https://doi.org/10.17221/76/2025-AGRICECON

Optimisation of agricultural logistics: A systematic review of modelling techniques and economic potentials

*Nikolas Bublik**, *Sebastian Hess*

Department of Agricultural Markets, University of Hohenheim, Stuttgart, Germany

**Corresponding author: nikolas.bublibk@uni-hohenheim.de*

Citation: Bublik N., Hess S. (2026): Optimisation of agricultural logistics: A systematic review of modelling techniques and economic potentials. Agric. Econ. – Czech, 72: 253–271.

Abstract: Agricultural logistics face unique challenges such as seasonal demand fluctuations, perishability, and geographic dispersion. The paper systematically analyses 63 peer-reviewed articles from 2013 to 2025, focusing on key optimisation techniques, including multi-criteria decision-making (MCDM), vehicle routing problems (VRP), and path planning problems (PPP). The findings highlight how logistics optimisation can reduce operational costs, improve resource utilisation, and enhance supply chain resilience. Additionally, the study identifies gaps in inbound logistics research and emphasises the need for further integration of digital technologies. Future research should focus on comprehensive, technology-driven solutions to improve adaptability and transparency in agricultural supply chains. Key findings reveal that optimised logistics models can lead to cost reductions of up to 58%, emissions savings of over 60%, and significant improvements in delivery time, field efficiency, and customer satisfaction.

Keywords: agricultural supply chains; vehicle routing problem; decision making in agriculture; path planning problem

Different crises like the COVID-19 pandemic underscore the critical role of global supply chains in economic stability as global supply chains were accounted for a significant portion of the GDP downturn during crisis, such as the pandemic (Bonadio et al. 2021). During the pandemic, Agricultural and Food Supply Chains (AFSC) are among the essential services because they face heightened risks as they contend with increased wastage and issues related to product life cycles (Kumar et al. 2021). Apart from crises the AFSC is challenged with reconciling rising consumer expectations for quality and sustainability against societal demands, such as environmental objectives and fair income distribution (Saitone and Sexton 2017). A functioning AFSC is therefore permanently important, not only in times of crises. Nevertheless, lessons can be learned from past crises in order to prevent future risks (Zavala-Alcívar et al. 2021). For all these reasons, it is important to optimise supply chains and their components: strengthen resilience during crises, improve resource efficiency and also contribute to a sustainable agricultural and food system.

Supply chains can be categorised into three levels: basic, extended, and ultimate. The basic supply chain consists of a company, its immediate supplier, and customer. The extended supply chain includes the suppliers and customers of these immediate parties. The ultimate supply chain covers all entities from the initial supplier to the final customer, incorporating all upstream and downstream flows (Mentzer et al. 2001).

Supply chain management includes the logistical flows, the customer order management and production process and the information flows. It can be seen

Publishing fees supported by Funding Programme Open Access Publishing of University of Hohenheim.

https://doi.org/10.17221/76/2025-AGRICECON

as an umbrella concept including, among other things, logistics. Logistics itself involves planning, implementing and controlling efficient flow and storage of goods and services from the beginning point of external origin to the company and from the company to the point of consumption (Lummus et al. 2001).

A part of the AFSC is therefore agricultural logistics (AL). AL includes the use of modern transportation and storage solutions, and covers transportation, storage, processing, handling, packaging, distribution, and information processing in agriculture (Xu 2011). The general aim of agricultural logistics is increasing the production of agricultural products to care for its continuous operation, optimise the cost of production, storage, transport and distribution, increase value-added agricultural products and satisfy consumers (Kramar et al. 2015). Kramar et al. (2015) refer in their review to various other sources as attempts to define agricultural logistics, but all of them were published before 2013. Although there is no uniform definition of agricultural logistics, Kramar et al. (2015) represent points of demarcation that separate agricultural logistics from the logistics of other areas:

i) large quantities and varieties of commodities

ii) inherent biological properties

iii) low price of the goods low price logistics required

iv) seasonal/geographic dispersion affecting business risks

v) solutions without contamination (e.g. living animal, plants).

Not every crop, fruit or vegetable can be grown in every place, which highlights the importance of regional availability. Secondly, seasonality of many agricultural products introduces the time factor regarding peak- and low times of regional supply. Finally, there are also time restrictions in transport, as these are often perishable products whose transport must meet quality standards regarding cooling and hygiene regulations (Chen et al. 2013).

These unique logistical challenges are becoming increasingly relevant due to a combination of external stressors, such as rising energy prices or a decline in resource availability. In light of this, Szabo et al. (2021) recommend to make more use of digitisation, sensor technologies, Big Data analytics, and Industry 4.0 tools to improve agricultural logistics. However, optimisation also concerns structural and operational aspects across the entire logistics chain. Rising energy prices, for instance, significantly inflate transportation and machinery operation costs, making logistics optimisation essential for maintaining profitability and competitiveness in the agricultural sector (Gao et al. 2019; Farghali et al. 2023; Jensen et al. 2025). In addition to rising energy prices, a general decline in resource availability, such as water scarcity, land degradation and other input shortages are reported by recent studies (Mamoudan et al. 2023).

Moreover, increasing economic inflation further intensifies the pressure to strengthen and optimise AFSCs, particularly through more efficient logistics operations (Olufemi-Phillips et al. 2024). At the same time, elevated sustainability demands, both regulatory and consumer-driven, are pushing agricultural producers to minimise carbon emissions, reduce waste, and adopt environmentally responsible practices (European Commission 2020; Sánchez-Bravo et al. 2021; Igwe et al. 2024). Additionally, the agri-food sector in many countries faces workforce shortages and rising wages. This adds pressure to streamline operations, reduce manual labour, and automate where possible (Aryal et al. 2021; Christiaensen et al. 2021; Mizik et al. 2025).

Optimisation models such as vehicle scheduling and route planning have been shown to reduce field working time by up to 32% and improve resource utilisation, thereby alleviating some of the strain caused by limited personnel availability (Bochtis et al. 2013; Seyyedhasani and Dvorak 2017). Optimised logistics solutions, such as green vehicle routing or inventory-routing models, have demonstrated the potential to cut carbon emissions by more than 60% (Wu and Wu 2021; Yao et al. 2022).

Taken together, these factors underscore the urgency of adopting effective optimisation strategies and the development of suitable analytical modelling techniques. Both can contribute to improving economic performance, meeting broader sustainability goals and ensuring the long-term resilience of agricultural and food supply chains.

To address these needs, the present study poses the following main research question: How can optimisation be effectively modelled in agricultural logistics, and what advantages can these optimisations bring regarding agri-food supply chain performance?

To address this research question, this paper adopts a systematic review methodology, focusing on modelling and optimisation approaches in agricultural logistics. The study examines 55 peer-reviewed articles published between 2013 and 2025, analysing their contributions to the optimisation of agricultural logistics processes.

https://doi.org/10.17221/76/2025-AGRICECON

MATERIAL AND METHODS

To ensure a structured and methodologically sound approach, this review employed the PICO framework (population, intervention, comparison, outcome) to formulate the main and sub-research questions. The PICO method is widely used in evidence-based practice and systematic reviews to frame and refine research questions, enabling precise and targeted searches of relevant literature (da Costa Santos et al. 2007). Based on the PICO methodology a main research question that was separated into two sub questions was formulated:

Main research question: How can optimisation be effectively modelled in agricultural logistics, and what advantages can these optimisations bring?

Sub-research questions:

RQ1: How can optimisation in agricultural logistics be effectively modelled, considering the unique characteristics and challenges of the sector?

RQ2: What benefits can be achieved through the optimisation of agricultural logistics, particularly regarding cost, sustainability, and efficiency?

