Measures to evaluate post-disaster trip resilience on road networks

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Abstract:

The resilience of transportation networks, one of the most critical infrastructure in post-disaster situations, will have a significant influence on post-disaster operations, community resilience and business continuity. Consequently, understanding the resilience of transportation networks following a natural disaster is crucial. This research proposes a new Trip Resilience (TR) measure to assess the resilience of trips on road networks following a disaster, integrating all three dimensions of resilience, namely robustness, redundancy, and recovery. The methodological approach includes an analysis of existing transport resilience measures presented in the literature to assess their ability to quantify robustness, redundancy and recovery in terms of the proposed conceptual model. The analytical formulations of the individual component measures are then developed, or adapted from previous research, along with a means of integrating all three into a combined Trip Resilience (TR) measure. A case study methodological approach is then adopted to verify the practicality of the proposed measures using the outcomes from a transportation simulation of a hypothetical Alpine Fault Magnitude 8 (AF8) scenario. A Normalised Trip Resilience (NTR) measure is also proposed that converts the TR to a normalised scale that is easily understandable to decision-makers. Finally, in order to facilitate ranking of the post-disaster impact on districts, a new measure, namely the Equivalent daily number of Impacted Trips (EIT), is proposed. The proposed measure provides an opportunity for decision-makers to estimate and rank the trip resilience between each (group of) Origin-Destination pair(s) using pre- and post-disaster flow and travel time. The resulting measures were capable of being calculated from the outputs produced by the transportation simulation model in the case study, thereby verifying their practicality in real-world situations. The importance of including both robustness (represented by the number of eliminated trips) and redundancy (represented by increased travel time), over the horizon of the post-disaster recovery phase was highlighted. Eliminated trips contributed significantly in areas that were cut off and isolated post-disaster, due to a lack of alternative routes, and increased travel time contributed as more roads were reopened but the alternative routes resulted in increased travel distances and, consequently, travel time.

Keywords: Trip Resilience, Robustness, Redundancy, Reliability, Natural Disasters, Road Network Performance, Impacted Trips, Recovery

1. Introduction

Natural disasters, such as flooding, earthquakes, tsunami, hurricanes, and volcanic eruptions, can disrupt transportation networks, potentially resulting in cities, towns and villages being isolated for a period of time. Such disruption causes post-disaster response issues, evacuation difficulties, accessibilities issues, increased travel costs, and economic losses. Consequently, understanding the resilience of transportation networks following a disaster is crucial for post-disaster operations, community resilience and business continuity. The resilience of transportation systems can be defined as the ability to reduce the loss of performance, or impacts in terms of disruption, and properly recover or adapt to a (new) original condition (Zhang et al., 2015, Mason and Brabhaharan, 2016).

The resilience of a road network following a disaster is typically assessed based on asset performance (Mitoulis et al., 2021, Wu et al., 2021, Argyroudis et al., 2020, Argyroudis et al., 2021, Misra et al., 2020, Dizhur et al., 2019, Herbert et al., 2018) and operational performance. Disasters cause damage to transportation assets such as bridges, tunnels, and roads, which in turn can influence the operational resilience of the road network, as measured by reduced capacity, increased travel time, and delay time. This research focusses on operational performance and resilience, while recognising that the hazard assessment (e.g. probabilities of occurrence of seismic events) and performance assessment of the physical assets (e.g. using fragility models to assess the expected damage and losses for given seismic intensity measures) need to be undertaken before the operational resilience of the transport network can be assessed.

To assess the operational resilience of transportation networks following a natural disaster, three approaches have been reported in the literature, namely: conceptual, analytical and a combination of analytical and simulation. The conceptual approach estimates the performance of the network using questionnaires and qualitative methods (Mason and Brabhaharan, 2016, Wang, 2015, Hughes and Healy, 2014, Tamvakis and Xenidis, 2012, Brabhaharan et al., 2006). The analytical approach utilises mathematical methods to assess the performance of the network (Zhang and Wang, 2016, Pokharel and Ieda, 2016, Zhang et al., 2015, Miller-Hooks et al., 2012, Chen et al., 2012, Taylor et al., 2006, Jenelius et al., 2006, Murray-Tuite and Mahmassani, 2004). The third approach applies simulation software to estimate the required traffic parameters, then evaluates the performance of the network using analytical methods and extracted traffic parameters (El-Rashidy and Grant-Muller, 2014, Balijepalli and Oppong, 2014, Luathep et al., 2011, Erath et al., 2009, Murray-Tuite, 2006, Scott et al., 2006).

The traffic parameters capable of being extracted from the above-mentioned simulation software are many and varied. Indeed, a variety of these Measures of Effectiveness (MOEs) are defined and applied, in the literature, to evaluate the performance of road networks. Dowling (2007) reported nine basic MOEs to evaluate traffic operations performance; namely travel time, speed, delay, queue length, number of stops, density, travel-time variance, level of service (LOS), and volume to capacity (V/C) ratio. The most common performance measures used by TRB (2010) are density, speed, V/C ratio, travel time, delay, and queue length. Other measures of interest, reported by Jeannotte et al. (2004), include Vehicle Miles Travelled (VMT)/Person Miles Travelled (PMT) and Vehicle Hours Travelled (VHT)/Person Hours Travelled (PHT). The aforementioned studies focused on the performance level of the networks in Business-As-Usual (BAU) conditions, not necessarily in a post-disaster situation. The appropriate MOEs should be justified based on the type of simulation software used and its capabilities, the goal of the project, and availability of resources and data. For instance, queue length and number of stops are important measures under normal operating conditions, while connectivity and redundancy are considered more important under emergency conditions.

The performance of road networks in a post-disaster environment has typically been assessed using two main concepts in the literature; namely vulnerability or resilience. Other concepts reported in the literature to evaluate the impact of natural disasters on transport networks include risk, reliability, robustness, flexibility, and survivability (Faturechi and Miller-Hooks, 2014). Table 1 provides a list of traffic parameters and MOEs categorized based on the concepts of vulnerability and resilience to assess the operational performance of a road network.

In order to determine which MOEs in Table 1 are likely to best represent the resilience of transportation networks, an adaptation of the four dimensions (robustness, redundancy, resourcefulness and rapidity) of physically and socially resilient systems proposed by Bruneau et al. (2003) is used to assess their suitability. Robustness and redundancy are considered as proposed, however, as resourcefulness and rapidity reflect the importance of resources and budget to achieve response and reconstruction goals in a timely manner, they can be represented by a single dimension in this study, namely recovery.

