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Network resilience modelling: a New Zealand forestry supply chain case

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2020, Emerald Publishing Limited. Purpose: The objective of this research is to model supply chain network resilience for low frequency high impact disruptions. The outputs are aimed at providing policy and practitioner guidance on ways to enhance supply chain resilience. Design/methodology/approach: The research models the resilience of New Zealand's log export logistical network. A two-tier approach is developed; linear programming is used to model the aggregate-level resilience of the nation's ports, then discrete event simulation is used to evaluate operational constraints and validate the capacity of operational flows from forests to ports. Findings: The synthesis of linear programming and discrete event simulation provide a holistic approach to evaluate supply chain resilience and enhance operational efficiency. Strategically increasing redundancy can be complimented with operational flexibility to enhance network resilience in the long term. Research limitations/implications: The two-tier modelling approach has only been applied to New Zealand's log export supply chains, so further applications are needed to insure reliability. The requirement for large quantities of empirical data relating to operational flows limited the simulation component to a single region Practical implications: New Zealand's log export supply chain has low resilience; in most cases the closure of a port significantly constrains export capacity. Strategic selection of location and transportation mode by foresters and log exporters can significantly enhance the resilience of their supply chains. Originality/value: The use of a two-tiered analytical approach enhances validity as each level's limitations and assumptions are addressed when combined with one another. Prior predominantly theoretical research in the field is validated by the empirical investigation of supply chain resilience.

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NETWORK RESILIENCE MODELLING: A NEW ZEALAND FORESTRY SUPPLY CHAIN CASE

Abstract

Purpose: The objective of this research is to model supply chain network resilience for low frequency high impact disruptions. The outputs are aimed at providing policy and practitioner guidance on ways to enhance supply chain resilience.

Methodology: The research models the resilience of New Zealand's log export logistical network. A two-tier approach is developed; linear programming is used to model the aggregate-level resilience of the nation's ports, then discrete event simulation is used to evaluate operational constraints and validate the capacity of operational flows from forests to ports.

Findings: The synthesis of linear programming and discrete event simulation provides a holistic approach to evaluate supply chain resilience and enhance operational efficiency. Strategically increasing redundancy can be complimented with operational flexibility to enhance network resilience in the long term.

Value: The use of a two-tiered analytical approach enhances validity as each level's limitations and assumptions are addressed when combined with one another. Prior predominantly theoretical research in the field is validated by the empirical investigation of supply chain resilience.

Research limitations: The two-tier modelling approach has only been applied to New Zealand's log export supply chains, so further applications are needed to insure reliability. The requirement for large quantities of empirical data relating to operational flows limited the simulation component to a single region.

Practical implications: New Zealand's log export supply chain has low resilience; in most cases the closure of a port significantly constrains export capacity. Strategic selection of location and transportation mode by foresters and log exporters can significantly enhance the resilience of their supply chains.

Introduction

The elongated nature of modern supply chains puts them at risk to spatially dispersed disruptions that can have unforeseen and dramatic consequences. Political, economic, infrastructural and cultural risks need due consideration when operating globally. Tsunamis, strikes, hurricanes, biosecurity threats and wars can have significant impacts on logistical networks. The labour strike in October 2002 resulted in 29 ports in America's west coast shutting down (Wilson, 2007) whilst in 2011 Toyota's production capacity dropped by 40,000 vehicles due to Japan's tsunami and the consequent nuclear crisis (Pettit et al., 2013). These events and their disastrous consequences show the importance of having contingency plans for such events to minimise their effect along supply chains.

Supply chain resilience has developed as an approach to counter the risks inherent in globally dispersed networks. The literature provides a good coverage of the types of supply chain resilience (Jüttner et al., 2003, Cox et al., 2011), resilience assessment techniques (e.g., Wang and Ip, 2009), and management strategies and conceptual frameworks to facilitate supply network resilience (Soni et al., 2014). As previous research proposes redundancy as a means to deal with high frequency low impact risks (e.g., Chowdhury and Quaddus, 2017), this strategy is less applicable to more disruptive risks that have longer term affects and typically occur less frequently, such as earthquakes. Meanwhile, despite the significant conceptual advances, there is a dearth of empirical applications and practitioner focused approaches to mitigating supply chain risks (Brandon-Jones et al., 2014), particularly those relating to transportation (Ho et al., 2015).

Researchers have used different modelling tools to simulate systems under different conditions to prepare for disruptions and accordingly improve their responsiveness and resilience. These modelling tools include linear programming (Santoso et al., 2005), fuzzy modelling (Petrovic et al., 1998), discrete event simulation (Terzi and Cavalieri, 2004) and hybrid models (Umeda and Zhang, 2006). Some researchers focus on aggregate level analysis (e.g., Meepetchdee and Shah, 2007, Towill, 1996) while other researches address the micro level by isolating a certain part of the supply chain to be studied in depth (e.g., Legato and Mazza, 2001, Cheng and Duran, 2004). The integration of multiple tools in one approach would capture both strategic and operational considerations in the decision-making process in order to produce more valid recommendations.

Globalisation has significantly increased the number of international trade transactions, as many customers now compare products and services offered by suppliers from all around the world.

Consequently, marine traffic has witnessed a constant growth that is expected to continue into the future (Huang et al., 2016). This trend had increased the importance of ports within logistical networks. Local and central governments make significant investments and develop infrastructure dedicated to enabling the import and export of goods. Through the resilience modelling of a nation's logistical network current vulnerabilities and contingencies can be identified. In particular port capacity constraints and associated risks could be highlighted for island nations such as New Zealand.

New Zealand is a major exporter of logs in the global market, and it relies on its ports to deliver these products to its international customers. The forestry industry is a major contributor to New Zealand's economy providing more than 18000 jobs in 2014 (NZFOA, 2017). In 2013, New Zealand made up more than 20% of the world's softwood log trade and became the world largest exporter of softwood logs (Scoop, 2014). The log industry is a large part of New Zealand's exports contributing more than 16 million m^3 of logs in 2014 (NZFOA, 2017). The disruption of this supply chain by a port closure could have catastrophic consequences on New Zealand's economy, necessitating the creation of contingency plans for such events. Thus we plan on modelling the network resilience of New Zealand's log exports.

The resilience modelling of an entire country's logistical network will provide a novel empirical application. Our aim is to not only model the aggregate resilience of the network but also evaluate the operational product flows of this economically significant industry. This will provide a novel contribution by focussing on operational resilience of a real world network in regard to port capacity and system flexibility. This operational information will have more potential value for commercial decision makers in regard to port allocation and inland routing in times of port closures. The modelling at the operational level could also provide those involved in the export sector guidance on improvement initiatives to enhance efficiency.

In order to model the operational resilience of an entire county's network, an aggregate model is first required to match supply with export node that trades-off economic drivers, and then a regional material process flow model is needed to validate the top level assumptions. This approach has the potential to contribute to knowledge methodologically by combining aggregate and product flow modelling techniques when assessing network resilience. The empirical investigation of an entire country's supply network, for a significant export commodity, will contribute to the practical exploration of resilience, whereas the operational emphasis and focus on high impact and low frequency disruptions will provide novel insights into supply chain resilience.

The remainder of the paper is organised as follows. The next section provides a theoretical basis for the research by discussing prior studies of supply chain resilience and risk management, both in regard to conceptual development and modelling techniques. The method section then explains and further justifies the proposed approach and is naturally followed by the results that are split into the macro national resilience assessment and micro regional flow evaluation. The discussion links the findings with prior research and highlights how the insights could be further extended, and finally a succinct conclusion is provided that summarises the contribution.

Literature Review

Supply chains are subject to a range of risks and disruptions, which can lead to negative consequences and significant losses. In the literature, supply chain risks are defined as the probability and the effect of any unforeseeable events and circumstances that might impair the performance of any part of the supply chain (Ho et al., 2015). Disruptions happen when an event prevents the flow of material from following its normal path and arriving on time (Svensson, 2000). Such disruptions could be small scale, such as machine breakdowns, or more significant due to major events such as wars, unforeseen disasters, and biosecurity threats (Blackhurst et al., 2005). Supply chain disruptions can significantly affect business performance, for example in 2000 Ericson lost 400 million Euros due to a fire at a supplier’s plant (Chopra and Sodhi, 2004).

Supply chain risk management literature is focussed on alleviating the negative consequences of supply chain disruptions. Typically, risk management is concerned with the identification, classification, and quantification of risks along the supply chain, and involves the development and implementation of mitigation strategies (Jüttner et al., 2003). While conventional risk management approaches provide guidance to mitigate frequently occurring risks, disruptions with a low probability, yet with long-lasting adverse effects, are often neglected (Ribeiro and Barbosa-Povoa, 2018). To address this, our work models a national log supply chain after low-probable but large-scale disruptions, and explores operational approaches to increase network resilience.

