AI-Powered Warehouses: A New Era of Sustainable Inventory Management

by

Elisa Ruiz Mugica
Bachelor of Science in Industrial Engineering, Instituto Tecnológico y de Estudios Superiores de Monterrey, 2020

and

Kyungmin Kook
Bachelor of Science in Management Science, University of California, San Diego, 2011

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Signature of Author: ______________________________
Department of Supply Chain Management
May 9, 2025

Signature of Author: ______________________________
Department of Supply Chain Management
May 9, 2025

Certified by: ______________________________
Dr. Josué Velázquez Martínez
Director of Sustainable Supply Chain Lab
Capstone Advisor

Certified by: ______________________________
Dr. Miguel Rodríguez García
Research Scientist at Omnichannel Supply Chain Lab
Capstone Co-Advisor

Accepted by: ______________________________
Prof. Yossi Sheffi
Director, Center for Transportation and Logistics
Elisha Gray II Professor of Engineering Systems
Professor, Civil and Environmental Engineering

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Elisa Ruiz Mugica
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Kyungmin Kook

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ABSTRACT

This capstone project evaluates the environmental impact of autonomous drone-based inventory automation in a U.S. fulfillment warehouse operated by a global logistics company. The central research question is: *What is the impact of warehouse inventory automation on greenhouse gas (GHG) emissions across Scope 1, 2, and 3?* To address this, we developed a quantitative decision-making framework grounded in the GHG Protocol and applied it to compare pre- and post-implementation scenarios using activity-based emissions modeling and life cycle assessment (LCA). Drawing on operational data, drone usage logs, and structured interviews, we modeled emissions from labor, material handling equipment, energy consumption, and inventory waste. The results show a 49.5% reduction in total annual emissions (from 79,200 kg CO_2e to 40,008 kg CO_2e), driven largely by a 40% decrease in inventory write-offs and a 70% drop in forklift energy use. Expanding drone coverage from 64% to 90% yields an additional 33% reduction in emissions, though with diminishing marginal returns. The study concludes that drone-enabled automation can significantly reduce indirect emissions—particularly Scope 3 sources such as employee commuting and inventory loss—while offering a scalable, data-driven tool for operational sustainability. The framework presented serves as a replicable model to support emissions-informed decision-making in warehouse automation initiatives.

Capstone Advisor: Dr. Josué Velázquez Martínez
Title: Director of Sustainable Supply Chain Lab

Capstone Co-Advisor: Dr. Miguel Rodríguez García
Title: Research Scientist at Omnichannel Supply Chain Lab

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1 INTRODUCTION

1.1 Motivation

Climate change is no longer a distant concern—it has become a pressing global challenge with immediate and widespread consequences. The Intergovernmental Panel on Climate Change (IPCC, 2023) confirms that rising greenhouse gas (GHG) emissions are causing significant environmental disruption, including global temperature increases, geographic shifts, changes in seasonal patterns, and increased severity of natural disasters.

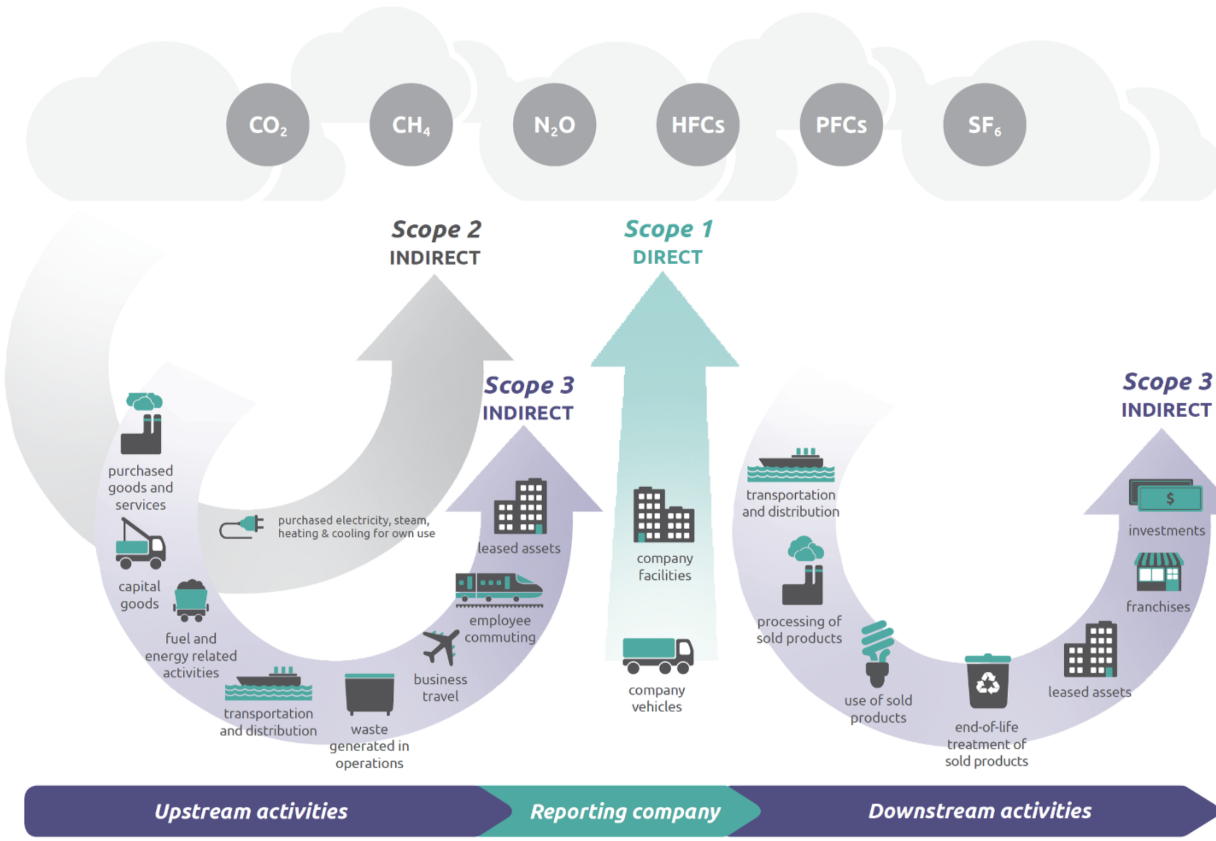
Among the contributors to global GHG emissions, the logistics and transportation sector holds a prominent position. According to the International Energy Agency (IEA, 2023), transportation accounts for nearly one-quarter of global CO2 emissions from fuel combustion. This is exacerbated by the rapid growth in e-commerce and omnichannel distribution, which has increased demand for storage and last-mile delivery services (Olson, 2022). Warehousing, a key component of the logistics chain, has emerged as a significant emissions source, contributing between 11–20% of total logistics-related emissions, depending on operational context and study scope (McKinnon, 2018; McKinsey & Company, 2024).

At the same time, the logistics industry is undergoing a transformation driven by automation. The rise of smart warehouses and automated inventory systems responds to evolving consumer expectations for speed and accuracy, while also offering opportunities to enhance environmental sustainability. Recent advancements in artificial intelligence (AI) have catalyzed a new era in warehouse automation. AI-powered autonomous drones are increasingly replacing manual inventory processes, offering real-time, data-driven visibility and near-zero error rates. These intelligent systems leverage AI algorithms to navigate complex warehouse environments, scan inventory, and integrate data seamlessly with warehouse management systems, thereby enhancing efficiency and accuracy (Fernandez-Carames et al., 2024).

Despite the momentum behind automation, limited academic attention has been devoted to understanding its actual impact on emissions. In response to this gap, our study focuses on evaluating the environmental implications of warehouse automation through the lens of GHG emissions. Specifically, we examine whether automated inventory systems contribute to reducing Scope 1, 2, or 3 emissions, and under what conditions these reductions occur. Our central research question (RQ) is: What is the impact of warehouse inventory automation on GHG emissions across different emission scopes? The goal is to uncover whether automation contributes to sustainability goals or introduces trade-offs that must be considered.

To contextualize our analysis, we adopt the GHG Protocol framework, which categorizes emissions into three distinct scopes: Scope 1 (direct emissions from owned or controlled sources), Scope 2 (indirect emissions from purchased electricity, steam, heating, and cooling), and Scope 3 (all other indirect emissions that occur in the value chain). Figure 1 illustrates this classification, providing the conceptual basis for the modeling approach used in our analysis.

Figure 1. Overview of GHG Protocol Scopes and Emissions Across the Value Chain (WRI/WBCSDl, 2023)



This research also challenges common assumptions—for instance, that employee commuting is the largest emissions driver in warehouse operations. By quantifying the emissions impact of traditional versus automated inventory systems, we provide evidence to support more informed sustainability strategies in warehousing (Gonzales & Peterson, 2022).

1.2 Case Study: Verity's AI-Powered Drone Inventory Automation

To address our research question, we partnered with a global company in the transportation and integrated logistics sector, focusing on their fulfillment warehouse located in the United States. The company is transitioning from traditional inventory management—characterized by high labor demands, manual scanning, and inventory inaccuracies—toward advanced automated systems.

The automation solution implemented is provided by Verity, a robotics and AI company headquartered in Zurich, Switzerland, with operations across Europe and North America. Verity is a recognized leader in autonomous inventory intelligence, specializing in the deployment of AI-powered systems that deliver real-time visibility for logistics, retail, and manufacturing environments. Their autonomous indoor drone platform combines proprietary artificial intelligence algorithms, enabling the system to continuously monitor inventory without the need for physical infrastructure changes.

Verity's drones autonomously navigate high-bay warehouse environments—even in darkness—scanning barcodes and identifying inventory discrepancies with zero-error precision. This allows for the creation of digital twin representations of warehouse stock in real time (Verity, 2024b). Unlike manual methods that rely on fossil-fuel-powered lifts and off-hour labor, Verity's system reduces both physical strain and energy consumption while enhancing data accuracy and reducing losses due to shrinkage or misplacement.

This case provides a valuable opportunity to quantify both the direct and indirect environmental impacts of transitioning to AI-powered warehouse automation. Through our collaboration, we obtained drone usage logs, warehouse operational data, and emissions factors. These inputs were used to model the GHG emissions associated with this technological shift, including changes in equipment energy demand, emissions from employee activities, and material life cycle impacts.

1.3 Organization of the Capstone Paper

The remainder of this paper is organized into five chapters. In Chapter 2, we present the literature review, outlining key concepts related to emissions modeling, warehouse operations, and automation technologies. In Chapter 3, we describe the methodology used to quantify GHG emissions across Scopes 1, 2, and 3, applying an activity-based modeling framework and standardized emissions factors. Chapter 4 presents the results of our emissions model, comparing traditional inventory processes with drone-enabled automation. In Chapter 5, we conclude the paper by summarizing our key insights, discussing the implications of our findings for operational decision-making, sustainability strategy, and policy, and suggesting directions for future research.

2 STATE OF THE PRACTICE

This chapter explores how automation, particularly autonomous drones, is shaping sustainability practices in warehouse operations. It begins with a review of recent literature on automation's role in sustainable supply chains, then narrows its focus to warehouse automation, highlighting its evolving application beyond material handling to include inventory counting. The chapter concludes with a structured review of methodologies used to measure Scope 1, 2, and 3 emissions in warehousing contexts, offering a foundation for the emissions modeling introduced in the following chapter.

2.1 Automation and Sustainability in Warehousing

The role of automation in promoting sustainability across manufacturing and supply chain processes has gained significant attention in recent years (Qu & Kim, 2024). Organizations are now prioritizing not only efficiency and cost-effectiveness when implementing new technologies or designing processes, but also the environmental and social dimensions of sustainability (Lofti et al., 2023). These include reducing energy consumption, minimizing greenhouse gas (GHG) emissions, and improving the long-term resilience of operations.

Within supply chain operations, warehouse activities have historically been studied primarily through the lens of operational and economic efficiency. However, emerging research has started to incorporate sustainability considerations, particularly through industrial design improvements and the integration of Internet of Things (IoT) technologies (Rezaei & Naghdbishi, 2024). Among the many automation technologies deployed in warehouses, material handling systems—such as conveyors, sortation systems, and automated storage and retrieval systems—have seen the most widespread adoption, driven by their clear efficiency benefits (Minashkina et al., 2023). In contrast, the automation of inventory counting remains a relatively underexplored area. As Minashkina et al. (2023) note, "the level of automation in warehouse stock counting using drones is still at an experimental stage," highlighting the novelty of this approach in current literature.

To support the selection of new technologies in logistics with sustainability in mind, Ferraro et al. (2023) developed a structured evaluation framework grounded in the Triple Bottom Line. Their study proposes a three-level Analytic Hierarchy Process (AHP) model that helps organizations compare technologies based on six sustainability indicators spanning economic, environmental, and social dimensions. The model evaluates emerging tools such as drones, exoskeletons, collaborative robots, and additive manufacturing, considering both their operational potential and their alignment with broader sustainability goals. This decision-support approach reflects growing interest in sustainable logistics and addresses a common challenge: how companies can prioritize investments across a wide range of automation options. Among these, autonomous drones have emerged as a particularly promising solution for inventory management.

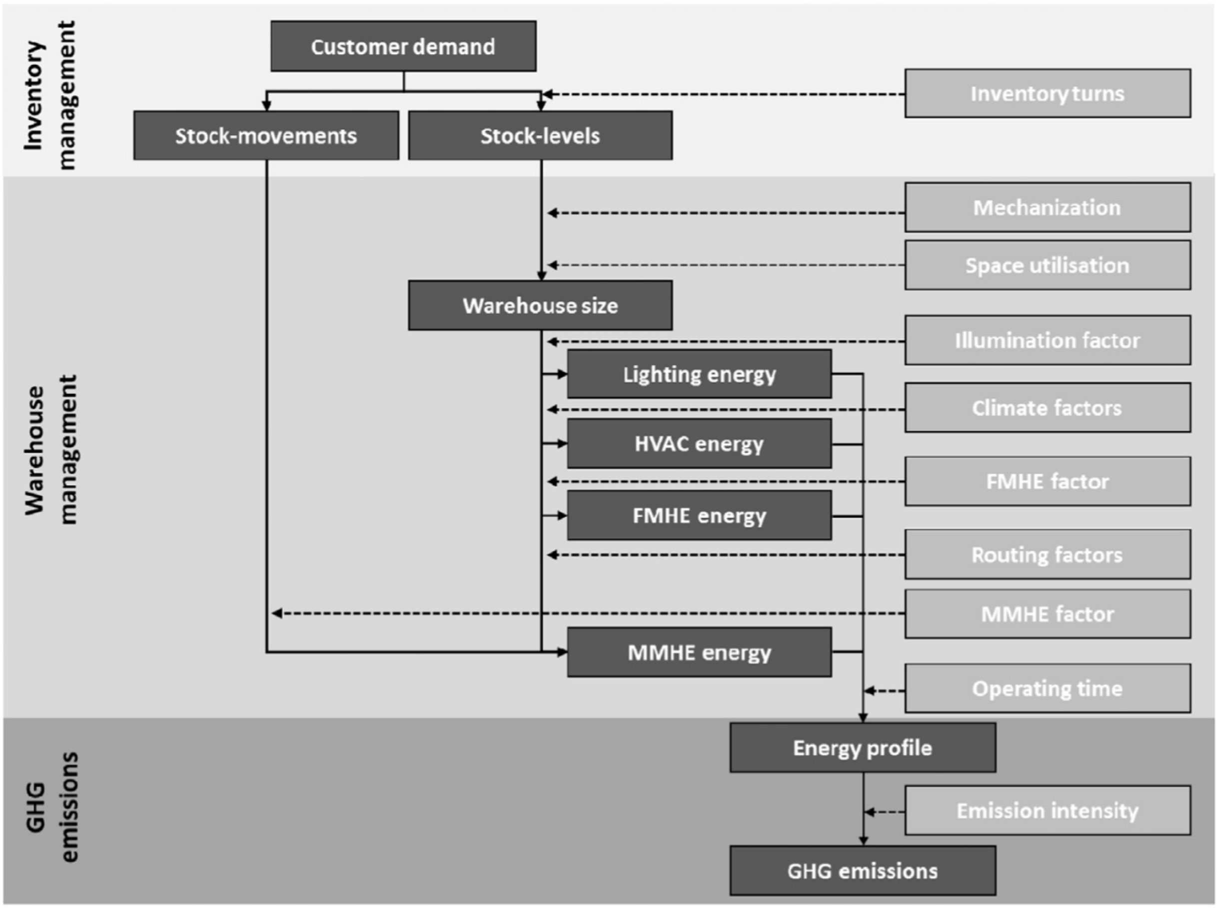
Early efforts in drone-based inventory management were largely limited to manual piloting or simple rule-based automation. However, recent advances in artificial intelligence (AI) have significantly enhanced the capabilities of drones in warehouse environments. AI-driven drones can now autonomously navigate complex indoor environments, perform inventory scans, and adapt to dynamic warehouse conditions without human intervention (Fernandez-Carames et al., 2024). This evolution marks a meaningful shift from traditional automation toward intelligent, adaptive systems. A growing body of research has shown that AI-powered drones improve key operational outcomes—such as storage layout, picking accuracy, and inventory audits—while enabling real-time, data-driven inventory visibility (Fernandez-Carames et al., 2024). These improvements not only enhance efficiency but also contribute to measurable sustainability outcomes, such as reduced reliance on fossil-fuel-powered equipment and minimized energy use during off-peak hours.

Despite these advancements, there is still limited empirical research analyzing the sustainability impact of drone-based inventory automation, particularly when it comes to quantifying its influence across different emissions scopes. This gap underscores the importance of developing structured methodologies for evaluating the environmental implications of this emerging technology, a focus explored in detail in the following sections.

