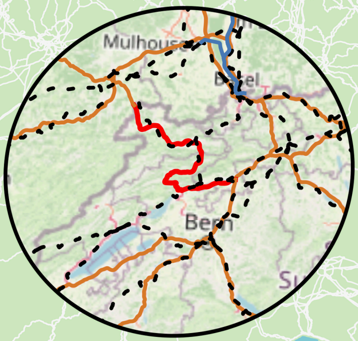
Identifying critical links in European multimodal freight networks

Sathvik Varma Gadiraju



TU Delft

Panteia

Identifying critical links in the European multimodal freight networks

A Simulation Framework for Strategic Resilience Planning

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Sathvik

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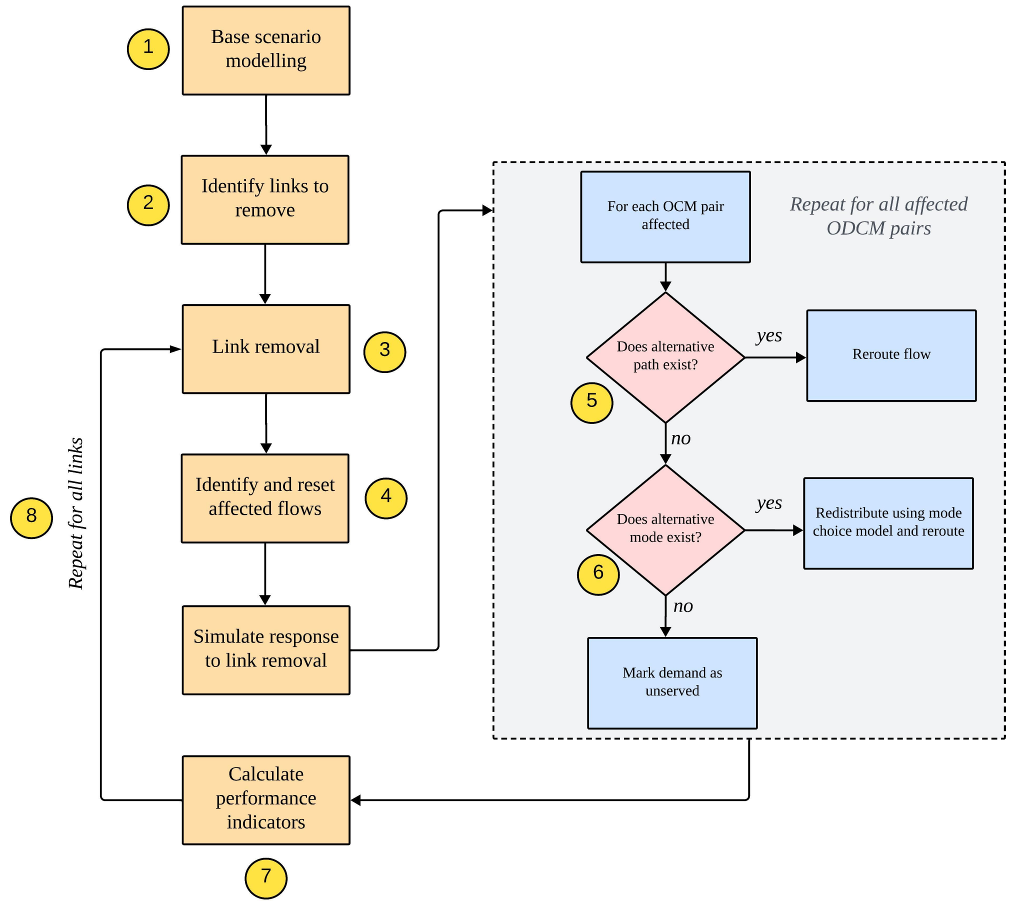
Executive Summary

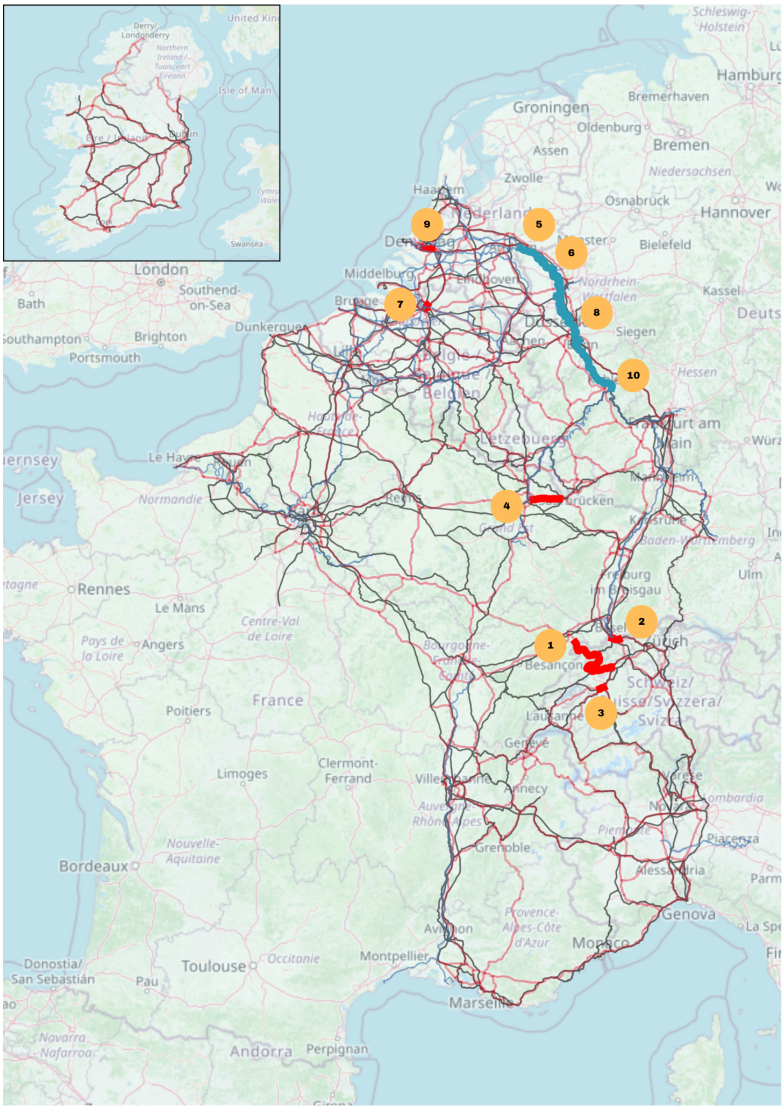
The Trans-European Transport Network (TEN-T) is the backbone of Europe , linking road, rail, and inland waterways to move freight efficiently while supporting economic growth, security, and policy goals. Yet these networks are prone to disruptions such as accidents, asset failures, maintenance closures, and climate-driven hazards. These disruptions range from day to day disruptions to long term impact with significant costs. Identifying critical infrastructure is one of the first steps towards building resilience. The EU's Critical Entities Resilience Directive also mandates member states to identify infrastructure whose failure would degrade essential services. The academic literature offers many ways to rank critical links, but most concentrate on single-mode road networks, require data-hungry congestion models, or rely on topology-only indices that miss operational realities in multimodal freight. This project addresses that gap with a scalable framework to identify links in European multimodal networks that cause the greatest impact when disrupted. It is guided by three questions: (1) what methods exist to measure link criticality; (2) which are suitable for multimodal freight; and (3) how can the effects of link removal be assessed empirically at macro scale?

The framework is demonstrated using the North Sea–Rhine–Mediterranean (NSRM) TEN-T corridor using an undirected multimodal graph. Nodes represent intersections, terminals, and NUTS-3 origins/destinations; links represent roads, railways, and inland waterways. The framework follows a traditional 4 step transport modelling approach for simulating the base scenario of the network. The Annual freight demand used is collected from Panteia's NEAC model, is represented in tonnes by NUTS-3 origin–destination pairs and aggregated to ten NST/R commodity classes. Mode choice is handled with a commodity-specific multinomial logit that uses generalised transport cost (GTC) to produce probabilities for road, rail, and inland waterway use. Assignment then applies All-or-Nothing (AON) shortest paths by mode using GTC as weight. This avoids heavy congestion modelling, which is impractical at corridor scale and with annual flows. The core methodological contribution is a selective full-scan criticality algorithm. Rather than recomputing flows for the entire OD table after removing each link, the algorithm (i) removes only links that carry non-zero base flow and (ii) recalculates only the OD-commodity-mode flows that actually used the removed link. Affected flows first attempt a new shortest path on the original mode; if none exists, the model triggers a mode choice step and reassigns to alternative modes



if feasible; otherwise, demand is marked unserved. Criticality is then measured with system-level indicators (changes in total GTC, time, distance, emissions, and unserved demand) and equity-style indicators (average relative changes for the affected flows). This design captures operational impacts and mode shifts while remaining computationally scalable for large networks.

The criticality analysis for the NSRM network shows that minor detours in road links translate into large network-wide cost increases when key links fail due to the level of tonnes exposed. The most critical links are located around Basel and Bern causing upto ≈€830 million/year when removed. Links near Rotterdam and Antwerp, are also very critical due to the sheer volume of freight flowing through them as they are major EU ports. Rail links rarely produce large system-wide shifts because the network is structurally redundant at corridor scale; however, particular southern segments impose substantial local delays when removed. Inland waterways also exhibit vulnerability near the linear river sections offer few detours, so removing a single Rhine segment,especially between Nijmegen and Strasbourg, forces costly mode shifts to road or rail. Overall, road and inland waterway disruptions generate the largest increases in total system GTC (commonly 0.25–1%, with top cases near 2.5%). These links make up the top 10 most critical links in the network.



Practically, the framework equips planners with a screening tool for strategic multi-modal resilience. The tools allows for analysing criticality in multimodal network while accounting for interdependent affects instead of analysing them in isolation. The outputs support several use cases: identifying links where redundancy should be added, prioritising maintenance to minimise systemic impact and designing diversion strategies with the best alternatives. By highlighting links whose failure would most impact performance, authorities can conduct comprehensive assessments of threats for that specific link to then reduce the impact or probability of failure. Finally, the model is highly modular and can be adapted to various applications such as national corridors and military mobility. The code used for the research can be found at `https://github.com/sathvikgadiraju/Link-criticality-framework`.

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1 Introduction

Transport networks serve as vital infrastructure enabling the efficient movement of both goods and passengers. As integral components of global supply chains, these networks ensure the timely distribution of raw materials, work-in-progress inventory, and finished products across locations. In that way, transport networks play a crucial role in a nation's economic development and growth prospects. Beyond their economic function, transport networks are strategic assets that serve a nation's security and policy interests [3].

The Trans-European Transport Network (TEN-T) represents the European Union's strategic policy framework designed to plan and develop an integrated, efficient, multimodal, and high-quality transport infrastructure system across member states. As part of the TEN-T policy, the European Union aims to accelerate the transition toward multimodal and synchromodal freight transport solutions throughout Europe. This shift aims to optimize the utilization of different transport modes based on their respective strengths and efficiencies, reduce environmental impacts and congestion on saturated corridors by promoting more sustainable alternatives and lastly enhance overall system resilience through diversified transport options and interconnected networks [7]. Please see Annex L for an overview of the European transport corridors under TEN-T.

1.1 Problem Definition

Networks consist of various connected components that are prone to disruptions or perturbations. These events can be caused by internal factors within the system such as accidents, infrastructure failures, maintenance or external factors often related to nature such as floods, landslides, wildfires, snowfall and storms [18]. The severity can range from "day to day" disruptions which lead to minor capacity reductions on a single link to critical segments being closed for long periods of time. The failure of certain critical infrastructure such as a bridge or a terminal can have cascading effects which can paralyse a network's performance for a time period leading to significant economic loss. The infamous Suez canal blockage in 2021 estimates to have a cost around 6 to 10 Billion USD a day [26]. The Rhine river which one of Europe's busiest inland waterway channel for freight was blocked due to a ship overturning and sinking in 2011. This lead to over 250 ships stranded on the river for more than 3 weeks [2]. The 2017 Rastatt incident, involving a train tunnel collapse in Germany, resulted in approximately 2 billion Euros in combined direct and indirect damages [15].

Identifying critical links within transport networks is crucial. The European Union's Critical Entities Resilience (CER) Directive [5] mandates that member states implement specific measures to maintain essential services, including transportation, which supports key societal and economic functions. One of the measures required to improve resilience includes the identification of critical infrastructure components within the transport network. According to Jenelius et al [18] link criticality can be defined as *"significance of individual links (e.g., roads, bridges, tunnels, channels, railways) in maintaining network functionality, where the failure of a critical link can disproportionately degrade system performance, such as increased travel times or reduced connectivity".* This definition can be extended further to include increases in travel costs, transshipment costs, and environmental impact. Insights gained from measuring and ranking critical links could inform the development of improved mitigation strategies, guide the prioritisation of funds for maintenance and repairs and identify regional disparities in infrastructure [18, 21, 27]. Taking proactive measures to address network vulnerabilities can significantly enhance network performance during severe disruptions, thereby strengthening the overall resilience and robustness of the transportation system.

1.2 Research Gap

The related literature in discussed in more detail in Chapter 2. Here we summarise the overall gaps that exist. Existing literature reveals numerous studies that have implemented various methods for identifying and ranking link criticality within transport networks. However, limitations exist in the current body of research. First, most studies have primarily focused on road transport networks [11, 16, 17, 20, 21, 27, 28, 32], with very few examining infrastructure criticality in multimodal freight networks that include road, rail, and inland waterways [34, 36]. The multimodal freight network of the Netherlands has served as a case study for robustness analysis in multiple studies [12, 35]. To the author's knowledge, no studies have examined link criticality at a macro scale, such as that of the European freight network. While most link criticality studies measure importance of link based on change in total network performance due to alternative route choice, they don't take into account user behaviour such as alternative mode choice due to disruption. Furthermore, measures and methods that incorporate traffic flow when determining criticality provide accuracy but are computationally intensive to execute and have high data requirements. This computational burden increases significantly as network size and level of detail expand. Conversely, graph-based link criticality metrics offer computational efficiency but neglect the operational dimensions of transportation networks. This presents a gap in existing methodologies, as there is scarcity of approaches that can balance computational efficiency with the incorporation of operational characteristics, particularly for large-scale network analysis. Lastly, there are numerous methods in literature for measuring link criticality but it is not quite clear which is the most suitable method for our case.

1.3 Scope

This graduation thesis project, conducted in collaboration with Panteia B.V., aims to develop a model for identifying critical links within Europe's multimodal freight transport network. The model will be implemented using the North Sea - Rhine - Mediterranean core TEN-T corridor as shown in Figure 1.1. The Links from the TEN-T comprehensive network that fall within this study area are also incorporated. Although a more detailed regional network exists below this macro-level network, it is omitted from the analysis to prevent excessive computational complexity resulting from the increased number of links. Moreover, these regional links are predominantly used by passenger traffic and traffic for transporting goods within zones. The study models freight demand at the Nomenclature of Territorial Units for Statistics (NUTS) level 3 matching the resolution detail of the transport network. Demand flows between regions are quantified in tonnes and categorized according to *Nomenclature uniforme des marchandises pour les Statistiques de Transport, Revisée* (NST/R) level 1 classification, encompassing 10 distinct commodity types.

The multimodal network consists of three primary transportation modes: road, rail, and inland waterways. Although air transport and short sea shipping also facilitate freight movement within Europe, they fall outside the project scope due to their fundamentally different criticality characteristics. The analysis leverages data from Panteia's European freight transport model NEAC [25], a traditional four-step transport model to simulate network behavior at NUTS2/NUTS3 regional resolution. Through iterative removal of links to simulate disruption, the research will determine which specific infrastructure links would cause the most significant performance degradation if compromised. The primary deliverable for Panteia B.V. will be a comprehensive assessment identifying and ranking critical links by applying the framework to a case study and an interactive impact assessment tool which allows for in-detail analysis of the link disruption on freight demand. Outcomes provide planners valuable insights for infrastructure management, investment prioritization and resilience planning. The total duration of the project is set to be 6 months long.

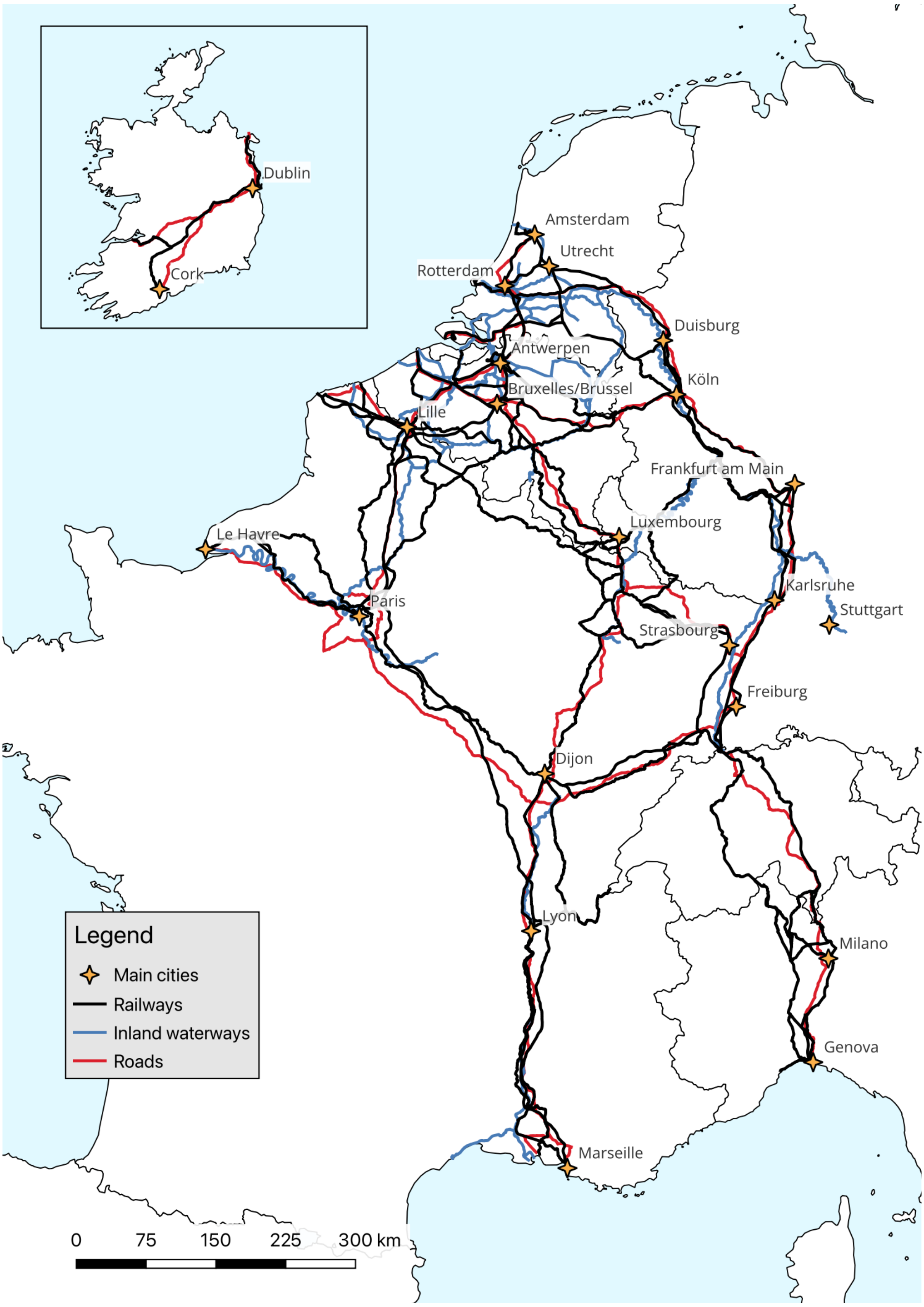

Figure 1.1: *Map of the North Sea - Rhine - Mediterranean core TEN-T corridor network*

1.4 Research question

Therefore the main research question that the project is aiming to answer is:

How can we identify critical links in the European multimodal freight networks which create the most impact when disrupted?

To answer the main research question, the following sub questions are formulated:

1. What are the state of the art methods of measuring and ranking critical links in transportation networks?
2. Which link criticality measures are most suitable for multimodal networks considering their strengths and limitations?
3. How to assess empirically the effects of link removal in the multimodal freight networks?

1.5 Outline

Following the introduction chapter, the thesis is structured as follows:
Chapter 2 provides an in-depth literature review of the measures and methods used to identify and rank critical links in previous studies. Additionally, it includes a brief review of freight transport behavior under disruptions.
Chapter 3 describes the experimental design and methodology for the freight transport model. This chapter also introduces a novel link criticality analysis algorithm for multimodal freight networks, along with the corresponding link criticality indicators.
Chapter 4 applies the methodology to the case study of the North Sea - Rhine - Mediterranean (NSRM) Trans-European Transport Network (TEN-T) corridor. This chapter presents the simulation results, including validation and discussion of findings.
Chapter 5 provides conclusions addressing the research questions. It also discusses practical and theoretical implications, limitations, and directions for future research.

2
Literature Review

This chapter presents a detailed literature review of link criticality research in transport networks. The aim of this chapter is to directly answer the first research subquestion "What are the state of the art methods of measuring and ranking critical links in transportation networks?" and partially answer the second research subquestion. The chapter is structured as follows: Section 2.1 presents the methodology used to conduct the literature review. Section 2.2 introduces the concept of link criticality and describes various approaches used to measure it in transport networks. Section 2.3 summarizes the literature on link criticality specifically within multimodal transport networks. Section 2.4 examines how freight travel behaviour is affected by network disruptions. Finally, Section 2.5 concludes by summarising the discussed literature, evaluating its applicability to multimodal freight networks, and identifying gaps in the current research.

2.1 Literature review methodology

To ensure a systematic and transparent review methodology, this section explains the process used to find, select, and analyze the literature. Our primary objective is to understand the state-of-the-art measures and methods for identifying critical links in transport networks. Table 2.1 presents the keywords and search terms employed in our literature gathering process. The search strategy centered on three main concepts: "Link criticality," "Transport network," and "Vulnerability analysis," along with various alternative keywords for each. Google Scholar served as our primary search engine for gathering literature, with the TU Delft Library portal used as a supplementary resource.

The primary selection criteria for inclusion in the review were studies published in peer-reviewed journals and conference papers. Figure 2.1 visualizes the process of filtering literature. Since identifying critical links in networks was a vast topic, we attempted to limit the literature search to transportation journals. Despite this constraint, we found literature from other domains such as computer science to be highly relevant.

Concept Groups	Link criticality; Transport Network; Vulnerability analysis	
Keywords	Link criticality	Vulnerable links, Critical links, Critical segments
	Transport network	Road transport network, Multimodal network
	Vulnerability analysis	Disruption analysis, Robustness analysis
Truncation	(Link criticality) AND (Transport network)	
	(Vulnerability analysis) AND (Transport network)	

Table 2.1: *Literature search terms*

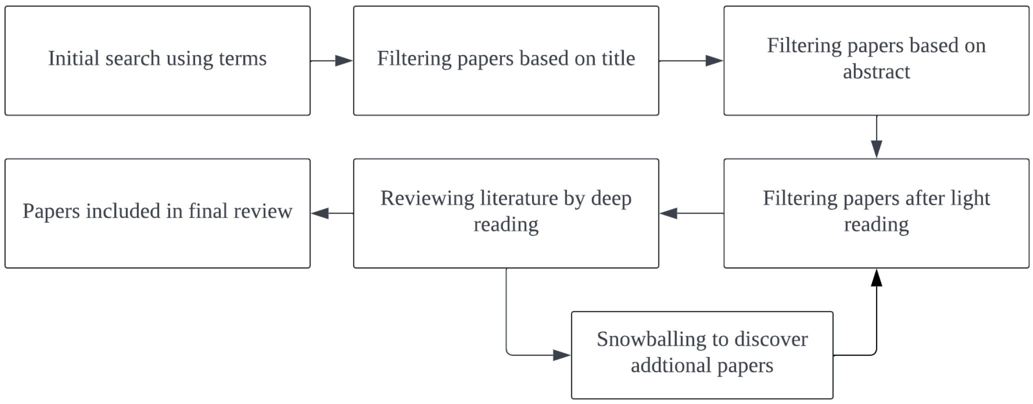

Figure 2.1: *Literature review process*

2.2 Link criticality literature

Link criticality is a concept that extends beyond transport networks and is discussed in various fields, including computer networks, power grids, social networks, and water infrastructure. A critical link is one whose failure or disruption would substantially degrade the performance, connectivity, or functionality of the network. Identifying these links is foundational for prioritizing mitigation and investment strategies that enhance network reliability, service, and efficiency [16, 21, 31]. Link criticality is closely related to the concept of network robustness. Network Robustness is the network's ability to maintain performance under both random and targeted disruptions. Networks with many critical links are less robust, because performance degrades sharply if any such link fails. Robustness is highest when no individual link is indispensable. There is a large body of literature on link criticality, within the context of transport networks. Growing risks associated with geopolitical conflicts, extreme weather events, and aging infrastructure have further highlighted the importance of identifying critical links.

Various measures have been proposed to measure the criticality of link in literature. They can be categorised into two main categories: 1) *Topological-based measures* and *Traffic based measures* [24]. The categorisation has been extended further by introducing *Hybrid measures* that combines both traffic and topological elements into a measure [31].

2.2.1 Topological measures

Topological based measures take into account the topological properties of the transport network and its connectivity. These measures are grounded in traditional graph theory and can be translated to other applications. Another advantage of such methods is that they are very simple to calculate and are less data hungry [24]. Additionally there are relevant when planning for disruption management under emergencies and relief care where travel demand and congestion can be neglected [29].

Traditional centrality measures such as Degree centrality, Eigenvector centrality (or) Eigen centrality, Closeness centrality and betweeness centrality are measures which to some extent give information regarding the importance of a node in a network. Among them, betweeness centrality is a particularly useful measure which can be also translated to the criticality of a link. By definition, the betweenness centrality of a link is its importance in a network based on how often it lies on the shortest paths between pairs of nodes [10]. It reflects the extent to which a link acts as a bridge or connector between different parts of the network. As we will see later many measures are built on top of this simple measure to incorporate transport related indicators.

