

Climate-Resilient Supply Networks for Small Island States

A Discrete event-based Approach

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Summary

Small Island Developing States (SIDS) face vulnerability to supply chain disruptions due to their geographical isolation, infrastructural limitations, and heavy dependence on imported goods. Despite advancements in logistics and resilience modeling, existing frameworks are typically designed for larger, more connected systems and fail to account for the unique logistical constraints of SIDS. This thesis addresses that gap by developing a discrete event model grounded in a four phase freight framework. The model simulates the flow of goods of like food, medicine, and fuel under conditions of uncertainty, using logic tailored to island infrastructure and behavior.

The model builds upon the framework proposed by the four step transport modeling approach, generation, distribution, mode choice, and assignment, but is adapted for SIDS through simplifications and extensions suited to low data contexts. Cold chain prioritization, fragmented demand generation, and congestion sensitive dispatching are all explicitly modeled to hold true to SIDS specific operationalization. a discrete base event queue manages system operations, enabling simulation of time based disruptions and network delays. By introducing perishability, transport constraints, and batch scheduling, the model balances simplicity with the complexity required to represent real world island conditions.

Insights from fieldwork in the Seychelles and expert conversations inform key behavioral parameters, such as the informal handling of cold goods, the limited separation of goods in transport, and the absence of formal distribution networks. bring empirical insight into storage constraints, inter island transport scheduling, and vehicle distribution rules to simulate realistic disruptions and recovery behavior.

With "service level" as performance indicator for the model an Monte Carlo simulation is done to bring insight in to the working of the model. which showcase that Storm duration and timing a larger effect have on performance the operational variables in the model. These correlations are further investigated during different disruptions showcasing showcasing that in the current model setup the build up of disruption have a larger effect then longer sustaining disruptions on service level. Different behavior for different islands groups (Main/inner/outer) are identified and showcase that the network wide approach is key for SIDS.

Different adaptations strategies are tested that showed promise for resilience building in the constraint environment that are SIDS. Through limitation in the model/approach not a conclusive answer was found however recommendations are made that a balancing of adaptations strategies is key in order to create network wide resilience in SIDS.

Acknowledgments

This thesis marks the conclusion of my Master's studies in Complex Systems Engineering. Over the years I questioned which subject would truly capture my attention, and for the past six months I have been fortunate to find a topic that fascinated me from start to finish. While I am relieved to be submitting this work, I can honestly say I thoroughly enjoyed every step of the journey. I believe the network-based approach developed here holds real promise for quantifying the impact of adaptation measures in SIDS logistics systems. Although this thesis breaks new ground, it also faces many limitations, challenges I almost preferred to tackle on my own. But tp everything has to end and ss they say in the Seychelles, **Finis coronat opus** ("the end crowns the work").

I am deeply grateful to my supervisors Prof. dr. Tina Comes, Dr Omar Kammouh, Adele Cadario and in particular Jasper Verschuur, for their guidance and support through this not always as easy process (for me). Jasper, thank you for providing critical data, for our motivating catch ups, and for encouraging me to keep going even when the project felt it was becoming to big.

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Contents

Summary	i
Acknowledgments	ii
Nomenclature	vii
1 Introduction	1
1.1 Problem statement	2
1.2 Objective and Research questions	3
1.3 Thesis Structure	3
2 Theoretical background	4
2.1 Current status of supply networks in SIDS	4
2.1.1 Maritime transport systems	5
2.1.2 Air transport system	5
2.1.3 Humanitarian aid logistics system	6
2.2 Impact measures on the community for SIDS	7
2.2.1 Impact on community	8
2.2.2 Performance indicators of a freight system	9
2.2.3 Resilience Curves	10
2.3 Resilience interventions	11
2.3.1 Adaptation strategies	12
2.3.2 Limitations of SIDS for resilience interventions	14
2.4 Holistic approach	14
3 Case study	16
4 Research Methodology	19
4.1 Expert opinions	19
4.1.1 Stakeholder selection	20
4.1.2 Outcomes of expert conversations	20
4.2 Modeling approach	23
4.2.1 Layout of the graph	23
4.2.2 Basis of four step transport model	24
4.2.3 Discrete event simulation	29
4.2.4 Batch Dispatch and Delivery	33
4.3 analytic approach	34
4.3.1 Disaster Disruptions in the model	34
4.3.2 Adaptation implementation in the model	36
5 Model results and Discussion	38
5.1 Monte Carlo Simulation	38
5.2 Disruption Scenario's	42
5.2.1 Storm Duration Effects	42
5.2.2 Disruption Type (3 ,Day Baseline)	43
5.3 Regional Variations	44
5.4 Strategic Implications for Resilience Planning	45
6 Discussion & limitations	47
6.1 Discussion	47
6.2 Limitations	48
6.2.1 Effect Size vs. Practical Relevance	48

6.2.2 Link to Future Work	48
7 Conclusion	49
7.0.1 Recommendations for Practice	49
7.0.2 Final Reflections	50
References	51
A Ai use	55
B Literature review overview	56
C Data gathering	58
C.1 Tables	58
C.2 Monthly Freight Volume (2018–2024)	58
D Reflections on Climate Modeling and Infrastructure Disruption Modeling in SIDS	67
D.1 Disaster Disruption Scenarios for Simulation	67
D.2 Adaptive Strategies in SIDS: A 5–10 Year Review	70
D.2.1 Integrating Climate Risk into Asset Management	70
D.2.2 Infrastructure Hardening and Design Standard Enhancements	70
D.2.3 Diversification of Supply Routes and Modal Integration	71
D.2.4 Digitalization, Early Warning, and Decision Support Frameworks	71
D.2.5 Pre positioning Stocks and Decentralized Logistics Hubs	71
D.3 Case Study: Seychelles	72
D.3.1 Vulnerability Profile	72
D.3.2 Vulnerability and Adaptive Response of Port Victoria	72
E Additional results	73

List of Figures

2.1	Freight costs as per cent of the value of imports (UNCTAD 2014)	4
2.2	Liner shipping connectivity, direct lines (UNC 2022)	4
2.3	Port cargo overview, (Goeverden et al. 2020)	6
2.4	Airport cargo overview	7
2.5	Classification of disruptive events that create risks for freight transport systems (Adapted from SIPA 2023).	8
2.6	Conceptual resilience curve suggested by (Sun et al. (2020))	10
2.7	Impact on infrastructure 1 (UNCTAD 2014)	12
2.8	Impact on infrastructure 2 (UNCTAD 2014)	12
2.9	Four classifications of adaptation strategies	13
3.1	Overview Seychelles	16
3.2	Overview Inner Islands	16
3.3	Port of Seychelles	18
3.4	Seychelles International Airport	18
3.5	Highlighted version of Ministries (Dark blue), departments (blue) and agencies (light blue) in Seychelles	18
4.1	Variations in interview instrumentation (Patton 1990)	19
4.2	Overview of points of interest and road infrastructure: (a) Mahe, (b) Praslin with La Digue, and (c) the full inter island network.	24
4.3	Examples of transport vehicles used in the Seychelles.	29
4.4	Overview of freight storage locations across the islands: (a) Mahé port warehouse, (b) Praslin warehouse, (c) La Digue storage, and (d) airport cargo zone.	30
5.1	service vs. storm duration	42
5.2	service vs. disruption mode	43
5.3	service vs. 5 day storm duration	45
D.1	Floods praslin 2004	68
D.2	Floods Mahe 2004	68
E.1	Quantile regression	74
E.2	Base case	74
E.3	1d Node Cap DG	75
E.4	5d Node Cap	75
E.5	7d Cap	76
E.6	7d Edge Cap DG	76
E.7	7d Node Cap DG	77
E.8	14d Node Cap Dg	77
E.9	Spread Main islands	78
E.10	Spread Inner islands	78
E.11	Spread outer islands	79
E.12	Overview of queue's in port and and ports for a disruption run of 14 days. Arrival peak of 15.000 T boat creates almost as high as queue	79

List of Tables

3.1	Major Disruptions in Seychelles (2002–2024)	17
4.1	Insights from Expert conversations	20
4.2	Node types and counts in the transport network (Total edges: 2848)	24
4.3	Direct month wise comparison of average imports (2016–2024) based on tourism (per person) and freight (Seychelles Rupee).	26
4.4	Assigned seasonal ratios for shops in Anse Royale, Mahé	27
4.5	Relative Percentage Change in Goods Transported High to Low Season	27
4.6	Overview of Transport Modes and Characteristics	28
4.7	Triangular Unloading Distributions and Node Unload Capacities	31
5.1	Monte Carlo sensitivity parameters: ranges, rationale, and baseline sources	39
5.2	Kpi outcomes at $n = 400$. Both KPIs lie within pre specified tolerances.	40
5.3	Summary of linear (Pearson), rank based (Spearman), and concordance (Kendall) correlations for key storm modifiers. Full table in Appendix E	40
5.4	Partial Rank Correlation Coefficients (PRCC) between each scenario modifier and key performance indicators, controlling for all other inputs.	41
5.5	Summary of resilience metrics	44
5.6	Adaptation evaluation under 3d storm	46
B.1	Search Keywords Categorized by Core Concepts	56
B.2	Comparison of Analyzed Papers, first 13; non specific - second 4; SIDS specific	57
C.1	Monthly goods imports in tonnes. AVG* excludes COVID-period years (2020–2021).	58
C.2	Monthly freight import volumes in kg (approximate).	58
C.3	HS Code Summary: Trade Volumes and Allocation Counts	59
C.4	HS Code Compatibility with Vessel and Facility Types	62
C.5	Mean and standard deviation of mt/hour by vessel subtype and year. Values shown as mean \pm standard deviation, with number of observations in parentheses.	65
C.6	Island Group Classification in Seychelles	66
E.1	Pearson's r , Spearman's ρ , and Kendall's τ correlations (with two-sided p -values) between each scenario modifier and the delivery rate and average delay KPIs.	73

Nomenclature

Abbreviations

Abbreviation	Definition
ABM	Agent Based Modelling
CAP	Capacity reduction disruption scenario (throughput cuts)
DES	Discrete Event Simulation
DG	Disaster Goods (supplementary humanitarian shipments)
DRMD	Disaster Risk Management Division (Seychelles)
EDGE	Edge disruption scenario (link failures)
F0	Initial functionality (baseline service level before disruption)
F1	Residual functionality (lowest service level during disruption)
GCM	Global Climate Model (used in broader climate risk assessment)
IPCC	Intergovernmental Panel on Climate Change
LP	Linear Programming
MC	Monte Carlo (simulation)
MILP	Mixed Integer Linear Programming
NDC	Nationally Determined Contribution
NODE	Node closure scenario (ports/airports shut)
PRCC	Partial Rank Correlation Coefficient
RCM	Regional Climate Model (used in climate risk assessment)
Ridx	Resilience Index (mean functionality during recovery)
RCP	Representative Concentration Pathway (climate scenario)
RRULE	Recurrence Rule (in iCal scheduling)
SCAA	Seychelles Civil Aviation Authority
SD	Standard Deviation
SEA	Sea Level Rise
SDG	Sustainable Development Goal
SLA	Service Level Agreement
SLTA	Seychelles Land Transport Agency
SIPA	Systemic Infrastructure Performance Assessment (adapted in risk classification)
SIDS	Small Island Developing States
SLR	Sea Level Rise
SPA	Seychelles Ports Authority
TEU	Twenty foot Equivalent Unit
VHF	Very High Frequency (radio)
VWP	Vessel Waiting Period

1

Introduction

Small Island Developing States (SIDS) consist of 57 nations with a combined population of 65 million as of 2023 (United Nations Office). Their geographic isolation, limited resources and lack of economic diversification make them heavily dependent on maritime imports, which supply roughly 80% of their fuel, food and medicines consumption. These goods arrive with a recurrent shipping connection to the island nation's single main port, which makes that ports their lifeline to the outside world. By contrast, the within country distribution network is more complex. Redistribute imports from the main port to peripheral islands, complemented to a lesser extent by air links. Lack of infrastructure and proper equipment on outer islands make reaching the many island for ships and ferries difficult (Bank 2017).

Due to climate change, extreme weather events are becoming more frequent, especially in the (sub)tropics. This makes SIDS, with a single point of access into the country, additionally vulnerable to a disruption (IPCC 2022). Sea level rise threatens to submerge low lying islands, while storms, flooding and high winds can shut down ports, airports and local wharves, severing essential supply lines (IPCC 2007; Nurse 2014). Recent events illustrate the potential impact: Hurricane Dorian (Bahamas 2019) and Cyclone Pam (Vanuatu 2015) destroyed critical transport hubs, delaying aid and isolating communities (Global Center on Adaptation 2024). Although SIDS contribute < 1 % of global emissions, they rank among the world's most exposed economies to climate related damage (Anthoff et al. 2010). Therefore, it is key that fitting adaptation interventions have to be implemented to build resilience and mitigate the effects of disruptions in SIDS.

Resilience can be defined through different lenses and interpreted differently. Commonly, resilience can be identified as the ability of an economy or a society to minimize welfare losses for a disaster of a given magnitude (World Bank 2014). Current practices in SIDS specific literature evaluate resilience on governance structure in place or by assessing the nationally determined contributions (NDC) of a country. (Robinson and Sa 2015; Klöck and Nunn 2019; Canales et al. 2017; Casella et al. 2021; Worldbank 2017). While these studies provide crucial insights into the complex situation SIDS find themselves in, they rarely offer holistic recommendations on how to design and implement adaptive infrastructure strategies. Duvat et al. (2020) and Sunkur et al. (2023), for example, discuss protecting critical infrastructure in SIDS, yet they focus solely on engineering measures. They do not address (i) how to identify which assets are critical, nor (ii) how the chosen adaptation measures impact across within country islands (cascading effect). Due to the complex island layout of SIDS, a network wide evaluation of adaptation strategies is key.

Reports that focus on improving the resilience of specifically the logistical system in SIDS include throughput of freight assessments for the Aegean Islands (Maria et al. 2024), disruption modeling for Puerto Rico's food supply (Orengo et al. 2022) and warehouse location optimization on Pacific atolls (Shen 2020). While this scarce amount of studies reveals leverage points for improving logistics resilience, each isolates only one subsystem and stops short of prescribing system wide strategies. Consequently, SIDS lack clear guidance on how to balance adaptation strategies like port hardening, buffer stocks and emergency management to improve the resilience of SIDS.

Large investments in SIDS rely heavily on financing from multilateral development banks (MDBs). To secure adaptation funding effectively (Global Center on Adaptation 2024), SIDS need a quantitative, network wide approach that prevents the misallocation of infrastructure funds and helps islands reduce their exposure to prolonged supply disruptions.

1.1. Problem statement

SIDS face unique logistical challenges compared to continental nations, requiring tailored adaptation strategies to address supply chain disruptions. These island states need comprehensive, evidence-based adaptation strategies to build resilience across their interconnected logistics systems.

Assessing these adaptation strategies requires modeling methods that account for SIDS' distinctive characteristics, particularly their reliance on single access points and complex inter-island networks. Multiple methods already exist that explore resilience in the context of logistical systems. To represent a logistic system accurately, most research relies on one of three main modelling approaches: discrete event simulation (DES), agent based modelling (ABM) and graph based optimisation. DES excels at showing how queues build up, but it pays little attention to the layout of the network, so it struggles to show how a broken link can trigger cascading disruption (Montagna et al. 2002). ABM helps reveal how actors might respond to a shock, yet it usually keeps the physical network fixed, meaning damage to ports or routes is not fully captured. Graph models are often combined with linear or mixed integer linear programming (LP or MILP), which is useful for pinpointing the most critical ports and connections (Becker et al. 2018; Hatefi et al. 2014). However, when the network grows larger, their results become harder to interpret, and these models can struggle with how to track how freight moves over time. As these three methods describe logistical systems for non-SIDS countries, each model comes with its limitations when representing the unique network of SIDS. Therefore, these models must be altered to specifically simulate cascading disruptions and allow SIDS to identify where and how disruptions affect their system, enabling resilience to be assessed at the level of individual islands.

Besides this, existing literature lacks in describing how to assess adaptation strategies quantitatively for SIDS. The lack of a quantitative method to balance adaptation strategies in networks exists for several reasons. Most supply chain models overlook the single gateway and low redundancy reality of SIDS. Also, they optimize mainly for economic efficiency, treating disruption scenarios as an afterthought rather than reaching the destination the primary goal.

Many supply chains are represented as static graphs where nodes stand for suppliers, distribution centers and customers, and edges represent transport links. Graph based analysis identifies key nodes whose failure would disrupt large parts of the network and uses metrics such as the size of the largest connected sub network and path lengths to measure resilience (Li et al. 2020a; Peng et al. 2011; Agarwal et al. 2021; Rabbani et al. 2020; Zhao et al. 2011). These models, however, do not follow the actual flow of goods over time and so cannot capture how delays build up or cascade when one disruption leads to others. Studies employing DES solve this issue, however, they lack the potential to test adaptation strategies on a network wide scale. Jabbarzadeh et al. 2012; Snyder et al. 2014 show how resilience can be improved by adding buffer stocks, extra routes and robustness to balance cost against resilience. Nonetheless, suggested solutions are based on assumptions in the model that holds multiple ports and road or rail connections. Such suggestions are not an option for SIDS considering their financial constraints and reliance on a single port, ship or air link for inter island transport.

Also, in most studies, resilience or impact is usually measured in economic terms as the logistics network being evaluated is optimized for profit or minimizing value loss under disruptions. (Peng et al. 2011; Jabbarzadeh et al. 2012). In island settings, resilience is often more about goods getting there. More recent research has expanded this focus by incorporating broader resilience dimensions, like operational resilience, social resilience and environmental resilience. These can provide more insightful metrics for evaluating the logistical network of SIDS, as these are not as subject to constraints and not optimized for any economic/financial metrics, especially during disruptions.

To conclude, Small Island Developing States currently have no way to choose resilience metrics that fit their unique geography, operations and budget constraints. To provide actionable, quantitative insights on adaptation strategies, existing logistic modeling methods must be adapted to represent the complex logistical system that makes SIDS vulnerable. Therefore, this thesis explores a tailored modeling

method that links the physical network with the actual flow of goods, assessed from both a qualitative as quantitative perspective.

1.2. Objective and Research questions

To address the problem SIDS face, this research proposes a study that focuses on understanding and modeling the resilience of interconnected supply networks in SIDS. A discrete event model that integrates graph based structures with a flow of goods could provide a nuanced approach. Capturing the constraints of limited infrastructure while creating insights into adaptive strategies for a more resilient supply chain. This will be applied to the Seychelles, an island nation vulnerable to climate change, and the national transport system (of both roads, air and ferry connections) being key for the distribution of essential goods important for people and the tourism sector.

Based on the identified research gap, the research questions are formulated as follows:

What is the resilience of supply network logistics in small island developing states, and how can resilience interventions improve this?

To address the main research question, the following sub questions have been formulated:

1. **What are the relevant system requirements for a supply network in the context of SIDS?**
2. **Which impact metrics best quantify the impact of disruptions for communities in SIDS?**
3. **What is the cascading effect in the supply network of SIDS due to disruption?**
4. **What are effective resilience interventions in the context of SIDS and their effect on the impact of disruptions?**

1.3. Thesis Structure

This thesis is structured across seven chapters, each contributing to the development, implementation, and evaluation of a resilience focused freight logistics model for Small Island Developing States, using the Seychelles as a representative case study. The research adopts discrete event simulation modeled in Python, and expert input to explore the impact of climate related disruptions and evaluate resilience strategies. Chapter 2 reviews the existing literature on supply networks in SIDS, including maritime and air transport systems and humanitarian aid flows. It introduces relevant impact metrics (e.g., delivery success, delay propagation, and resilience curves) and discusses potential resilience interventions. Chapter 3 introduces the case study providing context to the model. Chapter 4 elaborates The model is uses corner stones suggested by the four step freight modeling framework generation, distribution, mode choice, and assignment commonly used in transport modeling. The model consist of structured as following:

- **Graph based routing**, to simulate infrastructure layout and network bottlenecks.
- **Discrete event simulation (DES)**, to represent time based disruptions, queues, and cascading effects in delivery flows.

Expert conversations are conducted in two phases (conceptualization and case validation), serve to fill data gaps and validate outcomes. e delivery layers.(Chapter 5 Model Results) presents the outcomes of simulation runs under varying disaster scenarios. It evaluates how disruptions (e.g., port closures, storm delays) affect freight flows and delivery performance. Key metrics such as cold chain failure, delivery delay, and overflow peaks are reported. The effectiveness of different intervention strategies is analyzed to answer sub questions 3 and 4. Chapter 6 reflects on the simulation outcomes in the context of SIDS resilience planning. It discusses real world relevance, limitations of the modeling approach, and statistical robustness. The chapter connects simulation results back to expert insights and evaluates the broader applicability of the model. Chapter 7 concludes the research contributions and answers the main research question. It outlines key findings, discusses their implications for resilience policy and planning in SIDS, and proposes directions for future research and model refinement.

2

Theoretical background

2.1. Current status of supply networks in SIDS

This section identifies the supply chain characteristics essential to accurately represent Small Island Developing States in resilience-focused network modelling.

Supply chains in SIDS commonly rely on a centralised hub-and-spoke structure, where primary ports and airports serve as critical international gateways (Disaster Reduction et al. 2020). The main islands handle most inbound goods, subsequently distributed to peripheral islands through smaller-scale maritime and air connections, often combining passenger and freight due to low volumes. Maritime transport is the predominant mode used to carry cargo and freight, and air transport is relied upon primarily for passenger and tourist transport (UNCTAD 2014). While maritime transport typically dominates trade in SIDS, air transport can play a vital role during disruptions, ensuring fast deliveries such as medical supplies.

SIDS have few direct maritime connections (Figure 2.2), causing longer lead times and higher transport costs. This can increase up to two percentage points higher than global averages Figure 2.1 (UNC 2022). Such elevated costs create a vulnerability feedback loop, as infrequent shipments lead to shortages and reliance on costly emergency air freight during disruptions. Also, due to the imbalanced flow of a high amount of imports and lower exports, SIDS often pay extra for ships leaving the ports empty. (UNCTAD 2014)

The efficiency of both systems depends on structured logistics networks, robust port and airport infrastructure, and governance frameworks that enable smooth operations (CT3504 College 2-2, 2025). Therefore, to accurately reflect SIDS resilience dynamics, the supply network model must explicitly account for their hub-and-spoke infrastructure for both maritime and air transport logistics.

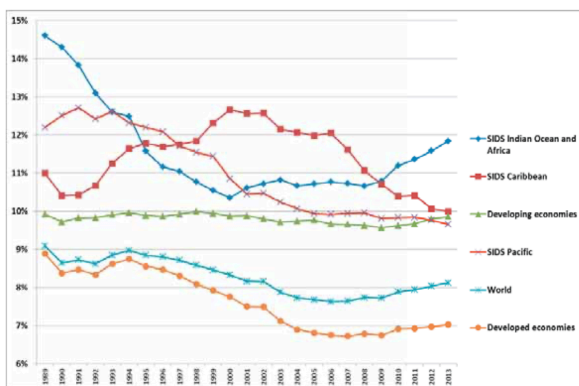


Figure 2.1: Freight costs as per cent of the value of imports (UNCTAD 2014)

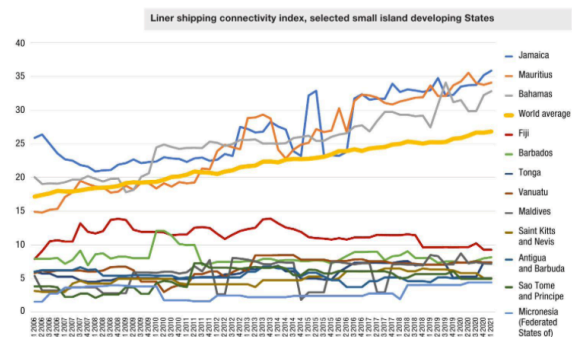


Figure 2.2: Liner shipping connectivity, direct lines (UNC 2022)

2.1.1. Maritime transport systems

Maritime transport is critical for SIDS due to their heavy dependency on imported essential goods like fuel, food, medicines, and construction materials. However, the remote geography, small populations, and limited trade volumes severely restrict economies of scale, making it challenging to attract frequent, direct, large scale shipping services. Consequently, SIDS heavily depend on smaller feeder ships or transshipment hubs (UNCTAD, 2014). Feeder ships transport cargo from larger regional transshipment hubs to smaller ports. In regional transshipment hubs, goods are consolidated and transferred onto larger vessels for onward international shipment. This reliance on feeder ships and transshipment hubs is unfavorable as it introduces additional logistical steps, increases transit times, and heightens vulnerability to disruptions. Not being able to facilitate the call time of a ship can lead to stock outs of goods.

SIDS ports often have shallow berths, severely limiting vessel size. This necessitates additional transshipment operations, increasing logistics complexity and delays (UNCTAD, 2014). Of the 51 international ports across SIDS, 31 are categorized as “very small,” limiting vessel size typically to under 3,000 TEUs due to berth depths less than 12 meters (UNCTAD, 2014). Moreover, many ports were built before containerization, lacking necessary infrastructure upgrades such as adequate berth lengths, quay aprons, storage spaces, and internal access routes. These issues are amplified as imports of SIDS are highly containerized and less reliant on bulk goods in comparison to non-SIDS countries (**portwatch**).

These physical constraints directly affect port performance. Limited cargo-handling equipment means vessels rely extensively on ship-based gear or small forklifts rather than efficient gantry cranes, causing prolonged berth occupancy and reduced throughput (Portwatch, 2025). Extended dwell times in storage yards further compound these delays (UNCTAD, 2014).

Cold chain logistics pose another significant resilience challenge. Harbours in SIDS frequently have minimal or inadequate refrigerated storage infrastructure, relying on the reefer containers them self as a storage facility. Consequently, essential perishable imports like food and pharmaceuticals must move swiftly inland or risk spoilage. Frequent power reliability issues on some islands exacerbate cold-chain vulnerabilities, especially during disruptions when rapid distribution is most needed.

Aging infrastructure, inadequate maintenance, limited cold storage capacity, and reliance on transshipment create critical bottlenecks. These limitations reduce the system’s flexibility and increase vulnerability to disruptions, making them critical to explicitly represent in resilience modeling.

Inter-island maritime transport often relies on a combination of small roll on roll off vessels (RoRo), small open boats and coastal ferries. Due to shallow draft conditions on outer islands cargo is off-loaded directly onto beaches or small piers. Inter-island logistics are often informal and risky, with aging vessels, manual unloading at non-standardized docks, and limited crew training leading to frequent delays and accidents (UNC 2022; Bank 2024b). The frequency and quantity of inter-island travel are unpredictable because on top of these problems, weather conditions such as strong currents and rough seas frequently disrupt transport schedules (UNCTAD 2014).

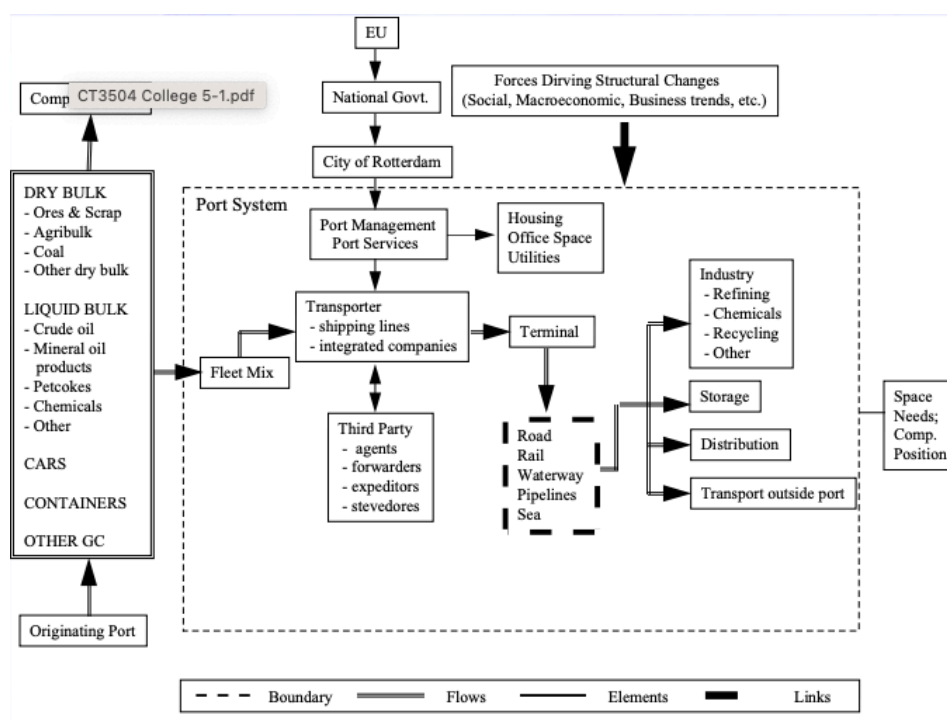
Therefore, to correctly capture the maritime transport logistics of SIDS the model should incorporate the lack of modern port equipment, feeder-based transshipment steps which lead to intermittent spiky import arrival patterns, insufficient handling equipment, prolonged dwell times in stacking areas of ports, and constrained cold-chain capabilities. Also, the model should incorporate the informal, inconsistent inter-island freight transport with widely varying unloading times.

