Policy Research Working Paper 6465

Ensuring Robust Flood Risk Management in Ho Chi Minh City

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Office of the Chief Economist
May 2013

Abstract

Ho Chi Minh City faces significant and growing flood risk. Recent risk reduction efforts may be insufficient as climate and socio-economic conditions diverge from projections made when those efforts were initially planned. This study demonstrates how robust decision making can help Ho Chi Minh City develop integrated flood risk management strategies in the face of such deep uncertainty. Robust decision making is an iterative, quantitative, decision support methodology designed to help policy makers identify strategies that are robust, that is, satisfying decision makers' objectives in many plausible futures, rather than being optimal in any single estimate of the future. This project used robust decision making to analyze flood risk management in Ho Chi Minh City's Nhieu Loc-Thi Nghe canal catchment area. It found that the soon-to-be-completed infrastructure may reduce risk in best estimates of future conditions, but it may not keep risk low in many other plausible futures. Thus, the infrastructure may not be sufficiently robust. The analysis further suggests that adaptation and retreat measures, particularly when used adaptively, can play an important role in reducing this risk. The study examines the conditions under which robust decision making concepts and full robust decision making analyses may prove useful in developing countries. It finds that planning efforts in developing countries should at minimum use models and data to evaluate their decisions under a wide range of conditions. Full robust decision making analyses can also augment existing planning efforts in numerous ways.

This paper is a product of the Office of the Chief Economist, Sustainable Development Network, and part of the Green Growth Knowledge Platform's (GGKP's) affiliated program on Data and Decision-Making Tools for Green Growth. The GGKP (www.greengrowthknowledge.org) is a joint initiative of the Global Green Growth Institute, Organisation for Economic Co-operation and Development, United Nations Environment Programme, and the World Bank. Publication of this paper is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted via alotsch@worldbank.org.

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Keywords: decision-making under uncertainty, long-lived infrastructure investments, climate change, flood risk management, adaptation

JEL: C44, D81, H54, O21, Q54

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The authors thank Ho Long Phi at the Steering Center for Flood Control in Ho Chi Minh City for his support; the many stakeholders from government, NGOs, and universities in Vietnam for valuable guidance; Jordan Fischbach, Debra Knopman, Keith Crane, Amber Jaycocks, David Groves, and Henry Willis from RAND for advice on model development, project organization, and workshop preparation; Maartje Wise - Hoevenaars at Royal Haskoning for linking our project with her firm's flood risk management studies; Marianne Fay, Stephane Hallegatte, Dzung Nguyen, Jennifer Sara, Madhu Ragunathan and Abhas Jha from the World Bank the for their support and guidance; Alice Thauvin for collaboration with SCE's Ho Chi Minh City office; Vu Canh Toan and Nguyen Quynh Anh from the National Institute for Science and Technology Policy and Strategy Studies, Ngo Cong Chinh, Tran Tuan Anh from the Asian Management and Development Institute, and To Quang Toan from the Southern Institute of Water Resource Research; and the peer-reviewers -- Richard Damania, Jordan Schwartz Marcelino Madrigal, Lauren N. Sorkin, Huyen Le, and Igor Linkov -- for constructive comments. This work was sponsored by the World Bank's Chief Economist for Sustainable Development, Marianne Fay, and co-funded by Korea's Global Green Growth Institute and the Global Facility for Disaster Reduction and Recovery.

1. Introduction

Ho Chi Minh City, a low-lying and fast-growing metropolis of 7.4 million people, faces significant and growing flood risk. Periods of intense rainfall regularly inundate the city, as does riverine flooding from the Saigon River and neighboring Mekong Delta. Climate change may worsen these risks. Ho Chi Minh City ranks fourth globally among coastal cities most threatened by climate change (Nicholls *et al.* 2008), which may increase the frequency of intense rainfall and swollen rivers. Rising sea levels combined with land subsidence compound the threat. The city's growing role in Vietnam and Southeast Asia's economies, as well as an expanding population with many poor people, further increases the social, economic, and environmental risks of future flooding.

Over the last fifteen years, Ho Chi Minh City has developed plans for and begun to implement numerous infrastructure projects designed to reduce its flood risk. These multi-billion dollar investments include 6000 km of canals and pipes to increase the discharge capacity of the storm water system and 172 km of dikes and river barriers for tidal control, based on a plan developed by the Japan International Cooperation Agency (JICA) (PCI 1999). These plans were made using best estimate projections available at the time of future climate, socioeconomic, and other conditions.

Over the last decade, however, conditions have diverged from those projections. The frequency of extreme rainfall events with more than 100 mm in precipitation has increased by a factor of three, significantly greater than predicted when the infrastructure was planned. Similarly, the past decades have seen unexpected urbanization in low-lying areas, which has increased exposure beyond previous planning assumptions.

There is little reason to believe any prediction made today will prove more accurate than those of the past. Climate change appears likely to affect the frequency of extreme events over the coming decades, but in ways climate scientists currently have difficulty predicting with high confidence (IPCC 2012). Future socioeconomic conditions may be equally surprising. Cities in emerging economies such as Vietnam are growing at rates unprecedented in human history, so are virtually certain to defy accurate predictions. The most effective flood risk management strategies will depend on how trends such as these unfold, as well as how the city's future infrastructure is built and maintained and how successfully residents adapt their behavior in the face of flood risk. Yet such patterns have been and will likely remain difficult to project with confidence.

Decision makers concerned with flood risk in Ho Chi Minh City must thus plan in the face of a difficult-to-predict future. This study demonstrates how an approach to uncertainty management called robust decision making (RDM) (Lempert *et al.* 2007; Lempert *et al.* 2011; Ministry of Planning and Investment 2011) can help Ho Chi Minh City address this challenge. RDM is an iterative, quantitative, decision support methodology that helps policy makers identify strategies that are robust, satisfying decision makers' objectives in many plausible futures, rather than optimal in any single best estimate of the future.

Traditional analyses begin by asking an often unanswerable question: "What will the future bring?" In contrast, RDM asks, "What are the strengths and limitations of our plans, and what can we do to improve them?" RDM runs models hundreds or thousands of times to estimate the performance of proposed plans over many combinations of uncertainties. Statistical analyses and visualization of the resulting database of model runs helps identify the type of futures where proposed plans perform well and poorly, and helps facilitate discussions on how to make plans more robust. RDM is not a new model. Rather, it is a better way of using existing data and models that helps decision makers plan for the future without first predicting it.

Ho Chi Minh City's Steering Center for Flood Control is currently pursuing an innovative flood risk management strategy that combines infrastructure investments with adaptation, land use, and other policies. This includes what Steering Center for Flood Control terms *adaptation*, e.g. building codes requiring that buildings are elevated to make them less susceptible to flooding and ensuring more porous urban surfaces that allow flood waters to recharge aquifers rather than contribute to runoff. An integrated strategy may also include what Steering Center for Flood Control terms *retreat*, such as concentrating housing and businesses on higher ground while using lower lying lands for interruptible uses like recreation, thereby reducing the impact of flooding on lives and economic activity.[1] Among its benefits, an integrated strategy offers more flexibility and responsiveness in the face of uncertainty. But developing such a strategy remains difficult with traditional planning approaches that seek to develop plans based on best estimate projections of the future.

Figure 1.1 Vietnam with Ho Chi Minh City highlighted (left) and Ho Chi Minh City with the Nhieu Loc-Thi Nghe catchment highlighted (right) .

This paper describes a demonstration RDM analysis of flood risk management in Ho Chi Minh City. The demonstration aimed to help Ho Chi Minh City improve the robustness of its plans, as well as help decision makers more broadly understand the principles of RDM, when it should be used, and the value it adds to a decision making

[1] Note that these additional policies are given many different names, including "non-structural" to contrast with "structural." This analysis adopts the terminology used by Steering Center for Flood Control, which refers to three types of policies: infrastructure, adaptation, and retreat.

process. In particular, this paper presents a RDM analysis of flood risk management in the Nhieu Loc-Thi Nghe canal catchment area in Ho Chi Minh City, shown in Figure 1.1. This area faces high flood risk and has received significant investments in flood risk management.

The original infrastructure planning for Nhieu Loc-Thi Nghe catchment did not include a full uncertainty analysis. As mentioned, in the years since, actual climate and socioeconomic conditions have changed significantly from what was projected at the time. Building on Steering Center for Flood Control's existing models and data, this study re-conducts the previous analysis, this time using an RDM framework to help manage uncertainty and help develop a robust, integrated plan. This choice of study design was motivated by two considerations. First, this study aims to demonstrate how the Steering Center for Flood Control and a wide range of other organizations can use RDM to augment their existing planning activities to improve their ability manage uncertainty. Thus, it was important to build this study on models and data that the Steering Center for Flood Control had previously used. Second, Steering Center for Flood Control is in the process of developing a more comprehensive integrated flood risk management strategy, using a new flood risk modeling system developed by the firms Royal Haskoning and Deltares. The plan resulting from this process will address flood risk over the entire city and is likely to be considerably more robust to future uncertainty than the infrastructure investments considered here. Nonetheless, the process used to develop this new plan does not yet take account the full range of plausible climatic and socio-economic futures facing Ho Chi Minh City and could benefit, as a next step, from the type of stress-testing described in this report.

The RDM analysis in this study found that the soon-to-be-completed infrastructure may reduce risk in best-estimate future conditions. However, the infrastructure may not be sufficiently robust over the full range of futures, that is, it may fail to reduce risk below current levels under many plausible future conditions. The analysis also suggests that adaptation and retreat measures, particularly when used adaptively, can play an important role in managing risk. In particular:

- The soon-to-be-completed infrastructure in Ho Chi Minh City's Nhieu Loc-Thi Nghe catchment will reduce risk compared to current levels if three-hour rainfall event intensities increase by no more than approximately 6% and if the Saigon River rises less than 45 cm. However, scientific evidence suggests both these thresholds may be exceeded by mid-century, in which case risk may rise above current levels even with this infrastructure in place.
- Augmenting this infrastructure with a full range of adaptation and retreat measures would ensure risk reduction for rainfall intensity increases up to approximately 35% and Saigon River level increases up to 100 cm. Little scientific evidence exists to suggest these levels would both be exceeded by mid-century. Additionally, uncertainties about trends in population and vulnerability appear less important that these climatic uncertainties in determining whether risk will rise above current levels.

- An adaptive plan, which adds some adaptation and retreat measures now and adds more in the future if needed, is almost as robust as a plan to undertake all measures now, but with potentially lower cost.

This project thus demonstrates how RDM can help Ho Chi Minh City decision makers develop flood risk management strategies that will prove successful over a wide range of unexpected and potentially surprising futures, and help facilitate the broad stakeholder interactions needed to build consensus for such strategies.

More broadly, this study addresses key questions regarding the applicability of RDM in developing countries: Can it provide significant value-added; what data, computational, and other technical challenges does it pose; and what local capacity is required? Our results suggests that RDM can provide significant value, by enabling decision makers to understanding and facilitate discussion regarding the combination of climatic and socio-economic conditions where risk management plans may fail to meet their goals and to use this information to craft more robust plans. Often these plans will be adaptive, that is, designed to evolve over time in response to new information. RDM contribute to a wide range of planning challenges, from stress-testing existing plans, to infrastructure design, to compare broad risk management options.

RDM does pose added computational and practical challenges, relative to traditional risk management approaches. However, these can be overcome, some of them readily. Moreover, RDM may address some of the difficulties of applying traditional approaches, as it is forgiving of the data and model gaps that loom large in many decision challenges.

The most significant challenge RDM poses is a conceptual one: RDM is a new way of thinking. Rather than ask, "What will happen?" RDM allows analysts and decision makers to ask, "What should we do today to most effectively manage the full range of events that might happen?" Using RDM requires training for analysts, and a path by which organizations become comfortable using new and more effective types of quantitative information. Past applications in developed countries (Groves 2005; Groves *et al.* 2008; Bureau of Reclamation 2012) suggest how developing countries can address such challenges.

Section 2 describes the RDM approach and Section 3 describes how it was used to engage with stakeholders in Ho Chi Minh City. Section 4 presents the data and models used, and Section 5 presents the results. The final section summarizes key findings. In addition, Appendix A accompanies Section 4, providing details on models and data, and Appendix B accompanies Section 5, with detailed discussion of methods and results from our analysis.

2. Robust Decision Making

RDM is an iterative, quantitative, decision support methodology designed to address the challenges of planning amid uncertainty about the future. The approach has been applied with increasing frequency to flood risk (Fischbach 2010) and water management applications (Groves *et al.* 2007; Groves *et al.* 2008; Means *et al.* 2010) in situations where decision makers face conditions deep uncertainty (Hallegatte *et al.* 2012). Deep uncertainty occurs when the parties to a decision do not know—or do not agree on—the best model for relating actions to consequences or the likelihood of future events (Lempert *et al.* 2003).

RDM rests on a simple concept. Rather than using models and data to describe a best-estimate future, RDM runs models over hundreds to thousands of different sets of assumptions to describe how plans perform in many plausible futures. The approach then uses statistics and visualizations on the resulting large database of model runs to help decision makers identify those future conditions where their plans will perform well and poorly. This information can help decision makers develop plans more robust to a wide range of future conditions.

This simple concept contains two particularly important ideas. First, quantitative risk and decision analysis typically uses a **predict-then-act** approach. Analysts assemble available evidence into best-estimate predictions of the future and then use models and tools to suggest the best strategy given these predictions. These methods, which include probabilistic risk analysis, work well when the predictions are accurate and non-controversial. Otherwise, the methods can produce gridlock and lead to solutions that fail when the future turns out differently than expected.

In contrast, RDM runs the analysis "backwards," using a **vulnerability-and-response** approach. Analysts begin with one or more strategies under consideration (often a current plan) and then, using potentially the same models and tools, characterize the future conditions where a strategy fails to meet its goals (is vulnerable). This serves as a stress test of strategies and helps decision makers identify "robust" strategies – those that perform reasonably well regardless of what the future brings -- and identify the key tradeoffs among potential robust strategies. Often, the robust strategies identified by RDM are adaptive,[2] designed to evolve over time in response to new information (Lempert *et al.* 2010).

Second, traditional risk and decision analysis condenses information about a range of potential futures into a single probabilistic prediction, i.e. the best estimate future. But RDM assembles the results of many hundreds, thousands, or even millions of computer simulation model runs and uses this database of runs to comprehensively explore and summarize the challenges and opportunities the future might bring. By embracing many plausible futures, RDM can help reduce overconfidence and the deleterious impacts of surprise, can systematically include imprecise information in the analysis, and can help

[2] Applied to strategies, the word "adaptive" denotes a plan explicitly designed to evolve over time in response to new information. This contrasts to the word "adaptation," which denotes a process of adjusting over time to changing conditions, such as due to economic development or climate change.

decision makers and stakeholders with differing expectations about the future nonetheless reach consensus on action (Lempert *et al.* 2005; Groves *et al.* 2007; Hallegatte *et al.* 2012).

RDM Includes an Iterative Process of Stakeholder Engagement

To implement the above concepts, RDM uses sophisticated analytic tools embedded in an explicit process of participatory stakeholder engagement (Lempert *et al.* 2006; Lempert *et al.* 2007). As shown in Figure 2.1, RDM follows an interactive series of steps consistent with the "deliberation with analysis" decision support process recommended by the U.S. National Research Council (2009). Deliberation with analysis begins with the participants to a decision working together to define the policy questions and develop the scope of the analysis to be performed. Subsequent steps involve expert data collection, modeling, and analysis, along with deliberations based on this information in which choices and objectives are revisited.

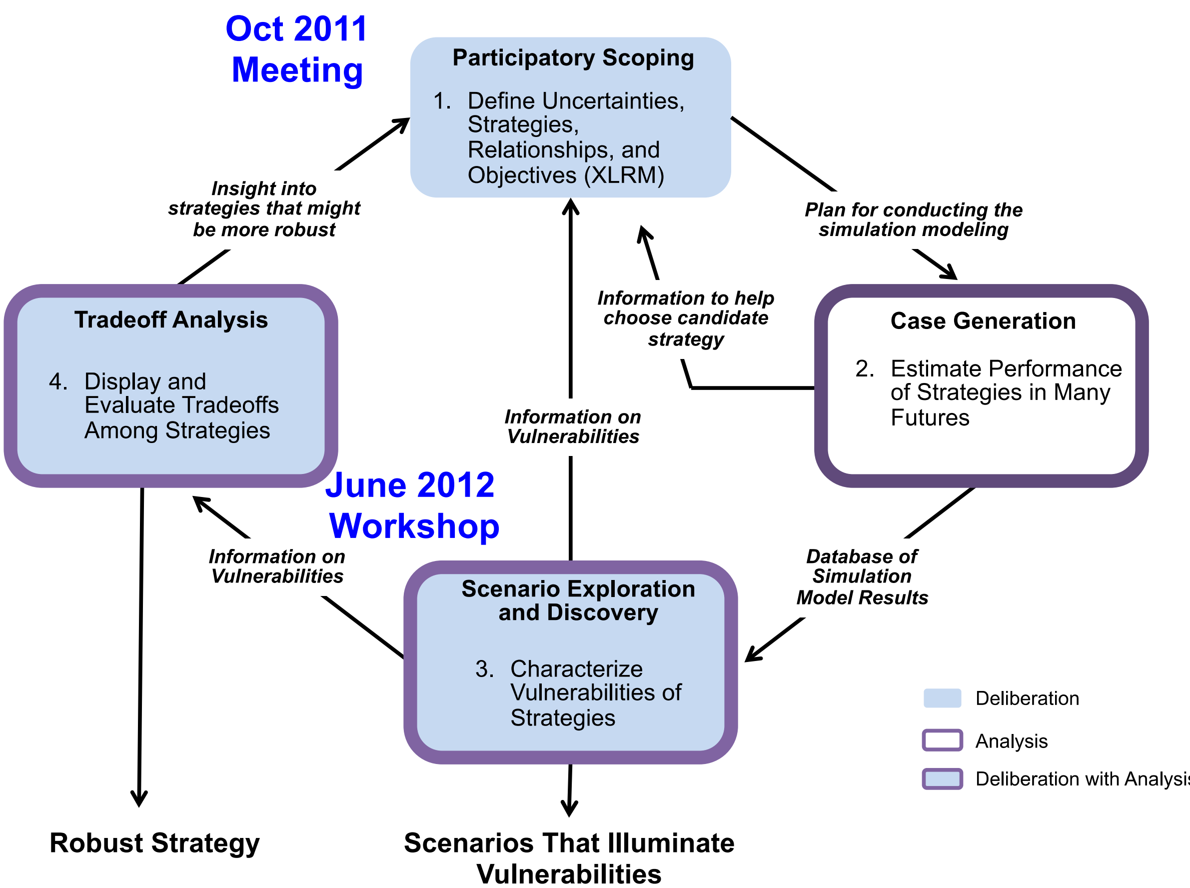

Figure 2.1: Iterative steps of a Robust Decision Making (RDM) Analysis. This project's stakeholder workshops contributed directly to Steps 1, 3, and 4.

The RDM process begins at the top of Figure 2.1 with a participatory scoping activity in which stakeholders and decision makers define the objectives and metrics of the decision problem, strategies that could be used to meet these objectives, the uncertainties that could affect the success of these strategies, and the relationships that govern how strategies would perform with respect to the metrics (Step 1). This scoping activity often uses a framework called "XLRM," described in Section 4 to organize the simulation modeling.

