Estimating the Societal Impact of Water Infrastructure Disruptions: A Novel Model Incorporating Individuals' Activity Choices

Yongsheng Yang [a,b], Hirokazu Tatano [b], Quanyi Huang [a*], Ke Wang [a] , Huan Liu [b,c*]

[a] *Institute of Public Safety Research, Department of Engineering Physics, Tsinghua University, Beijing, China*

[b] *Disaster Prevention Research Institute, Kyoto University, Kyoto, Japan*

[c] *Graduate School of Informatics, Kyoto University, Kyoto, Japan*

Declaration of Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[*] Corresponding author.
Institute of Public Safety Research, Department of Engineering Physics, Tsinghua University, Beijing, China *E-mail address:* qyhuang@tsinghua.edu.cn (Q. Huang)
Disaster Prevention Research Institute, Kyoto University, Kyoto, Japan *E-mail address:* huan.liu.b05@kyoto-u.jp (H. Liu);

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Abstract: The well-being of society can be severely impacted by infrastructure disruptions. This study proposes a novel mathematical model to estimate the societal impact of water disruption quantitatively from two aspects: the percentage of people who can perform certain water-related activities and the percentage of people who are intolerant to disrupted activities. The model incorporates the tolerance level (TL) to establish a suffering level function of the disrupted activity. Then, from the individual's perspective, an activity estimation model is developed to predict an individual's choice for activities with limited water due to infrastructure disruptions, and this model is mainly driven by prioritizing activities with the maximum suffering level. To quantify the societal impact in regions, a Monte Carlo simulation is adopted to take samplings for TL of simulated residents following lognormal or Weibull distributions, and the activity estimation model is conducted for each simulated resident; consequently, societal impacts can be aggregated and derived. Additionally, an illustrative case study of Osaka and sensitivity analyses are performed; the results validated the model's effectiveness and applicability. The proposed model provides insightful information to support emergency management and can be integrated with resilience models of infrastructure to better build human-centric sustainable and resilient cities.

Keywords: Societal impact, Infrastructure disruption, Water-related activity estimation, Suffering level, Disaster, Resilient cities

1 Introduction

Critical infrastructure systems, which provide essential resources and services (e.g., water, food, housing, and medical services), are the foundation of modern society and the well-being of individuals (McAllister, 2015). These systems can be disrupted by natural and human-made hazards, leading to reductions in the supply of essential goods and the disruption of services. In such situations, the daily activities of residents and the well-being of society tend to be significantly affected. As cities continue to develop, residents are increasingly relying on infrastructure, and the societal impact of disruptions become larger. To build resilient cities, high attention has recently been paid to evaluating the reliability and resilience of interdependent infrastructure systems, while the societal considerations caused by the disruptions of these systems have rarely been investigated (Esmalian et al., 2021; Nozhati et al., 2019). In the face of disasters causing widespread and increasing threats to infrastructure and societies, the need for developing human-centric models to estimate the societal impact of disruptive events is rapidly growing. A better understanding and quantification of the negative societal impact is critical for decision-makers to take the appropriate emergency response and recovery measures and plan mitigation strategies, which ultimately contribute to building resilient societies.

The societal impact of hazard events can be multifaceted due to the multidimensionality of society. The effects can be quantified in several ways, such as by the number of deaths or displaced people (Chang et al., 2009; Priest, 2007; UN-ECLAC & The World Bank, 2003), economic losses (Chang, 2016; Liu et al., 2021), negative sentiments (Alexander, 2014; Lu et al., 2015), psychosocial changes (Sutley et al., 2017), political impact (Albrecht, 2017; Xu et al., 2016), and well-being impact (Markhvida et al., 2020; Martin et al., 2020). When focusing on the societal impact of critical infrastructure disruptions, this can be measured using changes in well-being. Paolo Gardoni and Colleen Murphy first applied the capability approach to the disaster field and gauged the impact of disasters on well-being by examining changes in individuals' capabilities (Gardoni & Murphy, 2010; Murphy & Gardoni, 2006). They emphasized the definition of people's capabilities, which refers to people's genuine opportunities to achieve valuable functionings (doings and beings) with specific resources (Gardoni & Murphy, 2010; Halliday, 1995; Sen, 1990). Subsequently, Tabandeh et al. (2018, 2019) developed a reliability-based capability approach to assess the societal impact of infrastructure disruptions. Deshmukh et al. (2011) proposed a semi-quantitative framework to evaluate changes in socio-economic activity due to disrupted infrastructure. Overall, one of the important contributions of these studies is the incorporation of essential activities (e.g., drinking, eating, or working) and beings (e.g., being mobile, being nourished, being physically safe) into evaluations of the societal impact in the aftermath of disruptive events. However, the selected indicators in these studies rely heavily on the subjective judgments of experts and may lead to estimation bias.

Consequently, integrating individuals' activity estimations into well-being impact analyses is necessary, and some studies have been conducted to evaluate people's activities during infrastructure disruptions. For instance, Yang et al. (2021) estimated the fulfillment of water-related activities and need satisfaction levels using available water quantity in infrastructure disruption scenarios, but their work did not consider an individual's activity choice process when there is limited water. Burton et al. (2018) proposed a utility-based household decision model to predict people's actions when their houses are damaged (e.g., sell, reoccupy, abandon, or sell without repairing the house) and capture the social consequences. Furthermore, they also established an empirical probabilistic utility-based decision household model using survey data to estimate people's activities regarding damaged houses after disasters (Burton et al., 2019). Conversely, Han et al. (2021) proposed an activity-based approach to evaluate the impact of a disrupted transportation network due to storm surges on residents' travel activities, including working, shopping, schooling, leisure, and others. An activity-based model, driven by utility maximization, can capture travel activity shifts and help understand people's travel decisions in transportation assessments (Castiglione et al., 2014; Zhang et al., 2002). In summary, the mechanism of predicting an individual's choice of activities in disruptive scenarios is based on maximizing the utility function of individuals; however, establishing a utility function immediately after disruption events is challenging. Meanwhile, the connections between unperformed activities and the negative well-being of individuals are still not well discussed.

Hardship experience is proposed as a proxy to evaluate individuals' well-being changes from lifeline service disruptions (Dargin et al., 2020; Dargin & Mostafavi, 2020). Esmalian et al., (2019)and Dong et al. (2020) utilized the hardship experience of individuals to measure negative well-being and quantified it using the differences between the duration of disrupted lifeline services and household tolerance levels (TL). The smaller the difference, the higher the societal impact. If the duration of disruptions exceeds TLs, people will experience a negative well-being impact and become intolerant (Esmalian et al., 2021). They introduced the key concept of TL, which is defined as the amount of time a household can tolerate infrastructure service losses in a disaster, derived from a social investigation (Esmalian et al., 2019). Similarly, Petersen et al. (2020) investigated the TL for water disruption at the individual level under different influencing factors, such as the quantity of available water, income, and age. Gentaro et al. (2015) went further into the analysis of water service disruption and explored the TL for water-related activities, such as drinking, cooking, toileting, bathing, and laundry. In addition to hardship experience, deprivation cost has also been proposed in the field of post-disaster humanitarian logistics to quantify human suffering due to the reduction of essential resources or services (Holguín-Veras et al., 2013; Shao et al., 2020). However, their emphasis is on optimizing resource allocation to minimize human suffering, and the relationship between hardship experience and deprivation cost has not yet been discussed.

Considering the above challenges, this study focuses on water infrastructure disruptions and proposes a novel mathematical model to quantify the societal impact from two dimensions: individuals' choices of water-related activities and negative well-being impact (intolerant state). The main contributions of this study are as follows: individuals' choice of activities and their intolerant states due to infrastructure disruptions are aggregated to the societal impact, proposing a suffering level function of disrupted activities by combining deprivation cost and TL, and establishing a novel activity estimation model mainly driven by maximizing the suffering level of optional activities. The remainder of this study is organized as follows.

Section 2 illustrates the establishment of the mathematical model to estimate the societal impact. Then, an illustrative case study of Osaka city using the proposed model and the corresponding results are presented in Section 3. This is followed by the sensitivity analysis of important parameters in Section 4, which validates the effectiveness and applicability of the proposed model. Finally, Section 5 provides a discussion of the results and the conclusions of the study.

2 Methodology

This section illustrates how to establish a mathematical model for estimating the societal impact (illustrated in **Fig. 1**). In general, the societal impact is quantified from two dimensions: the percentage of people who can perform certain activities and the percentage of people who become intolerant to disrupted activities. As illustrated in **Fig. 1**, when infrastructure systems are damaged and disrupted due to disaster, the supply of essential goods or services is reduced. As a result of limited essential resources, not all daily activities of individuals can be performed, and the activities that individuals choose to perform and activities that they cannot tolerate aggregate the societal impact. Specifically, this study focuses on the impact analysis of water shortage due to infrastructure disruptions, and the daily activities related to water service are specified as drinking, cooking, toileting, bathing, and laundry. We use the terms *activities* and *water-use activities* interchangeably to refer to water-related activities throughout this paper. From an individual analysis scale, a mathematical model is built to estimate the individual's choice of water-related activities and intolerant states with limited water by introducing the concepts of TL and suffering level. To extend individuals' choice and intolerant states to the regional societal impact, this study adopts a Monte Carlo simulation to take samplings of TL for individuals following a specific probabilistic distribution.

