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SIMULATION-BASED OPTIMIZATION FOR LARGE-SCALE PERISHABLE AGRI-FOOD COLD CHAIN IN RWANDA: AGENT-BASED MODELING APPROACH

Aghdas Badiee[1], Adam Gripton[1], Philip Greening[1,] and Toby Peters[2]

[1] Center for Sustainable Road Freight, Heriot-Watt University, Edinburgh, UK
[2] Centre for Sustainable Cooling, University of Birmingham, Birmingham, UK

ABSTRACT

The global food supply chain faces significant challenges in maintaining the quality and safety of perishable agri-food products. This study introduces a novel approach to demonstrate the efficiency of using the perishable agri-food cold supply chain (FCC) by integrating optimization techniques and agent-based modeling (ABM) simulation. Addressing complexities and challenges such as precise temperature control, emission reduction, waste minimization, and finding the best implementation of cold chain infrastructure, the research applies ABM to model dynamic interactions within the FCC. By testing thousands of simulation scenarios in AnyLogic, the paper demonstrates how the proposed model can support strategic decision-making, demonstrate potential export levels, assess crop quality over time, and evaluate waste reduction compared to non-cold chain scenarios. The research further discusses the implementation of the proposed model in a real case study in Rwanda, Africa, showcasing its contribution to optimizing configuration, reducing food loss and CO2 emissions.

1 INTRODUCTION

Within the global food supply chain, the preservation of quality in perishable agri-food products presents a critical challenge. Perishable goods, including fruits, vegetables, dairy, and meat products, are highly susceptible to spoilage and degradation during transportation and storage (Yadav et al. 2022). Ensuring that these products maintain their freshness, nutritional value, and safety standards from farm to fork is essential not only for meeting consumer expectations but also for safeguarding public health and minimizing economic losses (Handayati et al. 2015). Therefore, implementing cooling systems and a cold chain network to overcome the aforementioned challenges is significant.

The "food cold-chain" (FCC) is a critical subset of the broader cold chain (CC), dedicated to maintaining the quality of perishable foods by keeping them at appropriate temperature and humidity levels to prevent contamination by harmful microorganisms. This process spans from farm to consumer, involving essential infrastructure components like pre-cooling facilities, containers, refrigerated transport, packaging, cold storage, and tracking tools (Joshi et al. 2011). Efficient management of the FCC offers significant advantages to all parties involved in the supply chain, including businesses, customers, and the broader community (Akram et al. 2023).

The past decade has seen a significant rise in the global demand for value-added food (Naylor et al. 2021). Evaluating the performance of the food cold-chain is uniquely challenging compared to other supply chains, due to the complexities of maintaining varied temperature requirements for different products during transport across multiple modes (León-Bravo et al. 2021). These challenges are especially pronounced in developing economies, where firms often face hurdles related to the food cold-chain, such asinadequate infrastructure, high costs, limited access to electricity, advanced technologies, and expertise (Joshi et al. 2011). For instance, in populous countries like China and India, inadequate cold-chain systems contribute to substantial post-harvest food losses, exacerbating food insecurity and malnutrition issues (Kumar et al. 2020). Sub-Saharan Africa, the region most affected by poverty and nutritional deficiencies (Cerchione et al. 2018), could see an economic benefit of $40 million annually from just a 1% reduction in food waste (Lau et al. 2021). So, the rising global demand for value-added food products has significantly increased the dependence on cooling systems, air conditioning and refrigeration. This surge, especially notable in rapidly developing countries grappling with climate change, complicates environmental issues. The use of hydrofluorocarbons (HFC) in refrigeration and air conditioning, along with the indirect emissions from the energy these systems consume, underscores the critical need for action. Moreover, the existing cold-chain infrastructure in developing nations is often marked by limited capacity and inefficiency, presenting a major barrier to achieving agricultural economic and nutritional objectives.

Therefore, this paper highlights the urgent need for sustainable solutions. The major contribution lies in a strategic project, the 'Africa Centre of Excellence for Sustainable Cooling and Cold-Chain' (ACES), aimed at tackling these issues in Rwanda, Africa. This project seeks to accelerate the shift towards eco-friendly refrigeration solutions, aiming to reduce both food wastage and carbon dioxide emissions significantly. The paper highlights the potential of a newly developed simulation-based optimization model that leverages agent-based modeling principles within AnyLogic. This approach facilitates the modeling of dynamic interactions within the food cold chain, allowing for the examination of thousands of simulation scenarios. Through this comprehensive testing, the paper illustrates the proposed model's capacity to aid in strategic decision-making, demonstrate potential export levels, assess crop quality over time, and evaluate waste reduction compared to non-cold chain scenarios. Moreover, a case study in Rwanda illustrates the model's effectiveness and contribution in optimizing configuration, and minimizing food loss and $CO2$ emissions, aligning with the Sustainable Development Goals (SDGs).