Table 1: Applied traffic factors in natural disaster-related transportation studies

STUDIES	CONCEPT	PERFORMANCE MEASURES
Zhang and Wang (2016)	Resilience	Reliable Independent Pathways (IPWs); node weighting factor (the shortest distance between a node and emergency response facility); IPW weighting factor (average daily traffic (ADT); length)
Pokharel and Ieda (2016)	Vulnerability	Population; shortest distance; detour ratio: alternative shortest path when one or more links fail/shortest path
Muriel-Villegas et al. (2016)	Vulnerability	Link weakness; link importance (% of traffic flow); link criticality (decreased flow)
Zhang et al. (2015)	Resilience	Flow, capacity, travel time, shortest distance, cost
Soltani-Sobh et al. (2015)	Resilience	Total travel time, flow, consumer surplus
El-Rashidy and Grant-Muller (2014)	Vulnerability	Flow, capacity, congestion density, free flow speed, link length
Balijepalli and Oppong (2014)	Vulnerability	Capacity, travel time
Omer et al. (2013)	Resilience	Travel time, CO_2 emissions, financial cost
Chen et al. (2012)	Vulnerability	Demand, travel time
Miller-Hooks et al. (2012)	Resilience	Post-disaster capacities; travel time; the cost of implementing recovery activities; implementation time of recovery activities; demand; the cost of implementation preparedness activities; given budget
Chen and Miller-Hooks (2012)	Resilience	Capacity; travel time; implementation recovery time; implementation cost; flow
Luathep et al. (2011)	Vulnerability	Demand, flow, capacity, travel time
Erath et al. (2009)	Vulnerability	Travel time costs, driving distance costs, accident costs
Jenelius et al. (2006)	Vulnerability	Travel cost, demand
Taylor et al. (2006)	Vulnerability	Change in travel cost; attractiveness of location (the number of opportunities available, population); a measure of remoteness (or accessibility to services)
Murray-Tuite (2006)	Resilience	Queue, travel time, speed, V/C
Murray-Tuite and Mahmassani (2004)	Vulnerability	Alternate paths; travel times; marginal costs; capacity

Robustness, usually measured as the impact of flow and demand variation on the post-disaster performance of the network, has been investigated by El-Rashidy and Grant-Muller (2014), Zhang et al. (2015), Soltani-Sobh et al. (2015), Chen et al. (2012), Miller-Hooks et al. (2012) and Jenelius et al. (2006). For instance, Miller-Hooks et al. (2012) and Chen and Miller-Hooks (2012) evaluated the resilience of a transport network for freight by calculating the expected fraction of demand that can be satisfied post-disaster. Balijepalli and Oppong (2014) used serviceability as the total available capacity of the link divided by the standard hourly link capacity (that is the maximum flow rate) per lane for the given road type. Chen et al. (2012) revealed the significant impact of demand variation and travellers' risk-taking behaviour on network vulnerability. Jenelius et al. (2006) estimated the importance pertaining to unsatisfied demand of any link using total demand of the network. Environmental resilience was estimated by Omer et al. (2013) using CO_2 emissions and flow variation.

Redundancy, usually measured as the impact of disruption in terms of travel cost or travel time variation, has been examined in numerous studies. Pokharel and Ieda (2016), for instance, estimated redundancy of an Origin-

Destination (OD) pair based on the detour ratio, the shortest path between an OD pair in a BAU and post-disaster environment. Unsatisfied Demand Impact (UnSDI) was proposed by El-Rashidy and Grant-Muller (2014) as a measure of the increased total travel time due to a disruption. Omer et al. (2013) measured the impact of disruption on the performance of the network using travel time resilience and cost resilience as “a ratio between the value delivery of the system before and after a disruption”. Balijepalli and Oppong (2014) and Erath et al. (2009) examined the vulnerability of links/networks using detouring. Zhang et al. (2015), Soltani-Sobh et al. (2015), Miller-Hooks et al. (2012), Chen and Miller-Hooks (2012), and Murray-Tuite (2006) used travel time as a key performance indicator (KPI) to measure the resilience of the network. However, a number of studies (Zhang and Wang, 2016, Pokharel and Ieda, 2016, Taylor et al., 2006) used only travel distance in their assessments, thereby ignoring congestion effects in their calculations. In rural areas, this is not a major drawback, as the probability of congestion on the network is low, with the increased travel time arising from the longer distance travelled on the alternative routes. In urban areas, however, a number of alternative routes are typically available, with similar or equivalent distance travelled. In such cases, the increased congestion on these routes may result in longer travel times, and therefore increased travel cost. In both urban and rural areas, increased travel time/cost is a critical performance measure following a major disruption.

Recovery considers the impact of time and resources (i.e. finance, materials, and workforce) on the recovery of the disrupted network and, ultimately, the resilience of the network. The impact of recovery actions on the resilience of the network was investigated by Chen and Miller-Hooks (2012), Miller-Hooks et al. (2012), and Zhang et al. (2015). Omer et al. (2013) measured the travel time resilience over the recovery period. A short recovery time indicates the network returned to the (new) normal condition faster and, therefore, the resilience of the network would be higher.

In terms of assessing resilience, it is clear from Table 1 and the above discussion that various MOEs, some more effective than others, have been adopted in the literature as part of proposed resilience measures or indices. These measures typically assess only elements of resilience, such as robustness or redundancy, and do not always include the recovery effort in the computation. To the best of the authors’ knowledge, based on a review of the relevant literature, the impact of eliminated trips together with increased travel time following a disaster has not been examined to date over the horizon of the post-disaster recovery phase in a single resilience measure. Indeed, the open question raised by Jenelius et al. (2006) regarding “how to value an unsatisfied demand (eliminated trip) in relation to increased travel cost?”, would still appear to stand.

Consequently, the main objectives of this paper are to:

- Develop or adapt measures capable of representing the *Robustness*, *Redundancy* and *Recovery* impact of trips in a post-disaster environment
- Develop a combined Trip Resilience (TR) measure for road networks, capable of integrating the individual components of *Robustness*, *Redundancy* and *Recovery.*
- Adapt the above Trip Resilience (TR) measure so that it is understandable to decision-makers, namely the proposed Normalised Trip Resilience (NTR) measure, and capable of ranking the impact on different areas post-disaster, namely the proposed Equivalent daily number of Impacted Trips (EIT).

The proposed new measures integrate all three concepts of resilience to determine the impact of eliminated trips (robustness) and increased travel time (redundancy) over the horizon of the post-disaster (recovery) phase. The inclusion of the recovery element in the measure is critical in order to calculate a measure of resilience over a period of time, rather than at a point in time. In fact, it can be argued that the latter, point in time, estimate is not a measure of trip resilience at all, but of trip reliability.

The remainder of the paper is structured as follows. In Section 2, the proposed conceptual model for trip resilience is first discussed, followed by the analytical formulations for the individual component and combined measures, namely Robustness and Redundancy (combined as Reliability), and then the Trip Resilience (TR) measure itself. The Normalised Trip Resilience (NTR) measure, a normalised version of TR capable of being easily understood by decision-makers, is then discussed. Finally, the Equivalent daily number of Impacted Trips (EIT) is proposed as a measure to rank the post-disaster impact on OD pairs. In Section 3, the newly developed trip resilience measures are demonstrated using a hypothetical Alpine Fault Magnitude 8 (AF8) scenario in the South Island of New Zealand. The South Island road network is first introduced, followed by the details of the AF8 scenario developed by Davies (2019), before the outputs of the post-disaster transportation simulation, modelled by Aghababaei et al. (2020), are used to calculate the Trip Resilience measure and its component parts, as well as the NTR and EIT. Finally, the findings of the paper are concluded in Section 4.

