators were selected to characterize the exposure of the elements at risk and the vulnerability curve to evaluate the flood risk in all plausible scenarios ([Supplementary](#)

materials Text 3). We then coupled the hydrological module and risk assessment module to assess the future risk (Supplementary materials Text 3). Three climate adaptation options are quantitatively characterized in the risk assessment system. The benefit-cost ratio (BCR) of all options is calculated according to the performances of the risk reduction rate over the life cycle cost (Supplementary materials Text 4).

4 Results

4.1 Robustness analysis

This section presents the performance evaluation results, including average risk reduction rate (ARRR) and Benefit-cost ratio (~~BCA~~BCR), to reflect the robustness of potential climate adaptation options (Supplementary materials Text 34). ~~Benefit-cost is the evaluation dimension for the robustness metrics, we evaluated their robustness under various plausible scenarios (Equation 1 in Section of ‘Methods’). It should be noted that benefit-cost, BCR~~ was defined as the average risk reduction rate (ARRR) per unit cost (Equation S4 in Supplementary materials Text 4) based on the robustness metrics of Laplace’s Principal of Insufficient Reason. ~~Specifically, the benefit is the reduction in expected flood losses compared to the no-action scenario (Equation 3), while the cost refers to the total implementation cost of each adaptation option (Equation S5 in Supplementary materials Text 4). We adopt Laplace’s principle of insufficient reason, assuming all scenarios are equally likely when calculating average outcomes across scenarios.~~ Given that drainage capacity reduction (γ) is the main factor affecting the solutions’ performance, thus the study selects γ as the only explanatory indicator to explore the failure scenario of options based on the PRIM method.

As depicted in Table 2, the ARRR is calculated (Equation 2) to analyze the effectiveness of (the combination of) options. The average yearly cost of single options, which includes increasing drainage capacity (Dr), expanding green areas (GA), and constructing a deep tunnel with 30% runoff absorption (Tun30), is at a comparative level, ranging from 39 to 41 million USD per year. Their performance is relatively unsatisfactory (the ARRR is less than 0.39.) However, the ARRR for the combined option (D+G), drainage improvement and public green area, is higher (0.62) than the sum of two single options (0.51), indicating that the composite option will be more effective of reducing flood risk. Furthermore, it demonstrates that the combined options (i.e., D+G and D+G+T30) are satisfactory in terms of ARRR performance but not economically attractive due to their relatively higher costs. It is noted that if an option defers a major investment (like the Tun30) to later years, in reality its present value cost would be lower with discounting, potentially making the strategy more economically attractive than our simple BCR suggests.

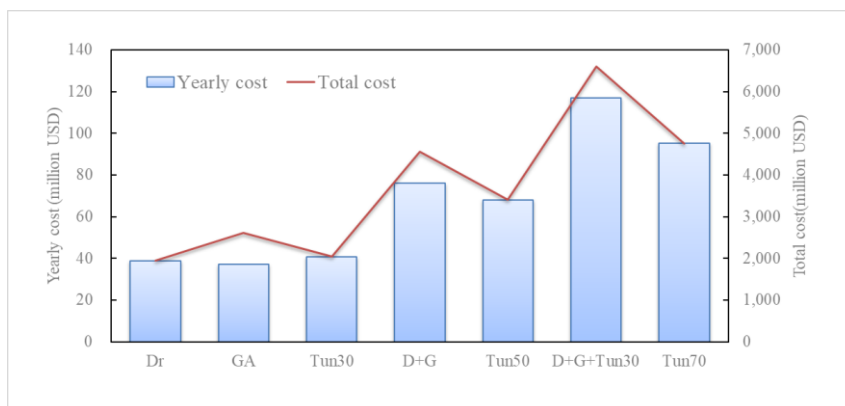


Figure 3-4 Yearly cost and total cost of alternative options

While two ~~single-single-options involving of~~ deep tunnel (namely Tun50, Tun70) seem very attractive ~~in terms of (achieving high ranks in~~ both ARRR and BCR).

