Facilitating Optimal People-centered Risk-Informed Infrastructure Design In Growing Cities, Through A Holistic Lens

Fabrizio Nocera
Postdoctoral Research Fellow, Department of Civil, Environmental and Geomatic Engineering, University College London, London, United Kingdom

Yahya Gamal
Research Associate, Institute of Risk and Disaster Reduction, University College London, United Kingdom

Gemma Cremen
Assistant Professor, Department of Civil, Environmental and Geomatic Engineering, University College London, London, United Kingdom

ABSTRACT: Past events around the world have highlighted the vulnerability of critical infrastructure to natural and anthropogenic hazards, which result in disruptions that have significant societal consequences. Many previous studies have focused on developing risk-modeling approaches and computational tools for quantifying the consequences of hazard events on critical infrastructure in urban environments. However, in the context of climate change, rapid population growth, and increasingly interconnected urbanization, there is a need for a novel theoretical framework that designs risk-informed critical infrastructure from a forward-looking, dynamic, and people-centered perspective. Furthermore, optimizing critical infrastructure design in terms of natural-hazard risk could have additional socioeconomic consequences (e.g., gentrification) that are not considered in conventional natural-hazard risk-modeling approaches. This paper addresses these two limitations of the state-of-the-art, proposing an innovative people-centered, risk-informed decision-making framework for urban infrastructure development. The proposed framework captures the (uncertain) performance of infrastructure in terms of serving the community's needs at different pre- and post-hazard temporal instances. In addition, it integrates a bespoke agent-based model that accounts for the implications of variations in infrastructure development on land values and resulting dynamic residential location decision making, measuring macro-scale effects that are not explicitly related to natural-hazard events like gentrification and segregation. We demonstrate the proposed framework by optimizing the transportation infrastructure design of a hypothetical expanding community of the Global South, balancing competing implications in terms of flood risk and the eviction of individuals from their homes due to rising prices. The holistic approach to decision making facilitated by this work can be used to guide inclusive risk-sensitive future infrastructure planning in tomorrow's cities.

1. INTRODUCTION

Critical infrastructure is vulnerable to natural and anthropogenic hazards, which can result in significant indirect consequences to communities that are many times larger than the direct costs of infrastructure repair (e.g., Zhang et al. 2020). Many previous studies have focused on developing engineering tools to model the consequences of hazards on critical infrastructure in urban environments. For instance, past work has simulated the performance of individual infrastructure components, like bridges (e.g., Gardoni et al. 2002), and translated damage to these components into changes in infrastructure functionality (e.g., Nocera et al. 2019). While these tools help to identify vulnerabilities and risks associated with current infrastructure, there is a need for new risk-modeling approaches that inform decision-making around designing disaster-resilient infrastructure (Cremen et al. 2022a). Furthermore, in the context of climate change, rapid population growth, and increasingly interconnected urbanization, these approaches must use a dynamic, forward-looking, and people-centered perspective, accounting for appropriate uncertainties (Cremen et al. 2022b; Filippi et al. 2023). However, optimizing infrastructure design purely in terms of hazard-induced impacts could have additional unintended socioeconomic consequences (e.g., gentrification or population segregation), which are not considered in conventional hazard-related risk-modeling approaches. Therefore, a so-called risk-informed infrastructure design may end up pricing low-income residents out of their homes and creating urban enclaves (e.g., Bagheri-Jebelli et al. 2021).

In this paper, we propose a people-centered, risk-informed decision-making framework for urban infrastructure development that addresses the current limitations of the literature. The framework first quantifies the (uncertain) ability of infrastructure to serve a community's needs, using an optimization procedure to balance its performance in business-as-usual conditions (i.e., before the occurrence of a hazard), in the immediate aftermath of a (future) hazard, and during the long-term recovery process, accounting for specific end-user priorities across time. Then, unintended consequences of optimal risk-informed infrastructure performance are modeled through a bespoke agent-based model (ABM) that accounts for the implications of infrastructure development on land values and resulting dynamic residential location decision making. Finally, we select the optimal infrastructure design, which (i) maximizes the performance of the infrastructure; while (ii) limiting unintended socioeconomic consequences to a pre-determined, end-user-specific acceptable level.