2. Methodology

An outline of the research methodology is presented in the flowchart included as Figure 1. The first step was to propose a trip resilience model capable of accounting for robustness, redundancy and recovery at a conceptual level. The second step analysed existing transport resilience measures presented in the literature, as summarised in Table 1, to assess their ability to quantify robustness, redundancy and recovery in terms of the conceptual model developed in the first step. The development of the trip resilience measures was undertaken in the third step. This included the development of new measures where necessary and the adoption (or adaptation) of existing measures where suitable. Finally, in the fourth step, the practicality of the proposed measures were verified using a case study. This was undertaken using the outcomes from a transportation simulation of a hypothetical Alpine Fault Magnitude 8 (AF8) scenario.

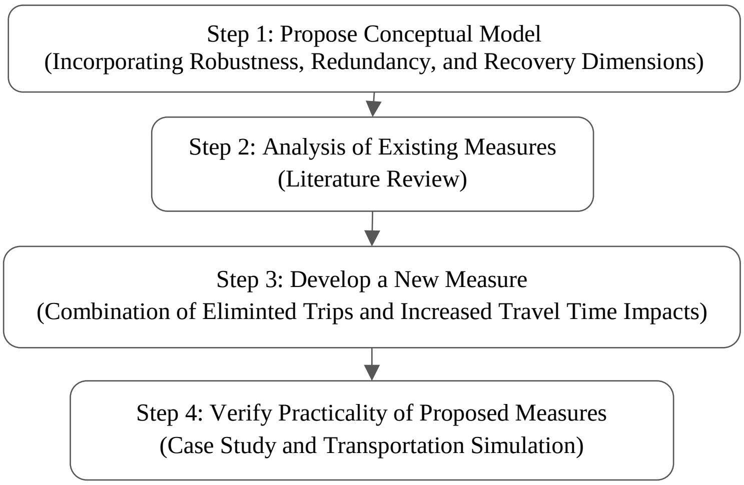

Figure 1: Outline of the Research; Steps to Develop and Apply the new Trip Resilience Measure

3. Development of the Trip Resilience Measures

3.1. Conceptual Model

Generally, two issues arise when a disaster occurs on a road network. First, some traffic zones (TZs) can end up completely disconnected and, hence, trips cannot be completed to or from these TZs. Second, some TZs with alternative routes available can experience increased travel time due to increased travelled distance (typically in rural areas) or congested routes (typically in urban areas). A new resilience measure namely the Trip Resilience (TR) measure is proposed to assess the resilience of trips between TZs on a road network. The Bruneau et al. (2003) study provided a generic definition of the concepts of robustness, redundancy, resourcefulness, and rapidity and proposed a conceptual framework for resilience assessment of a community. Their work was only conceptual in nature (i.e. they did not define how to calculate such measures), and they were not referring to transportation resilience. However, these four concepts are regularly used across all areas of resilience assessment. The proposed measure incorporates the four dimensions of resilient systems; robustness, redundancy, resourcefulness, and rapidity. Resourcefulness and rapidity reflect the importance of resources and budget to achieve response and reconstruction goals in a timely manner, hence, they can be represented by a single dimension, namely recovery. *TR* is, therefore, a function of *robustness*, *redundancy* and *recovery* as expressed in Eq. (1).

$$TR = f\,(Trip\ Robustness,\ Trip\ Redundancy,\ Recovery) \tag{1}$$

It should be noted that *robustness* and *redundancy* can vary over time due to the recovery effort and, at any point in time, when taken together they represent the reliability of the network. The *recovery* determines a time scale whereby the network structurally, and therefore operationally, improves.

Figure 2 graphically illustrates robustness, reliability and resilience in the event of a disaster using hypothetical data for demonstration purposes. Referring to Figure 2, trips occur as per BAU in the pre-disaster phase. When a disaster occurs (t_0), let us assume that the *robustness* decreases to 40% as a result of eliminated trips due to road closures. Let us further assume the *redundancy* of the network returns a value of 55% given that some trips, if their original route is blocked, will be subjected to longer journeys as they travel on alternative routes. However, redundancy can only be estimated for robust trips, that is for those that can occur. Therefore the redundancy impact will be an additional 18%, that is 55% of the remaining robustness value of 40%. Subtracting the 18% redundancy from the 40% *robustness*, returns a trip reliability value of 22%. Until t_1, the network does not change, and the reliability remains constant for this period. At t_1, some roads are reopened, allowing more trips to occur and, thereby, increasing Robustness from 40% to 75%. A proportion of these robust trips will be subjected to longer journeys, depending on the Redundancy on the network, resulting in a reliability value of 60%. At t_2, further roads are reopened, thereby increasing the robustness to 90%, and all remaining trips will occur using their original routes (no *redundancy* impact). The reliability of the network, thus, also increases to 90% and remains constant until t_3. At t_3, the network returns to the pre-disaster condition with the reopening of all remaining roads and reliability returns to 100%.

The shaded area represents the Trip Resilience (TR) of the network during the recovery period of t_0 to t_3. Assuming t_1, t_2, and t_3 occur 60, 120, and 180 days after the event, respectively, then the TR returns 103.2 units. The conceptual representation in Figure 2 is idealised in that it assumes knowledge of exactly when each road is reopened, thereby creating a stepped change in reliability.