[22] introduced a method to measure the efficiency of a network. This method calculates the global efficiency as the average of the reciprocals of the shortest path lengths (distances) d_{st} between all pairs of nodes in the network. Consequently, the change in network efficiency $\Delta E(G)$ resulting from the removal of a link can be used as a measure to identify critical links. Links whose removal causes a significant decrease in global efficiency are considered critical, as they play a vital role in maintaining the network's overall connectivity and performance.

Following a similar principle of measuring network performance before and after removal of a link [28] attributed linked criticality to accessibility. The accessibility score of the counties is calculated using distance and traffic volume The method was applied to rank the significance of highway links under flood damage in the state of Maryland, USA. The results indicated that the measures calculated based on distance and distance-traffic considerations were different. The percentage loss of accessibility was greater in the latter case.

2.2.2 Traffic based measures

Traffic-based measures consider the travel behavior of users when assessing the criticality of a link. These measures account for travel demand and route choice, making them more data-intensive than topology-based measures. However, they are also regarded as more informative and realistic.

The Network Robustness Index (NRI) was introduced in 2006 [27]. Previous to the method, network planners used Volume/Capacity (V/C) ratio to identify highly con-

Author	Measure	Equation	
[10]	Betweenness Centrality	$C_B(e) = \sum_{s \neq t \in V} \frac{\sigma_{st}(e)}{\sigma_{st}}$	σ_{st} is the total number of shortest paths from s to t; $\sigma_{st}(e)$ is the number of those paths passing through edge e. For node v, $\sigma_{st}(v)$ counts paths through v.
[22]	Global Efficiency	$E(G) = \frac{1}{N(N-1)} \sum_{s \neq t \in V} \frac{1}{d_{st}}$	N is the number of nodes. d_{st} is the shortest path length between nodes s and t. Efficiency reflects how well information or flow is exchanged across the network.
[28]	Accessibility Deterioration	$A^j = p^j \sum_i^n (A_i - A_i^j)$	A^j: Accessibility deterioration when link j is disrupted. p^j: Probability of link j being disrupted. A_i: Accessibility score of county i before disruption. A_i^j: Accessibility score of county i after disruption.

Table 2.2: *Topological based link criticality measures*

gested links. According to the authors, this resulted in localized solutions which did not consider system wide impacts. The V/C ratio, while appropriate for representing a link's capacity utilization, is inadequate for measuring its criticality. A link with a low V/C ratio but high traffic volume may be more critical than links with high V/C ratios but low traffic volumes. NRI measures the critical importance of a highway segment or link to the overall system. In other words, it is defined as the change in travel time cost associated with re-routing all traffic in the system should a segment or link become unusable. The travel time cost can also be easily generalised to monetary costs. To measure the traffic flows after the link is removed, the model has to run a user equilibrium assignment to calculate the rerouted flows. The total number of times the model is to be run is based on the number of links removed from the network i.e. n + 1 times. This makes the model computationally complex as the size of the study area or level of detail increase.

A vulnerability indicator V_{rs} was introduced which integrates travel demand and change in accessibility [32]. In the study, multiple indices for accessibility were tested such as generalised travel costs, Hansen integral accessibility index, and Accessibility/Remoteness Index of Australia. Similar to NRI, V_{rs} measures the global consequence of link failure. Method was demonstrated using the Australian national road network.

[18] proposed the importance score (IS) as a metric to evaluate the criticality of a network link. This measure can be computed from two distinct perspectives: the "equal opportunities perspective" and the "social efficiency perspective." In the equal opportunities perspective, all origin-destination pairs are assigned equal weights. In contrast, the social efficiency perspective assigns weights based on travel demand. This methodology is designed to assess the significance of a link relative to the entire network. It is

also the first method to account for unsatisfied demand along with traffic performance in link criticality.

[30] extended on the work from [27] and introduced two new measures of measuring link criticality and overall network robustness. They are the modified Network Robustness Index (NRI*) and the Network Trip Robustness (NTR). The NRI* method is similar to the original measure NRI introduced by [27] but the main difference is the ability to model and measure disruption that involve capacity reductions less than 100% unlike NRI. This allows for modelling of more realistic disruptions such as road maintainence, weather events or accidents that do not involve complete closure of links. They demonstrate that that modelling 100% capacity reductions to measure network robustness doenst not reflect actual link capacities resulting from day to day disruptions and does not produce worst case travel time scenarios due to the Braess' paradox. NTR is another meathod introduced that measures the overall robustness of the network based on NRI* and can be used to compare different network with different topological characteristics and connectivity.

Author	Measure	Equation	
[27]	NRI	$NRI = \sum_a t'_a(x_a)x'_a\delta_a - \sum_a t_a(x_a)x_a$	x_a traffic flow on link a; $t_a(x_a)$ travel time on link a; x'_a traffic flow of link a under disruption; $t'_a(x_a)$ travel time on link a under disruption; δ_a 0 if link a is removed, else 1.
[32]	V_{rs}	$V_{rs} = \sum_i \sum_j d_{ij}v_{ijrs}$	d_{ij} Travel Demand between node i and j; v_{ijrs} change in accessibility index between node i and j if link rs fails.
[18]	I_1	$I_1 = \frac{TC_a - TC}{Q}$	TC_a Total network travel time if link a is disrupted; TC base total system travel time; Q total demand.
[18]	I_2	$I_2 = \frac{\sum_w u_w(a)}{Q}$	$u_w(a)$ Unsatisfied demand between OD pair w if link a is disrupted; Q total demand.
[30]	NTR	$NTR_n = \frac{\sum_a NRI_a}{D_n}$	NRI_a Network robustness index of link a;D_n is the total demand between all OD pairs

Table 2.3: *Traffic based link criticality measures*

2.2.3 Other approaches

Hybrid measures are ones that combine both topological and traffic based measures. These measures aim to balance between the computational requirements and accuracy of ranking critical links. [11] proposed Travel-time weighted Betweenness Centrality (TTWBC) and used a stress test criticality simulation which reduced the capacities of links rather than completely removing them. In their study they also compared three other link criticality measures including Unweighted betweeness centrality, Betweeness centrality on entry and exit nodes and travel time weight betweeness centrality on entry and exit nodes. The results indicated a signficane difference in ranking between links depending upon the measure used.

[31] proposed nine more hybrid measures based on Betweenness Centrality of a link. They proposed nine different link attributes/weights to calculate hybrid betweenness centrality of the link. They are: Free flow travel time, Congested travel time, Travel time loss, Flow as a decay function, flow weighted BC,flow weighted free flow travel time, flow weighted congested travel time, flow weighted travel time loss and flow weighted flow BC. They compared the measures with existing traffic based measures for identifying critical links such as NRI, IS and NRI*. Based on the results Flow wegihted betweeness centrality, flow weighted free flow travel time betweenness centrality and flow weighted congrest travel time betweenness centrality ranked the closesest to the traffic based measures. The primary benefit of applying this method that it incorporates traffic based measures and topolical measures into a hybrid measures while does not need to run the experiment more than once. It provides a balalnce between accuracy and computational complexity.

[21] has taken a multi criteria approach in identifying critical links in the transportation network. The authors identified three important factors that determine the criticality of the link. The first factor (ω_1)is based on link flows at equilibrium i.e.. traffic usage. The second factor (ω_2) is based on disruption the link failure causes to critical services such as hospitals, fire stations, police stations, schools and grocery stores. The last factor (ω_3) is based on the number of Origin-Destination pairs the link serves prior to disruption. They argue that all the stated factors are important but different factors can have different preference weightage β based on various planning agencies. The links would be ranked based on the weighted sum of all three factors.

The traditional full scan method of identifying links involves iteratively removing links and measuring its impact on the performance of the network. [23] argue that this process becomes time consuming when identifying links in a large scale road network. This is because, after each link removal, the performance of the network is reevaluated by running a traffic assignment problem. This process becomes very exhaustive in large scale transport networks with a high amount of links present. They propose a new method called Traffic flow betweenness index (TFBI) to identifying critical links while reducing the computational burden of the process in comparison to the traditional method. The TBFI indicator is based on betweeness. In general, Betweeness is a rough indicator of the consequences of link closure but is not always accurate. For example in cases where a link has a high value of betweeness and low traffic flow, closure of such a link is not consequential compared to the other way around. The TFBI indicator considers the betweeness, the traffic flow and the rerouted Orgin-Destination demand. In the next step, the links are ranked based on the TBFI values to determine candicate links. Now the preselected candidate links are used to calculate the NRI_a values of the links to find the real critical links.

The Link Criticality Index (LCI), introduced by [1], offers a more efficient way to identify critical links in transportation networks. Unlike traditional methods that require removing each link individually and recalculating traffic patterns, LCI determines link importance using just one user equilibrium (UE) traffic assignment, saving computational time. The Frank-Wolfe Algorithm is commonly used to calculate user equilibrium, distributing traffic across network links. LCI works by monitoring how frequently each link is used across multiple iterations of this algorithm. A link is considered critical if it consistently carries traffic despite increasing congestion and travel costs. LCI uses link marginal cost (MC), which is tracked during each iteration of the Frank-Wolfe Algorithm. While the basic LCI calculation doesn't fully account for factors like origin-destination pairs served or network redundancy, additional weights can be incorporated to improve link criticality rankings. The main advantage of this method is that it requires only one run of the UE algorithm. Although the authors demonstrated that LCI performs comparably to other measures like Network Robustness Index (NRI) and Importance Score (IS), its main limitation is the need to enumerate all possible paths through the network, which can still be time-consuming.

Author	**Measure**	**Equation**	
[11, 31]	WBC	$WBC = w \cdot \sum_{st} \frac{\sigma_{st}(a)}{\sigma_{st}}$	w link attribute/ weight; $\sum_{st} \frac{\sigma_{st}(a)}{\sigma_{st}}$ Betweeness centrality.
[21]	MCLI	$MCLI = \beta_1\omega_1 + \beta_2\omega_2 + \beta_3\omega_3$	β_x weights; ω_x factors.
[23]	TFBI	$TFBI_a = [(TFB_a)_{nor}]^r \cdot [(d_{st})_{nor}]^{1-r}$	TFB_a flow weighted betweeness centrality of link a; r weight calculated through systemic indicators; d_{st} rerouted travel demand.
[1]	LCI	$LCI_a = \sum_0^{N-1} max([x_a^{n+1} - x_a^n], 1) \cdot \frac{mc_a(x_a^n)}{t_a(x_a^n)}$	mc_a marginal cost of link a; x_a^n Flow on link a under iteration n; $t_a(x_a^n)$ Travel time on link a with x_a^n flow; N set of interations n.

Table 2.4: *Hybrid and other link criticality measures*

2.3 Link criticality studies in multimodal transport networks

Compared to research on resilience in road transport and other single networks, the field of multimodal transport resilience has received limited scholarly attention [36]. A notable contribution comes from [12], who conducted a robustness analysis of the Netherlands' integrated road, inland waterway, and rail networks. Their study aimed to support maintenance planning by prioritizing critical infrastructure elements. The authors employed centrality measures to evaluate the criticality of interdependent infrastructure and nodes. Through experiments simulating various capacity degradation scenarios, they assessed network performance impacts. Their findings revealed that while interdependent nodes slightly reduced network performance, they ultimately improved overall travel time in the network. Additionally, they determined that node criticality was strongly correlated with freight volume passing through that node. [35] also studied the Netherlands's multimodal freight transport network but the focus was on the network's ability to withstand disruptions and function before collapsing. While their analysis aimed to assess network robustness rather than identify critical elements, the research offers a robust methodological framework for modeling transport networks and disruptions within multimodal freight systems.

Another study presents a traffic micro-simulation model to analyze the impact of disruptions in intermodal transport networks. The authors identified critical links by simulating individual transport unit decisions during disruptions, using real-life data from the Austrian transport system. The model helps assess network vulnerability via delay-based indicators such as "total disruption delay time", "average disruption delay time", "number of affected units" and influence of disruption [4]. [34] introduce a multi-modal transport model that simulates behaviours such as route changes, mode shifts, departure time adjustments, and trip cancellations—in response to infrastructure disruptions. Their model focuses on failures in the TEN-T network. The network is modelled using a hybrid approach: a highly detailed Local Disruption (LD) model for the area around the failure and a coarser Global Spillover (GS) model for the rest of Europe. This structure allows for high-resolution delay estimation while maintaining computational feasibility. The model was applied to a case study of the Port of Rotterdam, revealing that road bridge failures cause significant local delays but limited continental-scale effects.

2.4 Impact of disruptions on freight transport

To performs link criticality analysis on multimodal freight networks, we must also understand how freight transport behaviour is affected during disruptions. Compared to passenger transport there are relatively few studies regarding the impact of disruption on freight transport behaviour [34]. An ex post analysis of the Rastatt incident where a freight rail track was blocked for 7 weeks, 33% of freight volume still ended up being transported through rail after severe delays. 32% of the freight was transported through other modes such as road and ship while the rest of the freight demand was left unfulfilled [14]. In [4]'s study each transport unit independently chooses the route and mode that minimizes its transport time during a disruption. Units evaluate three options in order: continue through the disrupted link if there is residual capacity, reroute on the same mode, or switch to a different mode via intermodal terminals. Approximately 17% of transport units chose alternative routes/modes, particularly those on inland waterways, with accounted for 64% mode switches. [33] developed a stochastic mixed interger model to minimize operational costs of various modes and transfer costs at terminals but also penalty costs associated with unsatisfied demands. The model favored robust, lower-cost rail-road combinations but shifts to direct road transport when terminals are disrupted or rail capacity is reduced due the network being more dense and redundant. [13] used a hybrid simulation optimisation tool to optimally re-plan in response to disruption to minimise externalities in real time. In the first step when a disruption is detected a feasibility check is done to verify if affected units require re-planning. If yes, three options are presented : 1) Wait, 2) Transship at next point or 3) Detour. Best option is chosen based on minimum extra costs.

2.5 Conclusion

2.5.1 Summary

The summary of the state of the art link criticality measures has been provided in Table 2.5. [32] and [28] both proposed similar measures based on accessibility. The first study is more focused on the areas being disconnected if a link fails while the latter is more focused on link criticality of highway roads connecting counties. [18]'s Importance Score has a similar theme of measuring criticality based on network performance before and after disruption. It Introduces two perspectives of weighing links, A equal opportunities perspective where all links are important and a social efficiency perspective where links are weighed based on traffic flow through them. The NRI indicator incorporates rerouting costs in the form of travel time if a link fails and determines link criticality [27]. The modified NRI* has developed the measure further to model and measures disruptions which do not necessarily shut down the link [30].

[11] and [31] proposed measures that incorporate different link attributes as weights to the betweenness centrality measure of the link. A significant advantage of these methods is that they require to run the transport model once to retrieve the link attribute which can be used to calculate the measures. This reduces the exhaustive and computationally intensive process of performing a full scan analysis. Previous studies involve removing each link iteratively and performing a traffic assignment to measure link criticality. This full scan process gets more computationally challenging when dealing with a network with large number of nodes and links. The LCI method also addresses this problem by computing link criticality based on the traffic being assigned to the link between iterations of the Frank Wolfe UE algorithm [1]. The TFBI method preselects potential critical links which can be used to perform the full scan analysis reducing the number of steps in the process [23].

2.5.2 Applicability to multimodal freight networks

Topological measures, while computationally efficient and straightforward to calculate, are inadequate for multimodal link criticality analysis. These measures implicitly assume synchromodality where different transportation modes operate with perfect flexibility and real-time information enables seamless mode switching. However,

Table 2.5: *Summary of link criticality studies in transport networks*

Author(s)	Measure	Description
Jenelius et al. (2006)	Importance Score (IS)	Demonstration shown using the road network of Northern Sweden. Link travel times increased to ∞ to model disruption. Proposed two measures with equal opportunity and social efficiency perspective.
Taylor and Susilawati (2006)	Accessibility Remoteness Index of Australia (ARIA)	Australian National Transport Network is used as case study. Link removed and accessibility is measured. Focus more on affected nodes/cities over critical links.
Scott et al. (2006)	Network Robustness Index (NRI)	Proposed measure as alternative to traditional V/C ratio approach. Three hypothetical networks used to demonstrate the method. Quantifies criticality as the cost of rerouting all traffic if a link is failed.
Sohn (2006)	Accessibility Index	Measures change in accessibility index of counties if a link is removed. Takes into account probability of link failure but does not model link disruption. Case study of state road network of Maryland, USA.
Sullivan et al. (2010)	Modified Network Robustness Index (NRI*)	Modified NRI is capable of measuring disruptions with less than 99% capacity degradation. Additionally introduced global network measure, Network Trip Robustness (NTR) based on NRI*.
Gauthier et al. (2018)	Travel time weighted betweenness centrality (TTWBC)	Hybrid measure to integrate traffic flow data into topological measures. Case study - DIRIF network and link ranking were highly dependent on measure used.
Takhtfiroozeh et al. (2021)	Weighted betweenness centrality measures	Introduced nine other weighted BC measures and compared them to pure traffic based measures. Flow weighted betweenness centrality measures were highly correlated with other traffic based measures.
Almotahari and Yazici (2019)	Link criticality index (LCI)	LCI measures link criticality during the process of User equilibrium. It assigns a link higher score marginally as more flow is being assigned to it despite congestion.
Kumar et al. (2019)	Multi-criteria link importance	The measure consists of three factors which can have adjusted weights based on planner preference. Considers traffic flow, access to important services and OD pairs connected. Is limited to road networks.
Li et al. (2020)	Traffic flow betweenness Index (TFBI)	The measure acts as a preselection method to identify potential critical links. Second step involves removing preselected links and measuring criticality using NRI.

this assumption contradicts the operational reality of multimodal networks, where different modes function as subsystems connected only through specific transshipment points that introduce transfer costs, time penalties, capacity and commodity specific constraints. Moreover freight transport is dependant on long term contracts which makes switching modes less flexible. The study which has used topological metrics for infrastructure criticality analysis has made this key distinction of synchromodality [12]. Consequently, multimodal networks cannot be treated as single network, making topological metrics like betweenness centrality and efficiency not suitable of accurately measuring network criticality. Furthermore, these topological measures fail to incorporate actual travel demand patterns that determines operational importance.

In contrast, traffic-based measures such as Network Robustness Index (NRI), vulnerability index ($V_r s$), Importance Score (IS), and modified NRI* offer superior capabilities by explicitly incorporating traffic flow patterns and their system-wide implications. These measures quantify link importance through operationally relevant metrics such as travel time increases, generalized travel cost variations, and unserved demand levels when specific links are removed. Additionally, these measures are typically implemented using sophisticated traffic assignment models such as user equilibrium, which capture realistic route choice behavior. While this computational complexity presents scalability challenges for larger networks, traffic-based measures can be effectively adapted through appropriate experimental designs to analyze multimodal freight networks.

Hybrid measures theoretically address the computational complexity of traffic-based approaches by combining topological and flow-based elements under equilibrium assignments. However, implementing congestion modeling in freight networks presents significant practical challenges that limit their applicability. First, freight transport models typically operate in tonnage units rather than vehicle counts. Second, freight and passenger transport modes frequently share infrastructure, creating complex interdependencies that are difficult to model accurately. Third, calculating congestion effects across large-scale networks becomes computationally prohibitive as network size and detail increase, undermining the computational advantages hybrid measures are designed to provide. These constraints make congestion-based traffic assignment impractical for multimodal freight analysis. Consequently, faster computational approaches such as all-or-nothing assignment and probabilistic k-shortest path algorithms become more suitable for multimodal network applications. Under these simplified assignment methods, however, the computational benefits that justify hybrid measures become obsolete, as the measures lose their primary advantage of balancing accuracy with computational efficiency.

2.5.3 Research Gap

Based on this, several gaps in the literature can be identified. First, to the best knowledge of the author, only a few studies have focused on measuring the criticality of infrastructure in multimodal networks as shown in Section 2.3. Second, no studies have addressed link criticality on a macro/strategic scale, such as the European TEN-T network or its corridors. Lastly, existing approaches to model and measure link criticality are not suitable for marcoscopic multimodal networks. Many approaches either lack sufficient representation of the complex operational aspects of transport networks or are computationally time consuming and have high data requirements when applied to macroscopic network analyses. Furthermore, most current method do not adequately capture traveller behaviour in response to disruptions, such as rerouting, mode changes, and trip cancellations, all of which are essential for more′ realistic assessments. There is, therefore, a clear need for new frameworks that better balance computational efficiency with operational accuracy, and that more fully integrate traveller behaviour into the analysis of link criticality at strategic network scales.

3
Methodology

The preceding chapter identified a research gaps concerning the use of link criticality methods and measures in multimodal freight networks. In this chapter, we aim to directly address these gaps by presenting a comprehensive framework to identify critical links within such networks. Subsequently, this chapter addresses the third research subquestion: How can the effects of link removal in multimodal freight networks be assessed empirically? The chapter is structured as follows: Section 3.1 introduces the approach for representing multimodal freight networks in out simulation model. Section 3.2 details the resolution at which freight demand is modeled and explains how demand data between regions is estimated. Section 3.3 describes the methodology used to determine and distribute modal split probabilities for each Origin-Destination-Commodity (ODC) pair. Section 3.4 presents how the multimodal network is saturated and how annual freight demand flows through the network. Section 3.5 introduces the novel link criticality algorithm proposed in this research, outlining the key steps involved. Finally, Section 3.6 defines the indicators used to measure link criticality in multimodal networks that are applied in this study.

3.1 Multimodal freight network

TEN-T corridors function as a backbone of freight transport across Europe, designed to facilitate efficient, seamless, and sustainable movement of commodities between member states. It integrates road, rail, inland waterways, and maritime ports connected through strategically located terminals, logistic hubs, and urban centers. The corridor ensures coordinated infrastructure development, standardized technical requirements, and interoperable services, optimizing capacity and minimizing bottlenecks along these paths. It supports high volumes of freight traffic, facilitating modal transfers at intermodal terminals to leverage the strengths of different transport modes. TEN-T corridors help reduce transport times and costs, promotes modal shift towards environmentally friendly modes like rail and waterways, and increases overall network resilience by providing alternative routes in case of disruptions. In real-world freight networks, critical infrastructure assets like bridges, tunnels, barges, locks, weirs, and crossings play an important role. However, incorporating such detailed micro-level infrastructure falls beyond the scope of this research due to added complexity. Instead, this work focuses on representing the operational aspects of freight networks using a graph-theoretical approach, where intersections, terminals, and origin-destination points serve as nodes, and links correspond to segments such as roadways, railway tracks, or waterways connecting these nodes. This modelling framework captures the key elements of network structure and operational dynamics, including traffic flows and modal interactions, while accounting for transport costs. Graph-based models are widely recognized and used in simulating transport networks and are also very common in identifying critical infrastructure within these systems.

The multimodal freight network is represented in our model using a undirected graph $G = (\mathcal{N}, \mathcal{L})$. $\mathcal{N}$ represents the set of nodes and $\mathcal{L}$ represents the set of undirected link where movement can be done in both directions. While a directed graph represents the reality better, we chose to model the network as a undirected graph to reduce complexity.

$$\mathcal{N} = \mathcal{N}^{\text{road}} \cup \mathcal{N}^{\text{IWW}} \cup \mathcal{N}^{\text{rail}} \cup \mathcal{N}^{\text{OD}} \tag{3.1}$$

$$\mathcal{L} = \mathcal{L}^{\text{road}} \cup \mathcal{L}^{\text{IWW}} \cup \mathcal{L}^{\text{rail}} \cup \mathcal{L}^{\text{OD}} \tag{3.2}$$

The multimodal network consists of different network layers for each mode. Each mode is represented by a different sub graph with its own set of nodes and links. Additionally, another sub graph for Origin and Destinations G^{OD} includes centroids of regions according to the NUTS3 classification. To model the flow of freight demand in the network, the Origin-Destination (OD) nodes must be connected with the multimodal freight network. To achieve this connector links are generated using algorithm 1. For each OD node and each mode, the procedure assembles candidate nodes from the corresponding mode sub graph and retains those within a search radius $d_{\max}$. If the road layer yields none, the radius is expanded in 10 km increments until at least one candidate is found. The candidates are then ordered by distance and the k nearest are linked to the OD node, forming $\mathcal{L}^{OD}$. In this design k controls access redundancy, while $d_{\max}$ adapts to sparse areas without over-connecting dense regions. An example representation of the network is given in Figure 3.1. The connector links $\mathcal{L}^{OD}$ represents the underlying detailed regional road networks the exists beneath the study network. In the model these links are only used to serve the OD nodes and are not used by through traffic.

Algorithm 1: Generating connector links

Input: Full transport graph $G = (\mathcal{N}, \mathcal{L})$; origin node set $\mathcal{N}^{OD}$; nearest neighbour count k; mode set M; max distance $d_{\max}$.