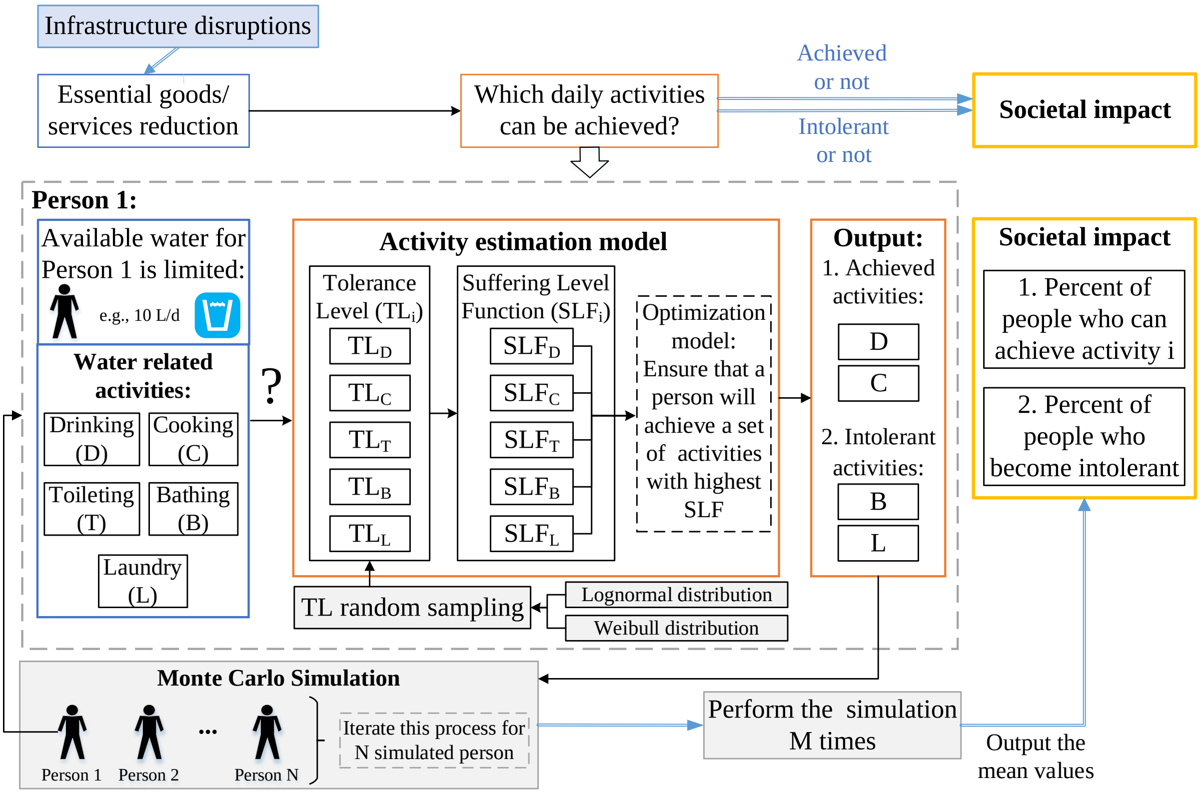


Fig. 1 Methodological framework for evaluating the societal impact of water disruption

2.1 The definition and measurement of societal impact

The societal impact of hazards is defined in terms of the expected changes in the capabilities of individuals, and capabilities usually refer to the doings (activities) or beings that individuals can achieve given limited resources caused by hazards (Gardoni & Murphy, 2010). To assess the societal impact, the changes of individuals' capabilities should be compared against two separate thresholds: acceptable threshold and tolerable threshold (Murphy & Gardoni, 2008). If the level of capabilities attainment temporarily falls below the acceptable threshold, individuals might still be tolerable, while they would become intolerant if the level falls below the tolerability threshold (Tabandeh et al., 2018). Similar to this idea, Esmalian et al. (2021) proposed a household gap model that incorporates desired service level and adequate service level to evaluate the societal impact of infrastructure service disruption; the difference between these two levels is the TL. If the disrupted service level of infrastructure is less than the adequate service level (duration of disrupted service is larger than the TL), a household would become intolerant and experience a negative well-being impact; otherwise, a household could still tolerate disruptions. Overall, how an individual's capabilities change and whether the changes are intolerable are two key points in evaluating societal impact.

In this study, the societal impact of water infrastructure disruption is measured from two aspects: the percentage of people who can perform certain water-related activities and the percentage of people who become intolerant to disrupted activities. The first aspect denotes the reduction of individuals' capabilities, and it provides important insights about the fulfillment of residents' water-related activities in a disruptive event. The smaller the percentage of people who can perform activities, the higher the societal impact. The second aspect evaluates the unperformed activities with the tolerable threshold and captures individuals' intolerant states; specifically, the individual becomes intolerant if the duration of a disrupted activity exceeds the tolerance level (TL). The higher the percentage of intolerant people, the higher the societal impact. This facilitates resources or service allocation and helps decision-makers capture the negative well-being of residents.

2.2 An individual activity estimation model

To calculate the defined societal impact, the fulfillment of individuals' water-related activity should be estimated during a disruptive event. With limited water due to disasters, individuals can still obtain water from emergency shelters or retail stores, which is supported by humanitarian logistics and commercial logistics, respectively (Davis, 2014; Yang et al., 2021). However, the quantity of available water is limited, and residents need to allocate the limited water to perform different activities because they cannot consume the same amount of water compared to their pre-disaster habits. To estimate an individuals' achievement of activities, this section illustrates the mathematical model that innovatively incorporates the TL and suffering level of disrupted activities. The analysis scale of the model is conducted at an individual level and indicates that the TL, water-related activities, and choice making are designed for individuals instead of households. Household activity choice estimation is more complicated and involves more factors, such as interactions, compositions, and the capacity of household members, which are not integrated into the proposed model.

2.2.1 Incorporating TL into an individual's activity estimation

Predicting individuals' priorities for water-related activities under various contexts and periods is challenging; however, what is clear is that disrupted activities with a higher suffering level from survival threats are always prioritized. Suffering is a proxy variable to measure an individual's bodily distress to threats (Ennis-McMillan, Michael, 2001). In disaster scenarios, the first priority should always be water for survival (drinking and cooking) and personal hygiene (toileting, bathing, and laundry) with limited water (Adams, 2021). Having water for drinking each day is more important than having water for personal hygiene, but people will still want and need to perform hygiene-related activities to prevent hygiene-related diseases (Reed & Reed, 2011). Hygiene diseases, such as diarrhea, malaria, and skin (eye) infections, can also threaten individuals' health and make the hygiene activity become priority (European

Commission's Directorate-General for Humanitarian Aid, 2005). For instance, the investigated Japanese residents explained that they could only tolerate toileting and washing disruptions for a short time but become concerned with bacteria and other hygiene problems if the disruptions extend over a longer period (Sudo et al., 2019). Another investigation conducted by the Japan LIXIL Housing Research Institute also demonstrated the importance of hygiene activities: considering the situation of water disruption, the first three water-related activities that Japanese people want to ensure is drinking (82.6%), toileting (67.5%), and cooking (44.7%), followed by bathing (33.5%) and laundry (14.0%;(LIXIL Housing Research Institute, 2016). Hence, to capture individuals' water use priorities, estimating the suffering level of disrupted activities in disaster scenarios is critical.

Incorporating TL can help to identify which activity is more suffering from threats, and further help to estimate people's achievement or priority of activities when resources are limited. The TL represents the ability of individuals to cope with the threats posed by the disruption of activities. As the duration of the unperformed activity approaches the TL, the individual's suffering level from life threats will keep increasing and become intolerable if the disruption duration exceeds the TL. Individuals have varying tolerance to different activities. With limited water quantity, individuals prioritize activities with higher suffering levels because reducing suffering is human nature. For example, if a person has a smaller TL (two days) to cooking disruptions than bathing disruptions (four days), cooking will be prioritized when there is limited water because the cooking disruption is closer to the TL and has a higher suffering level compared to bathing disruption.