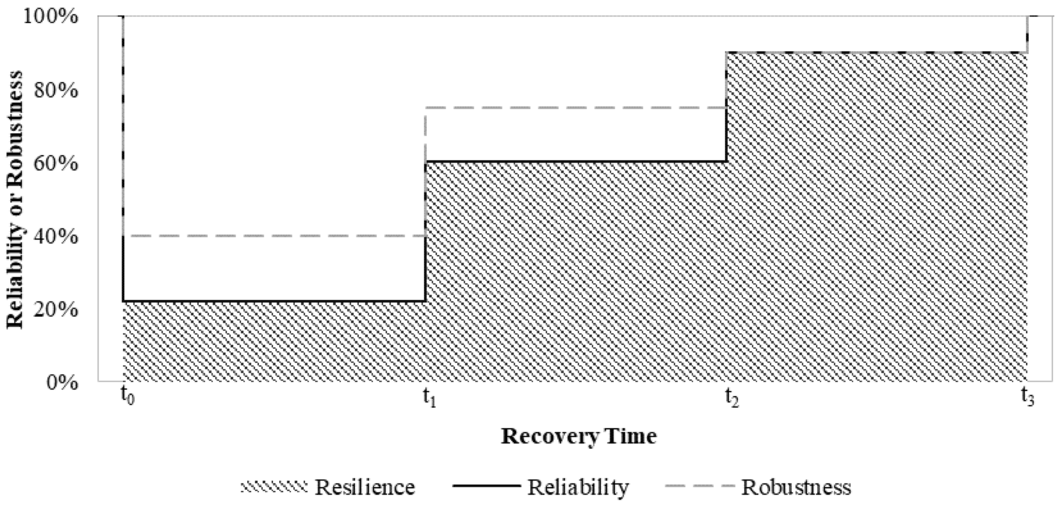

Figure 2: Conceptual Robustness, Reliability and Resilience of a Network

3.2. Analysis of Existing Measures

The existing transport resilience measures presented in the literature, as summarised in Table 1, were analysed to assess their ability to quantify robustness, redundancy and recovery in terms of the conceptual model outlined above. Initially, the analytical formulations in each study were broadly assessed and, then, classified as addressing robustness, redundancy and/or recovery at some level. This assessment is summarised in Table 2, where it can be seen that none of the studies integrate all the resilience concepts into one measure, to estimate the overall resilience of the network. Subsequently, a detailed analysis of the analytical formulations in the studies was undertaken to assess their suitability to quantify robustness, redundancy and recovery in terms of the proposed conceptual model. Focussing on robustness, the studies undertaken by Miller-Hooks et al. (2012) and Chen and Miller-Hooks (2012) provide a measure best aligned with our conceptual model. They evaluated the resilience of a freight network using "the expected fraction of demand that can be satisfied post-disaster". They also assessed this over the recovery period. This measure has the potential to be used in our model, albeit with some adaptation. Focussing on redundancy, the study undertaken by Omer et al. (2013) provides a measure best aligned with our conceptual model. They developed the Network Infrastructure Resilience Assessment (NIRA) framework and applied it to measure the impact of disruption on the performance of the network using three performance metrics including travel time resilience, environmental resilience, and cost resilience. Their travel time resilience measure is of interest to our study, and is represented as the ratio of travel time pre-event to travel time post-event. They assessed this in the case study over a unit of time (1 day), termed the temporal boundary, rather than over a recovery scenario. However, the analytical formulation presented is equally capable of being applied to a recovery scenario.

Table 2: Analysis of Existing Measures

Studies	Resilience Concepts		
	Robustness	**Redundancy**	**Recovery**
Zhang and Wang (2016)		•	
Pokharel and Ieda (2016)		•	
Muriel-Villegas et al. (2016)	•		
Zhang et al. (2015)†	•	•	•
Soltani-Sobh et al. (2015)	•	•	
El-Rashidy and Grant-Muller (2014)	•	•	
Balijepalli and Oppong (2014)		•	
Omer et al. (2013)		•	•
Chen et al. (2012)	•		
Miller-Hooks et al. (2012)	•		•
Chen and Miller-Hooks (2012)	•		•
Luathep et al. (2011)		•	
Erath et al. (2009)		•	
Jenelius et al. (2006)	•		

† Note: Although measures for all three concepts are included in Zhang et al. (2015) they are not integrated into one metric to measure overall resilience. Instead, they consider robustness with recovery and, then, redundancy with recovery, as separate interpretations of resilience.

3.3. Analytical Formulations

Robustness, in this study, relates to the structural and physical strength of the transportation network assets, where the impact of disruption following a disaster would be reflected in the total percentage of trips that can still be undertaken between an OD pair post-disaster. When a link or a group of links on the network are blocked or disrupted, some TZs might be disconnected from other TZs, which means trips between those TZs will not occur. In such cases, those trips are eliminated as their travel costs become infinite as demand is unsatisfied. Consequently, the robustness of trips between an OD pair (ij) during a recovery time (t_ζ) under post-disaster scenario ζ can be calculated as expressed in Eq. (2), where $Flow_{ij(\zeta)}$ and $Flow_{ij(BAU)}$ represent flow under post-disaster and BAU scenarios respectively. Eq. (2) can be used for an OD pair, a group of OD pairs, or the whole network.

$$Robustness_{ij}(t_\zeta) = \frac{Flow_{ij(\zeta)}}{Flow_{ij(BAU)}} \tag{2}$$

$Robustness_{ij} = 1$ represents a scenario where no trips are eliminated after the disaster while $Robustness_{ij} = 0$ represents a scenario where no trips can occur, that is all the trips are eliminated due to either the respective origin or destination being blocked. Eq. (2) seeks to quantify the proportion of trips undertaken post-disaster compared to BAU. These are termed robust trips. Assuming 1000 trips between an OD pair in BAU decreases to 600 in a post-disaster scenario, then the *robustness* of trips between this OD pair will be 0.6 or 60%, meaning 40% of trips will be eliminated due to post-disaster accessibility issues. The remaining 60% of trips will be completed either using the same route as the BAU scenario or using an alternative route based on the accessibility of the network, most probably with an increased travel time.

Where trips can occur, disruption on a network can result in longer travel times on alternative routes. On a regional road network, the additional travel time is typically due to long detours because of a lack of equivalent alternative routes. In an urban situation, a number of alternative routes are typically available, with similar or equivalent distance travelled. In such cases, the increased congestion on these routes may result in longer travel times. Such an increase in travel time post-disaster causes a decrease in the general performance of a trip. *Redundancy*, in this study, is therefore defined as the impact of post-disaster trip assignment (new route choice, the shortest alternative route) on travel time, where infinite post-disaster travel time indicates no *redundancy*. Hence, *redundancy* can be estimated as the ratio of the average travel time between an OD pair (ij) in BAU and post-disaster scenarios as expressed in Eq. (3). Similar to Eq. (2), it can be used for an OD pair, a group of OD pairs, or the whole network.

$$Redundancy_{ij}(t_{\zeta}) = \frac{Average\ Travel\ Time_{ij(BAU)}}{Average\ Travel\ Time_{ij(\zeta)}} \tag{3}$$

Redundancy, as defined in Eq. (3), decreases with an increase in post-disaster travel time but never reaches zero as long as a trip occurs. The *redundancy*, therefore, only impacts robust trips, the trips with finite post-disaster travel time. $Redundancy_{ij} = 1$ represents a scenario where the network yields the same average travel time for the BAU routes and the post-disaster routes. Assuming average travel time for an OD pair (ij) increased three-fold following a disaster, the *redundancy* will be 0.33 or 33% indicating a 67% drop in *redundancy*. Hence, following a disaster, trips are completely reliable if they can firstly be assigned to the network ($Robustness_{ij} = 1$), and then can travel with no increased travel time ($Redundancy_{ij} = 1$).

A combination of *robustness* and *redundancy* can be expressed as trip reliability. Following a major disaster, trip reliability deteriorates partly due to eliminated trips, reflecting the fact that a less robust network results in less robust trips (i.e. more eliminated trips) and, therefore, less reliable trips. The robust trips, however, may be assigned to different routes compared to BAU, potentially resulting in increased travel time (reflecting the *redundancy* concept). Trip reliability, as a result, is estimated in two stages, as presented in Eq. (4). Initially, the proportion of robust trips is calculated and, then, the lack of redundancy is deducted.

$$Reliability_{ij}(t_{\zeta}) = Robustness_{ij}(t_{\zeta}) - \left(Robustness_{ij}(t_{\zeta}) * (1 - Redundancy_{ij}(t_{\zeta})\right) \tag{4}$$

This can be simplified to the product of Robustness and Redundancy as represented in Eq. (5) below. Reliability is therefore estimated at a point in time and, similar to both *Robustness* and *Redundancy*, is unitless and has a scale between 0 and 1.

$$Reliability_{ij}(t_{\zeta}) = Robustness_{ij}(t_{\zeta}) * Redundancy_{ij}(t_{\zeta}) \tag{5}$$

Referring to Eq. (6), Trip Resilience (TR) is then estimated using the area under the trip reliability curve from recovery time of $t_{\zeta m}$ to $t_{\zeta n}$ where m represents the start time and n represents the end time of a stage of recovery. To estimate the TR for the whole period of recovery instead of a stage, m and n represent the impact time and the end of recovery, respectively.

