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Trade-offs and synergies in managing coastal flood risk: A case study for New York City

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Abstract

Decisions on how to manage future flood risks are frequently informed by both sophisticated and computationally expensive models. This complexity often limits the representation of uncertainties and the consideration of strategies. Here we use an intermediate complexity model framework that enables us to analyze a richer set of strategies, a wider range of objectives, and greater levels of uncertainty than are typically considered by more sophisticated and computationally expensive models. We find that allowing for more combinations of risk mitigation strategies can help expand the solution set, help explain synergies and trade-offs, and point to strategies that can improve outcomes.

KEYWORDS
flood defence measures, modelling, storm surge, strategy

1 | INTRODUCTION

Coastal communities are assessing the long-term risks from future storms and will choose among potentially expensive long-term risk mitigation strategies. These choices are often informed by state-of-the-art high-fidelity storm surge risk management modeling frameworks that evaluate options for at-risk regions such as New York City (NYC) (Aerts et al., 2013; Aerts et al., 2014; Groves et al., 2016) and the Louisiana coastal region (Fischbach et al., 2012). The magnitude of proposed investments in these regions justifies extensive site-specific research on both the future risks and the evaluation of risk-mitigation strategies. Current state-of-the-art high-fidelity modeling frameworks can pose considerable computational challenges in evaluating and optimizing a
large number of strategies considering a wide range of future risks and to address a wide range of potentially conflicting objectives.

In NYC, an important goal of decision-makers is to identify potential risk management strategies that cost-effectively satisfy the sometimes conflicting objectives of diverse stakeholder groups (New York City Special Initiative for Resilient Rebuilding, 2013; NYC Economic Development Corporation, 2014; Zhu & Lund, 2009). Previous risk mitigation proposals and risk mitigation strategy evaluations have broken important new ground but they have assessed relatively few risk mitigation strategies and have not explicitly addressed the aggregate effectiveness of implementing combinations of strategies or quantitatively addressed many objectives (e.g., Mayors Office of Recovery & Resiliency, 2015; New York City Special Initiative for Resilient Rebuilding, 2013). The high computational costs associated with these frameworks and the limited computational resources restrict the number of different strategies or strategy combinations that can be evaluated, the number of objectives that can be analyzed, and the extent of future risks that are considered. The relative sparsity of solutions combined with the limited number of objectives considered impose implicit a priori preferences to those objectives analyzed, thus potentially excluding consideration of the preferences of key stakeholders. Previous research is often silent on the potential for improvements that can be achieved for many objectives by considering a more complex decision analysis. Additional factors to consider can include different levels of protection investment than those evaluated, other strategies (such as flood insurance, implementation, or restoration of natural or large-scale ocean barriers) and their associated policy levers, deep uncertainties driving the risks, or additional trade-offs associated with divergent stakeholders with potentially competing objectives.

As an example, researchers in one study (Aerts et al., 2014) considered the NYC region and used a state-of-the-art storm surge risk mitigation framework consisting of a statistical/deterministic hurricane model using inputs from four climate models, two hydrodynamic models, and a wave height model. The Federal Emergency Management Agency’s HAZUS damage models were then used to estimate damages. Using this method, the study evaluated four defensive strategies and one combined approach considering three objectives. Considered decision-levers included improvements to buildings to make them less vulnerable to storm damage, three storm surge barrier options, and a fifth strategy that combined building resistance with a barrier. The study estimated the life-cycle cost of the strategy and damage reduction to calculate a benefit–cost ratio (BCR) for each solution in three climate scenarios. The study found mixed results. Some of the strategies achieved BCRs ranging from the lowest of 0.13 under current climate conditions to 2.45 under a middle climate change scenario and a 4% discount rate. Other than BCR, additional stakeholder objectives and methods to improve these results were not explicitly addressed. While a high BCR is desirable and often a necessary condition for major investments (USACE, 2018), stakeholders may value additional objectives (Gibbs, 2019) such as minimizing construction and maintenance costs, minimizing environmental impacts, or robustness of the strategy to uncertainties.

