Optimization of multiple storm surge risk mitigation strategies for an Island City On a Wedge

Robert L. Ceres¹, Klaus Keller²,³, Chris E. Forest¹,²,³,*

507 Walker Building
University Park, PA 16802

Abstract

Managing coastal flood risks involves choosing among portfolios of different options. Analyzing these choices typically requires a model. State-of-the-art coastal risk models provide detailed regional information, but can be difficult to implement, computationally challenging, and potentially inaccessible to smaller communities. Simple economic damage models are more accessible, but may not incorporate important features and thus fail to model risks and trade-offs with enough fidelity to effectively support decision making. Here we develop a new framework to analyze coastal flood control. The framework is computationally inexpensive, yet incorporates common features of many coastal cities. We apply this framework to an idealized coastal city and assess and optimize two objectives using combinations of risk mitigation strategies against a wide range of future states of the world. We find that optimization using combinations of strategies allows for identification of Pareto optimal strategy combinations that outperform individual strategy options.

Keywords: storm surge, flood risk, coastal, damage, resilience, multi-objective robust decision making, risk management, New York, Hurricane,
1. Introduction

Communities have used dikes (aka levees) to protect coastal areas from floods for centuries. In the Netherlands, for example, dikes have been used to protect small regions since the 13th century (Gerritsen, 2005). Numerous other defensive strategies are available to reduce the risk of storm surge. These risk mitigation strategies have different advantages and disadvantages that vary based on where the strategies are considered and which will appeal to varying degrees to different stakeholders. These strategies can include insurance, preservation or enhancement of natural barriers, construction of physical barriers and sea-gates across waterways, installation of active measures such as pumps, adoption of zoning restrictions, withdrawal or relocation of development, physical alteration of buildings, and resiliency improvements (FEMA, 2011; de Blasio and Bruno, 2014).

Regardless of which strategy or combination of strategies is considered, policymakers require means of assessing the needed level of protection and evaluating the performance of candidate strategies in terms of often divergent stakeholder objectives (Groves et al., 2016). Prior to 1953 in the Netherlands, the predominant practice had been to establish dike height based on the highest previously observed flood levels plus a three foot safety margin (van Dantzig, 1956; Battjes and Gerritsen, 2002).

Today, the most often used standard for establishing flood protection levels is based on a return level, the estimated height that is expected to be exceeded for a specified probability of occurrence. In the US, usage of the 100-year return level for that purpose has led to the widespread use of ‘base flood’ to refer to the water level that is expected to be reached or exceeded with a 1% probability in a given year, and the US government uses ‘base flood’ to set policy (US CFR 725 Executive Orders 11988, 1988, 2015; FEMA, 2015; Bellomot et al., 1999). Recently researchers and policymakers have expressed concerns about the adequacy of this standard and the efficacy of current implementation of the standard (Highfield et al., 2013; Ludy and Kondolf, 2012; Galloway et al., 2006; Wing et al., 2018).

Other approaches to estimating flood risk and establishing flood safety measures are possible. In January of 1953 in the Netherlands, a winter storm generated a storm surge, subsequently named the “Big Flood” that
caused extensive damage and killed 1,836 people (Gerritsen, 2005). In response, the government formed the “Delta Commission,” which turned to the Dutch mathematician David van Dantzig (van Dantzig, 1956; Gerritsen, 2005; Zevenbergen et al., 2013). He approached the problem from both a statistical and economic perspective. On the statistical side, he examined historical tide gauge data to estimate the likelihood that any flood height would be exceeded. On the economic side, he considered the current cost of constructing a dike and the corresponding net present cost of future damages that should be expected. The sum of these two quantities is the net present cost of constructing a dike. Minimizing this net present cost results in an optimal risk reduction strategy that sets an optimal dike height and a time interval for reexamining (and potentially increasing) that height.

Researchers have subsequently improved ‘van Dantzig style’ models to account for parameter uncertainty and improve flood probability models (Slijkhuus et al., 1997; Speijker et al., 2000; Huisman et al., 2010; Oddo et al., 2017; Wong et al., 2017) and to investigate various methods of learning for optimization of future height adjustments (Kok and Hoekstra, 2008; Garner and Keller, 2018). Several assumptions constrain ‘van Dantzig style’ models, however, by making them unrealistically simple and therefore unrepresentative of many at-risk coastal cities. The ‘van Dantzig style’ models are also restricted to evaluating a single protection strategy, such as construction of a levee or dike.

Policymakers today are interested in considering other approaches to risk mitigation and combinations of different strategies (Ligtvoet et al., 2012; New York City Special Initiative for Resilient Rebuilding, 2013; Fischbach et al., 2017). The van Dantzig model assumes dike cost is proportional to height and that damage due to flooding is zero until levees are breached or overtopped, at which point 100% damage occurs (van Dantzig, 1956). This may be a reasonable approximation for traditional dikes protecting flat terrain in the low polders found in the Netherlands, but this is a poor representation of many major cities located on a rising coast or hilly terrain.

Another potential weakness of a ‘van Dantzig style’ model is its focus on a single objective: the expected net cost, (aka net present value). The stakeholder community impacted by flood events and affected by flood risk mitigation efforts is large and diverse, with correspondingly diverse values (Harman et al., 2015; Bessette et al., 2017) and often conflicting sets of objectives (Harman et al., 2015; Porthin et al., 2013; Vezèr et al., 2018).

Neither base flood level nor ‘van Dantzig style’ approaches allow city
planners to evaluate changes to damage associated with surge heights above the selected return level. Additionally, return periods for these estimated levels are typically long compared to the record of surge observations available (Grinsted et al., 2012; 2013; Menéndez and Woodworth, 2010; Ceres et al., 2017; Lee et al., 2017). This relative sparsity of data leads to wide uncertainty in estimates of long-period return levels (Coles, 2001), and the potential for bias in estimating extreme event risks using common extreme value analysis methods (Coles et al., 2003; Ceres et al., 2017).

Researchers have developed other, more complex methods and models for assessing various aspects of storm surge risk. Superstorms Katrina and Sandy have motivated substantial investments in storm surge protection for the New Orleans and New York City metropolitan areas, respectively (Fischbach and Rand Gulf States Policy Institute, 2012; Aerts et al., 2013; Groves et al., 2016; Aerts et al., 2014; Small and Xian, 2018). The magnitude of proposed investments justified extensive, site-specific research on both future storm surge risk for these broad geographical regions and for evaluation of several proposals to mitigate that risk. To support these efforts, researchers have developed state-of-the-art storm surge modeling frameworks incorporating hurricane track and intensity prediction models driving hydrological storm surge models incorporating site-specific bathymetry and geography that in turn consider local topography and potential defensive measures and generate simulated inundation levels over a wide area. These inundation levels are then matched to detailed demographic data and damage models to produce area wide and location specific estimates of economic impact (e.g. Kerr et al., 2013; Taflanidis et al., 2013; Flowerdew et al., 2010; Orton et al., 2012; Fischbach and Rand Gulf States Policy Institute, 2012; Aerts et al., 2014).