2 LITERATURE REVIEW

Recently published papers underscore the transformative impact of simulation technologies on the agri-food supply chain, highlighting their critical role in improving efficiency, effectiveness, and resilience. Aiello et al. (2012) delved into the performance of cold chains, through simulation analysis based on time-temperature data and showcased the critical role of simulation in evaluating and enhancing cold chain operations. Saif and Elhedhli (2016) demonstrated the use of a simulation-optimization approach for designing eco-friendly cold supply chains and illustrated the practical benefits of simulation in streamlining supply chain operations. Mo et al. (2022) explored partner matching mechanisms within cold chain logistics through the application of Vensim and emphasized simulation's capacity to refine logistics processes. Zhu et al. (2014) utilized Flexsim to optimize operational processes at cold-chain logistics distribution centers.

Moreover, Verawati et al. (2022) showcased the application of AnyLogic to simulate and model queuing systems within a port environment and highlighted the flexibility of simulation software across diverse logistical challenges. (Taghikhah et al. 2021) presented an integrated model for extended agri-food supply chains and emphasized a systems approach to mitigate environmental pollution and reduce greenhouse gas emissions. Utomo at al. (2018) reviewed literature on agent-based modeling in agri-food supply chains, showing how simulations capture supply chain complexities effectively.

In addition, Huang et al. (2021) undertook a simulation study to forecast the impacts of the COVID-19 pandemic on food supply chains and emphasized the utility of simulation models in navigating the uncertainties affecting supply chain sustainability. Ganesh et al. (2017) delved into the application of AnyLogic in the field of agricultural supply chain management and provided valuable insights through a comprehensive literature review. Nakandala et al. (2017) demonstrated the capability of AnyLogic to model information flows and sharing matrices within fresh food supply chains and illustrated the software's effectiveness in optimizing information sharing across supply chain networks. Minegishi and Thiel (2000) highlighted the role of system dynamics in deepening the understanding of complex logistical patterns within the integrated food industry. Vostriakova et al. (2021) provided scientific validation for the theoretical and methodological principles of simulation modeling, alongside developing practical recommendations for improving the distribution system of agri-food logistics.

Gallego-García et al. (2023) introduced a pioneering digital twin model designed to enhance the resilience of smallholder farmers against crises such as COVID-19, by merging the principles of sustainability with advanced simulation technologies. Li et al. (2014) focused on sustainable food supply chain management and highlighted the importance of simulation technologies in navigating the uncertainties and risks, frequent within food supply chains. Railsback at al. (2006) provided key insights into agent-based simulation platforms, recommending tools like NetLogo, for their ability to model complex behaviors in food supply chains effectively. Leithner and Fikar (2019) developed a simulation model to examine the impact of quality data on organic fresh food supply chains, illustrating its potential to manage risks and improve efficiency. Tsiamas and Rahimifard (2021) introduced a simulation-based decision support system to enhance food supply chain resilience and emphasized the use of simulation software for realistic risk mitigation and stability.

The abovementioned references highlight the critical role of simulation software in optimizing food supply chains, addressing sustainability, managing cold chain temperatures, improving efficiency, and aiding decision-making. These techniques include three distinct simulation methods, each offering unique strengths for system analysis and improvement, as follows:

- *System Dynamics (SD)* models nonlinear interactions in complex systems over time using conceptual tools such as stocks, flows, feedback loops, and time delays.
- *Discrete-Event Simulation (DES)* models systems where changes occur at specific events. It helps optimize workflows and resource allocation based on event sequences and timing.
- *Agent-Based Modeling (ABM)* simulates micro-level interactions of autonomous agents to observe system-wide impacts and macro-level dynamics.

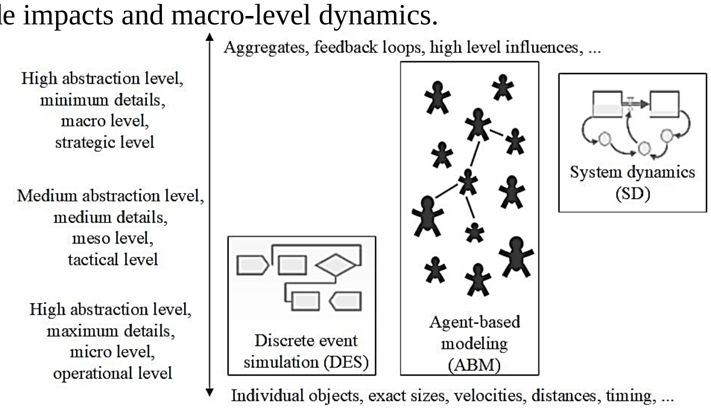


Figure 1: Comparative analysis of abstraction levels in simulation techniques (Borshchev 2013).