$$TR = \int_{t\zeta_m}^{t\zeta_n} \left(Reliability_{ij}(t_{\zeta})\right) dt \tag{6}$$

Given that the TR is unitless and, at least theoretically, has no upper bound, it was decided to normalise the TR during the recovery period to create a measure that is easily understandable to decision-makers. The resulting Normalised Trip Resilience (NTR) is estimated by Eq. (7) where an average of TR for a period of recovery (Δt)

reflects the *NTR*, presented as a percentage. If the network is completely reliable, then the *NTR* returns 100% representing a resilient network. Typically, *NTR* is estimated for the whole period of recovery, starting from the time of impact to the end of recovery, although *NTR* can be calculated for any time interval, such as different stages of recovery.

$$NTR = \frac{\int_{t\zeta_m}^{t\zeta_n} \left(Reliability_{ij}(t_\zeta) \right) dt}{\Delta t} * 100 \tag{7}$$

Finally, in order to facilitate ranking of the impact on districts post-disaster, the Equivalent daily number of Impacted Trips (EIT) is proposed in Eq. (8). The measure seeks to rank by impact, and is, therefore, a measure of vulnerability rather than resilience. The vulnerability is calculated by subtracting the NTR from unity, and this in turn is multiplied by traffic flow. Traffic flow is used as a criterion for importance in transportation and is commonly used when ranking or prioritizing.

$$EIT = (1 - NTR) * Flow_{(BAU)} \tag{8}$$

The EIT could potentially be used to facilitate resilience investment decision making on the network by ranking the impact on trips for different natural disaster scenarios and, subsequently, the reduced impact on trips under different investment options.

4. Demonstration Case Study

4.1. Study Area

New Zealand (NZ) consists of two main islands; the South Island with a land area of 150,437km^2 and a population of 1,058,052, and the North Island with a land area of 113,729km^2 and a population of 3,294,543 (StatsNZ, 2018). The South Island is the larger island, dominated by the Southern Alps which divides the east coast from the west coast, and contains seven regions and 23 districts. The transport network in New Zealand, including road, rail, sea, and air, is well-developed and well-connected containing: 11,000km of state highways; 80,000km of local roads; seven international airports; 28 regional airports; 4,000km of rail track; and 14 exporting seaports (MOT, 2017). The road network accounts for 84% of personal daily journeys and around 70% of freight tonne-kilometres (MOT, 2017). State highways carry around 50% of all flow, although they only cover 12% of all roads in NZ (MOT, 2017).

The State Highways and districts in the South Island are shown in Figure 3. State Highway 1 (SH1) connecting the north and the south of the island, along the east coast, carries the majority of traffic on the network, as the main cities including Christchurch and Dunedin are located on this side of the island. Parallel to SH1, there is SH6 on the west coast starting from Marlborough (on the top of the island) and ending in Invercargill (Southland District) where both SH1 and SH6 connect. Three corridors connect the east coast to the west coast, namely SH63, SH7 (Lewis Pass) and SH73 (Arthur’s Pass). In addition, SH6 connects the east and west, albeit at the very top of the island. In comparison to SH1, SH6 carries low traffic volumes on the west coast. The west coast is predominately a destination for tourists, with limited industries. The main ports and cities are all located on the east coast of the South Island, resulting in higher traffic volumes on this coast.

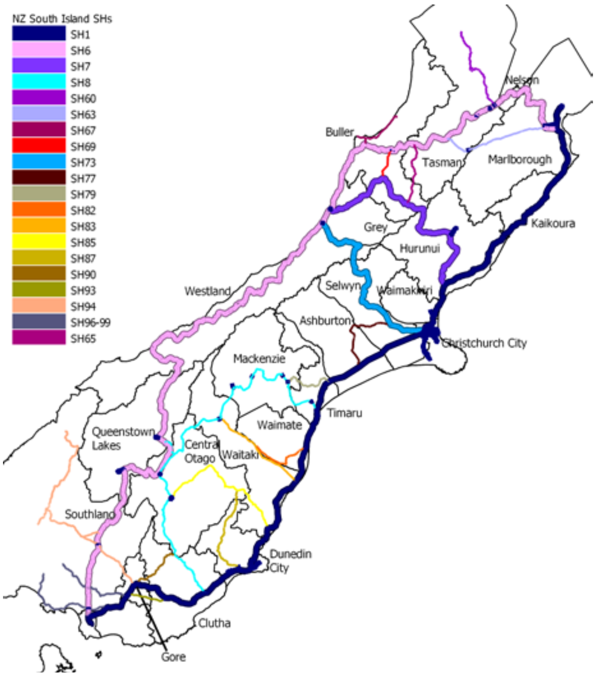

Figure 3: South Island State Highways and Districts

4.2. Alpine Fault Magnitude 8 (AF8) Earthquake Scenarios

The Alpine fault is the longest active fault in NZ, measuring more than 800km, with the largest average long term slip rate (Yetton, 2000). McCahon et al. (2006) stated that the effects of the AF8 earthquake will not be limited to only the West Coast and will, instead, influence the whole of the central South Island, including the main transportation corridors. Berryman et al. (2014) reported the probability of occurrence of an Alpine Fault Magnitude 8 (AF8) earthquake in the next 50 years as 30%, resulting in an estimated $10 billion in economic cost. Benn et al. (2002) reported that earthquakes (especially those associated with the Alpine Fault) have the potential to cause significant impact and damage to the West Coast Region. In response to this risk, the Alpine Fault Magnitude 8 (AF8) Project was established, funded through the Ministry of Civil Defence & Emergency Management's Resilience Fund. This is a collaborative effort to save lives by planning and preparing a coordinated response across the South Island after a severe earthquake on the Alpine Fault (AF8, 2020).

The most recent study detailing the potential physical impact of an AF8 earthquake on different infrastructure, including energy, telecommunication, water and wastewater, and transportation, was undertaken by Davies (2019). He extended the original 7-day Alpine Fault magnitude 8 earthquake scenario (Orchiston et al., 2016), from 7 days to 10 years, labelling it the AF8+ hazard scenario. The AF8+ scenario adopted the same northeast-directed 411 km rupture of the Alpine Fault between Fiordland and Lake Kaniere (F2K) as used in the original AF8 scenario, with corresponding ground shaking determined by Bradley et al. (2017). Disruptions to the transportation network were subsequently derived based on the scenario modelled fault rupture, shaking intensities, and landslide runout footprints, as well as information on local geology and asset vulnerability (Davies et al., 2021).

The physical disruptions to the transportation network following the event were then presented by Davies (2019), in a workshop environment, to relevant stakeholders, including representatives from various transportation agencies and civil defence personnel. They were asked to work through the recovery effort, given the actual resources at their disposal in practice and recent experience with the 2016 “Kaikōura” earthquake, and report on the status of infrastructure in terms of accessibility in ten time-steps. The ten time-steps, measured from the initial event, were one day, one week (7 days), one month (30 days), six months (183 days), one year (365 days), two years (730 days), three years (1095 days), four years (1461 days), five years (1826 days), and ten years (3652 days). The time steps provided points in time to report on the recovery effort, with greater spacing between steps as the time since the event increased.

Five of the scenarios are represented in Figure 4, namely one day, one week, one month, six months, and beyond six months after the earthquake. These five scenarios were used in this study and are briefly described below.