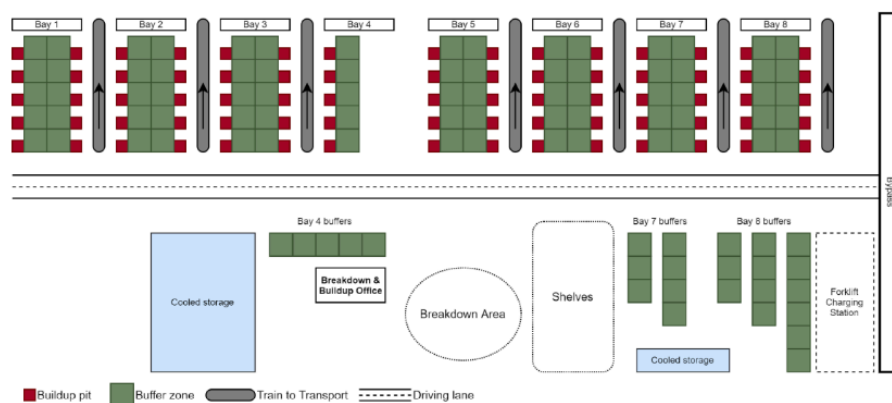
In Figure 2.3, a generalized overview of the characteristics of ports for cargo is given.

2.1.2. Air transport system

Air transport in SIDS is crucial due to its speed and reliability in delivering time-sensitive and high-value goods, especially pharmaceuticals, fresh food, and emergency supplies (UNEP/UNCTAD 2019). Unlike large continental airports, SIDS airports primarily rely on cargo carried in passenger aircraft (“belly cargo”) because dedicated freight aircraft are often economically unfeasible given low cargo volumes and infrequent flights (Transportsysteem, 2020). This dependence ties cargo logistics directly to passenger schedules, significantly limiting flexibility and capacity for cargo handling.

Airports in SIDS face substantial infrastructure challenges, such as short runways, limited aircraft park-





Credit: *Pedro Gamito MSc thesis*

Figure 2.4: Airport cargo overview

mal trade flows (U.S. Aid Report). Furthermore, aid is often mismatched with local needs, leading to inefficiencies and increased costs locally, as seen following Hurricane Maria in Puerto Rico, where essential consumer goods experienced significant price increases and prolonged supply disruptions (Sou et al. 2019).

Additionally, humanitarian logistics often operate separately from regular commercial flows, yet due to limited inter-island connectivity, humanitarian and commercial goods eventually compete for scarce transport capacity between islands (ODI 2025; Action 2025). Therefore, the model must incorporate humanitarian aid as a component of total supply flows, explicitly addressing its potential for creating logistical bottlenecks and capacity competition.

2.2. Impact measures on the community for SIDS

Freight disruptions in SIDS typically result from two primary types, from the demand side or the transport (supply) side. These disruptions are categorized in sudden shocks and slow-onset stressors Figure 2.5. As SIDS are heavily reliant on imports, this thesis will focus on the upper two quadrants. Meaning disruption can be interpreted as follows:

- Sudden disruptions, including hurricanes, floods, earthquakes, or infrastructure failures, causing immediate closures of infrastructures.
- Gradual disruptions, such as prolonged climate stressors (sea-level rise, erosion) that progressively degrade transport infrastructure and supply capacities over time (SIPA, 2023).

Both sudden and gradual disruptions can significantly reduce transportation capacity, damage critical infrastructure, and limit the availability of essential resources. In simulation studies, the most commonly identified disruption types in the literature are categorized as random failures (Agarwal et al. 2021), targeted attacks (Zhao et al. 2011; Li et al. 2020a), and regional failures (Li et al. 2020b).

As disruptions in SIDS are primarily climate-related, this study examines both types but explicitly distinguishes between hindering disruptions, which gradually reduce transport efficiency, and disruptions that cause a complete halt in supply chains. These disruption types are combined into scenarios involving targeted and regional failures to simulate cascading effects across the network, as proposed by Zhao et al. (2019) and Thacker et al. (2017).

These definitions help frame the impacts on communities across different islands within SIDS and provide a foundation for selecting appropriate metrics to evaluate resilience accurately.

Critical to resilience modeling is aligning metrics with local community needs, ensuring infrastructure, network, operator, and organizational needs are all addressed (Pettit et al., 2010; Orengo et al., 2022).

This alignment ensures the model accurately captures the varied and nuanced impacts of disruptions. Besides the definitions should be aligned with the quantitative approach of this study.

Resilience is interpreted in various ways across the literature, ranging from ecological resilience (Holling, 1973) and engineering resilience (Bruneau et al., 2003) to supply chain resilience (Sheffi & Rice, 2005) and community resilience (Norris et al., 2008). This thesis adopts a definition aligned with SIPA (2023), framing resilience as the capacity of SIDS freight transport networks to cope with, recover from, and dynamically adapt to external shocks.

Building on this definition, the research uses different disruption types to assess system performance under stress. This performance is then linked to the impacts on communities across the islands due to the high import dependencies of SIDS, ensuring that the simulation outcomes reflect the real-world consequences that are highly relevant for SIDS.

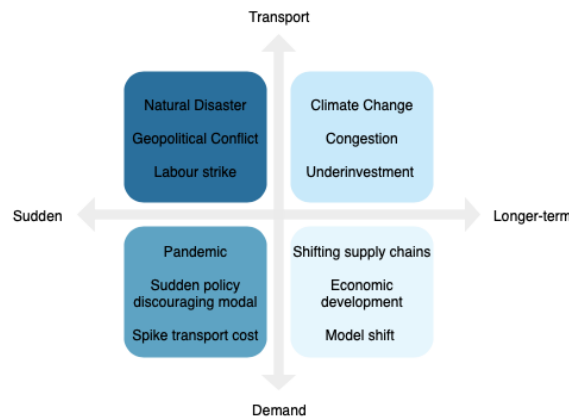


Figure 2.5: Classification of disruptive events that create risks for freight transport systems (Adapted from SIPA 2023).

2.2.1. Impact on community

Due to their high reliance on imports, communities in SIDS face immediate vulnerabilities when supply disruptions occur. Shortages in critical goods, food, medicines, and fuel rapidly lead to measurable community impacts. For example, delayed food imports directly heighten food insecurity, which in some studies is measured through indicators such as household-level shortages, increased food prices, or the adoption of emergency coping strategies (Guimaras, 2021; COVID Food Security, 2020).

SIDS are highly dependent on fossil fuel imports, most of them spend more than 30 per cent of their foreign exchange earnings on carbohydrates (UNCTAD 2014). Besides being used in the transports sector, factors like unstable power grids on SIDS contributed that most buildings have diesel backup generators. While backup generators are used for all sorts of utilities, from supermarkets who use them for cold storage, to residential buildings for air-conditioning, to tourist resorts. Fuel delays can threaten vital operations like hospitals, highlighting the urgency of modeling fuel flows explicitly (Bank 2017)

Besides the indirect effect of fuel availability on healthcare, delayed medical imports disrupt healthcare services. Increasing the frequency of medication shortages, canceled medical procedures, or missed vaccinations. Cold-chain goods present particular challenges for medicine and food. Even brief disruptions can lead to the spoilage of pharmaceuticals and perishables. In SIDS, despite partial spoilage due to missing/poorly functioning cold-chain logistics, inhabitants frequently use compromised goods, underscoring the need for the model to track realistic perishability outcomes and actual deliveries, not simply ideal storage conditions.

While the author acknowledges that the absence of goods affects communities in diverse ways, including issues of equity and household vulnerability (e.g., differing impacts on resorts versus local populations, or variations in access between men, women, youth, and elders). These nuanced metrics fall outside the immediate scope of the model. Nevertheless, recognizing this variability opens opportunities for future research to evaluate resilience through a more comprehensive equity lens.

Based on these insights, this research explicitly tracks three critical supply chains among all imported goods. Goods classified as (cold) food, (cold) medicines, and fuel are monitored as representative indicators, using measurable outcomes such as delay duration, perishability, and community-specific supply levels to realistically quantify the impact on island communities.

2.2.2. Performance indicators of a freight system

A variety of performance indicators have been defined that capture the behavior of the identified goods classes in a logistical model. A review by Poulin and Kane (Poulin et al. 2021) classifies common indicators into several broad types:

- **Magnitude-based metrics**, These look at the severity of impact at specific points. For instance, the lowest performance level reached (e.g. minimum percentage of freight delivered during the crisis) or peak congestion in a logistics network. In community terms, this could be the maximum shortfall, for example, only 30% of normal food supplies available at the worst moment.
- **Duration-based metrics**, These measure the time aspect of disruption. A common one is the time to recovery, how long it takes for performance to return to pre-event levels. Another is the duration above critical thresholds, such as the number of days a community had less than the minimum required fuel. Shorter disruption durations indicate higher resilience.
- **Integral-based metrics**, These capture the total impact over time by combining magnitude and duration. They measure the area under or deficit from the performance. An example is the aggregate volume of goods not delivered (or person-days of service outage) during the disruption. This could be quantified in terms of ton-days of missing food.
- **Rate-based metrics**, These focus on speeds of decline or recovery. One might measure how fast the system fails (rate of performance drop) or how fast it bounces back (rapidity of recovery). For example, a recovery rate in percent per day (e.g. supply levels improved by 10% per day) implies better resilience capacity.
- **Threshold-based metrics**, These relate performance to predefined critical levels. They measure the time spent below a critical performance threshold. In an island supply context, this could be the number of days the community had less than the fuel required for essential services. Another example: the number of days a port must operate above normal capacity after reopening to catch up.
- **Ensemble (composite) metrics**, These combine multiple aspects into one index. For example, an overall resilience index might weigh several elements like recovery time, severity, and capacity constraints. An ensemble could also be multi-dimensional, such as a radar chart or weighted sum representing overall system resilience.

Given the data-scarce environment common in many SIDS, not all performance indicators are equally feasible or informative. For example, threshold-based metrics often require precise definitions of critical levels and consistent data availability. Conditions that are difficult to meet in settings with irregular reporting and variable supply thresholds. Similarly, the intermittent and lumpy nature of supply arrivals in SIDS makes it challenging to apply metrics that assume steady-state flows, such as some integral-based or magnitude-based indicators.

While ensemble metrics offer a comprehensive view by combining several aspects of performance, they can be difficult to interpret consistently, particularly in systems where the nature of disruptions varies over time and context. The trade-off between comprehensiveness and interpretability limits their usefulness for communicating clear, actionable insights to stakeholders.

Therefore, this study focuses on a indicators that strike a balance between interpretability and practicality in the SIDS context. Duration-based metrics, (i) to capture how long critical supply shortages persist. Rate-based metrics, (ii) to quantify the speed of failure and recovery.

These indicators provide time-sensitive and intuitive insights into system performance, making them well-suited for simulating the impact of disruptions and visualizing resilience in freight systems serving island communities for this study.

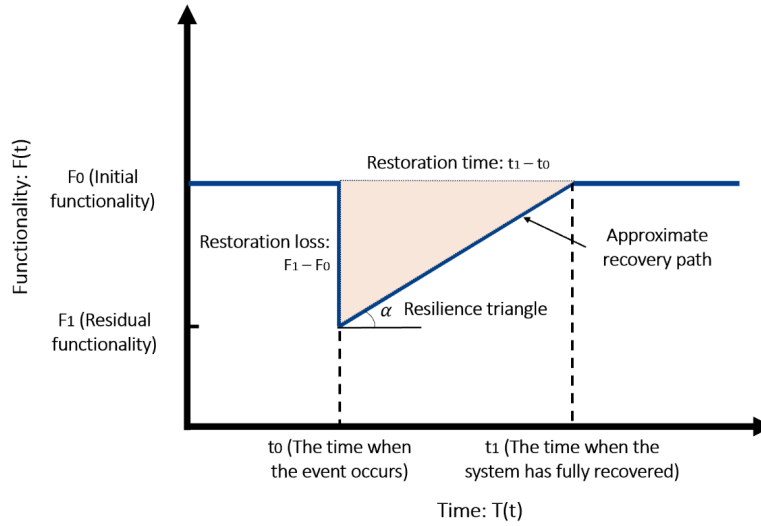


Figure 2.6: Conceptual resilience curve suggested by (Sun et al. (2020))

2.2.3. Resilience Curves

Resilience curves are commonly used to visualize and quantitatively assess the impact of disruptions on supply chain performance over time. Typically, resilience curves plot a system's functionality, with avg delivery time or service level as a performance indicator, during, and after a disruption event.

The most common representation is the resilience triangle framework, illustrated in Figure 2.6, which captures three critical aspects of disruption impact and recovery: (i) Initial functionality (F_0), representing baseline system performance before the event. (ii) Residual functionality (F_1), capturing the immediate performance degradation due to the disruption. The difference ($F_0 - F_1$) reflects the system's robustness and redundancy. (iii) Recovery path, characterised by the restoration time (from event occurrence at t_0 to full recovery at t_1) and the slope indicating recovery speed or rapidity (Verschuur et al., 2024).

To quantify resilience curves systematically, the following formulas suggested by (Sun et al. (2020)) can be employed:

- **Rapidity**, representing the rate of recovery, calculated as:

$$\tan(\alpha) = \frac{F_0 - F_1}{t_1 - t_0}$$

- **Resilience Loss**, measuring the total loss over time:

$$A = \int_{t_0}^{t_1} [100 - F(t)] dt$$

- **Resilience Index**, expressing overall system performance during recovery:

$$R(t_h) = \frac{\int_{t_0}^{t_h} F(t) dt}{t_h - t_0}$$

The resilience loss, represented by the shaded area within the triangle, quantifies the cumulative impact of the disruption. In a freight context, this might represent delayed deliveries measured in ton-days or backlog accumulated over the recovery period, depending on the performance indicator chosen (Blue line)

Additional complexity arises in real-world situations when recovery includes an overshoot, temporarily exceeding baseline performance levels to catch up on delayed shipments. Such scenarios form a

resilience trapezoid, indicating compensatory capacity and system constraints like infrastructure limits during recovery surges (Verschuur et al., 2024).

The formulas above illustrate the potential for applying an analysis of the performance indicators from the model outputs. By calculating a functionality measure $F(t)$ over time, it presents the possibility to rate the response of the network model to certain disruptions. To capture the network-wide impact, it is key to choose performance metrics that represent insightful values for network-wide insights but also for the different islands and good classes.

Therefore in this study *service level* is used as performance indicator of the system, which is defined as the percentage of total delivered tonnage that arrives on or before its expected delivery time. Where its expected delivery time is determined on the pre-disruption avg travel time for that destination in an 95% range. Where travel time is the time from unloading in the main port/airport till the good is at its final destination.

for L be a hinterland location, and consider all cargo unloaded from ship at L . Define for each hour h :

$$\begin{aligned} \text{Delivered}_L(h) &= \text{total tonnage unloaded at } L \text{ during hour } h, \\ \text{OnTime}_L(h) &= \begin{cases} \text{Delivered}_L(h), & \text{if that cargo reaches its destination within the target time,} \\ 0, & \text{otherwise.} \end{cases} \end{aligned}$$

Define the *average transit delay* before the storm at L as

$$A_L = \frac{1}{N} \sum_{i=1}^N (t_i^{\text{delivery}} - t_i^{\text{unload}}),$$

where the sum runs over the N shipments unloaded at L in the pre-storm period.

Then the Service Level at location L is

$$\text{SL}_L = \left[\frac{\sum_h \text{OnTime}_L(h)}{\sum_h \text{Delivered}_L(h)} \right] \times 100\% \times 0.95 A_L,$$

where the factor $0.95 A_L$ applies a 5% margin below the pre-storm average suggested by the author be less punitive to make $F(t)$ less volatile and more interpretable. All times h run from unloading off the ship at L until delivery at the final destination.

Service level is a duration/rate based performance indicator giving valuable insight in recovery time of a system. Also is categorizable per island, and per good class and comparability across scenarios. Making it possible to create insights in system wide effects but look at island specific impacts. Because service level is normalized to 0–100%, it can be used to compare performance under storms of varying severity, duration, and combinations of adaptations strategies. This method, as it presents a service time based on pre-storm deliveries, can also capture the overshooting effect that can occur after a disruption. Also service time is naturally interpretable as it shows a drop for when the logistical network is performing worse making the impact of adaptation strategies logical. If a disruption happens it can readily be interpreted “a 10 % drop in service level (restoration loss)” and with an adaptation measure in place this can be reduced to 8%.

This method allows a more structured and insightful evaluation of system resilience in response to disasters, highlighting not just the occurrence of disruptions but also the quality and speed of recovery over different time scales, which is interesting in light of the evaluation of adaptive strategies to improve the resilience of SIDS.

2.3. Resilience interventions

Disruptions come in many shape and sizes however for SIDS due to climate change the increase of extreme weather events has a large impact. Therefore besides the inherent difficulties supply chain

of SIDS face. It is key to know the impact of extreme weather events as the technical vulnerabilities of transport infrastructure are amplified by climate change, as illustrated in the figures. Ports, airports, helipads, and roads in these regions already suffer from limited redundancy, meaning that damage to a single transport hub or road network can isolate entire communities and disrupt the supply network. Increased rainfall, flooding, and storm surges accelerate coastal erosion and infrastructure corrosion, which is particularly problematic for port terminals, airport runways, and bridges that are often located in low-lying areas. Meanwhile, extreme temperatures and drought degrade road surfaces, weakening the already fragile inland transport networks that are essential for the movement of cargo from distribution centers to consignees. The thermal expansion of bridges and runways further compromises safety and can increase maintenance costs. Moreover, high exposure to wave action and storm surges can damage ring roads, airports and harbors, leading to logistical bottlenecks. These compounded effects reinforce the already high operational costs, maintenance challenges, and logistical inefficiencies that characterize SIDS' transport infrastructure.

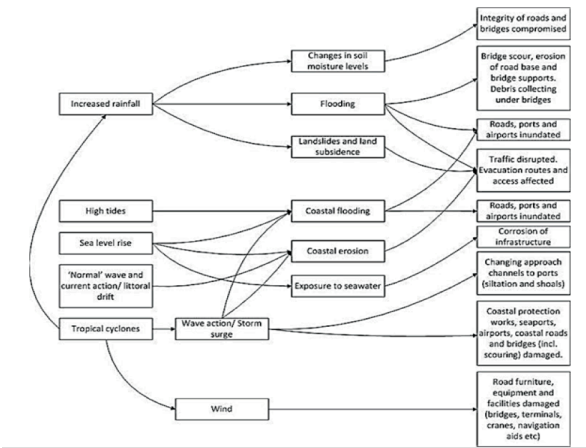


Figure 2.7: Impact on infrastructure 1 (UNCTAD 2014)

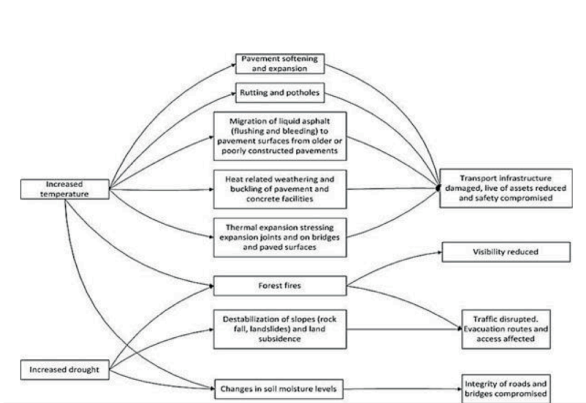


Figure 2.8: Impact on infrastructure 2 (UNCTAD 2014)

2.3.1. Adaptation strategies

As this research focuses on the resilience in the transport sector of SIDS it is important to make a distinction between the resilience of the transport infrastructure and the how the transport sector relies on imports and making that aspect more resilient. From an engineering perspective four classical infrastructural strategies can be defined, which can be seen in Figure 2.9. However, the UN Office for Disaster Risk Reduction (UNDRR) defines a broader scope by suggesting resilience as a system's capacity to "resist, absorb, accommodate, adapt to, transform, and recover from" the effects of hazards (Disaster Resilient Infrastructure (CDRI) 2023; Commission 2020). Therefore grouping adaptation strategies into infrastructure, organizational, operational, and digital measures is a more holistic approach. This is supported by various studies that emphasize strengthening physical assets ("hard" measures) as well as "soft" measures (policy, planning, and tech) are all crucial for resilience (Bank 2017). For example, the World Bank recommends a mix of hard infrastructure investments" (like building alternate roads or seawalls) and soft" capacity-building actions (like better asset management and planning tools) in SIDS transport resilience programs. In practice, SIDS must combine these strategies to create a robust logistics system for short and long term resilience.

Table 1 presents a typology of resilience strategies for SIDS freight transport, organized by these categories and resilience functions.

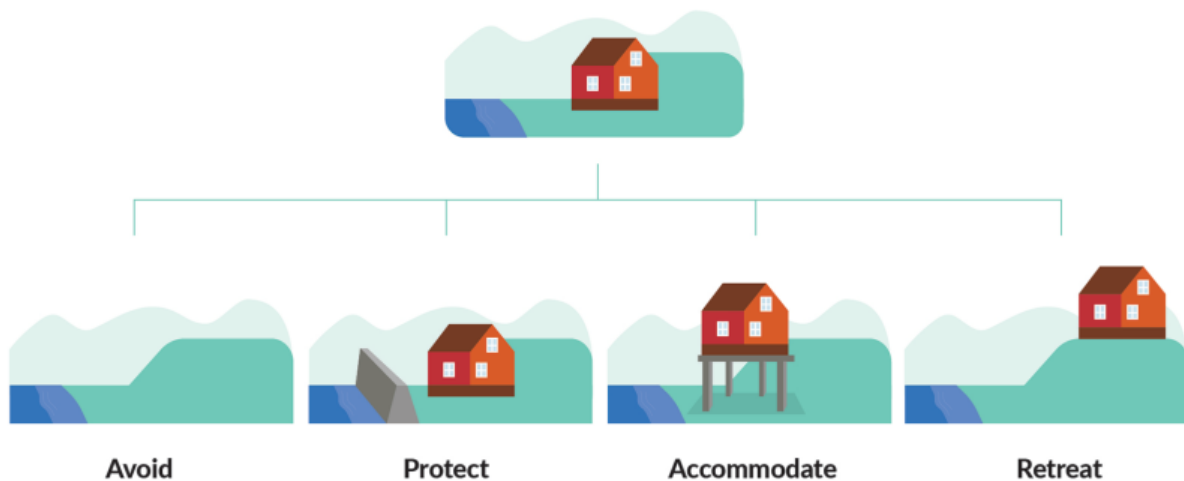


Figure 2.9: Four classifications of adaptation strategies

Resilience Function	Infrastructure-Based Strategies	Governance Strategies	Operational Strategies	Technological Strategies
Resist	Hardening infrastructure (e.g. ports, roads), protective defenses (seawalls, surge barriers)	Strict building codes, land-use planning in hazard zones	Preventive maintenance, adjust shipping schedules	Early warning systems, climate risk modeling
Absorb	Redundant infrastructure (e.g. backup ports), design margins for capacity	Disaster funds, mutual aid agreements	Strategic stockpiles,	Early warning systems , IoT prediction methods
Recover	Pre-positioned repair kits, modular rebuilds, build back better	Emergency logistics plans, institutional coordination	Mode substitution, streamlined procedures	, GIS recovery tools
Adapt	Infrastructure upgrades (e.g. elevation, retrofits), spatial reconfiguration	Policy integration, institutional capacity building	Adaptive supply chain strategies, local production	Predictive analytics,
Transform	New deep-water ports, nature-based coastal defense, strategic retreat	New agencies, regional coalitions, major policy reforms	National logistics redesign, stock mandates	Digital twins for decision making

In summary, SIDS logistics resilience strategies range from tangible projects (e.g. constructing cyclone-resistant ports) to intangible improvements (e.g. governance reforms and digital systems). The above typology provides a structured way to categorize and think about these interventions. However due to before mentioned constraints SIDS have, from economical, financial, operational and geographical which adaptation strategies are feasible in terms of real-world implementation across different island

regions.

2.3.2. Limitations of SIDS for resilience interventions

SIDS have unique structural challenges that make resilience difficult to achieve. Their location and size mean exposure to intense tropical cyclones, tsunamis, volcanic eruptions (for some), and now sea-level rise. Economies are heavily trade-dependent, SIDS import a large share of food, fuel, and goods and handle low freight volumes via limited transport infrastructure. They rely on a single international port and airport, and just a few main roads (Bank 2017). This lack of redundancy means a single point of failure can isolate an entire nation.

- **Lack of redundancy:** SIDS typically rely on limited critical infrastructure (often one major port and airport), making them vulnerable to single-point failures.
- **Financing Constraints** Resilience infrastructure demands high investment. Many SIDS have high debt and limited borrowing capacity, depending on climate funds and MDB's (Insights 2024). The gap between needs and actual funding keeps many projects on paper (Dominica 2019).
- **Human and Institutional Capacity** Limited technical staff and weak asset management practices hinder implementation (Disaster Reduction et al. 2020). Capacity gaps impact enforcement, planning, and the adoption of digital systems.
- **Geographic Remoteness and Scale** Redundancy is often physically or economically unfeasible. Delays in external aid exacerbate the impacts of disruptions (Bank 2017).
- **Dependence on Imports** SIDS depend heavily on a few import routes. Global supply chain shocks have disproportionate effects (McKinnon 2024). Fuel reliance especially makes energy security a critical issue (McKinnon 2024).

Resilience is however not a new topic for SIDS. It can be observed that no SIDS has a perfectly resilient transport system yet, most have critical gaps, but awareness and actions are increasing. Pacific islands started the idea of "community-owned resilience" where solutions are tailored to each atoll's needs, whereas Caribbean plans often rely on broad frameworks set by governments or international partners. A balanced approach is emerging: utilise global best practices and frameworks (general principles) but adapt them to each island's geography, culture, and economy. These strategic differences were noted in a 2024 analysis: "Pacific islands require regional collaboration... Caribbean islands benefit from global partnerships and national policy integration (Insights 2024). This approach of different levels

Across SIDS regions see partial implementation of many resilience strategies. Infrastructure hardening and redundancy measures are often most lacking (due to cost and physical constraints), whereas organizational preparedness and planning have advanced somewhat (thanks to regional cooperation and donor support). Operational improvements (like stockpiling, diversifying routes) are recognized in theory but uneven in practice. Digital and tech innovations are just beginning to play a role. Shared hurdles like funding, capacity, and inherent geographic constraints continue to limit progress, but there is also shared learning and solidarity as evidenced by initiatives like the Small Island States Resilience Initiative (SISRI) that pools knowledge for innovative solutions (Bank 2017).

Given these limitations, effective resilience interventions must strike a balance between globally recognized best practices and tailored, localized solutions. Regional collaboration (common in Pacific SIDS) and international partnerships (typical in Caribbean SIDS) offer promising paths forward, enabling sharing of knowledge, resources, and solutions while respecting local contexts.

Hence, the model has to consider these constraints by focusing on achievable, high-impact interventions adapted to local contexts, financial realities, and the unique geographical and infrastructural limitations inherent to SIDS.

2.4. Holistic approach

To address the specific vulnerabilities and barriers facing Small Island Developing States, a holistic perspective is essential. One that integrates system performance metrics, community impacts, and tailored intervention strategies. Resilience in freight and transport systems cannot be achieved through isolated measures, instead, it requires alignment between infrastructure planning, operational manage-

ment, institutional capacity, and local realities. The rationale for the simulation model presented in this thesis is grounded in the interconnected concepts introduced throughout this chapter. By capturing the dynamic impacts of disruptions, quantifying system resilience, and reflecting the limitations and opportunities unique to SIDS, the model provides a framework to evaluate the effectiveness of various resilience strategies in a realistic and context-specific way.

3

Case study

As previously mentioned, the case study used to apply the proposed approach is the Republic of Seychelles. In this chapter, contextual background on Seychelles is provided to illustrate its suitability as a case study. The impact of adaptation measures on logistical resilience is explored through this specific case. However, it is important to emphasize that the modelling approach itself is designed as a generalizable framework for investigating SIDS, recognizing that such states differ significantly in their geographic, economic, and institutional characteristics.

The contextual information presented here serves not only to provide context for the analysis but also to highlight the distinctions between Seychelles and other SIDS. This allows for comparative analysis, through which results from the model can be assessed for their broader relevance to SIDS, as well as for their specificity to the Seychelles context.