2. MATHEMATICAL MODELING OF INFRASTRUCTURE PERFORMANCE

This section reviews the general mathematical formulation for modeling infrastructure performance based on graph theory (Nocera et al. 2019; Sharma and Gardoni 2022). Networks are defined as a graph $G = (V, E)$ that includes attributes such as names, types, and state variables, as well as the topological information represented by the vertices V and edges E (Sharma and Gardoni 2022).

Following Sharma and Gardoni (2022), we model infrastructure as a collection of networks, each representing a specific function. The collection of all networks is $\mathcal{G} = \{G^{[k]} = (V^{[k]}, E^{[k]}): k = 1, \dots, K\}$, where superscript $[k]$ denotes the function captured by the k^{th} network. Then, the state of each network is characterized by a unique set of vectors: (i) capacity measures $\mathbf{C}^{[k]}(t)$; (ii) demand measures $\mathbf{D}^{[k]}(t)$; and (iii) supply measures $\mathbf{S}^{[k]}(t)$. The triplet $[\mathbf{C}^{[k]}(t), \mathbf{D}^{[k]}(t), \mathbf{S}^{[k]}(t)]$ is used to compute an overall performance measure $\mathbf{Q}^{[k]}(t)$ of $G^{[k]}$. Network measures are a function of dynamic state variables $\mathbf{x}^{[k]}(t)$, where the temporal dependence accounts for deterioration/aging processes (e.g., Jia and Gardoni 2018) or recovery activities (e.g., Sharma et al. 2020). To capture the time-dependent performance of infrastructure across a region, we define an aggregated measure $Q(t)$ of the component performances $\mathbf{Q}^{[k]}(t)$. Then, $\mathfrak{R}[Q(t)]$ denotes some specific societal benefit of infrastructure performance. $\mathfrak{R}[Q(t)]$ can be disaggregated based on socioeconomic factors (e.g., income, age, gender) to capture higher resolution effects of infrastructure performance (or non-performance) across diverse population segments.

3. AGENT-BASED MODELING OF UNINTENDED CONSEQUENCES

This section describes the ABM for residential location decision making (e.g., Alonso 1964). The ABM features buyer and seller agents interacting with a spatial context of residential units. The benefit gained by an agent from a residential unit is quantified using utility values, which depend on the agent's preferences towards various related attributes that depend on the state of infrastructure provision (e.g., proximity to services). Buyers relocate to maximize utility within the limits of their available budget (e.g., Magliocca et al. 2014).

Mathematically, we write the utility of a residential unit as

$$U_{r,i} = \sum_{j=1}^{n} \alpha_{i,j} \cdot u(\lambda_j) \qquad (1)$$

where $U_{r,i}$ is the total utility of residential unit r for the i^{th} agent, $\alpha_{i,j}$ is the weight representing the preference of the i^{th} agent towards attribute λ_j, $u(\lambda_j)$ is the utility associated with the j^{th} attribute and n is the number of attributes. We write $u(\lambda_j)$ as

$$u(\lambda_j) = \begin{cases} \dfrac{\lambda_j}{\max(\lambda_j)} \text{ if } \lambda_j \in \Lambda \\ 1 - \dfrac{\lambda_j}{\max(\lambda_j)} \text{ otherwise} \end{cases} \qquad (2)$$

where Λ is the set of desirable attributes. Next, we distinguish between agents as either buyers, b, or sellers, s, i.e., $i \in \{b, s\}$. We write the b^{th} buyer's willingness to pay for the r^{th} residential unit $WTP_{r,b}$, as

$$WTP_{r,b} = \frac{H_b \cdot U_{r,b}^2}{\beta_b + U_{r,b}^2} \qquad (3)$$

where H_b is the b^{th} buyer's available budget, β_b is a parameter controlling the convexity of $WTP_{r,b}$, reflecting the risk appetite of the buyer. The range of β_b is the same as that of $U_{r,b}$; high β_b indicates risk-averse behavior and low β_b indicates risk-taking behavior. We write the price of the r^{th} residential unit set by the s^{th} seller, $P_{r,s}$ as

$$P_{r,s} = \frac{H_s . U_{r,s}^2}{\beta_s + U_{r,s}^2} \qquad (4)$$

where H_s is the expected budget of the buyer, and β_s is analogous to β_b .