In Step 2, analysts use the simulation model to evaluate the strategy or strategies in each of many plausible futures. This generates a large database of simulation model results. In Step 3 analysts and decision makers use visualizations and "scenario discovery" (Bryant *et al.* 2010) (also described in Appendix B) to explore the data and identify the key combinations of future conditions in each candidate strategy might not meet decision makers' objectives. [3] For example, a flood risk management strategy involving dikes may fail to reduce risk if sea level rise proves higher than expected and rapid development results in a larger than forecast population living behind the dikes. This scenario (i.e. "high sea level rise and rapid development") concisely captures the vulnerabilities of the flood risk management strategy.

Having identified a scenario in which a strategy fails to meet its goals, decision makers can turn to scientific and other evidence to consider whether the scenario is sufficiently likely as to warrant modifications to the strategy. Decision makers may conclude, for example, that the threat of unexpectedly high sea level rise is sufficiently high to warrant modifying the dike plan or augmenting it with other policies.

These scenarios also provide the foundation for developing, evaluating, and comparing potential modifications to the alternative strategies that might reduce these vulnerabilities (Step 4). Knowing that dikes may fail to reduce risk in a future with high sea level rise and extensive urban development, decision makers might explore modifying the current plan to increase dike height or, alternatively, augment the original dike design with policies to shift development away from the dikes. Scenario discovery on each of these two alternatives would reveal the conditions to which each is vulnerable. The analysis might reveal that increasing the dike height cannot prevent overtop in all plausible cases of sea level rise, but that shifting development can reduce exposure sufficiently to mitigate risk to plausible sea level rise.

Based on a tradeoff analysis, decision makers may decide on a robust strategy. Or, they may decide that none of the alternative strategies under consideration proves sufficiently robust and return to the scoping exercise, this time with deeper insight into the strengths and weaknesses of the strategies initially considered.[4]

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[3] Specialized software tools are available to help analysts implement these steps. A package called CARs (Computer Assisted Reasoning) helps implement and organize thousands of simulation models runs, a scenario discovery toolkit to conduct the scenario discovery analysis (http://cran.r-project.org/web/packages/sdtoolkit/index.html), and a commercial package called Tableau helps visualize results in the database (http://www.tableausoftware.com).

[4] There are also other paths through the RDM process. Information in the database of model results might help identify the initial candidate strategy or information about the vulnerabilities of the candidate strategy may lead directly to another scoping exercise to revisit objectives, uncertainties, or strategies.

When to Use RDM

RDM is one of several alternative approaches for informing flood risk management decisions. As discussed in Section 6, RDM can pose implementation challenges because it requires more model runs than alternative approaches and, as a new approach, may require analysts to learn new skills and organizations to think in new ways. Thus, it is important to consider the types of situations where RDM adds significant value.

As shown in Figure 2.2, RDM often proves most useful when decision maker face deep uncertainty and complex situations that require computer modeling to evaluate alternative decision options and their consequences. First, decision makers should consider whether their decision challenge involves deep uncertainties. If it does not, then decision makers can usefully turn to methods such as probabilistic risk analysis that seek to predict or accurately characterize conditions and then solve decision problems.

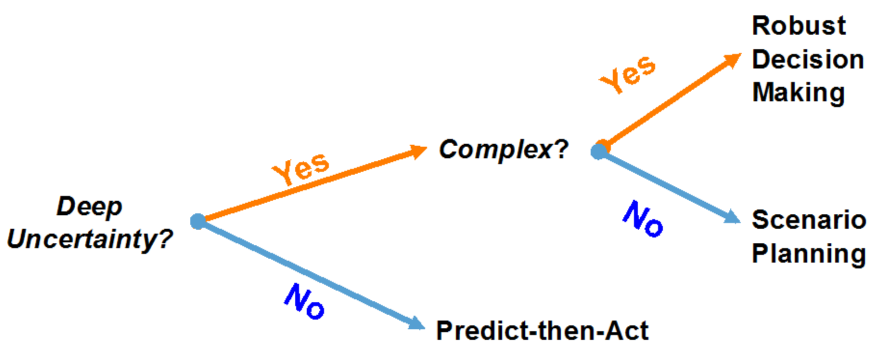

Figure 2.2: Factors determining situations where RDM proves useful

If uncertainties are deep, decision makers should consider the extent to which the challenges they face are complex, by which we mean they tend to require computer modeling to understand the implications of a full range of plausible futures and the consequences of alternative choices. Traditional scenario planning can often prove very effective in situations where experts have a good intuitive grasp of the most important futures and of the consequences of alternative decisions, i.e. decision challenges that are less complex. In a typical scenario planning exercise, analysts might develop two scenarios that describe different future climate conditions: in one scenario, the frequency of major storm events remains similar to that in the historical record and, in the other, storm frequency increases say by 30 percent. Such scenarios can prove highly effective at helping groups appreciate new planning challenges and think about potential responses in situations when insufficient data and scientific understanding exists to develop reliable probabilistic estimates. But they can be less effective when the choice of scenarios is not obvious or is controversial (Parson *et al.* 2007; Parson 2008) and when it is difficult to summarize the full range of relevant futures with a small number of scenarios (Lempert *et al.* 2005; Lempert 2007). It is also not always clear how to use a small number of non-probabilistic scenarios to choose between many complex risk reduction strategies.

RDM represents one example of a new class of decision making approaches labeled in the literature with names such as "context-first" (Ranger *et al.* 2010), "decision scaling"

(Brown 2011),"assess risk of policy" (Lempert *et al.* 2004; Carter *et al.* 2007; Dessai *et al.* 2007), and "vulnerability and robust response. An emerging literature has begun to assess strengths and weaknesses of these approaches -- see, for instance Hall et al. (2012) and Hallegatte et al. (2012). In the future, this literature will help decision makers better determine which robustness analysis to use when faced with deeply uncertain and complex decision challenges. This report uses RDM because it offers a set of analytic tools (such as scenario discovery) that work easily with an agency's existing planning models and a participatory process that we have found particularly useful.[5] Nonetheless, all these new approaches share the central idea of beginning with a proposed policy or policies, running models over many cases to identify vulnerabilities of policy (policies), and using this information to identify and evaluate potential robust policy responses that address those vulnerabilities. This reports key conclusions rest on these central ideas.

Overall, decision makers should use RDM and related approaches if their decision challenge involves deep uncertainties and complex interactions among problem components. These conditions certainly seem to hold for the integrated flood risk management challenge facing Ho Chi Minh City as well as for many other decision challenges throughout the developing world.[6]

3. Workshops and Other Stakeholder Engagement

Stakeholder engagement played an important role in this project. We organized two workshops and ongoing discussions with Steering Center for Flood Control according to the RDM "deliberation with analysis" process. As shown in Figure 2.1, these engagements were facilitated with outputs from the RDM analysis.

A meeting at Steering Center for Flood Control's office in Ho Chi Minh City on October 3, 2011 launched the participatory scoping phase of our analysis (Step 1 in Fig 2.1) and focused on the XLRM factors discussed in Section 4. This collaborative scoping activity continued for approximately two months, resulting in a project memorandum delivered to the client at the end of November 2011. [7] In addition to defining the analytical problem, this scoping step builds a common understanding of the problem and relationships between stakeholders and analysts. The value of this step cannot be overstated, particularly in analyses involving participants who are geographically dispersed, speak different native languages, and bring different skills to the effort.

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5 Analytic tools, such as robust optimization and robust control, also employ a robustness criterion (Chandrasekharan 1996; Hansen *et al.* 2008). Such tools do not emphasize the identification of vulnerabilities and are not designed around a participatory decision support process. They can, however, prove very useful in identifying new strategies in Step 4 of an RDM analysis.

6 It is also important to relate approaches, such as RDM, that emphasize robust decisions to the large literature on resilience (Berkes 2007; Park *et al.* 2012). While differing interpretations exist of the words robustness and resilience, we follow the view expressed by the IPCC (2010, p. 48) that the two are related concepts, with resilience generally taking a system-focused view and robustness taking a decision-focused view. Thus an observer outside Ho Chi Minh City might ask whether the city is resilient in the face of flood risk, but a decision-maker within the city might ask whether the particular policies they can pursue as part of this system are robust in the face of this risk.

7 Please contact the authors for a copy of this project memorandum.

On June 7-8, 2012, we conducted a second workshop in Ho Chi Minh City focused on the Scenario Discovery and Tradeoff Analyses steps in our analyses (Steps 3 and 4 in Fig 2.1) which are discussed in Section 5. Sponsored by Steering Center for Flood Control, the workshop assembled about thirty technical specialists, decision makers, academics, and representatives of donor agencies. The workshop was highly participatory, using modeling results to facilitate discussions of potential vulnerabilities of the city's baseline flood risk management strategies and potential robust responses. Our project team included Vietnamese partners with significant experience facilitating more traditional scenario exercises as part of the Rockefeller Foundation Asian Cities Climate Change Resilience Network.

The project team had other interactions with Steering Center for Flood Control. In the period leading up to the June workshop, the project team engaged in extensive phone discussions with Steering Center for Flood Control to review the model and initial analytic results. In the months after the June meeting, the project team made significant revisions to the analysis in response to suggestions made at the workshop.

4. Models and Data Used in the Ho Chi Minh City Analysis

One important goal of this project was to inform judgments about the types of models and data needed for RDM analyses in developing countries. Like many RDM exercises, this project employed an "XLRM" framework (Lempert *et al.* 2003) to help guide the model development and data gathering. In addition, the RDM analysis' participatory scoping (and re-scoping) steps in the October 2011 and June 2012 workshops relied heavily on this framework. XLRM proves useful because it helps organize relevant factors into the components of a decision-centric analysis. We expect that any future RDM exercises in Vietnam would also use this approach.

The letters X, L, R, and M refer to four categories of factors important to an RDM analysis:

- **Policy levers (L)** are near-term actions that decision makers want to consider, in this case as part of their integrated flood risk management strategy, e.g. investments in tide gates and pumps that could reduce flooding, and implementation of land use policies that could reduce exposure to any flooding that does occur;
- **Exogenous uncertainties (X)** are factors like climate change that are outside the control of decision makers but that may affect the ability of near-term actions to achieve decision makers' goals;
- **Metrics (M)** are the performance standards used to evaluate whether or not a choice of policy levers achieves decision makers' goals, e.g. risk to various segments of the population or to the economy; and
- **Relationships (R)**, generally represented by simulation models, describe how the policy levers perform, as measured by the metrics, under the various uncertainties.

In essence, RDM compares the performance of alternative combinations of policy levers, as evaluated by the metrics, over a wide range of uncertain futures using the relationships or models.

This section is organized around this XLRM framework, as summarized in Table 4.1.[8] Appendix A provides additional details. This section first describes the simulation models, the relationships (R), used in this project. The section then describes the specific risk metrics (M) used to judge the effectiveness of alternative flood risk management strategies, the exogenous uncertain factors (X) that might affect the performance of these strategies, and the policy levers (L) the comprise the specific flood risk management strategies considered in this study.

Table 4.1. XLRM Key Elements Considered in this analysis

Exogenous Uncertainties (X)	**Policy Levers (L)**

• Hazard-related uncertainties
  o Rainfall intensity increase
  o Relative Saigon River height
• Exposure-related uncertainties
  o Population
  o Geographic population distribution
  o Poverty rate
  o Average annual economic growth
  o Economic wealth distribution
• Vulnerability-related uncertainties
  o Population vulnerability
  o Economic vulnerability
	• Baseline infrastructure
	• Baseline infrastructure augmented statically and adaptively with
	  o Exposure-reducing options
	    ▪ Groundwater recharge
	    ▪ Rainwater capture
	    ▪ Relocating vulnerable areas
	  o Vulnerability-reducing options
	    ▪ Elevating buildings

Relationships and Models (R)	**Metrics (M)**
• SWMM model • ArcGIS model • Integrated Analytica risk model	• Risk to poor • Risk to non-poor • Economic risk

Relationships and Models (R)

As noted in Section 1, RDM is not a model, but rather a method for improving quantitative uncertainty analysis and management. To demonstrate how RDM can augment uncertainty management using existing models and data, this project employed a storm water management model (SWMM) previously used by Ho Chi Minh City to

[8] We conducted two analyses during the course of the study. The first used models, metrics, and uncertainties based on our October 2011 workshop and subsequent discussions with Steering Center for Flood Control. We presented that model and its results at the June 2012 workshop. Consistent with the RDM process, we refined our model and metrics and conducted another iteration of our analysis based on discussions at the workshop. This paper describes this second analysis and the results based on it.

help design the flood control infrastructure currently being deployed in the city. This SWMM model simulates the inundation in the Nhieu Loc-Thi Nghe area from of a rainfall event and the height of the Saigon River. The model considers such flooding with and without the drainage infrastructure that has recently been built based on the 1999 JICA master plan.

One could conduct an RDM analysis solely using this SWMM model, focusing on questions of flooding.[9] However, Steering Center for Flood Control and the other workshop participants were interested in a broader set of questions, in particular: measures of risk, the consequences of different assumptions about future socio-economic trends, and the effectiveness of integrated risk management strategies that include with adaptation and retreat policies along with infrastructure. To address such questions, it is useful to expresses risk as the product of hazard, exposure, and vulnerability. The recent Intergovernmental Panel on Climate Change (IPCC) report (IPCC 2012) on managing the risk of extreme events defines *hazard* as the potential occurrence of a physical event that may cause injury, damage, or loss; *exposure* as the presence of people and things they care about in places that could be adversely affected; and *vulnerability* as the predisposition of a person or group to be adversely affected. For instance, the hazard term for Ho Chi Minh City might include the likelihood that a storm of a certain sizes occurs during a certain time period. The exposure term might represent the number of people live in the path of the storm. The vulnerability term might describe the number of people exposed to a storm that would suffer harm.

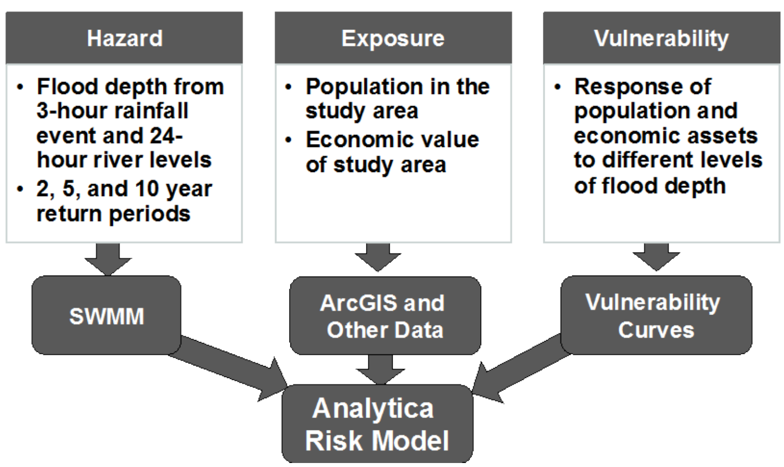

Figure 4.1. Schematic of the model components used to model

To address hazard, exposure, and vulnerability in the Nhieu Loc-Thi Nghe catchment, this study required additions to the SWMM model. In particular, the project used the Steering Center for Flood Control's geographic information system (GIS) data and statistics in the literature on the distribution of population, buildings, and economic

[9] For instance, such an analysis might identify the climate conditions for which the new Ho Chi Minh City infrastructure could and could not hold flooding below certain threshold levels. An RDM analysis might also use this SWMM model (with modifications not included in this study) to compare the future climate conditions under which alternative infrastructure investments might hold flooding below such threshold levels.

activity in Ho Chi Minh City to estimate ranges of future exposure. The project used simple depth-damage curves to estimate future vulnerability. As shown in Figure 4.1, we linked these components using a simple model built in the Analytica modeling environment.[10] This Analytica model also allowed comparison of the impacts of alternative adaptation and retreat measures as part of alternative integrated flood risk management strategies.

Measures of Risk (M)

Based on our workshops and discussions with Steering Center for Flood Control, this project employed three measures of risk to compare the potential consequences of alternative flood risk management strategies in our study area. Two measures focus on population risk and one on economic risk. These are:

1. Risk to the poor, measured as the expected number of people affected annually by flooding;
2. Risk to the non-poor, measured as the expected number of people affected annually by flooding; and
3. Risk to economic value, measured in percent GDP lost annually to flooding.

The analysis employs two measures of population risk because equity issues are important to Steering Center for Flood Control. The population risk measures distinguish between a cohort called "poor" and those of higher income in the Nhieu Loc-Thi Nghe catchment identified as "non-poor." Many definitions exist for "low-income" and the literature lacks any consensus about the distinction between the poor and non-poor even in the present. In this future this distinction becomes even less certain. As discussed in the uncertainty discussion below, this project treats the number of poor and non-poor in Ho Chi Minh City as fundamentally uncertain, drawing upon a range of data on poverty rates from the Vietnamese government and other sources to inform the range of possible future poverty rates.[11] Figure 4.2 shows risk to the poor population in what is described below as benchmark conditions.

The project employs a single measure of economic risk because the available data did not support any useful disaggregation. Note that we measure economic risk as a fraction of GDP rather than in absolute terms because Ho Chi Minh City's economic exposure and risk will almost certainly grow as Vietnam's economy expands. Thus, a more meaningful metric is whether or not risk grows faster or slower than the economy (Hallegatte 2012). In addition, this measure facilitates comparison of policies over many cases that vary in their assumptions about future economic growth rates.

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[10] Analytica, a visual modeling platform for quantitative risk and uncertainty analysis, allows analysts create influence diagrams that define how factors in analysis relate to each other and to quickly add or modify elements of the model during the course of the analysis and in response to input from stakeholders. Analytica is well suited for RDM because it can be easily configured to run many cases and save those cases to a database. See www.lumina.com.

[11] Steering Center for Flood Control was particularly interested in comparing risk to the poor and non-poor, and sufficient data were available to explore this formulation. However, one could also usefully segment the population along other dimensions, such as geography, age, and gender.

Figure 4.2. Risk to the poor for benchmark conditions.

Note: Benchmark conditions reflect risk based on recent climate and socio-economic data and without the recently constructed infrastructure based on the 1999 JICA master plan.

As discussed in Section 5, it proves useful to evaluate policies by focusing on *differences* in risk, rather than any absolute level. In particular, we ask whether the flood risk for a particular risk management strategy in some specific set of future climatic and socio-economic conditions is greater or smaller than the recent flood risk in the city. The recent flood risk is calculated using current climate and socio-economic data and the SWMM model without the new infrastructure based on the JICA 1999 Master Plan. We call this recent flood risk the *Benchmark* conditions. One could certainly consider other ways to calculate differences in risk. For instance, many RDM analyses compare the performance of a strategy in a set of future conditions to the performance of the best-performing strategy in those conditions -- see for instance Lempert & Collins (2007) and Lempert & Light (2009).[12] However, this project used recent risk as its benchmark conditions for two reasons. First, Steering Center for Flood Control and workshop participants requested it. Second, Ho Chi Minh City decision makers have experience with current levels of flood risk in their city and while future flood risk management strategies are expected to reduce risk future climatic and socio-economic trends are expected to increase it. Thus it seems reasonable to ask whether given a proposed management strategy and potentially adverse future trends, risk goes up or down compared to recent levels.

