Modeling the feedback between decision-making and hydrological vulnerability in urban landscapes

Andres Baeza1, Luis Bojorquez-Tapia2, Marco A. Janssen1, and Hallie Eakin1

1) School of Sustainability, Arizona State University, Tempe, Arizona, USA

2) Laboratorio Nacional de Ciencias de la Sostenibilidad (LANCIS), Universidad Autonoma de Mexico (UNAM), Mexico

# Abstract

Governments and other institutions invest billions of dollars in infrastructure to reduce urban vulnerability to water-related hazards. While these investments have provided tremendous benefits for urban development, the motivations and the criteria that drive managers’ decisions regarding how and where to invest limited resources are often obscure, making it difficult to assess the legacy of those decisions on present patterns of vulnerability. In this work, we present an approach to simulate the coupling between the decision-making processes of influential actors and infrastructure-related hazards. The purpose of the approach, which is based on combining agent-based modeling with multi-criteria decisions analysis and geographic information, is to identify spatial and temporal patterns of vulnerability and emerging trade-offs due to relative changes in multi-criteria evaluation of the agents.

We present the approach using a hypothetical megacity of the developing world represented by a landscape with urban neighborhoods exposed to flooding and/or water scarcity. The model simulates a water operator’s investment in potable water and sewer systems across the urban neighborhoods. Residents in turn respond to the authority’s decisions (or lack of) by protesting, creating socio-political feedback from residents’ local responses and regional decisions. The criteria, priorities, and actions that define investment are embedded in a multi-criteria policy scenario. By conducting numerical simulations over a vast parameter space of policy scenarios, we illustrate how minimal changes in preferences can have significant consequences on the emergent spatial and temporal patterns of vulnerability, even under similar biophysical and budgetary constraints. We discuss the utility of the approach in merging empirical, context-specific decision criteria from stakeholder interactions with biophysical models of infrastructure-related hazards to identify vulnerability tradeoffs at local (neighborhood) and regional (city) scales in urban systems.

# Significance

Megacities are highly vulnerable to climate change. Residents, authorities, and infrastructure providers respond to the impact of flooding, water scarcity, and associated health outcomes by investing in infrastructure. These investments are a response, in part, to the cultural norms, values, and political relationships that dominate the institutional and collective decisions of public and private actors. The legacy of these decisions has consequences lasting for decades or even centuries. Making those decisions tractable and transparent is therefore an urgent research and political challenge. In this work, we present an approach to incorporate and evaluate the factors and priorities involved in the decision-making of influential actors using agent-based models and multi-criteria decision analysis. We illustrate this approach in an intentionally simplified, hypothetical megalopolis to show how relatively small differences in the value an authority gives to socio-political versus technical factors can significantly impact urban vulnerability in different regions and periods of time.

# Keywords

Urban resilience; decision-making; climate change adaptation

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# Introduction

There is a growing concern among scientists and urban planners about the increasing vulnerability of megacities to hydrological- and infrastructure-related hazards around the world. In the context of adaptation to climate change, there is a persuasive tendency to focus on the exogenous biophysical drivers of vulnerability, such as precipitation extremes and storm surges, when considering investment in hard infrastructure (1, 2). Nevertheless, we also know that vulnerability is affected by the decisions of influential players such as infrastructure system managers and elected officials. These decisions are influenced by contextual cues, local social networks, political pressure, social norms, and the legacy of prior decisions on the landscape (3–6). Such decisions are not made on the basis of technical criteria alone; rather, they are grounded in the social, political, and economic priorities ofurban authorities, infrastructure providers, resources users, social organizations, and other stakeholders (7). The interacting priorities of these actors shape actions and investment in the urban landscape, resulting in material changes in the biophysical world that then, in turn, shape risk perceptions and decision priorities. The embedded nature of these priorities and their feedback within the biophysical landscape is what we refer to as socio-political infrastructure (8).

To improve urban risk management and hence increase resilience, it is necessary not only to understand how the actions of influential actors are expressed and manifested spatially, but to acknowledge the continual, coupled dynamics between the socio-political infrastructure and the biophysical processes that determine risk over time (2, 8–10). To do so, we require tools that can make these dynamics of “socio-hydrological vulnerability” explicit and transparent, and thus with the capacity to translate the perceptions and preferences of decision-makers into computational procedures (11). Once developed, these tools may help society navigate the complexity of vulnerability creation in urban environments. These tools can also help society recognize the feedback among decisions and various biophysical processes, with the overarching goal of understanding the implications for spatial and temporal patterns of vulnerability and the dilemmas and trade-offs that emerge as consequences of these decisions (12–14).

