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Modelling post-earthquake building recovery under human resource constraints

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ABSTRACT

Demand surge phenomenon as a result of shortages of human resources needed for post-disaster recovery and reconstruction can be detrimental to recovery outcomes. To quantify the impact of human resource constraints on the recovery of an urban environment, this research introduces a novel Dynamic Stochastic Queuing (DSQ) model, revealing such dynamic interplays over time. Central to this model is the incorporation of a spectrum of socioeconomic factors to formulate optimal recovery strategies under different dynamic resource mobilisation patterns. A recovery efficiency index is defined and employed as a proxy to facilitate comparisons across diverse recovery strategies. A case study is presented to illustrate the application of the model by simulating the building recovery of a portfolio of residential buildings in New Zealand following the 2010–2011 Canterbury Earthquake Sequence (CES). The findings indicate that proactive resource mobilisation strategies can significantly enhance both recovery efficiency and speed. It becomes possible to shorten the post-disaster recovery time significantly by strategically sequencing repairs of damaged structures while taking into account resource mobilisation strategies.

1. Introduction

Buildings damaged in a large earthquake event often face a prolonged recovery process. Fourteen years after the initial shock of the 2010–2011 Canterbury Earthquake Sequence (CES) in New Zealand, Christchurch is still in the midst of restoring its damaged buildings [1]. Similarly, over a decade after the 2011 Tohoku earthquake in Japan, more than 31,000 people still reside in temporary accommodation across the affected areas [2]. Likewise, four years after the 2015 Nepal earthquake, only 10 % of the severely damaged government buildings had been rebuilt, with the majority still pending decision due to significant workforce shortages [3].

The slow pace of recovery of the built environment has spurred intensified academic efforts to simulate and model post-earthquake building recovery. The Federal Emergency Management Agency (FEMA) P-58 methodology provides structured computational procedures for assessing building-level recovery impacts by quantifying the direct and indirect consequences of repairing damaged components [4]. Research by Comerio [5] and Almufti and Willford [6] further highlights the critical role of impeding factors in delaying the initiation of repair activities, which are essential for accurately estimating recovery timelines. These factors include building damage inspection, engineering mobilisation and review/redesign, financing, permitting, and contractor mobilisation. More

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recent studies have identified additional delays caused by building cleanup operations and temporary or local stabilisation repairs as further barriers that must be addressed before full-scale repairs can commence [7,8]. The complexity of modelling building recovery is further exacerbated by various contextual factors, such as the scale of the event (i.e., repetitive aftershocks and spatial distribution of damage) [1,9,10], the prolonged decision-making process [11], legal complexities [12,13], safety cordons [14,15], and human resource constraints [1,16].

In modelling building recovery while incorporating impeding and socioeconomic factors, the Resilience-based Earthquake Design Initiative (REDi) provides a foundational methodology for estimating several "controllable" impeding factors. These include building damage inspection, engineering mobilisation and review/redesign, financing, permitting, and contractor mobilisation [6]. The resulting delays are estimated using impeding curves, which characterise possible delays for different buildings through lognormal cumulative distribution functions. These curves are calibrated to approximate conditions for a 475-year return period earthquake, providing a rational "best estimate" of potential delays. It is important to note, however, that these impeding curves were originally developed for buildings in San Fransisco, limiting their direct applicability to other geographic and socioeconomic contexts. Refinements to the REDi methodology by Paul et al. [17] have expanded its scope, incorporating uncertainty, updated repair class logic, enhanced worker allocation and contractor mobilisation delay estimates, and more explicit considerations of residual drifts and demolition requirements.

In comparison to other impeding factors explored in the literature, human resource constraints and their impacts on building recovery at regional or community levels remain the least researched [1,16,18]. A persistent shortage of engineering and construction personnel has posed significant challenges in past reconstruction efforts [16]. In many cases, the overwhelming reconstruction workload forces organisations to rely on unskilled workforces, leading to compromised recovery efforts due to poor workmanship and the subsequent need for remedial work [19,20]. This issue is further exacerbated by post-disaster demand surges, which can drive costs upward by 20 % or more [21]. Collectively, these challenges render human resource constraints a persistent and formidable obstacle to timely and efficient post-disaster recovery.

Despite numerous attempts to account for human resource constraints in building recovery [16,18,22,23], several critical aspects remain underexplored. Firstly, it is essential to recognise the mobility of the workforce, as it introduces a dynamic interplay between resource demand and supply, which fluctuates with the progression of recovery efforts [24]. Secondly, the prioritisation of repairs, or the sequencing of recovery, plays a pivotal role in shaping recovery timeframes at both individual and community levels. The strategic allocation of limited human resources to address the most critical needs is essential to facilitate an efficient recovery process while minimising downtime [25]. However, without an improved understanding of dynamic resource mobilisation in conjunction with the recovery sequencing strategies implemented, it remains challenging to realistically capture the temporal impacts of human resource constraints on the building recovery process.

To address this gap, this research aims to develop a model that quantifies the temporal effect of human resource constraints on building recovery. The following research queries guide this study.

- RQ1: What temporal effects of varying resource mobilisation strategies could have on building recovery timeframes?
- RQ2: How does the intricate interplay between dynamic workforce mobilisation and recovery sequencing impact building recovery timeframes under resource constraints?

Building on queueing theory and leveraging empirical data from post-earthquake scenarios, this research introduces a Dynamic Stochastic Queue (DSQ) model to explicitly capture delays resulting from human resource constraints. By integrating various human resource mobilisation strategies and repair sequencing approaches, the model enables the identification of optimal recovery strategies while uncovering the intricate interplay between these factors and recovery timeframes. The model is designed to assist policymakers and recovery stakeholders in establishing recovery priorities and strategies, providing a robust tool to support more informed decision-making for optimising post-earthquake recovery efforts.

2. Human resource constraints and post-disaster recovery

The shortage of rebuilding-related human resources remains a major barrier to post-disaster recovery, exacerbating challenges faced by already vulnerable communities [26,27]. Following the 2004 earthquake and tsunami in Aceh, Indonesia, an acute shortage of skilled labour and contractors caused significant delays in reconstruction, forcing many individuals to remain in temporary shelters for over 15 months and prolonging their hardships as rebuilding efforts stagnated [28]. Similarly, more than two and a half years after the 2015 Nepal earthquake, approximately 70 % of the affected population continued to reside in temporary shelters due to a critical shortage of skilled construction workers and the incremental, informal nature of local building practices [29]. The 2010–2011 CES in New Zealand further highlights the profound consequences of human resource shortages on building recovery timelines. A lack of structural engineers and building inspectors led to prolonged damage assessments, extending over several months [30]. Compounding these challenges, difficulties in mobilising skilled construction workers and uncertainties within the reconstruction market [31] further impeded subsequent rebuilding efforts. These delays have had enduring consequences, with Christchurch's recovery still ongoing 14 years after the initial event [1].

Addressing these challenges necessitates effective human resource mobilisation, which becomes especially critical when political pressures and time constraints demand swift reconstruction efforts [32,33]. Human resource mobilisation, however, is not a static exercise but a dynamic and adaptive process [34], involving the continuous reallocation of human resources to address the evolving needs of affected areas. Strategic and timely mobilisation of resources to address the most urgent needs has been shown to significantly accelerate recovery, minimise downtime, and enhance overall recovery efficiency [24,35]. Yet, much of the existing research conceptualises resource availability at the community level as a static constant [23,36]. While these models provide a useful starting point for simulations, they often fail to capture the dynamic and evolving nature of resource management in real-world post-disaster contexts. By contrast, incorporating the inherently dynamic aspects of human resource mobilisation into recovery planning enables decision-makers to identify and address emerging resource bottlenecks proactively, fostering a more responsive and efficient recovery process.

The influence of human resource constraints on the building recovery timeline is deeply intertwined with the recovery strategies employed [23,37]. An effective recovery strategy that prioritises the repair sequence of damaged buildings is essential for achieving optimal recovery efficiency under resource constraints [38–40]. However, the development of such strategies is often contingent upon local contexts and socioeconomic considerations [41]. For instance, following the 2018 Lombok earthquake, the Indonesian government prioritised the reconstruction of severely damaged buildings [42,43]. In contrast, after the 2009 L'Aquila earthquake, lightly damaged buildings were repaired first, enabling faster reoccupation and community stabilisation before addressing major repairs [45].

In addition to addressing the extent of damage, recovery strategies are often shaped by the need to prioritise buildings with critical functions, such as hospitals and emergency facilities. The rapid restoration of these facilities is crucial for ensuring the resumption of essential services, which is fundamental to broader community recovery efforts [46,47]. Recent advancements in this area include initiatives by the Functional Recovery Task Committee of the Building Seismic Safety Council (BSSC) in the United States, which is developing new functional recovery design provisions for the 2026 National Hazards Earthquake Reduction Program (NEHRP) and ASCE 7–28 updates [48]. These provisions aim to categorise buildings based on their essential functions, thereby aligning recovery priorities with overarching community resilience goals.

Beyond function-specific considerations, government policies also play a pivotal role in shaping recovery priorities. For instance, some guidelines stipulate prioritising structures that pose elevated life-safety risks in the aftermath of disasters [49]. Such policies are particularly valuable when human resources are constrained, as they ensure recovery efforts target the most critical vulnerabilities first. Given the diverse outcomes that can arise from varying recovery strategies under resource constraints, it is essential to evaluate these strategies within their specific contexts to ensure they remain both contextually relevant and practically effective.