Simulation tools in academic research offer a comprehensive framework for understanding and improving agri-food supply chains and allow researchers to model, analyze, and optimize complex processes from various perspectives, providing insights into system dynamics, uncertainties, and behaviors to support decision-making. Figure 1 shows how each simulation method corresponds to different levels of abstraction. SD is used for high-level strategic modeling, DES is suitable for medium to medium-low abstraction levels with a process-centric approach, and ABM spans from detailed simulations of physical objects to abstract scenarios of competing companies or governmental entities.

The rest of this paper is structured as follows: Section 3 delves into the problem definition and solution approach, Section 4 outlines the proposed simulation-based optimization model, Section 5 presents the case study and summarizes the results analysis, and Section 6 concludes with limitations and future study directions.

3 PROBLEM DEFINITION AND SOLUTION APPROACH

The Africa Centre of Excellence for Sustainable Cooling and Cold-Chain (ACES) addresses the need for eco-friendly refrigeration in Rwanda. This initiative promotes sustainable cold chain practices to reduce food spoilage, lower CO_2 emissions, improve health standards, and boost exports. ACES proposes a virtual model to strategically establish adaptable cold chain infrastructure aligned with Rwanda's socio-economic goals. This model should be able to support strategic decision-making, contribute to optimizing configuration, illustrate potential export levels, assess crop quality over time, and evaluate waste reduction compared to non-cold chain scenarios. Detailed data analysis covers product details, storage logistics, and agricultural operations, essential for developing a sustainable cold chain system supporting Rwanda's future.

Therefore, our research aims to develop a comprehensive model that facilitates the strategic deployment of new cold chain infrastructure in Rwanda, characterized by:

- An optimized proposal for the placement and configuration of cold chain systems, including the locations of cold storage warehouses, their number and size, as well as the number and size of required refrigerants, and the types of refrigerants needed in them.
- The capability to examine and validate performance across thousands of scenarios, such as potential export levels over time, crop quality levels over time, and waste reduction in export levels by using a cold chain network versus not using one on the operational efficiency of the cold chain network.

In addition, we should consider the following points in our solution methodology:

- The large size and complexity of the system, characterized by extensive interdependencies and conceptualized as a large network of interconnected sub-systems. Therefore, we can't represent the system's behavior using only traditional mathematical equations
- The system's dynamic nature involves individuals making decisions based on their own processes.
- The interactions within the system and feedback mechanisms cause individual decisions to have a cascading effect, influencing others and necessitating adaptive reactions.
- The emergent nature of outcomes within the system, which are not predetermined but result from the system's internal dynamics.
- The high fidelity required in representing system details, demanding a strategic design of experiments to consider this complexity.

Then, the simulation approach for this complex agri-food supply chain network requires capabilities that include being sophisticated, designed from the bottom-up, scalable, agent-based, efficient at large scale, transparent, and cost-effective. The question that arises here is: Why should agent-based modeling simulation techniques be employed? Agent-based modeling captures the complexity of systems where each actor or agent operates according to its own set of models, objectives, and decision-making processes. In such systems, every decision and state change made by an agent can have significant implications for the overall system, leading to a complex feedback loop. This loop, in turn, gives rise to unpredictable and nonlinear emergence, demonstrating that the system's behavior is not simply an input-output relationship but rather a dynamic interplay of its constituent parts. Therefore, small variations in an individual agent's behavior may lead to disproportionately large changes in the overall system, illustrating the importance of understanding micro-level interactions to predict macro-level outcomes. This sensitivity to initial conditions is a characteristic of complex systems and underscores the need for policy interventions that can guide agents towards desirable behaviors.

Designing effective policy in this context requires a thorough exploration of the solution space through well-designed experiments. Agent-based modeling provides a virtual environment to test these policies, offering insights into the emergent, unpredictable nature of complex systems. It allows for the identification of strategies that can influence agents in a way that aligns with desired outcomes, despite the inherent unpredictability of their interactions.

The following steps outline our approach within the agent-based simulation environment:

- Model Design: We construct a virtual model of the system, ensuring that each agent's behavior is accurately captured in terms of objectives, decision-making processes, and inter-agent interactions.

- System Validation: By comparing the simulated results with real-world data and outcomes, we refine our model to ensure that it provides an authentic representation of the actual system.
- Iterative Refinement: Our prototyping environment allows for iterative enhancements, enabling us to refine our model with each new finding and to adapt our approach in response to the complex and evolving nature of the system.