Resilience originates from ecological systems (Holling, 1973), and has subsequently been extended to economic systems, transportation systems, and supply chain networks. In regard to the latter resilience is the adaptive capability “to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function” (Ponomarov and Holcomb, 2009). To achieve resilience a supply chain network requires both proactive and reactive capabilities, the former includes redundancy and flexibility, and the latter relates to the ability to respond quickly during critical situations (Chowdhury and Quaddus, 2017, 2016, Pettit et al., 2010).

To measure resilience, supply chain network studies have two distinct approaches: one has its roots in graph theory, which views the networks as nodes, arcs and flows and focuses on the topological properties, and the other approach is system-based and focuses on the demand and supply aspects of a network (Mattsson and Jenelius, 2015). When studying a nation-wide network, it is necessary to take the system approach and measure the resilience of the network as a whole. Thus, this work follows the definition in Christopher and Peck (2004) who conceptualises resilience as “the ability of a system to return to its original state or move to a new, more desirable state after being disturbed”, and compares the after-disruption state with the original state to indicate network resilience.

Different measures have been used to evaluate network resilience when disruptions occur. Quantifying resilience as dependent on demand and supply, Wang and Ip (2009) applied resilience to aircraft service, and developed a network resilience metric based on the weighted sum of the resilience of each node. Falasca et al. (2008) assessed supply chain resilience to disasters from three dimensions: density, complexity, and node criticality. Soni et al. (2014) identified major enablers of resilience through a survey, and proposed a resilience index which incorporates several aspects including agility, collaboration, adaptive capability, and network structure. Further, Kim et al. (2015) differentiated nodes/arcs disruptions versus network disruptions, and proposed a metric for supply network resilience based on the proportion of node/arc disruptions resulting from a network disruption. Consistent with Chen and Miller-Hooks (2012) and Meepetchdee and Shah (2007), this work considers the reduced throughput after disruptions, and uses the ratio of quantity that can be exported before and after disruption as a resilience index. In addition to the network flow optimisation considered in previous works, we go one step further and model the implications on operational constraints post-disruption.

The performance of a supply chain network after disasters depends not only on its network design but also the actions that can be taken after the disruption (Chen and Miller-Hooks, 2012). Zhang et al. (2019) identified three typical approaches used to mitigate the outcome of low-probability high-consequence natural disasters in order to increase network resilience. The first approach is to increase system redundancy by creating extra capacity for the same type of services. The second one is system hardening strategies, by strengthening the innate ability to resist disruptive events. The third approach is operational resilience strategies, referring to activities and operations for increasing system flexibility and responsiveness. Among these three strategies, the first two focus on building the proactive capability upfront before disruptions, and the third one primarily focuses on operations post-disruption but could be designed beforehand in the network. Not surprisingly, operational resilience approaches have demonstrated superior advantages over the other two, because effective operational strategies make the system flexible and reconfigurable and are more economical achievable (Zhang et al., 2019).

To effectively leverage operational resilience after disruptions requires flexible and responsive reconfiguration of the network, and this is consistent with the principle that resilience building is dynamic and adaptive (Chowdhury and Quaddus, 2015, Ambulkar et al., 2015). There are several recent studies employing the operational resilience strategy, for example, Arıkan et al. (2017) included aircraft cruise speed control decisions in airline recovery modelling, and Fang et al. (2016) combined capacity expansion and transmission switch installation decisions when modelling resilience of electric systems. While these papers include operational decisions for responses after disruptions, they model resilience of airline scheduling, electricity transmission, or engineering systems, which are distinct from a supply chain network. The latter network requires dynamic resilience strategies to maintain continuity of operations which can include rerouting, input and output substitution, and removing operation impediments (Cox et al., 2011). As current resilience work focuses on rerouting and substitution, the remove operational impediments are yet to be fully explored. Thus our work incorporates post-disruption operations into the analysis, and studies how effective operational decisions can help enhance resilience.

Resilience has been quantified and evaluated through different modelling approaches, depending on the scope and application of the models. Optimisation is a classic way to solve network design problems and has been extended to incorporate network resilience. Harrison et al. (2013) conducted resilience analysis by iteratively removing a node and re-optimising the remaining network, and this relatively simple approach generates useful insights. More comprehensive resilience optimisation models soon become very complex (Hasani and Khosrojerdi, 2016) especially when combined with inventory management considerations (Boone et al., 2013, Spiegler et al., 2016). When modelling disruptions containing uncertainty and complex factors, simulation provides the flexibility and relevance to quantify resilience. Berle et al. (2013) used Monte Carlo simulation combined with optimisation to model resilience after maritime transport disruptions. Munoz and Dunbar (2015) built a simulation model to quantify resilience from multiple transient response measures across multiple tiers in a supply chain, whereas Adjetey-Bahun et al. (2016) modelled a network both before and after disruptions and derived resilience indexes. All these studies used numerical examples to implement their proposed models, but there are very limited empirical studies with real data and practical applications in supply chain resilience (Kamalahmadi and Parast, 2016). Thus studies of resilience that use data from actual networks are needed to enhance theory development and validation.

The scope and decision level at which network resilience is studied varies. Resilience is usually considered a holistic network property, thus most studies aim to address resilience at the strategic level and look at top level decisions (Ribeiro and Barbosa-Povoa, 2018). There are minimal studies that consider operational decisions, perhaps due to the empirical data required for such research. With real data from a national logistical network, this research will help bridge these research gaps by investigating both the aggregated level and the operational level decisions. While it enables the identification of weak nodes/links and sequential mitigation actions in operations, this work also provides a feasible tool to quantify network resilience and mitigate the effects of infrequent yet large-scale disruptions.

Research Methodology

A two-tiered modelling approach was developed to evaluate the resilience of a supply chain network, as illustrated in Figure 1. In order to optimise the overall supply chain and identify the subsequent resilience of the network, linear programming was utilised. Once this top level, aggregate technique allocated forests to ports using different modes of transport, the planned allocation became inputs into the regional discrete event simulation. This micro level analysis provides feedback into the linear programming model as a means of validation so the theoretical resilience level derived in the linear programme model can be achieved. Linear programming was selected for its ability to optimise the objective function (Bazaraa et al., 2011) whereas discrete event simulation was utilised to simulate dynamic systems (Law, 2006). By combining linear programming and simulation, this work provides a more holistic and realistic view of operational supply network resilience.

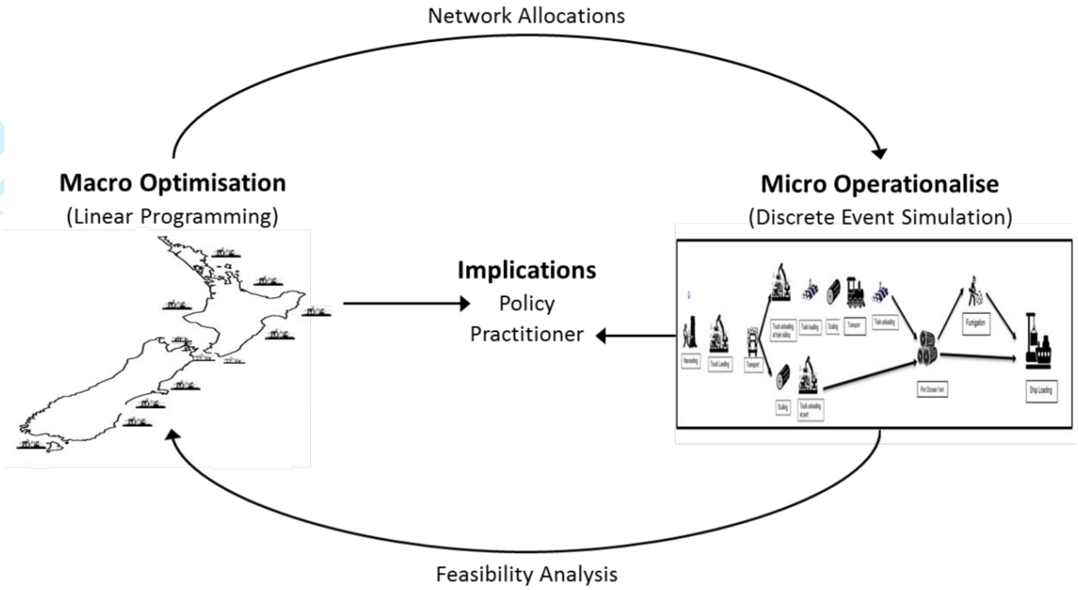

Figure 1. Two Tier Iterative Resilience Modelling Approach

A linear programme model was created to evaluate New Zealand's logistical network under different port closure scenarios. The objective function optimised supply chain profitability by allocating logs harvested in different forests across the country to available ports. This model provides an aggregate view of the country's logistical network, evaluates the resilience index, and identifies focal ports worthy of further investigation. However, as this model considers port and transportation capacity at the aggregated level without incorporating specific operational activities, the resilience index is theoretical and subject to the operational capability of the network. Through the simulation at the operational level, specific constraints preventing the full implementation of the allocation were identified and elevated, and so the targeted throughput identified in the linear programme can be realised and the estimated resilience level achieved across the network.