In New Orleans, for example, the Coastal Louisiana Risk Assessment (CLARA) model is used to estimate flood extent, associated flood depths, and resulting damages that would occur to the entire Louisiana coastal region (Fischbach and Rand Gulf States Policy Institute, 2012; Johnson et al., 2013). Policymakers can use this approach to evaluate the effectiveness of several risk mitigation strategies in response to specific storms area wide, or for specific locations. For instance, the CLARA model was recently used to evaluate five Lake Pontchartrain storm surge barrier options for reducing storm surge damage across 15 counties against 77 storms (Fischbach et al., 2017). These models are complex and computationally intensive. Using the approach to evaluate the effectiveness of multiple risk mitigation strategies against the full range of possible future storms, and to select optimal mit-
igation strategies is usually computationally unfeasible. Additionally, the expense associated with creating similar models for other regions will exceed the resources available to many communities. This suggests a need for a new framework with different modelling capabilities.

Here we develop the island City On a Wedge (iCOW), a model framework that bridges the gap between ‘van Dantzig,’ and ‘CLARA style’ modelling approaches. Using an idealized geography of a city situated on a rising coastline, the model simulates the increasing damage that occurs with larger storm surges and the distribution of those damages across the city. The iCOW framework can evaluate multiple risk reduction strategies in terms of several objectives over differing time scales, such as investment cost, investment timing, median or maximum annual storm surge damage, and the distribution of damage within the city. The framework is flexible enough to incorporate other effects such as economic loss associated with withdrawal strategies or potential value shifts associated with construction of levees or dikes.

Unlike the ‘CLARA style’ models described above, iCOW is computationally quite inexpensive to run. As a result, iCOW is capable of evaluating the efficacy of multiple combinations of storm surge risk mitigation strategies over a wide range of potential futures. While computationally inexpensive, iCOW improves upon ‘van Dantzig style’ models in several important respects. The framework incorporates typical characteristic features of coastal cities, features intended to improve its overall fidelity.

The remainder of this article explains the general characteristics and features of the iCOW, describes the iCOW computational environment and experimental design, and presents and discusses results and conclusions.

2. iCOW features

We next explain the physical characteristics that the iCOW framework in terms of the city characteristics, available mitigation strategies and resultant division of the city into zones, the availability of strategy levers, and a description of damage functions.

2.1. City characteristics

The first characteristic of iCOW is the gradually rising elevation of the city with distance from the city’s waterfront. Many cities (e.g. Boston, NYC, and San Diego), are situated at the water’s edge and consist of a gradually
rising terrain. In these cases, higher surge levels will result in larger areas and greater depths of inundation. The waterfront areas in these cities (such as Manhattan, New York City, NY, Fig. 1) are often densely packed with tall buildings.

Figure 1: An aerial view of the South Street Seaport area of Manhattan, NY that inspired the idealized iCOW. The elevation change from South Street to the Fulton subway station is approximately 7 meters. Courtesy Google Maps. (Maps data ©2018 Google).

To represent these features, iCOW simulates a city surrounded by water and situated on a coastline (Fig. 2). The city terrain is elevated from the normal water level by a seawall. iCOW buildings are approximated as uniformly tall and higher than the highest potential surges. Based on volume,
real estate value is initially assumed to be constant regardless of building height or location relative to the waterfront. In the simplest configuration, city value and density are uniformly and continuously distributed from water’s edge to the highest city elevation. As defensive strategies are added, this value density may change. The addition of defensive strategies divides the city into zones of different damage vulnerabilities as described below.

2.2. Risk mitigation strategies and city zones

Within iCOW, we currently consider one fixed and three adjustable defensive strategies that can be implemented to varying degrees and in combination. The fixed defensive strategy is the presence of a seawall around the city. The three adjustable defensive strategies are: i) withdrawal from at-risk areas, ii) improving resistance to damage, and iii) construction of a dike. All strategies are assumed to be implemented uniformly across the width of the city parallel to the coastline (see Fig. 2a).

The iCOW design assumes an existent seawall of fixed height surrounding the city. No damage occurs to the city as long as surge heights are below the level of the seawall. When surge height exceeds the seawall, the height of water that affects the city is equal to the amount of excess and an additional height caused by wave run-up.

The first iCOW adjustable strategy is to specify withdrawal from regions of the city below some withdrawal height and relocation to the city’s higher levels. In iCOW, we model this by creating a zero value zone (zone 0) and redistributing the value that had been contained in that zone over the remaining area of the city, subsequently and uniformly increasing the value density in the remaining city area. The cost to relocate is based on the area to be relocated, and the total remaining area in the city available for relocation. A fraction of the displaced infrastructure will relocate outside the city. Once withdrawal is implemented, no damage will occur to city areas below the withdrawal height, \( W \) (zone 0). Above this height, city density is higher and damage will therefore be proportionally higher per volume when surge heights reach the levels above the withdrawal area. The cost to implement withdrawal is,

\[
C_w = \frac{v_i \times W \times f_w}{\text{cityHeight} - W},
\]

where \( v_i \) is the initial city value, \( \text{cityHeight} \) is the highest city elevation measured from the seawall, and \( f_w \) is a factor intended to adjust for any
Figure 2: The overall topology of the iCOW model is shown panel a. In Zone 0 (black) city infrastructure is relocated to higher elevations, thus no damage accrues. In Zone 1 (magenta) buildings are resistant to surge damage to a specified elevation. If this elevation is lower than the dike base height an unprotected area, Zone 2 (grey) exists. Zone 3 (orange) between the dike base height and the dike height is protected by the dike. Damage will only occur if the dike fails or is over topped. Zone 4 (green), the city heights, extends from the dike top elevation to the highest area of the city and is unprotected. Damage curves for each city zone (by color) and the total city damage (black) are shown in panel b. Curves are generated using iCOW to evaluate a combined strategy against a range of surge heights. In the dike protected area (zone 3 in orange) damage accrues at a very low rate for surges below the dike height unless the dike fails. Instances of dike failure are indicated by the damage spikes in this section of the figure.

local conditions (such as the presence of historic buildings, or heavy industry facilities) that might make it more or less expensive to relocate.

The value of the city after withdrawal, $v_w$, is,

$$v_w = v_i \ast \left(1 - f_i \ast \frac{W}{\text{cityHeight}}\right),$$

where $f_i$ is the fraction of infrastructure that will leave rather than relocate within the city.

The second adjustable strategy is implementation of resistance to damage based on a fixed height, $R$, above the withdrawal height. In the resistant zone
(zone 1), buildings are resistant to damage to a fixed height relative to the withdrawal level. The upper extent of zone 1, in terms of the city elevation, is constrained by the lower of the resistance height or by the elevation of a dike base, $B$. Building volume flooded below the building’s resistance height is subjected to less damage than nonresistant buildings. Flooded volumes above the resistance height are subjected to damage at the nonresistant rate. The fraction of building damage to surges (compared to nonresistant buildings) can be varied to any value between zero and one.