In this paper, we present an approach for incorporating and evaluating the influence of managers and decision-makers on the spatial distribution of socio-hydrological vulnerability in urban areas. The approach is based on combining agent-based modeling (ABM) (15, 16) with multi-criteria decision analysis (MCDA) and geospatial information (17). We present the modeling approach applied to a hypothetical case of an urban area with a multi-attribute landscape to represent interactions between agents and infrastructure systems in a spatially-explicit platform. The initial conditions of the urban landscape exemplify many characteristic patterns of aged megacities in the developing world that suffer from hydrological vulnerability: a landscape with topographic complexity, a highly densified core with old infrastructure systems, and a significant lack of services in less-populated areas of the periphery (18).

The model simulates the decision-making process of a water authority with respect to providing functional infrastructure across urban neighborhoods according to a specific policy. A policy in the model is defined by the set of criteria, priorities, and actions that determine the multi-criteria decision-making process of the water authority. Guided by the priorities of the implemented policy, the water authority responds to both the state of the infrastructure (i.e., potable water and sewer systems) and the residents’ discontent with their vulnerability expressed in the form of protests. Protests are caused by residents’ persistent exposure to water scarcity and flooding, which are related to infrastructure failures and the lack of public sector response (Fig. 1).

We first present the general structure of the model with emphasis on the decision- making process of the water operator. We then show results from simulating the model under three hypothetical policy scenarios that differ only in the contrasting priorities of a set of fixed and limited number of criteria. We show how relative differences in priorities translate into significant differences in spatial and temporal patterns of hydrological vulnerability over a relatively long timescale, without changing the set of criteria or the conditions of the landscape. We then show results from simulating the model using a vast ensemble of possible policy scenarios to illustrate how the model can help to compare and identify emerging trade-offs of vulnerability outcomes under different policies, and the sensitivity of the neighborhoods to policy changes.

The modeling approach thus aims to internalize the continual feedback among social-political and technical priorities, hard infrastructure, and biophysical factors that undergird the production and spatial heterogeneity of socio-hydrological vulnerability in urban environments (19). We discuss the simulation results by emphasizing the potential of the approach for empirically understanding the patterns and processes behind the decision-making of influential actors, especially in megacities of the developing world that suffer from low spending on civil and collective infrastructure.

# The model

The ABM simulates the decisions of two types of agents: a water authority,, and local residents from a group of neighborhoods, , located in a landscape with variation in altitude, lack of infrastructure at the periphery, and aged infrastructure in the densified core (Fig. S1). A neighborhood with is exposed, , to two infrastructure hazards depending on its position in the landscape: exposure to disruption in water supply in the highlands, , and exposure to flooding, , in the lowlands, with (methods). A neighborhood may or may not have access to infrastructure; this is denoted by the variable . The water authority decides in which neighborhoods to allocate investments to reduce the risk of water supply or flooding hazards associated with two infrastructure systems, with for water supply infrastructure and for sewer system. These investments involve a set of possible actions from the water authority, , with maintenance and new infrastructure. The decision to invest in either infrastructure system or in selected neighborhoods entails a suitability analysis through multi-objective site selection (20, 21)(Methods). This procedure accounts for the interdependencies and feedback between the attributes of the urban landscape and a policy scenario, . The latter defines the priorities that the water authority gives to a set of criteria to take action to reduce the risk of infrastructure hazards. The goal is to allocate investment in the neighborhoods where it is most needed, according to the implemented policy. The goal is achieved by computing a distance metric, , that represents the distance from an ideal point (21). This ideal point represents a fictional, utopian neighborhood with the optimal conditions of the landscape attributes associated with the criteria in the policy. The distance metric is determined by a linear combination of the set of criteria,, standardized between 0 and 1, and a set of criteria weights, , with and for . In this theoretical example, the policies depend on four criteria () that define the priorities for each infrastructure system investment: the first of these is the criterion 1) social pressure,, which is a socio-political, non-technical criterion that represents how residents respond to the decisions of the water authority. It is operationalized in each neighborhood as the number of protests, , by residents in a fixed period of time. The action of protesting depends on the residents’ tolerance of cumulative exposure, to infrastructure hazards and to the lack of response from the authority. Protests thus simulate a form of political action that effectively creates feedback loop between local-level outcomes (flooding and water scarcity) and higher-level decision-making in infrastructure investment (Fig. 1). The other three criteria are technical: 2) the age of infrastructure systems, , , which influences the condition of the infrastructure systems, , , and their propensity to fail; 3) the lack of infrastructure coverage, which refers to the lack of provision of infrastructure. The final 4) criterion is the indirect benefit of an investment, , which refers to the population density in the vicinity of each neighborhood. This criterion represents the understanding that by investing in densely populated areas, the beneficiaries of any investment will be maximized operator.

The criteria are represented in standardized form,, using step functions and cut-off parameter values to represent the relationship between the magnitude of the geographic attribute in the landscape related to a criterion and an action in infrastructure system at time (methods). These cut-off values can be interpreted as the decision-makers’ judgment about the importance of an observable stimulus (e.g., neighborhood attribute value) for the water authority’s decision (22). In an empirical application of this approach, the standardized form,, would be defined by stakeholders.

