Louvain School of Management
and Instituto Superior Técnico

Evaluating the Impact of Supply Prepositioning and UAVs on Flood Preparedness in Belgium

A Two-Stage Scenario-Based Optimizaion Approach

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During the preparation of this master's thesis, I, António Pereira, utilized the AI service ChatGPT for the following purposes:

1. **Debugging OPL Code:** ChatGPT assisted in identifying errors and suggesting fixes in my Optimization Programming Language (OPL) code.
2. **LaTeX Assistance:** ChatGPT provided guidance on using LaTeX for document preparation, ensuring proper formatting of the thesis.
3. **Writing Refinement:** ChatGPT helped refine the text of the thesis, offering suggestions for clearer communication of my research findings.

After using ChatGPT, I diligently reviewed and edited the content produced by the tool. I take full responsibility for the final content presented in this thesis.

By signing this declaration, I affirm that the content of this master's thesis reflects my original work, augmented by the responsible use of AI.

António Pereira

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Abstract

Floods are among the most devastating natural disasters, posing significant risks to communities worldwide. In recent years, the increasing frequency and severity of floods, exacerbated by climate change, have underscored the need for enhanced disaster preparedness, particularly in vulnerable regions like Belgium. This research explores the potential of strategically pre-positioned disaster relief centers and the integration of Unmanned Aerial Vehicles (UAVs) to improve flood preparedness and, consequently, improve disaster response time in Belgium.

Through a two-stage scenario-based optimization model, this research evaluates the impact of establishing multiple relief centers across Belgium and incorporating UAVs into the disaster relief fleet. To apply the model to the specific case of Belgium scenarios were developed through historical flood data and geographical analysis. Through this scenarios the model is able to identify optimal locations for relief centers and determine the most effective quantities of emergency supplies to pre-position.

The findings demonstrate that the strategic placement of relief centers significantly reduces response times and enhances the flexibility of supply distribution, ensuring the timely delivery of critical resources during flood events. Additionally, UAVs offer a valuable advantage by quickly accessing damaged or hard-to-reach areas, surpassing traditional transportation methods in speed and efficiency. This research underscores the importance of innovative logistical strategies in building a resilient disaster response system and provides actionable insights that can improve Belgium's flood preparedness and mitigate the adverse effects of future flood events.

Keywords: flood preparedness; unmanned aerial vehicles; scenario-based optimization; Belgium; disaster relief centers; supply pre-positioning

Contents

Chapter 1

Introduction and Research Framework

1.1 Introduction

The European Environment Agency (EEA) describes natural disasters as a violent, sudden, and destructive change in the environment without cause from human activity (EEA, 2004). Floods are the most common natural disaster and occur when excess water from heavy rainfall, rapid snowmelt, or coastal storm surges from cyclones or tsunamis inundates normally dry land. Depending on their intensity, floods can cause widespread devastation leading to the loss of life and destruction of public and private property (World Health Organization, 2017).

In 2023, more than 54 million people worldwide were affected by floods, with the death toll reaching 7,398 individuals (Salas, 2023). The 2021 floods in Belgium and Germany resulted in over 200 fatalities, highlighting that developed countries are also significantly impacted by this hazard (Salas, 2023). In the first five months of 2024 alone, two major flood events occurred: in April, the UAE and Oman experienced over a year and a half's worth of rainfall in just 24 hours, leading to widespread flooding across both countries (Dewan, 2024), and in May, the state of Rio Grande do Sul in Brazil was also hit by severe rainfall that caused deadly floods (Buschschlüter, 2024).

Climate change is a reality that is influencing the intensity and frequency of natural disasters (EEA, 2021). Climate models, developed in several research articles, lead to the conclusion that flood risk and the number of people exposed to it will increase throughout the current century (Arnell and Gosling, 2014; Hirabayashi et al., 2013). Additionally, the increase in costs due to flooding has been associated with climate change. For example, historical precipitation changes in the United States are estimated to be responsible for a 36% increase in the cost of flood damage, and climate models indicate that anthropogenic climate change increased the likelihood that heavy precipitation is associated with this cost (Davenport et al., 2021).

Belgium is not free from the consequences of climate change. Projections from climate models indicate that Belgium will experience changing precipitation patterns, with increased rainfall during the winter and more frequent heavy rain episodes. While predicting storms is more challenging, there is a potential for both their frequency and intensity to rise. Studies on Belgian hydrographic basins suggest that the flood risk will increase throughout this century. Additionally, rising sea levels and potential storm surges pose significant threats to Belgium's coastal regions. (Marbaix, 2004)

Belgium governmental bodies are aware of the country's exposure to this hazard and regularly conduct risk assessments. The National Crisis Center's risk assessment for 2018-2023 identified three main types of flood risks: fluvial flooding, pluvial flooding, and flooding from the sea. Flooding from the sea was classified as highly impactful but the least likely, while fluvial flooding (overflow of river banks) and pluvial flooding (rainwater runoff) are more probable, with fluvial flooding being the most impactful out of the two. (National Crisis Center, 2023)

Humanitarian or disaster relief supply chains are responsible for securing the required resources and getting them to the disaster site, helping both the recovery and response process (Day et al., 2012). Humanitarian relief organizations meet the demand for these resources from several sources such as pre-positioned supplies, in-kind donations, and procured supplies (Balcik et al., 2014). Thus, setting a distribution network with pre-positioned supplies capable of efficiently arriving at disaster sites plays a critical role in increasing preparedness and mitigating the negative impact of disasters, such as floods (Torabi et al., 2018).

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have emerged as a revolutionary technology in disaster relief operations. UAVs can quickly reach areas that are inaccessible due to flooding, providing a rapid response mechanism for delivering essential supplies such as food, water, and medical aid. Their ability to bypass ground-based obstacles makes them particularly valuable in the immediate aftermath of a disaster when traditional transportation infrastructure may be compromised. (Rejeb et al., 2021)

Given the increasing exposure to flooding in Belgium due to climate change, it is important to establish a well-prepared distribution network capable of rapidly delivering critical relief supplies to affected populations. The recent establishment of a disaster relief center by Amazon in Rheinberg, Germany, exemplifies a proactive approach to managing flood events through strategic supply positioning (Belga, 2024). Expanding the number of such facilities within Belgium and incorporating UAVs in the response fleet could significantly enhance the country's flood preparedness. By strategically pre-positioning supplies and introducing disruptive technologies, Belgium can ensure a swift and effective response to flood emergencies, thereby mitigating the negative impacts of such disasters and improving overall disaster resilience.

1.2 Research Question

This thesis aims to study how the introduction of additional relief centers and the use of UAVs can improve Belgium's flood preparedness, particularly their ability to deliver emergency aid in a rapid and flexible manner. The main objective is to evaluate the benefits of pre-positioning supplies and establishing disaster relief centers in Belgium, focusing on reducing response times and enhancing the effectiveness of emergency supply delivery.

As presented in the introduction, floods pose a significant risk to Belgium, and with climate change likely to increase the frequency and severity of such events, there is an urgent need to develop more efficient and effective response mechanisms. By exploring the strategic placement of relief centers and the integration of UAVs, this research aims to provide actionable insights that can enhance the resilience of Belgium's disaster relief efforts.

The thesis will address the following research questions:

- How does the strategic placement of multiple relief centers improve flood preparedness and response times in Belgium?
- What is the impact of integrating UAVs into disaster relief logistics on the efficiency and speed of emergency supply distribution during flood events in Belgium?

These research questions can improve the understanding of how innovative logistical strategies can mitigate the adverse effects of floods, ensuring that aid reaches affected populations effectively. The findings from this research have the potential to inform policy and operational decisions, contributing to a more prepared response framework in Belgium.

1.3 Methodology

This research employs a two-stage scenario-based optimization model to enhance flood preparedness in Belgium. The model focuses on determining the optimal placement of distribution centers and the quantities of relief supplies to pre-position, integrating the use of UAVs for efficient emergency supply distribution.

To develop the model, a literature review on disaster relief modeling techniques along with a benchmark of disaster relief management were conducted. This review considered several approaches and methodologies used in the field, providing a solid theoretical foundation and some practical insights required for creating a robust model. The acquired knowledge enabled the identification of critical factors in disaster relief operations and subsequent modeling, ensuring that the developed model effectively addresses relevant aspects of humanitarian logistics.

For model implementation, data will be collected on historical flood events and geographical information. This data will help create realistic scenarios that reflect potential flood impacts, disruptions, and response times. Additionally, logistics data, including transportation networks, distances between facilities and rescue points, and associated costs, will be used to set the necessary parameters for the model.

The expected results include assessing the benefits of strategies such as pre-positioning supplies at relief centers and introducing technologies like UAVs to minimize response times and improve the efficiency of emergency supply delivery. By analyzing different configurations, such as the introduction of multiple distribution centers and the integration of UAVs, the model will provide insights into how these strategies can enhance flood preparedness.

These results will directly address the research questions by demonstrating how the strategic placement of relief centers and the use of UAVs can improve the rapid and flexible delivery of emergency aid during flood events in Belgium. This will ultimately contribute to a more resilient and prepared disaster response framework in the country.

1.4 Limitations

While this master thesis aims to provide a robust analysis of possible improvements of flood preparedness in Belgium through the strategic placement of relief centers and the integration of UAVs, several limitations must be acknowledged:

- **Data Availability and Quality**: The accuracy and overall quality of the model is higly dependent on the quality and availability of the required data. Gaps or inaccuracies in historical flood data, climate projections, and logistical information will impact the model's outcomes.
- **Simplified Assumptions**: The model incorporates several simplified assumptions, especially in the second stage decisions. For instance, the delivery optimization is reduced to a basic supplies allocation model, without considering more complex vehicle routing optimization techniques. This simplification does not reflect some of the logistical challenges of actual emergency supply distribution.
- **Transportation Fleet**: The model's comprehensiveness could be enhanced by incorporating fleet decisions at each facility in the first stage. However, this would significantly increase computational complexity. For simplicity, transportation fleets are assumed to be constant across all relief facilities to avoid misleading results. Despite this simplification, fleet availability remains a critical factor that can influence the effectiveness of disaster relief operations and should be considered in future studies.
- **Focus on Response Time**: Emphasizing response time may overlook other important aspects of disaster relief, such as long-term recovery and resilience building. This focus may lead to strategies optimal for immediate relief but not sustained disaster management.
- **Lack of Stakeholder Validation**: Due to time constraints, scenarios and model parameters will not be validated by experts, potentially introducing some bias or inaccuracies.
- **Integration of UAVs**: Assumptions about UAV capabilities and performance may vary significantly, depending on the chosen models. Additionally, some ethical concerns are still being raised about this technology. This means that possible future regulatory restrictions on the use of this technology are not considered.
- **Budget Constraints**: Actual costs for setting up distribution centers, pre-positioning supplies, and deploying UAVs can vary. Estimations used may not fully capture financial complexities, affecting cost-benefit analysis accuracy.

These limitations highlight possible areas for further study. Despite these limitations, the research offers relevant insights into the potential benefits of strategic distribution center placement and UAV integration in enhancing flood preparedness in Belgium.

1.5 Outline

This thesis is structured into six chapters, each focusing on a vital component of the research. The current Chapter, *Introduction and Research Framework*, provides an overview of the research topic, outlines the research questions, and establishes the framework for the study. It introduces the importance of flood preparedness in Belgium and the potential role of strategic distribution centers and UAVs. Following this, Chapter 2, *Literature Review*, reviews existing literature on disaster relief logistics, scenario-based optimization models, and the use of UAVs in emergency response, identifying gaps in the current research and positioning this study within the broader academic context.

Building on the literature review, Chapter 3, *Mathematical Formulation*, details the two-stage scenario-based optimization model used in the study, explaining the model's structure, decision variables, objective function, and constraints. With the model framework established, Chapter 4, *Data Collection and Processing*, describes the data collection process, including the types of data gathered for scenario development and parameter setting, and discusses the methods used to process and integrate this data into the model.

Chapter 5, *Model Implementation and Results*, covers the implementation of the model using GAMS, presenting the results and highlighting the effectiveness of various strategies for improving flood preparedness and response times. Finally, Chapter 6, *Conclusion*, summarizes the key findings of the research, discusses the implications for flood preparedness in Belgium, suggests areas for future research, and reflects on the limitations of the study. This logical progression ensures a comprehensive exploration of the research problem, from theoretical foundations to practical implementation and analysis.

Chapter 2

Literature Review

The literature review of this thesis aims to provide an overall understanding of disaster relief management, present different disaster relief models and introduce the use of UAVs in disaster relief operations. This review is structured into three main sections.

The first section will provide an overview of disaster relief management, while also focusing on the importance of humanitarian logistics to disaster relief along with some of its key-components and challenges.

The second section will focus on reviewing different disaster relief models, with a particular emphasis on two-stage scenario based optimization models. These models will be analyzed in order to identify key features and methodologies that could be incorporated in a disaster relief model that can assist the decision-making process regarding strategic considerations to improve flood preparedness in Belgium.

The third section will look into the role of technology in enhancing humanitarian logistics, specifically on the application of unmanned aerial vehicles (UAVs) during disaster relief operations. This section will explore key capabilities and performance outcomes of UAVs, drawing from relevant academic literature and case studies. The analysis aims to highlight the operational opportunities presented by UAVs, providing insights into how their deployment can improve the efficiency and quickness of disaster response efforts.