Modifying buildings to be completely invulnerable to storm surge damage is generally unfeasible due to increasing cost, and cost varies based on building type and materials. Intuitively, the cost of implementing resistance should rise as the percentage of resistance, $P$, incorporated increases, and increase sharply as resistance approaches 100%. We model this characteristic cost structure using a linearly increasing resistance cost ($c_R$) per unit value until a threshold percentage is reached. As resistance percentage increases above this value, we add an exponentially increasing term that increases sharply as resistance percentage approaches 100%, so that the cost fraction of resistance with respect to $P$ ($f_{cr}$) increases in accordance with the equation:

$$f_{cr} = f_{lin} * P + \frac{f_{exp} * \max(0, P - \text{threshold})}{(1 - P)},$$ (3)

where $f_{lin}$ is a factor that controls the linear rate of increase in cost at low percentage increases, $f_{exp}$ is a factor that controls the exponential rate of increase, and $t_{exp}$ is the threshold where cost begins to increase exponentially.

At low percentage levels, increasing the percentage resistance to damage results in a linear increase in cost. As resistance percentage increases above a threshold and approaches one (where building volume would be completely invulnerable to surge damage) cost per volume increases sharply, such that increasing resistance fraction to one would be infinitely costly.

We assume that the total cost of implementing resistance increases at a rate proportionally to the volume being made resistant, but because the width and slope of the city is constant the relationship can be greatly simplified and expressed solely in terms of elevation changes. In cases where resistance is not constrained by the presence of a dike, resistance cost, $c_R$, is,

$$c_R = \frac{v_w * f_{cr} * R * (R/2 + b)}{h * (cityHeight - W)},$$ (4)
where $b$ is the representative basement depth, and $h$ is the the city building height.

When a dike exists and $B$ is less than $R$ the area behind the dike is not made resistant. The resistance cost in this case is,

$$c_R = \frac{v_w \cdot f_{cr} \cdot B \cdot (R - B/2 + b)}{h \cdot (\text{cityHeight} - W)}$$

The third adjustable strategy is the construction of a levee or dike. Real dikes have sloped sides, or, when they have a constant width profile with respect to height, $D$, require greater strength at the base compared to the top of the dike. Therefore, with all other factors being equal, taller dikes are more expensive than shorter ones (Zhu and Lund 2009). iCOW currently models all surge barriers as having sloped sides. iCOW dikes have sloped sides, and a flat top, thus the volume of a dike increases approximately geometrically with height. Dikes are modeled as perpendicular to the waterfront. To prevent surges from flowing around the dikes, iCOW dikes are U shaped. Therefore the overall length of a dike will increase, based on the additional length of dike required to be constructed upslope. These upslope portions of the dike are irregular tetrahedrons. Because the city slope, $S$, is low, the length of the wings is long compared to the dike height which allows for the simplifying assumption that dike wing lengths at the top and bottom of the dikes are equal. iCOW modeled dike cost is proportional to volume. Additionally, large scale projects such as dikes typically incur a fixed startup cost which reflects the costs necessary to plan and approve projects, cost to acquire and prepare dike sites, and to make the initial and wrap up costs for large scale projects that are site dependent and may be dependent on dike height or volume (Zhu and Lund 2009). For simplicity, we emulate start up cost as a fixed additional height.

The dike volume ($V_d$) used to calculate cost is based on a height $h$ (which is the sum of the design height and a fixed initial startup height), city width, $W_{city}$, dike top width, $w_d$, slope of the dike sides, $s$, and slope of the city, $S$, according to,
\[
V_d = W_{city} h \left( w_d + \frac{h}{s^2} \right) + \frac{1}{6} \left[ - \frac{h^4 (h + \frac{1}{s})^2}{s^2} - \frac{2h^5 (h + \frac{1}{s})}{S^4} - \frac{4h^6}{s^2 S^4} + \frac{4h^4 (2h (h + \frac{1}{s}) - \frac{4h^2}{s^2} + \frac{h^2}{s^2})}{s^2 S^2} + \frac{2h^3 (h + \frac{1}{s})}{S^2} \right]^{\frac{1}{2}} + w_d \frac{h^2}{S^2}. \tag{6}
\]

As a result, startup costs will be larger but account for a lower percentage of total costs for taller dikes. The iCOW model specifies dikes based on the location of the dike base relative to the withdrawal height and the height of the dike from the dike base. Cost of the dike, \( c_D \), is calculated by multiplying dike volume, \( V_d \) from equation (6) with the per cubic meter cost of the dike, \( c_{dpv} \).

\[
c_D = V_d * c_{dpv}. \tag{7}
\]

2.3. Strategy levers

We simulate implementation of these strategies through five model levers, corresponding to the variables that characterize the city described above, that can be employed in combination, Withdrawal height (\( W \)); Resistance height (\( R \)); resistance Percent (\( P \)); dike Base height (\( B \)); and Dike height (\( D \)). The levers are summarized in Table 1.

| Variables | Name              | Description                                      |
|-----------|-------------------|--------------------------------------------------|
| \( W \)  | Withdrawal height | height from the seawall below which all structures are relocated |
| \( R \)  | Resistance height | height from \( W \) that structures are resistant to damage |
| \( P \)  | resistance Percent| percentage reduction achieved in resistant city volume |
| \( D \)  | Dike height       | height of a dike measured from the dike base      |
| \( B \)  | dike Base         | elevation of the dike base measured from \( W \) |

The relationship between strategy levers and resultant zones is illustrated in Fig. 2a.
2.4. Damage functions

Building damage from storm surges increases with exposure to higher water levels and flow velocity. The actual damage function for particular buildings, however, varies by building usage, construction type, and more broadly, by regional location (Prahl et al., 2018). The iCOW framework adopts a generic damage model where, in an unprotected state, damage to a structure starts occurring when the water level exceeds the building base elevation. At that level, a set damage occurs associated, for instance, with basement flooding. Above this level damage is proportional to the volume of the building flooded. In the resistant area (zone 1), damage is reduced by the resistance fraction for resistant volumes flooded. Damage otherwise accrues at the normal, nonresistant rate for volume flooded above the resistant height. When calculated in this way, the damage function that emerges for aggregated iCOW city areas align with other research into damage functions for urban areas (Prahl et al., 2018).

When they function properly and when they are not over topped, dikes greatly reduce the damage in the protected zones. Dikes, however, will fail when they are over topped, and may fail for a variety of reasons (such as improper design, incorrect operation, inadequate maintenance, or foundation erosion) prior to water levels exceeding their design protection heights (Tobin, 1995; Apel et al., 2004; Sills et al., 2008). iCOW represents this nonzero probability of failure with a low fixed probability of failure at all surge heights ($h_{\text{surge}}$) below a high percentage of the dike height. Above this threshold, $t_{df}$, probability of failure, $p_{df}$, increases linearly with height until it reaches one at the dike’s design height, when Surge height is less than the threshold,

$$p_{df} = \frac{h_{\text{surge}} - t_{df}}{D - t_{df}}.$$ (8)

When the dike holds, damage in zone 3 is reduced by a fraction of what would otherwise accrue in the dike protected zone. If the dike fails or is over topped, damage will accrue in the dike protected zone at a rate greater than the unprotected rate.