Exogenous Uncertainties (X)

This study aims to consider the performance of alternative integrated flood risk management strategies over a wide range of future conditions. The study focused on nine factors describing future climatic and socio-economic conditions and their effect on future hazard, exposure, and vulnerability in the Nhieu Loc-Thi Nghe catchment. Table 4.2 lists these nine factors, the range of values over which we vary them, and the data sources for each factor. In our RDM analysis, a future is given by a specific combination of values for each of these factors, that is one specific value for an increase in rainfall

12 This difference between a given and the optimum strategy in a specific future is called "regret" in the decision analytic literature. Regret was less useful in this project because lack of cost data and differing judgments on the difficulty of implementing alternative strategies made it challenging to identify an optimum strategy.

intensity, an increase in Saigon river levels, the total Ho Chi Minh City population, and so on. These nine factors were identified during participatory scoping discussions in the two workshops and in discussions with Steering Center for Flood Control. Appendix A describes these factors in more detail.

Table 4.2. Exogenous uncertainties and their range of plausible values.

Uncertain Factor	**Range of values**	**Relevant sources of data**
Increase in rainfall intensity over 1980-2000 levels	+0% to +60%	IPCC (2012)
Increase in Saigon River level over 1990-2000 levels	+30 cm to +100 cm	MONRE (2009, 2010); NOAA (2012); Vermeer and Rahmstorf (2009); Discussions with Steering Center for Flood Control
Total Ho Chi Minh City population	7.4 M to 19.1 M	Ho Chi Minh City Statistics Office (2011); Ministry of Planning and Investment (2011); World Bank (2010)
Geographic distribution of population	World Bank estimate to current	Ho Chi Minh City Statistics Office (2011); World Bank (2010)
Poverty rate	2.4% to 25%	ADB(2010); (Coulthart *et al.* 2006); UNDP(2010)
Average annual economic growth	6% to 12%	Hawksworth et al. (2009); ADB (2010); Voice of Vietnam (2001)
Geographic distribution of economic growth	Equitable to Inequitable	Ho Chi Minh City Statistics Office (2011). *See Appendix A.*
Population vulnerability	10% to 100%	*Developed in this study. Reflects percent of population affected at 10cm of depth. See Appendix A.*
Economic vulnerability threshold	0% to 22%	*Developed in this study. Reflects economic loss at 10cm of depth. See Appendix A.*

Policy Levers (L)

The policies considered in this study represent alternative configurations of an integrated flood risk management strategy that combines infrastructure, adaptation and retreat options. Ho Chi Minh City's flood control infrastructure, recently constructed as broadly described in the 1999 JICA Master Plan for Drainage Infrastructure (PCI 1999), provides this study's Baseline strategy. We add to this baseline alternative combinations of four adaptation and retreat policies that seek to reduce exposure and vulnerability. We choose these four options in consultation with the Steering Center for Flood Control, seeking a balance between policies of most interest to the agency and the feasibility of representing the policies in our risk model. These policies are:

1. Groundwater management. Subsidence is a major contributor to increasing effective height of the Saigon River. High rates of groundwater extraction, in turn, contribute to subsidence, though other factors are also at play. We therefore consider groundwater management and recharge as one potential method of reducing exposure by reducing rates of subsidence.[13]
2. Rainwater capture. Capturing rainwater may offer a second method of reducing the flood exposure by reducing the amount of rainwater that reaches the drainage system during the extreme rainfall event.
3. Relocation of vulnerable areas. Our model of flooding in the study area shows that inundation is not uniform. Rather, areas along the Nhieu Loc-Thi Nghe canal and near the tide gate suffer from higher levels of inundation than other areas. Relocating residents offers a third way to reduce exposure.
4. Elevating homes. Elevating homes reduces the vulnerability of residents. This policy applies to all 1-story buildings; it does not apply to other buildings, under the assumption that larger buildings cannot be elevated or replaced.

Population Risk Management Strategies

The integrated flood risk management strategies considered in this study consist of alternative combinations of these individual policies. This study evaluates and compares ten such strategies to manage population risk. The first eight strategies are static: they implement their component policies for the entire period 30-year period from 2015 to 2045. The last two are adaptive, implementing some policies now and others later in response to information that becomes available in the future:

Static Strategies

1. **Baseline**: Infrastructure currently being deployed according to JICA 1999 Master Plan;
2. **Groundwater**: Baseline strategy plus groundwater management;
3. **Rainwater**: Baseline strategy plus rainwater capture;
4. **Relocate**: Baseline strategy plus relocating vulnerable areas;
5. **Elevate**: Baseline strategy plus elevating homes management;
6. **Groundwater + Rainwater**: Baseline strategy plus groundwater management and rainwater capture;
7. **Elevate + Relocate**: Baseline strategy plus elevating homes and relocating vulnerable areas; and
8. **All Options**: Baseline strategy plus all four augmentation options.

Adaptive Strategies

9. **Groundwater + Rainwater with Adaptive Elevate + Relocate**: Baseline strategy plus groundwater management and rainwater capture implemented from 2015 to

[13] There are other mechanisms for counteracting subsidence, such as land fill.

2045, with elevating homes and relocating residents implemented from 2025-2045 if needed.

10. **Elevate + Relocate with Adaptive Groundwater + Rainwater**: Baseline strategy plus elevating homes and relocating vulnerable areas implemented from 2015 to 2045, with groundwater management and rainwater capture implemented from 2025-2045 if needed.

As strategies 9 and 10 illustrate, adaptive strategies have three components:

- A set of near term policies that are initially implemented;
- One or more signposts or conditions that are monitored and trigger additional policies;
- A set of deferred policies, implemented when the signpost is detected.

In the first adaptive strategy, for example, groundwater management and rainwater capture are initially implemented (the near term actions). If after 10 years, evidence suggests that both the poor and the non-poor will have higher risk than under benchmark conditions (the signpost), then efforts to elevate homes and relocate particularly vulnerable areas are begun. Strategy 10 is the inverse. In both adaptive strategies, the success of the deferred policies is reduced because they will have been implemented for shorter periods of time.

Economic Risk Management Strategies

This study also considered a set of strategies to manage economic risk. Groundwater management and rainwater capture both reduce the flood hazard so are applicable to essentially any asset affected by inundation depth. However, without adequate information on the type or distribution of economic assets, it is not feasible to analyze a relocation or elevation strategy. Therefore, we construct flood risk management strategies for economic risk from two options: groundwater management and rainwater capture. The resulting strategies are:

<u>Static Strategies</u>

1. **Baseline**: Infrastructure currently being deployed according to JICA 1999 Master Plan;
2. **Groundwater**: Baseline strategy plus groundwater management;
3. **Rainwater**: Baseline strategy plus rainwater capture;
4. **Groundwater + Rainwater**: Baseline strategy plus groundwater management and rainwater capture;

<u>Adaptive Strategies</u>

5. **Groundwater + Adaptive Rainwater:** Baseline strategy plus groundwater management from 2015 to 2045, with rainwater capture implemented from 2025-2045 if needed; and
6. **Rainwater + Adaptive Groundwater:** Baseline strategy plus rainwater capture from 2015 to 2045, with groundwater management implemented from 2025-2045 if needed.

5. Results of RDM Analysis for Ho Chi Minh City

This section describes how we conducted the steps of the RDM analysis shown in Figure 2.1 using the simulation model and data presented in Section 4. This section focuses on population risk, which is a more stressing measure than economic risk in Ho Chi Minh City. The section first considers population risk for two alternative plausible futures. This initial discussion motivates the need for running the model many times over a wide range of conditions and introduces some of the visualizations we will subsequently use. We then examine how the Baseline Strategy performs over many plausible futures. A statistical scenario discovery confirms that the Baseline Strategy may not be sufficiently robust and confirms the need for an integrated flood risk management strategy that augments it with adaptation and retreat policies. We next examine the robustness of alternative combinations of such adaptation and retreat policies by analyzing how they how they each perform over many plausible futures. Finally we identify the tradeoffs between cost and robustness. The section concludes with a summary of a similar analysis for economic risk, and then offers some final observations.

This analysis aims to demonstrate how Ho Chi Minh City could use existing models and data to examine the robustness of integrated flood risk management strategies and potentially identify strategies more robust than those the city has heretofore considered. Such robust risk management strategies would reduce risk in a wide range of climate and socio-economic futures at reasonable cost.

Comparing Risk in Few Futures Is Insufficient for Decision Making

We first assess the performance of the Baseline Strategy given our best estimate of future conditions, i.e., one that is consistent with official estimates and available information about future rainfall intensity in Ho Chi Minh City, Saigon River levels, the city's population, population distribution, and poverty rates.[14] Figure 5.1 plots the risk to poor and non-poor populations in these conditions (blue mark) as calculated by the simulation model described in Section 4.[15] It shows that the Baseline Strategy could keep risk at acceptable levels (i.e., less than levels of risk experienced prior to the new infrastructure (the origin)) for both the poor and non-poor. This approach establishes a desired level of performance that can be used to compare alternative strategies over

[14] This 20% increase in rainfall intensity for Ho Chi Minh City is consistent with the IPCC mean estimate for the increase in precipitation intensity for Southeast Asia in 2045-2065 (2012). Consistent with MARD's sea level rise estimate for 2040 and 2050 shown in Appendix A, we assume in this case a 30 cm rise in the level of the Saigon River. Consistent with the Ministry of Planning and Investment's estimates, we assume a 2045 Ho Chi Minh City population of 11.1 million. Lacking reliable predictions to the contrary, we assume the population distribution and poverty rate in 2045 remain at their recent levels.

[15] To calculate each point on Figure 5.1, we run the model with the Baseline Strategy for a specific set of assumptions about the six hazard, vulnerability, and exposure uncertainties: the rainfall intensity, Saigon River level, Ho Chi Minh City population, population distribution, poverty rate, and population vulnerability. We then run model again, without the JICA 1999 Infrastructure, to calculate the benchmark risk using the values for recent conditions for rainfall intensity, Saigon River level, Ho Chi Minh City population, population distribution, and poverty rate, but using the same population vulnerability value as in the corresponding Baseline Strategy run. The difference between the risks in those two paired runs gives the location of a dot in Figure 5.1.

many plausible futures. Discussions in our workshops and with Steering Center for Flood Control suggested that the city's earlier risk, prior to the development of JICA 1999 infrastructure, provided a valuable benchmark, as described in Section 4. A strategy that keeps risk below this level would appear successful. A strategy that allowed risk to rise above this benchmark might be regarded as less successful.

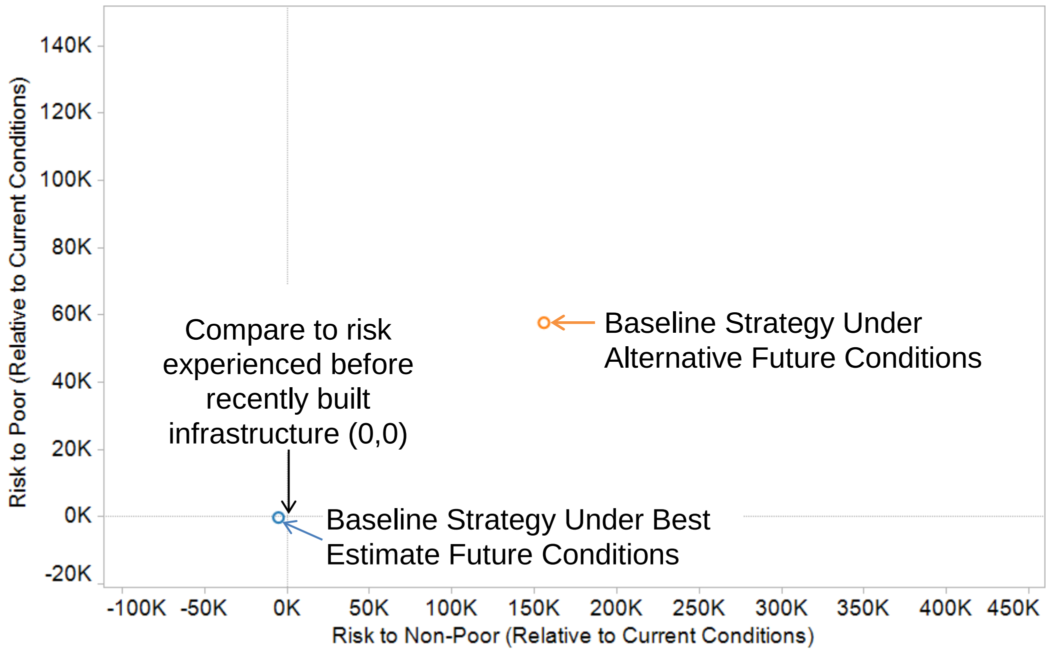

Figure 5.1. Risk to poor and non-poor populations in the Baseline strategy under best estimate (blue) and alternative (orange) future conditions.

However, it is premature to conclude that the Baseline Strategy sufficiently manages risk. These precise conditions may not be accurate descriptions of the future, which may unfold differently than expected. Moreover, these conditions are optimistic with respect to the full range of possible future outcomes, as shown in Figure 5.2. It makes sense to run the model again, computing risk under another possible future[16] whose conditions are shown in orange in Figure 5.2.[17] These conditions are less optimistic, assuming higher rainfall intensities, Saigon River levels, and population. As shown in Figure 5.1, the risk in this alternative future increases beyond acceptable benchmark levels, suggesting that the Baseline Strategy may not sufficiently reduce risk.

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[16] As described in Section 4, a future is one specific combination of values for each model uncertainty. Both sets of conditions described in Figure 5.1 are "futures" – the set of values representing current conditions can be thought of as a future that represents no change from the present.

[17] The full RDM analysis considers multiple futures, but this discussion of only two futures helps introduce figures that will reappear throughout this section, explains how the model from Section 3 generates data that appears on these figures, and shows how projections of future risk compare to benchmark levels.

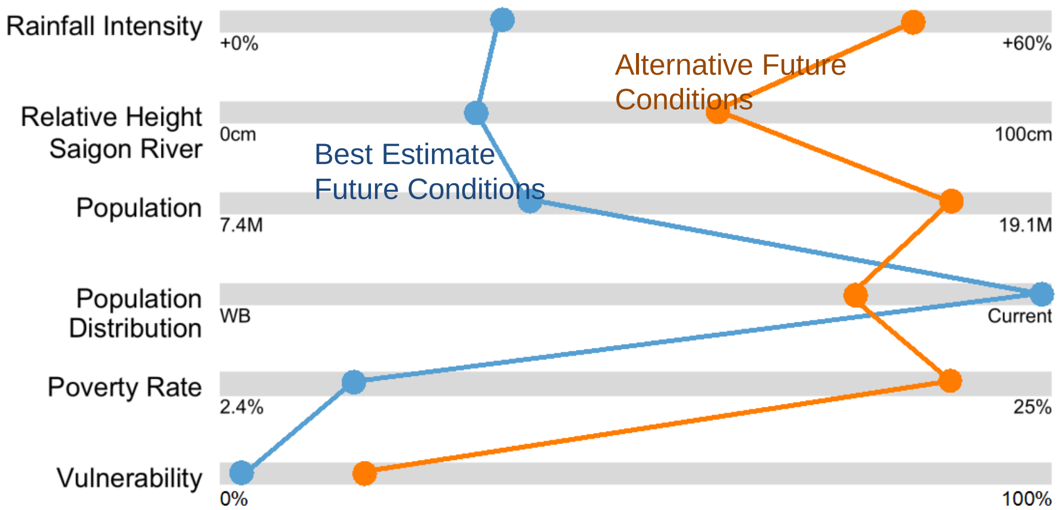

Figure 5.2. Assumptions for model input parameters that define best-estimate (blue) and alternative (orange) future conditions shown in Figure 5.1

RDM Evaluates The Baseline Strategy Over Many Plausible Futures

The analysis summarized in Figure 5.1 compares the performance of the Baseline Strategy in two plausible futures. Many traditional analyses of flood risk management similarly compare the performance of strategies over a small number of futures. But it is clear from the full range of plausible conditions shown in Figure 5.2 that neither of these two futures is guaranteed to represent well the future that Ho Chi Minh City will come to face. As with many decision problems, the future conditions that affect the near term choice of actions are unknown. When there is deep uncertainty, making decisions based on a small number of best-estimate projections may lead to poor decisions. To make sound decisions, the city should examine how its flood risk management plans perform over a much wider range of plausible futures.

Figure 5.3 shows the performance of the Baseline Strategy in each of 1,000 different futures, each of which represents a unique combination of the six uncertainties in Figure 5.2. Each point on the figure shows the risk relative to benchmark levels under one future.

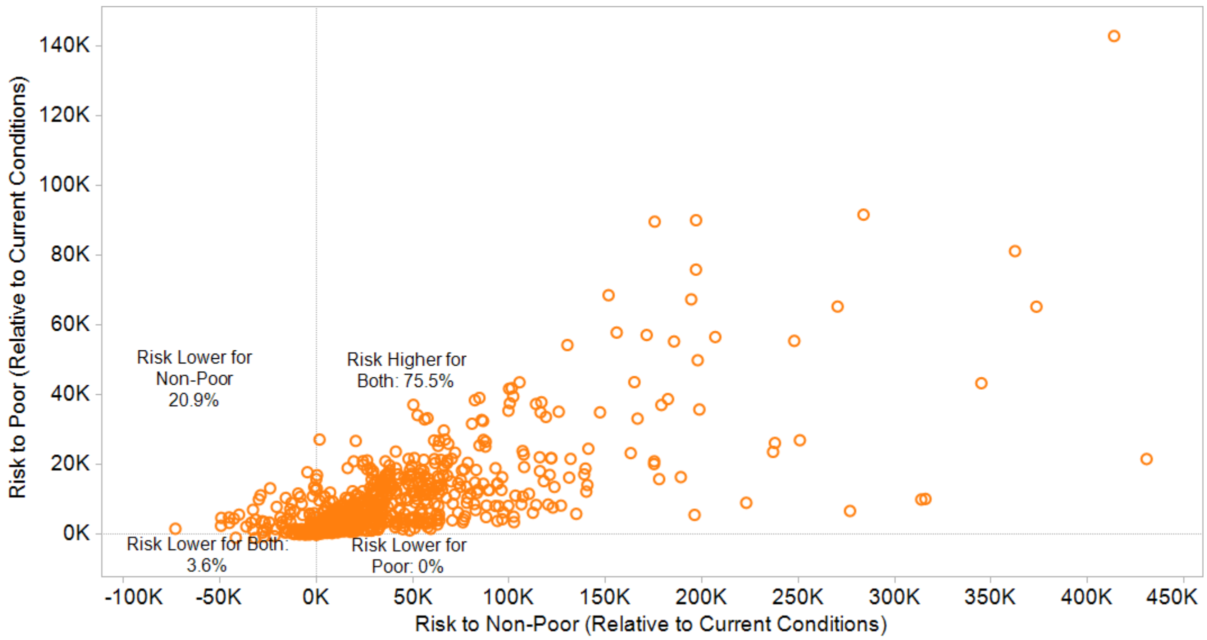

Figure 5.3. Risk to the poor and non-poor for Baseline Strategy for each of 1000 futures.