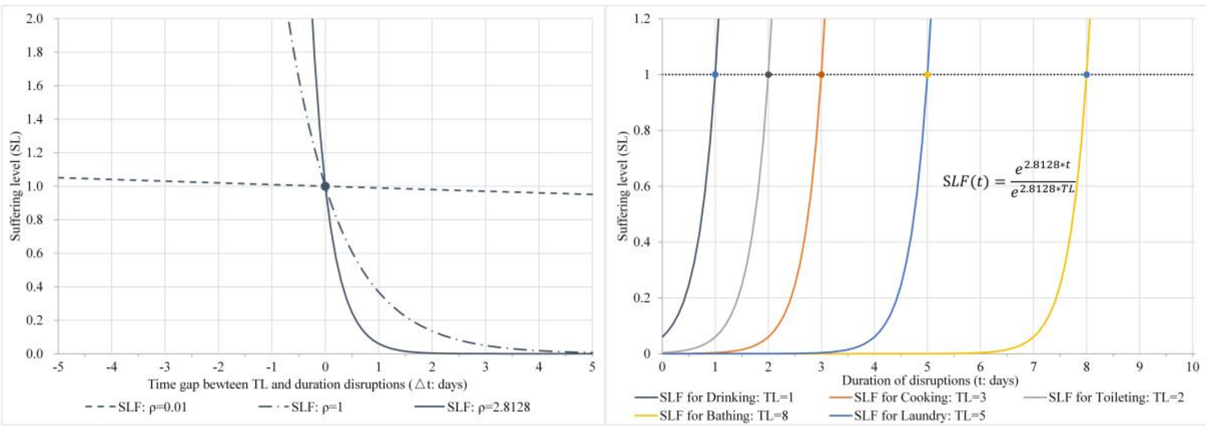
To estimate the fulfillment of activities at time t after a disaster, the duration of activity disruption should also be considered. For example, as above, assume a person's TL for cooking, and bathing is two and four days, respectively; if cooking was achieved yesterday and bathing has not been achieved for four days, this person would prefer to perform bathing rather than cooking because the cooking disruption is still under the TL while bathing disruption has reached the TL limit. The proposed model introduces a variable $t_i(t)$ to represent the duration of the disrupted activity i at time t. If activity i is performed on the previous day $(t-1)$, the duration of this disrupted activity at t would be 1 $(t_i(t)=1)$; otherwise, the duration of i would continue to accumulate and increase by one $(t_i(t)=t_i(t-1)+1)$. In fact, the gap between the tolerable day and duration of the disrupted activity, $\Delta t_i = TL_i - t_i(t)$, dominates the decision-making process of individuals. When Δt_i becomes smaller, which means that the duration of disrupted activity i approaches the maximum tolerable day (or TL), people would have a high suffering level and prefer to achieve activity i as a priority. If Δt_i is large, people still have space to tolerate activity i, and they can achieve other more suffering activities. More importantly, if Δt_i is smaller than 0 $(\Delta t_i < 0)$, the disrupted days of activity i exceed the TL, which would be intolerable for the individual; thus, the TL can also connect the activities and the intolerant state of individuals. In general, a smaller time gap Δt_i corresponds to a higher suffering level, and individuals are prone to achieve this activity in priority. A previous empirical analysis also shown a significant negative correlation of suffering level and the time gap (Esmalian et al., 2021). To denote this relationship quantitatively, this study first (Section 2.2.2) defines the suffering level function (SLF) for disrupted activity i, and then (Section 2.2.3) proposes a mathematical model to estimate individuals' activity choice.

2.2.2 *Suffering level function of disrupted activities*

To quantify the individuals' suffering level from the survival threats of disrupted activities, the following SLF is proposed by integrating the concepts of TL and deprivation cost function (DCF), which is proposed by researchers in the field of post-disaster humanitarian logistics, as illustrated in Equation 1.

$$SLF_i(TL_i, t_i(t)) = e^{-\rho*\Delta t_i} = e^{-\rho*(TL_i - t_i(t))} = \frac{e^{\rho*t_i(t)}}{e^{\rho*TL_i}} \quad (1)$$

where SLF_i is the suffering level of activity i and is the exponential function of Δt_i (**Fig. 2** (a)); Δt_i is the time gap between the tolerance level (TL_i) and duration of disruption of activity i at time t ($t_i(t)$); and the parameter ρ controls the slope of the function and denotes the individual's suffering perception towards disruptions of activities or essential resources. As shown in **Fig. 2** (a), with a larger ρ, individuals experience less suffering before the duration $t_i(t)$ exceeds TL_i ($\Delta t_i > 0$), while they have a higher suffering level when the duration $t_i(t)$ surpasses TL_i ($\Delta t_i < 0$). For one individual, TL_i and ρ are usually determined and specified, and illustrative curves of the SLF_i with respect to the duration of disrupted activity i are illustrated in **Fig. 2** (b).



(a) (b)

Fig. 2 (a) Illustrative suffering level functions with regards to Δt_i for different ρ; (b) Illustrative suffering level functions for activities;

The functional term of SLF is determined with the DCF. Deprivation cost is the economic measurement of people's suffering caused by basic needs unsatisfaction or a lack of essential resources in disasters, such as water, food, personal hygiene, and medical services. This study focuses on individuals' water-related activities, the disruptions of which would lead to unsatisfaction of survival needs or hygiene needs and further cause individuals' suffering. Hence, it is reasonable to apply the DCF to measure the suffering level of disrupted activities. Moreover, the SLF in this study adopts the exponential function for the following two reasons. First, the exponential function includes the important properties of individuals' suffering (deprivation cost); for instance, with a longer duration of disrupted activities ($t_i(t)$) or deprivation time, the suffering level increases monotonically and has an acceleratingly increasing trend (non-linear and convex). These properties of suffering level reflect the natural consequence of how human beings deal with shortages of life-supporting resources: at first, most healthy individuals can deal with short-term disruptions; as they use up their body reserves, their suffering level increases quickly until it reaches the maximum (Holguín-Veras et al., 2013). Second, some researchers have already developed DCF for various essential goods using empirical data, where the exponential function is one of the most popular forms, and exponential function is also suitable for depicting individuals' suffering from water and hygiene shortages in disaster scenarios (Holguín-Veras et al., 2016; Shao et al., 2020).

The proposed SLF is actually a transformed DCF, and its functional form is similar to the DCF proposed by Moreno et al. (2018). The main difference between the SLF and the DCF is the introduction of the TL as the scale $\frac{1}{e^{\rho * TL_i}}$ in Eq. (1). The aims of making these modifications are as follows: 1) standardize the suffering level into non-monetary value to make the suffering of different activities comparable; and 2) take the intolerable activity equally for individuals, which means that if the duration of disruptions equals the limit of the tolerable day ($t_i(t) = TL_i$), the corresponding suffering level would be 1 regardless of the type of activity. In fact, the TL represents the tolerable limit of deprivation time, which is usually derived from social investigations of individuals' tolerable days for disruptions. At this point, different disrupted activities have the same level of suffering, which is intolerable for individuals, and the TL is smaller than the terminal deprivation time in DCF at which an individual dies at the maximum cost (value of life).

2.2.3 Mathematical modeling of activity estimation

Based on the above, this study proposes a multi-objective binary linear optimization model to estimate individuals' fulfillment of activities with limited water quantity. The model assumes 1) that people will prioritize activities that are associated with a higher suffering level to reduce the total experienced suffering; and 2) that people will choose activities on a daily basis, which means that they will consume all the available water on each day without remaining. The mathematical formulation of the activity estimation model is as follows.

$$\max f_1 = \sum_{i=1}^{n} ACH_i(t) * SLF_i\big(TL_i, t_i(t)\big) = \sum_{i=1}^{n} ACH_i(t) * e^{-\rho * \Delta t_i} \tag{2}$$

$$\max f_2 = \sum_{i=1}^{n} \frac{WQ_i(t)}{NorWQ_i} \tag{3}$$

Subject to

$$ACH_i(t) \in \{0,1\} \tag{4}$$

$$\Delta t_i = TL_i - t_i(t) \tag{5}$$

$$t_i(t) = \begin{cases} t_i(t-1)+1 & if\ ACH_i(t-1) = 0 \\ 1 & if\ ACH_i(t-1) \neq 0 \end{cases} \tag{6}$$

$$WQ_i(t) \geq MinWQ_i * ACH_i(t) \tag{7}$$

$$WQ_i(t) \leq NorWQ_i * ACH_i(t) \tag{8}$$

$$\sum_{i=1}^{n} WQ_i(t) \leq \mathrm{AW}(t) \tag{9}$$

The activity estimation model includes two objective functions, which are presented in Eq. (2) and Eq. (3). Objective (1) (Eq. (2)) is the main problem, which estimates the achievement of activity i ($ACH_i(t)$) by maximizing the total suffering level of optional activities at day t; this objective function ensures that an individual would perform a set of activities with the highest suffering levels, and indicates that an individual actually experiences a minimum total suffering level of unperformed (disrupted) activities; $ACH_i(t)$ is the binary decision variable (Eq.(4)), and it equals to 1 if the individual has performed activity i, and otherwise equals to 0; $e^{-\rho*\Delta t_i}$ is the SLF of activity i, which quantitatively depicts the level of suffering with respect to the time gap Δt_i. As previously mentioned, the time gap, Δt_i, is the gap between the tolerable day (TL_i) and the duration of disruption at time t ($t_i(t)$), and the calculation is illustrated in Eq. (5)–Eq. (6).