2.1 Disaster Relief Management

Disaster can be classified according to three different aspects: source, location and speed of onset (Ergun et al., 2008; Apte, 2009) as illustrated in Figure 2.1. The onset and location characteristics of the disaster determine the degree of effort required to achieve an effective disaster response. A slow-onset disaster does not require an urgent response, as relief items demand for such events appears more gradually. Sudden onset disasters, on the other hand, strike suddenly without a transitional phase, creating a mismatch problem between the relief items delivered and the demand from affected communities. (Duran et al., 2013)

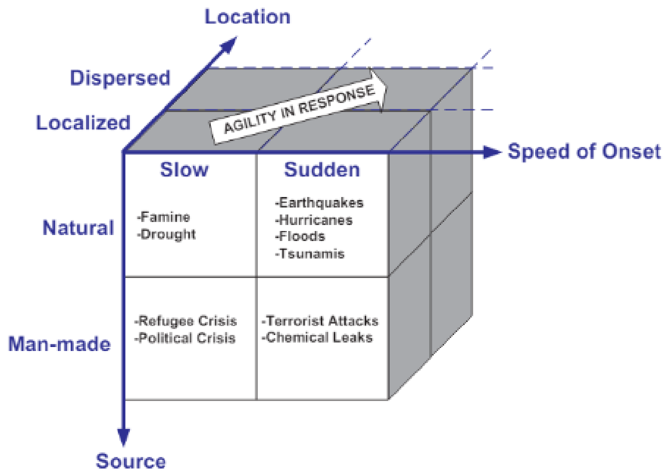


Figure 2.1: Classification of Disasters (Source: Duran et al., 2013)

Disaster management encompasses a wide array of activities, displayed in Figure 2.2, designed to reduce the impact of natural and man-made disasters. These activities are typically categorized into four phases: mitigation, preparedness, response, and recovery. Mitigation involves long-term measures to prevent or minimize the effects of disasters, such as building codes and land-use planning. Preparedness includes the development of emergency plans and training, ensuring that systems are in place to respond efficiently when a disaster occurs . Response activities focus on immediate actions taken during and after a disaster to save lives and reduce harm, such as emergency medical assistance and evacuation. Recovery involves restoring communities to normal or improved conditions after a disaster. (McLoughlin, 1985)

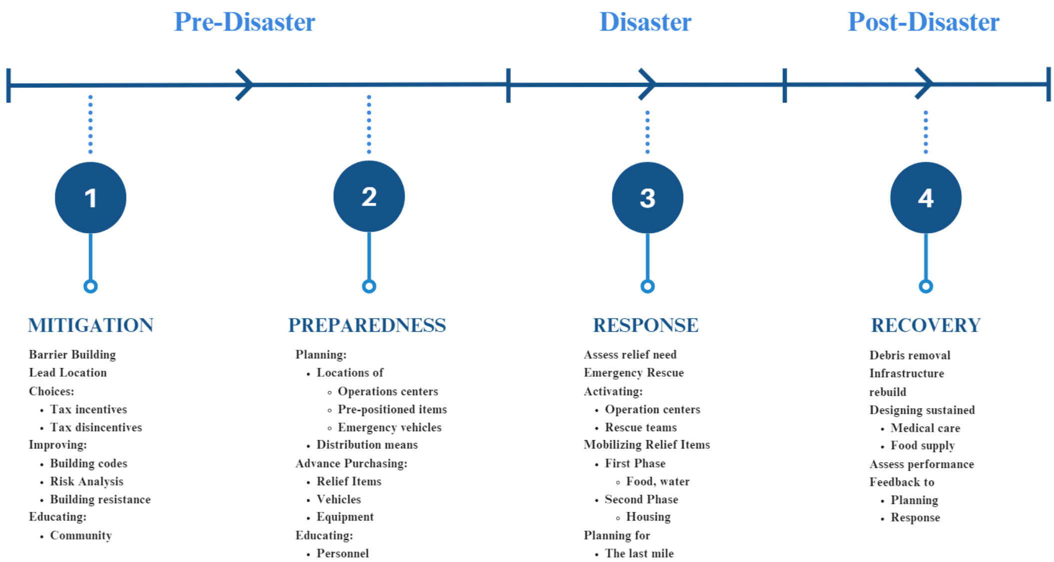


Figure 2.2: Disaster Relief Phases (Duran et al., 2013)

Humanitarian logistics plays a crucial role in all phases of disaster management. It involves the planning, implementing, and controlling of efficient, cost-effective flow and storage of goods and materials, from the point of origin to the point of consumption, with the goal of meeting the needs of disaster-affected people (Thomas et al., 2005). Humanitarian logistics is distinguished from commercial logistics by its focus on unpredictability, urgency, and the need for flexibility and agility in response to rapidly changing situations (Duran et al., 2013; Kovács & Spens, 2007; Çelik et al., 2012).

Logically, in order to achieve effective disaster management, it is essential to focus on quality humanitarian logistics. Given the complexities inherent to this field, certain components stand out as particularly crucial for achieving the objectives of disaster relief:

- **Pre-Positioning and Stockpiling:** Pre-positioning involves storing relief supplies in strategic locations to ensure quick deployment during a disaster. This strategy reduces the time required to deliver aid and can significantly enhance the efficiency of disaster response. The effectiveness of pre-positioning depends on the careful selection of storage locations, types of supplies, and quantities stored. The use of advanced purchasing agreements also helps in procuring necessary supplies at optimal prices and in time, enhancing preparedness. (Duran et al., 2013)
- **Stakeholder Coordination:** Disaster relief involves multiple stakeholders, including governmental agencies, non-governmental organizations (NGOs), military, private sector, and donors. Effective coordination among these parties is crucial for successful disaster management (McLoughlin, 1985). Governments typically lead the efforts in mitigation and preparedness, while NGOs and international organizations often take charge during response and recovery phases (McLoughlin, 1985; Van Wassenhove, 2006). Collaboration between these entities ensures that resources are used efficiently and that efforts are not duplicated (Van Wassenhove, 2006).
- **Last Mile Distribution:** The ”last mile” refers to the final leg of the supply chain, where relief items are delivered directly to the affected populations. This phase is often the most challenging due to damaged infrastructure, security issues, and the need to reach remote or dispersed populations (Kovács and Spens, 2007). Effective last mile distribution requires meticulous planning, local knowledge, and often innovative solutions to overcome logistical barriers (Van Wassenhove, 2006).

Humanitarian logistics faces a wide array of challenges that can significantly impede the effectiveness of disaster relief operations. These challenges affect the critical components discussed above and must be addressed with careful consideration when developing preparedness strategies. The primary obstacles include:

- **Resource Constraints :** Limited financial and material resources can damage the ability to stockpile sufficient supplies or to respond promptly to disasters (Duran et al., 2013).
- **Infrastructure Damage:** Disasters often damage critical infrastructure, making transportation and communication difficult. This can delay the delivery of aid and complicate coordination efforts (Kovács and Spens, 2007).
- **Coordination Issues:** With multiple stakeholders involved, coordination can be challenging. Differences in organizational cultures, objectives, and operating procedures can lead to inefficiencies and delays (McLoughlin, 1985; Van Wassenhove, 2006).

- **Unpredictability and Uncertainty:** The unpredictable nature of disasters makes it difficult to plan and prepare effectively. Humanitarian logistics must be flexible and adaptable to respond to changing circumstances (Duran et al., 2013; Kovács and Spens, 2007).

2.2 Disaster Relief Modeling

Disaster relief models encompass a broad spectrum of methodologies, each one able to address different characteristics of disaster management. Among these, the application of game theory in the preparedness stage, as delineated by Seaberg, Devine, and Zhuang (2017), concentrates on studying the dynamics of stakeholder interactions throughout this stage along with its impact on the latter stages. These models tend to show that cooperation between entities leads to better outcomes for disaster relief efforts. For example, a study on the joint stockpiling of medical inventory among multiple hospitals revealed that a centralized decision model, instead of a non-cooperative strategic game where each hospital wants to minimize their cost with stocks, originates a lower aggregate stock cost along with increased disaster preparedness (Adida et al., 2011). Despite game theoretic models not being the most relevant to study optimal relief network setups, insights driven from such models can be used to develop more comprehensive quantitative models.

The aforementioned quantitative models are discussed by Baxter, Wilborn Lagerman, and Keskinocak (2020) and align more closely with the objectives of this thesis, particularly regarding the strategic placement of disaster relief facilities and the optimization of supply pre-positioning. Leveraging such models can improve facility location and supply prepositioning decision-making, originating more effective relief chains. This entails that these models can originate better outcomes such as a reduction on the overall cost of the relief chain along with minimal post-disaster response time.

Interdependencies, such as dependency between relief supplies, often arise while attempting to depict a disaster through quantitative models. Incorporating them in the model leads to more accurate representation of the disaster, however the complexity introduced by these additions might lead to infeasibility or excessive computational times. (Baxter et al., 2020)

Two-stage scenario based models are quantitative models particularly relevant in the disaster management field. This approach divides decision-making into two distinct phases, each corresponding to different stages of disaster management. Initially, decisions are made prior to the full realization of a disaster's impact, allowing for preparatory actions such as the strategic pre-positioning of relief supplies. These first-stage decisions are made with an understanding that they are based on predictions and available data, and not on the complete picture of the disaster's specifics. Subsequently, once the disaster occurs and its effects become evident, second-stage decisions are taken to adjust the response according to the actual needs and conditions observed. This model's strength lies in its ability to integrate flexibility and adaptive capacity into disaster response strategies, making it possible to optimize resource allocation and effectiveness in both pre and post-disaster scenarios. (Grass et al., 2016)

Renkli and Duran (2014) propose a nuanced approach to disaster management through a mixed integer programming (MIP) model designed for the strategic pre-positioning of warehouses and allocation of relief items. The model aims to optimize the logistics of disaster response by minimizing the response time required to deliver relief items to affected areas. An interesting feature of their methodology is the extension of the initial model through the introduction of probabilistic constraints, addressing the uncertainty inherent in disaster impact, particularly on infrastructure. Initially, the model starts with an uncapacitated location problem (UNLP), focusing on minimizing the total weighted distance between disaster response facilities (DRFs) and affected areas, which directly correlates with reducing response times.

The subsequent iteration, UNLP with chance constraints (UNLP-C), incorporates the concept of infrastructure vulnerability by ensuring a certain level of reliability in relief transportation. This adjustment reflects an advanced consideration of real-world disaster scenarios where the physical damage to infrastructure can significantly impede relief efforts. The transition from a deterministic to a chance-constrained model addresses some of the complexity of disaster response logistics, where not only the strategic location of supplies matters but also the assurance that these supplies can reach their intended destinations despite potential infrastructure failures.

Balcik and Beamon (2008) developed a model aimed at optimizing the configuration of distribution centers in the global humanitarian relief chain, specifically designed for quick-onset disasters. This model is a variant of the common maximal covering location model, which integrates decisions on the pre-positioning of relief supplies. It achieves this by identifying the optimal number and locations of distribution centers from a predetermined set, as well as the appropriate quantities of relief supplies to be stocked at each center.

The model's objective is to maximize expected benefits, quantified by the weighted coverage of demand across various disaster scenarios, with each scenario assigned a probability to reflect the uncertainties related to disaster occurrences and demand levels. This approach ensures that resources are allocated efficiently, aiming to meet the needs of affected populations as effectively as possible, considering the high degree of variability associated with natural disasters.

An interesting characteristic of the model is the incorporation of varying criticality levels of relief supplies, which are modeled through specific weights and designated coverage levels dictated by response time requirements. By differentiating the supplies, the model can prioritize the allocation of resources to maximize the impact of relief efforts. This detail contributes to more effective considerations by the optimization model, ensuring that the most critical needs are addressed.

The model was applied to a hypothetical problem, with the outcomes underscoring the crucial role of pre-disaster investments. These findings contest the conventional focus on post-disaster efforts, demonstrating that effective disaster response is predominantly driven by strategic pre-disaster preparations rather than over reliance on post-disaster funding.

The research paper developed by Rawls and Turnquist (2009) presents a two-stage stochastic mixed integer program that provides emergency response pre-positioning strategy, taking into account uncertainty regarding demand, transportation network availability and the survival of prepositioned stocks.

Similarly to other reviewed models, the first stage decision variables represent storage facility locations and supply quantities while the second-stage decisions pertain to distribution decisions, and vary according to the disaster's impact represented in each scenario. The model's objective is to minimize the total expected costs, encompassing pre-positioning, transportation, and penalty costs associated with unmet demands. This approach aims to optimize the relief network from a cost-effective perspective.

The computational complexity for large instances of this formulation led the authors to develop a heuristic algorithm which was named the Lagrangian L-shaped method (LLSM). The characteristics of this algorithm are not relevant for the present literature review, however it is important to be aware that disaster relief models can have high degrees of computational complexity.

In order to validate the model and assess the algorithm's effectiveness, the model was applied to a case study focusing on hurricane threats in the Gulf Coast area of the United States. The results showcase the model's capability to suggest optimal locations for supply facilities and appropriate levels of stockpiles to prepare for potential disasters effectively.

Chang, Tseng, and Chen (2007) developed a decision-making tool aimed at enhancing the efficiency of flood emergency logistics. This tool is composed of two models designed to optimize the organization and distribution of rescue resources. The initial model, a classification and grouping model, organizes different disaster rescue areas and classifies their level of emergency by minimizing the expected shipping distance. This model ensures that rescue efforts are coordinated and that the dynamics between different disaster areas are delineated. Building on the cooperation dynamics established by the first model, the second component is a two-stage stochastic programming model. This model aims to minimize the total expected costs of flood response operations. In the first stage, it determines the optimal locations for setting up local rescue bases immediately after a disaster. In the second stage, it specifies the quantities of rescue equipment to be stored in these bases and formulates transportation plans for distributing the equipment.

