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A federated pre-event community resilience approach for assessing physical and social sub-systems: An extreme rainfall case in Hong Kong

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ABSTRACT

Comparative community resilience ranking illuminates resources prioritization in the pre-disruption mitigation process. Nonetheless, previous researchers address community resilience assessment in isolated manner by considering the technical side or social capabilities only. The myopic results generated from the solely designated assessment can be misleading and may affect the subsequent resilience building efforts. More importantly, a single modeling paradigm is insufficient to capture the disparate characteristic of interconnected socio-technical sub-systems in a community. This paper proposes a federated approach to assess the pre-event socio-technical community resilience. It assembles the topological-based evaluation, physics-based performance simulation, and multicriteria decision analysis into a unified framework whereby the results derived from the topological and physics-based methods are treated as inputs for the subsequent multi-criteria decision analysis model to generate comparative socio-technical community resilience ranking. A practical case in Hong Kong is used to demonstrate the applicability of the federated approach. Using the holistic socio-technical assessment results in the illustrative case, mitigation resources can be sensibly prioritized. The strategic implications indicate that the comparative resilience ranking outperforms the results produced by models focusing on the technical or social aspect only. Since the federated approach integrates the strength of multiple models when investigating the static structures and dynamic behaviors of complex socio-technical systems at the community level, it can lead to more reliable and balanced decision making process.

1. Introduction

Community resilience has garnered attention from both practitioners and academia in recent years due to the intensifying consequences associated with natural hazards and their negative impacts on sustainable urban development. While resilience research is transforming from conceptual debates to operational paradigm and subsequently to the development of resilience management and engineering, a reliable assessment methodology shall be formulated as the precursor to monitor and track the resilience progress and to support the community resilience decision making process (Linkov et al., 2014). Common methodologies like the topology-based frameworks, flow-based approaches, hybrid methods, etc. attempt to assess infrastructure system resilience from the technical perspective irrespective of the importance of social capability-based community resilience which is usually underpinned by empirical-based assessment methods (Cutter, Ash, & Emrich, 2014; Koliou et al., 2018; Ouyang, 2014; Renschler et al., 2010). Evaluating resilience from the scope of community is extremely challenging as a community is constituted of interconnected socio-technical sub-systems with disparate characteristics, and this makes it difficult to orchestrate those socio-technical sub-systems by adopting a unified assessment framework. As a result, research endeavors so far have only been addressing infrastructure system resilience or community social resilience in isolation, let alone their possible mutual interactions. Results of a single designated assessment instead of those generated through a multi-dimensional lens of assessment are myopic and could lead to misguided resilience building efforts. Community resilience should, therefore, be pursued under a consolidated paradigm by considering diversified technical and social concerns concurrently.

Despite that, it is unlikely to have a one-size-fits-all modeling approach to characterize different facets of a community. For instance, the

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topological metric-based methods are incapable of incorporating sufficient flow-based information. The general maximum flow-based methods with node or edge capacity constraints, on the other hand, cannot capture the specific operating characteristics of infrastructure systems, not to mention about the fact that those capability-based community resilience assessment approaches might neglect the adverse effects triggered by infrastructure system malfunctioning (Yang, Ng, Zhou, Xu, & Li, 2019). Therefore, it is imperative to combine the strengths of multiple models developed in different disciplines to (i) understand and predict the static structures and dynamic behaviors of complex socio-technical systems at the community level; (ii) simulate and estimate the interdependency and adaptive characteristics of a system corresponding to the uncertainties through the use of the reduced analytical functions and hybrid models with varying initial or boundary conditions; and (iii) derive a comprehensive understanding of a system by agglomerating the weighted results of different models and algorithms.

This paper proposes a federated assessment approach for community resilience from the socio-technical aspect. It assembles the topological-based evaluation, physics-based performance simulation and multi criteria decision analysis within a unified framework so that the evaluated results generated from both the topological and physics-based methods can be used as inputs for subsequent multi-criteria decision analysis model to generate comparative socio-technical community resilience ranking. An illustrative case emphasizing on community resilience against extreme rainfall event in Hong Kong is used to demonstrate the applicability and effectiveness of the proposed federated approach. The results obtained from the case study can also help provide strategic implications in terms of resources prioritization for hazard preparedness and mitigation. As postulated by Taba, ndeh, Gardoni, Murphy, and Myers (2019), it is necessary to guarantee the immediate aftermath of a disruptive event is tolerable, in particular for the purpose of pre-disruption risk mitigation and management. To this end, the proposed federated approach can be adopted to assist decision-makers developing pragmatic mitigation strategies at the pre-event resilience stage. The proposed investigation shall fill the research gaps by contributing a multi-paradigm based, integrated and open community resilience framework to end-users, which should facilitate the analysis of community resilience from a holistic perspective by using multiple analytical models, hybrid simulation models and multi-criteria decision analysis models, and this would reinforce stakeholders' abilities in making rational decisions under extremely uncertain and dynamic conditions for resilience.

The remainder of this paper is organized in five further sections. Section 2 reviews the literatures related to infrastructure and community resilience and justifies the necessities for the use of a federated approach. Section 3 introduces the concepts of the federated approach as proposed in this research. Section 4 exemplifies the proposed approach with a demonstrative case in Hong Kong. Section 5 provides strategic implications for resources prioritization to mitigate any expected adverse consequences after a hazard. Finally, conclusions and directions for future research are provided in Sections 6.

2. Literature review

2.1. Infrastructure system and community resilience

Infrastructure systems are posited as the backbone of social services and any disruption to their functionality due to natural hazards or antagonistic attacks could cause significant economic losses and social inequity. Research towards infrastructure system resilience mainly emphasizes the constrained functionality degradation and rapid recovery process after disruptions (National Academies, 2012). In response, many resilience assessment frameworks and toolkits have emerged with representative studies encompassing the system-theoretic accident model and process (STAMP), functional resonance analysis method (FRAM) and resilience analysis grid (RAG) methods (2012, 2015, Hollnagel, 2011; Woods, 2006), 4R model (Bruneau et al., 2003), four-cornerstone model (Hollnagel et al., 2009; Woods, 2015), three-stage resilience analysis framework (Ouyang, Dueñas-Osorio, & Min, 2012), compositional demand / supply framework (Re-CoDes) (Didier, Broccardo, Esposito, & Stojadinovic, 2017) and physics-based framework (Yang et al., 2019) to address resilience assessment pertinent to the urban infrastructure systems and even the community. As for the resilience metrics used, researchers generally designate key performance indicators directly from each infrastructure system domain or devise integration-based resilience metrics (Nan & Sansavini, 2017; Tran, Balchanos, Domercant, & Mavris, 2017; Zhang & Wang, 2016).