3.1. Modeling details

The ABM captures the behavior of household agents in the form of a relocation action. Relocation occurs for the b^{th} household buyer agent when $P_{r,s} > WTP_{r,b}$. Relocating households move to the first residential unit r^* (within a set of θ residential units in their current neighborhood) that satisfies (i) $WTP_{r,b} \geq P_{r,s}$ and (ii) $U_{r,b} \geq U_b^*$, where U_b^* is a utility threshold equal to the average utility value of the θ residential units. If none of the θ residential units meet these conditions, the household instead emigrates out of the urban system. Thus, relocations are triggered by changes in $P_{r,s}$ and/or $WTP_{r,b}$; these result from changes to λ_j that arise from infrastructure development. Unintended consequences of infrastructure development are quantified in terms of the total number of triggered relocations ε (i.e., the number of times $P_{r,s} > WTP_{r,b}$ is valid for household buyer agents). In summary, ε can be thought of as forced evictions, which are a proxy for gentrification.

4. PROPOSED FRAMEWORK

This section presents the proposed framework for facilitating people-centered, risk-informed infrastructure design, accounting for unintended consequences. The framework integrates the mathematical modeling of infrastructure (reviewed in Section 2) with the ABM for residential relocation decision making (detailed in Section 3). We formulate the infrastructure design/development as an optimization problem, maximizing the overall performance of the infrastructure across three temporal phases, i.e., (i) business-as-usual operations; (ii) in the immediate aftermath of a hazard event (i.e., the response phase); and (iii) during long-term recovery efforts (i.e., the recovery phase) that are prioritized according to end-user input. The design process further considers the tolerable level of unintended gentrification consequences ε resulting from the infrastructure layout.

4.1. Mathematical formulation of the optimization process

We write the objective function Z of the optimization problem as

$$\max Z = \mathbb{E}[(\gamma_1 \cdot Z_1 + \gamma_2 \cdot Z_2 + \gamma_3 \cdot Z_3)] \quad (5)$$

where $\mathbb{E}[\cdot]$ is the expected value operator; γ_1, γ_2, and γ_3 are weights, defining the end-user-dependent relative importance of the business-as-usual operations, response, and recovery phase in the infrastructure design; and Z_1, Z_2, and Z_3 represent infrastructure performance in the three corresponding temporal phases. Z_1 is formulated as

$$Z_1 = \frac{1}{n_a}\sum_{a=1}^{n_a} \omega_a \frac{1}{N_H}\sum_{i=1}^{N_H} w_i \mathfrak{R}_{i,a}[Q(t_{0^-}; \mathbf{g})] \quad (6)$$

where n_a is the number of considered infrastructure needs (types), ω_a is the weight (priority) placed on the a^{th} infrastructure need, N_H is the number of household agents in the community, w_i is the weight (priority) placed on meeting the i^{th} household's infrastructure needs. $\mathfrak{R}_{i,a}[Q(t_{0^-}, \mathbf{g})]$ describes a specific aspect (benefit) of infrastructure performance at household-level during t_{0^-} (before the occurrence of the hazard event) and $\mathbf{g}$ is the set of $E^{[k]}$ to be added as part of the infrastructure development, such that different $G^{[k]}$ will result in different values of $\mathfrak{R}_{i,a}[Q(t_{0^-}; \mathbf{g})]$. In the example case of using a topology-based approach to measure the performance of transportation infrastructure, we can define $\mathfrak{R}_{i,a}[Q(t_{0^-}, \mathbf{g})]$ as

$$\mathfrak{R}_{i,a}[Q(t_{0^-}, \mathbf{g})] = \frac{\eta_{i,a}^{(H)}(t_{0^-}, \mathbf{g})}{\eta_{i,a}^{*}(t_{0^-}, \mathbf{g})} = $$