Researchers have developed lower complexity models to address the limitations of higher-complexity and higher-cost state-of-the-art models. These intermediate complexity models can supplement the more complicated models’ capabilities and improve their relevance to decision-makers. One study (Jafino et al., 2019) uses an environmental impact assessment model coupled with a land use change model and simulates hypothetical land use adaptations on the Waal River in the Netherlands. The study assesses the potential impact of these changes on the effectiveness of adaptive mitigation approaches in mitigating the increasing flooding associated with a range of future climate scenarios. Another study (van Berchum et al., 2019) develops a simplified model of the Houston Galveston Bay region to identify trade-offs arising from the interactions associated with various and sometimes overlapping strategies. Maybe closest to the island City On a Wedge model (used in this study and initially described in Ceres et al., 2019) is the Flood Risk Reduction Evaluation and Screening (FLORES) model (van Berchum et al., 2020). FLORES adopts a reduced complexity approach to simplify the analysis of a wide range of potential future storm surge scenarios (van Berchum et al., 2020). The FLORES model evaluates multiple and potentially interdependent risk mitigation strategies at a spatial resolution that resolves different terrain types and flooding modes. The FLORES model can also help decision-makers to identify risk mitigation trade-offs within the system and understand how flood risk management decisions can change costs and impacts. Another study (Miura et al., 2021) uses a simple model to optimize multiple risk mitigation strategies for the objective of maximizing reduction in expected losses.

The recently developed island City On a Wedge (iCOW) framework (Ceres et al., 2019) enables the analysis of high-dimensional objective spaces by using a simple storm surge model that evaluates a limited spatial domain. Because iCOW imposes relatively low computational costs, it can easily be coupled with multiple objective evolutionary algorithms (MOEA; e.g., Hadka & Reed, 2012, 2013). While iCOW is considerably less computationally expensive and easier to configure than high-
fidelity modeling frameworks (Aerts et al., 2014; Fischbach et al., 2017), it incorporates many critical characteristics of US coastal communities. As a result, iCOW can be implemented at relatively low cost and is capable of evaluating and optimizing many combinations of risk management strategies while considering many objectives representing the sometimes divergent priorities of many stakeholders. The iCOW framework is broadly adaptable to modeling many features typical of large coastal cities. Here we modify the generic iCOW parameters to better reflect key features of Manhattan in terms of physical characteristics, demographics, and vulnerability. Next, we optimize three combinations of storm surge risk mitigation strategies using five implementation levers and develop a large set of Pareto optimal options considering six objectives.

State-of-the-art storm surge modeling frameworks can provide useful high-fidelity representations of risk strategy effectiveness in a geospatially resolved region, but they impose high computational cost. This relatively high cost may reduce the number of strategy combinations, limit the number of stakeholder objectives, and restrict the range of risk that can be evaluated with a given computational budget. The iCOW framework, in comparison, sacrifices a degree of realism and spatial resolution for computational efficiency. This trade-off makes iCOW potentially useful for different classes of applications of interest to many community stakeholders and potentially useful for extending and improving the results of studies using state-of-the-art modeling frameworks. It offers the ability to explore many strategy combinations while considering many objectives and it includes the ability to identify the full approximate Pareto front of optimal strategy combinations. These capabilities and relatively low cost allow decision-makers to use iCOW when insufficient resources are available to implement state-of-the-art frameworks or to supplement the decision relevant insights those studies provide. This model also allows decision-makers to consider more choices that may better satisfy the needs of diverse stakeholder groups.

The remainder of the article provides an overview of the iCOW model, results from an application to the island of Manhattan, and a discussion and conclusion of the analysis.

2 | ISLAND CITY ON A WEDGE

Overview

The city simulated by the iCOW framework resembles the general physical and demographic profile of many major coastal cities including Manhattan (Ceres et al., 2019). The Borough of Manhattan is situated on Manhattan Island. According to the US Census bureau, the borough is approximately 21.6 km long, is approximately 3.7 km wide at its widest point, has an area of 59.2 km² (US Census Bureau, 2018) and is surrounded by a seawall or natural elevation barriers. The overall topography of Manhattan resembles a ridge oriented parallel to the north–south axis of the borough. iCOW simulates a city along a waterfront and situated on a rising coast of constant slope. To make for a good conceptual fit, we consider the east and west sides of the borough as a single coastline and adjust the dimension to achieve a reasonable representation of the irregularly shaped Manhattan with the rectangular shape of the City Model. We therefore select a city coastline of 40 km, and a city depth of 1.5 km, resulting in a total area of 60 km². The city is initially uniformly dense and buildings are uniformly tall (relative to the potentially largest storm surges).

