A Simulation Framework for Reducing Scope 2 Emissions with Autonomous Drones

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ABSTRACT

This capstone assesses Scope 2 emission reductions achieved by autonomous drone-based inventory scanning compared to traditional forklift-based inventory scanning in warehouse operations. Conducted in collaboration with Verity and a major third-party logistics provider (3PL), this study develops two discrete-event simulation models to capture and compare drone-based and forklift-based inventory scanning operations across varying warehouse sizes and geographic regions. The models incorporate vehicle movement, energy consumption, drone and forklift fleet sizes, warehouse lighting requirements, and regional electricity emissions factors across North America and Europe. Operational differences between drones and forklifts, including travel distance, lighting usage, and scanning capabilities, are used to estimate total energy consumption and resulting emissions. Across all modeled scenarios, drone-based inventory scanning produced significantly lower Scope 2 emissions than forklift-based operations, with reductions of approximately 99.4% once lighting-related emissions are included. Even when only vehicles are compared and all warehouse-related emissions are excluded, forklift scanning operations still produced substantially higher emissions due to greater energy consumption during travel and material handling. The resulting simulations provide a scalable decision support tool to help prioritize drone deployments within the 3PL's global network from a sustainability-focused perspective.

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TABLE OF CONTENTS

1 INTRODUCTION

1.1. Motivation

Warehouse operators are under growing pressure to become more sustainable as logistics networks expand and companies face increasing expectations to reduce greenhouse gas (GHG) emissions. Many warehouse processes remain labor-intensive and rely on conventional equipment such as forklifts, which can be inefficient for repetitive tasks like inventory scanning. As a result, companies are increasingly investing in automation technologies that improve operational efficiency and reduce environmental impact.

The sponsor of this project, Verity, specializes in autonomous drone systems and inventory solutions designed to address these operational challenges. Verity's drones are particularly useful for scanning high-bay and hard-to-reach storage locations within warehouses. Compared with traditional forklift-based manual methods, the company reports that drones can scan inventory more quickly, while reducing operator risks arising from falls and repetitive motion.

A major reason the 3PL is investing in this type of automation is its commitment to achieving net-zero carbon emissions by 2050. This goal is measured by reductions in Scope 1, 2, and 3 emissions, as defined by the Greenhouse Gas (GHG) Protocol. As an interim goal, the 3PL aims to reduce Scope 1 and 2 emissions by 50% by 2030. Scope 1 emissions are direct GHG emissions from sources a company owns or controls, such as vehicle fuel or on-site heating. Scope 2 emissions are indirect emissions associated with the purchase of electricity, steam, heat, or cooling. Although Scope 2 emissions physically occur at the facility where they are generated, they are part of a company's GHG emissions because they result from the organization's energy use (EPA, 2025a). Scope 3 emissions are also indirect and occur outside a company's direct control but result from the firm's own activities, such as supplier manufacturing, transportation, or waste disposal (EPA, 2025b).

Within the 3PL's warehouses, a significant portion of Scope 2 emissions is attributed to forklift usage, particularly during inventory scans. Currently, inventory counts at many of its warehouses are performed manually using forklifts, where items are lowered and scanned by personnel before being returned to their original positions. If an error occurs during traditional scanning, the item must be retrieved and scanned again. This repeated effort increases energy consumption and costs across the 3PL's thousands of employees and hundreds of warehouses.

1.2. Problem Statement and Key Questions

Although autonomous drones promise lower-emission warehouse operations, many organizations currently lack decision support tools to evaluate their environmental benefits before deployment. Building a reliable decision support tool requires a clear understanding of the Scope 2 emission reductions achieved by autonomous drone-based inventory scanning compared to traditional forklift-based inventory scanning in warehouse operations.

The 3PL has over 1,000 warehouses worldwide, and this decision depends on identifying which facilities will benefit the most from drone deployment. The project builds a reliable mechanism that enables stakeholders to identify warehouse facilities that can achieve the most significant reductions in Scope 2 emissions through drone deployment. Therefore, the primary project objective is to develop a simulation-based model that is consistent, data-driven, and practical to run at scale. The model estimates potential Scope 2 emission reductions from deploying Verity's autonomous drone system across warehouses within the 3PL's network.

To develop this model, we conducted a literature review on warehouse simulations and energy efficiency. We evaluated feasible simulation approaches, which included discrete-event and agent-based simulation. We also conducted interviews with Verity and the 3PL staff to understand inventory scanning operations and align model inputs and outputs with Verity's key performance indicators (KPIs). Using data on drone and forklift specifications, energy consumption, and warehouse lighting usage, we built and iterated on our simulation model. We began with one of the 3PL's warehouses in the EU (European Union) to validate our simulation logic and establish a proof of concept before scaling across the network. Once the initial simulation model was built in Python, we added an interactive user interface called DroneSim. This self-serving mechanism enables stakeholders across Verity and the 3PL to set relevant drone, forklift, and warehouse parameters to run simulations and test scenarios. The user interface also includes a dashboard providing a clear visual aid for decision-making.

1.3 Project Goals and Expected Outcomes

The overarching objective of this project is to build a scalable simulation framework to estimate Scope 2 emission impacts of inventory scanning using Verity's autonomous drone systems. Our model provides a quantitative comparison of forklift versus drone scanning energy consumption and emissions at the process level. The resulting analyses will inform evidence-based recommendations to Verity and the 3PL regarding the prioritization of warehouse sites for future deployment.

The resulting deliverables include a process-level comparison of forklift and drone-based scanning, a decision-support tool for evaluating warehouse deployment scenarios, and recommendations for prioritizing future drone implementation across the 3PL's warehouse network.

Across the modeled scenarios, drone-based inventory scanning produced approximately 99.4% lower Scope 2 emissions than traditional forklift-based scanning when lighting emissions were included. The results also indicated that warehouses in regions with higher electricity emissions factors, larger warehouse footprints, and greater lighting-related energy usage lead to higher potential for emission reduction. Beyond informing Verity and the 3PL's deployment strategy, this framework offers a broader contribution for sustainability stakeholders seeking a practical method to evaluate the emissions implications of warehouse automation and support more informed and sustainable decision-making.

2 STATE OF THE PRACTICE

As the 3PL pursues its goal of reaching net-zero emissions across its operations by 2050, reducing Scope 2 emissions from purchased electricity remains a key step toward that goal. The objective of our project is to develop a reliable, scalable simulation model to quantify Scope 2 emission reductions resulting from the implementation of our sponsor, Verity's, drone-based inventory scanning solution.