3. Methodology

This research presents a Dynamic Stochastic Queue (DSQ) model designed to capture the temporal impacts of human resource constraints on post-earthquake building recovery. A key feature of the DSQ model is its integrated approach to recovery sequencing and dynamic resource availability, enabling the assessment of delays caused by human resource constraints on both individual and community recovery timelines. Resource mobilisation in this context specifically refers to the deployment and management of human resources. As depicted in Fig. 1, the DSQ model comprises four primary modules: building inspection, stochastic queuing system, dynamic human resource pool, and human resource allocation and release.

In the aftermath of an earthquake, building inspections are conducted to evaluate structural damage and assign usability placards,

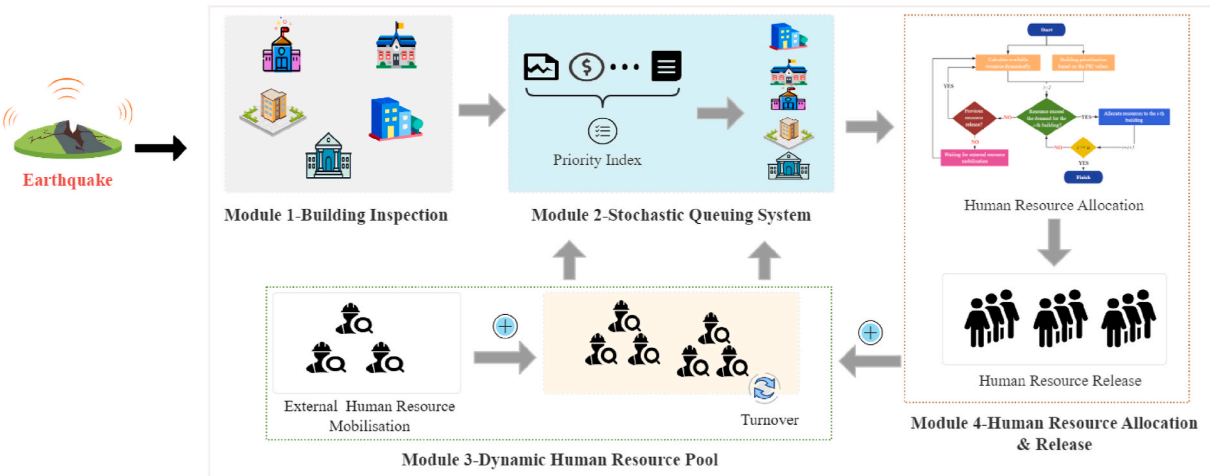

Fig. 1. The scheme of the Dynamic Stochastic Queuing model at the community level.

gauging the event's impact and aiding building owners and engineers in making repair or demolition decisions. Following this assessment, the DSQ model evaluates the human resources available for deployment and determines a prioritised sequence for repairing damaged structures. Specifically, a dynamic human resource pool is introduced and modelled as a stochastic, time-dependent variable to capture human resource availability fluctuations over time. A stochastic queuing system is also developed to support an optimised recovery sequence through a Priority Index (PRI), incorporating multiple decision factors. By aligning resource allocation rules with PRI-driven prioritisation, the DSQ model facilitates the efficient deployment of human resources to damaged structures, with delays and recovery times systematically estimated at individual and community levels.

3.1. Module 1: building inspection

Following an earthquake, authorities and recovery agencies typically initiate rapid damage inspections conducted by practising engineers, who leverage their expertise to assess structural damage and assign placards indicating each building's safety status [53]. These assessments provide critical information for emergency managers and decision-makers, enabling prompt interventions such as establishing cordon zones, initiating stabilisation measures, or proceeding with demolitions to protect public safety. Additionally, these assessments offer building owners preliminary guidance on whether repair or demolition is the appropriate course of action. This research specifically focuses on buildings designated for repair. It is important to note that delays associated with building damage inspections, specifically those driven by constraints in inspector availability, are beyond the scope of this study.

In countries such as the United States, Japan, and New Zealand, coloured placards are commonly utilised to denote the damage severity of structures [51–53]. Typically, building inspection outcomes include damage placards—such as Red, Yellow, and Green—that signify the safety status of a structure, alongside a damage ratio representing the estimated repair cost as a proportion of the building's replacement cost (excluding contents). Since damage placards are categorical data and the damage ratio is numerical, integrating these data types into a unified damage score is essential. To achieve this, one-hot encoding is employed to transform the categorical placard information into numeric values, which are combined with the damage ratio to produce a cohesive damage score [54]. This unified damage score serves as a key input for calculating the PRI in Module 2, as further elaborated in the case study section.

3.2. Module 2: stochastic queuing system

Under resource constraints, the effective management and allocation of human resources to damaged structures are critical for the success of emergency response and recovery efforts, with the recovery sequence of these repairs playing a crucial role in optimising outcomes. The proposed DSQ model incorporates a stochastic queuing system designed to establish an optimised recovery sequence (queue disciplines) that operates within resource limitations. This system integrates multi-criteria decision-making (MCDM) to aid decision-making during crises.

The stochastic queuing system is grounded in the principles of queuing theory, which typically comprises three key components: customers, servers, and the calling population [55]. As shown in Fig. 2, "customers" represent damaged buildings that have been inspected and identified as requiring repair or reconstruction, "servers" denote the dynamic human resource pool tasked with delivering these repair services, and the "calling population" includes all buildings potentially requiring repair but awaiting inspection.

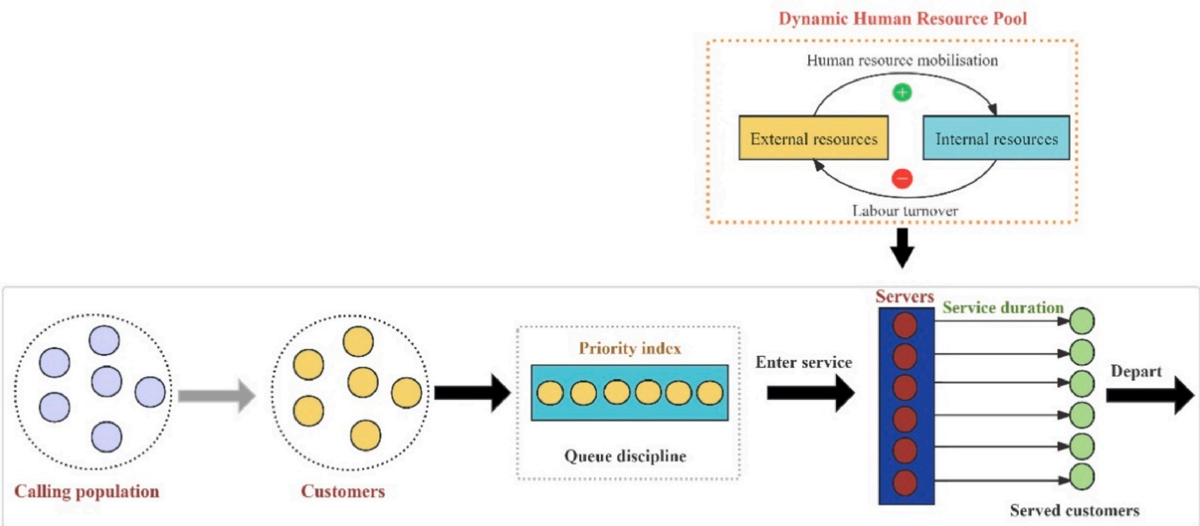

Fig. 2. The scheme of the stochastic queuing system.

Following building inspections detailed in Module 1, damaged structures enter a queue for service, with the repair time to full recovery serving as a proxy for the service duration. A defining characteristic of this stochastic queuing system is its use of queue disciplines to determine the recovery sequence of damaged structures, thereby enhancing resource allocation efficiency and supporting more effective recovery processes.

In conventional queuing models, various queue disciplines are employed, such as First-Come-First-Served (FCFS), Last-Come-First-Served (LCFS), Service-in-Random Order (SIRO), and Priority Service (PRS) [55,56]. In the competitive post-disaster environment of human resource allocation, PRS disciplines are practical for prioritising repairs under resource constraints [42,57]. However, determining PRS disciplines via the MCDM is a complex, often nonlinear process [58].

In circumstances that necessitate swift selection among various options, decision-makers face the challenge of balancing speed and accuracy [59]. In post-disaster scenarios, while achieving high precision is desirable, it is often necessary to balance prompt action with absolute accuracy. Decision-making should be based on the best available information, prioritising timely and effective responses over waiting for perfection. In light of this, a linear PRI is proposed to incorporate multiple decision factors into a coherent recovery sequence, ensuring operational simplicity. The PRI ranking for the i-th building can be determined by

$$PRI_i = \sum_{j=1}^{n} w_j \times \overline{P}_{ij} \tag{1}$$

Where w_j denotes weight coefficients associated with the j-th decision factor, $0 \leq w_j \leq 1$, indicating its relative importance in recovery prioritisation; $\overline{P}_{ij}$ presents the normalised value of the j-th factor for the i-th building, $0 \leq \overline{P}_{ij} \leq 1$; n is the number of decision factors considered.