Damage accumulating by zone for a range of surge heights for one combination of mitigation strategies is illustrated in Fig. 2. Damage to each zone, ($d_z$), is calculated based on the value of the zone $Val_Z$, the volume of the zone, $Vol_z$, the volume flooded, $Vol_F$, and the per volume rate of damage...
incurred by flooding based on the strategy implemented in the zone, \( f_{damage} \),

\[
d_Z = Val_Z \times \frac{Vol_F}{Vol_Z} \times f_{damage},
\]

where \( Vol_F \) depends on both levers and surge height.

iCOW features many permutations of this damage function depending upon the lever settings, the resulting city zone configuration, and the height of the surge relative to the heights of the city zones and implemented protective strategies.

The iCOW model parameters used in this paper are inspired by the situation in Manhattan in that the building heights are tall relative to potential storm surges, dikes are inexpensive relative to the assets protected behind them, there is an existing seawall, and the breadth of the coastline is long relative to the volume of city protected. The model parameters are easily customizable such that they can represent a particular city with greater fidelity. Differences between iCOW and ‘van Dantzig style’ models are summarized in Table 2. At this point we have presented the iCOW setup and definitions. The implementation is described in section 3.1, results are described in section 4, and conclusions are summarized in section 6.

3. Methods

3.1. iCOW framework computational description

The iCOW framework consists of two modules, the iCOW model and a set of multi-objective evolutionary algorithms. Together, these work in tandem to evaluate and optimize multiple risk mitigation strategies. We follow an XLRM framework for robust decision making (Lempert et al., 2006). Fig. 3 shows the logical relationships between exogenous factors (X), model strategy levers (L), modeling relationships (R), and performance metrics (M) described in section 2.3.

3.1.1. iCOW module

We developed the iCOW module in C for computational efficiency. It consists of one program with two major components executed in sequence. The first component takes the exogenous factors associated with the initial baseline city, and characterizes the city (in terms of the value distribution, zones, and damage functions, described in section 2.2) in response to the chosen
Table 2: A comparison of ‘van Dantzig style’ model and the iCOW framework.

|                        | ‘van Dantzig style’ | iCOW model framework |
|------------------------|---------------------|----------------------|
| area protected         | polder              | zones based on protection strategies |
| protection strategies  | dike                | withdrawal, resistance, dike |
| damage functions       | fixed cost upon dike topping | cost proportional to volume flooded, taking into account, the protective strategies implemented. |
| dike cost              | proportional to height | proportional to dike volume with start-up cost |
| resistance cost        | n/a                 | proportional to volume of city protected and dependent on the fraction of resistance implemented. |
| withdrawal cost        | n/a                 | proportional to the area of the city relocated. |
| surges                 | probability of exceedance | annual max surge based on GEV |

strategy lever settings described in 2.1. The costs to implement the strategy lever inputs and city value changes are iCOW module output metrics. The second component takes the city’s value distribution, zones, and damage functions as inputs, and evaluates the city’s response to the exogenous set of storm surge sequences, described in section 3.1.2 below, to generate the remaining module output metrics.

For this study, the defensive strategies are established at time zero, and hence, the first component to characterize the city is evaluated only once, and the characteristics for the city are set for all storm surges evaluated. The impacts of storm surge output metrics can include average cost in dollars over a time span (as discussed above), flood frequency, dike breach frequency, or frequency of events over an unacceptable damage threshold. For this article, we use the cost of implementing strategies, and the total cost of damages over 50 years as the input metrics for the multi-objective evolutionary algorithm (MOEA) discussed in sections 3.1.3 and 4 below.
3.1.2. Surge simulation

Storm surges are simulated as annual highest surge heights generated from nonstationary generalized extreme value (GEV) equations such that the 100-year storm surge is increasing at a rate of one m per century due to an increase in both the location and scale parameters (Ceres et al. [2017]). Some storm surges generated in this manner may be larger than physically plausible. Storm surges used for this study are clipped such that surge heights exceeding a threshold are capped at the threshold. The thresholds used in this article start at 12 m for the first year and increase by 0.01 m per year thereafter. This threshold is chosen as a compromise between the goal of accounting for the full range of risk exposure based on the statistical model used to generate the surges and the desire to provide fidelity to physical reality.

We use 5,000 realizations of 50-year sequences of storm surges for all examples discussed in this article. This number represents a compromise between computational efficiency and stable results. See the supplemental materials (Appendix B) for additional figures and discussion on the number of realizations used.
3.1.3. MOEA module

As more strategies are considered to provide varying degrees of protection, and as the number of objectives increases, selecting optimal solutions becomes much more challenging (Hadka and Reed, 2013). Even with a greatly simplified model (compared to CLARA), selecting the ‘best’ mix of surge risk mitigation strategies for a given set of objectives is nontrivial. We use the Borg MOEA to solve the optimization problem because of its high computational efficiency and easy scalability to parallel computing environments (Hadka and Reed, 2013, 2015). The Borg MOEA is not a single MOEA algorithm, rather, it is an auto-adaptive class of high performance MOEA algorithms based on the evolutionary progress of a population of candidate solutions (Hadka and Reed, 2013). We use initial Borg population sizes of 200 members. This initial population evolves over 1 million functional evaluations to final larger populations of more than 1,000 members for all figures in this article. We compared results generated using the Borg MOEA with solutions generated by the NSGAII algorithm (Deb et al., 2000) and find generally consistent solutions.

3.2. Experimental design

We explore Pareto optimal strategies for protecting cities against future storm surges. We identify multiple cases with increasing complexity for optimization. We start with the relatively simple ‘van Dantzig style’ single objective, single lever solution (section 3.2.1). To demonstrate the capabilities of the iCOW module, we then increase the number of objectives to two and increase complexity by examining the one, two, four, and five lever cases.

3.2.1. Single objective optimization

Optimizing ‘van Dantzig style’ models with one lever (dike height) and one objective (to minimize net present cost) is trivial, and can, in many cases, be solved analytically (e.g. van Dantzig, 1956). The iCOW model can be configured to emulate ‘van Dantzig style’ behavior by varying implementation of one strategy with the other strategies held constant (i.e. vary dike height, but fix withdrawal height, dike setback, and resistance height to zero), and measuring the net cost that results from every dike height. The optimal solution that emerges is a point defined by an optimal dike height and a resultant net cost (see supplemental section Appendix A for additional discussion and examples).
Note that a single optimal solution can miss important features of the decision problem. Decision-makers’ funds available for storm surge risk mitigation investments might compete with funding for mitigation of other risks, or funding for other economically valuable investments such as education or sports facilities. Fully funding a ‘van Dantzig style’ economically optimal level may not be possible. Alternatively, other stakeholders may prefer the lower variability and uncertainty in future risk over the more tangible current investment costs. In these cases, being able to examine higher levels of storm surge risk mitigation investment (in terms of reducing the variability of future risk) is appropriate.

3.2.2. Multiple objective optimization with multiple levers

To provide decision-makers with more options, we increase the complexity of the problem by incrementally increasing the number of levers to provide many combinations of strategies and determine Pareto optimal two objectives solutions. For the first case, we compare the cost and risk reduction associated with a dike height (D) only single lever strategy, with a dike height and resistance height (R) two lever strategy. In the single lever example, a dike can be constructed at the seawall to any height. The resultant city consists of zones 3 and 4. In the two lever example, policy makers can either construct a dike, or incorporate resistance (to a fixed percentage). Given the structure of the iCOW model, the two levers are mutually exclusive. The resultant city then consists of either zones 3 and 4, or zones 2 and 4.