The Battery Park seawall is approximately 1.2 m above the mean high water (MHHW) mark of the NOAA tide gauge located adjacent to the park (NYC Economic Development Corporation, 2014). The authors are not aware of other published data on the average height of the seawall surrounding Manhattan, but visual observation indicates it is usually somewhat higher. In the iCOW model no damage occurs when storm surges are below the seawall height. The storm surge from Hurricane Sandy (shown in Figure 1) reached 2.8 m above MHHW at The Battery and caused extensive flooding. Whereas the storm surge from Hurricane Donna in 1960 (shown in Figure 1) reached just over 1.6 m, it did not cause enough flooding and damage to be measured and recorded in NYC reports. Similarly, the winter storm of November 1960, nicknamed the Great Appalachian Storm (shown in Figure 1), reached a peak storm surge of 2.3 m, but the storm tide only reached 1.2 m above MHHW. This storm did cause some flooding in Manhattan but did not result in extensively reported damage. Hence, we establish a uniform iCOW seawall height of 2.0 m as a reasonable representative seawall height. Storm surges below this level generate no damages, whereas storm surges above this level accumulate damages.

A plaque situated in Bennett Park marks Manhattan’s highest point and lists the elevation as 265 ft. The peak elevation of the ridge at other locations is considerably lower, and as elevation from the waterline increases, the rectangular shape of the City Model less faithfully models the actual borough terrain. However, above the maximum surge heights, City Model objectives, such as damage functions, are not affected by this mismatch. We therefore derive a representative iCOW
city height based on NYC’s reported inundation extent from Superstorm Sandy of $P_i = 11\%$ of buildings damaged (for all five boroughs). From this percentage, and the observed Superstorm Sandy surge height of $S_{\text{Sandy}} = 2.8$ m, we derive a representative iCOW peak elevation of $17$ m.
The basic iCOW Damage function assumes that damages are proportional to the volume of infrastructure that is inundated but this damage function is modified in response to implementation of defensive strategy levers described in the next paragraph. Not all buildings within a flooded area are necessarily damaged. In Manhattan, Superstorm Sandy’s storm surge damaged 39% of buildings within the inundation footprint (de Blasio & Bruno, 2014). We therefore establish a parameter $F_{\text{damaged}} = 0.39$ to represent this fraction.

The remaining city parameters of the uniform city building height, average structure vulnerability, and total city value are interrelated. We assume a uniform iCOW building height, $h_{\text{building}} = 30$ m. This height is higher than the maximum storm surges, but considerably shorter than the tallest buildings in Manhattan.

The authors know of no definitive estimates of Manhattan's total asset value. Therefore, we develop a representative overall value for Manhattan, $V_{\text{city}}$, based on iCOW dimensions, and NYC's estimates of inundation extent and reported damage associated with Superstorm Sandy in accordance with relationship,

$$v_{\text{damage from Sandy}} = P_{\text{volume inundated}} / V_{\text{city}},$$

where,

$$P_{\text{volume inundated}} = \frac{(\text{surge}_\text{Sandy} - h_{\text{seawall}})^2}{2},$$

and,

$$V_{\text{city}} = h_{\text{buildings}} \times \text{city width} \times E_{\text{representative max}}.$$

The resultant representative total city value is $1.5$ trillion.

The parameters developed above are summarized in Table 1. The remaining parameters relating to the cost and damage functions for the iCOW city zones are as described in Ceres et al. (2019). Data within the scientific literature on these parameters are sparse, but more realistic city specific parameters could be developed by local policy makers. For instance, the construction costs for a levee or dike will vary regionally based on labor rates, site accessibility, local environmental concerns, material costs, degree of exposure to open seas, or ground and soil conditions. Local policymakers and stakeholders will typically have better estimates of these factors which should be incorporated to improve the overall fidelity of the iCOW framework.

By modifying the original city-scape’s defenses, we can analyze three risk mitigation strategies that are implemented through five strategy levers. For this proof-of-concept study, we consider static strategies that do not adjust as new information may become available. Dynamic adaptive strategies have the potential to considerably improve outcomes (Garner & Keller, 2018; Haasnoot et al., 2013, 2019).

The first defensive strategy is withdrawal from low-lying at-risk areas. The second defensive strategy is to improve resistance by modifying buildings and infrastructures to reduce their vulnerability to flood damage. The third available strategy is to construct a dike (a.k.a. levee). Each strategy is defined by one or more levers that control the characteristics of the strategy. In this study, the three strategies considered are associated with five decision levers (see the XLRM framework used by Lempert et al., 2003). The withdrawal height lever is an elevation demarcation below which buildings are relocated to higher elevation regions of the city. Resistance is associated with two levers, the resistance height and the resistance percent. The third strategy, building dikes, is associated with two levers, the dike height and the location of the dike base. (see figure 3 and table 1 in Ceres et al., 2019 for additional details.) Other mitigation strategies are possible but for simplicity, are not included in this study. Examples could include insurance, enhancement of natural features that reduce the impact of storm surges, or harbor-scale surge barriers.