For a more in-depth examination of Seychelles, Appendix D provides a comprehensive overview of historical disruptions and their impacts, along with an analysis of freight data to better understand pre- and post- disruption supply chain flows (disaster/humanitarian goods). In Appendix D, a summary of existing resilience measures in the Seychelles is presented, including their observed effectiveness to date. Additionally, Chapter 5 elaborates on the specific datasets collected and used in the simulation model.

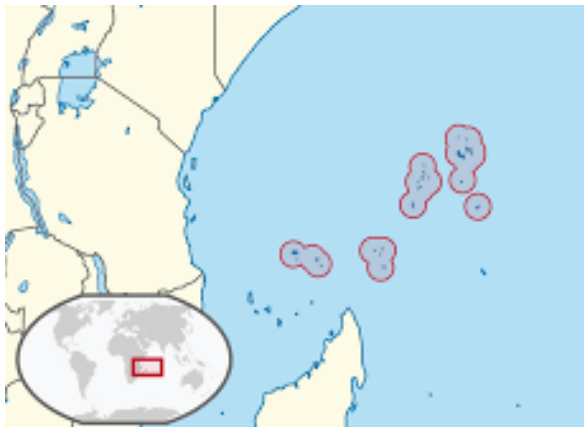


Figure 3.1: Overview Seychelles

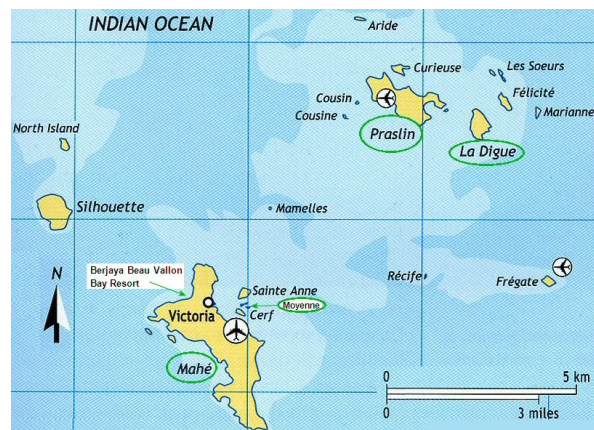


Figure 3.2: Overview Inner Islands

Seychelles is a small island nation in the Indian Ocean, comprising 115 islands, of which 26 are inhabited. However, the vast majority of the approximately 120,000 residents, around 106,000 people live on the three main inner islands: Mahé, Praslin, and La Digue, as shown in Figure 3.2. Mahé is the most populated island and hosts the capital city, Victoria, as well as the country's only commercial seaport, Port Victoria.

Port Victoria handles approximately 400,000 tonnes of cargo annually and serves as the entry point for about 98% of all goods entering the country MTBS 2012. The remaining 2% of goods are imported via air through the Seychelles International Airport, located just south of the port. Maritime imports arrive primarily through international liner services connecting Seychelles to major trading partners in the Middle East and Africa.

Unusually for a SIDS, Seychelles has a relatively large and active port with throughput that occasionally serves nearby islands. Exports mainly consist of products such as canned tuna and spices, however, approximately 95% of all cargo handled at the port is destined for domestic consumption. This cargo is highly containerized, about 71.2%, which is a common characteristic of SIDS logistics systems (Port-watch,2025).

Located in a tropical cyclone zone, Seychelles is increasingly vulnerable to extreme weather events such as heavy rainfall, strong winds, and rising sea levels. These risks have intensified in recent years due to climate change especially in cyclone season which can occur from November to April. For example, the most recent deadly storm in January 2023 caused four fatalities and widespread flooding and landslides across Mahé Ministry of Transport 2025. These environmental challenges place considerable pressure on Seychelles' logistics infrastructure and emergency response systems. An short overview of past disruptions are highlighted in Table 3.1.

Table 3.1: Major Disruptions in Seychelles (2002–2024)

Date / Event	Island(s)	Impact
Sep 2002, Cyclone “Gerry”	Mahé, Praslin, La Digue	50 homes destroyed on Praslin, 375 families homeless, major outages, €50k ecological damage.
Dec 2004, Landslide	Mahé (Vista do Mar)	170 mm/day rainfall caused landslide, homes damaged.
Dec 2004, Indian Ocean Tsunami	Coastal Mahé	2 deaths, infrastructure and homes flooded, bridges collapsed.
Jan 2006, Cyclone Bondo	Farquhar, Providence, Mahé	60% crop loss (Providence), building destruction, coastal erosion, 1 injured.
Apr 2013, Cyclone Fellingeng	Mahé, Praslin, La Digue	18 fatalities, US\$8.4M damage, 1,000 families affected.
Apr 2016, Cyclone Fantala	Farquhar Atoll	Category 5 cyclone, 19 of 50 buildings destroyed, US\$4.5M damage.
Feb 2014, Flooding	Mahé	Major flooding
Mrt 2020, Covid 19	Seychelles	Major disruption to world wide transport, Cargo flights needed for supplies
2021, Tropical Storm Jobo	Seychelles	Flooding recorded, no major losses reported.
Dec 2023, Flooding + Explosion	Mahé (Victoria, Cascade)	3 deaths, 178 injured, severe building and airport damage, state of emergency declared.

Despite having a relatively high gross national income per capita, largely due to a thriving tourism sector divided in high(winter) and low (summer) season. The Seychelles remains constrained in its ability to invest in large scale infrastructure projects. A 2016 masterplan for upgrading and expanding the port was never implemented due to insufficient funding (MTBS 2012). Currently, a new feasibility study is being conducted with support from the World Bank as part of a \$15 million loan aimed at strengthening the transport sector.

Financial limitations and harsh climatic conditions have contributed to infrastructure degradation, especially at Port Victoria. According to the (UNc 2022), the port's commercial quay, where all larger vessels dock, is in a state of serious disrepair and lacks sufficient space for future expansion. More-

over, the airport's direct coastal location leaves it highly vulnerable to sea-level rise and overtopping, as it currently lacks adequate coastal defenses.

To understand the governmental structure and the public–private relationships relevant to this study, Figure 3.5 presents an overview of the key ministries in Seychelles. The figure highlights the authorities relevant to transport, port, and emergency logistics, and indicates the agencies they report to.

The republic of Seychelles is well suited as a case study due to its geographic fragmentation, vulnerability to disruptions, and the inherent constraints faced by SIDS. Although comparatively it has more financial resources than many other SIDS, this also facilitates improved data availability and institutional capacity. Both of which support the operationalization and validation of the proposed modelling approach.



Figure 3.3: Port of Seychelles



Figure 3.4: Seychelles International Airport

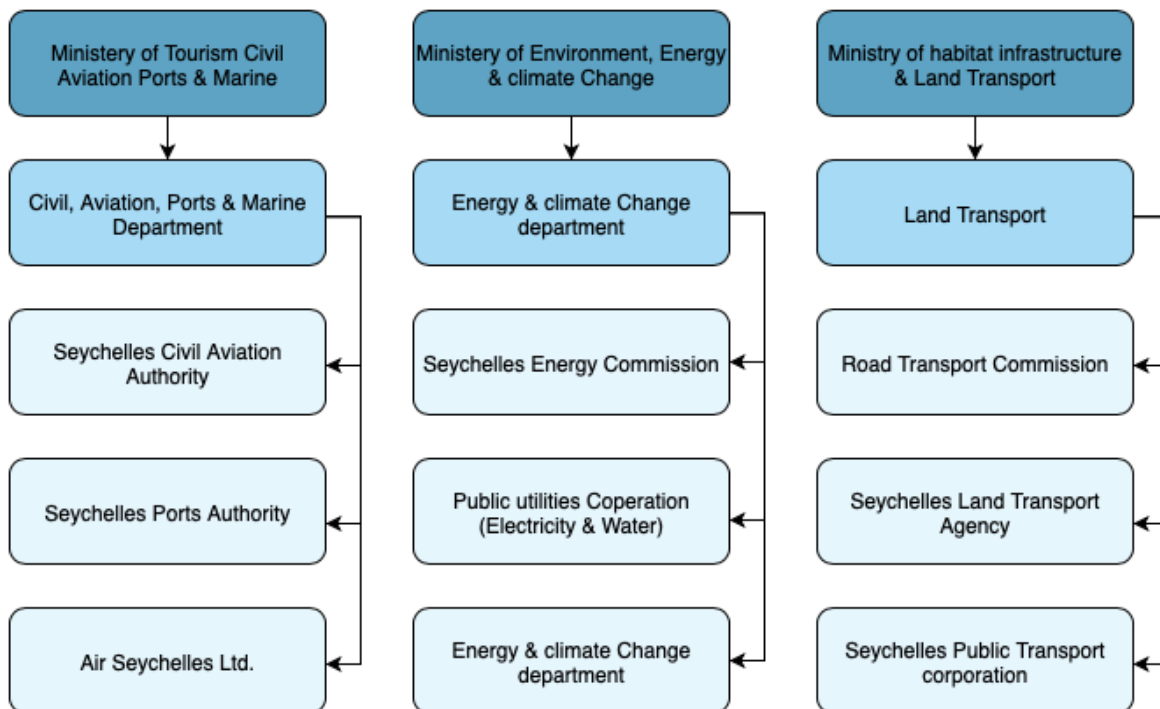


Figure 3.5: Highlighted version of Ministries (Dark blue), departments (blue) and agencies (light blue) in Seychelles

Research Methodology

4.1. Expert opinions

The two types of methods of approaching stakeholders applied in this case study are: *the informal conversational*, and *the standardized open ended* conversation. Both qualitative approaches to extraction information have one thing in common: they ask sincere open ended questions that give stakeholders the opportunity to respond in their own words and express their personal perspectives. It is important that they feel free to speak and share their thoughts and feelings. This research will use different types of questions within the two methods, and the advantages and disadvantages of each method are discussed in the table below.

Type of Interview	Characteristics	Strengths	Weaknesses
Informal conversational interview	Questions emerge from the immediate context and are asked in the natural course of things; there is no predetermination of question topics or wording.	Increases the salience and relevance of questions; interviews are built on and emerge from observations; the interview can be matched to individuals and circumstances.	Different information collected from different people with different questions. Less systematic and comprehensive if certain questions do not arise naturally. Data organization and analysis can be quite difficult.
Interview guide approach	Topics and issues to be covered are specified in advance, in outline form; interviewer decides sequence and wording of questions in the course of the interview.	The outline increases the comprehensiveness of the data and makes data collection somewhat systematic for each respondent. Logical gaps in data can be anticipated and closed. Interviews remain fairly conversational and situational.	Important and salient topics may be inadvertently omitted. Interviewer flexibility in sequencing and wording questions can result in substantially different responses from different perspectives, thus reducing the comparability of responses.
Standardized open-ended interview	The exact wording and sequence of questions are determined in advance. All interviewees are asked the same basic questions in the same order. Questions are worded in a completely open-ended format.	Respondents answer the same questions, thus increasing comparability of responses; data are complete for each person on the topics addressed in the interview. Reduces interviewer effects and bias when several interviewers are used. Permits evaluation users to see and review the instrumentation used in the evaluation. Facilitates organization and analysis of the data.	Little flexibility in relating the interview to particular individuals and circumstances; standardized wording of questions may constrain and limit naturalness and relevance of questions and answers.
Closed, fixed-response interview	Questions and response categories are determined in advance. Responses are fixed; respondent chooses from among these fixed responses.	Data analysis is simple; responses can be directly compared and easily aggregated; many questions can be asked in a short time.	Respondents must fit their experiences and feelings into the researcher's categories; may be perceived as impersonal, irrelevant, and mechanistic. Can distort what respondents really mean or experienced by so completely limiting their response choices.

Figure 4.1: Variations in interview instrumentation (Patton 1990)

Based on these formats, several types of questions will be used in this study. One of the main types are opinion and value questions. These questions aim to gain insight into people's cognitive and interpretive processes and focus on opinions, judgments, and values. They tell more about how people think than about their actions or behavior. The answers tell what people think about certain experiences or issues. They provide insight into people's goals, intentions, desires, and expectations. Examples of such questions are: *"What do you believe about...?"*, *"What is your opinion on...?"*, *"What would you like to see happen at...?"*, *"What do you think about...?"*

There are also knowledge questions, which obtain factual information from the respondent. These are

not opinions or feelings but actual knowledge. For instance, questions about the status quo such as: “What are the number of operational cargo vessels for inter island transport?”. A knowledge question can also concern a specific program, such as what services are available, who qualifies, what the rules and regulations are, like: “what resilience strategies are that are currently in place within land based transport?”.

Furthermore, it is important to take into account the concept of a “time frame question”, in which the respondent is guided through their answer in a phased way: first what they currently do, then what they have done in the past, and finally what they would like to do in the future. This created a fuller understanding of the context and for this research provides insight in to historical events, current views, and expected changes.

The expert conversations that are conducted will be not recorded or transcribed in anyway. Aswel as during the all conversation any mentions to personal details will be disregarded to treat these conversations as an information source but not as direct citations. Stakeholder are presented below as profiles that are approached and with their prospected information and initial insights.

4.1.1. Stakeholder selection

Specific stakeholders were contacted based on their expected contributions to different components of the model and validation process. The Seychelles Ports Authority (SPA) and Seychelles Civil Aviation Authority (SCAA) were engaged to provide insight into port and airport capacity, cold chain handling, and disruption response, forming the basis for both the operational capacity constraints and resilience scenarios modeled. The Seychelles Land Transport Agency (SLTA) was contacted to validate assumptions about inland distribution delays and terrain related vulnerabilities, which fed into intra-island delay logic. The Disaster Risk Management Division (DRMD) and humanitarian organizations were targeted for their expected knowledge on emergency logistics and historical disruption knowlegde. Also providing knowledge about current resilience practices in place and opinion against adaptation stratagies. Ferry operators and cargo/logistics companies where targeted to understanding inter-island transport delays, informal workaround strategies, and operational insights, supporting delay modeling and fall-back logic. Local actors like corner stores, the Seychelles Trading Company (STC), and residents informed the social impact dimension, perishability handling, and distribution behavior, validating the assumptions on minimal route optimization and decentralized delivery. Distributors of essential goods (pharmacies/hospitals/SEYPAC (carbohydrates)) were hoped to clarify safety stock strategies and delivery routines, though limited contact was made. Finally, visits to related infrastructure (e.g., ports, airports) provided on site validation of physical layouts, capacity bottlenecks, and cold chain limitations, crucial for tailoring the case specific model and validating conceptual assumptions. Each stakeholder thus played a targeted role in bridging field observations with the model’s logic, balancing general SIDS behavior with Seychelles specific constraints.

4.1.2. Outcomes of expert conversations

This section summarizes practical insights gathered through fieldwork and expert conversations. These findings reflect both Seychelles specific logistics behavior and patterns generalizable to other SIDS. Numerical data and validation related insights are discussed in the Modeling approach and Results.

Table 4.1: Insights from Expert conversations

Organisation	Relevant Information	Initial Insights
Seychelles Ports Authority (SPA)	Port capacity data, disruption response, validation of model prediction on historical events.	unexpected port delay patterns, mostly due to capacity constraints, operational delays due to workers. Inter island disruptions mainly due to sea conditions, limited fallback procedures for perishables. Larger ship used for outer islands

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Organisation	Relevant Information	Initial Insights
Seychelles Civil Aviation Authority (SCAA)	Cargo volumes, cold chain capacity, and resilience of air logistics.	Cold chain weaknesses at small airports, influence of tourist sector on cargo on inter island planes, limited fallback procedures for perishables.
Seychelles Land Transport Agency (SLTA)	Ground transport vulnerabilities and validation of inland distribution assumptions.	Response times for past landslides faster than expected, delays due to traffic, vulnerabilities due to steep terrain and limited vehicle access, prohibited times for vehicles carrying containers
Disaster Risk Management Division (DRMD)	Historical disaster response flows and emergency logistics.	Document discussing past disasters (awaiting), past mismatches between origination and ministries, disaster prep is in document fase, awareness but no plans in place.
Ferry Operators (person) (Cat Cocos, Inter Island Ferry)	Empirical data on delays and vessel capacity.	Unscheduled service cancellations, weather dependent network fragility, clear separation of freight and people
Cargo / Logistics Companies	Realistic constraints and strategies in private logistics, order quantities	Unofficial workaround strategies during road/ferry failure, use of informal networks,
Corner Stores and Seychelles trading company, STC	Validation of social impact and local supply chain continuity.	Reliance on single supply routes, more supermarket chains than assumed, perishability not priority, Cornerstones depend on STC, Lack of refrigeration during outages, Goods retrieval own responsibility, refrigerated transport not always possible, shortage of fresh produces often processed
Distributors of Essential Goods (fuel (Seypec), medicine)	Insights in distribution and order methods for medicine and safety stocks	No connection was able to be established during site visit, except through pharmacies. Central ordered and distributed over islands.
Households / Residents	Ground level experience for social impact analysis.	Improvised community level distribution, aware of lack of production (and their vulnerability) but to a lesser extend extreme weather, Shared refrigeration during blackouts.
NGOs / Humanitarian Organisations (Redcross)	Response capacity and historical data on supplied goods	No connection was able to be established during site visit
Port Infrastructure (e.g., Port Victoria, La Digue Jetty)	Photographic documentation. Physical layout for validation.	Port design limitations for container handling in emergencies, old infrastructure and superstructure, lack of space, or no infrastructure on outer islands
Local Airports (Praslin or outer island)	Infrastructure validation and layout details.	Cargo transport in flights increases in tourist seasons, outer regions more supplied with planes, unscheduled service cancellations, weather dependent network fragility

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Organisation	Relevant Information	Initial Insights
Storage Facilities (e.g., warehouses, cold stores)	photographic documentation. Cold chain and fallback strategy validation.	Use of outdated backup generators, Limited shared cold storage between sectors. Regular trucks with boxes of ices or styrofoam used for island transport

Cold Chain and Perishability

As confirmed in both desk research and expert input from Pacific SIDS, perishability is not a key priority in small island logistics. Due to the circumstance it is being made difficult, factors include limited cold storage, high surrounding temperature temperatures, the cost of refrigerated transport, and inconsistent delivery times. These factors for example, in 30°C heat, goods like lettuce spoil quickly in being stored styrofoam boxes if ships are delayed by even a few hours and can cause food poisoning. Despite this, all goods, including spoiled ones, are still delivered and consumed, as shops and consumers have limited alternatives. While stakeholders in Seychelles expressed interest in improving cold chain logistics, no system exists to measure spoilage or prioritize perishable goods. Prioritization only occurs ad hoc e.g., shop owners unload cold goods first from trucks, but without coordinated systems.

Cold storage at the Port of Victoria is handled via reefer containers used as permanent facilities. Airport cold storage is almost non existent. However at the warehouse of the main supermarket/ imported STC their is a magazine with cold storage. The conceptual model's simplified perishability logic and prioritization behavior were therefore validated. However, the assumption that cold and regular goods are always transported separately was partly invalid. Most trucks combine both types, often using styrofoam lined boxes in open pickup trucks. The same applies to inter island ships. Given that Seychelles is one of the more developed SIDS, this behavior is assumed to be generalizable as a minimum standard and adapted.

Intra Island Distribution

The assumption that shops, gas stations, and hospitals are directly supplied without intermediate distribution hubs was validated through site visits and conversations with STC, the national food importer. Shops collect goods directly from wholesale points, and manage their own transport.

Medical goods are collectively ordered by hospitals and clinics but picked up individually. While the conceptual model assumed corner stores are independent, it was discovered that some owners operate two or three shops. Still, due to limited truck capacity, they make multiple trips, validating the model's assumption of minimal route optimization.

Resorts also import goods independently and tend to use more professional transport (e.g., enclosed trucks), unlike the standard pickup trucks used by smaller retailers. The case specific model accounts for this with three truck types: pickup (most common), small trucks, and container trucks. These differ in loading capacity and access constraints.

One critical insight was that trucks with containers are banned from roads during peak traffic hours (7:00–8:30, 12:00–13:30, 16:00–18:00). While this level of detail is too specific for the conceptual model, its structure allows this behavior to be added in tailored implementations. This is an example like mentioned in Chapter 2. Trade offs, that shows the constraint of developing a conceptual model and island specific behaviour that influence the intrinsic behavior. Add to much of this insights and the case study model is no longer the conceptual model.

Traffic and Terrain Constraints

Seychelles has over 40,000 vehicles, mostly on the main island. With only one lane mountain roads and sharp elevation changes, congestion is a real issue during peak hours. This is modeled in the case specific version by assigning delay factors to road segments.

However, congestion is not generally a problem across other SIDS, or besides the main island in the Seychelles. Many are flatter (coral atolls) and have far fewer vehicles per capita. While the conceptual model allows for edge based delays, congestion is only modeled as a variable where relevant.

Inter Island Transport Delays

Multiple stakeholders cited varying reasons for inter island transport delays. Port workers pointed to weather, equipment failures, and late cargo pickup. Government officials highlighted broader issues such as lack of training and inconsistent work culture. The conceptual model uses bounded random distributions per link to simulate delays. As no systematic data exists on delay causes even in data rich Seychelles, this remains a valid approach.

Mode Split and Transport Modes

In standard four phase models, mode split is based on shipper preferences, route characteristics, or policy constraints predicted by choice driven models. In SIDS, this logic simplifies: there is no rail or inland water transport. Intra island movement is by road, inter island by ship or, for cold goods, occasionally by plane.

The conceptual model assumes that only cold goods use air transport, and the rest use maritime shipping. This reflects capacity constraints and the high cost of air freight. It also assumes that passenger planes sometimes carry cargo when no dedicated cargo service exists.

During the site visit, it was found that one old passenger plane had been repurposed into a weekly cargo service to Praslin for cold goods. This is not generalizable stakeholders from other SIDS confirmed that if cold cargo is urgent, passenger services are sometimes cancelled to prioritize cargo. In the case specific model, this was modeled as a weekly cargo flight rather than daily passenger based shipments.

Another Seychelles specific insight is that outer islands with no resorts or tourist infrastructure often have irregular or limited cargo service. During high tourist seasons, passenger flights increase and occasionally carry extra cargo. However, this behavior varies within Seychelles and is not generalizable. Therefore, the conceptual model bases mode choice on compatibility (cold vs. non cold) rather than flight frequency or destination type. The case specific model adds mode splits per island, as explained in the next chapter.

4.2. Modeling approach

In this chapter an explanation of and the adaptation to the four step freight framework are given. First, the general structure of a four phase model is explained, and how it is typically implemented. Additionally, the specific modifications are required to tailor the model to small island contexts. Applied are insights from the chapter 2 and section 4.1. This is modeled as as a discrete event, hub spoke network simulation focused on essential goods, multimodal transport, and operational bottlenecks. This section explains how the casestudy model was built, which data sources were used, how these were processed, and what assumptions underpin the system behavior. The goal is to allow testing of different strategies of adaptation measures under disruptions.

4.2.1. Layout of the graph

To make the complete graph of the seychelles the following procedure was applied. First, the road network of all the islands was extracted via Open Street Map(OSM), and all relevant locations such as shops, gas stations, hospitals, ports, airports, helipads were identified using open source GIS data. Governmental regions were then overlaid on this spatial data. All gas stations and hospitals were included as individual nodes and during the site visit, significant shops at s were selected as nodes in the model. As including all shops would overcrowd the graph shop locations were selected more carefully, with a minimum of one shop assigned to each governmental region to ensure that demand from inland areas (hinterlands) could be properly modeled (see ??). For some governmental regions, multiple shops were included based on insights from the site visit as that region was prone to being cut off during disruption (Ring road prone to disruption). This lead to a simplified hub spoke graph of the Seychelles where further features could be added on. In Figure 4.2 a representation of given were the inter island edges are omitted for visibility.

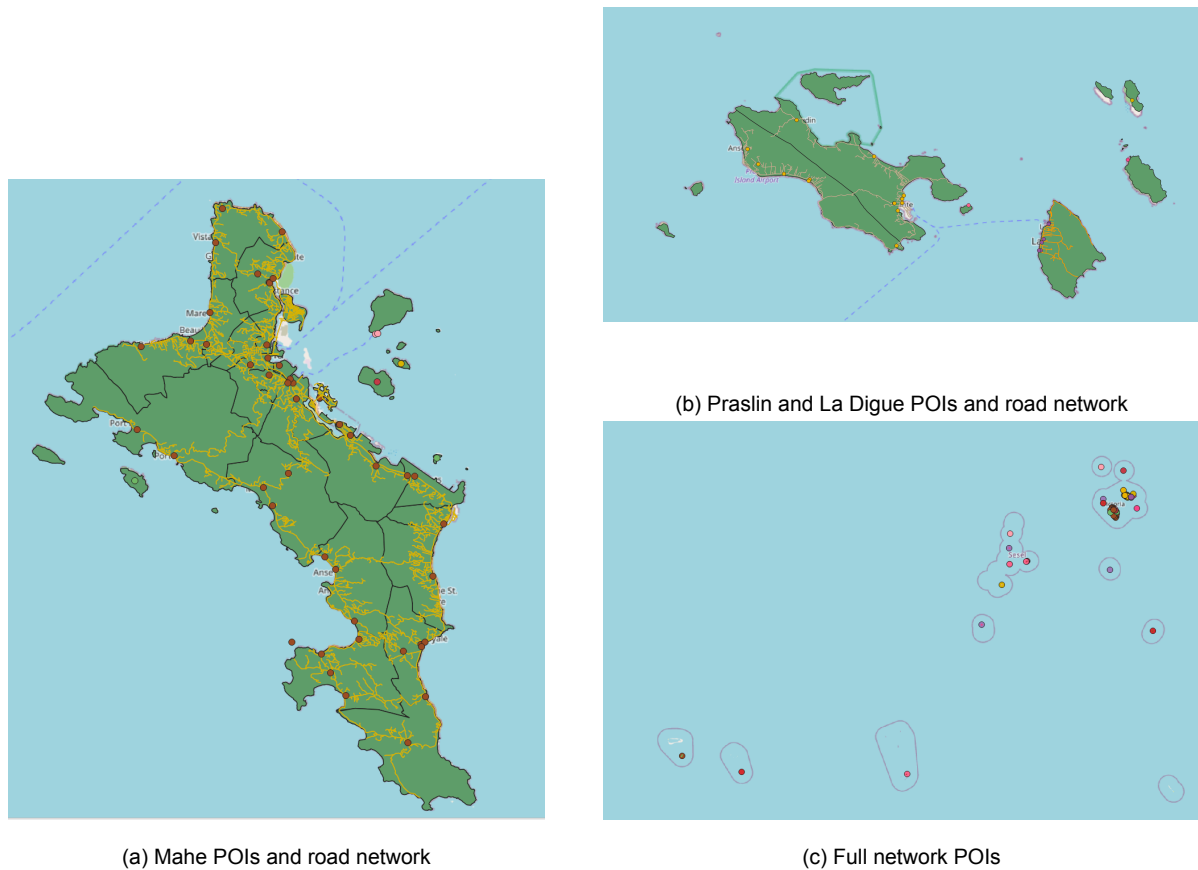


Figure 4.2: Overview of points of interest and road infrastructure: (a) Mahe, (b) Praslin with La Digue, and (c) the full inter island network.

Nodes & edges

As previously discussed nodes represent logistical infrastructure points. Separated in Global (Mahe), Regional (Praslin & La Digue), and hinterland nodes consisting of Shops, Hospitals, Gas stations and Local Ports. Edges consist out of ship, plane or road connection. Hinterland locations are linked both to the port and airport at each island, ensuring that goods can arrive either by sea or air. Local ports do not have any hinterland connections. On the Seychelles and other small islands where there is no formal transport network on the outer island (often only sand roads), and goods are collected manually by individuals directly from the port. This was confirmed for the Seychelles during the site visit and for other SIDS during a conversation with Expert Opinions 1. Local ports are directly connected with the global port or to the a regional port or airport that serves confirmed by the SCAA and SPA. This constraint simulates the real world limitation in SIDS where inter island ferry or small plane services typically operate as single isolated links without redundancy. The total network consist out of the following nodes:

Table 4.2: Node types and counts in the transport network (Total edges: 2848)

	Shop	Local Port	Hospital	Gas Station	Local Airport	Regional Port	Global Port	Global Airport	Regional Airport
Count	43	26	12	12	12	2	1	1	1

4.2.2. Basis of four step transport model

To guide the design of the model components and ensure that key logistical behaviors are systematically represented, the four-step freight modeling framework is adopted as a conceptual scaffold. This approach which is widely used in freight studies to structure input data and model logic (Tavassy 2011), helps integrate demand generation, flow distribution, transport mode selection, and routing into both

graph based and simulation based modeling environments.

Step 1: Generation and Attraction

The generation and attraction step estimates the inflow and outflow of goods per zone, laying the foundation for network based demand modelling. In the SIDS, this model is simplified to focus solely on import related flows, given the structural import dependency of such economies. This distinction marks a deviation from classical freight transport models that consider both inbound and outbound flows across industrial zones.