The model assumes that the risk of infrastructure-related hazards is proportional to the condition of the infrastructure within each neighborhood, without considering the condition of the infrastructure in adjacent neighborhoods (however, see Fig. S4). The condition of the infrastructure in each neighborhood decays exponentially over time due to aging, but investment in maintenance and construction of new infrastructure can reduce this deteriorative process by modifying the attribute “infrastructure age.”

We simulated the model for three policies designed to show the consequences of contrasting priorities in socio-political versus technical criteria. We used these three designed policies to show the contrasting spatial and temporal patterns that emerge under each policy. We also conducted Monte Carlo simulations over a homogeneous parameter space that defines the possible policy scenarios to obtain the “optimal policies” that maximize or minimize individual indicators of vulnerability. We illustrate the trade-offs that emerge between designed and optimal polices for different socio-political and technical indicators of vulnerability at the scale of the neighborhood (sensitivity to policy) and at the scale of the entire urban landscape (see Methods, below, for further details).

# Results

## Spatial and temporal patterns of socio-hydrological vulnerability

The three policy scenarios designed to illustrate contrasting priorities of the water operator (Squeaky Wheel, Repair First, and Expand Access) produced distinct patterns of socio-hydrological vulnerability in the urban landscape. We illustrate these differences in figures 2, 3, and 4 by showing the spatial and temporal heterogeneity of the age and extent of the infrastructure systems, and the state of the social pressure in the system as represented by the number of protests over time. Under the Squeaky Wheel policy, the pattern observed for the potable water system is one of low expansion of new infrastructure into the periphery and high levels of investment into high altitude neighborhoods that are already equipped with infrastructure (Fig. 2). This policy generates an old infrastructure system for potable water at the center of the urban landscape, since more protests related to water scarcity occurred at the periphery. This policy is the most effective in reducing overall average exposure and protests in the city (Fig. 4) and in the areas that actually suffer the most from water supply scarcity. However, this policy produces the least spatial coverage of functioning infrastructure systems overall (Fig. 2), although it lowers the city-average exposure, since exposure to water scarcity and protests are strongly related (methods) and are concentrated in neighborhoods at high altitude. This mismatch between the spatial distribution of resources based on policy and exposure suggest the possible emergence of trade-offs in achieving city-average indicators of performance (Fig. 4).

The Expand Access policy, in which investments are heavily located in neighborhoods that lack infrastructure or have very aged infrastructure, at first produced an expansion to the urban periphery, followed by the creation of a patchy, highly heterogeneous landscape, resembling a chess board, with clusters of neighborhoods with new or old infrastructure distributed across the landscape for both systems (Fig. 2 and Fig. S2). Overall, Expand Access generates the maximum area covered, high social pressure, relatively low inequality, and newer infrastructure systems. Finally, the Repair First policy generated early investment in the core of the city, in neighborhoods where infrastructure was already aged. This pattern of investment persists over time, generating homogeneous infrastructure systems in terms of age across the landscape. Over time, Repair First creates lower levels of inequality but the most protests (Table S1).

The time series of protests and area covered with functional infrastructure also illustrates how each policy produces different patterns at different points in time (Fig. 3). The Repair First policy generates more area covered with infrastructure compared to the other policies. Expand Access does not increase the area with infrastructure as much as Repair First, because the early attempt to Expand Access is to provide access for a broader population. However, over the long term, the policy results in more areas in need that arise because of the constant presence of budgetary constraints. This then creates more neighborhoods with infrastructure in poor condition than neighborhoods covered by functional infrastructure.

## Trade-off in vulnerability indicators

Results from simulating the model using the full set of possible combinations of policies illustrates the diversity of policies that must be considered to minimize or maximize a particular vulnerability indicator. Specifically, there is large diversity of criteria weights that will produce a desirable one-dimensional outcome (Fig. S2). Consequently, significant trade-offs are evident when comparing policies that optimize for a particular performance indicator (the optimal policies), or when a particular criterion is prioritized (designed policies). Figure 4 and Figure S5 show the trade-offs in three indicators of vulnerability at the scale of the city using a graphical comparison of mean age of infrastructure systems, total area covered, and mean exposure. When comparing the designed policies (triangles in Fig. 4 and Fig. S5), we observed that the Repair First and Expand Access policies are more effective in reducing the age and increasing the extent of the infrastructure systems, yet they generate higher exposure than the Squeaky Wheel policy. Alternatively, a policy that successfully minimizes the average exposure to both flooding and scarcity results in the least area covered with infrastructure and relatively aged systems. The point of the figure is to show that the distribution of decisions in space and time can have important consequences for the vulnerability at multiple scales, and that these consequences can also be evaluated at multiple scales using the approach described here.