Objective (2) (Eq. (3)) is the sub-problem, which estimates the quantity of water allocated to the achieved activity i ($WQ_i(t)$) by maximizing the sum of the ratios of $WQ_i(t)$ to the normal water quantity ($NorWQ_i$). Objective (2) ensures that the activity with low normal consumption (e.g., drinking or cooking) will be prioritized, especially for the occasion that objective (1) has multiple optimal solutions. The decision variable in objective (2) is $WQ_i(t)$, which represents the water quantity allocated to activity i. $WQ_i(t)$ takes values of either 0 (activity is not achieved) or the value between the minimum ($MinWQ_i$) and normal water quantity ($NorWQ_i$), interpreted as the constraints in Eq. (7) –Eq. (8). The total water quantity consumed for the achieved activities has a restriction on the water resources individuals can obtain (Eq. (9)), which is denoted as available water in a disaster scenario ($\mathrm{AW}(t)$), including inventory water in the household, emergency water in the shelter, bottled water in commercial facilities, or untreated water in wells.

Overall, Eq. (2)–Eq. (9) constitute the activity estimation model for individuals considering the suffering of disrupted activities. It is worth noting that a hierarchical approach was adopted to derive the optimal solution. Specifically, objective (1) is optimized in priority in the model to estimate a set of performed activities with maximum suffering level, and then objective (2) will be optimized without degrading the values of objective (1). The optimal solution would be a set of the achieved activities with the highest suffering level under limited water quantity. Additionally, the fulfillment of activities on each day can be estimated by considering the previously performed (chosen) activities and the restoration of the water service. Moreover, individuals who become intolerant to the disrupted activity ($\Delta t_i < 0$) can also be identified. The *GUROBI solver* in Python is utilized to yield an optimal solution of this model (OPTIMIZATION, 2014).

2.3 Monte Carlo simulation: Aggregated individual activity choices for societal impact

In this model, the TL for activities is critical for estimating an individual's fulfillment of activities, and the TL value is influenced by many factors, such as demographic factors, property factors, risk perception, previous experience, resources, and sensitivity (Coleman et al., 2020). Different individuals have varying TLs; however, in statistics, we can find some patterns of individuals' TL to disruptions, which follow a specific probability distribution, such as lognormal, Weibull, and log-logistic distributions (Esmalian, Dong, & Mostafavi, 2021; Gentaro et al., 2015). This can be viewed as an important feature of residents in a survey region and provides opportunities to adopt the Monte Carlo simulation method to capture the TL variations among a population. The Monte Carlo simulation method is defined as a method for obtaining estimates of the solution of mathematical problems by means of random numbers (Matsuoka, 2013). Some researchers have already applied the Monte Carlo method to generate population attributes (population synthetic) and then conducted microsimulations (Farooq et al., 2013; Han et al., 2021). The idea of this study is similar to their work, which generates the TL of each activity for a simulated population using random sampling according to the probability distribution of TL, and then conducts an activity estimation model for each simulated individual.

Integrated with the Monte Carlo simulation, the detailed procedure of the methodology is illustrated in **Fig. 1**. For each individual, the TL_i of each activity i can be derived from the random sampling based on the probability distribution of the TL_i. The larger the simulated population, the more similar the sampled TL distribution to the actual probability distribution would be, and as such, the sampled results can represent the feature (TL) of the whole population. Then, the sampled TL_i for each activity can be imported into the activity estimation model, and the achievement of activities at each time for this individual can be predicted. If we take samples of TL_i for N people in the region, the achievement of activities for these individuals and the number of intolerant people can be estimated in a disaster scenario, and this is the quantitative societal impact defined in this study. Additionally, if we take another N samplings, the TL of each activity for simulated individuals and the estimated societal impact will change correspondingly. Thus, to reduce the uncertainty of TL random sampling, we conduct this process M times and take the mean value as the final estimated societal impact.

3 Illustrative case study

In this section, the proposed model is applied to a specific city to analyze the societal impact of water-related infrastructure disruptions under disaster scenarios. Considering the consistency of data sources, the city of Osaka, Japan, was selected as the case study.

3.1 Data descriptions

3.1.1 Water consumptions of activities in Osaka

Osaka is one of the most populous cities in Japan, with a total estimated population of 2.69 million, and the average water consumption of Osaka residents is approximately 260 L/d per person. Specifically, the daily average normal consumption of water ($NorWQ_i$) for Osaka residents' activities are shown in **Table 1**, sourced from the Osaka Municipal Waterworks Bureau (OMWB). The required minimum water quantity of activity i ($MinWQ_i$) was obtained and refined from various literature or reports (Gleick, 1996; Howard et al., 2003).

Table 1 Essential parameters in the model

	Normal WQ (units: L/day)	Minimum WQ (units: L/day)	Distribution type of TL	α_i	β_i
Drinking	3	2	NA	NA	NA
Cooking	41	2	Lognormal	-0.416	1.65
Toileting	52	3	Lognormal	-0.994	1.7
Bathing	96	5	Weibull	0.93	4.02
Laundry	47	4	Weibull	0.8	3.11

3.1.2 Disruptive scenarios

The disruptive scenarios in this study are adopted from Yang's previous published work, which include disruptions or damages of water supply systems, electricity systems, transportation systems, emergency services, and commercial facilities in Osaka (Yang et al., 2021). Under these disruptions, the available water quantity that Osaka residents can obtain is calculated considering the availability of tap water (TW), emergency water (EW), and bottled water (BW), and the results are illustrated in **Fig. 3** (Yang et al., 2021). Approximately 414,000 residents (15.4% population) cannot access TW under these disruptive scenarios, but they can still obtain EW from emergency shelters and BW from commercial stores (5 L/d [EW], 8 L/d [EW+BW]). With available water of 5 L/d and 8 L/d, the societal impact that incorporates peoples' choices can be estimated using the proposed model (illustrated in Section 4.3). To validate the proposed model, available water of 10 L/d ($\mathrm{AW}(t) = 10\ L/d$) is first applied in this section, and $\mathrm{AW}(t)$ is keep constant in the post-disaster period (simulation time: T = 30 days) to explore the societal impact pattern.

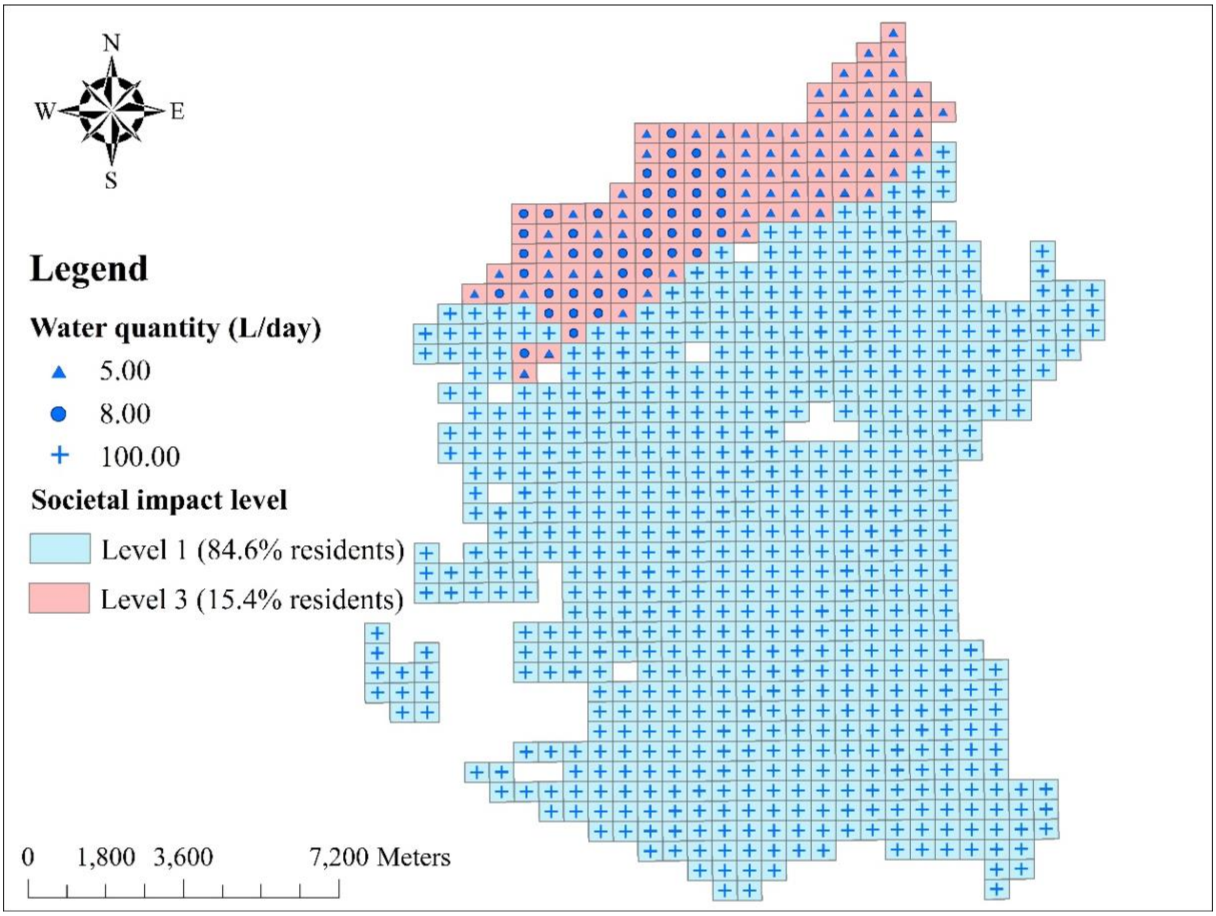


Fig. 3 Spatial distribution of available water quantity in Osaka (Yang et al., 2021).