According to Equation (1), both decision factors and decision rules (weight coefficients) must be adapted to reflect local conditions, as the relative importance of each factor can vary significantly across different built environments when establishing recovery sequences. For instance, while damage severity is a universal consideration, the Indonesian government prioritised the repair of significantly damaged buildings after the 2018 Lombok earthquake [42]. Conversely, following the 2011 L'Aquila earthquake, priority was placed on lightly or moderately damaged buildings [45]. Therefore, for recovery sequences to be both practical and contextually appropriate, it is essential to calibrate decision factors to the specific local context, as illustrated in the case study below.

Decision rules, which establish the relative importance of various considerations among different stakeholders, play a crucial role in shaping recovery timeframes at both individual and community levels. Ideally, these rules should align with collective perceptions and societal expectations. To achieve this alignment, an integrated approach is recommended, combining expert consultations, questionnaire surveys, and the Analytic Hierarchy Process (AHP) [57]. Expert consultations provide initial benchmarks for key factors within the local context, while questionnaire surveys capture the preferences and perceptions of stakeholders. The AHP method is then employed to generate priority vectors from each respondent's pairwise comparisons, allowing for the aggregation of these vectors into a comprehensive decision rule. This integrated decision rule effectively reflects collective preferences and supports recovery strategies that resonate with broader societal expectations.

3.3. Module 3: dynamic human resource pool

Community-level human resources exhibit inherent dynamism, fluctuating over time in response to the evolving demands of disaster-affected areas. The dynamic resource pool serves as a flexible repository, integrating external human resources as required, while local resources may be reallocated to other sectors, such as through employee turnover. Once buildings have completed the requisite preparatory activities, such as damage inspection, engineering mobilisation, permitting, financing, and contractor mobilisation, and are primed for repair or reconstruction, subsequent delays in resource allocation are captured. In this study, a uniform commencement point for these subsequent delays is assumed. The available human resources at any given time t, denoted by $R(t)$, can be conceptually represented by

$$R(t) = R_0 + R_{in}(t) - R_{out}(t) + \varepsilon \tag{2}$$

Where R_0 represents the initial internal human resources retained for reconstruction; t (measure in days) denotes the duration of resource mobilisation, with t_0 indicating the point in time at which a building has completed the requisite preparatory activities and is awaiting the allocation of human resources for repairs or reconstruction; $R_{in}(t)$ is a time-dependent variable representing mobilised external human resources at the time t; $R_{out}(t)$ reflects human resources redirected to other sectors at the time t; and ε captures stochastic fluctuations in resource availability.

In the aftermath of significant disasters, the mobilisation of international human resources has become pivotal to recovery efforts. For example, Christchurch's reconstruction witnessed a substantial influx of Filipino workers, while the 2010 Haiti earthquake necessitated the deployment of international contractors and humanitarian experts [60]. Similarly, the 2004 Indian Ocean tsunami spurred large-scale deployments of overseas personnel and agencies in affected regions such as Indonesia and Sri Lanka [61]. The efficacy of this mobilisation is influenced not only by the immediate need to repair damaged structures but also by broader socio-economic factors. For instance, restrictive migration policies can delay the arrival of skilled international personnel by imposing significant administrative barriers [62]. Additionally, challenges related to cultural compatibility and relocation logistics—such as language barriers, divergent work practices, and differing social norms—can reduce the readiness of external workers to engage effectively [63]. Moreover, in the wake of disasters, the sudden surge in demand for skilled labour intensifies competition among sectors, including reconstruction, emergency response, and infrastructure maintenance. This competition can lead to wage inflation and a shortage of specialised expertise [21]. Financial constraints associated with recruiting, relocating, and integrating international talent further exacerbate these challenges, particularly in economically vulnerable communities [64]. It is critical to recognise that the extent to which these socio-economic factors affect the mobilisation of human resources depends on the specific local context. Although these factors have been examined within the context of CES, their influence extends broadly to a broad spectrum of post-disaster recovery scenarios. Collectively, these multifaceted factors underscore the necessity of accurately modelling $R(t)$ within the local context, thereby necessitating the integration of empirical data.

In contexts where the rebuilding workforce is both limited and heavily reliant on skilled immigrant labour, data on rebuild-related work visa approvals serves as a critical quantitative resource. Disaster managers routinely monitor the influx of external human resources to balance the demand for skilled workforce with the imperative to safeguard local employment opportunities. Such data forms a critical foundation for estimating $R_{in}(t)$ through time series or regression analyses, thereby facilitating the development of models that closely align with observed empirical trends. Given the intricate interplay of socio-economic factors influencing $R_{in}(t)$, its behaviour may exhibit nonlinear characteristics, necessitating the use of advanced mathematical techniques to capture its dynamics accurately. Nevertheless, computational efficiency remains paramount, as post-earthquake recovery scenarios demand rapid and reliable decision-making.

In contrast, $R_{out}(t)$ tends to be particularly volatile in post-earthquake construction contexts. Factors such as job-related stress, burnout, suboptimal working conditions, and intense competition for labour across sectors and projects often result in high turnover rates [16]. Expert consultation is therefore crucial for generating reliable estimates of potential resource outflows. Such consultations also inform proactive interventions, such as expanding recruitment efforts, to mitigate anticipated shortages and support the recovery process.

3.4. Module 4: human resource allocation and release

Once the recovery sequence is established and $R(t)$ is determined, resource allocation proceeds according to the rules outlined in Fig. 3. For the purposes of this analysis, it is assumed that other resources, such as materials and equipment, are readily available, and potential delays caused by other impeding factors are excluded from consideration due to data limitations.

Guided by Module 3, $R(t)$ is calculated and aggregated at the community level over time. It is assumed that buildings allocated the required resources will immediately commence repairs. According to the PRI established in Module 2, $R(t)$ is first allocated to the highest-priority building i, among all buildings n for which $R(t) \geq D_i$, where D_i represents the human resources required for the i-th

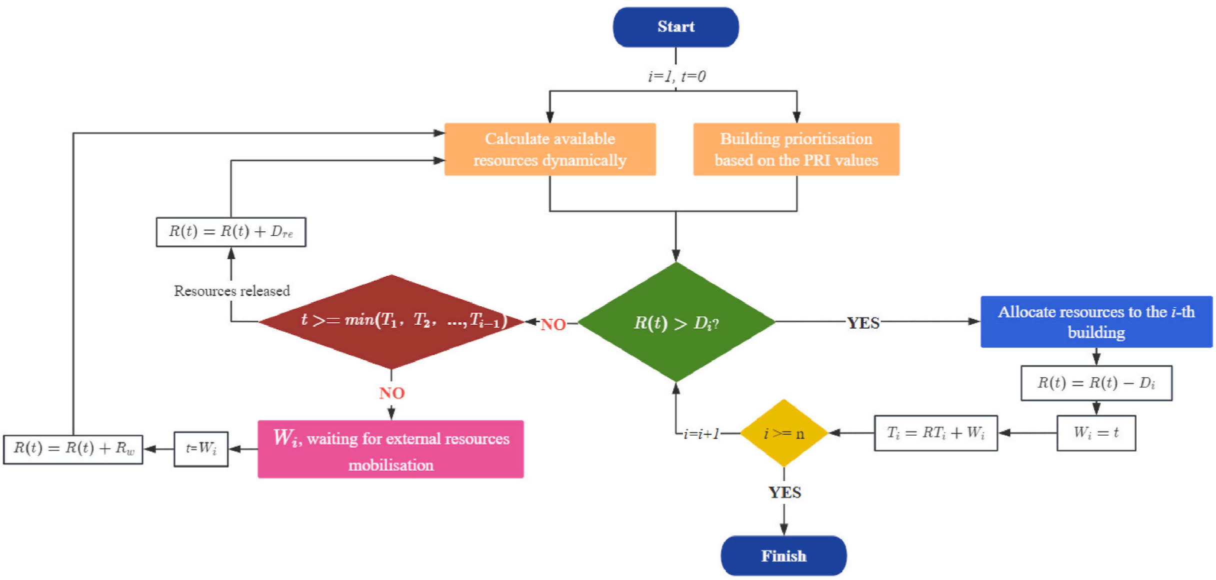

Fig. 3. Flowchart of the dynamic human resource allocation.

building. In such cases, the building's waiting time (W_i) is zero, and its total recovery time (T_i) is calculated as $T_i = W_i + RT_i$, where RT_i denotes the repair time to full recovery. This approach explicitly captures the temporal impacts of human resource constraints through W_i and enables the estimation of overall recovery timeframes under resource limitations.

If the available human resources are insufficient ($R(t) < D_i$), the building remains in the queue, awaiting either the mobilisation of external resources or the release of previously allocated resources. Once $t \geq min\{T_1, T_2, \cdots, T_{i-1}\}$, the resource pool is updated to include the released resources, i.e., $R(t) = R(t) + D_{re}$, where D_{re} represents the resources released from the earliest repaired buildings. At this point, if the updated resource pool is sufficient to meet the resource demand ($R(t) \geq D_i$), resources are allocated according to the previously established procedures. Otherwise, the building remains in the queue until sufficient resources are mobilised. During the waiting period W_i, the additional resources required R_w are mobilised, which is calculated as $R_w = D_i - R(t)$, where $R(t)$ represents the currently available resources prior to any external resource mobilisation.

Following resource allocation, individual-level W_i and T_i are aggregated and visualised through a Gantt chart, illustrating the dynamic restoration of damaged buildings under human resource constraints. Additionally, an aggregated recovery trajectory at the community level is also developed to provide a comprehensive overview of overall recovery progress, as demonstrated in Fig. 4.