Unlike larger and more industrialised countries where freight generation is often linked to manufacturing output or domestic production hubs, the primary drivers of freight demand in SIDS are end consumers, residents and tourists. This consumer based demand profile emerges due to the limited presence of export oriented industries and the high dependence on external sources for basic goods, construction materials, and equipment.

In Seychelles, this pattern is particularly evident. The majority of inbound freight serves consumption purposes, either by the local population or the rapidly fluctuating tourist population. The national freight system is thus closely tied to population dynamics and seasonal tourism trends, which create substantial peaks in demand. As a result, traditional generation models based on industrial output are not suitable.

This SIDS specific interpretation diverges from classical generation and attraction methods used in large scale freight models, where economic activity and historic shipment records typically inform freight generation (Bombelli 2024). However, literature on disaggregated demand modelling supports the use of harmonised commodity data (HS codes) to inform freight decomposition and allocation, particularly when disaggregating imports to demand zones and vessel compatibility (sheffi2005; rodrigue2017). This thesis aligns with these principles by integrating HS-code based demand profiles and vessel compatibility matrices.

The simulation imports historical trade statistics and disaggregates annual volumes by HS code, scaled to the seasonal window of interest. Freight generation is modelled by applying a set of precomputed ratios to estimate total expected demand per HS code for a given season. These ratios were constructed by analysing import volumes from 2016 to 2022 (excluding COVID-19 years) and smoothing outliers using standard deviations. Attraction, in turn, is performed by distributing these volumes across compatible vessels in a season, based on their available capacity and HS-code compatibility. The following datasets are used:

- `hs_compatibility` — Defines compatibility of HS codes with vessel types (expert-defined).
- `port_calls` — Timestamped arrival data and available tonnage per vessel (Portwatch).
- `trade` — Monthly historical import values per HS code (Seychelles Bureau of Statistics).
- `ratios` — Derived average ratios of HS code shares (2016–2022), corrected for outliers.
- `count` — Frequency of HS code occurrences in COMPTAD, normalised to the selected season.

The model filters the dataset for the selected year and season (e.g., High = September–November), retaining only vessels or planes with non-zero import tonnage. Total seasonal capacity is then calculated. For each HS code, the estimated tonnage is allocated across compatible vessels, using a cap on both vessel capacity and allowed delivery frequency (from `count`).

A core hypothesis of this study is that seasonality in freight imports is partially driven by the tourism sector. In Seychelles, the presence of over 8,000 tourists per month during the high season constitutes nearly 7% of the resident population. This, combined with the typically higher consumption rates of Western tourists (as noted by SPA stakeholders), results in seasonal peaks in freight arrivals. Data from Portwatch confirms this, with increased vessel arrivals during high tourism months.

To model this effect, the simulation filters vessel arrivals by season: *High Season* (September, October, November) and *Low Season* (April, May, June). These months were selected based on a comparative analysis of monthly average tourism arrivals and freight import values (in SCR). The analysis revealed a partial overlap between peak tourism and import periods, likely influenced by additional factors such as cyclone driven prestocking in late Q4.

Table 4.3: Direct month wise comparison of average imports (2016 2024) based on tourism (per person) and freight (Seychelles Rupee).

Metric	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
zTourism Avg (AVG*)	25,591	31,873	33,725	33,898	24,429	23,226	28,860	30,328	25,214	34,664	30,950	33,594
Freight Avg (AVG*)	1,450,401	1,366,252	1,544,323	1,532,808	1,600,182	1,518,869	1,734,525	1,565,708	1,803,527	1,740,444	1,565,791	1,549,636

Interviews with the Disaster Risk Management Division (DRMD) and Seychelles Port Authority (SPA) supported the seasonal logic. DRMD confirmed that while some prestocking occurs before the cyclone season, the practice is limited due to unpredictability and storage costs. SPA confirmed that the port is busiest during the tourist season, which aligns with observed patterns in vessel arrivals and aligns with Portwatch data.

Step 2: Distribution Modelling

Distribution modelling allocates total incoming flows among origin–destination (OD) pairs across the islands. In classical freight models, distribution is typically implemented through gravity or entropy based formulations (Tavassy 2011). These techniques rely on the assumption of relatively stable, large scale demand and production flows e.g., between industrial hubs and major consumption centers. They operate by estimating flows between zones as a function of generalized cost (such as distance or travel time) and zonal attributes like production and attraction capacities.

In SIDS and in particular in the Seychelles, such models are less effective due to the absence of strong inter zonal economic production or logistics corridors. Industrial production is minimal, and freight flows are almost entirely consumption driven. This makes traditional OD-based gravity assumptions less meaningful. As a result, distribution logic must be adapted to reflect the structure of demand generation, aka the spatial population densities and the location specific variation in tourist occupation. Goods are not distributed between producers and markets but instead routed from ports and airports to Points of Interest (POIs) based on where consumption occurs.

To accommodate this structure, the model substitutes classical gravity logic with a scenario dependent distribution mechanism based on seasonal demographics. Each region or island receives a seasonal demand ratio, calculated as a function of its population and tourist load during the relevant season. For example, a shop in a region that hosts more tourists during high season will attract a proportionally larger share of imported goods.

This approach results in dynamic seasonal redistribution. The model defines:

- *High Season:* September, October, November
- *Low Season:* April, May, June

Each Point of Interest (e.g., hospital, shop, gas station) is linked to a region with a calculated share of national consumption demand for that season.

The implementation proceeds as follows:

1. The share of demand per region is computed as:

$$\text{Share}_{\text{region}} = \frac{\text{inhabitants}_{\text{region}} + \text{tourists}_{\text{season, region}}}{\text{total population}_{\text{island}} + \text{total tourists}_{\text{season}}}$$

2. For each region, this share is then divided equally among all POIs of a given type (e.g., supermarkets, clinics) that are eligible to receive goods based on HS code compatibility.

Hospitals and gas stations are assigned to specific regions using geographic clustering, based on OpenStreetMap (OSM) coordinates. The same seasonal logic is used to assign demand shares to these POI's.

The result is a node level demand matrix in tonnes per HS code for the simulation horizon. Demand is disaggregated to the POI level, enabling precise tracking of delivery needs. For instance, Table 4.4 shows the resulting low-season allocation for two shops in the Anse Royale region of Mahé. The

Table 4.4: Assigned seasonal ratios for shops in Anse Royale, Mahé

Node Name	Type	Lat	Lon	Island	OSM Node	Name	Shop	Region ID	Region	High	Low
mahé_shop_38	shop	4.7426	55.5096	Mahé	303944485	SPR Shopping	supermarket	SC05	Anse Royale	1.293	1.309
mahé_shop_77	shop	4.7409	55.5170	Mahé	303397304	ISPC Supermarket Fresh	supermarket	SC05	Anse Royale	1.293	1.309

combined regional share of goods is 2.618%, which is divided evenly between the two shops, each receiving 1.309% of the total low-season tonnage of compatible HS-coded imports.

While the seasonal effect of tourism on freight demand is visible across all islands, the magnitude of change differs. Table 4.5 shows the relative increase in goods transported during the high season compared to the low season. The difference is most pronounced on La Digue and Mahé, which host a larger and more variable tourist population. Outer islands and Praslin show less variation, suggesting more stable yearround demand, either due to more consistent tourist inflow or lower tourist densities overall.

Table 4.5: Relative Percentage Change in Goods Transported High to Low Season

Island	Relative Change (%)
Mahé	21.69
Praslin	15.22
La Digue	24.88
Other	18.25

The demographic distribution of inhabitants was sourced from national data. Tourist densities per region per month were derived from aggregated accommodation statistics and spatial analysis of hotel locations. All POIs were sourced from OSM using spatial filters, and geographic clustering was performed to assign them to their respective regions. The resulting seasonal ratios per node are provided in full in Appendix D.

Distribution modelling in this SIDS context shifts away from classical cost-based freight flows and towards demand based logic. By integrating population, tourist flows, and POI level demand, the model produces a spatially disaggregated freight demand profile tailored to the unique structure of the Seychelles. This approach captures the uneven and seasonal nature of demand, especially relevant for resilience and disruption analysis in the later simulation stages.

Step 3: Mode Selection and Conversion

In freight transport modelling, mode selection is traditionally determined by the characteristics of the shipment urgency, cost and infrastructure availability. Standard approaches often employ discrete choice models such as Multinomial Logit or Mixed Logit models (Maria et al. 2024; Helsdingen 2023; Montagna et al. 2002), incorporating socio-economic variables, shipper preferences, and service characteristics to simulate rational decision-making across available options.

In the context of Small Island Developing States, this level of complexity becomes both infeasible and unnecessary. Modal diversity is extremely limited, and freight transport options are constrained to a narrow set of maritime and air links. Land-based transport is typically limited to short-haul trucking on a small number of islands. Moreover, freight and passenger services often share infrastructure particularly in air travel and inter-island shipping to reducing the space for true modal competition. As such, mode “choice” is less a matter of preference or trade-off, and more a matter of availability.

In addition, the presence of informal, unregulated logistics behavior further limits the applicability of rational choice modelling. Unregistered deliveries, ad hoc arrangements between suppliers and consumers, and mixed-use transport (e.g., carrying both passengers and small cargo) are difficult to capture with mathematically driven choice models. Hence, a direct substitution approach is used.

Instead of applying a formal choice model, this thesis assigns transport modes based on network structure and compatible vehicle sampling. The selected route determines the feasible mode (e.g., road,

sea, or air), after which a transport vehicle is randomly drawn from a defined fleet for that mode. Vehicle properties such as speed, capacity, delay, and cargo compatibility are used to simulate delivery times and resource usage. This mirrors operational logistics practices in Seychelles, where actual deliveries are made using a small set of vehicle types confirmed by stakeholders including SLTA and freight forwarders.

Mode selection is implemented through a structured algorithm that combines feasibility constraints with stochastic sampling. The steps are as follows:

- **Step 1:** Define the fleet of available vehicles, grouped by mode:
 - Each vehicle type is assigned a unique ID, speed (km/h), operational delay (hours), capacity range (tonnes), supported cargo classes (`normal`, `cold`, `gas`), and possible route restrictions.
- **Step 2:** For a selected transport route:
 - Filter the fleet for vehicles within the required mode.
 - Only include vehicles that can handle the cargo's class (e.g., cold chain requirements).
 - If a vehicle is route-restricted (e.g., planes only servicing Praslin–Mahé), ensure compatibility.
- **Step 3:** Perform weighted sampling to mimic realistic distribution across vehicle types:
 - Apply an exponential weighting to favor smaller vehicles: $w_i = e^i$.
 - Normalize weights and randomly sample a vehicle from the filtered list.
 - Draw a vehicle capacity uniformly from its specified range.
 - Calculate travel time using vehicle speed and edge length.
 - Apply operational delay (if any), scaled by a percentage of travel time.

This process is applied dynamically to each transport event in the simulation.

Table 4.6: Overview of Transport Modes and Characteristics

Mode	Speed (km/h)	Delay (h/factor)	Capacity (t)	Classes	Distribution (%)
Truck_small	40	0.2%	1–2	normal, cold	±70%
Truck_medium	40	0.2%	2–3	normal, cold	±25%
Truck_large	15	0/1	4–5	normal, cold	±5%
Truck_gas	15	0.2%	25–35	gas	100%
Ship_small	20	1–3 h	25–30	normal, cold, gas	±25%
Ship_medium	18	2–5 h	50–60	normal, cold, gas	±55%
Ship_large	16	0.1%	90–100	normal, cold, gas	±20%
Plane_freight	200	1–3 h	1–2	cold	100%
Plane_passenger	200	1–3 h	1–2	normal, cold, gas	100%

The weighting between different vehicles reflects operational realities confirmed by stakeholders. For instance, small trucks dominate intra-island delivery operations due to narrow roads and small delivery volumes, while medium boats are most common for inter-island freight, as confirmed by the SPA's vessel registry. Constraints such as container ship docking limits and cold chain compatibility further reduce the feasible set of vehicles for specific goods and routes. Photographic references of selected transport vehicles are shown in Figure 4.3, providing visual context for the physical infrastructure underpinning the simulation.

Step 4: Allocation and Assignment

The assignment phase allocates vehicle movements to the infrastructure network. In conventional models, this involves flow based algorithms sensitive to route capacities, travel times, and congestion. These methods most of the time assume that all users (e.g., shippers) act to minimise travel time or

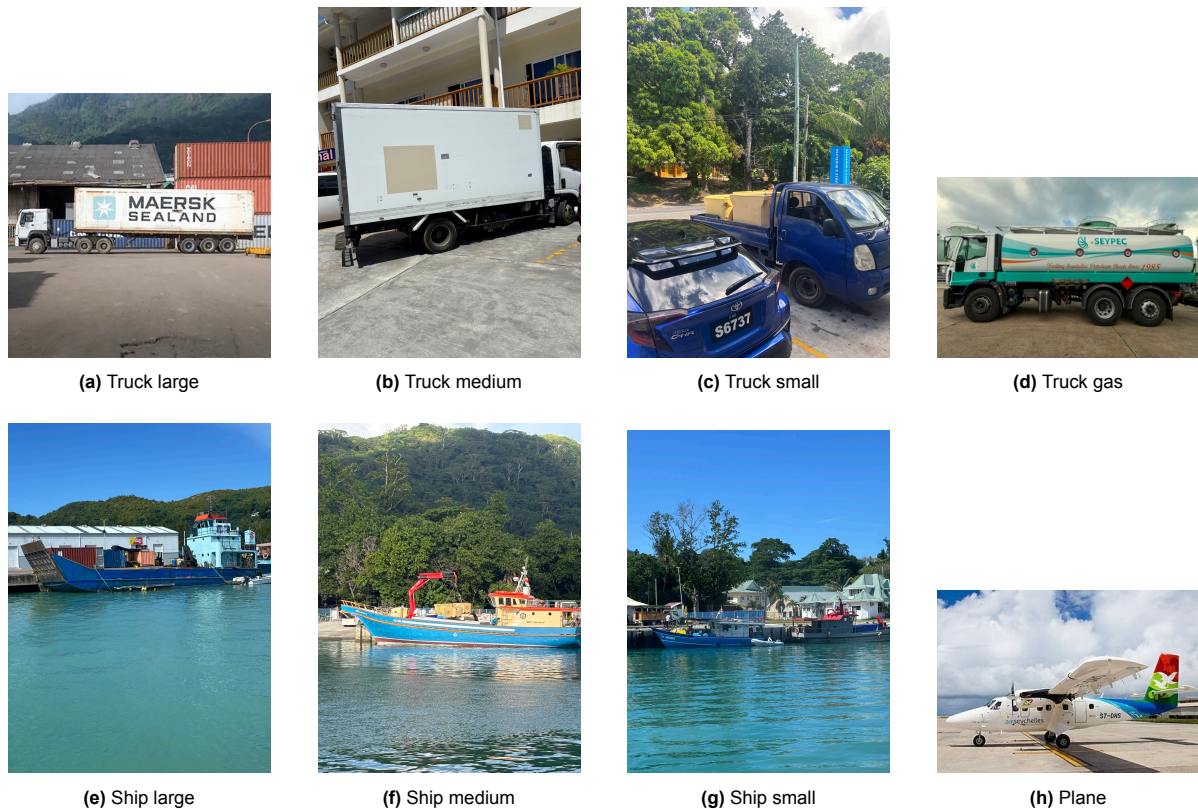


Figure 4.3: Examples of transport vehicles used in the Seychelles.

cost, subject to network constraints. Mathematically, this involves solving optimisation problems specific to the issue at hand as shown below. As identified in the literature research, this is not the priority or an option in SIDS, especially during disasters caused by extreme weather. In freight specific models, these flows are usually aggregate volumes (tonnes or vehicles per time unit), statically allocated across the network. The proportional allocation logic, combined with compatibility filters, resembles multi commodity flow and matching models where goods must be assigned to limited capacity transport nodes or vehicles (e.g., capacitated network design models). Therefore This step is simulated with an discrete event simulation. Which can handle the queue of ports and airpods without becoming too complex.

4.2.3. Discrete event simulation

The Discrete event simulation start consist of the following events. Which will be discussed per event in more detail below.

- **Arrivals:** Goods reaching a node.
- **Unloading:** Moving goods into storage or dispatch queues.
- **Customs:** Clearance delays.
- **Storage:** Queueing goods based on capacity.
- **Overflow storage:** If queue is full moves to overflow storage.
- **Batch Dispatch:** Sending batches along edges.
- **Delivery:** delivery to next node or final destination.

Arrival and Unloading

All international goods entering the Seychelles are first handled at the main global port or airport before undergoing any domestic distribution. Containerized logistics is limited in both scope and infrastructure. Most imported goods are not handled through structured container terminals but are instead manually unpacked and directly transferred into warehouses, where they are temporarily stored until collection.

Although reach stackers are available at the Port of Victoria (Mahé) to handle containers, a large proportion of containers are opened quayside, and their contents are manually offloaded into general storage facilities.

Cold chain storage is provided through reefer containers placed at the port. Dedicated cold warehouses are absent. Gasoline and diesel imports (grouped as gas or “carbohydrates”) are pumped directly into designated tanks upon arrival and follow a somewhat separate logistical path, operated by SEYPAC which does use the same commercial quay. For example, gas truck board directly on Ro-Ro vessels for inter island transport, aggregating again with other good classes. Regional islands such as Praslin and La Digue possess limited general storage facilities, and goods arriving there are often placed directly onto the quay or small platforms. At regional airports, particularly on Mahé and Praslin, there is no formal warehouse infrastructure, goods are laid out in designated cargo zones until picked up for delivery or reloaded onto connecting flights.

These differences are illustrated in Figure 4.4, which shows the heterogeneity in freight handling locations across the islands.



Figure 4.4: Overview of freight storage locations across the islands: (a) Mahé port warehouse, (b) Praslin warehouse, (c) La Digue storage, and (d) airport cargo zone.

To represent these logistics conditions, the model classifies incoming goods into operationally relevant classes:

- **Normal** , Food and medicine not requiring refrigeration and other goods.
- **Cold** , Refrigerated food and cold-chain medicine.
- **Gas** , Carbohydrates such as diesel, petrol, and LPG.

This classification determines storage eligibility, handling speed, and perishability behavior. In practice, cold goods are only reliably stored at Mahé using reefer containers, while regional islands lack sufficient cold storage capacity. Gas handling is structurally separated from other goods, often under private ownership and pumped directly into storage tanks.

Batch formation for transport is modeled without pallets or containerized grouping. Instead, goods are collected into batches opportunistically, depending on available vehicle capacity and compatibility. When a transport dispatch window opens, goods of the same class are drawn from the queue. Cold goods nearing spoilage are prioritized. Otherwise, no load optimization is performed.

Upon arrival of vessels or aircraft, unloading is triggered by a scheduled `unloading_dispatch` event. This event executes a multi-step logic adapted to local infrastructure:

- Step 1:** Check whether the node is affected by disruption (e.g., storm closure). If closed, delay unloading by a fixed time increment.
- Step 2:** Apply unloading speeds using a triangular distribution specific to the vessel or node type.
- Step 3:** Loop through queued goods on board:

- If the good fits into available storage: unload it directly.
- If not: split it into two sub goods (one stored, one remaining onboard) and assign unique IDs.

Step 4: Record unloading time and progress.

Step 5: Schedule downstream event:

- Global port/airport → customs (partial).
- Regional/local nodes → storage.

Step 6: If goods remain, reschedule `unloading_dispatch` in the next time step.

The unloading speed is sampled from triangular distributions defined per vessel type, as shown in Table 4.7. For regional and local ports, fixed or approximated unloading capacities are used. For gas tankers (carbohydrates), minimum capacities are assumed due to incomplete unloading time records and special handling setups under SEYPAC, a private operator.

Table 4.7: Triangular Unloading Distributions and Node Unload Capacities

Category	Type / Node	Unloading Speed or Capacity
Global ship unloading speed distributions (tonnes/hour)		
Ship Type	BULK CARRIER	Triangular(43.17, 141.15, 238.13)
Ship Type	CEMENT CARRIER	Triangular(18.24, 106.02, 253.22)
Ship Type	CONTAINER SHIP	Triangular(16.76, 94.82, 211.54)
Ship Type	CARGO/CONTAINERSHIP	Triangular(21.84, 94.82, 211.54)
Ship Type	GENERAL CARGO	Triangular(32.66, 86.23, 191.54)
Ship Type	OIL PRODUCTS TANKER	Triangular(20, 57.7, 114.3)
Ship Type	LPG TANKER	Triangular(20, 57.7, 114.3)
Ship Type	CRUDE OIL TANKER	Triangular(20, 57.7, 114.3)
Ship Type	OIL/CHEMICAL TANKER	Triangular(20, 57.7, 114.3)
Regional/local Unloading Capacities (tonnes/hour)		
Node Type	Regional Port / Airport	100 t/h, unload time = 4h
Node Type	Local Port / Airport	Triangular(4, 24, 48)

Cold goods are prioritized during unloading and dispatch based on their perishability window. Each cold good is assigned a randomly sampled shelf life from one of three uniform distributions, reflecting short, medium, or long risk perishables:

$$T_{\text{perish}} \sim \mathcal{U}(24, 48) \text{ or } \mathcal{U}(72, 120) \text{ or } \mathcal{U}(240, 336) \quad (4.1)$$

This perish time is independent of external temperature, reflecting expert interviews and observations that goods are frequently exposed to ambient heat without altering their formal expiry treatment. In line with observations from Seychelles and literature on humanitarian logistics (aung2014; coldchain2008), goods that exceed their perishability limit are not discarded, but still delivered, mirroring real world behavior in SIDS, where alternative supplies are unavailable and formal disposal procedures are lacking.

Cold goods are prioritized in transport dispatch queues but still subject to route frequency limitations. For instance, a good near spoilage may remain delayed due to ferry availability.

Customs and Storage

In the Seychelles, customs procedures are generally not a significant bottleneck for incoming freight. According to expert interviews with the Seychelles Ports Authority (SPA) and the Seychelles Civil Aviation Authority (SCAA), only a small subset of goods, primarily automotive parts and live flora or fauna, are subjected to additional inspection and delay.

Automotive parts are scrutinized because vehicle modification and construction are legally prohibited under safety regulations enforced by the Seychelles Licensing and Transport Authority (SLTA). Meanwhile, flora and fauna are tightly regulated due to the endemic and entropic nature of the Seychellois ecosystem, which customs aims to protect from invasive species.

Despite these checks, both categories represent only a small fraction of total imports. For the majority of cargo, customs clearance is either perfunctory or occurs informally. This aligns with broader findings on SIDS customs effectiveness: due to limited staffing, weak institutional frameworks, and underdeveloped procedures, customs checks are often minimal or bypassed altogether (UNC 2022).

Based on site visits and stakeholder input, customs are modeled as a lightweight event with minimal delay. A small share of goods is randomly selected for inspection, and a short time penalty is applied. No queueing or priority system is modeled, reflecting the relatively frictionless nature of this process in practice.

The customs and storage workflow is modeled through a series of discrete events, executed as follows:

Step 1: Customs Event Handling

- On receiving a `customs` event, check if the node is closed (e.g., due to a disruption). If so, reschedule to the next timestep.
- Record the event and assign a timestamp to the good's `customs_time`.
- Schedule a downstream `storage` event, using a fixed delay for the node.

Step 2: Storage Assignment

- If the node is a logical placeholder (not a physical storage site), redirect the event to `customs` logic.
- Determine the appropriate storage class (`normal`, `cold`, `gas`) based on the HS classification of the good.
- Fetch current available capacity for the given class.
- Sum total tonnage already stored in the queue for that class at the node.

Step 3: If Capacity Is Available

- Store the good in the corresponding storage queue and update its `storage_time`.
- Trigger a single `batch_ready` event for the node to initiate transport dispatch planning.

Step 4: If Storage Is Full

- Redirect the good to the node's `overflow_storage`.
- Increment the node's overflow counter and record the event.
- Schedule a retry through `overflow_delay_dispatch`, applying a delay based on queue congestion.

Overflow storage is handled as a separate queue at each node. Goods routed to overflow retry insertion into main storage after a penalty delay, which increases dynamically with the congestion level. This reproduces the “backlog effect” commonly observed in small island port systems, where limited storage quickly results in cascading delays.

The penalty delay is calculated as follows:

$$\text{Penalty}(n) = 2 + 5 \times \left(\frac{\text{Total Goods Queued at } n}{\text{Max Storage at } n} \right) \quad (4.2)$$

Equation 4.2 defines the delay (in hours) imposed before retrying a storage event at node n . It combines a fixed base delay of 2 hours with a dynamic multiplier proportional to the node's utilization ratio. This design was proposed by the author based on interviews with SPA staff and observations of real world storage limitations at the Port of Victoria.

Notably, this penalty mechanism is essential for recreating the nonlinear delays and persistent congestion patterns typical of constrained island systems, where space is limited and temporary overflow solutions (such as container yards with stelcon tiles) incur added time penalties.

4.2.4. Batch Dispatch and Delivery

In traditional freight flow models, goods are assigned continuously along transport paths, with minimal delay between readiness and departure. However, this logic fails to reflect the transport realities of Small Island Developing States, where low transport frequency, batch consolidated shipments, and operational constraints are the norm. Instead, the model developed for this thesis implements *interval based dispatching*, whereby goods are only moved when a dispatch window (batch interval) is triggered.

In Seychelles, this logic is critical. Interviews with shop owners, port workers, and freight operators indicated that transport is not organized for continuous throughput. Trucks do not operate through the night, and inter-island ferries and flights have limited daily capacity. Routes have "rest windows" or minimum headways that constrain how frequently goods can be dispatched. This batching mechanism mirrors ferry bottlenecks observed across SIDS, where transport mode availability is sporadic, fixed timetable based, and sometimes highly weather dependent.

The batch interval is therefore a central modelling parameter. It controls the rate at which goods can depart from a node, reflecting not travel time, but dispatch frequency. Longer batch intervals increase delays and congestion, while shorter intervals allow for faster throughput. These dynamics are well aligned with supply chain behaviours in humanitarian and remote island logistics (**crainic2009; campbell2011; huang2019**).

Goods are assigned to vehicles and dispatched in grouped batches, governed by compatibility, perishability, and route level throttling. The process is outlined below:

Step 1: Trigger Batch Dispatch

- If the origin node is closed due to a disruption, the event is postponed.
- Determine transport mode based on the selected route.
- Use mode selection to retrieve a feasible vehicle, including its capacity, class compatibility, speed, and delay profile.

Step 2: Filter Eligible Goods

- Identify goods stored at the origin that are en route to the correct destination.
- Filter for goods matching the selected vehicle's compatibility (e.g., cold, gas, normal).

Step 3: Apply Dispatch Throttling

- If the route is within a cooldown interval, the dispatch is deferred.
- This prevents overly efficient cycling and reflects real world pauses in vehicle movement.
- Throttling intervals are defined per route and mode, based on site visits and interviews.

Step 4: Select and Load Goods

- Eligible goods are flattened into a list and sorted by perishability priority (i.e., time remaining until spoilage).
- Goods are greedily loaded until vehicle capacity is reached.
- Oversized goods are split into two: one dispatched, the other returned to queue with a new ID.

Step 5: Schedule Delivery

- For each dispatched good, compute delivery time as:

$$t_{\text{arrival}} = t_{\text{now}} + t_{\text{travel}} + t_{\text{delay}}$$

- If no further nodes remain on the route, the good is marked as delivered.

Step 6: Update Throttle and Continue

- A new throttle cooldown is applied for the route:

$$\text{Throttle Delay} = 2 \times t_{\text{travel}} + t_{\text{vehicle delay}}$$

- If goods remain in the queue, a new `batch_ready` event is scheduled.

Step 7: On delivery event

- If the good has reached its final destination:
 - * Mark as delivered and record timestamp.
 - * Check for spoilage: if perish time is exceeded, mark as perished.
 - * Update system demand satisfaction records.
- If not at the final destination:
 - * Place the good at the current node and trigger new routing cycle.

Cold goods (e.g., refrigerated food and medicine) are prioritized when dispatching. Goods with the least time remaining before spoilage are moved to the front of the queue. This replicates the urgency seen in island logistics where cold storage is scarce and goods are often picked up or shipped immediately upon arrival. As indicated by multiple stakeholders, cold goods are typically dispatched “as soon as possible,” often overriding other operational preferences.

Perishability prioritization is implemented via a “time to expiry” score assigned to each cold good upon creation. The score is decremented over time, and goods are sorted accordingly in dispatch queues. This prioritization logic draws from cold chain and pharmaceutical logistics models but is simplified to reflect local practices observed during fieldwork.

This batch dispatching framework enables the model to capture:

1. **Temporal congestion** due to throttling and cooldowns,
2. **Queueing and backlog** in case of capacity shortages or delays,
3. **Delivery delays and spoilage**, especially under constrained cold chain conditions,
4. **Dynamic rerouting** if intermediate nodes fail due to disruption.