In this section, we present the state of practice based on a review of research and industry literature from the past decade, with an emphasis on peer-reviewed publications in leading journals. We categorized our review into four topics, all critical to achieving our project's objective. These four topics are:

- Drone Operations and Emissions
- Simulation Methods for Modeling Warehouse Processes
- Methods for Calculating Scope 2 Emissions
- Warehouse Electricity Drivers: Material Handling and Lighting

2.1 Drone Operations and Emissions

Unmanned aerial vehicles (UAVs), commonly known as drones, play a vital role in modern warehouses (Malang et al., 2023). Our review focuses on aerial drones with autonomous navigation and environmental perception capabilities. In warehouse operations, research shows that these drones can perform autonomous flight, indoor navigation, obstacle avoidance, and precise landings (Proia et al., 2025). Antoniades and Stamelos (2022) studied the operational viability of using drones as Automated Warehouse Inspection systems. Their research demonstrated that drones could fly independently to specific 3D coordinates within warehouses, stop mid-flight, hover, scan the contents of the rack, and transmit the information wirelessly. Although these studies demonstrate the operational viability and technical capabilities of warehouse drones, limited research has measured emissions associated with such operations.

Academic research on the sustainability of drones has primarily focused on drone-based delivery. Kumar et al. (2025) conducted a structured literature review on the environmental implications of drone-based delivery systems. They concluded that the ecological benefits of drones, such as reduced emissions and improved energy efficiency, are context-dependent. For instance, drones yield more favorable energy consumption and emissions outcomes than traditional delivery methods in traffic-prone urban settings (Kumar et al., 2025). Balassa et al. (2023) substantiated the comparative efficiency of drones using discrete-event simulation. Their study found that drone-assisted last-mile delivery services consumed less fuel and emitted less CO_2 than traditional delivery vehicles. Both studies demonstrate the potential for sustainability improvements from drone use in outdoor logistics, but neither addresses the sustainability of drone-based inventory scanning in indoor warehouses.

While Ruiz and Kook (2025) have provided insights on emissions from drone-based inventory scanning, the broader literature on this topic is limited. Our study builds on these findings by specifically quantifying the Scope 2 emissions of autonomous drones in warehouses using actual energy consumption and operational data from our sponsor company to inform our analysis. This information would establish a reliable baseline for our scalable simulation model.

2.2 Simulation Methods for Modeling Warehouse Processes

For this study, we built a simulation model to estimate Scope 2 emissions from deploying autonomous drones in warehouses for inventory management tasks. Simulation is a tool used to evaluate the performance of a system, existing or proposed, under different configurations and long time periods. A simulation model studies the behavior of a system as it evolves over time (Banks et al., 2001). It helps identify bottlenecks within a system, test hypotheses about the system, and experiment with new or unknown situations where little information is available (Maria, 1997). Discrete-event simulation and agent-based simulation are among the most used and discussed simulation modeling techniques (Braglia et al., 2019).In a discrete-event simulation, systems and processes are modeled as sequences of discrete events that occur at finite intervals (Akpan et al., 2024). The system evolves through these events, each representing a discrete change in the model's state. Discrete-event simulation has been used extensively in warehouses and distribution centers for the allocation of machines, equipment, and personnel. Antoniades and Stamelos (2022) validated the operational feasibility of drone-based inventory tracking through discrete-event simulation. Their study primarily sought to predict task completion times and failure rates. Discrete-event simulation also helped optimize system performance by adjusting control parameters, such as the number of drones and drone battery levels.

Agent-based simulation focuses on the behavior of individual agents within a warehouse. These models simulate the simultaneous operations and interactions of autonomous agents, such as human workers, mobile material handling resources, including forklifts, and autonomous mobile robots (AMRs). The interacting agents are autonomous decision-making entities in the system (Akpan et al., 2024). Each agent is assigned specific properties, behaviors, and decision-making abilities to depict their interactions within the warehouse system. While agent-based modelling provides a realistic representation of dynamic warehouse interactions, the need for extensive granular data and detailed behavioral rules makes developing these precise models challenging and time-intensive (De Vito et al., 2024).For our project, discrete-event simulation is the preferred method, as our assumptions and conversations with stakeholders indicate that the inventory scanning workflow for both drones and forklifts is a sequential process. Given that agent-based simulations require complex granular data, discrete-event simulation would allow us to calculate energy consumption without undue complexity.

2.3 Methods for Calculating Scope 2 Emissions

The greenhouse gas (GHG) framework classifies Scope 2 emissions as indirect emissions from the use of purchased electricity, steam, heat, or cooling. These emissions can be quantified using two methods: location-based and market-based. For both approaches, the emissions are calculated by multiplying the purchased electricity during the year by the appropriate emissions factors. An emissions factor is a representative value that relates the quantity of a pollutant released into the atmosphere to an activity associated with that release (EPA, 2025c). The location-based method accounts for average emissions factors for electricity grids, including the Direct Line, Regional, and National Emissions factors. Meanwhile, the market-based method considers contracts in which the organization obtains power from specific sources, such as fossil, renewable, or other generation facilities. The market-based emissions factors include Energy Attribute Certificates, Contracts, Supplier-Specific Emissions Factor, and Residual Mix Factor (EPA, 2025a).

Ruiz and Kook (2025) developed a quantitative decision-making framework grounded in the GHG Protocol for calculating emissions, applying an activity-based emissions modeling approach. Their foundational calculation for emissions is: $Emissions_{activity} = Activity\ Level * Emissions\ Factor$ **(*Equation 1)***. The activity level for Scope 2 activities is measured in kWh (kilowatt hours) consumed. This study calculated the emissions factor based on the regional electricity grid mix, which aligns with the principles of the location-based method under the GHG Protocol.

2.4 Warehouse Electricity Drivers: Material Handling and Lighting

In warehouse operations, Scope 2 emissions are influenced by material-handling equipment, lighting, and heating, ventilation, and air conditioning (HVAC) systems powered by electricity.

Forklifts, the primary material-handling equipment, have been used extensively in warehouse operations for tasks such as loading and unloading, picking, and inventory counting. Within the context of this study, the primary material-handling equipment would be a forklift widely used within the 3PL's operations, in particular the Toyota BT Reflex. These forklifts are powered by electricity, and the forklift energy consumption would be determined by the VDI 2198 test, which serves as a standardized industry-wide benchmark (Zajac & Rozic, 2022). Prior research estimates that a forklift utilizes roughly 50 times as much energy as a single drone (Ruiz & Kook, 2025). Additionally, because Verity's drones can operate in complete darkness, drone-based scanning may reduce lighting-related electricity use and Scope 2 emissions. This presents an opportunity for our study to simulate and subsequently analyze how the implementation of autonomous drones can alter lighting requirements within a single warehouse of constant size. In their research, Ruiz and Kook (2025) initially hypothesized that drone implementation might alter HVAC needs; however, their findings showed that their target warehouse kept HVAC schedules and operational settings consistent in both pre- and post-drone implementation scenarios.