Following the research methodology outlined by Petersen et al. (2008), this study undertook three essential steps: specifying the search string, selecting databases, and obtaining results. The first step involved identifying keywords and their related terms to ensure comprehensive coverage. The primary search phrase used was 'agricultural logistics', with related terms including 'optimization', 'optimisation', 'modeling', and 'efficiency'. Preliminary title-based searches revealed that many relevant studies do not explicitly mention 'agricultural logistics' in their titles. Instead, they often focus on specific products or logistics applications, such as 'biomass transportation', 'olive oil collection', or 'raw milk scheduling'. To address this issue and to avoid overlooking pertinent literature, a full-text search was conducted.

The literature search was conducted using Google Scholar (GS) for the publication period 2013–2023. Google Scholar was chosen for its broad multidisciplinary coverage and comprehensive recall capabilities. Previous studies have demonstrated that GS provides a high recall rate for systematic reviews, with Gehanno et al. (2013) reporting a 100% recall rate for studies in gold standard databases, and Bramer et al. (2016) finding GS covered 97.2% of systematic review references. While 'modeling' and 'modelling' are often treated as equivalent by Google Scholar due to stemming of the common root 'model', 'optimization' and 'optimisation' are considered distinct lexical entries (Uyar 2009; Singh and Gupta 2017a, b). As a result, searches for either combination do not reliably return results for the other, and both spellings must be included explicitly in systematic literature searches.

To refine search results and ensure relevance, the following inclusion and exclusion criteria were applied (Table 1).

A systematic literature review (SLR) was conducted following a structured methodology to ensure a comprehensive and objective analysis of the selected studies. The process was carried out as follows: the initial set of search results was screened based on titles and abstracts. Studies meeting the inclusion criteria proceeded to a full-text review. Articles that did not align with the research questions or criteria were excluded. The final set of studies was organised and analysed using MAXQDA© software, enabling systematic coding and categorisation of key findings. To further refine the selection, the first two passes of the three-pass approach, as introduced by Keshav (2007), were applied. The first pass involved a quick review of the title, abstract, and introduction, skimming section headings, and evaluating conclusions for alignment with research objectives. The second pass involved a more detailed examination of figures, diagrams, and illustrations, focusing on graphical representations of data and summarised findings. After applying

Table 1. Inclusion and exclusion criteria of review

Inclusion criteria (IC)	Exclusion criteria (EC)
studies published between 2013 and 2025	studies unrelated to agricultural logistics optimisation
studies relevant to agricultural logistics, specifically focusing on optimisation methods	studies published in languages other than English
studies written in English	non-scientific publications, such as blogs or opinion pieces
peer-reviewed journal articles, conference proceedings, book chapters, or systematic reviews	research discussing outdated or obsolete optimisation techniques

Source: Own elaboration

https://doi.org/10.17221/76/2025-AGRICECON

this multi-stage filtering process, a total of 63 studies were selected (out of an initial sample of 1 720 studies) for inclusion in the literature review, ensuring a comprehensive and focused analysis of agricultural logistics optimisation. For this purpose, the studies were further divided into four categories.

In various sectors, logistics is classified into different categories to better manage and optimise processes. For instance, in the automotive industry, Chandra et al. (2016) classified logistics into inbound, internal, and outbound categories. This approach is adopted in this review to categorise the studies analysed in agricultural logistics. This framework provides a more granular understanding of agricultural logistics, highlighting its complexity and the specific challenges faced within each subdomain:

i) Inbound logistics involves the procurement and delivery of essential inputs, such as seeds, fertilisers, animal feed, and diesel, to the farm. Delays in this stage, such as late delivery of fertilisers, can disrupt planting schedules, resulting in lower yields or cascading delays in subsequent processes.

ii) Intra-farm logistics refers to the movement of goods, equipment, and resources within the farm. Examples include transporting crops from fields to silos, feeding livestock across multiple stables, and coordinating agricultural operations across scattered fields. These tasks are heavily influenced by local conditions, such as weather and terrain, which can limit accessibility or require alternative routes during adverse conditions.

iii) Outbound logistics pertains to the distribution of agricultural products to markets, processing facilities, or end consumers. For instance, transporting harvested grain, livestock for slaughter, or processed products (e.g. meat or vegetables) to the market. This stage is often complicated by global trade dynamics, where delays caused by political or environmental factors can significantly affect supply chains.

iv) Supply chain logistics takes the logistics along the whole supply chain into account.

RESULTS

In this section, the results are presented in order of the type of modelling approach, in addition, each of the studies is classified into one of the categories inbound, outbound, intra-farm or supply chain logistics as well as the concrete advantages that could be determined according to this study. The supergroup of agricultural logistics problems (ALP) can be divided into different subgroups. Figure 1 provides an overview.

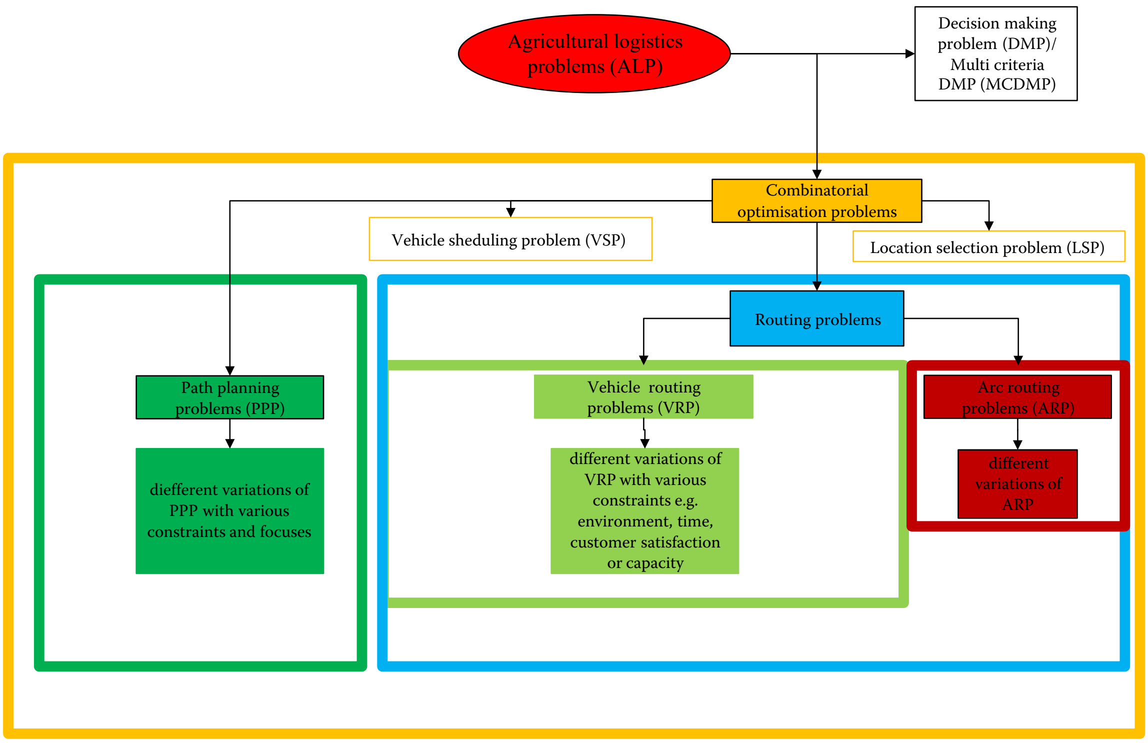

Figure 1. Overview of agricultural logistics problems

Source: Own elaboration

https://doi.org/10.17221/76/2025-AGRICECON

Table 2. Decision making problems in agricultural logistics (n = 5)