3.1.3 TL sampling for Osaka residents

As mentioned in the methodology, individuals' TL for different activities follows a certain probability distribution, reflecting the important property of residents in a certain region. This study adopts Gentaro's results, which estimates the probability distribution of TL for water-related activities using empirical data from a social investigation in Osaka (Gentaro et al., 2015). In the investigation, Osaka residents who had experienced a water suspension were asked how many days they could tolerate the survival threats from disrupted activities. Additionally, Akaike's information criterion (AIC) was utilized to identify the best fit model, and the results demonstrated that the TL for cooking and toileting among Osaka residents corresponded to the lognormal distribution (Eq. (10)), while bathing and laundry followed a Weibull distribution (Eq. (11)). The estimated parameters of these distribution models for each activity are listed in **Table 1**.

$$F_i(t) = \int_0^t \frac{1}{\sqrt{2\pi\beta_i x}} \exp\left(-\frac{(lnt-\alpha_i)^2}{2{\beta_i}^2}\right) \tag{10}$$

where α_i denotes the mean, β_i represents the standard deviation, and t is the disruption duration for activity i.

$$F_i(t) = 1 - \exp\left(-\left(\frac{t}{\beta_i}\right)^{\alpha_i}\right) \tag{11}$$

where α is the shape parameter, β is the scale parameter of the Weibull distribution, and t is the disruption duration for activity i.

Based on these probabilistic distributions, we can take samples of the TL for the simulated population, and the illustrative TL sampling results for each activity from the Monte Carlo simulation are shown in **Table 2**. Noting that this case study assumes the TL for drinking to be 1 day because drinking is a basic survival need. The number of residents that can access 10 L/d water is scaled down to a population of 1000 simulated individuals (N = 1000) to improve the efficiency of the calculation. Also, the number of the simulated population (N = 1000) is large enough to represent the whole because there are relatively small differences between the cumulative distribution functions (CDF) of each activity's TL from Gentaro's work (the curves in **Fig. 4**) and the sampling results of TL (discrete points in **Fig. 4**). To reduce the uncertainty of TL sampling, we perform the proposed model 100 times (M=100) and then calculate the mean value as the final societal impact.

Table 2 Illustrative sampling set of tolerance level (TL) for each activity (unit: days)

	TL_1	TL_2	TL_3	TL_4	TL_5
Sampling 1	1	1	1	1	10
Sampling 2	1	2	1	2	1
Sampling 3	1	4	1	7	2
Sampling 4	1	1	1	1	7
Sampling 5	1	3	2	8	5
…	1	3	1	4	3
Sampling N	1	1	1	4	5

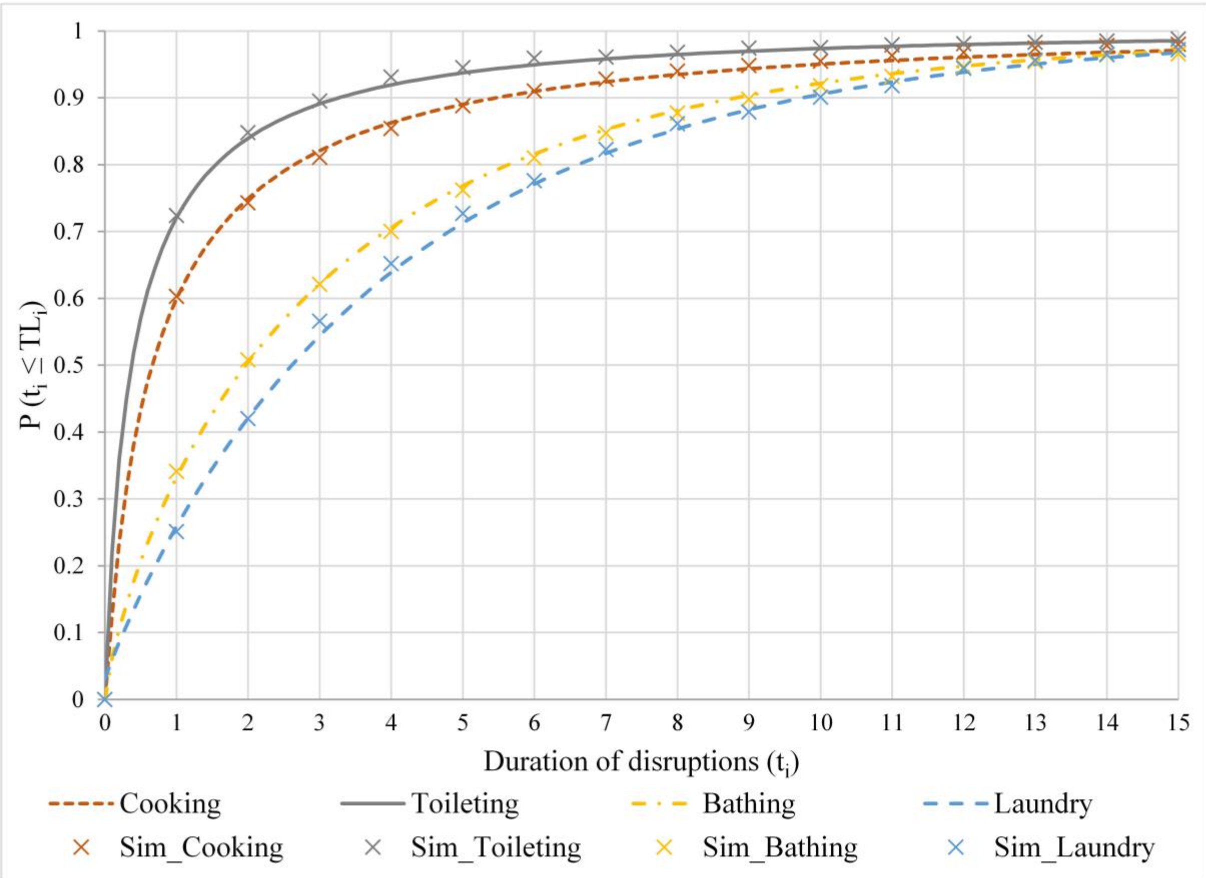


Fig. 4 Monte Carlo sampling validation with the probability distribution

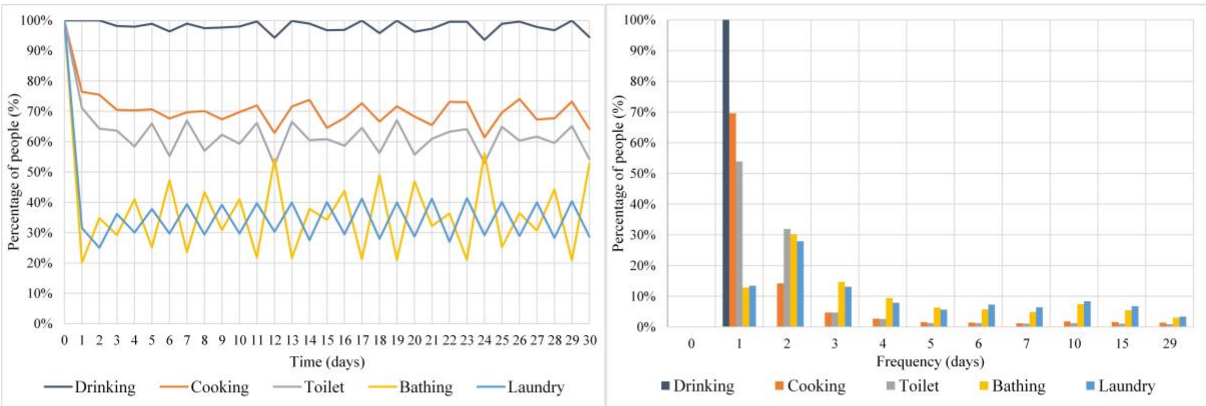
Another critical parameter ρ in SLF is assigned as 2.8128, which corresponds to the parameter in DCF of water (Holguín-Veras et al., 2013). Based on the above parameter settings (including the simulated population of 1000, sampled TL for each individual, available water of 10 L/d, simulation time of 30 days, $NorWQ_i$, $MinWQ_i$, ρ=2.8128, and performed 100 times), the simulated individuals' activity choice on each day can be estimated and aggregated to the regional scale societal impact of water infrastructure disruption.

3.2 Results of the estimated societal impact

3.2.1 The achievement of activities

As illustrated in **Fig. 5** (a), over time, people's choices for each activity fluctuate at a certain percentage. Almost all individuals can ensure drinking (over 95%) every day with limited available water (10L/d). Approximately 70%, 60%, 35%, and 35% of people consume water for cooking, toileting, bathing, and laundry, respectively. Additionally, the percentage of people achieving bathing has the largest variation during these 30 days, and it has an inverse trend with other activities. When the percentage of people choosing bathing reaches the peak, the number of people choosing other activities decreases abruptly, indicating the substitution effect among the activities. The substitution effect between bathing and other activities is most apparent in this situation.