Given that our study focuses on emissions resulting from reduced use of material-handling equipment and lighting, driven by drone implementation, the primary Scope 2 activities to be modeled include: drone usage, forklift usage, and lighting usage.

3 METHODOLOGY

This section outlines the methodological framework for this study, including the data collection and analysis procedures shown in Figure 1, and describes how the methodology was applied to evaluate strategies for reducing Scope 2 emissions within the 3PL's warehouses through the deployment of Verity's autonomous drone systems.

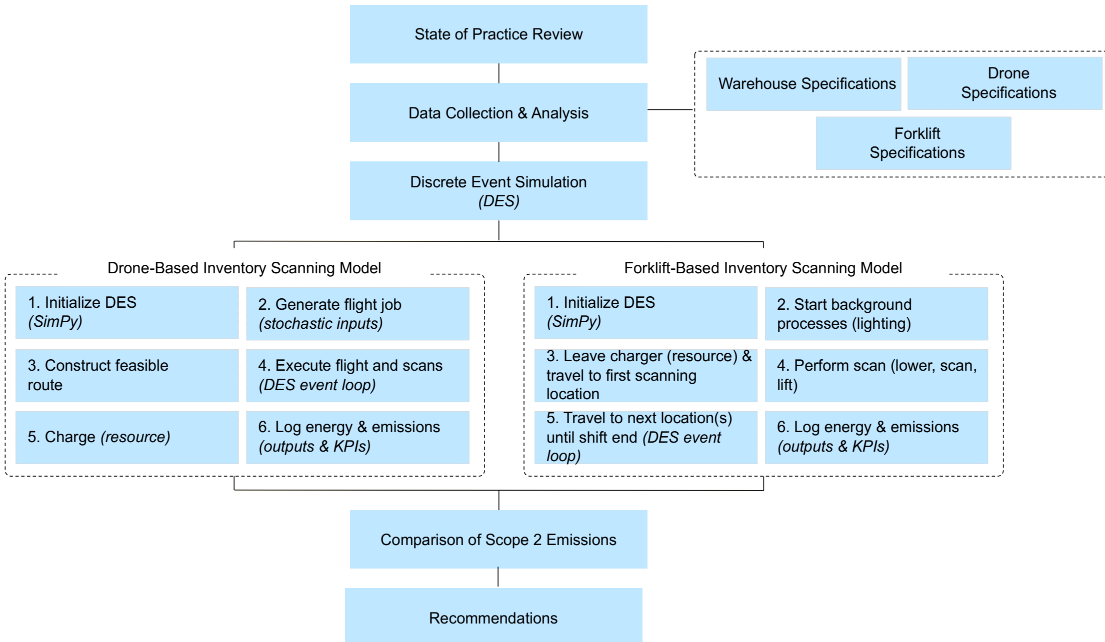

Figure 1. Overview of Project Methodology and Simulation Framework

3.1 Methodology Selection

The goal of this project is to create a simulation model that can be implemented across the 3PL's warehouses within North America and Europe. This model will compare drone and forklift inventory-scanning operations within designated warehouses, which can then be used to calculate energy use and carbon emissions (specifically, Scope 2 emissions). These carbon emission metrics will then inform our sponsors of which warehouses would benefit the most from drone implementation.

Within warehouses, inventory scans are systematic and event-driven processes. Drones travel to pallet locations, stabilize, take pictures of barcodes, travel to other pallets, scan them, and then return to their charging locations. Forklifts also conduct scanning activities in a similar manner, with the addition of bringing the pallet down so that it can be scanned by hand. These separate inventory scanning processes are shown in Figure 2. In both instances, each vehicle (drone or forklift) will consume varying amounts of energy depending on its state (charging, travelling, or stationary).

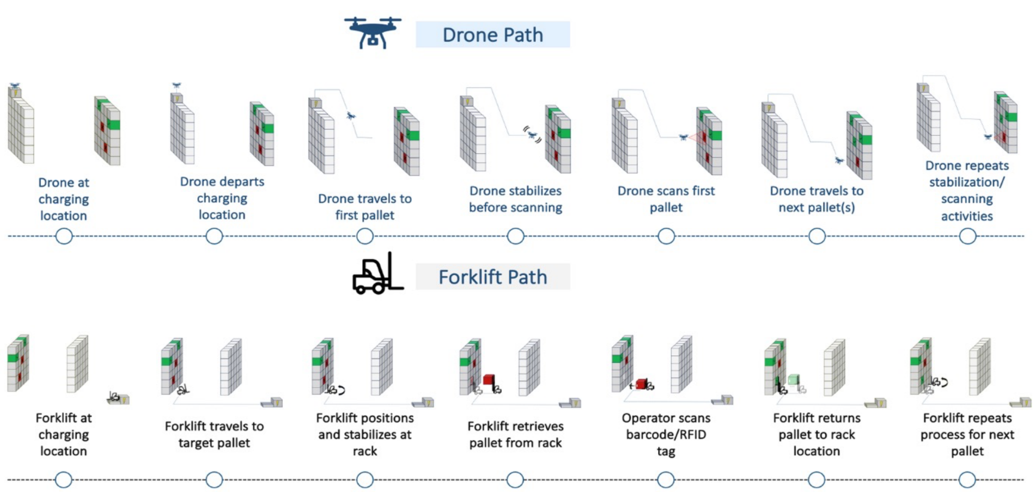

Figure 2. Inventory Scanning Processes of Drones and Forklifts

Therefore, a discrete-event simulation (DES) is an appropriate model for comparing carbon emissions between drones and forklifts within the 3PL's warehouses due to its ability to model warehouse operations as a series of discrete, state-altering events (Antoniades & Stamelos, 2022).

3.2 Data Collection and Preparation Process

The model was based on an EU (European Union) warehouse, which was selected because it had experienced both pre- and post-drone implementation operations. Verity provided several documents and data points, including drone scan logs and past energy consumption. Much of the historical data provided was limited to the period between October 1, 2024, and October 31, 2025. Due to these data limitations, our team supplemented the missing information through additional research, calculations, and sponsor-verified assumptions.

We organized data collection efforts by separating information into three separate data pools: warehouse data, drone data, and forklift data. Each of these data groups informed different portions of the simulation model. The reference warehouse's managers also provided operational and layout data.

This warehouse is divided into three modules: Module 1, Module 2, and Module TC (temperature-controlled). Each module conducts inventory scanning operations independently, with drones and forklifts assigned to specific modules. Therefore, for our simulation, we separated the warehouse into distinct zones for each vehicle where drones and forklifts are not permitted to travel between modules.