Output: OD subgraph $G^{OD} = (\mathcal{N}^{OD}, \mathcal{L}^{OD})$.

foreach *OD node* $n \in \mathcal{N}^{OD}$ **do**
    foreach *mode* $m \in M$ **do**
        Initialize candidate node set $C_m \leftarrow \emptyset$
        foreach *link* $(u, v) \in \mathcal{L}^m$ **do**
            Add u and v to C_m
        Initialize list of valid distances $D_m \leftarrow \emptyset$
        foreach *node* $c \in C_m$ **do**
            Compute $d(n, c)$ **if** $d(n, c) \leq d_{\max}$ **then**
                Add $(d(n, c), c)$ to D_m
        `// Road progressive search: expand` $d_{\max}$ `until at least one candidate exists`
        if $m = ROADS \wedge |D_m| = 0$ **then**
            while $|D_m| \leq 0$ **do**
                $d_{\max} \leftarrow d_{\max} + 10\,\text{km}$
                foreach *node* $c \in C_m$ **do**
                    Compute $d(n, c)$
                    if $d(n, c) \leq d_{\max}$ **then**
                        Add $(d(n, c), c)$ to D_m
        Sort D_m by distance and select the k nearest **foreach** (d, c) *in top* k *of* D_m **do**
            Create OD link (n, c); add link to $\mathcal{L}^{OD}$
return $G^{OD} = (\mathcal{N}^{OD}, \mathcal{L}^{OD})$

$$GTC_i = K_m \cdot d_i + T_m \cdot (\frac{d_i}{v_m}) \tag{3.3}$$

Lastly, to prepare the network for by assigning weights on links. Link distance and link travel times can be used in transport model but in order to simulate the network more realistically a form of generalised transport costs (GTC) are calculated for each link. Equation 3.3 is used to calculate the GTC of all links which has been used in previous research [12, 19, 35]. In this equation, K_m and T_m denote the cost per unit distance and time for mode m respectively, while d_i represents the length of link i and v_m indicates the average travel speed. The parameter values used in this study are presented in Table 3.1. It represents the average cost of transporting a tonne of freight over a particular link. Since, OD links were generated as a straight line between the centroids and the links, the distance is multiplied by 1.5 to have a conservative estimate

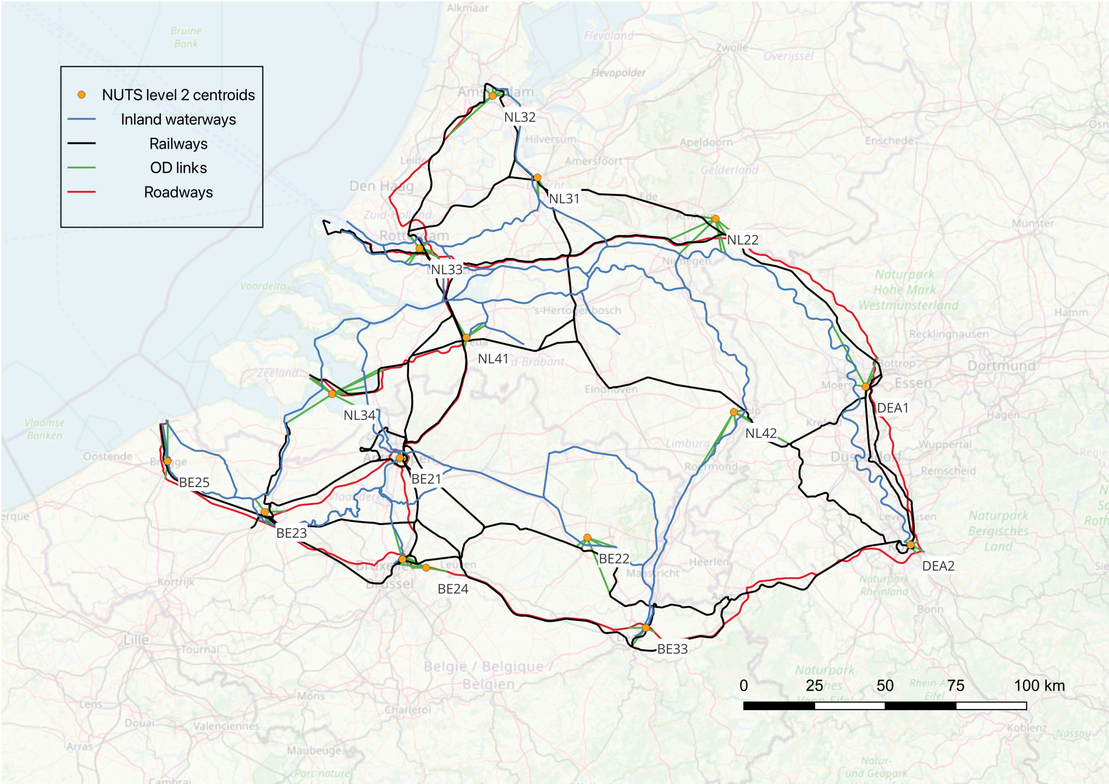

Figure 3.1: *Example representation of the multimodal network*

of the real world distance of the underlying regional roads [35].

Parameter	Symbol	Value	Unit
Unit cost per unit of time for			
waterway	T_{IWW}	0.13	€/tonne/h
road	T_{Road}	3.98	€/tonne/h
railway	T_{Rail}	1.00	€/tonne/h
Unit cost per unit of distance for			
waterway	K_{IWW}	0.004	€/tonne/km
road	K_{Road}	0.038	€/tonne/km
railway	K_{Rail}	0.004	€/tonne/km
Average speed for			
waterway	v_{IWW}	10	km/h
road	v_{Road}	70	km/h
railway	v_{Rail}	25	km/h
OD	v_{OD}	30	km/h

Table 3.1: *Transport parameters and cost values* [19, 35]

3.2 Freight transport demand

The freight demand data used in our model is derived from the broader NEAC model provided by Panteia. Specifically, it originates from the model's mode chain builder, which estimates transshipment points and transport modes per commodity for each

NUTS3 OD pair. A key input to the mode chain builder is a trade model that estimates commodity flows between NUTS3 regions. Equation 3.4 illustrates the functional form of this model, which is used to forecast freight demand [25]. The α parameters are calibrated by log-linearizing the equation and applying the ordinary least squares (OLS) method. The base year for demand data is 2019, with forecasts for subsequent years adjusted using economic growth factors. Since the network is modeled at the NUTS3 and NST/R 1 level, the commodity demand data was aggregated accordingly by converting the NST/R 2 level to NST/R 1 level. After filtering, the freight demand is represented in terms of Origin Zone (NUTS3), Destination Zone (NUTS3), Commodity (NST/R 1), and Tonnes. For more detailed explanation about the freight demand model please refer to the NEAC model's documentation [25].

$$T_{ijg} = \alpha_1 \cdot P_{ig}^{\alpha_2} \cdot A_{jg}^{\alpha_3} \cdot D_{ij}^{\alpha_4} \cdot e^{\alpha_5 \cdot \text{DUMMY}} \tag{3.4}$$

Where:

T_{ijg}	The trade of a commodity between region i and j in tonnes
P_{ig}	The added value (GVA) of the sector that supplies the commodity in region i
A_{jg}	The added value (GVA) of the sector that consumes the commodity in region j
D_{ij}	The economic distance (cost of transport) between region i and j
DUMMY	Dummy variable capturing economic co-operation or grouping
α	Model parameters

3.3 Modal split

The specific demand between Origin and Destinations per commodity must be further distributed between the available modes. The distribution is based on the total GTC incurred of using a mode m between Origin i and Destination j. A Multinomial logit model is used commonly to calculate the relative probability of choosing a mode over others. The cost function i.e utility V_{ijm}^{g} of the model is specified in Equation 3.5. ASC_m^g is the alternative specific constant which represents the baseline preference/ bias of commodity g towards a mode m. β_{gtc}^{g} is the sensitivity parameter or the marginal utility of GTC for commodity g. GTC_{ijm} is the total GTC of using mode m between i and j. The probability p_{ijm}^{g} is calculated using Equation 3.6 and demand is distributed accordingly. The parameters have been tuned based on the NEAC mode chain builder output. Refer to Annex M for the commodity specific parameters.

$$V_{ijm}^{g} = ASC_m^g + \beta_{gtc}^{g} \cdot GTC_{ijm} \tag{3.5}$$

$$p_{ijm}^{g} = \frac{e^{-V_{ijm}^{g}}}{\sum_{m \in M} e^{-V_{ijm}^{g}}} \tag{3.6}$$

Where:

- V_{ijm}^{g}: Systematic utility of mode m between origin i and destination j for commodity g
- ASC_{m}^{g}: Alternative-specific constant for mode m for commodity g
- β_{gtc}^{g}: Coefficient for the generalized travel cost (GTC) for commodity g
- GTC_{ijm}: travel costs between origin i and destination j using mode m
- p_{ijm}^{g}: Probability of choosing mode m for the OD pair (i, j) for commodity g
- M: Set of available transport modes

3.4 Route choice and assignment

Freight demand assignment on the network enables the simulation of freight transportation flows and provides insights into how link disruptions affect traffic patterns. This study implements All-or-Nothing assignment for route choice. In the All or Nothing assignment all demand for each mode specific origin destination pair is assigned to the shortest path between them. The algorithm assumes that there is no congestion in the network and the traveller has prior knowledge of the exact costs incurred by choosing the route. This means that the travel costs of choosing the shortest path is fixed and does not vary based on the flow travelling through the links. The use of all-or-nothing assignment can be justified by noting that, unlike passenger demand, freight demand is typically planned and scheduled in advance. As a result, freight movements are less affected by perceived travel time errors or random route choice variability. Moreover, freight is managed by profit-driven companies that generally prioritize cost minimization in their routing decisions. The generalised travel costs calculated are used as link weights for the shortest path calculation. Although other traffic assignment methods such as User Equilibrium assignment offer more realistic modeling capabilities, they are not appropriate for this research due to several limiting factors.

The model operates at a macroscopic level, where demand data represents annual freight flows across an extensive network. Implementing User Equilibrium assignment would require calculating congestion parameters, which demands additional data inputs and significant computational resources. Given that the full scan methodology involves executing traffic assignment algorithms multiple times to evaluate network responses to disruptions, employing computationally intensive methods would be impractical for a network of this magnitude. Therefore, the selected assignment algorithms provide a more feasible approach for analyzing freight flow patterns and disruption impacts within the constraints of this study. We implemented a custom Dijkstra's algorithm to compute the shortest paths from a single node to all other nodes in a mode-specific graph. This custom function ensures that OD connector links are excluded from the shortest path calculation, except when the connector is connected to the origin or destination node.

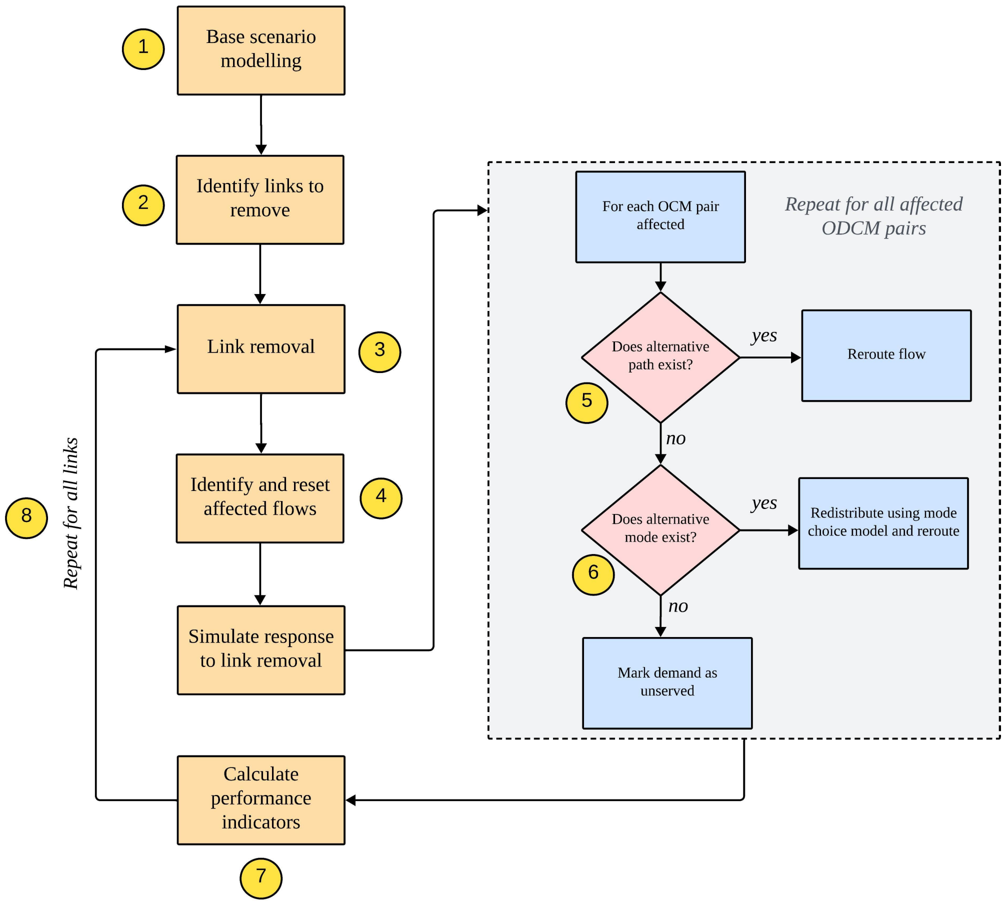

Figure 3.2: *Conceptual framework of the multimodal link criticality analysis*

3.5 Link criticality analysis

In this section we describe the methodology for the link criticality analysis process which will help us measure the criticality of links in the multi-modal network.

The link's criticality is determined by the extent of impact its removal causes within the network. Highly critical links generate significant negative impacts on overall transportation performance. This evaluation process also highlights the quality and availability of alternative routes when a given link is removed. The traditional full scan method is a common technique used to analyse link criticality in transport networks. In the method, first a base overall system performance of the network is measured (eg. total network travel time). In the next step, a link is removed from the network and the transport model is run again and the overall system performance is measures. The criticality of the link is then the difference in the overall system performance of the network. The higher the difference the more critical the link is.

The algorithm is exhaustive and the number of iterations increases as the number of links the network increases. Moreover, the larger the network the more computationally challenging it becomes to run a single iteration of the the transport model. To combat this a a new algorithm 2 is proposed to measure the link criticality. The process is as follows:

Step 1: **Base scenario modelling**. Similar to the traditional full scan method we first run a base iteration of the transport model to capture the performance of the network under normal conditions.

Step 2: **Identify links to remove**. In this process only links who's flows f_l in the base iteration are greater than 0 are removed. Connecter links which have been artifically generated are also not removed. This reduces the number of iterations that are run in the algorithm.

$$\mathcal{L}_{\text{removed}} = \left\{ l \in \mathcal{L} \;\middle|\; f_l > 0 \text{ and } l \notin \mathcal{L}^{OD} \right\} \tag{3.7}$$

Step 3: **Link removal**. For each iteration of the process, a single link l is removed from the orignal network G creating a new modified network G'.

Step 4: **Identify and reset affected flows**. When a link l is removed from the transport network, the flows assigned to that link must be recalculated. In the base transport model, for each Origin–Destination–Commodity–Mode (ODCM) flow, demand q_i is assigned along a path, and the indices of these flows are stored on every link l in that path. We denote by $\mathcal{F}_l$ the set of flow indices associated with link l. Upon removal of link l, the set $\mathcal{F}_l$ becomes the set of affected flows, denoted $\mathcal{F}_{\text{affected}}$. The model then recalculates the flows on all links that are part of the paths corresponding to flows in $\mathcal{F}_{\text{affected}}$, updating the network to reflect the disruption. This process significantly reduces the number of ODCM pairs which have to be re-simulated capture the effect of a disruption.

$$\tilde{f}_l = \max\left(0,\; f_l - \sum_{i \in \mathcal{F}_l \cap \mathcal{F}_{\text{affected}}} q_i\right), \quad \forall l \in \mathcal{L} \tag{3.8}$$

Step 5: **Re-routing.** In this step, all ODCM pairs in the set $\mathcal{F}_{\text{affected}}$ are considered for re-routing. For each affected pair, an alternative shortest path is calculated using the updated network G'. The underlying assumption is that freight operators typically do not alter their chosen routes unless the travel impedance has increased significantly or the destination becomes unreachable via the originally selected mode. Furthermore, due to the long-term nature of freight transport contracts, there is often limited flexibility to switch between transport modes in response to disruptions [34]. For those ODCM pairs for which feasible alternative paths are identified, the associated demand is reassigned to the network.

Step 6: **Mode switch** For ODCM pairs where the destination cannot be reached using the originally assigned mode, a mode choice model is applied across the set of available alternative modes. The demand is then redistributed according to the resulting mode choice probabilities. In practice, not all freight demand can necessarily be shifted to other modes. For example, during the Rastatt incident, approximately 33% of the disrupted freight was successfully transshipped using alternative modes, while another 33% remained unserved and demand was instead met through alternative regions. In this study, however, we assume that suitable alternative modes are always available in order to evaluate the resulting changes in network performance. Lastly, the shortest path for alternative mode are found and demand is assigned accordingly.

Step 7: **Calculate Performance Indicators.** If no feasible alternative mode is found for an ODCM pair, the corresponding demand is marked as unserved. After all affected pairs have been processed—either reassigned or identified as unserved—the network performance indicators are recalculated to reflect the impact of the disruption. Finally, the removed link is reinstated into the network to restore its original state. At this stage we measure operational performance difference between the base scenario and the scenario with the link absent and other relavent metrics.

Step 8: **Repeat step 3-7 until all links have been analysed.**

The primary distinction between the traditional full scan method and our approach lies in the handling of flow reassignment following the removal of a network link. In contrast to the conventional method, which reassigns all flows regardless of their exposure to the removed link, our method updates only those flows directly affected by the link's removal. This targeted reassignment is logical and efficient, as it avoids unnecessary computation for unaffected flows. However, in scenarios where route choice decisions are influenced by network congestion, removing a link could impact travel times on alternative routes, potentially resulting in cascading adjustments across the network. Despite this, our approach enables a much faster evaluation of link criticality. For links that affect a minimal number of flows, the computational effort is significantly reduced compared to the traditional method, which requires a complete reassignment of all flows after each link removal. Table 3.2 shows the big O notation of different assignment and link criticality algorithms. The notation for the link criticality analysis in given in two parts. The first part of the equation is to model the base scenario which is similar to the computation required for the AON (Multimodal) method. The second part of the equation represents the selective reassignment that we propose, which is overall faster than the traditional full scan method as the number and size of dimensions are reduced.

Method	Time complexity
AON (Unimodal)	$\mathcal{O}(\mathcal{K}\,(\mathcal{N}+\mathcal{L})\log\mathcal{N})$
AON (Multimodal)	$\mathcal{O}(\mathcal{K}\cdot\mathcal{M}\,(\mathcal{N}+\mathcal{L})\log\mathcal{N})$
Congested assignment Frank-Wolfe algorithm (Unimodal)	$\approx \mathcal{O}(\mathcal{K}\cdot\mathcal{T}\,(\mathcal{N}+\mathcal{L})\log\mathcal{N})$
Traditional full scan method (Unimodal)	$\approx \mathcal{O}((\mathcal{L}+1)\cdot\mathcal{K}\cdot\mathcal{T}\,(\mathcal{N}+\mathcal{L})\log\mathcal{N})$
This study - Link criticality algorithm (Multimodal)	$\mathcal{O}(\mathcal{K}\cdot\mathcal{M}\,(\mathcal{N}+\mathcal{L})\log\mathcal{N}) + \mathcal{O}\Big(\sum_{\mathcal{L}_{\text{removed}}}\mathcal{F}_{\text{affected}}\cdot\mathcal{M}\,(\mathcal{N}+\mathcal{L})\log\mathcal{N}\Big)$

Table 3.2: *Time–complexity of different assignment and link criticality algorithms*

Algorithm 2: Link criticality analysis

Input: Network graph $G = (\mathcal{N}, \mathcal{L})$; demand table D;

Output: Results $\mathcal{R}$ with criticality metrics per link

```
foreach l ∈ 𝓛 ∀ f_l ≥ 0 and l ∉ 𝓛^OD do
    Create a graph copy G′ ← G
    Identify affected ODCM pairs affected 𝓕_affected by link l
    Remove link l from G′
    foreach affected ODCM pair i ∈F_affected do
        Attempt to compute an alternative shortest path
        if Alternative path does not exist then
            Attempt to reroute using alternative modes M
            if Alternative path does not exist in any mode then
                Mark demand as unserved
            else
                Assign flow based on new mode choice probabilities and new
                 shortest paths
        else
            Assign flow based on new shortest paths
    Record metrics for removing link l
Return 𝓡
```

3.6 Peformance Indicators

Various approaches have been proposed to assess link criticality, as summarized in Chapter 2. In this study, we focus on traffic-based measures to evaluate link criticality, as topological measures previously discussed are less relevant for our context. Assessing the reduction in network performance following a link removal serves as a good indicator of that link's significance within the network. Among available system-wide performance metrics, total system generalized travel costs is particularly useful, as it accounts for both distance and travel time increases, providing an integrated measure of overall link criticality. However, it is important to note that different transport modes prioritize performance changes differently. For instance, in road transport, increases in travel time are typically more critical than cost increases, whereas in lower cost modes such as rail and inland waterways, increases in travel cost are generally more significant than additional travel time. Therefore, in addition to total system GTC change, this study also examines total system travel time, distance, and emissions change to capture a comprehensive picture of network performance across different modes.

$$\Delta\text{Total system travel time} = \frac{TT^{G'} - TT^{G}}{TT^{G}} \tag{3.9}$$

$$\Delta\text{Total system generalized travel cost} = \frac{GTC^{G'} - GTC^{G}}{GTC^{G}} \tag{3.10}$$

$$\Delta\text{Total system travel distance} = \frac{TD^{G'} - TD^{G}}{TD^{G}} \tag{3.11}$$

$$\Delta\text{Total system emmisions} = \frac{E^{G'} - E^{G}}{E^{G}} \tag{3.12}$$

When a link is removed that serves as the only connection between an OD node and the rest of the network, it is possible for all the demand associated with that node to go unserved. In these cases, metrics for total system performance might actually appear to improve. For example, the calculated overall travel time could decrease simply because the system no longer attempts to serve the affected demand, and those unserved demand are excluded from the results. To give a more accurate picture, we include total unserved demand as an additional metric to help identify those links that are essential for maintaining connectivity in the network. We also consider the total volume of goods affected by a link removal. This information can help estimate the monetary value of the affected commodities, which provides another perspective on the criticality of links.

$$Q_{\text{unserved}} = \sum_{i \in \mathcal{F}_{\text{unserved}}} q_i \tag{3.13}$$

$$\text{Total volume of goods affected} = f_l^G \tag{3.14}$$

In addition to system-wide measures, it is important to evaluate link criticality from an equity perspective by examining performance changes specifically for the flows affected by a link removal. We use four additional metrics: average relative travel time change, travel distance change, gtc, emission change. These metrics quantify the proportional change in travel time, distance, cost, and emissions, averaged to the flows experiencing the disruption. Such metrics ensure that criticality assessments account for localized effects and the fairness of consequences faced by affected flows, rather than purely total system performance.

$$\text{Average relative travel time change} = \frac{1}{|\mathcal{F}_{\text{affected}}|} \sum_{i \in \mathcal{F}_{\text{affected}}} \left(tt_i^{G'} - tt_i^{G} \right) \tag{3.15}$$

$$\text{Average relative travel distance change} = \frac{1}{|\mathcal{F}_{\text{affected}}|} \sum_{i \in \mathcal{F}_{\text{affected}}} \left(td_i^{G'} - td_i^{G} \right) \tag{3.16}$$

$$\text{Average relative generalized travel cost change} = \frac{1}{|\mathcal{F}_{\text{affected}}|} \sum_{i \in \mathcal{F}_{\text{affected}}} \left(gtc_i^{G'} - gtc_i^{G} \right) \tag{3.17}$$

$$\text{Average relative emissions change} = \frac{1}{|\mathcal{F}_{\text{affected}}|} \sum_{i \in \mathcal{F}_{\text{affected}}} \left(e_i^{G'} - e_i^{G} \right) \tag{3.18}$$

3.7 Conclusion

In this chapter, we presented a multimodal freight network model designed to simulate traffic volumes, expressed in tonnes, across the network's links. The freight demand used in this study is based on data from Panteia's NEAC model. To accurately reflect the heterogeneity in mode preferences among different commodity groups, we implemented a commodity-based mode choice model. We use the All-or-Nothing assignment using Dijkstra's algorithm to route freight demand along cheapest path, assuming no congestion effects. This approach is chosen for its computational efficiency and suitability for large-scale networks. A key contribution of this chapter is the introduction of a new link criticality algorithm, which enables iterative and efficient removal of individual links to assess their impacts on network traffic. Link criticality is then quantified using a range of operational, traffic-based measures, allowing for evaluation from both system-wide and local perspectives. The code for the framework is available at `https://github.com/sathvikgadiraju/Link-criticality-framework`.

4

Case study - North Sea Rhine Mediterranean (NSRM) TEN-T corridor

Following the methodology described in the previous section, we demonstrate the implementation of the link criticality analysis algorithm for multimodal networks on the North Sea–Rhine–Mediterranean TEN-T corridor. Section 4.1 introduces the NSRM network corridor, detailing its structure, coverage, and the components included in this study. Section 4.2 presents the freight demand data between zones, highlighting sections with the high trade volumes both between and within countries. Section 4.3 shows the results of the modal split model and the distribution of commodity freight flows across modes. Section 4.2 visualizes the results of the traffic assignment and Section 4.5 validates them against observed flows. Section 4.6 and Section 4.7 present the results of the link criticality analysis, identifying and mapping the network's most critical links.

4.1 The North Sea - Rhine - Mediterranean Corridor

The North Sea Rhine Mediterranean transport corridor is a major European transport corridor established as part of the TEN-T (Trans-European Transport network) policy. The NSRM corridor plays a crucial role in connecting Europe's largest economic zones, ports and multimodal hub. It is the result a merger between two former TEN-T corridors, the Rhine-Alpine Corridor and the North Sea - Mediterranean corridor under the regulation (EU) 2024/1679. The corridor spans across eight countries namely: Ireland, the Netherlands, Belgium, Luxembourg, France, Germany, Italy and Switzerland. The core network spans over 12150 km of railway lines, 5000km of roadways and 5030km of inland waterways. The network analyzed includes links from both the NSRM core network and the TEN-T comprehensive network, which differ in their implementation timelines and requirements. The core network, representing the most strategically important connections, must meet specific EU standard requirements by 2030, while the comprehensive network, which provides broader connectivity beyond the core infrastructure, has a deadline of 2050 to meet these standards.

The multimodal network here consists of 774 roads links, 1186 railway links and 481 inland waterway links. 253 NUTS3 level zones are modeled and an additional 1641 OD connector links were generated to connect them to the network using the algorithm described in the previous section. Figure 4.1 shows the visual representation of the network imported into the model along with prominent cities along the network. Within our modeling approach, freight demand is exclusively simulated between NUTS 3 regions, which serve dual functions as both origin-destination points for freight flows.