The scenarios developed by Chang et al. (2007) are meant to represent the possible realizations of unknown problem parameters, such as rescue demand, which are dependent on the inherent uncertainty associated with rainfall. To build these scenarios, flooding potential maps for different rainfall situations were created through data processing and network analysis functions of a Geographic Information System (GIS). The methodology employed to create these maps comprises a detailed three-step process that ultimately identifies rescue demand points and determines associated rescue equipment demand for the different flooding scenarios.

The model presented in the study by Alem, Clark and Moreno (2016) is quite complex, incorporating not only prepositioning but also fleet sizing decisions in the first-stage and procurement, distribution, budgeting and inventory decisions in the second stage. Additionally, the model accounts for multiple periods, which mirrors the real-world scenario where emergency aid delivery spans several days, requiring continuous coordination and adaptive decision-making. The objective function minimizes a combination of costs associated with prepositioning, transportation, inventory holding, and penalties for unmet demand, thus reflecting both the economic and operational pressures faced during disaster relief efforts.

Given the high degree of computational complexity of the model, the authors built a heuristic solution method to ensure that solutions can be obtained within a reasonable timeframe. The effectiveness of the heuristic is demonstrated through numerical tests, which show that it performs well for both real and random instances.

In order to develop the scenarios for the practical application of their model, Alem et al. (2016) investigated and classified historical data from previous disasters using the scaling system proposed by Eshghi and Larson (2008). This classification allowed them to generate plausible disaster scenarios that reflect the variability and uncertainty of real-world events. The scenarios were then used to test the model in the context of the floods and landslides in Rio de Janeiro, Brazil, in 2011. The case study demonstrated that the model could effectively plan and organize disaster relief efforts, providing good service levels across various scenarios.

2.3 UAVs application in Disaster Relief

Technology plays a crucial role in humanitarian logistics, similarly to conventional logistics. The heightened uncertainty surrounding disaster relief operations requires even more versatility of response, which can be improved through the application of appropriate technologies. For instance, the implementation of basic IT tools has proven to be particularly beneficial during the response phase. Ergun et al. (2014) presents the use of the UPS trackpad system to streamline the registration of camp residents following the January 2010 earthquake in Haiti.

Unmanned Aerial Vehicles (UAVs), more commonly referred to as drones, can be described as an aircraft that does not require on board human control in order to operate. This technology has been gaining relevance within the humanitarian field, and academic literature on the different applications of UAVs during disaster relief operations has increased significantly from 2016 onwards. The research on the topic has continuously associated the deployment of drones in the humanitarian logistics field with operational, economic, and social opportunities. (Rejeb et al, 2021)

The literature review on humanitarian drones conducted by Rejeb et al. (2021) presented three main capabilities of UAVs that make them useful in a humanitarian context:

- **Transportation and delivery capabilities:** Drones can be a highly effective transportation mode in humanitarian logistics (HL) and an essential tool for providing immediate relief to vulnerable civilians and communities. Instead of relying on road transportation or in the absence of an interconnected transportation network, UAVs helicopters can efficiently deliver water and emergency supplies to affected regions.

- **Surveying and monitoring capabilities:** Due to their remote sensing capabilities and rapid spatial information collection, drones have been widely used in emergency surveying. A remote sensing system fitted on UAVs can provide clear and high-resolution aerial photographs, enabling the surveying of hazardous areas that are otherwise impassable, such as swampy fields and steep slopes. In case of disasters, drones can reach specific locations, reducing the danger for human rescue teams while also increasing the quality of information.

- **Communication and integration capabilities:** When a disaster occurs, drones can serve as unmanned aerial base stations and as part of the network architecture for maintaining public safety communications. They can be used to develop emergency communication networks and provide wireless access to communities in specific locations, which is particularly helpful in hostile disaster environments.

Additionally, Rejeb et al. (2021) also identifies three key performance outcomes of utilizing UAVs in disaster relief operations:

- **Flexibility and responsiveness:** Humanitarian organizations can use drones to bypass disrupted roads and debris-blocked infrastructure, enabling more timely and adaptable rescue operations. Drones can swiftly gather first-hand information, develop a unique emergency response capacity, and support evidence-based decision-making processes, thereby enhancing the overall efficiency of humanitarian logistics systems.

- **Cost reduction:** Drones are increasingly recognized by the humanitarian community as a cost-effective and reliable mode of aerial delivery. They offer a versatile solution to the challenges posed by infrastructure damage and traffic congestion. The costs of transporting medical supplies during shortages can be significantly lower with drones compared to traditional medical transport methods.

- **Sustainability:** Academic studies have shown that lightweight UAVs minimize energy consumption while extending operation time for transportation to disaster locations. UAVs with large wingspans enable medium-altitude flights and further reduce energy consumption. Beyond their humanitarian and life-saving benefits, drones also enhance the ecological and environmental dimensions of humanitarian logistics.

The introduction of a UAVs fleet can significantly enhance the effectiveness of pre-positioning emergency supplies, particularly due to their usefulness in last-mile distribution. In the context of flooding. UAVs' transportation and delivery capabilities mean that pre-positioned supplies can be rapidly deployed to affected areas, bypassing flooded roads or debris-blocked infrastructure. This flexibility ensures that critical supplies such as food, water, and medical aid reach vulnerable populations in a timely manner, even in the most inaccessible regions. By strategically placing UAVs and supplies nearby flood-prone areas, governmental bodies and humanitarian organizations can significantly reduce response times and increase the efficiency of relief operations.

For instance, drones can swiftly deliver essential medical devices, such as automated external defibrillators, directly to victims, as noted by Emery (2016). This rapid response not only prevents the spoilage of critical perishable supplies during transportation but also ensures their immediate availability during emergencies. Additionally, Young (2018) highlights that drones can play a crucial role in the initial wave of aid by providing focused, rapid, resilient, and targeted delivery of critical supplies in the form of small packages or payloads, thereby minimizing the loss of human lives and enhancing the overall efficiency of emergency response operations.

Chapter 3

Mathematical Formulation

The mathematical model developed is a two-stage scenario-based optimization model designed to address preparedness decisions for flood disasters in Belgium. This model effectively manages uncertainties inherent in disaster management, such as variable demand and unpredictable conditions, as detailed in Chapter 2.

Central to the model are decisions regarding the storage and transportation of emergency supplies. Pre-disaster decisions involve selecting which facilities to open and determining the quantities of supplies to pre-position, considering factors like storage capacity and budget constraints. Post-disaster decisions focus on allocating and distributing these supplies to meet the demands at affected locations, using the available transportation options.

The primary objective of this model is to minimize the total expected response time for delivering emergency supplies. This involves optimizing preparedness decisions to ensure rapid and efficient supply delivery across affected areas. The model carefully accounts for the capacities and speeds of different transportation vehicles, the strategic pre-positioning of supplies, and the realistic constraints of facility operations. By quantifying unmet demands and incorporating penalties for these shortfalls, the model not only enhances the speed of response but also improves the reliability and effectiveness of meeting the critical needs of disaster-stricken populations. Additionally, the introduction of weights for each type of supply allows for the prioritization of resources based on urgency, reflecting the criticality of the relief provided by each supply. A more clear and simple overview of the optimization model structure can be observed in the diagram presented in Figure 3.1.

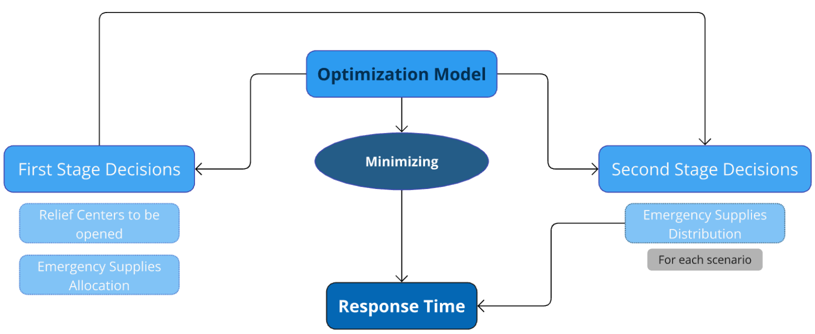


Figure 3.1: Model Structure Diagram

To effectively implement the optimization model, it was necessary to define key components such as sets and indices, parameters, decision variables, and constraints. These elements collectively form the foundation of the model, enabling it to address the complex logistics of disaster preparedness. For instance, sets and indices categorize the locations, supplies, and scenarios involved, while parameters provide the necessary numerical values, such as capacities and costs, to drive the model's calculations. Decision variables represent the actionable choices within the model, such as how supplies are allocated or which facilities are activated. The constraints ensure that these decisions adhere to practical limitations like budget and storage capacity. Together, these components allow the model to approach the goal of minimizing response time. The notation used for these components, along with concise explanations, is provided in the following sections.

3.1 Sets and Indices

- I: Set of potential facility locations, where emergency supplies can be pre-positioned.
- J: Set of demand points, indicating locations where emergency supplies are required post-disaster.
- K: Set of emergency supply types, that are required once a flood occurs in order to aid the affected population.
- T: Set of transportation options, each representing a mode of transport available for delivering the emergency supplies.
- S: Set of discrete scenarios, each depicting a different potential flood outcome in Belgium.

3.2 Parameters

- C: Maximum storage capacity of the considered facilities.
- l_t: Maximum transportation capacity of vehicle type t.
- r_{ts}: Average speed of transportation option t under scenario s. This affects the delivery time calculations, as different scenarios might impact the operational speeds due to factors like road conditions or weather.
- n_t: Number of transportation option t available in each facility.
- c_k: Volume taken up by emergency supply k at each facility and vehicle.
- d_{ij}: Distance from facility i to demand point j.
- D_{jks}: Demand for emergency supply k at demand point j under scenario s.
- P_s: Probability of scenario s occurring.

- B: Maximum amount of money to be spent. This budget constraint ensures that the total cost of operation does not exceed available funding.
- p_k: Cost of purchasing supply k.
- f: Cost of opening a facility. It covers the expenses involved in establishing a relief facility.
- α_k: Represents the urgency weight for each supply type k, prioritizing the delivery of critical items. Higher weights expedite the allocation of essential supplies, directly impacting the response effectiveness of items according to their criticality.
- λ_k: Time penalty factor imposed for not meeting demand for supply k. This factor introduces a time cost when there is a failure to meet the aiding needs of the affected population.

3.3 Decision Variables

- s_{ik}: Amount of emergency supply type k stored at facility i. As a first-stage variable, it is determined prior to any disaster scenario.
- y_i: Binary variable indicating whether facility i is operational (1) or not (0). This first-stage variable dictates the setup of the emergency supply network, influencing both operational readiness and the economic aspects of facility management.
- x_{ijkts}: Quantity of emergency supply type k transported from facility i to demand point j using vehicle type t under scenario s. This second-stage variable is critical as it determines the post-disaster distribution of resources, which is scenario-dependent and directly impacts the effectiveness of the emergency response.
- z_{jks}: Represents the unmet demand for emergency supply type k at demand point j under scenario s. This second-stage variable quantifies shortages in emergency supply distribution, facilitating the application of penalties for undelivered essential resources.

3.4 Objective Function

The primary goal of this model is to minimize the total expected response time for delivering emergency supplies after a disaster event. This involves optimizing both pre-disaster preparedness and post-disaster responses to ensure rapid and efficient supply delivery. The objective function is formulated as follows:

$$\min \left(\sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} \sum_{s \in S} P_s \alpha_k \left(\frac{d_{ij}}{r_{ts}} x_{ijkts} \right) + \sum_{j \in J} \sum_{k \in K} \sum_{s \in S} P_s \lambda_k z_{jks} \right) \tag{3.1}$$

3.5 Constraints

Flow Conservation: This constraint ensures that the total quantity of each emergency supply type k dispatched from all facilities to each demand point j under each scenario s either satisfies the demand or contributes to the recorded unmet demand.

$$\sum_{i \in I} \sum_{t \in T} x_{ijkts} + z_{jks} = D_{jks}, \quad \forall j \in J, k \in K, s \in S \tag{3.2}$$

Facility Capacity: This constraint ensures that the total volume of all emergency supplies stored at each facility does not exceed the facility's maximum storage capacity, and only if the facility is operational.

$$\sum_{k \in K} c_k s_{ik} \leq C_i y_i, \quad \forall i \in I \tag{3.3}$$

Inventory Limitation: This constraint ensures that the total quantity of each emergency supply type k dispatched from any facility i under any scenario s does not exceed the amount of that supply pre-positioned at the facility.

$$\sum_{j \in J} \sum_{t \in T} x_{ijkts} \leq s_{ik}, \quad \forall i \in I, k \in K, s \in S \tag{3.4}$$

Transportation Capacity: This constraint ensures that the total volume of emergency supplies dispatched from each facility using any given transportation mode does not exceed the available capacity of that mode at the facility. This accounts for both the number of vehicles available and their respective capacities.

$$\sum_{j \in J} \sum_{k \in K} c_k x_{ijkts} \leq l_t n_t, \quad \forall i \in I, t \in T, s \in S \tag{3.5}$$

Budget Constraint: This constraint ensures that the total preparedness cost, incurred from opening facilities and stocking them with supplies, does not exceed the predefined budget.

$$\sum_{i \in I} f y_i + \sum_{i \in I} \sum_{k \in K} p_k s_{ik} \leq B \tag{3.6}$$

Binary and Non-negativity: These constraints ensure the model maintains logical and physical consistency. They prevent unrealistic values for decision variables and enforce binary decisions where necessary:

$$y_i \in \{0, 1\}, \quad \forall i \in I, \qquad \text{(Facility operational status)} \tag{3.7}$$

$$x_{ijkts} \geq 0, \quad \forall i \in I, j \in J, k \in K, t \in T, s \in S, \qquad \text{(Dispatched supplies)} \tag{3.8}$$

$$s_{ik} \geq 0, \quad \forall i \in I, k \in K, \qquad \text{(Stored supplies)} \tag{3.9}$$

$$z_{jks} \geq 0, \quad \forall j \in J, k \in K, s \in S \qquad \text{(Unmet demand)} \tag{3.10}$$

Chapter 4

Data Collection and Processing

4.1 Facility Location and Cost

The selection of facility locations is crucial for ensuring effective disaster response and efficient distribution of relief supplies. To achieve a relevant coverage and enhance flood preparedness, the potential facility locations must be strategically spread across Belgium, covering a significant portion of the country's area.