Note: Quadrants labeled with percent of cases where risk is reduced for both poor and non-poor; increased for poor and reduced for non-poor; and increased for both populations. In no case is risk reduced for poor but increased for non-poor.

This figure also highlights the performance criteria used in this study to determine whether or not a risk management strategy satisfies decision makers' goals. As discussed in Section 4, this study defines a flood risk management strategy as achieving its goals in a particular future if the strategy holds risk for both poor and non-poor populations lower than benchmark levels in that future, i.e. lies in the lower left corner of Figure 5.3. Conversely, if risk increases, the strategy would not meet decision makers' goals. As one of its most salient features, Figure 5.3 shows that there are only a small number of cases (36 out of 1,000, or 4%) in which the Baseline Strategy satisfies decision makers' objectives. In roughly 21% of the cases, the Baseline Strategy keeps risk below benchmark levels for the non-poor population but increases risk for the poor. In roughly 76% of the cases, the risks to both poor and non-poor increase.

Scenario Discovery Suggests the Baseline Strategy is Not Sufficiently Robust

Figure 5.3 suggests that the Baseline Strategy does not meet decision makers' goals in many plausible combinations of future hazard, exposure, and vulnerability. It is important to note, however, that we do not know the likelihood of the various individual futures in Figure 5.3. To determine whether Ho Chi Minh City should seriously consider augmenting the Baseline Strategy, we must first understand the conditions in which it does or does not satisfy objectives, and then review scientific evidence about potential for these conditions to occur.

The third RDM step in Figure 2.1, Scenario Discovery helps address these questions (Bryant *et al.* 2010; Hallegatte *et al.* 2012). As described in more detail in Appendix B, we apply scenario discovery algorithms to the database of 1,000 cases to identify the combinations of uncertain conditions that most reliably distinguish those 36 cases in which it satisfies objectives from the 974 cases where it does not.

Scenario Discovery reveals that four conditions together describe a scenario in which the Baseline Strategy satisfies objectives:

1. The increase in rainfall intensity is less than 6%,
2. The Saigon River rises by less than 45 cm,
3. Ho Chi Minh City's population is les than 18 million, and
4. Ho Chi Minh City's poverty rate is less then 23%.[18]

Assumptions about population distribution and about the vulnerability of the population have much less effect on whether or not the Baseline Strategy satisfies decision makers' risk management objectives.

Scenario discovery also reveals that future population and poverty rates are statistically less important predictors of strategy performance than are rainfall intensity and Saigon River rise. Moreover, as long as rainfall intensity and Saigon River rise remain below 6% and 45cm, respectively, the Baseline Strategy satisfies objectives in almost the full range of population (up to 19.1 million) and poverty rate (up to 25%) that we consider in this study. Therefore, we focus our attention on rainfall intensity and Saigon River levels in assessing robustness.

Figure 5.4 plots the range of rainfall intensity increase (6%, on the horizontal axis) and Saigon River levels (45 cm, on the vertical axis) under which the Baseline Strategy meets its objectives. We use this visualization to compare these conditions to the best available scientific evidence about future rainfall intensity and Saigon River levels. The IPCC Special Report on Extreme Events (IPCC 2012) suggests that future rainfall intensity could increase by as much as 35%, with a middle estimate of 20% (noted by vertical reference lines on Figure 5.4). These projections significantly exceed the 6% threshold to which the Baseline Strategy is robust. The Vietnamese Ministry of Natural Resources and the Environment (MONRE) projects that eustatic sea level rise will be approximately 30 cm by mid-century, compared to 1980-1999 levels. However, more recent studies suggest that it may higher due to rapid melting of ice sheets and glaciers, which was not taken into account in previous studies. The U.S. National Oceanographic and Atmospheric Administration (2012), for example, suggests an increase of approximately 40 cm by mid-century. When coupled with even modest rates of subsidence, one plausible future is an increase in height of 75 cm (noted by horizontal reference lines in Figure 5.4). Other factors, such as the construction of dikes around the river or faster subsidence, may further increase the height.

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[18] Appendix B provides a more complete summary of this Section's scenario discovery results. In particular, three scenarios, each with relatively low coverage and density, are required to achieve adequate total coverage and density to describe the future conditions where the Baseline Strategy reduces risk for both poor and non-poor populations. For simplicity, we only describe here the one scenario from this group of three with highest coverage and density. However, the best-estimate future conditions shown in Figure 5.2 lie in one of the other two scenarios.

Although we cannot predict the future height of the Saigon River, this evidence suggests that the height of the Saigon River may significantly surpass the 45 cm threshold to which the Baseline Strategy is robust. This further suggests that the Baseline Strategy does not meet its objectives in a wide enough range of plausible conditions, i.e. is not sufficiently robust. It strongly supports the city's desire to seek additional flood risk measures, and supports Steering Center for Flood Control's pursuit of an integrated flood risk management strategy that augments the infrastructure described by the Baseline Strategy.

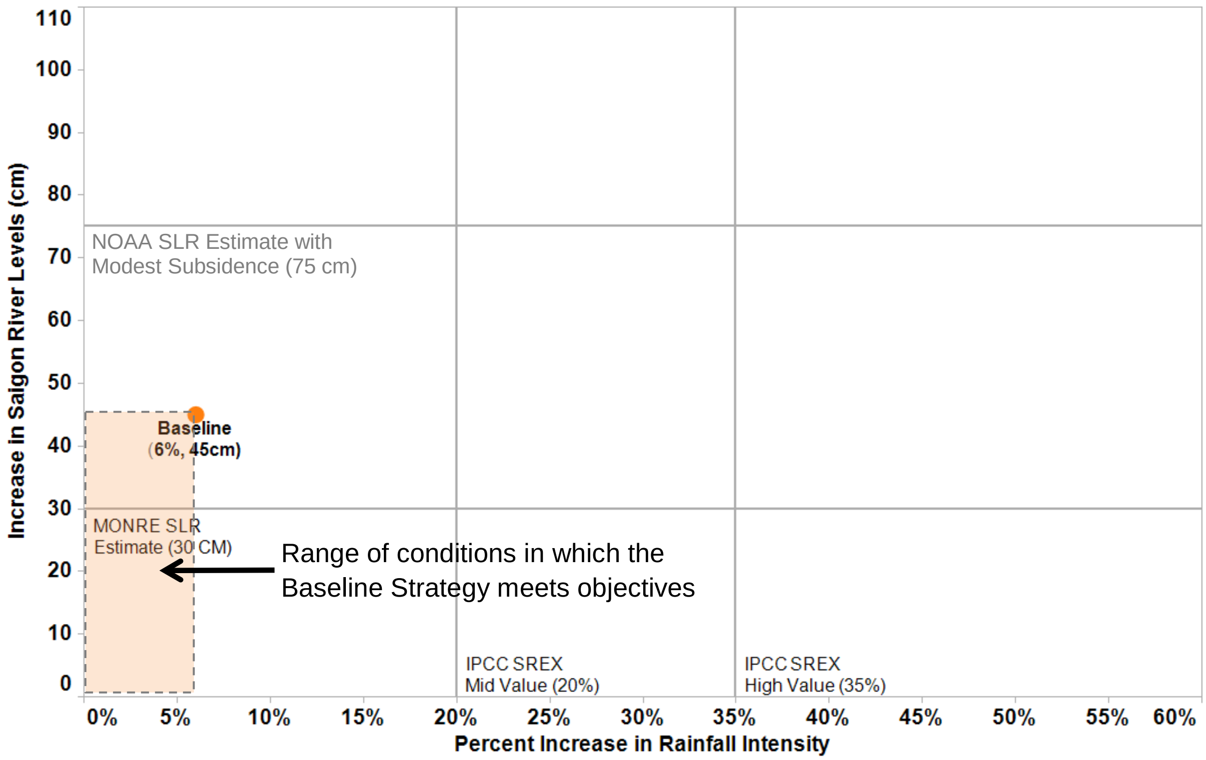

Figure 5.4. Range of future conditions in which the Baseline strategy meets decision makers' objectives, defined as reducing risk for the poor and non-poor.

Note: Vertical lines over rainfall intensity estimates show IPCC SREX mean and high projections for extreme precipitation events in Southeast Asia in 2045-2065. Horizontal lines over Saigon River levels show recent estimates of eustatic sea level rise and eustatic sea level rise with subsidence.

Scenarios Help Compare the Robustness of Alternative Strategies

The analysis so far suggests that Ho Chi Minh City should consider augmenting the Baseline Strategy. This section examines the performance of the Baseline Strategy when augmented with a variety of adaptation and retreat options that Ho Chi Minh City might pursue, in particular the nine alternative strategies described in Section 4. The analysis aims to help decision makers ask two key questions: Which options or combination of options offer sufficient robustness? Which options should be implemented now, and which can reasonably be delayed?

To answer these questions, we run the model for each of these strategies over the same 1,000 futures shown in Figure 5.3 and perform scenario discovery to assess the conditions in which they meet decision makers' objectives. Scenario discovery reveals that increases in rainfall intensity and increases in Saigon River levels remain the two uncertainties most relevant for determining performance.

Figure 5.5 is analogous to Figure 5.4, showing the range of rainfall intensity and Saigon River levels under which each strategy meets its objectives. Such visualizations help decision makers compare strategies in meaningful ways, which traditional analyses cannot. The figure denotes each strategy with a different colored mark. Strategies that combine the Baseline infrastructure with a single option are denoted with crosses, while strategies that augment it with multiple options are shown as asterisks. Adaptive strategies are noted with triangles.

Note that, as expected, augmenting the Baseline Strategy with either rainwater capture (pink), groundwater management (red), elevating homes (brown), or relocating residents (teal) increase robustness. Rainwater capture and relocating residents are robust to the maximum increases in Saigon River levels that we considered in this study, while elevating homes is robust to significantly greater increases in rainfall intensity. Decision makers might prioritize strategies in part based how future conditions emerge, e.g. favoring a relocation strategy over elevating homes if Saigon River levels appear to be increasing faster than rainfall intensity.

Discussions with stakeholders highlight another way in which such visualizations support deliberation. While relocating residents may be a powerful risk reduction strategy, stakeholders report that is also very difficult to implement and has significant social ramifications. Decision makers might reasonably ask, "What other risk management options are comparably robust?" Figure 5.5 shows that implementing groundwater management and rainwater capture in combination (purple) provides nearly the same degree of robustness along both dimensions – 14% increase in rainfall intensity and 85cm in Saigon River levels – and could be more feasible in practice. Even more, an adaptive strategy in which the city implements groundwater management and rainwater capture immediately and elevates homes and relocates residents only if needed (in teal), provides the same robustness as relocating residents immediately. This demonstrates the merits of a plan that implements certain options in the near term, while deliberately leaving others as augmentations that could be triggered in the future.

The analysis also suggests that undertaking all four options in combination and immediately can improve robustness significantly. The All Options strategy (blue) is robust to the full range of Saigon River levels we consider, and to rainfall intensity increases up to 32% -- near the upper end of the IPCC's projection. However, this may not be possible and, if future change is modest, this strategy could be over-aggressive and costly. Again, RDM helps assess adaptive strategies. For example, elevating homes and relocating residents in vulnerable areas immediately, while undertaking groundwater management and rainwater capture only if needed (in yellow), offers nearly the same degree of benefit as doing everything at once.

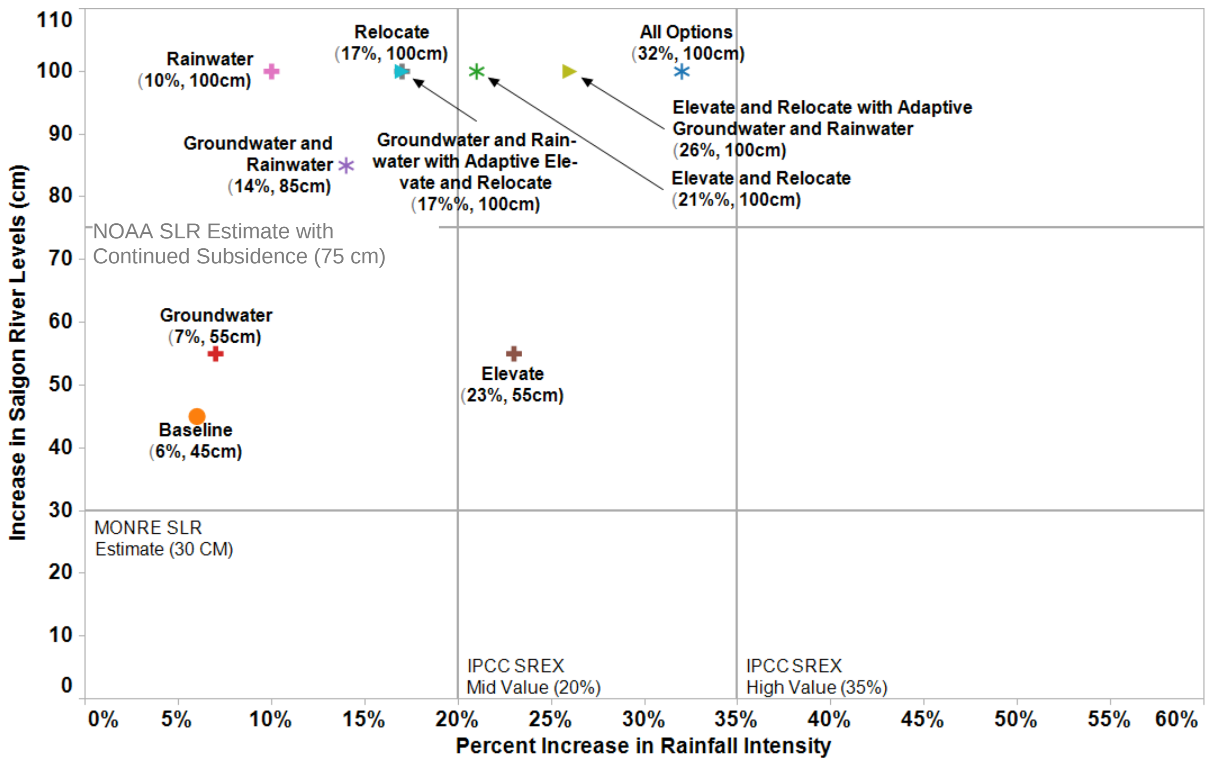

Figure 5.5. Scenario Discovery results showing the extent to which the ten strategies are robust to increases in rainfall intensity and Saigon River levels.

Note: Strategies that combine the Baseline infrastructure with a single option are denoted with crosses, while strategies that augment it with multiple options are shown as asterisks. Adaptive strategies are noted with triangles. As in Figure 5.4, vertical lines over rainfall intensity estimates show IPCC SREX mean and high projections for extreme precipitation events in Southeast Asia in 2045-2065. Horizontal lines over Saigon River levels show recent estimates of eustatic sea level rise. Note that these reference lines do not include increases in river levels due to subsidence or dike construction, which may be considerable.

Consider Tradeoffs among Strategies

As the previous discussion highlights, resources such as time, money, and political and social capital are limited. This raises the important question addressed in Step 4 of an RDM analysis – how should Ho Chi Minh City choose among the strategies based on their risk reduction, cost, and other factors?

Figure 5.6 shows a tradeoff curve that begins to answer such questions. The figure compares the risk reduction provided by alternative strategies with a rough measure of the cost of implementing those strategies. One important step needed to inform such a tradeoff analysis is gathering data on the potential cost of implementing the alternative policies. This study did not have the opportunity to gather quantitative cost data from external sources. However, we did obtain rough comparative estimates through expert elicitation. At the June workshop in Ho Chi Minh City, we asked participants to use their expertise to rank the strategies in terms of cost. The lower bound of 0 represents no additional cost beyond that already expended on the Baseline Strategy. The upper bound of 10 represents the cost of the All Options strategy, which implements immediately all the policies considered here. We gathered estimates from each participant individually and showed the group the aggregate results, but not the rankings from each individual. Such an elicitation clearly has limitations: the strategies are modeled too coarsely to make real cost estimates, the workshop participants may not be experts in cost estimation, and a ranking of cost gives no information about the scale or timing. Nonetheless, these results are sufficient to illustrate the kind of tradeoff curves generated in an RDM analysis.

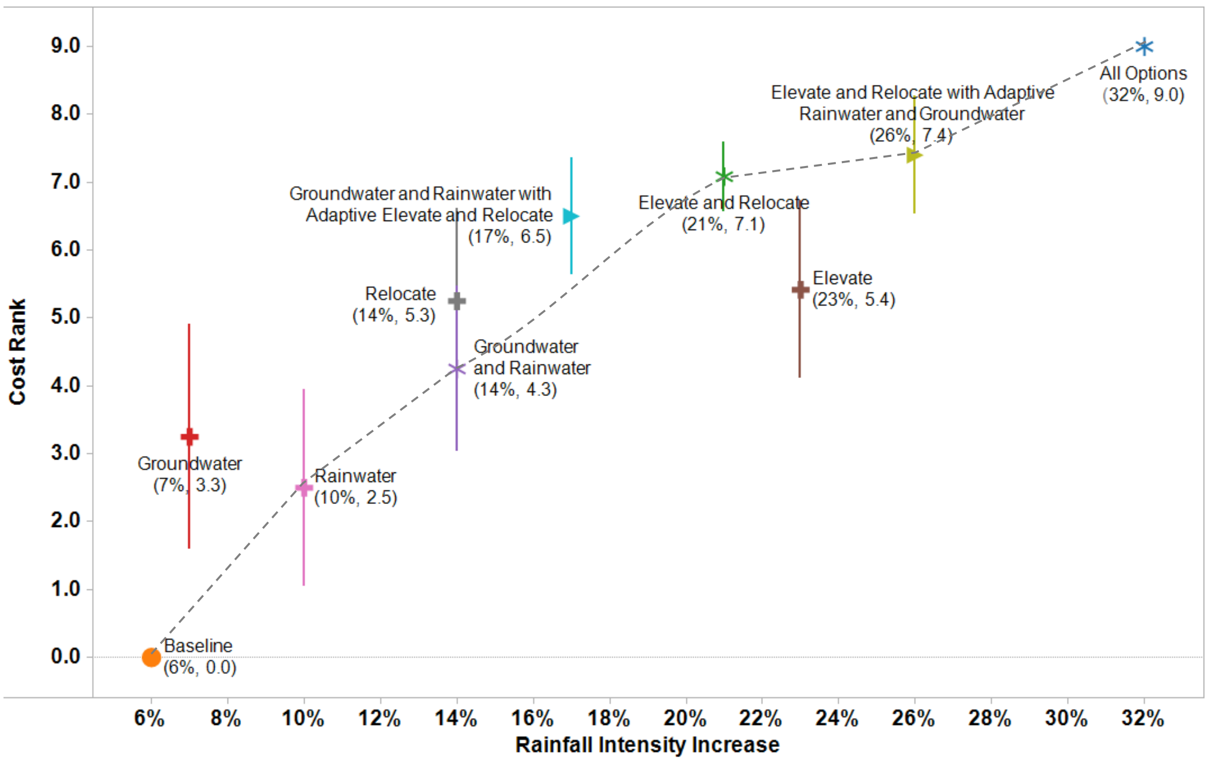

Figure 5.6 Tradeoff between cost and maximum allowable increases in rainfall intensity.

Note: Vertical bars show error bars and dotted line shows frontier of non-dominated strategies.