$$= \frac{1}{N(i)}\sum_{m=1}^{N(i)} \frac{d_{i,a(m)}^{*}}{d_{i,a(m)}} \quad (7)$$

where $N(i)$ is the number of individuals in household i that have infrastructure need a, $d_{i,a(m)}$ is the distance from the residence of household agent i to the activity (location) of interest of the m^{th} individual in household i, and $d_{i,a(m)}^{*}$ is a reference value for normalizing $d_{i,a(m)}$ (e.g., the maximum value of $d_{i,a(m)}$ within the corresponding socioeconomic group) so that each component of the objective function in Eq. (5) can be added together. Z_2 is expressed as

$$Z_2 = \frac{1}{n_{a'}}\sum_{a'=1}^{n_{a'}} \omega_{a'} \frac{1}{N_H} \sum_{\substack{i=1,\\ p(i)\subseteq i\in\Omega_{a'}}}^{N_H} w_i \mathfrak{R}_{i,a'}[Q(t_{0^+}), \mathbf{g}] \quad (8)$$

where $\omega_{a'}$ is the weight associated with the a'^{th} infrastructure need in the response phase t_{0^+}, $p(i) \subseteq i \in \Omega_{a'}$ identifies the individuals (in household i) associated with the a'^{th} infrastructure need in the response phase, and $\mathfrak{R}_{i,a'}[Q(t_{0^+}, \mathbf{g})]$ describes some aspects of infrastructure performance in the response phase. In the context of using a topology-based approach to measure the performance of transportation infrastructure, we can define $\mathfrak{R}_{i,a'}[Q(t_{0^+}, \mathbf{g})] = \eta_{i,a'}^{(H)}(t_{0^+}, \mathbf{g})/\eta_{i,a'}^{(H)}(t_{0^-}, \mathbf{g})$, capturing the increase in distance to each location of interest at the household level compared to those distances at t_{0^-}. Since at t_{0^+} the focus could be on preserving life, locations of interest captured by $\mathfrak{R}_{i,a'}[Q(t_{0^+}, \mathbf{g})]$ may be different to those captured by $\mathfrak{R}_{i,a}[Q(t_{0^-}, \mathbf{g})]$ in Eq. (7), and could be limited to shelters (for those who are displaced) and hospitals (for those who are injured), for instance. Finally, Z_3 is expressed as

$$Z_3 = \frac{1}{T_R}\sum_{\tau=t_{0^+}}^{T_R} \frac{1}{n_a}\sum_{a=1}^{n_a} \omega_a \frac{1}{N_H}\sum_{i=1}^{N_H} w_i \mathfrak{R}_{i,a}[Q(\tau, \mathbf{g})] \quad (9)$$

where T_R represents the time at which recovery activities are completed, and $\mathfrak{R}_{i,a}[Q(\tau, \mathbf{g})]$ is a time-varying measure of some aspect of infrastructure performance during the recovery process. Considering a topology-based approach to measuring transportation infrastructure performance, we can define $\mathfrak{R}_{i,a}[Q(\tau, \mathbf{g})] = \eta_{i,a}^{(H)}(t, \mathbf{g})/\eta_{i,a}^{(H)}(t_{0^-}, \mathbf{g})$ analogous to $\mathfrak{R}_{i,a'}[Q(t_{0^+}, \mathbf{g})]$ in Eq. (8), where the locations of interest are the same as those captured by $\mathfrak{R}_{i,a}[Q(t_{0^-}, \mathbf{g})]$ in Eq. (7).

The first constraint of the optimization is

$$C_p \leq M_p \quad (10)$$

where C_p is the cost of implementing a specific infrastructure design, and M_p is the budget allocated to the infrastructure development process. We also force the resulting $G^{[k]}$ to be a connected network, which can be written as