To accomplish this, potential facility locations will be considered in each of Belgium's provinces, specifically in small cities near the capital of each province. This approach is justified by several factors. Firstly, the capital cities of each province generally have higher population densities, which means that relief facilities located nearby can serve a larger number of people in a shorter time. Secondly, areas nearby province capitals are typically well-connected through transportation networks, facilitating a more efficient movement of supplies. Lastly, this approach allows for more cost-effective land acquisition, as facilities will be built in areas that are less expensive than the highly-priced capital regions. Overall, by positioning facilities near provincial capitals, a healthy balance between accessibility and coverage is more likely to be achieved.

Considering these factors, the chosen cities for potential facility locations are enumerated in Table 4.1, along with some relevant data about the respective province. The population data presented in the table is sourced data the latest census, in 2024.

Table 4.1: Facility and Capital Cities in Belgian Provinces (Source: City Population)

Facility City	**Province**	**Capital City**	**Population**
Kapellen	Antwerp	Antwerpen	1,926,522
Sint-Pieters-Leeuw	Brussels Capital Region	Brussels	1,249,597
Evergem	East Flanders	Gent	1,572,002
Bierbeek	Flemish Brabant	Leuven	1,196,773
Quaregnon	Hainaut	Mons	1,360,074
Herstal	Liège	Liège	1,119,038
Genk	Limburg	Hasselt	900,098
Habay	Luxembourg	Arlon	295,146
Profondeville	Namur	Namur	503,895
Rixensart	Walloon Brabant	Wavre	414,130
Zedelgem	West Flanders	Brugge	1,226,375

The geographical positioning of the candidate location within Belgium can be visualized in the map presented in Figure 4.1. The coordinates required to develop the map were sourced from google maps.

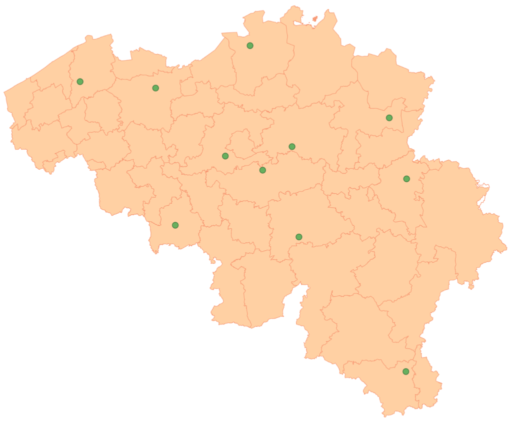


Figure 4.1: Possible Facilities Location in Belgium Map

When considering costs, it is crucial to balance facility opening costs with supply pre-positioning costs to ensure budget considerations and cost analyses yield valid results. Given the difficulty in identifying precise costs for opening facilities in Belgium, this study adopts the cost values provided in the paper by Rawls and Turnquist (2009). Although these values are outdated and not specific to Belgium, they offer a relatively consistent framework for comparing different cost components.

This approach introduces a minor limitation, the disregard for location-specific land costs. It remains acceptable given that the primary objective of the study is to assess the strategic advantages of facility placement and supply pre-positioning in regard to response times and not a detailed analysis on optimal relief centers positioning.

This simplified approach allows for a somewhat meaningful cost analysis, acknowledging the budget constraints typically faced in humanitarian logistics. It ensures that the cost considerations are still relevant and can be analyzed to some extent, providing some insights into the cost aspects of disaster relief operations.

For consistency reasons, facility sizes will also be derived from Rawls and Turnquist (2009). The research considers the possibility of opening 3 different sizes of facility location, this thesis will employ the small sized facility which has an associated cost of 19 600$ (18 078€) and a size of 36 400 ft^3 (1030 m^3).

4.2 Disaster Locations

In Belgium there are 581 municipalities, each representing a potential demand point in the context of disaster relief logistics. However, considering a demand point for each municipality would introduce significant complexity into the model. To balance model complexity with the relevance of the results, arrondissements were used as the basis for demand points.

Arrondissements are subdivisions within the provinces of Belgium, providing a more manageable yet acceptable representation of the population distribution. By aggregating demand at the arrondissement level, the model approximates the total demand for all municipalities within a given arrondissement and considers the distance from relief facilities to the more populated municipality within said arrondissement. This approach simplifies the model while maintaining a good level of relevance in the results.

There are 43 arrondissements in Belgium, and their respective populations and associated province are detailed in Table A.1 (Appendix A). The data was sourced from the website City Population, as with the facilty data.

The geographical distribution of the possible demand points around Belgium, represented by the 43 arrondissements, can be observed in Figure 4.2.

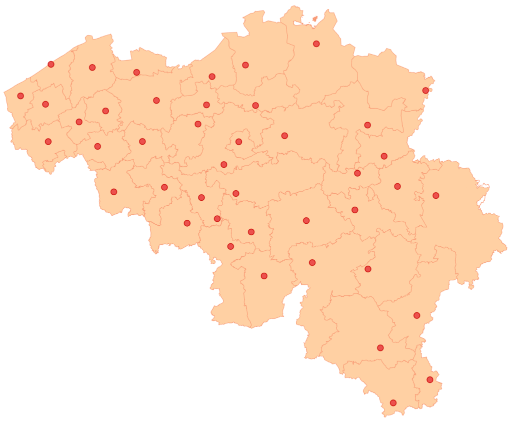


Figure 4.2: Demand Points in Belgium Map

4.3 Distance Matrix

Having identified all demand points and potential facility locations, it was necessary to determine the distances between these points to optimize supply pre-positioning. The distance matrix between potential facility locations and demand points was calculated using the Haversine formula. This method provides accurate distances based on latitude and longitude coordinates, which were gathered as mentioned in the previous sections.

The Haversine formula calculates the distance between two points on the Earth's surface by accounting for the curvature of the Earth. The formula is defined as:

$$d = 2r \cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1)\cdot\cos(\phi_2)\cdot\sin^2\left(\frac{\Delta\lambda}{2}\right)}\right) \tag{4.1}$$

where d is the distance between two points, r is the Earth's radius (6,371 km), ϕ_1 and ϕ_2 are the latitudes of the points in radians, $\Delta\phi$ is the difference in latitudes, and $\Delta\lambda$ is the difference in longitudes.

By applying this formula in Microsoft Excel across all pairs of facility locations and demand points, a distance matrix was generated. This matrix is organized in a tabular format, with rows representing facilities and columns representing demand points.

4.4 Emergency Supplies Characteristics

The models detailed in Chapter 2 primarily focus on three types of emergency supplies: water, food, and medical kits. While there could be interest in considering more specific and time-sensitive emergency supplies, the broader objectives of this work align more with the use of simpler, more generalized supplies, similar to the approach taken by Rawls and Turnquist (2009).

Each type of supply is associated with a standardized unit to facilitate modeling and logistical planning. Water is measured in units of 5,000 liters, reflecting bulk storage. Food is represented as Meals-Ready-to-Eat (MREs) and quantified in units of 1,000 meals, for the same reason. Medical kits, essential for addressing immediate health needs in disaster scenarios, are considered in single units.

In order to maintain consistency with the parameters selected for facility cost and capacity, the values for this parameters will also be obtained from the research by Rawls and Turnquist (2009), and converted to european metrics. In the case of water, considering that units are in a different measurement, the values were adjusted accordingly.

Table 4.2 summarizes the key parameters of these emergency supplies, including unit measurements, cost estimates, and storage requirements.

Table 4.2: Key Parameters of Emergency Supplies

Supply Type	**Unit Measurement**	**Cost Estimate (per unit)**	**Volume**
Water	5,000 liters	782€	5.41m^3
Food (MREs)	1,000 meals	4962€	2.36m^3
Medical Kits	1 unit	128€	0.03m^3

It is assumed that each person requiring water aid will need 3 liters of water, each person requiring food aid will need 4 meals, and each person requiring medical aid will need 1 medical kit. The number of people requiring aid is specific for each supply, thus considering that the needs for impacted individuals may vary. Some may solely require water and food aid due to displacement, while others may specifically need medical aid. This values will determine demand levels and are considered in the equations presented in the section *Scenario Considerations and Development*.

Lastly, Chapter 3 introduced an urgency weight and a penalty for unmet demand for each type of emergency supply, reflecting their relative importance in disaster response. This parameters ensures that the model prioritizes the distribution of more critical supplies, requiring careful tuning to achieve optimal results. These adjustments and their implications will be addressed in Chapter 5, which discusses the model's implementation and results.

4.5 Fleet Characteristics

The characteristics of the transportation fleet are crucial, as they allow for a comparative analysis of UAVs and conventional transportation methods during the disaster response phase. Cost-effective transportation options for a country the size of Belgium include vans and trucks, which are suitable for delivering supplies efficiently. The models for the ground vehicles are assumed to be a long Mercedes Sprinter panel van and a Volvo FL truck with a 16-tonne load capacity. These vehicles are commonly used for covering regional distances, making them suitable for the present context. The UAV model considered is the Wingcopter 178 Heavy Lift, which has been used in disaster relief situations worldwide and was designed for, among other applications, emergency supply delivery.

The characteristics of the considered transportation methods are summarized in Table 4.3.

Table 4.3: Characteristics of Transportation Fleet

Vehicle	Speed (km/h)	Capacity (cubic meters)
Van	79	14
Truck	63	45
UAV	100	0.51

The speed of each transportation method reflects not only its typical operational speed but also accounts for the fact that distances are calculated in a straight line. This means that the average speed for ground vehicles was adjusted to reflect traveling routes, and that the UAV speed is unchanged, considering it is able to travel in a straight line. The transportation capacity is determined by the volume that each vehicle can carry, providing a measure of their logistical capability.

The number of available vehicles is assumed to be the same at all facilities to ensure consistency across the different facility points. More details regarding the tuning of this parameter are available in Chapter 5.

This standardized approach ensures that the model is able to assess the benefits and limitations of each transportation method, particularly highlighting the potential advantages of UAVs in improving response times.

4.6 Scenario Considerations and Development

4.6.1 Geographical Characteristics

Understanding the geographical characteristics of Belgium is essential for assessing flood risk and developing relevant flood scenarios. The two major rivers, the Schelde and the Meuse, play a critical role in the hydrology of Belgium and are significant contributors to flood events in the country. To better understand their impact and location in Belgium, information from the Encyclopedia Britannica was consulted. The position of the rivers can be seen in Figure 4.3.

The Schelde River originates in northern France and flows through western Belgium before reaching the North Sea in the Netherlands. The river passes through several key regions in Belgium, including

Figure 4.3: Belgium's River Map (Souce: Free World Maps)

the provinces of Hainaut, East Flanders, and Antwerp. The Schelde River basin is characterized by a network of tributaries, including the Leie and the Dender, which contribute to its flow and potential flood risk. Flooding along the Schelde River can impact both urban and rural areas, particularly in the provinces of East Flanders and Antwerp. The river's lower course and estuarine characteristics increase the likelihood of flooding during periods of heavy rainfall and storm surges.

The Meuse River, with a length of about 925 kilometers, also originates in France and flows through Belgium and the Netherlands. In Belgium, the Meuse River primarily impacts the provinces of Namur, Liège, and Luxembourg. The river's course through the Ardennes region, characterized by steep valleys and narrow floodplains, makes these areas particularly susceptible to flooding. Additionally, the Meuse River is fed by several tributaries, including the Sambre and the Ourthe, which can exacerbate flood conditions. Flood events along the Meuse River are often triggered by prolonged periods of heavy rainfall and rapid snowmelt, leading to significant impacts on communities and infrastructure in the affected provinces.

The geographical characteristics of these two major rivers highlight the regions in Belgium that are most vulnerable to flooding. The provinces of East Flanders and Antwerp are particularly at risk from the Schelde River, while the provinces of Namur, Liège, and Luxembourg are more vulnerable to flooding from the Meuse River. Understanding these geographical factors is important for developing a realistic set of scenarios.

The flood risk associated with these rivers is fluvial flooding, which is the most impactful form of flooding in Belgium. However, it is important to note that pluvial flooding, caused by heavy rainfall overwhelming drainage systems, can strike any location regardless of its proximity to rivers. This means that no city in Belgium is completely free from flood risk, highlighting the need to develop preparedeness strategies that can aid any province.

4.6.2 Historical Flood Events

To develop a representative and realistic set of scenarios, it is essential to study and analyze past flood events in Belgium. The Royal Meteorological Institute (IRM), a federal scientific institute that provides meteorological services and conducts climate research, has documented historical flood events in a series of articles covering the period from 1188 to 2020. These articles detail floods as recorded in ancient manuscripts, books, and newspapers published in Western Europe prior to the 20th century. Starting from 1900, the articles are grounded in data that started being collected as the Belgian climatological network began to expand. For more recent flood events in 2021 and 2024, which are not included in the IRM's articles, information was sourced from recent news outlets.

Based on these articles, several significant flood events were compiled in Table 4.4 detailing the year, type of flood, and main impacted areas.