Source	Problem	Level	Area	Advantages
Amiama et al. (2015)	DMP; VRP	if	field logistics	reduces distances by 20%, achieves 12% cost savings, and provides time savings of up to 6 h
Kumar et al. (2021)	MCDM	SC		enhances collaboration, improves business continuity, ensures financial sustainability, leverages digital technologies, mitigates risks, increases transparency, and supports better decision-making in perishable food supply chains during the COVID-19 pandemic
Kumar and Kumar Singh (2022)	MCDM	SC		enhances resilience, improves collaboration, reduces disruption risks, optimises decision-making, increases efficiency, and supports policy development in agri-food supply chains
Yazdani et al. (2022)	MCDM	SC		enhances resilience, improves risk assessment, supports better decision-making, promotes sustainability, increases cost efficiency, and strengthens coordination by identifying the most resilient actors in the food supply chain
Gupta et al. (2023)	MCDM	SC		improves risk mitigation, enhances decision-making, promotes sustainability and efficiency in agri-logistics, and prepares the sector to adapt to risks such as natural disasters and social disruptions

DMP – decision making problem; if – intra farm logistics, MCDM – multi-criteria decision making; SC – supply chain; VRP – vehicle routing problem

Source: Own elaboration

Multi-criteria decision-making problems. Multi-criteria decision-making (MCDM) is one of the main decision-making problems, which aims to determine the best alternative by considering more than one criterion in the selection process (Taherdoost and Madanchian 2023). Resilience and risk minimisation are key concerns in agricultural logistics. Table 2 provides an overview of decision-making problems concerning agricultural logistics optimisation.

Despite of these decision-making problems, there are various combinatorial optimisation problems in agricultural logistics.

Vehicle scheduling problem and location selection problem. Reasonable location selection for logistics distribution centres is an effective means of achieving the traceability of agricultural products. As shown in Table 3, Gu et al. (2023) use the location selection problem (LSP) for this purpose to describe the location selection for agricultural logistics distribution. Similarly, the Vehicle scheduling problem (VSP) involves assigning scheduled trips to available vehicles, ensuring each trip is associated with one vehicle that starts and returns to its designated depot. VSP aims to minimise an objective function representing total traveling costs, working time, traveling time, distance, etc., while meeting customer demands and scheduling constraints (Dantzig and Fulkerson 2003). In the last 40–50 years this problem has been addressed by various kind of literature (Bunte and Kliewer 2009). It is mostly related to the public transport systems or for practical situations of transporting goods in production enterprises and often combined with the vehicle routing problem (VRP) (Anokić et al. 2020). While VRP focuses on optimising routes, VSP focuses on assigning trips to the vehicle.

Vehicle routing problem. The VRP generalises the traveling salesman problem (TSP), where multiple vehicles, rather than a single traveller, are used to serve customers (Dantzig and Ramser 1959). VRP is a well-known combinatorial optimisation problem (Ismail et al. 2021), in which customers and depots are represented as graph vertices, and edges represent travel paths with associated costs (Khajepour et al. 2020).

https://doi.org/10.17221/76/2025-AGRICECON

Table 3. Location selection problem (LSP) and vehicle scheduling problem (VSP) in agriculture (n = 6)

Source	Problem	Level	Area	Advantages
Spekken and Bruin (2013)	TSP	if	field logistics	reduces turning manoeuvre time by up to 50%, particularly on small fields without servicing requirements
Liu et al. (2019)	VSP	ob	fresh agricultural products	enhances efficient route planning, improves quality and freshness of agricultural products, reduces logistics losses, and optimises resource utilisation
Anokić et al. (2020)	VSP	ob	agricultural products	reduces costs, saves time, improves efficiency, enhances resource utilisation, lowers emissions
Sun et al. (2020)	VSP	if	robotics	improves efficiency, reduces costs, lowers energy consumption, enhances resource utilisation, increases scalability, promotes sustainability, and supports better decision-making in agricultural UAV operations
Gu et al. (2023)	LSP	ib/ob	distribution centres	improves accuracy, increases efficiency, reduces costs, and provides flexible and adaptable solutions for logistics site selection
Kang and Chang (2024)	two-echelon location routing problem (2E-LRP)	ob	agricultural products	improves routing efficiency and reduces fuel

ib – inbound logistics; if – intra farm logistics; ob – outbound logistics; TSP – tarvelling salesman problem; VSP – Vehicle sheduling problem; LSP – Location selection problem

Source: Own elaboration

The objective is to determine the least-cost vehicle fleet to meet customer demand. The problem involves finding a set of minimum-cost routes, starting and ending at a depot, ensuring that:

i) Each route begins and ends at the depot.

ii) Each customer is visited by exactly one vehicle.

iii) The total demand on any route does not exceed vehicle capacity.

Additional constraints may apply depending on the problem's context and solution approach (Laporte and Osman 1995). Various VRP extensions address real-world complexities by incorporating additional constraints, which can be combined to better reflect practical scenarios:

i) Capacitated VRP (CVRP): Here, the capacity of vehicles is limited (Zhang et al. 2014).

ii) VRP with time windows (VRPTW): All customers have to be reached during allowed delivery times and time windows (Solomon 1987).

iii) VRP based on customer satisfaction (VRPCS): According to Wu and Wu (2022) the measurement methods of customer satisfaction can be divided into three categories: measure satisfaction by the freshness of products, by product delivery time, and by the combination of freshness and delivery time.

iv) Multiple depot vehicle routing problem (MDVRP): Service initiation does not occur at a single depot; instead, it can be initiated from multiple depots. Each depot serves as the point where demanded items are loaded into the vehicle for delivery (Mahmud and Haque 2019).

v) Multi compartment vehicle routing problem (MCVRP): Here, a fleet of identical vehicles, each equipped with a number of compartments of limited capacities is used (Fallahi et al. 2008).

vi) VRPs with environmental impacts:

- Green VRP (GVRP): optimisation of energy consumption of transportation (Erdoğan and Miller-Hooks 2012)

https://doi.org/10.17221/76/2025-AGRICECON

- Environmental VRP (EVRP): reduce the amount of the emission of carbon dioxide (Zhang et al. 2014)

vii) Inventory routing problem (IRP): In the IRP, a customer's demand in a specific period can be served in a previous visit (Archetti et al. 2014).

Table 4 provides an overview of how the above-mentioned logistics modelling approaches are used in agricultural logistics.

Khajepour et al. (2020) separate the routing problems in two classes. The first is formed by the VRPs, while ARPs form a second separate class. Here the customers and their demands are considered on the edges of a graph. Considering the need to transport agricultural products, the capacity of machines is crucial. The capacitated ARC routing problem (CARP) is utilised for modelling various operations like harvesting, seeding, and spraying, aiming to minimise total cost and time (Khajepour et al. 2020) as shown in Table 5.

Different types of VRPs can be combined to address complex logistics challenges, as shown in Table 6. For instance, some models integrate quality and environmental considerations (Chen et al. 2019b) or dynamic processes (Seyyedhasani and Dvorak 2018). Many VRP approaches intersect with cold chain logistics (Wu et al. 2022; Wu and Wu 2022), particularly for perishable agricultural goods, integrating environmental concerns, customer satisfaction, and time constraints.