Verity managers provided sketches and floorplans of the reference warehouse, but due to the complexity of the layout, our simulation standardized the aisle length and width, rack length, and number of pallets per bay. We utilized the number of aisles per module, area of each module, and width of the aisles to calculate the aisle length. Additionally, we assumed that racks stand on both sides of each aisle and have uniform width throughout all modules. This assumption allowed us to determine the total number of racks per module as well as the complete dimensions of each rack. This rack organization is illustrated in Figure 3 and provides additional clarity on how storage elements are represented in our simulation model.

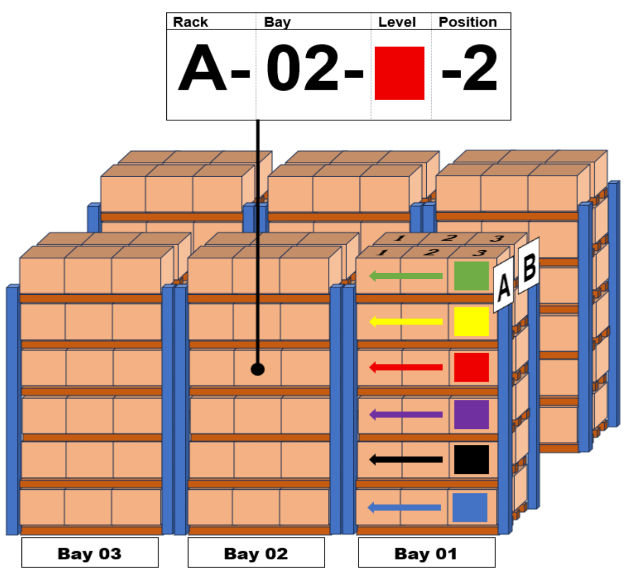

Figure 3. Rack, Bay, Level, Position Organization

Additionally, the data and floorplans provided by Verity did not have information on the forklift or drone charging locations. Therefore, through conversations with staff, we confirmed that the drone charging locations will be positioned on racks at the center of each module, while forklift charging locations will be located at the front left corner of each module.

Verity also provided detailed data on drone scanning operations as well as the full specifications of each drone. Unfortunately, they were unable to provide the routing algorithm (how drones travel from point A to B) due to data and trademark sensitivity. Therefore, to calculate the distance travelled per scanning job, we assumed that Verity utilizes Manhattan distance, which measures how far two points are from each other when movement is restricted to horizontal and vertical directions. This is the ideal distance metric for our simulation since it restricts an object's movement (forklift or drone) to grid-like paths (i.e., they cannot pass through storage shelves), which results in the shortest routing distance between two locations in a warehouse (Lin et al., 2016).

Although Verity had little data on forklift scanning operations, they were able to provide us with the forklift model—Toyota BT Reflex—with lithium-ion batteries. Through our research, we were able to find the forklift specifications, including speed (travelling and lifting), charging time, and energy consumption (Toyota Material Handling Europe, 2023). Verity provided data on the number of pallets moved per week within each module, which we assumed to be directly correlated to the number of scans conducted per week.

After extensive analysis, we were able to categorize the data into the following buckets:

Warehouse Specifications:

- Energy usage: Lighting, Material Handling
- Area of warehouse
- Aisle specifications: length, width, number of aisles, rack organization (levels per rack, bays per rack, positions per level, as shown in Figure 3)
- Operating hours: 8 hours for forklifts with 1 hour break in-between and 8 hours for drones
- Detailed floorplan, layout, charging locations for forklifts and drones
- Grid-based emissions factor

Drone Specifications:

- Number of drones assigned per module
- Model specifics: horizontal speed, vertical speed, run time per charge, charging time, power draw, scan time per location
- Drone categorization of scan jobs (area scan, single pallet scan, etc.)
- Drone minimum and maximum flight duration

Forklift Specifications:

- Number of forklifts utilized for scanning purposes
- Model specifics: travel speed, lifting/lowering speed, charging time, power draw
- Forklift scan time per pallet
- Forklift scan issue rate

3.3 Simulation Model

Building a discrete-event simulation model involves defining the system's key components, such as variables, states, constraints, and events, and specifying how they interact over time to reflect real operational behavior. The primary entities we modeled are the warehouse configuration, drones, and forklifts. We developed two separate simulations: one representing drone operations and the other capturing forklift activities. This approach enables a systematic comparison of energy consumption and carbon emissions over an extended time horizon, providing insights into the relative sustainability of each mode.

The warehouse operates in two states: daytime shift (9:30 am to 5:30 pm) and nighttime shift (9:30 p.m. to 5:30 a.m.), where drones conduct inventory scans during the nighttime shift, and forklifts scan inventory during the day. The reference warehouse operates without any lighting during the nighttime shift, since the drones do not require lighting to scan pallets.

The distance travelled, scanning activities, scan error rate, and energy consumption of drones and forklifts are set as probability distributions (range of values). Each vehicle will likely travel different distances and have different scan tasks on a daily basis, thus resulting in different amounts of energy consumed. Modelling these values as a distribution allows the simulation model to account for the random events that can occur throughout inventory scanning periods.

By applying the above methodology, we aim to accurately measure Scope 2 emissions for the reference warehouse. Our initial simulation will then act as a framework that can be iterated and extended to the 3PL's other warehouses within North America and Europe.

3.3.1 Drone Simulation Model

To estimate the Scope 2 emissions from drone-based inventory scanning, our discrete-event simulation model showed each drone flight as a series of operational events within a warehouse shift. The repeatable flight events across the shift include: travelling to the target location, scanning (travelling to the next location and scanning), returning to the charging location, and charging. This allowed us to calculate the energy consumption and emissions at the flight level and at the shift level. Because Verity's drones operate in the dark, there were no emissions from warehouse lighting.

Based on the warehouse configuration, our model represented scanning (storage) locations defined by aisle, rack side, bay, rack level, and pallet position. We used the Manhattan-style distance metrics with horizontal and vertical components to represent the boundaries of the drone's motion. We computed the travel time between the scanning locations by dividing each distance component by the corresponding drone speed. Each drone is assigned a charger, and it begins and ends each flight at the charger position. We built the model such that for each simulated flight, the model samples a flight time capacity, scan type ("area" versus "sparse"), and a scan rate (locations scanned per minute). From this information, our model builds a feasible route to maximize the scan locations within the sampled flight time capacity. Area scans are modeled such that the drone scans all pallet locations within the selected bay, and sparse scans are modeled as distinct target locations. The model uses the nearest neighbor heuristic to optimize the route. During the simulation, the model tracks the drone as it travels and scans each location, records the number of locations scanned, and returns to the charger to complete the flight.