2.2 Framework for Emissions Analysis in Warehousing

We investigated methodologies to measure variables associated with Scope 1, 2, and 3 emissions within contexts relevant to warehousing and automation. This review is organized into three segments, each corresponding to the respective scope of emissions. It is framed by a structured approach to assessing GHG emissions from material handling processes and warehouse operations, aligned with the GHG Protocol and recent applications in logistics operations (Perotti et al., 2022), as shown in **Error! Reference source not found.**.

Figure 2. Structured Approach to Assessing GHG Emissions (Fichtinger et al., 2015)



2.3 Scope 1: Direct Emissions from Warehouse Operations

Scope 1 emissions represent the direct GHG emissions generated from warehouse operations. These emissions can stem from HVAC systems and forklifts, depending on the energy sources powering them. They also encompass fuel consumption by stationary and mobile equipment, including vehicles, with emissions varying based on the type of fuel and equipment used. Recent studies highlight the significance of managing these direct emissions to enhance warehouse sustainability (Zschausch & Rosenberger, 2023).

2.4 Scope 2: Indirect Emissions from Energy Consumption in Material Handling

Scope 2 emissions arise from the indirect consumption of energy within warehouse operations, significantly influenced by material handling equipment, lighting, and HVAC systems running on electricity. Key characteristics of warehouses, such as illumination and HVAC requirements, are generally proportional to warehouse size, which accounts for a substantial portion of emissions in simulation studies (Lewczuk et al., 2021). While the size of the warehouse itself may remain constant, the implementation of autonomous drones can alter these characteristics by changing the operational demands for lighting or HVAC.

To achieve a truly comprehensive and sustainable warehouse design, it is essential to consider the environmental impact of all material handling equipment. By incorporating emissions from both fixed and mobile equipment—such as conveyors, cranes, and forklifts—into optimization models, a more accurate assessment of the warehouse's full lifecycle environmental impact can be achieved (Perotti et al., 2022). This approach ensures that the indirect contributions of equipment to Scope 2 emissions are properly accounted for in sustainable design efforts.

Moreover, while emissions from drone usage are primarily studied in the context of last-mile delivery, researchers have also assessed these emissions based on factors such as drone aerodynamics, mass, and battery capacity (RawView, 2024). Considering drones' potential impact on warehouse characteristics, particularly through altered illumination and HVAC needs, it becomes even more critical to integrate these variables into a holistic evaluation of warehouse operations and their environmental footprint.

2.5 Scope 3: Indirect Emissions from the Broader Supply Chain

Scope 3 emissions encompass a broader range of environmental impacts associated with warehouse operations, extending beyond direct energy use to include upstream and downstream processes. For instance, improved inventory accuracy and the use of drones for inventory counts can reduce reliance on forklifts in warehouse operations. A decreased demand for forklifts lowers the need for their production, thereby reducing embodied carbon emissions, as highlighted by Zschausch & Rosenberger (2023) in their analysis of logistics equipment. However, introducing drones into warehouse systems also necessitates evaluating the emissions associated with their production and operation, particularly for battery-powered drones. These emissions align with findings by RawView (2024), who analyzed the environmental impact of drones in warehouse inventory management. Balancing these trade-offs is critical to assessing the overall sustainability impact of warehouse automation.

Beyond equipment impacts, inventory automation fundamentally reshapes employee workflows, enabling greater operational efficiency and reducing the need for additional labor. Automated inventory checks and reduced trips from misplaced inventory streamline operations, allowing warehouses to function effectively without expanding headcounts. This shift not only boosts efficiency but also decreases emissions tied to employee commutes, as analyzed by Zschausch & Rosenberger (2023), who measured commute-related environmental impacts.

Enhanced inventory accuracy contributes to optimizing economic order quantity (EOQ) and reducing wastage. Incorporating environmental costs such as transportation emissions and waste into the EOQ models enables larger lot sizes and less frequent orders, striking a balance between cost efficiency and sustainability (Perotti et al., 2022). These changes have far-reaching implications for upstream production, where improved order quantities can refine production schedules and delivery frequencies, reducing lead times, transportation costs, and CO_2 emissions.

These insights inform the hypothesis-driven model introduced in Section 3, where we map expected changes in emissions to operational variables such as inventory accuracy, forklift usage, and workforce footprint. The model builds on the structure of Perotti et al. (2022) and adapts variable mapping practices described in Fichtinger et al. (2015), whose structured approach is visualized in Figure 3.

This study builds on prior literature and expert input to define the operational variables most likely to be affected by inventory automation. The hypothesis mapping in Chapter 3 is informed by a triangulated review of peer-reviewed research, insights from drone system providers, and practitioner knowledge of warehouse operations. These sources guided the formulation of expected variable shifts and modeling assumptions, helping ensure the framework's relevance to real-world warehouse dynamics. While the literature on drone-enabled stock counting remains nascent (Minashkina et al., 2023), our synthesis offers a grounded basis for evaluating sustainability impacts.

3 METHODOLOGY

This chapter describes the step-by-step process used to model the environmental impact of autonomous drone-based inventory automation. The methodology is designed to assess emissions across Scope 1, 2, and 3, following the GHG Protocol framework. First, we define the operational variables most likely to be affected by drone adoption and formulate hypotheses about their expected behavior. Next, we explain how data was collected from warehouse systems, drone logs, and interviews. We then justify our selection of emissions factors and outline the emissions modeling framework, which integrates both activity-based and life cycle assessment (LCA) methods. Finally, we describe our comparative before-and-after modeling structure and present the sensitivity analysis design used to explore the robustness of results.

3.1 Key Variable Definitions

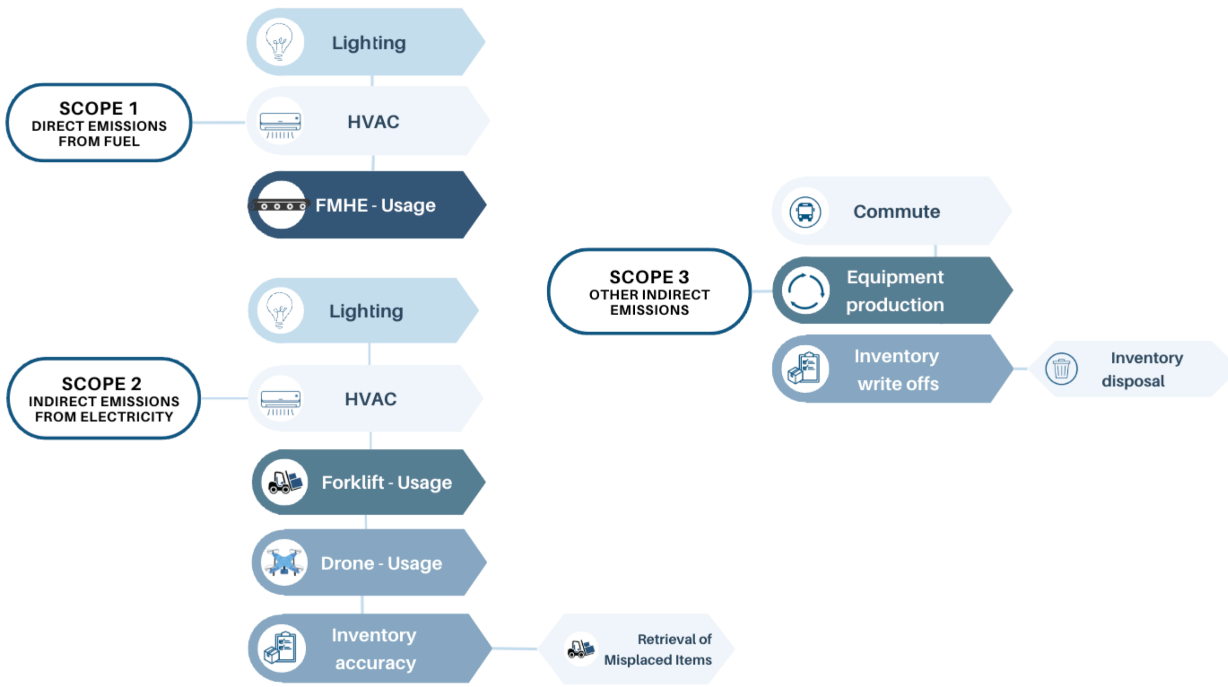
To develop this framework, we identified the key variables to be evaluated and the emissions scopes they influence. Variables were selected by prioritizing those most likely to be affected by the adoption of drone-based inventory automation and those with significant potential impact on overall emissions. Factors such as packaging materials and last-mile transportation were excluded, as they fall outside the scope of internal warehouse operations and are not materially influenced by drone deployment.

To enhance clarity and facilitate modeling, we systematically defined each variable, including its unit of analysis and associated emission scope. These variables were grounded in warehouse operations data, drone specifications, and emissions modeling literature. The definitions below form the analytical foundation for our emissions estimation model and scenario analysis.

- **Drone Usage** *(kWh/year)* – Electricity consumed by drones performing inventory scans. This variable contributes to Scope 2 emissions and scales with drone activity levels.
- **Forklift Usage** *(kWh/year)* – Energy consumed by forklifts for manual cycle counts and associated lifecycle emissions from equipment manufacturing.
- **Fixed Material Handling Equipment (FMHE) Usage** *(kWh/year and units)* – Energy consumption and embodied emissions related to equipment such as AS/RS. Although hypothesized to decrease, FMHE usage was later excluded from final modeling due to lack of observed variation.
- **Lighting and HVAC Usage** *(kWh/year)* – Electricity required for lighting and temperature control. While hypothesized to shift with drone implementation, as drones do not require lighting or HVAC to operate
- **Employee Commuting** *(miles/year)* – Distance traveled by staff dedicated to inventory counting. Modeled under Scope 3 using region-specific emissions factors.
- **Inventory Write-Offs** *(units/year)* – Quantity of inventory scrapped due to misplacement or inaccuracy. The term "units" is warehouse-dependent and refers to the inventory handling level used at the facility, such as individual items, cases, or pallets, depending on how products are stored, tracked, and accounted for. This variable is a key driver of Scope 3 emissions from waste and replacement production.
- **Addressing Inventory Discrepancies** *(kWh/year)* – Forklift energy expended in addressing inventory discrepancies. Emissions are attributed to Scope 2.
- **Drone Manufacturing** *(kg CO_2e/unit)* – Embodied emissions from drone production, normalized over a 5-year lifespan and categorized under Scope 3 (LCA).
- **Forklift Manufacturing** *(kg CO_2e/unit)* – Lifecycle emissions from forklift equipment, amortized over a 10-year lifespan and attributed to Scope 3 (LCA).

These definitions inform the variable classification and emissions modeling structure shown in Figure 3, which maps each operational variable to its corresponding GHG emissions scope.

Figure 3. Categorization of Model Variables by Scope



With these variables identified, we developed a methodology that aims to quantify total GHG emissions from key operational activities, compare emissions before and after drone implementation, and analyze the sensitivity of the results to changes in critical input variables. This multi-step approach begins by selecting the operational variables most likely to be affected by the adoption of drone technology and formulating hypotheses about their expected direction of change. We then describe the data collected to quantify these variables and justify the sources and assumptions used. To estimate emissions, we apply standardized emission factors from established sources such as the EPA Emission Factors for Greenhouse Gas Inventories from GHG Emissions Factors Hub (2024). These are integrated into a mathematical model that links activity levels to emissions outputs through formula-based calculations. The model is then applied to simulate emissions for both the baseline (manual operations) and post-implementation (drone-enabled) scenarios, using actual operational data and carefully constructed assumptions where needed. Finally, a sensitivity analysis explores how variations in key variables influence the overall emissions outcome, allowing us to identify which factors have the greatest potential for reducing environmental impact.

3.2 Variable Selection and Hypothesis Mapping

Building on the variable definitions presented above, we now organize them into five operational categories and outline the expected direction and rationale of change.

The starting point of this analysis is to identify the operational variables most likely to be affected by the introduction of the new technology to perform inventory counting. Understanding how these variables change is essential to quantifying the sustainability impact of the technological shift and structuring the emissions model accordingly. To guide this analysis, we formulated a set of hypotheses about the expected direction and rationale of change for each variable. These hypotheses are based on a review of relevant literature, discussions with drone system providers, and our understanding of warehouse operations.

The affected variables span across five main operational categories:

1. **Energy Consumption and Infrastructure**

   Lighting and HVAC: Changes in operating hours due to drone implementation may affect lighting and HVAC needs. Drones can operate without lighting, and fewer employees on the warehouse floor could lead to optimized HVAC settings.

2. **Material Handling Equipment**

   Forklifts (Mobile MHE): We hypothesize a decrease in the usage and number of forklifts. Drones are expected to reduce the need for forklifts to perform inventory checks, as they can capture data without interrupting warehouse flow.

   Fixed Material Handling Equipment (FMHE): A decrease in the usage and number of FMHEs is anticipated. Drones can verify inventory in its current location, potentially reducing the need for Automated Storage and Retrieval System (AS/RS) cycles.

3. **Drone Usage**

   Drone Operations: The implementation of drone operations in the warehouse is expected to increase electricity consumption, as these devices require energy for their operation regardless of operational efficiency. Consequently, the overall energy demand within the facility is expected to rise in direct proportion to the number of drones deployed.

4. **Inventory Management**

   Inventory Levels and Accuracy: The implementation of drones is expected to enhance inventory accuracy by reducing instances of misplaced or unaccounted-for stock. Through automated and frequent cycle counting, drones can help identify discrepancies more quickly than manual cycle counts, minimizing errors in recorded inventory levels. This improvement reduces the likelihood of inventory being written off as obsolete or scrapped due to misplacement. Additionally, drones can assist in real-time inventory tracking, enabling warehouse personnel to locate items efficiently, thus preventing unnecessary replenishment orders and optimizing storage utilization.

5. **Employee-Related Factors**

   Employee Commute: The implementation of drone-assisted inventory cycle counts is expected to reduce the aggregate employee commute distance. This reduction is primarily due to a decreased need for dedicated personnel performing manual cycle counting. By automating part of the inventory process, drones can free up human resources, leading to potential changes in standard work processes and overall staffing requirements related to physical inventory management.

To organize these hypotheses and structure the subsequent emissions analysis, Table 1 presents the selected variables, their expected direction of change, and the corresponding emissions scopes under the GHG Protocol.

Table 1. Key Variables, Expected Direction of Change, and Emissions Scope

Variable	Expected Direction of Change	GHG Emissions Scope
Use of drones for inventory counting	Increase ↑	Scope 2
Use of forklifts for inventory tasks	Decrease ↓	Scope 2
Fixed material handling equipment use	Decrease ↓	Scope 2
Energy consumption (drone charging)	Increase ↑	Scope 2
Energy consumption(forklift charging)	Decrease ↓	Scope 2
Employee commute	Decrease ↓	Scope 3
Inventory write-offs	Decrease ↓	Scope 3
Addressing Inventory Discrepancies	Decrease ↓	Scope 2
Lighting and HVAC usage	Decrease or shift in timing (fewer operating hours) ↓	Scope 2
Drone lifecycle emissions (LCA)	Increase (introduced new equipment) ↑	Scope 3 (LCA)
Forklift lifecycle emissions (LCA)	Decrease (partial allocation) ↓	Scope 3 (LCA)

These hypotheses were used to guide both the design of the emissions model and the structure of the data request submitted to the warehouse and drone service provider Verity. Interviews were held with the companies involved, particularly with the warehouse operations teams, to validate and quantify the above hypotheses and ensure they accurately reflect real-world processes on the warehouse floor.

3.3 Data Collection and Source Justification

To quantify the variables in this study, it was essential to define the type of data associated with each variable and identify their respective sources. Data collection methods included structured interviews with warehouse personnel, warehouse management system (WMS) reports, and outputs from the autonomous drone system. These sources were selected to provide both quantitative and qualitative insights into inventory operations before and after automation.

The primary dataset was collected from a fulfillment warehouse located in the United States, covering operations from January to March in both 2024 and 2025. This facility was selected based on the availability of comparable pre- and post-drone implementation data within the designated time window. According to warehouse management, overall throughput volumes during these two quarters were consistent, supporting the validity of before-and-after comparisons for inventory-related activities.

Operational data was extracted from the WMS and included detailed records of cycle counts, such as date, number of locations counted, item descriptions, license plate number (LPN) counts, system-recorded quantities, quantities counted, and both net and absolute discrepancies. This dataset enabled the historical analysis of inventory accuracy, identification of discrepancies, and inference of manual counting efforts using forklifts. Structured interviews with warehouse staff were conducted to contextualize the data, validate modeling assumptions, and understand operational nuances, such as manual error rates, scheduling practices, and workforce allocation to inventory tasks.

Drone performance specifications and usage logs were provided by Verity. This dataset included the number of drone cycles performed, average cycle duration, energy consumption profiles, and the number of items or locations scanned. The system also logged discrepancies detected by drones, allowing for the calculation of issue rates and scan coverage.

Where inconsistencies or gaps were found across datasets, proxy values were derived using industry benchmarks, academic literature, or expert insights from warehouse personnel. These assumptions were validated through cross-referencing with available site data or by triangulating multiple sources to ensure robustness.

In addition to raw inputs, several intermediate variables—such as the number of personnel needed for inventory counting, forklift allocation, and the manual share of locations—were calculated using warehouse-specific assumptions to perform the sensitivity analysis, including scan capacities, shift durations, and drone coverage capabilities. These values were not treated as static inputs but rather modeled dynamically in response to operational parameters detailed in Section 3.6. Table 2 summarizes the key warehouse-specific inputs and assumptions used in the development of the emissions model.