One day after the earthquake: The two main highways namely SH7 (Lewis Pass) and SH73 (Arthur's Pass) connecting the east of the South Island to the west and most parts of SH6 will be completely blocked causing three Districts, namely Buller, Grey, and Westland on the west coast to be isolated. Therefore, almost all inter-district trips from these three districts will be eliminated for at least six months. On the south-west part of the network, SH94 connecting Milford Sound to Te Anau will be disrupted, causing a significant number of eliminated trips for at least six months.

One week to one month after the earthquake: The NZ Transport Agency priority will be working towards opening SH7, SH 65, and SH69 to lower Buller (Davies, 2019), although they will remain closed to all types of vehicles for at least a month post-disaster, at which time only emergency vehicles will be allowed to travel on some corridors. Only a few local trips will occur between the three aforementioned districts where local roads will be reopened to provide accessibility.

Six months after the earthquake: SH65 and SH7 (Lewis Pass) will have returned to full functionality. As a result, compared to the previous scenario, fewer traffic zones will be blocked and more trips will be undertaken.

Beyond six months after the earthquake: Some parts of SH6 connecting Westport to Greymouth and connecting Franz Josef to Lake Hawea and also SH73 (Arthur's Pass) will still be closed causing ongoing unsatisfied demand.

To remove ambiguity in the time span it is assumed that the beyond six months scenario will occur one-year post-disaster. For this paper, it is also assumed that one-year post-disaster is the new normal and the end of the recovery process. The earthquake disruption will significantly impact the west coast of the South Island where three districts in this area, namely Grey, Buller, and Westland are significantly impacted. In addition to the three most impacted districts, other districts will be influenced moderately or slightly, depending on the distance from the earthquake epicentre and their number of trips to the most impacted districts.

The above scenarios provide estimates of the network accessibility at the pre-determined time steps. The reopening of sections of the network occurs between time steps – in contrast to the conceptual resilience plot presented in Figure 2. Consequently, the resilience plots in the following sections do not have stepped changes but, instead, depict gradual changes between time steps.

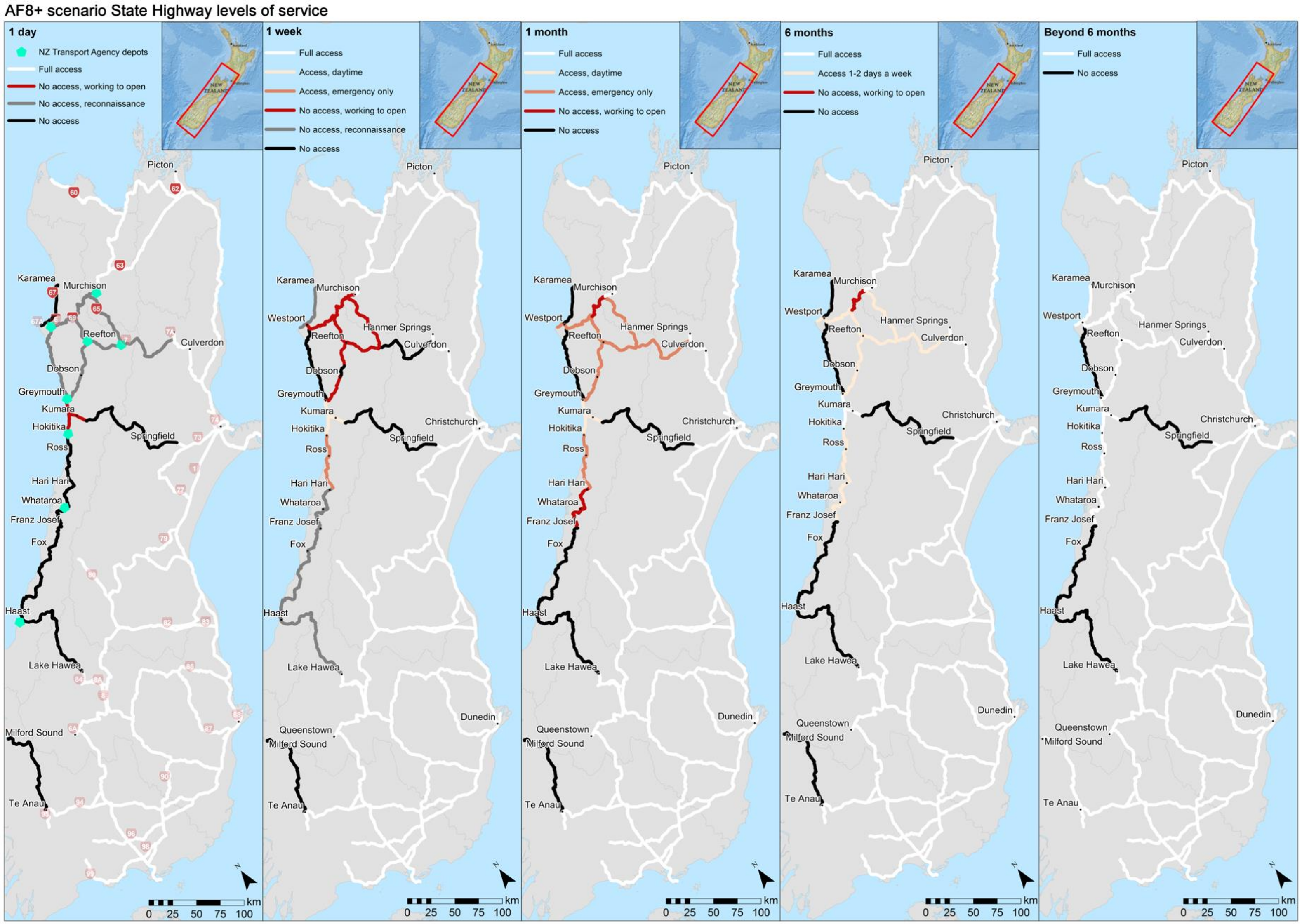

Figure 4: Expected Level of Services of the Road Network in Five Time Steps for AF8+ Scenarios (Davies, 2019)

4.3. Trip Resilience by District

A previously developed traffic simulation model of the South Island road network was used to calculate operational performance measures pre and post a potential Alpine Fault Magnitude 8 (AF8) earthquake, as reported in Aghababaei et al. (2020). In the simulation, trips are assigned to the calibrated network applying mesoscopic dynamic assignment and a stochastic route choice model. This allows re-assignment of trips to alternative routes when some roads are blocked and, to some extent, captures the stochastic nature of decision making in response to such an event. Specifically, the relevant Measures of Effectiveness (MoEs) were extracted for each OD pair at the chosen time steps outlined in the scenarios above, as well as for the pre-disaster situation. These operational measures were then used to calculate the resilience measures presented in Section 3 above.