We modeled the energy consumption using power draws of the drone for each stage (horizontal flight, vertical flight, and charging) multiplied by the duration spent in each stage. The total "flying" energy consists of horizontal travel, vertical travel, scanning, and the "charging" energy was computed from charging power and the modeled charging time. Based on stakeholder-provided information each drone has a dedicated charger resource assigned. The Scope 2 emissions were calculated by multiplying the energy consumption by the site-specific emissions factor. The simulation then output flight and shift level metrics, which can be adjusted to varying levels of detail.

3.3.2 Forklift Simulation Model

Our discrete-event simulation model representing forklift-based inventory scanning shows each forklift shift as a sequence of operational events within the warehouse. The events include: travelling from the home location (charging location) to a target storage location, performing lifting/lowering and scanning operations at that location, travelling between subsequent locations, taking a scheduled break each shift (idle period), and returning to the home position at the end of the shift. In addition, the model takes into account a charging event at the beginning of each shift. Like the drone simulation model, the forklift simulation model enables the energy consumption and emissions to be calculated both at the task level and the shift level. However, unlike drones, forklifts operate under standard warehouse lighting. Hence, the lighting energy per shift is included in the Scope 2 emissions calculation.

The forklift simulation models the warehouse configuration of scanning locations and travel distances between locations, in the same way as the drone simulation model. Travel time is calculated by dividing the horizontal and vertical distances between locations by forklift travel and lift speeds. The model supports multiple forklifts operating simultaneously.

Verity and the 3PL's staff have confirmed that there are two scanning policies. On weekdays, forklifts perform sparse scanning, where each job targets a random location within the warehouse configuration. On weekends, the forklifts perform area scanning, where they scan all locations within a specific area of the warehouse. On the subsequent weekend, the forklift would resume scanning from the next unvisited location. During the simulation execution, the discrete-event simulation model advances time through travel, lift, scan, idle, and records the number of locations scanned before returning to the charger at the end of the shift.

Forklift energy consumption was calculated by estimating the energy used in each operating stage as the product of stage-specific power demand and stage duration, and then summing these values to determine total energy use. This includes horizontal travel, lifting (unloaded and loaded), scanning, and idle activity. Aggregating this energy provides us with the forklift operational energy for each shift. In addition, since the forklift charges at the beginning of each shift, the charging energy is also accounted for. The lighting energy is assumed to be a constant kWh each shift. Scope 2 emissions are calculated by multiplying the energy consumption by the emissions factor, which can be adjusted based on the location of the facility. The model then outputs scan and shift level records, which can be used for further analysis.

Our initial forklift simulation uses operational data from the reference warehouse, which utilizes the Toyota BT Reflex forklift. However, the Toyota BT Reflex is not typically sold in North America. Through further discussions with the 3PL, we identified lithium-ion reach trucks as the standard configuration for future deployments. Therefore, a comparable North American model was selected. The Hyster N45ZR3 lithium-ion single-reach truck was chosen due to its similar narrow-aisle configuration, high-lift capability, and compatibility with lithium-ion battery systems.

Furthermore, forklifts in North America are typically not rated using the VDI energy consumption standard. To maintain standardized energy consumption inputs, the Hyster N45ZR3 battery specifications were used to estimate total available energy. The manufacturer's documentation (Hyster Company, n.d.) provides lithium-ion battery configurations directly in kilowatt-hours, with the largest configuration corresponding to approximately 43.5 kWh. This value represents the total available stored energy for the selected high-capacity lithium-ion configuration.

Since the Hyster N45ZR3 does not publish a VDI energy rating, a comparable hourly energy consumption was estimated using a similar forklift duty cycle. An operational distribution of 75% horizontal travel, 20% lifting, and 5% idle time was assumed based on measured power-time duty cycles for electric forklifts reported by Battini et al. (2021).

To obtain a VDI-comparable hourly energy consumption value, the total battery energy (43.5 kWh) was normalized over a representative operating period. Prior forklift energy studies assume standardized operations over a typical 8-hour shift (Battini et al., 2021; Zajac & Rozic, 2022). This approach is consistent with prior studies that calculate average forklift energy consumption from battery capacity and operation cycles to derive standardized energy consumption metrics per hour (Zajac & Rozic, 2022). The average hourly energy consumption was calculated as:

$$E_{avg} = \frac{E_{battery}}{t} \quad \rightarrow \quad E_{avg} = \frac{43.5\ kWh}{8\ hours} \quad \rightarrow \quad E_{avg} = 5.44\ kWh\ per\ operating\ hour$$

(Equation 2)

where*:*

- $E_{avg} = average\ energy\ per\ operating\ hour$ *(kWh/h)*
- *t = time*

Therefore, the Hyster N45ZR3 lithium-ion reach truck was estimated to consume approximately 5.44 kWh per operating hour, which is comparable to the 5.2 kWh per hour VDI-based energy consumption value reported for the Toyota BT Reflex.

3.3.3 User Interface Model

In addition to our models, we built DroneSim, an interactive user interface that allows the stakeholders to adjust key inputs (e.g., warehouse size, number of drones or forklifts, speeds, shift length, emissions factor, etc.) and run the simulation. The interface generates KPI summaries, graphs, and downloadable tables across the simulated shifts. This output supports an effective comparison of assumptions and parameters across the 3PL's different sites and will provide a more consistent method of evaluating potential Scope 2 emissions impact.

3.4 Forklift Vs. Drone Scenario Modeling

Based on discussions, our team identified the inputs and scenarios that were most relevant to warehouse operations in Europe and North America. The scenario analysis was structured around warehouse size, regional emissions factors, shift configurations, and vehicle counts (drone and forklift). Rather than running a single test case, our models were designed to evaluate drone and forklift performance over a wide range of warehouse scenarios and environments. This approach allowed our team to assess how drones and forklifts perform across varying warehouse specifications and geographic regions while also estimating the Scope 2 emissions associated with each scenario.

The final scenario inputs used in both the forklift and drone models were refined through stakeholder discussions to reflect realistic operating conditions. Each scenario was evaluated using the following standardized assumptions:

- 30 shifts per scenario
- Drone count: 2 drones for small warehouses, 3 drones for medium warehouses, and 4 drones for large warehouses
- Forklift count: 1 forklift for every 10,000 square meters
- Shift length: 8 hours with a 1-hour break
- Size of warehouse: small, medium, large
- Warehouse type: traditional storage facilities, with approximately 78% of total area allocated to pallet storage (Hübner et al., 2019)
- Regional emissions factors: Spain, Denmark, Poland, Germany, Canada, United States

The selected regions were chosen to reflect both the baseline simulation context and potential deployment priorities. The United States and Canada were selected to represent North American operations, while Spain, Germany, Denmark, and Poland were included because they represent European markets with the 3PL's significant warehouse presence and subsequent potential for future drone implementation. These regions also differ in their electricity emissions factors. Because Scope 2 emissions are calculated by multiplying electricity consumption by the corresponding locations' emissions factor, the same level of warehouse energy use can produce different emissions outcomes depending on the carbon intensity of the local electricity grid (EPA, 2025a; EPA, 2025c).