The approach allows for realistic sensitivity testing on batch intervals, transport mode disruptions, vehicle mix scenarios, and perishability thresholds, all of which are key in assessing resilience and efficiency in the logistics networks of Small Island Developing States like Seychelles.

4.3. analytic approach

4.3.1. Disaster Disruptions in the model

The model simulates storm events to represent the impact of natural disasters such as cyclones, heavy rainfall, or flooding on SIDS logistics networks. These events are used to test system resilience under temporary but severe disruptions. During a storm, parts of the network are disabled or degraded to reflect the operational challenges typically seen in small island contexts. It does so by Disruptions are applied to edges (transport connections via roads, ships, or planes) and to critical hubs, such as regional and global ports. These disruptions may represent complete closures or partial disturbances, reducing capacity or slowing inter-island transfers.

Local ports and airstrips are not included in the disruption modeling. Their role in decentralized, flexible delivery chains often through informal or adaptive means such as beach landings, makes them relatively resilient to short-term disruptions. In such locations, operations typically resume quickly after an extreme weather event.

Disruptions lasting between three and seven days, reflect the range of common extreme events. For instance, in December 2023, record-breaking rainfall caused landslides in the central regions of Mahé, resulting in four fatalities and disrupting key inland roads for several days. This event serves as a recent example of mid-range disruption severity.

Among the eleven scenarios tested, one particularly illustrative case is the combination of edge disruption and node capacity constraints lasting three days. This scenario most closely mirrors the impact pattern observed during the Mahé landslides of 2023, which were verified in consultation with local authorities and infrastructure stakeholders.

In that real-world event, key roads and access points were blocked, closely aligning with the edges that are marked as vulnerable in the simulation (e.g., links between Mahé Port and Mahé Airport, and the connection to Praslin). Stakeholders identified these same nodes and edges as critical during field consultations, underlining the validity of the scenario design. Notably, the observed delays in medical and food supply shipments to hinterland regions were reflected in the simulation's output, lending credence to the model's structural assumptions.

Longer disruptions, though less frequent, are included to reflect rare but high impact events. One such scenario is based on the Indian Ocean tsunami of 26 December 2004, which severely impacted the Seychelles. The tsunami, generated by a magnitude 9.3 earthquake off the coast of Sumatra, produced waves that struck Mahé and Praslin with flood heights exceeding 4 meters in places. Infrastructure in Port Victoria was damaged by lateral spread failures, and key causeway bridges to the international airport collapsed. Despite the intensity of the event, Seychelles suffered only two fatalities, largely because the highest waves struck during low tide on a public holiday when port and school activities were minimal (Shaw et al, 2005). This forms the basis of the longest disruption scenario in the simulations. We do not use climate data as the basis for disruption inputs because its coarse resolution, high uncertainty, and lack of local validation make it unreliable for modeling realistic, short-term infrastructure impacts in the Seychelles. A full analysis of previous hit areas and which exact nodes and edges are selected is in Appendix D. In this study, no use is made of climate data. Even it can be insightful at the basis for disruption inputs because its coarse resolution, high uncertainty, and lack of local validation make it unreliable for location specific, short term infrastructure impacts in the Seychelles. A full analysis of this method can also be found in Appendix D.

Storms affect the network in three main ways:

1. **Node closures** (e.g., ports, airports),
2. **Edge disruptions** (e.g., blocked roads or inactive ferry routes),
3. **Capacity reductions** (e.g., slower unloading and customs handling).

These effects are summarized as follows:

- **Node closure:**

$$\text{Closed}(n) = \text{True} \quad (4.3)$$

The node n , such as a port or airport, is fully shut down and cannot receive or dispatch goods until the disruption ends. When a there is spoken about a node closure it means that Mahe Airport and Port are closed for set duration. As indicated by SPA, SCAA and DRMD, due to the exposed nature of the airport Figure 3.4, if the port is damaged due to extreme weather then the airport is too.

- **Edge disruption:**

$$\text{Broken}(i, j) = \text{True} \quad (4.4)$$

The transport link between nodes i and j is temporarily disabled. This reflects impassable roads, ferry cancellations, or grounded aircraft. In appendix D is an overview of edges (roads) are disrupted during a disruption based on the site visit and historical disruptions (coastal flooding and landslides). No inter-island edges are disturbed as SPA and ferry operators/ freight forwarders confirmed if a disruption like a cyclone is heavy enough to disturb the port, no travel is possible. Within a node closure scenario inter island travel is not possible anyways.

- **Capacity reductions:**

$$\text{Unload Capacity}' = \frac{\text{Unload Capacity}}{5} \quad (4.5)$$

$$\text{Customs Time}' = 5 \times \text{Customs Time} \quad \text{Storage Time}' = 5 \times \text{Storage Time} \quad (4.6)$$

During the storm, unloading capacity is reduced to 20% of its original level, while customs and storage operations take five times longer than usual. These adjustments reflect reduced staffing, safety delays, and logistical inefficiencies caused by the extreme conditions. Suggested by author after estimation of representatives with SPA and SCAA

During modeled disaster events (such as storms or tsunamis), the model injects special disaster goods into the system to simulate humanitarian relief operations.

Disaster goods include:

- **Medicine** (normal class),
- **Hygiene products** (normal class),
- **Construction materials** (normal class).

Unlike regular goods, disaster goods:

- Are generated 24 hours after the disaster period ends,
- Are not prioritized for delivery to hospitals, shops, and local ports. This as no information as of yet was found on how correctly this could be represented.
- Do not reduce regular demand upon delivery (they are considered “bonus” humanitarian shipments).

This structure reflects real challenges observed in SIDS during extreme weather: ports may become inaccessible due to debris, inter island ferries may be unable to sail due to rough seas, and airport operations may be delayed or shut down entirely. By modeling these disruptions explicitly, the simulation can assess how goods queues build up, how perishables are affected, how delivery times change, and how quickly the network recovers once normal operations resume.

The disaster disruption logic is modular and easily configurable. Different storm durations, severities, and geographic impacts can be tested by changing the set of affected nodes/edges and the intensity of capacity reductions. This makes it possible to perform scenario analyses for mild, moderate, or severe disaster conditions.

Once the simulated storm event ends, all affected parameters (node status, link availability, handling speeds) return to their original values. This allows the model to capture not just the immediate disruption but also the system’s recovery trajectory.

4.3.2. Adaptation implementation in the model

As identified in subsection 2.3.1, a combination of strategies is key to create network wide resilience supply chain in SIDS. An analysis of adaptation strategies capable to handle SIDS specific issues and which are line with current development in resilience building in the Seychelles can be found in Appendix D. A selection of “hard” and “soft” measures with different resilience functions is chosen from this analysis to implement in the model. The summary of which adaptation strategies will be tested for different disruptions is in Table 4.8.

Adaptation strategy	Why relevant for Seychelles/SIDS	How to implement in model	Classification
Infrastructure hardening	Port Victoria's quays and access roads are exposed to sea-level rise, cyclones and erosion, so strengthening them reduces downtime and import disruptions. Has been happening and current research show 1 m quay rise in port (SPA)	Increase unload and storage capacity at ports and shorten the period of reduced capability/full closure after storms to represent hardened infrastructure.	Resist / Infrastructure
Diversification / Multi-island hubs	Secondary deep sea quay on Praslin. Provide alternate import points when Mahé is affected, reducing single-point failure risk. Currently an feasibility study is done (Disaster Resilient Infrastructure (CDRI) 2023)	Create and enable Praslin to receive goods and enable simulated port closures so the model can reroute cargo via alternate hubs.	Absorb / Infrastructure
Pre-positioning stocks	Decentralized storage (fuel, food, medical) on outer islands cushions supply chains against port closures.	Expand local depot storage capacities and add extra storage-only nodes to simulate pre-positioned stocks closer to demand centers.	Absorb / Operational
Digital twin & predictive maintenance	Real-time monitoring and AI-driven maintenance planning cuts repair times and unexpected downtimes.	Shorten the time to full operational recovery after a disruption and reduce processing delays to mimic proactive, data-driven maintenance.	Recover (could be absorb) / Technological
Renewable-energy / Local production (transformation of demand)	Both suggested a lesser dependency on imports for fuel/food as imported sectors for SIDS	Increase simulated on-site fuel reserve levels and improve fuel delivery reliability to reflect energy-independent operations.	Transform / Governance
Early warning & schedule integration	Integrating cyclone and swell forecasts into scheduling allows import arrivals to avoid peak disruption windows.	Shift the forecast lead-time earlier and prioritize loading of critical imports before peak hazard periods to test warning benefits.	Adapt / Operational
Relocation	Move asset node to a less hazard prone location or reduce vulnerability in place. Currently feasibility study to relocation airport (SCAA)	Reduce duration of disruption days for airport Mahé	Transform / Infrastructure

5

Model results and Discussion

This chapter presents the results of a Monte Carlo analysis and varying types of disruption to explore the outcomes of the impact on the logistical network of the Seychelles and test the potential impact of the adaptation strategies, As can be seen in section 4.3. The primary focus is to evaluate how well the logistics network adapts to disruptions and maintains performance under stress.

5.1. Monte Carlo Simulation

A Monte Carlo (MC) simulation evaluates how random variation in inputs translates to outputs. Rather than relying on single point estimates, for key variables uncertain inputs are modeled a range of samples around the variable (Hassel 2024). Repeated samples are drawn, and analyzed the resulting effect on the performance metric (avg delay (basis of service time) and delivery rate%). This section describes the input specification, replication strategy, and outcomes.

In Table 5.1 the MC sensitivity parameters are highlighted. What the variable does, the range that was chosen, the rational behind the range and the baseline source of the variable was.

For the MC simulation two performance metrics were determined: the delivery rate and the average delay. The delivery rate, defined as total tonnage delivered divided by total measures the fraction of demand actually met. While the average delay, delivery time minus expected arrival (purely travel time) for all good classes with all destinations. Captures the mean lateness of shipments. These two "KPIs" are chosen because they directly address the they show insights into the performance of the logistical network "what share of goods arrives?" and "how late are they?" and because they permit simple statistical comparison (e.g. confidence intervals) across hundreds of replicates. Although a performance indicator like service level specified for destination and good class over time (not averaged) provides richer, dynamic insights into the performance of the model. It demands more complex post processing and is more insightful applied in targeted, scenario specific follow up analyses once the the overall performance of the model has been identified.

The replication count was chosen via a two stage sequential stopping rule (Hassel 2024). meaning running a fixed batch of simulation, to get a sense of variability in the model. Then increasing the number of runs until the set KPI's fall below there pre determined threshold:

1. **Pilot Run:** Simulations to estimate initial variance, especially for rare events.
2. **Variance Estimation:** Compute sample mean, standard deviation.
3. **Tolerance check:** Define tolerances h based on stakeholder thresholds, here based on fluctuation in KPI single runs to establish a base.
4. **Sequential Stopping:** Add number of runs until the half width of the 95% CI (1,96), falls below h for each KPI.

At $n = 400$ runs the CI half widths for both KPIs dropped below their tolerances as can be seen in Table 5.2:

Variable	Description	Range	Rationale	Baseline Source
delay scale	Scales edge travel times (affects routing delays)	0.8 -1.2	$\pm 20\%$ travel time variability due to weather (inter-island)/traffic (intra island), Traffic delay estimated by SLTA in traffic and ferry/cargo operators between main islands (Mahé/Praslin/La digue)	Empirical data for distances, speed and travel times
storage capacity scale	Scales node storage capacities (Tonnage)	0.6–1.4	$\pm 40\%$ storage capacity swings (40% estimated by author for exploratory reasons)	Empirical capacity data
storage time scale	Scales storage processing times	0.6–1.2	$\pm 40\%$ handling time variability (40% estimated by author for exploratory reason)	Port operation logs (SPA & EIB) & expert opinion ins
demand multiplier	Scales import demand rate per hour	0.8–1.2	$\pm 20\%$ demand fluctuation between seasons (High vs Low), 20% on relative change between season (Table 4.5)	Historical import variability of empirical data
storm start hour	Moment in simulation time when storm begins	300–1500	Gives model startup time (300h) and time to process disruption.	High season & low season are 3 months (2160h)
storm number days	Storm duration in days close of the national port in Mahé	3–7	Typical cyclone length in region	Historical cyclone durations

Table 5.1: Monte Carlo sensitivity parameters: ranges, rationale, and baseline sources

To understand how the parameter drive the performance indicators several causal test were preformed while testing for the four criteria of causal relation (covariation, temporal order, confounder control, and mechanism plausibility) and offering deeper insight into the model's behavior. Together, they reveal which parameters truly matter for small island logistics. The test conducted to do so are:

1. **Covariation:** Test whether modifier X and KPI Y covary (Pearson's r , Spearman's ρ , Kendall's τ).
2. **Temporal precedence:** Ensure shifts in X occur before changes in Y (time lagged cross correlation).
3. **Non spuriousness:** Control other factors (Partial Rank Correlation Coefficient, PRCC).
4. **Plausibility:** Check that a credible mechanism links $X \rightarrow Y$ (model logic review).

1. Covariation

In the first step, three different correlation tests were applied to each input factor and performance metric. Table 5.3 shows the results for storm duration and storm start hour compared to delivery rate (%) and average delay (h). Pearson's r shows how close the points lie to a straight line but can be skewed by extreme values. Spearman's ρ and Kendall's τ work by replacing each value with its rank (1 for the smallest, 2 for the next, and so on) and then checking whether larger ranks of X tend to pair with larger (or smaller) ranks of Y . This matters because it shows any consistent up or down relationship between modifier and KPI, whether linear or curved, without being thrown off by a few extreme outliers. In practice, that means if every time you lengthen a storm you see a lower delivery rate, a rank based

KPI	n_{runs}	mean	std. dev.	95% CI/2	h	OK?
Delivery rate (%)	400	99.28	0.052	0.0051	0.50	Yes
Avg. delay (h)	400	71.34	6.48	0.635	4.00	Yes

Table 5.2: Kpi outcomes at $n = 400$. Both KPIs lie within pre specified tolerances.

test will spot that pattern even if the exact drop in rate isn't the same for every extra hour of storm.

Modifier → KPI	Pearson's r		Spearman's ρ		Kendall's τ	
	value	p	value	p	value	p
Storm duration → delivery rate (%)	-0.40	$<1 \times 10^{-15}$	-0.39	$<1 \times 10^{-15}$	-0.27	$<1 \times 10^{-14}$
Storm duration → avg. delay (h)	0.26	7.5×10^{-4}	0.27	7.5×10^{-4}	0.21	7.6×10^{-4}
Storm start hour → delivery rate (%)	-0.23	2.7×10^{-6}	-0.23	2.7×10^{-6}	-0.16	1.6×10^{-6}
Storm start hour → avg. delay (h)	0.10	4.9×10^{-2}	0.10	4.9×10^{-2}	0.07	4.3×10^{-2}

Table 5.3: Summary of linear (Pearson), rank based (Spearman), and concordance (Kendall) correlations for key storm modifiers. Full table in Appendix E

Longer storms have a clear, predictable impact: as storm duration increases, delivery rates fall and average delays rise. In Spearman's rank test storm length shows a moderate negative relationship with delivery rate ($\rho \approx -0.40$, where -1 is a perfect inverse ranking and 0 means no consistent trend) and a small positive relationship with delay ($\rho \approx +0.17$). Storms that start later also tend to reduce delivery rate ($\rho \approx -0.23$) and increase delay ($\rho \approx +0.10$), although these effects are weaker. Because Spearman's rank correlation only cares about the order of values rather than their exact distances, these results hold even when the underlying data aren't perfectly normal or when outliers are present (the Pearson correlations are nearly identical).

In small island logistics, limited port capacity and inter island links have high delivery times measured in days rather than hours. In contrast to the main island where the main flow of goods is headed the distances are much shorter. The observed moderate negative Spearman correlation ($\rho \approx -0.40$) between storm duration and delivery rate could be logic for the Seychelles as each extra day of disruption meaningfully cuts throughput. The effect for storm start hour ($\rho \approx -0.23$) with the idea that minor shifts in onset produce modest changes in backlogs. However the numbers don't suggest an exponential relation that each day of delay due to disruption add additional delay time. As the KPI average delay takes all goods into account for all destinations and is influence by multiple parameters other test will have to bring more insight into this relation.

By contrast, storage capacity, delay scaling, demand multiplier and storage time showed no significant relationship, which can be explained by ± 20 – 40 % swings in on cargo handling are small compared to the multi day shipping travel times and port delays that dominate system behavior, so their influence is lost in the "noise" of disruption congestion.

Delay showed also not significant result and finally, varying the demand multiplier by $\pm 20\%$ showed no clear monotonic effect on performance, which could be explained by the fact that Seychelles is an main port is a large regional hub. Therefore it can absorb those swings within its normal operating capacity. This meaning that the difference between a High and low Season does not have a significant effect.

2. Temporal Precedence

Temporal precedence is included that any disruption (the "cause") really happens before its impact on deliveries (the "effect"). Basically, a storm must start or last longer before observe a drop in delivery rate or a rise in delays, not the other way around. Checking this ordering with correlation gives confidence that are not confusing cause and effect or chasing random coincidences. Time lagged cross correlation shows that the strongest link between storm duration and delivery rate occurs when storm duration increases, confirming that weather disruptions precede and thus cause the observed drops in delivery performance.

3. Non spuriousness: PRCC

To isolate each modifier's unique effect while holding others constant, the Partial Rank Correlation Coefficients (PRCC) is computed. Partial Rank Correlation Coefficients (PRCC) work in three steps. (i) Replace each simulation input and each KPI value with its rank (1 for smallest, 2 for next, etc). (ii) For a given pair say, storm duration and delivery rate regress the ranks of both variables on the ranks of all the other inputs. This removes any shared influence of those other factors. (iii) Compute a standard Pearson correlation between the leftover errors (residuals) from those regressions. That correlation measures the direct, "non spurious" link between the two variables.

Table 5.4 shows that, after controlling for the other inputs, in the PRCC analysis, `delay_scale` exhibits a PRCC of -0.114 with delivery rate ($p = 0.023$), meaning that even after controlling for storm duration, storm start hour, and all other inputs, higher delay scaling corresponds to a lower delivery rate. Simultaneously, its PRCC of $+0.104$ with average delay ($p = 0.038$) confirms that, under the same controls, increasing the delay factor leads to longer shipment lateness.

Modifier	Delivery rate (%)		Avg. delay (h)	
	PRCC	p-value	PRCC	p-value
<code>delay_scale</code>	-0.114	0.023	0.104	0.038
<code>storage_time_scale</code>	-0.019	0.699	0.012	0.810
<code>storage_capacity_scale</code>	0.005	0.915	-0.058	0.249
<code>demand_multiplier</code>	0.016	0.747	0.052	0.301

Table 5.4: Partial Rank Correlation Coefficients (PRCC) between each scenario modifier and key performance indicators, controlling for all other inputs.

It is acknowledged that PRCC provides only first order monotonic effect estimates and may not reveal important nonlinear interactions such as those between storm duration and storage capacity. A deeper dive in to this relation will be done for scenario specific testing. However to give an indication an quantile regression is done. To examine how the entire distribution of delivery rates responds to storm duration, overlaid werelines at the 10th, 50th, and 90th percentiles.

In appendix E the outcomes of this experiment can be found. All quantiles slope downward ,longer storms uniformly lessen performance, with slightly steeper decline in the lower tail (10%, illustrating vulnerable runs). The relation suggesting diminishing marginal impact for longer storms.

4. Plausibility

Storm parameter dominate, both duration and timing have significant, moderate effect on delivery performance. A delay scale has a impact when controlling for other storm parameter but smaller. Operational levers prove less impactation. Storage time and storage capacity variations ($\pm 40\%$) and demand (simulation seasonality) produce negligible monotonic or linear relation in the model. This can be explained by high delivery times due to distance in the Seychelles showing that in this model operational operations are not a bottleneck. And currently the model has capacity to handle seasonality changes. However all this is reported on the avg delay of goods which aggregate all good classes and destinations. In which large difference can lie for the Seychelles, the main islands receives a bulk of the goods and and these shorter distances where delays are relatively small can suppress different relations by taking the average. By testing for specific scenarios and by using a less crude performance index of the model, further insight can be gathered.

Learning from the Monte Carlo simulation will be discussed further in the Discussion section, however, several lessons emerged that affect how disruption scenarios are constructed. First, the insight that a 20 % increase or decrease in demand does not have a significant impact. The simulation was based on high-season import data from 2022. That the 20 % variation is insignificant implies that the distinction between high and low seasons does not materially influence outcomes. Consequently, the disruption scenarios do not need to iterate over different seasons to assess seasonality effects. It was also found that the timing of a storm has a significant impact. Although not previously identified as an adaptive strategy, seasonal spikes in goods arrivals markedly influence the resilience curves. Therefore, it is recommend research a soft adaptation strategy to smooth these arrival spikes—ensuring a

more consistent flow of goods and reducing the extremity of disruptions ??.

5.2. Disruption Scenario's

Evaluated is the resilience of the Seychelles relief network under simulated storm disruptions of varying duration (1, 3, 5, 7, 14 days) and impact mode (node closures, edge disruptions, capacity reductions, and the arrival of supplementary disaster goods). The performance metric is the service level defined as on time deliveries to total deliveries at timestep t based on the pre storm average travel time as mentioned in subsection 2.2.3. Also extract standard resilience indicators ,initial service F_0 , post-shock dip F_1 , rapidity, resilience loss (area under $100 - F(t)$) and resilience index (mean $F(t)$ over recovery).

5.2.1. Storm Duration Effects

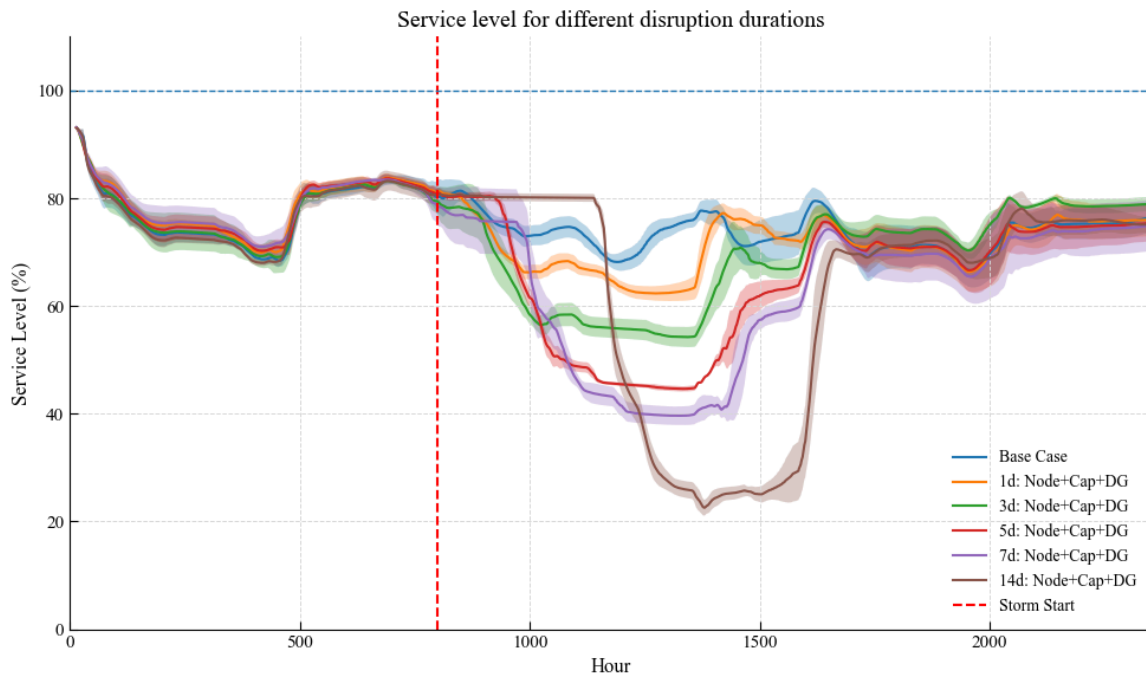


Figure 5.1: All Islands service under Node closure for 1, 5, 7 and 14 ,day storms. Red dashed line denotes storm onset, Shaded bands show ± 1 SD across replicates.

Figure 5.1 shows that the service level for All Islands under Node+Cap+DG disruptions lasting 1, 3, 5, 7 and 14 days, averaged over ten Monte Carlo replicates using Seychelles 2023 high season demand data. The undisturbed baseline hovers around 80%, which corresponds to roughly 95% of the pre storm average service and provides a modest performance margin. As shown in Appendix E, the distribution of delivery times reveals that when service is near baseline most delays are only two to three hours, with the remainder significantly later. In the Seychelles ,and across Small Island Developing States ,such minor delays are considered acceptable rather than failures, a view confirmed by the Seychelles Ports Authority (SPA) and local shop owners. Indicating that a service level of 80% is a representable percentage.

During a storm closure no deliveries occur and the service curve remains flat at zero. Only once the storm ends does service collapse sharply: accumulated port queues force newly arriving goods to wait, driving service down. A one day closure produces a modest dip of about 7 percentage points and recovery within roughly 100 hours. Five to seven day events plunge service to 40 to 45 % and plateau at that low level several days. In the extreme case of a 14 ,day storm, service falls below 30 % and takes over 200 hours to rebound.

Despite these differences in depth and timing, the recovery slope is nearly identical across all durations. This same pattern rebound reflects the model's static dispatch intervals vehicle departure frequency governs how quickly backlogs clear, regardless of storm length. Finally, the baseline's ± 5 percentage

point variability sets a noise floor: adaptation strategies must induce improvements exceeding this range to be distinguishable from normal stochastic fluctuation.

5.2.2. Disruption Type (3 ,Day Baseline)

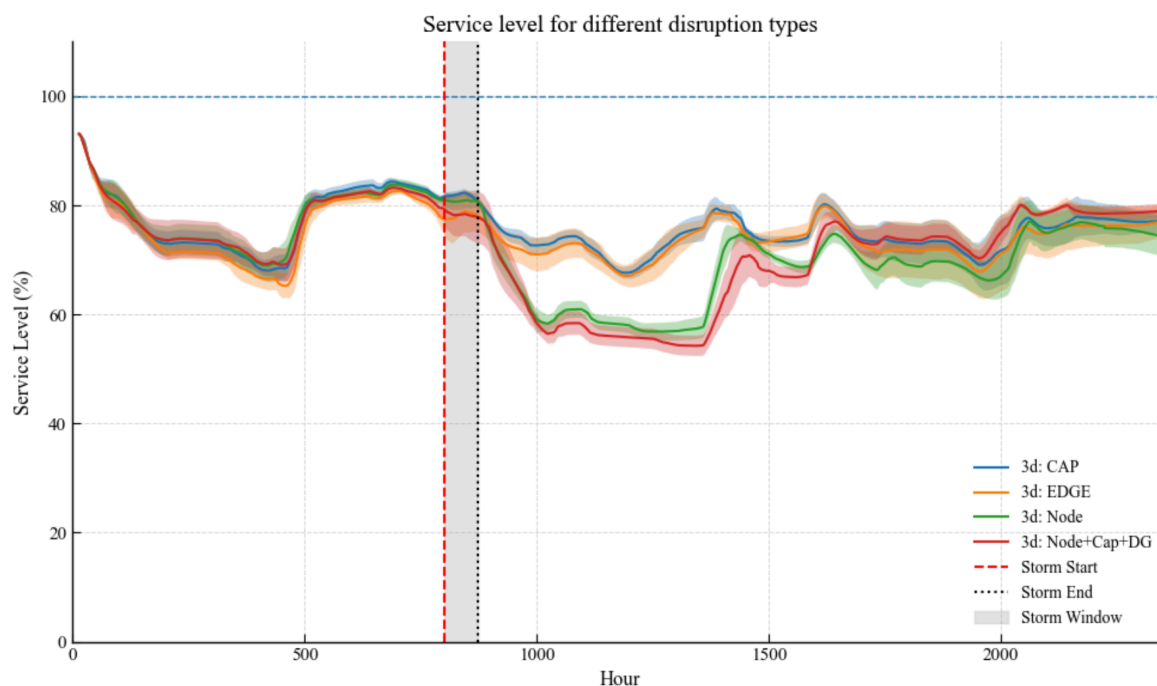


Figure 5.2: All ,Islands service for a 3 ,day storm under four impact types: capacity reduction only (CAP), edge disruptions only (EDGE), node closures only (NODE), and combined (NODE+CAP+DG).