$$\forall v_1, v_2 \in V^{[k]}, \exists\, \varphi(v_1, v_2) \qquad (11)$$

where v_1 and v_2 are two generic nodes in $V^{[k]}$, and $\varphi(v_1, v_2)$ is a path between them. We include additional non-negative constraints $\omega_a \geq 0, \forall a$, $w_i \geq 0, \forall i$, $\omega_{a'} \geq 0, \forall a'$, and $\gamma_1, \gamma_2, \gamma_3 \geq 0$, and ensure that sets of weights ω_a, w_i, $\omega_{a'}$, and γ_1, γ_2 and γ_3 sum to one. The final constraint of the optimization is $\eta_{i,a}^{(H)}(\tau^*, \mathbf{g}) / \eta_{i,a}^{(H)}(t_{0^-}, \mathbf{g}) \geq \xi(\tau^*), \forall \tau^*$, where $\xi(\tau^*)$ represents a lower threshold for infrastructure performance at time τ^*, facilitating a possible requirement for the infrastructure to be restored to pre-hazard performance levels within a certain period from the occurrence of the hazard event.

4.2. Solving for the final infrastructure design

The proposed infrastructure development formulation in Section 4.1 is a combinatorial optimization problem. The optimal infrastructure layout (topology) results from a finite set of possible infrastructure interventions, i.e., added edges, such as new roads in a transportation infrastructure. The overall workflow is laid out in Figure 1. We start with an augmented infrastructure layout that includes the existing infrastructure components and the full set of potential (candidate) edges for development. Several procedures can be used to obtain the augmented layout, such as (i) manually digitizing the candidate edges in a geographic information system, (ii) defining a grid of points based on digitized geospatial data in a geographic information system and finding the least cost paths among all the points in the grid or (iii) using a fully-automated interactive procedural modelling approach based on tensor field theory (e.g., Chen et al. 2008). First, we find the combination of new edges to be added that maximizes the objective function in Eq. (5) and satisfies the constraints discussed in Section 4.1.

An exhaustive search of every possible combination of new edges is not feasible because of several computational complexities, such as

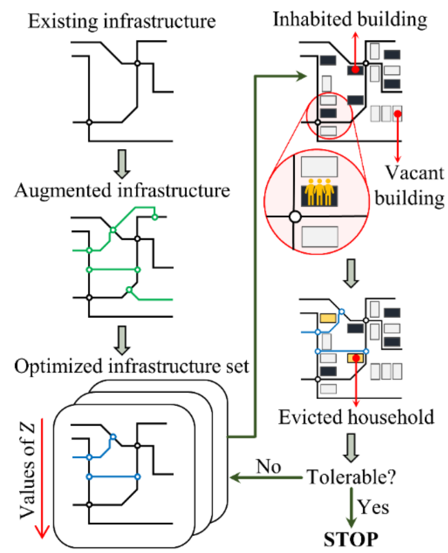

Figure 1: Workflow for finding the final infrastructure design

nonlinearity, non-convexity, and non-differentiability of the objective function in Eq. (5). However, heuristic approaches can be used to obtain near-optimal solutions, and we propose using a simulated annealing (SA)-based metaheuristic procedure in our framework. SA-based heuristics maximize/minimize an objective function by applying small random changes to the decision variable $\mathbf{g}$, i.e., the edges to add from the full set of candidates. If a new solution improves the value of the objective function, a further search is initiated in the neighborhood of this point to determine a solution that further improves the objective function. If a further solution cannot be found, the current solution is accepted with a certain probability, i.e., $\exp(-Z/T)$, in which Z is the objective function in Eq. (5), and T is one of the hyperparameters of the optimization algorithm, typically known as the temperature.

We start the search for the optimal infrastructure layout by randomly selecting a subset of candidate edges that satisfy the constraints discussed in Section 4.1. We evaluate the objective function using this subset as the initial optimization solution. Then, the initial solution is perturbed by making small changes to the current subset of candidates. For each perturbation, we randomly select one of the following options: *add*, *remove*, or *replace*. If *add* is selected, we randomly add a new edge candidate from the full set of candidates to the current subset. If *remove* is selected, we randomly remove a candidate from the current subset. If *replace* is selected, we randomly replace a candidate from the current subset with a new candidate from the full set of candidates.