Notwithstanding the wide spectrum of research on the technical metrics, social and institutional considerations should not be oversighted when evaluating the resilience of community. Community hereinafter refers to a place bounded geographically that functions under the jurisdiction of a governance structure, such as a town, city or county (NIST, 2015). Adopting such definition is beneficial as impacts related to any disruptive events and improvements to specific systems or services can be explicitly assessed within the designated boundary. Sub-communities should also be recognized since changes to the jurisdiction could differentially impact the sub-communities within that place. Community resilience stretches the analyses boundary of critical infrastructure system resilience with integrative social and economic system considerations and their interactions with physical systems (Koliou et al., 2018). For instance, Bruneau et al. (2003) suggested conceptually envisaging a community as interlaced technical, organizational, economic and societal sub-systems. Considering the complexity of abstracting the interaction behavior between agents or components within different systems, many works treat resilience as an intrinsic property of certain community so that it can be evaluated through different capitals ranging from built (physical), social, financial (economic), political, human, cultural, and natural (NIST, 2015). With that, assessment schemes encompassing both quantitative indicators based on numerical data and qualitative indicators found on expert judgment or public perceptions, such as disaster resilience scorecard for cites (UNISDR, 2014); baseline resilience indicators for communities (BRIC) (Cutter et al., 2014); and PEOPLES resilience framework (Renschler et al., 2010), have been developed and favorably adopted by local authorities or organizations in reality (Sharifi, 2016).

2.2. Methods for community resilience assessment

Since community resilience does not only encapsulate the resilience of infrastructure systems, but it should also take into account the resilience of the social and economic sub-systems, diverse methods shall be adopted to investigate different sub-system resilience behaviors depending upon their disparate operational characteristics. Studies on community resilience with the main focus on physical infrastructure systems (e.g. buildings, water, power, transportation, etc.) gradually evolve from solely using the topological-based approaches (which can only analyze the structure or topology level) to a coordinated method with flow information duly incorporated (Lee, Mitchell, & Wallace, 2007; Zhao, Li, & Fang, 2018). However, the network flow information in those research works is general materialized as the weightings to modify the topological metrics or modeled according to the generalized maximum flow principle within the constraints of node capacity, edge capacity and demand of end-users. Such generalized flow model is not suitable for all infrastructure systems as they may have their specific and distinguished operating mechanisms, which necessitates delving into the physics-based models which govern the behavior of respective infrastructure system (Yang et al., 2019). On the other hand, scholars have suggested capturing the dynamic resilience behaviors of interdependent infrastructure systems at the functional level by adopting systemic modeling frameworks, such as the hierarchical holographic modeling (HHM) (Ouyang, 2014) and high level architecture (HLA)

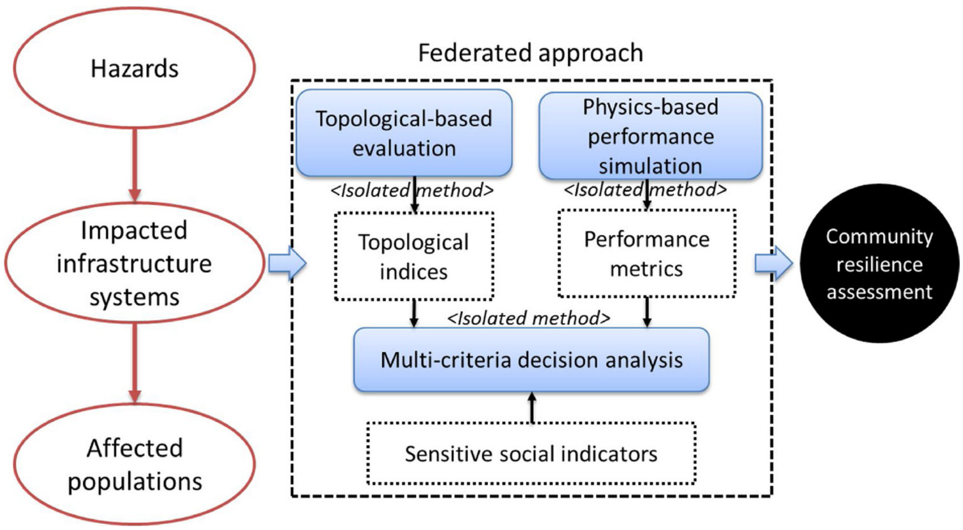

Fig. 1. Schematic representation of the proposed federated approach for community resilience assessment.

(Nan & Sansavini, 2017), as well as a distributed simulation framework enabled by the lightweight communications and marshalling (LCM) libraries (Lin et al., 2019).

Social scientists have attempted to assess social resilience from the theoretical and conceptual perspectives according to the broader context of disasters and natural hazards. They conceive that community resilience is associated with the existence, development and engagement of community capitals / resources by community members after a disaster (Cutter, 2016; Kontokosta & Malik, 2018; Magis, 2010). Representative methods constitute the reliability-based capability approach (Tabandeh et al., 2019), PEOPLES framework (Kammouh, Noori, Cimellaro, & Mahin, 2019), BRIC (Cutter, Burton, & Emrich, 2010), resilience inference model (RIM) (Lam, Reams, Li, Li, & Mata, 2015), social vulnerability index (SoVI) (Cutter, Boruff, & Shirley, 2003), and so on. Instead of focusing on specific hazard risks, these methods look into the general demographic characteristics which make a community more vulnerable or resilient to any other hazards. On the other hand, economic resilience is scrutinized through economic models like the input-output inoperability model (IIM), computable general equilibrium model (CGE), and spatial CGE. Since interdependency are designated as economic relationships between different sectors, these models are suitable for developing macroeconomic-level and industry-level mitigation strategies and consequence analysis after certain hazards though they fail to analyze the interdependencies at the component levels (Ouyang, 2014).

Despite the methods in each isolated aspect, methodological advancement is needed to integrate the engineering systems with both social and economic ones in resilience analysis at multiple spatial and temporal scales. Masoomi and van de Lindt (2019) have adopted a two community-level resilience metric, namely population outmigration and hazard-induced casualties, in assessing the resilience of residential buildings against tornados. Eid and EI-adaway (2017) captured the stakeholders' interaction between local agencies, residential sector, and economic sectors during the disaster recovery process using an agent-based model. Several studies also investigated the recovery process enabled by agent-based modeling to mimic the different behaviors and their interactions between the involved agents and the decision-making process of relevant infrastructure operators in the community (Batouli & Mostafavi, 2018; Sun, Stojadinovic, & Sansavini, 2019). However, due to the complexity of interdependent infrastructure systems and the interaction between stakeholders in different systems, only limited agent interactions can be explored while the underpinning agent behaviors is difficult to be justified theoretically and statistically.