The sensitivity analysis indicates that neighborhoods in areas at the edge of the urban landscape in the highlands, where exposure to water scarcity is the highest, are the most impacted by changes in policy (Fig. S6). This is followed by neighborhoods that suffer from both issues and are located in the zone between the lowlands and highlands. Finally, the distribution of neighborhoods with low sensitivity tends to be rather uniform across the lowlands, reflecting the regional effect of rainfall as the dominate driver of flood variability.

## The role of local socio-political factors

Our results indicate that the feedback between responding to social pressure and the spatial and temporal manifestation of the risk matters. For instance, while the Squeaky Wheel policy is very effective in reducing protests related to chronic and localized water scarcity, the same policy is not so effective in reducing protests related to flooding, which are less frequent and more randomly distributed events in space (Fig. 3). Similarly, when local exposure is influenced by the condition of the infrastructure in other neighborhoods (connected infrastructure systems), Squeaky Wheel policy is not as effective in reducing protests and, therefore, exposure (Fig. S4).

# Discussion

The dynamic and spatially-explicit modeling approach presented here aims to make explicit the linkages between decision-making processes and the outcomes of those decisions for urban vulnerability and infrastructure conditions. We emphasize that this approach makes visible the social-political factors that are often excluded in vulnerability assessments. This is done by purposely endogenizing these factors into the processes that contribute to the production of vulnerability. In this stylized implementation, the incorporation of “social pressure” as a socio-political decision criterion acknowledges that choices regarding infrastructure investment are often influenced by less technical criteria, such as preferences for specific socioeconomic groups, electoral constituencies, or the need to respond to specific events with high political visibility.

These criteria steer decisions and investment toward particular regions or groups (23, 24), and they can transform the built environment in significant ways, in part determining the preparedness of future generations to confront these environmental hazards. Therefore, because the implications of these investments transcend the space and time where those initial decisions are made, it is critical to find tools that can elicit the full spectrum of criteria, priorities, values, and actions that steer the production of vulnerability (8). In our research in Mexico City, for example, we have observed that protests are linked to demands related to infrastructure investment. Protests are triggered when conditions become critical for the water system users, and this produces immediate responses that steer resources to these foci of political attention (8). In addition, election cycles provoke social mobilizations designed to divert financial and material resources to areas with strong social organizations and voting power. This may occur at the expense of other groups that are in greater need, but that may be less influential or less organized (24, 25). Over time this socio-political infrastructure can generate inequalities in resource distribution, in addition to long-lasting impacts on infrastructure and the built environment. Making these social and political forces explicit as part of decision-making is a first step to be able to evaluate the impact of such criteria on the production of urban vulnerability, providing opportunities to disrupt pervasive cycles of inequality.

In theory, trade-offs in performance are inevitable as society seeks to control some aspects of risk at the expense of others (26). These robustness-vulnerability trade-offs are particularly prevalent in complex socio-ecological systems, or “coupled human infrastructure systems” (14). Therefore, we must expect that decision-makers will be constantly confronted with trade-offs among policy alternatives. However, they often lack frameworks and specific tools with which such trade-offs can be evaluated or justified (12, 13, 26–28). Our modeling approach aims to provide a kind of tool that can reveal the trade-offs that emerge from the constant reinforcement of specific decision priorities over time: in other words, trade-offs among distinct adaptation pathways (3). Our model echoes these theoretical insights and calls for action by developing a modeling framework that can identify and make explicit and visible these trade-offs for policy comparison.

When applied to a theoretical landscape, our approach illustrates that trade-offs can emerge across different forms of risk exposure (e.g., between flood control and water access), different types of infrastructure systems (e.g., potable water and sewer system), across space and time, and across different indicators and optimal policies. Moreover, we illustrate how investments made to address specific aspects of risk can, in turn, amplify risk exposure and social dissatisfaction in other ways, contributing to the generation and persistence of spatial and temporal patterns of socio-hydrological vulnerability. The stylized model thus serves to illustrate that the role of social pressure – the only “non-technical” criterion included in the model – differs in terms of its influence on patterns of flooding and water scarcity. Residents’ protests served as feedback to managers’ decisions, but this feedback is modulated by the frequency of the hazard: flooding was simulated as episodic and driven by climatic variability, while scarcity was simulated as a chronic risk, though both issues arose from the conditions of infrastructure systems. The socio-political feedback, via residents’ protests, effectively translated the frequency of the hazard events into the spatial-temporal pattern of managers’ infrastructure investments. Focusing on indicators with different frequencies can shape the safe operational space of urban areas under climate change, which, in turn, can influence how resilient a coupled human-natural system can be to different disturbances (27).