3.4.1 Forklift Scenario Modeling

The forklift scenario model was developed to represent conventional pallet-handling operations in traditional warehouses across Europe and North America. Utilizing this framework, forklifts acted as the baseline inventory scanning operations to compare against drones. The model was used to evaluate forklift energy usage, operational performance, and associated Scope 2 emissions across warehouse scenarios detailed above.

Since forklifts are the established vehicles for inventory scanning operations currently at the 3PL's warehouses, drones act as the reference case to assess whether drone deployment could offer operational or emission reduction benefits under similar conditions.

3.4.2 Drone Scenario Modeling

Comparatively, the drone scenario model was designed to evaluate how drone operations perform under the same general warehouse conditions used in the forklift analysis, while accounting for drone specifications. Since drones are capable of scanning significantly more pallets per shift than forklifts, fewer drones were required per square meter of warehouse space as shown in our standardized assumptions above. This structure allows the drone model to assess performance across increasing warehouse sizes while maintaining realistic deployment scenarios, which we used to provide a basis for comparing energy use and emissions relative to traditional forklift operations.

4 RESULTS AND DISCUSSION

The following section highlights the simulation results from the drone and forklift models across 18 forklift scenarios and 18 drone scenarios. Using the scenario framework presented in Section 3.4, we compared the Scope 2 emissions of drone-based and forklift-based inventory scanning spanning three different warehouse sizes (small, medium, and large) and six geographical regions (Spain, Germany, Denmark, Poland, Canada, and the United States). Each scenario was simulated over 30 shifts with an 8-hour shift length. The results from these simulation runs aim to help identify the warehouse conditions where Verity's autonomous drone system can provide the most significant Scope 2 emissions reduction when compared with traditional forklift-based scanning.

4.1 Forklift Results and Discussion

We ran the forklift simulation model across 18 scenarios. This serves as our baseline for current warehouse scanning. Table 1 summarizes the outputs by the region and warehouse size.

Region	Size Category	Forklifts	Forklift Total Energy (kWh)	Lighting Energy (kWh)	Total Energy (kWh)	Total Emissions ($kgCO_2e$)
Spain	Small	5	4,905	14,595	19,500	3,218
Spain	Medium	7	6,869	20,433	27,302	4,505
Spain	Large	9	8,831	26,271	35,102	5,792
Germany	Small	5	4,907	14,595	19,502	6,494
Germany	Medium	7	6,868	20,433	27,301	9,091
Germany	Large	9	8,828	26,271	35,099	11,688
Denmark	Small	5	4,905	14,595	19,500	1,209
Denmark	Medium	7	6,869	20,433	27,302	1,693
Denmark	Large	9	8,830	26,271	35,101	2,176
Poland	Small	5	4,907	14,595	19,502	10,648
Poland	Medium	7	6,869	20,433	27,302	14,907
Poland	Large	9	8,831	26,271	35,102	19,166
Canada	Small	5	4,990	14,595	19,585	2,350
Canada	Medium	7	6,986	20,433	27,419	3,290
Canada	Large	9	8,982	26,271	35,253	4,230
USA	Small	5	4,991	14,595	19,586	6,502
USA	Medium	7	6,987	20,433	27,420	9,103
USA	Large	9	8,983	26,271	35,254	11,704

Table 1. Forklift Simulation Results: Energy Consumption and Scope 2 Emissions by Region and Warehouse Size (30 Shifts)

An important finding from the forklift model is the dominant role of warehouse lighting in the total energy consumption. Across all the runs, lighting accounted for approximately 75% of total energy use. This pattern held across all regions and warehouse sizes. Granular data on lighting consumption were not made available and our team calculated these using assumptions and estimates. Using the sponsor-provided baseline data for energy consumption per shift, we scaled the lighting energy linearly with the warehouse size. This is broken down in Table 2.

Warehouse Size	Baseline Lighting Energy per Shift (kWh)	Shifts	Total Lighting Energy (kWh)
Small	486.5	30	14,595
Medium	681.1	30	20,433
Large	875.7	30	26,271

Table 2. Forklift Lighting Energy Assumptions by Warehouse Size

Forklift operational energy consumption remained relatively stable across the regions with the same warehouse size. For example, in the large warehouse size scenario, Denmark and Poland both consumed approximately 35,100 kWh in total energy. However, in terms of total Scope 2 emissions, Denmark generated 2,176 $kgCO_2e$ while Poland generated 19,166 $kgCO_2e$. These differences can be attributed to differences in the emissions factors for both of these regions, which can be seen in Figure 4.

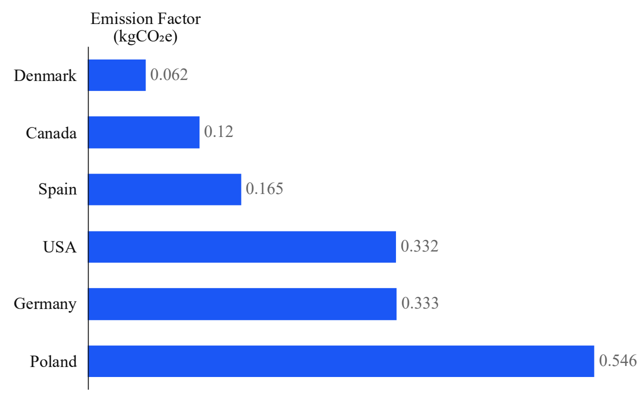

Figure 4. Location-Based Emissions Factors by the Region

For forklift-based inventory scanning, the operational energy scales with warehouse size, while the Scope 2 emissions are driven by the emissions factor of the warehouse location. This implies that forklift-based inventory scanning becomes more emissions-intensive in larger warehouses and in regions that have more carbon-intensive grids. In addition, it can help explain why the same drone deployment can have different Scope 2 emission reduction benefits depending on the location of the warehouse.

4.2 Drone Results and Discussion

We ran the drone simulation model across 18 scenarios. The baseline fleet sizes included 2 drones for small warehouses, 3 for medium warehouses and 4 for large warehouses. We assumed that the drones operate in darkness, hence lighting energy was not included in the drone simulation scenarios. Table 3 summarizes the outputs.