Path planning problem. Path planning is a crucial aspect of optimising agricultural operations, enabling machines and robots to navigate fields efficiently, avoid obstacles, and minimise operational costs. It plays a key role in agricultural logistics, material input operations, and automated fieldwork by enhancing efficiency, reducing energy consumption, and ensuring systematic field coverage. Various path planning strategies have been developed to address specific challenges in agricultural applications, which can be categorised into several subproblems. Coverage path planning (CPP) focuses on ensuring complete and systematic coverage of an area and is commonly applied in agricultural unmanned aerial vehicles (UAVs) for tasks such as spraying and monitoring (Valente et al. 2013). The agricultural route planning problem (ARP) aims to minimise the total distance travelled by machines to cover all field tracks while considering factors such as machine utilisation, input cost minimisation, and obstacle avoidance (Utamima et al. 2019a, b, c). Another relevant problem is the joint inventory-transport optimisation problem (JITOP), which integrates path planning with inventory decisions to optimise storage locations and transportation routes based on supply and demand data (Dong et al. 2022). Additionally, the mechanical harvester route planning (MHRP) problem, a variant of the shortest path problem (SPP), focuses on finding the shortest path for harvesters without covering all vertices, as seen in sugarcane harvesting operations (Sethanan and Neungmatcha 2016). Path planning problems in agriculture are closely related to well-established optimisation problems such as the traveling salesman problem (TSP) and the VRP, which further enhance agricultural operations by improving efficiency, reducing costs, and increasing sustainability. Figure 2 provides a graphical overview while Table 7 shows literature concerning PPP in agriculture.

Over time, both modelling approaches and research topics in agricultural logistics have evolved. Initially, studies focused on distinct areas: inbound, outbound, and intra-farm logistics. Additionally, some research addressed logistics across the entire agricultural value chain.

Figure 3 highlights a fluctuation in research focus over time. Initially, intra-farm logistics (IF) and supply chain (SC) considerations were predominant. Over the years, there has been an increasing trend in outbound logistics (OB) research, particularly after 2019. Notably, 2019 saw the highest number of papers, with a strong emphasis on intra-farm logistics. In later years, a balanced distribution across multiple categories emerged, reflecting a more comprehensive approach to agricultural logistics research. The analysis shows that inbound logistics (IB) has received minimal attention, with only a single paper addressing this area over the past decade.

Benefits through the optimisation of agricultural logistics and challenges arising. The advantages of logistics optimisation in agriculture have been thoroughly examined in Tables 2–7 of the analysed papers, with each study detailing specific benefits observed through various optimisation strategies. A comprehensive review of all collected data reveals that logistics optimisation offers a wide range of advantages that contribute to improving efficiency, accuracy, and overall cost-effectiveness in agricultural operations. One of the most significant benefits is increased operational efficiency, achieved through optimised planning of field activities, transportation routes, and resource allocation. By streamlining these processes, agricultural

https://doi.org/10.17221/76/2025-AGRICECON

Table 4. Vehicle routing problems (VRP) in agriculture (*n* = 26)

Source	Problem	Level	Area	Advantages
Bakhtiari et al. (2013)	CVRP	if	field logistics	reduces in-field non-working distance by 19.3–42.1%, decreases total non-working distance by 18–43.8%, and increases field efficiency by 69.3–74.7%
Bochtis et al. (2013)	VRP	if	field logistics	achieves up to 58.65% savings in non-working travel distance and increases processed area per unit time by up to 19.23%
Tang et al. (2013)	VRP	ob	cold chain	reduces transport distance by 235.9 km, leading to significant cost savings
Gracia et al. (2014)	biomass collection problem (BCP) = VRP	if	field logistics	reduces transport distances by up to 20%
Lahyani et al. (2015)	MCVRP	ob	agricultural products	reduces transportation costs, achieving cost savings of up to 7%
Conesa-Muñoz et al. (2016)	CVRP	if	field logistics	reduces total distance by up to 56.8% and operating costs by up to 43.3%
Sethanan and Pitakaso (2016)	MCVRP	ob	agricultural products	reduces total costs by up to 8.3% and decreases the number of deployed vehicles by up to 16.7%
Yang et al. (2017)	fresh agricultural products distribution problem (FAPDP) = VRP	ob	fresh agricultural products	optimises distribution, minimises spoilage by considering product time sensitivity, reduces travel times, and preserves product freshness
Sun and Pang (2017)	VRP	ob	agricultural products	fuel consumption can be reduced by up to 33%, depending on the route
Kandiller et al. (2017)	MCVRP	ib	feed supplier	reduces transportation costs by up to 25%, decreases the number of required vehicles by up to 20%, shortens total travel distances by up to 18%, and reduces delivery times by up to 15%
Seyyedhasani and Dvorak (2017)	VRP	if	field logistics	reduces field completion times by up to 32% and increases field capacity through even machinery distribution
Patidar et al. (2018)	VRP	ob	agricultural products	reduces costs and optimises the agri-food supply chain network
Mahmud and Haque (2019)	agricultural robot routing problem (ARRP) = VRP	if	robotics	6% shorter distance, reduces total travel distance
Andric Gusavac et al. (2019)	multi depot VRP (MDVRP)	if	robotics	reduces costs, improves resource allocation, and minimises travel distances
Guitián de Frutos and Casas-Méndez (2019)	VRP	ib	feed supplier	develops an interface for improved transport vehicle logistics optimisation
Liu et al. (2020)	joint-distribution green VRP (JD-GVRP)	ob	cold chain	reduces total costs by 6.80%, lowers carbon emissions by 25.27%, optimises fleet utilisation, reduces travel distance by 34.91%, balances economic and environmental benefits, and enhances industry collaboration

https://doi.org/10.17221/76/2025-AGRICECON

Table 4 To be continued

Source	Problem	Level	Area	Advantages
Lujak et al. (2021)	agricultural fleet-VRP	if	field logistics	improves efficiency, reduces costs, enhances resource utilisation, increases scalability, promotes sustainability, enables dynamic and decentralised coordination
Xiong (2021)	VRP	ob	cold chain	reduces transportation costs, shortens delivery times, improves routing efficiency, enhances convergence speed, and optimises resource utilisation
Yu et al. (2021)	VRP	ob	agricultural products	reduces costs, enhances resource utilisation, and ensures timely and accurate agricultural product delivery
Katiyar et al. (2021)	VRP with Time windows (VRPTW)	ob	fresh agricultural products	reduces delivery times, minimises logistics costs, improves food quality retention, optimises vehicle utilisation, and enhances customer satisfaction
Pratap et al. (2022)	inventory routing problem (IRP)	ob	fresh agricultural products	reduces costs, lowers carbon emissions, improves delivery efficiency, enhances sustainability, supports better decision-making, and increases resilience
Yao et al. (2022)	green VRP (GVRP)	ob	cold chain	reduces carbon emissions by 56%, decreases total distribution costs by up to 16.4%, improves economic benefits through investment in freshness-keeping costs, and enhances customer satisfaction
Ren (2022)	VRP with time windows (VRPTW)	ob	fresh agricultural products	reduces distribution costs by 52%, improves efficiency, achieves over 95% customer satisfaction under various traffic conditions, and minimises transportation time
Miao (2024)	dynamic, capacitated vehicle routing problem with soft time windows (DVRP-STW-C)	ob	perishable products	reduces costs by 32%, increases load efficiency by 25%, supports dynamic customer demand
Zhou et al. (2024)	MO-CVRP-TW (multi-objective capacitated VRP with time windows)	ob	fresh agricultural products	reduces fuel consumption by ~ 20% and increases average freshness by over 12% through multi-objective optimisation
Rahim et al. (2024)	single-period capacitated vehicle routing problem (SP-CVRP)	ob	fresh agricultural products	ensures 100% vehicle capacity use; optimises routing for cost efficiency in daily operations

CVRP – capacitated vehicle routing problem; ib – inbound logistics; if – intra farm logistics; MCVRP – multi compartment vehicle routing problem; ob –outbound logistics