Operation of the levers specifies a candidate city that is divided into distinct zones (Table 2) with different values of densities and vulnerabilities to surge damage. For example, policymakers might adopt a strategy consisting of withdrawal from the lowest 0.2 m of the city, construction of a 5 m dike 1 m above the lowest city elevation, and implementation of building modifications to reduce flood damage by 50% to a height of 5 m for the buildings located between the withdrawal area and the dike. In this case, the candidate city will consist of zones zero, one, three, and four from Table 2.

| Parameter | Value | Units |
|-----------|-------|-------|
| Building height | 30 | m |
| City elevation | 17 | m |
| City depth | 2 | km |
| City length | 43 | km |
| City value | 1.5 | $\text{trillion} |
| Damage factor | 0.39 | none |

The authors know of no definitive estimates of Manhattan's total asset value. Therefore, we develop a representative overall value for Manhattan, $V_{\text{city}}$, based on iCOW dimensions, and NYC's estimates of inundation extent and reported damage associated with Superstorm Sandy in accordance with relationship,
We evaluate candidate city strategies against possible future storm surges using objectives that different stakeholder communities might have. For this study, we consider six objectives: (1) minimize total investment cost, (2) minimize average annual damage (over a 50-year period), (3) maximize return on investment (ROI), (4) maximize total monetary net benefit of investment, (5) maximize the frequency of a positive total monetary net benefit, and (6) minimize the annual frequency of large threshold events.

The City Model calculates the total investment cost objective for a candidate city strategy at time zero. To calculate the remaining objectives the City Model evaluates damages from 5000 50-year sequences of annual highest storm surges that represent the annual highest water levels. We use the Generalized Extreme Value distribution (GEV) and adjust its parameters such that the 100-year storm surge level increases by 1 m per century (Ceres et al., 2017; Ceres et al., 2019).

To optimize candidate cities considering many potential objectives and using many combinations of defensive strategies, we use a MOEA (Hadka & Reed, 2012, 2013) to generate an initial random population of candidate strategies, each defined by their associated lever settings and evaluate the objectives against the 5000 sequences spanning 50 years each of storm surges (resulting in 250,000 annual highest storms for each candidate strategy). The MOEA then recombines the traits of successful population members to evolve the population of candidate strategies toward the Pareto-optimal surface spanned by the objectives. See Zitzler et al. (2003) for more details on how MOEAs function. We selected the BORG MOEA based on its performance in optimizing problems with discrete choices, exploring and generating diverse solutions in problems with multi-modal solution regions, and its computational efficiency (Hadka & Reed, 2013). We use data visualization tools to illustrate the potential trade-offs and synergies. The goal of this optimization and visualization is to better inform stakeholders and decision-makers about the trade-offs associated with different combinations of defensive strategies without any a-priori preference for particular objectives. The interaction between the iCOW modules is depicted in Figure 2.

3 | METHODS

To assess the iCOW framework’s ability to adequately model Manhattan’s storm surge risk we evaluate the fully parameterized iCOW model of an undefended city against a range of storm surges up to and exceeding surge...
levels experienced during Superstorm Sandy. We also use the full iCOW framework to assess the overall performance of the unprotected city against the aggregate exogenous sequences of storm surges. We compare the performance of the unprotected city to established risk estimates currently being used by NYC and estimated by other research. For conceptual simplicity, in this study we assume no growth, inflation, or discount rate. Our projection of damage resulting from Superstorm Sandy is $6.4 billion, which is roughly consistent with estimates of actual damage to Manhattan ($7.0 billion) (de Blasio & Bruno, 2014). Over the full 5000 sets of 50-year storm surge sequences in this analysis, average annual damage to the undefended iCOW city ($374 million/year) is substantially higher than those estimated by other studies (Aerts et al., 2014; Reed et al., 2015). We also estimate the risk of future threshold events (resulting in damages of $4 billion or more).

To test the framework’s ability to inform stakeholders evaluating storm surge risk mitigation strategy options, we evaluate and optimize the six objectives using the five strategy levers against the exogenous storm surges. We conduct this optimization using 100 cores in parallel and run the optimization for 12 h, resulting in a converged final population of more than 18,000 members.