Figure 5 shows the robustness, reliability, and resilience of trips on the whole network, as well as from the three most impacted districts, namely Grey, Buller, and Westland, to all other districts. To provide some context, the total number of BAU trips from all districts, Grey, Buller, and Westland are 637620, 12689, 5469, and 3223, respectively. The whole South Island road network resilience, presented in Figure 5a, considers all impacted and non-impacted trips on the network. It can be seen that the number of eliminated trips one day after the earthquake is around 2% of total BAU trips, and therefore, the network robustness drops to 98% followed by a further 1% reduction due to the lack of equivalent alternative routes, returning a reliability value of 97% for the whole road network. The reliability slightly rises to 98% after a week as more trips occur and robustness increases, with no further change for a month. With the reopening of SH65 and SH7 (Lewis Pass) six months post-disaster, almost all trips can occur. A negligible proportion of trips, compared to the total number of trips on the whole network, would occur with increased travel time. The reliability increases to 99% one year after the earthquake. Given that many local and inter-district trips network-wide (around 98%) will not be impacted by AF8, the *TR* and *NTR* of the whole network after one year of recovery are 357 units and 98%, respectively.

Referring to Figure 5b, 5c, and 5d, the impact of eliminated trips is significant in the three most impacted districts immediately after the earthquake, where the reliability drops to around 50% in all cases. Most of the remaining trips, predominantly intra-district trips, would occur with no increased travel time and, therefore, the reliability would decrease primarily due to eliminated trips. Reliability for Grey and Westland districts increases after a week, due to increased accessibility, mostly within districts, with no further change for a month. However, the reliability for Buller remains relatively unchanged. With the reopening of SH65 and SH7 (Lewis Pass) after six months, the robustness increases for all three districts – significantly in the case of Buller and Westland. While this provides more accessibility for a number of TZs, a proportion of the regenerated trips will be required to take a longer alternative route, resulting in increased travel time and, therefore, reduced redundancy. This is evident in Figure 5, particularly for Westland, where the proportion of the impact on reliability due to increased travel time increases, relative to that from eliminated trips. This is particularly pronounced in Westland as trips outside of the West Coast Region are required to first head north on SH6 and then across on SH7 (Lewis Pass) due to the continued closure of SH6 south of Franz Josef and SH73 (Arthur's Pass). After one year, the reliability improves further for Buller, in particular, with the opening of SH 67 linking Westport with Karamea and a section of SH63 East of Murchison.

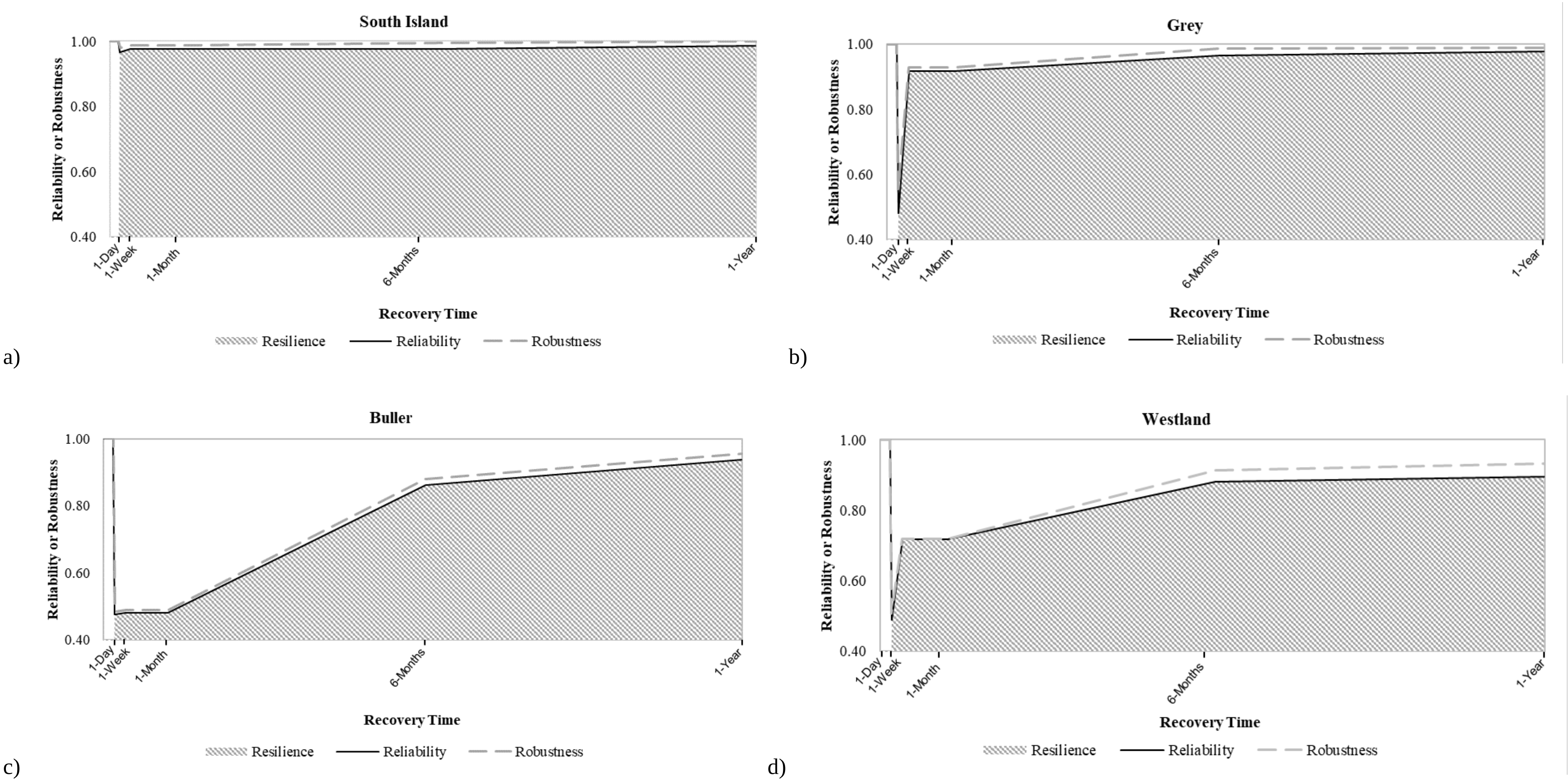

Figure 5: Robustness, Reliability and Resilience of Trips a) on the whole network b) from Grey District c) from Buller District d) from Westland District

Referring to Table 3, *NTR* was estimated for trips from the three most impacted districts to all other districts over the one-year recovery period. It can be seen that most of the intra-district trips for these three districts (highlighted ones) would occur without increased travel time, resulting in high *NTR*. Grey returns the highest *NTR* (95%), followed by Westland (83%) and Buller (77%). This can be explained by the fact that several TZs in Buller will remain inaccessible even one-year post-disaster, resulting in a lower overall *NTR* in comparison to the other two districts. *NTR* of trips from Westland to Queenstown and Southland are particularly low (3% and 11%, respectively), due to the isolation of some popular tourism areas in Westland for the whole recovery period (one-year) and the long alternative route from those TZs where travel can occur.

Referring again to Table 3, *EIT* was calculated to determine the most impacted OD pairs over the one year recovery period. Note that *EIT* is only estimated from the three most impacted districts to all other districts. In total, 635, 1265 and 534 equivalent daily trips from Grey, Buller, and Westland are impacted by the earthquake, returning 5%, 23%, and 16% of BAU trips, respectively. What is interesting is that although BAU trips from Grey are greater than Buller and Westland, the overall *EIT* from Grey is lower than the other two districts. The fact is that greater accessibility is provided for trips from Grey, albeit with increased travel time. The highest *EIT* occurs for trips within Buller, where disruption to some local roads results in eliminated trips. Given that the *EIT* from the three most impacted districts to Buller is relatively high (132, 611 and 185 from Grey, within Buller, and from Westland, respectively), trips within Buller would be recognised as a high priority to improve trip resilience.