Table 2. Warehouse-Specific Inputs and Assumptions

Input Variable	Value	Units	Source
Total warehouse locations	97,165	locations	WMS / facility layout
Locations scannable by drones	78,560	locations	Warehouse standard
Locations not scannable by drones	18,605	locations	Calculated (difference)
Inventory loss rate (before implementation)	1.60%	% of total inventory	NRF Survey (2023)
Issue rate (Locations counted manually)	17.51%	% of locations	WMS historical data
Issue rate (Locations counted by Drones)	6.59%	% of locations	Verity logs (drone-only scans)
Weekly scans (post-implementation)	8,836	scans/week	Verity
Average employee commute distance	47.80	miles/day	Employee survey / assumption
Human counting capacity	60	locations/hour	Warehouse operations
Shifts per day	2	shifts/day	Warehouse standard
Hours per shift	8	hours	Warehouse standard
Working days per week	5	days	Warehouse standard
Counting cycle length	12	weeks	Operational policy
Forklift energy consumption	2.8	kWh/hour	Estimated based on battery specifications
Drone energy consumption	0.0167	kWh/hour	Verity
Drone operating time (per drone)	14.40	hours/week	Verity

3.4 Emission Factor Selection

To convert measurements into emissions calculations and assess their sustainability impacts, we adopt a systematic approach using emissions factors (EFs). These coefficients quantify the GHG emissions associated with specific operational or life cycle activities, such as electricity consumption, employee commuting, equipment production, or inventory disposal. Emissions factors link measurable activities to emissions outputs and allow us to consistently estimate impacts across Scopes 1, 2, and 3 as defined by the GHG Protocol.

Given the diversity of activities included in this analysis, ranging from equipment operation to waste generation and lifecycle emissions from material handling equipment, we sourced emissions factors from a combination of government publications, vendor-provided data, and peer-reviewed databases. Each factor was selected based on its relevance to warehouse operations, the geographic location of the case study, and the specificity of the activity measured.

For operational activities such as drone energy use and forklift charging, we used emissions factors from Verity (2024a) and the U.S. Energy Information Administration. For employee commuting, we relied on standard emissions factors provided by the U.S. Environmental Protection Agency (2024), as commuting data was not provided. For example, drone energy consumption was modeled using Verity's equipment-specific performance data, and forklift electricity use both applied an emissions factor (EF) of 0.5289 kg CO_2e/kWh, aligned with the fulfillment center's regional electricity grid mix (U.S. EIA, 2024; XtraPower Batteries; Dobers & Jarmer 2023). Employee commuting emissions were calculated using the U.S. EPA standard of 0.4 kg CO_2e/mile, consistent with national averages for passenger vehicle use (EPA, 2024).

Table 3 summarizes the emissions factors applied to operational activities, organized by source category and citation.

Table 3. Operational & Commute Related Emission Factors

Category	Activity	Emission Factor (EF)	Source / Citation
Labor	People commute	0.4 $kgCO_2e/mile$	U.S. Environmental Protection Agency. (2024). Average passenger vehicle emissions.
Forklift Ops	Cycle Count	0.5289 $kgCO^2e/kWh$	U.S. Energy Information Administration (2024) XtraPower Batteries. (n.d.)
	Addressing Inventory Discrepancies		
Waste	Inventory disposal	12.892$kgCO_2e/kg$	Carbonfact (2023), WRAP (2020), Textile Exchange (2021)
Drone Ops	Cycle Count	0.5289 $kg\ CO_2/kWh$	U.S. Energy Information Administration (2024) XtraPower Batteries. (n.d.)

In addition to operational emissions, we accounted for Scope 3 emissions from equipment production and transportation by applying life cycle assessment (LCA)-based emissions factors. These factors represent the cradle-to-gate embodied carbon of material handling equipment, normalized over estimated equipment lifespans. Drone production emissions were modeled based on material-level assessments provided by Verity and supported by LCA databases and literature (Liang, Q., & Yu, L. M. ,2023; American Chemistry Council, 2022). For forklifts, production emissions were significantly higher due to the scale, material intensity, and battery systems involved, with estimates drawn from comprehensive electric MHE lifecycle analyses (Hao et al., 2017; Net Zero Carbon Guide; Sipert et al., 2024). Transportation-related emissions were modeled using DEFRA-based emissions factors (UK Department for Energy Security and Net Zero, 2024), accounting for delivery distances and equipment weight.

Table 4 outlines the LCA-related emissions factors used in the model, covering both production and transportation stages.

Table 4. LCA-Related Emission Factors

Emission Source	Emission Factor (EF)	Source / Citation
Drone Production	$10.98\ kg\ CO_2e$	Liang, Q., & Yu, L. M. (2023); City of Winnipeg (2012); American Chemistry Council (2022); CarbonChain (n.d.); Verity (2024a)
Drone Transportation	$16.675\ kg\ CO_2e$	UK Department of Energy Security and Net Zero (2024)
Forklift Production	$1{,}171.48\ kg\ CO_2e$	Net Zero Carbon Guide (n.d.); Hao et al. (2017); CarbonChain (n.d.); Sipert et al. (2024); ScienceDirect (2024)
Forklift Transportation	$2{,}295.22\ kg\ CO_2e$	UK Department of Energy Security and Net Zero (2024)

By triangulating multiple sources and aligning factors to the specific processes observed in the warehouse, this emissions factor framework supports robust and transparent modeling. Full derivations of emissions equations and assumptions associated with each EF are presented in Appendix A.

3.5 Mathematical Modeling of Emissions

A core component of this analysis involves evaluating the impact of operational changes on both direct and indirect GHG emissions. Emphasis is placed on quantifying emissions associated with inventory discrepancies, especially write-offs caused by misplaced or inaccurately counted items, as these serve as a critical lever for emissions reduction. Improvements in inventory accuracy through drone-based cycle counting are expected to reduce the frequency and severity of such discrepancies. To validate this assumption and improve model fidelity, structured interviews were conducted with warehouse personnel to understand the practical consequences of these discrepancies and their operational context.

Based on this investigation, we identify four primary emissions outcomes associated with poor inventory accuracy:

1. **Operational Overhead**: Increased labor and equipment usage for manual cycle counting and addressing inventory discrepancies.
2. **Inventory Write-Offs**: Items that are lost, unaccounted for, or later deemed unsellable due to mishandling, leading to waste and replacement emissions.
3. **Expedited Shipments**: Triggered by stockouts from inaccurate inventory data, often involving air freight or other high-emissions transport modes.
4. **Intra-Network Transfers**: When items must be shipped from alternate warehouse locations to fulfill orders, resulting in additional transportation emissions.

These emissions consequences were modeled using a before-and-after comparative design focused on operations at the selected warehouse where autonomous drones were introduced in January 2025. The model quantifies changes in emissions across key activities using operational data and emission factors detailed in Section 3.3.

3.5.1 Modeling Approach and Workflow

Our emissions estimation follows a four-step process that aligns with methodological best practices outlined in Dobers and Jarmer's (2023) GHG accounting guide for logistics hubs, particularly in its functional area-based allocation of electricity and ISO 14083-compliant reporting:

1. Pre-Implementation Baseline Estimation: Establishing GHG emissions from traditional inventory management operations (Jan–Mar 2024).
2. Post-Implementation Projection: Simulating emissions under drone-enabled inventory automation (Jan–Mar 2025).
3. Sensitivity Analysis: Exploring how variations in key assumptions affect emissions outcomes (detailed in Section 3.6).
4. Result Interpretation: Estimating net emissions impact and identifying primary drivers of sustainability gains or trade-offs.

Emissions are calculated using a standard activity-based modeling framework in which each variable is represented as

$$Emissions\ activity = Activity\ Level \times Emission\ Factor$$

where Activity Level refers to a measurable quantity such as kWh consumed, miles traveled, or items scrapped, and Emission Factor (EF) refers to the carbon intensity of that activity, typically expressed in kg CO_2e per unit.

3.5.2 Activity-Based Emissions Modeling

The model evaluates a set of selected operational activities expected to be influenced by drone deployment, such as employee commuting, forklift usage, energy consumption for drone charging, and inventory write-offs. Emissions for each activity are calculated separately for both the baseline and post-implementation periods using the formulas and variables defined in Table 5.

Table 5. Emissions Model Structure by Activity

Category	Activity	Activity Level Formula	Emission Factor (EF)	Emissions Equation
Labor (Scope 3)	Employee commuting	$Individuals \times Days\ commuted \times Av\ Miles\ traveled$	0.4 kg CO_2e / mile	$E = Miles \times EF$
Drone Operations (Scope 2)	Drone inventory scans	$Drones \times Avg\ Drone\ Fly\ Time\ per\ Week \times Avg\ Power\ Draw\ per\ Flight$	0.5289 kg CO_2e / kWh	$E = Energy \times EF$
Forklift Operations (Scope 2)	Inventory counting	$Forklifts\ used\ for\ Counting \times Working\ Hours \times Avg\ Energy\ Consumption\ per\ Hour$	0.5289 kg CO_2e / kWh	$E = Energy \times EF$
Inventory Management (Scope 3)	Inventory write-offs	$Item\ Loss\ Rate \times Total\ Inventory$	12.892 kg CO_2e / item	$E = Items \times EF$
Forklift Operations (Scope 2)	Inventory Discrepancies	$Forklifts\ used\ for\ discrepancies \times Working\ Hours \times Av\ Energy\ Consuption\ per\ Hour$	0.5289 kg CO_2e / kWh	$E = Items \times EF$
Lifecycle (Scope 3)	Drone manufacturing	$Drones\ employed$	5.531 kg CO_2e / unit	$E = Units \times EF$
Lifecycle (Scope 3)	Forklift manufacturing	$Forklifts\ employed$	1401 kg CO_2e / unit	$E = Units \times EF$

In Appendix B, we include all the assumptions we use in each formula—such as scan rate, power draw, and average distance per forklift cycle—which we also examine through sensitivity analysis in Section 3.6.

3.5.3 Life Cycle Assessment Integration

To enhance the environmental impact assessment, a Life Cycle Assessment (LCA) was incorporated to quantify emissions generated across the full lifecycle of key equipment used in inventory counting operations. LCA provides a standardized, data-driven framework to evaluate environmental footprints from material extraction and manufacturing to transportation, use, and eventual disposal (International Organization for Standardization [ISO], 2006a). Unlike activity-based emissions, which focus on operational energy use, LCA offers a more comprehensive evaluation by capturing the embodied carbon in warehouse assets and infrastructure.

We structured the life cycle assessment (LCA) according to the phases outlined in ISO 14040 and ISO 14044 (ISO, 2006b). In the goal and scope definition phase, we defined the objective as a comparison of annualized emissions from drones and conventional forklifts used for inventory counting. The system boundary encompasses production, transportation, and the operational lifespan of each equipment type. In the life cycle inventory (LCI) phase, we gathered data on material inputs, energy consumption, logistics, and manufacturing processes for both systems. During the life cycle impact assessment (LCIA), we quantified GHG emissions using the Global Warming Potential (GWP) metric, expressed in kilograms of

CO_2 equivalent (CO_2e). Finally, in the interpretation phase, we validated the results, addressed data uncertainties, and contextualized the findings within the broader emissions model of the warehouse operation.

For our model, LCA calculations were based on data from manufacturer specifications, academic literature, and government databases. For instance, Verity (2024a) and Liang & Yu (2023) provided component-level data on the autonomous drones, while the Raymond 560-OPC30TT forklift was modeled using emissions factors from published LCA studies (Hao et al., 2017; UK Department of Energy Security and Net Zero, 2024).

Total cradle-to-gate emissions for the forklift were estimated at approximately 14,010 kg CO_2e over a 10-year lifespan (or 1,401 kg CO_2e/year), reflecting contributions from steel, lithium-ion batteries, plastics, and transportation. In contrast, the autonomous drone system, composed primarily of lightweight polymers, optics, and a small battery, was found to have a total lifecycle footprint of 27.65 kg CO_2e over a 5-year lifespan (or 5.53 kg CO_2e/year).

LCA was applied across three impact categories:

1. **Inventory Write-Offs and Waste Reduction**

   Misplaced or lost inventory leads to unnecessary disposal and emissions from replacement production. By improving inventory accuracy, drones reduce write-off frequency and minimize associated embodied emissions. We apply an average embodied carbon factor of 12.892 kg CO_2e per unit based on category-level apparel data (WRAP, 2020; Carbonfact, 2023).

2. **Mobile Equipment Utilization**

   Conventional forklifts are a significant source of Scope 2 and 3 emissions. Drone adoption displaces these emissions through reduced equipment cycles. Based on revised LCA inputs, forklifts contribute approximately 1,401 kg CO_2e/year, while drones contribute only 5.53 kg CO_2e/year, a >99% reduction in embodied equipment emissions.

3. **Drone Infrastructure Emissions**

   Although drones reduce operational emissions, they introduce emissions from equipment production and infrastructure (e.g., charging stations, battery systems). These impacts were estimated and incorporated into the annual emissions model, ensuring a balanced view of both costs and benefits.

By integrating LCA with operational modeling, we obtain a comprehensive assessment of emissions impacts and can more accurately evaluate the net sustainability benefit of drone-based inventory automation. A detailed explanation of assumptions and calculations is provided in Section 3.4.4 and Appendix A.

3.5.4 LCA Calculation Approach

To quantify life cycle emissions of both drone systems and conventional forklifts, we developed a Life Cycle Inventory (LCI) based on component-level material breakdowns, energy usage, logistics, and equipment lifespan. Emission factors were applied using data from peer-reviewed studies, government databases, and environmental modeling platforms (e.g., UK Government GHG Conversion Factors, CarbonChain, ScienceDirect).

Forklift System (Raymond 560-OPC30TT)

The LCI was based on an industrial-grade forklift weighing 3,882 kg, including:

- Steel frame: 2,254 kg × 2.8 kg CO_2e/kg = 6,311.2 kg CO_2e
- Lithium-ion battery (27.9 kWh): 61.5 kg CO_2e/kWh × 27.9 = 1,715.85 kg CO_2e
- Other mixed materials (483 kg): 7.635 kg CO_2e/kg = 3,687.69 kg CO_2e
- Transport emissions (800 km trucking): ≈ 295.26 kg CO_2e

Total emissions: 11,714.76 + 295.26 = 14,010 kg CO_2e

Annualized over 10 years: 1,401 kg CO_2e/year

Drone System (Verity Autonomous Drone)

The drone system was modeled using component-level mass and specific emissions factors:

- PA12 frame (0.5 kg): 5.7 kg CO_2e/kg = 2.85 kg CO_2e
- PC/ABS housing (0.2 kg): 4.518 kg CO_2e/kg = 0.90 kg CO_2e
- Optics and electronics (0.15 kg): 24.865 kg CO_2e/kg = 3.73 kg CO_2e
- Lithium-ion battery (0.25 kg): ≈ 3.5 kg CO_2e
- Transport emissions (air and truck): 16.675 kg CO_2e

Total embodied emissions: 11.0 + 16.675 = 27.65 kg CO_2e

Annualized over 5 years: 5.53 kg CO_2e/year

All lifecycle emissions were normalized to the same functional unit: kg CO_2e per year per equipment unit, ensuring comparability between conventional and automated inventory solutions. The results reinforce the significant sustainability advantage of drone adoption in inventory operations, particularly in contexts where forklifts are primarily used for counting rather than material movement.

3.6 Before-and-After Scenario Modeling

To assess the net impact of drone implementation on sustainability outcomes, we developed two modeled scenarios representing operations before and after the introduction of autonomous drones. These scenarios are based on actual warehouse data and are supplemented with validated assumptions, as detailed in earlier sections.

Each scenario incorporates emissions from various sources, categorized according to the GHG Protocol into Scopes 2 and 3, and life cycle emissions. Scope 2 includes electricity consumption associated with drone charging, forklift operations, and other energy-dependent warehouse activities. Scope 3 covers indirect emissions from employee commuting, inventory write-offs and losses, addressing inventory discrepancies, and the manufacturing and transportation of operational equipment. Lifecycle emissions represent the embodied carbon from the production, delivery, and use-phase amortization of drones and forklifts, based on values derived through life cycle assessment (LCA) modeling.

Scope 1 emissions were intentionally omitted from this analysis. Scope 1 typically includes direct emissions from on-site fossil fuel combustion—such as diesel-powered material handling equipment or natural gas-based HVAC systems. However, during interviews and follow-up validation with warehouse personnel, it was confirmed that the implementation of drone-based inventory automation did not alter on-site fuel usage patterns. The warehouse maintained consistent HVAC schedules and operational settings both before and after drone deployment. Therefore, as no change in Scope 1 emissions could be attributed to the technology transition, they were excluded from the comparative emissions modeling.

The modeled scenarios are designed to represent a three-month operational window, covering January through March for the years 2024 (pre-implementation) and 2025 (post-implementation). All variables were either measured directly or derived from structured interviews, WMS datasets, and Verity drone flight data. Where data was missing, assumptions were calculated or conservatively estimated using industry benchmarks and validated against contextual information.

A central feature of the model is the introduction of a target percentage of locations counted by drones, which acts as the master variable governing several downstream operational and emissions outcomes. According to the warehouse operator, the planned future state will allow drones to complete 90% of all cycle counting tasks for the reserve storage area, which includes 78,560 out of 97,165 total warehouse locations. This means that only 7,800 reserve locations will continue to require manual counting, while an additional 18,605 locations, which are not drone-accessible, will always be counted manually. This assumption creates a calculated manual share of locations, which becomes the primary driver for estimating required personnel and equipment for cycle counting in the after-implementation sensitivity analysis.

The drone coverage percentage also influences inventory accuracy by lowering the average issue rate (percentage of scanned locations that trigger discrepancies) and, indirectly, the inventory loss rate (percentage of inventory written off). Both values are modeled as linear functions of drone coverage, based on observed issue rates in drone-scanned and manually counted locations.

For the post-implementation scenario, the initial values for issue rate and inventory loss rate were not directly observed but calculated using calibrated linear relationships based on available warehouse data.