4.2 Freight transport demand

The freight demand data is derived from the NEAC model using trade data from 2010, which has been updated using growth factors. While the simulation operates at the NUTS3 level, this visualization aggregates the demand between NUTS3 regions to NUTS2 level to provide a clearer understanding of inter-zonal demand patterns in Figure 4.2. The diagonal boxes outlined in black represent intra-country demand i.e. freight movement within the same country which consistently show high demand (bright yellow/green colours), showing that most freight movement is occurring domestically. Countries with major ports, especially the Netherlands and Belgium, show high freight demand as both origins and destinations, reflecting their substantial import and export activities. The regions around Rotterdam and Antwerp, two key European ports, also experience the highest freight demand. The demand matrix implemented within the model has dimensions of 253 × 252 × 10, representing origins, destinations, and commodity types respectively, totalling 637,560 individual entries.

4.3 Modal split

The mode split model was applied as described in the previous chapter, with parameters detailed in the annex. The commodity-wise breakdown of mode choice is presented in Figure 4.3. The results indicate that road transport is the predominant mode in the network (79.8%), followed by rail and inland waterways. This preference stems from the high utility that roadways provide for short-distance transport. As distances increase, generalized transport costs rise accordingly, leading the utility function to favor alternative modes such as rail and inland waterways. Additionally, the availability and accessibility of modal networks significantly influence mode choice decisions.

Figure 4.4 presents the commodity-wise mode split, which follows a similar overall pattern. However, there are notable discrepancies where large quantities of oil and ores appear to be transported by roadways, which does not reflect real-world practices.

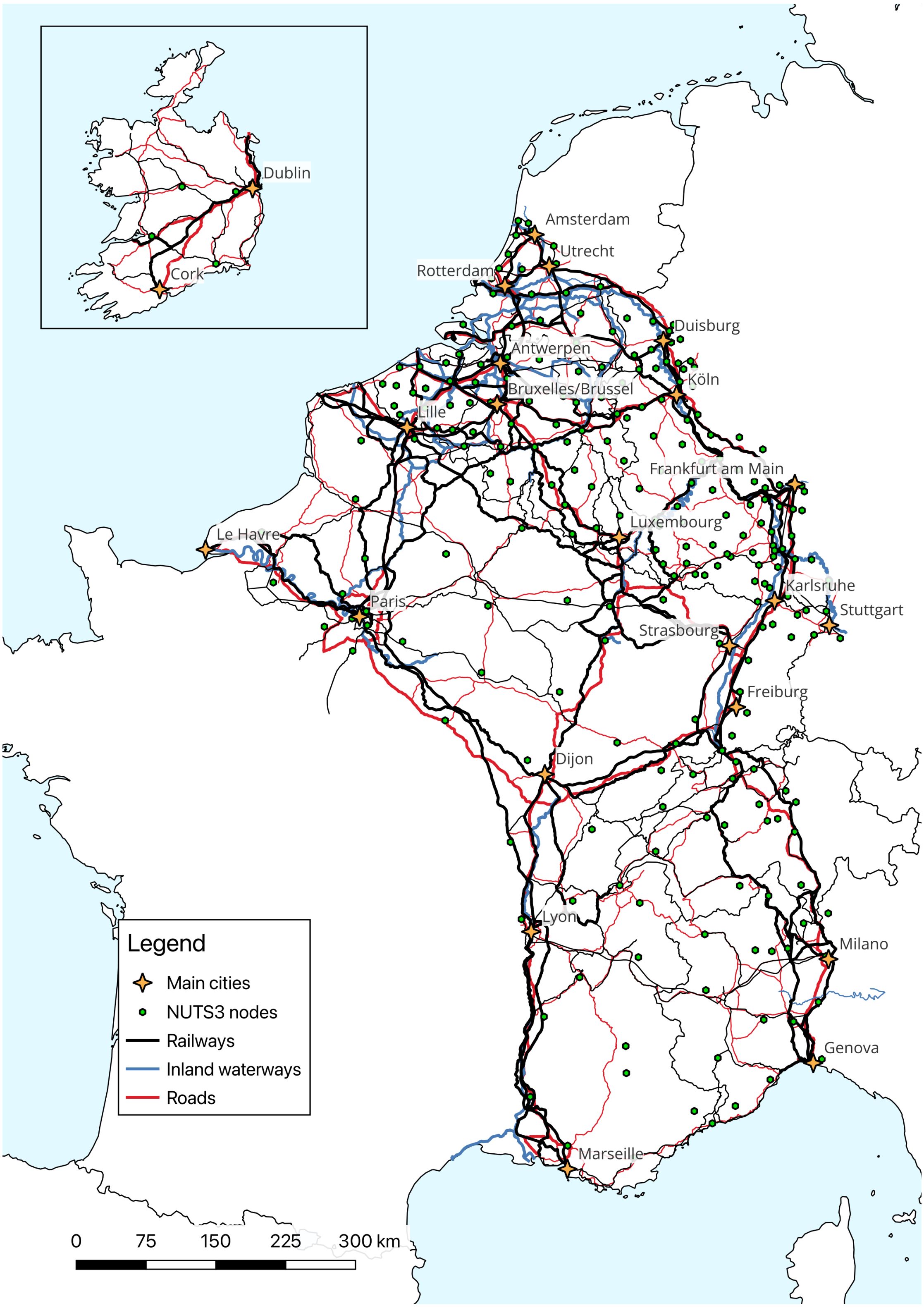

Figure 4.1: *North Sea Rhine Mediterranean corridor network*

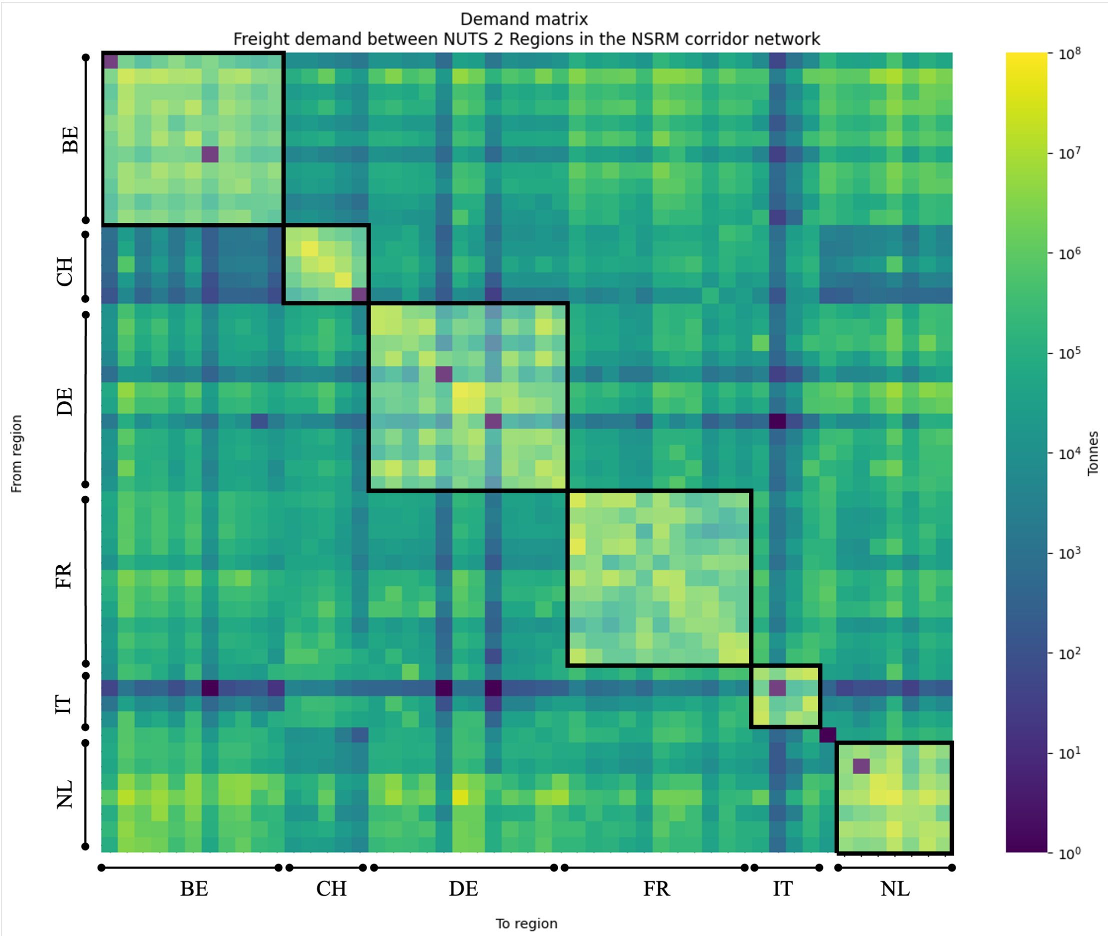

Figure 4.2: *Freight demand between NUTS 2 Regions in the NSRM corridor network*

In reality, oil is typically transported between regions through dedicated pipeline networks, which are not considered in this study. Ores, conversely, are predominantly transported in bulk via railways rather than road transport. A specific study of the Rhine Alpine corridor by [6] found that inland waterways dominate the modal split at 50.8%, followed by road transport at 28.8%, and rail at 20.4%. In contrast, according to [8], the overall freight transport modal share in the EU—excluding maritime and air transport—is led by road transport at 75.7%, with rail at 16.7% and inland waterways at 4.9%. The model results align more closely with these broader EU figures. Since the model parameters are trained on data aggregated across the entire EU, they do not capture the notably high preference for inland waterways seen in the Rhine Alpine network; however, compared to EU-wide data, the model shows an increased modal share for both road and inland waterways.

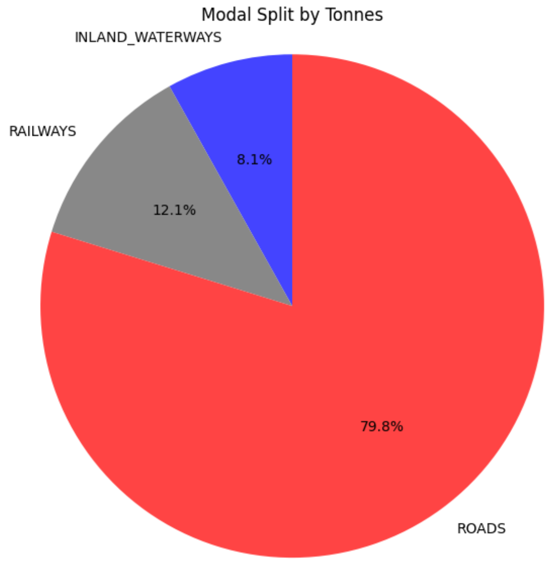

Figure 4.3: *Aggregated modal split in the NSRM corridor*

4.4 Traffic assignment results

The traffic assignment is done using the All or nothing assignment. Figure 4.5 shows a picture of the AON assignment taken from the python model. The width of the link represents the amount of flow passing through it annually in term of kilotonnes. To provide a more in depth visualization of the traffic assignment in the base scenario and also compare the flows estimated by the model to data available regarding observed flows were present Figure 4.6, Figure 4.7 and Figure 4.8. Observed values were collected from publicly available datasets, accessed via Eurostat [9], and subsequently processed and compiled by Panteia B.V.. The observed values reflect the actual traffic on the link, including traffic traveling within the NUTS3 region, through traffic, as well as traffic originating from or destined outside the study area.

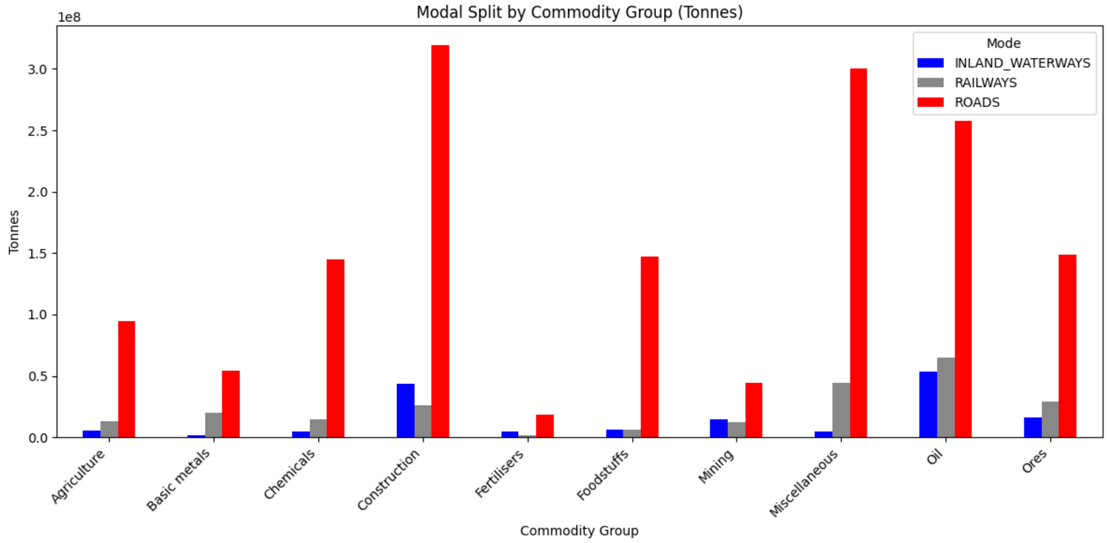

Figure 4.4: *Commodity wise breakdown of mode choice probability in the NSRM corridor network*

The traffic assignment process was executed through a two-stage process. Initially, the shortest paths from each origin node to all other nodes were pre-computed for all transportation modes using Python's NetworkX library. Subsequently, freight from the demand data was iteratively assigned to the network until completely allocated. The computational performance for the base scenario traffic assignment was evaluated on an Apple MacBook Pro equipped with 10 CPU cores, requiring approximately 2 minutes and 13 seconds to complete.

4.5 Validation

The road traffic assignment results have been validated against observed flow data, as presented in Figure 4.6. The observed flow data, provided in heavy-duty vehicles per day, required conversion from the model's annual tonnage output by dividing by 3,650 (assuming 10 tonnes per heavy-duty truck and 365 operating days). The validation scope is constrained by the spatial coverage of the observed dataset, which encompasses only the core NSRM network rather than the complete study region. Both datasets demonstrate similar patterns, including heavy traffic concentrations around the ports of Antwerp and Rotterdam, and higher traffic density in the northern portions of the network compared to the southern areas.

The model captures north-south traffic flows in both directions but exhibits limitations in representing east-west movements. This discrepancy is particularly evident in the central and southern portions of the network. Additionally, the observed data shows significantly more traffic activity in the vicinity of Paris than the model predicts. These differences can be attributed to several modeling limitations. First, the model does not account for through-traffic that neither originates nor terminates within the study region. Second, demand flows originating or terminating outside the

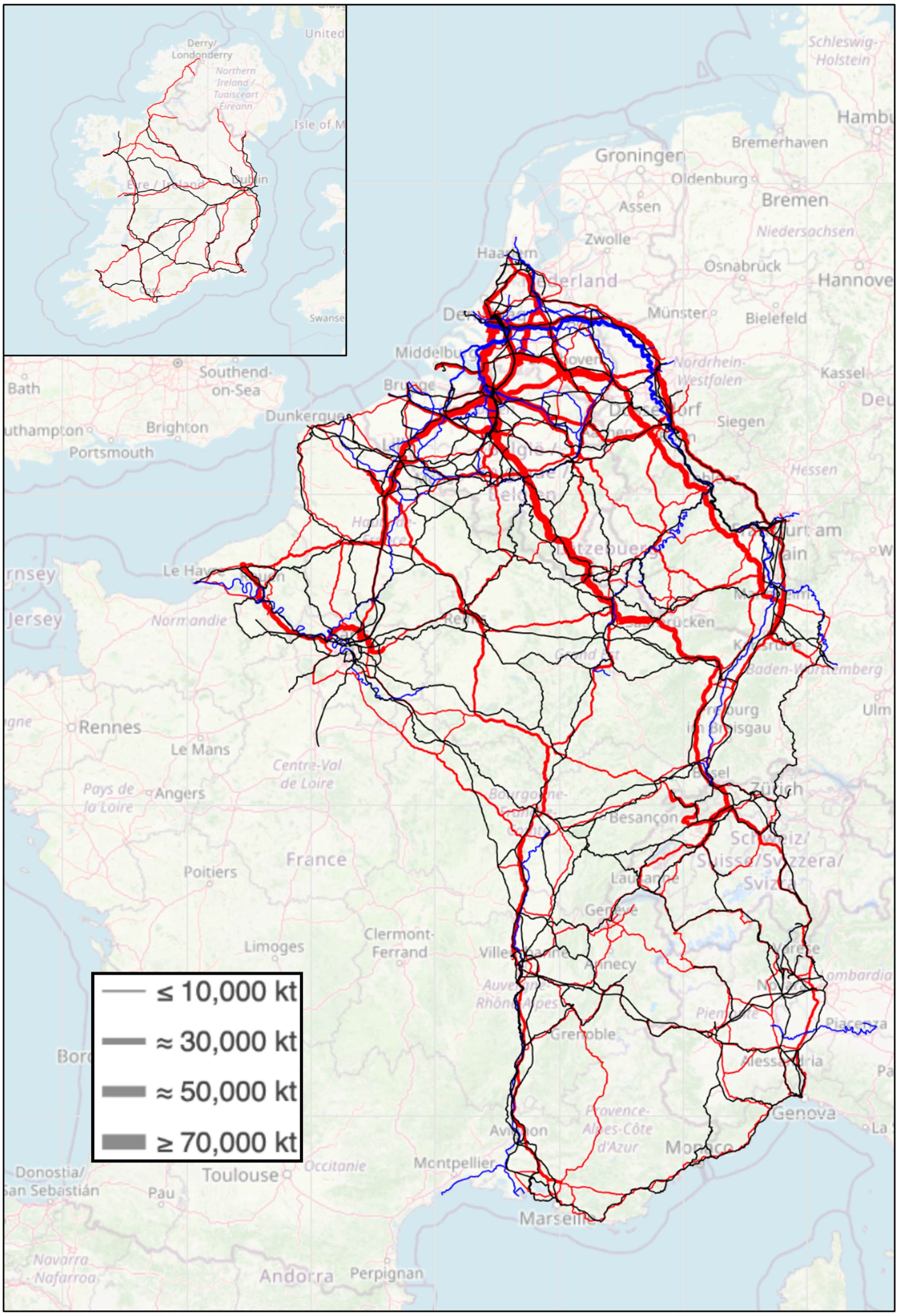

Figure 4.5: *AON assignment of NSRM corridor - Picture from python model*

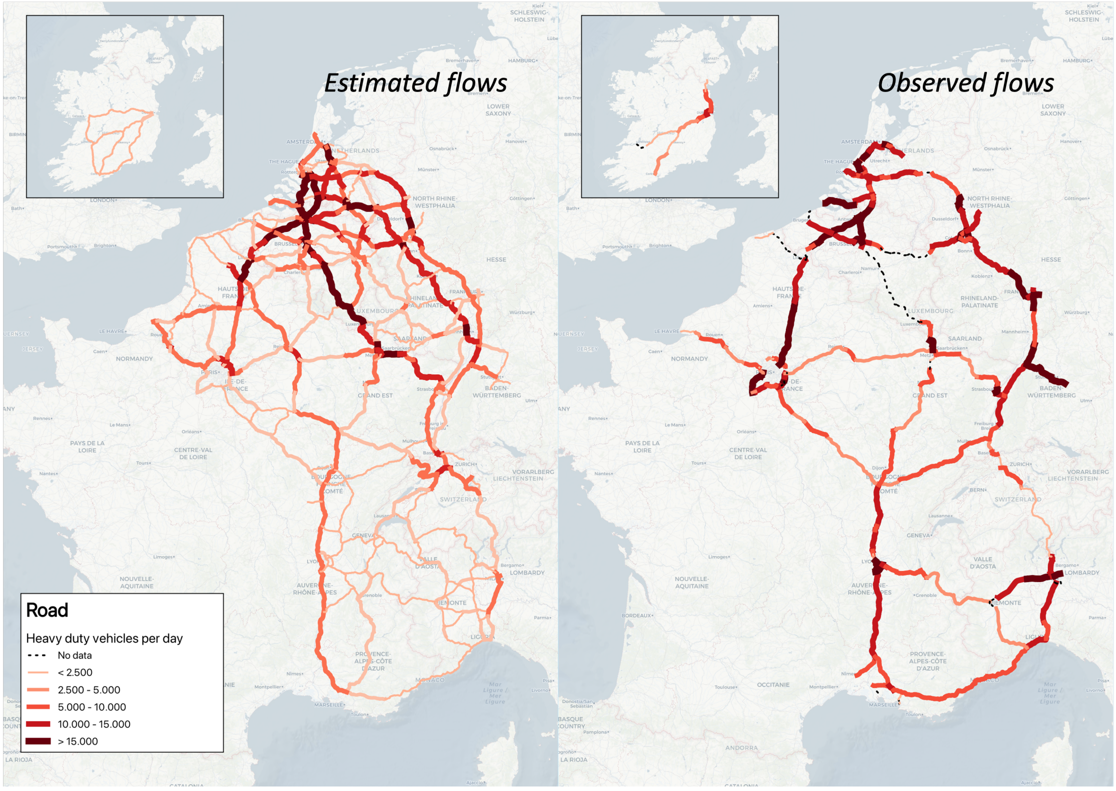

Figure 4.6: *Comparision of road traffic assignment - Estimated vs Observed flows*

study boundaries are not represented. Furthermore, the traffic assignment methodology assigns demand along single optimal paths, even when alternative routes have marginally different costs, potentially underestimating traffic distribution across parallel corridors.

Similarly, the rail assignment results are compared to observed values in Figure 4.7. The annual freight demand was converted to daily train movements by dividing by 164,250 (assuming 450 tonnes per train and 365 operating days). The observed data reveals substantial train movements along the Old Rhine-Alpine TEN-T corridor, particularly the route from Duisburg to Basel, which represents a critical European rail artery. However, the assignment model fails to adequately capture these high-volume flows, indicating a underestimation of rail preference along this corridor. This discrepancy suggests that the mode choice and assignment model does not fully account for the established rail infrastructure advantages or operational efficiencies that make this particular corridor highly attractive for rail freight transport.

Lastly, the inland waterway assignment is compared to observed values in Figure 4.8. The comparison reveals strong similarities in relative traffic density patterns, with both data showing high concentration along the main Rhine artery between Rotterdam and Strasbourg, and progressively decreasing traffic volumes on smaller tributary waterways. However, there is a significant discrepancy in absolute demand levels, with observed values substantially higher than model predictions. This difference can be attributed to two primary factors: first, the model may underestimate the modal share for inland waterways, failing to fully capture the cost advantages and operational preferences that make waterway transport attractive for bulk commodities. Second, the model does not account for intra-regional freight flows that utilize the waterway network for shorter-distance movements within the study regions, which could also contribute to the total observed traffic volumes on these routes.

4.6 Link criticality analysis

In this section we report the link-criticality results. As outlined in the methodology, we remove one link at a time and quantify the resulting changes in network performance to assess that link's importance. The algorithm ran on a MacBook Pro using 10 CPU cores and finished in 3 h 17 min; because the procedure is parallelized, allocating more cores would further reduce runtime.