4 SIMULATION-BASED OPTIMIZATION MODEL

For this research project, we aim to create a fast-prototyping environment tailored to our needs using AnyLogic platform. AnyLogic's flexibility and powerful simulation capabilities make it ideal for designing and validating the system's complex dynamics. This approach allows us to rapidly explore the system's variables and interdependencies in a virtual environment, bridging the gap between theory and practice and providing actionable insights into the real-world implications of complex system dynamics.

Figure 2 illustrates the contributing agents and their interactions in the proposed model for the cold chain network, identifying farms and import center as production sites, and retail stores along with Kigali airport as demand points. Additionally, we can see the relationships between the considered agents, including farmers, carriers, cold storage providers, and retailers/exporters, which emphasize the central role of carriers in facilitating the movement of goods between these agents. For example, the state chart for a carrier between a farm and a cold storage warehouse, as shown in Figure 3, models a cyclic process where the vehicle alternates between different states. It starts at the farm, and when there is a message related to an order, all the volume should be loaded. Then it moves towards the cold storage warehouse, unloads the goods, and finally returns to the farm to repeat the cycle. Each state represents a specific action or location, and transitions show the vehicle's movement and task progression in logistics or supply chain operations. This comprehensive layout underscores the complexity of the cold chain and the critical agents where efficient management can significantly impact overall performance.

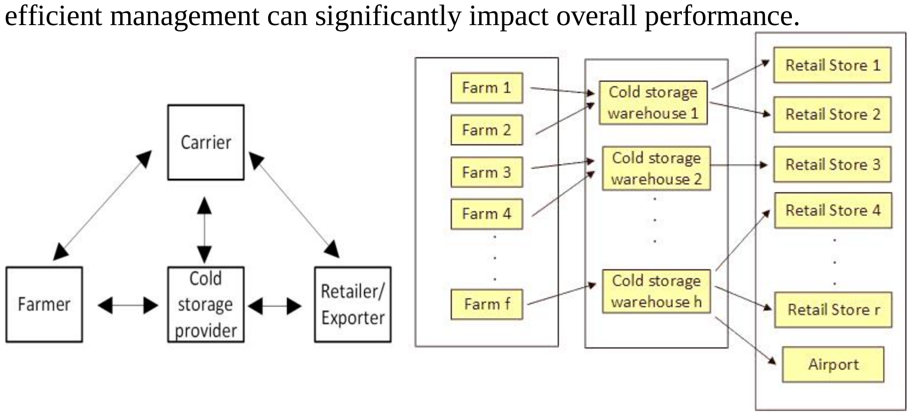


Figure 2: Contributing agents and their interactions in the model.

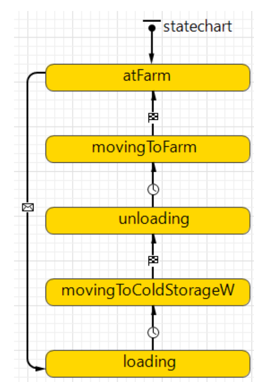


Figure 3: State chart of carrier.

Considering the network and relationships, total emissions and wastage should ultimately be reduced. The initial step involves seeking an optimized proposal for the placement and configuration of cold chain systems. This includes determining the locations, number, and size of cold storage warehouses, as well as specifying the quantity and types of refrigerants required in them. Subsequent steps will involve simulating potential export levels, crop quality over time, and waste reduction compared to non-cold chain scenarios, using ABM capabilities. Then our approach involves both agent-based simulation modeling and an optimization method, each serving different purposes in our study. Optimization method addresses the optimal number and locations of cold storage warehouses within the FCC, while the agents considered in ABM interact with each other, reflecting real-world operations at the end of the project, including:

- Farmers: Responsible for the production and initial handling of crops, and making decisions about what, when, and how much to produce based on production schedules and market demand.

- Carriers: Manage the logistics of moving products from farms to storage facilities and retailers/exporters including loading, unloading, queuing, handling delivery delays and load efficiency, route optimization, and temperature control.
- Cold storage providers: Ensure proper storage conditions to maintain product quality, manage inventory, and make decisions about what, when, and how much to order.
- Retailers/Exporter: Handle the distribution/shipment process of products to consumers/importers and make decisions about what, when, and how much to order.

So, the ABM and optimization methods are integrated, where the optimization algorithm provides strategic recommendations, and the ABM simulates the implementation and outcomes of these recommendations.

To effectively determine the best locations, several factors must be considered to ensure that the cold storage warehouses are close to high-volume production sites and demand points, which means they are strategically placed to serve these points efficiently. In this regard, we should define specific parameters and sets which are necessary for this step:

- F: Set of farms
- D: Set of demand points
- P_f: Product volumes at farm f
- (x_i, y_i): Center of cluster j
- N_h: Number of cold storage warehouses (clusters)
- Q_d: Demand quantities at demand point d
- (x_f, y_f): Farms' Coordinates (latitude & longitude)
- (x_d, y_d): Demand points' Coordinates (lat. & long.)