For the second case we add two additional levers, dike base location (B) and resistance percentage (P) and compare results to the first case. In this four level example, dike height and resistance height are no longer mutually exclusive. Dikes can be constructed to any height at any location, and resistance can be incorporated in front of the dike to any height at any percentage.

For the third illustrative case, we add the additional lever of complete withdrawal (W) from the lowest city levels, (a five lever example) and compare results with the other cases.

4. Results

In examining this first case (with one and two levers) for our hypothetical iCOW city (see Fig. 4a), when the only solution available is construction of a dike, the iCOW framework identifies an optimal solution associated with no
investment. No optimal solutions emerge as investment level increases until the investment cost exceeds the dike fixed start-up cost, and when the dike is so low that increased damages associated with a failed or overtopped dike exceeds the damages avoided when the dike is not present. Once this dike investment threshold is reached the framework continues to identify solutions with taller, more expensive dikes until additional dike height no longer reduces damages. Incorporating a resistance option allows policy makers to identify sensible low cost solutions that substantially decrease storm surge damage. However, once the dike investment threshold is reached, the optimal strategy shifts abruptly to increasing dike height.

Figure 4: Optimal two objective (damage and investment costs) risk mitigation strategies identified by the iCOW framework. Panel a shows the one and two lever cases. Panel b shows the four lever case. Panel c shows the five lever case. The resultant Pareto fronts are shown in the left panels (a, c, and e). In panels a, c, and e, the green quarter circles identify the preferred objective (i.e., zero investment and zero damages.) The fractional contribution of individual strategies are shown in panels b, d, and f.
For the second case (with four levers), the optimal strategy combinations that emerge are superior to the one and two lever examples in that equal or lower damages can be obtained for any given investment level (see Fig. 4b). Fig. 4e shows the shift in the percentage of optimal investment for any given level of investment allocated to each strategy that occurs as the level of investment increases. At low levels of investment the optimal strategy is based solely on implementation of resistance. At higher investment levels, better performance is achieved using a dike only solution. At the highest considered levels of investment the optimal solution consists of combining strategies by setting the dike back from the seawall and implementing resistance in the area between the waterfront and dike base.

In the third case (with five levers), the additional withdrawal lever allows for the identification of further Pareto improvements at the highest investment levels, as shown in Fig. 4e and f).

In both the four and five lever cases, jagged fractional contribution are evident between $30 - $60 billion in Fig. 4 panels d and f. These variations occur when the BORG MOEA algorithm identifies diverse solutions with approximately equivalent trade offs between the two objectives (damage and investment cost) resulting over multiple combinations of lever settings.

To help visualize the solutions for a given level of investment, we can also identify the city elevations for the Pareto optimal strategies (Fig. 5 for the five lever example). At the lowest levels of investment, the lowest cost damage reduction strategy is to implement resistance into an increasing area of the city. Once a sharp cost threshold is reached, the Pareto optimal strategy shifts abruptly to implementation of an increasingly tall dike at the city seawall. As the amount of investment continues to increase, corresponding to the objective to further decrease damage, the optimal solution sets the dike back from the seawall at gradually increasing elevations, and with slightly increasing dike heights. The area between the seawall and the dike is initially fortified through implementation of resistance, and as investment continues to increase, through a combination of withdrawal and resistance. The jagged fractional contributions visible in Fig. 4 manifests itself in Fig. 5 as variations in the city elevations for adjacent (in terms of investment cost) strategies.

The character of these optimal solutions are highly dependent and sensitive to iCOW model parameters. For instance, very small parameter changes to the cost of resistance relative to withdrawal and dike costs can result in surprising and nonlinear changes to the character of the resulting solution sets.
Figure 5: Dependence of city elevation heights on investment costs derived from the set of Pareto optimal risk mitigation strategies using five levers and two objectives.

5. Discussion and limitations

Simple conceptual storm surge damage models may fail to provide sufficient fidelity in simulating storm surge risk mitigation. More complicated regional storm surge damage models improve upon these simple models in terms of realism, fidelity, and the area covered, but may be too difficult to design and implement. Additionally, using these frameworks to optimize multiple combinations of risk mitigation strategies, over a wide range of future storm surge risk, and considering the differing objectives of various stakeholder communities is computationally expensive. The combination of these drawbacks may make this approach impracticable for some communities.

We use the iCOW framework to analyze an idealized city designed to resemble major cities such as New York. To make iCOW useful to city
planners at a specific site requires adjusting iCOW to reflect city specific characteristics. At a minimum, such site specific adjustments need to account for the following factors: site specific projections of storm surges, local economic demographics and their relationship to the site topography, typical building heights, and adjustments to damage functions that account for site specific building usage and construction type. Additionally, some simplifying assumptions described in this paper may need to be refined to reflect site specific factors. Examples of such simplifying assumptions could include the assumption of uniform city density and value with respect to elevation from the waterfront, or the cost basis for constructing dikes or implementing resistance. Two objective optimal solutions are highly sensitive to iCOW parameters as discussed above, but developing estimates of this sensitivity is probably not computationally feasible.

6. Conclusions

We developed the iCOW as a storm surge risk modeling framework of intermediate complexity for policymakers and storm surge risk stakeholders. The framework is intended to fill the gap between simple and inexpensive conceptual storm surge damage models and complex and expensive state-of-the-art regional storm surge risk modeling frameworks. We demonstrate the capabilities of the iCOW framework to evaluate and optimize surge risk mitigation strategies ranging from a simple single-objective, single-lever problem to more complicated and computationally challenging two-objective five-lever problem. Policymakers can use iCOW to explore a more comprehensive set of strategies over a wider range of future risk scenarios than more complicated regional state-of-the-art models. Stakeholders can use iCOW to supplement insights gained from those higher complexity models and illustrate trade offs between conflicting objectives. iCOW provides one degree of spatial resolution in terms of distance from the waterfront, and thus represents a compromise between the point (single polder) solutions provided by ‘van Dantzig style’ approaches, and regional gridded results produced by state-of-the-art frameworks. iCOW is relatively simple to implement, and so may be useful to policymakers with limited resources, but who nevertheless need methods to identify, evaluate, and illustrate the multiple trade offs implicit in any storm surge risk mitigation strategy. The iCOW framework can be easily modified or extended and can be integrated with other modeling systems such as BRICK (Wong et al., 2017) to further explore storm surge risk in a
regional or global context.

7. Acknowledgements

We thank D. Hadka for outstanding technical support with the Rhodium multi objective tool kit and the Borg MOEA. We thank B. Lee, M. Haran, D. Titley, R. Lempert, and J. Lawrence for helpful discussions. This research was partially supported by the National Science Foundation (NSF) through the Network for Sustainable Climate Risk Management (SCRiM) under NSF cooperative agreement GEO-1240507 and the Penn State Center for Climate Risk Management. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the NSF. Errors and opinions are, of course, those of the authors.