Figure 5.6 combines the results of this cost elicitation with the risk results from Figure 5.5 to provide a cost and risk reduction tradeoff curve for alternative flood risk management strategies. The vertical axis in Figure 5.6 plots the average rank across the 14 respondents, with error bars of one standard deviation.[19] The horizontal axis shows the maximum rainfall intensity to which each strategy is robust. Three strategies – Groundwater (red), Relocate (grey), and Groundwater and Rainwater with Adaptive

19 We omitted the highest and lowest rank for each portfolio. Averages and standard deviations of ranks are based on the middle 12 responses.

Elevate and Relocate (teal) – are dominated by other strategies. That is, for these three strategies there exists another strategy that appears to provide at least the same level of robustness to rainfall intensity increase for less cost. This is illustrated in Figure 5.6 with a dashed grey line representing the frontier of non-dominated strategies.[20]

Similarly to Figure 5.5, tradeoff curves such as Figure 5.6 can facilitate deliberations among stakeholders on how to balance risk reduction and costs associated with alternative strategies. Consideration of such tradeoff curves can also generate insights on how to design even more effective strategies (Lempert *et al.* 2003; Hall *et al.* 2012). It is worth emphasizing that the cost information in Figure 5.6 is only illustrative. A more comprehensive analysis would clearly include more detailed representations of the alternative policies than available here, informed by richer data on their costs, feasibility, and other implementation factors. A more comprehensive analysis would also include uncertainties about such cost and implementation challenges in the RDM analysis. The result would be a reliable understanding of the cost and risk reduction tradeoffs among alternative strategies and deeper insight into how modifications to these strategies or additional types of policies might yield even more robust options.

Finally, we conducted a similar analysis for the measure of economic risk, which we present in greater detail in Appendix B. This project's analysis of strategies to reduce both population and economic risk not detailed enough to draw any definitive conclusions about the synergies and tradeoffs among the two. Nevertheless, the results of our analysis would suggest that adaptation and retreat options could significantly reduce economic risk. Moreover, as with population risk, implementing the full set of adaptation and retreat measures considered in this study would reduce economic risk for rainfall intensities almost up to the high IPCC estimate of 35%. However, population risk in Ho Chi Minh City, measured by the expected number of people affected by flooding, may increase more under plausible future climate conditions than economic risk, as measured by expected percentage of GDP affected by flooding. Correspondingly, more adaptation and retreat measures are required to reduce population risk by comparable levels.

6. Key Findings and Policy Recommendations

RDM has proven valuable in the United States and in other developed countries. This project examined the applicability of the approach in a developing country. In particular, the project helps address several key questions:

- Can RDM provide significant value-added to the decision challenges faced in developing countries?
- What are data, computation, and other technical challenges to applying RDM, and can they be overcome?
- What are key concerns related to building local RDM capacity, and can they be addressed?

[20] Note that Elevate and Relocate (green) is not dominated by Elevate (tan) because the latter is less robust to increases in the height of the Saigon River.

To help answer these questions, this project conducted an RDM analysis of flood risk management in Ho Chi Minh City based on existing models and data. The RDM analysis found that Ho Chi Minh City's soon-to-be completed infrastructure investments will reduce economic and population risk in the Nhieu Loc-Thi Nghe catchment compared to recent (pre-infrastructure) levels in current climate and socio-economic conditions. It will also keep risk below pre-infrastructure levels in the best-estimate future conditions. However, the analysis also identifies many plausible future conditions where this infrastructure may fail to reduce risk. This project thus demonstrates how RDM can help Ho Chi Minh City decision makers understand the range of future socio-economic and climate conditions over which their infrastructure investments can successfully manage risk.

This analysis also identified adaptation and retreat measures that, in combination with the soon-to-be-completed infrastructure, could significantly expand the range of future socio-economic and climate conditions over which an integrated flood risk management strategy could reduce risk. Decision makers may find some types of adaptation and retreat measures technically, politically, and economically easier to implement than others. The RDM analysis provides tradeoff curves to help decision makers choose a strategy that provides an appropriate balance between risk reduction and implementation feasibility. In particular, the RDM analysis shows how adaptive strategies, in which some policy options are implemented immediately and others only implemented if needed in the future, can achieve almost the same level of risk reduction as a strategy that implements all such options immediately. In some cases, decision makers may find such adaptive strategies attractive because they can achieve high levels of risk reduction while deferring implementation of some, potentially more difficult or costly options, until it is clear they are needed.

RDM Can Improve Risk Management in Developing Countries

These findings suggest that RDM can offer significant value-added to the challenge of developing effective risk management strategies in fast-changing and deeply uncertain developing country environments. In particular, this project helps demonstrate RDM's capability to:

- Develop a detailed understanding of the combinations of future climate and socio-economic conditions where a proposed flood risk management strategy will and will not meet its risk reduction goals;
- Use this information to compare the quantitative and qualitative tradeoffs among alternative strategies, including cost, feasibility, the impacts on different populations, and the impacts between economic and population risk;
- Consider adaptive strategies, which may more effectively reduce deeply uncertain risk by evolving over time in response to new information;
- Suggest signposts, which can help decision makers know when to trigger deferred investments and actions as part of an adaptive strategy; and

- Facilitate structured discussions among stakeholders regarding vulnerability and tradeoffs even in the face of deep uncertainty.

With these attributes, RDM can help decision makers develop strategies that will prove successful over a wide range of unexpected and potentially surprising futures, and help facilitate the broad stakeholder interactions needed to build consensus for such strategies.

Based on these findings and on discussions with decision makers in Vietnam, there appear to be many decisions that RDM might usefully inform. First, RDM can augment existing planning efforts by evaluating the strengths and weaknesses of a specific plan or project that has emerged from a standard planning process. For instance, this study shows how RDM can be used to assess the strengths and weaknesses of an existing or accepted plan that has been developed through an alternative, non-RDM process (e.g. the 1999 JICA plan). This project also considered how RDM might augment ongoing work to develop an integrated flood risk management strategy that is being undertaken by Royal Haskoning. A future RDM analysis could use the simulation model being developed by Royal Haskoning to stress-test the study's recommended plan over a wide range of possible futures.

RDM could also be used to evaluate a particular action or policy (e.g., a sluice gate) and, third, the strengths and limitations of the *design* of the particular action or policy (e.g., the height or siting of sluice gate). Finally, RDM can be used to compare among alternative plans or projects. For instance, RDM might compare alternative infrastructure choices (e.g., a sluice gate versus a waste water treatment plant), or alternative adaptation and retreat policies.[21] RDM has also been used to develop more comprehensive plans, by comparing portfolios of many projects (Bureau of Reclamation 2012; in particular see Appendix G: System Reliability Analysis and Evaluation of Options and Strategies).

RDM might also usefully inform qualitative scenario exercises. Scenario workshops have become common in Vietnam and other cities in emerging economies facing growing risk. For instance, the Rockefeller Foundation's Asian Cities Resilience Network conducts many such scenario exercises. The city of Can Tho conducts what it calls Shared Learning Dialogue scenario exercises. While RDM has generally been used as a set of analytic methods and tools, the fundamental concepts can also be employed in such qualitative exercises (Lempert *et al.* 2011). In particular, RDM uses scenarios to illuminate the vulnerabilities of proposed policies, rather than only to explore how policies perform in a few handcrafted futures, as is done in traditional scenario analyses (Hallegatte *et al.* 2012). Thus, in RDM, scenarios are concise summaries of the future states of the world in which a proposed policy would not meet its goals. This concept has helped structure qualitative scenario exercises in the United States (for instance, for the Metropolitan Water District's Blue Ribbon Committee (MWD 2011)) and do so as well for scenario exercises in Vietnam. This might not only improve the impact and effectiveness of these

[21] In these cases, RDM can use a more standard metric, for instance revealing future conditions under which the benefit/cost ratio for an option meets (or, conversely, fails to meet) some target, thus favoring (or disfavoring) investment in that option.

exercises, it could help diffuse important RDM ideas and ease the way for future quantitative analyses.

Implementing RDM in Developing Countries

RDM is designed to employ existing models and data. Thus, in cases where decision makers are already using quantitative analysis to inform their choices, RDM can augment such activities in order to provide a richer understanding of uncertainty and the best ways to respond to it. The models used in RDM analyses can be simple or complex. For instance, an analyst using a simple spreadsheet model to compare the cost-benefit ratios of alternative investments could use RDM to run the spreadsheet over many thousands of combinations of assumptions and to identify those futures where one investment was consistently more cost-effective than another. Analysts with a large, complex flood risk management model could similarly use RDM to stress test the risk management strategies that emerge from their analysis.

RDM does raise potential data, computation, and other technical challenges. As one potential implementation barrier, RDM requires more computer processor time than a traditional approach, to conduct hundreds to thousands of runs and more computer storage to save the results. In practice these are not significant constraints. Analysts with spreadsheet models will generally have more than sufficient storage and processing power on a laptop to run the spreadsheet thousands of times. Analysts running a complicated flood risk management model may require hundreds or thousands of processors to run their models over numerous cases. These are increasingly available (for instance, Amazon now rents time on its huge stock of multiprocessors) and those with the skills to build complicated models can also access such multiprocessor systems.

Configuring a model to run over hundreds to thousands of cases often represents the greater challenge. For instance, staff skilled at developing cost-benefit spreadsheets may not know how to run the spreadsheet automatically over thousands of cases. Complex models may have an input file structure that makes it difficult to efficiently run thousands of cases. Both situations may require training and some reworking of computer code to enable analysts to generate and batch runs. Fortunately, this software and training proves to be a sound investment as it is generally useful for a wide range of analyses.[22]

Decision makers and analysts in developing countries often face significant data shortages. The question thus arises whether RDM has more severe data requirements than more traditional analytic approaches. This project suggests the converse: because RDM manages deep uncertainty, data gaps (one source of deep uncertainty) are less prohibitive with RDM than with other approaches. For example, this project faced two significant data gaps. First, there was a lack of reliable projections from climate models of the intensity of future extreme 3-hour rainfall events in Ho Chi Minh City. This RDM

[22] For instance, running the models in this project multiple times proved simple because project staff could draw on past experience using Analytica models with RDM and because the SWMM input file structure made it easy to run multiple cases.

analysis considered a wide range of possible increases and identified the threshold increase that would cause various strategies to fail to reduce risk. Second, there was a lack of reliable depth-damage curves representing the vulnerability of various Ho Chi Minh City populations to flooding. The RDM analysis considered a wide range of depth-damage curves and found that this relationship (whatever it may be) was less important than other factors in determining the performance of the different strategies considered.

This project does suggest, however, one way in which RDM analyses can prove more demanding of data. Traditional analyses are often usefully confined to providing hazard or exposure maps for one or a few scenarios. However, in identifying vulnerabilities of proposed plans and identifying robust responses to those vulnerabilities, RDM tends towards more integrative, system-wide analysis. For instance, the SWMM model at the core of this project was originally used to evaluate how new infrastructure investments would reduce flooding in a best-estimate future scenario. To understand the range of climate and socio-economic conditions for which these investments would reduce risk, this project needed to link the existing SWMM model with an Analytica model of the entire system. Building this system model consumed much of the effort in this current project. Once built, this system model also allowed us to analyze how combinations of adaptation and retreat options, coupled with the infrastructure investments, could reduce risk over a wider range of uncertain future conditions.

In sum, for any given policy question, RDM analyses will have less demanding data requirements than traditional analyses, and RDM's greater computational and configuration challenges can be overcome. But RDM analyses may tend to lead decision makers to ask broader questions. These broader questions may lead to better decisions, but may also increase the demands for data and model development.

RDM Involves New Ways of Thinking about the Future

In meetings with decision makers in Vietnam, a number of questions arose regarding the ability to apply RDM methods locally and build local capacity. One concern stems from the fact that local decision making in developing countries often relies heavily on external analytical expertise, and sometimes also external funding. In these cases, the role of local agencies may be to frame the terms of reference for externally-performed engineering analyses to use an RDM approach, emphasizing running models many times and identifying robust decisions. Alternatively, with some training, local agencies and universities may be able to lead the RDM analysis, while still potentially relying on engineering consultants to run models. This is to some degree the arrangement within our project team. RAND analysts were responsible for specifying the SWMM model runs and strategies and analyzing the resulting database of results. SCE modeled the strategies and performed the runs. In this situation, local agencies would play RAND's role in framing the analysis.

A second concern stakeholders cited was that the complex and sometimes contentious political process in developing countries may not allow for a complex analysis. However, RDM is designed to facilitate collaboration among stakeholders because, by using multiple views of the future, it includes a wide range of perspectives and objectives. It also focuses decision makers' attention on those assumptions and concerns that are most relevant to a decision. RDM has proved successful facilitating contentious stakeholder processes in developed countries, and we hypothesize that these benefits could be realized in developing country settings as well.

Finally, perhaps RDM's most significant implementation challenges arise because it represents a new way of thinking about how near-term actions can best manage future risks. Analysts are generally trained in predictive thinking and the decision makers they inform often expect predictive quantitative information. RDM answers a fundamentally different question. Rather than ask, "what will happen?" RDM allows analysts and decision makers to ask, "What should we do today to most effectively manage the full range of events that might happen?" Using RDM requires training for analysts, and a path by which organizations become comfortable using new and more effective types of quantitative information. Experience with the adoption of RDM in developed countries provides examples of how organizations in developing countries can become comfortable using RDM. One successful path involves conducting a demonstrations project, similarly to this one for Ho Chi Minh City, parallel to the organization's regular planning activities. Once the demonstration is complete, the organization can use this experience to begin to fold the new RDM methods into it's planning.

Conclusion

Decision makers in Ho Chi Minh City must craft flood risk management strategies in the face of hard-to-predict climatic and socio-economic futures. Effective decisions require quantitative analysis, but plans designed for best-estimate futures may perform poorly if a different future comes to pass.

Today, alternatives to predict-then-act methods have become available. Decision makers and analysts can run their models many times to explore how plans perform over a wide range of plausible futures. They can use visualization and statistical tools to draw information from the resulting database of model runs, revealing plans' vulnerabilities and helping make them more robust. Implementing these new methods is not without challenges – it can require training and organizational shifts toward new ways of thinking. But these challenges can and should be overcome to develop robust plans in the face of uncertain future opportunities and dangers, given that the well being of communities, cities, and countries is often at stake.

Appendix A: Additional Detail on Models and Data

Section 4 of this report briefly describes the models and data used in this study using an XLRM framework. This appendix provides more details on these elements.

Measures of Risk (M)

As described in Section 4, risk can be defined as a product of three components – hazard, exposure, and vulnerability. For our study:

- *Hazard* is a probabilistic measure of a particular rainfall and tide event that may result in flooding;
- *Exposure* refers to the poor population, non-poor population, or economic assets that are exposed to the hazard; and
- *Vulnerability* is a measure of how the exposed populations or economic assets are affected by the particular hazard.

Suppose, for example, that an extreme rainfall event with a 2-year return period has a rainfall intensity of 80mm (the hazard). This rainfall inundates an area of Ho Chi Minh City in which 4 million people live in total, of which 3.6 million are non-poor and 0.4 million are poor (the exposure). Suppose further that the resulting inundation adversely affects 10% of the non-poor but 25% of the poor because the poor are more vulnerable to inundation. In this case, the annual risk from a 2-year event is:

$$Risk_{nonpoor} = \frac{1}{2}\ x\ 3{,}600{,}000\ x\ 0.1 = 180{,}000 \text{ people affected}$$

$$Risk_{poor} = \frac{1}{2}\ x\ 400{,}000\ x\ 0.25 = 50{,}000 \text{ people affected}$$

We use this approach to calculate annual risk to the poor and non-poor, and risk to the economy as a fraction of GDP from 2, 5, and 10-year events rainfall events. We describe this further in our discussion below of modeling hazard.

Relationships and Models (R)

This project integrates several modeling components shown in Figure 4.1 into an Analytica model that computes population and economic risk. Figure A.1 shows a schematic of the Analytica model developed for the purpose of calculating population risk. The model developed for calculating economic risk uses a similar structure. First, data related to hazard (inundation depth from SWMM), exposure (GIS data and population and poverty data), and vulnerability (depth-damage curves) are input into the model (orange trapezoids on the left). From this data, we calculate the percent of the poor and non-poor affected in each subcatchment, the number of poor and non-poor in each sub-catchment, and, in combination, the risk to the poor and non-poor in each event (blue rectangles). As described next, risk is calculated for extreme rainfall events with 2, 5, and 10-year return periods and using different infrastructure operation rules. We assume infrastructure operators will apply the operating rules that best reduces risk in each event (green square). Lastly, we calculate the total risk as a combination of risk from 2, 5, and 10-year rainfall events.

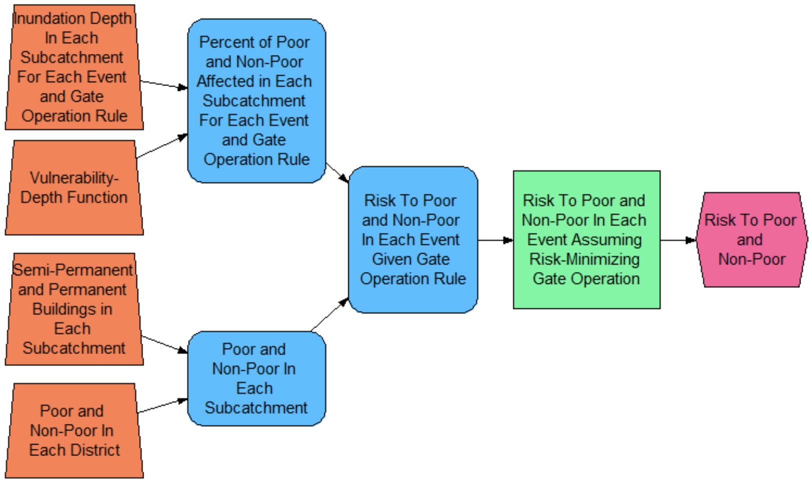

Figure A.1 Schematic illustration of the Analytica risk model for calculating population risk given SWMM, ArcGIS and other inputs.

Figure A.2 shows a screenshot of our actual Analytica model, which we structure visually as an XLRM table. The upper left shows an input table of uncertainties (X). The upper right corner allows one to choose a combination of policy levers (L) to use as part of an integrated flood risk management strategy. The lower right provides the results of the simulation as tables of economic and population risk (M). Finally, the influence diagram model (R) is presented in the lower right. Each module shown in this top level of the influence diagram contains a number of embedded modules that calculate the distribution of population and economic value, impacts of inundation, and other components of risk. This top-level diagram shows how two policies, rainwater capture and groundwater management, affect inundation depth. These depths are then input into modules that calculate economic risk and population risk. We next offer additional details on how we model hazard, exposure, and vulnerability.