We project the results using two and three-dimensional plots and parallel axis plots. For different stakeholders with differing objectives and differing abilities to affect decisions, we expect they would have different ideas on how to display data to best visualize trade-offs among their priorities. Moreover, using an interactive display often improves comprehension of complex and high dimensional data. Therefore, we also provide an online visualization tool to interactively explore the data sets developed for this study at datacommons.psu.edu.

4 | RESULTS AND DISCUSSION

The iCOW framework maps out the approximate Pareto front. We discuss a sample of strategies located at this Pareto front. We identify a zero investment (“do nothing”) strategy that results in damages of $389 million per year. The most expensive (“all in”) strategy costs $6.5 trillion to implement and is associated with an average estimated annual damage of $6.6 million/year. This all-in strategy is dike-free and includes a withdrawal from the waterfront to 0.33 m and unprotected buildings made 99.5% resistant to damage to a height of 13 m above the withdrawal height. A “lowest damage” strategy combines a withdrawal from the waterfront to 0.37 m and unprotected buildings made 99.5% resistant to damage to a height of 13.9 m above the withdrawal height. There is a 10 m dike located 5.9 m above the withdrawal height. This strategy cost $4.3 trillion but results in estimated damages of just $0.3 million/year.

Optimization of the fully parameterized iCOW Manhattan model results in a diverse Pareto dominant solution set consisting of 18,756 members. We show the Pareto front for all solutions requiring less than $25 billion investments (Figures 3-5). In comparing the results
FIGURE 4  Three-dimensional data visualization of Manhattan iCOW emulation showing damage (z axis) versus investment (x axis) versus BCR (y axis) for the Pareto dominant solution with investment cost less than $25 billion. Color scale shows Pareto dominant values for the annual frequency of threshold events. The most preferred solutions (near zero cost and damage) with a low frequency of threshold events and high BCR are located in the lower left forward corner of the plot marked with the large dark blue circle.

FIGURE 5  Two-dimensional data visualization of Manhattan iCOW emulation showing BCR (y axis) versus investment (x axis) for the Pareto dominant solution with investment cost less than $25 billion.
with those generated using two objectives (Ceres et al., 2019), we find that the inclusion of additional objectives results in a more diverse and larger solution set.

4.1 The need for more complex data visualizations

Many iCOW two axis objective plots clearly reveal the Pareto dominant front for the two axis objectives as a well-defined edge closest to each axis’ objective goal (e.g., zero damage and no investment cost in Figure 3). Points fanning behind this front are associated with other objectives, but the two-dimensional plot fails to illustrate the trade-offs associated with these other objectives. Encoding information about these objectives via adding a third axis, a color scale, or a point-size scale may help or hinder policymaker understanding, as can additional 2D plots showing different objective trade-offs. Figures 4 and 5, for example, provide a far better representation of the bifurcation and gaps seen in Figure 3 that correspond to regions in the solution space where no feasible solutions exist. By providing a visual representation of trade-offs, the additional information may help, but the associated visual complexity may create further barriers to understanding an already a complicated problem. Using a three-axis plot, we allow for the display of an additional objective (as in Figure 4), at the cost of potentially obfuscating the relationships between objectives due to the projection of a complicated three-dimensional shape onto a two-dimensional surface. An effective approach that overcomes many of these limitations may be to allow for interactive data visualization techniques where the user can adjust the view to their preferences.

Alternative data visualization approaches, such as parallel axis and matrix plots, can help highlight the complicated inter-dependencies and trade-offs between the levers and objectives. As one example, a parallel axis plot can show the richness of solutions in a Pareto front. However, this display does not always allow for clear identification of Pareto fronts.

The Pareto dominant population assumes no a priori preference for objectives and spans a wide range of objectives and lever settings. Not all stakeholders have the ability to influence all of the levers, and resources to implement levers may be limited. For example, a city government may have a fixed range of investments available for capital investment in structural solutions such as constructing dikes or levees. They also may have some control over other levers such as the ability to impose reasonable zoning restrictions that improve structural resistance to damage. And, they may have no control over the withdrawal of private infrastructure to higher locations in the city. Other stakeholders may have strong preferences that city governments may wish to consider. For instance, the waterfront business community may not prefer dikes or levees located at the waterfront that restrict access to their business locations. The data visualization can provide controls that allow stakeholders with divergent objectives to mutually explore and clearly illustrate the trade-offs inherent in the Pareto dominant solution space.