After finding the appropriate amount of weights for farms and demand points we should normalize them to ensure they are comparable.

Weights for farms: $w_f = \frac{P_f}{Max\ (P_f)}$; Weights for demand points: $w_d = \frac{Q_d}{Max\ (Q_d)}$

Next, a weighted K-means++clustering algorithm (Arthur and Vassilvitskii 2007) should be performed, incorporating weights for both production and demand points to identify best potential locations for cold storage warehouses, as follows:

1. Define the number of cold storage warehouses, N_h
2. Select the first potential center randomly from F
3. Select the next center from F which is farthest from the first center
4. Select the next center from F which is at maximum distance from the existing centers
5. Repeat 4. until the total number of existing centers equals N_h
6. Assign other farms to the closest center and generate initial clusters,
7. Update centers of existing clusters as new centers, considering the weighted mean of the points assigned to each cluster,
$$(x_j, y_j) = \frac{\sum_{f \in F} w_f (x_f, y_f)}{\sum_{f \in F} w_f}$$
8. Reassign points to the closest updated centers and generate new clusters
9. Repeat 7. and 8. until convergent
10. Assign demand points to the closest center resulted in 9. and generate new clusters
11. Repeat 9., considering weights w_d
12. Obtain final centers and clusters.

Now, we need to decide on the optimal number of clusters as potential points for cold storage warehouses. So, we should evaluate the performance of the clustering algorithm with different values of N_h. The *Silhouette score* is a metric used to evaluate the quality of clustering results (Rousseeuw 1987). This score is calculated by measuring each data point's similarity to the cluster it belongs to and its difference from other clusters, averaged over all the points.

$$\text{Silhouette coefficient} = \frac{b - a}{Max\ (b\ , a)}$$

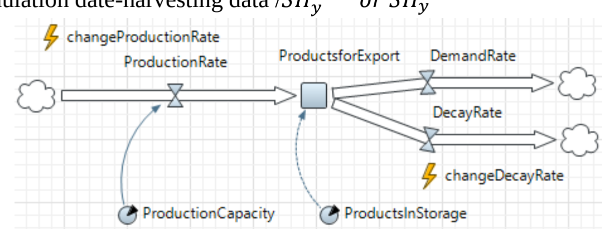
where a represents the mean distance to other points in the same cluster and b represents the mean distance to other points in the next nearest cluster. This coefficient ranges between -1 and 1. More positive values indicate that the point is assigned correctly, meaning it is inside its own cluster.

After identifying the best locations for potential cold storage warehouses in Rwanda, the agent-based simulation modeling capabilities should be used to illustrate potential export levels over time, assess crop quality levels over time, and evaluate waste reduction in export levels through the utilization of a cold chain network compared to scenarios where it is not used. Parameters are input values defining the system's framework, some of which are dynamic and crucial for simulating real-world operations and analyzing system behavior. The parameters considered in this part are as follows:

- H: Set of potential locations for cold storage warehouses.
- F: Set of farms and airport for import.
- D: Set of demand points (retailers and airport for export).
- P_t: Production rate for crop type t during a day
- Q_d: Demand quantities at demand point d
- DR_t: Domestic demand rate for crop type t during a day
- HT_t: Harvesting time for crop type t during a year
- (T_t^{min}, T_t^{max}) : Safe range temperature for crop type t
- D_h: Crop quantity shipped from cold storage warehouse h for domestic demand
- SH_t^{safe}: Shelf lifetime for crop type t in the safe range temperature using cold chain network
- $SH_t^{ambient}$: Shelf lifetime for crop type t in ambient temperature without using cold chain network
- M_{gn}: Maintenance cost of refrigerant g using refrigeration technology n
- E_{gn}: Emission production by refrigerant g using refrigeration technology n
- C_{gn}: Purchase cost of refrigerant g using refrigeration technology n
- G : Set of refrigerants
- T : Set of crop types
- N : Set of refrigeration technologies
- DS_t: Density in storage crop type t
- P_f: Product volumes at farm f
- S_g: Capacity or size of refrigerant g

Table 1 outlines the desired outputs of the proposed ABM, detailing the necessary input data and functions used for their calculation.

Table 1: ABM outputs, input data, and calculation functions.