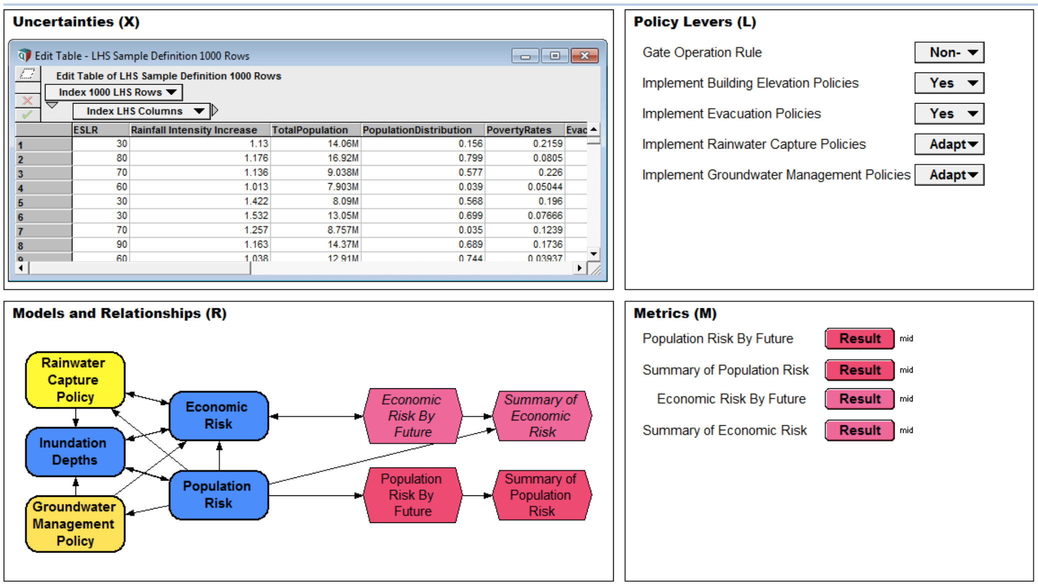

Figure A.2. Screenshot of the Analytica risk model used in this analysis.

Modeling Hazard

We use the Steering Center for Flood Control's SWMM model of the Nhieu Loc-Thi Nghe catchment area to calculate the inundation results from a particular rainfall event and Saigon River water levels, and given the physical infrastructure in the area. SWMM is a one-dimensional rainfall-runoff simulation model used, in this case, to model the effect of individual 3-hour rainfall events and river levels over a 24-hour period.[23] SWMM models water quality and quantity from rainfall on a series of subcatchment areas and then routes this through conduits, pumps, and other infrastructure to an outfall point.

The Steering Center for Flood Control provided us with two variations of the SWMM model: the **Baseline** model and the **Benchmark** model. The baseline SWMM model describes infrastructure that has recently been constructed, based on the 1999 JICA master plan and as well as several augmentations, including a series of pumps, a wastewater treatment plant, and a tide gate where the canal meets the Saigon River. We use this infrastructure as the baseline integrated flood risk management strategy and augment it using other options; we therefore term it the Baseline strategy.

The Benchmark model represents the earlier drainage infrastructure in the city without the infrastructure described in the 1999 JICA master plan. We use this model to calculate the benchmark risk, against which we compare the Baseline and other flood risk management strategies.

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[23] We focus on the 3-hour extreme rainfall event because it has proved in the past and is expected to prove in the future the climate-related hazard most stressing to the city's flood control systems.

The baseline model for the Nhieu Loc-Thi Nghe catchment area is shown in Figure A.3. Each yellow polygon represents a drainage area or subcatchment. Each subcatchment (orange circle) has a local output node into which rainwater may drain or from which it may rise, causing flooding. The output nodes are connected by a series of conduits that represent the drainage network (green and pink line segments). The Nhieu Loc-Thi Nghe canal (in red) is an open channel into which the drainage system flows. The canal meets the Saigon river at the outfall node (large green circle), which, in the Baseline strategy, includes a tide gate and pumps.

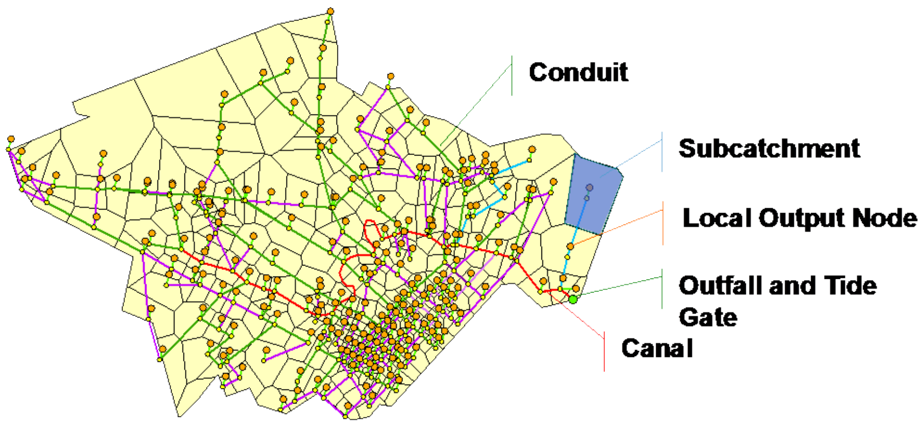

Figure A.3 SWMM model of the Nhieu Loc-Thi Nghe catchment area in the Baseline strategy

We input recent rainfall event and Saigon River height data provided by the Steering Center for Flood Control into SWMM to calculate the benchmark hazard (i.e., without the baseline infrastructure). Figure A.4 show three maps of inundation for each of the rainfall event as calculated by our simulation model.

Importantly, SWMM does not model overland flow or flood plains. As a result, there are discontinuities in water depth between adjacent catchments, leading to over and under-estimates of inundation in some subcatchments. Additionally, using SWMM limits the uncertainties and policy options that can be considered in this analysis. For instance, the model projects inundation from rainfall events, but cannot be used to model storm surge dynamics. It also cannot take into account complex effects of land use changes. Nevertheless, the model and methods suffice to illustrate how RDM could be used and, in Appendix B, we explore how RDM can be applied with more sophisticated models that are currently under development.

A key feature of the recently built- infrastructure embedded in the Baseline model is the tide gate that separates the Nhieu Loc-Thi Nghe canal from the Saigon River. When the tide gate is closed, pumps move water from the canal to a wastewater treatment plant. The operating rules for the tide gate and pump in particular play an important role in determining inundation.

In this study, we begin rainfall at 11:15 so that drainage coincides with the peak tide (i.e., the worst-case scenario) and examine risk under four different tide gate operating rules:

1. Tide gate opens at the peak level
2. Tide gate opens 2 hours after peak level
3. Tide gate opens 3 hours after peak level
4. Tide gate is always open.

In the first three cases, the gate remains open for 5 hours. Pumps operate whenever the tide gate is closed.

Because the tide gate operation is under the control of the city, we do not treat it as uncertain. Instead, we assume that tide gate operators would choose the best operating rule for the impending event.[24]

Benchmark Hazard Under Recent Conditions

We input recent rainfall event and Saigon River height data provided by the Steering Center for Flood Control into the SWMM to calculate the benchmark hazard (i.e., without the baseline infrastructure), as shown in Figure A.4. This calculation uses data on recent 3-hour rainfalls with 2, 5, and 10-year return periods which have intensity an intensity of 83, 104, and 118mm, respectively. The height of the Saigon River fluctuates with the tide, from a relative maximum of approximately +1.5m to a low of -1m.

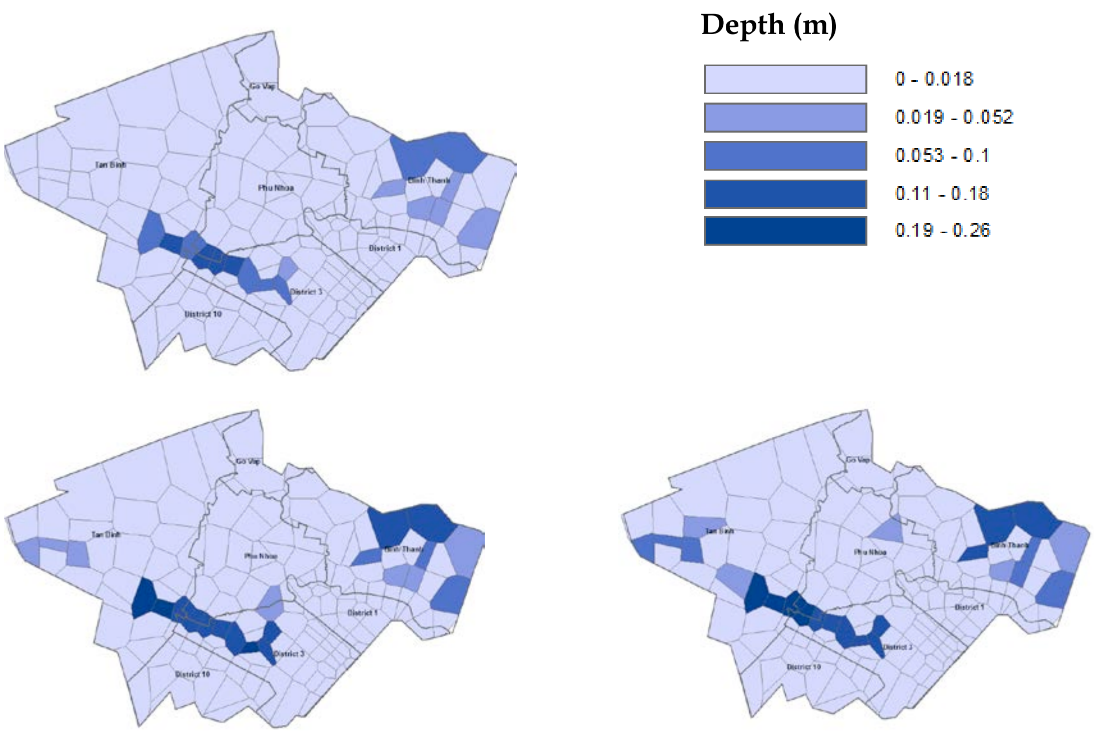

Figure A.4. Inundation in meters from recent 3-hour rainfall events.

[24] To simulate this, each hazardous event (rainfall and river height sequence) is modeled using each of these four operating rules, and the lowest risk is chosen. Note that the operating rule with the lowest average or median depth may not necessarily produce the lowest overall risk because both inundation and exposure patterns vary over the study area and contribute to risk.

Note: This figure shows return periods of 2 (top), 5 (bottom left), and 10 (bottom right) years using the benchmark model (without recently built infrastructure).

Modeling Exposure With Socioeconomic and GIS Data

Social and economic exposure depends on the geographic distribution of the poor and non-poor and of economic assets throughout the study area. However, detailed models of exposure do not exist for Ho Chi Minh City and even data about present conditions is tenuous. We have developed simple models of exposure given the kinds of data and projections that are available.

We use district-level estimates of population and poverty rates to calculate the exposure of the poor and non-poor in each district. GIS data from the Steering Center for Flood Control describes the distribution of semi-permanent and permanent buildings at the sub-district level. Assuming that the poor live in semi-permanent buildings and non-poor live in permanent buildings, we can then map the exposure of the poor and non-poor in each subcatchment.

For economic exposure, we use as a proxy indicator the contribution of each district to the city's overall GDP, which can be approximated given available economic data. We again use GIS building data provided by the Steering Center for Flood Control to map subcatchment-level exposure. We assume that the fraction a district's economic value that resides in a particular subcatchment is proportional to the fraction of the district's permanent (i.e. wealthier) buildings that are in the subcatchment.

Poor and Non-Poor Exposure

We use several variables to calculate poor and non-poor exposure. We first calculate $Population_{Di}$, the population in the study area in each district Di.

$$Population_{Di} = Population_{HCMC}\ x\ PercentPopulation_{Di}\ x\ PercentArea_{Di}$$

where

$Population_{HCMC}$ is the total population of Ho Chi Minh City;

$PercentPopulation_{Di}$ is the percent of the total Ho Chi Minh City population in district Di;

$PercentArea_{Di}$ is the percent of district Di that is in the study area;

Knowing the poverty rate $Poverty_{Di}$ in each district, we can calculate $Poor_{Di}$ and $NonPoor_{Di}$, the number of poor and non-poor, respectively, in the study area in each district:

$$Poor_{Di} = Population_{Di}\ x\ Poverty_{Di}$$

$$NonPoor_{Di} = Population_{Di} - Poor_{Di}$$

While this gives us district-level exposure, our model calculates hazard by subcatchment. We use GIS data provided by the Steering Center for Flood Control to determine the distribution of the population in each subcatchment. The GIS data provides geographic information on the buildings in the study area, as well as the each building's area, height in stories, and whether it is semi-permanent or permanent. By overlaying district and subcatchment boundaries on the GIS data, we have a mapping between districts and subcatchments. With this mapping we can calculate $SemiPermanent_{DiSj}$ and $Permanent_{DiSj}$, the total semi-permanent and permanent building areas in each district Di and in each subcatchment Sj.

We assume that the poor live in semi-permanent buildings and non-poor live in permanent buildings. With this assumption, we can calculate $Poor_{Sj}$ and $NonPoor_{Sj}$, the poor and non-poor in each subcatchment, respectively, as:

$$Poor_{Sj} = \sum_{D=1}^{|Districts|} \frac{SemiPermanent_{DiSj}}{SemiPermanent_{Di}} x Poor_{Di}$$

$$NonPoor_{Sj} = \sum_{D=1}^{|Districts|} \frac{Permanent_{DiSj}}{Permanent_{Di}} x NonPoor_{Di}$$

Where $SemiPermanent_{Di}$ and $Permanent_{Di}$ are the total areas of semi-permanent and permanent buildings in each district.

Economic Exposure

The distribution of economic assets in the city is also not readily available. We use as a proxy indicator the contribution of each subcatchment to the country's overall GDP, which can be approximated given available economic data.

The literature provides us with data about Ho Chi Minh City's contribution to Vietnam's GDP, GDP_{HCMC}. If we assume that a district's contribution to Ho Chi Minh City's GDP is proportional to its contribution to Ho Chi Minh City's tax revenue, then GDP_{Di}, the GDP contribution of district Di is.

$$GDP_{Di} = GDP_{HCMC} \ x \ \frac{Revenue_{Di}}{Revenue_{HCMC_{Di}}}$$

Where $Revenue_{Di}$ and $Revenue_{HCMC}$ are the tax revenues generated in district Di and in Ho Chi Minh City, respectively.

We again GIS data provided by the Steering Center for Flood Control to determine the distribution of economic value in each subcatchment. We use the distribution of permanent buildings across subcatchments as an indicator of the distribution of wealth. Specifically, we assume that subcatchment Sj's contribution to district Di's GDP is proportional to the fraction of permanent building area in Di that is also in Sj. Then, we can calculate GDP_{Sj}, the economic value of catchment Sj as:

$$GDP_{Sj} = \sum_{D=1}^{|Districts|} \frac{Permanent_{DiSj}}{Permanent_{Di}} x GDP_{Di}$$

Exposure Under Recent Conditions

We used recent socioeconomic data to calculate poor and non-poor and economic exposure in each subcatchment. Here we describe the basis of those estimates. The Ho

Chi Minh City Statistical Office provides information on population in each district in the city and for the city as a whole. The most recent data we were able to obtain on poverty rates is from 2003 from the Inter-Ministerial Poverty Mapping Task Force work, as cited by the Asian Development Bank (2010). [25] We use this data, coupled with the Steering Center for Flood Control's GIS map of buildings in districts and catchments to determine the number of poor and non-poor in each subcatchment. District population and poverty rates are listed in Table A.1.

The Ho Chi Minh City Statistical Office also provides information on tax revenues in each district in the city and for the city as a whole. Vietnam's GDP in 2011 was estimated by the World Bank at US$106.4 billion and the ADB estimates that Ho Chi Minh City contributes 23% of this. The GDP for Ho Chi Minh City is then US$24.5 billion. We use this data, coupled with the Steering Center for Flood Control's GIS map of buildings in districts and catchments to determine the economic value in each subcatchment. District revenue and GDP data are provided in Table A.2.

Table A.1. 2010 population and 2003 poverty rates in Ho Chi Minh City and in districts in the study area.[26]

	2010 Population (millions)	Percent of Total Ho Chi Minh City Population	2003 Poverty Rates
Ho Chi Minh City Total	*7.4*		*5.4%*
Binh Thanh	0.50	6.4%	5.0%
District 1	0.78	2.5%	2.4%
District 10	0.32	3.1%	3.0%
District 3	0.30	2.6%	2.8%
Go Vap	0.61	7.4%	6.9%
Phu Nhua	0.26	2.4%	3.7%
Tan Binh	0.66	5.8%	5.5%

[25] There are other measures of income disparity such as the GINI Coefficient (UNDP, 2011). We used poverty rates in our case study because it is an intuitive measure and appropriate for demonstration.

[26] Population data are from the Ho Chi Minh City Statistics Book, Table 2.01. Poverty rates are from the Inter- ministerial Poverty Mapping Task Force, 2003 but accessed from Asian Development Bank (ADB). 2010. Ho Chi Minh City. Adaptation to Climate Change. In collaboration with the Ho Chi Minh City People's Committee and DONRE. Prepared by ICEM - International Center for Environmental Management. Pg. 54.

Table A.2. Revenues collected by Ho Chi Minh City from each district in 2010 and the resulting estimate of economic value in each district.[27]f

	2010 Revenues (billion VND)	Percent of Total Ho Chi Minh City Revenue	Economic Value (billion USD)
Ho Chi Minh City Total	*11,225*		*24.5*
Binh Thanh	470	4.5%	1.10
District 1	187	6.9%	1.70
District 10	232	2.9%	0.70
District 3	189	2.7%	0.65
Go Vap	548	5.4%	1.33
Phu Nhua	175	2.3%	0.57
Tan Binh	430	5.9%	1.44

Modeling Vulnerability

The vulnerability of people or economic assets can depend on a number of factors related to flooding – the flood depth, duration, rate, etc. Many vulnerability functions found in the literature are depth-damage relationships, mapping a certain level of depth to a certain percent of impact or loss. We use depth-damage curves in this study as well, given that SWMM provides us with information about inundation depth but not other flood characteristics.

Depth-damage curves for the population and economic assets in Vietnam or for comparable countries are not well developed, though recent efforts have begun to gather data that could support the development of such functions (Phi *et al.* 2012). Given the lack of good data on vulnerability, we have developed candidate depth-damage curves, but we treat key parameters of this relationship as uncertain and include them in the exogenous factors varied in the analysis. Importantly, as our analysis in Chapter 5 reveals, although vulnerability is deeply uncertain, the comparative performance of the strategies we consider is not strongly affected by this uncertainty. Other factors play a much more important role. Thus, uncertainty regarding vulnerability turns out not to be decision-relevant in this study.

Population Vulnerability

In the absence of other information, we have chosen a sigmoid function to describe the population depth-damage relationship shown in Figure A.5. Sigmoid functions have

[27] Tax revenue data are from the Ho Chi Minh City Statistics Book, Table 3.11.

an "S" shape and can be thought of as smoothed out step functions: they have small effects initially, increase rapidly, and then level off as maximum effect is reached. Sigmoid functions are often used when other information about relationships with these patterns is unknown.

Our population depth-damage curves reflect the percent of the population that is affected by a particular level of inundation. We assume that 0% of the population is affected by 0 m depth, and that 100% of the population is affected by some depth d which is unknown and treated as uncertain. Each value of d results in a unique depth-damage curve from (0,0) to (d, 100). However, in the risk management literature, vulnerability is more often discussed in terms of the percent of people or resources affected or lost at a particular level of depth. Therefore we identify each unique depth-damage curve by the percent of the population that is affected by a 10cm inundation depth.