This study further investigates the frequency pattern for the fulfillment of different activities. As illustrated in **Fig. 5** (b), the x-axis is the frequency of each activity, representing how often each activity is achieved, and the y-axis demonstrates the percentage of people in a different frequency. This study takes the lower bound value of the activity frequency; for example, if the frequency is in the range of 1 and 1.99, this study will take the lower bound 1. The results illustrate that most people can achieve drinking and cooking once a day; in particular, 100% of people consume water for drinking once a day. The frequency of toilet use is mainly distributed once a day or once for two days. As for bathing and laundry, their distributions are very similar, and about 30% of people are inclined to realize them every two days. Furthermore, people may achieve an activity at other frequencies, such as once in three days, four days, five days, six days, seven days, ten days, 15 days, and 29 days, among which taking a bath or laundry is dominant compared to other activities.



(a) (b)

Fig. 5 (a) The percentage of people achieving different activities; and (b) the percentage of people with a different frequency of achieving each activity.

3.2.2 Percentage of people getting intolerant

The proposed model is also capable of predicting people who cannot tolerate disrupted activities. As mentioned earlier, for one individual, if there is any activity that becomes intolerable, this individual will not tolerate the disruption. In the illustrative case, the percentage of intolerant people (PIP) on each day is presented as the PIP curve in **Fig. 6**, which demonstrates a growing trend during the first four days, and then fluctuates at approximately 55%, with a maximum of 66% and a minimum of 46%. This result indicates that the societal impact has an increasing trend in the first several days, after which the societal impact tends to be stable. Furthermore, the proportion of people with an intolerable activity has a similar trend. Intolerable toileting and bathing account for a large proportion, and intolerable drinking has the lowest proportion. The percentage of people dissatisfied with bathing also had the largest variation (**Fig. 6**), from 10% to 47%.

To validate the results, this study defines the concept of an accumulative percentage of intolerant people (APIP), which refers to the cumulative number of people who have already experienced intolerable activity. As shown in **Fig. 6**, when the available water is 10 L/d, the APIP exhibits an increasing trend, then stabilizes at approximately 85% during these 30 days. This tendency is similar to the results of Petersen's work (denoted as the validation point in **Fig. 6**), which conducted a social investigation to ask people how many days they can manage with 10 L of water per day (Petersen et al., 2020). The main distinction between the PIP and APIP is that the former refers to intolerant people due to unachieved activities on the day, while the latter considers the intolerant people before that day and denotes the accumulation. Thus, the social investigation results in Petersen's work correspond to the simulated results of the APIP, and their consistency validates our proposed model to some extent.

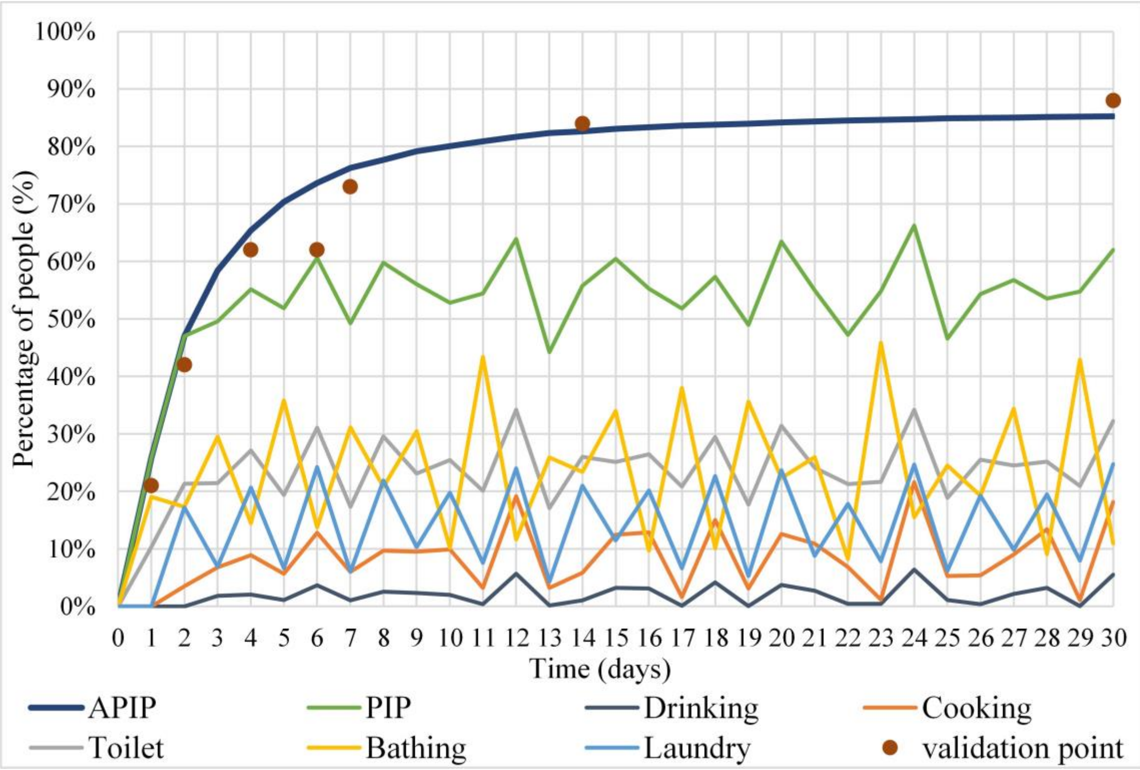


Fig. 6 Estimated intolerant people and activities under 10 L/d available water

3.3 The uncertainty of TL to the estimated societal impact

As previously mentioned, the proposed model was performed 100 times for 1000 simulated individuals, and the mean value was taken as the output of the societal impact. To examine the variance of the societal impact caused by the TL sampling, the maximum and minimum of the simulated results in these 100 simulation times are also analyzed and illustrated in **Fig. 7**.

The results reveal two interesting patterns. First, the difference in simulated societal impacts is within a relatively small range (smaller than 10%), which means that the uncertainty of the model caused by TL_i sampling is limited. Second, the trends of the maximum and minimum results are almost consistent, indicating that the choice pattern of different activities is stable under the benchmark setting of parameters despite different sampling of TL_i. Overall, these results prove the effectiveness of integrating Monte Carlo sampling of the TL with the activity estimation model.

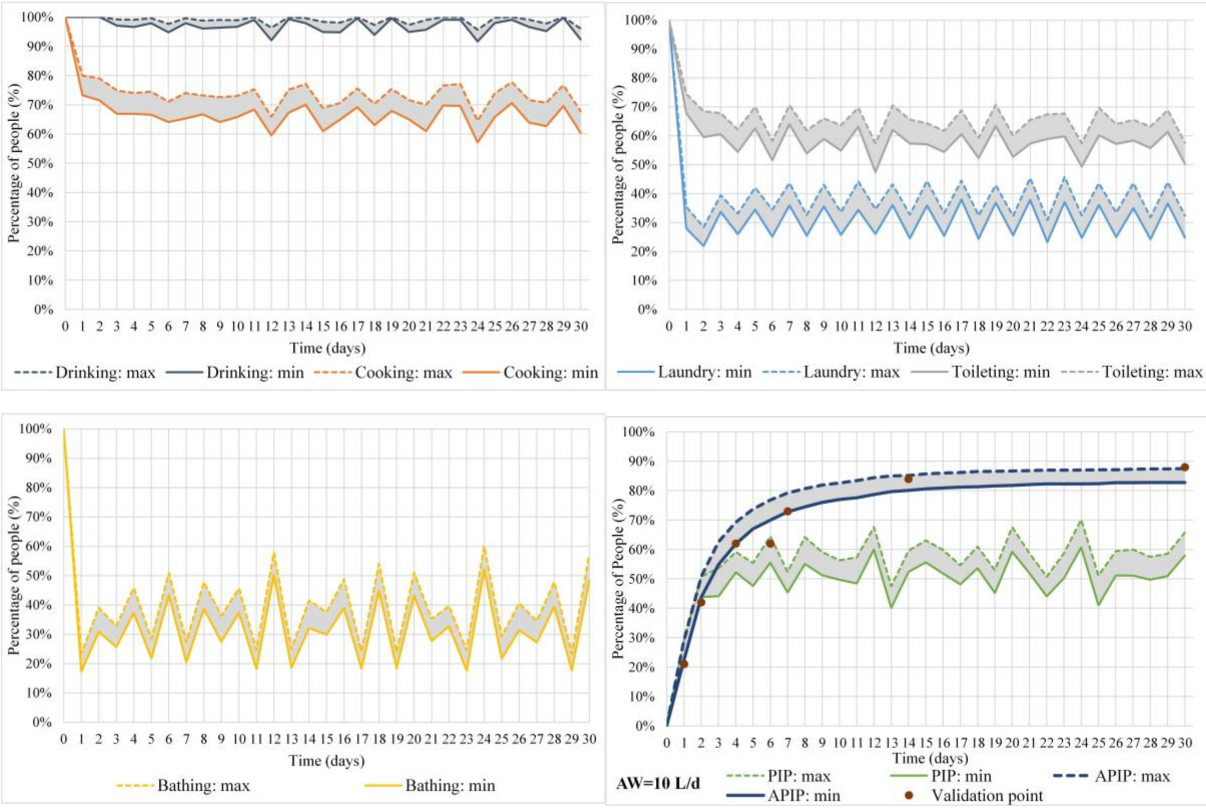
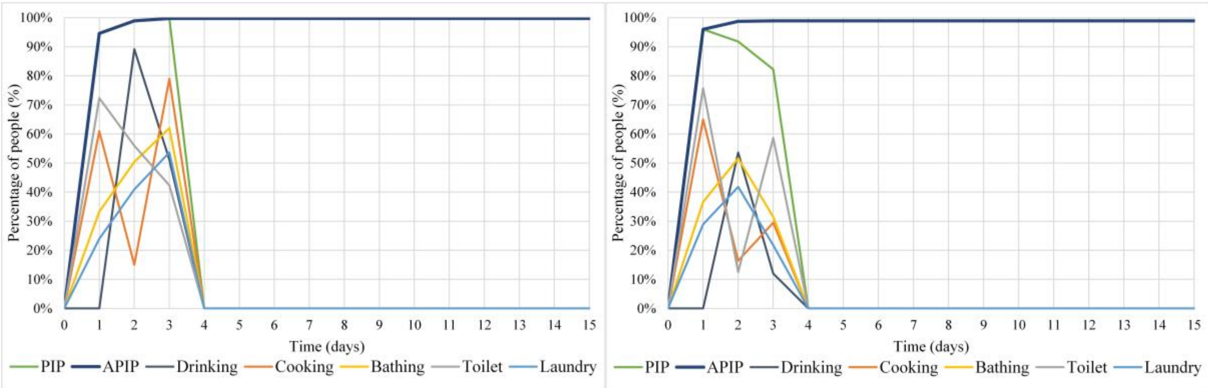