Output	input data	Calculation function
Number & size of required refrigerants	$G, N, T,$ $(T_t^{min},$ $T_t^{max}),$ S_g, D_h, DS_t	Based on the monthly demand quantity for each cold storage warehouse, the average holding period of different crop types, and their density in storage, the near-optimum size of each warehouse can be derived. Then, based on the crop type and its safe temperature range, we can determine the total amount of crops that need to be stored in refrigerated equipment. Finally, based on the capacity or size of each refrigerant, we can optimally determine how many refrigerants are required in each cold storage warehouse.
Type required refrigerants	$M_{gn}, C_{gn},$ E_{gn}	By analyzing the emission production of each refrigerant across different refrigeration technologies, along with their purchase and maintenance costs, we can make informed decisions about the types of refrigerants required.
Potential Export level over time	$HT_t, P_t,$ $DR_t,$ SH_t^{safe} $SH_t^{ambient}$	The production rate for each crop type throughout the day, combined with the related harvesting times, provides us with the total available crop that can be consumed domestically or exported. Then, by reducing this amount according to the domestic demand rate and the decay rate over time, we can determine the potential export level over time. Decay rate = Simulation date-harvesting data /SH_y^{safe} or $SH_y^{ambient}$ 

Crop Quality level over time	SH_t^{safe}, $SH_t^{ambient}$	Quality level = 1 − Decay rate
Waste reduction in export level	HT_t, P_t, DR_t, SH_t^{safe} $SH_t^{ambient}$	The yearly production quantity of each crop type, along with the respective harvesting periods, gives us the total crop quantity available for either domestic consumption or export. Multiplying the total crop quantity by the crop quality level over time (adjusted stock quantity) and considering scenarios both with and without the use of a cold chain network, enables us to calculate the amount of waste reduction.

5 CASE STUDY AND RESULTS ANALYSIS

According to the ACES project, the proposed integrated model is applied to the case of Rwanda, which experiences significant post-harvest loss without implementation of cold chain infrastructure. In this regard, we assume that all farms can produce different types of perishable crops in the 30 districts of Rwanda including maize, sorghum, rice, wheat, other cereals, cassava, sweet potatoes, Irish potatoes, yams & taro, banana, plantain, beans, peas, ground nuts, soya beans, vegetables, and fruits (National Institute of Statistics of Rwanda. 2023a). In Table 2, we use available data on total "production volumes" from 2023 to forecast for 2024, considering a 5% growth. For "domestic demand quantities," we use data from 2021 (National Institute of Statistics of Rwanda, 2023b) and forecast for 2024 based on future population growth (14.4 million vs. 13.4 million).

Table 2: Forecasted production volumes and demand quantities for each district in Rwanda, 2024 (tons).

District	Population percent	production volume	Demand quantity	District	Population percent	production volume	Demand quantity
Bugesera	4.2%	433853	328000	Ngoma	3.1%	637738	240477
Burera	2.9%	339365	230765	Ngororero	2.8%	345486	218996
Gakenke	2.8%	552196	217411	Nyabihu	2.4%	343190	189887
Gasabo	6.6%	173380	523456	Nyagatare	4.9%	653401	389159
Gatsibo	4.2%	699241	328037	Nyamagabe	2.8%	306500	221106
Gicumbi	3.4%	409827	267127	Nyamasheke	3.3%	281668	258436
Gisagara	3.0%	309138	236313	Nyanza	2.8%	295645	217665
Huye	2.9%	279269	227296	Nyarugenge	2.8%	59192	222784
Kamonyi	3.4%	386547	268332	Nyaruguru	2.4%	264105	189339
Karongi	2.8%	433043	222516	Rubavu	4.1%	349473	325370
Kayonza	3.5%	544260	272086	Ruhango	2.7%	378263	213738
Kicukiro	3.7%	40957	292664	Rulindo	2.7%	289544	214347
Kirehe	3.5%	676614	274290	Rusizi	3.7%	377734	288973
Muhanga	2.7%	503356	213329	Rutsiro	2.8%	324885	219725
Musanze	3.6%	284796	283612	Rwamagana	3.7%	490842	288630

These forecasts are used to assign weights to production and demand points. Due to the lack of exact data on farm locations, we consider three farms per district as representative samples. Therefore, our model includes 90 farms, in addition to the airport location for imports. Similarly, without exact data on demand point locations, we consider 100 demand points across Rwanda, proportional to the available population distribution data, along with the airport location for exports. Similarly, the forecasted amounts of export and import for the considered products from the Kigali airport would be 647,850 and 777,313.43 tons per year, respectively.