Depth-damage curves may differ between individuals based on a number of factors, e.g. whether they are poor or non poor, where they live, and their age. However, we have little additional information to inform these distinctions. The only distinction we make is that people living on the ground floor are more vulnerable at a particular level of depth than are people living on higher stories. This is illustrated in Figure A.5.

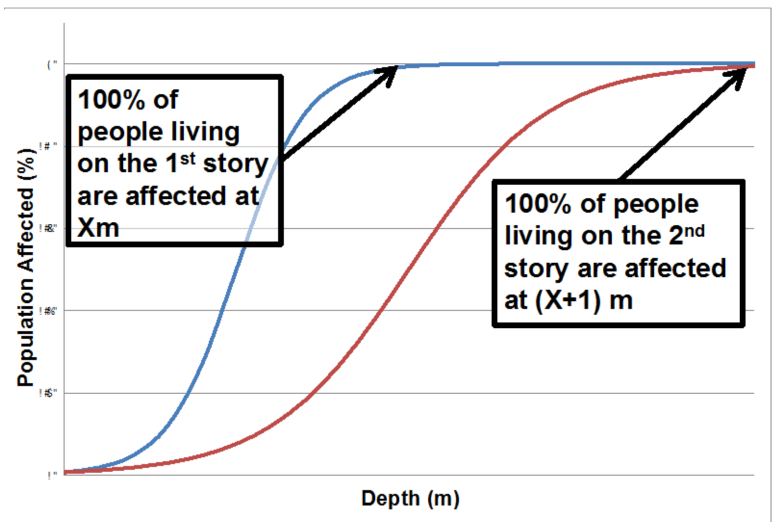

Figure A.5 Depth damage curves provide a relationship between depth and the percent of the population affected, based on building story.

Economic Vulnerability

There is somewhat more information about economic depth-damage curves. Royal Haskoning is developing economic depth-damage curves as part of their ongoing work on developing an integrated flood risk management strategy for Ho Chi Minh City. Their interim report (2012) provides a candidate depth-damage relationship to which we fit a logarithmic curve, shown in Figure A.6[28]:

$$y = 0.202 \ln(x + 0.106) + 0.453$$

[28] Since SWMM does not provide information about depths less than 0m, we give this curve an endpoint of (0,0).

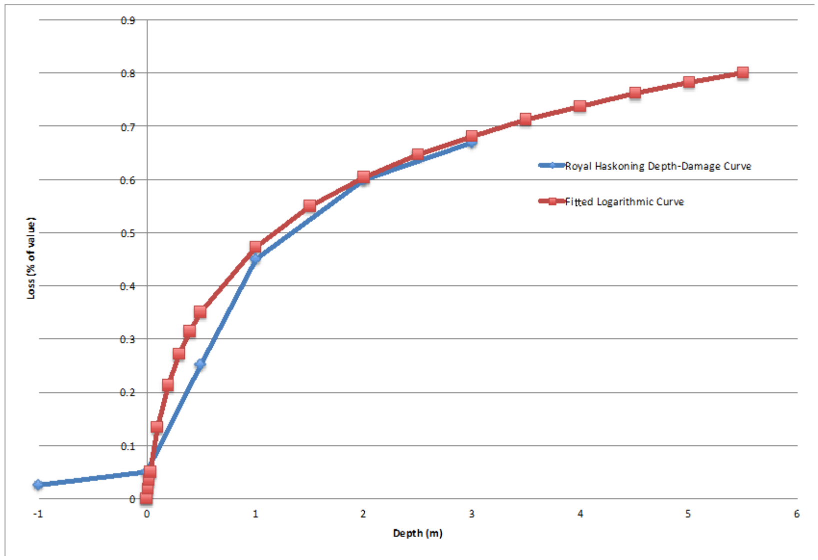

Figure A.6. Logarithmic curve fitted to Royal Haskoning's depth-damage curve

Whereas in the population depth-damage relationship we treat the placement of the curve along the x-axis as uncertain, here we treat the shape of the curve as uncertain while fixing the location of the curve along the x-axis. Both vary the percent of people affected or economic value lost at a particular level of depth, but they achieve this in different ways. We describe this in detail in our discussion of uncertainties.

Exogenous Uncertainties (X)

This project examines nine uncertainties related to hazard, exposure, and vulnerability. Some of these uncertainties affect population risk or economic risk, while others affect both. These uncertainties are highlighted in Table A.3. When in Section 5 we construct a set of future cases for population risk experiments or economic risk experiments, we include uncertainties for only those uncertainties relevant to population risk or economic risk, respectively.

Table A.3. Uncertainties affecting population risk and economic risk.

Uncertainty	Population Risk	Economic Risk
Increase in Rainfall Intensity	X	X
Increase in Saigon River Levels	X	X
Total Ho Chi Minh City Population	X	
Geographic Distribution of Population	X	
Poverty Rate	X	
Average Annual Economic Growth		X
Geographic Distribution of Economic Growth		X
Population Vulnerability	X	
Economic Vulnerability		X

Uncertainties Associated with Future Hazard

The first two factors relate to the future hazard: the increase in intensity of future 3-hour rainfalls and the increase in the mean level of the Saigon River.

Change in Rainfall Intensity

The IPCC Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX) provides an analysis of how future rainfall intensity may change. For Southeast Asia, global climate models suggest that the intensity of a daily precipitation event in the time period 2045-2065 could be similar to that in the period 1981-2000 or may increase by as much as 35%. We use this as the basis for developing the range of potential rainfall intensities for future 2, 5, and 10-year events. For each return period, we consider a wide range of intensities. To increase confidence that we include the full range of plausible futures, our range exceeds that of the IPCC SREX report. Intensities range from the historical baseline to a 60% increases in intensity, as shown in Table A.4

Table A.4. Range of intensities (mm) for 3-hour rainfalls with 2, 5, and 10-year return periods.

Return Period	Recent (mm)	60% Increase (mm)
2-Year	83	133
5-Year	104.1	167
10-Year	118	189

Saigon River Height

There are several factors that contribute to a change in the Saigon River's height:

- Eustatic sea level rise brought about by anthropogenic climate change;
- Subsidence caused by falling groundwater levels and other processes; and
- Construction of dikes, which may narrow the width of the river.

Subsidence and dike construction may vary locally. However, modeling local variation sin SWMM is a significant modeling effort and beyond the scope of this project. Instead, for demonstration we consider uniform subsidence and dike construction. Additionally, because SWMM cannot model overland flow, the effects of these changes on the model are equivalent: they each change the difference in height between the outfall and the Saigon river. Thus, we vary a single uncertainty – Saigon River height – that encompasses many different potential contributors to this effect.

The Vietnam Ministry of Natural Resources and the Environment (MONRE) has developed a series of SLR projections for Vietnam (2009). These are based on the IPCC Fourth Assessment Report (IPCC, 2007) using the IPCC B1, B2, and A1F1 emissions scenarios, which correspond to low, medium, and high emissions. In these scenarios, SLR ranges from 28cm to 33cm by mid-century. Consistent with traditional single-scenario methods, MONRE further recommends that the medium scenario be used for planning.

However, recent research suggests that the Fourth Assessment Report estimates may significantly underestimate sea level ride because they do not take into account rapid ice flow changes. Two sources provide data that takes into account rapid ice melt. Vermeer and Rahmstorf (2009) and NOAA (2012) both estimate that SLR by 2045 could be approximately 40cm

Ho Chi Minh City is built upon marsh and swampland, and development coupled with groundwater extraction and development has resulted in significant subsidence over the past years. A study of by MONRE (2010) found that subsidence in the city varied from 1 cm/year to, in some places, 5 cm/year, on average between 1 and 3 cm/year. Assuming even a modest rate – 1 cm/year --, subsidence could reach 25 cm by 2025 and 45 cm by 2045 over 2000 levels. The Water Resources Plan for Flood Control in Ho Chi Minh City (MARD, 2008) proposes the construction of 172km of dikes around Ho Chi Minh City and 13 tide gates at the mouth of the drainage canals that discharge in the Saigon River. By constraining the expansion area of the river, the dikes may increase the height of the river. In discussions with the project team, the Steering Center for Flood Control estimated an increase of 20-30cm from dike construction and noted that a revised plan for dike construction is being considered to reduce these effects.

The combined effect of eustatic sea level rise, subsidence, and dike construction may be an increase in river height of over a meter by 2045. However, for the purposes of this study, we consider a range between 20 and 100cm. Levels less than 20 cm are inconsistent with climate and subsidence projections. Levels higher than 1m would result in overland flow and permanently or semi-permanently inundate certain areas. This should be explored with more sophisticated 2-D models with detailed topographic data, and we suggest it as a key next step in the roadmap in Appendix C.

Uncertainties Associated with Future Exposure

Future population and economic exposure are also uncertain. The total Ho Chi Minh City population, the geographic distribution of the population in the city, and the poverty rate determine the exposure of the poor and non-poor in the study area. The average annual economic growth and the geographic distribution of that economic growth in the city determine the exposure of economic assets.

Ho Chi Minh City Population

The Ho Chi Minh City Statistics Office estimates the city's 2010 population at 7.4 million people (2011). The population is expected to grow in the coming decades, and the literature offers several projections. The Ministry of Planning and Investment estimates a population range from 9.4 million to 10.55 million people in 2034, depending on assumptions about fertility rate (Ministry of Planning and Investment 2011). The Word Bank offers a wide range of population projections, from a low of 12 million to a high of 20.8 million by 2050 (World Bank, 2010). By scaling the highest of these projections – the Bank's estimate of 20.8 million by 2050 to the year 2045, we consider cases in which population in the city overall is as much as 19.1 million people.

While the lowest scaled projection for 2045 is 10.3 million (based on the Ministry of Planning and Investment's low-growth case), we use 7.4 million as the lowest possible estimate, corresponding to a future with no change in population. This allows us to explore risk in cases in which the future is similar to benchmark conditions, even though these cases may be inconsistent with expectation of population.

Distribution of Ho Chi Minh City Population

Few estimates exist about how the city's population will be distributed across districts. Recent distribution of population in the districts in our study area offer one estimate. World Bank (2010, Table 3.14) offers a second estimate of future population distribution, which reflects a projection that the bulk of the population growth will take place beyond the study area, on the outskirts of the city. These distributions are listed in Table A.5. We use these two estimates as boundary cases for population distribution, with the World Bank estimate of population distribution as the low end of the distribution range, and the recent distribution as the high end of the range. The distribution in different futures varies between these bounds.

Table A.5. Recent and possible future distribution of Ho Chi Minh City's Population in districts in this study area.

	2010 Percent of Total Ho Chi Minh City Population	2050 Percent of Total Ho Chi Minh City Population (World Bank estimate)
Binh Thanh	6.4%	3.0%
District 1	2.5%	1.12%
District 10	3.1%	0.83%
District 3	2.6%	0.71%
Go Vap	7.4%	2.8%
Phu Nhua	2.4%	0.7%
Tan Binh	5.8%	3.23%

Ho Chi Minh City Poverty Rate

The most recent official estimate of Ho Chi Minh City's poverty rate by district is from the Inter- ministerial Poverty Mapping Task Force in 2003 (ADB 2010). This study estimates an overall poverty rate of 5.4%. The literature did not offer estimates of future poverty; therefore, we use estimates of recent poverty to provide a plausible range for this value. Estimates of recent poverty rates vary widely based on methodology and definitions of poverty. The United Nations Development Program conducted an Urban Poverty Survey that estimates the poverty rate of Ho Chi Minh City at 13.9%, using an annual income threshold of 12 million VND per person (2010, p.90).[29]

One can also distinguish between the poor and non-poor according to their housing facilities, a differentiator that may be important when considering exposure to flood. The GIS data provided by the Steering Center for Flood Control suggests a poverty rate of 2.4% under the assumption that the area of semi-permanent homes relative to the area of permanent homes indicates poverty levels. Another study cites the percent of housing the government classifies as "slum" or "temporary" as 25% (Coulthart *et al.* 2006). Clearly there is much variation in recent estimates, and little can be said with confidence about future estimates. We therefore use a wide range of values for poverty rate -- 2.4% as a lower bound and 25% as an upper bound. We assume that the relative poverty rates of districts in our study area remain the same as estimated by the 2003 Inter- ministerial Poverty Mapping Task Force.

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29 The Vietnam Household Living Standards Survey of 2008 estimated the overall poverty rate in Vietnam at 13.4% and estimated a poverty rate of 0.3% in Ho Chi Minh City. The Ho Chi Minh City estimate has been questioned for having methodological shortcomings (UNDP, 2010). The UNDP's Urban Poverty Survey was aimed at overcoming these shortcomings.

Economic Growth

There are several projections of year-over-year economic growth for Ho Chi Minh City and for Vietnam as a whole. A study by PricewaterhouseCoopers (PWC) ranks urban cities around the world in terms of GDP and projected annual growth in GDP. It ranks Ha Noi and Ho Chi Minh City first with a projected 7% annual real growth from 2008 to 2025 (Hawksworth J. *et al.* 2009). In a related study, PWC estimated a 6% annual growth at purchasing power parity between 2007 and 2050. A study by the Asia Development Bank (2010) of Ho Chi Minh City's ability to adapt to climate change estimates Ho Chi Minh City's growth at 8.7% between 2011 and 2025, and, 8% between 2026 and 2050. The city has also set its own targets for growth – 12% annually between 2010 and 2015 (Voice of Vietnam 2011). We use these estimates to inform the range of economic growth for Ho Chi Minh City, from a low of 6% to a high of 12% annually.

Distribution of Economic Growth

The literature does not offer projections of how the city's economic growth will be distributed across districts. We have developed two boundary cases of this distribution informed by information about the recent distribution of wealth. This information is presented in Table A.6.

One boundary case represents an equitable distribution of future wealth. It describes the case where wealth is distributed uniformly across all areas of the city, i.e. a district accrues Ho Chi Minh City's future wealth proportional to its geographic size. The third column of Table A.6 lists the percent of future wealth each district receives using this rule.

A middle case represents parity with today's distribution of wealth. In this case, the distribution of future wealth is consistent with a district's recent contribution to the city's wealth. Thus, District 1 contributes 6.9% to Ho Chi Minh City's wealth (as indicated by its contribution to Ho Chi Minh City's tax revenues), and so would receive 6.9% of future wealth.

However, it may be important to examine the case in which wealthy areas become disproportionately still wealthier, reflecting a growing gap between rich and poor areas. The other boundary case represents an increasingly inequitable distribution of future wealth. In this case, a district accrues Ho Chi Minh City's future wealth proportional to its *wealth per unit area*. That is, District 1 accounts for 6.9% of Ho Chi Minh City's wealth today but only 0.24% of the city's area. Therefore, its wealth relative factor, 6.9/0.38 is 18.12. We calculate this for each district (Table A.6, Column 4) and then normalize (Table A.6, Column 5). This normalized wealth factor is the percent of Ho Chi Minh City's future wealth that each district would accrue under an inequitable future. District 1 would account for 28% of Ho Chi Minh City's wealth. The distribution in different futures ranges between these boundary cases.

Table A.6. Economic value and geographic data used to calculate boundary cases of wealth distribution across districts.[30][31]

	Percent of Total Ho Chi Minh City GDP	Percent of Total Ho Chi Minh City Area *(Equitable wealth distribution)*	Wealth Factor (Percent GDP/ Percent Area)	Normalized Wealth Factor *(Inequitable wealth distribution)*
Binh Thanh	4.5%	1.00%	4.47	7%
District 1	6.9%	0.38%	18.12	28%
District 10	2.9%	0.29%	10.03	15%
District 3	2.7%	0.24%	11.14	17%
Go Vap	5.4%	0.95%	5.67	9%
Phu Nhua	2.3%	0.24%	9.69	15%
Tan Binh	5.9%	1.05%	5.61	9%
Other Districts	69.5%	96%	0.72	1%

Uncertainties Associated with Future Vulnerability

The next factors relate to the future population and economic vulnerability to different flood depths.

Population Vulnerability

We consider a range of population vulnerability curves, varying the percent of the population that is affected as a function of depth. Highest vulnerability occurs when 100% of those living on the ground floor are affected by inundation of only 0.1m and 100% those living on other stories are affected by an inundation of 1.1m (1m higher than the ground floor threshold). Lowest vulnerability occurs when 2% of those living on the ground floor are affected by inundation of 1m and, correspondingly, 2% of those living on other stories are affected by an inundation of 2.1m.

Economic Vulnerability

For demonstration, we use a different approach to examining a range of vulnerabilities for economic assets. Here, we assume that 0m of depth corresponds to 0% loss, while a depth of 5.5m results in 80% loss, based on initial data in the Royal-Haskoning interim study report (2012). We vary the shape of this curve, i.e. how changes in depth affect loss between these two endpoints. In the highest vulnerability curve, 22% of economic value is lost at a depth of 10cm; in the lowest vulnerability curve, essentially 0% of economic value is lost at a depth of 10cm.

[30] Tax revenue data are from the Ho Chi Minh City Statistics Book, Table 3.11.

[31] Geographic data are from the Ho Chi Minh City Statistics Book, Table 2.01.

Policy Levers (L)

Section 4 describes four individual policies we use to construct integrated flood risk management strategies:

- Groundwater management
- Rainwater capture
- Relocation of vulnerable areas
- Elevating homes

Here, we describe these policies in greater detail.

Subsidence is a major contributor to increasing effective height of the Saigon River. High rates of groundwater extraction, in turn, contribute to subsidence, though other factors are also at play. We therefore consider groundwater management and recharge as one potential method of reducing hazard by reducing rates of subsidence.[32] The effects of groundwater extraction on subsidence, and the potential for groundwater management to mitigate subsidence, depends greatly on a variety of factors such as land use and soil composition, and is not well understood for Ho Chi Minh City. For the purposes of this study, we are agnostic towards the groundwater management policies used to reduce extraction and encourage recharge. Instead, we examine the risk effects of slowing the rate of subsidence, regardless of how it is brought about. We use a subsidence rate reduction of 0.33 cm/year, amounting to a maximum of 10 cm of avoided subsidence over the entire 30 years of our study.

Rainwater capture may offer a second method of reducing the flood hazard by reducing the amount of rain water that reaches the drainage system during the extreme rainfall event. Potential rainwater harvesting systems in Vietnam range from small plastic bins that can store 100 liters (0.1 cubic meters) of water to large cement tanks that can store 10,000 liters (10 cubic meters) (Patrick *et al.* 2009). While we were unable to find surveys of rainwater technology adoption in Vietnam, we drew on related studies from neighboring Thailand which found that ceramic jars with a 2000 liter (2 cubic meter) capacity were most popular and sufficient for storing water for a family of six (0.33 cubic meters per person).[33] For population risk experiments in which population is an exogenous uncertainty, we assume that a rainwater capture policy would seek to provide 0.33 cubic meters of storage capacity per person in our study area.[34] In our economic risk experiments, population is not an uncertainty and so we assume a fixed level of implementation that is the average of the rainwater capture capacities in the population experiments. This policy effectively reduces the intensity of the rainfall event by 10mm.

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[32] There are other mechanisms for counteracting subsidence, such as land fill.