As discussed in Module 3, the established recovery sequence is influenced by specific contextual factors and corresponding decision rules. Given that different recovery sequences can yield distinct recovery outcomes, it is essential to apply a method for statistically comparing the efficiency of these strategies. To this end, a recovery efficiency index is introduced, defined as the area (A) beneath the recovery trajectory curve. The mathematical expression for A is formulated as follows:

$$A \approx \sum_{i=1}^{n} \frac{(t_{i+1} - t_i)}{2} [f(t_{i+1}) + f(t_i)] \tag{3}$$

Where t_i and t_{i+1} represent consecutive time points along the recovery trajectory; $f(t_i)$ denotes the recovery level at the time t_i, interpreted as the proportion of recovery completed. When all buildings are fully repaired, $f(t_i) = 1$. The variable n represents the total number of time intervals (or days) required to achieve full recovery.

A large area of A signifies a more efficient recovery process, as it indicates that a higher proportion of recovery was achieved more quickly. Fig. 4 delineates three demonstrative recovery options, each characterised by a distinct prioritisation sequence. Option 1 adopts a severity-based approach, whereby structures exhibiting the most extensive damage are prioritised for repair. Option 2 utilises a function-based strategy, directing recovery efforts toward buildings that serve critical community functions (e.g., hospitals, schools, emergency services), irrespective of the damage extent. Option 3 synthesises multiple decision factors, including damage severity, functional criticality, financing availability, and policy preferences, to establish an optimised recovery sequence. In this case, Option 3 exhibits the largest area (1620.18), demonstrating its superior efficiency in utilising human resources to optimise recovery outcomes while minimising downtime.

4. Case study

While the DSQ model is designed to be applicable across a range of building typologies, this section presents a focused case study grounded in empirical data, specifically investigating a portfolio of residential buildings affected by the 2010–2011 CES in New Zealand. This section details the broader disaster context, the state of the construction market before and after the earthquakes, the

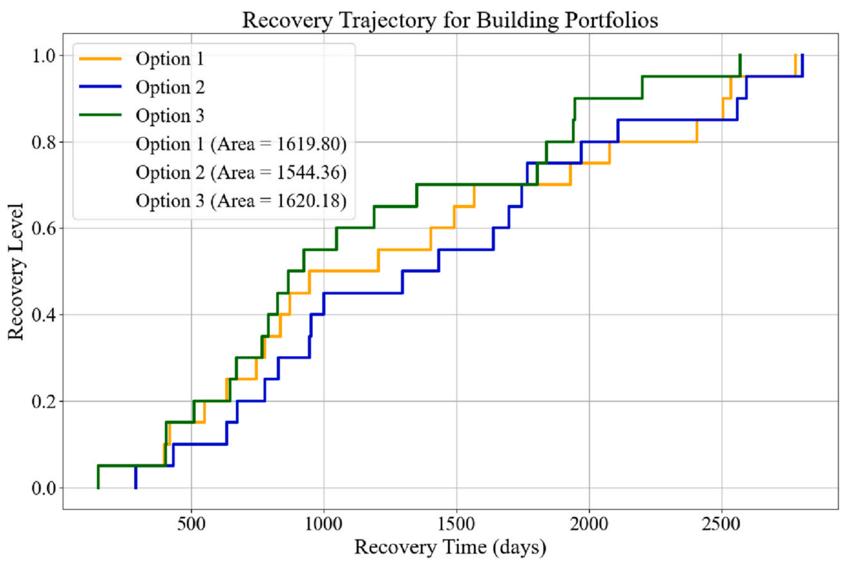

Fig. 4. Conceptual representation of recovery differences among recovery strategies.

collected statistical and empirical data, and the systematic application of the proposed model.

4.1. The 2010–2011 Canterbury Earthquake Sequence

The Canterbury region of New Zealand experienced a series of significant earthquakes in 2010 and 2011, with two major events being particularly noteworthy. The first was the moment magnitude (Mw) 7.1 Darfield earthquake on September 4, 2010, which struck west of Christchurch. This was followed by the devastating Mw 6.3 Christchurch earthquake on February 22, 2011. The catastrophic impact of the 22 February event was exacerbated by the proximity of the epicentre to Christchurch's Central Business District (CBD), the earthquake's shallow depth, distinctive directionality effects from the fault rupture, and cumulative damage from earlier quakes [65]. This earthquake led to the tragic loss of 185 lives, the demolition of nearly 1600 buildings in the Christchurch CBD, and widespread liquefaction and rockfall [65–67]. The CES is distinguished not only by the scale of its physical destruction but also by the profound and ongoing challenges it has posed to recovery efforts. By 2022, nearly 80 % of the damaged structures had been repaired or rebuilt, yet some, such as the iconic Christchurch Cathedral, remain under construction as of 2024 [1].

4.2. Overview of the construction market before and after the earthquakes

Before the 2010–2011 CES, the New Zealand construction industry was in a recessionary phase, marked by reduced activity and sluggish productivity growth across the country, largely as a result of the 2008 global financial crisis [68]. The CES, however, triggered a significant surge in construction activity, encompassing both demolition and rebuilding efforts throughout the Canterbury region [69]. As per the Jobs Online Canterbury vacancies trend index, there was a notable upswing in demand for labourers driven by reconstruction needs [70], as shown in Fig. 5. Each line illustrates the change in job vacancy levels relative to a baseline of August 2010 = 1000. From the initial September 2010 Darfield earthquake to the culmination of December 2013, there was a persistent escalation in the demand for skills, specifically in the construction and engineering sectors.

To mitigate the shortage of skills required for reconstruction efforts, the Canterbury Skills and Employment Hub was established in 2012 with a focus on attracting international migrants [71]. In the immediate aftermath, Canterbury experienced a surge in departures in September 2011. This trend reversed in subsequent years, with departures declining in 2012 and 2013 before stabilising [72]. Conversely, the influx of migrant arrivals into Canterbury initially decreased in 2010 and remained low throughout 2011. Beginning in September 2012, however, the number of arrivals steadily increased, eventually peaking in September 2015 [69]. Within this cohort of migrants, there was a noticeable rise in the presence of migrant workers in the Canterbury construction sector, predominantly holding short-term work visas [73]. However, from 2016 onwards, the influx of migrants associated with rebuilding activities began to decline, reflecting reduced demand for reconstruction-specific skills as the recovery efforts transitioned into the long-term recovery stage [74, 75].

4.3. Statistical and empirical data

This research conducted extensive data collection in collaboration with the Natural Hazards Commission Toka Tū Ake (NHC), the Ministry of Business, Innovation and Employment (MBIE), and Immigration New Zealand (INZ). The collected data informs the modules (Modules 1, 2, and 3) of the proposed model, enabling the determination of damage scores, the modelling of the dynamic resource pool, and the strategic allocation of human resources. Table 1 provides a summary of the collected data.

The NHC manages insurance payouts for insured residential buildings affected by earthquakes and maintains detailed recovery

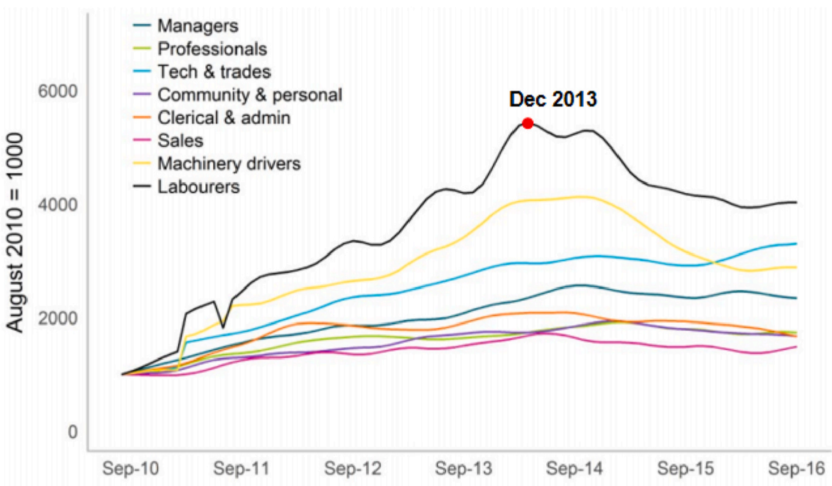

Fig. 5. Jobs Online Canterbury vacancies trend index for occupations (Source: MBIE, Jobs Online).

Table 1
Summary of the collected data.

Number	Data details	Source	Note
1	Basic building information	NHC	Building ID, number of stories, structural system, building age, construction year, floor area, Importance Level (IL), building materials, etc.
2	Repair time		It is calculated by deducting the latest repair completion date from the earliest repair scoped date.
3	Cap status		It indicates whether a building's repair costs exceed the NHC cap.
4	Policy preferences	Building Performance	Earthquake-prone Building (EPB) policy
5	Repair cost	NHC	Total building paid (including GST)
6	Rebuild-related work visa arrivals and departures	INZ, MBIE	The rebuild-related work visa encompasses various types of human resources for Christchurch's rebuilding efforts, including both labourers and professionals.

Table 2
Factors for characterising policy considerations.