Next, we avoid infeasible solutions that violate the constraints discussed in Section 4.1 by adding a dynamic penalty function (Michalewicz and Schoenauer 1996) to the solution of the objective function. Mathematically, this means that we rewrite Eq. (5) as

$$Z' = \begin{cases} Z & \text{if } \mathbf{g} \in \Omega_f \\ Z + P(\mathbf{g}) & \text{otherwise} \end{cases} \tag{12}$$

where Ω_f is the set of feasible solutions, and the penalty function $P(\mathbf{g})$ is introduced if there is a violation of the constraints discussed in Section 4.1. Following Michalewicz and Schoenauer (1996), $P(\mathbf{g})$ can be expressed as $P(\mathbf{g}) = (1/2T) \cdot [Y(\mathbf{g})^2]$, where $Y(\mathbf{g})$ is a constraint of Z, and all other variables are as previously defined.

The optimization result is a sorted list of infrastructure development layouts ranked in terms of the value of the objective function in Eq. (5) and is the optimized infrastructure set shown in Figure 1. The final selected infrastructure layout is the one ranked highest by the optimization that yields $\varepsilon \leq \varepsilon_T$, where ε_T is a pre-determined, end-user-specific acceptable level of unintended consequences, and ε is quantified using the ABM described in Section 3.

4.3. A participatory process

The proposed framework is inherently participatory in nature. Infrastructure needs a and a' can be identified through discussions with affected communities, ensuring that the infrastructure development process is based on local people's requirements. Values of γ_1, γ_2, γ_3, ω_a, and $\omega_{a'}$ should be defined by relevant local decision makers. Values of w_i can be assigned based on socioeconomic characteristics such as income, which can help to prioritize the needs of lower-income populations and support a pro-poor approach (e.g., Galasso et al. 2021).

5. ILLUSTRATIVE EXAMPLE: TRANSPORTATION INFRASTRUCTURE DEVELOPMENT

This section demonstrates the proposed framework for designing an expansion of the transportation infrastructure in the 500-ha virtual urban testbed of Tomorrowville (TV). TV is expected to experience rapid future urbanization and accommodate over 10,000 more households in the next 50 years. It was developed by combining synthetic and empirical physical and socioeconomic data from Kathmandu, Nepal, and Nairobi, Kenya, to broadly represent a typical urban context in the Global South (Menteşe et al. 2023). The testbed is a geospatial database of urban features that includes information on land use, building and infrastructure (physical) characteristics, household (social) characteristics (such as income levels), and individual (social) characteristics, as well as detailed data on each person's daily infrastructure needs. The hazard event considered is the 100-year return period fluvial flooding event presented in Jenkins et al. (2023). We focus on the performance of the transportation infrastructure during business-as-usual operations t_{0^-} and the response phase t_{0^+} (i.e., $\gamma_3 = 0$), assuming that the infrastructure needs include access to hospitals (h), schools (e), and workplaces (l) in both temporal phases, i.e., $a = a' = \{h, e, l\}$. We then estimate $\mathfrak{R}_{i,a}[Q(t_{0^-}, \mathbf{g})]$ and $\mathfrak{R}_{i,a'}[Q(t_{0^+}, \mathbf{g})]$, using a topology-based approach and assuming that a road segment is inaccessible if the water height of the flood is greater than 0.3 m (Pregnolato et al. 2017).