[33] http://www.unep.or.jp/ietc/Publications/Urban/UrbanEnv-2/9.asp

[34] As an example of its effect, suppose that there are 2.23 million residents in the study area (consistent with the current population) and every resident has 0.33 cubic meters of rainwater storage capacity. Further suppose a 100mm 3-hour rainfall event, which produces a total of 8.7 million cubic meters of rainfall over the 87 square km of Ho Chi Minh City. The rainwater capture capacity in the study area would reduce this volume by 0.75 million cubic meters, resulting in 7.95 million cubic meters of rainfall reaching the drainage system. This is equivalent to a 90mm rainfall event without rainwater capture. Under these conditions, rainwater capture reduces the effective intensity of the rainfall event by 10%.

Relocating residents offers a way to reduce exposure. Our model of flooding in the study area shows that inundation is not uniform. Rather, areas along the Nhieu Loc-Thi Nghe canal and near the tide gate suffer from higher levels of inundation than other areas, as shown in Figure A.7. As a candidate policy, we assume that 14 sub-areas in the SWMM model that consistently experience high inundation are completely relocated. This accounts for 2.3% of the total population in the study area.

As a final policy, we examine the effect of raising homes to reduce the vulnerability of residents. This policy applies to all 1-story buildings; it does not apply to other buildings, under the assumption that larger buildings cannot be elevated or replaced. The effect is that those living in 1-story buildings are subject to the same vulnerability-depth curves as those living in taller buildings.

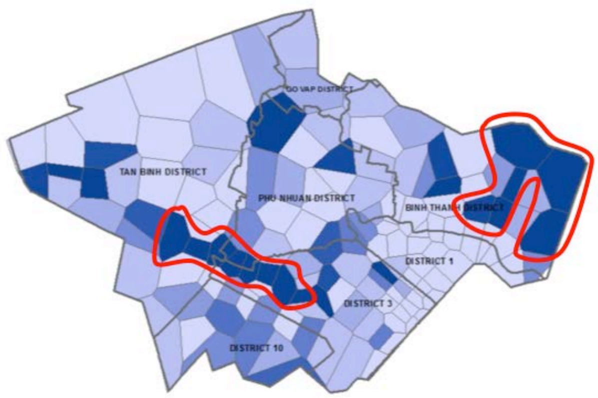

Figure A.7 Areas of the city that are particularly vulnerable to inundation because of their proximity to the Nhieu Loc-Thi Nghe canal (left) and the outfall (right).

Appendix B: Scenario Discovery Method and Results

In this appendix, we provide greater detail on the results presented in Section 5. We begin by describing the scenario discovery method and then provide full scenario results for population risk to accompany the figures in Section 5. We also provide results and figures from the analysis of economic risk.

Scenario Discovery Method

RDM's third step —identifying scenarios that characterize the vulnerabilities of proposed strategies—is integral to this project's analyses and workshops. We summarize here the analysis methods used to help identify the scenarios described in Section 5.

Scenario Discovery uses statistical cluster-finding algorithms to provide concise descriptions of the combination of future conditions that lead a strategy to fail to meet its objectives. These descriptions of conditions can be thought of as *decision-relevant scenarios* in a decision support process, because they help focus decision makers' attention on the uncertain future conditions most important to the challenges they face and help facilitate discussions regarding the best ways to respond to those challenge (Groves *et al.* 2007; Bryant *et al.* 2010). In other words, decision-relevant scenarios emerge from a systematic analysis of performance under a wide range of future conditions. In contrast, in traditional scenario planning, analysts handcraft a handful of scenarios based on intuition about the important factors driving performance.

Scenario discovery begins with the database of simulation model results (or cases) generated in Step 2 of the RDM analysis. Each case in the database consists of a description of the future under which the strategy was simulated (i.e., particular levels of future sea level rise, rainfall intensity, population growth, and other factors) and the resulting performance of the strategy according to the performance metrics. Users define thresholds for one or more performance metric that distinguish futures in which a strategy meets its objectives from those in which it does not. A strategy is vulnerable in those futures where it fails to meet its objectives.

In this study, we chose the 1000 cases shown in Figure 5.3 using a Latin Hypercube (LHC) sample for five of the six parameters and a full factorial design for Saigon River level. There are an infinite number of combinations of plausible values of the model input parameters. We chose LHC because it provides an efficient, finite sample of these combinations (Saltelli *et al.* 2000). LHC is a randomized experimental design based on the higher dimensional generalization of a Latin Square. Our experience to date suggests LHC is more useful for RDM than other standard sampling methods, such Monte Carlo or full-factorial, because it provides the most complete exploration of the model's behavior over the input space for the fewest number of points in sample.

We then use the Patient Rule Induction Method (PRIM) (Friedman *et al.* 1999) to analyze the database of cases and present candidate scenarios to the user. These scenarios are each defined by some combination of constraints on one or more model input parameters. For instance, a scenario might indicate that a particular flood management strategy would increase risk if rainfall intensity exceeded some level at the same time that the poverty rate exceeded some other level. The user then chooses the candidate scenario most appropriate for their application.

Three measures of merit help guide this process:

- **Coverage**: the fraction of all the vulnerable cases[35] in the database that are contained within the scenario. Ideally, the scenario would contain all the vulnerable cases in the database and coverage would be 100%.
- **Density**: the fraction of all the cases in the scenario that are also vulnerable. Ideally, all the cases within the scenario would be vulnerable and density would be 100%.

[35] Alternatively, the scenario can be chosen to describe cases where the strategy meets its goals. The scenario discovery analysis in Section 4 uses this criterion, in that it looks for scenarios where flood management strategies reduce risk.

- **Interpretability:** the ease with which users can understand the information conveyed by the scenario. The number of uncertain conditions used to define the scenario serves as a proxy for interpretability. The smaller the number of conditions, the higher the interpretability.

These three measures are generally in tension with one another. For instance, increasing density may decrease coverage and interpretability. PRIM thus generates a set of decision-relevant scenarios and presents tradeoff curves that help the users to choose the one with the combination of density, coverage, and interpretability most suitable for their application. Figure B.1 provides an example of such a tradeoff curve.

Scenario discovery is most useful in situations in which some combinations of uncertain factors are significantly more important than others in determining whether or not a strategy meets its goals. In such situations, the analysis can help decision makers recognize those combinations of uncertainties that require their attention and those they can more safely ignore.

Figure 5.5 summarizes the results of the scenario discovery analyses that identified scenarios in which each of the alternative strategies meets its objectives, i.e. reduces risk for both the poor and non-poor populations. In particular, this figure shows only the constraints on rainfall and Saigon River Level that define each scenario. However, other uncertainties also help define these scenarios for many of the strategies. Here, we give more complete details on both the process and results of the scenario discovery analysis, so the reader can better understand the context for the material presented in Section 5.

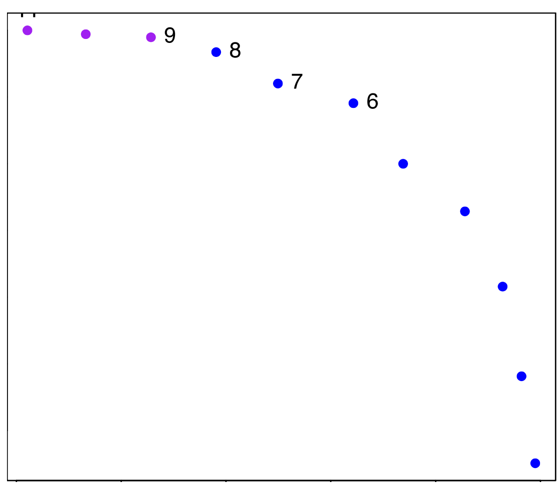

Figure B.1. Tradeoff curve generated by PRIM scenario discovery algorithm showing coverage, density, and interpretability for alternative "Both Better" scenarios for the All Option strategy.

As described in detail in previous publications (Lempert *et al.* 2006; Groves *et al.* 2007; Bryant *et al.* 2010), the PRIM algorithm used for scenario discovery does not provide the user a single scenario. Rather, the algorithm provides a tradeoff curve of scenarios with different combinations of coverage, density and interpretability. Figure B.1 gives an example of one such tradeoff curve for the All Options strategy, as defined in Section 2. The figure shows eleven alternative scenarios with differing combinations of coverage (horizontal axis) and density (vertical axis). The color of the dot indicates the number of parameters used to define the scenario, which is the measure of interpretability. The blue dots show scenarios defined by one parameter (rainfall intensity) and the purple dots show scenarios defined by two parameters (rainfall intensity and Saigon River level). The numbered dots indicate the scenarios the analysts examined in detail. We chose the dot labeled '6' as the scenario with the best combination of coverage, density, and interpretability to give the scenario for All Options shown in Figure 5.5

Figure B.1 shows relatively high coverage and density for all its alternative scenarios. In some cases, however, no single scenario can provide adequate coverage and density. In such situations, the PRIM algorithm allows the user to conduct multiple passes through the data. The user identifies a scenario and the algorithm removes the cases within that scenario from the database. The user then reruns PRIM and identifies another scenario from the remaining data. This process can be repeated indefinitely. The resulting set of multiple scenarios may reduce interpretability, but can increase coverage and density.

Scenario Discovery Results for Population Risk

Table B.1 provides the full results of the scenario discovery analysis reported in Section 5. For each strategy the table shows the constraints on all the parameters identified as important by the scenario discovery process, along with the coverage and density for each scenario. The strategies that reduce risk for both poor and non-poor populations for many cases have relatively simple scenarios with high coverage and density. For instance, the All Options "Both Better" scenario has a constraint on only one parameter (rainfall) and achieves a coverage and density of 82% and 95%.

In contrast, the strategies that reduce risk in only a small number of cases have more complicated scenarios. In particular, the Baseline strategy requires three scenarios that among the have constraints on five of the six uncertain parameters. As a group, the three scenarios have coverage and density of 63% and 81%. But each individual scenario has much lower coverage and density. We report the first scenario in Section 4 and Figure 4.4, because it has the highest coverage and density of the three. But the reader may note that the best-estimate future shown in Figure 5.1 lies in the third, not the first, "Both Better" scenario for the Baseline strategy.

Table B.1. Conditions defining scenarios in which each strategy meets population risk objectives, and the coverage and density for each scenario.

Strategy	Conditions	Coverage/Density
Baseline	Scenario 1: • Increase in Rainfall Intensity < 6%; • Increase in Saigon River Levels < 45 cm; • Population < 16 million • Poverty Rate < 23% • 35% < Population vulnerability < 71 % Scenario 2: • Increase in Rainfall Intensity < 4%; • Increase in Saigon River Levels < 93cm; • Poverty Rate < 9% • Population vulnerability < 90 cm Scenario 3 • Increase in Rainfall Intensity < 27%; • Increase in Saigon River Levels < 35cm; • Poverty Rate < 15% • Total Population < 14 million	Total: 63% / 81% Scenario 1: 31% / 85% Scenario 2: 28% / 77% Scenario 3: 22% / 40%
Groundwater	• Increase in Rainfall Intensity < 7% • Increase in Saigon River Levels < 55cm • Poverty Rate < 23%	50% / 72%
Rainwater	• Increase in Rainfall Intensity < 10% • Increase in Saigon River Levels < 85cm • Poverty Rate < 20%	50% / 84%
Relocate	• Increase in Rainfall Intensity < 14% • Poverty Rate < 14%	65% / 81%
Elevate	• Increase in Rainfall Intensity < 23% • Increase in Saigon River Levels < 55cm • Population Vulnerability < 74cm	43% / 80%
Groundwater & Rainwater	• Increase in Rainfall Intensity < 14%; • Increase in Saigon River Levels < 85cm; • Poverty Rate < 22%.	67% / 77%
G&W with Adaptive E&L	• Increase in Rainfall Intensity < 17%	72% / 93%
Elevate & Relocate	• Increase in Rainfall Intensity < 21% • Population Vulnerability < 76cm	56% / 95%
E&L with Adaptive G&R	• Increase in Rainfall Intensity < 26%;	75% / 96%
All Options	• Increase in Rainfall Intensity < 32%;	82% / 95%

Economic Risk

We conduct a similar analysis for the measure of economic risk. Here, we consider six rather than ten alternative strategies and construct an experimental design over a different set of uncertainties. We consider six strategies that involve augmenting the Baseline strategy with groundwater management and rainwater capture in different combinations.[36] We evaluated the economic risk for each of six strategies in each of 1000 plausible futures generated over the rainfall intensity, Saigon river levels, average annual economic growth, geographic growth dispersion, and economic vulnerability parameters in Table 4.2.[37]

As expected, the Baseline strategy performs least well, reducing risk in only 44% of the cases. Analogously to the All Options strategy for population risk, the Groundwater and Rainwater strategy performs the best, reducing risk in 62% of the futures. The Groundwater strategy alone does not reduce risk in a significantly larger number of cases compared to the Baseline strategy, but the Rainwater strategy offers substantial improvements. Given the superior performance of the Rainwater strategy over the Groundwater strategy, the Rainwater with Adaptive Groundwater strategy not surprisingly reduces risk almost as well as the strategy with both policies. The Groundwater with Adaptive Rainwater reduces risk in slightly fewer cases, 57% as compared to 62%.

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[36] We exclude options to elevate homes and relocate vulnerable areas because, as discussed in Section 3, the available data on economic activity in the city does not support any estimate of the economic effects of these policies.

[37] We consider different uncertainties because, as shown in Table 3.6, four of the model inputs that affect population risk do not affect economic risk and three of the parameters that affect economic risk do not affect population risk.

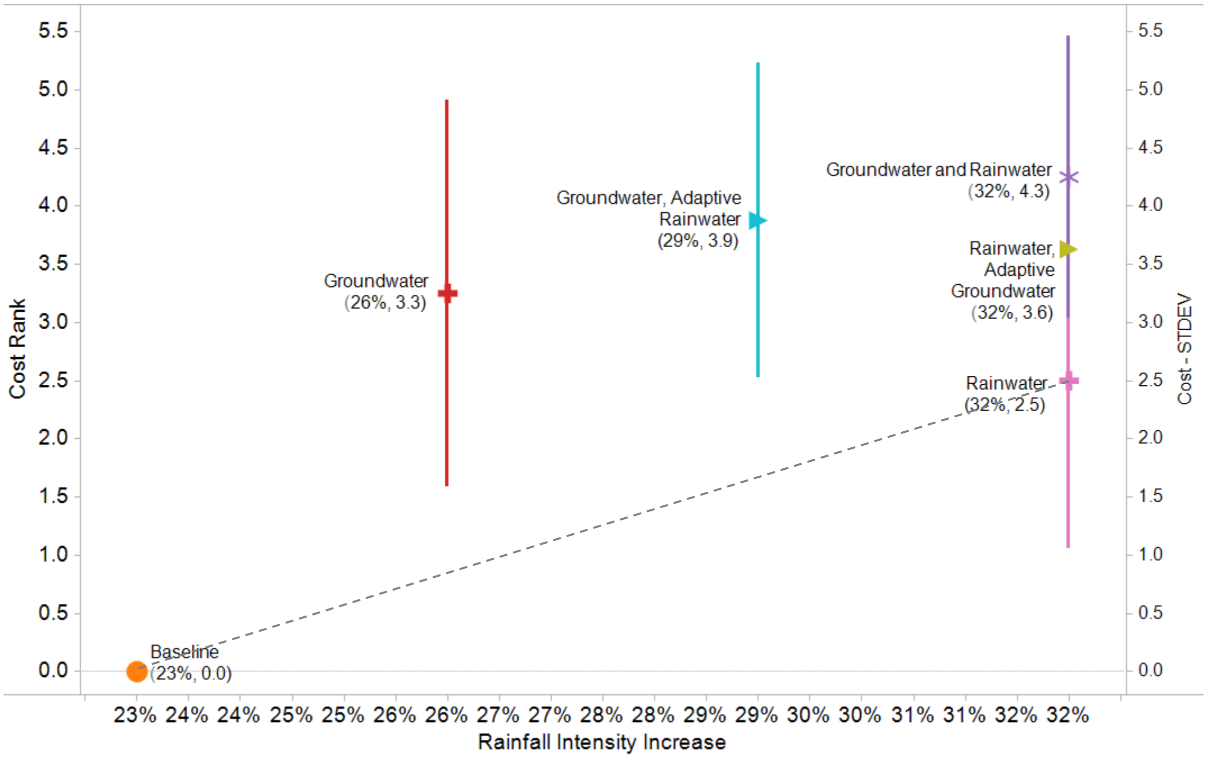

Figure B.2 Tradeoffs between cost and maximum allowable increase in rainfall intensity.

Note: Vertical bars show error estimates and the dotted line indicates non-dominated strategies.

The scenario discovery analysis identifies the conditions under which each strategy meets its objectives. The analysis finds that rainfall intensity alone is sufficient to explain when strategies meet their objectives. These scenarios are described in Table B.2. Figure B.2 combines the scenario discovery results with the results of the cost elicitation with workshop participants.

First, as this shows, all six strategies reduce risk for rainfall intensity increases larger than the IPCC mean estimate of +20% for the years 2045-2065. The Baseline strategy is least robust – to a 23% increase in rainfall intensity. The three strategies that include rainwater capture – Rainwater (purple), Rainwater and Groundwater (green), and Rainwater with Adaptive Groundwater (brown)-- reduce risk for rainfall intensity increases close the high IPCC estimate of a + 35% increase.

Second, of the six strategies, only two – Baseline and Rainwater – are not dominated by other strategies. Since Rainwater appears both more effective and less expensive than Groundwater, our results never show a strategy with the latter as a reasonable choice for reducing economic risk.

This project's analysis of strategies to reduce both population and economic risk not detailed enough to draw any definitive conclusions about the synergies and tradeoffs among the two. But comparing the results in Figures 5.7 and 5.8 does provide some illustrative initial insights.

A comparison of the two figures suggests that population risk in Ho Chi Minh City, measured by the expected number of people affected by flooding, may be more vulnerable to plausible future climate condition than economic risk, as measured by expected percentage of GDP affected by flooding. For poor and non-poor populations, the Baseline Strategy only reduces risk up to a 6% increase in rainfall intensity, significantly smaller than the IPCC mean estimate of 20%. In contrast, the Baseline Strategy reduces economic risk up to increases of 23% in rainfall intensity, approximately as large as the IPCC mean estimate.

The comparison also suggests that implementing the full set of adaptation and retreat measures considered in this study would reduce both population and economic risk for rainfall intensities almost up to the high IPCC estimate of 35%. The policy considered here that reduces economic risk most successfully – Rainwater – also generates a modest reduction in population risk. But to reduce population risk well past the IPCC mean projection for extreme rainfall, also requires Elevation and potentially Relocation measures that in our model are not treated as having an effect on economic risk.

Overall, our analysis suggest that policies that reduce economic risk also reduce population risk, but that significant additional policies are required to reduce the latter by comparable levels.

Table B.2. Conditions defining the scenarios in which each strategy meets economic risk objectives, and the coverage and density for each scenario.

Strategy	Conditions	Coverage/Density
Baseline	• Increase in Rainfall Intensity < 23%;	86% / 97%
Groundwater	• Increase in Rainfall Intensity < 26%	92% / 96%
Rainwater	• Increase in Rainfall Intensity < 35%	94% / 97%
Groundwater with Adaptive Rainwater	• Increase in Rainfall Intensity < 32%	91% / 98%
Rainwater with Adaptive Groundwater	• Increase in Rainfall Intensity < 35%	93% / 98%
Groundwater & Rainwater	• Increase in Rainfall Intensity < 35%	93% / 98%

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