The model uses a target drone coverage percentage as a control variable, which influences accuracy-related metrics. Specifically, the issue rate was modeled using the equation

$$Issue\ Rate\ total = 6.59\% \times pd + 17.51\% \times (1 - pd)$$

where pd is the proportion of drone-scannable locations covered by drones, and the constants were derived from observed rates in manually and drone-scanned areas. The inventory loss rate was assumed to improve at the same proportional rate as issue rate and is calculated using

$$Inventory\ Loss\ Rate\ total = 1.6\% \times \left(\frac{Issue\ Rate\ total}{17.5\%}\right)$$

These equations reflect operational data showing that drone-scanned locations have significantly lower discrepancy rates and that improvements in inventory visibility reduce the likelihood of write-offs. In the initial post-implementation model, current drone coverage was estimated at 64% out of the 90% goal, based on WMS cycle count logs and interviews with warehouse personnel. At this coverage level, the model produced an estimated issue rate of 10.53% and an inventory loss rate of approximately 1.0%.

In addition to calculating inventory issues and loss rate, the model also estimates forklift utilization for addressing inventory discrepancies based on the number of locations flagged as issues during drone scans. These locations require manual verification and physical access using forklifts. The number of locations with issues per week was calculated as

$$Locations\ with\ issues\ week = Weekly\ Scans \times Issue\ Rate$$

This value was then used to determine the weekly workload associated with misplacement retrieval. To translate this into energy use and equipment needs, the model calculates the fraction of a forklift needed using the following logic: given a known capacity for how many locations a forklift-and-operator team can address in a week, the total number of locations with issues is divided by that capacity to yield a fractional equipment count. This figure is multiplied by the number of operational hours per week and the average power draw per hour to determine forklift energy consumption. Forklift energy for addressing issues is calculated as

$$Forklift\ Energy\ Discrepancies = \left(\frac{M}{C_f}\right) \times H \times P$$

where M represents the number of locations requiring issue resolution each week, C_f the known capacity of a forklift-and-operator team to process a given number of locations per week, H the number of working hours per week, and P is the average energy consumption per hour. This value is modeled as continuous and fractional to reflect real-world resource sharing, rather than assuming full-time equipment is dedicated to misplacement recovery.

It is important to note that for this initial baseline comparison, the number of personnel and forklifts for inventory counting operations was treated as static input values derived from current warehouse operations. While later sensitivity analyses model these resources dynamically as a function of drone coverage and task demand, the base after-implementation scenario preserves actual staffing levels to anchor the model in real-world conditions.

By simulating the same operational setting with and without drone-enabled inventory automation, this scenario-based modeling approach isolates the marginal impact of drone deployment on key sustainability indicators. The emissions outcomes from these scenarios serve as the basis for the comparative analysis presented in Section 4 and the sensitivity analysis in Section 3.6.

To quantify the environmental impact of drone implementation, we calculated the net emissions change across each modeled activity using the following formulation

$$\Delta\, Emissions \;=\; Emissions\ pre - Emissions\ post$$

A negative value of $\Delta\, Emissions$ indicates a reduction in GHG emissions attributable to drone deployment.

3.7 Sensitivity Analysis Design

To better understand the influence of key drivers, a sensitivity analysis is conducted. This component of the methodology aims to identify which input variables—such as labor requirements, inventory accuracy, or equipment allocation—have the most significant effect on sustainability outcomes, and how variations in these factors affect total emissions. Rather than isolating causal effects through statistical control groups or regression models, this approach focuses on estimating plausible impacts by systematically testing how changes in operational assumptions shape emissions outcomes.

The sensitivity analysis quantifies the emissions impact of individual parameters by evaluating the change in total emissions relative to percentage changes in each variable. This helps determine which variables produce the largest emissions shifts when adjusted and informs recommendations by highlighting which levers are realistically modifiable in practice. The model supports a range of operational levers, including personnel allocation strategies, inventory counting coverage, and discrepancy resolution effort.

This enables supply chain stakeholders to explore implementation scenarios and evaluate emissions savings under varied warehouse conditions.

The target percentage of locations to be counted by drones is the central feature of the model's sensitivity structure. This variable represents the share of drone-scannable locations covered by autonomous drones and is varied across a range of values, from the current estimated state (64%) to the warehouse's future target (90%), and up to 100% to assess the implications of maximum achievable automation. As this percentage increases, the manual share of locations to be counted decreases accordingly, and this directly impacts the number of human personnel and forklifts required for inventory counting.

Personnel needed for manual inventory counting is dynamically calculated as a function of the remaining locations to be counted and the scanning capacity of an operator. Forklift needs for this task are set to match the number of people assigned, assuming a 1:1 human-equipment ratio. In contrast, the number of forklifts needed for addressing inventory discrepancies is determined independently, based on the number of issues flagged per week, calculated from the average issue rate and weekly scan volume, and the weekly capacity of a forklift team. This ensures that misplacement-related activity remains partially independent and responsive to the issue rate, which itself is also modeled as a function of drone coverage.

All personnel values—whether for inventory counting or issue resolution—are aggregated and rounded up to determine total headcount for commuting emissions (Scope 3). The number of forklifts is then derived as a ratio of total personnel, assuming that forklifts can operate across two shifts per day, while employees only cover one. This ratio-based calculation enables fractional allocations of emissions in both Scope 2 (energy) and Scope 3 (lifecycle) categories, reflecting shared asset use in practice.

Inventory accuracy metrics, specifically the issue rate and inventory loss rate, are also dynamically modeled as linear functions of drone coverage. As drone coverage increases, the model assumes proportional improvements in these metrics, based on observed data from manually and drone-scanned areas. These improvements reduce both the number of discrepancies requiring manual intervention and the number of items written off entirely, thereby lowering emissions associated with waste and retrieval labor.

By structuring the model this way, the sensitivity analysis not only identifies the most impactful variables but also shows how they interact. This is particularly valuable for illustrating operational trade-offs, such as how increasing drone coverage beyond 90% continues to reduce emissions, but with smaller incremental gains. Similarly, staffing requirements decrease with automation, but tend to level off once most manual tasks have already been replaced. Line graphs and scenario-based comparisons, presented in Section 4, illustrate how emissions change in response to incremental increases in drone adoption and provide actionable insight for warehouse operations planning.

4 RESULTS AND DISCUSSION

This chapter presents the results of the emissions modeling and scenario analysis comparing manual inventory processes with drone-enabled inventory automation. We begin by reporting total modeled emissions across Scope 1, 2, and 3 under both the baseline and post-implementation scenarios. Next, we analyze emissions changes by operational category, highlighting the specific variables that drove reductions or increases in each scope. We then examine the results of the sensitivity analysis, which evaluates how variation in key input assumptions—such as drone energy usage, inventory accuracy improvements, and employee commute distance—affect total emissions. Finally, we present a comparative summary that integrates these findings and quantifies the net sustainability impact of drone adoption under different modeling assumptions.

4.1 Results

Following the application of the mathematical model, the first step involved calculating the total emissions generated by each activity category using the activity-based formulas developed in Section 3.4. Emissions for each activity were determined by multiplying its modeled activity level by the corresponding emissions factor. To enhance the understanding of environmental impact, the total emissions were annualized. Although the dataset was initially provided at a quarterly level (Q1), the cyclical nature of inventory counting—defined as a scheduled and repetitive process—justifies replicating Q1 operational parameters across all four quarters of the year. This practice reflects industry standards where inventory cycle counts are consistently performed each quarter to achieve full inventory coverage targets.

Summing the emissions from all categories yielded a total footprint for each scenario: pre- and post-implementation of drone technology. Additionally, the model calculated the percentage contribution of each activity to total emissions, facilitating the identification of the most significant emission contributors and the changes observed between the two scenarios.

The initial results indicated that total annual emissions decreased from 609,451 kg CO_2e to 358,619 kg CO_2e, representing a reduction of 41%. This net decrease of approximately 250,832 kg CO_2e was primarily driven by changes in waste from inventory write-offs. Table 6 disaggregates emissions by category, showing emissions before and after implementation, the absolute change, and each category's share of the total footprint.

Table 6. Scenario 1 Annual Emissions by Category: Before vs. After Implementation

Category	Activity	Before: Emissions (kg CO2e)	After: Emissions (kg CO2e)	Δ Emissions (kg CO_2e)	% Change	% of Total Carbon Footprint
Labor	People commute	29,827.20	14,913.60	-14,913.60	-50.0%	4.16%
Forklift Operations	Forklift energy (inventory count)	16,662.19	5,014.77	-11,647.42	-69.9%	1.40%
Drone Operations	Drone inventory energy	0	26.38	26.38	N/A (new source)	0.01%
Waste	Inventory disposal	556,939.53	334,647.19	-222,292.35	-39.9%	93.32%
Forklift Operations	Forklift energy (addressing discrepancies)	1,819.69	1,193.18	-626.52	-34.4%	0.33%
Equipment	Drone LCA	0.00	22.12	22.12	N/A (new source)	0.01%
Equipment	Forklift LCA	4,203.00	2,802.00	-1,401.00	-33.3%	0.78%
Total		**609,451.61**	**358,619.23**	**-250,832.38**	**-41.16%**	

A closer examination of the results shows that inventory disposal (waste) was the leading contributor to emissions in both the before and after implementation scenarios, accounting for about 93% of total emissions. This outcome is due to the modeling assumption that each lost inventory unit corresponds to an individual item, with a total inventory of 2.7 million units. This approach significantly overstates the environmental impact of waste, as in practice, the warehouse stores items in cases or boxes rather than at the single-item level. In the absence of actual data on inventory scrap rates, the model utilized an industry average of 1.6% inventory loss, based on the NRF Survey (2023).

To better align the model with the operational structure of the warehouse, we refined the original assumption regarding inventory granularity. Instead of modeling emissions from item-level inventory (2.7 million individual units), we redefined the inventory as 129,381 cases, which better reflects how products are physically handled and stored on site. This adjustment significantly altered the magnitude and distribution of modeled emissions and yielded the revised results presented in Scenario 2 (Table 7). Under this case-based model, total annual emissions prior to drone implementation were calculated at 79,200 kg CO_2e, while post-implementation emissions dropped to 40,008 kg CO_2e, reflecting a 49.48% reduction in relative terms. Compared to Scenario 1, this change also resulted in a 87% decrease in the total magnitude of modeled emissions, emphasizing the impact of inventory-level assumptions on absolute emissions figures.

Table 7. Scenario 2 Annual Emissions by Category: Before vs. After Implementation

Category	Activity	Before: Emissions (kg CO2e)	After: Emissions (kg CO2e)	Δ Emissions (kg CO_2e)	% Change	% of Total Carbon Footprint
Labor	People commute	29,827.20	14,913.60	-14,913.60	-50.0%	37.28%
Forklift Operations	Forklift energy (inventory count)	16,662.19	5,014.77	-11,647.42	-69.9%	12.53%
Drone Operations	Drone inventory energy	0	26.38	26.38	N/A (new source)	0.07%
Waste	Inventory disposal	26,687.92	16,035.92	-10,652	-39.9%	40.08%
Forklift Operations	Forklift energy (addressing discrepancies)	1,819.69	1,193.18	-626.52	-34.4%	2.98%
Equipment	Drone LCA	0	22.12	22.12	N/A (new source)	0.06%
Equipment	Forklift LCA	4,203	2,802	-1401	-33.3%	7.00%
	Total	**79,200**	**40,008**	**-39,192**	**-49.48%**	

The redistribution of emissions across categories in Scenario 2 is particularly notable. While inventory disposal remains the largest contributor post-implementation, its share of total emissions dropped dramatically from 93% in Scenario 1 to 40%. At the same time, employee commuting rose from just 4.16% to 37.28% of total emissions, becoming the second-largest contributor. This shift underscores the importance of properly calibrating inventory structure and activity volumes to operational realities, as category weightings are highly sensitive to underlying assumptions. The emissions share from forklift operations also increased proportionally, moving into third place at 12.5% of the total.

Despite these shifts, drone implementation continues to offer strong sustainability gains while introducing only marginal emissions from new activities. Drone electricity consumption contributed just 26.4 kg CO_2e per year, and drone lifecycle emissions added 22.1 kg CO_2e, together accounting for only 0.12% of post-implementation emissions. Meanwhile, energy use from forklifts performing inventory counts was reduced by approximately 70%, falling from 16,662.2 kg CO_2e to 5014.8 kg CO_2e, as drone automation replaced a substantial portion of manual activity. Lifecycle emissions from forklift equipment also dropped by one-third, from 4,203 kg CO_2e to 2,802 kg CO_2e, while drones contributed only a negligible addition.

To help interpret the shifting impact of individual emissions categories, Figure 4 provides a side-by-side bar chart comparing the percentage of emissions reductions by category for Scenario 2, and Figure 5 illustrates how each category contributes to total emissions savings. These visualizations support a more intuitive understanding of how drone implementation reshapes the emissions profile of warehouse inventory operations and helps identify the most significant levers for sustainability improvements.

Figure 4. Comparison of Emissions Reduction by Category

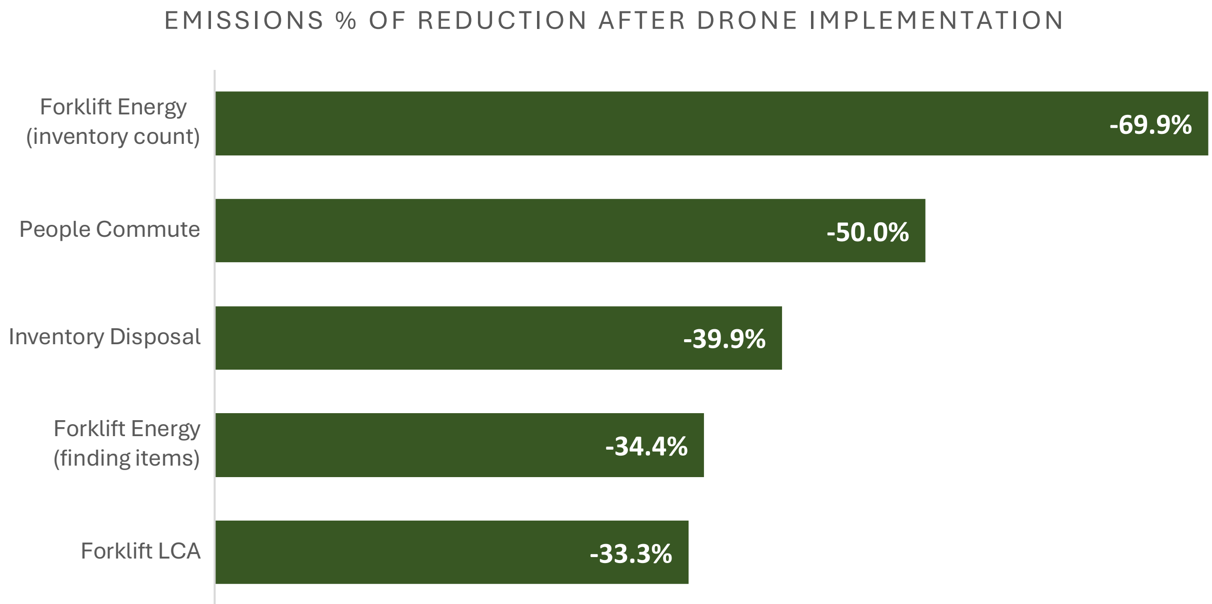
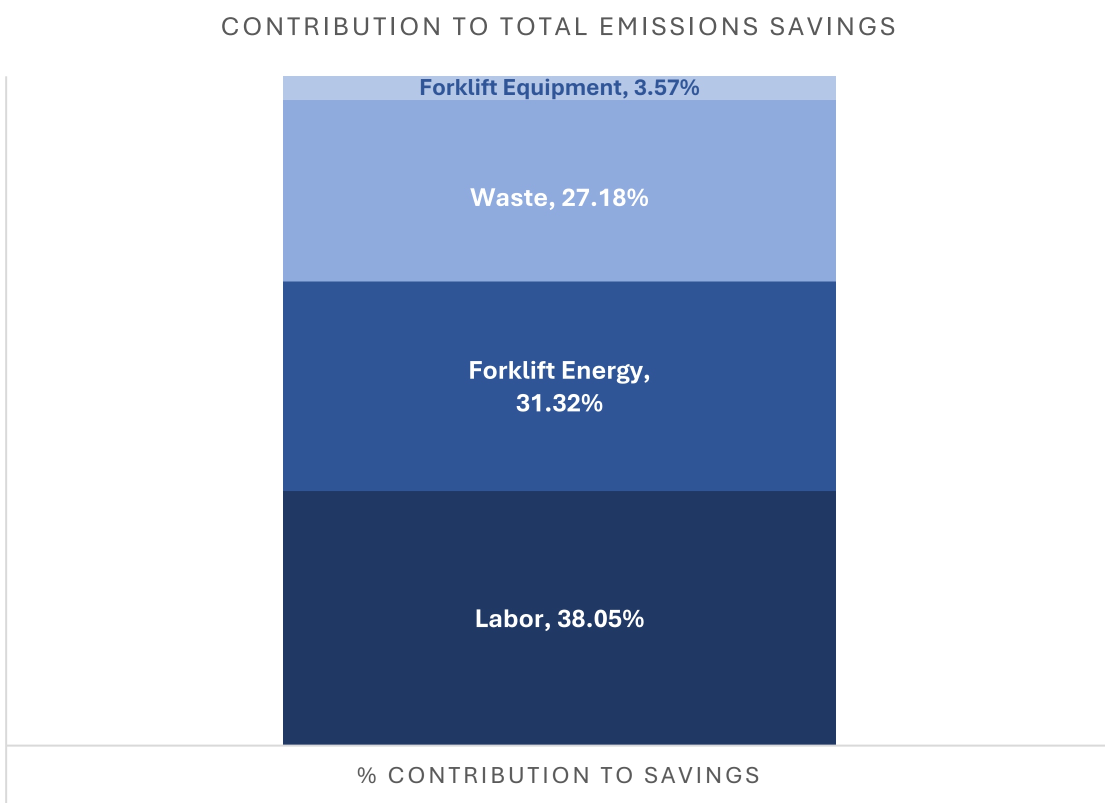


Figure 5. Contribution of Each Category to Emissions Savings



To complement the absolute emissions analysis, we developed a comparative line graph that visualizes the relative contribution of each emissions category to total emissions before and after drone implementation. Figure 6 and 7 illustrate how the percentage share of each activity evolves across scenarios, highlighting the redistribution of carbon intensity within warehouse operations. For instance, emissions from drone operations—nonexistent in the baseline—appear in the post-implementation scenario, increasing modestly from 0% to 0.07% for drone energy and 0.06% for drone manufacturing. These additions remain minimal, underscoring the carbon efficiency of the drone system.