Table 2 The ratio of the benefit-cost of each adaptation options

Option	ARRR (without control target, %)	Cost (million USD / year)	Benefit-cost ratio (%)
Dr	0.25	39	0.09
GA	0.26	37	0.10
Tun30	0.39	41	0.14
D+G	0.62	76	0.12
Tun50	0.74	68	0.16
D+G+Tun30	0.85	117	0.10
Tun70	0.87	95	0.13

4.2 Adaptiveness analysis

Scenario discovery validates the decrease of drainage capacity is the most critical uncertainty in defining the risk reduction rate of performance objective. The failure scenarios ~~could be~~ are identified when the flood control target $F_0=0.7$ is not met. We further interpret failure scenarios by selecting subspace of each alternative options under flood control target using PRIM algorithm to optimize the combined value of coverage and density. ~~Table 3 summarizes these metrics, where coverage and density are derived from PRIM-identified failure boxes, and ARRR is calculated as the average performance within those clusters. The valid period is defined by the point (characterized by γ) when a single option or combination no longer meets the performance target. The valid period is determined as the point when the single options or the combinations cease to fulfill the flood control target, indicated by the time which~~

is characterized by γ (the reduction in drainage capacity).

According to the results in Table 3, it was found that within the 70% risk reduction control target (Equation 3), the single options of Dr and GA performed less favorably (relatively smaller ARRR) and can quickly fail to meet the risk reduction target (with no larger than 0.1 of γ). Tun30 and D+R are very comparative since they perform very closely (similar results on ARRR and γ) but still not attractive. While Tun50 seems very attractive in terms of ARRR (0.89), however, it does not possess higher ~~valid~~ period effectiveness period (γ) than both D+G+Tun30 and Tun 70. Surprisingly, both D+G+Tun30 and Tun70 can function well in an effective way for a longer time. So far, D+G+Tun30 and Tun70 have proven to be highly competitive in terms of cost-effectiveness and ~~valid~~ period effectiveness period over time.

Table 3 ARRR and coverage and density of success scenarios in each option combinations under 70% risk reduction control standard

Option	ARRR (with control target, %)	Coverage	Density	Decreased drainage capacity (γ) (valid <u>period effectiveness period</u>)
				<u>period</u>
GA	0.59	1	0.22	0.04
Dr	0.62	1	0.20	0.07
Tun30	0.73	1	0.75	0.1
D+G	0.74	0.9	0.82	0.11
Tun50	0.89	0.95	0.98	0.29
D+G+Tun30	0.86	0.99	0.98	0.48
Tun70	0.87	1	1	0.5

~~we~~ We define flexibility as the number of transitions by enumerating overall option combinations regarding adaptive transferable pathways from the original option (current flood control infrastructure) to the destination options (e.g., D+G+Tun30 and Tun70, Figure 56). For example, the D+G+Tun30 comprises three single options, allowing it to begin with any of the three and delay further action until a tipping point approaches, giving it a convertibility score of three (Table S6). Therefore, each single option has a value of one for convertibility.

4.3 Multi-objective trade-off

~~The robustness-focused analysis (e.g., looking only at ARRR and BCR) would rank options like Tun50 and Tun70 as the top performers, whereas the adaptiveness-focused analysis (looking at effectiveness period and flexibility) made D+G+Tun30 the most appealing. These differing outcomes demonstrate why it is crucial to evaluate multiple criteria together. Only by considering all metrics simultaneously (a true multi-objective trade-off) can we identify strategies that strike an appropriate balance for long-term flood management. Robustness analysis suggests Tun50 and Tun70 might be attractive while adaptiveness analysis indicates D+G+30 as the most appealing. Therefore, the single objective metrics yield different decision choices, it is crucial to evaluate all the metrics to conduct a multi-objective trade-off among the alternative options to assist the robust and adaptive decision making.~~ Multi-objectives of (the combination of) options consider all four metrics, including BCR, and performance of the risk reduction control criteria (ARRR>70%), ~~valid period~~ effectiveness period (γ), and the flexibility. We solved the multi-objective problem using normalized and equally