Figure 4.9 plots impact versus tonnes affected. Impact is measured as the average relative change in delay, generalized transport cost (GTC), emissions, and distance for the flows that used the removed link. The orange iso-contribution lines show the product of tonnes affected and impact i.e., the share of the total system cost increase. Because roads carry most freight, removing a road link typically affects more tonnes. Most road removals raise average GTC by 1–10 EUR/tonne, with a few outliers. Inland-

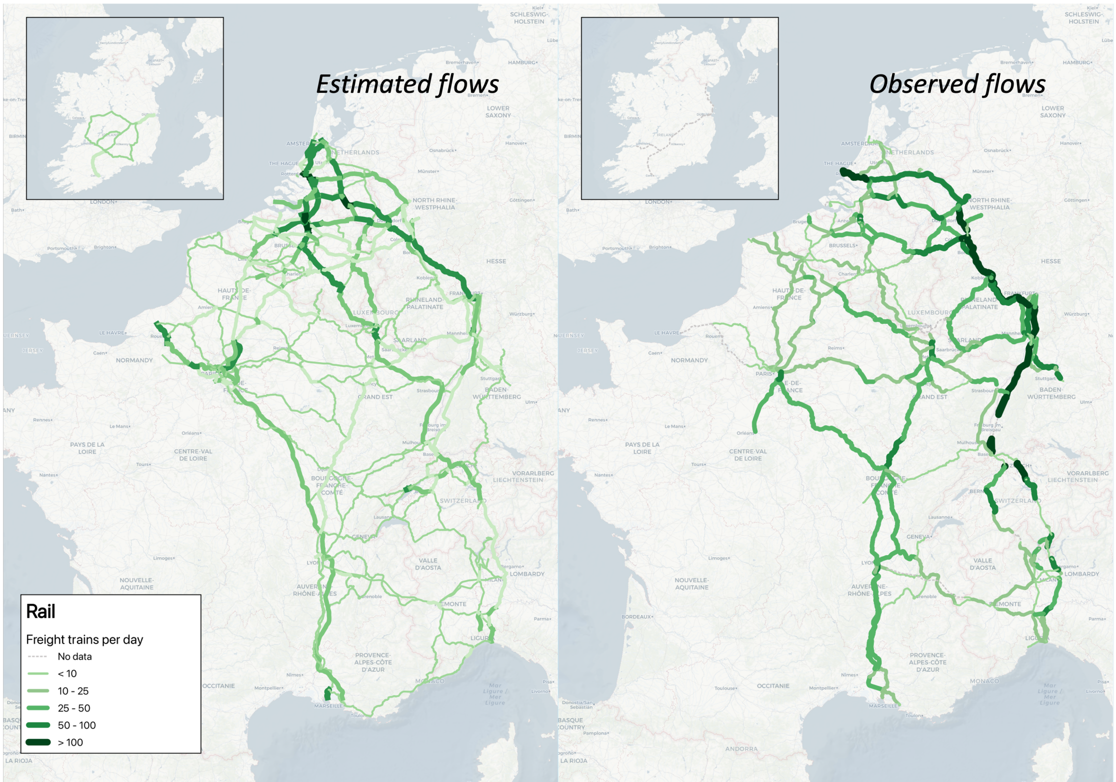

Figure 4.7: *Comparision of rail traffic assignment - Estimated vs Observed flows*

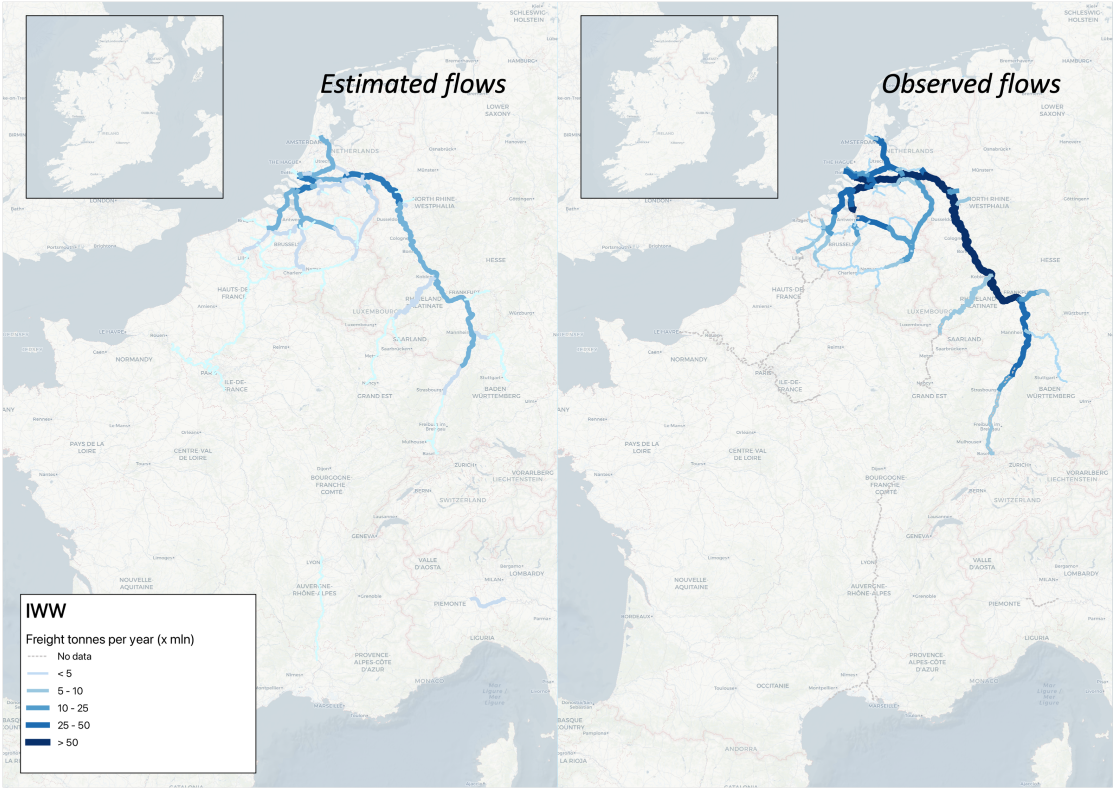

Figure 4.8: *Comparision of inland waterway traffic assignment - Estimated vs Observed flows*

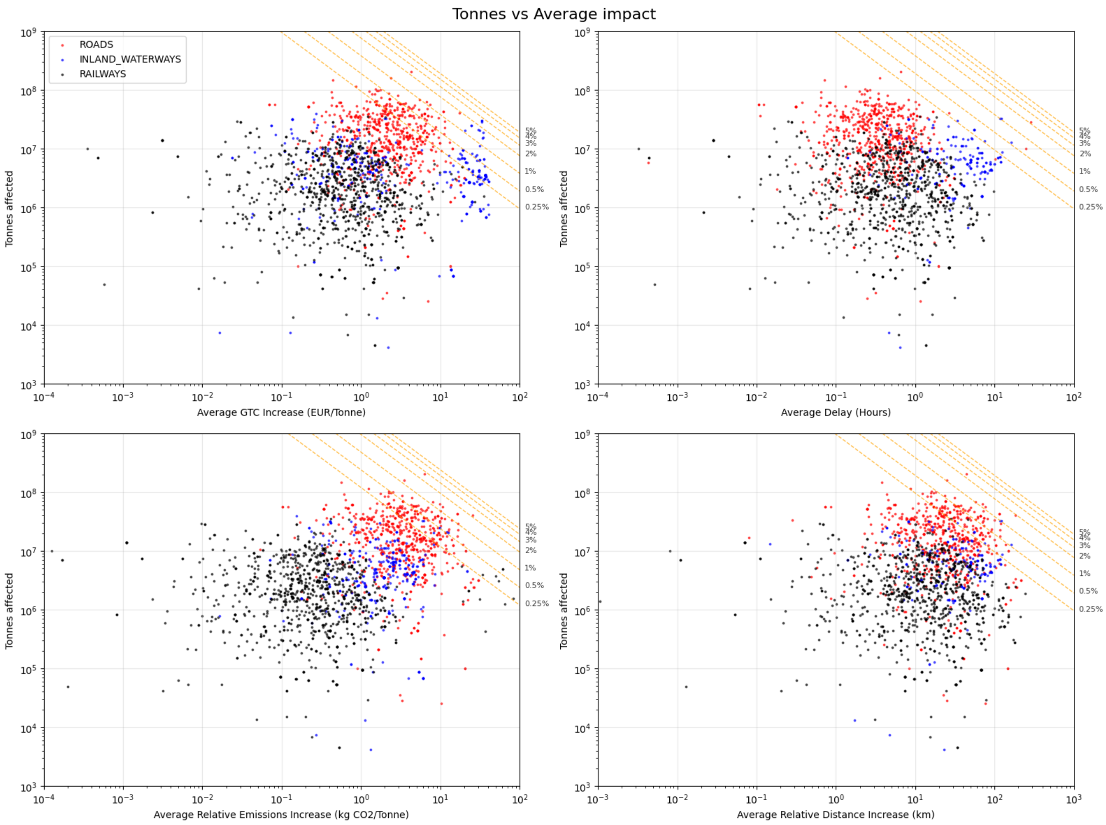

Figure 4.9: *Tonnes affected vs impact - Link criticality analysis*

waterway removals display much greater dispersion, including a small cluster with very large GTC increases consistent with forced shifts to road. At the system level, road and inland-waterway removals generally produce the largest cost increases: most links raise total system GTC by 0.25 -1%, while the most critical approach 3%. Rail removals are comparatively contained.

For delay, most road removals reroute substantial demand but keep average increases under 3 h, except for a few cases where mode shifts drive large delays. Inland-waterway removals affect fewer tonnes but exhibit a wide spread; some even yield negative relative delay when traffic shifts to faster modes. Rail removals are the most contained, influencing fewer tonnes and producing smaller network-wide effects. Emissions follow a similar pattern: roads show the largest relative increases, inland waterways change little on average, and rail is generally low with a few notable spikes involving limited demand. For Average distance increases, the additional detour length when a link is removed are broadly comparable across modes, though some road and rail links require detours exceeding 150 km/tonne.

Finally, Figure 4.10 summarizes the variance of impact across modes. Roads carry the largest demand but show relatively moderate per-tonne effects. Inland waterways exhibit the widest spread in delay, GTC, and detour distance with heavy-tailed outliers and the share of mode switches. Rail is the most stable overall with lower medians and tighter spreads, though a small number of links still trigger long delays detours. Emission penalties are highest when traffic diverts to road, while IWW and rail shifts add little on average.

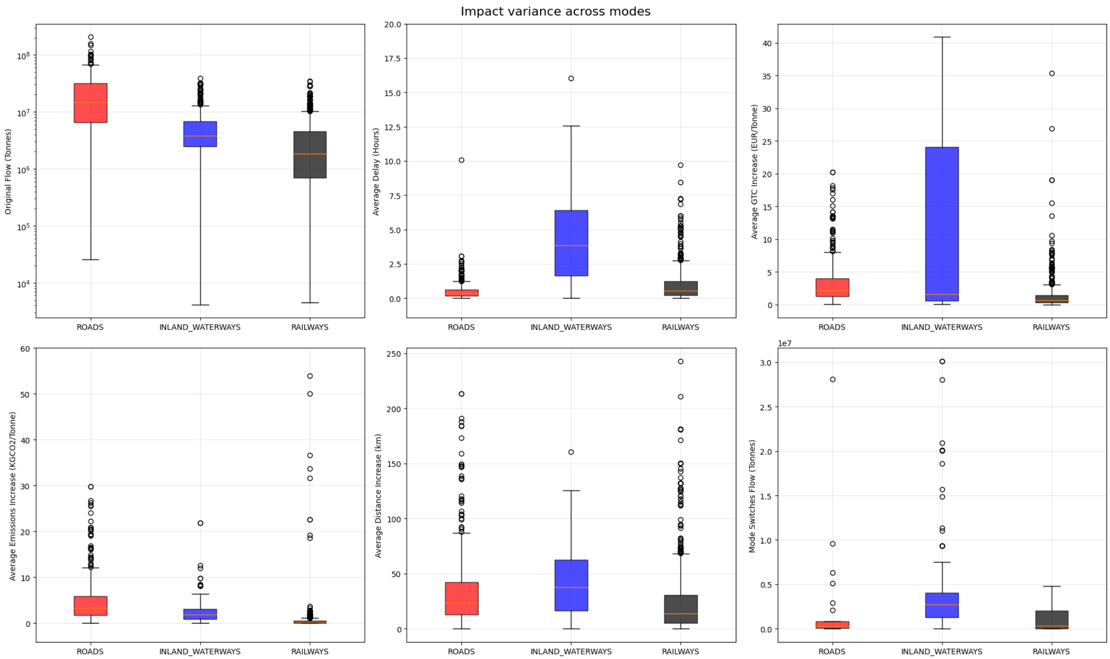

Figure 4.10: *Variance of average impact across modes*

4.7 Geospatial Visualization of Critical Links

The link criticality results have been plotted geographically using Geographic information system (GIS) software. In this section, we present some of the notable results of the process. Complete results can be found in appendix A .

4.7.1 Road network

Figure 5.6 identifies critical road network links that significantly impact total system GTC (Top-left) when removed. The most notable increases occur near Basel and Bern, where three key links; Bern (Forsthaus) ↔ Bern (Wankdorf), Basel (Oberer tunnel) ↔ Kaiseraugst, and Luterbach ↔ Boncourt (border CH-FR),cause total system GTC to increase by more than 2%. Links connecting the major ports of Rotterdam and Antwerp also demonstrate similarly high impact when disconnected.

The figure also presents the average GTC increase (Top-right) and delay (Bottom-left) imposed on affected tonnes when individual links are removed. These figures highlight links that are critical based on their impact severity on the affected freight. The southern network contains more links that cause substantial cost and travel time increases compared to the northern network. The Basel and Bern region links again demonstrate high impact, causing significant GTC and travel time increases when removed. The link connecting Genoa and Monaco (Albenga ↔ Ventimiglia) shows the most severe impact, with more than 15 EUR/tonne increase in GTC when removed. Due to low density of infrastructure in Ireland the link connecting the ports are also critical. The road link connecting Switzerland and Italy (Martigny <–> Gondo (border CH-IT)) causes 10+ hours in travel time increase when removed.

4.7.2 Rail network

Compared to road network, the rail network Figure 5.6 (Bottom-left) is seen to not create significant impact to total system performance. Most system performance change can be seen near the railway tracks leading towards Rotterdam. Large number of railway links cause high delays (4-10 hours) to the tonnes affected. these links are especially present where the network is not as dense as shown in Figure 4.12 (Top-left).

4.7.3 Inland waterway network

As shown Figure 4.12 (Top-right), Links from the main Rhine river artery from Nijmegen causes a significant increase in total system GTC when removed. This river section represents one of Europe's busiest inland waterway corridors. Since the river topology in this section offers no alternative routes or redundancy, any link disruption forces freight flows to shift to alternative transport modes, effectively disconnecting the inland waterways sections. The number of mode shifts which occur due to the IWW link being removed can be seen in Bottom-right plot. Figure 4.12 (Bottom-left) shows

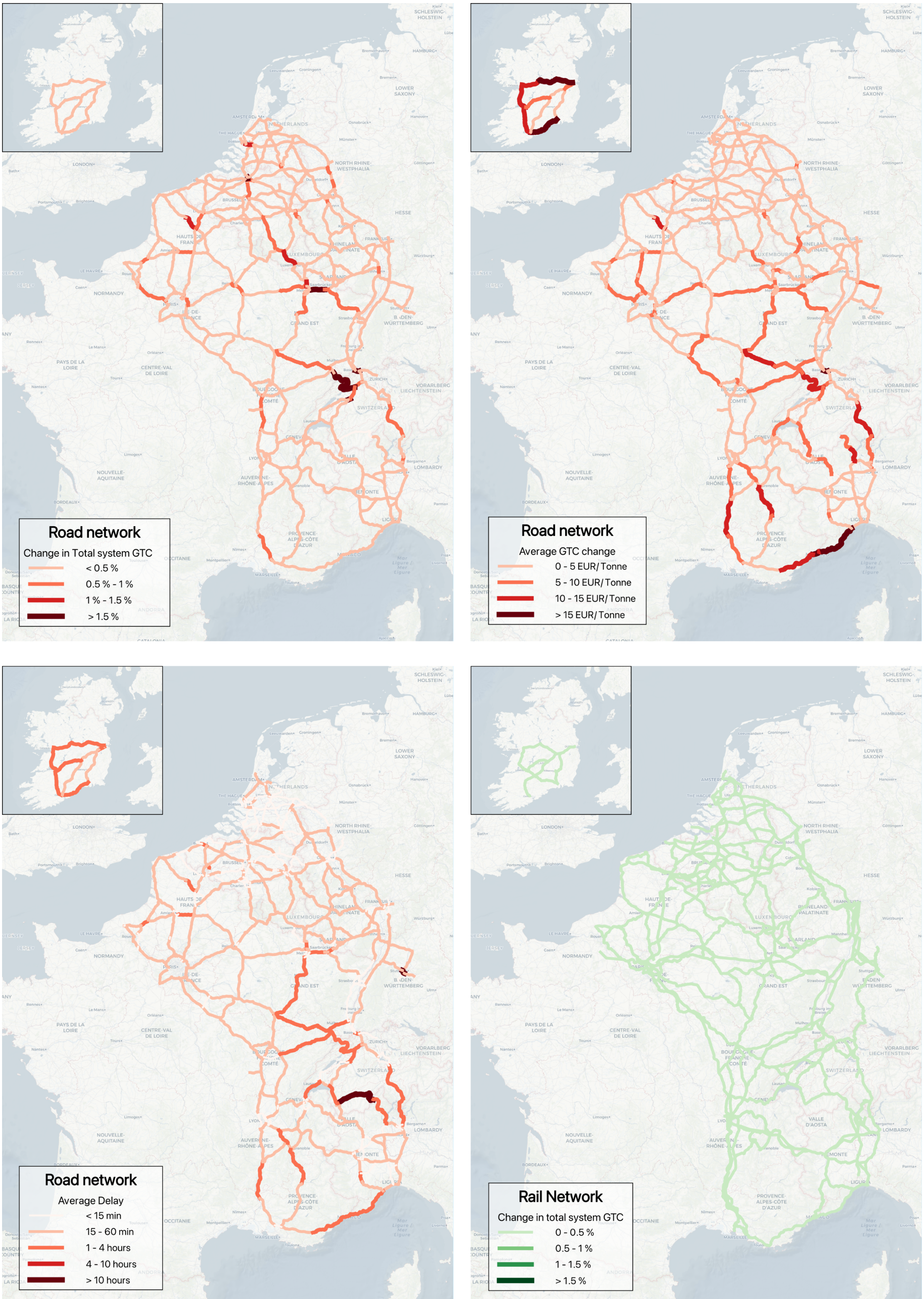

Figure 4.11: *Geospatial visualisation of link criticality measures in the NSRM network: Road - Change in total GTC (Top-left), Road - Average GTC change (Top-right), Road - Average delay (Bottom-left), Rail - Change in total GTC (Bottom-right)*

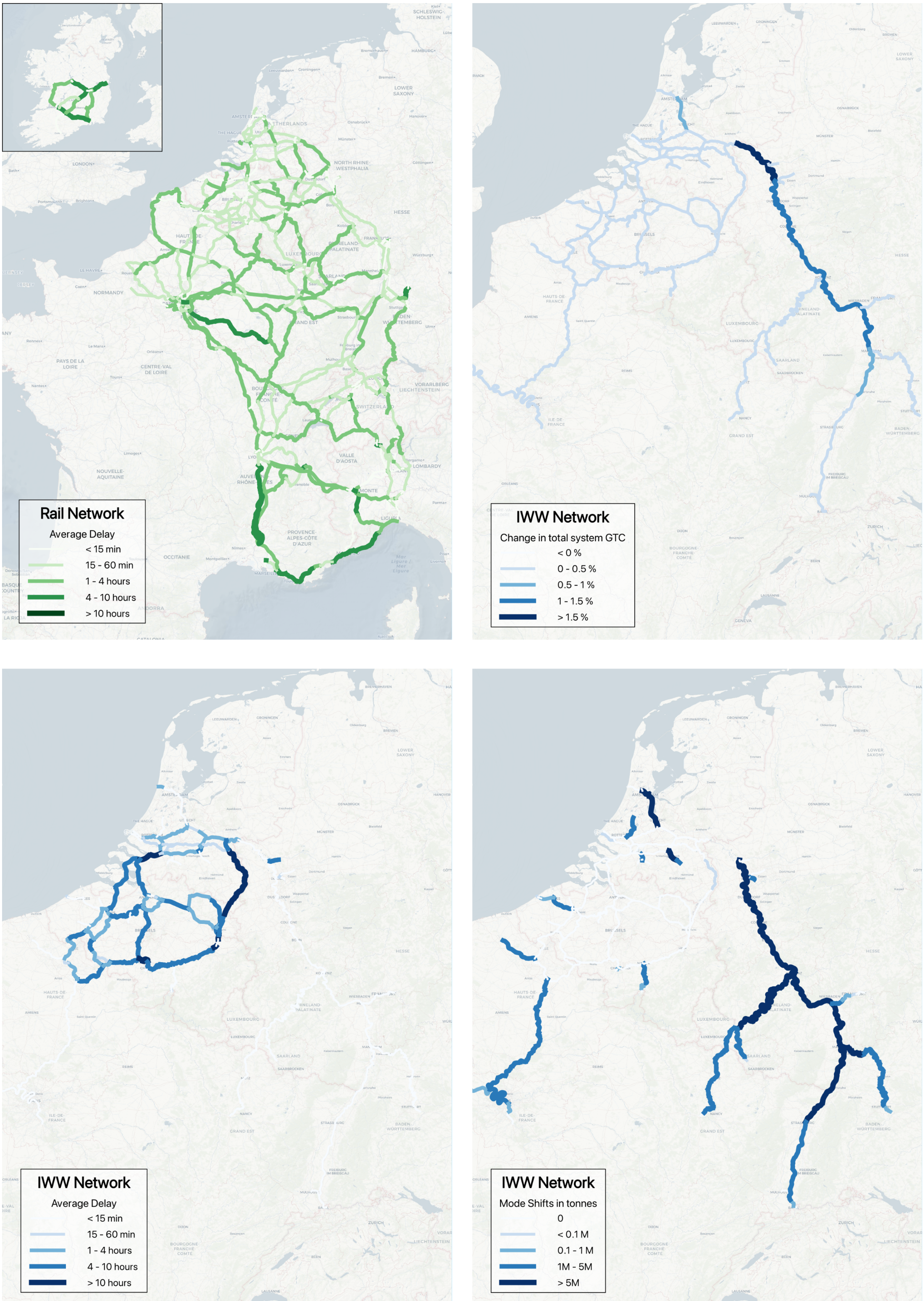

Figure 4.12: *Geospatial visualisation of link criticality measures in the NSRM network: Rail - Average delay (Top-left), IWW - Change in total GTC (Top-right), IWW - Average delay (Bottom-left), IWW - Mode shifts (Bottom-right)*

the links that have alternative detours available within the IWW network, allowing freight to reroute when they are disconnected.

4.8 Discussion

The results reveal distinct patterns of link criticality across different transportation modes. The road network shows dense connectivity with abundant alternative routes. However, as the predominant freight transport mode, road links generate marginal impacts that translate into substantial economic costs. Despite the availability of alternative routes within the road network, these links remain critical due to the high traffic volumes they serve. The rail network presents a contrasting scenario. The network topology demonstrates considerable redundancy on paper, resulting in no individual railway links significantly impacting overall network performance. Nevertheless, few links cause substantial localized disutility, particularly in the southern network where infrastructure density is lower. Inland waterways results identifies several critical links in areas where river sections are narrow and constrained. Link removal here triggers significant economic cost increases as shifts to more expensive modes such as road transport. These cost increases often exceed twice the price of fulfilling demand through inland waterways, creating large impact on total system performance and for the traffic affected.

In terms of link criticality measures, Change in total system GTC provides an economic value of the effects of link removal. The measure encompasses changes in travel time, distance, emissions (which is a function of distance) and also mode shifts. By translating operational performance into monetary terms, the approach enables the representation of criticality combined with risk metrics as a cost of inaction that is, the economic consequence of failing to address potential link failures or vulnerabilities. This makes this measure a general suitable measure for link criticality in multimodal networks. However, other system wide metrics remain important. Different modes are chosen based on varying priorities, including sensitivity to price, travel time, and emissions levels. For example, a nominal price increase to road transport may not be particularly significant, but when the same price increase affects railways, that increase is felt more acutely. Similarly, travel time is especially important for roadway transport when compared to inland waterways. Although GTC provides a general indicator for link criticality, individual metrics can be utilized as well to capture mode-specific impacts. When adopting an equity perspective, average impact measures provide a more detailed representation of the localized effects of link removal, which highlights structural weaknesses within the network.

The top 10 most critical links of the NSRM corridor are shown in Figure 4.13. Road links near Basel and Bern represent the three most critical links in the network. The link removal causes a total system GTC increase of 2.2% or € 830 million annually. These

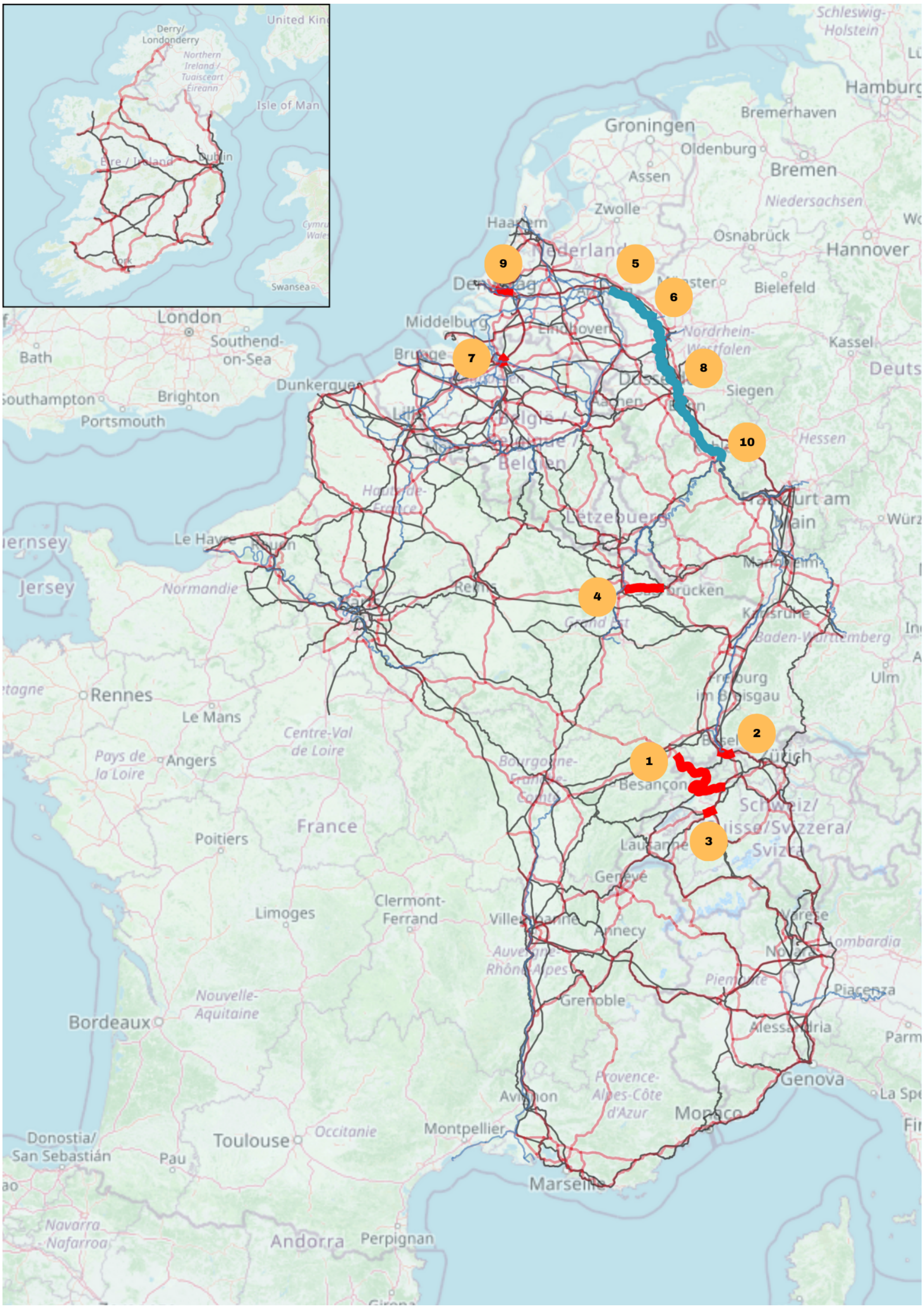

Figure 4.13: *The Top 10 Most critical links in the NSRM network*

sections contain multiple tunnels that function as single points of failure. The main Rhine river artery, which constitutes one of Europe's busiest inland waterway channels, also proves critical for network operations. Any disruption in this section forces freight to shift modes to rail or road transport, increasing total system GTC between 1.9% to 1.4% (€ 750 - € 530 million). Links near Rotterdam and Antwerp, which serve substantial traffic volumes, appear among the critical links because, despite the existence of viable alternatives, the volume of traffic they handle makes them essential to network performance.