Region	Size Category	Drones	Total Flights	Locations Scanned	Total Energy (kWh)	Total Emissions (kgCO₂e)
Spain	Small	2	1,366	67,936	106	18
Spain	Medium	3	2,041	116,315	160	26
Spain	Large	4	2,714	175,981	214	35
Germany	Small	2	1,373	68,112	106	35
Germany	Medium	3	2,050	115,233	160	53
Germany	Large	4	2,716	177,145	214	71
Denmark	Small	2	1,367	67,836	106	7
Denmark	Medium	3	2,044	116,571	160	10
Denmark	Large	4	2,718	175,969	214	13
Poland	Small	2	1,372	68,102	106	58
Poland	Medium	3	2,046	115,336	160	87
Poland	Large	4	2,714	176,497	214	117
Canada	Small	2	1,371	67,750	106	13
Canada	Medium	3	2,050	114,242	160	19
Canada	Large	4	2,719	175,609	214	26
USA	Small	2	1,370	67,557	106	35
USA	Medium	3	2,051	114,627	160	53
USA	Large	4	2,718	177,968	214	71

Table 3. Drone Simulation Results: Energy Consumption and Scope 2 Emissions by Region and Warehouse Size (30 Shifts)

Across all the scenarios modeled, the energy consumption and Scope 2 emissions increase with the warehouse size and the number of drones. This is represented in Figure 5. The region-specific emissions factor again played a key role in measuring Scope 2 emissions for each warehouse, suggesting that geographic location should be a priority criterion when evaluating drone deployment.

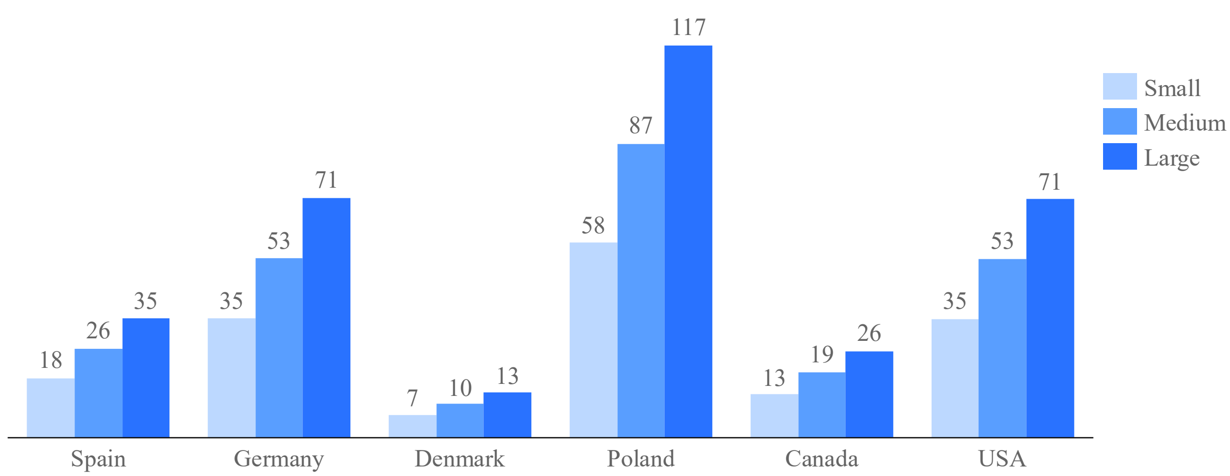

Figure 5. Drone Scope 2 Emissions (kgCO₂e) by Warehouse Size and Region

4.3 Comparative Results: Drone vs. Forklift Emissions

Across all scenarios modeled and run, we found that drone-based inventory scanning produced substantially lower Scope 2 emissions compared to the traditional forklift-based inventory scanning. This result was consistent across the warehouse sizes and geographical regions we analyzed. As shown in Table 4 drone-based inventory scanning reduced scanning-related Scope 2 emissions across the modeled scenarios by approximately 99.4%.

Region	Size Category	Forklift + Lighting Emissions ($kgCO_2e$)	Drone Emissions ($kgCO_2e$)	Reduction ($kgCO_2e$)	Reduction (%)
Spain	Small	3,217.55	18	3,200	99.4%
Spain	Medium	4,504.82	26	4,479	99.4%
Spain	Large	5,791.86	35	5,757	99.4%
Germany	Small	6,494.08	35	6,459	99.5%
Germany	Medium	9,091.15	53	9,038	99.4%
Germany	Large	11,688.10	71	11,617	99.4%
Denmark	Small	1,209.02	7	1,202	99.4%
Denmark	Medium	1,692.75	10	1,683	99.4%
Denmark	Large	2,176.29	13	2,163	99.4%
Poland	Small	10,647.88	58	10,590	99.5%
Poland	Medium	14,907.06	87	14,820	99.4%
Poland	Large	19,165.93	117	19,049	99.4%
Canada	Small	2,350.23	13	2,337	99.4%
Canada	Medium	3,290.26	19	3,271	99.4%
Canada	Large	4,230.30	26	4,204	99.4%
USA	Small	6,502.42	35	6,467	99.5%
USA	Medium	9,103.45	53	9,050	99.4%
USA	Large	11,704.17	71	11,633	99.4%

Table 4. Comparative Scope 2 Emissions: Forklifts + Lighting vs. Drone Operations by Region and Warehouse Size (30 Shifts)

The emissions reductions were consistent across regions and warehouse sizes. For the small warehouse scenario in Spain, forklift-based scanning produced 3,218 $kgCO_2e$, compared with 18 $kgCO_2e$ from drone-based scanning. This pattern remained consistent when observing Spain's large warehouse scenario with forklift-based scanning producing 5,792 $kgCO_2e$, compared with 35 $kgCO_2e$ from drone-based scanning. The difference was even larger in the United States large warehouse scenario, where forklift-based scanning produced 11,704 $kgCO_2e$, compared with 71 $kgCO_2e$ from drone-based scanning. Even in Denmark, which had the lowest regional emissions factor at 0.062 $kgCO_2e/kWh$, the medium warehouse scenario showed 1,693 $kgCO_2e$ from forklift-based scanning compared with 10 $kgCO_2e$ from drone-based scanning. Across all modeled scenarios, there is an approximate 99.4% reduction in Scope 2 emissions when transitioning from forklift-based to drone-based inventory scanning. These results indicate that drone-based scanning produced substantial and consistent emissions reductions across all warehouse sizes and regions.