Table 3: *NTR* and *EIT* of Three Most Impacted Districts Following AF8

Districts	**Grey**			**Buller**			**Westland**		
	BAU Trips (#)	***NTR***	***EIT***	**BAU Trips (#)**	***NTR***	***EIT***	**BAU Trips (#)**	***NTR***	***EIT***
Grey	11,211	98%	174	216	39%	132	692	91%	61
Buller	213	35%	138	4,267	86%	611	294	38%	181
Westland	668	92%	56	319	42%	185	1,785	97%	48
Christchurch	296	53%	139	308	56%	136	201	47%	107
Queenstown	103	51%	51	70	40%	42	44	3%	43
Marlborough	77	61%	30	145	51%	71	72	62%	27
Hurunui	35	69%	11	5	69%	2	16	65%	6
Nelson	29	67%	10	46	36%	30	32	58%	13
Selwyn	22	41%	13	23	44%	13	21	34%	14
Tasman	12	65%	4	24	39%	15	19	63%	7
Waimakariri	7	55%	3	15	54%	7	15	52%	7
Mackenzie	2	36%	1	2	52%	1	8	46%	4
Timaru	7	71%	2	4	65%	1	-	-	-
Kaikoura	5	67%	2	-	-	-	2	67%	1
Southland	2	25%	1	-	-	-	10	11%	9
Ashburton	-	-	-	12	21%	9	2	22%	2
Otago	-	-	-	7	19%	6	-	-	-
Dunedin	-	-	-	4	12%	4	1	47%	1
Invercargill	-	-	-	2	34%	1	-	-	-
Waitaki	-	-	-	-	-	-	5	70%	1
Overall	12,689	95%	635	5,469	77%	1265	3,219	83%	534

The top three impacted destinations from Grey are within Grey itself, to Christchurch, and to Buller with 174, 139, and 138 *EIT*, respectively, where disruption on SH6, connecting Grey to Buller, and SH7 (Lewis Pass), connecting the east coast to Christchurch, resulted in a high *EIT*. Over 1000 *EIT* in total arises from Buller to Grey, Westland, Christchurch and within Buller, indicating the high priority of these four districts for trips from Buller. The most impacted destination from Westland is Buller with an EIT of 181, around 62% of BAU trips, followed by Christchurch with an EIT of 107 (53% of BAU trips).

5. Application of Proposed Measures

The proposed measures can be applied to support the increase of resilience in transport infrastructure in a number of ways. In terms of recovery planning following a natural hazard event, such as the AF8, the proposed measures can be used to objectively compare the impact of different emergency response plans on trip resilience. The measures include the impact on resilience due to eliminated trips and, for those trips that can occur, increased travel time. In particular, the impact is assessed over the horizon of the post-disaster recovery phase. Response plans can differ in terms of, for example, the order of reopening of blocked links or the re-distribution of resources to accelerate the reopening of particular links. As an example, two proposed emergency response plans with equal recovery periods can be objectively compared and the plan which results in the greater trip resilience over the recovery period can be selected for implementation. The measures were also designed to enable emergency plans with different recovery periods to be compared. In such a scenario, one plan may seem attractive because it has a shorter recovery period, however, the recovery plan with the longer recovery period may in fact result in less impact on trips.

It is also possible to use the measures to assist with the prioritisation of proposed resilience mitigation measures in a constrained financial environment, typical of most road agencies. Such mitigation measures could include earthquake strengthening of bridges, slope stabilisation, passive rockfall protection structures or, indeed, the construction of alternative, more resilient, transportation routes. The financial cost-based metrics (Argyroudis et al., 2021, Zhang et al., 2015) commonly used in such assessments, can be supplemented with pre- and post-mitigation scenarios to quantify the improvement in trip resilience for each proposed mitigation measure.

Finally, the measures can also be used to determine the relative criticality of particular road links. For example, taking a hazard agnostic approach, the impact on trip resilience of a link being “broken”, for whatever reason, can be determined. Such critical links could then be given priority in terms of resilience assessment and, if required, funding.

6. Conclusion

The resilience of transportation networks, one of the most critical infrastructures in post-disaster situations, will have a significant influence on post-disaster operations, community resilience and business continuity. A trip resilience measure, which incorporates all three dimensions of resilience, namely *robustness*, *redundancy*, and *recovery*, in a combined measure has not been reported in the literature to the knowledge of the authors. Such a measure is needed if the complete picture of the post-disaster impact on trips is to be understood. Similarly, such a measure should be understandable to decision-makers and be capable of ranking the impact on different areas post-disaster, if it is to be of practical use to the profession.

In this paper, a conceptual Trip Resilience (*TR*) model is proposed to assess the resilience of trips on road networks following a disaster, integrating the three resilience concepts of *robustness*, *redundancy*, and *recovery*. The analytical formulations of measures capable of calculating the *robustness*, *redundancy*, and *recovery* impact on trips in a post-disaster environment were also developed or adapted from previous research, along with a means of integrating all three into a combined Trip Resilience (TR) measure. The measure is unitless and, at least theoretically, has no upper bound, hence it was decided to normalise the TR during the recovery period to create a measure that is easily understandable to decision-makers. The resulting Normalised Trip Resilience (NTR) measure reflects the resilience of trips in percentage for the period of recovery. Finally, in order to facilitate ranking of the impact on districts post-disaster, the Equivalent daily number of Impacted Trips (EIT) is proposed. The measure seeks to rank by impact, and is, therefore, a measure of vulnerability rather than resilience. The vulnerability is calculated by subtracting the NTR from unity, and this in turn is multiplied by traffic flow. Traffic flow is used as a criterion for importance in transportation and is commonly used when ranking or prioritizing. The EIT could potentially be used to facilitate resilience investment decision making on the network by ranking the impact on trips for different natural disaster scenarios and, subsequently, the reduced impact on trips under different investment options.

A regional case study was also conducted, to demonstrate the newly developed trip resilience measures, using a hypothetical Alpine Fault Magnitude 8 (AF8) scenario in the South Island of New Zealand. The resulting measures were capable of being calculated from the outputs produced by a transportation simulation model, thereby verifying their practicality in real-world situations. The importance of including both *robustness* (represented by the number of eliminated trips) and *redundancy* (represented by increased travel time), over the horizon of the post-disaster *recovery* phase was highlighted. Eliminated trips contributed significantly in areas that were cut off and isolated post-disaster, due to a lack of alternative routes, and increased travel time contributed as more roads were reopened but the alternative routes resulted in increased travel distances and, consequently, travel time.

In urban areas, where a number of alternative routes are typically available with similar or equivalent distance travelled, redundancy is expected to be high. In such cases, the increased congestion on these routes may result in longer travel times and, therefore, increased travel cost. It is recommended, therefore, that further research examine the use of the new resilience measures in an urban environment and for different network topologies. In addition, it could be used to assess the effectiveness of different recovery plans.

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