4.2 Implications

The reduced complexity approach taken with the iCOW approach drastically increases the number of feasible function evaluations for a given computational budget. This, in turn, enables the consideration of more strategies and strategy combinations or the consideration of more objectives compared to more complex model structures (e.g., Aerts et al., 2014, Fischbach et al., 2017). Furthermore, the intermediate complexity approach simplifies the identification of the approximate Pareto front that illustrates the trade-offs between many objectives over a wide range of possible futures. For example, the Aerts et al., 2014 study briefly described in the introduction examines five strategy combinations for New York City costing $10.4–$23.8 Billion with BCRs ranging from 0.13 under current climate conditions to 2.45 under a moderate climate change scenario and a 4% discount rate. These are very valuable insights, but this study is silent on the question whether each of the individual strategy combinations studied could be improved through changes to investment levels or changes in implementation details (Aerts et al., 2014). Based on our study examining more strategies and strategy combinations across many objectives and a larger range of storm surge scenarios, the results suggest that there may be lower-cost resistance-only based strategies that have very high BCRs than those examined by previous studies (e.g., Aerts et al., 2013). These previously unidentified strategies may be preferred by some stakeholders such as risk averse individual asset owners with sites having special cultural or functional value such as art museums or transportation hubs. Another potential use for the iCOW modeling framework is in quickly and inexpensively supplementing state-of-the-art modeling frameworks in terms of evaluating new strategies (such as insurance) and evaluating the robustness of strategies against much wider ranges of future storm surge risk. This added insight from the iCOW results, however, comes at the cost of providing less detailed information.
and lower fidelity information regarding any particular solution.

The iCOW framework estimate of expected annual storm surge damage over the next 50-years for the undefended model ($389 million/year) is substantially larger than the $174 million/year estimate for NYC (the entire city) from previous research (Aerts et al., 2013). Many factors may contribute to this difference. For example, one potential source for the larger damages found in this study is that the GEV location and scale parameters are increasing such that the 100-year storm surge is increasing at 1 m per century. Alternatively, we can express this imposed change in terms of shorter return periods for major surges. For the observed 2.8 m surge from Hurricane Sandy, for instance, the estimated return period decreases from 130 to 60 years for the 50th year in the simulations considered here. We have repeated the analysis for the case where GEV parameters are held constant at current estimates and results are qualitatively. Another source for larger damages may result from iCOW’s assumptions regarding seawall height (which precludes most storms from causing any damage), and iCOWs assumed linear relationship between city volume flooded and damage. The net effect of these assumptions is that damage rises very rapidly for surges larger than Superstorm Sandy’s 2.8 m (above MHHW) surge.

Taking advantage of the iCOW framework’s capabilities to support actual decision-making for NYC (or any city) will require improvements to the overall fidelity of the iCOW framework beyond this proof-of-concept study. City policymakers and stakeholders can draw upon the city’s considerable collective experience and local expertise to identify factors that are specific to local conditions. This additional knowledge may justify changes to the iCOW framework such as adjustments to cost parameters, cost algorithms or damage functions for dikes, resistance, and withdrawal. Stakeholders may wish to consider additional risk mitigation strategies not considered in this study, such as expanded insurance coverage, enhancement of natural barriers, or city resiliency improvements. For example, the current damage functions are calibrated to result in zero damage for surges below the seawall height and to generate approximate “Sandy-scale” damages from “Sandy-scale” surges. Results from other model frameworks (Aerts et al., 2013; Lin et al., 2012) can be used to explore the iCOW framework’s emulation performance and to identify, quantify, investigate, and potentially remedy sources of deviation. In addition, local expert knowledge may lead to the addition of other decision levers such as installation of pumps or a strategy to not rebuild after damage. Similarly, local stakeholders may also have additional site-specific objectives such as defense of specific critical infrastructure or places of particular cultural importance. There is a relative paucity of studies regarding the costs of implementing defensive measures such as the dike, withdrawal, and resistance strategies included in this study. These costs depend, of course, on the particular community under consideration. Communities, however, have considerable programmatic expertise (in terms experienced local engineering firms, and city planners) and historic data (e.g., from previously executed contracts for similar projects or from the experiences of other communities facing similar challenges) that can be brought to bear if stakeholders intend to use the iCOW model. Lastly, stakeholders and decision-makers may also wish to alter the zero growth, no inflation, and no discount rates that are assumed for this study to better reflect local projections and preferences for the particular area under study.