2.3. The necessity for the federated approach

Despite an abundancy of methods in studying community resilience, they have specific emphasis which renders the use of a sole method biased and inconclusive. For example, the topological-based approaches do not provide sufficient information about the behavior of commodity flow in infrastructure systems and vice versa. Likewise, the physical-based methods support decision making with limited social concerns. Moreover, the stances of different stakeholders may influence the approaches they choose to reveal community resilience. For planning and design purposes, decision-makers are inclined to adopt the topological-based methods while functional flow-based approaches are more suitable for by used by operation units to control and monitor infrastructure systems. As for community-level decision making, empirical toolkits are desirable in order to provide the recovery priorities. To address different aspects of community resilience, it is necessary to integrate other modeling approaches into a uniform analysis framework for holistic decision support. Details of our proposed federated assessment approach are interpreted in the following section.

3. The federated assessment approach

This section interprets the federated assessment approach for community resilience, which consists of four sub-components, namely (i) hazards, impacted infrastructure systems, and affected populations identification; (ii) topological-based evaluation; (iii) physics-based performance simulation; and (iv) multi-criteria decision analysis. The schematic representation of the federated approach is shown in Fig. 1. The main aim of this federated approach is that the evaluated results obtained from both the topological and flow-based methods are treated as inputs for the subsequent multi-criteria decision analysis model. With that, information from both the physical infrastructure system and social dimensions are converged for the community-level resilience assessment so that decisions can be made in regard to which at-risk communities should be given priority towards resources allocation. Since the federated approach takes advantage of methods designed to address the disparate aspects of community resilience, informed decision related to vulnerability identification and mitigation strategies formulation can be generated at the system-level to meet the needs of different stakeholders. The details of the proposed approach are explained as follows.

3.1. Hazards, impacted infrastructure systems, affected populations identification

Communities can suffer from different natural or man-made hazards due to diverse topography, geological conditions, climatic and atmospheric conditions, cultural and religious backgrounds (Yang, Ng, Xu, & Skitmore, 2018). Correspondingly, the infrastructure system and its components vulnerable to each specified hazard could vary a lot. For example, electric sub-stations are susceptible to be damaged by earthquake and flooding while robust enough to withstand hurricanes by design. Conversely, transmission and distribution lines may be easily damaged when hurricanes hit (Ouyang & Dueñas-Osorio, 2014). Similarly, the impacts on different groups of population should be distinguished in order to identify the most sensitive social groups after different types of hazards occur (Saja, Goonetilleke, Teo, & Ziyath, 2019). The physiological needs such as emergency shelter in a community inflicted by a devastated earthquake would be the first concern of local government as priority should be given to the displaced people (Masoomi & van de Lindt, 2019; FEMA, 2018). When considering urban flooding with modest casualties and property losses, the sensitive social groups would be the elderly who demand special medical care and students who need schooling (Rufat, Tate, Burton, & Maroof, 2015). Hence, a sequential context analysis should be conducted to define the studied hazards, impacted infrastructure systems and the affected populations, as outlined in Fig. 1. This step is the prerequisite for selecting appropriate methods for the assessment of community resilience. Since this step addresses community resilience according to specific hazard rather than the broader community resilience concept being bolstered by diverse social capitals, the assessment results and mitigation strategies should be more actionable and productive (Saja, Teo, Goonetilleke, & Ziyath, 2018).

3.2. Topological-based evaluation

Topological-based evaluation provides direct assessment of infrastructure vulnerability from the aspect of network characteristics. Indicators are usually adopted from the domain of complex networks, such as largest connected component (LCC) and average / maximum path length in LCC (Zhou, Wang, & Yang, 2019). Despite that, due to the nature of service-oriented and directed commodity flow, infrastructure systems are being abstracted as supply networks whereby indicators originated from the complex network domain shall be adapted or modified to allow for the influences from the supply and demand nodes. Representative metrics are formulated to measure the availability, connectivity and accessibility of supply network, which constitute supply availability rate, size of largest functional sub-network (LFSN), and average / maximum supply path length in LFSN (Ribeiro & Barbosa-Povoa, 2018; Zhao, Kumar, Harrison, & Yen, 2011). In addition, the accessibility to critical facilities (e.g. hospitals, schools, etc.) from each designated community is used as a measure from the aspect of network topology and to gauge the satisfaction of community demands (Ford, Barr, Dawson, & James, 2015). It should be noticed that integrative network-level indicators are infeasible to be applied for comparative community resilience assessment. Instead, the accessibility from one community to another in a given district should be assessed and it would reveal both the inner- and cross-district traffic scenarios since a proportion of single trip trajectory overlaps with the studied district regardless of whether the origin or destination of a trip locating within the investigated area or not. So if the overlapped road segments are impacted by the disruptive event, the aggravated accessibility can also be approximately quantified in circumstance that an inner community within the district has travel demand to the neighborhood communities outside the investigated region. Furthermore, we assume that large proportion of residents in the bounded district would preferentially choose the nearest healthcare facilities within the regions since the outside ones are quite far away. Besides, the travelers are likely to make instantaneous decision when encountering disruptive event rather than planning the optimized route at the early beginning. So the travel path is supposed to be alternated locally compared to the original ones. The above two assumptions are envisaged to assure the feasibility of the topological-based method. Although such manipulation is not precise since the theoretically optimized travel trajectory to the destination outside the studied area would be changed, it provides a practical method to calculate the degraded accessibility especially for large-scale network problems.

3.3. Physics-based performance simulation

Physics-based performance simulation complements the results obtained through topological-based evaluation with micro-level functional properties pertaining to the studied infrastructure systems. Probable adverse consequences brought by hazards should be saliently simulated with the support of the physics-based approach, which leads to a more valid assessment of pre-event resilience performance of communities. In this section, a physics-based framework previously for resilience assessment of interdependent infrastructure systems proposed by the authors is referred to (Yang et al., 2019). Domain knowledge is required when selecting the physics-based models to depict the operating regime of particular infrastructure systems. Representative domain models include the DC power flow model (Ouyang, Hong, Mao, Yu, & Qi, 2009), recursive load redistribution algorithm (Crucitti, Latora, & Marchiori, 2004) for electricity power transmission and distribution systems, gas delivery model and maximum network flow model for natural gas supply systems (Coffrin, Hentenryck, & Bent, 2012), 1D and 2D hydrodynamic models leveraged to delineate the stormwater draining behavior (Teng et al., 2017), and car following model utilized to characterized the road traffic flow (Fellendorf & Vortisch, 2010). Afterwards, interdependency is operationalized by means of discrete or continuous mathematical formulae, in which the propagating effects across different infrastructure systems can be investigated. Besides, the deterministic connection between components within different infrastructure systems and the probabilistic means would be introduced to flexibly characterize the intensity of interdependences. The aggregated adverse impacts can thus be assessed within the "system of systems" context.