Our hypothetical example purposely simplifies the biophysical complexities that influence environmental risk (29). By simplifying those biophysical aspects of vulnerability, our aim was to make explicit the consequences of decisions on the emergence of vulnerability and trade-offs. An integrated dynamic model that links biophysical sub-models (i.e., hydrological, infrastructural, climatic, land change) with empirically-based information about actors’ decisions and their motivations and, more importantly, how this information is connected to biopsychical processes would constitute the next step in the evaluation of the coupled dynamics of socio-hydrological vulnerability. However, it is important to note that these models should and must be used in a context in which they can serve to bring different stakeholders together, provide a means of common problem understanding, and ignite conversation among multiple actors of society. This will in turn lead to open discussion about current practices and possible ways of moving forward using the best synthetized information available, rather than provide actual predictions of future scenarios.

We recognize that it is a major challenge, scientifically and politically, to elicit the full range of social and political criteria that undergird decision-making and the factors that guide policy implementation. Particularly difficult are those intangible factors often associated with cultural bias within organizations and institutions, which are shaped by the organization’s perception of causes and consequences of the problem. Formal institutional or agency perspectives may tend to highlight more socio-political criteria, while low- to mid-level managers may tend to focus on more technical criteria, obfuscating these more intangible “soft” decision metrics. Close collaboration with actors at different hierarchical levels of the organization is critical to build trust and to reveal the inner workings of decision processes (8). Soft modeling techniques and mental model elicitation should be instrumental in identifying socio-political factors (11, 30–36). Multi-criteria decision analysis techniques such as analytical or hierarchical networks processes (37) can be used to elicit the set of criteria, criteria-weights, and actions embedded in policy implementations (21, 38). Coupling these techniques with biophysical and infrastructure models (39–41) should provide opportunities for researchers to help elicit feedback that shapes decisions in space and time. This effort should be conducted in tight collaboration with stakeholders and residents to validate the model and the policies (21, 42).

Managers and decision-makers should use these exploratory models to reveal hidden vulnerabilities that may only be apparent when considering the coupling between the biophysical process and the set of managerial decisions. These models could then be used to explore hypothetical policies that could reflect very different decision priorities, for example, those that reflect the values and interests of marginalized groups. Comparing and discussing such policies in light of current practices should provide valuable information to reveal emergent patterns, dilemmas, and trade-offs specific to each different policy. Evaluating new options and alternative decision pathways might also lead to the validation of current practices (3), thus enhancing the transparency of those existing practices (7, 21, 31).

# Conclusion

The approach presented in this paper substantiates calls for focusing on the endogenous, social-political dimensions of risk in vulnerability assessment. Our results demonstrate that vulnerability in urban landscape is a dynamic property that emerges from the coupling of the influence of social and political factors that shape decision-making processes, the investment in hard /grey infrastructure, and the socio-environmental forces that shape risk. Our approach provides a basis for proposing stylized models that can empirically and systematically implement the decisions of influential actors into Earth system modeling and provide a new avenue for transdisciplinary engagement in vulnerability research. These stylized models should provide decision support tools to facilitate the engagement of decision-makers and stakeholders.

# Methods

We describe here the formalization of the decision-making process of the water authority, the production of infrastructure-related risk and hazards, the response of the residents, and the construction of policies and indicators.

The formalization of the decision-making process entails a calculation of a suitability assessment to identify neighborhoods for investment. This is followed by a site selection that identifies a maximum return. To calculate these two steps, the identification of criteria and criteria weights associated with measurable attributes and features in the neighborhoods of an urban landscape must be identified, along with the standardized functions. Here, we explain how to construct these assumptions in the context of the hypothetical landscape.

## Suitability assessment

Each neighborhood’s suitability for investment is obtained through a process of multicriteria evaluation that takes into consideration the relative importance of the decision criteria:

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where is the distance to the ideal point of neighborhood with respect to decision (invest in new or maintenance) and system (sewer or potable water system); is the criterion weight of criterion related to system ; is the standardized score in a neighborhood of a landscape attribute corresponding to criterion of system and decision ; is the departure of an alternative from the ideal point for a criterion; and, , , , and are indices for criteria, neighborhood, action, policy scenario, time, and infrastructure system, respectively. In Equation 1, the standardized score, , represents a judgment about the importance of an observable value of a certain criterion for the water authority’s decision. Given that the variables representing the four criteria are continuous and interval- and ratio-scaled, these scores are obtained by means of value functions (22), which transform the natural scale of a criterion to a [0, 1] value scale (0 represents the most undesirable state and 1 the most desirable state).

## Site selection

Every 10 time-steps, site selection is invoked for choosing a single investment,, in a specific action for a number of neighborhoods that is established by budgetary constraints, . Formally, this involves using a 0-1 (or binary) programming model (43), in which the objective function maximizes . In this way, the model simulates a preference for investing in the neighborhoods where infrastructure is most needed; formally:

subjected to

where is the number of neighborhoods where investment can take place; is the 0-1 decision variable (equals 1, if neighborhood is selected for investment in action for system , or 0 otherwise); and and are the 0-1 mutually exclusive decision variables related to investment in potable water systems, , and sewer systems,, respectively. Operationally, the neighborhoods are sorted in descending order by their suitability scores () and selected sequentially until the budget is exhausted.