weighted metrics (Equation 4). Figure 4-5 depicts the results of BCR, ARRR in control criteria, ~~valid period~~effectiveness period, and flexibility of each option's combination. The higher the normalized rating, the greater the payoff. The outcome demonstrates that both GA and Dr perform poorly, whereas Tun30 and D+G are not robust enough compared to Tun 50, D+G+Tun30, and Tun70. It needs to be highlighted that Tun 50, D+G+Tun30, and Tun70 possess high priority; ~~—, however, —~~We found that the D+G+Tun30 pathway achieved a well-balanced performance across risk reduction, cost-effectiveness, and our flexibility metric~~D+G+Tun30 outperforms due to its well-balanced overall risk control performance and high value of flexibility~~ (Table S7). ~~In our initial analysis, this made D+G+Tun30 appear as the most promising option overall. However, as discussed, this planned flexibility advantage does not necessarily mean a single-component strategy cannot be adapted later. It is important to note that this conclusion is contingent on including the flexibility metric. If flexibility were defined differently or given less weight, another option – for example, the single large tunnel Tun70 – could emerge as preferable for long-term risk control.~~

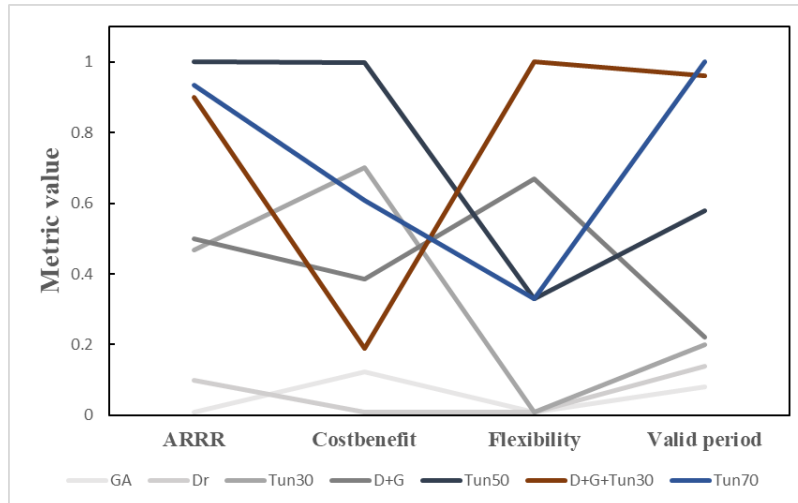


Figure 4-5 Multi-objective trade-off of alternative options with normalized value of robustness metrics (the preference of priority is accepted from low(bottom) to high(top)).

4.4 Robust adaptive pathway

Pathway identification

The candidate pathway was identified by enumerating the possible combinations of options. In this study, we found two potential pathways including from Tun30 to Tun70, and from Dr or GA to D+G+Tun30. It can be observed from Figure 5-6 that when γ increases, the performance of options of Dr (or GA, vice versa) steadily diminishes until the risk control target are not satisfied.

The drainage capacity, affected by the compound event of land subsidence, sea level rise, and storm surge, is deemed to be undermined (which is reflected by drainage capacity reduction rate γ) over time. Figure 5-6 illustrates the concept of an option combination's valid period using Dr+GA+Tun30 as an example.

ARRR to begin with Dr is 0.62, with an increase in γ , Dr fails ($\gamma=0.07$), and ARRR will decrease further if no additional options are taken. The addition of GA can increase the ARRR to 0.74 before Dr and D+G fail ($\gamma=0.11$). The ARRR will continue to decrease if options are not strengthened. Before D+G completely fails, incorporating Tun30 can increase the ARRR to 0.86; as γ increases, D+G+Tun30 fails at $\gamma=0.48$. To ensure the adaptive robustness of the combination of options, decision-makers can increase the service coverage area and rainwater absorption capacity of the deep tunnel project in the core area prior to the total failure of D+G+ Tun30. In other words, the transition from Tun30 to Tun50 and even Tun70, along with the combination of options, will be stable over the long-term time horizon. It is noted that the slight rise in performance after GA and Tun30 installation reflects a short ramp-up period in our model, during which newly implemented measures gradually reach full effectiveness, then performance begins to decline as expected under continued climate-induced stressors.