3.4. Multi-criteria decision analysis

Apart from the infrastructure systems, social dimension should be consolidated into the community resilience analysis framework. However, it is difficult to delineate the patterns of how different population groups are affected by the infrastructure system in question under engineering principles. Alternatively, empirical evidences can be leveraged during the comparative assessment of social resilience. Through which, the inherent characteristics and capacities of communities can be measured by means of a set of surrogate indicators. Following that, MCDA tools, such as TOPSIS, ELECTRE and PROMETHEE, can be harnessed to identify the trade-off among various criteria and provide comparative assessment of community resilience (Tzeng & Huang, 2011). Intermediate results obtained from both the topological-based evaluation and physics-based performance simulation are inherited as input indicators together with the hazard-specific social indicators selected from census tract statistics for MCDA assessment of community resilience. It is notable that the opinions of local experts and preference of stakeholders can also be integrated into the analysis as they can be represented by diverse weighing schemes. Since community resilience is a multifaceted concept, the significance of certain criteria may vary between different contexts and time scales (Frazier, Thompson, Dezzani, & Butsick, 2013). It is, therefore, reasonable to apply an unequal weighting method should there be sufficient knowledge on the relative importance of indicators (Moghadas, Asadzadeh, Vafeidis, Fekete, & Kötter, 2019).

4. Illustrative case study

This section demonstrates the applicability of the proposed federated approach in comparative community resilience assessment. Since the approach is hazard-specific, contextualization shall come to the forefront to identify the impacted infrastructure systems and those sensitive social population groups. Constituent models for each group of methods are elaborated according to the critical features of the infrastructure systems and the targeted community. Afterwards, data requirements and various data sources are explained. The results would reveal the comparative spatial patterns of community resilience and provide guidance to decision-makers about which sub-communities would call for intervention and improvements. Sensitivity analysis is further conducted to investigate the reliability of the assessment results which may be influenced by uncertainties of the weighting factors and the thresholds considering the inherited characteristics of the MCDA methods.

4.1. Contextualization

Flooding induced by intensive and frequent rainfall is reported as the prevalent hazards that imposes threats to the Hong Kong communities (ARCADIS, 2015). Because of that, stormwater drainage system and road transport system are the two impacted infrastructure systems mostly associated with surface water flooding. Stormwater drainage system can be overwhelmed when heavy and acute rainfall occurs and any overflow of node could inundate the road segments in vicinity and thus causing road closure and degraded traffic performance. Socially sensitive population groups identified in this scenario are those whose daily activities (e.g. commuting, schooling, health care needs, etc.) are likely to be hindered by degraded traffic conditions as induced by heavy rainfalls.

A district called Wanchai located in the mid-northern part of Hong Kong Island is chosen for the case study. The district has a relatively low-lying topography with many recorded inundation blackspots. Over 90% in district is impervious built environment with tightly coupled underground utilities. The boundary of the district is identified according to local planning regulations. Communities in Wanchai are generated with reference to the tertiary planning units (TPU) and street blocks and village clusters (SBVC) which are used for statistic investigation by the Planning Department in Hong Kong. Since public statistic data is only available at the TPU level, some divided communities in the case study would share the identical value of social characteristics unless high-resolution information at SBVC level is acquired. A total of 25 communities in Wanchai district are produced which are coded for easy reference, and the critical facilities like schools and hospitals (denoted by A to G) are located in Communities 11, 14, 15 and 16, as indicated in Fig. 2.

4.2. Constituent model selection for the federated approach

For the topological-based methods, the average supply path length is chosen as the indicator to denote the impacted accessibility to destinations by means of road transport due to inundation by flooding water. We consider the accessibility for three types of purposes, which represents the affected social needs for different population groups. They are accessibility to workplace, accessibility to schools and accessibility to healthcare facilities, respectively. Commuting distance from one sub-divided community to the others is calculated using the average supply path length and is formulated into a matrix. Likewise, the accessibility from one given sub-divided community to a designated school and health care facility can also be quantified with this indicator. The network analyst toolkits embedded in ArcGIS platform facilitate the computation of this indicator.

In terms of physics-based performance simulation, models are selected based on the specified knowledge in each domain. The one-dimensional Saint-Venant equations and the microscopic psycho-physical car following model by Wiedemann are referred to in this case to respectively simulate the operating schemes of stormwater drainage system and road transport system. Node flooding area is chosen as the indicator to delineate the stormwater drainage system while post-hazard traffic congestion is used to interpret the road traffic performance. The detailed simulation procedure is articulated in Yang et al. (2019). The intermediate results obtained through physics-based simulation are manipulated as inputs for the subsequent MCDA-enabled comparative community resilience assessment.

As for the models for MCDA, ELECTRE III is implemented due to its advantage over other methods. ELECTRE III compares alternatives according to the notation of concordance and discordance and computes the credibility of outranking relations. It introduces the indifference, preference and veto threshold definition, which not only allow decision-makers to incorporate their judgments but also facilitate them to adapt any imprecision and uncertainty of available data in the non-compensatory criteria evaluation (Banias, Achillas, Vlachokostas, Moussiopoulos, & Tarsenis, 2010). The detailed procedures of ELECTRE III are elaborated in Hashemi, Hajiagha, Zavadskas, and Mahdiraji (2016)).

4.3. Data acquisition

Data pertaining to infrastructure systems and social characteristics are indispensable for the federated approach. Particularly, the intermediate results calculated by the topological-based methods and physics-based performance simulation are both manipulated as the inputs for MCDA-enabled comparative community resilience assessment. Information related to the infrastructure systems constitutes the topography data, stormwater drainage system network configuration, road transport system network configuration, and community traffic demand profiles. A high-resolution (1 × 1 m) digital elevation model (DEM) data set is obtained from the Lands Department of the HKSAR Government. The geographic and geometric information of over 700 pipelines and manholes pertinent to the stormwater drainage system in Wanchai district are retrieved from Geoinfo Map – a GIS system being governed by the Lands Department of the HKSAR Government. The configuration information of the road transport system including the lane connection layout and direction of turning in each intersection is sourced from Google map and OpenStreetMap, while the 2008 Base District Traffic Models (BDTM) for urban area provided by the Transport Department of the HKSAR Government are utilized in order to build the community peak-hour traffic demand profiles. On the other hand, the social characteristics are derived from census tract statistics 2011 to assure that the selected indicators would adequately reveal the properties of sensitive social populations affected by the specified hazard. The abovementioned data is deemed reliable as it is either authenticated by the government or from popular open source platforms. The data set is summarized, processed and integrated into the ArcGIS platform for further use.