Category	High/medium seismic risk areas	Factor	Low seismic risk area	Factor
Category A	Unreinforced masonry buildings	5	Unreinforced masonry buildings	2
Category B	Pre-1976 buildings that are either three or more storeys or 12 m or greater in height above the lowest ground level (other than unreinforced masonry buildings in Category A)	4	Pre-1976 buildings that are either three or more storeys or 12 m or greater in height above the lowest ground level (other than unreinforced masonry buildings in Category A)	1
Category C	Pre-1935 buildings that are one or two storeys (other than unreinforced masonry buildings in Category A)	3		

data, including building information, key dates in the claims process (e.g., repair initiation and completion dates), and repair costs. For this study, twenty residential buildings requiring substantial repairs were selected, excluding cases involving remedial work due to poor workmanship. It is presumed that buildings with negligible or minor damage can be readily managed by the property owners.

Policy-related data were collected to calculate the PRI in Module 2. This case study incorporates policy considerations from the Earthquake-Prone Building (EPB) policy implemented in 2017 [49], which classifies buildings into three categories—A, B, and C—based on seismic risk zone location, construction type, and occupancy [76]. Category A buildings are identified as highly vulnerable, more susceptible to earthquake damage, and presenting significant life-safety risks, including an elevated risk of collapse during an earthquake. Consequently, these buildings are assumed to require prioritisation in recovery efforts if not structurally strengthened to mitigate potential risks. Table 2 outlines the predefined factors for each building category across seismic risk zones. These factors can be adjusted flexibly based on expert judgment and local context.

Immigration-related data were collected from the INZ and MBIE, focusing on work visa approvals specifically for rebuild-related occupations in the Canterbury region from 2011 to 2019. It is assumed that all immigrants holding these visas are skilled human resources relevant to the reconstruction sector. The total number of visa applications was not used, as it may not accurately reflect mobilised resources due to potential cancellations for administrative reasons, such as the submission of incorrect visa categories. Furthermore, the INZ data relies on a manual recording system, where immigration officers assign code numbers to each application. This process may result in some work visa arrivals lacking recorded occupations in the dataset. Despite these limitations, the data from INZ and MBIE is deemed sufficiently reliable to represent human resource fluctuations within the reconstruction sector.

4.4. Application of the DSQ model

4.4.1. Determining damage score

The first step of the proposed DSQ model entails determining a damage score based on rapid inspection data. However, rapid inspection results are unavailable in this case study, as the NHC utilised detailed engineering evaluations to assess each building's residual structural capacity and determine insurance payouts. These engineering assessment reports, however, were not fully digitised at the time of the CES and are currently inaccessible from the NHC's database. Following consultations with NHC engineers, it was recommended to use "Cap status" and "Total building paid (including GST)" as proxies to represent the damage severity of insured residential buildings. "Cap status" is a binary variable indicating whether a building's repair costs exceed the NHC cap, triggering additional insurance payouts. To create a unified damage score for the selected buildings, one-hot encoding was applied to integrate "Cap status" and "Total building paid (including GST)", resulting in a numerical score ranging from 0 to 1.

4.4.2. Determining the recovery sequence

In New Zealand, no formal prioritisation guidelines were established following the CES. For this case study, four key factors were integrated to establish a prioritised recovery sequence: repair cost, building Importance Level (IL), damage score, and policy preference, based on data availability and contextual relevance.

Incorporating repair costs into the prioritisation reflects the distinctive insurance context in New Zealand, where most repairs are contingent on insurance payouts. Delays in these payouts significantly hindered recovery efforts after the CES [1,12,77]. This factor underscores the financial dependencies critical to recovery timelines. Additionally, IL, as specified in AS/NZS 1170.0:2002, defines a building's ultimate limit state (ULS) shaking threshold based on the consequences of failure [78]. Structures with higher ILs, such as hospitals, adhere to stricter design criteria to ensure functionality and serviceability post-disaster, aligning with New Zealand's prioritisation strategies. However, IL was excluded from the PRI calculation for this case study as all selected residential buildings were classified as IL2. It is noteworthy that these IL categories are currently under review, as they may not fully capture the criticality of services provided by these buildings. A functionality-based categorisation is recommended for better alignment with community priorities. The damage score was included to account for structural damage severity, while policy preferences derived from the EPB policy were incorporated to address potential life-safety risks with certain buildings after earthquakes, as outlined in Table 2.

An integrated approach of expert consultation, questionnaire surveys, and the AHP has been proposed to define recovery sequences. This method is particularly effective during the emergency response phase, as it captures stakeholders' perceptual priorities in a crisis context. For illustration, the first experiment explored the temporal impacts of various human resource mobilisation strategies on building recovery. This was conducted under a simple recovery sequence where decision rules assigned equal weights (0.25) to each factor, with the PRI calculated using Equation (1).

Recognising the significant role decision rules play in shaping recovery sequences under resource constraints, a secondary experiment was conducted to investigate how different prioritisation strategies influence community recovery timeframes. Three recovery options were considered, as detailed in Table 3.

- Option 1 (baseline): Equal weighting for all factors, with each contributing 0.25 to the recovery sequence.
- Option 2 (financing-centred): Emphasised repair cost with a weight of 0.7, underscoring the critical role of financial readiness in accelerating recovery.
- Option 3 (damage-centred): Prioritised the damage score with a weight of 0.7, focusing on addressing the most severely damaged structures to mitigate potential immediate risks.

4.4.3. Determining dynamic human resource pool

To examine the temporal impacts of varied human resource mobilisation patterns on the building recovery process, this study evaluates three distinct scenarios.

- Scenario 1 (S1): This baseline scenario reflects the resource mobilisation strategy implemented after the CES.
- Scenario 2 (S2): An optimistic scenario incorporating enhanced mitigation measures such as specialised recovery visas [79] and strong financing incentives to expedite mobilisation. A mitigation factor of 2 is applied to demonstrate this acceleration effect.
- Scenario 3 (S3): A pessimistic scenario where restrictive immigration policies hinder resource mobilisation. An amplification factor of 0.5 is applied to represent extended delays.

The mitigation and amplification factors are illustrative and should be determined through expert consultation and empirical data analysis to reflect realistic variations before and after policy changes. For instance, following New Zealand's extreme flooding and cyclone events in 2023 [79], a specialised "recovery visa" was implemented to attract skilled labour for relief efforts in the North Island, resulting in 1487 approvals between April and September 2023. By comparison, only 109 rebuild-related work visas were approved post-CES from February to December 2011. Although the hazard scenarios differ, this comparison suggests a mitigation factor of 13.64 (1487/109).

To model the baseline scenario (S1), this study utilised data on onshore and offshore rebuild-related migrants as proxies for workforce influx in Christchurch post-CES. Initial exploratory data analysis was conducted to identify trends and seasonal patterns, followed by regression and time series analyses to determine the most appropriate model fit for S1. The results indicated that linear regression was suitable for modelling changes in mobilised workforce resources over time, with a confidence level of 95 %. Model performance was evaluated using R-squared, adjusted R-squared, and P-values. The internal workforce turnover rate was set at 30 %, based on Chang-Richards et al. [31], with an initial resource pool assumed to be 40. Scenarios S2 and S3 were then derived by applying

Table 3
Details of different decision-making rules.

Recovery strategy	Factors	Decision Rules
Option 1 (baseline)	Repair cost	0.25
	Damage score	0.25
	Importance Level	0.25
	Policy preferences	0.25
Option 2 (financing-centred)	Repair cost	0.7
	Damage score	0.2
	Importance Level	0.05
	Policy preferences	0.05
Option 3 (damage-centred)	Repair cost	0.2
	Damage score	0.7
	Importance Level	0.05
	Policy preferences	0.05

the mitigation and amplification factors to the baseline S1.

4.4.4. Allocating and releasing human resources

In the absence of component-level damage data, a demonstration parameter of one worker per 500 square feet was employed to approximate the aggregate human resource requirements for repair and reconstruction activities. A more rigorous estimation of worker demands, incorporating both the average damage state of individual components and the extent of damage as indicated by the number of affected units, is provided by Terzic and Yoo [80]. Once the dynamic resource pool (S1, S2, or S3) and PRI were established, resource allocation was conducted following the rules outlined in Fig. 3. This process continued until all buildings were fully repaired, with individual-level waiting times and recovery times systematically recorded for subsequent analysis.

To address RQ1, the first experiment combined the baseline recovery scenario (Option 1) with three resource mobilisation scenarios (S1, S2, and S3). This experiment illustrated how the proposed DSQ model captures the temporal impacts of varying resource mobilisation strategies on building recovery timelines. To address RQ2, the second experiment explored the interaction between three recovery options (Option 1, Option 2, and Option 3) and the three resource mobilisation scenarios (S1, S2, and S3), resulting in nine combinations. This setup enabled a detailed investigation into the temporal effects of varying recovery sequences and mobilisation strategies on overall recovery timeframes. Given data limitations, the damage score in the first experiment was derived through one-hot encoding, with buildings exhibiting minor damage being excluded from the analysis. To mitigate potential biases associated with this derived score and to enhance the robustness of the analysis, the second experiment assigned a random value between 0 and 1 as the damage score, thereby capturing the heterogeneity in damage severity across buildings. All simulations were conducted using Python 3.12.

5. Results

5.1. Determination of human resource mobilisation patterns

The statistical distribution of mobilised human resources within the reconstruction sector over the observed period is depicted in Fig. 6. The data shows a marked increase in worker arrivals from 2011 to 2015, followed by a gradual decline beginning in 2016. This trend reflects the shifting demands and dynamics of the reconstruction efforts in the Canterbury region.