Table 4.4: Notable Historical Flood Events in Belgium

Year	Type of Flood	Main Impact Area
1188	Heavy Rainfall	Liège
1280	Flash flood	Huy (Liège)
1374	River Overflow	Namur
1408	Snowmelt Flood	Tournai (Hainaut)
1577	Rainfall	Huy (Liège)
1614	Rainfall	Huy (Liège)
1643	Severe River Overflow	Liège
1674	River Overflow	Spa (Liège)
1779	River Overflow	Rousbrugge (West-Flanders)
1820	Heavy Rainfall	Brussels Capital Region and Flanders
1841	Snowmelt	Liège
1879	Prolonged Heavy Rainfall	Liège
1893	Rainfall	Huy (Liège)
1910	Heavy Rainfall and Snowmelt	Dinant, Namur (Namur)
1926	Heavy Rainfall and Snowmelt	Liège, Namur, Luxembourg
1932	Heavy Rainfall	Across Belgium
1953	Storm Surge	Antwerp, West Flanders, East Flanders
1976	Storm Surge	Antwerp
1984	Heavy Rainfall and Snowmelt	Luxembourg
1993	Extreme Rainfall	Wallonia
1995	Heavy Rainfall and Snowmelt	Wallonia, Brussels
2010	Heavy Rainfall	Walloon Brabant, Brussels, Hainaut
2011	Heavy Rainfall and Snowmelt	Liège, Namur, Luxembourg
2021	Heavy Rainfall	Limburg, Liège, Namur
January 2024	Heavy Rainfall	Luxembourg, East Flanders
May 2024	Heavy Rainfall	Limburg, Liège

Figure 4.4 presents a bar chart illustrating each provinces number of floods, according to the IRM's flood historical records and recent news outlets, along with the respective population.

This data is crucial for developing relevant flood scenarios and assigning appropriate probabilities, ensuring that the model accurately reflects the varying flood risk levels across different provinces.

4.6.3 Scenarios

Flood Events

To develop the scenarios, a set of 10 different flood events were developed considering the geographical and flood history considerations presented in the previous subsections. Each event impacts

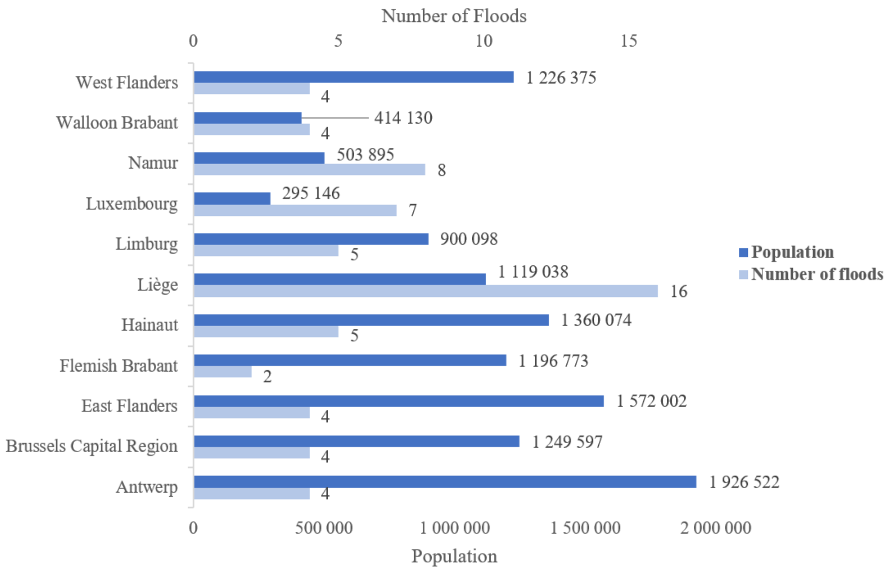


Figure 4.4: Number of historical floods and Population per province.

specific provinces, generating demand for the three types of emergency supplies at each associated arrondissement, while also reducing the speed of land transportation vehicles, when applicable. The details of these flood events, including their intensity, affected provinces, and the percentage reduction in vehicle speed, are presented in Table 4.5.

Table 4.5: Flood Events and Respective Parameters

Event ID	Flood Intensity	Impact Area	Vehicle Speed Reduction (%)
1	1	BCR, FBR, WBR	0
2	1	EF, WF	0
3	1	A, L, N	0
4	2	L, Li, FBR, BCR	2
5	2	H, N, Li, Lux	2
6	3	EF, WF, BCR, WBR	5
7	3	WBR, EF, A	5
8	4	N, Li, Lux, L	10
9	4	H, A	10
10	5	N, Li, Lux	25

Note: BCR = Brussels-Capital Region, FBR = Flemish Brabant, WBR = Walloon Brabant, EF = East Flanders, WF = West Flanders, A = Antwerp, L = Limburg, H = Hainaut, N = Namur, Li = Liège, Lux = Luxembourg.

The intensity of each flood event is categorized on a scale from 1 to 5, with 5 representing the most severe level. As flood intensity increases, the demand for each type of emergency supply also rises, expressed as a percentage of the population. The percentage of the population requiring water and food aid is the same for all intensity levels, as individuals who are displaced typically need both supplies simultaneously. The percentage of the population requiring medical kits is lower across all intensity levels, as temporary displacement is more common than injury during such events.

Using this information and parameters, the demand generated by each flood event can easily be calculated through simple equations. In case a province is impacted by a certain flood event the associated arrondissments aid requirements is determined by the following equations:

Table 4.6: Percentage of population requiring aid for each supply and flood intensity

Flood Intensity	Water Demand (%)	Food Demand (%)	Medical Kit Demand (%)
1	0.1	0.1	0.05
2	1.0	1.0	0.1
3	2.5	2.5	0.5
4	10.0	10.0	2.0
5	25.0	25.0	10.0

$$Demand_{water} = \frac{P_{water} \times TP_{arrondissement} \times 3}{5000} \tag{4.2}$$

$$Demand_{food} = \frac{P_{food} \times TP_{arrondissement} \times 4}{1000} \tag{4.3}$$

$$Demand_{medicalkit} = P_{medicalkit} \times TP_{arrondissement} \tag{4.4}$$

In this equations the P represents the percentage of population requiring aid for the associated supply at that flood intensity level and TP represents the total population of the arrondissment under calculation. The other numbers are specific only to each supply and are presented in Table 4.2.

By using these equations, the model ensures that the demand for supplies is proportional to the severity of the flood and population, providing a reasonable estimation of the resources needed in each flood event. The results of this calculations are present in Table A.2, in Appendix A.

Scenarios

The scenarios were developed by using each of the presented flood events individually and by combining them in groups of two. Each scenario has an associated probability, assigned based on the information presented in the previous subsections. Logically, scenarios that combine several flood events will be less likely. By incorporating a range of possible flood events with varying intensities and affected areas, the model can simulate a wide array of potential disaster situations.

The single-event scenarios have a combined probability of 80%, while the multiple-event scenarios collectively have a probability of 20%. This distribution reflects the higher likelihood of individual events compared to simultaneous occurrences of multiple events.

The 30 scenarios are presented in two tables, available in Appendix A. Table A.2 shows the scenario data for the single-event scenarios, and Table A.3 presents the data for the multiple-event scenarios. The data presented covers the flood events considered, probability, vehicle speed reduction and demand for each supply.

To provide a clearer understanding of the aid requirements generated by the developed scenarios, the chart in Figure 4.5 was developed. This chart showcases the distribution of the expected demand for each emergency supply across different provinces. Each bar in the chart represents the percentage of the total expected demand that each province accounts for in relation to the specific type of emergency supply.

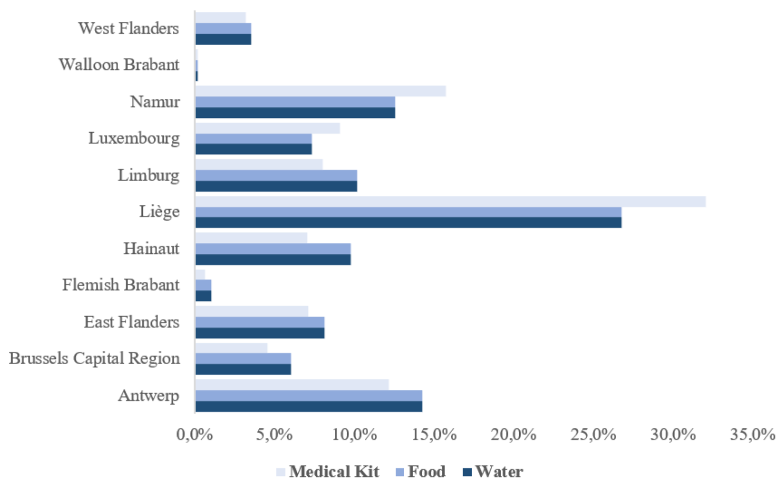


Figure 4.5: Percentage of Total Expected Demand Per Province Per Supply.

It is evident that Liège has the highest share of expected demand for all supplies followed by Namur and Antwerp, reflecting both historical records and the population of each province, as displayed in Figure 4.4. The equal share of demand for water and food across all provinces stems from the assumption that the same percentage of the population in each region would require these supplies, for all flood intensity levels. The values for medical kits logically differ, since the assumed percentage of population requiring aid is different from the other supplies.

Chapter 5

Model Implementation and Results

5.1 Model Implementation

The model was implemented using IBM CPLEX Optimization Studio (Version 22.1), which utilizes the Optimization Programming Language (OPL). The CPLEX solver was chosen for its ability to handle large-scale mixed-integer linear programming (MILP) problems and advanced scenario-based optimization. The develop OPL code is available in Appendix B.

5.1.1 Data Configuration

The data configuration for the model was based on the information detailed in Chapter 4. The model was tested under three distinct setups to address the research questions outlined in Chapter 1.

Setup 1: Single Relief Center Setup

This configuration imposes a new straightforward constraint on the model, effectively limiting it to opening only one relief center:

$$\sum_{i \in I} y_i \leq 1 \tag{5.1}$$

Under this setup, the model is restricted to selecting a single facility location from the available options. Consequently, the ability to distribute emergency supplies across multiple regions of Belgium is significantly constrained. This limitation can lead to challenges in maximizing both the availability and flexibility of supplies, as the centralization of resources in one location may delay response times to affected areas further away from the chosen center.

Given that this setup is restricted to a single facility, the available storage and fleet capacity are significantly reduced, if no adjustments are made. To ensure that meaningful comparisons can be made with other configurations, the parameters outlined in Table 5.2, along with the facility size and cost, are scaled based on the number of facilities opened in the setup under comparison. Specifically, if a particular budget allows for the opening of four facilities, the associated costs, size, and fleet parameters are multiplied by four. This adjustment ensures a more accurate evaluation of performance differences, effectively isolating the impact of the single facility constraint from variations in resource availability.

Moreover, this configuration excludes the use of UAVs for supply distribution. Instead, the model relies solely on the other transportation methods presented in chapter 4, vans and trucks, to deliver emergency supplies.

Setup 2: Multiple Relief Centers Setup

The second setup enables the opening of multiple relief centers, offering a decentralized approach to disaster response. Unlike the first setup, which restricts operations to a single center. This setup, theoretically, allows for a more flexible and efficient distribution of emergency supplies across Belgium, reducing response times and enhancing the ability to meet the unpredictable disaster relief demands.

UAVs remain excluded in this setup, isolating the impact on key metrics, such as response time and amount of demand fulfillment, on the introduction of more relief centers, and not the possibility of distributing supplies through UAVs.

Setup 3: Enhanced Fleet with UAVs Setup

The third setup expands upon the multiple relief centers configuration by integrating UAVs into the fleet at each location. This enhancement is designed to assess the impact of UAV technology on disaster response efficiency, as discussed in previous chapters.

5.1.2 Parameter tuning

Parameter tuning was essential to ensure the model's outputs were realistic and provided valuable insights. Specific adjustments were made to align with the practical objectives of disaster relief operations.

Penalties for Unmet Demand: The penalties for unmet demand were calibrated to mirror the critical importance of delivering emergency supplies. In real-world disaster scenarios, not delivering essential items can have severe consequences, including loss of life and exacerbation of injuries. Therefore, the model assigns high penalties for unmet demand to emphasize the urgency of delivering these supplies. Among the considered types of supplies, medical kits were assigned the highest penalties. This decision reflects their crucial role in providing immediate medical assistance, which can be life-saving. In contrast, although still important, the penalties for not delivering water and food were set lower than those for medical kits, recognizing the relative differences in their immediate impact on survival during disaster response operations.

Urgency Weights: Urgency weights were employed to ensure that the delivery of more critical supplies was prioritized. The weights were assigned based on the relative importance of each supply type in disaster relief operations. Medical kits received the highest urgency weight, for the same logic explained above. This prioritization ensures that the model focuses on minimizing delivery times for supplies that are most critical for saving lives and addressing severe injuries.

To achieve the desired outcomes outlined above, the model underwent a series of trial-and-error runs using a simplified dataset. This iterative process allowed for the refinement of key parameters, ensuring that the model accurately reflects the practical objectives of disaster relief operations. After several iterations, the final tuned parameters displayed in Table 5.1 were reached.

Table 5.1: Tuned Parameters of Emergency Supplies

Supply Type	**Urgency Weight**	**Unmet Demand Penalty**
Water	1	75000
Food (MREs)	1	75000
Medical Kits	1.5	85000

Fleet Capacity: The fleet capacity at each relief center was adjusted to match the storage capacity, ensuring that the logistics network could effectively utilize the pre-positioned supplies. In the setup that incorporates UAVs, their capacity was integrated such that they replaced the volume equivalent to one van's capacity. The specific fleet configurations for each setup are detailed in Table 5.2.

Table 5.2: Fleet distribution in each setup

Setup	**Vans**	**Truck**	**UAVs**	**Distribution Capacity** (m^3)
1	26	15	0	1039
2	26	15	0	1039
3	25	15	27	1039

The values for the fleet capacity are balanced across different transportation methods follows: trucks were assigned approximately 65% of the total fleet capacity, with vans making up the remaining 35%. UAVs were introduced in a proportionate manner to ensure they effectively supplemented the existing fleet without causing an imbalance, thus replacing the equivalent to one van's capacity.