4.4. Community resilience indicator scheme and parameters setting

The community resilience indicator scheme for MCDA analysis accommodates the information for two impacted technical infrastructure systems, i.e. stormwater drainage system and road transport system, and also the social dimension. Besides, the indicators are either calculated from topological-based analysis and physics-based performance simulations or extracted from census tract statistics. Table 1 interprets each indicator in detail, and supporting evidences are compensated to justify the context specificity of the selected social indicators. The topological indices are distance-based since the time-varying traffic profiles for each road segments are not obtainable to further generate the time-based metrics. We adopt the distance variation of the shortest path length from the origin community to the destination ones (i.e.

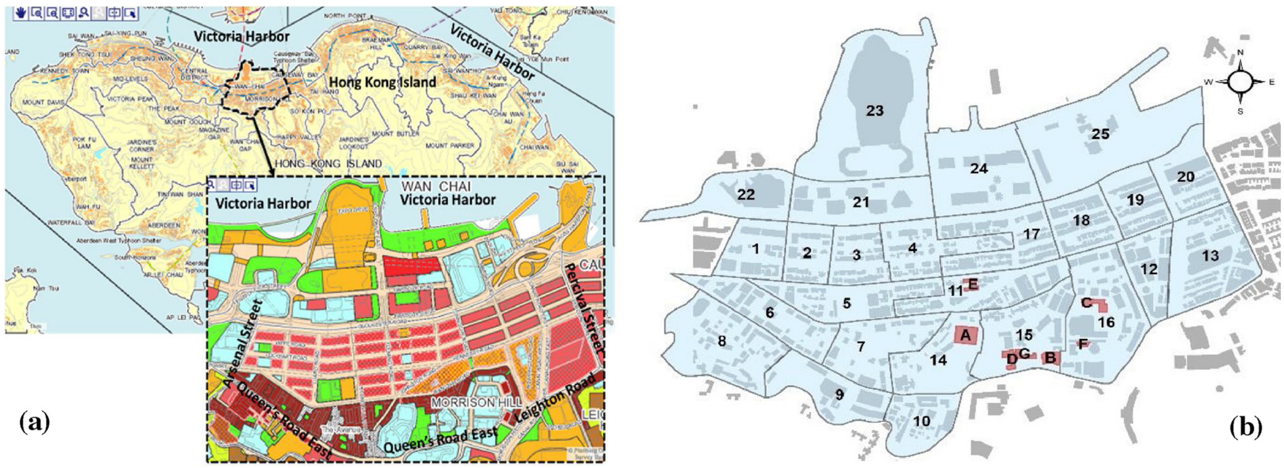

Fig. 2. (a) The location of the case study area Wanchai within Hong Kong Island, source: screenshot from open-source Statutory Planning Portal 2, Planning Department, HKSAR (https://www2.ozp.tpb.gov.hk/gos/); (b) 25 sub-communities within Wanchai district and public facilities (i.e. hospitals and schools) in communities 11, 14, 15 and 16.

workplace, schools and hospitals) between the normal and flooded scenarios. Traffic congestion induced by inundated road segment is categorized into five scales ranging from 1 to 5, with 1 representing the weakest road congestion while 5 indicating the most serious traffic congestion in the studied communities. The flooding-prone area in each generated community and the social indicators are denoted by numeric values directly generated from the simulation results and census tract statistics respectively. The preference direction is also highlighted in the table. A positive preference direction implies the higher the evaluation of criterion and thus a better alternative, and the vice versa.

According to the ELECTRE III method, the weighting factors, preference, indifference, and veto thresholds for each criterion should be predefined. Moreover, sensitivity analysis is necessary when determining the parameters in the MCDA approach, as the parameter values in real-life applications shall be originated from estimations which should be more reliable (weighting factors, thresholds, criteria qualitative values, etc.). As for the weighting strategies, priorities should vary in order to address the relative importance between the technical infrastructure systems (i.e. road transport system and stormwater drainage system in this case) and the social dimensions. In response, four diverse strategies are formulated to assign the weighting to the selected criteria as: (i) equal weighting between the road transport systems, stormwater drainage system and the social dimension (as denoted by W); (ii) weighting is inclined to the technical infrastructure systems (as denoted by W1); (iii) all weighting is given to the technical infrastructure system with no social considerations (as denoted by W2); and (iv) identical weights between the technical infrastructure system and social dimension (as denoted by W3). On the other hand, Eq. (1) is referenced to when calculating the preference threshold p_i. In this context, the preference p_i is equal to the difference between the maximum and minimum for each criterion and is divided by the number of different alternatives (n) (Banias et al., 2010). With that, the discriminative power of the method can be emphasized as more alternatives would lead to a finer threshold to help discriminate them. The indifference threshold is computed based on Eq. (2), which indicates three variants. While the veto thresholds for all the criteria are set to null in the case study unless more evidences can support a total rejection of one alternative outranking the other in terms of a single criterion. The performance of the 25 divided communities for the selected criteria and values for different weighting strategies as well as thresholds can be found in the supplementary materials.