Scion (Scion, 2016), the country's leading forestry Crown Research Institute, provided the majority of the primary data, in conjunction with other governmental agents and multiple actors of the log export sector. The data collected from Scion will be referred to as (Scion, 2016) or (Scion, 2017) depending on the year of collection. The national level modelling first required estimating the port capacity and the log supply for export. The capacity of each port was evaluated using historical data of the log export volume handled by each port during the period January 2010 to June 2016, which was obtained from the Ministry of Primary Industry (MPI). Figure 2 provides a breakdown of quarterly volume in m^3 by port, and highlights the importance of Whangarei, Tauranga and Gisborne ports; these three north island ports account for 64% of export volume.

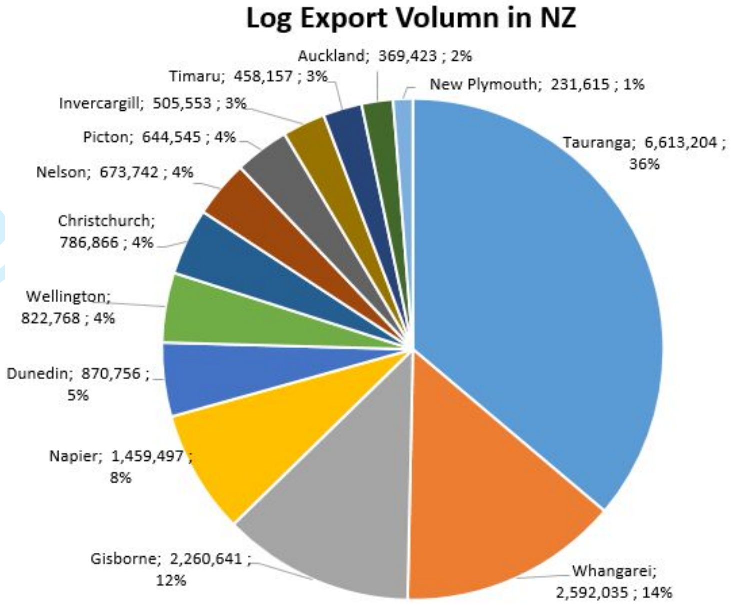

Figure 2. New Zealand Logs Exports by Port (adopted from NZFOA, 2017)

For each port, the annual volume was obtained by multiplying the historical maximum quarterly volume by four, and was assumed to be 70% of the port's maximum annual capacity (Scion, 2017). The derived capacity for each port is shown in Figure 3, together with their geographic locations. The North Island is divided into five wood supply regions and the South Island is divided into four, with each region consisting of several forest districts. The annual regional volume for export from each forest district was derived by deducting the domestic demand from the total forestry production volume.

The linear programming optimisation was run multiple times. The initial allocation of forests to ports provided a baseline then each of the ports was closed sequentially, creating different disruption scenarios. The resilience level was derived by comparing the volume of logs being exported in each scenario with the base case, thus identifying vulnerabilities and contingencies in the national network.

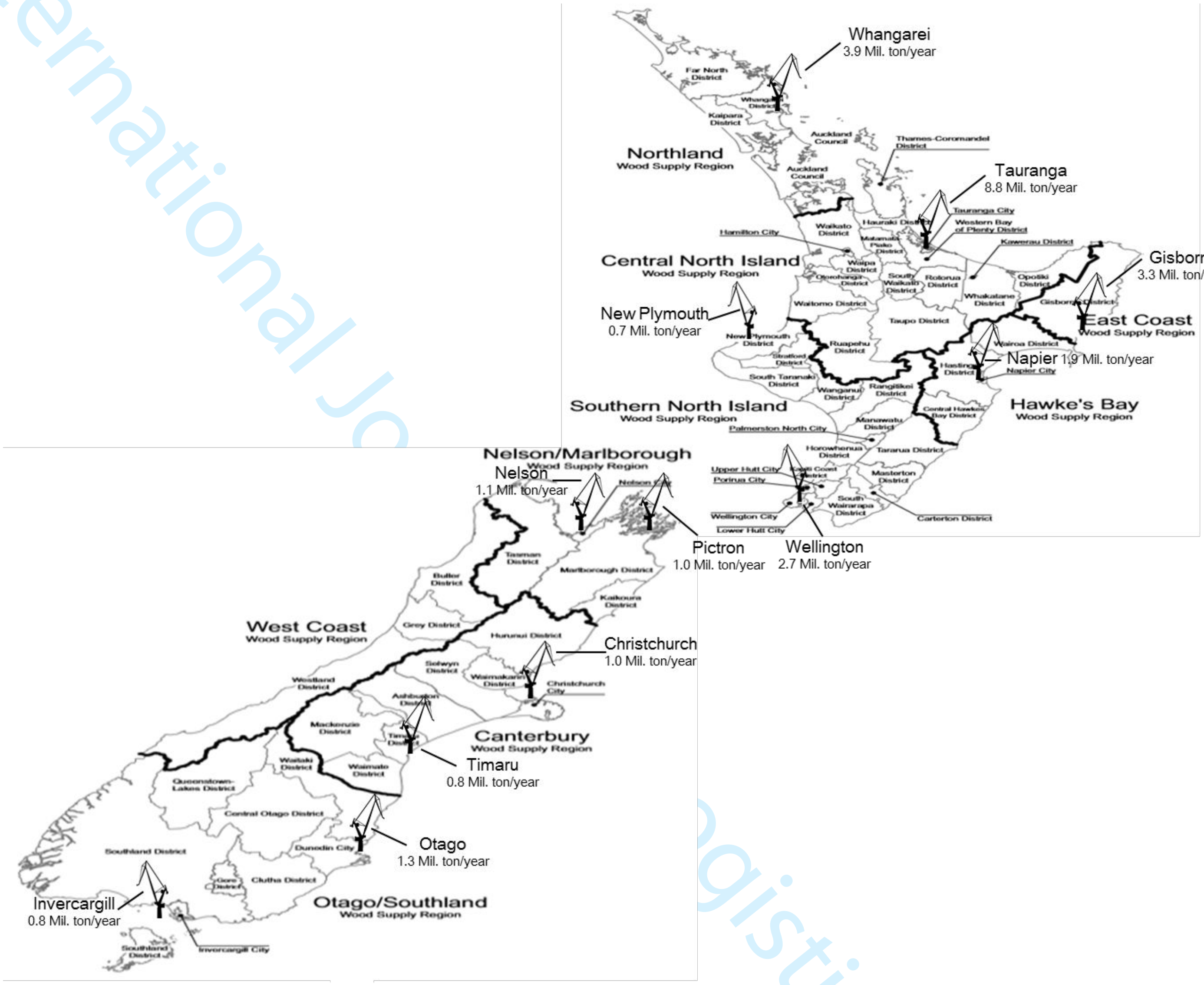

Figure 3. New Zealand Log Port Capacity, Regions and Territorial Districts (adopted from MPI, 2017)

In order to model the operational flows, a simulation model was built based on the processed logs proceed through from harvesting until loaded onto a ship (see Figure 4). The sequence of activities, along with available capacities and the statistical distributions of time needed to execute each activity were collected from practitioners and secondary sources. There are two transportation modes for inland transport, rail or road, costs associated with each are evaluated and compared, and the least cost option is selected for each forest. The simulation model was conducted using the discrete event simulation software ExtendSim.