More revealing, however, are the shifts among traditional emission sources. While total emissions from inventory disposal decreased in absolute terms, their share of the total footprint increased from 33.7% to 40%. This relative growth reflects the fact that other categories, such as operational energy use, declined even more dramatically. Forklift lifecycle emissions followed a similar pattern, rising from 5.31% to 7%, despite a drop in equipment quantity, due to slower depreciation relative to faster-declining operational activities.

In contrast, people commuting, once the largest contributor at 37.66%, fell to 37.28% of total emissions, and forklift energy use for inventory counting dropped from 21% to 12.5%. These changes demonstrate how drone automation reduces labor requirements and equipment energy use, shifting the emissions profile from labor- and equipment-heavy operations toward a structure where waste and capital goods play a larger role.

This visual representation helps isolate not just which categories have grown or diminished, but how automation reconfigures the emissions landscape. It offers a clearer view of the new sustainability profile emerging from drone adoption—not only through overall reductions, but through a fundamental change in which activities drive warehouse emissions post-automation.

Figure 6. Change of Drone Contribution to Total Carbon Footprint

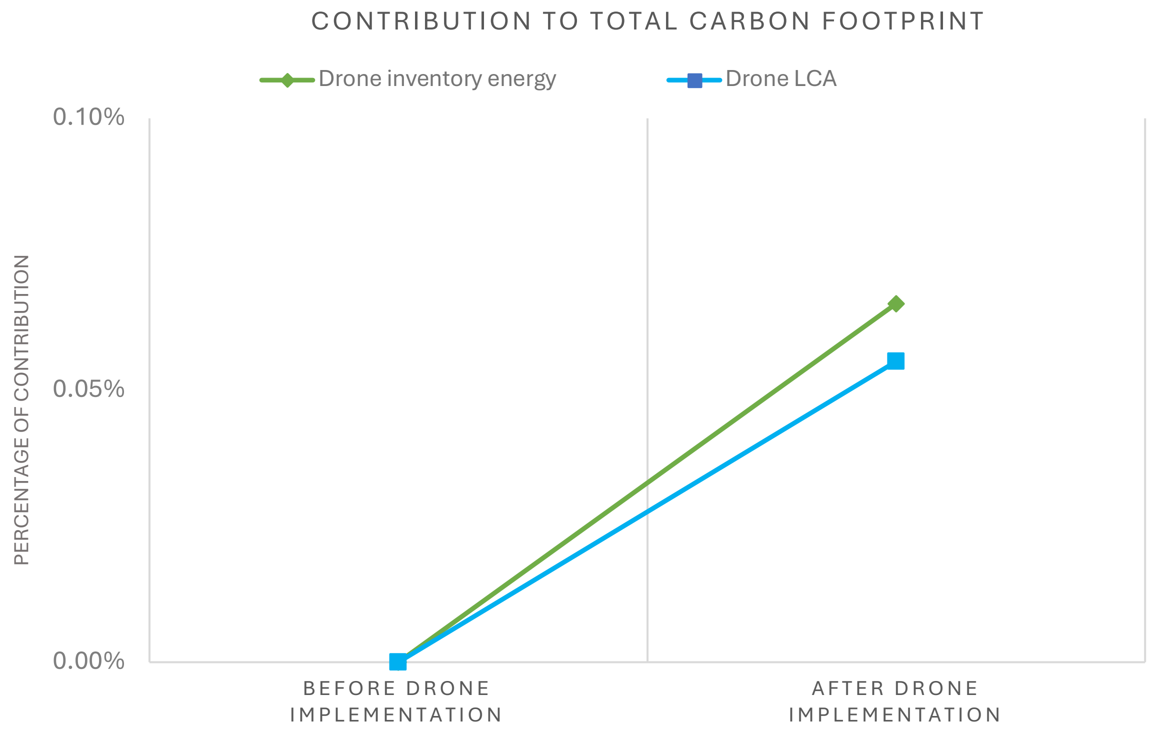
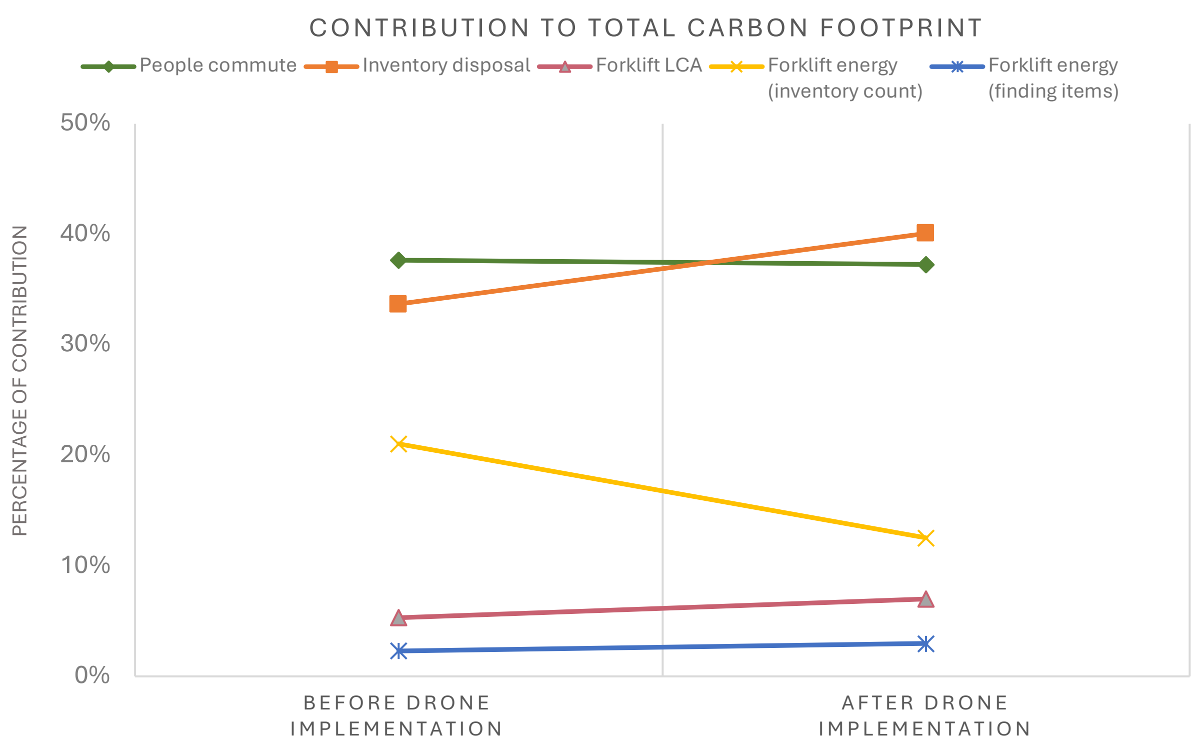


Figure 7. Change in Contribution to Total Carbon Footprint by Activity



To further contextualize the emissions distribution in the post-implementation scenario, we introduced two additional visual breakdowns. Figure 8 categorizes emissions by operational source, showing that waste and transportation account for the vast majority of the warehouse's footprint, contributing 40.1% and 37.3%, respectively. Emissions from core warehouse operations account for 15.6% total footprint, while equipment-related emissions make up just 7.1%. This breakdown reinforces the earlier finding that even after automation, the warehouse's emissions profile is still shaped largely by upstream and downstream activities, such as product loss and employee commuting.

In parallel, Figure 9 disaggregates emissions by GHG Protocol scope, highlighting the dominance of Scope 3 emissions, which account for 84.4% of the total footprint. Scope 2 emissions from electricity usage are still significant, accounting for 15.6% of emissions, and Scope 1 emissions are entirely absent, consistent with the facility's use of electric equipment and external service providers. This scope-based visualization emphasizes that the environmental impact of drone adoption lies primarily in its ability to reduce indirect emissions—especially those related to labor, transportation, and waste—rather than altering the facility's direct energy footprint.

Figure 8. Emissions by Operational Category – Post-Implementation Scenario

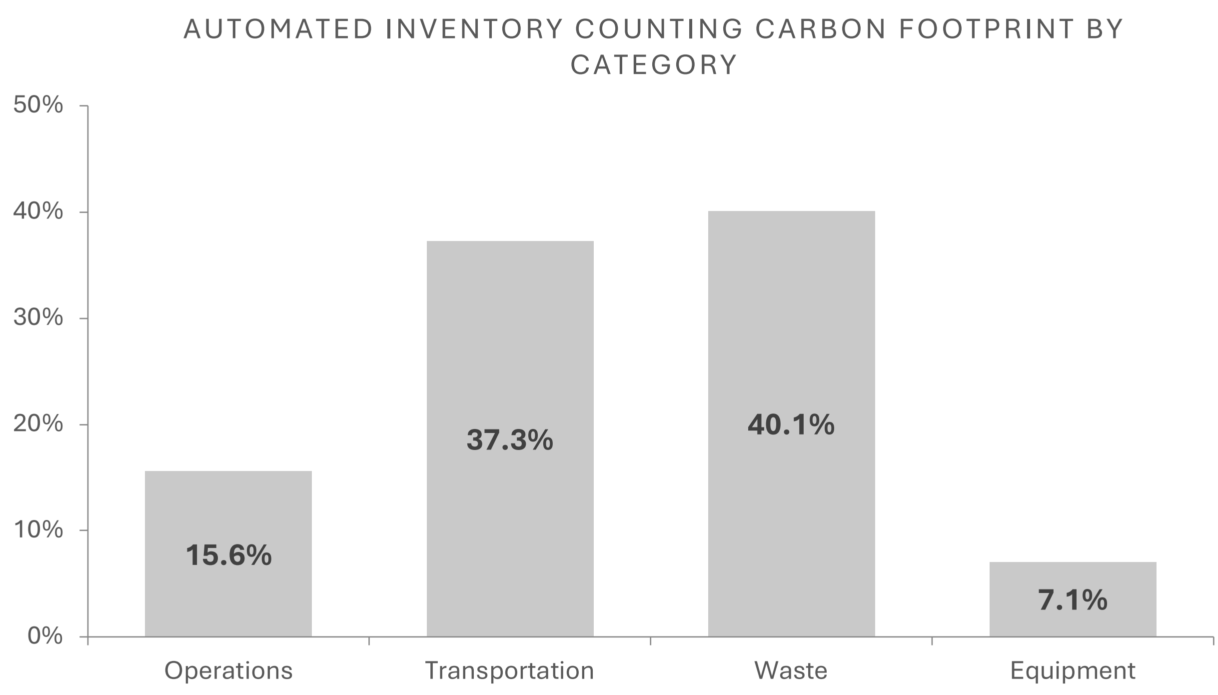
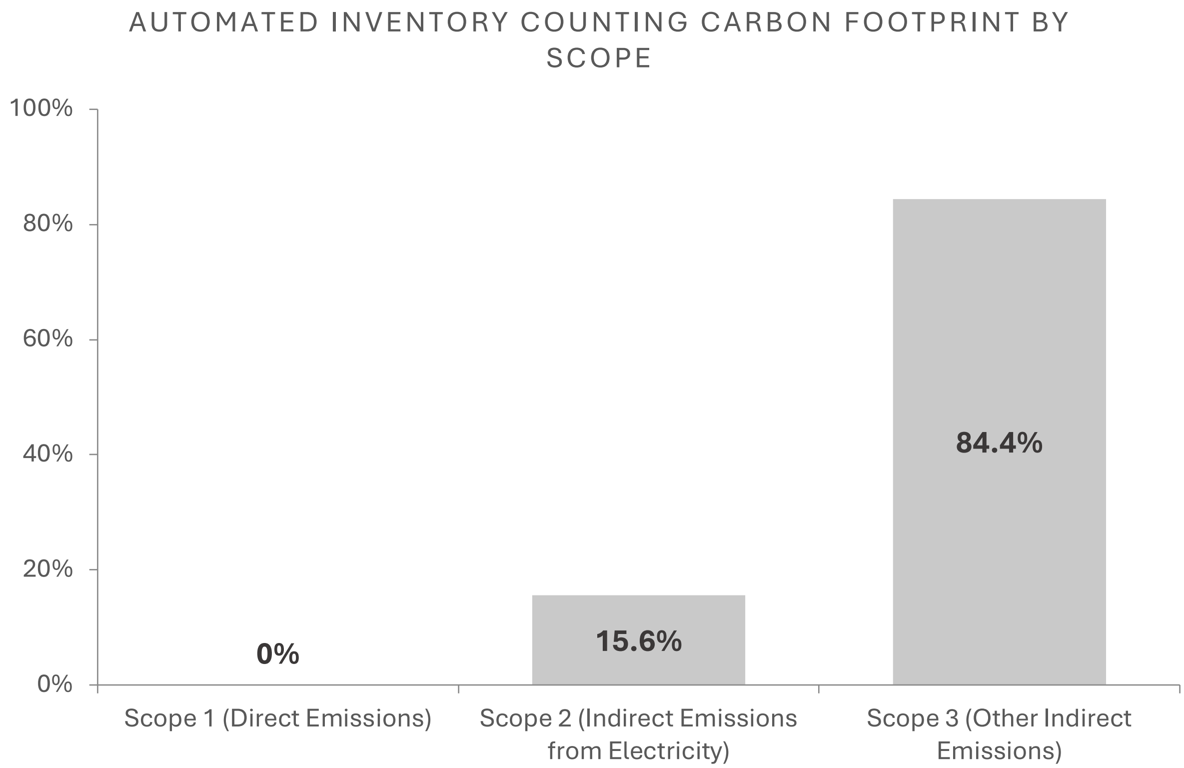


Figure 9. Emissions by GHG Protocol Scope – Post-Implementation Scenario



4.1.1 Drone Coverage Sensitivity Analysis

For the sensitivity analysis, we transitioned from using fixed warehouse inputs to modeling key variables as functions of the target percentage of locations to be counted by drones. This parameterized approach allowed us to explore how incremental increases in drone adoption influence emissions outcomes by dynamically adjusting related operational factors, such as labor requirements, inventory accuracy, and equipment usage.

We began by calculating the manual share of locations, which determines the number of inventory locations requiring human verification. This is calculated as the difference between the total scannable locations and those covered by drones, combined with a set of locations that drones can never count due to layout or classification constraints. Formally

$$Manual\ Locations = (1 - pd) \times Drone\ Countable\ Locations + Non\ Drone\ Countable\ Locations$$

where pd is the target percentage of drone coverage, and for this warehouse, 78,560 out of 97,165 total locations are considered drone-countable, while 18,605 locations are not. As a result, even at 100%

drone coverage, a significant portion of the facility—approximately 19%—will still require manual inventory operations, implying that a fully autonomous solution is operationally unattainable in this context.

From the manual locations, we calculated the number of people needed for inventory counting by dividing the total by the number of locations one operator can scan over a full inventory cycle. Assuming a 12-week cycle, 8-hour shifts, 5 days per week, and a counting capacity of 60 locations per hour, each operator can verify 28,800 locations per cycle:

$$Peoplecounting = \frac{Manual\ Locations}{28{,}800}$$

We separately modeled the labor required for addressing inventory discrepancies, which depends on the issue rate, itself a weighted average of drone and manual performance based on coverage:

$$Issue\ Rate = pd \times Drone\ Issue\ Rate + (1 - pd) \times Manual\ Issue\ Rate$$

Multiplying this rate by the average number of locations scanned weekly yields the number of locations with issues per week, which we then use to calculate the labor and equipment needed to resolve discrepancies. Rather than treating issue resolution as a separate process, we assume that each flagged discrepancy requires an operator to return to the affected location and perform a manual verification. This aligns with actual warehouse behavior and allows us to treat issue resolution as an extension of the cycle counting task.

Although the labor requirements for inventory counting and discrepancy resolution were calculated independently, we summed both to determine the total number of people commuting for inventory-related tasks. The total was rounded up to the nearest whole number, reflecting the warehouse's practice of assigning staff to full 8-hour shifts. While this rounding was necessary to calculate Scope 3 commuting emissions, tracking the contributions of each activity separately helped identify the proportional labor intensity of each task.

For forklifts, we applied the same division between inventory counting and issue resolution, but modeled the energy consumption of each as a fractional value based on the time spent on each activity. Unlike personnel, forklifts can remain idle or be reassigned when not in use. However, for lifecycle emissions (Scope 3), we estimated the number of forklifts as a function of total personnel. Since forklifts can be used across two shifts per day, we assumed each unit serves two employees. Thus, the required number of forklifts was calculated as the ceiling of half the total number of commuting personnel

$$Forklift\ LCA = \lceil \frac{Peopletotal}{2} \rceil$$

This assumption reflects standard warehouse practices for equipment utilization and reduces the emissions attributed to capital assets. We then applied life cycle emissions factors based on this adjusted equipment count, linking drone coverage not only to energy and labor but also to infrastructure-related emissions.

To evaluate the potential for further emissions reduction through increased automation, we modeled the impact of expanding drone coverage from the current post-implementation level of 64% to the warehouse's target of 90%, and then to a hypothetical maximum state of 100%. These scenarios allow us to assess not only the carbon savings associated with incremental drone adoption, but also how operational parameters and emissions distributions shift as drone deployment expands.

As shown in Table 8, increasing drone coverage to 90% would reduce total annual emissions from 40,008 kg CO_2e to 26,801 kg CO_2e, representing a 33% reduction relative to the current state. Compared to the baseline scenario (before implementation), this equates to a 66.16% total reduction. In a maximum coverage scenario, where all drone-compatible reserve locations are automated, emissions would fall further to 19,202 kg CO_2e, yielding a 75.76% reduction compared to the baseline and a 52% improvement over the current post-implementation performance.