The model equips planners with a tool for scanning large multimodal networks to identify and rank critical links without requiring extensive data collection or computational power. This initial screening enables planners to focus their attention where it matters most, performing comprehensive assessments toward those links whose failure would have the most significant system-wide impacts. For each identified critical link, planners can explore potential disruption threats for that specific link and develop targeted mitigation measures to reduce the likelihood or severity of failure. Disruptions are not always day to day, climate changes can have long term impacts on the usability of certain modes. For example, planners can model the annualised effect of extended low water levels on inland waterways, recognising that such issues cannot be resolved immediately and require strategic adaptation measures. In the context of maintenance planning, the model's results can inform decisions if careful planning is required for long term maintenance works. As the model integrates all modes into a unified performance view, it also helps identify the most effective substitutes when a particular link is closed. The model also quantifies the "cost of inaction" by estimating the economic and operational consequences of leaving a vulnerable link unaddressed, and conversely, it can assess the benefits to the overall network from adding new links, supporting robust cost–benefit analyses for infrastructure projects. Beyond civilian logistics, the framework's outputs are also relevant in the context of the EU's Military Mobility plan, which envisions the TEN-T network as dual-use infrastructure for both civilian and defence purposes. In such scenarios, the model can identify highly vulnerable links whose disruption would hinder rapid military deployment. Here, performance indicators such as average travel time or network accessibility become more critical than purely cost-based measures, as there is more priority for rapid troop and equipment movement to border regions during emergencies.

As part of the research we have also developed a interactive impact assessment dashboard. This dashboard allows use to quickly simulate the removal of any link in the network and visualise the impact through an interactive graph. As shown in Figure 4.14, we can observe the changes in freight flow in the network see the changes in freight volumes on each link by hovering over them. On the right side of the dashboard, the criticality metrics of the link are also provided. This dashboard allows for an in-depth exploration of the exact effects of link removal.

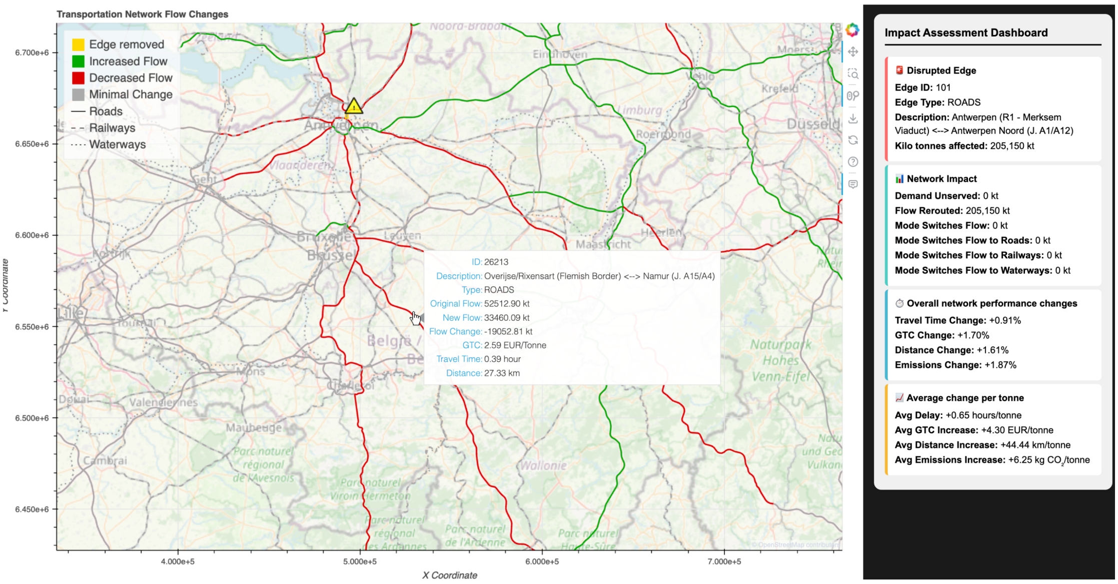

Figure 4.14: *Impact assessment dashboard*

There are simplifications in the model to trade between computational efficiency and realism. Our graph-based framework represents every NUTS-3 region with a single OD node, which is connected to the nearest road, rail, and waterway links. We assume that local access infrastructure such as regional roads, rail-road terminals, or ports lie close enough to those links for transshipment, simplifying the first/last-mile network and terminal operations into the OD connector rather than modelling them explicitly. Second, our model uses all or nothing assignment ignoring congestion and capacity constraints. While this that means detour links may unrealistically accept additional flow without degrading speeds or increasing operating costs beyond the base assumptions. Third we implicitly treat all links as technically compatible. For instance, it assumes any train can operate on any rail segment, regardless of gauge, axle-load, or electrification differences. As a result, our findings likely understate how critical certain railway links truly are. Finally, the analysis omits both intrazonal demand and through-traffic, factors that could have an impact on the criticality results.

5 Conclusion

This thesis set out to develop a method critical links in European multimodal freight networks. Critical links are those who degrade network performance disproportionately when failed. Identifying critical elements in the network is one of the first steps towards improving robustness and overall resilience in the network. Measuring criticality allows us to prioritise investments to reinforce or introduce good enough alternatives in case of disruptions. While link criticality has been extensively studied in road networks, very few studies have examined component criticality in multimodal networks. This gap is significant because multimodal networks are interdependent as infrastructure failure in one mode can trigger cascading effects across others, making it essential to study these networks together rather than in isolation. Previous studies of link criticality have also overlooked important behavioural responses to network failures, such as mode shifting and trip cancellation. Additionally, existing methods that capture the operational aspects of networks are computationally intensive and require extensive datasets for analysis.

5.1 Key findings

Along with our main research question we have formulated three research sub questions which have been answered below:

1. What are the state of the art methods of measuring and ranking critical links in transportation networks?
This question is addressed through the literature review presented in Chapter 2. Link criticality measures are commonly categorized into three groups: topological, traffic-based, and hybrid approaches. This study offers a comprehensive and up-to-date overview of state-of-the-art methods for assessing link criticality in transportation networks, as summarized in Table 2.5.

2. Which link criticality measures are most suitable for multimodal networks

considering their strengths and limitations?
Topological measures are very easy to compute and require minimal data, but they are not suitable for identifying critical links because they assume synchromodality in the network, which is not the case in reality. Additionally, they do not take into account the traffic demand, which makes them inaccurate. Traffic-based measures are suitable in capturing the traffic effects and also capture system-wide effects. The downside is that they require more data and are computationally very complex if we use more traffic assignment methods which take congestion into account. But they can be adapted to be used in the case of multimodal networks using simpler traffic assignment methods. The main advantage of hybrid methods is to balance computational efficiency and metric accuracy. This benefit becomes irrelevant when we choose to use simpler traffic assignment methods such as All or Nothing. To summarise, we have adapted traffic-based measures from literature such as change in total system travel time and total system travel costs but also propose other operational metrics described in Chapter 3. Out of the measures used in our study, Total system GTC change is the most representative metric for criticality as it incoporates the effects of distance, travel time, mode shifts and emissions (which is a function of distance) into a single metric. The change can also be translated into a monetary value which can be used by planner to prioritise investments.

3. How to assess empirically the effects of link removal in the multimodal freight networks?
To empirically assess the effects of link removal in multimodal freight networks, a link criticality analysis algorithm is introduced. This involves first simulating a base scenario to establish benchmark network performance indicators. Links with zero flow or artificially created connectors are excluded to reduce computational load. For each remaining link, the network is modified by removing the link, and only flows using that link are recalculated. Affected Origin-Destination-Commodity-Mode (ODCM) pairs are rerouted along alternative paths within the same mode, and if no feasible route exists, a mode-switching model is applied. If no alternative mode is available, the demand is marked as unserved. After reassignment, system performance metrics are recalculated and compared with the base scenario to quantify the impact of each link removal, capturing operational changes.

"How can we identify critical links in the European multimodal freight networks which create the most impact when disrupted?".

Using the North Sea - Rhine - Mediterranean (NSRM) TEN-T corridor as a case study, we demonstrated a framework for identifying critical links in European multimodal freight networks. Our analysis reveals patterns across transport modes. Road network disruptions affect the largest volume of tonnes but cause relatively moderate impacts per affected shipment. Due to this even links with cause marginal affects become critical when removed due to the number of tonnes being rerouted. Railway networks show the most resilient performance when links are removed, as their high network density provides multiple alternative routes. While the railway links don't rank highly in total system criticality measures, they create significant impact locally, especially in the southern part of the network where the density of infrastructure is lower. Conversely, inland waterway networks are most vulnerable to link removal, generating the highest number of modal shifts due to linear sections with limited branching or alternative routes. Geographically, critical road network links around Basel, Bern, Rotterdam, and Antwerp, created significant systemic cost increase. For inland waterways, the Rhine river segment between Nijmegen and Strasbourg emerges as particularly critical infrastructure. These critical links when removed cause the total system gtc to increase between € 530 - 830 million.

5.2 Theoretical implications

The model introduced in our study contributes to the literature by addressing research gaps in link criticality in transport networks. The link criticality algorithm is computationally simple and less data hungry. While traditional methods of full scan criticality analysis provide a more accurate representation of criticality as they take into account link capacity and congestion, they are very exhaustive. They are also difficult to scale for larger networks and require more data. Our model strikes a balance between computational complexity and operational accuracy. We also contribute to the less popular area of link criticality in multimodal networks. By analysing the networks together, we measure the effect of link removal in one network and also simulate the cascading effects into another network.

5.3 Practical implications

We identified critical links in the region near Basel and Bern, an area which has extensive tunnel infrastructure that creates potential vulnerabilities for transport connectivity. The terrain in this region necessitates numerous tunnels for both road and rail networks, making these links particularly susceptible to disruption from natural disasters, maintenance issues, or structural failures. Additionally, the main artery of the Rhine river, which serves as a crucial waterway for freight transport, presents significant criticality due to its vulnerability to disruption from low water levels during drought periods and potential accidents.

The model gives planners a fast, data-lean way to identify and rank critical links across multimodal freight networks, so they can target mitigation and investment where it delivers the biggest payoff. By screening for the links whose failure would most increase the generalised transport costs, authorities can prioritise reinforcement or create viable alternatives, reducing disruption risk and keeping freight moving efficiently.

Demonstrated on the NSRM corridor, the approach scales to the full TEN-T and to national networks, and it aligns with dual-use objectives in the EU with roughly 93% TEN-T overlap with member-state military networks, a single pipeline of projects can strengthen both civilian and military resilience. An accompanying interactive dashboard supports rapid "what-if" testing—removing any link, visualising flow reassignments and link-level criticality metrics. The model is also highly modular, parts of the model can be modified/upgraded as needed by the planner depending upon the scope of the analysis.

5.4 Future direction

This study has several limitations due to scope and time constraints that future research can address. First, the simulation does not explicitly model rail-road terminals and ports, including their capacities, transshipment times, and costs. Incorporating these elements would produce more realistic traffic assignments. Additionally, the All-or-Nothing assignment method assigns all traffic to a single path, even when slightly more expensive alternatives exist. This limitation could be addressed using stochastic assignment methods that account for path overlap to introduce heterogeneity in traffic distribution. Future research should also integrate congestion effects using precomputed flow-speed curves, particularly for road networks which are more susceptible to congestion impacts. Second, the current approach evaluates behavioural responses to link removal through incremental checks, which may not capture the full complexity of shipper decision-making. A more sophisticated simultaneous choice model could better represent shippers' behaviour by incorporating commodity-specific transshipment willingness, price sensitivity, and travel-time sensitivity. This approach would evaluate all alternatives simultaneously and produce more consistent mode and route choices under disruption scenarios. Third, the criticality measures developed in this study could be enhanced by incorporating risk elements to provide a more comprehensive assessment of network vulnerability. For example, combining criticality measures with hazard maps or infrastructure failure probabilities would enable the calculation of expected impact metrics that better reflect real-world conditions and provide more actionable insights for transportation planning and risk management. Lastly, the model would benefit from richer datasets that incorporate additional network characteristics and constraints. Future studies should consider directional graphs, technical compatibility between different vehicle types and specific links, and region-specific cost models that reflect local conditions. Furthermore, expanding the freight transport model to include other networks such as pipelines would provide a more comprehensive representation.

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Simulation framework to measure and rank critical links in multimodal freight networks

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Abstract—**Growing geopolitical risks and climate extremes have prompted renewed interest in to strengthen the resilience of its transport networks to ensure economic competitiveness and stability. Identifying critical components in the network is a crucial step in resilience planning. While existing literature has extensively investigated ways to measure link criticality in transport networks, implementation for freight networks is challenging due to their multimodal, multi-commodity nature. This study develops a simulation framework to evaluate the criticality of links in multimodal freight networks at a transnational scale, balancing operational accuracy with computational efficiency. The framework integrates mode choice and routing algorithms while preserving key operational characteristics of multimodal freight networks. The approach consists of a traditional transport model for simulating the base scenario and link criticality analysis algorithm to measure the impact of link disruption on the network performance. By systematically removing links, we quantify network-wide impacts using operations-based metrics. A case study on the North Sea–Rhine–Mediterranean TEN-T corridor demonstrates the tool's practicality. The framework equips planners and policymakers with the ability to quantify the impacts of link removals, supporting decision making on where to invest resources, ultimately enhancing the resilience and sustainability of freight transport systems.**

Index Terms—**Transport infrastructure planning, Network Resilience, Vulnerability measures**

I. Introduction

Transport networks are essential infrastructure for global supply chains, enabling the efficient and timely movement of goods. They play a crucial role in supporting a nation's economic growth, security, and policy objectives. These networks are made up of components, each susceptible to various types of disruption. Such disruptions can stem from factors including infrastructure maintenance or failure, accidents, extreme weather events, and targeted attacks. Their severity can range from minor, day-to-day capacity reductions to major incidents with severe, cascading effects across both space and time. The failure of critical infrastructure can lead to substantial economic losses. For example, the Evergreen blockage in the Suez Canal was estimated to cost between \$6 - \$10 billion per day (Russon, 2021), while the 2017 Rastatt rail incident incurred approximately €2 billion in direct and indirect costs (HUPAC, 2018). Such events can create bullwhip effects that ripple through supply chains, making transport network resilience essential for maintaining economic continuity (ITF, 2024).

Identifying critical links is a crucial step towards resilience. According to Jenelius et al. (2006) link criticality can be defined as *"significance of individual links (e.g., roads, bridges, tunnels, channels, railways) in maintaining network functionality, where the failure of a critical link can disproportionately degrade system performance, such as increased travel times or reduced connectivity"*. Insights from identifying critical links help transport operators and planners prioritise maintenance, implement mitigation strategies, and direct investments effectively (Kumar et al., 2019; Scott et al., 2006).

There have been numerous studies related to link criticality in transportation networks but most of them focus on road networks (Gauthier et al., 2018; Jafino et al., 2020; Jenelius and Mattsson, 2015; Knoop et al., 2012; Kumar et al., 2019; Scott et al., 2006; Sohn, 2006; Taylor et al., 2006). Limited studies have researched criticality in multimodal networks that include roadways, inland waterways and railways. Notable exceptions include W. J. L. van Dam (2017) and He et al. (2021), who conducted robustness analyses of the Netherlands' multimodal freight network and identified critical nodes. The European Union's Critical Entities Resilience (CER) Directive mandates member states to identify critical infrastructure components within transport networks as part of broader measures to ensure essential services (CyberRisk, 2025). To the author's knowledge, no studies have investigated link criticality at the strategic, macro scale of transnational freight networks. Existing methods are computationally intensive and require large amounts of data (Takhtfiroozeh et al., 2021). Their complexity grows exponentially with the size of the network and the inclusion of additional transport modes. Furthermore, previous studies have not accounted for travel behaviours such as mode shifting and trip cancellations alongside re-routing in response to disruptions.

In this study, we propose a simulation framework for assessing link criticality in multimodal freight networks. The framework is designed to operate at a transnational scale while maintaining computational efficiency, integrating mode choice, routing, and re-routing behaviour to capture realistic responses to link removals. It extends beyond traditional link removal approaches by selectively reassigning only affected flows and modelling mode shifts and trip cancellations. The methodology is applied to the North Sea–Rhine–Mediterranean TEN-T corridor as a case study, demonstrating its capability to identify critical links across various performance measures. The resulting tool provides planners and policymakers with a practical means to pinpoint vulnerabilities, evaluate trade-offs, and prioritise investments that enhance the robustness and sustainability of freight transport systems.

II. Related Literature

Link criticality is a concept that extends beyond transport networks and is discussed in various fields, including computer networks, power grids, social networks, and water infrastructure. A critical link is one whose failure or disruption would substantially degrade the performance, connectivity, or functionality of the network (Akbarzadeh et al., 2019). Identifying these links is foundational for prioritizing mitigation and investment strategies that enhance network reliability, service, and efficiency (Jafino et al., 2020; Kumar et al., 2019; Takhtfiroozeh et al., 2021). There is a large body of literature on link criticality within the context of transport networks. Growing risks associated with geopolitical conflicts, extreme weather events, and ageing infrastructure have further highlighted the importance of identifying critical links in these networks. Various measures have been proposed to quantify link criticality in the literature. They can be categorised into two main categories: *topological-based measures* and *traffic-based measures* (Mattsson and Jenelius, 2015).

A. Topological measures

Topological-based measures assess the structural properties and connectivity of a transport network, drawing on traditional graph theory and adaptable to other domains. They are relatively simple to compute, require less data (Mattsson and Jenelius, 2015), and are particularly relevant for disruption management in emergencies or relief operations where travel demand and congestion can be neglected (Sugiura and Kurauchi, 2023). Traditional centrality measures such as degree, eigenvector (or eigen) centrality, closeness centrality, and betweenness centrality provide insight into the relative importance of nodes in a network, with betweenness centrality being especially valuable for assessing link criticality. By definition, the betweenness centrality of a link quantifies how often it lies on the shortest paths between node pairs, reflecting its role as a bridge or connector between network segments (Freeman, 1977). Building on such concepts, (Latora and Marchiori, 2001) introduced a network efficiency measure, defined as the average reciprocal of shortest path lengths d_{st} between all node pairs, where the change in efficiency $\Delta E(G)$ following the removal of a link indicates its criticality. While these measures are simple, easy to compute and require minimal data, they do not take into account traffic behaviour.

B. Traffic based measures

Traffic based measures address this issue by integrating travel demand and routing when assessing the criticality of link making them more accurate. The traditional full scan method is a common approach for assessing link criticality in transport networks. In this method a base scenario is computed to benchmark the network performance under normal conditions. After this, a link is removed from the network and the transport simulation is re-run to measure the change in total network performance to represent the criticality of that particular link. This process is then repeated for all the links in the network making it very exhaustive. Most commonly a User Equilibrium traffic assignment is used to calculate congestion in the network. While this makes the traffic assignment realistic, it is highly computationally expensive and is unfeasible to scale to larger networks.

Commonly, traffic based measures use total travel time and generalised travel cost as a peformance indicator to measure criticality. The Network Robustness Index (NRI) quantifies the change in travel time cost after re-routing traffic due to a link failure (Scott et al., 2006). Taylor et al. (2006) proposed the vulnerability indicator V_{rs}, combining travel demand with changes in accessibility, demonstrated on Australia's national road network. The importance score (IS) evaluates links under equal-weight and demand-weighted perspectives, accounting for unsatisfied demand (Jenelius et al., 2006) . Sullivan et al. (2010) introduced the modified NRI (NRI*) for partial capacity losses and the Network Trip Robustness

(NTR) to compare robustness across networks, addressing limitations of full-closure assumptions.

C. Other approaches

Few other approaches have been used to reduce the computational requirements of the traditional full scan method while maintaining the operational accuracy. Gauthier et al. (2018) proposed Travel-time Weighted Betweenness Centrality (TTWBC) with a stress test simulation using partial capacity reductions, comparing it with other betweenness-based criticality measures. Takhtfiroozeh et al. (2021) developed nine hybrid betweenness measures with different link weights, finding that flow-weighted variants aligned most closely with traffic-based measures such as NRI, IS, and NRI*. Kumar et al. (2019) applied a multi-criteria approach combining traffic usage, disruption to critical services, and number of OD pairs served, weighted according to planning priorities. (Li et al., 2020) proposed the Traffic Flow Betweenness Index (TFBI), which preselects candidate links using betweenness, flow, and rerouted demand before performing a more intensive criticality analysis for the selected links. (Almotahari and Yazici, 2019) introduced the Link Criticality Index (LCI), identifying critical links in a single user equilibrium assignment by tracking marginal cost in the Frank–Wolfe algorithm.

D. Criticality analysis in multimodal networks

Research on resilience in multimodal transport networks remains limited compared to single-mode systems (Zhou et al., 2019). He et al. (2021) analysed the robustness of the Netherland's integrated road, inland waterway, and rail networks to support maintenance planning, using centrality measures and capacity degradation scenarios. The results showed node criticality correlated strongly with freight volume passing through the node. W. J. L. van Dam (2017) also studied the Netherlands' multimodal freight network, focusing on overall robustness of a synchromodal freight network rather than critical link identification. Another study applied a traffic micro-simulation model with Austrian data to identify critical intermodal links via delay-based indicators (Burgholzer et al., 2013). Van Der Tuin and Pel (2020) developed a multimodal disruption model for the TEN-T network that integrates a detailed Local Disruption model with a coarser Global Spillover model. Applied to the Port of Rotterdam, the approach showed that road bridge failures generated substantial local delays but had limited impacts at the continental scale. The model offers a framework for assessing disruption effects at both local and global levels.

In summary, existing link criticality methods present a trade-off between accuracy and scalability. Traffic-based approaches offer operational realism but are computationally prohibitive for large, multimodal networks, while topological measures are efficient but oversimplify network dynamics. Furthermore, explicit studies on link criticality in multimodal freight systems remain scarce, with most work focused on single-mode or regional networks. No established framework currently balances computational efficiency with behavioural realism in a way that can be applied to large-scale, strategic freight corridors.

III. Methodology

The methodology section is divided into two parts. In the first section, we introduce the multimodal freight transport model and the techniques used to simulate the traffic behavior within the network. In the section part, we introduce the link criticality analysis algorithm. This methodology will be later demonstrated using the case of the NSRM TEN-T corridor.

A. Base scenario modelling

Multimodal freight networks integrate road, rail, inland waterways, and maritime ports through strategically located terminals, logistics hubs, and urban centres. They enable coordinated infrastructure development, standardisation, and interoperability, supporting high freight volumes, facilitating intermodal transfers, and enhancing resilience by providing alternatives during disruptions. While these networks also include micro-level assets such as bridges, locks, weirs, crossings and tunnels, their detailed representation is beyond the scope of this study. Instead, we adopt a graph model where intersections, terminals, and origin–destination (OD) points are nodes, and links represent road, rail, or waterway segments between them. This approach captures network structure, traffic flows, modal interactions, and costs, and is widely used in transport network analysis and criticality studies.

The multimodal freight network is represented as an undirected graph $G = (\mathcal{N}, \mathcal{L})$, where $\mathcal{N}$ is the set of nodes and $\mathcal{L}$ the set of links. Although a directed graph would better reflect reality, an undirected representation is adopted here to reduce complexity. Nodes and links are classified by mode as:

$$\mathcal{N} = \mathcal{N}^{\text{road}} \cup \mathcal{N}^{\text{IWW}} \cup \mathcal{N}^{\text{rail}} \cup \mathcal{N}^{\text{OD}}$$

$$\mathcal{L} = \mathcal{L}^{\text{road}} \cup \mathcal{L}^{\text{IWW}} \cup \mathcal{L}^{\text{rail}} \cup \mathcal{L}^{\text{OD}}$$

The multimodal network is structured as separate layers for each mode, each represented by a subgraph

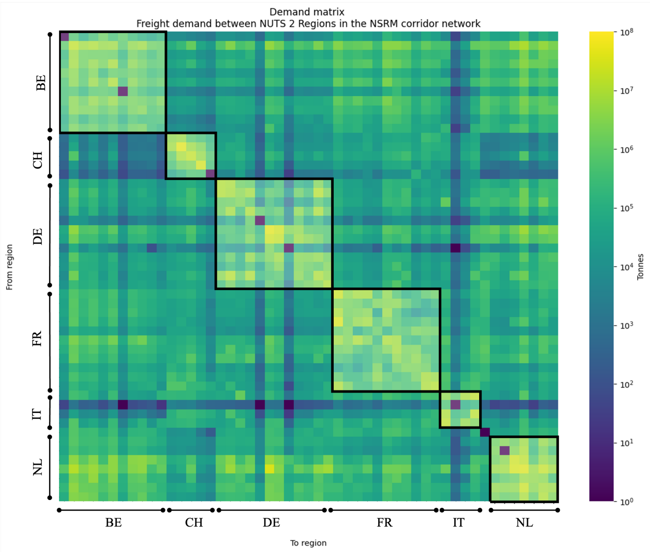

Fig. 1. Annual freight demand between regions (NUTS3 and NST/R 1 commodities have been aggregated to NUTS2 for visual purposes)

with its own nodes and links. An additional OD subgraph G^{OD} contains region centroids based on the NUTS3 classification. To link OD nodes to the multimodal freight network, connector links $\mathcal{L}^{OD}$ are generated. For each OD node, connector links are generated and they aim to represent the underlying regional road network.