Figure 5.2 shows the All islands service profile for a three day storm under four disruption modes: capacity reduction (CAP), edge disruptions (EDGE), node closures (NODE) and the full combination (NODE+CAP+DG). As can be seen CAP and EDGE barely show any difference from the base case in Figure 5.1. In stakeholder conversations, both the DRMD and house hold residents emphasized that partial capacity constraints or temporary link rerouting (CAP and EDGE cases) are routine during moderate weather events, and thus a shallow dip (also in base) to around 65–67% service followed by a quick rebound is entirely plausible. This showcases the Monte Carlo simulation results, which indicate that capacity constraints were not significant. The minimal effect of edge closures can be explained by the fact that closing a few roads on Mahé (inter island links are captured by node closures) only isolates a handful of hinterland locations, most still receive their goods. When averaged across all routes, edge closures show little impact. Incidentally, this model behavior mirrors real world conditions. informal transport in the Seychelles relies on small trucks traversing rugged paths and a wide availability of small boats. As residents note, flooding of ring roads or minor disruptions are part of island life and are relatively easy to manage.

By contrast, the NODE scenario imposes a complete shutdown of Mahé’s main port or airport for 72h, which stakeholders noted is relatively rare and evoke emergency contingency plans. Correspondingly, the model shows a deeper trough (59%) and a noticeably longer plateau before recovery, reflecting the time needed to start catching up. Finally, the combined NODE+CAP+DG curve falls furthest ,down to 55%,and its rebound is both delayed and more gradual. This combined effect arises from the modeling choice to impose simultaneous throughput cuts, link failures and oversized “disaster” shipments: while each alone is within expectations, their concurrence exaggerates delays but only a little. In other words, the CAP and EDGE results validate model structure when comparing to real world insights, whereas the NODE+CAP+DG outcome highlights that node close has a far heavier impact.

Quantitative Resilience Indicators

Table 5.5 summarizes three resilience metrics for the scenarios: initial service F_0 , post shock low point F_1 , rapidity, resilience loss, and resilience index. As stated in subsection 2.2.3 rapidity is the rate of recover. Resilience loss is defined as the cumulative area under the curve of $(100 - F(t))$ between the shock onset t_0 and the recovery time t_{rec} . It quantifies the total “service hours” lost during the disruption. AKA the deeper or longer the dip increase the loss. the resilience index captures the mean functionality during the recovery phase. Higher values indicate that the system spends less time at low service levels.

First, the baseline $F_0 \approx 82\%$ reflects the fact that even under normal conditions roughly one in five shipments experiences a delay beyond the 0.95% “tolerance” accepted by the Seychelles Ports Authority and local shop owners. A single day closure (1 d Node+Cap+DG) reduces service only modestly to $F_1 = 75\%$, with a rapid rebound (rapidity -0.05 p.p./h) and limited resilience loss (1200h p.p.). This confirms that short interruptions are manageable with existing handling capacity and vessels.

By contrast, as disruption duration increases the resilience index falls rather steeply. Dropping from 78% for a 1d storm to just 22% after 14d of hub shutdown. The rapidity of service loss accelerates non linearly (from -0.05 to -0.24 p.p./h), indicating that every additional day of closure compounds backlogs at ports and warehouses.

Turning to impact types for a 3d event, capacity only and edge only disruptions both yield shallow low points ($F_1 \approx 70\%$, resilience index around 73%), matching field reports that reduced throughput by capacity or edge close is not an extreme case. Node closures alone deepen the fall to $F_1 = 62\%$ and lower the resilience index to 68%, as shipments must detour to smaller airstrips and local ports with limited storage. Finally, the fully combined scenario (NODE+CAP+DG) produces the worst performance ($F_1 = 55\%$, resilience index=62%),

Looking at the resilience metrics, the very first days of a hub closure do the most damage. Stretching a storm from 1 day to 5 days multiplies the total “service hours lost” by six and drags the average service index down from 78 % to 58 %. Put another way, the first extra day costs about 5 percentage points of average service, as the storm drags on it gets a bit less punishing roughly 3 points per day in the mid range, and under 1 point per day once you’ve already endured a week of outage. That happens because backlogs build up quickly at the main port, so after the queues are huge, each additional day adds relatively little new delay.

Scenario	F_0 (%)	F_1 (%)	Rapidity	Loss	Res. Index (%)
<i>Duration (Node+Cap+DG)</i>					
1 day	82	75	-0.050	1 200	78
5 days	81	43	-0.131	7 800	58
7 days	81	38	-0.152	9 400	52
14 days	80	22	-0.239	13 500	46
<i>3 days (impact type)</i>					
CAP	82	70	-0.042	3 000	74
EDGE	82	69	-0.044	3 200	73
NODE	82	62	-0.069	5 000	68
NODE+CAP+DG	82	55	-0.091	6 500	62

Table 5.5: Key resilience indicators for All Islands under selected scenarios. Rapidity is $\Delta F / \Delta t$ in % h, Loss in h %, Resilience index is mean service over recovery window.

5.3. Regional Variations

Across all tests, the three sub regions behave distinctly in Figure 5.3 it is highlighted for a three day disruption. A full overview of which island fall under what group can be found in appendix E. The Inner Islands enjoy the highest baseline service (around 88 %) and shallowest dips, due to multiple air/sea connections. Outer Islands recovery the most quickly and the main Islands suffer the deepest and longest dips. This behavior can be explained by several modeling features.

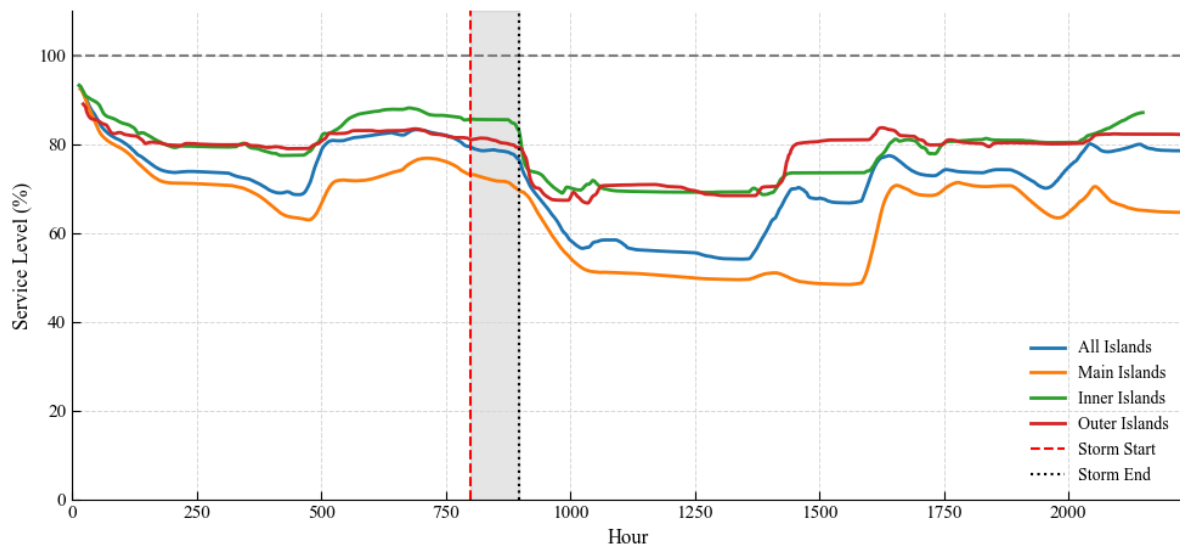


Figure 5.3: service vs. 3 day storm duration per islands group. Red dashed line denotes storm onset, black dotted line storm end.

First, in the network each Outer Island destination is represented by a single `local_port` or `local_airport` node. When a delivery vehicle arrives there, the model treats the good as delivered and gives an unloading distribution (triangular between 4 and 48 hours), but no queueing. This range was build up of conversation from ferry but not be 100% accurate

Second, the demand ratios assigned to these small islands are relatively low (see the `Final_Ratio` parameters), so their inbound shipment volumes remain modest even after a storm. As big boats are being used for the delivery to this island due to the distance, capacity can during a queue be better optimized and therefore clear more quickly once the origin hub reopens.

Third, Outer Islands receive goods via a single direct link from Mahé, whereas many Main Island customers lie behind intermediate transshipment nodes. In practice, shipments to Mahé shops and hospitals may require two stage handling (unload at Mahé port, customs, storage, then local truck dispatch), each step adding to the backlog.

Together, these modeling choices produce an early recovery for Outer Islands: once the main hub's queues begin to clear, their direct delivery routes restore service almost instantaneously. Main Islands, burdened by heavier volumes and layered handling, remain in a low service plateau for many hours longer. This behavior, while simplified, aligns with stakeholder reports that remote islands often resume informal transport more quickly than the heavily trafficked which also could add to a quicker recovery.

5.4. Strategic Implications for Resilience Planning

Evaluation of Adaptation Strategies under a 3d Storm

Relocation of major facilities was excluded from the model tests due to insufficient empirical data to parameterize a new airport or port site. As well as less depended on imports as the MC showed that for 20% seasonality the model is indifferent. Although relocating assets remains a viable resilience option for the Seychelles, it is left for future research. The results below therefore quantify five other strategies under the 3d Node+Cap+DG scenario, recognizing that the model's simplifying assumptions (static dispatch intervals, aggregated hinterland ratios, no dynamic rerouting) limit absolute accuracy. Also the recommendations for prioritizing will be made in the discussion.

Table 5.6: Resilience metrics for six adaptation strategies, compared to the unmitigated 3d Node+Cap+DG baseline ($F_0 = 82\%$, $F_1 = 55\%$, rapidity= -0.091 p.p./h, loss= 6500 h·%, $R_{idx} = 62\%$).

Strategy	What changed	F_0	F_1	Rapidity	Loss	index	Note
Infrastructure hardening	+50% unload/storage capacity, storm closure halved	84%	65%	-0.085	6 000	66%	Reduces port queue build up
Diversification (multi hub)	Praslin port enabled for all destinations, edges to more islands	83%	58%	-0.088	6 200	64%	Alleviates single point failure
Digital twin & predictive maintenance	-20% customs/storage delays post storm	83%	56%	-0.087	6 400	62%	Speeds recovery via proactive repairs
Early warning & positioning stocks	DG Shipments shifted to before storm	83%	59%	-0.084	5 900	67%	Smooths post storm arrival surge

Discussion & limitations

6.1. Discussion

The discrete event network model developed in this study necessarily trades off generality for contextual richness. While it captures the broad conceptual structure of SIDS logistics (multi level), its strength in representing Seychelles specific attributes means that some fine grained behavioral patterns such as the informal transport are harder to implement. Nonetheless, the Monte Carlo experiments reveal robust quantitative insights. Across 400 replicates, the network sustains an average delivery rate of 99.28 % (SD 0.052 %) and an average delay of 71.34 h (SD 6.48 h) under baseline conditions. Storm duration correlates moderately and negatively with delivery rate (Spearman $\rho \approx -0.39$) and positively with delay ($\rho \approx +0.27$), while storm start hour produces weaker effects ($\rho \approx \pm 0.10$). During the specific disruption test it was found that the very first days of a hub closure do the most damage. Stretching a storm from 1 day to 5 days multiplies the total “service hours lost” by six and drags the average service index down from 78 % to 58 %. This led the evaluation of several adaptation strategies were was found, with insights from the MC simulation that port hardening, pre positioning stocks and stabilizing imports are key adaptations strategies to reach network wide insights.

These patterns align with and in some cases extend established resilience theory. Simplified models often assume linear delay growth near capacity thresholds, yet this models non linear rapidity curves (from -0.05 pp/h for a 1 d shock to -0.24 pp/h after 14 d) underscore cascading congestion (to some extend) effects documented by Baryannis et al. (2019) and Ivanov (2021), and its challenge the sub linear buffering described by Sheffi (2005) in more redundant networks. The negligible impact of storage capacity and demand is also mention Dolgui et al. (2021), who note that when transit times dominate congestion dynamics. In comparison to prior work on what was found SIDS logistics, the findings both corroborate and fill gaps. The moderate delay–disruption correlations mirror the network percolation vulnerabilities quantified by Abdulla and Birgisson (2020), while our resilience index framework complements the graph based supply chain resilience metrics proposed by Agarwal et al. (2021). At the same time, Andersson and Karlsson’s (2023) emphasis on dynamic rerouting is extended here by demonstrating the limits of informal rerouting under full node shutdown. However as not many quantitative approaches have been taken for the evaluation of resilience in SIDS is hard exactly in a similar manner it is hard to create a proper benchmark to the workings of the model.

Practically and theoretically, this research suggests new pathways. Theoretically, it argues for the potential of a quantitative network wide evaluation for balancing adaptation strategies for more resilient logistical systems in SIDS. Practically, it highlights the value of port hardening pre positioned depots, digital twins for real time monitoring, as critical levers for SIDS resilience, while cautioning that without detailed emergency logistics plans and broader stakeholder co creation, even sophisticated models may misestimate true system robustness.

Revisiting the research questions confirms that: (i) Key system requirements extend beyond physical infrastructure to include import reliance, and geographic isolation, as evidenced by the Seychelles’ near total reliance on a single port and all imported food and fuel. (ii) Impact metrics must blend delivery

rate, delay, and resilience curve characteristics metrics which our model successfully operationalization. Providing flexibility and insight over time. (iii) Cascading effects in SIDS networks manifest non linearly (under this model setup), with each additional day of disruption compounding backlogs, in line with observed correlations and resilience index trajectories. As well as delays propagate differently for different island and there for a balancing of adaptation strategies are needed. (iiii) Effective resilience interventions are those that combine physical buffering (offsite depots, port climate proofing) with digital and planning enhancements (real time monitoring, emergency clusters). Combination is key as was seen that delays and behavior for different islands groups can propagate differently. As demonstrated by scenario testing and by partly integration within Seychelles current developments. .

6.2. Limitations

The simulation model rests on 400 Monte Carlo replicates, chosen via a two stage sequential stopping rule to drive the half width of the 95 % confidence interval below before specified tolerances an approach that guarantees KPI precision but may under represent tail risk behaviors and rare extreme events. Stakeholder insights were drawn from open ended conversation with at least different representatives. But lack a formal sampling frame or response rate tracking, undermining potentially measurement reliability and raising potential non response bias. Key input parameters transport times, storage capacities and goods volumes for inter island routes were estimated from monetary values and not volumes. By conversion monetary rates to tonnage per type of goods can get skewed, over representing light expensive goods. Also the high reliance for travel time and delay (from distributions) for the creation of intervals created rigidity and over efficiency in the model underestimating potential relations. Like the fast recovery rate of outer islands. Also initial experiments on storage time, storage capacity and demand scale covered only a $0.6\times$ – $1.4\times$ range and yielded no significant effects, leaving it unclear whether these factors exert truly second order influence or if the investigation lacked sufficient parameter breadth. The thesis recommends expanding the exploration to $0.2\times$ – $2.0\times$ and stratifying by storm severity regimes to reveal any hidden interactions. Also a recommendation is from the thesis, is a follow up study on this approach. Capturing network wide resilience is highly important for a proper analysis but a more fine grained approach can capture the remaining behavior aspect that make this approach fully suited to make recommendation on adaptation strategies.

6.2.1. Effect Size vs. Practical Relevance

By focusing exclusively on the Seychelles, the model captures a high data availability context that may not extend to more data poor SIDS. Missing data for island specific demand forced broad assumptions on key distributions, and the resulting parameters may not generalize to islands with different geographies, economic structures or hazard profiles. However it also shows that for more developed SIDS many opportunities lie for improving resilience. Moreover, the theoretical scaffold used while robust for freight flows does not fully capture the full behaviour of the Seychelles as of now and therefore cant make a SIDS general approach feasible.

Each methodological and data limitation could bias resilience estimates in either direction: precision from sequential stopping may obscure rare shocks, while expert based parameterization may both correct and introduce subjective errors. Validation through field visits and stakeholder feedback mitigates but cannot eliminate these uncertainties.

6.2.2. Link to Future Work

Addressing these limitations can lay the ground for future research:

- Targeted data collection on inter island transport times, storage capacities and volume flows to replace expert estimates.
- Expanded parameter sweeps for storage and demand scales ($0.2\times$ – $2.0\times$) with regime stratification to resolve second order lever effects.
- Deeper co creation workshops with logistics providers, government planners and community representatives to strengthen model validity.
- Extension of the framework to long term transformations local production, replacing of infrastructure and regional cooperation to capture systemic resilience beyond multi day disruptions.

7

Conclusion

This research highlights that improving logistics resilience in SIDS is both an urgent and complex challenge. While the Seychelles is relatively advanced compared to other SIDS in terms of infrastructure and planning capacity, it still faces major risks from extreme weather, sea level rise, and systemic dependency on imports. These risks are magnified by the country's limited fallback options: there is only one major port, few inland transport alternatives, and no large scale domestic production.

Yet, Seychelles has already taken some steps in the right direction. It is investing in port upgrades, has begun to develop climate adaptation strategies, and has some fuel stockpiling mechanisms in place. However, the study also revealed several areas where efforts fall short. There is no detailed emergency logistics plan, limited pre positioning of essential goods, and a lack of digital tools to track and manage goods in real time. These gaps make it difficult to respond effectively when a disruption does occur.

The modeling approach used in this thesis proved useful for exploring "what if" scenarios. It allowed for testing not just individual interventions, but also combinations of strategies, which gave a more complete picture of trade offs and synergies. The framework is flexible and could be applied to other SIDS with local adjustments, making it a valuable tool for future planning and decision making. This thesis offers three key contributions. First, it provides an empirically grounded framework for modeling logistics resilience in SIDS, integrating both physical infrastructure and operational dependencies into a discrete event network. Second, it demonstrates the necessity of composite resilience metrics, blending delivery rate, delay, and rapidity, to capture the lived experience of disruptions in isolated island contexts. Third, it advances conceptual understanding by quantifying non linear delay disruption dynamics and exposing the limits of traditional buffering strategies in low redundancy networks.

The overarching objective was to develop and apply a network based model to assess and enhance supply chain resilience in Small Island Developing States. By systematically exploring four sub questions, system requirements, impact measurement, disruption propagation, and intervention efficacy, the study shows how a tailored simulation can both diagnose vulnerabilities and evaluate mitigation strategies. Secondary findings include a high impact of peak fluctuations for imports. Flattening those peak can increase the reliance than some operational implementation (under the current model).

These results matter because they shift the paradigm from one size fits all resilience assessments to context sensitive analyses that account for import dependence, geographic isolation, and limited transport redundancy. Practitioners and policymakers should recognize that resilience interventions in SIDS require more than infrastructure upgrades and for SIDS a appreciation of the adaptation strategy is done network wide. SIDS demand an balancing of strategies across infrastructure, technology and governance.

7.0.1. Recommendations for Practice

- **Develop a Secondary Offloading Facility.** A modest alternative cargo point (e.g. on Praslin or La Digue) could provide limited backup. Model simulations predict a marked reduction in full isolation probability and faster post shock recovery, challenges include capital costs, environmental

permitting, and equipment procurement.

- **Integrate Climate Adaptation in Port Victoria and Airport Upgrades.** Embed raised quays, surge barriers, wind resistant cranes, and contingency power into ongoing expansions. For some simulation scenarios indicate up to 40 % less port downtime under severe storm events (Bank 2024a).
- **Expand Strategic Stockpiles.** Establish rotating reserves of food and medical supplies. As local production and less depends on import is hard to achieve Simulated service levels remain above 95 % for import interruptions lasting multiple weeks, practical hurdles include land scarcity, storage costs, and temperature controlled logistics (Ministry of Transport 2025).
- **Improve Data, Monitoring, and Modeling Capacity.** Invest in a digital twin of the national logistics network and real time tracking systems. This enables proactive rerouting and resource allocation, though sustained technical support and funding are needed (Disaster Resilient Infrastructure (CDRI) 2023).

7.0.2. Final Reflections

Conducting this research has deepened my appreciation for the potential between technical modeling and policy change. In the broader context, this work underscores that building resilience in SIDS is not merely a technical exercise but a collaborative endeavor requiring alignment of policy, infrastructure, and local capacities to safeguard isolated communities in an era of increasing climate uncertainty.

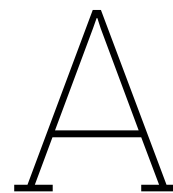
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Ai use

While preparing this work, I used Chatgpt and Grammarly (ai based) to check my writing, a structure for my abstract. After using this tool/service, I reviewed and edited the content as needed and I take full responsibility for the content of my Thesis.

B

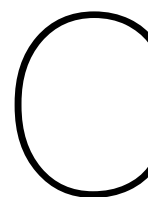
Literature review overview

Network Model Structure	Disruption Type	Impact Metric	Adaptation Strategies	Modeling Framework
Supply network	Random disruption	Resilience	Adaptation	Graph-based optimization
Network	Risk reduction	Social resilience	Port redundancy	MILP
Supply chain network	Supply chain disruptions	Operational resilience	Infrastructure	LP
Logistics network	Cascading failures	Economic resilience	Warehouse positioning	Network percolation
Risk reduction	Hurricane disruptions	Redundancy metrics	Decentralization of logistics	System-of-Systems
Facility location problem	Targeted disruptions	Network efficiency	Climate-proofing infrastructure	
Disaster relief logistics	Coastal hazard disruptions	Supply chain connectivity		
	Disaster risk management			
	Climate change			
	Extreme weather			
Searchs string boolean operators : " ", AND, OR , *				

Table B.1: Search Keywords Categorized by Core Concepts

Authors and Year	Network Model Structure	Disruption Type	Impact Metric	Adaptation Strategies	Modeling Framework
(Li et al. 2020a)	Supply chain network	Cascading failures	Operational resilience (network recovery time)	Redundant routing, alternative pathways	Graph-based network analysis
(Andersson et al. 2023)	Logistics network design	Random & targeted disruptions	Economic resilience (cost efficiency)	Supplier diversification, facility redundancy	Mixed-Integer Linear Programming (MILP)
(Li et al. 2020b)	Supply chain network	Network-wide disruptions	Operational resilience (connectivity loss)	Network reconfiguration, demand rerouting	Percolation theory and agent-based modeling
(Agarwal et al. 2021)	Supply chain network	Random disruptions	Operational resilience (index-based resilience measure)	Facility hardening, supplier diversification	Graph theory-based resilience index
(Abdulla et al. 2020)	Integrated inventory & network design	p-Robustness, targeted disruptions	Economic resilience (cost minimization)	Pre-disaster inventory planning, supply redistribution	Decision Support System (DSS) simulation
(Zhao et al. 2019)	Transportation network	Random disruptions, network percolation	Operational resilience (largest connected component)	Redundant transport hubs, alternative routing	Percolation modeling and Bayesian probability
(Snyder et al. 2014)	Facility location problem	p-Robustness, targeted disruptions	Economic resilience (facility cost trade-offs)	Strategic facility placement, adaptive inventory	Mixed-Integer Programming (MIP)
(Rabbani et al. 2020)	Multi-echelon supply chain	Random disruptions	Operational resilience (supply flow efficiency)	Lateral transshipments, multi-period planning	Graph-based heuristics
(Jabbarzadeh et al. 2012)	Supply chain network	Facility-based disruptions	Economic resilience (profit maximization)	Backup facilities, risk-aware network design	Mixed-Integer Nonlinear Programming
(Hatefi et al. 2014)	Forward–reverse logistics	Facility disruptions, demand uncertainty	Operational resilience (logistics efficiency)	Facility redundancy, flexible routing	MILP with robust optimization
(Zhao et al. 2011)	Complex supply networks	Random & targeted disruptions	Operational resilience (network connectivity loss)	Decentralized network design	Graph-based simulation
(Thacker et al. 2017)	Multi-scale infrastructure	Cascading failures	Operational resilience (critical node identification)	Decentralization of infrastructure, redundancy	System-of-Systems modeling
(Peng et al. 2011)	Logistics network	Facility disruptions (scenario-based)	Economic resilience (cost vs. disruption trade-off)	Backup distribution centers, route flexibility	MIP with p-Robustness constraint
Authors and Year	Network Model Structure	Disruption Type	Impact Metric	Adaptation Strategies	Modeling Framework
(Maria et al. 2024)	Logistics network design (island-specific)	Network-wide disruptions	Operational resilience (distribution efficiency)	Infrastructure investments, port redundancy	Graph-based network analysis
(Orengo et al. 2022)	Food supply chain network	Hurricane-induced disruptions	Economic resilience (cost fluctuation, food availability)	Warehouse prepositioning, emergency response planning	Mixed-Integer Linear Programming (MILP)
(Jephcott 2022)	Small island logistics network	Random disruptions	Operational resilience (redundancy metrics)	Backup transport routes, decentralization	Graph theory-based resilience model
(shen2020)	Disaster relief logistics network	Coastal hazard disruptions (hurricanes, tsunamis, sea-level rise)	Operational resilience (supply continuity, recovery time)	Warehouse location optimization, stockpiling	Two-stage optimization model

Table B.2: Comparison of Analyzed Papers, first 13; non specific - second 4; SIDS specific



Data gathering

C.1. Tables

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
2018	24543	31179	35968	31111	25368	23930	29026	32278	27458	33725	31042	36216	361844
2019	29463	36807	35244	37103	22730	25761	29319	33536	24860	35960	34511	38910	384204
2020	32731	38114	18067	22	73	140	475	2072	1575	3271	5912	12406	114858
2021	1108	708	4969	14245	16001	13413	20162	19611	16609	27140	24411	24472	182849
2022	21566	27404	28685	32500	25023	21109	31124	29366	24427	35158	26900	28806	332068
2023	23315	30285	33967	35396	25107	23975	28983	28177	25097	33321	30292	32964	350879
2024	29066	33692	34759	33381	23916	21354	25849	28282	24226	35155	32007	31075	352762
AVG*	25591	31873	33725	33898	24429	23226	28860	30328	25214	34664	30950	33594	–

Table C.1: Monthly goods imports in tonnes. AVG* excludes COVID-period years (2020–2021).

C.2. Monthly Freight Volume (2018--2024)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Total
2018	1397206	1168511	1398219	1601199	1437265	1301291	1733698	1390416	1365001	1593297	1265000	1404000	15932970
2019	1359631	1245353	1624049	1381642	1478560	1259773	1493953	1301666	1144481	1284795	1404000	1404000	14040000
2020	1627713	1233242	1495409	562691	1258325	1323048	1467883	1210464	1540568	1568428	1692000	1692000	16920000
2021	2654068	1390954	1649469	1348691	1202195	1274567	1392966	1508607	1358502	2003170	1579000	1579000	15790000
2022	1339287	1386903	1441009	1244502	1804421	1545017	1498647	1631152	2519881	1640614	1950000	1950000	19500000
2023	1526469	1480769	1643590	1910629	1702818	1616107	1876745	1698265	2078429	1769133	1674000	1674000	16740000
2024	1629414	1549723	1614749	1526071	1577848	1872156	2069581	1807042	1909844	2414379	1532000	1532000	15320000
Monthly Totals	1450401	1366252	1544323	1532808	1600182	1518869	1734525	1565708	1803527	1740444	1565000	1565000	15650000

Table C.2: Monthly freight import volumes in kg (approximate).