The differing curvature of the performance decline is due to the interaction of measures. For the Dr-only strategy, once implemented, its risk reduction gradually diminishes at an accelerating rate as climate stressors intensify – producing a concave-down curve (initially gentle slope, steepening later). In contrast, the strategies with multiple measures (D+G and D+G+Tun30) show a more linear decline. This is because when drainage alone begins to lose effectiveness, the next measure (GA, and later Tun30) either has just been implemented or is concurrently mitigating risk, effectively offsetting some of the non-linear drop. The combined result is a more steady (approximately linear) decrease in performance over time, as the measures' effects

complement each other. We normalized time as $\gamma = t/T$ (with $T=50$ years, the simulation period), so γ corresponds to the year 2070.

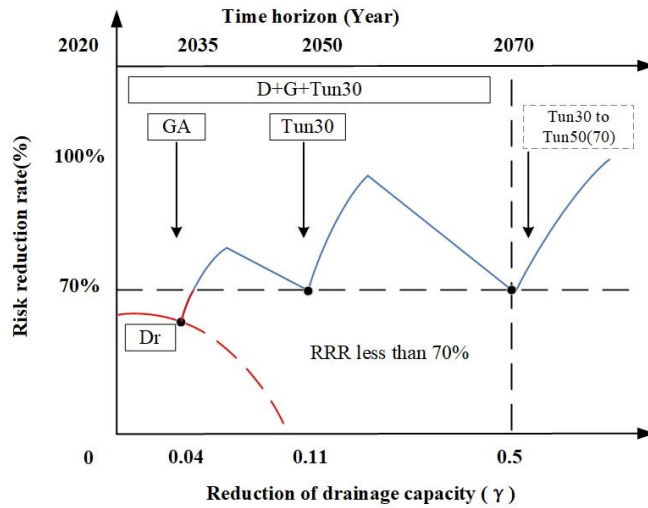


Figure 5-6 Flexible pathway of combination options of drainage improvement (Dr), green area increment (GA), and deep tunnel with 30% absorption (Tun30), representing the risk reduction rate undermines with the reduction of drainage capacity. An example of Dr+GA+Tun30, γ is a dimensionless time, where $\gamma = 1$ corresponds to Year 2070, the end of our planning horizon

Pathway generation

We comprehensively evaluated the candidate pathways by considering performances, BCR, ~~valid-period~~effectiveness period, and flexibility. The time frame lacks an absolute time reference but still offers a relative tracking of the rate at which relative sea levels are rising.

Figure 6-7 depicts two robust transition pathways: D+G to D+G+Tun30 and Tun30

to either Tun50 or Tun70. The two pathways D+G+Tun30 and Tun30 to Tun70, provide adaptive short and long-term pathway schemes from a flexibility standpoint. The short-term options are used as transitional schemes, and new options can be added before their failure, i.e., pathway transition, to maintain the risk control objectives. In addition, the two schemes can complement each other and incorporate new options before the system's long-term robustness is compromised. Additionally, D+G+Tun30 and Tun70 leave room for upgrading to the costlier and more durable D+G+Tun70 in the long run when γ exceeds 0.5 (e.g., sea level or land subsidence exceeds observing increase speed).

We observed that Tun70 offered the highest robustness in terms of ARRR and the longest effectiveness period among all single options. Tun70 possesses the highest robustness and the longest valid period; However, its lack of initial flexibility – requiring a large up-front investment in gray infrastructure – could lead to path dependency if future conditions turn out to be mild. In contrast, strategies that start with smaller measures (like Dr or GA) and can add on bigger projects later avoid that risk of over-commitment. This underscores the classic tension in planning: a strategy like Tun70 is robust but inflexible, whereas a phased approach is flexible but may initially be less robust. Our framework attempts to balance these aspects by evaluating both. however, the early investment in large gray infrastructure will lead to a path-dependency dilemma if the mild scenarios unfold in the future. Considering that Dr and GA have been gradually implemented according to Shanghai Urban Rainwater Drainage Planning (2020–2035) (Shanghai Municipal Water Authority, 2020) and that

combining green and grey options is in line with the direction of sustainable urban development and has been widely adopted domestically. In conclusion, A promising robust adaptive pathway should initially begin with GA and Dr, followed by a combination of D+G. Ultimately as time goes by with gradually undermined drainage capacity, it should incorporate Tun30 with the flexibility to expand to Tun70.