The cost of transporting a unit of freight on a link is calculated using Equation 1, following previous studies (de Jong et al., 2011; He et al., 2021; W. J. L. van Dam, 2017). In this equation, K_m and T_m denote the cost per unit distance and time for mode m respectively, while d_i represents the length of link i and v_m indicates the average travel speed. For OD links generated as straight lines between regional centroids and the network, the distance is multiplied by 1.5 to conservatively approximate the actual travel distance on underlying regional roads (W. J. L. van Dam, 2017).

$$GTC_i = K_m \cdot d_i + T_m \cdot (\frac{d_i}{v_m}) \tag{1}$$

The base scenario simulation follows the traditional four-step transport modelling framework. In conventional applications, the first two steps involve estimating demand between origins and destinations. In this study, we use Panteia's NEAC model, which estimates annual multi-commodity freight demand between NUTS3 regions based on economic and trade data (Newton et al., 2015). Freight demand is specified between each Origin–Destination (NUTS3) pair and commodity type (NST/R 1) in tonnes. Figure 1 illustrates the resulting demand matrix for the NSRM TEN-T corridor.

The specific demand between Origin, Destinations and Commodity (ODC) pair must be further distributed between the available modes. The distribution is based on the total GTC (GTC_{ijm}) incurred of using a mode m between Origin i and Destination j. A Multinomial logit (MNL) is used to calculate the relative probability of choosing a mode over others . The cost function i.e utility V^g_{ijm} of the model is specified in Equation 2. ASC^g_m is the alternative specific constant which represents the baseline preference/ bias of commodity g towards a mode m. β^g_{gtc} is the sensitivity parameter or the marginal utility of GTC for commodity g. The probability p^g_{ijm} is calculated using Equation 3 and demand is distributed accordingly. The parameters have been tuned based on the NEAC mode chain builder output. This approach captures commodity-specific mode choice behaviour by accounting for both cost sensitivity and modal preferences, resulting in freight flows that more accurately represent real-world operations.

$$V^g_{ijm} = ASC^g_m + \beta^g_{gtc} \cdot GTC_{ijm} \tag{2}$$

$$p^g_{ijm} = \frac{e^{-V^g_{ijm}}}{\sum_{m \in M} e^{-V^g_{ijm}}} \tag{3}$$

Freight demand assignment on the network enables the simulation of freight transportation flows and provides insights into how link removal affect traffic patterns. This study implements All-or-Nothing assignment for route choice. In the All or Nothing assignment all demand for each mode specific origin destination pair is assigned to the shortest path between them. The algorithm assumes that there is no congestion in the network and the traveller has prior knowledge of the exact costs incurred by choosing the route. This means that the travel costs of choosing the shortest path is fixed and does not vary based on the flow travelling through the links. The use of all-or-nothing assignment can be justified by noting that, unlike passenger demand, freight demand is typically planned and scheduled in advance. As a result, freight movements are less affected by perceived travel time errors or random route choice variability. Moreover, freight is managed by profit-driven companies that generally prioritize cost minimization in their routing decisions. The generalised travel costs calculated are used as link weights for the shortest path calculation.

Although other traffic assignment methods such as User Equilibrium assignment offer more realistic modelling capabilities, they are not appropriate for this research due to several limiting factors. The model operates at a macroscopic level, where demand data represents annual freight flows across an extensive network. Implementing User Equilibrium assignment would require calculating congestion parameters, which demands additional data inputs and significant computational resources. Given that the link criticality methodology involves executing traffic assignment algorithms multiple times to evaluate network responses to disruptions, employing computationally intensive methods would be impractical for a large network.

B. Multimodal link criticality analysis

In this section, we describe the methodology for multimodal link criticality analysis. A link's criticality is determined by the change in network performance after its removal; highly critical links cause substantial degradation. As mentioned previously, traditional full-scan methods evaluate each link by removing it, performing complete network reassignment, and comparing performance to the base case. The conceptual model for our framework is shown in Figure 2. The process is described as follows:

Step 1: Base scenario modelling. Run the transport model under normal conditions to establish baseline performance.

Step 2: Identify links to remove. Consider only links with non-zero flows ($f_l > 0$) and exclude artificial connector links:

$$\mathcal{L}_{\text{removed}} = \{l \in \mathcal{L} \mid f_l > 0,\, l \notin \mathcal{L}^{OD}\}.$$

Step 3: Link removal. Remove one link l from the network G to obtain G'.

Step 4: Identify and reset affected flows. Determine flows $\mathcal{F}_{\text{affected}}$ that are affected by the removal of link$l$ and remove the freight demand of the affected flows from the network.

$$\tilde{f}_l = \max(0, f_l - \sum_{i \in \mathcal{F}_l \cap \mathcal{F}_{\text{affected}}} q_i), \quad \forall l \in \mathcal{L}.$$

Step 5: Re-routing. For each affected ODCM pair, calculate an alternative shortest path in G' and reassign demand if feasible. The underlying assumption is that freight operators typically do not alter their chosen routes unless the travel impedance has increased significantly or the destination becomes unreachable via the originally selected mode. Furthermore, due to the long-term nature of freight transport contracts, there is often limited flexibility to switch between transport modes in response to disruptions Van Der Tuin and Pel (2020).

Step 6: Mode switch. If no route exists in the original mode, we perform mode choice using the MNL model to

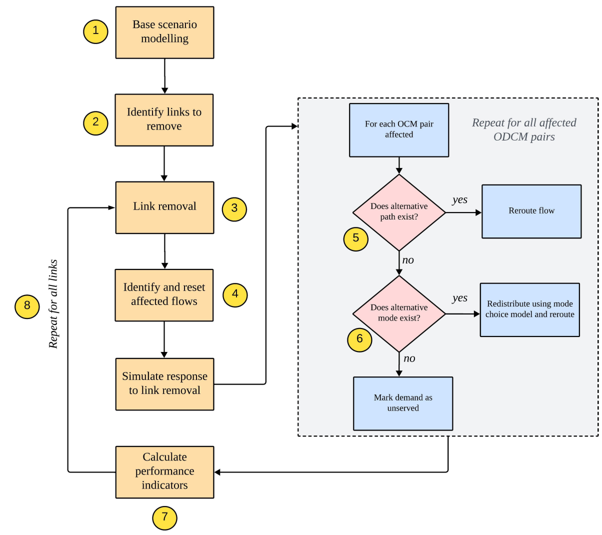

Fig. 2. Conceptual framework of the multimodal link criticality analysis model

re-distributed affected freight using the available modes between the regions.

Step 7: Calculate performance indicators. If no path exist to fulfil a ODCM pair, mark demand as unserved and recompute performance metrics. Finally add the removed link l back to the network.

Step 8: Repeat. Continue steps 3–7 until all candidate links have been analysed.

C. Criticality Indicators

This study focuses on traffic-based measures, as the previously discussed topological measures are less relevant in our context. The reduction in network performance after a link removal is used as the primary indicator of its significance. Among system-wide metrics, total system generalized travel cost (GTC) is particularly valuable, as it incorporates both distance and travel time, offering an integrated view of link importance. Since different modes weigh performance changes differently we also track changes in total system travel time, distance, and emissions. To represent these, we use a generic relative change formula:

$$\Delta M = \frac{M^{G'} - M^G}{M^G},$$

where M can be travel time, GTC, distance, or emissions.

In addition to system-wide measures, we assess equity impacts by calculating the average proportional change in travel time, distance, GTC, and emissions for only

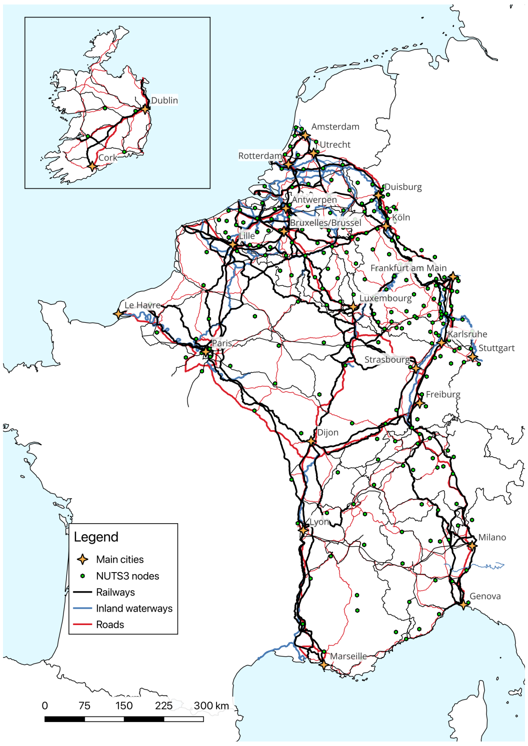

Fig. 3. The North Sea–Rhine–Mediterranean corridor network

those flows affected by the disruption. These localized metrics ensure that the analysis captures both aggregate network effects and the fairness of impacts on disrupted flows.

$$\overline{\Delta M} = \frac{1}{|\mathcal{F}_{\text{affected}}|} \sum_{i \in \mathcal{F}_{\text{affected}}} \left(m_i^{G'} - m_i^{G} \right) \tag{4}$$

IV. Case-Study

The framework is demonstrated using the case of the North Sea–Rhine–Mediterranean (NSRM) TEN-T corridor. It is a major European transport corridor established as part of the TEN-T (Trans-European Transport network) policy. The NSRM corridor plays a crucial role in connecting Europe's largest economic zones, ports and multimodal hub. The corridor spans across eight countries namely: Ireland, Netherlands, Belgium, Luxembourg, France, Germany, Italy and Switzerland. The core network spans over 12150 km of railway lines, 5000km of roadways and 5030km of inland waterways. The network analyzed includes links from both the NSRM core network and the TEN-T comprehensive network, which differ in their policy implementation timelines and requirements. The multimodal network here consists of 774 roads links, 1186 railway links and 481 inland waterway links. 253 NUTS3 zones are modelled and an additional 1641 OD connector links were generated.

We use the multi-commodity freight demand from the NEAC model and distribute the tonnes according to the mode choice model. The route assignment is performed using an all-or-nothing (AON) approach. The base scenario takes approximately two minutes to run on an Apple MacBook Pro with 10 CPU cores. The traffic flow in the base scenario is visualised in Figure 4. The modal split of the model is predominantly Road (79.8%), followed by Railways (12.1%) and Inland Waterways (8.1%). It is important to note that the model simulates demand only between regions, not within them. Additionally, we exclude demand that originates or terminates outside the network, as well as through-traffic. This pattern can be observed in the results, as there is minimal demand moving from the east/southeast to the west of the network. The network shows particularly high traffic near the major EU ports of Rotterdam and Antwerp.

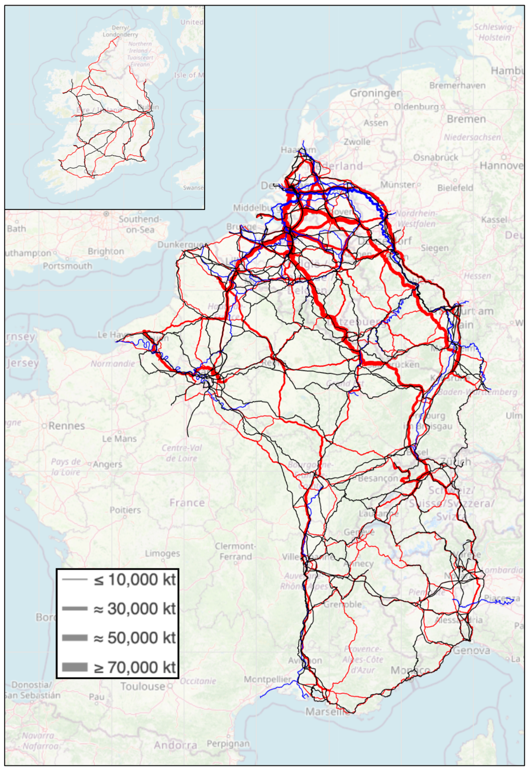

Fig. 4. AON traffic assignment of the NSRM corridor - Picture from the python model

Next we perform the link criticality analysis for the NSRM network. The algorithm ran on 10 CPU cores and finished in 3 h 17 min; because the procedure is parallelized, allocating more cores would further reduce runtime. Figure 5 plots impact versus tonnes affected. Impact is measured as the average relative change in

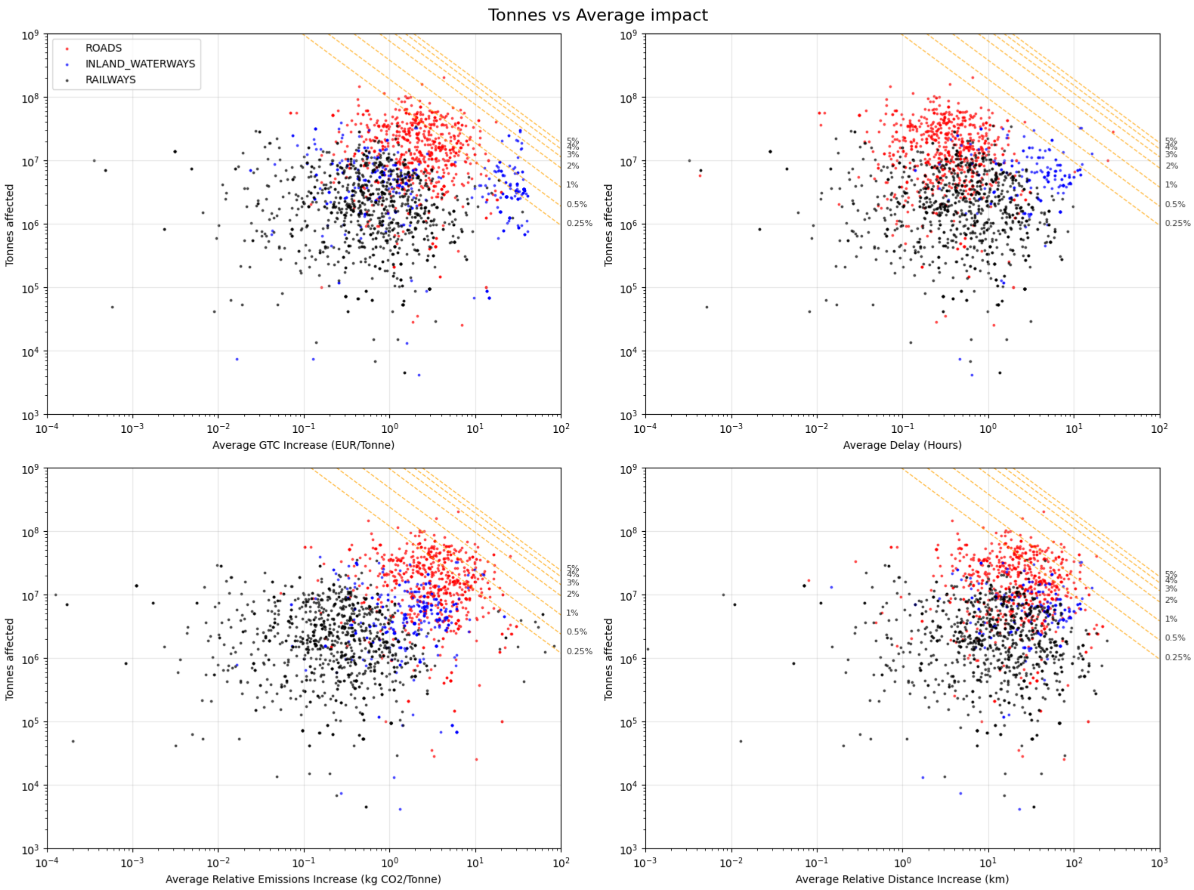

Fig. 5. Tonnes affected vs impact - Link criticality analysis

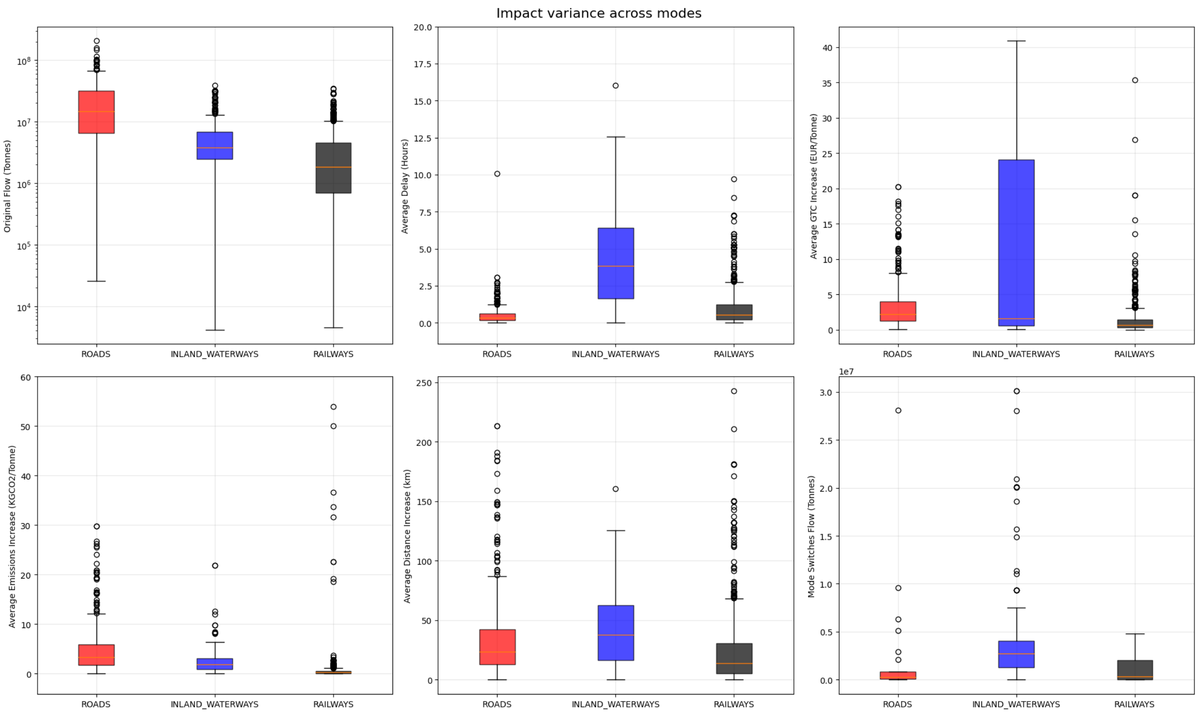

Fig. 6. Variance of average impact of different measures across modes

delay, generalized transport cost (GTC), emissions, and distance for the flows that used the removed link. The orange iso-contribution lines show the product of tonnes affected and impact i.e., the share of the total system cost increase. Because roads carry most freight, removing a road link typically affects more tonnes. Most road removals raise average GTC by 1–10 EUR/tonne, with a few outliers. Inland-waterway removals display much greater dispersion, including a small cluster with very large GTC increases consistent with forced shifts to road. At the system level, road and inland-waterway removals generally produce the largest cost increases: most links raise total system GTC by 0.25 -1%, while the most critical approach 2.5%. Rail removals are comparatively contained.

For delay, most road removals reroute substantial demand but keep average increases under 3 h, except for a few cases where mode shifts drive large delays. Inland-waterway removals affect fewer tonnes but exhibit a wide spread; some even yield negative relative delay when traffic shifts to faster modes. Rail removals are the most contained, influencing fewer tonnes and producing smaller network-wide effects. Emissions follow a similar pattern: roads show the largest relative increases, inland waterways change little on average, and rail is generally low with a few notable spikes involving limited demand. For Average distance increases, the additional detour length when a link is removed are broadly comparable across modes, though some road and rail links require detours exceeding 150 km/tonne.

Finally, Figure 6 summarizes the variance of impact across modes. Roads carry the largest demand but show relatively moderate per-tonne effects. Inland waterways exhibit the widest spread in delay, GTC, and detour distance with heavy-tailed outliers and the share of mode switches. Rail is the most stable overall with lower medians and tighter spreads, though a small number of links still trigger long delays detours. Emission penalties are highest when traffic diverts to road, while IWW and rail shifts add little on average.

The top 10 most critical links of the NSRM corridor are shown in Figure 7. Road links near Basel and Bern represent the three most critical links in the network. The link removal causes a total system GTC increase of 2.2% or € 830 million annually. These sections contain multiple tunnels that function as single points of failure. The main Rhine river artery, which constitutes one of Europe's busiest inland waterway channels, also proves critical for network operations. Any disruption in this section forces freight to shift modes to rail or road transport, increasing total system GTC between 1.9% to

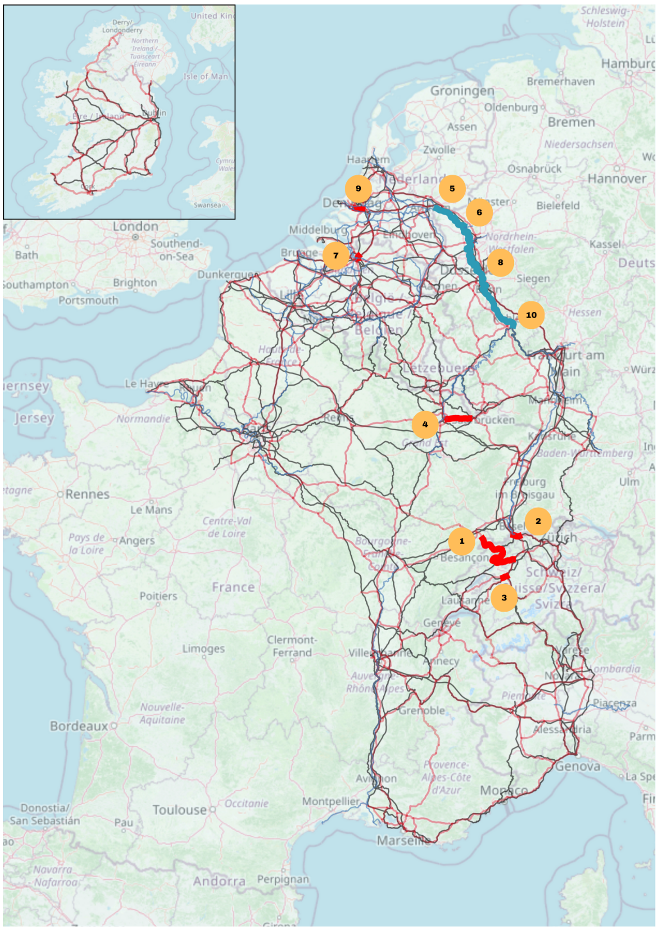

Fig. 7. Top 10 most critical links in the NSRM network based on change in total system GTC

1.4% (€ 750 - € 530 million). Links near Rotterdam and Antwerp, which serve substantial traffic volumes, appear among the critical links because, despite the existence of viable alternatives, the volume of traffic they handle makes them essential to network performance.

The results reveal distinct modal patterns for criticality. Road links, particularly carry the largest freight volumes and, despite abundant alternative routes, create significant total system cost increases when disrupted due to the sheer volume affected. Railways show high redundancy at the system level, but have high localised impacts particularly in the southern part of the network. Inland waterways, especially near sections where the river becomes narrow, exhibit high vulnerability because of limited rerouting options, with link removals forcing costly modal shifts to road and rail.

Among the criticality measures tested, change in total system generalised transport cost (GTC) proved most comprehensive, capturing travel time, distance, emissions (as a function of distance), and mode shifts in a single monetary metric. The most critical links increased total system GTC by €530–830 million annually. Nonetheless other metrics are also important when comparing links within a modality. This is because different modalities value have varying preference for different parameters. For example, a nominal price increase to road transport may not be particularly significant, but when the same price increase affects railways, that increase is felt more acutely. Similarly, travel time is especially important for roadway transport when compared to inland waterways. When adopting an equity perspective, average impact measures provide a more detailed representation of the localized effects of link removal, which highlights structural weaknesses within the network irrespective of traffic volume.

V. Conclusion

Transport resilience has become a highly relevant field in recents years due to growing geopolitical and climate change risks. This study developed and demonstrated a computationally efficient framework to identify and rank critical links in multimodal freight networks at a strategic level. Using the North Sea–Rhine–Mediterranean (NSRM) TEN-T corridor as a case study, we applied a multi-commodity freight demand model (NEAC), mode choice modelling, and all-or-nothing (AON) route assignment to assess the impacts of link removal on network performance using a novel multimodal link criticality model.

The model addresses gaps in link criticality research by incorporating multimodality and behavioural responses into a computationally light framework. While it simplifies certain aspects such as aggregating demand at the NUTS-3 level, assuming technical compatibility across all links, omitting intrazonal and through-traffic, and ignoring capacity and congestion, it balances realism with scalability. These trade-offs allow application to larger networks such as the larger comprehensive TEN-T network.

Practically, the proposed framework equips planners with a tool for scanning large multimodal networks to identify and rank critical links without requiring extensive data collection or computational power. This initial screening enables planners to focus their attention where it matters most, performing comprehensive assessments toward those links whose failure would have the most significant system-wide impacts. For each identified critical link, planners can explore potential disruption threats for that specific link and develop targeted mitigation measures to reduce the likelihood or severity of failure. Disruptions are not always day to day, climate changes can have long term impacts on the usability of certain modes. For example, planners can model the annualised effect of extended low water levels on inland waterways, recognising that such issues cannot be resolved immediately and require strategic adaptation measures. In the context of maintenance planning, the model's results can inform decisions if careful planning is required for long term maintenance works. As the model integrates all modes into a unified performance view, it also helps identify the most effective substitutes when a particular link is closed. The model also quantifies the "cost of inaction" by estimating the economic and operational consequences of leaving a vulnerable link unaddressed, and conversely, it can assess the benefits to the overall network from adding new links, supporting robust cost–benefit analyses for infrastructure projects. Beyond civilian logistics, the framework's outputs are also relevant in the context of the EU's Military Mobility plan, which envisions the TEN-T network as dual-use infrastructure for both civilian and defence purposes. In such scenarios, the model can identify highly vulnerable links whose disruption would hinder rapid military deployment. Here, performance indicators such as average travel time or network accessibility become more critical than purely cost-based measures, as there is more priority for rapid troop and equipment movement to border regions during emergencies.

Future work could enhance the framework by incorporating greater network detail, such as explicitly modelling terminals, ports, and directed links, to more accurately represent real-world infrastructure and operational constraints. Integrating capacity measures would allow the analysis to capture how the removal of a particular link affects the throughput of connected infrastructure. The framework could also be combined with hazard maps or failure probability data to produce risk maps, enabling prioritisation not only by criticality but also by likelihood of disruption. Finally, extending the methodology to other infrastructure systems such as pipelines would broaden its applicability and support more interdependent network resilience planning.