All authors contributed to the iCOW conceptual design. RC developed detailed model designs, wrote all software code and integrated iCOW software with the BORG MOEA algorithm. All authors developed the experimental plan. RC designed and executed experiments and conducted analysis of results. CF and KK provided guidance for the project. RC wrote the article and all authors contributed to editing.

8. Code availability

All iCOW software code used to create the figures in this article are currently available from the corresponding author, they will be open source under a GNU non commercial license and distributed by a repository.

9. Supplemental material

Supplemental material in the appendices provides additional discussion on emulation of van Dantzig style model emulation, and information on convergence and computational expense associated with changing the number of futures evaluated, and tables listing model parameters.

10. Conflict of interest

The authors are not aware of financial or personal relationships that would pose a conflict of interest.
Appendix A. ‘van Dantzig style’ model emulation

The iCOW framework is capable of emulating ‘van Dantzig style’ single objective optimization. For example, the ‘van Dantzig style’ optimal dike height for the illustrative city used in this journal is shown in Fig. A.6. While the emulation produces a single ‘optimal’ dike height and a visually similar result, there are some differences and the resultant optimal dike heights will not be equal to those obtained directly from van Dantzig (1956). iCOW van Dantzig emulation shown in Fig. A.6 shows optimization of dike height with respect to the net cost over a fixed 50 year timespan. The optimization performed by van Dantzig did not consider a fixed time interval (van Dantzig, 1956). His solution comprised an optimal height based on then current analysis of tidal records and considering the net present value of both current investments and damages incurred for the entire span of the future. (van Dantzig, 1956). The dike cost model used in van Dantzig (1956) is a simple linear relationship to dike height that incorporates no start up costs. iCOW dike cost is based on the wedge-shaped geography of the City Model, the resultant dike volume, and a startup cost as described in section 2.2 and equations (6) and (7). The resultant relationship between dike height and cost is nonlinear.
Fig. A.6 shows a gap between a zero dike height and approximately 0.7 m where no solutions exist. Moreover, Fig. A.6 shows an increase in net cost between the no investment maximum damage point and next optimal point above this gap. This gap and subsequent increase in net cost is due to the fixed start up cost of dikes assumed in the iCOW module that does not occur in van Dantzig’s model (van Dantzig 1956), for instance, as implemented by Oddo et al. (2017). Additionally, because the iCOW framework increases damage behind a dike if the dike fails or is breached, at very low dike heights, total damage increases with increased dike height. The BORG MOEA algorithm therefore does not identify any optimal solutions in these dike height ranges. See discussion in 2.2.
Appendix B. Relationship between states of the world evaluated and wall time

Each iCOW framework state of the world consists of an exogenous 50-year sequence of storm surges. The representation of risk associated with the most extreme storm surges improves with more states of the world evaluated. Evaluating more states of the world, however, adds computational cost. To understand this relationship, we measure the computational wall time required to conduct five lever iCOW optimizations using 1 to 20,000 states of the world for 100,000, 500,000, and 1 million functional evaluations (Fig. B.7). We select 5,000 states of the world as a compromise between computational efficiency and stable results for use in all experiments described in this article.

Figure B.7: Relationship between computational cost and states of the world evaluated. The wall time in seconds (y-axis) required to evaluate states of the world (where one state of the world is a 50 year sequence of annual highest storm surges) (x-axis)

Appendix C. iCOW model parameters
### Table C.3: Manhattan iCOW parameters

| Name          | Value | Units | Description                                      |
|---------------|-------|-------|--------------------------------------------------|
| $v_i$         | 1.5   | $T$   | initial city value                               |
| $B$           | 30    | m     | Building height                                  |
| $cityHeight$  | 17    | m     | Height of the city                               |
| $Depth_{city}$| 2     | km    | distance from seawall to highest point           |
| $Length_{city}$ | 43   | km    | Length of the lowest (seawall) coast             |
| $H_{seawall}$ | 1.75  | m     | Seawall height                                   |

### Table C.4: iCOW cost algorithm parameters

| Parameter       | Value | Units   | Description                                                                 |
|-----------------|-------|---------|-----------------------------------------------------------------------------|
| Dike start      | 3     | m       | Equivalent height added to actual height so larger dikes have larger startup costs. |
| Dike top width  | 4     | m       | Controls the width of the dike top to adjust dike volume.                   |
| $s$             | 0.5   | m       | Controls the width profile of the dike to adjust dike volume.               |
| Dike cost       | 10    | $/m^3$  | Dike cost per volume                                                         |
| Dike value ratio| 1.1   | none    | Controls increase in value for areas protected by a dike                    |
| unprotected ratio | 1.0  | none    | Controls increase in value for areas protected                               |
| $f_w$           | 1.0   | none    | withdrawal factor adjusting cost to relocate                               |
| Withdrawal fraction | 0.01 | none    | Fraction of population and infrastructure that will leave if withdrawn     |
| $f_{lin}$       | 0.35  | none    | Linear factor relating percent resistant to resistance cost.               |
| $f_{exp}$       | 0.9   | none    | Factor for exponential cost increase when percent resistant $i$, $t_{exp}$. |
| $t_{exp}$       | 0.6   | none    | Percent resistant threshold above which resistance cost increases exponentially. |
| Basement depth  | 3.0   | m       | Representative depth associated with damage occurring when surge extent reaches building. |
| Parameter               | Value | Units | Description                                                  |
|-------------------------|-------|-------|--------------------------------------------------------------|
| $f_{\text{damage}}$    | 0.39  | none  | Fraction of inundated buildings damaged.                     |
| Protected damage factor | 1.3   | none  | Increased damage that occurs in protected areas if dike fails.|}

The table above summarizes the parameters used in the iCOW damage algorithm and their descriptions.

- **Parameter**
  - $f_{\text{damage}}$
  - Protected damage factor
  - $t_{df}$
  - Threshold level
  - Wave runup

- **Value**
  - 0.39
  - 1.3
  - 0.95
  - $v_i/375$
  - 1.1

- **Units**
  - none

- **Description**
  - Fraction of inundated buildings damaged.
  - Increased damage that occurs in protected areas if dike fails.
  - Dike height fraction above which failure probability increases with surge height.
  - Damage amount above which damage increases more rapidly.
  - Surge factor when surge exceeds seawall height.
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.
URL sciencemag.org/cgi/doi/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. Risk Analysis 33 (5), 772–788.
URL doi.wiley.com/10.1111/risa.12008

Apel, H., Thieken, A. H., Merz, B., Bischl, G., 2004. Flood risk assessment and associated uncertainty. Natural Hazards and Earth System Science 4 (2), 295–308.
URL nat-hazards-earth-syst-sci.net/4/295/2004/hess-4-295-2004.pdf

Battjes, J. A., Gerritsen, H., 2002. Coastal modelling for flood defence. Philosophical Transactions: Mathematical, Physical and Engineering Sciences 360 (1796), 1461–1475.
URL jstor.org.ezaccess.libraries.psu.edu/stable/3066452

Bellomot, D., Pajak, Sparks, J., 1999. Coastal flood hazards and the National Flood Insurance Program. Journal of Coastal Research (Special Issue NO. 28. Coastal Erosion Mapping and Management).
URL jstor.org/stable/25736181