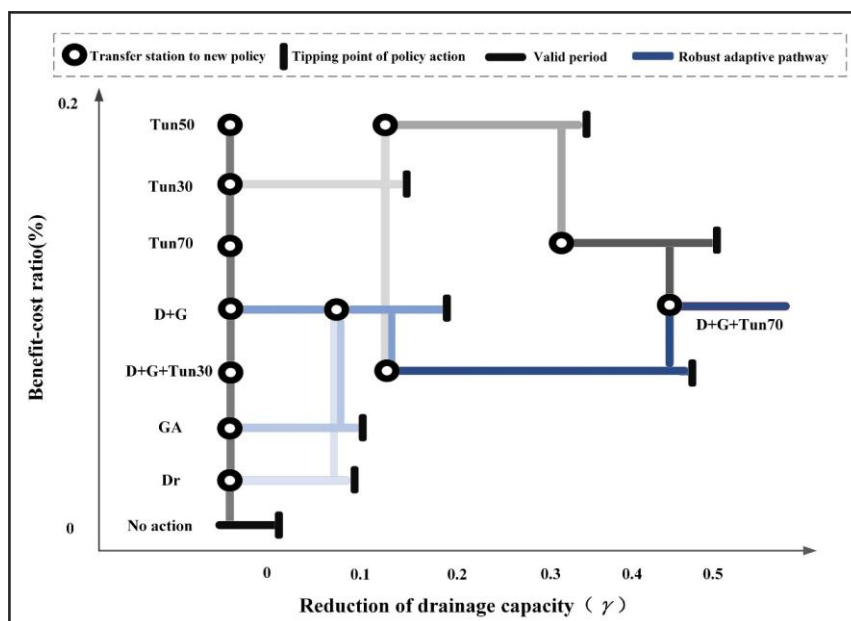


Figure 6-7 Generation of robust adaptive pathways with two potential pathways from either Dr or GA to D+G+Tun30, and from Tun30 to Tun70 as the reduction of drainage capacity over time (x-axis). The options are sequenced in an upward relative higher BCR (y-axis, also see in Table 2).

5 Discussion

5.1 Key findings

Applying this framework to the case of the reoccurrence in the 2050s (of the

extreme rainfall events on 13 September 2013) in Shanghai reveals informative findings to urban planners and other stakeholders. First, the performance of climate adaptation options (for addressing pluvial flood risk) decreases as the drainage capacity reduction rate (γ) increases (Table 3). This result is indirectly supported by events in June 2015 and July 2021, which caused severe inundation in central Shanghai for days because the high water levels of rivers in the region prevented rainwater from being pumped or drained from the drainage system into the river network. This finding also suggests that drainage capacity is a key determining factor for the performance of options in other delta cities which may rely on discharge to the rivers (e.g., Guangzhou, Ho Chi Minh City, London, etc.) (Hu et al., 2019). Urban planners in those cities need to consider scenarios of high-water levels in the river with a joint of extreme storm surge under typhoon takes place in a high astronomical tide period at estuary. Such an event would significantly undermine the drainage capacity thus leading to severe flooding inside the city and bringing potential disastrous impacts (e.g. Zhou et al., 2019).

Second, as the drainage capacity decreases(γ), ~~valid period~~effectiveness periods of different option combinations varied significantly, showing a discrete distribution, which ranged from 0.04~0.5 with a corresponding ARRR ranging from 0.59~0.89 (Table 3). Moreover, the most cost-effective solution may not always offer the longest ~~valid period~~effectiveness period within an explicit flood control target (e.g. 70% risk reduction as a target in our case study), and therefore cannot be considered satisfactory (Figure 45). The findings highlight the importance of the discussion regarding the long-term robustness of solutions which has been overseen in many flood- risk control works

in delta megacities. It is also further implying that if there is no consideration of the flood risk reduction target, discussions about a robust decision plan with stakeholders is meaningless. This urges to pay great attention to be proactive by strengthening the dynamic pathway and closely monitoring the decrease of the drainage capacity ahead of the pace of relative sea level rising (Figure 56).