Source: Own elaboration

https://doi.org/10.17221/76/2025-AGRICECON

Table 5. Arc routing problems in agriculture (n = 1)

Source	Problem	Level	Area	Advantages
Khajepour et al. (2020)	capacitated arc routing problem (CARP)	if	field logistics	reduces operational costs, improves efficiency, enhances resource utilisation, adapts to different field conditions, saves time, and provides better planning accuracy

if – intra farm logistics
Source: Own elaboration

enterprises can reduce unnecessary movements, minimise idle times, and ensure better synchronisation of tasks, leading to smoother operations and higher productivity. Another key advantage is improved accuracy, particularly in decision-making and execution. Advanced logistics solutions allow for better tracking of materials, precise scheduling, and real-time monitoring, which helps reduce errors and enhance the overall reliability of agricultural supply chains. Cost reduction is another major outcome of logistics optimisation. Efficient planning and resource utilisation contribute to lower transportation and operational costs, reduced fuel consumption, and better inventory management, all of which lead to significant financial savings for agricultural businesses. In addition to financial and operational benefits, logistics optimisation supports environmental sustainability by reducing carbon emissions, minimising waste, and promoting the efficient use of inputs such as fertilisers and water. This contributes to more sustainable farming practices that align with environmental regulations and consumer expectations. Further advantages include shorter delivery and processing times, ensuring timely supply of agricultural products to markets, which is crucial for maintaining product quality and meeting demand. Improved logistics also facilitate better coordination across the supply chain, enhancing communication and collaboration among farmers, suppliers, and distributors. Lastly, logistics optimisation enhances flexibility and adaptability, allowing agricultural businesses to respond more effectively to changing conditions such as weather fluctuations, market demands, and resource availability. This flexibility is crucial for ensuring resilience in agricultural operations and maintaining competitiveness in the sector.

However, the implementation of logistics optimisation measures in agriculture can be hindered by high initial investment costs, insufficient digital infrastructure, and limited interoperability between existing systems. Moreover, social factors must be considered: farm managers, drivers, and other stakeholders along the value chain need

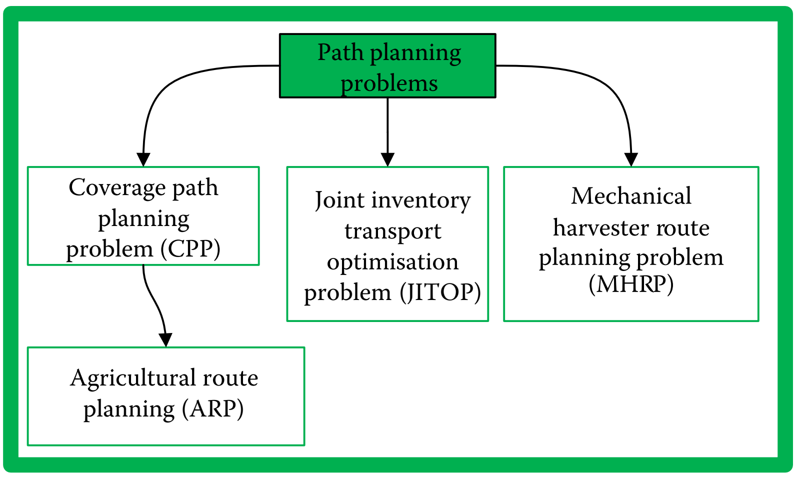

Figure 2. Variants of the path planning problem

Source: Own elaboration

https://doi.org/10.17221/76/2025-AGRICECON

Table 6. Combined vehicle routing problems (VRPs) with more than 1 constraint (*n* = 11)

Source	Problem	Explanation	Level	Area	Advantages
Liao et al. (2013)	inventory-distribution routing problem (IDRP)	inventory routing problem (IRP) + multi-period VRP (MP-VRP)	SC	agricultural products	reduces overall costs
Seyyedhasani and Dvorak (2018)	dynamic multi-depot VRP (DMDVRP)	dynamic VRP + MDVRP	if	field logistics	total working time reduced by up to 22% compared to the original plan, field efficiency per vehicle increased by up to 6% through optimised task allocation
Chen et al. (2019b)	low carbon and freshness degrees VRP (LCFD-VRP)	VRP + fuel costs (carbon emission) + time windows penalty costs (quality aspect)	ob	cold chain	total costs reduced by 4.94%, CO_2 emissions lowered by 8.9%, and actual transportation distance decreased by 5.50%
He and Li (2019)	two echelon multi-trip VRP with a dynamic satellite (2E-MTVRPDS)	VRP with multi trips + satellites	if	field logistics	improves efficiency, reduces operational costs, minimises waiting times, enhances resource utilisation, and provides decision support for farm management
Qin et al. (2019)	VRP with customer satisfaction and carbon emissions (VRP-CSC)	VRP + customer satisfaction + cold chain logistics + carbon emissions	ob	cold chain	improves customer satisfaction, reduces carbon emissions, enhances cost-effectiveness, provides insights into trade-offs, adapts to carbon pricing, and optimises distribution routes for greater efficiency
Theeraviriya et al. (2021)	multi-level location RP (MLLRP)	multi levels of depots	ob	agricultural products	reduces costs, minimises environmental impact, improves efficiency, optimises resource utilisation, adapts to real-world conditions, and enhances profitability
Wu and Wu (2021)	time depend green VRP with soft time windows (TDG-VRPSTW)	GVRP + time windows	ob	fresh agricultural products	achieves cost reduction of up to 54.2%, carbon emission reduction of 61.6%, and freshness loss reduction of 17.1%
Wu et al. (2022)	cold chain VRP (CCVRP)	GVRP + VRPTW + VRPCS	ob	cold chain	reduces costs, minimises carbon emissions, enhances customer satisfaction, improves efficiency, decreases vehicle usage, and ensures practical applicability by considering real-world constraints
Wu and Wu (2022)	time-depend split delivery green VRP with multiple time windows (TDSDG-VRPMTW)	GVRP + time windows	ob	cold chain	reduces total costs, improves customer satisfaction, enhances energy efficiency, lowers carbon emissions, optimises resource utilisation, and adapts to real-world conditions

https://doi.org/10.17221/76/2025-AGRICECON

Table 6 To be continued

Source	Problem	Explanation	Level	Area	Advantages
Wu et al. (2023b)	time-depend split delivery green VRP with multiple time windows (TDSDG-VRPMTW)	GVRP + time windows	ob	cold chain	reduces distribution costs, improves customer satisfaction, and lowers carbon emissions
Wu et al. (2023a)	green capacitated VRP with dynamic demand (GCVRPDD)	GVRP + CVRP + dynamic demand	ob	fresh agricultural products	reduces total costs by up to 43.82% and lowers carbon emissions by up to 43.93%

CVRP – capacitated vehicle routing problem; if – intra farm logistics; GVRP – green vehicle routing problem; MDVPR – multiple depot vehicle routing problem; ob – outbound logistics; SC – supply chain; VRPCS – vehicle routing problem based on customer satisfaction; VRPTW – vehicle routing problem with time windows

Source: Own elaboration

to be convinced of and trained in these new processes, as theoretically optimised models can only deliver their full potential when successfully translated into practice under real-world conditions.