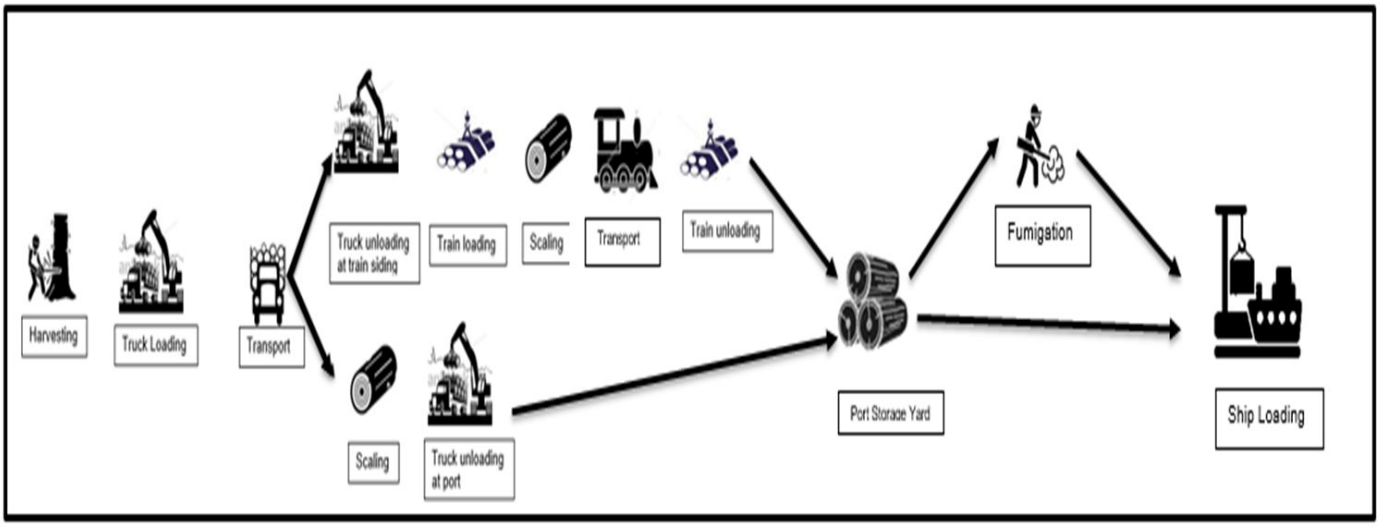

Figure 4. Domestic Log Supply Chain Activities

Macro Analysis and Results

The allocation of logs for export distributed through the network was solved by the linear programme. The decision variable of interest is the quantity of logs to be exported from each forest district through available ports, where Q_{ij} denotes the quantity of logs handled in port i from forest district j. The port capacity and the exported log volume set constraints for the linear programme to decide Q_{ij}. The capacity of port i is denoted by C_i, and the log volume to export from forest j is denoted by M_j. Essentially the model solves a network allocation problem that has been well studied, so the linear programme formulation was adapted from Meepetchdee and Shah (2007) and appropriately tailored for the log network studied herein. The mathematical formulations are included as an Appendix.

The objective function maximises the total profit of the entire network via the allocation of logs to ports. The total network profit is formulated as the total revenue minus costs, where the total revenue equals the total exported volume ($\sum_i Q_{ij}$) multiplied by the selling price and the cost terms include harvesting, transport, and port operations. The same selling price coefficient is applied for all ports under normal circumstance, and during disruptions price is adjusted in line with resultant supply reductions. Both the total network profit as the objective function and the set of constraints are formulated using decision variables Q_{ij}, capacity C_i, supply M_j, and different price and cost factors (see Appendix). The model is run with the set of constraints under the objective function of maximising the total profit, and solves the shipping quantity Q_{ij}. Then, $\sum_j Q_{ij}$ gives the total volume shipped through port i, and the port utilisation is calculated by $\sum_j Q_{ij}/C_i$.

In discussion with Scion and industrial representatives, it was decided to model a 12 month closure as this was a likely duration due to a significant earthquake or bio-security issue. The initial allocation is the base scenario where all ports are operating then the linear programme was run for each of the ports being closed. As a result, forest allocation changed as some forests were rerouted to alterative ports from the one originally allocated. An alternative to reallocation is the delay of forest harvesting thus creating a 'waiting' option. This resulted from the special feature of the forest industry: forest owners can choose to not harvest in order to avoid log shipping delays when ports are closed, and naturally the trees continue to grow during the postponement. While waiting incurs an additional maintenance cost to manage the forest, the growth increases the value of logs when harvested after the closed port reopens (see Table 1). This is different from conventional inventory where the value of the goods remains consistent or often decreases when shipping is delayed. A dummy port was added to the model to represent the waiting option.

	Profit	Total cost
Without port closure (normal condition)	Average price * Quantity shipped − Total cost	Transportation cost + Forest harvesting cost + Port operations cost
With port closure (after disruptions)	Increased price during port closure* Quantity shipped + Decreased price after port closure * Quantity waiting + Additional revenue due to forest growth during waiting − Total cost	Transportation cost + Forest harvesting cost + Port operations cost + Waiting cost

Table 1. Profit and Cost Components Before and During Port Closure

Beside the waiting option, the log price is volatile and fluctuates with changes in supply when a port is closed; this is likely to happen given New Zealand is the world's largest exporter of softwood logs and is influential in global log prices. Thus, the selling price of logs is assumed to increase proportionally to the volume that is scheduled to be exported through the port; this assumption was verified by practitioners. Similar external effects exist when the closed port reopens: selling price will restore to a lower level, and can even be lower than the original price because excess logs due to waiting may flood the market.

For this national log supply chain network, how logs are reallocated indicates the network's ability to cope with port closure events, in regard to whether logs can be rerouted and exported through other ports, or need to be delayed and wait for the port to reopen. This can be reflected by the resilience index of the network. Following Chen and Miller-Hooks (2012) and Meepetchdee and Shah (2007), calculation of the resilience index considers the reduced volume of logs that can be exported after port closure, and compares the after-disruption volume with the before-disruption volume of exported logs. Accordingly the resilience index is $\beta = \sum_{i \neq a,\ i \neq 0} Q_{ij} / \sum_j M_j$, where port a is closed and port 0 is the dummy port i.e. waiting option. A high resilience index would indicate sufficient operational capacity is available across the network to support the closed port, as a high proportion of logs can still be exported.

	North Island						
	All Ports Working	Tauranga Shut Down	Wellington Shut Down	Napier Shut Down	New Plymouth Shut Down	Whangarei Shut Down	Gisborne Shut Down
Tauranga	77%	Closed	83%	83%	90%	93%	83%
Wellington	77%	77%	Closed	100%	81%	77%	99%
Napier	77%	99%	100%	Closed	77%	77%	100%
New Plymouth	77%	87%	85%	85%	Closed	77%	77%
Whangarei	77%	77%	77%	77%	77%	Closed	77%
Gisborne	77%	100%	77%	88%	77%	77%	Closed
Resilience index	—	92%	95%	95%	87%	95%	88%
	South Island						
	All Ports Working	Nelson Shut Down	Christchurch Shut Down	Otago Shut Down	Invercargill Shut Down	Timaru Shut Down	Picton Shut Down
Nelson	57%	Closed	57%	57%	57%	57%	57%
Christchurch	72%	72%	Closed	72%	72%	72%	76%
Otago	83%	83%	83%	Closed	83%	83%	83%
Invercargill	29%	29%	29%	100%	Closed	31%	29%
Timaru	70%	70%	75%	83%	70%	Closed	70%
Picton	58%	58%	58%	58%	58%	58%	Closed
Resilience index	—	83%	83%	83%	94%	85%	85%

Table 2. Port Utilisation and Network Resilience Results

Table 2 contains the resilience index and port utilisation results for the alterative scenarios. The two islands have been modelled separately as the cost to transport logs between them is excessive and exceeds the value of the product. In the initial state, where all ports are operating, all logs are exported, and the ports operate at 77% capacity in the north island and between 29% and 83% in the south island. These can be combined with utilisation ratios in port closure scenarios to indicate the efficiency and importance of each port and the network vulnerabilities. It is clear that the impact on the network resilience varies depending on which port is disrupted. When the more isolated ports are closed, such as

New Plymouth and Gisborne in north island and the majority of south island ports, a large proportion of logs cannot be exported, leading to a low resilience index (below 90%) for the network.

Figure 5 graphically illustrates the resilience under each port closure scenario. The bar on the right represents the log quantity that could be exported through each port without disruptions and the left bar shows the quantity of logs waiting to be harvested because of the port closure. A small difference between the two bars represents a low resilience level, because most of the logs that are supposed to be exported through the port wait and are not exported; as in the case of Port Nelson and Christchurch. Yet this is not always the case as the resilience index formula is relative to the total quantity scheduled for the whole network, not an individual port. The North Island ports are well supported by one another, except New Plymouth port as the majority of logs are forced to wait resulting in a low resilience level. The dispersed nature of the South Island means most of the logs remain waiting during a shut down, leading to low resilience levels for the South Island ports.