Bessette, D. L., Mayer, L. A., Cwik, B., Vezr, M., Keller, K., Lempert, R. J., Tuana, N., 2017. Building a values-informed mental model for New Orleans climate risk management. Risk Analysis 37 (10), 1993–2004.
URL doi.wiley.com/10.1111/risa.12743

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), 221–235.
URL doi.org/10.1007/s10584-017-2075-0

Coles, S., 2001. An Introduction to Statistical Modeling of Extreme Values. Springer Series in Statistics. Springer Verlag, London.
Coles, S., Pericchi, L. R., Sisson, S., 2003. A fully probabilistic approach to extreme rainfall modeling. Journal of Hydrology 273 (1-4), 35–50. URL linkinghub.elsevier.com/retrieve/pii/S0022169402003530

de Blasio, B., Bruno, J. F., 2014. New York City Hazard Mitigation Plan 2014. Hazard Mitigation Unit, New York City Office of Emergency Management. URL http://www.nyc.gov/html/oem/downloads/pdf/hazard_mitigation/\plan_update_2014/1_introduction_final.pdf

Deb, K., Agrawal, S., Pratap, A., Meyarivan, T., 2000. A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. In: Goos, G., Hartmanis, J., van Leeuwen, J., Schoenauer, M., Deb, K., Rudolph, G., Yao, X., Lutton, E., Merelo, J. J., Schwefel, H.-P. (Eds.), Parallel Problem Solving from Nature PPSN VI. Vol. 1917. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 849–858. URL link.springer.com/10.1007/3-540-45356-3_83

FEMA, 2011. FEMA P-55, Coastal Construction Manual: Principles and Practices of Planning, Siting, Designing, Constructing, and Maintaining Residential Buildings in Coastal Areas, 4th Edition (2011), 4th Edition. Federal Emergency Management Agency, Mitigation Directorate,, Washington, DC.

FEMA, 2015. Implementing-Guidelines-for-EO11988-13690_08oct15_508. URL fema.gov/media-library-data/1444319451483-\ f7096df2da6db2adfb37a1595a9a5d36/FINAL-Implementing-Guidelines\ -for-EO11988-13690_08Oct15_508.pdf

Fischbach, J., Johnson, D., Molina-Perez, E., 2017. Reducing Coastal Flood Risk with a Lake Pontchartrain Barrier. RAND Corporation. URL rand.org/pubs/research_reports/RR1988.html

Fischbach, J. R., Rand Gulf States Policy Institute (Eds.), 2012. Coastal Louisiana risk assessment model: technical description and 2012 coastal master plan analysis results. No. TR-1259-CPRA in Technical report. Rand Corp, Santa Monica, Calif, oCLC: ocn817540572.

Flowerdew, J., Horsburgh, K., Wilson, C., Mylne, K., 2010. Development and evaluation of an ensemble forecasting system for coastal storm surges.
Galloway, G. E., Baecher, G. B., Plasencia, D., Coulton, K. G., Louthain, J., Bagha, M., Levy, A. R., 2006. Assessing the adequacy of the national flood insurance programs 1 percent flood standard. Water Policy Collaborative, University of Maryland. College Park, Maryland.
URL fema.gov/media-library-data/20130726-1602-20490-5110/fnip_eval_building_standards.pdf

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.
URL linkinghub.elsevier.com/retrieve/pii/S1364815217307727

Gerritsen, H., 2005. What happened in 1953? The Big Flood in the Netherlands in retrospect. Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences 363 (1831), 1271–1291.
URL rsta.royalsocietypublishing.org/content/363/1831/1271

Grinsted, A., Moore, J. C., Jevrejeva, S., 2012. Homogeneous record of Atlantic hurricane surge threat since 1923. Proceedings of the National Academy of Sciences 109 (48), 19601–19605.
URL pnas.org/cgi/doi/10.1073/pnas.1209542109

Grinsted, A., Moore, J. C., Jevrejeva, S., 2013. Projected Atlantic hurricane surge threat from rising temperatures. Proceedings of the National Academy of Sciences 110 (14), 5369–5373.
URL pnas.org/cgi/doi/10.1073/pnas.1209980110

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.
URL rand.org/pubs/research_reports/RR1449.html

Hadka, D., Reed, P., 2013. Borg: An auto-adaptive many-objective evolutionary computing framework. Evolutionary Computation 21 (2), 231–259.
URL mitpressjournals.org/doi/10.1162/EVCO_a_00075
Hadka, D., Reed, P., 2015. Large-scale parallelization of the Borg multi-objective evolutionary algorithm to enhance the management of complex environmental systems. Environmental Modelling & Software 69, 353–369. URL linkinghub.elsevier.com/retrieve/pii/S1364815214003041

Harman, B. P., Heyenga, S., Taylor, B. M., Fletcher, C. S., 2015. Global lessons for adapting coastal communities to protect against storm surge inundation. Journal of Coastal Research 314, 790–801. URL bioone.org/doi/10.2112/JCOASTRES-D-13-00095.1

Highfield, W. E., Norman, S. A., Brody, S. D., 2013. Examining the 100-year floodplain as a metric of risk, loss, and household adjustment: Perspective. Risk Analysis 33 (2), 186–191. URL doi.wiley.com/10.1111/j.1539-6924.2012.01840.x

Huisman, J., Rings, J., Vrugg, J., Sorg, J., Vereecken, H., 2010. Hydraulic properties of a model dike from coupled Bayesian and multi-criteria hydrogeophysical inversion. Journal of Hydrology 380 (1-2), 62–73. URL linkinghub.elsevier.com/retrieve/pii/S0022169409006702

Johnson, D. R., Fischbach, J. R., Ortiz, D. S., 2013. Estimating surge-based flood risk with the Coastal Louisiana risk Assessment Model. Journal of Coastal Research, 109–126. URL jstor.org/stable/23486540

Kerr, P. C., Donahue, A. S., Westerink, J. J., Luettich, R. A., Zheng, L. Y., Weisberg, R. H., Huang, Y., Wang, H. V., Teng, Y., Forrest, D. R., Roland, A., Haase, A. T., Kramer, A. W., Taylor, A. A., Rhome, J. R., Feyen, J. C., Signell, R. P., Hanson, J. L., Hope, M. E., Estes, R. M., Dominguez, R. A., Dunbar, R. P., Semeraro, L. N., Westerink, H. J., Kennedy, A. B., Smith, J. M., Powell, M. D., Cardone, V. J., Cox, A. T., 2013. U.S. IOOS coastal and ocean modeling testbed: Inter-model evaluation of tides, waves, and hurricane surge in the Gulf of Mexico. Journal of Geophysical Research: Oceans 118 (10), 5129–5172. URL doi.wiley.com/10.1002/jgrc.20376

Kok, d. J., Hoekstra, A. Y., 2008. Living with peak discharge uncertainty: The self-learning dike. Proceedings international Congress on Environmental Modeling and Software. URL doc.utwente.nl/61135/1/Kok08living.pdf
Lee, B. S., Haran, M., Keller, K., 2017. Multidecadal scale detection time for potentially increasing Atlantic storm surges in a warming climate. Geophysical Research Letters 44 (20), 10,617–10,623. URL agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2017GL074606