5.2 Robustness and adaptiveness trade-off

The comparison in Section 5.1 brings up a vital decision-making issue on the trade-offs between the benefit and cost of alternative options. In general, options with better performance required higher costs, which was also proved in any distinctive option in Table 2 and Table S6. It is also demonstrated that the combination of alternative options such as D+G showed a better performance than the single option of Dr and GA at the same cost. However, the cost of an option is not strictly proportional to its benefit (risk reduction rate) (Figure 34). For instance, Tun 50 possesses better performance in reducing inundation risks associated with the relatively low yearly economic cost compared to D+G. Because it is difficult to measure the pros and cons of the costly solution to maintain a higher protection standard and economical solution to possess an acceptable performance (cost-effectiveness), planners typically underestimate both influences by a large margin.

In recognition of this limitation, it can be realized that single-objective targets e.g., flood control performance (ARRR), or financial control (BCR) may lead to biased decisions or maladaptation for the long-term horizon. For example, Table 2 shows that Tun50 has the highest cost-effectiveness (0.16), while the D+G+Tun30 is positioned at

an average level, both of which performed well in reducing flood risk. In sharp contrast, the adaptiveness analysis shows that the D+G+Tun30 behaved significantly better during a reasonable period than Tun 50, which is a more flexible and adaptive option for long-term planning (Figure 67). Therefore, it tends to a biased decision if the decision maker only focus on economic return (BCR). Besides, it illuminates the decision maker that priorities on grey infrastructure (e.g., Tun 50) at the starting point yields good performance (74% of ARRR) but may lead to over-investment and path dependency. Moreover, there is concern that the ~~valid period~~effectiveness period could be ~~shortens~~shortened if decision-makers opt for the most cost-effective solution (Tun50) instead of choosing a more expensive but very effective combination (D+G+Tun30). This example enriches the literature on “no regret” planning, which should be robust, adaptive, and financially efficient at the starting point for decision-makers, keep options open (flexible), and avoid lock-ins. To minimize regret in the near to long future, the adaptation solutions should pay great attention to both robustness and adaptiveness, which also illuminates the importance of multi-objective trade-off as mentioned in previous work (Kirshen et al., 2015; Ramm et al., 2018a).

Furthermore, we directly compare the top contenders Tun70 and D+G+Tun30. Notably, Tun70 actually achieved higher values than D+G+Tun30 on several individual metrics – it provided the greatest average risk reduction and a superior cost-benefit ratio, and it had the longest effectiveness period among single strategies. The multi-component D+G+Tun30 pathway, on the other hand, had a moderate cost-benefit ratio and slightly lower risk reduction, but scored much higher on planned flexibility. This

illustrates a trade-off: if one prioritizes near-term performance and economic efficiency, Tun70 is very attractive; if one prioritizes incorporating flexibility to adapt over time, D+G+Tun30 gains the edge. Our framework's value lies in revealing this trade-off clearly.

5.3 Optimization of the synthesis framework

Although there is a myriad of research running flood risk simulations and assessing the BCR of solutions in Shanghai and other megacities in the coastal areas, seldom of which considers the entire process in making the applicable decision (Du et al., 2020; Sun et al., 2021; Ward et al., 2017). In filling up this niche, this study has proposed a synthesized planning-supporting framework that is capable of considering the entire cascade of procedures from the uncertainties of future urban rainfall pattern, to the sampling of future scenarios, to the hydrological modeling, and to flood risk assessment for the robustness and adaptiveness of alternative options, allowing for making robust and adaptive pathways (refer to Figure 1).

Compared to other DMDU theories, the synthesized framework asks for finding proxies for solutions' performances in reducing risk, decision-making in terms of cost and benefit, and identifying priorities and adaptive pathways from option combinations in the multi-objective fusion process. The conversations established a fast modeling-interpreting-remodeling feedback mechanism between the analyst and decision maker, which helps reduce the complexities and uncertainties encountered in ROA or other related work (e.g. Kind et al., 2018), and defining explicit objective (Raso et al., 2019). Upon that, incorporating the multi-dimensions of constraints allows for rapidly

minimizing disruption factors, balancing alternative solutions' interpretability, coverage, and density, and visualizing the applicable pathway.