$$p_i = \frac{1}{n}(V_{i,max} - V_{i,\,min}) \tag{1}$$

$$q_i = 0.3p_i \text{ or } q_i = 0.2p_i \text{ or } q_i = 0.1p_i \tag{2}$$

4.5. Comparative community resilience assessment

After determining the performance values for the divided communities in terms of the selected criteria, weighting factors and thresholds, an open-sourced toolkit J-Electre-v2.0 which is available on GitHub as shared by Pereira, Costa, and de Oliveira Nepomuceno (2019)) is adopted to solve the ELECTRE III problem of the case. Two complete pre-orders are constructed through the descending and ascending distillation procedure. Afterwards, an integrated relative ranking is generated as outlined in Fig. 3. If one does not consider the social dimension in community resilience assessment, the results remain stable whatever the indifference threshold is assigned between 0.3 to 0.1, as outlined in Fig. 3(a)–(c). Those with the best resilience performance are Communities a20, a21 and a3. While Communities a13, a16 and a25 receive the worst comparative performance ranking. Conversely, when social considerations are appropriately incorporated, the resilience of Communities a13, a16 and a25 are improved due to better performance in terms of social aspects, as delineated by the red hollow blocks in the figure. Similarly, the resilience ranking of Communities a17 and a21 have been advanced in the assessments which solely rely on the technical performance, compared to those cases with both technical and social considerations being accommodated. This demonstrates the technical forces outweigh the social ones and thus leading to such an integrative ranking, as highlighted by the blue circles in the figure. The best resilient communities (i.e. Communities a3 and a20) sustain amongst the diverse weight strategies and the indifference threshold values as interpreted in Fig. 3(d) and (e). However, the worst ranking of communities should be altered as finer values shall entitle the threshold more discriminative power. For example, when a = 0.3p, we cannot determine the relative performance between Communities a19 and a5, a10, a11, a16, a22 and a25. While if the indifference threshold is reduced to 10% that of the preference threshold, we can distinguish the resilience performance of Community a19 from that of the aforementioned communities. As the results are more robust conditioned on the weighting strategies with social aspects (i.e. W, W1, W3) and finer indifference threshold values below 0.3, it is suggested to adopt such reliable outcomes with the variation of weighting strategies and threshold options being neglected. In response, we select Communities a1, a6, a19 and a17 as the branch of communities with the worst socio-technical resilience performance.

Table 1
Selected criteria for assessing community resilience against extreme rainfall.

Facet	Criteria	Unit of Measurement	Description, Justification and Preference Direction	Data Source
Road transport system	C1. Average supply path length	km	Indicator for investigating the accessibility in supply networks. It denotes the average of the shortest supply path length between all pairs of supply and demand nodes in the largest functional sub-network (LFSN). Preference direction for this indicator is negative, which means that shorter average path length indicates the better accessibility (Sakakibara, Kajitani, & Okada, 2004; Bozza, Asprone, & Manfredi, 2015).	Topological-based indices
	C2. Post-hazard traffic congestion	1-5 scale (categorical)	Simulated traffic density variation in each divided community is referred and converted to categorical indicator. Grade 1 represents slightly impacted and even improved traffic condition, while Grade 5 denotes the seriously degraded post-hazard traffic condition. Preference direction for this indicator is negative.	Physics-based performance simulation
Stormwater drainage system	C3. Node flooding area	m^2	Node flooding area is approximately calculated based on simulated node overflow volume while considering the effects from topographical conditions. Larger area of inundation reflects the worse performance of stormwater drainage system and widely affected community activities. Preference direction for this indicator is negative.	Physics-based performance simulation
Sensitive social indicators	C4. Proportion of population speaking Cantonese	%	This indicator supposes that indigenous inhabitants could act promptly, communicate easier with local governments and frontline emergency teams, and behave better as veteran than immigrants when hazard occurs. This indicator serves as proxy of proportion of local residents. Preference direction for this indicator is positive (Cutter et al., 2010, 2014).	Census tract statistics
	C5. Proportion of non-student population aged 20 and over having attained post-secondary education	%	This indicator assumed that appropriate educational experiences would empower the impacted population to handle the case and minimize the losses more sensibly and craftily. Preference direction for this indicator is positive (Joerin, Shaw, Takeuchi, & Krishnamurthy, 2014; Qasim et al., 2016).	Census tract statistics
	C6. Proportion of working population have monthly income exceeding the median from main employment	%	Residents with good financial condition assume to be less impacted and they have more choices and can recover promptly compared with disadvantaged population. Preference direction for this indicator is positive (Kwok, Doyle, Becker, Johnston, & Paton, 2016; Saja et al., 2018).	Census tract statistics
	C7. Proportion of population aged 0 to 14	%	Population aged 14 years old below is treated as easily affected groups facing road links being inundated induced by extreme rainfall events since they need to go to school. Preference direction for this indicator is negative (Frazier et al., 2013; Chakraborty, Tobin, & Montz, 2005).	Census tract statistics
	C8. Proportion of population aged 65 and above	%	Population aged 65 years old above is treated as easily affected groups facing road links being inundated induced by extreme rainfall events since they need medical services away from their home. Preference direction for this indicator is negative (Frazier et al., 2013; Chakraborty et al., 2005).	Census tract statistics
	C9. Proportion of persons attending full-time courses in educational institutions in Hong Kong with place of study in same district	%	This indicator addresses the importance of commuting. Students with school outside the studied district suffer more when heavy rain occurs since they need to commute for a long distance. Preference direction for this indicator is positive (Parsons et al., 2016; Saja et al., 2018).	Census tract statistics
	C10. Proportion of working population with place of work in same district	%	This indicator also addresses the importance of commuting. Working groups with workplace outside the studied district suffer more when heavy rain occurs since they need to commute for a long distance. Preference direction for this indicator is positive (Parsons et al., 2016; Saja et al., 2018).	Census tract statistics