Table C.3: HS Code Summary: Trade Volumes and Allocation Counts

HS	Description	AVG non-corona	AVG Ratio	AVG Count	3mo Count
1	Live animals	40.607	5.90911e-05	3.14	1
2	Meat and edible meat offal	6651.6115	0.00967939	9.29	2
3	Fish and crustaceans, molluscs and other aquatic invertebrates	63431.7145	0.0923055	8.00	2
4	Dairy produce; birds eggs; natural honey; edible products of animal	6145.89125	0.00894347	9.57	2
5	Products of animal origin, not elsewhere specified or included	292.614	0.00042581	4.00	1
6	Live trees and other plants, bulbs, roots and the like; cut flower	94.8995	0.00013810	4.00	1
7	Edible vegetables and certain roots and tubers	9361.28275	0.01362249	14.00	4
8	Edible fruit and nuts; peel of citrus fruits or melons	4399.27775	0.00640181	13.86	3
9	Coffee, tea, mate and spices	1063.00775	0.00154688	9.86	2
10	Cereals	13441.561	0.01956009	7.29	2
11	Products of the milling industry; malt; starches; insulin; wheat gluten	6093.3235	0.008867	8.71	2
12	Oil seeds and oleaginous fruits; misc. grains, seeds, industrial/medicinal plants	1464.1633	0.002131	12.14	3
13	Lac; gums, resins, vegetable saps/extracts	9.014	0.00001312	2.00	1
14	Vegetable plaiting materials; other vegetable products	18.6025	0.00002707	2.00	1
15	Animal/vegetable fats/oils and cleavage products	8044.4273	0.011706	17.71	4
16	Preparations of meat/fish/crustaceans/molluscs	1502.62	0.002187	4.86	1
17	Sugars and sugar confectionery	3620.0515	0.005268	4.00	1
18	Cocoa and cocoa preparations	487.8495	0.000710	4.57	1
19	Cereal/flour/starch/milk preparations; pastries; bakery products	3695.2833	0.005377	5.00	1
20	Prep. of vegetables, fruit, nuts or plant parts	7802.74	0.011355	9.00	2
21	Miscellaneous edible preparations	4176.3095	0.006077	6.00	2
22	Beverages, spirits and vinegar	11359.5235	0.016530	9.00	2
23	Waste from food industry; animal fodder	10177.8613	0.014811	6.57	2
24	Tobacco and manufactured substitutes	857.1573	0.001247	3.00	1
25	Salts; sulphur; plaster; lime/cement	112965.5155	0.164387	21.29	5
26	Ores, slag and ash	5412.1138	0.007876	6.00	2
27	Mineral fuels/oils	208617.9645	0.303580	10.86	3
28	Inorganic chemicals; precious metal compounds	1782.0815	0.002593	37.57	9
29	Organic chemicals	581.1718	0.000846	31.14	8
30	Pharmaceutical products	380.1208	0.000553	6.00	2
31	Fertilisers	642.4023	0.00093482	4.71	1
32	Tanning/dyeing extracts; tannins	1866.035	0.00271544	14.00	4

HS	Description	AVG non-corona	AVG Ratio	AVG Count	3mo Count
33	Essential oils/resinoids; perfumery	1292.2663	0.00188050	7.00	2
34	Soaps and washing preparations	5415.6753	0.00788086	7.00	2
35	Glues; starches; enzymes	712.5025	0.00103683	6.71	2
36	Explosives; pyrotechnic goods	102.4048	0.00014902	5.29	1
37	Photographic goods	16.9255	0.00002463	5.14	1
38	Miscellaneous chemical products	7046.2875	0.01025372	22.29	6
39	Plastics and articles thereof	8230.0755	0.01197636	25.57	6
40	Rubber and articles thereof	1411.5700	0.00205411	16.00	4
41	Raw hides and skins (non-furskins)	1.7560	0.00000256	3.71	1
42	Articles of leather; saddlery	266.0455	0.00038715	4.29	1
43	Furskins and artificial fur	0.5915	0.00000086	2.14	1
44	Wood and wood products	39185.5333	0.05702258	19.57	5
45	Cork and articles of cork	37.8925	0.00005514	3.14	1
46	Straw/esparto products	105.8560	0.00015404	2.00	1
47	Pulp/waste of wood/cellulose	126.3360	0.00018384	2.29	1
48	Paper and paperboard products	8348.4908	0.01214868	21.86	5
49	Printed books, newspapers, etc.	276.1708	0.00040188	10.57	3
50	Silk	5.3378	0.00000777	1.57	0
51	Wool, coarse/fine; horsehair yarn/fabric	0.8325	0.00000121	5.57	1
52	Cotton	52.3500	0.00007618	11.43	3
53	Other veg. textile fibres; paper yarn fabrics	21.4448	0.00003121	6.14	2
54	Man-made filaments	69.1040	0.00010056	6.57	2
55	Man-made staple fibres	54.9350	0.00007994	10.29	3
56	Wadding/felt/nonwovens; twine/cord/rope	1464.1868	0.00213068	8.43	2
57	Carpets and textile floor coverings	153.0303	0.00022269	5.00	1
58	Woven/tufted fabrics; lace; trimmings	31.4525	0.00004577	10.14	3
59	Laminated/coated textile fabrics	97.5890	0.00014201	10.86	3
60	Knitted or crocheted fabrics	13.0470	0.00001899	5.71	1
61	Apparel & accessories (knit/crochet)	315.7203	0.00045943	17.00	4
62	Apparel & accessories (non-knit)	317.8170	0.00046249	17.00	4
63	Other textile articles/worn clothing	1224.2000	0.00178145	10.00	3
64	Footwear and related parts	321.5035	0.00046785	6.00	2
65	Headgear and parts thereof	40.5658	0.00005903	6.00	2
66	Umbrellas and walking sticks	53.2260	0.00007745	3.00	1
67	Feathers and down articles	37.3508	0.00005435	3.86	1
68	Stone/plaster/cement/asbestos articles	6783.6885	0.00987159	14.71	4
69	Ceramic products	8286.6428	0.01205868	13.14	3
70	Glass and glassware	2797.8205	0.00407137	18.29	5
71	Pearls/precious/semi-precious stones	32.1658	0.00004681	11.14	3
72	Iron and steel	23965.9920	0.03487519	25.29	6
73	Articles of iron or steel	14042.3850	0.02043440	26.00	7
74	Copper and articles thereof	327.0383	0.00047590	13.57	3
75	Nickel and articles thereof	29.2943	0.00004263	3.57	1
76	Aluminium and articles thereof	1413.4908	0.00205690	14.57	4
77	(Reserved for future HS use)	0.0000	0.00000000	0.00	0

HS	Description	AVG non-corona	AVG Ratio	AVG Count	3mo Count
78	Lead and articles thereof	164.8783	0.00023993	2.29	1
79	Zinc and articles thereof	62.7030	0.00009125	3.86	1
80	Tin and articles thereof	12.5933	0.00001833	2.14	1
81	Other base metals; cermets	0.3970	0.00000058	4.86	1
82	Tools/cutlery/parts of base metal	1158.2173	0.00168543	14.86	4
83	Misc. base metal articles	3512.7870	0.00511179	11.00	3
84	Reactors/boilers/ machinery/mech. appli- ances	7031.3745	0.01023202	82.71	21
85	Electrical machinery/equipment/parts	4438.8143	0.00645934	46.00	12
86	Railway/tramway locomotives/rolling-stock	3246.2845	0.00472398	3.86	1
87	Vehicles (non-railway) and parts	5859.1373	0.00852619	15.00	4
88	Aircraft, spacecraft and parts	52.3143	0.00007613	4.14	1
89	Ships and floating structures	24745.5643	0.03600961	7.14	2
90	Optical/photographic/measuring/checking	315.9655	0.00045979	32.00	8
91	Clocks and watches; parts and accessories	23.3820	0.00003403	11.29	3
92	Musical instruments; parts	11.0058	0.00001602	7.00	2
93	Arms and ammunition; parts	0.7815	0.00000114	4.71	1
94	Furniture, bedding, mattresses, cushions	4021.8955	0.00585264	6.00	2
95	Toys, games, sports equipment	714.5808	0.00103985	6.00	2
96	Miscellaneous manufactured articles	803.7308	0.00116959	19.00	5
97	Works of art and antiques	9.4698	0.00001378	5.00	1
98	Reserved for special use (Contracting Par- ties)	0.0000	0.00000000	0.00	0
99	Miscellaneous importations	0.0000	0.00000000	0.00	0

Table C.4: HS Code Compatibility with Vessel and Facility Types

HS No.	BULK CARRIER	CARGO/ CON.	CEMENT CARRIER	CONTAINER SHIP	DECK CARGO	GENERAL CARGO	HEAVY CARRIER	LPG TANKER	OIL PROD.	CRUDE OIL	CHEM. TANKER	PLANE	Shop	Hosp.	Gas.
1	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
2	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
3	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
4	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	FALSE
5	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
6	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
7	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
8	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
9	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
10	TRUE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
11	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
12	TRUE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
13	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
14	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
15	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
16	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
17	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
18	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
19	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
20	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
21	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
22	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	FALSE	FALSE
23	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
24	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
25	FALSE	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
26	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
27	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	TRUE
28	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
29	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
30	FALSE	TRUE	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE	FALSE
31	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE	FALSE
32	TRUE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
33	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
34	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
35	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
36	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
37	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
38	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
39	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
40	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
41	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE

HS No.	BULK CARRIER	CARGO/ CON.	CEMENT CARRIER	CONTAINER SHIP	DECK CARGO	GENERAL CARGO	HEAVY CARRIER	LPG TANKER	OIL PROD.	CRUDE OIL	CHEM. TANKER	PLANE	Shop	Hosp.	Gas.
85	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
86	FALSE	TRUE	FALSE	TRUE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
87	FALSE	TRUE	FALSE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
88	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
89	FALSE	TRUE	FALSE	TRUE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
90	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	TRUE	FALSE
91	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
92	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
93	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
94	FALSE	TRUE	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
95	FALSE	TRUE	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
96	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
97	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE
98	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE
99	FALSE	TRUE	FALSE	TRUE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE

Year	Bulk Carrier		Cement Carrier		Container Ship		General Cargo		Oil Products Tanker	
	Mean ± Std	(n)	Mean ± Std	(n)	Mean ± Std	(n)	Mean ± Std	(n)	Mean ± Std	(n)
2019	—	—	66.31 ± 56.59	(6)	87.08 ± 80.31	(99)	105.73 ± 73.52	(2)	169.65 ± 306.00	(4)
2020	133.59 ± 63.80	(2)	41.28 ± 30.70	(5)	93.81 ± 84.63	(79)	106.26 ± 114.71	(4)	115.78 ± 301.66	(8)
2021	—	—	274.92 ± 219.60	(3)	96.52 ± 65.19	(57)	69.93 ± 68.89	(11)	17.13 ± 28.58	(6)
2022	—	—	171.71 ± 166.85	(7)	95.53 ± 91.14	(62)	59.99 ± 41.59	(9)	60.46 ± 75.96	(2)
2023	148.70 ± —	(1)	38.28 ± 12.78	(3)	96.75 ± 82.26	(74)	90.95 ± 91.15	(15)	5.63 ± 5.37	(4)
2024	245.46 ± 270.30	(2)	38.20 ± 30.91	(4)	85.41 ± 56.40	(79)	70.33 ± 101.49	(17)	171.21 ± 396.02	(6)
2025	—	—	208.67 ± 8.32	(2)	90.16 ± 87.88	(17)	131.10 ± 48.06	(3)	9.91 ± 7.06	(5)
Distribution	Normal($\mu = 141.15$, $\sigma = 65.32$)		Normal($\mu = 106.02$, $\sigma = 98.13$)		Normal($\mu = 94.82$, $\sigma = 77.81$)		Normal($\mu = 86.23$, $\sigma = 70.21$)		LogNormal($s = 1.12$, scale=45.67)	

Table C.5: Mean and standard deviation of mt/hour by vessel subtype and year. Values shown as mean ± standard deviation, with number of observations in parentheses.

Table C.6: Island Group Classification in Seychelles

Group	Islands
Main Islands	mahé_, praslin_, la_digue_
Inner Islands	silhouette_island, frégate_island, north_island, cerf_island, round_island, st_anne_island, long_island, île_thérèse, bird_island, île_denis, eden_island, port_island, perseverance_island, félicité, grande_soeur, ile_anonyme, chauve_souris, aride_island
Outer Islands	coëtivy_island, islet_platte, île_alphonse, île_assomption, île_astove, île_desroches, île_d'arros, île_marie_louise, île_poivre, farquhar_atoll, remire_island

D

Reflections on Climate Modeling and Infrastructure Disruption Modeling in SIDS

While climate modeling and risk assessments are essential tools in anticipating the impact of extreme weather on infrastructure, their application in SIDS like Seychelles presents both clear advantages and notable limitations.

On the positive side, global and regional climate models (GCMs and RCMs) offer structured, data driven frameworks for assessing long term risk trends. They help identify hazard prone zones, estimate exposure to sea level rise, and quantify risks from future climate scenarios such as RCP 4.5 or 8.5. This data supports forward looking planning and justifies investments in resilient infrastructure. With proper down scaling techniques whether statistical or dynamical climate models can be refined to provide higher resolution insights, potentially aligning with the geographic scale of island transport assets.

However, these models also have some significant drawbacks when used to simulate realistic infrastructure disruptions in operational simulations. As mentioned in reviews of Climate Risk Assessment methodologies (GCA, 2025)), many climate models suffer from coarse spatial resolution, poor calibration, and lack of validation against local observational data. In Seychelles, the rugged topography, microclimates, and spatial clustering of infrastructure make generic gridded outputs insufficient. Examples of these are some island who have an max elevation of two meter while an uncertainty due to downscaling global data the uncertainty of the sea level rise can be 1,5 meters. This also applies for low laying ring roads. An example for micro climates is extreme rain. in fine forecasting models this is done to a square kilometer, in SIDS this means it either misses the island or is hit badly. Moreover, the different interpretations of assumption in modeling frameworks ranging from different hazard definitions to inconsistent reference periods further reduces their reliability for use in real time supply chain or logistics modeling.

Because of these limitations, the approach used in this study prioritizes historical event analysis and stakeholder verified disruptions over purely model driven hazard inputs. Disruptions in the simulation are not abstracted from uncertain mid or long term projections, but instead derived from real past disasters, such as the 2004 Indian Ocean tsunami and the extreme rainfall event of December 2023. These events provide grounded, empirically observable impacts like port infrastructure damage, landslides on inland roads, and inter island transfer delays which have been verified by local government officials, contractors, and community stakeholders during fieldwork. This allowed the identification of the most realistic and operationally significant infrastructure disruptions for inclusion in the model.

D.1. Disaster Disruption Scenarios for Simulation

Flood areas for Mahe and Praslin in 2004

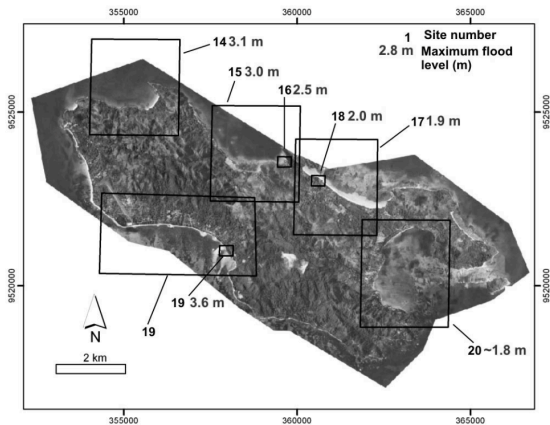


Figure D.1: Floods prasin 2004

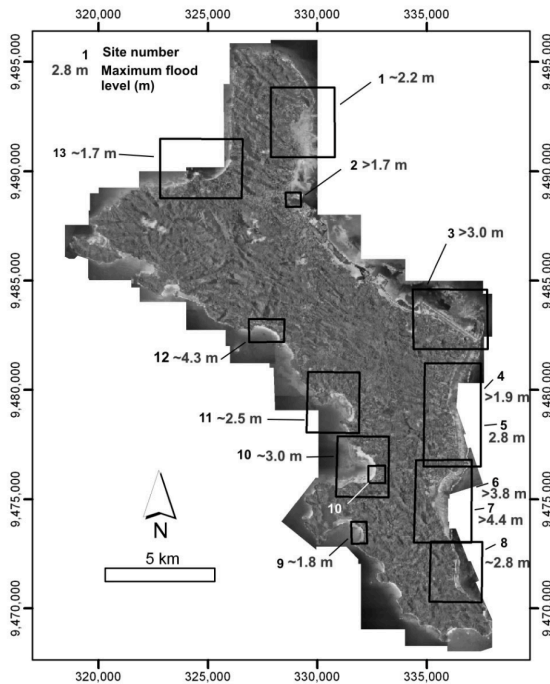


Figure D.2: Floods Mahe 2004

Analysis of Disaster Induced Import Patterns

Approach

In order to detect which two digit HS codes act as proxies for “disaster goods,” we aligned monthly import data (2009 – 2025) with six major disruption events in the Seychelles (Cyclone Felleng Apr 2013, Flooding Feb 2014, Cyclone Fantala Apr 2016, COVID 19 Mar 2020, Tropical Storm Jobo Apr 2021, Flooding + Explosion Dec 2023). For each event:

1. it was computed a *6 month pre event baseline* by averaging imports of each HS code over the six months immediately preceding the month of impact.
2. it was computed a *5 year same month baseline* by averaging imports of the same calendar month over the five years prior to the event.
3. it was quantified both *absolute* and *relative* deviations of the import value in the month following the event against each baseline.

This dual baseline approach isolates (a) short term surges (vs. recent imports) and (b) deviations beyond normal seasonality critical in the Seychelles, where tourist driven import cycles produce strong intra annual patterns (e.g., higher April–May activity)(Bank 2014; UNHCR 2013).

Rationale for Baseline Selection

- **6 month baseline:** Captures immediate pre disruption supply trends (e.g. routine restocking), highlighting sudden spikes in emergent relief categories.
- **5 year same month baseline:** Controls for seasonality essential given Seychelles’ high/low tourism seasons so that amplified imports (e.g. cement in January) can be distinguished from normal post holiday rebounds(Bank 2014).

Results and Interpretation

Cyclone Felleng (Apr 2013) Post event spikes (May 2013) in HS 27 (fuels), HS 84 (machinery), HS 89 (vessels) exceeded the 6 month baseline by +38 %, +45 %, +72 % respectively, and the 5 year May average by +12 %, +20 %, +40 %. This confirms urgent fuel imports for generators and pre positioning of marine craft for evacuation/logistics(Disaster et al. 2013; UNHCR 2013).

Flooding Feb 2014 March 2014 saw HS 68 (cement) rise +150 % over its 6 month baseline and +90 % over the March 5 year average, HS 10 (cereals) rose +260 % and +200 % respectively. These dual comparisons underscore true emergency provisioning above the typical January March food import uptick ahead of tourist season(ReliefWeb 2014; Bank 2014).

Cyclone Fantala (Apr 2016) May 2016 imports of HS 27 (fuels) and HS 44 (wood) jumped +33 %/+40 % vs. 6 month and +18 %/+25 % vs. 5 year, signaling elevated generator and construction timber imports above normal April peaks(Seychelles 2016).

COVID 19 Disruption (Mar 2020) April 2020 saw HS 30 (pharmaceuticals) +90 % vs. 6 month and +60 % vs. 5 year, HS 10 (cereals) +120 % and +80 %. Elevated medicine and staple imports exceed even the typical March–April rush to stock up before tourist lockdowns(Government of Seychelles 2020).

Tropical Storm Jobo (Apr 2021) No statistically significant deviations beyond seasonal norms, reflecting the storm’s minimal infrastructural impact and corresponding lack of large scale import surges.

Flooding + Explosion Dec 2023 January 2024 HS 68 (cement) rose +180 % vs. 6 month and +110 % vs. 5 year, HS 73 (iron/steel) +160 % and +95 %, corroborating major rebuilding efforts beyond normal post holiday low imports(World Health Organization 2023).

- **UNHCR on tents/tarpaulins:** Documented in kind distributions not visible in HS data, explaining absence of an HS spike for shelter items ((UNHCR 2013)).

- **WHO/UNICEF water kit reports:** Note water purification kit deliveries, again often off customs channels ((WHO/UNICEF 2020)).
- **World Bank flood impact:** Seasonal adjustment necessity due to January–March tourism restocking cycles ((Bank 2014)).

Implications for Logistical and Resilience Modeling

The quantified import surges can parameterize your model's *influx functions* for relief goods. As goods change per season it can change, average fluctuation in tonnage's is about 200 to 700 (+30 % above 5 year average) in research months. specifically: These elements will allow your logistical model to replicate both baseline seasonality and disaster driven deviations, yielding more accurate resilience assessments and inventory planning under extreme events.

D.2. Adaptive Strategies in SIDS: A 5–10 Year Review

D.2.1. Integrating Climate Risk into Asset Management

The Japan–World Bank GFDRR Resilient Transport in SIDS (RT SIDS) Program has supported countries in embedding climate and disaster risk assessments within transport asset management systems, ensuring that new investments and maintenance schedules explicitly factor in projected hazard intensities and frequencies (GRDFR). Systematic vulnerability assessments ranging from geotechnical analyses of port breakwaters to scenario based flooding models enable SIDS to prioritize interventions where they yield the greatest risk reduction benefit.

Recognizing shared vulnerabilities, SIDS are forging regional resilience platforms. For example, the Global SIDS Debt Sustainability Support Service (in collaboration with the IIED) includes a mechanism for coordinated debt swaps and contingency funds earmarked for transport infrastructure rehabilitation (Doe 2022). Such pooled resources are particularly valuable for smaller SIDS that individually lack the fiscal space to rapidly rebuild critical assets after disasters.

D.2.2. Infrastructure Hardening and Design Standard Enhancements

Across the Pacific, the World Bank's Pacific Climate Resilient Transport Program has upgraded key roads, bridges, and eight maritime sites to withstand higher wind speeds and wave heights, often through elevated quay levels and reinforced quay walls (World Bank 2021). Similarly, Asian Development Bank projects have introduced climate proof design standards such as higher freeboard requirements for jetties and use of corrosion resistant materials to reduce asset vulnerability to saltwater intrusion and storm surge (ABD)).

Coastal protection works have been implemented in key road sections on Mahé and are planned for Praslin (Ministry of Transport 2025). These provide partial protection but are not comprehensive. Notably, in 2023, SPA partnered with CDRI to conduct a climate risk assessment for Port Victoria and design adaptive infrastructure measures (Disaster Resilient Infrastructure (CDRI) 2023). This initiative explicitly acknowledges the lack of full climate proofing and calls for new operational protocols and physical redesign (Disaster Resilient Infrastructure (CDRI) 2023).

On Mahé, roads are constrained by mountainous terrain. A tunnel construction project is in planning, aimed at reducing congestion but also offering resilience benefits by providing inland, hazard protected routes (Worldbank 2017).

Most infrastructure and population are concentrated in low lying coastal areas of Mahé, especially around the capital Victoria where the main port and airport are located (Bank 2017).

Seychelles is heavily dependent on imports for food, fuel, and goods, being over 1,000 km away from major trade hubs. Transport is vital to its tourism and fisheries based economy. Coastal erosion and sea level rise threaten essential infrastructure, including the international airport and Port Victoria, which are just 0.5 above sea level and the airport just 5 meters along the ocean (PICTURE!). The Minister of Transport has highlighted these risks (Ministry of Transport 2025). Coastal roads on Mahé already suffer from wave induced erosion, occasionally cutting access.

As climate change intensifies, extreme events are expected to become more frequent and severe.

This raises the question of whether disruption durations should increasingly be informed by predictive climate models and long term risk databases rather than only historical occurrences. Indeed, several districts in Seychelles such as Beau Vallon and Anse La Blague are already prioritized for infrastructure resilience projects. These include elevating roads, restoring mangroves, and building concrete flood barriers. The country has also adopted ecosystem based adaptation strategies to buffer against floods and has secured international funding for long term planning through instruments like the Blue Bond and Green Climate Fund.

D.2.3. Diversification of Supply Routes and Modal Integration

To avoid single point failures, several Caribbean SIDS have negotiated multi port trans shipment agreements, enabling cargo to be rerouted through neighboring ports during local disruptions (United Nations Department of Economic and Social Affairs 2019; World Bank 2023). Complementing this, some SIDS now integrate short sea shipping with domestic barge networks and, where feasible, air freight for high priority goods creating a multimodal resilience corridor that reduces the impact of a single transport link failure.

D.2.4. Digitalization, Early Warning, and Decision Support Frameworks

UNCTAD's SIDSport ClimateAdapt project developed a "Climate Risk and Vulnerability Assessment Framework" and accompanying decision support tools, allowing transport planners to simulate operational disruptions under varied climate scenarios and to plan adaptive responses (United Nations Conference on Trade and Development 2022). In the Maldives, ports now regularly conduct vulnerability assessments and use GIS based digital twins to monitor sea level trends and schedule proactive maintenance of high risk assets (United Nations Economic and Social Commission for Asia and the Pacific 2021).

D.2.5. Pre positioning Stocks and Decentralized Logistics Hubs

Several SIDS have invested in inland bulk storage for critical imports such as fuel, potable water, and staple foods across multiple islands to ensure local availability even if a primary port is incapacitated (United Nations Framework Convention on Climate Change 2020; Smith 2019). In the Maldives, this approach is complemented by enhanced cold chain facilities at dispersed island depots, reducing spoilage risks and easing logistical congestion at the capital's harbor.

Seychelles incorporates resilience into national strategies like its National Development Strategy and NDC under the Paris Agreement. The 2024–2028 World Bank Country Partnership Framework identifies transport resilience and disaster preparedness as key goals (Bank 2024a).

The Department of Risk and Disaster Management (DRDM) oversees contingency planning. Cyclone risk is low, but plans exist for rainfall and flooding events. Scenario based preparedness is supported by UNICEF and WFP. Regional cooperation is limited due to Seychelles' isolation, but bilateral partnerships – particularly with India – have supported surveillance and emergency preparedness. Discussions about fallback port access (e.g., via Mauritius) are ongoing (Ministry of Transport 2025).

Seychelles participates in the African Risk Capacity insurance mechanism and is trying to establish a domestic contingency fund (Bank 2024a). However, pandemic induced fiscal stress has slowed progress.

Operational Practices Operational resilience practices include:

- Fuel stockpiling by the national petroleum company, providing several weeks of reserves (Ministry of Transport 2025).
- Minimal relief prepositioning on outer islands by the Red Cross and government.
- Use of ferries and small aircraft for inter island connectivity, which could serve emergency distribution.
- Private sector provisions – hotels maintain buffer stocks for supply disruptions.
- Potential use of cold storage from fisheries and repurposing fishing vessels for emergency cargo transport (Disaster Resilient Infrastructure (CDRI) 2023).

D.3. Case Study: Seychelles

D.3.1. Vulnerability Profile

The Republic of Seychelles relies heavily on its principal maritime gateway Port Victoria for over 90% of its food, fuel, and industrial imports. Rising sea levels, increased cyclone intensity, and coastal erosion threaten quay structures and hinterland access roads, risking prolonged import disruptions and price spikes (CDRI 2023, UNFCCC Seychelle

D.3.2. Vulnerability and Adaptive Response of Port Victoria

The Republic of Seychelles depends on Port Victoria for over 90% of its food, fuel and industrial imports, making the nation highly exposed to coastal hazards. Rising sea levels, stronger cyclones and ongoing coastal erosion threaten quay structures and the key access roads that connect the harbor to the hinterland, risking prolonged import interruptions and sudden price spikes (CDRI, 2023).

To counter these threats, Port Victoria is currently being transformed under the “Sustainable Port Concept,” which integrates on site renewable energy microgrids, advanced wastewater treatment and a real time digital performance monitoring system. This green and smart port upgrade is shaping a model of environmental, economic and social resilience tailored to a SIDS context . In parallel, the Blue Economy and Climate Change project led by Nature Seychelles and CDRI completed a comprehensive climate risk assessment of Seychelles’ seaports. Their findings have directly informed dredging plans, quay reinforcements and the elevation of access roads to ensure continued operations under higher sea levels and storm surges (CDRI, 2023). Recognizing that navigational incidents can halt imports just as effectively as structural damage, the Ministry of Transport has begun sharing high resolution hydrographic charts with regional partners. By improving maritime safety and reducing accident related closures, this data sharing initiative helps stabilize import schedules during critical periods. At the policy level, Seychelles’ updated Nationally Determined Contribution now requires all future port expansions to align with the Green Ports Initiative. This means new terminals must source renewable power, pursue zero waste operations and minimize marine pollution cementing resilience and environmental stewardship as core design principles.

Finally, under the 2024–2028 UN Sustainable Development Cooperation Framework, Seychelles has secured international technical assistance and concessional financing. These resources are being used to embed climate resilience into national transport policy and fund critical port upgrades, ensuring long term sustainability and reliability (IMF 2024, UNDP, 2021).

Emerging Strategies

Looking ahead, the Port Authority is procuring an advanced asset management system that will fuse climate scenario modelling with live sensor feeds to optimize maintenance and predict failure points before they occur. At the same time, feasibility studies for outer island logistics hubs propose building smaller wharves with protected storage facilities, thereby reducing reliance on Port Victoria for internal distribution and enhancing supply chain flexibility under future shocks.

E

Additional results

Modifier	KPI	Pearson r	p-value	Spearman ρ	p-value	Kendall τ	p-value
delay_scale	delivery rate (%)	0.06	1.02×10^{-1}	0.082	1.02×10^{-1}	0.054	1.05×10^{-1}
	avg. delay (h)	-0.09	6.20×10^{-2}	-0.090	6.20×10^{-2}	-0.062	6.66×10^{-2}
storage_time_scale	delivery rate (%)	-0.02	7.05×10^{-1}	-0.019	7.05×10^{-1}	-0.012	7.15×10^{-1}
	avg. delay (h)	0.02	8.02×10^{-1}	0.010	8.02×10^{-1}	0.006	8.58×10^{-1}
storage_capacity_scale	delivery rate (%)	0.02	7.59×10^{-1}	0.015	7.59×10^{-1}	0.010	7.66×10^{-1}
	avg. delay (h)	-0.03	2.22×10^{-1}	-0.060	2.22×10^{-1}	-0.039	2.40×10^{-1}
demand_multiplier	delivery rate (%)	0.02	5.52×10^{-1}	0.030	5.52×10^{-1}	0.019	5.74×10^{-1}
	avg. delay (h)	0.03	3.77×10^{-1}	0.040	3.77×10^{-1}	0.052	3.01×10^{-1}
storm_duration	delivery rate (%)	-0.40	$<1 \times 10^{-15}$	-0.392	$<1 \times 10^{-15}$	-0.265	3.37×10^{-15}
	avg. delay (h)	0.16	7.52×10^{-4}	0.170	7.52×10^{-4}	0.113	7.59×10^{-4}
storm_start_hour	delivery rate (%)	-0.26	2.69×10^{-6}	-0.232	2.69×10^{-6}	-0.161	1.58×10^{-6}
	avg. delay (h)	0.10	4.95×10^{-2}	0.100	4.95×10^{-2}	0.068	4.32×10^{-2}

Table E.1: Pearson's r , Spearman's ρ , and Kendall's τ correlations (with two-sided p -values) between each scenario modifier and the delivery rate and average delay KPIs.