One advantage of our decision-support tool is that it can run comprehensive evaluations for thousands of future-option combinations within a few days, using only moderate amounts of input data. This computational efficiency is largely due to our use of a simplified model (SCS-CN) and a relatively small case-study area. However, this highlights a trade-off: using a more detailed 1D-2D model or expanding to a larger region would substantially increase computational time and data requirements. In other words, the 'moderate' resource demand we experienced may not hold in cases that require high-resolution modeling. This limitation suggests that careful model selection (or the use of techniques like emulators and parallel computing) is important when applying the framework to bigger or more complex systems.

~~The advantage of our decision-supporting tool in running comprehensive evaluations for thousand combinations of scenarios within one or a few days and with moderate demand for input data implies its disadvantage in lack of details at the finer grid-cell level, e.g., 10m or even smaller grid cells, or at larger research area. The second limitation is that~~Another limitation is our risk assessment scope: we considered direct flood losses (inundation damage) but did not model disruptions to transportation or other urban functions, nor wider cascading effects across sectors. Similarly, our cost-benefit analysis focused mainly on direct financial costs; we did not fully quantify co-benefits like ecosystem services or social benefits of adaptation options, which means our economic evaluation was somewhat narrow. Additionally, our cost estimates didn't

account for certain practical factors such as human resource efforts (e.g., time and coordination required for implementation) or land availability constraints (for instance, the feasibility of allocating sufficient space for new green infrastructure in Shanghai). These simplifications should be kept in mind when interpreting the results. Future work could explore dynamic adaptation difference of “on-the-fly” upgrades versus planned pathways to provide a more direct assessment of flexibility in the real-world sense. ~~he risk assessment in our work considered only the direct losses caused by inundation while ignoring influences on transportation and other urban functions and the cascading effect across urban sectors. Moreover, when discussing cost-benefit analysis, there is a limitation in fully accounting for the social and environmental benefits. These overlooked aspects lead to a narrow focus on financial costs, while the broader impacts on communities and ecosystems are neglected. Besides, cost should not be limited to financial expenditure alone. Human resources, such as the effort and time required for design and implementation in cross-sector collaboration, are significant components of cost, particularly when implementing nature-based solutions. Additionally, it is important to consider whether Shanghai has sufficient land resources available for the expansion of green spaces, as this is a critical factor in the cost assessment.~~

In addition, further work needs to discuss the determination the weights of multi-objectives when conducting trade-off analysis. The balance between robustness and adaptiveness may vary depending on whether the priority is for immediate, high-impact actions or long-term sustainability. The weight assigned to each factor should reflect the specific goals. Besides, scenario discovery was implemented to find the

combination option rather than an optimization algorithm to search for the best optimal combinations in many alternative options. We demonstrated a case study with a manageable set of options so that solving the optimization problem was outside the scope. Future work may apply ~~machine learning methods, for example~~ evolutionary optimization~~genetic~~ algorithms, to solve complex problems of multi-objective targets if there were hundreds of possible interventions or sequences~~under different robust metrics.~~

6 Conclusion

This work provides a novel decision-making framework for flood mitigation in coastal megacities by synthesizing and building upon established DMDU methods (such as RDM and DAPP). Rather than introducing a new theory, our contribution lies in the innovative combination and application of these methods to address the joint challenges of robustness and adaptiveness in flood risk management. ~~From short to long term planning, managing inundation risk caused by future extreme flooding events is challenged by physical, environmental, social-economic and political uncertainty, etc.~~ This research presents a robust adaptive pathway framework that integrates robustness and adaptiveness to evaluate flood control options. We demonstrated this framework in a case study, evaluating flood management strategies across multiple criteria – including performance, cost-effectiveness, effectiveness period, and flexibility – under many plausible futures. The results showed that traditional evaluation using only short-term effectiveness or cost-efficiency can be insufficient for long-term planning. Integrating the additional metrics of effectiveness period and flexibility provides more