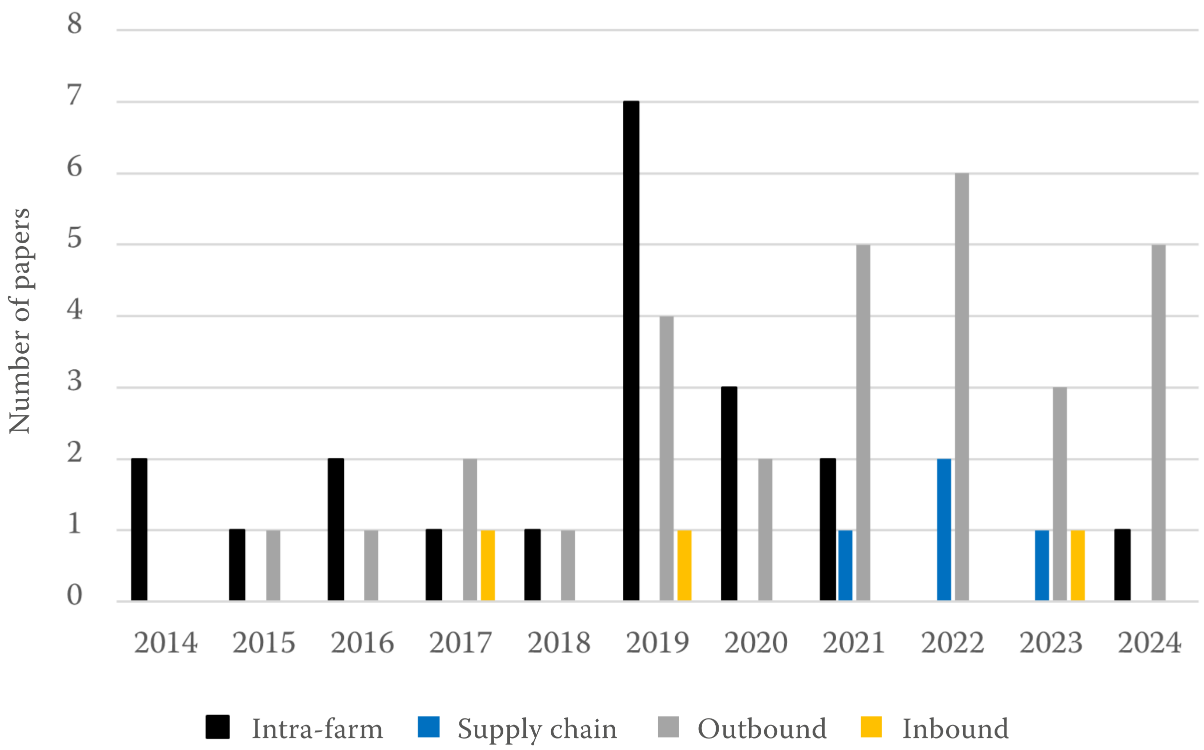

Figure 3. Focuses of relevant papers

Source: Own elaboration

https://doi.org/10.17221/76/2025-AGRICECON

Table 7. Path planning problems (PPPs) in agriculture (*n* = 13)

Source	Problem	Level	Area	Advantages
Valente et al. (2013)	CPP	if	robotics	reduces number of turns in coverage paths, leads to shorter mission duration, increases safety for operators and UAVs, optimises resource utilisation, lowers operational costs
Hameed (2014)	PPP	if	robotics	reduces energy consumption by an average of 6.5%
Sethanan and Neungmatcha (2016)	mechanical harvester route planning (MHRP)	if	field logistics	reduces travelled distances by up to 15%, increases harvested sugarcane per unit time by up to 12%, and lowers total costs by up to 8%
Utamima et al. (2019c)	CPP	if	field logistics	reduces non-working distance by 10.68%
Utamima et al. (2019b)	ARP	if	field logistics	minimises the distance travelled by agricultural machines, leading to reduced fuel consumption and operational costs
Mai et al. (2019)	PPP as TSP	if	robotics	improves efficiency, reduces measurement time and energy consumption, enhances precision irrigation, and adapts to farmland constraints, ensuring better resource utilisation and scalability
Chen et al. (2019a)	PPP	ob	cold chain	reduces total distribution costs, enhances energy efficiency, and lowers carbon emissions
Utamima et al. (2019a)	ARP	if	field logistics	reduces non-working distance by 8%, improves efficiency, and achieves cost savings
Utamima et al. (2020)	ARP	if	field logistics	reduces non-working distance by 8.45%, improves computational efficiency by being three times faster, lowers operational costs, enhances resource utilisation, scales to multiple fields, and supports better decision-making in agricultural operations
Muthukumaran et al. (2021)	ARP as TSP	if	field logistics	improves efficiency, reduces costs, and enhances accuracy in agricultural spraying robots by optimising routes and avoiding obstacles
Dong et al. (2022)	joint inventory transport optimisation problem (JITOP)	ob	agricultural products	reduces costs, improves efficiency, lowers environmental impact, enhances decision-making, optimises resource utilisation, and offers scalability for various logistics scenarios
Wang and Xie (2024)	PPP	if	warehouse logistics	avoids collisions, shortens paths, improves safety and smoothness in automated handling
Xu (2024)	PPP	ob	agricultural products	enables last-mile delivery; minimises energy use; extends reach in rural terrain

ARP – agricultural route planning; CPP – coverage path planning problem; if – intra farm logistics; ob – outbound logistics; TSP – travelling salesman problem

Source: Own elaboration

https://doi.org/10.17221/76/2025-AGRICECON

DISCUSSION

The optimisation of agricultural logistics holds substantial potential for reducing costs, increasing efficiency, and enhancing environmental sustainability. Prior research by Szabo et al. (2021) has underscored the importance of digitalisation, big data analytics, and the integration of modern technologies in agricultural logistics. Our findings corroborate these observations, particularly in the context of path planning algorithms and autonomous machinery, such as UAVs, for precision operations. However, unlike the aforementioned studies, our review also reveals that optimisation can be effectively implemented in more accessible, operational domains – such as field traversal and transport route optimisation – benefiting not only from digitalisation but also from data-driven, real-time decision-making supported by technologies like MCDM and VRP models.

Numerous of the reviewed studies demonstrated the quantifiable benefits of optimisation techniques. For instance, the use of VRP approaches in intra-farm logistics led to reductions in non-productive travel distance by up to 58.65%, and simultaneously increased the processed area per unit of time by over 19% (Bochtis et al. 2013). Similarly, Seyyedhasani and Dvorak (2017) found that optimised field machinery routing could reduce field completion times by up to 32%. These findings are particularly relevant in the context of labour shortages and increasing wages in rural regions (Aryal et al. 2021; Christiaensen et al. 2021). Environmental and economic benefits were also prevalent in the literature.

Green VRP models, such as those proposed by Wu and Wu (2021), demonstrated a reduction in carbon emissions by up to 61.6% and logistics cost reductions of 54.2%, highlighting the dual benefit of ecological and financial performance Wu and Wu (2021). Additional studies confirmed similar improvements in carbon efficiency and freshness preservation through time-window-based and multi-objective VRP variants (Qin et al. 2019; Yao et al. 2022; Wu et al. 2023b). This aligns with consumers demand for more efficient and environmentally responsible production systems (Sánchez-Bravo et al. 2021; Igwe et al. 2024). Moreover, MCDM frameworks have proven valuable in enhancing supply chain resilience, especially in the context of the COVID-19 pandemic. Kumar et al. (2021), Kumar and Kumar Singh (2022) and Yazdani et al. (2022) reported improvements in risk mitigation, business continuity, and collaborative decision-making in agri-food supply chains under stress.

Despite these best practices, several critical research gaps remain, which should be addressed in future studies. One of the most pressing challenges is the limited focus on inbound logistics. While numerous studies have concentrated on intra-farm and outbound processes, the procurement and timely delivery of essential agricultural inputs such as seeds, fertilisers, and equipment have received minimal attention. Addressing this gap could significantly enhance overall supply chain efficiency. Additionally, the scalability of existing optimisation models presents a challenge. Many current approaches have primarily been tested in small to medium-sized operations, while their applicability to large-scale, complex agricultural supply chains, particularly in developing regions, remains uncertain and requires further empirical validation.