Figure 4 shows the Silhouette scores for different values of N_h, evaluated for 101 demand points and 91 production sites, weighted by their production volume and demand quantity. Higher scores indicate that the objects are well matched to their own cluster and poorly matched to neighboring clusters. The results indicate that 5 and 6 have the top close scores, but due to lower establishment costs, 5 is the optimal number of locations for cold storage warehouses, providing a good balance of cohesion and separation. This figure shows that the score generally decreases as the number of clusters increases, indicating that the clustering becomes less distinct with more clusters. Figure 5 illustrates the derived final clusters, which should be covered by 5 different cold storage warehouses. As seen, each cold storage warehouse should cover a different amount of demand, not equally, based on the minimization of required transportation time, which leads to less transportation cost, waste, and emissions. Obviously, making decisions about the size of each warehouse can be derived from their monthly demand quantity, the average holding period of different crop types, and their density in storage (m^3/ tonne), as noted in Table 4 (Rittenschober et al. 2012). Thus, we need to have 5 cold storage warehouses with different sizes and required refrigerants. Table 3 shows the derived location dimensions for warehouses and their yearly demand quantity in tons.

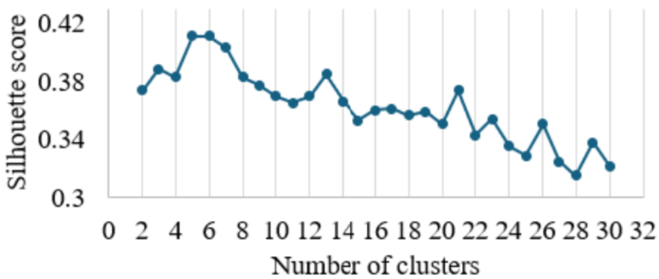


Figure 4: Silhouette score for different values of N_h.

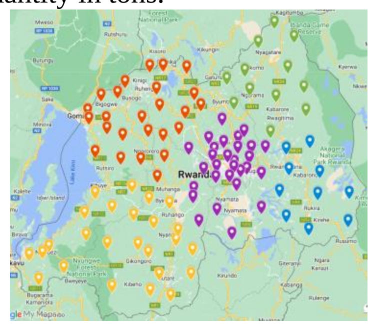


Figure 5: Result of clustering.

Table 3: Best locations for potential cold storage warehouses in Rwanda and their demand.

Warehouse #	Location	Demand quantity
1	[-2.1403562,30.5877895]	840475
2	[-1.7150094, 29.62464011]	1970548
3	[-2.02615123,30.07803046]	2803146
4	[-1.51543958,30.35124212]	985977
5	[-2.42278024,29.49227882]	1931584

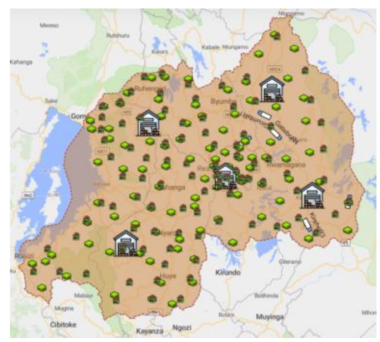


Figure 6: Snapshot of simulation modelling in Anylogic.

Table 4: Density in storage of crop types.

Crop type	Maize	Sorghum	Rice	Wheat	Cassava	Sweet potato	Potato (Irish)	Banana	Bean	Pea	Ground nut	Soy bean
Density in storage	1.64	1.85	1.39	1.30	1.59	1.52	1.69	1.05	1.05	1.37	1.89	1.35

Figure 6 presents a snapshot of the simulation modeling in AnyLogic, illustrating 91 production sites, 101 demand sites, and 5 cooling hubs derived from clustering, strategically located between farms and demand points. By testing thousands of simulation scenarios, the proposed model illustrates strategic decision-making, potential export levels, crop quality over time, and evaluates waste reduction compared to non-cold chain scenarios. To determine the potential export levels and crop quality over time, we assume carrots as a sample, which should be harvested from April to July. The best recommended temperature for handling and storage is 0 degrees Celsius, and its shelf life is around 6 months at this temperature, while it is only 6 weeks in the ambient temperature of Rwanda, which is considered around 20 degrees Celsius.

Figure 7(a) represents the scenario with the use of cold storage warehouses. There is a gradual decline in the volume of crops available for export over time. This trend is consistent with the assumption of a 6-month shelf life for crops stored in these facilities. In contrast, Figure 7(b), which represents the scenario without the use of cold storage warehouses shows a much sharper decline. This is in line with the 6-week shelf life assumed for crops not stored in cold storage facilities. The graphs suggest that the use of cold storage significantly extends the availability of crops for export by maintaining their quality over time. The purple line across both graphs indicates the quality level of the crops over time from 0 to 1. It's observable that in the scenario with cold storage warehouses, the quality level remains higher for a longer period, gradually decreasing yet extending beyond the shelf life of the crops without cold storage. This visual comparison highlights the impact of cold storage solutions on both the quantity available for export and the sustained quality of perishable goods. Figure 8 compares scenarios with and without using cold storage warehouses, which are derived from the stock amount multiplied by its quality, called *adjusted stock quantity*. The brown line peaks sharply before declining, suggesting a rapid increase and then a decrease over time. However, The green line appears to maintain a higher level of adjusted stock quantity for a more extended period before eventually declining. This indicates that using cold storage warehouses potentially stabilizes adjusted stock quantity over a more extended period compared to scenarios without such facilities, resulting in more than a 68% reduction in waste for carrots. This reduction is compatible with reality and serves as a validation of the model.