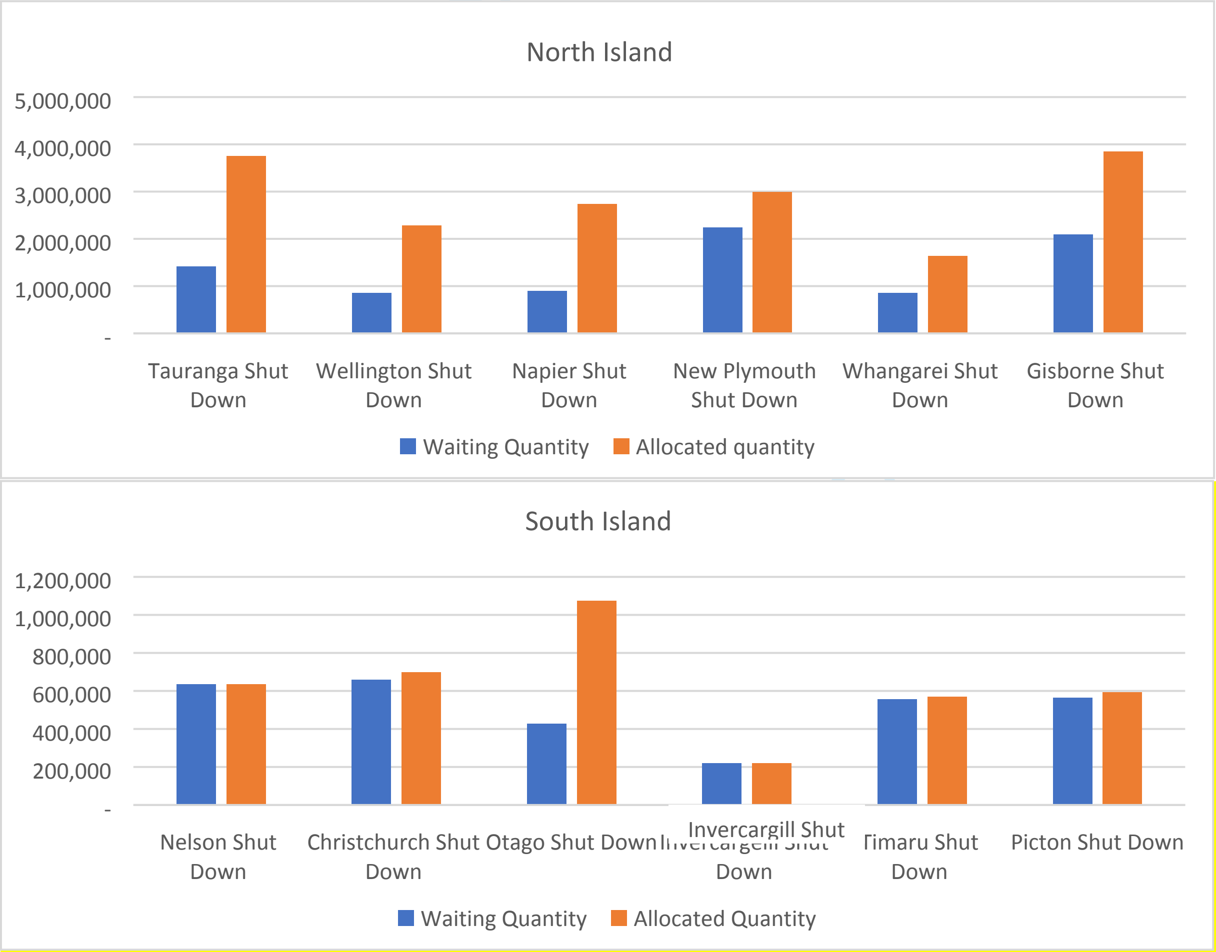

Figure 5. Resilience Results: Allocated versus Waiting Log Quantities

The macro analysis identifies focal ports that are critical in improving the resilience of the whole network. Napier port is a good example because this port is almost fully utilised in three out of five port closure scenarios, as shown in Table 2. Even without disruptions, it is necessary to improve its operational capabilities or expand the capacity for Napier port when possible, so it can better support the wider network. On the other hand, the South Island does not have such a focal port which means they are less supported and the network is less resilient, it does however constrain the impact of disruptions to regional areas so the extended influences on other ports are limited.

Key findings from the macro analysis are the different mitigation strategies and management approaches appropriate for the different ports, based on their individual situations and importance to the resilience of the network. Each closure event forced the linear programme to redistribute forests to available ports differently, which provides insight into the strategic importance of some ports. The analysis reveals the relations between the different factors that affect the resilience of the logistical network. The effect of transportation costs and price changes highlight how these influence the resilience and profitability of the supply chain. Detailed analysis of each forest district can assist forest owners in selecting more resilient forest locations that can better cope with unexpected port closures.

Micro Analysis and Results

While the macro analysis provides insights on how well each port is supported in the network, the reallocation may not be fully achievable because of factors not considered in the optimisation, such as inland transportation and port operations. This leads to the micro-level analysis, using simulation for the port closure scenarios, in order to develop a more holistic risk mitigation plan that includes both strategic and operational level insights. To investigate operational constraints and their impact on the network, the iterative thinking process of theory of constraints was employed to identify, investigate, and address bottlenecks.

To illustrate how this operational-level simulation model works, the closure of Wellington port for a period of one year was analysed. Wellington port was forced to suspend its operations because of an earthquake in 2016, thus providing a realistic example to compare with the results derived in this study. As is shown in Figure 6 (a), Wellington port serves eight forest districts under the normal situation. After the port is closed, these districts are either waiting until the port reopens or rerouted to Napier and New Plymouth ports. Figure 6 (b) shows how the linear programme redistributed the forests to the supporting ports. It is interesting to notice that some of the forests that were originally allocated to

Napier port (which was not closed) were reallocated to other ports, thus making capacity available at Napier port. The reallocation clearly puts pressure on the logistical network, especially on the supporting ports and the local facilities which will need to process additional volumes.

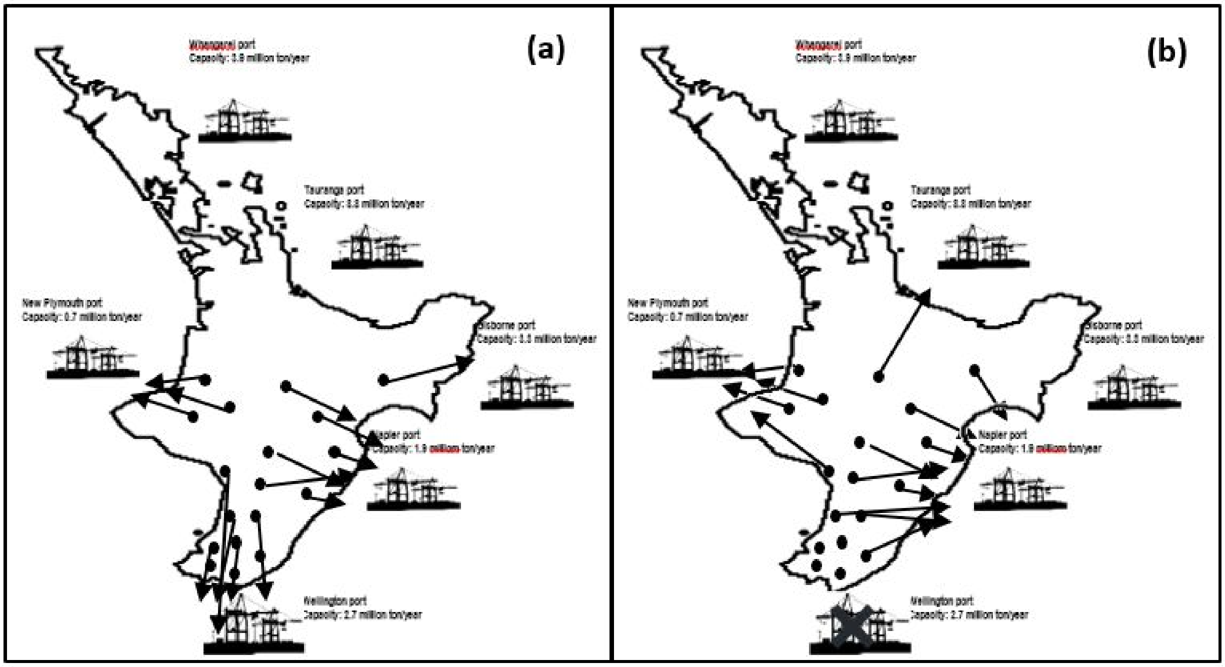

Figure 6. Forest Allocation Before and After Wellington Port Closure

Two types of forests are modelled: those originally allocated to Wellington port that require rerouting; and others that will be sharing the same facilities with the rerouted forests such as train sidings, trucks, port storage yards, and vessels. By adding the second type of forests, the spill-over effects of the closure of Wellington port are included in the model, thus exploring the externality of the rerouted logs. To uncover the operational constraints for the Wellington port closure scenario, a series of simulation models were run to iteratively address the constraints/bottlenecks. Table 3 lists the simulation results for the four scenarios modelled. The first simulation model ('Initial Status' in Table 3) identified what the network can process at each of the different operational stages without making any improvements. The results of this base scenario simulation showed that the total throughput of Napier and New Plymouth ports was less than 50% of the total amount allocated to them after closing Wellington port. This suggests the network fails to export the total volume allocated by the linear programming model, so the achieved throughput ratio is lower than the resilience level derived in Table 2. The next step is to identify the operational constraints that prevent rerouted logs from being shipped and to explore ways to elevate the operational constraints.