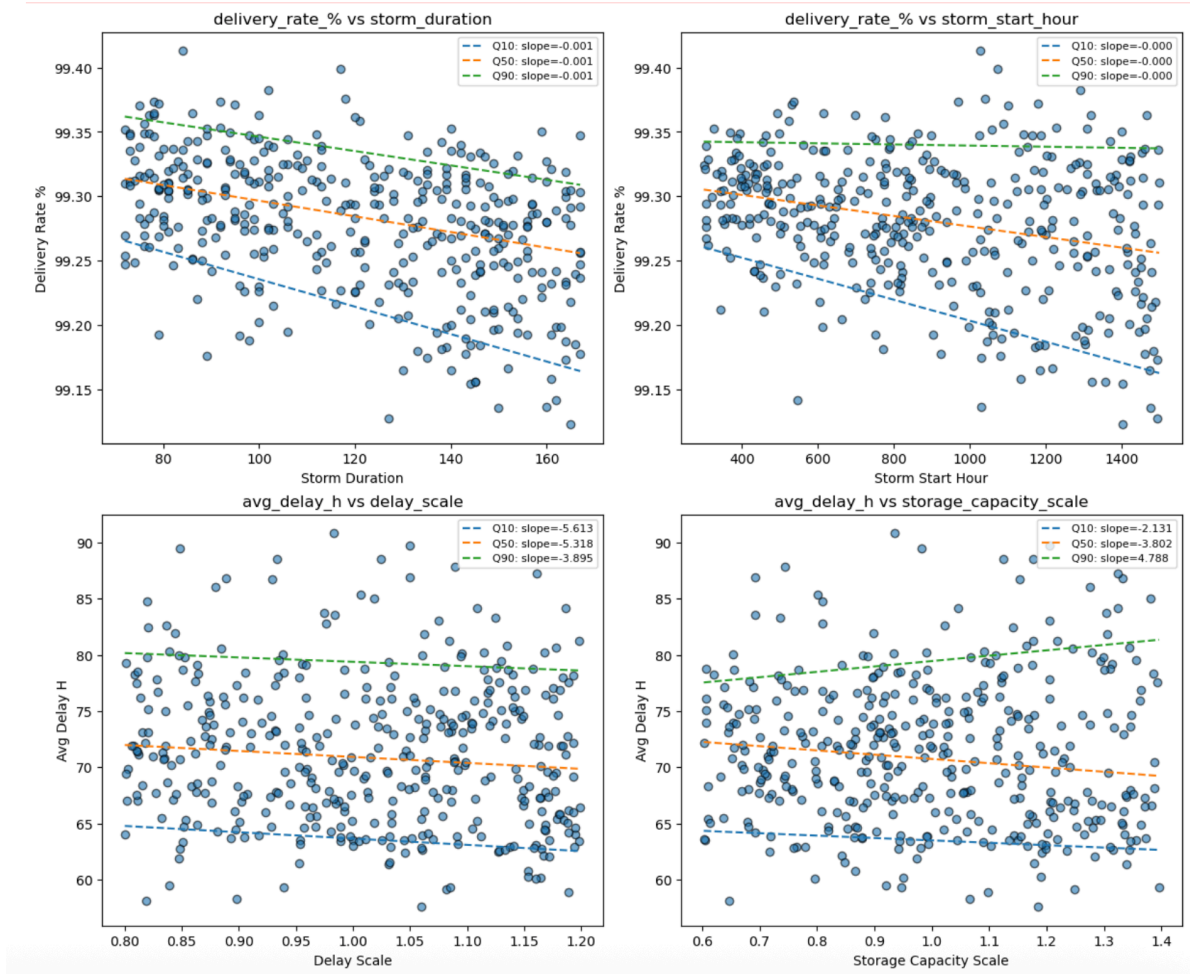


Figure E.1: Quantile regression

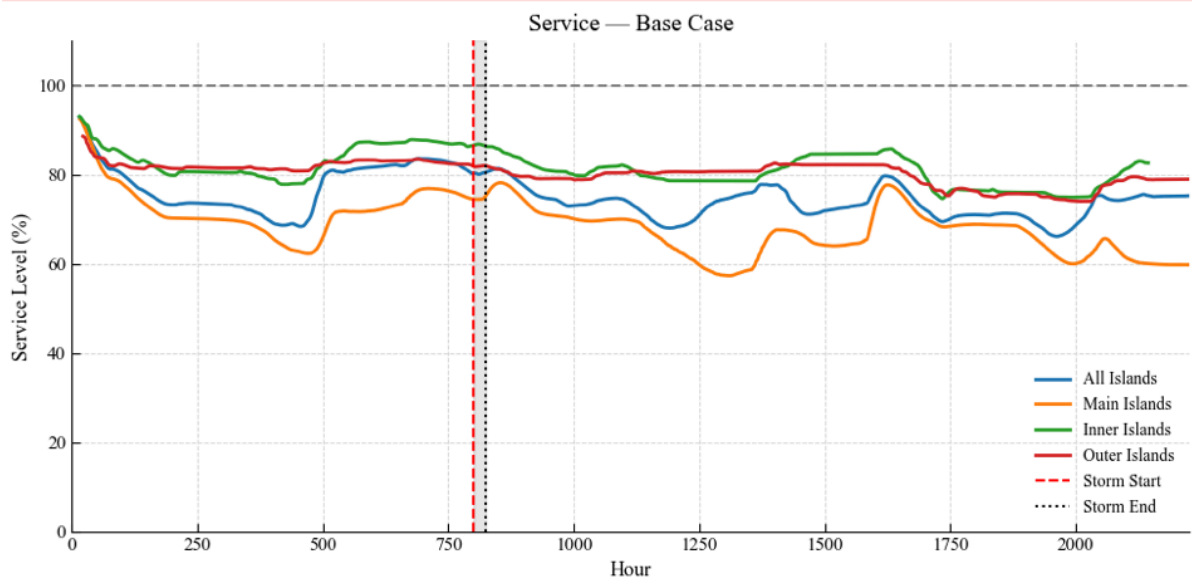


Figure E.2: Base case

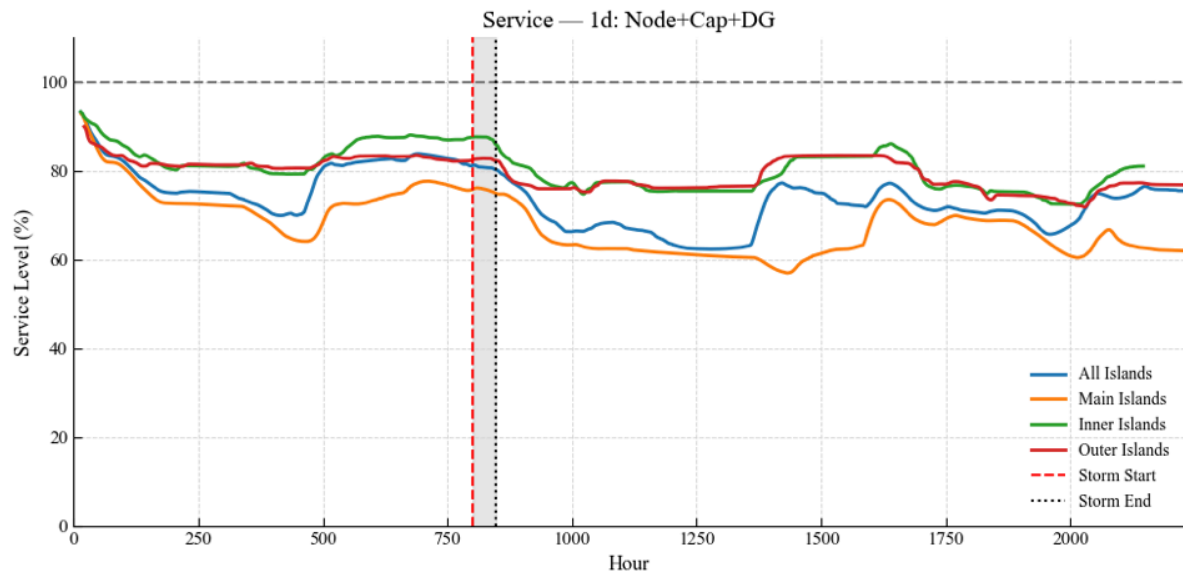


Figure E.3: 1d Node Cap DG

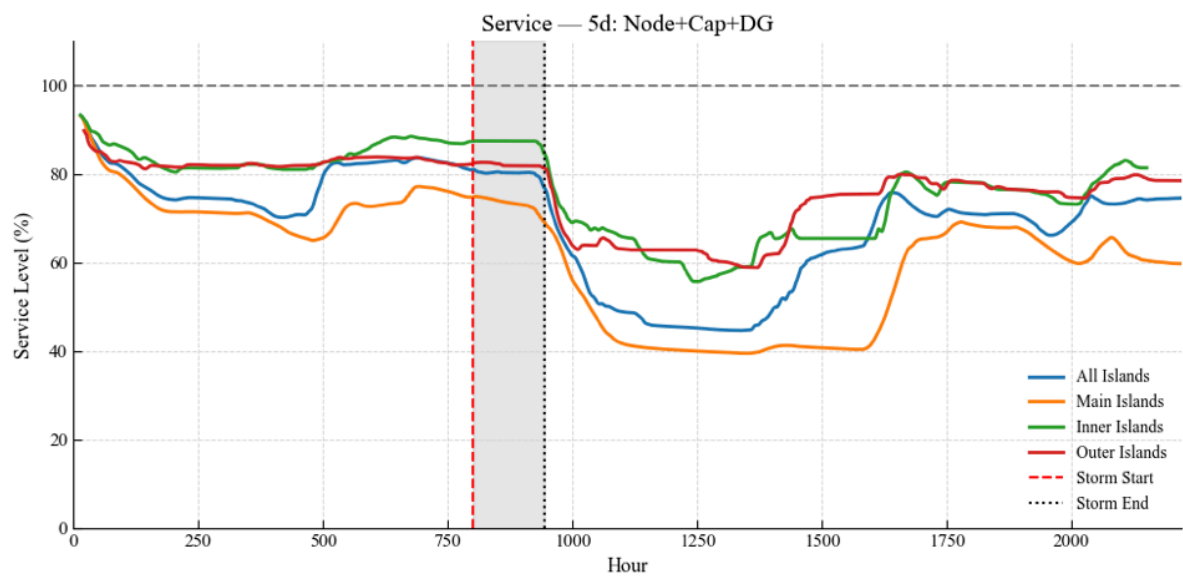


Figure E.4: 5d Node Cap

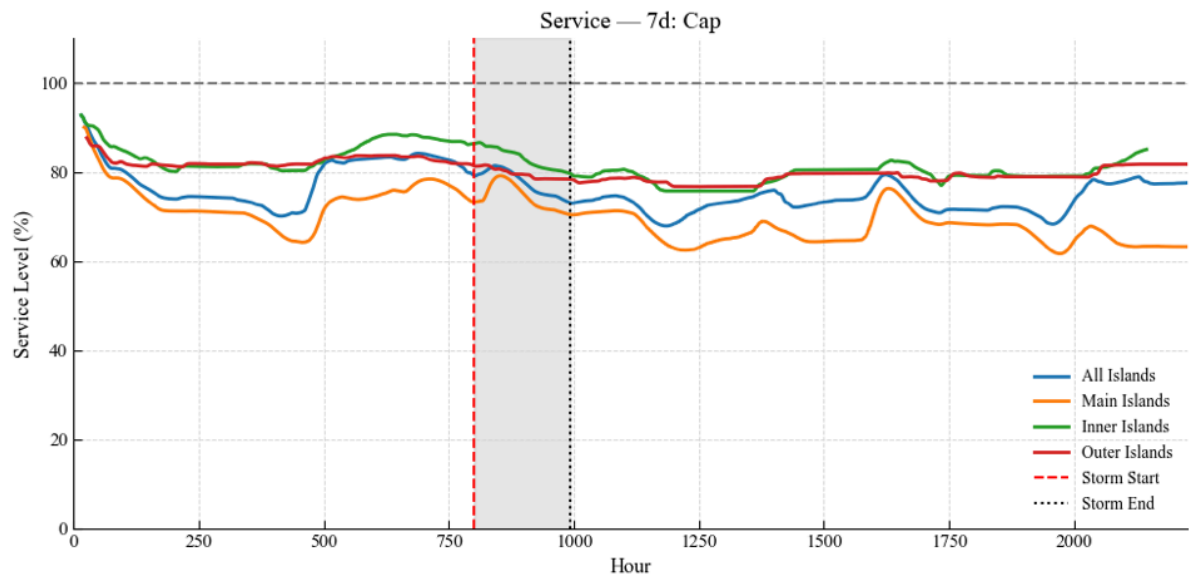


Figure E.5: 7d Cap

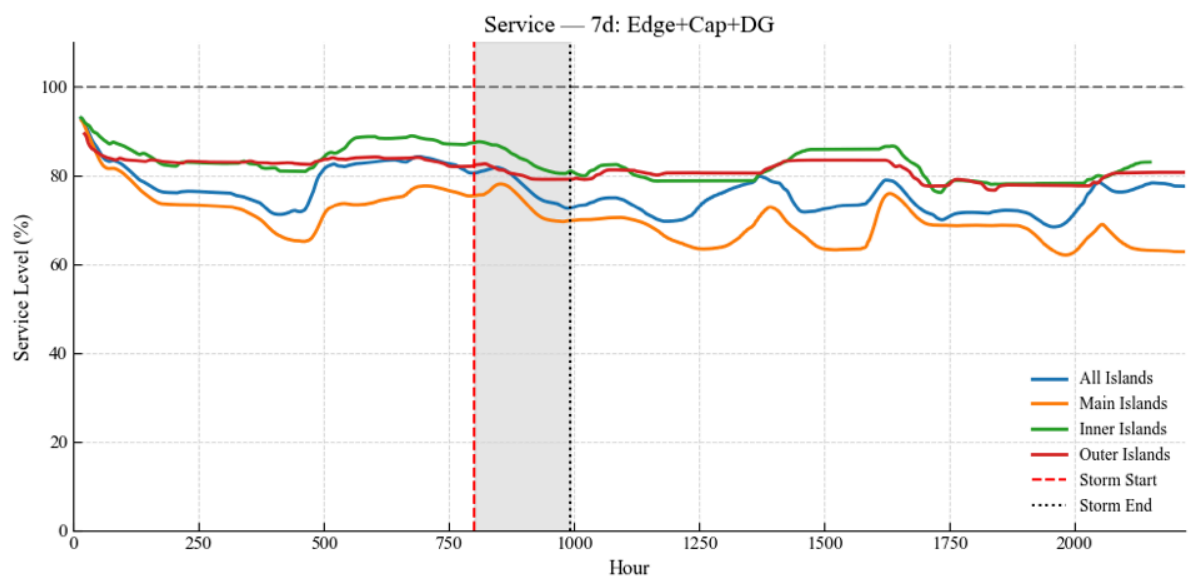


Figure E.6: 7d Edge Cap DG

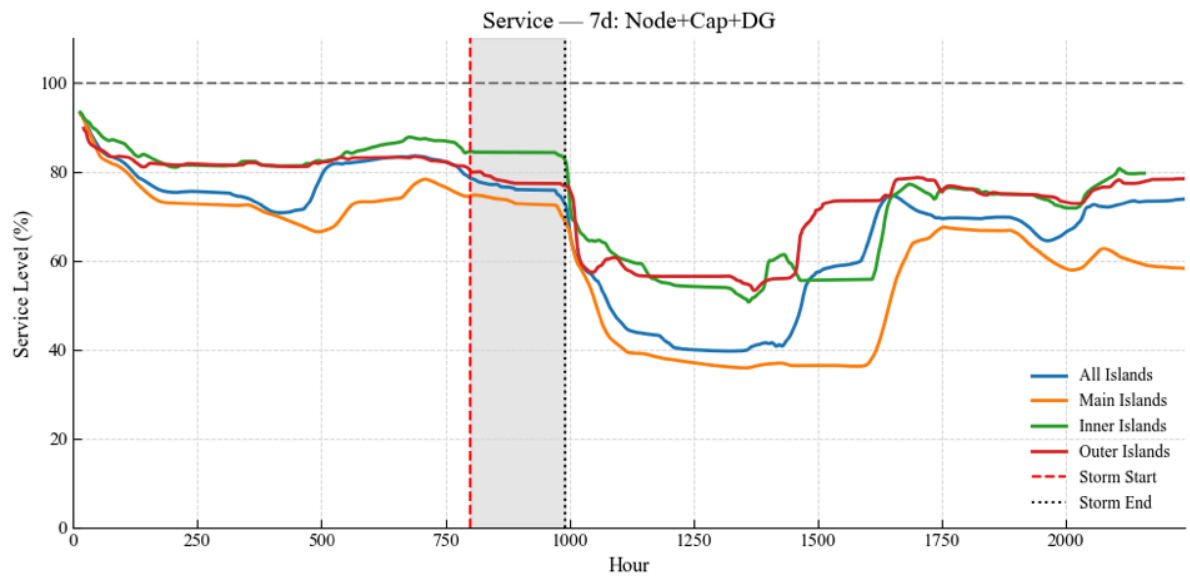


Figure E.7: 7d Node Cap DG

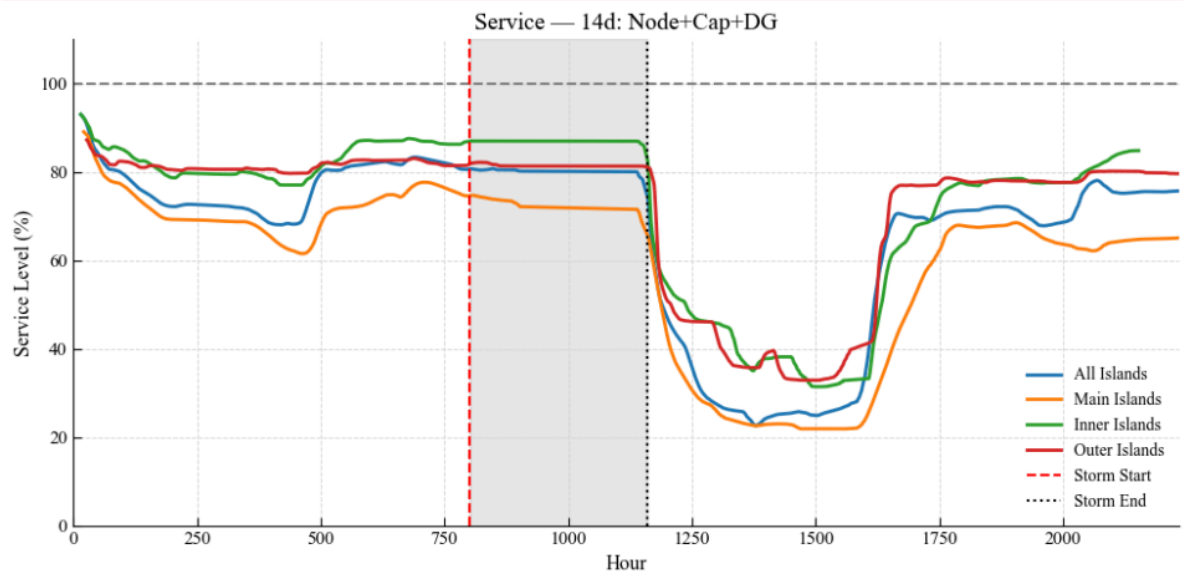


Figure E.8: 14d Node Cap Dg

Main Islands Delivery Performance

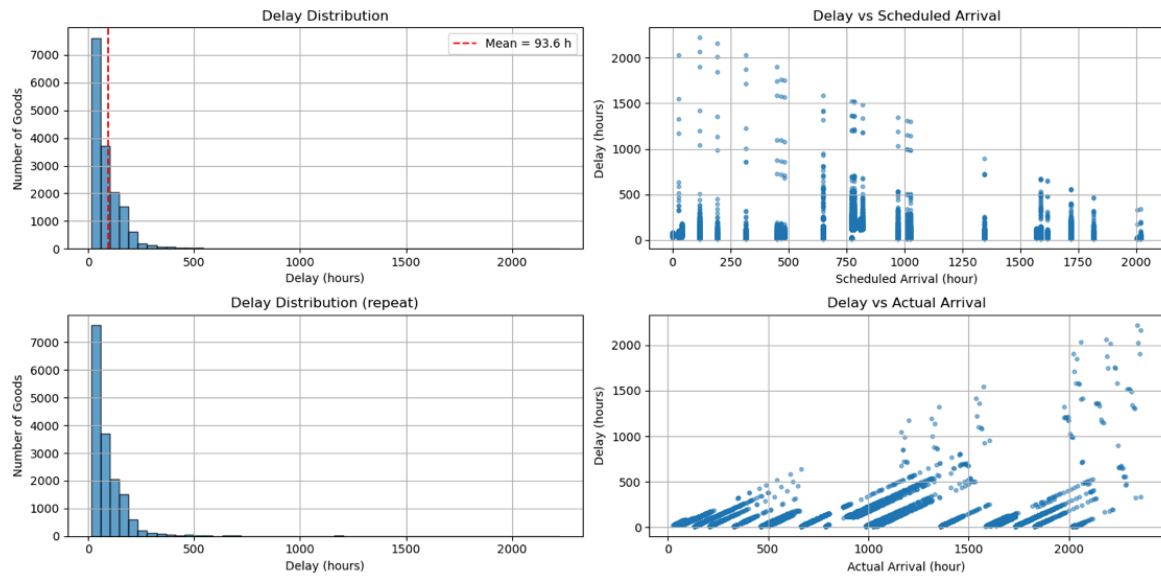


Figure E.9: Spread Main islands

Inner Islands Delivery Performance

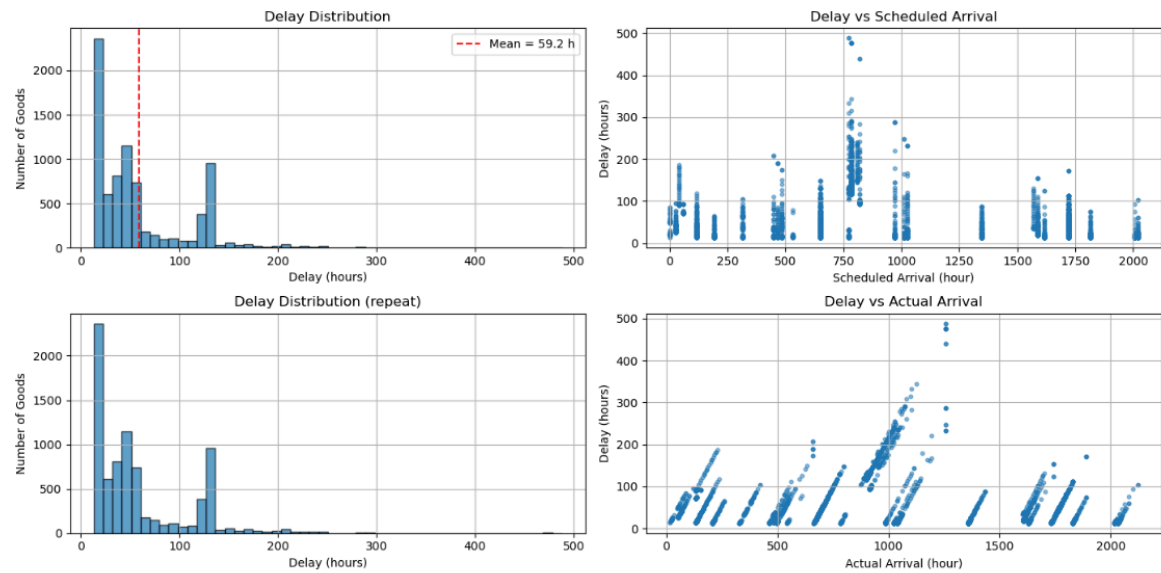


Figure E.10: Spread Inner islands

Outer Islands Delivery Performance

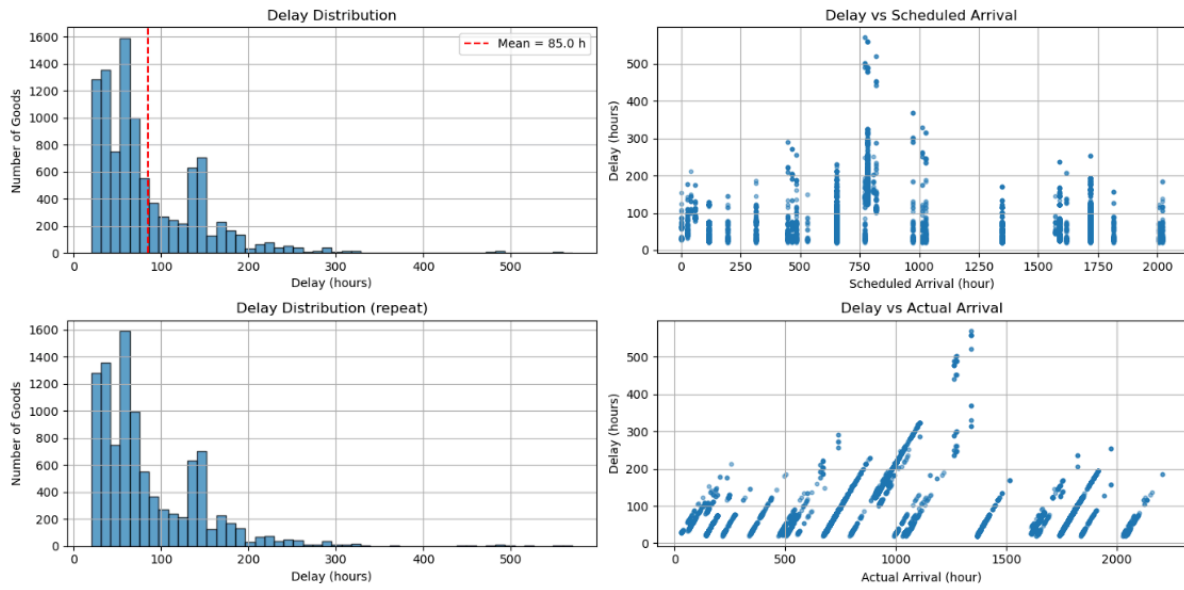


Figure E.11: Spread outer islands

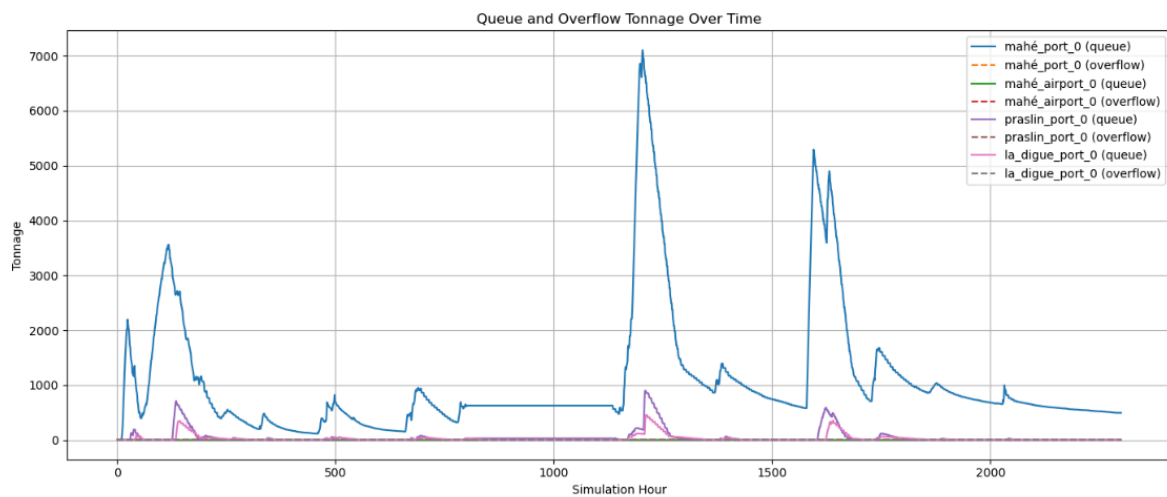


Figure E.12: Overview of queue's in port and and ports for a disruption run of 14 days. Arrival peak of 15.000 T boat creates almost as high as queue