Budget: The budget is a crucial parameter that directly influences the capacity to prepare and respond effectively to disasters. As discussed in Chapter 2, financial constraints are a significant factor in disaster relief management, affecting the ability to deliver timely and adequate aid. It is essential to evaluate how varying budget levels impact each setup's effectiveness in assisting the affected population. To assess this, the model was implemented across four different budget scenarios for each setup: an unlimited budget, and constrained budgets of €10 million, €20 million, and €30 million.

5.1.3 Key Performance Indicators

To systematically evaluate the performance of different model setups, several Key Performance Indicators (KPIs) were incorporated into the OPL code, enabling an automated and objective assessment of each configuration's effectiveness.

The key performance indicators employed are as follows:

1. Average Response Time: This metric measures the mean time required for each type of emergency supply to reach the affected population across all scenarios. It provides an estimate of the response efficiency under a given setup. While this value is influenced by assumptions such as straight-line distances, making it an approximation rather than a precise measure, it serves as a valuable comparative tool to evaluate the relative speed of different configurations. The average response time is expressed in minutes.

2. Demand Fulfillment: This metric, expressed as a percentage, represents the proportion of the total demand for a specific supply that was met across all scenarios. It provides a clear and straightforward measure of a setup's ability to satisfy overall demand, offering a indication of the effectiveness in addressing the needs of the affected population, across all scenarios.

3. Average Unmet Demand: This metric, also expressed in units specific to each supply, calculates the mean unmet demand across all scenarios. It offers insight into the expected shortfall of supplies under each flood scenario, helping to estimate the average level of demand that might remain unaddressed in practice.

4. Average Maximum Response Time: In disaster response, the timeliness of aid is critical, particularly for life-saving supplies such as medical kits. This metric tracks the average maximum time required to deliver supplies across all scenarios, and is expressed in minutes. While average response times provide a general sense of efficiency, outliers in maximum response times can indicate potential risks of severe consequences, including fatalities or significant injuries, if aid is delayed.

5. Fully Covered Scenarios: This metric counts the number of scenarios where all demand was fully met, with no unmet needs remaining. It serves as an indicator of the each configuration's reliability, showing how often the model was able to completely fulfill the requirements of the impacted population across the developed scenarios.

6. Average Fleet Capacity Utilization: This metric measures the percentage of the fleet's capacity that was utilized for each type of vehicle. It provides insights into the efficiency of fleet usage, highlighting which vehicles were most heavily relied upon in the distribution process.

7. Supply Distribution by Vehicle Type: To understand how pre-positioned supplies were allocated among different vehicle types, this metric reports the percentage of each supply type that was transported by each vehicle. It helps identify the priority given to certain supplies and the logistical strategies employed in different scenarios.

5.2 Results Analysis and Discussion

The demand fulfillment rate was consistent across all three setups, primarily due to the standardized capacity applied to each configuration. In Setup 1, the capacity was specifically adjusted to align with that of Setup 2, and the associated costs were proportionally scaled. Consequently, the budget allocated for pre-positioning supplies remained identical, resulting in analogous decision-making processes regarding amount of supplies to pre-postion. The only distinction between Setup 2 and Setup 3 was the substitution of one van's capacity with UAVs. This modification did not alter the facility capacity or cost parameters, and therefore also had no impact on the quantity of supplies to be pre-positioned. The effects of this change were solely reflected in the response time metrics, where the most significant differences between the setups emerged, and are addressed in the following sections.

The demand fulfillment rate for each budget scenario is presented in Figure 5.1. The impact of budget constraints on demand fulfillment is evident, particularly highlighting the urgency of medical kits. Within the constrained budgets of €10 and €20 million, only the fulfillment rate for medical kits increased. Notably, the model began addressing the demand for food supplies only within the budget range of €20 to €30 million. This delay can likely be attributed to the higher costs associated with providing food aid, which results in a per-person cost of €19.85, compared to just €0.47 per person for water aid. Balancing the budget allocation between food and water aid would, therefore, lead to a significantly reduced provision of water aid with only a marginal increase in food aid.

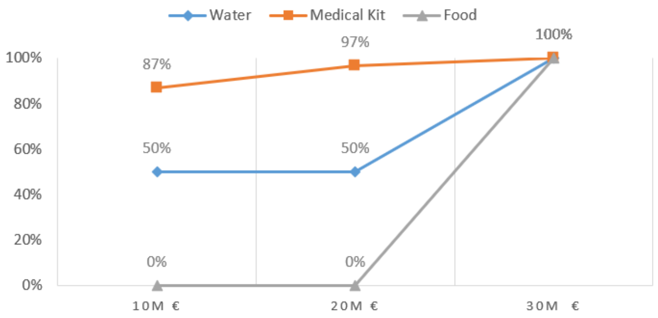


Figure 5.1: Demand Fulfillment for different budgets

The distribution of opened facilities across the different setups is consistent between Setup 2 and Setup 3, but understandably differs from Setup 1 due to its constraint of operating a single facility. The specific facilities opened under each setup across varying budget levels are depicted in Figure 5.2.

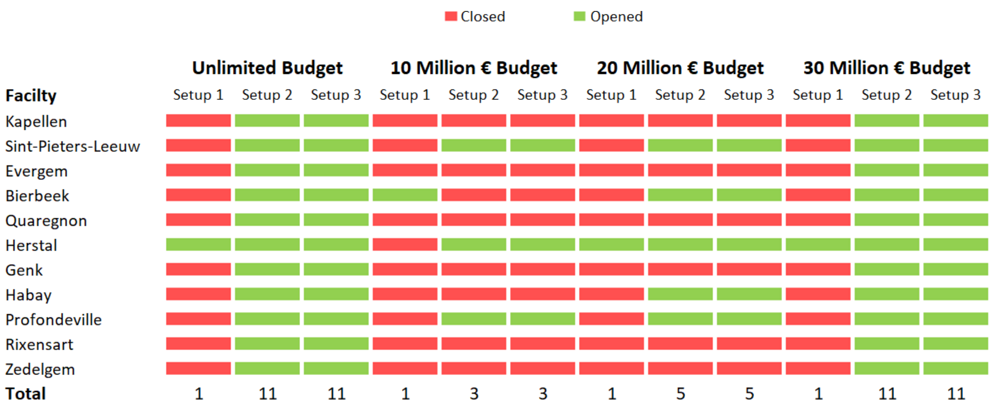


Figure 5.2: Facility distribution across setups and budget scenarios

As anticipated, the number of facilities that are opened increases with higher budgets in both Setup 2 and Setup 3. Notably, the facilities in Sint-Pieters-Leeuw (Brussels Capital Region), Profondeville (Namur), and Herstal (Liège) are consistently opened in these setups, regardless of the budget scenario. This suggests that these locations are strategically critical, under the developed scenarios, likely due to their geographic position and ability to serve high-demand areas, such as the Ardennes, efficiently.

In Setup 1, the facility selected varies with the budget. For a budget of €10 million, the facility in Bierbeek is chosen, while for the €20 million and €30 million budgets, the facility in Herstal is selected. This shift reflects the increased capacity that comes with a higher budget, allowing the model to prioritize proximity to areas with more severe flood scenarios. Herstal emerges as the most frequently selected position across all setups and budgets, a consequence of its strategic location in the Liège province, which has the highest demand due to its significant historical exposure to flood events and its substantial population.

5.2.1 Introduction of Multiple Relief centers

The introduction of multiple relief centers has a significant impact on KPIs used to evaluate disaster response efficiency in this research. By strategically distributing relief centers across Belgium, the model demonstrates how such an approach can considerably enhance response times.

When budget constraints are removed, the response time KPIs show a marked improvement when multiple relief centers are established. The results, depicted in Figure 5.3, indicate substantial reductions in response times across all supply categories. Specifically, the Average Response Time (ART) for water is reduced to 43% of that in Setup 1 (S1), for food to 37%, and for medical kits to just 19%. This means that medical kits are delivered 5.16 times faster in Setup 2 (S2) compared to S1. Similarly, the Average Maximum Response Times (AMRT) also experiences considerable improvements, with water, food, and medical kit response times being 2.12, 2.31, and 4.30 times longer, respectively, in S1.

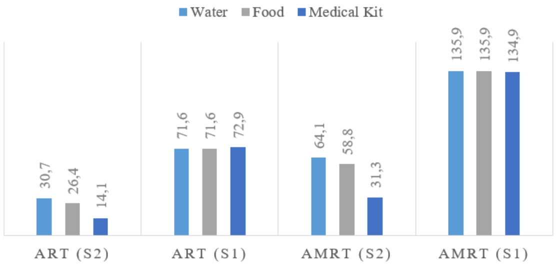
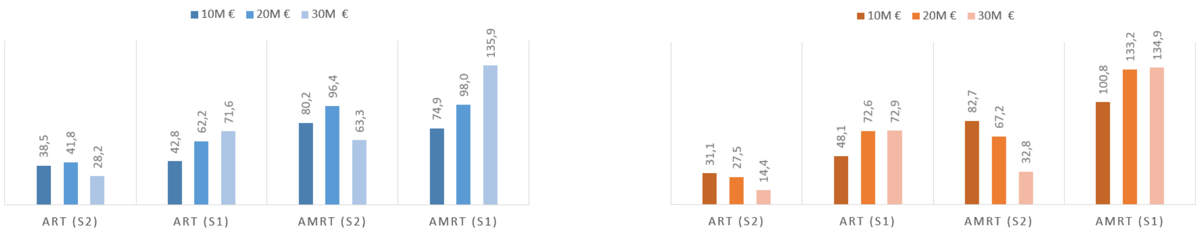


Figure 5.3: Budgetless response time comparison between setup 1 and 2

When introducing budget constraints, a similar trend is observed and the results reveal that increased budgets particularly benefit the multiple relief center setup (Setup 2). Figure 5.4 illustrates the differential impact of budget increases on water and medical kit response times, depending on the setup. Food response times are excluded from this analysis as food was not supplied under the €10 million and €20 million budget scenarios, thus not providing a basis for comparison.



(a) Water Response Time KPIs

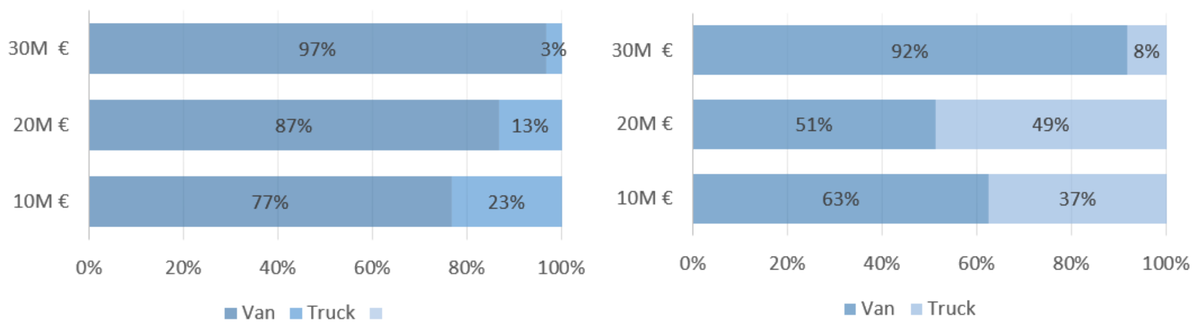
(b) Medical Kits Response Time KPIs

Figure 5.4: Response time KPIs for different budgets in setups 1 and 2

In S1, increasing the budget paradoxically leads to longer response times. This counter intuitive result occurs because, without the ability to open additional relief centers, the model can only increase capacity. While this allows the system to address higher-intensity flood scenarios, it also results in higher demand and more challenging transportation conditions, which collectively worsen average response times.

In contrast, S2 benefits significantly from increased budgets, which enable the opening of additional relief centers and thus introduce greater operational flexibility. Despite the ability to address more severe scenarios and improve demand fulfillment rates, response times improve considerably. Notably, the ART for medical kits decreases from 31 minutes with a €10 million budget to 14 minutes with a €30 million budget, while the AMRT improves from 82 minutes to 33 minutes. The improvements for water are less pronounced due to the lower urgency associated with this supply. In fact, response times for water worsen from the €10 million to the €20 million budget scenarios. This occurs because the additional budget is allocated to increasing the availability of medical kits, which leads to a higher fulfillment of medical kit demand via vans, which in turn results in water being delivered primarily by trucks, which are a slower option, especially under speed-reducing conditions.

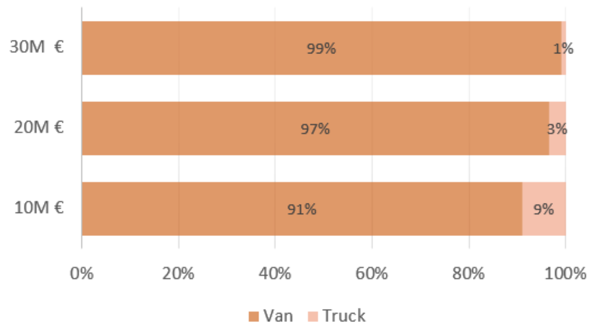
Vehicle usage data further clarifies these dynamics, as shown in Figure 5.5. The van usage rate for water drops from 63% to 51% between the €10 million and €20 million budget scenarios, while the van usage rate for medical kits steadily increases with budget. The urgency of medical kits is also evident in Figure 5.6, where it is clear that they are rarely distributed by trucks. In Setup 1, with a €30 million budget, nearly 100% of medical kits are distributed by vans. This does not occur in Setup 2, where the fleet is dispersed across multiple locations, leading some facilities that only store medical kits to rely on trucks to distribute their supplies.