In the base scenario, the performance of the operational facilities at different stages of the supply chain was investigated, such as truck loading and unloading, train scaling and unloading, port operations, and ship loading and unloading (See Table 3 'Initial Status' results). It turned out that most of these activities were underutilised with rates lower than 50%; the highest utilisation was 72% for the train scaling and unloading at Napier Port, which, though relatively high, suggests adequate capacity for additional volumes. So loading and unloading activities were not the constraints, and the bottleneck is somewhere else in the supply chain. A further investigation of the operational activities revealed that the truck scaling and unloading at New Plymouth port were blocked for 71% of the time. That is, trucks had to wait at New Plymouth port for scaling and unloading, and this created significant congestion. The New Plymouth yard turned out to be the main cause of the congestion: while the scaling and unloading facilities were underutilised and remained well below full capacity, the New Plymouth yard was full most of the time, leaving no space for incoming trucks to unload logs. The congestion at New Plymouth yard was also affecting the throughput of Napier and other ports because the constrained truck resources were restricting the transportation of logs to other ports and train sidings.

Process	Location	Initial Status		New Plymouth Loading Rate		Napier Train Unloading		New Plymouth Ship Arrival	
		Util. %	% Que	Util. %	% Que	Util. %	% Que	Util. %	% Que
Port Fumigation	Napier	38	0	58	60	0	0	67	0
Wharf 2 loading	New Plymouth	36	0	34	39	0	0	50	0
Wharf 1 loading	New Plymouth	36	0	33	38	0	0	50	0
Wharf 3 loading	Napier	18	0	24	30	0	0	36	0
Wharf 2 loading	Napier	18	0	24	29	0	0	36	0
Wharf 1 loading	Napier	19	0	26	31	0	0	37	0
Truck unloading	New Plymouth	18	71	29	32	38	1	39	0
Truck scaling	New Plymouth	28	71	44	71	38	1	64	1
Truck unloading	Napier	9	0	12	14	0	0	19	1
Truck scaling	Napier	11	0	22	24	1	0	31	0
Train unloading/ scaling	Napier	72	0	100	60	0	0	70	0
Rail line	Woodville to Napier	8	41	18	18	20	85	20	29
	Waingawa to Woodville	4	25	7	8	8	91	10	12
	Palmerston North to Woodville	0	21	1	2	6	88	4	10
Train loading	Woodville	3	8	7	8	3	54	10	6
	Waingawa	8	11	17	19	2	83	22	3
	Palmerston North	8	7	16	18	1	69	20	0
Truck unloading	Woodville	1	0	1	2	0	0	4	0
	Waingawa	2	0	5	5	0	91	8	0
	Palmerston North	1	1	5	5	1	22	8	0
Truck loading	Tararua	23	0	49	50	0	0	40	0
	Hastings	22	0	48	49	0	0	37	0
	Ranagatiki	21	0	42	40	0	0	32	0
	Central Hawkes Bay	23	0	48	48	0	0	36	0
	Stratford	22	0	48	47	0	0	36	0
	Ruapehu	8	0	10	14	0	0	12	0
	Waitomo	29	0	54	60	0	0	94	0
	Wanganui	30	0	56	62	0	0	95	0
	Masterton	29	17	56	57	27	24	64	38
	Horowhenua	21	0	40	40	0	0	30	0
	Manawatu	24	0	49	48	0	0	40	0

Table 3. Simulation Scenario Results: Process Utilisation (Util. %) and Percentages of Queuing Time (% Que)

There are several potential ways to address the bottleneck of New Plymouth port yard, yet not all options are plausible. One intuitive solution would be to increase the size of the yard at New Plymouth Port; however it fails to solve the issue for two reasons. One, the cost of expanding the yard is prohibitive, and the expanded yard would not be sustainable after Wellington port reopens. Two, experimenting with the simulation model shows that even after expansion the yard simply fills up again and the network quickly becomes congested once more. Seemingly an alternative could be to divert trucks to other neighbouring ports like Napier. Though it can ease the tension at New Plymouth, it creates problems by generating congestions at other port yards and inland transportation. Further, diverting forest outputs to other ports is a sub-optimal solution from the network's perspective. One viable approach is to increase the ship loading rate at New Plymouth port. Initially this does not require installing new cranes, but can be achieved by directing all available cranes to log ship loading when possible. Nevertheless, it would require the port to make a relatively small investment in machinery and labour, which could be justified by the improvement in throughput. The network throughput increased by 64% after increasing the loading rate at New Plymouth port. Although the improvement was only performed at New Plymouth port, the throughput of other ports increased as well because of the improved efficiency in the shared truck resource. Further, the utilisation of other activities in the supply chain increased because the quantity of logs handled increased. This confirms that the New Plymouth port was the network bottleneck and that exploiting it generates positive externality to other elements of the logistical network.

The increase in throughput by exploiting the New Plymouth port yard was not sufficient to discharge all the logs scheduled for shipping as total throughput only improved to 71%, which is still lower than the 95% resilience level calculated in Table 2. Further improvements are needed to enhance the performance of the network, and again the bottleneck needed to be identified and addressed. This was done by investigating the operational performance of different activities after exploiting the New Plymouth port loading rate (see Table 3, 'New Plymouth Loading Rate' results). The bottleneck moved to the train sidings at Napier port, because of an increased log arrival rate, thus putting pressure on both inland transportation and port operations. This was confirmed by the increased utilisation rates in all scaling and loading/unloading facilities at the ports and forests sites, regardless of transportation mode. Of all these facilities, the train scaling and the unloading operation at Napier Port could not cope with the increased volume and quickly reached capacity. Consisted with Theory of Constraint principles (Goldratt and Cox, 2016) addressing one constraint often reveals a new bottleneck for the elevated system.

The strategy to address this new constraint was similar to the previous one: to increase the speed of train scaling and unloading activity at Napier port, since increasing the number of trucks or the size of the train sidings will not help. To achieve faster processing for the train scaling and unloading requires an additional team for both tasks. The standard process started with scaling the first three wagons of the train, which provides space for unloading machinery to work safely; the unloading operation starts once the first three wagons are scaled, and then both operations are carried out in parallel on the same train. Having an additional team for both scaling and unloading would allow operations from both ends of the train, and this could decrease the time needed by approximately 50%. This strategy improved the system throughput by 13%, allowing more logs to be shipped. However, with this change, some of the logs diverted from Wellington port could still not be shipped, with about 20% still being held back. So, further improvements were needed to export all rerouted logs.

Results of the ‘Napier Train Unloading’ scenario of Table 3 suggest that exploiting the constraint at Napier port moved the bottleneck back to the port at New Plymouth as the yard became congested once more. This is because the operational changes at Napier port generate a ripple effect on the volume going to New Plymouth port. To resolve this problem, the discharge rate at New Plymouth port needed to increase to allow more log ships to call at the port. At the operational level, one solution would be to reroute non-log ships to other ports so more log ships can be discharged at New Plymouth port. This would require coordination with other ports, but could save significant infrastructure investments that will be required for other alternatives like building a wharf or installing a crane, and thus was considered plausible under the temporary closure of Wellington port. This change generated a 24% increase in the network throughput, and now all the rerouted logs can be shipped, since all operational activities are able to cope with the allocated quantities of logs (See Table 3, ‘New Plymouth Ship Arrival’ scenario). The reallocation plan derived from the macro level analysis was fully implemented, leading to the realisation of the 95% resilience index for the Wellington port closure scenario.