Figure 7: Available crop export volumes and their quality over time; a.) with, b.) without cold storage warehouses.

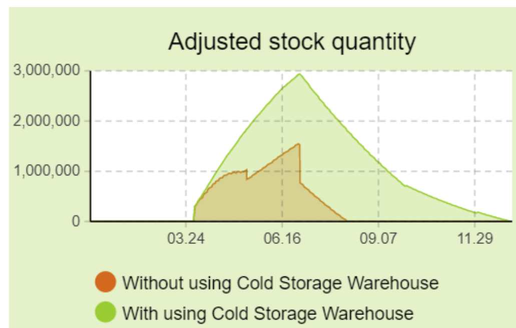


Figure 8: Waste reduction for carrot by adjusted stock quantity.

6 CONCLUSION

This study highlights the significant impact of the 'Africa Centre of Excellence for Sustainable Cooling and Cold-Chain' (ACES) project on the perishable agri-food cold supply chain within Rwanda and potentially across East and Southern Africa. This project marks a pivotal shift towards the adoption of refrigeration technologies and improved logistics strategies, aiming to mitigate food loss, reduce carbon dioxide emissions, and enhance both health outcomes and export levels. By integrating optimization techniques and agent-based modeling (ABM) within AnyLogic software, we have illustrated the substantial benefits of simulation-based optimization models in strategic planning and improving the placement and configuration of cold chain systems. Our approach carefully addresses the challenges facing the FCC, including temperature regulation, emission reduction, waste management, strategic deployment of cold chain infrastructure, and demonstrating the proposed model's productivity in real-world cases. It should be mentioned that our findings will expand with the passage of time, and this paper is intended to show the early-stage findings of the project.

However, the study has several limitations. The model's accuracy depends on the quality and precision of input data, which can vary across regions and time periods. Incorporating real route and distance data, rather than just Euclidean distances, will enable dynamic adjustments and effective decision support. Additionally, future research will focus on expanding what-if analyses to test the model's resilience against a broader range of disruption scenarios, such as extreme weather events, rising temperatures, market changes, inaccessible transportation routes, equipment failures, transportation delays, and fluctuating prices. Exploring the concept of a digital twin to create a real-time, interactive model of the cold chain system could further enhance decision-making and operational efficiency. Extending the model to other regions and considering different types of perishable goods in various production sites will help generalize the findings and provide a comprehensive understanding of FCC dynamics.

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AUTHOR BIOGRAPHIES

AGHDAS BADIEE is a Post-Doctoral Research Associate at Edinburgh Business School, Centre for sustainable road freight at Heriot-Watt University. She is an expert in supply chain modeling and logistics analysis, particularly using data-driven decision-making, operations research, data mining, optimization, simulation, and statistical analysis. In addition, she has a strong background in developing simulation and optimization tools for network design with applications for green logistics operations, transportation procurement, freight distribution, cold chain network and humanitarian services. Her email address is a.badiee@hw.ac.uk.

ADAM GRIPTON is an Assistant Professor at the Centre for Sustainable Road Freight at Heriot-Watt University since 2018, focuses on developing mathematical models and algorithms for green logistics operations. Before joining Heriot-Watt, he spent six years as a maritime software engineer at QinetiQ, working on complex system analysis and design for resilience. His interests span a broad range, including agent-based modeling, operational resilience, complex systems, robustness, transportation systems, Bayesian inference, inverse problems, optimization, and software development.. His email address is a.gripton@hw.ac.uk.

PHILIP GREENING is the Director of Centre for Sustainable Road Freight at Heriot-Watt University. His research encompasses a wide range of methodologies, such as corporate case studies, roadmap development, and traditional logistics modeling, including agent-based modeling, sustainability, and operational research. His primary interest lies in creating large-scale, high-fidelity, self-organizing models. These models, often referred to as digital twins or virtual worlds, are instrumental in investigating the effects of disruptive innovations. His email address is p.greening@hw.ac.uk.

TOBY PETERS is Professor of Cold Economy at the University of Birmingham and Heriot-Watt University, and the Director of the Centre for Sustainable Cooling. He is an award-winning developer of Liquid Air Energy Storage technologies with extensive experience in energy systems and sustainable cooling systems for food and health. His research drives major programs across the UK, Europe, and developing countries, and he advises multiple international organizations on cold-chain issues. His email address is t.peters@bham.ac.uk.