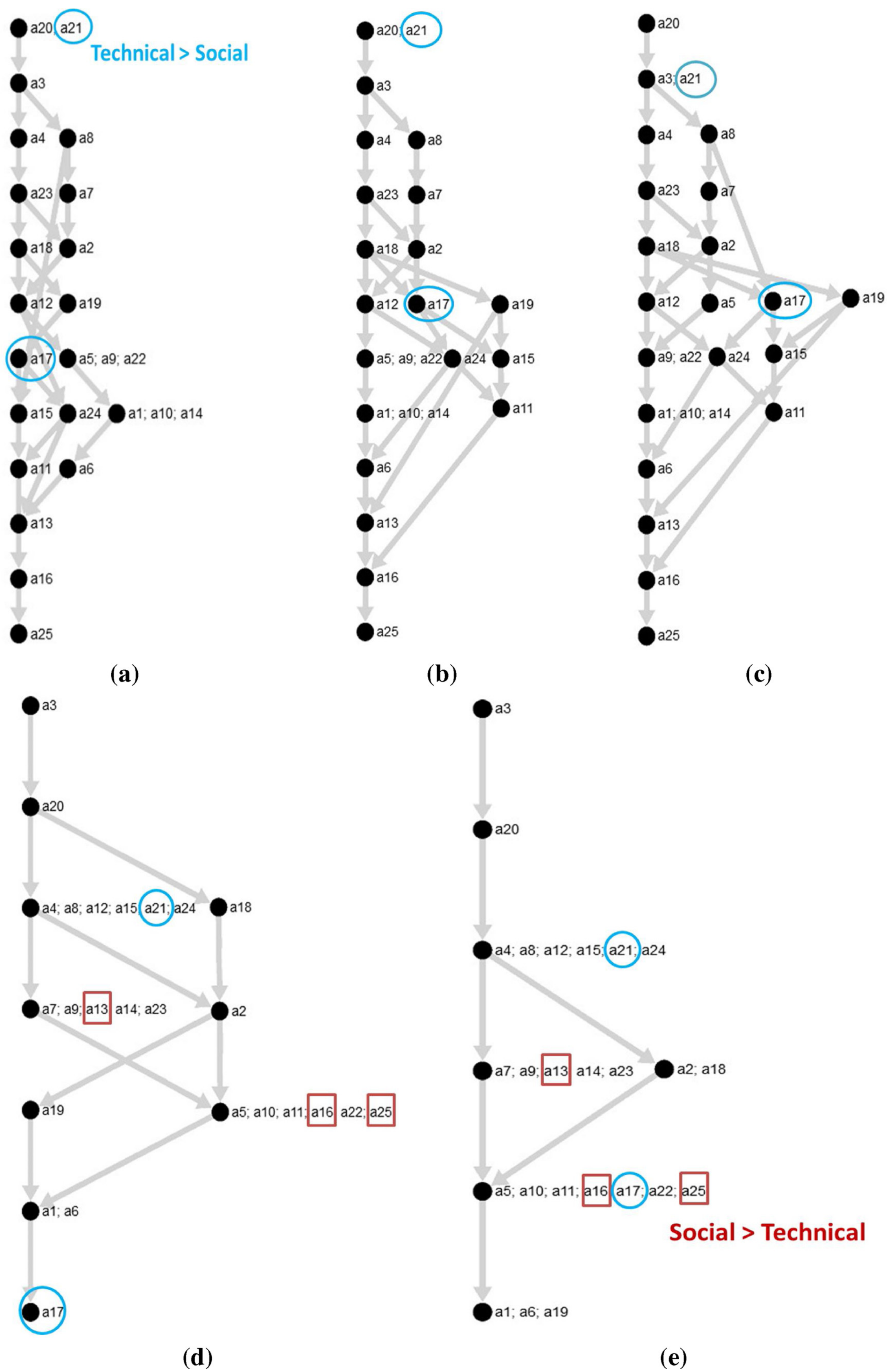

Fig. 3. Comparative community resilience assessment conditioned on diverse weight strategies and indifference threshold values; (a) W2 (no social dimension), q = 0.3p; (b) W2 (no social dimension); q = 0.2p; (c) W2 (no social dimension); q = 0.1p; (d) W, W1, W3; q = 0.3p; (e) W, W1, W3; q = 0.1p; q = 0.2p. (*Note*: W, W1, W2, W3 refer to diverse weight strategies introduced in section 4.4).