Figure 7 summarises the impact of exploiting each constraint on the throughput of each port and the resultant work in process (WIP) inventory level in the supply chain. Herein the WIP represents the quantity of logs that are allocated to be exported according to the macro level analysis but are held up due to insufficient operational capacity. The WIP level in the base scenario was higher than both ports’ throughput combined. Releasing the first constraint significantly improved the throughput of both ports and caused the WIP level to drop. Reducing the train unloading time to address the second constraint also increased the exports volume in both ports, more so at Napier. After exploiting the third constraint, the WIP dropped to almost zero, which indicates the logistical network was able to export the vast majority of the allocated quantity.

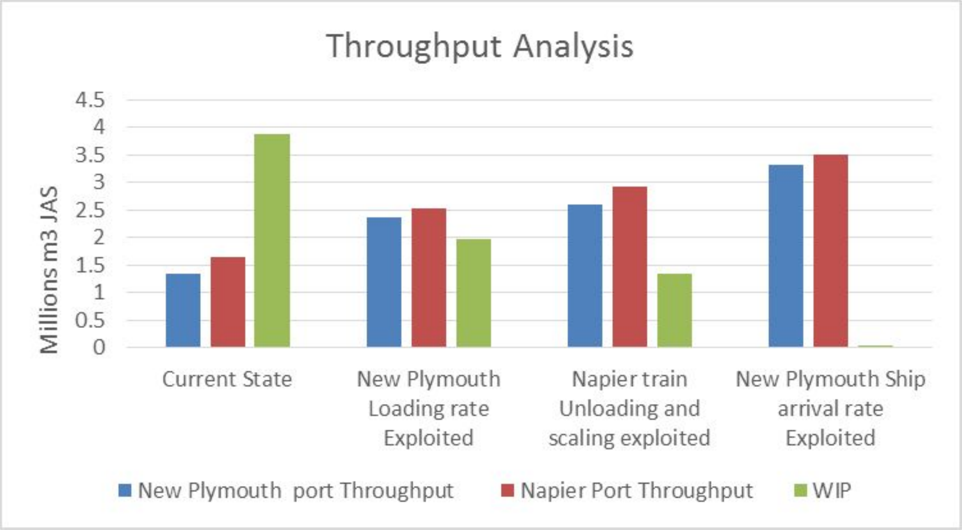

Figure 7. Impact of Releasing Constraints on the Logistical Network Throughput

Overall, the results from the operational level simulation model conform to what happened in 2016 when a major earthquake forced Wellington port to suspend operations. During that time, logs were rerouted to Napier port, which caused congestion in the network. This is consistent with the results of the linear programme and the simulation. However, because the closure in 2016 only lasted for two months, the spill-over effect to New Plymouth port did not emerge as the model predicted. Still the disruption caused by the earthquake revealed some of the dynamics of responding to a Wellington port closure and helps to validate the results of this research. By considering port closure for an extended period, i.e., a year, this research provides insights on severe disruptions that could push the logistical network to its limits, and proposes operational mitigation strategies to enable a more resilient export log network.

Discussion

The overriding objective of this research was to model the operational resilience of a supply chain network and identify strategies to increase system flexibility. This was achieved by synthesising macro and micro level modelling techniques that iteratively evaluated supply network resilience. Approaches used to date tend to focus on strategic or operational level analysis yet fail to capture both levels simultaneously, e.g. Meepetchdee and Shah (2007) at the macro level and Legato and Mazza (2001) at the node level. The approach adopted herein provides researchers with insights into the benefit of using multiple analytical tools. The linear programming model provides a theoretical resilience index that assumes no operational constraints. This shortcoming is addressed by the simulation that models the specific operational activities and sequentially removes operational constraints.

By focussing on low frequency high impact disruptions, it has become clear that simply increasing network redundancy is insufficient (e.g., Zhang et al., 2019) to enhance resilience in the long term. Due to the availability of rich empirical data it was possible to model the entire network, not just reconfiguration strategies from a focal firm perceptive (e.g., Legato and Mazza, 2001), thus providing a means to evaluate system wide supply chain network resilience. Flexibility came to the fore as a means to achieve resilience when modelled holistically, whilst the ability of alterative nodes to take up the stress when others were out of action was closely related to spatial dispersion (Nair and Vidal, 2011) and contingent capacity.

The research identifies which of New Zealand's ports are of strategic importance for overall resilience. Napier port in the North Island is called upon in most scenarios, whereas Otago and Wellington ports are well covered by neighbouring ports. New Plymouth port is identified as a significant weak point in the logistical network. In addition to the top level policy input for central and regional government, our approach also provides guidance for practitioners. The simulation of operational flows identifies bottlenecks and mechanisms to enhance supply chain efficiency. Input into decisions regarding transportation mode and forest-port allocations are provided. The resilience of regional forests export channels are evaluated, and costs associated with domestic supply chain operations are identified. With further enhancement the two tier modelling approach could be developed into a decision support tool for forest owners and log exporters.

Limitations in the proposed method stem from the nature of the analytical tools used. Even though the sequential use of linear programming and discrete event simulation captured more details of the logistical network, some real world assumptions were still required. These limit the ability of the model to reflect the growing complexity of globally elongated modern supply chains. The empirical data used in the research provided a rare contribution to supply chain resilience modelling in practice, however the quantity of primary data on regional supply chain flows inhibited the full application of the proposed method. The selected product, forestry, is also novel in regards to the potential to delay harvest rather than store inventory. This is both a unique modelling context and an area that requires further research to verify the results in more typical supply chains, such as automotive. The analytical focus of our approach overlooked the behavioural aspects of different companies operating in the industry as well as their assets, contracts and relational drivers that affect their decisions during a port closure. Finally, more work is also needed to evaluate port capacity rather than using historical data as an estimate.

Conclusion

This research has contributed to knowledge in two ways. Methodologically, via the development and testing of a two-tiered modelling approach for network resilience using empirical data, this approach has overcome many of the inherent weaknesses of using a single method by cross-validation of an aggregate optimisation tool with a detailed operational simulation technique. In combination they provide accurate policy and practitioner guidance to enhance the resilience of supply chain network of an entire industry, and also offer specific operational insights within regions.

Several theoretical contributions can be argued resulting from the research. The focus on operational resilience via system flexibility complements prior research that predominantly model strategic resilience leading to the development of contingency plans. On the contrary the research demonstrated how increasing network redundancy can be insufficient to enhance resilience in the long term. This research has also provided new insights into low frequency high impact disruptions, such as earthquakes, rather than the more traditional noise type resilience modelling.

Application of the tool provided insights for policy makers in regard to the vulnerabilities and overall resilience of the country's port capacities. As an island nation, dependent on the export of commodities, this insight is critical for the economic sustainability of New Zealand. The approach also provided practitioners with insights into the operational material flows of their domestic supply chains and mechanisms to enhance efficiency and resilience.

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Appendix: Formulation of the Macro Level Linear Programming Model

Notation	Meaning
Q_{ij}	Decision Variables: the quantity of logs handled in port i from forest district j, where $i = 0,\cdots,E$ and $j = 1,\cdots,n$.
M_j	The total volume of logs for export from forest district j, where $j = 1,\cdots,n$.
C_i	The capacity measured in total volume of logs that can be exported through port i, where $i = 0,\cdots,E$; and $i = 0$ represents the dummy port for the waiting option.
X_{ij}	A binary variable showing whether port i is the primary port for forest j, that is, $X_{ij} = \begin{cases} 1, \text{If port } i \text{ is the primary port for forest } j, \\ 0, \text{Otherwise.} \end{cases}$
XS_{ij}	A binary variable showing whether port i is a secondary port for forest j, that is, $XS_{ij} = \begin{cases} 1, \text{If forest } j \text{ is allowed to use port } i \text{ as a secondary port,} \\ 0, \text{Otherwise.} \end{cases}$
Y_i	A binary variable showing whether port i is closed due to disruptions, that is, $Y_i = \begin{cases} 1, \text{If port } i \text{ is closed due to disruptions,} \\ 0, \text{Otherwise.} \end{cases}$

Table A1. Key Notation in the Linear Programming

Constraints	Formulation	Meaning
Logistics flow feasibility	$Q_{ij} \le M_j \cdot (X_{ij} + XS_{ij}), \forall\, i,j$	Port i can only receive logs from forest j if it is a primary or secondary port for forest j, and the quantity of logs coming from forest j is less than or equal to the total volume available for export from forest j.
Port availability	$Q_{ij} \le C_i \cdot Y_i, \forall\, i$	Port i cannot be assigned any logs quantity if it is closed
Port capacity	$\sum_{j=1}^{n} Q_{ij} \le C_i, \quad \forall\, i$	The total volume of logs allocated to port i from all forests should not exceed the port capacity C_i.
Forest volume capacity	$\sum_{i=0}^{E} Q_{ij} = M_j, \quad \forall j$	The total quantity handled by all the ports, including the dummy port, for forest j should equal the total volume available for export from forest j.
Alternate port availability	$XS_{ij} + \ X_{ij} \le 1, \forall\, j,i$	Port i cannot be both the primary and secondary ports for any forest j.
	$XS_{ij} \le Y_i, \forall\, j,i$	Port i cannot be the secondary port for any forest j if it is closed.
Primary port constraint	$\sum_{i=1}^{E} X_{ij} = 1, \quad \forall\, j$	There is only one primary port for each forest j.
Non-Negativity constraint	$Q_{ij} \ge 0$	The quantity should be non-negative.