These reductions are largely driven by declines in labor demand, energy consumption, and waste. As drone coverage increases, the number of inventory personnel drops from 3 to 2, and then to 1; forklifts for inventory counting decrease accordingly. Although drone usage remains constant at 4 units, greater coverage increases the efficiency of each drone cycle; however, their relative share of the total footprint increases slightly, reflecting the declining contributions from traditional activities. Still, these drone-related emissions remain minor—collectively under 1% of the total carbon footprint—highlighting the efficiency of automation even at full deployment. Lifecycle emissions from forklift equipment drop as fewer assets are required, while inventory loss rate improves from 0.96% to 0.70%, and further to 0.60% in the full automation scenario. The misplacement issue rate, which drives the labor and energy required for item retrieval, declines in parallel, from 11% to 8%, and finally to 6.59% when 100% of locations are counted by drones.

Table 8. Emissions and Emissions Share by Category – Current vs. Future State (90% Drone Coverage)

Activity	Current State Emissions (kg CO2e)	Future State Emissions (kg CO2e)	Δ Emissions (kg CO_2e)	% Change	Current % of Total Carbon Footprint	Future % of Total Carbon Footprint
People commute	14,913.60	9,942.40	-4,971.20	-33.3%	37.3%	37.1%
Forklift energy (inventory count)	5,014.77	2,830.15	-2,184.63	-43.6%	12.5%	10.6%
Drone inventory energy	26.38	26.38	0.00	0%	0.1%	0.1%
Inventory disposal	16,035.92	11,708.44	-4,327.48	-27%	40.1%	43.7%
Forklift energy (addressing discrepancies)	1,193.18	871.19	-321.98	-27%	3.0%	3.3%
Forklift LCA	2,802.00	1,401.00	-1,401.00	-50%	7.0%	5.2%
Drone LCA	22.12	22.12	0.00	0.0%	0.1%	0.1%
Total	**40,008**	**26,801.67**	**-13,206.3**	**-33%**		

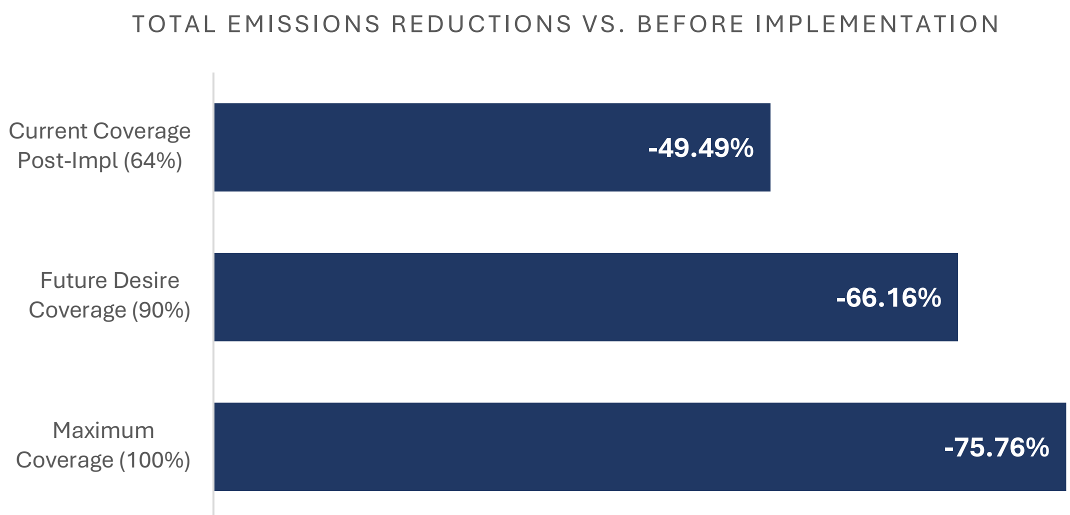
To better illustrate the operational drivers behind these reductions, we present Table 9, which summarizes how key activity parameters shift across the three modeled scenarios. Labor, equipment needs, and accuracy-based metrics (inventory loss and issue rate) all respond to increased drone coverage. As shown, greater automation translates directly into fewer people and forklifts needed for inventory operations.

Table 9. Operational Parameters Across Drone Coverage Scenarios

Parameter	Current State Post-Impl	Future Desire State	Maximum State
Target percentage of locations counted by drones	64.0%	90.0%	100.0%
Inventory personnel	3	2	1
Forklifts (inventory counting)	1.63	0.92	0.65
Drones (inventory counting)	4	4	4
Forklifts (LCA)	2	1	1
Drones (LCA)	4	4	4
Inventory loss rate (%)	0.96%	0.70%	0.60%
Misplacement issue rate (%)	10.52%	7.68%	6.59%
Total emissions reduction vs. Before Implementation	-49.49%	-66.16%	-75.76%
Additional savings vs. Current scenario	–	-16.67%	-26.27%

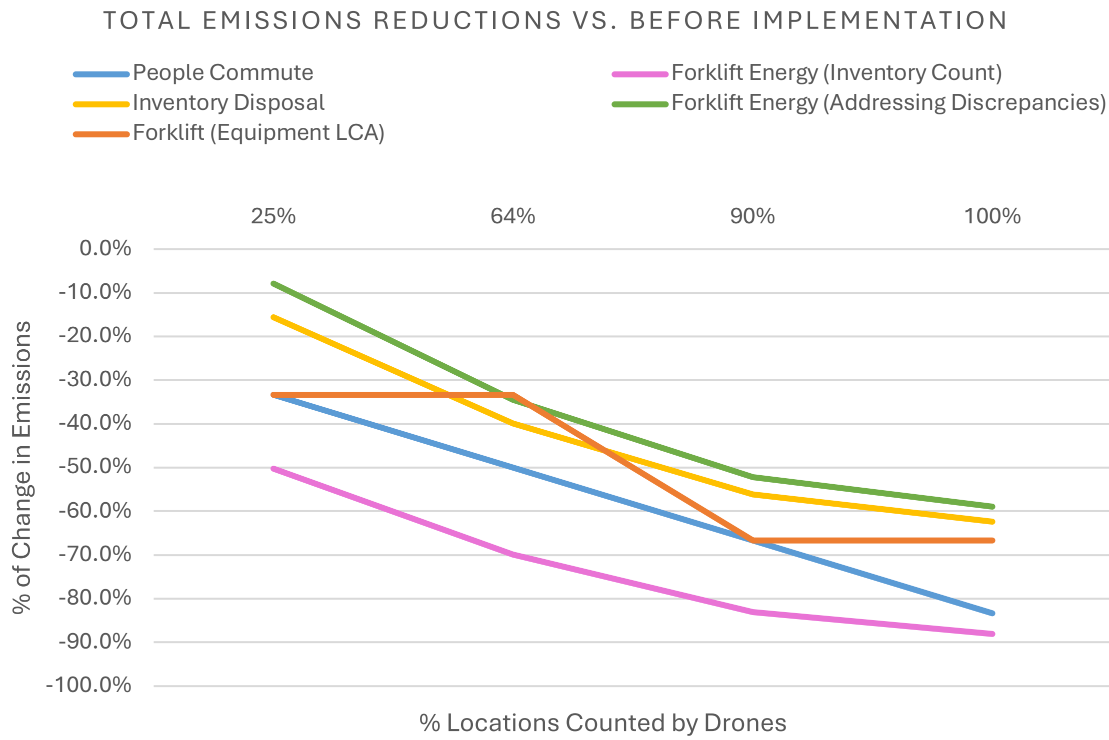
To illustrate the cumulative emissions savings across the three modeled scenarios, Figure 10 presents a bar chart comparing total annual emissions at 64%, 90%, and 100% drone coverage levels. This visual highlights the magnitude of improvement associated with reaching the warehouse's future target and demonstrates the additional gains that could be unlocked through full drone coverage. The chart clearly shows that increasing drone coverage from 64% to 90% yields a substantial additional reduction of 16.67%, while pushing toward full automation provides a further 9.6% reduction beyond that. However, the visual also helps emphasize that while total emissions continue to decrease, the rate of improvement begins to taper as automation approaches its upper limit, suggesting diminishing returns in some categories. This representation reinforces the value of reaching the 90% goal while also supporting a cost-benefit analysis of pursuing complete coverage.

Figure 10. Total Emissions Reductions Across Drone Coverage Scenarios (64%, 90%, 100%)



Building on the total emissions analysis, we disaggregated reductions by activity category across four drone coverage levels: 25%, 64%, 90%, and 100%. Figure 11 presents this multi-line chart, illustrating how key operational emissions decline as drone adoption increases.

Figure 11. Emissions Reduction by Category as a Function of Drone Coverage



The results show that employee commuting and forklift energy use for inventory counting experience the steepest and most consistent declines, reaching over 80% reduction at full drone coverage. This reflects the direct replacement of manual labor and operational forklift usage as drones take over an increasing share of cycle counting. These categories are highly sensitive to automation because their emissions are tightly coupled with the volume of human-driven activity.

Inventory disposal—representing emissions from scrapped goods due to miscounts or misplacements—also exhibits a significant decline of over 60% by the time drone coverage reaches 100%. This trend confirms the hypothesis that increased automation leads to improved inventory accuracy, reducing the number of items written off and the upstream emissions associated with producing replacements. The curve is somewhat less steep than that of commuting, reflecting the fact that inventory loss is influenced not only by the quantity of manual counting but also by systemic processes, operator behavior, and detection capabilities.

Similarly, forklift energy for addressing inventory discrepancies shows a clear downward trend as issue rates decline with higher drone adoption. The reduction surpasses 50% at full drone coverage, illustrating how drone-generated visibility reduces the operational effort required to resolve discrepancies. This category, while smaller in overall contribution, demonstrates how automation helps reduce emissions even from secondary activities like discrepancy resolutions.

In contrast, forklift lifecycle emissions decrease in stepwise increments rather than a smooth curve. A reduction of 33% occurs between 64% and 90% drone coverage—likely the point at which one piece of equipment is no longer needed—reflecting further workforce consolidation. Because lifecycle emissions are amortized over fixed equipment units rather than tied to marginal usage, their reductions occur only when a full asset can be removed from operations.

This visualization illustrates how drone implementation not only reduces total emissions but also transforms the structure of operational demand. High-frequency, labor- and equipment-intensive tasks shrink steadily, while capital-dependent emissions decline in fixed intervals. As drone coverage increases, warehouses can expect emissions reductions to occur both continuously (through efficiency gains) and structurally (through changes in equipment and staffing requirements). These insights provide a clearer understanding of where sustainability gains are most responsive to automation, and where diminishing returns may appear as operations become increasingly optimized.

4.1.2 What-If Sensitivity Analysis

We conducted a series of what-if scenarios to evaluate how the model responds to deviations from key assumptions and edge-case operational conditions. Unlike previous analyses where drone coverage was the main variable, these scenarios test the robustness of emissions reductions under alternate conditions. Each test isolates a specific factor, such as initial inventory accuracy, drone system enhancement, or failure to improve accuracy with automation, and evaluates its impact on overall emissions and emissions structure.

Scenario 1: High-Accuracy Baseline

To evaluate whether drone implementation remains a valuable emissions reduction strategy in warehouses that already operate with high inventory accuracy, we modeled a scenario where both the initial inventory loss rate and the issue rate were set significantly lower than in the baseline analysis. Specifically, we assumed a starting loss rate of 0.5% and an issue rate of 7%, simulating an environment where manual processes already perform with relatively low error. The goal was to test whether drone automation would still yield meaningful emissions savings when improvements to accuracy—and therefore to waste reduction—are limited.

Even under this high-accuracy baseline, drone adoption continues to deliver notable emissions reductions, though the magnitude is somewhat lower than in the original model. The transition from a manual system to 64% drone coverage resulted in a 48% total emissions reduction, compared to 49.5% in the original model. Increasing drone coverage to 90% improved total emissions reduction to 62.4%, and extending it to full (100%) drone-compatible coverage further reduced emissions by 72% relative to the high-accuracy baseline. However, these values are slightly lower than in the base case (where reduction reached 75.8%), indicating that the benefits of automation diminish when fewer errors can be prevented.

The improvement in inventory disposal was relatively modest, with emissions decreasing from 8,340 kg CO_2e to 8,027 kg CO_2e—an absolute drop of only 3.8%. This reflects the smaller baseline of avoidable waste.

Importantly, the emissions profile shifted heavily toward commuting, which represented 49% of pre-implementation emissions, and remained the largest contributor post-implementation. In contrast, inventory disposal accounted for just 13.7% before and 25.4% after drone adoption, highlighting how category importance is relative to the total. These findings confirm that automation remains beneficial even in accurate systems, largely by eliminating manual labor and equipment reliance, but its impact on waste reduction is naturally constrained.

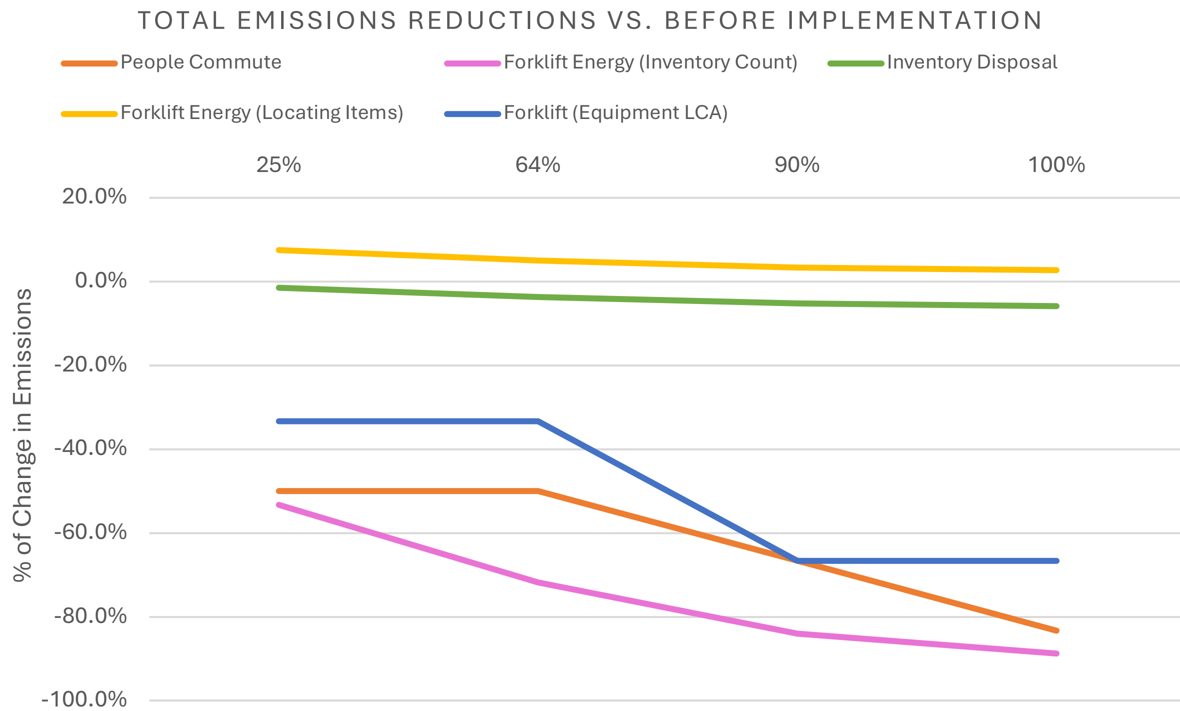
An interesting finding from this scenario is that emissions from forklift energy used to address inventory discrepancies show a temporary increase of approximately 5% after drone implementation begins. As illustrated in Figure 12, this occurs because the number of locations scanned per week increases significantly with drone deployment, while the inventory issue rate does not decrease at the same pace. As a result, the absolute number of discrepancies identified rises, which increases the operational demand for addressing them. This intermediate effect reflects the lag between expanded coverage and improved accuracy, and highlights how partial automation, without concurrent improvements in data quality, can temporarily increase workload in secondary activities like item retrieval, even as total emissions decline. Over time, as accuracy improves further, this category returns to a downward trend.

Table 10 summarizes the emissions breakdown across key categories, while Figure 12 displays the shift in total emissions as drone coverage increases within a high-accuracy environment.

Table 10. Operational Parameters – High-Accuracy Baseline Scenario

Parameter	Before Impl.	Current State Post-Impl	Future Desire State	Maximum State
Target percentage of locations counted by drones	0.0%	64.0%	90.0%	100.0%
Inventory personnel	6	3	2	1
Forklifts (inventory counting)	5.76	1.63	0.92	0.65
Drones (inventory counting)	0	4	4	4
Forklifts (LCA)	3	2	1	1
Drones (LCA)	0	4	4	4
Inventory loss rate (%)	0.50%	0.48%	0.47%	0.47%
Misplacement issue rate (%)	7.00%	6.74%	6.63%	6.59%
Total Emissions Reduction vs. Before Implementation		-48.12%	-62.41%	-72.05%
Additional savings vs. Current scenario	–	–	-14.29%	-23.93%

Figure 12. Emissions Changes by Category – High-Accuracy Baseline



Scenario 2: Adding a Drone to Improve Frequency and Accuracy

In this scenario, we explored the impact of adding a fifth drone beyond the warehouse's target of 90% inventory coverage. While total coverage remains constant, the intent behind this adjustment is to increase scanning frequency—allowing the drone system to revisit locations more often—and to test whether doing so yields additional emissions savings through improved inventory accuracy. We assumed that enhanced scanning would reduce the inventory issue rate for drone-counted locations to 5%, and that this would translate into a lower overall inventory loss rate of 0.46%.