## Decision criteria

### Exposure and Social pressure

Social pressure results from accumulated exposure, expressed as protests by the residents of the neighborhoods. Exposure of neighborhoods to infrastructure hazards is assumed to be related to the average risk of water supply disruption and flooding events. In addition to the effect of elevation (that assumes that exposure to water scarcity increases, and to flooding decreases, with elevation), the risk associated with infrastructure hazards depends on the condition of clean water and sewer systems,; formally (44):

where is the rate of decline, is the infrastructure age, and is time in months. is a Boolean variable that defines the presence or absence of infrastructure in neighborhood . Thus, when neighborhood is connected to system .

#### Exposure

Our model assumes that infrastructure systems can be disconnected or connected. This implies that the risk of infrastructure hazards in a neighborhood may also be influenced by the condition of infrastructure in contiguous neighborhoods. Accordingly, the risk factor associated with the condition of the infrastructure,, is assumed to correspond with the average conditions of the infrastructure within the set, of neighborhoods, which, in our simulation, is defined by the von Neumann vicinity with distance ,, and the focal neighborhood itself:

where is the cardinality of set , with }. Given that , when then , which means that risk is adjusted to a lower value as the conditions of clean water systems improve, and vice versa. By varying the distance we can define the connectivity of the system, such that when the system is fully disconnected, and when it is connected. In the main document we present results from simulating a disconnected system (), but we also conducted simulations assuming connected systems () (SI. Fig. 3 and Fig. 4).

Given that exerting social pressure (protests) entails costs for residents, we assume that they are only likely to engage in this form of action following a specific threshold of risk exposure and tolerance. It is assumed then that the effects associated with water supply disruption are accumulated over time and perceived by residents only after certain period. Accordingly, the exposure to water supply disruption, , is calculated as the average risk of disruption of clean water supply in a neighborhood during a previous period:

where is the standardized score of elevation for neighborhood as computed through a linear increasing value function, and is the time period (in our simulation = 1 cycle of decision).

We assume that the risk that sewer systems will fail in a neighborhood depends on the magnitude of spatially uniform rainfall events,. Thus, the risk associated with the magnitude of a rainfall event, , corresponds to a realization from a lognormal distribution (in our case using and ) normalized by the maximum value obtained after 10,000 realizations from the same distribution, :

Individual flooding events are simulated as occurring whenever the value of the risk associated with flooding is higher than a random number generated from a uniform distribution, :

where is the standardized score (obtained through a decreasing linear function) of the elevation at neighborhood , and is a random number generated from a uniform distribution,.

Exposure to flooding, , is then estimated as the average frequency of rainfall events of sufficient magnitude,, during period to :

#### Protests

Protests are modeled as the primary way in which residents can signal their dissatisfaction with their hazard exposure. Thus we assume that protests in a neighborhood, , are triggered in proportion to exposure to infrastructure hazards, the response of the water authority, and the tolerance of local inhabitants to those hazards; accordingly:

where  is either exposure to water supply disruption or flooding; if any investment was made by the authority in the past time step to either maintain current, clean water and sewage systems or construct new ones; is the tolerance of inhabitants to infrastructure hazards; parameter is the relative importance that residents give to exposure due to lack of investment; and is a random number generated from a uniform distribution.

#### Social pressure

Social pressure, , is a measure that results from the accumulation of protests in a neighborhood, subject to a fading effect associated with the earlier protests occurring in a neighborhood. For example, if residents choose not to protest in a time step, the effects of protests from previous time steps begin to lose importance. Formally:

where is the fading effect of social pressure with time. This fading effect of social pressure represents the degree to which the accretion of protests diminishes whenever residents do not protest in a time step. Thus, when , then ; when , then ; and when , then .

We use a linear value function to represent the importance of social pressure in decisions using:

where is the maximum level of social pressure for a particular value of . In our simulations, we set , such that .

### Age of infrastructure

It is assumed in the model that the condition of the infrastructure system in a neighborhood, , declines over time as it ages. This change over time is captured by the following expression:

where is the age of system in neighborhood at time step , and it increases by one unit in a single time-step.

The “maintenance” action reduces the age of infrastructure proportionally to its effectiveness, formally:

where is the effectiveness of maintenance (in the simulation, , which signifies a 10% reduction in infrastructure age), while the construction of new infrastructure in a neighborhood is .

A triangular value function is used to depict the water authority’s perception of the importance of infrastructure age when making decisions regarding investment in maintenance, ; formally:

where the age at which the state of infrastructure reaches its maximum importance in decision-making. After this point, the decision-maker assigns less importance to repairs and more importance to creating new infrastructure. All the simulations presented in the main documents were obtaining assuming .