5 CONCLUSIONS

The iCOW framework can be useful to decision-makers in several ways. First, it can help to examine “real-world” strategy options over a wide range of uncertainties to stress test these strategies. Second, it can be used to analyze a larger set of objectives. Third, when used in combination with state-of-the-art solutions where multiple objectives have not been considered or a multi-objective optimization has not been performed, the iCOW framework may be able to point out potential Pareto improvements to these candidate strategies. Last, but not least, given the complexity and large costs, many coastal communities lack the resources required to implement state-of-the-art storm surge risk modeling frameworks. In these cases, the iCOW framework can be employed relatively inexpensively and quickly to support coastal community decision-making.

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**CONFLICT OF INTEREST**
The authors are not aware of financial or personal relationships that would pose a conflict of interest.

**CODE AND DATA AVAILABILITY STATEMENT**
All iCOW software code and the final dataset used to create the figures in this article are available at: https://github.com/rceres/ICOW_Manhattan. This is a research study, and the results are not to be used to inform actual decision-making. All results, data, and tools are distributed under the GNU non-commercial license 3.0 (https://www.gnu.org/licenses/lgpl-3.0.html) (see especially the disclaimer of warranty and limitation of liability).

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**REFERENCES**
Aerts, J. C. J. H., Botzen, W. J. W., Emanuel, K., Lin, N., de Moel, H., & Michel-Kerjan, E. O. (2014). Evaluating flood resilience strategies for coastal megacities. *Science*, 344(6183), 473–475. https://doi.org/10.1126/science.1248222
Aerts, J. C. J. H., Lin, N., Botzen, W., Emanuel, K. A., & de Moel, H. (2013). Low-probability flood risk modeling for New York City: Low-probability flood risk modeling for New York City. *Risk Analysis*, 33(5), 772–788. https://doi.org/10.1111/risa.12008
Ceres, R. L., Forest, C. E., & Keller, K. (2017). Understanding the detectability of potential changes to the 100-year peak storm surge. *Climatic Change*, 145(1–2), 221–235. https://doi.org/10.1007/s10584-017-2075-0
Ceres, R. L., Forest, C. E., & Keller, K. (2019). Optimization of multiple storm surge risk mitigation strategies for an Island City on a wedge. *Environmental Modelling & Software*, 119, 341–353. https://doi.org/10.1016/j.envsoft.2019.06.011
de Blasio, B., & Bruno, J. F. (2014). *New York City hazard mitigation plan* (2014). Hazard Mitigation Unit, New York City Office of Emergency Management. http://www.nyc.gov/html/oem/downloads/pdf/hazard_mitigation/plan_update_2014/1_introductioon_final.pdf
Fischbach, J., Johnson, D., & Molina-Perez, E. (2017). *Reducing coastal flood risk with a Lake Ponchartrain barrier*. RAND Corporation.
Fischbach, J. R., & Louisiana, & Rand Gulf States Policy Institute. (2012). *Coastal Louisiana risk assessment model: Technical description and 2012 coastal master plan analysis results*. Rand Corp.
Garner, G. G., & Keller, K. (2018). Using direct policy search to identify robust strategies in adapting to uncertain sea-level rise and storm surge. *Environmental Modelling & Software*, 107, 96–104. https://doi.org/10.1016/j.envsoft.2018.05.006
Gibbs, K. (2019). EP_1105-2-57-2 Stakeholder engagement, collaboration, and coordination. US Army Corp of Engineers. www.publications.usace.army.mil/Portals/76/Users/182/86/2486/EP_%5F201105-2-57.pdf?ver=2019-04-03-150516-977
Groves, D., Kuhn, K., Fischbach, J., Johnson, D., & Syme, J. (2016). *Analysis to support Louisiana’s flood risk and resilience program and application to the national disaster resilience competition*. RAND Corporation. https://doi.org/10.7249/RIR1449
Hadka, D., & Reed, P. (2012). Diagnostic assessment of search controls and failure modes in many-objective evolutionary optimization. *Evolutionary Computation*, 20(3), 423–452. https://doi.org/10.1162/EVCO_a_00053
Hadka, D., & Reed, P. (2013). Borg: An auto-adaptive many-objective evolutionary computing framework. *Evolutionary Computation*, 21(2), 231–259. https://doi.org/10.1162/EVCO_a_00075
Haasnoot, M., Kwakkel, J. H., Walker, W. E., & ter Maat, J. (2013). Dynamic adaptive policy pathways: A method for crafting robust decisions for a deeply uncertain world. *Environmental Change: Human and Policy Dimensions*, 23(2), 485–498. https://doi.org/10.1016/j.gloenvcha.2012.12.006
Haasnoot, M., Brown, S., Seussolini, P., Jimenez, J., Vafeidis, A. T., & Nicholls, R. (2019). Generic adaptation pathways for coastal archetypes under uncertain sea-level rise. *Environmental Research Communications*, 1, 1–12. https://doi.org/10.1088/2515-7620/ab1871
Jafino, B. A., Kwakkel, J. H., & Haasnoot, M. (2019). What are the merits of endogenising land-use change dynamics into model-based climate adaptation planning? *Socio-Environmental Systems Modelling*, J, 16126. https://doi.org/10.18174/sesmo.2019a16126
Lempert, R. J., Popper, S., & Bankes, S. (2003). *Shaping the next one hundred years: New methods for quantitative, long term policy analysis*. RAND Corporation.
Lin, N., Emanuel, K., Oppenheimer, M., & Vanmarcke, E. (2012). Physically based assessment of hurricane surge threat under climate change. *Nature Climate Change*, 2(6), 462–467. https://doi.org/10.1038/nclimate1389
Mayors Office of Recovery & Resiliency. (2015). *Nyc_ndrc_phase2_english.pdf*. New York City.
Miura, Y., Dinenis, P. C., Mandli, K. T., Deodatis, G., & Bienstock, D. (2021). Optimization of coastal protections in the presence of climate change. *Frontiers in Climate*, 3, 83. https://doi.org/10.3389/fclim.2021.613293
New York City Special Initiative for Resilient Rebuilding (2013). PlaNYC: A stronger, more resilient New York [special report]. http://www.nyc.gov/html/sirr/html/report/report.shtml.
NOAA & (n.d.). Water Levels—NOAA Tides & Currents. NEW YORK (The Battery), NY Station ID: 8518750. Retrieved October 8, 2021, from http://tidesandcurrents.noaa.gov/waterlevels.html?id=8518750&units=metric&bdate=20210209&edate=2021030&timezone=GMT&datum=MHHW&interval=&action=NYC Economic Development Corporation. (2014). Southern Manhattan coastal protection study: Evaluating the feasibility of an MPL.
Reed, A. J., Mann, M. E., Emanuel, K. A., Lin, N., Horton, B. P., Kemp, A. C., & Donnelly, J. P. (2015). Increased threat of tropical cyclones and coastal flooding to New York City during the anthropogenic era. *Proceedings of the National Academy of Sciences*, 112(41), 12610–12615. https://doi.org/10.1073/pnas.1513127112
US Census Bureau. (2018). U.S. Census Bureau QuickFacts: New York County (Manhattan Borough), New York. https://www.census.gov/quickfacts/fact/table/newyorkcountymanhattanborough/newyork/BZA210216