Despite the slight increase in drone-related emissions—drone electricity usage rises by 25%, and drone LCA emissions increase proportionally due to the additional hardware—the total warehouse emissions drop meaningfully. Total annual emissions decline from 40,008 kg CO_2e to 24,470 kg CO_2e, representing a 38.9% improvement over the current post-implementation state, and a 69.1% reduction compared to the pre-drone baseline. This makes it the largest reduction observed across all modeled scenarios.

Notably, this strategy also reshapes the emissions distribution across categories. The percentage of total emissions attributed to inventory disposal falls from 40.1% to 39%. Conversely, commuting emissions become more prominent (increasing from 37.3% to 40.6%), becoming the largest contributor, simply because they decline at a slower rate compared to the accelerated improvements in other categories. This shift indicates that increasing drone performance does not only reduce absolute waste-related emissions—it also changes the emissions structure, making waste a less dominant share of the overall footprint.

Drone-related emissions—both in terms of energy (up from 26.38 to 33 kg CO_2e) and equipment (LCA rising from 22.1 to 27.7 kg CO_2e)—increase modestly and remain marginal in relative terms (still under 0.2% combined). These additions are more than offset by the substantial gains in inventory accuracy, reduced issue rates, and lower equipment use from cycle counting and item retrieval.

This scenario demonstrates that even in a highly automated warehouse, investing in drone system performance can yield additional sustainability gains, especially in areas where automation improves data quality and operational accuracy. While it introduces minor emissions costs, the environmental return on that investment, particularly in reducing waste and increasing system-wide efficiency, is clearly positive.

To illustrate the impact of enhanced scanning frequency, Table 11 summarizes how each variable changes with adding a fifth drone, and Table 12 shows emissions by category when evaluating the future state of 90% coverage under this scenario vs the current scenario. Figure 13 visualizes the changing emissions structure, quantifying each category's contribution to total emissions. These results show that modest increases in drone-related emissions are offset by significant reductions in inventory disposal, reinforcing the value of performance-driven automation strategies.

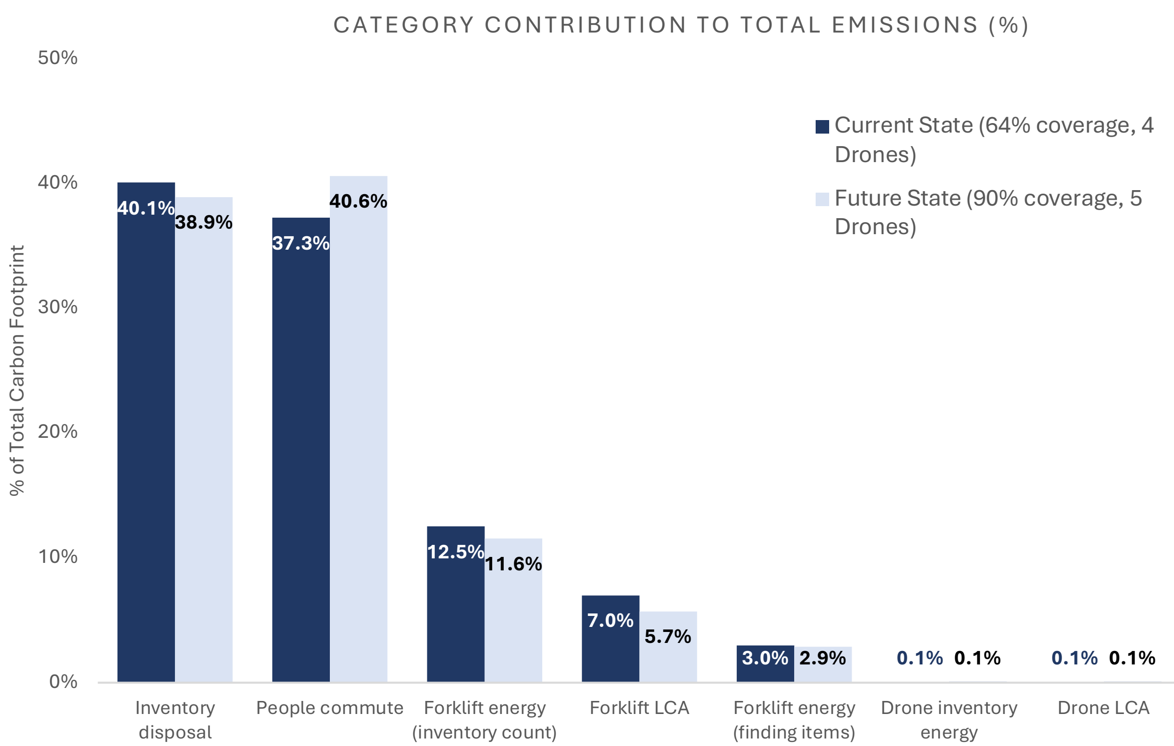
Table 11. Operational Parameters – Adding One More Drone and Improving Accuracy Scenario

Parameter	Before Impl.	Current State Post-Impl	Future Desire State	Maximum State
Target percentage of locations counted by drones	0.0%	64.0%	90.0%	100.0%
Inventory personnel	6	3	2	1
Forklifts (inventory counting)	5.4	1.6	0.9	0.6
Drones (inventory counting)	0	4	5	5
Forklifts (LCA)	3	2	1	1
Drones (LCA)	0	4	5	5
Inventory loss rate (%)	1.60%	0.96%	0.57%	0.46%
Misplacement issue rate (%)	17.50%	10.52%	6.25%	5.00%
Total emissions reduction vs. Before Implementation		-49.49%	-69.10%	-79.03%
Additional savings vs. Current scenario	–	–	-19.62%	-29.54%

Table 12. Emissions by Category With Addition of a Fifth Drone (90% Drone Coverage, 5% Issue Rate)

Activity	Current State (64%) Emissions (kg CO2e)	Future State (90%) Emissions (kg CO2e)	Δ Emissions (kg CO_2e)	% Change
People commute	14,913.60	9,942.40	-4,971.20	-33.3%
Forklift energy (inventory count)	5,014.77	2,830.15	-2,184.63	-43.6%
Drone inventory energy	26.38	32.97	6.59	25.0%
Inventory disposal	16,035.92	9,527.39	-6,508.53	-40.6%
Forklift energy (addressing discrepancies)	1,193.18	708.91	-484.27	-40.6%
Forklift LCA	2,802	1,401	-1,401	-50.0%
Drone LCA	22.12	27.66	5.53	25.0%
Total	**40,008**	**24,470.5**	**-15,537.5**	**-38.84%**

Figure 13. Category Contribution to Total Emissions (%) – With Fifth Drone Addition in Future State



Scenario 3: Stress-Testing the Assumption of Improved Accuracy

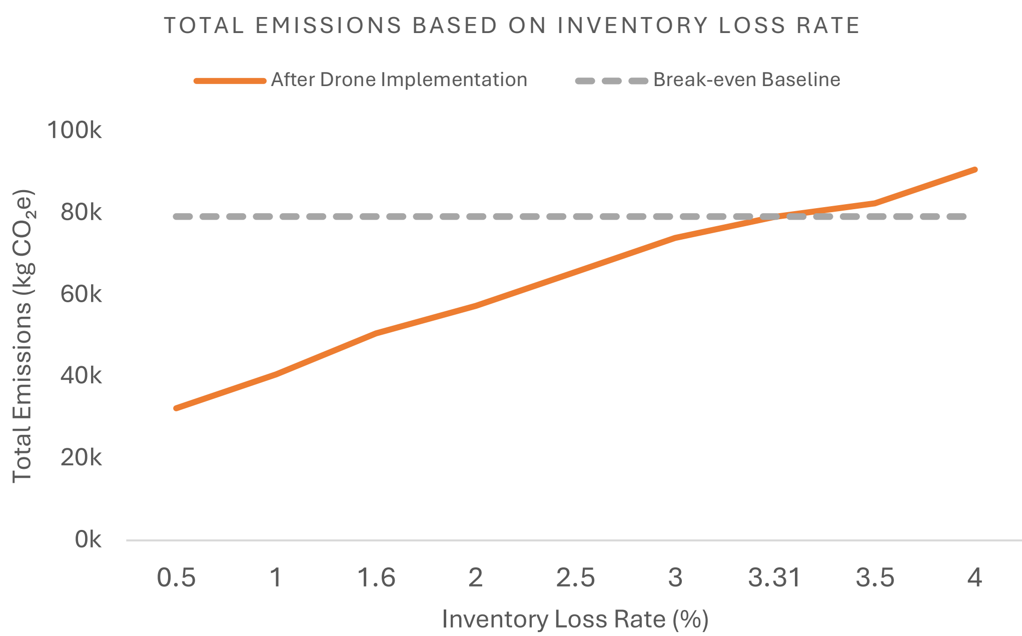
This final scenario reverses the core assumption that automation always improves performance. Instead, we modeled a situation where inventory loss increases with higher drone coverage, whether due to implementation issues, poor integration, or over-reliance on automation. The goal was to identify the break-even point where inventory disposal emissions outweigh the reductions from labor and equipment.

We found that if the inventory loss rate rises to approximately 3.31%, the system reaches a point of zero net emissions benefit. At this level, the emissions generated by increased waste offset all other sustainability gains. This threshold marks a critical inflection point: beyond it, further investment in drone automation would result in higher total emissions rather than reductions.

This scenario illustrates the model's high sensitivity to inventory disposal emissions, which carry a much higher carbon intensity per unit than labor or energy-related sources. While categories such as commuting and forklift use shrink consistently with automation, waste remains a dominant driver of total emissions. At a 3.31% loss rate, emissions from inventory disposal outweigh the reductions achieved elsewhere, particularly as other categories begin to plateau with higher drone coverage. This emphasizes the importance of ensuring that drone performance translates into measurable improvements in accuracy, rather than simply displacing human effort. In this context, drone implementation must be coupled with ongoing monitoring, calibration, and error-correction workflows to ensure it achieves its intended environmental benefits.

Figure 14 presents a break-even chart, demonstrating how total emissions increase sharply beyond a 3.31% loss rate, emphasizing the model's sensitivity to inventory disposal and the critical importance of maintaining accuracy during automation.

Figure 14. Break-Even Emissions Curve Based on Inventory Loss Rate



4.2 Scope Refinement and Excluded Variables

While the initial hypothesis mapping (Section 3.1) identified a broad range of variables expected to be affected by drone implementation, not all were included in the final emissions model due to data limitations or lack of observed variation. For instance, lighting and HVAC-related energy usage were excluded, as drone operations did not lead to measurable changes in facility runtime, ambient conditions, or staffing patterns that would warrant adjustments to energy settings. Similarly, Fixed Material Handling Equipment (FMHE), such as automated storage and retrieval systems, showed no meaningful change in usage attributable to drone-based inventory scanning and were therefore not modeled.

Additionally, while inventory accuracy improvements were hypothesized to reduce unnecessary replenishment and scrapping, actual order quantities and product ownership remained outside the scope of available data and operational control, limiting the ability to quantify downstream impacts such as overproduction or transportation emissions. As a result, the emissions model focuses on observable, measurable impacts, including energy use from mobile equipment, embodied emissions from capital assets, commuting-related emissions, and inventory write-offs.

4.3 Implications

The analysis reveals several critical insights for warehouse sustainability strategy and technology adoption. First, the deployment of AI-powered drone inventory automation has the potential to significantly reduce total carbon emissions associated with inventory counting processes by nearly 50% in both modeled scenarios, and up to 79% in enhanced drone configurations. However, the magnitude and distribution of these reductions are highly sensitive to operational parameters and foundational modeling assumptions, reinforcing the need for context-aware implementation.

A key modeling insight involves the definition of inventory units. The contrast between Scenario 1, which used item-level inventory assumptions, and Scenario 2, which modeled inventory at the case level, underscores the importance of aligning emissions calculations with actual warehouse storage and counting practices. Under item-level assumptions, waste emerged as the dominant emissions category due to high-volume multipliers. When revised to a case-based inventory structure, commuting overtook waste as the largest emissions contributor, shifting the emissions profile and highlighting how data granularity and modeling precision shape sustainability conclusions.

Several operational design choices also emerged as influential emissions drivers. One such factor is the total number of locations that drones are eligible to count, which, in this study, was capped at 78,560 of 97,165 locations. The presence of non-droneable areas effectively establishes a ceiling on automation potential, meaning that some manual processes—and their associated emissions—will persist unless warehouse layouts or drone hardware evolve. This highlights the value of including automation compatibility assessments in future warehouse planning.

Another key variable is the target percentage of drone coverage. Although the warehouse currently operates at ~64% drone coverage, the model demonstrated that increasing this to 90% or 100% could significantly amplify emissions reductions, especially in waste and labor categories. Importantly, the inventory issue rate was modeled as 6.59% for drone-counted locations based on current performance, but scenario testing showed that this rate can continue to decline with more frequent scans or improved route logic. These improvements, in turn, have cascading effects on both inventory loss and addressing inventory discrepancies needs, further shrinking emissions.

The model also accounts for the allocation of labor and equipment across shifts, which has implications for equipment-related lifecycle emissions. Forklifts were assumed to be shared across two shifts, while employees were allocated on a per-shift basis. This logic allowed for reduction in total forklift assets even when headcount remained constant. In parallel, operator counting capacity, set at 60 locations per hour, determined how many staff were required to cover the remaining manual locations in each drone coverage scenario. Together, these assumptions show that even modest changes in workforce efficiency or shift strategies can have outsized effects on both Scope 2 (energy) and Scope 3 (lifecycle and commuting) emissions.

From a broader sustainability planning standpoint, these findings suggest that drone automation introduces minor new emissions but enables significant reductions in legacy emissions categories, most notably waste, manual labor energy use, and commuting. These benefits are amplified by the intelligence layer provided by AI, which enables dynamic route optimization, real-time discrepancy detection, and proactive operational adjustments.

The model also reveals overlooked opportunities, such as employee transportation. In revised scenarios, commuting became the largest single contributor to emissions. This suggests that sustainability initiatives should expand beyond equipment and automation to include transport policy interventions like carpooling incentives, electric shuttle fleets, or remote inventory reconciliation roles.

Finally, this study demonstrates the value of pairing operational innovation with emissions modeling to support strategic decision-making. The findings confirm that automation alone is not sufficient: the emissions benefits depend on how technologies are implemented, how performance is monitored, and how surrounding workflows are optimized. As AI-powered drone adoption continues to scale, warehouses can expect to capture meaningful emissions reductions, particularly when modeling frameworks are grounded in site-specific data, operational constraints, and measurable performance metrics.

4.4 Limitations

While this study presents a comprehensive assessment of the environmental impact of drone-based inventory automation, several limitations must be acknowledged regarding the modeling scope, data availability, and generalizability of results. We categorized these limitations across seven thematic areas, reflecting both methodological constraints and contextual boundaries that influence the interpretation and application of the findings.

1. Modeling Approach Limitations

The emissions model employed is a deterministic, rule-based framework rather than a probabilistic or statistical model. It does not attempt to quantify uncertainty or variability in operational conditions. As such, factors such as fluctuating energy loads, equipment degradation, drone idle time, and manual override events are excluded. Additionally, the model does not capture temporal variations such as peak vs. off-peak electricity use. These simplifications are necessary for tractability but limit the model's real-world fidelity.

Similarly, sensitivity analyses were conducted under deterministic assumptions, varying one parameter at a time without accounting for interaction effects or confidence intervals. The absence of probabilistic modeling (e.g., Monte Carlo simulation) restricts our ability to assess the robustness of results under real-world variability.

2. Lifecycle Emissions Estimation

Lifecycle emissions estimates for drones and forklifts were derived from secondary sources (e.g., Net Zero Carbon Guide) and sponsor input, relying on average material compositions and production energy profiles. These sources lack granularity, omitting emissions from smaller subcomponents such as PCBs, sensors, and lithium controllers. Moreover, no data was available on supplier-specific practices (e.g., use of recycled materials, green manufacturing) or end-of-life treatment. Consequently, these LCA estimates represent high-level approximations rather than full cradle-to-grave footprints.

3. Data Availability and Input Assumptions

Several data-related constraints shaped the modeling boundaries:

Transportation Emissions: Logistics-related Scope 3 emissions were estimated using average distances along assumed trade routes, as specific supplier origins for drones and forklifts were not disclosed.

Equipment Composition: Component-level detail (e.g., motors, controllers) was unavailable, requiring aggregation based on dominant materials (e.g., steel, batteries, polymers).

Inventory Data: The sponsor-provided data excluded SKU-level and financial details, limiting the model's ability to reflect emissions variability tied to non-standard SKUs or seasonal fluctuations.

Commute Emissions: Scope 3 employee commuting emissions were modeled using average regional distances, not individual employee data. Variations in carpooling, home locations, and remote work practices were not captured.

Collectively, these assumptions affect the precision of Scope 1, 2, and 3 emissions estimates, particularly for categories sensitive to input heterogeneity.

4. Assumptions About Operational Substitution

The model assumes that drones fully replace manual inventory checking within the process scope. However, in practice, hybrid workflows may persist due to contractual or operational requirements mandating human oversight. In such cases, drones act as supplementary tools rather than replacements, which could lead to an underestimation of operational emissions and an overstatement of potential GHG savings.

5. Emissions Factor Generalization

Emission factors were sourced from public databases and applied as regional or global averages:

Grid Emissions: Regional average emission factors do not capture hourly or seasonal carbon intensity variations.

Material Emissions: Factors for materials such as steel, aluminum, and batteries reflect global averages and overlook specific supplier or facility characteristics like renewable energy use or recycled content.

While these factors provide accessible benchmarks, they may either overstate or understate true emissions depending on the actual sourcing and energy infrastructure.

6. Generalizability and Context Dependency

This analysis is based on a single warehouse in the United States, and its conclusions are context dependent. Operational emissions are influenced by facility layout, labor scheduling, energy infrastructure, and storage systems. In warehouses located in regions with different emissions intensity or labor policies—or in those handling irregular or non-palletized goods—automation's sustainability benefits may vary. The modeling framework should be adapted to local operational and regulatory contexts for broader application.