A regression analysis was conducted to model the S1 scenario, with the results detailed in Table 4. This analysis yielded an R Square value of 0.1965, indicating that only 19.65 % of the variance in the dependent variable is explained by the independent variable. Additionally, the P-value of 0.2542 exceeds the significance threshold of 0.05, which suggests that the null hypothesis cannot be rejected. These results collectively indicate that the regression model is not statistically robust and fails to provide a reliable fit for predicting resource mobilisation based on the current dataset.

In fact, the temporal impacts of human resource constraints varied significantly across different recovery stages. Human resource constraints had a particularly pronounced effect during the short to medium recovery stages, specifically from 2011 to 2015, prior to the disestablishment of the Canterbury Earthquake Recovery Authority (CERA) in 2016. This transition marked a critical shift from a government-led recovery to the establishment of long-term, locally-led recovery and regeneration efforts. As a result, the computation of the S1 scenario was adjusted to align with the simulation timeline from 2011 to 2015. The revised regression analysis results are presented in Table 5.

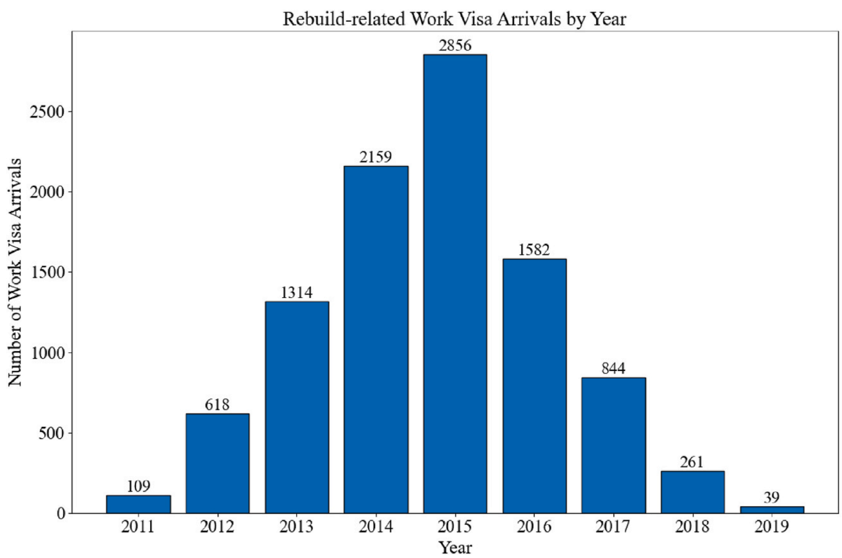

Fig. 6. The number of rebuild-related work visa arrivals quarterly from 2011 to 2019.

Table 4
Regression analysis statistics.

Regression Statistics		*ANOVA*					
Multiple R	0.4433		df	SS	MS	F	Significance F
R Square	0.1965	Regression	1.0000	1.5166	1.5166	1.4671	0.2713
Adjusted R Square	0.0626	Residual	6.0000	6.2023	1.0337		
Standard Error	1.0167						

Table 5
Adjusted regression analysis statistics.

Regression Statistics		*ANOVA*					
Multiple R	0.9996		df	SS	MS	F	Significance F
R Square	0.9991	Regression	1	3.3573	3.35727	2267.6083	0.00044
Adjusted R Square	0.9987	Residual	3	0.00296	0.00148		
Standard Error	0.0385						

	Coefficients	Standard Error	t Stat	P-value
Intercept	−2.1569	0.0632	−34.1145	0.0009
Variable	0.8194	0.0172	47.6194	0.0004

The adjusted results indicate a Multiple R-value of approximately 0.9996, signifying a strong positive linear association. The R-Square value of 0.9991 implies that approximately 99.91 % of the variability in the dependent variable is explained by the independent variable in this model. Despite these high R-values, the model's significance was further validated using the F-statistic and P-values. As displayed in Table 5, the large F-statistic combined with a low P-value confirms that the regression model is statistically significant in explaining the variability in the dependent variable. Consequently, it is reasonable to conclude that the current regression model is statistically robust and well-suited for application in the S1 scenario. The workforce turnover rate was set as 0.3 [31]. Using the results in Table 5 and Equation (2), three resource scenarios were determined as follows.

$$S_1 = (40 + 0.8184t - 2.1569) \bullet 0.7;$$

$$S_2 = (40 + 2 \bullet (0.8184t - 2.1569)) \bullet 0.7$$

$$S_3 = (40 + 0.5 \bullet (0.8184t - 2.1569)) \bullet 0.7 \tag{4}$$

5.2. *Temporal effects as a result of varying resource mobilisation patterns*

This section explores the temporal impacts of varying resource mobilisation patterns on building recovery timeframes under a basic

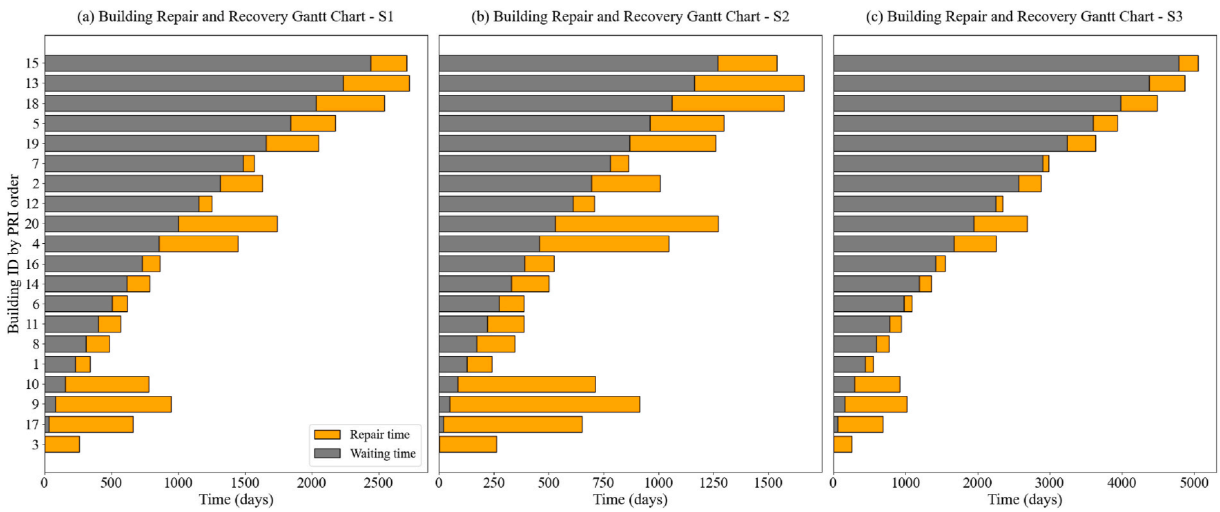

Fig. 7. Building repair and recovery Gantt chart for (a) S1 baseline workforce mobilisation strategy, (b) S2 optimistic workforce mobilisation strategy with mitigation efforts, and (c) S3 pessimistic workforce mobilisation strategy.

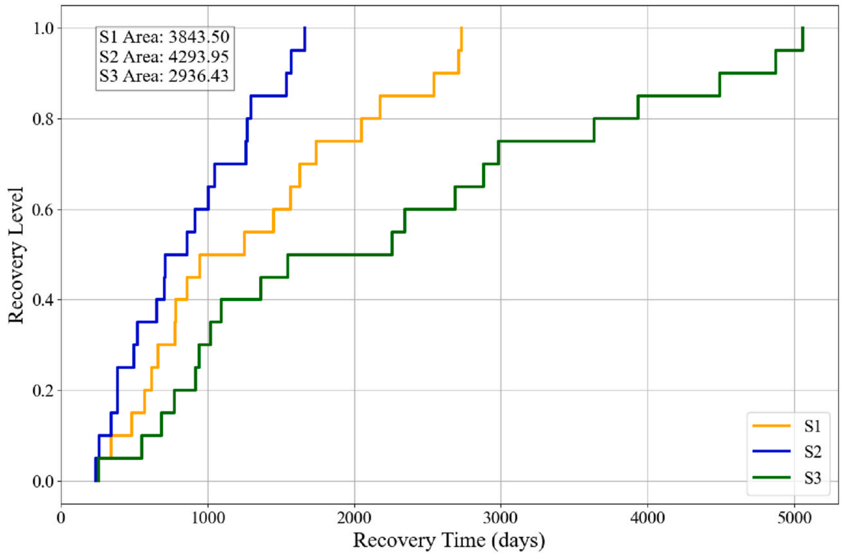

Fig. 8. Recovery trajectory for building portfolios under three resource scenarios.

recovery strategy (Option 1). The Gantt charts in Fig. 7 illustrate building recovery across the three distinct resource mobilisation scenarios. Results indicate that the optimistic scenario (S2) achieved a faster recovery timeframe of 1540 days, compared to 2710 days for the baseline (S1) and 5057 days for the pessimistic scenario (S3). Specifically, the implementation of mitigation strategies in S2 increased overall recovery speed by 43.17 % relative to S1 and by 69.55 % relative to S3.

At the recovery of individual buildings, a notable disparity in building waiting times was observed across damaged buildings. For example, although the repair time for Building ID 15 was only 270 days, its total recovery time was extended to 5057 days under S3 due to substantial delays in obtaining sufficient resources to initiate repairs. This highlights the importance of recovery sequences when modelling building recovery under human resource constraints, underscoring the need for further scrutiny to optimise recovery outcomes at both community and individual levels.