USACE. (2018). ASCE Federal Project BCR and Scoring Information Paper. US Army Corp of Engineers. https://www.asce.org/uploadedFiles/News_Articles/asce-bcr-paper-2018.pdf

van Berchum, E. C., Mobley, W., Jonkman, S. N., Timmermans, J. S., Kwakkel, J. H., & Brody, S. D. (2019). Evaluation of flood risk reduction strategies through combinations of interventions. *Journal of Flood Risk Management*, 12, e12506. https://doi.org/10.1111/jfr3.12506

van Berchum, E. C., van Ledden, M., Timmermans, J. S., Kwakkel, J. H., & Jonkman, S. N. (2020). Rapid flood risk screening model for compound flood events in Beira, Mozambique. *Natural Hazards and Earth System Science*, 20(10), 2633–2646. https://doi.org/10.5194/nhess-20-2633-2020

Water Levels—NOAA Tides & Currents (n.d.). Retrieved September 5, 2018, from https://tidesandcurrents.noaa.gov/waterlevels.html?id=8518750&units=metric&bdate=19600912&edate=19600912&timezone=GMT&datum=MHHW&interval=h&action=

Zhu, T., & Lund, J. R. (2009). Up or out?—Economic-engineering theory of flood levee height and setback. *Journal of Water Resources Planning and Management*, 135(2), 90–95.

Zitzler, E., Thiele, L., Laumanns, M., Fonseca, C. M., & da Fonseca, V. G. (2003). Performance assessment of multiobjective optimizers: An analysis and review. *IEEE Transactions on Evolutionary Computation*, 7(2), 117–132. https://doi.org/10.1109/TEVC.2003.810758

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