In summary, the proposed framework offers a scalable, adaptable, and decision-oriented method for evaluating multimodal freight network robustness, enabling targeted investments that deliver the greatest system-wide benefits. The code for the framework and the data used can be found at `https://github.com/sathvikgadiraju/Link-criticality-framework`.

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Appendices

A Geospatial visualisation of link criticality

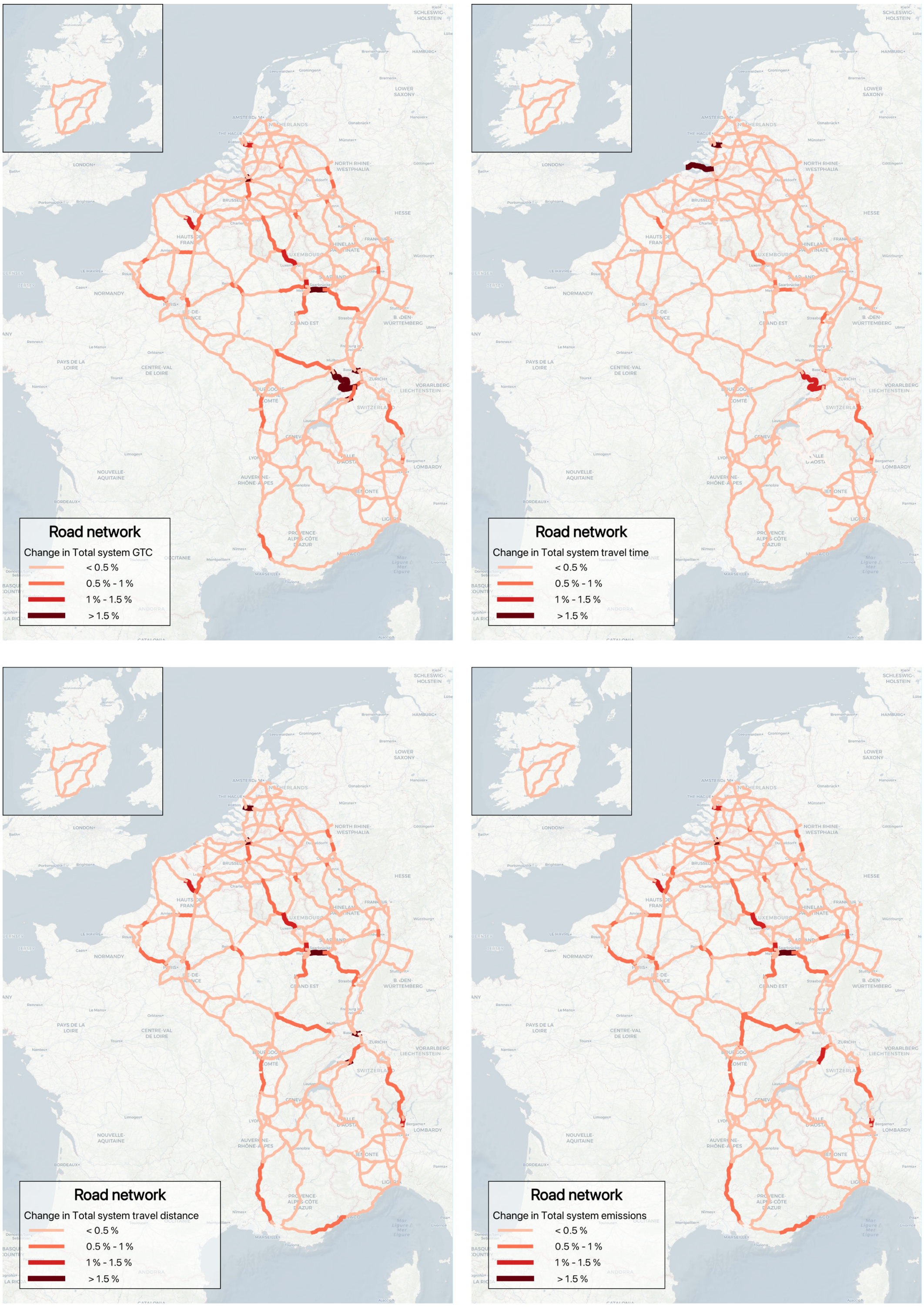

Figure 5.1: *Geospatial visualisation of total system metrics in the road network*

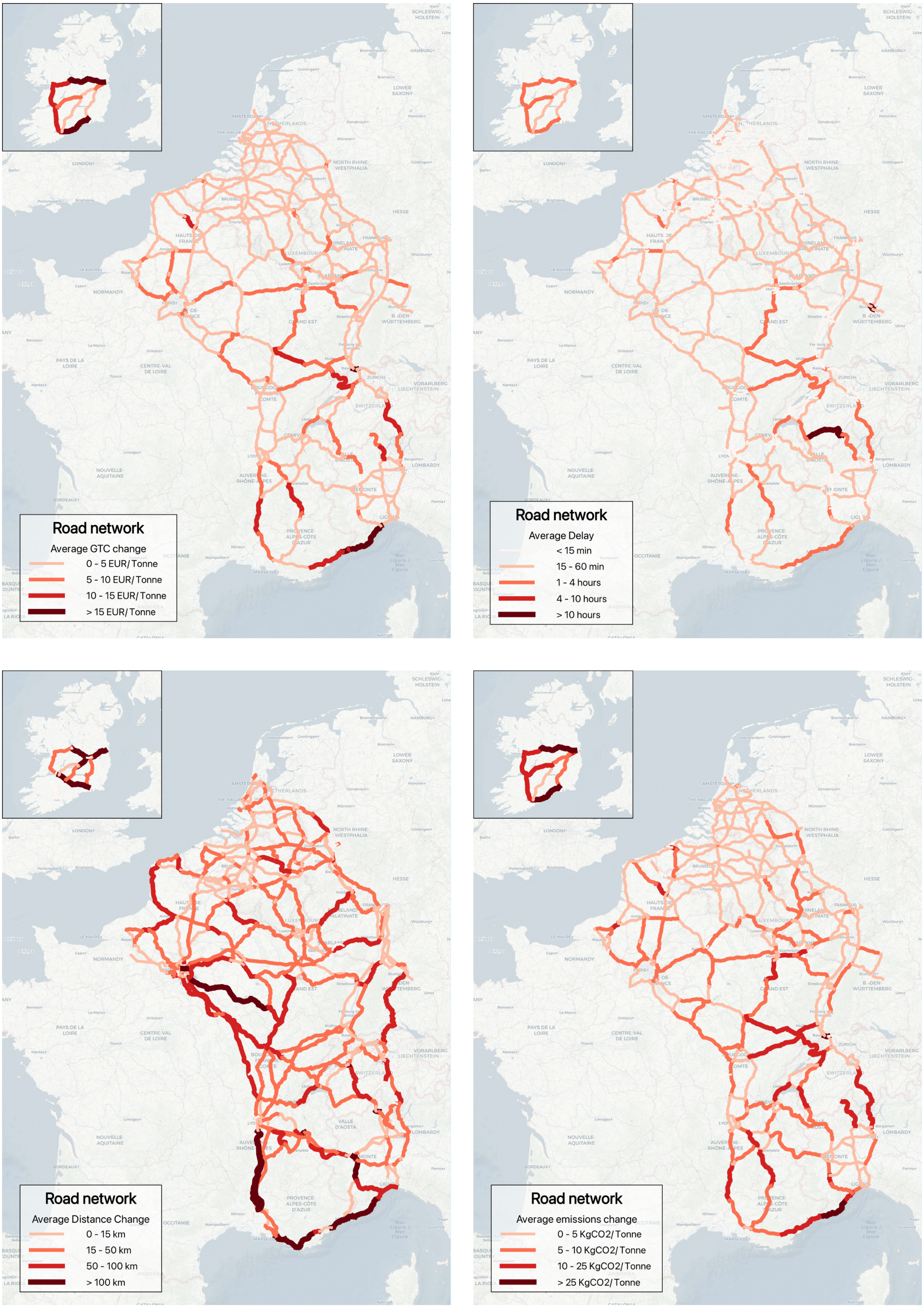

Figure 5.2: *Geospatial visualisation of average impact metrics in the road network*

Figure 5.3: *Geospatial visualisation of total system metrics in the rail network*

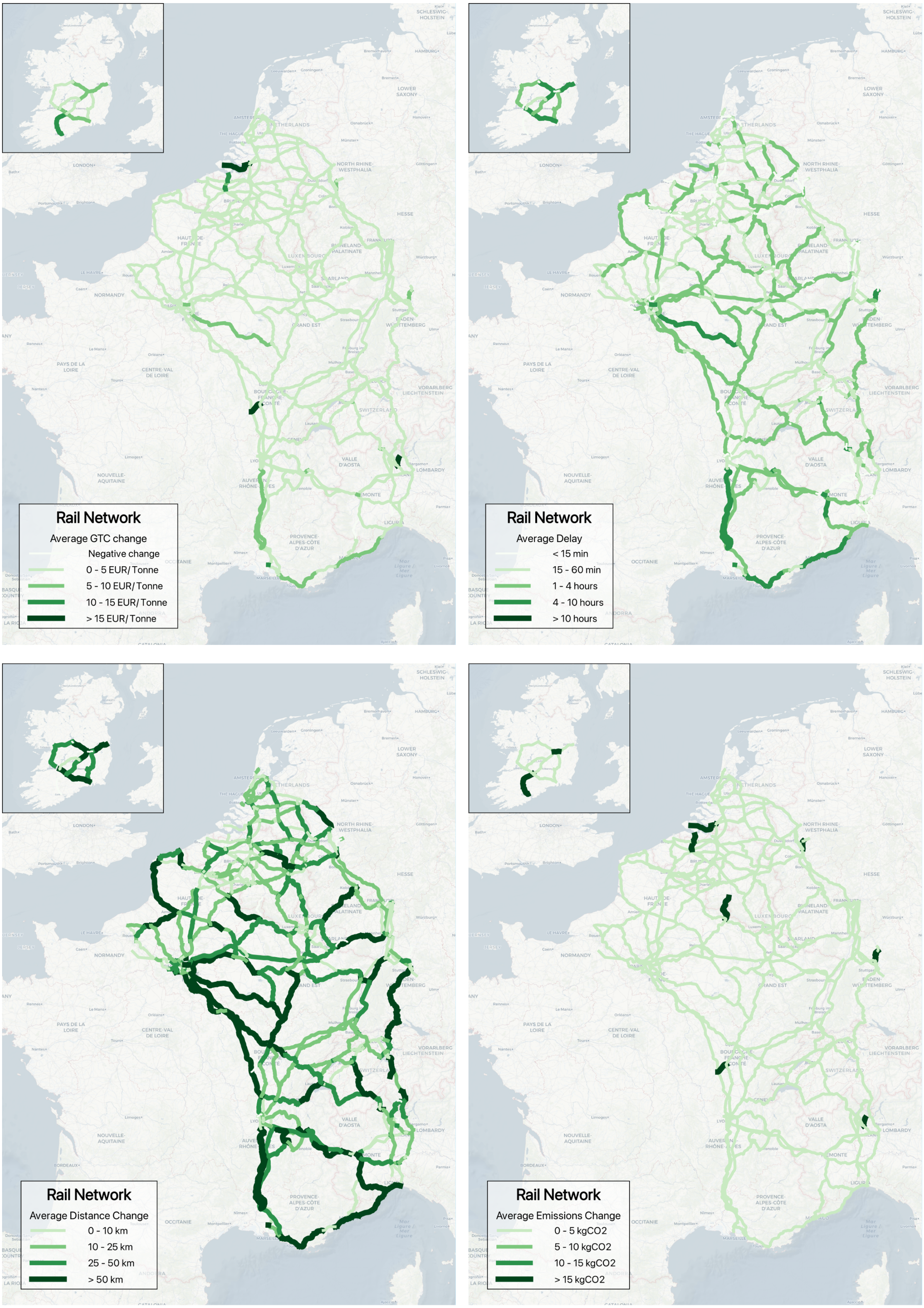

Figure 5.4: *Geospatial visualisation of average impact metrics in the rail network*

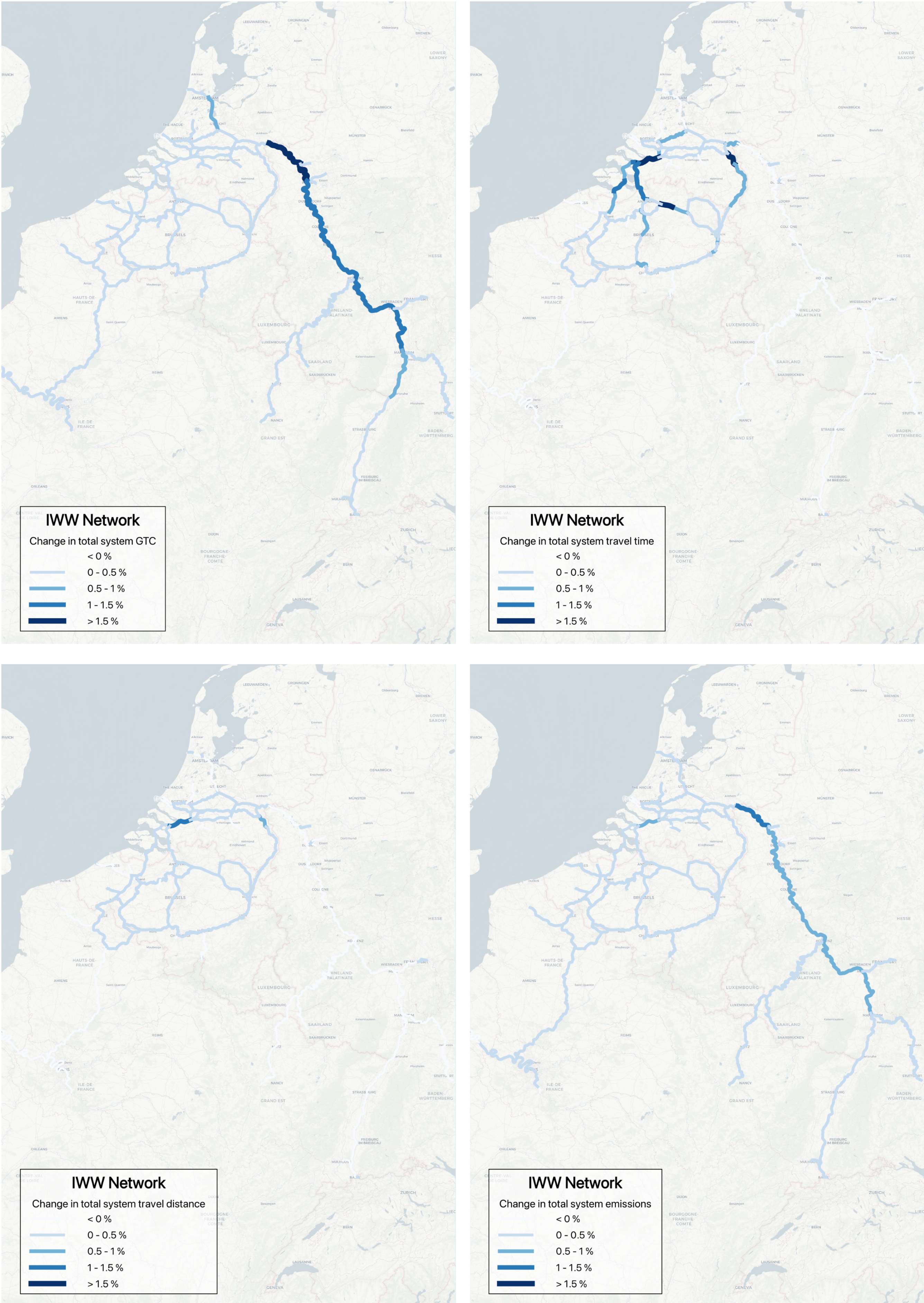

Figure 5.5: *Geospatial visualisation of total system metrics in the IWW network*

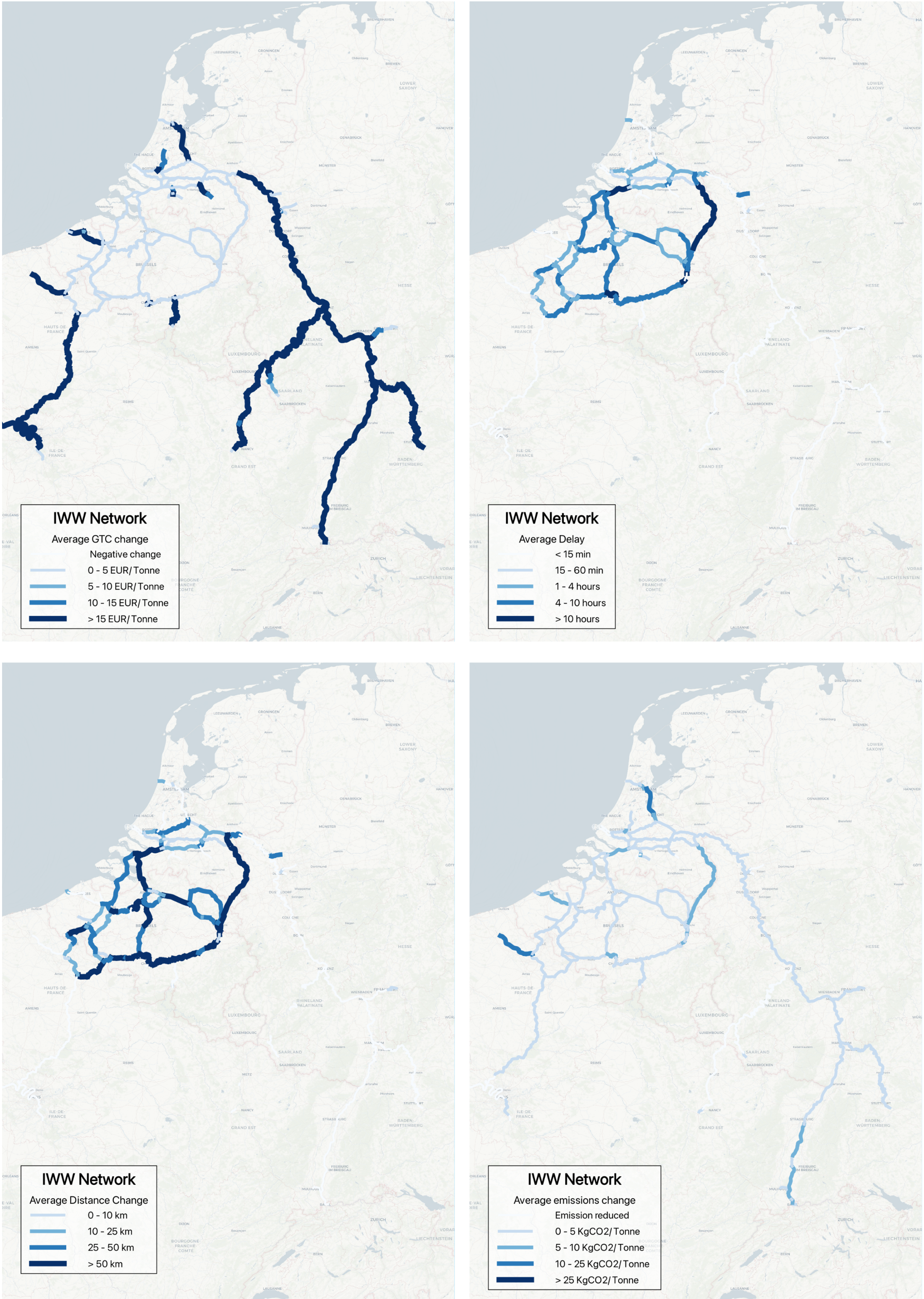

Figure 5.6: *Geospatial visualisation of average impact metrics in the IWW network*

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Annexes

L TENT Corridor

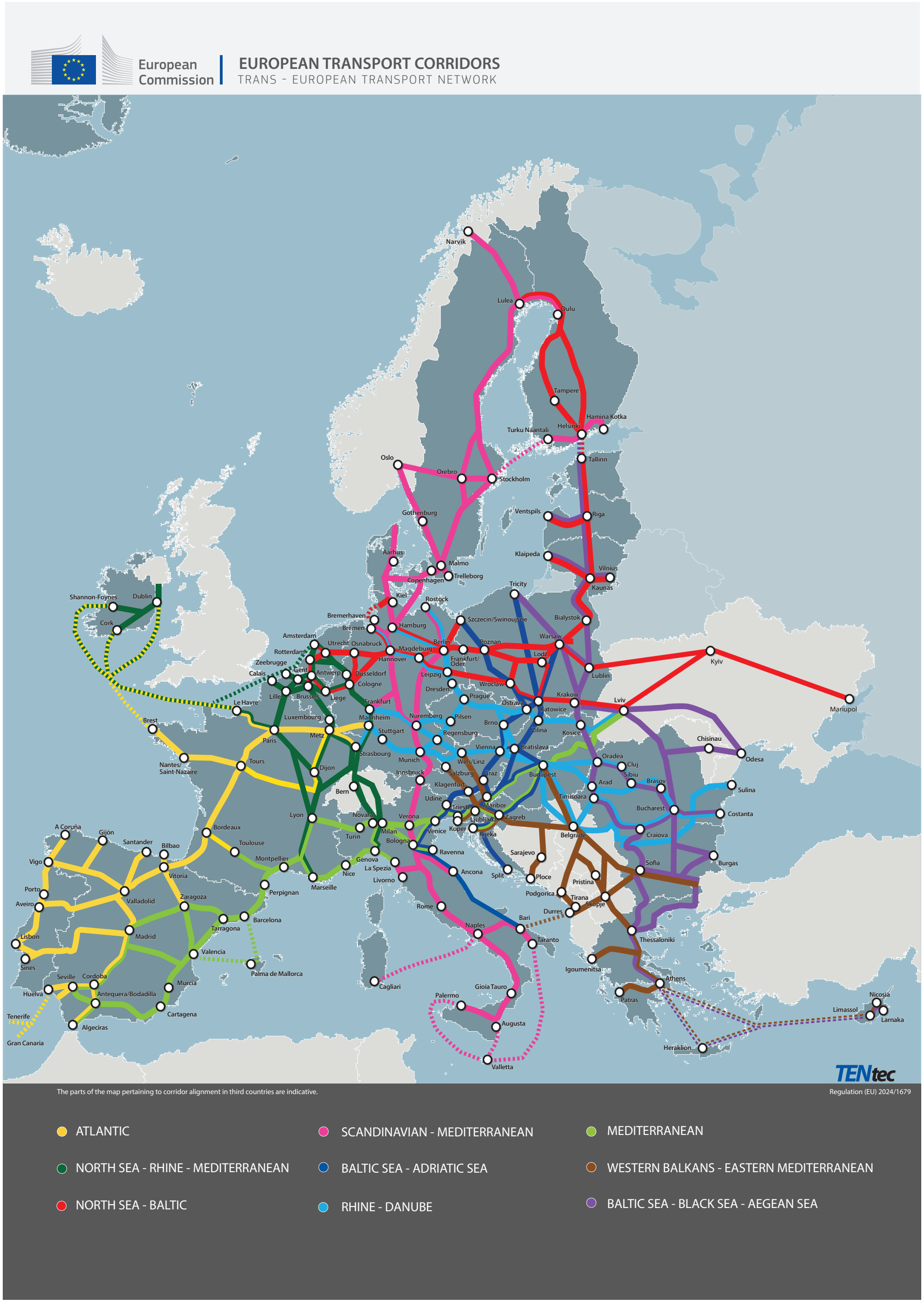

Figure 5.7: *TENT map*

M NEAC Mode split model parameters

	nstr0	nstr1	nstr2	nstr4	nstr5	nstr6	nstr7	nstr8	nstr9	nstr10
A_RAIL	-1.9225	-3.1145	-1.0756	-1.6209	-0.8901	-2.7242	-2.6939	-2.3372	-1.8668	-1.3862
A_INLWW	-2.0620	-2.6490	-0.4265	-1.4461	-2.7086	-1.2998	-0.8092	-2.9036	-3.7000	-0.9052
A_SEA	-0.4138	-0.4076	0.6971	0.0731	0.5149	0.0063	-0.5515	0.2736	0.0835	0.9607
ARAILE	5.2743	2.8520	1.7196	1.0463	3.4922	3.1458	2.5742	3.1979	2.0749	2.4966
AIWWE	-2.1590		-4.2746	-4.5100	-1.0760	-3.1421				
ASEAE	-1.7732	-1.7764	-2.3677		-2.6656	-2.1006		-1.4949	-2.2051	-1.0672
ARAILWE	5.2397	2.5573	3.8239	3.7283	2.9102	2.0834	3.9495	4.0129	0.6811	2.3404
AIWWWE	-0.6044						1.9336	-0.8149	-1.5599	
ASEAWE	0.3403		1.5127		-0.8794		2.9763	-0.0936	-0.9325	0.4747
B_ROAD		-0.6850							-0.3768	
B_RAIL	-1.4129	-0.7757	-2.5009	-2.4415	-0.7071	-1.2590	-1.7007	-1.2655	-0.7522	-1.5663
BCOST	-0.0061	-0.0048	-0.0051	-0.0143	-0.0041	-0.0093	-0.0257	-0.0044	-0.0052	-0.0061
BCROADE	-0.0079	-0.0084	-0.0304	-0.0205	-0.0163	-0.0216		-0.0057	-0.0067	
BCRAILE	-0.0306	-0.0237	-0.0503	-0.0265	-0.0159	-0.0879		-0.0260	-0.0052	-0.0388
BCIWWE										
BCSEAE	x	x	x	x	x	x	x	x	x	x
BCROADWE					-0.0062	-0.0027				
BCRAILWE	-0.0334	-0.0334	-0.1266	-0.1364	-0.0147	-0.0697	-0.0897	-0.0603	-0.0047	-0.0606
BCIWWWE						-0.0661				
BCSEAWE	x	x	x	x	x	x	x	x	x	x
BC5SEA	-0.0083		-0.0411		-0.0074	-0.0092	-0.0321	-0.0108	-0.0163	

Figure 5.8: *NEAC mode split model parameters*