The integration of digital solutions is also hindered by various challenges. Issues such as interoperability between different systems, high implementation costs, and concerns about data security pose significant barriers to widespread adoption. Future research should focus on developing cost-effective, scalable, and user-friendly digital solutions that are accessible, particularly to smallholder farmers. Another critical aspect is the resilience of agricultural logistics to external disruptions. Climate change, geopolitical uncertainties, and market fluctuations pose substantial risks, necessitating the development of adaptive logistics strategies that incorporate predictive modelling and resilience planning to minimise the impact of such uncertainties. Lastly, there is a need for a comprehensive assessment of cost-benefit trade-offs in agricultural logistics optimisation. While many studies emphasise cost reductions, it is essential to consider social and environmental factors to ensure long-term sustainability. Addressing these challenges requires an interdisciplinary approach that integrates logistical, technological, and socio-economic perspectives. A holistic perspective will be crucial in further improving the adaptability, efficiency, and sustainability of agricultural logistics, ultimately creating a resilient and future-proof supply system. Addressing these gaps will require an interdisciplinary research approach that combines expertise from logistics, agricultural sciences, data analytics, and sustainability studies. Collaboration between academia, industry stakeholders, and policymakers will be key to developing innovative solutions that enhance the efficiency, adaptability, and sustainability of agricultural logistics systems. By focusing on these areas, future research

https://doi.org/10.17221/76/2025-AGRICECON

can contribute to building more resilient, technology-driven agricultural supply chains that can support the growing global demand for food while minimising environmental impacts and ensuring economic viability for all stakeholders involved.

CONCLUSION

This study explored the optimisation of agricultural logistics, addressing how it can be effectively modelled and what benefits of optimisation can be expected in terms of cost, sustainability, and efficiency. Various modelling approaches, such as multi-criteria decision-making (MCDM), vehicle routing problems (VRP), and path planning problems (PPP), have proven effective in tackling the sector's unique challenges. These methods optimise transportation, reduce costs, and enhance resource utilisation, contributing to more efficient and resilient supply chains. Logistics optimisation offers significant benefits, including cost reduction, improved sustainability through lower environmental impact and enhanced operational efficiency. However, gaps remain, particularly in the optimisation of inbound logistics and the integration of advanced technologies such as IoT and blockchain to improve transparency and responsiveness. Despite the growing relevance of logistical challenges and external stressors such as rising energy prices, the existing body of research on agricultural logistics optimisation remains highly fragmented. Many studies focus on isolated applications such as optimising routing for a specific crop, or improving one logistical stage like outbound transport, without offering a comprehensive comparison of methods, their contexts of use, or measurable advantages. Furthermore, while individual studies provide evidence of benefits like cost savings, emission reductions or efficiency improvements, these findings are dispersed across different subfields and lack a unifying framework that captures the full scope of agricultural logistics. As a clear gap exists in systematically identifying and comparing optimisation opportunities within agricultural logistics, this study contributes to the existing literature by providing a structured review of modelling and optimisation approaches.

In summary, agricultural logistics optimisation is key to achieving cost-effective and sustainable operations. Future research should focus on comprehensive, technology-driven solutions to further enhance efficiency and adaptability across the agricultural supply chain.

REFERENCES

Amiama C., Cascudo N., Carpente L., Cerdeira-Pena A. (2015): A decision tool for maize silage harvest operations. Biosystems Engineering, 134: 94–104.

Andric Gusavac B., Stanojevic M., Cangalovic M. (2019): Optimal treatment of agricultural land – Special multi-depot vehicle routing problem. Agricultural Economics – Czech, 65: 569–578.

Anokić A., Stanimirović Z., Davidović T., Stakić Đ. (2020): Variable neighborhood search based approaches to a vehicle scheduling problem in agriculture. International Transactions in Operational Research, 27: 26–56.

Archetti C., Bianchessi N., Irnich S., Speranza M.G. (2014): Formulations for an inventory routing problem. International Transactions in Operational Research, 21: 353–374.

Aryal J.P., Rahut D.B., Thapa G., Simtowe F. (2021): Mechanisation of small-scale farms in South Asia: Empirical evidence derived from farm households survey. Technology in Society, 65: 101591.

Bakhtiari A., Navid H., Mehri J., Berruto R., Bochtis D.D. (2013): Operations planning for agricultural harvesters using ant colony optimization. Spanish Journal of Agricultural Research, 11: 652.

Bochtis D.D., Sørensen C.G., Busato P., Berruto R. (2013): Benefits from optimal route planning based on B-patterns. Biosystems Engineering, 115: 389–395.

Bonadio B., Huo Z., Levchenko A.A., Pandalai-Nayar N. (2021): Global supply chains in the pandemic. Journal of International Economics, 133: 103534.

Bramer W.M., Giustini D., Kramer B.M.R. (2016): Comparing the coverage, recall, and precision of searches for 120 systematic reviews in Embase, MEDLINE, and Google Scholar: A prospective study. Systematic Reviews, 5: 39.

Bunte S., Kliewer N. (2009): An overview on vehicle scheduling models. Public Transport, 1: 299–317.

Chandra S., Ghosh D., Srivastava S.K. (2016): Outbound logistics management practices in the automotive industry: An emerging economy perspective. Decision, 43: 145–165.

Chen S., Gan M., Tang Y. (2013): Analysis of predicting the diversity regional logistics demand based on SVR: The case of Sichuan in China. Applied Mathematics & Information Sciences, 7: 645–651.

Chen L., Ma M., Sun L. (2019a): Heuristic swarm intelligent optimization algorithm for path planning of agricultural product logistics distribution. Journal of Intelligent & Fuzzy Systems: Applications in Engineering and Technology, 37: 4697–4703.

Chen J., Gui P., Ding T., Na S., Zhou Y. (2019b): Optimization of transportation routing problem for fresh food by improved ant colony algorithm based on tabu search. Sustainability, 11: 6584.

https://doi.org/10.17221/76/2025-AGRICECON

Christiaensen L., Rutledge Z., Taylor J.E. (2021): Viewpoint: The future of work in agri-food. Food Policy, 99: 101963.

Conesa-Muñoz J., Pajares G., Ribeiro A. (2016): Mix-opt: A new route operator for optimal coverage path planning for a fleet in an agricultural environment. Expert Systems with Applications, 54: 364–378.

da Costa Santos C.M., de Mattos Pimenta C.A., Nobre M.R.C. (2007): The PICO strategy for the research question construction and evidence search. Revista Latino-Americana de Enfermagem, 15: 508–511.

Dantzig G.B., Ramser J.H. (1959): The truck dispatching problem. Management Science, 6: 80–91.

Dantzig G.B., Fulkerson D.R. (2003): Minimizing the number of tankers to meet a fixed schedule. Stanford Business Books, Stanford, California

Dantzig G.B., & Fulkerson D.R. (1954): Minimizing the number of carriers to meet a fixed schedule.

Dong B., Duan M., Li Y. (2022): Exploration of Joint optimization and visualization of inventory transportation in agricultural logistics based on ant colony algorithm. Computational Intelligence and Neuroscience, 2022: 2041592.

Erdoğan S., Miller-Hooks E. (2012): A green vehicle routing problem. Transportation Research Part E: Logistics and Transportation Review, 48: 100–114.