912 nuanced insights, helping to develop adaptive pathways that remain effective as
913 conditions change.~~The new framework was tested to carry out the research on robust~~
914 ~~adaptive pathways regarding the multi-objective that includes solutions' performance,~~
915 ~~cost-effectiveness, valid period, and flexibility under many plausible climate change~~
916 ~~futures.~~

917 ~~The results showed that traditional evaluation criteria, such as effectiveness and~~
918 ~~cost-efficiency, are insufficient for addressing long-term robustness in climate~~
919 ~~adaptation options, as they may result in biased and path-dependent outcomes.~~
920 ~~Therefore, integrating valid period and flexibility metrics will offer more rational~~
921 ~~insights for developing adaptive pathways that can respond to future dynamic changes.~~

922 Our case study also illustrated the trade-offs between robustness and adaptiveness. For
923 instance, a high-robustness single option (Tun70) performed very well in meeting flood
924 control targets and had a strong BCR, but it lacked flexibility to adjust if future
925 conditions turned out less severe than anticipated. On the other hand, a multi-
926 component strategy (D+G+Tun30) achieved a high overall score when both robustness
927 and adaptiveness were considered, due to its balance of risk reduction and planned
928 flexibility. This comparison highlights that the “optimal” strategy can change
929 depending on which criteria decision-makers prioritize. In practice, our robust adaptive
930 pathways approach allows stakeholders to see how emphasizing or de-emphasizing
931 flexibility (or other metrics) would lead to different preferred strategies, thus supporting
932 more informed decision-making.~~Our case study showed that the high robustness option~~
933 ~~(e.g., Tun 50 and Tun 70) performs well under flood control targets and may yield a~~

934 better BCR(Tun50). While it possesses low flexibility if the decreased of drainage
935 capacity(γ) induced by future sea level rising and land subsidence unfold to be not
936 attractive/satisfactory. D+G+Tun30, achieves the highest score of multi-objective trade-
937 off if both robustness and adaptiveness are taken into account in long-term planning
938 under uncertainty.

939 Overall, this work provides a novel framework to inform Shanghai's long-term
940 flood adaptation planning under climate change. Beyond this case, the approach
941 contributes a theoretical foundation and practical insights for other coastal megacities
942 facing similar challenges, helping decision-makers integrate robustness and
943 adaptiveness into their climate adaptation strategies to better cope with deep uncertainty
944 in extreme flood risks. This work can not only provide a scientific framework for
945 Shanghai's adaptation strategic policies planning in coping with extreme weather and
946 climate events under climate change, but also provide both the theoretical foundation
947 of decision-making methods and best practices to support the decision-making process
948 for other coastal megacities to adapt to the changing climate and mitigate the extreme
949 pluvial flood risk.

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Code/Data availability

Case study region data in Shanghai can be found via Shanghai Statistic Yearbook, Shanghai Flood Control and Drainage Plan (2020-2035). Figures are made in ArcGIS Pro 3.0 and Microsoft Excel. Models in this paper are mainly coding in Rust environment. All the data and software will be opened to the research community upon acceptance of publication. Data sample can be found via open-accessed figShare via following URL:

Hu, Hengzhi (2023). Robust Adaptive Pathway for Long-term Flood Control Planning: Urban Delta in Coping with Pluvial Flood Risk under Future Deep Uncertainty. Multi-criteria trade-off.xlsx. figshare. Dataset. <https://doi.org/10.6084/m9.figshare.24899340.v1>

Author contribution

Hengzhi Hu conceived the study, designed the framework, collected the data and led the analysis of the result and responsible for writing the manuscript and ensuring its intellectual content. Qian Ke contributed to the design and implementation of the decision-making framework, and conduct the manuscript writing and revising. Wei Wu supported the climate projection of the case study area of Shanghai and identified the scenario uncertainties. Min Zhang validated the simulation result of pluvial flood and funding support. [Yanjuan Wu assessed the pluvial flood risk in plausible futures.](#) [Chengming Jin manipulated the boundary condition data of flood simulation in study region.](#) Jiahong Wen supervised the project and provided expertise in flood risk management, and assisted in finalizing the manuscript.

Competing interests

The authors declare that they have no competing interests.

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