A key reason for the difference is the energy consumption and corresponding emissions from lighting. Forklift-based scanning operations include both forklift and warehouse lighting energy consumption, while drone-based inventory scanning does not require warehouse lighting. Lighting energy is attributed only to the nighttime scanning window modeled in the forklift baseline, during which the manual scanning requires warehouse lighting. The drone scenario assumes scanning occurs in the same nighttime window without lighting. Daytime warehouse lighting for non-scan activities is held constant across both scenarios, so the reported reduction reflects scanning-window emissions, rather than total facility lighting elimination. However, even when lighting is excluded and only machine-related emissions are compared, forklifts produce roughly 43 times higher Scope 2 emissions than drones for the same warehouse sizes.

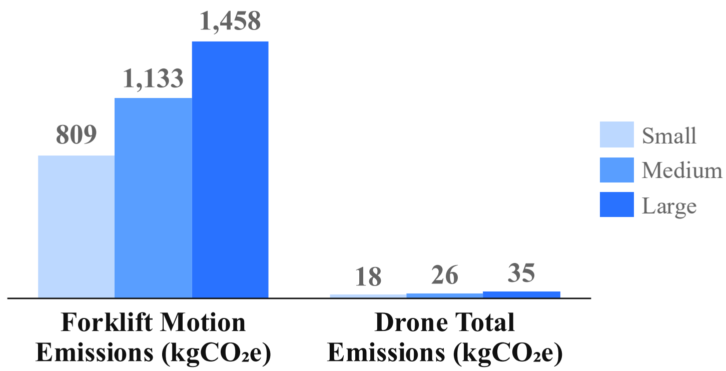

Figure 6. Comparative Scope 2 Emissions: Forklifts vs. Drone Operations for Spain (30 Shifts)

As shown in Figure 6, in Spain, the forklift-only emissions ranged from 809 kgCO2e to 1,458 kgCO2e across warehouse sizes, as compared to 18 kgCO2e to 35 kgCO2e for drones.

4.4 Limitations

This section outlines the primary limitations of the simulation framework, highlighting the assumptions and data constraints that may influence the accuracy of the results and how well they apply to other warehouse settings.

This model was developed using data from the reference warehouse in the EU. Although the framework was designed to generalize across multiple warehouse sizes and regions, warehouses with different layouts or operating procedures may produce different results. Some historical data was limited, and several inputs had to be supplemented with research, calculations, and sponsor-verified assumptions. The model should be interpreted as a decision-support tool rather than a perfect digital twin of warehouse operations.

Because Verity's proprietary routing algorithm was unavailable, drone routing logic was approximated using Manhattan distance and nearest-neighbor assumptions, which could lead to inter-aisle travel and produce different scan rates.

The forklift simulation was developed under similar data constraints. Detailed forklift scanning logs were unavailable. In practice, forklift-based scanning includes yielding to warehouse traffic, and navigating physical constraints that drones do not face. Additionally, the number of forklifts allocated across warehouse sizes was assumed to scale linearly.

These limitations suggest that energy savings deriving from inventory automation as estimated in this capstone are conservative and possibly understated. While results should be treated as directional estimates rather than hard figures, the consistency of the findings across all scenarios supports the overall conclusion.

5. RECOMMENDATIONS

5.1 Management Recommendations

This study developed a discrete-event simulation framework to evaluate the Scope 2 emissions impact of drone-based versus forklift-based inventory scanning across warehouse environments. Using operational data from the reference EU facility and scenario analysis across multiple regions and warehouse sizes, the model estimated energy consumption and associated emissions for both technologies. The results consistently showed that drone-based scanning reduced Scope 2 emissions by approximately 99.4%, primarily driven by lower energy consumption and the elimination of lighting requirements. These findings provide a data-driven foundation for prioritizing drone deployment across the 3PL’s warehouse network.

The findings of this study show that facilities located in regions with higher electricity emissions factors should be prioritized, as these locations produce higher Scope 2 emissions under forklift-based operations and therefore offer the largest potential reductions when transitioning to drone-based scanning. Additionally, larger warehouses should be targeted, as both forklift energy consumption and lighting-related emissions scale with warehouse size, increasing the overall impact of drone implementation.

The results highlight warehouse lighting as a critical driver of Scope 2 emissions since drone-based scanning eliminates the need for lighting during inventory operations. Therefore, facilities with high lighting energy usage present a significant opportunity for emissions reduction. These findings suggest that deployment decisions should not be based solely on operational efficiency, but also on the interaction between warehouse size, lighting demand, and regional electricity characteristics.

From a strategic perspective, implementing drone-based inventory scanning across prioritized facilities can significantly accelerate progress toward the 3PL's Scope 2 emissions reduction targets. The simulation framework developed in this study provides a scalable decision-support tool that enables stakeholders to evaluate deployment scenarios and identify opportunities across a large, global warehouse network.

5.2 Future Work

Although this study provides the sponsor company with a scalable solution for evaluating Scope 2 emission implications of drone-based inventory scanning as opposed to traditional scanning methods, there are several opportunities to extend the analysis. Future work should expand the model to capture additional operating environments and warehouses since the present study was developed using data and assumptions derived from the reference warehouse. Warehouses throughout Europe and the United States differ in rack layout, aisle configurations, storage density, and scanning practices. Alterations to these factors could have a substantial impact on the energy consumption and subsequent emissions.

Currently, the drone simulation relies on several assumptions that may influence the resulting outputs. For instance, due to the unavailability of Verity's proprietary drone routing algorithm, the model was developed to have a nearest-neighbor approach based on Manhattan distance. Access to this routing information could improve the realism of the model and may even lead to more accurate estimates of Scope 2 emissions. Additionally, Verity has indicated that they are currently developing and piloting a new drone model with enhanced performance capabilities, and the simulation framework developed in this study is sufficiently flexible to accommodate this new technology when the specifications become available.

In contrast, the forklift simulation model was developed under several additional assumptions that could be refined with more detailed operational data. For example, the number of forklifts allocated across warehouse sizes was assumed to scale linearly, at a rate of one forklift per 10,000 square meters of warehouse space. In addition, the 3PL was unable to provide detailed information on how warehouse lighting energy consumption is measured or tracked at the facility or regional level. Access to this data would improve the representation of forklift operations and lighting demand, thereby increasing the accuracy of the forklift model.

Future studies could also examine hybrid operating environments where drones and forklifts run simultaneously. Facilities may adopt only partial drone coverage for scanning operations, especially during phased implementations or due to warehouse constraints. Therefore, modeling mixed deployment scenarios could improve realism and allow for assessment of incremental emissions reductions.

Beyond the scope of this project, the framework provides a practical approach for evaluating the sustainability impact of warehouse automation and offers value to logistics providers and supply chain stakeholders seeking to reduce emissions through operational innovation.

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