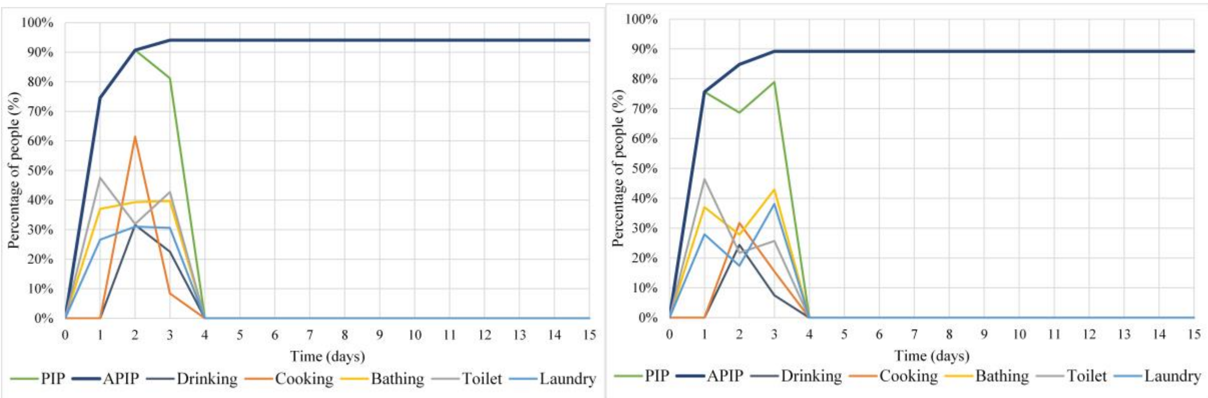
Fig. 7 Variations of societal impact with different TL samplings

3.4 Incorporating with post-disaster infrastructure recovery

Critical infrastructure systems will be restored through the emergency response of governments or other organizations after disaster events, and the available water that individuals can access could increase correspondingly with time. The major concern for the government is grasping the societal impact changes with recovery. This section sets up several recovery scenarios to illustrate the capability of the proposed model to calculate the dynamic societal impacts. Considering the resource limitations from disasters, a practical emergency response strategy adopted by OMWB is providing 3 L/d of water during the first three days of the disaster and then providing 20 L/d. The recovery scenario of available water ($\mathrm{AW}(t)$) is represented as {3, 3, 3, 20, 20, 20, 20…}, and the corresponding societal evaluation results are illustrated in **Fig. 8** (a). Additionally, the water quantity that people can obtain could be larger, considering the resilience of the water supply infrastructure. Therefore, three other post-disaster recovery scenarios are simulated as well: {3, 5, 8, 20, 20, 20, 20…}, {5, 5, 8, 20, 20, 20, 20…}, {5, 8, 8, 20, 20, 20, 20…}, and their results are shown in **Fig. 8** (b), **Fig. 8** (c), **Fig. 8** (d), respectively.



(a) (b)



(c) (d)

Fig. 8 Intolerant people under different AW recovery scenarios

As illustrated in **Fig. 8**, APIP grows in the first three days and then tends to stabilize at a certain value for all scenarios. The percentages of stable intolerant people were 99.69%, 98.90%, 94.10%, and 89.20% from **Fig. 8** (a) to **Fig. 8** (d), respectively. The stability is because the available water is 20 L/d after three days, and people can achieve all activities using this minimum amount of water. Additionally, under different recovery scenarios, the PIP changes differently with time. As for the PIP on each day, if they have no increment of AW for the next day, the number of intolerant people will rise; otherwise, the PIP becomes smaller than the previous day. After three days, the PIP remained constant at 0. The peak of PIP was 99.69% on day 3, 96.00% on day 1, 90.7% on day 2, and 78.90% on day 3 for recovery scenarios (a), (b), (c), and (d), respectively.

4 Sensitivity analysis

This section analyses the effects of the external parameters in the proposed model on the societal impact. The parameter ρ in SLF and available water quantity $\mathrm{AW}(t)$ are mainly examined, considering their vital role in the model. The activity estimation model is driven by minimizing the suffering of people's disrupted activities, and the accuracy of the SLF, which is mainly controlled by TL_i and ρ, will have a significant impact on the solution of the model. The uncertainty of TL_i has been examined in Section 3.3, whereas the parameter ρ, which is determined based on the literature, has not been explored. Hence, the parameter ρ has been selected for the sensitivity analysis in this section. Additionally, the available water volume is investigated not only because its value will influence the solution of the activity estimation model but also because it works as a bridge to connect the infrastructure disruption and societal impact. In detail, the available water in a disaster scenario is determined by the condition of interdependent infrastructure systems (Yang et al., 2021), and various water quantities lead to different societal impacts; thus, the available quantity of water for individuals is investigated.

4.1 Effects of parameter ρ on societal impact

Based on the benchmark scenario with ρ equal to 2.8128 in Section 3, we changed the value of ρ continuously to investigate its impact on the simulated results. Parameter ρ reflects the individuals' perception of suffering towards disrupted activity. It is challenging to determine the exact value of ρ for activities; thus, to reduce the effects of this parameter on prioritizing activities, this study takes the equal value of ρ for each water-related activity of simulated individuals and then conducts a sensitivity analysis of this parameter. The estimated results are illustrated in **Fig. 9**.

Along with the change in the parameter ρ, the simulated results vary within a certain range, as illustrated in the shaded area in **Fig. 9**. Note that the value of ρ should not be too large (less than 3) because the precision of the *GUROBI* solver is limited to 10E-05. The percentage variations for achieving water-related activities have smaller ranges under the available water of 10 L/d, especially for laundry. Similarly, the curves of APIP and PIP exhibit small variations with different values of ρ. This pattern indicates a strong application of the proposed model. Although the parameter ρ is uncertain, we can still estimate the range of societal impacts under disaster scenarios, which could provide important insights for decision-makers.