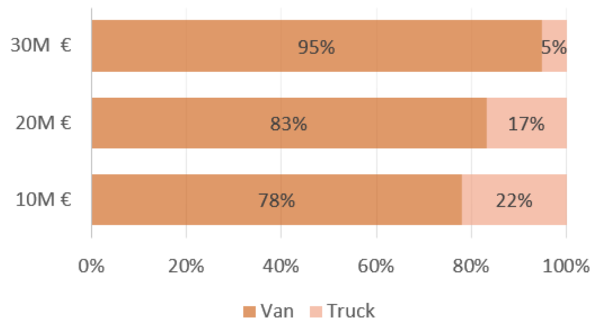
(a) Water Vehicle Usage (Setup 1)

(b) Water Vehicle Usage (Setup 2)

Figure 5.5: Water Vehicle Usage for different budgets in setups 1 and 2



(a) Medical Kit Vehicle Usage (Setup 1)



(b) Medical Kit Vehicle Usage (Setup 2)

Figure 5.6: Medical Kit Vehicle Usage for different budgets in setups 1 and 2

5.2.2 Introduction of UAVs

The key distinction between S2 and Setup 3 (S3) is the integration of UAVs into the relief supply distribution fleet, as previously noted. The KPIs presented in this section are essential for assessing the potential benefits of incorporating UAVs, specifically in terms of their impact on the response time of disaster relief operations.

The increased speed and direct flight paths of UAVs, as compared to traditional vehicles like vans and trucks, significantly enhance their potential for rapid aid delivery. According to the parameters detailed in Chapter 4, the considered UAVs can deliver aid up to 16 minutes faster than a van and 35 minutes faster than a truck over a 100 kilometers distance. This speed advantage underscores the UAVs' potential to improve response times, particularly in scenarios where quick delivery is critical.

When budget constraints are removed, the differences in ART and AMRT between S2 and S3 are shown in Figure 5.7. These KPIs indicate that, on average, the introduction of UAVs led to a marginal improvement in response time of approximately 1 minute. However, slightly more substantial improvements were observed in the average maximum response time.

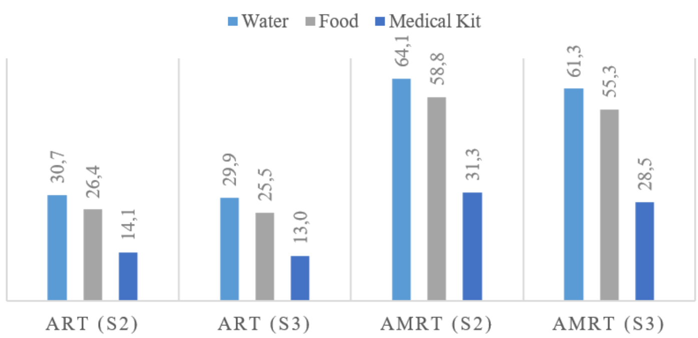
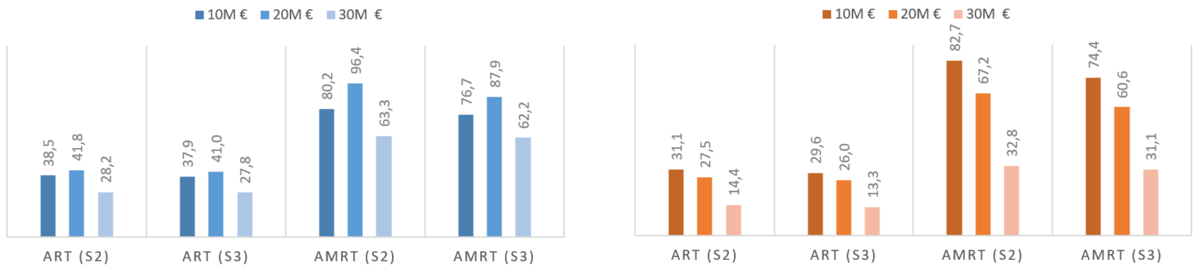


Figure 5.7: Budgetless response time comparison between setup 2 and 3

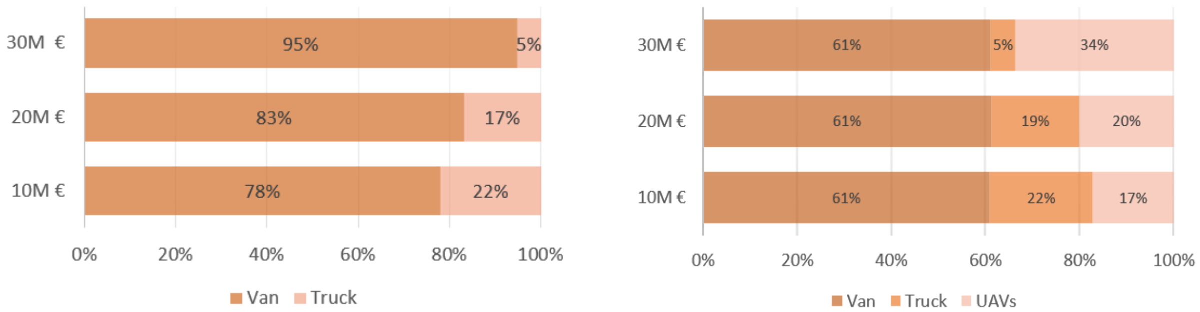
When examining the influence of budget on these KPIs, it is apparent that increasing the budget significantly enhances response times, especially considering that demand fulfillment levels also improve, indicating that more supplies are being delivered with better efficiency. This budget impact on Water and Medical Kit response times is illustrated in Figure 5.8. The response time KPIs for food are not presented, as food was only distributed under a €30 million budget.



(a) Water Response Time KPIs (b) Medical Kits Response Time KPIs

Figure 5.8: Response time KPIs for different budgets in setups 2 and 3

Analyzing the evolution of vehicle usage for each supply as the budget increases offers insights into the utilization of UAVs. Figure **??** illustrates the distribution of vehicles used to transport medical kits across different budget scenarios for Setups 2 and 3. The data clearly shows that with an increased budget, medical kits are more frequently distributed using faster vehicles. In Setup 2, the share of van usage increases with the budget, while the share of truck usage diminishes. Conversely, in Setup 3, the UAV share increases as the truck share decreases. This trend likely results from the opening of more facilities, providing greater vehicle availability and consistently prioritizing the distribution of medical kits in the faster vehicles.



(a) Medical Kit Vehicle Usage (Setup 2) (b) Medical Kit Vehicle Usage (Setup 3)

Figure 5.9: Medical Kit Vehicle Usage in Setup 2 and 3

5.2.3 Discussion

The results of this study offer insights into the effectiveness of different disaster response strategies, particularly the strategic placement of relief centers and the integration of UAVs into disaster operations.

First Research Question: Strategic Placement of Multiple Relief Centers

The first research question aimed to evaluate how the strategic placement of multiple relief centers improves flood preparedness and response times in Belgium. The deployment of multiple relief centers across Belgium demonstrated a clear and substantial improvement in both ART and AMRT. These metrics are crucial in disaster relief operations, where rapid delivery of supplies can mean the difference between life and death.

The comparison between a single centralized relief center and multiple dispersed centers reveals that the observed improvements in response times are solely attributable to the strategic geographic distribution of pre-positioned supplies. This strategic placement ensures that relief resources are closer to potential disaster zones, reducing the time required to deliver aid.

The most pronounced improvement was observed in the delivery of medical kits, which are particularly time-sensitive. The ART for medical kits in the multiple relief center setup was reduced to 19% of the time required in the single center setup, under unlimited budget, highlighting the critical importance of dispersing such essential supplies. This finding suggests that in Belgium, a decentralized approach to disaster preparedness, with multiple relief centers spread across the country, is significantly more effective than relying on a single, centralized hub. Moreover, this strategy not only improves response times but also enhances the resilience of the disaster response system by reducing the risk of a single point of failure.

Second Research Question: Impact of UAVs on Disaster Response

The second research question focused on understanding the impact of integrating UAVs into disaster relief logistics on the efficiency and speed of emergency supply distribution during flood events in Belgium. The introduction of UAVs in the disaster response fleet yielded mixed results. While there was some improvement in response times, the impact was less significant compared to the benefits gained from the strategic placement of multiple relief centers.

Although UAVs did not drastically improve overall delivery times, the findings reveal that they still made a valuable contribution. UAVs replaced the equivalent of one van's capacity and managed to improve average response times by 1 minute, suggesting that items delivered by UAVs were being delivered significantly quicker. Considering their limited transportation capacity, UAVs are not the most effective tool for improving overall response time, especially in scenarios where large volumes of supplies need to be delivered. Nonetheless, their ability to meet demand 1.27 times faster than vans and 1.59 times faster than trucks should not be overlooked.

It is important to recognize the specific contexts where UAVs can play a critical role, which are not depicted in the developed model. UAVs excel in delivering targeted aid to specific areas that become inaccessible due to the disaster, such as isolated communities cut off by flooding. In these scenarios, the agility and flexibility of UAVs can make them indispensable, providing rapid delivery of critical supplies like medical kits. Additionally, UAVs can be deployed to conduct rapid assessments of disaster-stricken areas, providing real-time data that can inform decision-making and prioritize resource allocation. Although their role in improving overall response metrics was limited in this study, UAVs offer unique advantages that make them a valuable component of a comprehensive disaster response strategy, particularly in addressing specific challenges posed by difficult terrain and disrupted infrastructure.

Other Considerations

Beyond the primary research questions, the study revealed several additional insights that are relevant for disaster response planning. Notably, the integration of UAVs into the fleet did not influence the decision on which facilities to open. This suggests that UAVs, while providing a valuable supplementary benefit in terms of faster delivery, do not play a critical role in determining the optimal locations for relief centers. Their presence enhances operational flexibility but does not fundamentally alter the strategic decisions regarding facility placement.

An additional important insight from the results concerns the limiting effects of budget constraints. Financial restrictions are a common reality in disaster relief operations, and the results clearly demonstrate the significant impact these constraints can have on affected populations. While the urgent need for medical kits ensured their coverage even under limited budget scenarios, the delivery of less urgent relief supplies, such as water and especially food, was significantly compromised. This highlights the critical need for adequate funding to ensure comprehensive disaster response, as financial limitations can severely restrict the ability to meet basic needs.

Chapter 6

Conclusion

This work has presented a comprehensive analysis of potential improvements to flood preparedness in Belgium, with a focus on the strategic placement of disaster relief centers and the integration of Unmanned Aerial Vehicles (UAVs). Through the application of a two-stage scenario-based optimization model, this research has provided valuable insights into enhancing the response times of emergency supply distribution during flood events in Belgium.

This research contributes to the theoretical discourse on disaster relief logistics by highlighting the critical role of supply chain flexibility and strategic pre-positioning in enhancing disaster response. The findings suggest that the establishment of multiple relief centers substantially improves the efficiency of the supply pre-positioning process, thereby enhancing Belgium's preparedness for flood disasters.

Although the introduction of UAVs did not yield a substantial reduction in overall response times, their ability to deliver targeted aid in hard-to-reach areas is an advantage that cannot be overlooked, and the developed model does not address. The versatility of UAVs in bypassing damaged infrastructure and reaching isolated regions underscores their potential in complementing traditional disaster relief methods.

Moreover, the two-stage scenario-based optimization model demonstrated its utility as a robust tool for evaluating the implications of various disaster relief strategies. The model's ability to account for different scenarios and assess the effectiveness of strategic decisions offers a structure that can be adapted for future research and practical applications in disaster management.

The managerial implications of this research are both practical and actionable, providing clear strategies for enhancing flood preparedness and response in Belgium. The results underscore the importance of decentralizing disaster relief operations by strategically placing multiple relief centers, as opposed to relying on a centralized approach. This decentralization is crucial for reducing response times and increasing the overall efficiency of disaster relief efforts.

The integration of UAVs into the disaster relief fleet represents a significant advancement in logistical capabilities, particularly in last-mile delivery. Despite the study's findings that UAVs did not significantly improve average response times, their superior speed and accessibility in difficult terrains make them a valuable asset in disaster scenarios. Investments in UAVs deserve consideration, not only for its operational benefits but also for the strategic flexibility it offers in diverse disaster conditions.

This study also identifies opportunities within the realm of Corporate Social Responsibility, particularly in the intersection between humanitarian logistics and conventional logistics. The financial constraints inherent in disaster relief management highlight the critical role that private sector involvement can play in enhancing preparedness and response efforts.

Establishing partnerships with public entities or NGOs allows private companies to contribute meaningfully to the community while gaining valuable logistical insights that can be applied to their operations. Such collaborations not only bolster community resilience but also align with broader CSR objectives, demonstrating a commitment to social responsibility.

While this research provides valuable insights, it is important to recognize its limitations. The simplifications inherent in the model, such as its uni-stage characteristic, limit its ability to fully capture the evolving nature of disasters. For instance, the model does not account for the dynamic movement of vehicles back and forth between supply points and disaster sites, which is a critical aspect of real-world disaster logistics.

Additionally, the response stage in the model is highly simplified. A more comprehensive approach would incorporate vehicle routing, enabling more accurate estimations of response times. This would provide a stronger basis for using the model's results as reliable estimates rather than mere comparison points.

Another limitation is the quality of the data used. Ideally, the scenarios developed in this study should be validated by experts and cross-referenced with flood risk maps to ensure their realism. The reliance on data from external sources, particularly regarding facility costs and sizes derived from a relevant research, means that the model does not fully reflect the specific conditions in Belgium.