Accordingly, the importance of infrastructure age for investment related to construction of new infrastructure, , is assumed to be a step-linear increasing function from :

That is, at the same time that the importance given to repair starts to decline, the importance of building new infrastructure increases.

### Lack of coverage

Each neighborhood can have access to the sewer and potable water system. The number of neighborhoods without infrastructure changes over time as investments are made in new infrastructure. In addition, a neighborhood can have access to infrastructure, but the infrastructure may be too old, according to the applied policy, to reduce the risk of infrastructure failure. Therefore, we define the lack of coverage of infrastructure system at time , as the proportion of neighborhoods in the vicinity of a focal neighborhood with and . Formally, the criteria “lack of coverage” is calculated by defining the number of neighborhoods in a von Neumann vicinity in a radius , with , without infrastructure or with infrastructure, over the threshold at which it is beyond functional:

where represents the neighborhoods without functional infrastructure in the vicinity of neighborhood , . The value function for this criteria is assumed to be linear, using:

where is the cardinality of set , and is the total number of neighborhoods in the vicinity of neighborhood , for all actions and infrastructure systems.

### Indirect benefit

We included a criterion that considers the density of neighborhoods in the vicinity of a focal neighborhood , to account for the perception that more densified areas often receive more attention than less populated ones. Formally, we define as the set of neighborhoods in a von Neumann vicinity of radius , . By dividing the cardinality of , that is by the cardinality of the set of possible neighborhoods in the same vicinity, we obtain the four criteria:

where is the cardinality of with , and . In all our simulations, the criterion weight associated with this criterion was set to 0.1 for all policies. Therefore, in this implementation, the “indirect benefits” criterion does not influence the comparison between policies. It was included so that it would be possible in future model iterations to consider urban growth.

## Policy scenarios

A policy scenario is defined by the set of criteria , priorities , and actions, , of the water authority defined for each infrastructure system, . Thus, formally, a policy is defined as:

where and are the set of criteria and criteria weights associated with policy , for systems and respectively, and are the set of actions. To calculate the suitability assessment, , and for each policy and system (Fig. S2).

### Designed policies

Three policy scenarios illustrate contrasting priorities regarding which criteria are more important for deciding where to build new or maintain clean water or sewer systems:

Policy scenario 1, “Squeaky Wheel” (from “the squeaky wheel gets the grease”), prioritizes reducing social pressure by investing in the neighborhoods that protest the most. Therefore, priority is given to the social pressure criterion, which implies for both infrastructure systems.

Policy scenario 2, “Expand Access,” constructs new infrastructure where it is lacking. For this policy, higher importance is given to areas with lack of coverage by setting .

Policy scenario 3, “Repair First,” prioritizes the maintenance of existing systems, thus more importance is given to neighborhoods with aged infrastructure, (Fig. S2).

### Optimal policies

In addition to the evaluation of the three hypothetical policies, we generated 2,000 sets of criteria weights, at random, using Latin hypercube sampling (45). This technique produces a homogenous multi-dimensional sampling space for each of the four decision criteria in both sewer and potable water systems subjected to the constraints that and . After simulating the model using the sample space, we extracted the scenarios that: 1) maximized access to a potable water system; 2) maximized access to a sewer system; 3) minimized city-level social pressure caused by water supply failure; 4) minimized city-level social pressure caused by flooding; 5) minimized the age of the potable water system; 6) minimized the age of the sewer system; 7) maximized average access to both infrastructure systems; 8) minimized average social pressure of both issues; and 9) minimized the city-average age of both infrastructure systems simultaneously.

In summary, we began with three designed policies that can be seen as contrasting policy prioritization for investment (technical versus socio-political), and we compared them against the nine optimal policies that maximize or minimize particular indicators (12 in total; Fig. S2). In total, 2,003 policy scenarios (2,000 + 3 designed policies) were simulated, and for each one, a total of 30 replications were conducted. Each simulation (60,090) was evaluated using the indicators of performance described below.

### Indicators of vulnerability

We assumed that the decision-maker would evaluate policy according to the decision criteria used and the effectiveness of the decisions in managing risk exposure. Thus, at the end of the period of simulation we obtained the indicators described below.

#### City-average age of infrastructure systems

This indicator corresponds to the average age of the infrastructure in the city over the last 10 decision cycles of the simulation, formally,

where is the average age of either the sewer system or potable water system, and the number of neighborhoods in the urban landscape.

#### Extent of functional infrastructure

This indicator records the number of neighborhoods that are covered with infrastructure below age . Formally,

where is the number of neighborhoods with functional infrastructure from system at the end of the simulation, .

#### City-average exposure

where is either the exposure to events of flooding,, or scarcity, in neighborhood at time *t*. is the final time-step of the simulation and the number of neighborhoods in the urban landscape.