The recovery trajectories for the selected building portfolios under three different resource mobilisation patterns are illustrated in Fig. 8. Recovery efficiency was calculated using Equation (3). The results indicate that S2 (optimistic) exhibited the highest recovery efficiency, with an area value of 4293.95, while S3 (pessimistic) demonstrated the lowest recovery efficiency, with an area value of 2936.43. Specifically, the recovery efficiency of S2 was increased by 11.72 % and 46.23 % compared to S1 and S3, respectively.

5.3. Temporal effects as a result of different recovery sequences and resource mobilisation patterns

This section examines the temporal influences of the complex interplay between human resource mobilisation (S1, S2, and S3) and recovery sequences (Options 1, 2, and 3) in influencing community-level building recovery outcomes. Updated Gantt charts in Appendix A illustrate building recovery progress under these options within each mobilisation scenario, with summarised results presented in Table 6. The findings reveal notable discrepancies in recovery modes arising from different decision rules, with the PRI

Table 6
Results of estimated building recovery times under different combinations.

Resource mobilisation scenario	Recovery option	Experiment ID	Building ID/the maximum waiting time (days)		Portfolio-level recovery time (days)	Recovery efficiency (*A*)
S1 (Baseline)	Option 1	E1	ID5	2444	2780	4043.21
	Option 2	E2	ID8	2632	2807	3954.30
	Option 3	E3	ID5	2235	2571	4219.17
S2 (Optimistic)	Option 1	E4	ID5	1265	1601	4503.97
	Option 2	E5	ID8	1359	1534	4459.52
	Option 3	E6	ID5	1161	1497	4590.99
S3 (Pessimistic)	Option 1	E7	ID5	4803	5139	3121.68
	Option 2	E8	ID8	5179	5354	2943.87
	Option 3	E9	ID5	4389	4725	3469.36

rankings for damaged buildings varying significantly across the three options. These variations lead to distinct recovery outcomes at both individual and portfolio levels.

Among the nine configurations outlined in Table 6, E3 (Option 3 under S1), E6 (Option 3 under S2), and E9 (Option 3 under S3) emerged as the optimal scenarios under S1, S2, and S3, respectively. The consistent selection of Option 3 (damage-centred) across these combinations underscores its superior effectiveness compared to Option 1 (baseline) and Option 2 (financing-centred) within this investigation, demonstrating the DSQ model's capability to identify the most contextually appropriate recovery strategies. Further analysis revealed that, under the S1 baseline scenario, transitioning from Option 2 to Option 3 reduced the recovery timeframe by 236 days (E2 to E3). Similarly, under the S2 optimistic scenario, shifting from Option 1 to Option 3 shortened the recovery timeframe by 104 days (E4 to E6). Under the S3 pessimistic scenario, changing from Option 2 to Option 3 reduced recovery time by 629 days (E8 to E9). Collectively, these findings highlight the temporal influence of recovery sequences on portfolio-level recovery timeframes, demonstrating that even in cases where human resource mobilisation strategies cannot be further enhanced, selecting an optimal recovery option can significantly reduce overall recovery times by years.

The analysis further revealed that, under fixed recovery sequences (i.e., Option 2), a strategic adjustment in human resource mobilisation from a pessimistic approach (S3) to an optimistic approach (S2) produced a substantial reduction of 3820 days in the portfolio-level recovery timeframe, as demonstrated in experiments E5 and E8. This finding underscores the critical importance and potential impact of optimised human resource mobilisation strategies in significantly reducing recovery delays.

From a broader perspective, the optimal recovery scenario, E6 (Option 3 under S2), achieved the shortest recovery timeframe of 1497 days, whereas the least efficient scenario, E8 (Option 2 under S3), resulted in a protracted recovery period of 5354 days. The transition from E8 to E6 represents a remarkable reduction of 3857 days, illustrating the profound temporal effects resulting from the interplay between human resource mobilisation and recovery sequencing. These results highlight the necessity of optimising both aspects to enable more efficient and timely post-disaster recovery outcomes.

The portfolio-level building recovery trajectories under nine different combinations of human resource mobilisation and recovery sequences are illustrated in Fig. 9. The analysis confirmed that E6 (Option 3 under S2) emerged as the optimal recovery strategy, achieving the highest recovery efficiency with the largest area value of 4590.99. This was followed by E4 (Option 1 under S2) and E5 (Option 2 under S2), both of which demonstrated superior recovery efficiency compared to other experimental settings. The consistent selection of the S2 (optimistic) scenario across these cases highlights the critical role of strategic resource mobilisation in accelerating building recovery.

6. Discussion

This research developed a DSQ model to capture the temporal impacts of human resource constraints on the building recovery process and to elucidate the complex interplay between human resource mobilisation, recovery sequencing, and building recovery trajectories. The model offers a robust quantitative framework for analysing the effects of human resource constraints and recovery strategies on post-disaster recovery outcomes.

The findings reveal the substantial benefits of proactive workforce mobilisation strategies combined with mitigation efforts in

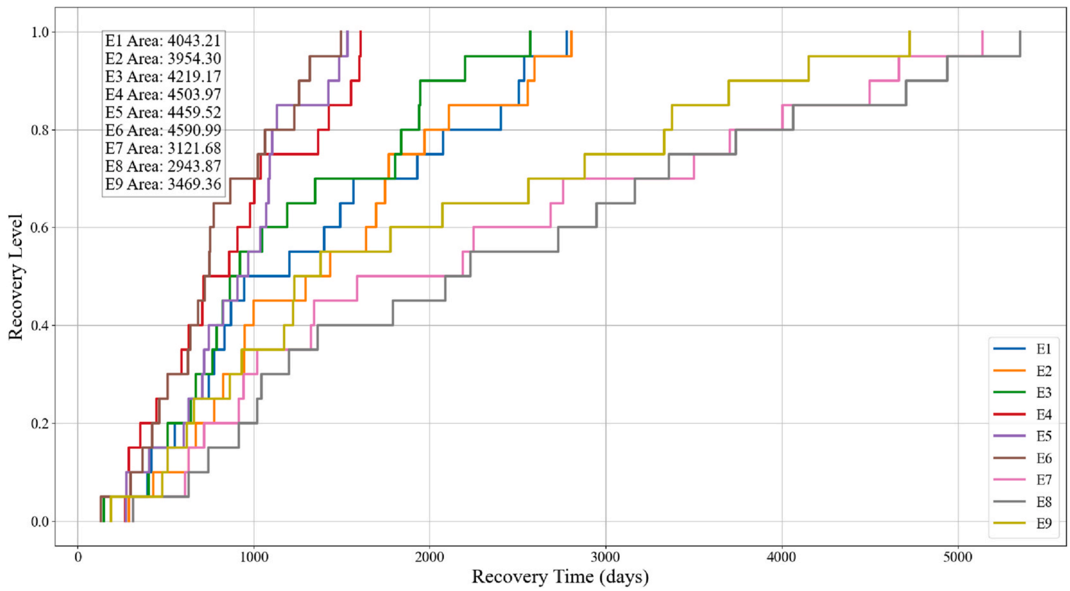

Fig. 9. Recovery trajectories for nine different combination scenarios.

enhancing recovery efficiency. When applied to a fixed recovery sequence, these strategies can potentially shorten recovery timelines by nearly a decade compared to pessimistic scenarios driven by restrictive immigration policies or insufficient financial incentives. This underscores the transformative potential of adopting forward-thinking mobilisation approaches to address workforce shortages. Conversely, when mobilisation strategies are fixed, optimising the recovery sequence alone can possibly reduce community-level recovery timelines by several years. These results highlight the pivotal role of strategic repair sequencing, even in scenarios where workforce availability is constrained.

More importantly, the integration of dynamic workforce mobilisation strategies with recovery sequencing demonstrates a synergistic effect, amplifying their combined impact. The study shows that delays stemming from the interaction of these two factors can extend recovery timelines by over a decade if not managed effectively. This emphasises the necessity of coordinated planning that simultaneously addresses workforce constraints and optimises repair sequencing, thereby mitigating compounding delays and improving recovery outcomes.

Historically, recovery decision-making has relied heavily on subjective expert judgments and past experiences [81], lacking systematic frameworks to assess actions taken and their potential impacts on building recovery outcomes. The DSQ model bridges this gap by offering a structured approach that can be deployed immediately after post-earthquake inspections. Its capacity to function effectively under conditions of incomplete information is particularly beneficial for decision-makers tasked with rapid recovery planning amidst uncertainty. By facilitating the systematic evaluation of recovery options, the DSQ model empowers policymakers to identify optimal strategies and assess the adequacy of available resources. This capability not only ensures that recovery timelines meet acceptable thresholds but also enables proactive adjustments throughout the recovery process. In doing so, it helps avoid reactive, wait-and-see approaches that often lead to prolonged delays and undermine long-term community resilience.

Moreover, a persistent challenge in recovery planning lies in determining an effective and consistent repair sequence, a task further complicated by conflicting stakeholder priorities and preferences [1,43,82]. Existing research often employs simplistic methods based on predefined sequences or single criteria, such as damage severity [36,42,83], rendering them less practical for real-world applications. In contrast, the DSQ model integrates a PRI to establish mathematically robust recovery sequences tailored to local contexts. By incorporating diverse socioeconomic factors, the PRI enables the development of adaptive recovery strategies that align with community-specific needs and broader societal expectations.