Lempert, R. J., Groves, D. G., Popper, S. W., Bankes, S. C., 2006. A general, analytic method for generating robust strategies and narrative scenarios. Management Science 52 (4), 514–528. URL pubsonline.informs.org/doi/abs/10.1287/mnsc.1050.0472

Ligtvoet, W., Franken, R., Pieterse, N., van Gerwen, O.-J., Vonk, M., van Bree, L., Jan van den Born, G., Knoop, J., Kragt, F., Paardekoooper, S., Kunseler, E., van Minnen, J., Pols, L., Reudink, M., Ruijts, A., Tennekes, J., 2012. Climate adaptation in the Dutch delta, Strategic options for a climate-proof development of the Netherlands. Tech. rep., PBL Netherlands Environmental Assessment Agency. URL pbl.nl/en/publications/2012/climate-adaptation-in-the\ discretionary{-}{}{}dutch-delta

Ludy, J., Kondolf, G. M., 2012. Flood risk perception in lands protected by 100-year levees. Natural Hazards 61 (2), 829–842. URL http://link.springer.com/10.1007/s11069-011-0072-6

Menéndez, M., Woodworth, P. L., 2010. Changes in extreme high water levels based on a quasi-global tide-gauge data set. Journal of Geophysical Research 115 (C10). URL doi.wiley.com/10.1029/2009JC005997

New York City Special Initiative for Resilient Rebuilding, 2013. PlaNYC: A Stronger, More Resilient New York. Special Report. URL nyc.gov/html/sirr/html/report/report.shtml.

Oddo, P. C., Lee, B. S., Garner, G. G., Srikrishnan, V., Reed, P. M., Forest, C. E., Keller, K., 2017. Deep uncertainties in sea-level rise and storm surge projections: Implications for coastal flood risk management. Risk Analysis. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/risa.12888
Orton, P., Georgas, N., Blumberg, A., Pullen, J., 2012. Detailed modeling of recent severe storm tides in estuaries of the New York City region. Journal of Geophysical Research: Oceans 117 (C9).
URL doi.wiley.com/10.1029/2012JC008220

Porthin, M., Rosqvist, T., Perrels, A., Molarius, R., 2013. Multi-criteria decision analysis in adaptation decision-making: a flood case study in Finland. Regional Environmental Change 13 (6), 1171–1180.
URL link.springer.com/10.1007/s10113-013-0423-9

Prahl, B. F., Boettle, M., Costa, L., Kropp, J. P., Rybski, D., 2018. Damage and protection cost curves for coastal floods within the 600 largest European cities. Scientific Data 5, 180034.
URL nature.com/articles/sdata201834

Sills, G. L., Vroman, N. D., Wahl, R. E., Schwanz, N. T., 2008. Overview of New Orleans levee failures: lessons learned and their impact on national levee design and assessment. Journal of Geotechnical and Geoenvironmental Engineering 134 (5), 556–565.
URL ascelibrary.org/doi/10.1061/(ASCE)1090-0241(2008)134:5(556)

Slijkhuis, K. A. H., Van Gelder, P., Vrijling, J. K., 1997. Optimal dike height under statistical-construction-and damage uncertainty. Structural Safety and Reliability 7, 1137–1140.
URL citg.home.tudelft.nl/fileadmin/Faculteit/CiTG/Over\ _de_faculteit/Afdelingen/Afdeling_Waterbouwkunde/sectie_ waterbouwkunde/people/personal/gelder\/publications/papers/ doc/paper12.pdf

Small, M. J., Xian, S., 2018. A human-environmental network model for assessing coastal mitigation decisions informed by imperfect climate studies. Global Environmental Change 53, 137–145.
URL linkinghub.elsevier.com/retrieve/pii/S0959378017306027

Speijker, L. J., Van Noortwijk, J. M., Kok, M., Cooke, R. M., 2000. Optimal maintenance decisions for dikes. Probability in the Engineering and Informational Sciences 14 (01), 101–121.
URL journals.cambridge.org/abstract_S0269964800141087

33
Taflanidis, A. A., Kennedy, A. B., Westerink, J. J., Smith, J., Cheung, K. F., Hope, M., Tanaka, S., 2013. Rapid assessment of wave and surge risk during landfalling hurricanes: Probabilistic approach. Journal of Waterway, Port, Coastal, and Ocean Engineering 139 (3), 171–182. URL ascelibrary.org/doi/10.1061/%28ASCE%29WW.1943-5460.0000178

Tobin, G. A., 1995. The levee love affair: a stormy relationship? JAWRA Journal of the American Water Resources Association 31 (3), 359–367. URL onlinelibrary.wiley.com/doi/abs/10.1111/j.1752-1688.1995.tb04025.x

US CFR 725 Executive Orders 11988, 1988. 18 CFR 725 - Implementation of executive orders 11988, Floodplain management and 11990, protection of wetlands. URL gpo.gov/fdsys/granule/CFR-1998-title18-vol2\CFR-1998-title18-vol2-part725

US CFR 725 Executive Orders 11988, 2015. 18 CFR 725 - Executive Orders 11988, establishing a federal flood risk management standard and a process for further soliciting and considering stakeholder input. URL obamawhitehouse.archives.gov/the-press-office/2015/01\30\executive-order-establishing-federal-flood-risk-management-\standard-and-

van Dantzig, D., 1956. Economic decision problems for flood prevention. Econometrica 24 (3), 276–287. URL jstor.org/stable/1911632

Vezèr, M., Bakker, A., Keller, K., Tuana, N., 2018. Epistemic and ethical trade-offs in decision analytical modelling: A case study of flood risk management in New Orleans 147 (1), 1–10. URL http://link.springer.com/10.1007/s10584-017-2123-9

Wing, O. E. J., Bates, P. D., Smith, A. M., Sampson, C. C., Johnson, K. A., Fargione, J., Morefield, P., 2018. Estimates of present and future flood risk in the conterminous United States. Environmental Research Letters 13 (3), 034023. URL stacks.iop.org/1748-9326/13/i=3/a=034023?key=\crossref.24d912bcd108784fd19679ea77fb6c79
Wong, T. E., Bakker, A. M. R., Ruckert, K., Applegate, P., Slangen, A. B. A., Keller, K., 2017. BRICK v0.2, a simple, accessible, and transparent model framework for climate and regional sea-level projections. Geoscientific Model Development 10 (7), 2741–2760.
URL [geosci-model-dev.net/10/2741/2017/](geosci-model-dev.net/10/2741/2017/)

Zevenbergen, C., van Herk, S., Rijke, J., Kabat, P., Bloemen, P., Ashley, R., Speers, A., Gersonius, B., Veerbeek, W., 2013. Taming global flood disasters. Lessons learned from Dutch experience. Natural Hazards 65 (3), 1217–1225.
URL [link.springer.com/10.1007/s11069-012-0439-3](link.springer.com/10.1007/s11069-012-0439-3)

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.
URL [ascelibrary.org/doi/abs/10.1061/(ASCE)0733-9496.135:2(90)](ascelibrary.org/doi/abs/10.1061/(ASCE)0733-9496.135:2(90))