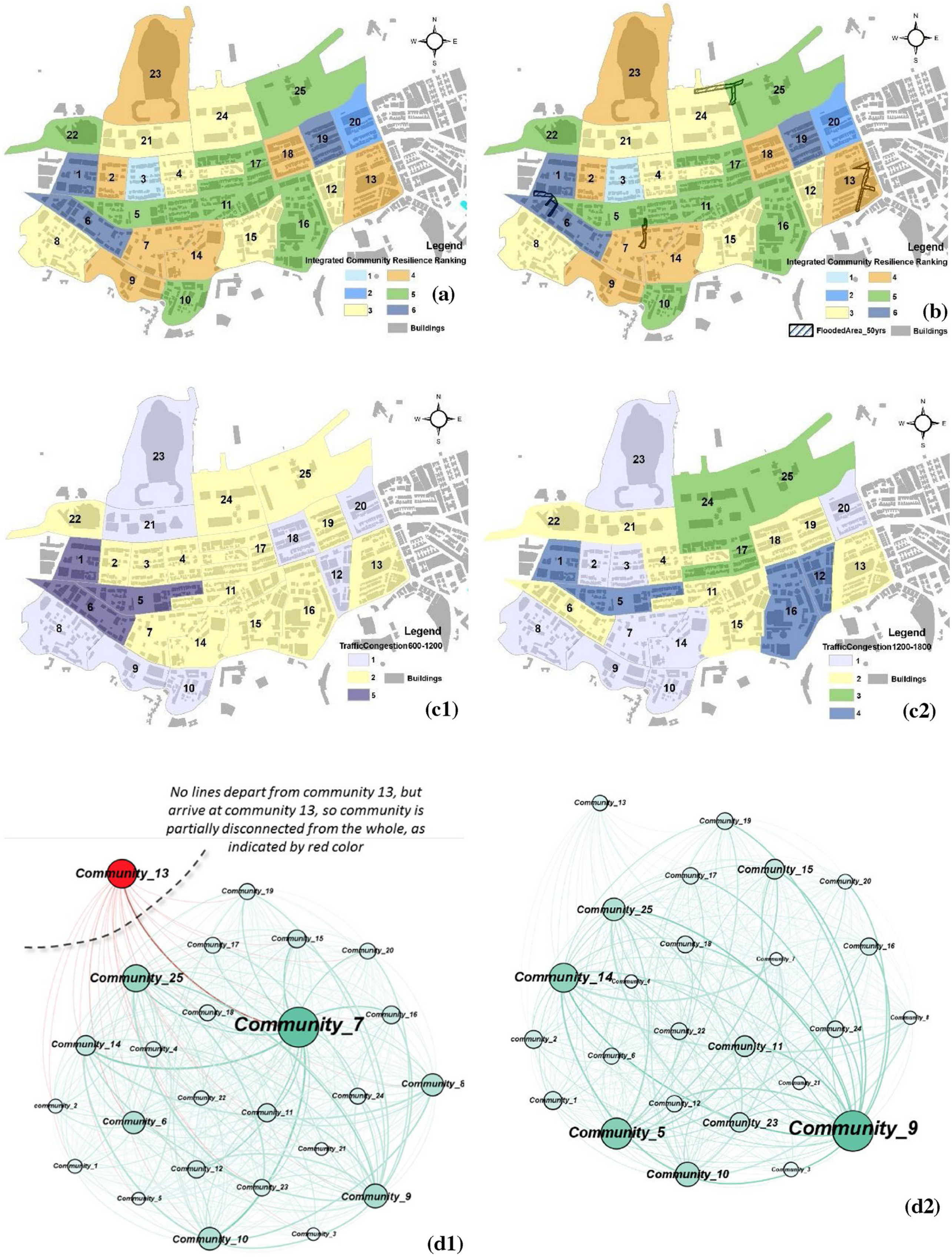

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Fig. 4. Comparative community resilience assessment from multi-dimensional aspects: (a) Socio-technical integrated community resilience assessment; (b) The flooding vulnerability map superimposed on Figure (a); (c1) Road traffic congestion in simulated time interval 600–1200 s; (c2) Road traffic congestion in simulated time interval 1200–1800 s; (d1) Topological-based accessibility from the ORIGIN side; (d2) Topological-based accessibility from the DESTINATION side. (Note: the coded communities in sub-figures (a), (b), (c1), (c2) are represented by the number in each colored block; and in sub-figures (a), (b) the rankings are represented by a spectrum of colors where the most resilient community is rendered by light blue while the least resilient one is rendered by dark blue; in sub-figures (c1), (c2) the road traffic density is indicated by a spectrum of colors where the least congested community is rendered by light purple while the most congested community is rendered by dark purple; the size of the green circles in sub-figures (d1), (d2) interprets the magnitude of flooding impact on each community, and bigger size denotes more serious impact exerted on communities) (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

5. Implications for hazards preparedness and mitigation

While resources for hazards preparedness and mitigation in municipalities are usually restricted, priorities should be given to those communities which are most severely affected. The multi-dimensional criteria shall be assessed to identify the priorities rather than solely relying on the technical (i.e. infrastructure performance degradation) or social considerations (i.e. community capacity). To this end, the integrated assessment results by applying the proposed federated approach can provide convictive evidences for decision-makers to allocate the limited resources. We presume that the resources are disposable and are administrated by infrastructure managers and operators. Their usage is exclusive to the restoration or replacement of the malfunctioned components in the infrastructure system after hazards occur. As in our case, if the Drainage Service Department provides limited emergency crews and equipment to drain out floodwater on streets, the authority should determine which inundated area the emergency crews shall be deployed to first.

Fig. 4(a) represent the comparative socio-technical resilience ranking according to the assessment results in the above section. In addition, the decomposed assessment results of community resilience ranking are generated solely on the following technical aspects. Fig. 4(b) delineates the flooding vulnerability map in Wanchai sourced from our previous work Yang et al. (2019). Similarly, we extracted the traffic flow simulation results obtained by applying our physic-based model, as indicated in Fig. 4(c). Fig. 4(d) interprets the topological-based network accessibility from both the origin and destination sides. It can be seen that the assessment results from different dimensions could vary considerably. For example, Community 13 suffers most in term of accessibility after the street flooding occurs as denoted in Fig. 4(d1) while it behaves much better when assessed from other dimensions. In contrast, the topological performances of Communities 1 and 6 are more acceptable with a small portion of increase in travel distance as induced by the urban flooding compared to that of other communities. However, they rank the lowest when accommodating all the dimensions during comparative community resilience evaluation, as denoted in Fig. 4(a). Inspired by this, we presume that the convincing strategies would be enacted only when synergizing these conflicting assessment results.

If the municipality possesses limited resources to alleviate the adverse consequences caused by street flooding, and only one inundated area in Fig. 4(b) can be recovered in a time scale, the sequence of recovery should be planned in advance. The inundated area located at the boundary between Communities 1 and 6 is considered to be first area to be restored as these two communities are characterized as being sensitively affected by urban street flooding, as highlighted in Fig. 4(a). Meanwhile, the two communities also experience serious traffic congestion as vehicles are stuck in the intersection and lined up to traverse the inundated road links (see Fig. 4(c1)). The second flooded area to be recovered is the one posited at the boundary between Communities 5 and 7, as Community 5 is similarly featured by the residence of affected social groups and the traffic performance in Community 5 is largely degraded. Besides, Community 5, 7, 9, 10 and 14 constitute the significantly affected ones in terms of network accessibility following the street flooding event, as delineated in Fig. 4(d1) and (d2). Subsequently, the street flooding issue in Community 13 can be resolved, although the integrated community resilience assessment indicates that it has a relatively acceptable level of resilience. However, if the inundation impacts are continuously amplified due to acute and intense rainfall, this community would possess a possibility of being partly disconnected as the road links originating from Community 13 to other ones are seriously inundated and thus completely closed, as delineated by Fig. 4(d1). Ultimately, the resources can be redirected to settle the street flooding problem in Community 24.

6. Conclusion and future work

This paper proposed a federated approach for pre-event community resilience assessment from the socio-technical aspect. It synthesized the commonly leveraged methods for resilience studies, i.e. topological-based evaluation and physics-based infrastructure performance simulation, as well as the multi criteria decision analysis module in order to incorporate both the infrastructure resilience behavior and community social resilience capacities into a unified socio-technical assessment framework. Besides, the federated assessment approach is distinct from the prevalent general community resilience assessment methods, as it is hazard-specific so that the mitigation strategies can be targeted towards relieving the potential adverse consequence induced by a specific hazard type. By adopting this approach, comparative resilience ranking can be acquired and this will facilitate decision making in term of allocating limited mitigation resources. The Hong Kong case demonstrates the applicability of the federated approach as it can assist the formulation of pre-disruption mitigation strategies from a holistic socio-technical standpoint. The federated approach can effectively and sufficiently balance the social and technical vulnerabilities when prioritizing the mitigation resources. Since the proposed approach integrates the strength of multiple models developed in different disciplines, both the static structures (i.e. network characteristics and social configurations in a community) and dynamic behaviors (i.e. resilience performance of infrastructure system against hazards) of complex socio-technical systems can be revealed at the community level.

The federated approach is transferable to other hazards not limited to the urban flooding induced by extreme rainfall. Similarly, end-users should define the specific hazard that may threaten the community, and thus the potentially most affected infrastructure systems and social groups. Based on this, the criteria could be selected for hybrid socio-technical community resilience assessment. Therefore, it is a necessity to consider other types of hazards in a given community and the assessments of different hazards can be further consolidated to formulate a multi-hazard community resilience assessment result in future research. The federated approach converges to the MCDA method in the last step, so as to accommodates the community social dimensions which is difficult to be modeled using the physics-based approaches as the infrastructure systems. Attributed to the nature of MCDA methods, the stakeholders should define the thresholds and weighting for criteria when adopting the ELECTRE III model. In our paper, we designed twelve strategies in terms of varying weighted scores and threshold values to reveal the different preferences of decision-makers. However, when leveraged in reality, stakeholders seldom interpret the relative importance between criteria and the exact numeric value of threshold. Therefore, linguistic terms may be useful to express their opinions. In such situation, the ELECTRE III method should be enhanced by considering the intuitionistic fuzzy information, which would also constitute the future research agenda.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.scs.2019.101859.

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