The DSQ model is designed to deliver actionable insights based on available data rather than relying on idealised, perfect information. It incorporates key assumptions, such as mitigation and amplification factors, which require careful estimation through expert judgment and empirical data analysis. The model's high sensitivity to resource demands underscores the critical importance of detailed data on damaged structures for accurately estimating individual and community-level recovery timelines. While this study relies on assumptions to estimate resource demands within a specific case study, access to more granular and comprehensive data would further enhance the model's precision and contextual applicability. Moreover, this study exclusively considers delays attributable to human resource constraints. Due to data limitations, delays arising from external factors (e.g., aftershocks or restricted building access due to safety concerns from adjacent structures) and other building-level impeding factors, such as building inspection, engineering mobilisation and review/redesign, permitting, financing, and contractor mobilisation, have not been incorporated into the analysis. It should be noted, however, that in recovery scenarios where these additional delays dominate the overall recovery timeframe, rendering the impact of human resource constraints negligible, expert judgment should then play a crucial role in developing effective policies and strategies to mitigate adverse impacts of human resource constraints.

The DSQ model bridges theoretical resource-allocation frameworks with the practical exigencies of post-disaster recovery by integrating both centralised governance and decentralised, firm-specific contexts. In scenarios characterised by large-scale public recovery initiatives—particularly in developing economies or following major disasters—government and emergency management agencies frequently assume a centralised coordination role by negotiating labour-sharing agreements, expediting work visa processes, and deploying financial incentives to mobilise domestic and international labour pools. The model's dynamic resource pool, informed by historical data on workforce mobilisation capacity, simulates this process by projecting community-level labour availability and identifying critical intervention points for expanded recruitment. Conversely, acknowledging that construction workers are predominantly employed by individual firms within inherently fragmented markets, the DSQ framework exhibits notable adaptability by disaggregating into firm-level sub-pools to simulate practical impediments such as contractual constraints, recruitment delays, and multifaceted legal challenges. This dual approach not only reconciles the centralised coordination of emergency responses with the intricate realities of decentralised labour markets but also equips decision-makers with a robust tool to forecast human resource mobilisation timelines and prioritise targeted interventions across a diverse spectrum of post-disaster recovery environments.

7. Conclusions

Local authorities and decision-makers need efficient and reliable resource planning and management tools to achieve desired levels of community resilience. This study presents a Dynamic Stochastic Queuing (DSQ) model designed to reveal the temporal impacts of human resource constraints on the building recovery process. Central to this model is the explicit integration of dynamic resource mobilisation patterns and recovery sequence of damaged structures under human resource constraints. A case study is presented to demonstrate the applicability of the proposed model, revealing the complex temporal impacts of resource mobilisation strategies and recovery sequences on building recovery timeframes at both individual and community levels.

The analysis of building recovery under three workforce mobilisation patterns revealed that proactive resource mobilisation, especially when coupled with targeted mitigation efforts, can significantly improve recovery efficiency and speed. An optimised recovery sequence can further reduce recovery timeframes by years, even under strict resource constraints. Notably, the compounded temporal impacts of recovery can be markedly intensified by the complex interaction between resource mobilisation strategies and recovery sequences. Recovery timelines can be reduced by up to a decade when proactive resource mobilisation aligns with an optimised recovery sequence for damaged structures, underscoring the essential role of strategic workforce mobilisation and optimised recovery sequencing in addressing the challenges posed by human resource constraints.

The proposed model advances the field by recognising the dynamic nature of human resource constraints and demonstrating the necessity for coordinated consideration of both dynamic resource mobilisation and recovery sequencing. Each factor independently affects recovery timelines, and their combined influence is critical in determining final outcomes. The DSQ model serves as a decision-support tool in situations where information may be incomplete, but swift action is essential, providing a structured framework for assessing the implications of different recovery priorities and resource mobilisation strategies on community recovery timelines. This evidence-based approach equips policymakers with the rationale to determine whether intensified resource mobilisation is justified and to evaluate the relative effectiveness of various recovery options. Thus, the model holds broad applicability in studies on community resilience, post-disaster recovery planning, and the development of decision-making tools for policymakers.

This study focuses exclusively on the time required to achieve a full recovery state. Future studies are encouraged to incorporate a more nuanced consideration of additional recovery states, such as reoccupancy and functional recovery. Moreover, the delays considered in this study exclusively refer to those arising from human resource constraints. For a comprehensive and accurate estimation of the building recovery trajectory, it is crucial to account for delays caused by other impeding factors, such as building inspections, financing, engineering mobilisation and review/redesign, permitting, temporary and stabilisation repairs, and contractor mobilisation. Furthermore, it is important to acknowledge that various types of resource constraints collectively influence building recovery dynamics. Future studies should delve deeper into this aspect to explore the mechanisms through which different resource types interact and impact recovery processes.

CRediT authorship contribution statement

Lianyan Li: Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alice Chang-Richards:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Megan Boston:** Writing – review & editing, Supervision, Conceptualization. **Ken Elwood:** Writing – review & editing, Supervision. **Carlos Molina Hutt:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Lianyan Li reports financial support was provided by China Scholarship Council. If there are other authors, they 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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Appendix A

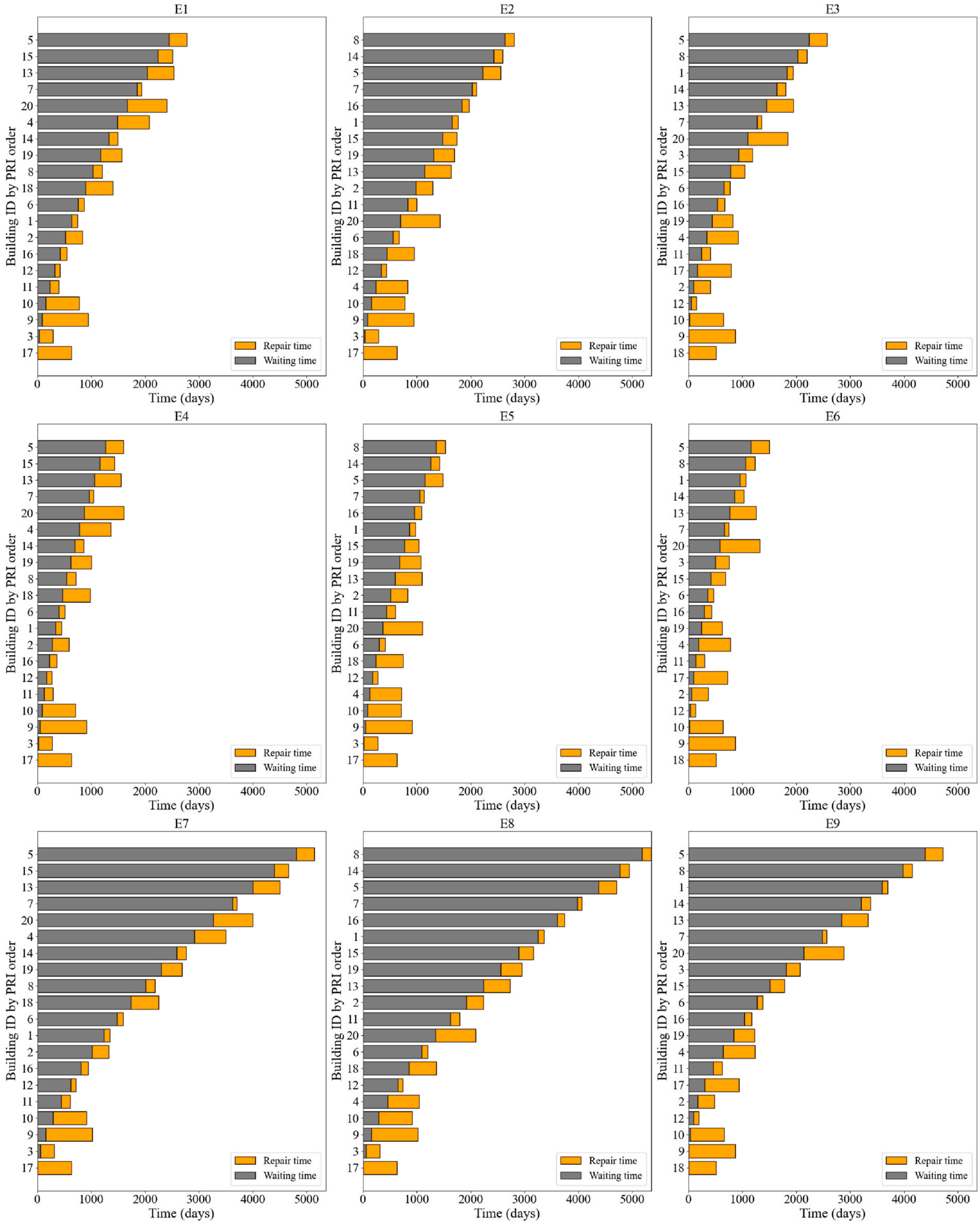

Fig. A. Building recovery Gantt charts for three options under different resource scenarios.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2025.105389.

Data availability

The Python code and sample data utilised in this study are available in the following GitHub repository: https://github.com/Lianyan7/Post-Earthquake-Recovery-under-Human-Resource-Constraints.git.

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