We make the following additional assumptions: (i) $\gamma_1 = \gamma_2 = 0.5$, and $\boldsymbol{\omega}_a = \boldsymbol{\omega}_{a'} = [1/3\,, 1/3\,, 1/3]$, reflecting an objective stakeholder who places equal importance on each temporal phase and infrastructure need when making decisions; (ii) $\mathbf{w}_i = [0.7, 0.2, 0.1]$, where the entries of the vector respectively refer to low-income, middle-income, and high-income households, reflecting stakeholders that adopt a pro-poor approach; (iii) the cost of building a new road is equal to 5,000 £/m, M_p is 20M £, and $\varepsilon_T = 920$; (iv) $H_s \sim \text{Uniform}(a_s, b_s)$, where $\{a_s, b_s\} = \{0,1\}$ for low-income households, $\{a_s, b_s\} = \{1,2\}$ for middle-income households, and $\{a_s, b_s\} = \{2,3\}$ for high-income households; (v) $H_b \sim \text{Uniform}(a_b, b_b)$, where $\{a_b, b_b\} = \{0, 1.2\}$ for low-income households, $\{a_b, b_b\} = \{1.2, 2.4\}$ for middle-income households, and $\{a_b, b_b\} = \{2.4, 3.6\}$ for high-income households; (vi) $\beta_b = \beta_s = 1$ for all agents, reflecting a risk-neutral outlook; (vii) $\alpha_{i,h} \sim \text{Uniform}(0,1)$, $\alpha_{i,e} \sim \text{Uniform}(0,1)$, and $\alpha_{i,l} \sim \text{Uniform}(0,1)$; (viii) The set of λ_j considered are all desirable; Λ comprises transport distance from residence to hospital λ_1, school λ_2, and work λ_3; (ix) $\boldsymbol{\alpha}_b = [1,1,1]$ and $\boldsymbol{\alpha}_s = [1,1,0]$.

Figure 2 displays the augmented transportation infrastructure layout of Tomorrowville (on the left) and the results of the people-centered, risk-informed infrastructure development (on the right), as well as the extent of the considered flood. The existing transportation infrastructure is indicated in black. The full set of candidates is shown in green, which we obtain by manually digitizing the candidate edges, hypothetically reflecting the outcome of a conversation with potential stakeholders. The right panel provides the top-ranked optimized infrastructure layout, and the one finally selected that produces tolerable unintended consequences. The results show that the top-ranked optimized infrastructure layout would lead to ε =1,080 evicted households. Instead, the final selected layout reduces ε by 15%, with a Z value less than 1% smaller than the top-ranked one.

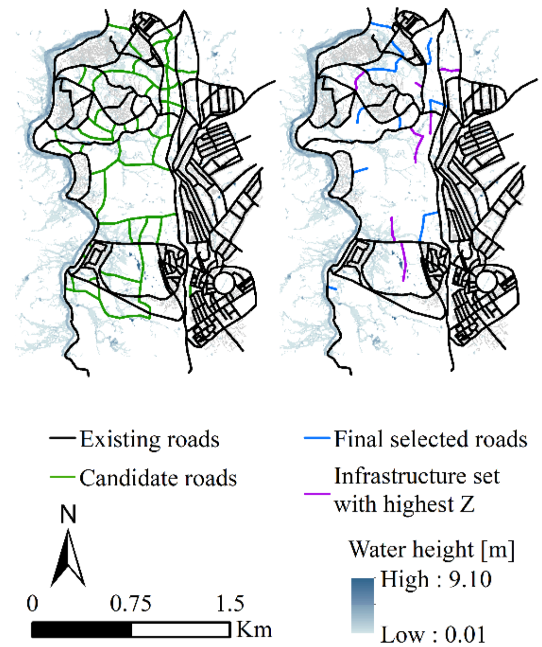

Figure 2: Case study application

6. CONCLUSIONS

This paper proposed a novel people-centered, risk-informed decision-making framework for future infrastructure development in growing cities. The framework extends beyond conventional natural hazard infrastructure impact assessments by (i) focusing on future infrastructure design; (ii) adopting a holistic lens, explicitly accounting for unintended consequences of risk-informed infrastructure development (e.g., gentrification); and also (iii) facilitating external participation in the design process.

We formulated the risk-informed infrastructure development process as a combinatorial optimization problem, in which the objective is to maximize the performance of the infrastructure in three distinct temporal phases, i.e., business-as-usual conditions, in the immediate aftermath of a (future) hazard, and during the long-term recovery process, according to stakeholder/end-user priorities and needs. The final infrastructure layout selected is one that also leads to an acceptable level of unintended consequences, which are quantified using a bespoke agent-based model that captures the implications of variations in infrastructure development on land values and resulting dynamic residential location choices. The example application demonstrated that the framework can produce an infrastructure design with tolerable unintended consequences at the expense of only a slight decrease in risk-informed performance. While the example focused on the transportation infrastructure of a virtual testbed in the Global South, the proposed formulation is general enough for application to any critical infrastructure and hazardscapes of interest.

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