Future research should focus on incorporating more accurate data, including specific costs associated with land acquisition in the proposed facility locations. By refining the model with better data it would be possible to identify the most strategic locations for disaster relief centers, thereby further enhancing Belgium's capacity to swiftly deploy emergency supplies.

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Appendix A

Data Tables

Table A.1: Population and Province of Belgian Arrondissements

Arrondissement	**Province**	**Population**
Antwerpen	Antwerp	1,087,249
Mechelen	Antwerp	359,299
Turnhout	Antwerp	479,974
Aalst	East Flanders	304,838
Dendermonde	East Flanders	207,562
Eeklo	East Flanders	89,175
Gent	East Flanders	578,015
Oudenaarde	East Flanders	128,081
Sint-Niklaas	East Flanders	264,331
Halle-Vilvoorde	Flemish Brabant	66,933
Leuven	Flemish Brabant	527,443
Ath	Hainaut	130,448
Charleroi	Hainaut	399,742
La Louvière	Hainaut	142,019
Mons	Hainaut	260,855
Soignies	Hainaut	108,487
Thuin	Hainaut	92,684
Tournai-Mouscron	Hainaut	225,839
Huy	Liège	11,583
Liège	Liège	628,381
Verviers	Liège	290,756
Waremme	Liège	84,071
Hasselt	Limburg	431,328
Maaseik	Limburg	258,469
Tongeren	Limburg	210,301
Arlon	Luxembourg	65,565
Bastogne	Luxembourg	50,851
Marche-en-Famenne	Luxembourg	57,667
Neufchâteau	Luxembourg	65,901
Virton	Luxembourg	55,162
Brussels	N/A	1,249,597
Dinant	Namur	113,173
Namur	Namur	323,859
Philippeville	Namur	66,863
Nijvel	Walloon Brabant	41,413
Brugge	West Flanders	286,616
Diksmuide	West Flanders	5,255
Ieper	West Flanders	108,129
Kortrijk	West Flanders	302,332
Oostende	West Flanders	160,032
Roeselare	West Flanders	159,509
Tielt	West Flanders	9,562
Veurne	West Flanders	61,587

Table A.2: Single Flood Events Scenarios

Scenario ID	Event	Probability (%)	Speed Reduction (%)	Water Demand	Food Demand	Medical Kit Demand
1	1	12.0	0	0.38	1.89	943
2	2	10.0	0	0.53	2.67	1,333
3	3	8.0	0	0.67	3.33	1,665
4	4	10.0	2	7.52	37.59	3,759
5	5	12.0	2	6.35	31.74	3,174
6	6	6.0	5	19.78	98.90	19,780
7	7	4.0	5	17.70	88.50	17,700
8	8	7.0	10	54.28	271.39	54,279
9	9	5.0	10	65.73	328.66	65,732
10	10	5.0	25	90.69	453.46	181,383

Table A.3: Multiple Flood Events Scenarios

Scenario ID	Events	Probability (%)	Speed Reduction (%)	Water Demand	Food Demand	Medical Kit Demand
11	1, 2	2.0	0	0.91	4.55	2,275
12	1, 3	2.0	0	1.04	5.22	2,608
13	1, 4	1.5	2	7.89	39.47	4,702
14	1, 5	1.5	2	6.72	33.62	4,117
15	1, 6	1.5	5	20.16	100.79	20,723
16	2, 3	1.0	2	6.88	34.40	4,506
17	2, 4	1.0	5	20.31	101.57	21,113
18	2, 5	1.0	5	18.23	91.16	19,032
19	2, 6	1.0	10	54.81	274.06	55,611
20	3, 4	0.8	2	8.18	40.92	5,424
21	3, 5	0.8	2	7.01	35.07	4,839
22	3, 6	0.8	5	20.45	102.23	21,445
23	4, 5	0.7	5	13.87	69.33	6,933
24	4, 6	0.7	5	27.30	136.49	23,539
25	4, 7	0.6	5	25.22	126.09	21,459
26	5, 6	0.6	5	26.13	130.64	22,954
27	5, 7	0.6	5	24.05	120.24	20,874
28	6, 7	0.5	5	37.48	187.40	37,480
29	6, 8	0.5	10	74.06	370.29	74,059
30	7, 8	0.5	10	71.98	359.89	71,978

Appendix B

Optimization Programming Language Developed Code

B.1 OPL Model Code

```
// Sets and Indices

int I=...; //number of potential facility locations
int J=...; //number of demand points
int K=...; //number of emergency supply items
int T=...; //number of transportation options
int S=...; //number of scenarios

range Facilities=1..I;
range DemandPoints=1..J;
range Supplies=1..K;
range Vehicles=1..T;
range Scenarios=1..S;

// Parameters

int C=...; // maximum storage capacity of each facility
float l[Vehicles]=...; // maximum transportation capacity of vehicle type t
float r[Vehicles][Scenarios]=...; // average speed of transportation option t under
    scenario s
int n[Vehicles]=...; // number of transportation option t available in each facility
float c[Supplies]=...; // volume taken up by emergency supply k
float d[Facilities][DemandPoints]=...; // distance from facility i to demand point j
float D[DemandPoints][Supplies][Scenarios]; // demand for emergency supply k at demand
    point j under scenario s
float P[Scenarios]=...; // probability of scenario s occurring
int B=...; // maximum budget
float p[Supplies]=...; // cost of purchasing supply k
```

```
int f=...; // cost of opening a facility
float alpha[Supplies]=...; // urgency weight for each supply type k
float lambda[Supplies]=...; // time penalty factor for not meeting demand for supply k
int MaxF =...; // maximum number of opened facilities

float Temp[1..J*K*S]=...;

execute {

  var count=0

  for (var j in DemandPoints){
    for (var k in Supplies){
      for (var s in Scenarios){

        count=count+1
        D[j][k][s]=Temp[count]
      }
    }
  }
}

// Decision Variables
dvar float+ st[Facilities][Supplies]; // amount of emergency supply type k stored at
    facility i
dvar boolean y[Facilities]; // whether facility i is operational
dvar float+ x[Facilities][DemandPoints][Supplies][Vehicles][Scenarios]; // quantity of
    emergency supply k transported from i to j using t under s
dvar float+ z[DemandPoints][Supplies][Scenarios]; // unmet demand for emergency supply k
    at demand point j under scenario s

// Objective Function to minimize total expected response time

minimize
  sum(i in Facilities, j in DemandPoints, k in Supplies, t in Vehicles, s in Scenarios) P
      [s] * alpha[k] * (d[i][j] / r[t][s]) * x[i][j][k][t][s] +
  sum(j in DemandPoints, k in Supplies, s in Scenarios) P[s] * lambda[k] * z[j][k][s];

// Constraints
subject to {

  // Flow Conservation
  forall(j in DemandPoints, k in Supplies, s in Scenarios)
    sum(i in Facilities, t in Vehicles) x[i][j][k][t][s] + z[j][k][s] == D[j][k][s];

  // Facility Capacity
  forall(i in Facilities)
    sum(k in Supplies) c[k] * st[i][k] <= C * y[i];

```

```
  // Maximum Number of Facilities Open
  sum(i in Facilities) y[i] <= MaxF;

  // Inventory Limitation
  forall(i in Facilities, k in Supplies, s in Scenarios)
    sum(j in DemandPoints, t in Vehicles) x[i][j][k][t][s] <= st[i][k];

  // Transportation Capacity
  forall(i in Facilities, t in Vehicles, s in Scenarios)
    sum(j in DemandPoints, k in Supplies) c[k] * x[i][j][k][t][s] <= l[t] * n[t];

  // Budget Constraint
  sum(i in Facilities) (f * y[i] + sum(k in Supplies) p[k] * st[i][k]) <= B;

}

// Metrics to assess performance

dexpr float budgetUsed = sum(i in Facilities) (f * y[i] + sum(k in Supplies) (p[k] * st[i
    ][k]));

float totalUnmetDemand[Supplies][Scenarios];
float totalVolumeOccupied[Facilities][Supplies];
float VehicleUsage[Vehicles][Scenarios];
float averageResponseTime[Supplies][Scenarios];
float supplyCarriedByVehicle[Vehicles][Supplies][Scenarios];
float MaxResponseTime[Supplies][Scenarios];

  // Auxiliary Variables

float Temp2[1..T*K*S];

float totalResponseTime = 0;
float totalOperations = 0;
float currentResponseTime = 0;

// Execute block to calculate performance metrics

execute {
  for(var k in Supplies) {
    for(var s in Scenarios) {
      totalUnmetDemand[k][s] = 0; // Initialize the array position for each scenario and
          supply

      for(var j in DemandPoints) {
        totalUnmetDemand[k][s] += z[j][k][s]; // Accumulate unmet demand for each supply
            in each scenario
      }
    }
```

```
  }
}



// Execute block to calculate total volume occupied for each facility and each supply

execute {
  for(var i in Facilities) {
    for(var k in Supplies) {
      totalVolumeOccupied[i][k] = 0; // Initialize the array position for each facility
          and supply

      totalVolumeOccupied[i][k] = st[i][k] * c[k]; // Calculate total volume occupied
    }
  }
}



execute {
  for(var t in Vehicles) {
    for(var s in Scenarios) {
      VehicleUsage[t][s] = 0; // Initialize the volume for each vehicle and scenario
      for(var i in Facilities) {
        for(var j in DemandPoints){
          for(var k in Supplies) {
            VehicleUsage[t][s] += x[i][j][k][t][s] * c[k]; // Calculate total volume used
          }
        }
      }
    }
  }
}


execute {
  for(var k in Supplies) {
    for(var s in Scenarios) {
      totalResponseTime = 0;
      totalOperations = 0; // This could be the total units shipped for supply k in
          scenario s

      for(var i in Facilities) {
        for(var j in DemandPoints) {
          for(var t in Vehicles) {
            if (x[i][j][k][t][s] > 0) {
              // Calculate response time, assuming 'r' is the time per unit shipped
              totalResponseTime += d[i][j] / r[t][s] * x[i][j][k][t][s];
```

```
                totalOperations += x[i][j][k][t][s];
              }
            }
          }
        }

        // Store the average response time for each supply in each scenario
        if (totalOperations > 0) {
          averageResponseTime[k][s] = totalResponseTime / totalOperations;
        } else {
          averageResponseTime[k][s] = 0; // Handle cases with no operations
        }
      }
    }
}


execute {
  for(var t in Vehicles) {
    for(var k in Supplies) {
      for(var s in Scenarios) {
      supplyCarriedByVehicle[t][k][s] = 0; // Initialize to ensure clean calculation

      for(var i in Facilities) {
        for(var j in DemandPoints) {
            supplyCarriedByVehicle[t][k][s] += x[i][j][k][t][s] * c[k]; // Accumulate the
                 total quantity of each supply carried by each vehicle
          }
        }
      }
    }
  }
}


execute {

  var count=0

  for (var t in Vehicles){
    for (var k in Supplies){
      for (var s in Scenarios){

        count=count+1
        Temp2[count] = supplyCarriedByVehicle[t][k][s]
      }
    }
  }
}
```

```
execute {
  for(var k in Supplies) {
    for(var s in Scenarios) {
      MaxResponseTime[k][s] = 0; // Initialize the maximum response time for each supply
          in each scenario

      for(var i in Facilities) {
        for(var j in DemandPoints) {
          for(var t in Vehicles) {
            // Only calculate response time for shipments that occur
            if (x[i][j][k][t][s] > 0) {
              currentResponseTime = d[i][j] / r[t][s];

              // Update the maximum response time if the current one is greater
              if (currentResponseTime > MaxResponseTime[k][s]) {
                MaxResponseTime[k][s] = currentResponseTime;
              }
            }
          }
        }
      }
    }
  }
}
```

Listing B.1: OPL Code for the model

B.2 OPL Data Extraction Code

```

 SheetConnection my_sheet("Data_Setup3.xlsx");

// Inputs

I from SheetRead(my_sheet, "I");
J from SheetRead(my_sheet, "J");
K from SheetRead(my_sheet, "K");
T from SheetRead(my_sheet, "T");
S from SheetRead(my_sheet, "S");

// Single-dimensional parameters
C from SheetRead(my_sheet, "StorageCapacity");
l from SheetRead(my_sheet, "VehicleCapacity");
n from SheetRead(my_sheet, "FleetSize");
P from SheetRead(my_sheet, "Probabilities");
B from SheetRead(my_sheet, "Budget");
f from SheetRead(my_sheet, "FacilityCost");
```

```
alpha from SheetRead(my_sheet, "SupplyUrgency");
lambda from SheetRead(my_sheet, "Penalty");
c from SheetRead(my_sheet, "SupplyVolume");
p from SheetRead(my_sheet, "SupplyCost");
d from SheetRead(my_sheet, "Dist");
r from SheetRead(my_sheet, "Speed");
MaxF from SheetRead(my_sheet, "MaxFacilities");


// Multi-dimensional parameters

Temp from SheetRead(my_sheet, "D");


// Output Results

budgetUsed to SheetWrite(my_sheet, "budgetUsed");
totalUnmetDemand to SheetWrite(my_sheet, "totalUnmetDemand");
totalVolumeOccupied to SheetWrite(my_sheet, "totalVolumeOccupied");
VehicleUsage to SheetWrite(my_sheet, "VehicleUsage");
averageResponseTime to SheetWrite(my_sheet, "averageResponseTime");
Temp2 to SheetWrite(my_sheet, "supplyCarriedByVehicle");
MaxResponseTime to SheetWrite(my_sheet, "MaxResponseTime");
```

Listing B.2: OPL Data Input and Output Code

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
Louvain School of Management
Place des Doyens, 1 bte L2.01.01, 1348 Louvain-la-Neuve, Belgique | **www.uclouvain.be/lsm**