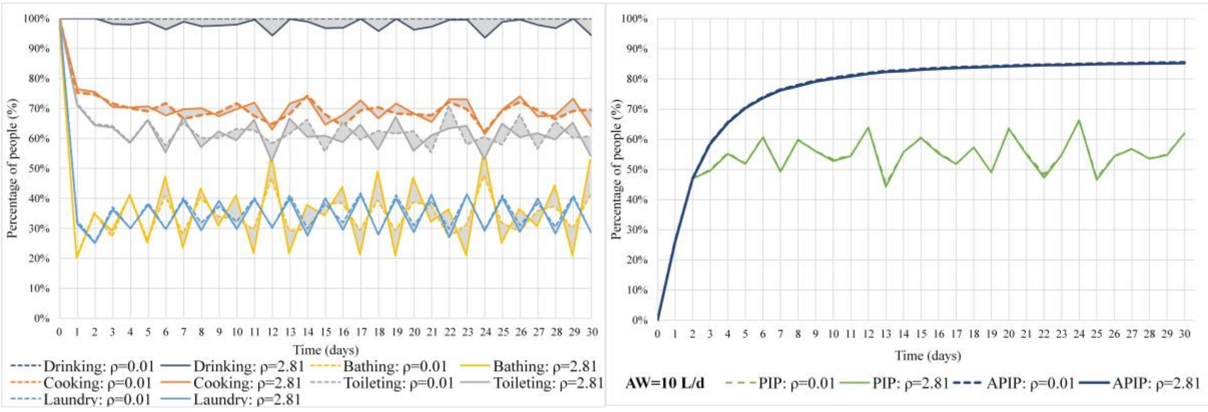


Fig. 9 Variations of societal impacts with different ρ

4.2 Effects of available water on societal impact

For the sensitivity analysis of available water quantity, the benchmark is also the illustrative case (in Section 3), and this section assigned different amounts of water for the activity estimation model (5 L/d, 8 L/d, 10 L/d, 12 L/d, and 14 L/d) to check its effect on the societal impact. The results are illustrated in **Fig. 10**, and the societal impact is presented in **Fig. 9** for $\mathrm{AW}(t) = 10\ L/d$. It is worth noting that the intolerant people are equal to 0 when the available water quantity is larger than 16 L/d because all activities can be achieved using $MinWQ_i$ for each activity and there would be no intolerant people due to disrupted activities.

In general, with a certain amount of water, the societal impact demonstrates an increasing trend during the first several days after the disaster, then tends to be stable around a certain value. For the stabilized value of the societal impact, the lower the available water quantity, the higher the PIP and APIP, which means that the societal impact will be larger when the available water quantity is smaller. Another interesting finding is that the uncertainty of the societal impact (the variation range) is relatively small with different ρ values, except for the case of the PIP with available water of 8 L/d. For 8 L/d water, the reachable combinations of activities are as follows: {{ D+C+T}, {D+C+L}, {T+B}, {D+B}, {C+B}, {T+L}}. If the value of ρ is very small (e.g., 0.01), the accelerating rate of the SLF will be become small with respect to a longer disruption duration time (t), which will result in the activity sets of D+C+T and D+C+L dominating individuals' choices (the SLF of three activities is larger than that of two). As such, bathing activities will not be achieved even though bathing becomes intolerable with time. These are the reasons for the high uncertainty of PIP with different ρ values when the available water for individuals is 8 L/d.

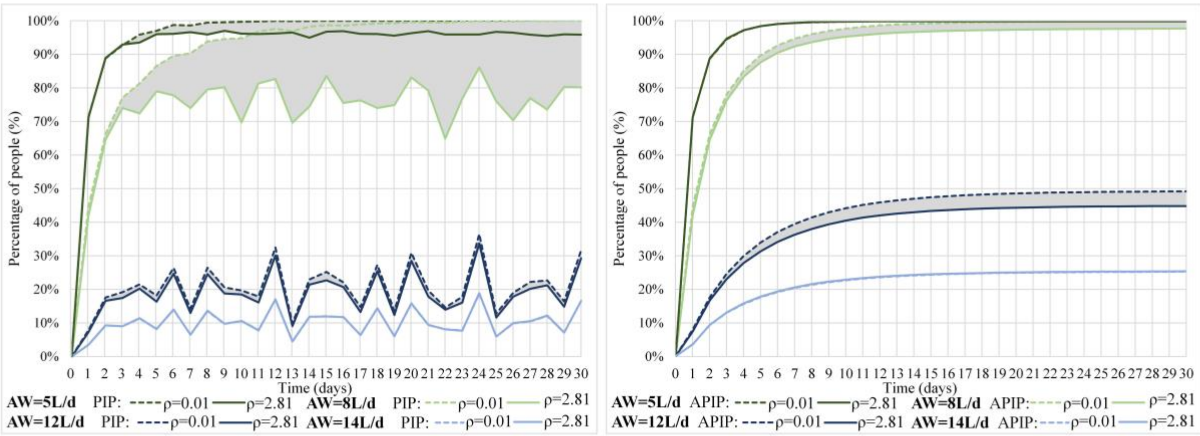


Fig. 10 Variations of PIP and APIP with different quantities of available water

5 Discussion and conclusion

Critical infrastructure is vulnerable to disasters, and its disruption will directly reduce water supply, leading to the interruption of individuals' daily activities and negative well-being. In a disaster scenario, governments are concerned about the societal impact caused by resource reductions and attempt to recover people's well-being as soon as possible. However, it is challenging to estimate the societal impacts quantitatively in the field of disaster management and risk reduction. To fill this gap, this study proposes a mathematical model to predict the impact of limited available water on people's fulfillment of certain activities and their intolerant states. The proposed model mainly consists of an activity estimation model and Monte Carlo simulation. The individual's activity estimation model is driven by prioritizing the activities with higher suffering levels, which are quantitatively measured by the proposed SLF combing the TL and DCF of each activity. Monte Carlo sampling is utilized to derive the TL of each activity for simulated individuals following a certain probabilistic distribution. Combining these two parts, the percentage of people who can perform certain water-related activities and who become intolerant under limited water resources can be estimated, which are the quantitative societal impact described in this study.

The illustrative case study demonstrated the application of the proposed model to estimate the societal impact of disasters, providing reference information for decision-makers. The results indicate that the proposed model can dynamically estimate the achievement of activities and intolerant people each day. In general, people tend to show specific activity choice patterns with limited water, and drinking, cooking, and toileting ranking in the top three prioritized activities with 10 L/d available water. The number of intolerant people increases quickly in the first four days after a disaster and then fluctuates around a certain percentage, where intolerable toileting and bathing disruption account for the main percentage. Besides, to some extent, the model has been validated by comparing the predicted APIP from our model with the results of social investigations from previous work (Petersen et al., 2020).

Uncertainty and sensitivity analyses were conducted separately to explore the effects of the TL sampling, parameter ρ, and AW on the estimated results of the proposed model. The activity estimation model is mainly driven by the suffering level of each activity; hence, the uncertainty of TL and ρ significantly influences the estimated results. Through the uncertainty analysis of TL and sensitivity analysis of ρ, an important finding is that the uncertainty of the estimated results can be controlled within a relatively small range. This finding indicates the applicability of the proposed model, although the exact values of these two parameters cannot be determined (**Fig. 7** and **Fig. 9**). For the sensitivity analysis for AW, the trends of societal impact (APIP and PIP) under different AW are similar, and the societal impact is larger with a smaller water quantity on the same day. Additionally, the uncertainty induced by ρ is relatively small under different AW, except for the PIP under 8 L/d. Thus, when applying the proposed model to societal impact evaluations, we still need to test different values of ρ to include the uncertainty of the estimation.

Overall, the estimated societal impact in our model could provide supporting insights for government decision-makers in emergency management. The model's outputs can be used to distinguish which activity is more intolerable and estimate when intolerant people grow to the peak under infrastructure disruption scenarios (or given limited available water). This information can also direct emergency responses to effectively allocate water to mitigate suffering level of residents and thus minimize the negative societal impact. For water restoration policies, the results highlight that increasing the supply of EW and BW once the coping capacity gets recovered would help to reduce the negative societal impact. Besides for water supply, some substitution resources for supporting more intolerable activities, such as toilet bags, wet tissues, temporary toilet facilities, bathing facilities, laundry facilities, and others, could be allocated to individuals in priority before intolerant people increase to the peak value.

The proposed model can also be implemented with physical infrastructure models to holistically evaluate infrastructure resilience by considering the societal impact and thus, contributes to the development of human-centered resilient cities. In details, the extent of water service disruptions and available water quantity under different disaster scenarios can be estimated using the advanced resilience model of infrastructure systems. These results can then be added to our proposed model to capture the societal impact regarding individuals' choices for water-related activities in cities. Accordingly, to minimize the negative societal impact of disruptions, governments or decision-makers can design and optimize service restoration orders and resource allocation in infrastructure models. As such, a social and engineering integrated resilience evaluation model can be built for better disaster risk management. It is worth noting that the parameters in our proposed model are designed for Osaka; particularly, the TL variable, which is derived from a social survey in Osaka, reflects the property or water use habits of Osaka residents. To apply this model in other cities or regions, the TL for water-related activities and other parameters in the proposed model should be investigated in local communities.

Future work could extend the proposed model from the following four aspects. The first is incorporating social vulnerability into the model, and one possible method is to establish the relationship between available water quantity and social vulnerability. Vulnerable people have less access to essential resources (e.g., older adults, people with disabilities, and those who are economically disadvantaged), which leads to a higher negative societal impact. Second, other residents' behaviors in a disaster scenario (e.g., household interactions, preserved water, and supporting each other) could also be included in this model to better estimate people's achievement of activities. Third, smaller spatial scale data can be imported to the proposed model, such as the local communities' TL, water consumptions habits, and available water quantity under disruptive scenarios, to estimate the spatial and temporal distribution of the societal impact in a city. Fourth, to estimate the societal impact of infrastructure disruptions more effectively, this methodology should be extended to analyze other daily activities, such as activities supported by electricity, transportation, and communication systems.

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