5 CONCLUSION

Sustainability has become a critical priority in modern logistics, driven by growing stakeholder expectations, regulatory pressures, and the increasing urgency of climate action. Warehouses, as key nodes in the supply chain, offer meaningful opportunities for emissions reduction through the adoption of intelligent technologies. This research evaluated the environmental impact of AI-powered inventory automation, focusing on the use of autonomous systems that replace manual cycle counting with real-time, data-driven visibility.

To assess the emissions impact of this transition, we developed a methodology grounded in the GHG Protocol. The model integrated activity-based accounting with LCA to evaluate Scope 1, 2, and 3 emissions across traditional and AI-automated inventory workflows. Key operational variables, such as forklift usage, energy consumption, inventory discrepancies, and labor requirements, were analyzed to understand how intelligent automation reshapes emissions profiles at the warehouse level.

Our results show that AI-driven inventory automation can reduce total annual GHG emissions by approximately 50% compared to manual operations. These reductions are primarily driven by decreased labor-related emissions, lower energy consumption from forklifts, and reduced inventory waste. Together, these three drivers account for over 95% of the modeled emissions savings, while the AI-powered drone system itself contributes negligible direct emissions. This demonstrates that intelligent automation's true environmental value lies in its ability to reshape broader warehouse operations.

Sensitivity and scenario analyses validated the robustness of these findings under varied assumptions of drone coverage, scan frequency, and operational structure. This confirms the broader potential of AI-powered systems to serve as levers for emissions reduction in warehouse environments.

To operationalize these insights, we developed a set of managerial recommendations (Section 5.1) for logistics and sustainability leaders—ranging from emissions modeling alignment to phased equipment retirement and drone eligibility expansion. These actionable strategies are intended to guide implementation decisions and ensure that automation investments translate into measurable sustainability outcomes.

Finally, we propose two directions for future research (Section 5.2): expanding the empirical rigor of this analysis through a Difference-in-Differences (DiD) framework and enhancing model realism through mathematical simulations of operational scenarios. Together, these future steps will enable broader generalization and continuous improvement of emissions modeling in warehousing contexts.

Ultimately, this study contributes a replicable framework for evaluating automation's sustainability impact and highlights the critical role of AI in shaping the future of decarbonized logistics. By embedding intelligent systems into inventory operations, warehouse managers can achieve operational excellence while meaningfully advancing environmental goals.

5.1 Managerial Insights

The findings of this study yield several actionable insights for warehouse operations and sustainability management. The following recommendations are proposed to guide strategic decision-making and facilitate the adoption of low-carbon inventory practices.

Prioritize AI-powered drone inventory automation. The implementation of drone-based inventory counting is associated with a substantial reduction in total annual emissions of approximately 50% in both scenarios. Management should consider scaling the deployment of drone technology, particularly in facilities with high inventory turnover or frequent cycle counting requirements, to capitalize on its environmental and operational benefits.

Align emissions modeling with operational realities. The comparative analysis between unit-level and case-level modeling underscores the importance of accurately reflecting warehouse inventory structures in emissions estimation. Future sustainability assessments should incorporate site-specific data on inventory loss rates, packaging units, and activity frequencies to improve the fidelity of emissions modeling and ensure appropriate allocation of mitigation resources.

Leverage AI-powered drone coverage as a master lever for emissions optimization. The model demonstrated that drone coverage acts as a central driver of emissions performance by influencing multiple downstream variables, most notably the number of manual locations to be counted, employee headcount for inventory operations, forklift equipment requirements, and indirectly, the inventory loss and issue rates. Sensitivity and what-if analyses showed that increasing drone coverage yields compounded environmental benefits, not only by directly reducing labor and equipment emissions, but also by improving inventory accuracy and reducing waste. Accordingly, the target percentage of drone-covered locations should be treated not as a fixed operational decision but as a strategic lever. Management should periodically reassess drone eligibility criteria and explore layout changes or technology upgrades to increase the share of drone-accessible locations over time.

Address Scope 3 emissions from employee commuting. In the revised modeling scenario, employee commuting emerged as the primary contributor to post-implementation emissions. Although often overlooked in operational decarbonization strategies, Scope 3 emissions from workforce transportation represent a significant opportunity for reduction. Management may consider implementing employee mobility programs, such as subsidized public transit, carpooling incentives, or flexible work arrangements, to further reduce the warehouse's indirect carbon footprint.

Phase out high-impact legacy equipment. As drone coverage expands, reliance on traditional inventory scanning equipment, such as forklifts, is expected to decline. Management should develop a phased retirement strategy for high-emission equipment, informed by life cycle assessment (LCA) data, to support emissions reduction while maintaining operational continuity.

Incorporate life cycle emissions in capital investment decisions. The LCA analysis of drone hardware demonstrated a significantly lower embodied emissions profile relative to traditional machinery. As such, future procurement processes should integrate life cycle emissions as a criterion for evaluating new technologies. This approach aligns procurement strategy with broader organizational sustainability objectives.

Ensure AI-powered drone adoption delivers measurable accuracy gains. The model reveals that emissions from inventory disposal carry significantly higher carbon intensity than those from labor or equipment usage. As a result, improvements in inventory accuracy represent one of the most powerful levers for reducing warehouse emissions. Management should ensure that drone deployment is not treated as a plug-and-play solution, but as a system requiring continuous calibration, monitoring, and integration with warehouse processes. Without measurable improvements in discrepancy detection and inventory loss, drone implementation may fail to deliver its full environmental benefit. Ongoing performance validation—such as tracking issue rate reductions and scrap avoidance—is essential for maintaining emissions improvements over time.

Develop a long-term emissions monitoring framework. To ensure accountability and continuous improvement, management should establish a standardized emissions monitoring framework. This system should leverage available operational data—such as equipment usage logs and energy consumption records—to support annual reviews of emissions performance and validate the impact of automation technologies over time.

By adopting these recommendations, warehouse operations can enhance environmental performance, improve resource efficiency, and contribute meaningfully to the organization's overall sustainability strategy.

5.2 Future Work

To build on this study's findings and strengthen the generalizability and decision-making utility of the model, we propose two key areas for future research. First, we recommend expanding the empirical rigor of the analysis through a Difference-in-Differences (DiD) approach that compares warehouses with and without AI-powered inventory automation over time. Second, we suggest incorporating mathematical modeling techniques to simulate operational dynamics and evaluate emissions outcomes across a range of drone deployment scenarios. Together, these efforts can enhance causal attribution, support scenario planning, and provide a more robust foundation for sustainable warehouse design.

5.2.1 Expanding the Difference-in-Differences (DiD) Analysis

While this study provides a preliminary assessment of the sustainability impacts of drone implementation through Life Cycle Assessment (LCA), future work should incorporate a more robust causal inference framework using a Difference-in-Differences (DiD) approach. This method would enable the comparison of changes in key operational metrics (e.g., emissions, inventory accuracy, equipment runtime) between facilities that adopt drone technology and those that do not, both before and after implementation.

To improve the reliability of the DiD analysis, future work should include:

- A larger sample size of warehouses across varied operational profiles and geographies.
- Clear identification of treatment and control groups with similar baseline characteristics.
- Consistent time intervals for pre- and post-treatment measurements.
- Integration of LCA-derived metrics (e.g., normalized CO_2e/year) as outcome variables.

This approach would enhance the attribution of sustainability improvements specifically to drone implementation, while controlling for unrelated external factors.

5.2.2 Incorporating Mathematical Modeling for Operational Factors

Given the sensitivity of emissions outcomes to operational assumptions, future research should integrate mathematical modeling to simulate warehouse performance under varying conditions of drone-assisted inventory management. This approach can help validate empirical findings and enable more dynamic scenario planning. Key factors identified from this study that warrant inclusion in future models are:

- Frequency of Cycle Counting: Alters the volume of activity, affecting energy consumption and inventory waste rates.
- Inventory Structure Granularity (Case vs. Unit): Significantly impacts waste emissions calculations; models should accommodate toggling between unit and case-level assumptions.
- Drone Flight Time and Coverage Constraints: Determines how many drones are required and how often manual support is needed due to battery or coverage limitations.
- Equipment Sharing and Utilization Rates: Reflects the interplay between drones, forklifts, and forklifts in mixed-technology environments, which influences total energy use and emissions.
- System Downtime and Maintenance: Incorporating probabilistic maintenance and failure events can simulate operational disruptions and their impact on emissions and productivity.

These parameters can be modeled using discrete-event simulations, queuing theory, or stochastic optimization methods to evaluate cost, emissions, and operational efficiency across different implementation scenarios. When combined with LCA data, this modeling approach provides a more robust framework for strategic technology adoption and sustainability planning in warehouse operations.

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APPENDICES

Appendix A

Table A1. Emissions Parameter Table for Drone and Forklift Operations, Transportation, and Lifecycle Assessment

Category	Activity	Formula with EF	Notes / Variables	Citations
Drone Operations	Cycle Count(daily)	$\mathrm{E} = \mathrm{E_d} \times \mathrm{EF_{grid-global}}$	$E_d = 0.01665\ kWh, EF_{grid-\mathrm{global}} = 0.709\ \mathrm{CO_2e/kWh}$	[1]
	Annual Electricity Consumption	$E = E_d \times N \times EF_{grid-\mathrm{global}}$	N=1,500 cycle/year → E = 0.01665 x 1,500 x 0.709 = 17.71 kg CO_2e/kWh	[1]
	Daily Electricity Consumption	$E = \frac{Annual\ Electricity\ Emission}{250}$	250 operating days/year assumed $\frac{17.71}{250} = 0.0708\ kg\ \mathrm{CO_2e/day}$	[1]
Forklift Operations	Cycle Count / Addressing Discrepancies	$E = E_h \times hr \times EF_{grid-WH}$	$E_h = 1.875\ kWh/hour, hr = 8\ hours/day,$ $EF_{grid-WH} = 0.5289\ \mathrm{kg\ CO_2e/kWh}$	[2]
Drone Transportation	Logistics for component and delivery	$E = D \times Ci \times N \times EFj$	$D = distance(km), C_i = component\ weight(kg),$ $N = number\ of\ cycle,$ $EF_j = transmort\ mode\ EF(air/truck, kg\ \mathrm{CO_2e/ton\ km})$	[3]
Forklift Transportation	Logistics for component and delivery	$E = D \times C \times N \times EF$	$D = distance(km), C = picker\ weight(kg),$ $N = number\ of\ shipment, EF = transport\ EF$	[3]
Drone Production	Component EF	$\frac{E = \sum Ci \times EFi}{V}$	$C_i = Material\ mass\ for\ component\ i$ $EF_i = EF\ for\ PA12, PC/ABS, optics, V = 5\ years$ Total embodied = 5.531 kg CO_2e	[4]
Forklift Production	Component EF	$\frac{E = \sum Ci \times EFi}{V}$	V = vehicle life, C_i = component i weight, EF_i = EF for component i	[4]
Commute	Work commute	$E = Dc \times EF$	$Dc = 47.8 miles,$ $EF = 0.404 kg\ \mathrm{CO_2e}/mile$	[5],[6]
Waste	Inventory disposal	$E = I \times AVG(EF)$	I = Lost inventory, AVG[EF] = average carbon intensity factor for lost item	[7]

Ref	Source
[1]	Verity — Drone energy use and embodied component EF
[2]	XtraPower Batteries. (n.d.); U.S. Energy Information Administration — Forklift energy and grid EF
[3]	UK Department of Energy Security and Net Zero (2024) — GHG Conversion Factors
[4]	Hao, H., Mu, Z., Jiang, S., Liu, Z., & Zhao, F. (2017); Net Zero Carbon Guide (n.d.); CarbonChain (n.d.); American Chemistry Council (2022); Liang, Q., & Yu, L. M. (2023); City of Winnipeg (2012); Sipert et al. (2024), Supplychain Connect, ScienceDirect
[5]	EPA — Average passenger vehicle emissions
[6]	Axios – Average commute distance
[7]	WRAP (2020), Carbonfact (2023), Textile Exchange (2021)

The table outlines all major emissions-related parameters, equations, and assumptions used for estimating operational and lifecycle carbon impacts.

- Structure: Category: Operational or lifecycle phase (e.g., drone operations, commute).
- Activity: Specific function or emission-generating task.
- Formula with EF: Emissions formula integrating activity-specific emission factors.
- Notes/Variables: Definition of each variable and any key assumptions.
- Citations: Reference to data sources used for emission factors or values.
- Coverage: This framework includes Scope 1 (e.g., on-site energy), Scope 2 (e.g., grid electricity), and Scope 3 (e.g., transportation, waste, embodied carbon).
- Assumptions: 250 operating days/year for drone use. Emission factors aligned with GHG Protocol, and EPA. Commute and waste emissions treated with average factors due to data confidentiality.

Table A2. Category-Level Inventory Emissions Estimates Using Aggregated Warehouse Data

Category	Units	Estimated kg CO_2e per unit	Proportion to Total Inventory	Source/Note
Boots	11,318	5	0.0042	Carbonfact (2023); Light polyester or nylon underlayer (e.g., thermals)
Baselayer	4,766	20	0.0018	WRAP (2020); Includes leather/synthetic boots; assumes mid-range material intensity
Dress	36,980	22	0.0137	Carbonfact (2023); Mid- to full-length cotton/polyester blend
Graphic Fleece	35,366	12	0.0131	Carbonfact (2023); Printed polyester fleece sweatshirt with decoration
Graphic T's	55,790	7	0.0207	Carbonfact (2023); Printed cotton/polyester blend t-shirts
Jackets	371,657	25	0.1380	WRAP (2020); Insulated outerwear (synthetic/down fill)
Knit Bottoms	33,257	7	0.0123	WRAP (2020); Sweatpants or leggings, often cotton/poly blend
Knit Tops	571,763	6.5	0.2123	WRAP (2020); Basic long-sleeve or short-sleeve knit shirts
One Piece	2,360	10	0.0009	Textile Exchange (2021); Jumpsuits or bodysuits; midweight mixed fibers
Outer Layer Polyflc	680,639	18	0.2527	WRAP (2020); Heavyweight fleece jackets with full polyfill
Pants	11,752	8	0.0044	WRAP (2020); Woven trousers, chinos, or cotton-polyester pants
Sandals	738	5	0.0003	Carbonfact (2023); Foam or synthetic sandals, minimal upper construction
Shoes	11,909	13	0.0044	Carbonfact (2023); General athletic shoes made of EVA, rubber, polyester upper
Sportswear Fleece	71,630	10	0.0266	WRAP (2020); Lightweight athletic fleece jacket
Vests	14,030	12	0.0052	WRAP (2020); Insulated vest with synthetic fibers
Woven Bottoms	415,859	9	0.1544	WRAP (2020); Denim or twill trousers
Woven Tops	363,172	7	0.1349	WRAP (2020); Button-down shirts, light woven fabrics
Grand Total	2,692,986			**Avg Emissions per Unit: 12.892 kg CO_2e** *** Weighted average of all inventory units multiplied by their respective per-unit CO_2e values.**

** Inventory quantities are based on confidential internal data provided by the warehouse operator and aggregated at the product category level. The weighted average emissions figure was calculated by multiplying the unit count for each category by its estimated per-unit CO_2e value.*

Appendix B

Table B1. Variables, Parameters and Sources for Before Implementation Model

Activity	Variable Name	Value	Units	Source / Notes
People commute	# of inventory personnel commuting	6	people	Ops team / assumption
	Days commuted per week	5	days	Ops team
	Average miles traveled per individual	47.8	miles	Survey / assumption
Forklift energy (inventory count)	# of forklifts for inventory counting	5.41	units	Calculated
	Avg inventory counting hours per week	40	hours/week	WMS / estimate
	Avg energy consumption per hour	2.8	kWh	Estimated based on battery spec
Inventory disposal	Inventory Loss Rate	1.60%	items	NRF Survey 2023
	Total inventory	129,381	cases	WMS
Forklift energy (addressing discrepancies)	Locations count per week	8,097.08	locations	Ops / assumptions
	Issue rate	17.5%		Verity/Assumptions
	# of locations with issues per week	1417.8	pallets/week	Ops / assumptions
	Total forklifts used for inventory discrepancies	0.59	forklifts/week	Calculated
	Working Hours per Week	40	hours/week	Warehouse spec
	Avg energy consumption per hours	2.8	kWh	Estimated based on battery spec
Equipment	# of forklifts	3	units	Warehouse spec

Table B2. Variables, Parameters and Sources for After Implementation Model

Activity	Variable Name	Value	Units	Source / Notes
People commute	# of inventory personnel commuting	3	people	Ops team / assumption
	Days commuted per week	5	days	Ops team
	Average miles traveled per individual	47.8	miles	Survey / assumption
Drones energy (inventory count)	# of drones	4	units	Verity
	Avg drone cycle time per week	14.4	hours/week	Verity
	Avg power draw of drone	0.01665	kWh	Verity
Forklift energy (inventory count)	# of forklifts for inventory counting	1.63	units	Calculated
	Avg inventory counting hours per week	40	hours/week	WMS / estimate
	Avg energy consumption per hour	2.8	kWh per hour	Estimated based on battery spec
Inventory disposal	Inventory Loss Rate	0.96%	items per year	Calculated
	Total inventory	129,381	cases	WMS
Forklift energy (addressing discrepancies)	# of locations with issues per week	929.65	locations	Ops / assumptions
	Avg Total Scans per Week	8,836	locations	Verity
	Avg Issue Rate	10.5%		Verity
	Total forklifts used for addressing inventory discrepancies	0.39	forklifts/week	Calculated
	Working Hours per Week	40	hours/week	Warehouse spec
	Avg energy consumption per hours	2.8	kWh per hour	Estimated based on battery spec
Equipment	# of Forklifts	2	units	Warehouse spec
	# of Drones	4	units	Verity