#### City-average socio-political pressure

This index is calculated using the accumulated protests over the last 100 time-steps of the simulation and then divided by the total number of neighborhoods:

#### Inequality in exposure

This indicator is obtained by calculating the Gini coefficient. The Gini coefficient is a measure of dispersion often used to measure the distribution in income and wealth in a population. We use it here to evaluate the dispersion in combined exposure to flooding and scarcity. The Gini coefficient is an index between 0 (completely equal) and 1 (completely unequal). Thus, the larger the value of the index, the higher the inequality in exposure. The Gini is effectively calculated (46) by

where N is the population of neighborhoods.

is the exposure to flooding or scarcity at time *t*, indexed in increasing order (), with . The inequality index is then the average of the Gini coefficient over the last 10 decision cycles:

It is important to note that, because a more equal exposure is not equivalent to less exposure, this index does not consider the magnitude of the exposure. It simply states how similar the exposure is across neighborhoods.

#### Spatial sensitivity to policy change

To evaluate the sensitivity of each neighborhood to changes in the policy scenarios, we calculated the coefficient of variation in exposure,. The coefficient of variation is a measure of the variance in a sample relative to its mean, as calculated with:

where is the mean of exposure to hazard in neighborhood in a sample obtained from a set of simulation runs, measured at the end of the simulation,. Parameter is the standard deviation of the sample. Thus, if neighborhood has a higher coefficient of variation than neighborhood, we say that neighborhood is more sensitive than ) to changes in policy.

### Code repository

The code of the model is in NetLogo (<https://ccl.northwestern.edu/netlogo/>) and can be downloaded from <https://github.com/sostenibilidad-unam/abm2>, along with documentation and R-scripts to replicate the analyses and the results.

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# Figure legends

Figure 1: Flow diagram of the agent-based model.

The figure shows the conceptualization of the approach with emphasis on the feedback between decision-making, infrastructure-related hazards, and the socio-political infrastructure. Water operators operate under different policy scenarios defined by a set of criteria, priorities, actions, and objectives (Panels a and b). These policies are operationalized using suitability analysis and site-selection with a multi-criteria decision metric (Panel b). The suitability analysis and site-selection define the neighborhoods selected for investment in the infrastructure systems. The condition of the infrastructure systems, in synergy with the biophysical context (Panel c), produces hazard events and vulnerability outcomes (Panel d). One of the vulnerability outcomes, exposure, generates protests by residents, which in turn contributes to the socio-political landscape. Water operators consider this a form of socio-political action (a criteria we called “social pressure”), creating feedback between the decisions and the outcomes. Different policies are compared using a set of indicators of performance (Panel f).

Figure 2: Spatial patterns of infrastructure condition and access under three designed policies.

The figure illustrates the differences in age and extent of infrastructure systems resulting from three designed policies at the end of the simulation period (new=[0-10[; mature=[10-20[; old=[20-30[; very old=[>30]; green=non-urban areas). The Squeaky Wheel policy creates an old potable water infrastructure at the core and newer infrastructure at the periphery. This policy generates a newer and more homogenous sewer system and, again, low expansion to the periphery. This policy does not expand infrastructure as much as the other two policies, for both types of system. The Repair First policy maintains the relatively new infrastructure system conditions at the core of the urban landscape, but at the expense of older systems at the periphery. Overall, this policy increases the access to infrastructure. The Expand Access policy generates a landscape with more neighborhoods with access to infrastructure systems, and a more homogenous infrastructure age.

R-file to generate this figure: SP\_ro0tau300.Rmd

Figure 3: Temporal patterns of two indicators of vulnerability under the three designed policies.

This figure shows time-series of protests and the extent of infrastructure system coverage. The plots to the left correspond to protests related to flood exposure (top-left) and the extent of the sewer system (bottom-left). The panels to the right show protests related to potable water shortage (top-right) and the extent of the potable water system (bottom-right). The green lines show the temporal dynamics of water operators that prioritize investment in areas with old infrastructure (Repair First). The blue lines show outcomes associated with a policy that is responsive to social pressure. Red lines illustrate a policy that prioritizes investment in areas with lack of coverage.

R-file to generate this figure: time\_series\_ro0tau300

Figure 4: Trade-offs in policy performance.

The figure shows the outcome of the 13 policies for three indicators of vulnerability: city-average age of infrastructure systems (left), city-average social pressure (, center); and extent of functional infrastructure (, right). The x-axes correspond to indicators associated with the potable water system and water scarcity, while the y-axes for indicators relate to the sewer system and flooding. Triangles represent the three designed policies: Squeaky Wheel (yellow), Repair First (purple), and Expand Access (black). The circles represent the 9 optimal policies obtained from simulating over the space of possible policies. The particular indicator at which the policy is optimal is represented by the different colors of the circles. Dashed lines define the midpoint between best and worst conditions. The figure illustrates the trade-off among indicators, policies, and infrastructure systems. The full range of indicators and policies are presented in SI table 1.

R-file to generate this figure: table\_2\_indicatorsResults\_ro0\_tau300.Rmd