Table A2. Key Constraints in the Linear Programming

Cost Components	Formulation	Notation and Assumptions
Total transportation cost for the network, which is based on the following two items:	$\sum_{i=1}^{E}\sum_{j=1}^{n} \min\left\{Ct_{D_{ij}}, \min_{s}\left(Ct_{F_{js}} + C_r RL_{si}\right)\right\} Q_{ij}$	The transportation cost from forest j to port i is the smaller cost between the train cost and the trucking cost.
Trucking cost from forest j to port i	$Ct_{D_{ij}} Q_{ij}$	$Ct_{D_{ij}}$: The trucking unit cost per ton for the trucking distance between forest j and port i
Train cost from forest j to port i	$\min_{s}\left(Ct_{F_{js}} + C_r RL_{si}\right) Q_{ij}$ That is, to compare the train costs of using different sidings, and the siding with the lowest train cost is chosen.	$R_i = \begin{cases} 1, \text{If port } i \text{ has rail facilities,} \\ 0, \text{Otherwise.} \end{cases}$ $Ct_{F_{js}}$: The trucking unit cost per ton for the distance between forest j and train siding s, where $s = 1, \cdots, k$ C_r : The train unit cost per ton per Km RL_{si}: The rail distance between train siding s and port i if $R_i = 1$, and $RL_{si} = M$ if $R_i = 0$, where M is a sufficiently large number. That is, the rail cost will be prohibitively large if there is no rail facilities in port i.
Forest waiting cost of forest j	$'W_j = CH_j + \sum_{i=1}^{E} \min\left\{Ct_{D_{ij}}, \min_{s}\left(Ct_{F_{js}} + C_r RL_{si}\right)\right\} Q_{0j} X_{ij}$	CW_j: The total forest waiting cost of forest j. Note the waiting quantity needs to be transported and exported through its primary port after the closed port reopens, so the waiting cost includes the transportation cost of shipping the waiting quantity to its primary port.
Holding cost of forest j	$CH_j = (CM_j + CO_j) Q_{0j}$	CH_j: Inventory holding cost of forest j CM_j: The cost of maintaining a ton of logs from forest j for another year CO_j: The lost opportunity cost resulting from delaying selling a ton of logs from forest j Q_{0j}: The quantity of logs allocated to wait from forest j. Note port $i = 0$ represents the dummy port for the waiting option.
Cost of port and harvesting	$\sum_{i=1}^{E}\sum_{j=1}^{n} (Cp_i + Cv)\, Q_{ij}$	Cp_i: The port cost for shipping per ton of logs at port i. Cv: The sum of general harvesting costs for per ton of logs.
The total cost	$Cst = \sum_{i=1}^{E}\sum_{j=1}^{n} \min\left\{Ct_{D_{ij}}, \min_{s}\left(Ct_{F_{js}} + C_r RL_{si}\right)\right\} Q_{ij} + \sum_{j=1}^{n} CW_j + \sum_{i=1}^{E}\sum_{j=1}^{n} (Cp_i + Cv)\, Q_{ij}$	

Table A3. Cost related functions in the Linear Programming

Revenue/Profit components	Formulation	Notation and Assumptions

Revenue due to increased price during port closure	$IP_i = Pa \cdot (1 + I_i)$	IP_i: The increased log price per ton after port i is closed. Pa: The average price of log per ton for the last 20 years. I_i: The price increase percentage when port i is closed.
Revenue due to decreased price after port closure	$RP_i = Pa \cdot (1 - L_i)$	RP_i: The reduced log price per ton after port i closure finishes. L_i: The price reduction percentage after port i closure finishes.
Additional revenue due to forest growth during waiting	$IR_j = N_j Q_{0j}$	IR_j: The total increase in revenue for the quantities waiting in forest j. N_j: The increased revenue per ton of logs from forest j after one year's waiting.
Profit	$\text{Profit} = \sum_{j=1}^{n} (\sum_{i=1}^{E} IP_i Q_{ij} + \sum_{i=1}^{E} RP_i Q_{0j} X_{ij} + IR_j) - Cst$ The objective function is $\max_{Q_{ij}} \text{Profit}$.	

Table A4. Revenue and profit functions in the Linear Programming

Revisions: Network Resilience Modelling: A New Zealand Forestry Supply Chain Case

The reviewer's comments have been instrumental for improving the manuscript, we are very grateful for their insightful critic. The following table states the actions taken to address each recommendation and the location of the revisions within in the manuscript.

Section	Reviewer Comments	Actions Taken to Address
Introduction	R1: A very high similarity has been noticed with the previously published paper, thus authors are advised to reduce it significantly.	The modifications made to the paper in line with the reviewer's recommendations have significantly altered the paper so similarities with other works should be minimised.
	R2: The authors mention that modelling resilience of a network is novel but the contribution needs to be positioned carefully, given there are literature on this topic. You need to argue how your work is different from others.	The latter half of the introduction has been modified to specifically position the research in regard to its novel focus on low impact/ high frequency disruptions and empirically modelling operational resilience.
Literature Review	R1: More recent and relevant articles need to be quoted for improving its literature. R1: Relationship to Literature; need to cite a few more articles. R2: Literature review is extensive and nicely articulated. However, I find that there is a lack of reviewing recent papers on resilience. I also suggest the authors including some of the important papers in the literature section as for example Chowdhury and Quaddus 2015; Ambulkar et al. 2015; Chowdhury and Quaddus 2016; Pettit et al. 2013. R2: I also suggest the authors conceptualizing resilience in accordance with the theme of the paper. For example in some papers resilience is conceptualized as the ability to return to normal/original state or even better state (see Christopher and Peck 2004; Chowdhury and Quaddus 2017 as example). So based on the theme of your paper you need to conceptualize resilience so that it lays the foundation of your findings and analysis.	The literature review has been significantly overhauled with changes to paragraphs 3-9. Specifically several recent and relevant articles, along with the ones suggested by R2, have been added to the literature review. This highlights the contributions of the work and its relationship with previous literature. As R2 suggested, following Christopher and Peck (2004), resilience has been conceptualised as "the ability of a system to return to its original state or move to a new, more desirable state after being disturbed". This is linked to the resilience index defined in this research, which compares the after-disruption state with the original state.

Research Methods	R1: Methodology; Not clearly described. R2: Methodology has been well written and easy to follow. I suggest the authors include the mathematical equations relating to optimization in the methodology section.	The methods applied for the two techniques utilised have been further explained (paragraphs 2, 4 and 5) in the methods section. The LP equations have been included as an appendix.
Results	R1: The interpretation of the result is not very clear and it should be adequately written where the application of linear programming is not understandable. R2: Presentation of results need to improve specifically- need to include graphs/tables to show simulation results. I also suggest more explanation and literature support relating to the formula-resilience index.	The results have been streamlined and clarified by moving some of the method explanations to the proceeding sections and the addition of two further results visuals (Figure 5 and Table 3). Further, literature has been added to validate the resilience index used and emphasis placed on the connections between the two levels of analysis.
Discussion	R1: Results; Needs to be improved by comparing with other works. R2: Well written R2: The paper needs to show fundamental contribution with regards to theory and methodology.	In line with the revised introduction the discussion has been re-written to focus on the originality of the research (paragraphs 1 and 2); conceptually in regard to operational resilience flexibility and high impact low frequency disruptions and methodologically in regard to the integration of two techniques to model resilience based on a rich empirical dataset.
Conclusions	R1: The author should focus more on stating the outcome of the research in a precise manner and rewrite the conclusion section.	The conclusions have been completely re-written focussing on the methodological, theoretical and practical contributions.
Articulation	R1: Quality of Communication; Average. Needs improvement.	The paper is been proof read and abbreviated significantly to streamline the narrative.