European Commission (2020): Farm to Fork Strategy. Brussels, European Commission. Available at https://food.ec.europa.eu/horizontal-topics/farm-fork-strategy_en

Fallahi A.E., Prins C., Wolfler Calvo R. (2008): A memetic algorithm and a tabu search for the multi-compartment vehicle routing problem. Computers & Operations Research, 35: 1725–1741.

Farghali M., Osman A.I., Mohamed I.M.A., Chen Z., Chen L., Ihara I., Yap P.-S., Rooney D.W. (2023): Strategies to save energy in the context of the energy crisis: A review. Environmental Chemistry Letters, 21: 2003–2039.

Gao T., Erokhin V., Arskiy A. (2019): Dynamic optimization of fuel and logistics costs as a tool in pursuing economic sustainability of a farm. Sustainability, 11: 5463.

Gehanno J.-F., Rollin L., Darmoni S. (2013): Is the coverage of Google Scholar enough to be used alone for systematic reviews. BMC Medical Informatics and Decision Making, 13: 7.

Gracia C., Velázquez-Martí B., Estornell J. (2014): An application of the vehicle routing problem to biomass transportation. Biosystems Engineering, 124: 40–52.

Gu Z., Liu W., Ren Y., Hai L., Xue Y. (2023): An Improved path optimization method of logistics site selection for agricultural products. JESTR, 16: 44–51.

Guitián de Frutos R.M., Casas-Méndez B. (2019): Routing problems in agricultural cooperatives: A model for optimization of transport vehicle logistics. IMA Journal of Management Mathematics, 30: 387–412.

Gupta H., Kharub M., Shreshth K., Kumar A., Huisingh D., Kumar A. (2023): Evaluation of strategies to manage risks in smart, sustainable agri-logistics sector: A Bayesian-based group decision-making approach. Business Strategy and the Environment, 32: 4335–4359.

Hameed I.A. (2014): Intelligent coverage path planning for agricultural robots and autonomous machines on three-dimensional terrain. Journal of Intelligent & Robotic Systems, 74: 965–983.

He P., Li J. (2019): The two-echelon multi-trip vehicle routing problem with dynamic satellites for crop harvesting and transportation. Applied Soft Computing, 77: 387–398.

Igwe A.N., Eyo-Udo N.L., Toromade A.S., Adewale T.T. (2024): Policy implications and economic incentives for sustainable supply chain practices in the food and FMCG Sectors. Comprehensive Research and Reviews Journal, 2: 23–36.

Ismail A.H., Hartono N., Zeybek S., Caterino M., Jiang K. (2021): Combinatorial bees algorithm for vehicle routing problem. Macromolecular Symposia, 396: 2000284.

Jensen T.A., Antille D.L., Tullberg J.N. (2025): Improving on-farm energy use efficiency by optimizing machinery operations and management: A review. Agricultural Research, 14: 15–33.

Kandiller L., Eliiyi D.T., Taşar B. (2017): A multi-compartment vehicle routing problem for livestock feed distribution. In: Dörner K., Ljubic I., Pflug G., Tragler G. (eds): Operations Research Proceedings 2015. Vienna, Austria, Sept 1–4, 2015: 149–155.

Kang J.-R., Chang M.-H. (2024): The Application of elite genetic algorithm in sustainable agricultural transportation. In: Proceedings of the 2024 International Conference on Information Technology, Data Science, and Optimization. Taipei, Taiwan, May 22–24, 2024: 6–11.

Katiyar S., Khan R., Kumar S. (2021): Artificial bee colony algorithm for fresh food distribution without quality loss by delivery route optimization. Journal of Food Quality: 4881289.

Keshav S. (2007): How to read a paper. SIGCOMM Computer Communication Review, 37: 83–84.

Khajepour A., Sheikhmohammady M., Nikbakhsh E. (2020): Field path planning using capacitated arc routing problem. Computers and Electronics in Agriculture, 173: 105401.

Kramar U., Topolšek D., Lipičnik M. (2015): How to define logistics in agriculture?

Kumar A., Mangla S.K., Kumar P., Song M. (2021): Mitigate risks in perishable food supply chains: Learning from COVID-19. Technological Forecasting and Social Change, 166: 120643.

Kumar P., Kumar Singh R. (2022): Strategic framework for developing resilience in Agri-Food Supply Chains during

https://doi.org/10.17221/76/2025-AGRICECON

COVID 19 pandemic. International Journal of Logistics Research and Applications, 25: 1401–1424.

Lahyani R., Coelho L.C., Khemakhem M., Laporte G., Semet F. (2015): A multi-compartment vehicle routing problem arising in the collection of olive oil in Tunisia. Omega, 51: 1–10.

Laporte G., Osman I.H. (1995): Routing problems: A bibliography. Annals of Operations Ressearch, 61: 227–262.

Liao L., Li J., Wu Y. (2013): Modeling and optimization of inventory-distribution routing problem for agriculture products supply chain. Discrete Dynamics in Nature and Society: 409869.

Liu L., Wang H., Xing S. (2019) Optimization of distribution planning for agricultural products in logistics based on degree of maturity. Computers and Electronics in Agriculture 160: 1–7.

Liu G., Hu J., Yang Y., Xia S., Lim M.K. (2020): Vehicle routing problem in cold Chain logistics: A joint distribution model with carbon trading mechanisms. Resources, Conservation and Recycling, 156: 104715.

Lujak M., Sklar E., Semet F. (2021): Agriculture fleet vehicle routing: A decentralised and dynamic problem. AI Communications: The European Journal on Artificial Intelligence, 34: 55–71.

Lummus R.R., Krumwiede D.W., Vokurka R.J. (2001): The relationship of logistics to supply chain management: Developing a common industry definition. Industrial Management & Data Systems, 101: 426–432.

Mahmud N., Haque M.M. (2019): Solving multiple depot vehicle routing problem (MDVRP) using genetic algorithm. In: 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE). Cox'sBazar, Bangladesh, Feb 7–9, 2019: 1–6.

Mai T., Shao S., Yun Z. (2019): The Path planning of agricultural AGV in potato ridge cultivation. Annals of Advanced Agricultural Sciences, 3: 21–30.

Mamoudan M.M., Jafari A., Mohammadnazari Z., Nasiri M.M., Yazdani M. (2023): Hybrid machine learning-metaheuristic model for sustainable agri-food production and supply chain planning under water scarcity. Resources, Environment and Sustainability, 14: 100133.

Mentzer J.T., DeWitt W., Keebler J.S., Min S., Nix N.W., Smith C.D., Zacharia Z.G. (2001): Defining supply chains management. Journal of Business Logistics, 22: 1–25.

Miao H. (2024): Logistics distribution path optimization and application based on swarm intelligence optimization algorithm. In: Mezhuyev V., Becker Westphall C., Uden L., Wolfson O., Agaian S.S.: Intelligent Transportation and Smart Cities, Proceedings of the 1st International Conference (ICITSC 2024). Wuhan, China, March 7–8, 2024: 57–64.

Mizik T., Nagy J., Molnár E.M., Maró Z.M. (2025): Challenges of employment in the agrifood sector of developing countries – A systematic literature review. Humanities and Social Sciences Communications, 12: 62.

Muthukumaran S., Ganesan M., Dhanasekar J., Loganathan G.B. (2021): Path planning optimization for agricultural spraying robots using hybrid dragonfly – Cuckoo search algorithm. Alinteri Journal of Agriculture Sciencea, 36: 412–419.

Olufemi-Phillips A.Q., Ofodile O.C., Toromade A.S., Igwe A.N,. Adewale T.T. (2024): Stabilizing food supply chains with Blockchain technology during periods of economic inflation. International Journal of Advanced Economics, 6: 612–651.

Patidar R., Venkatesh B., Pratap S., Daultani Y. (2018): A sustainable vehicle routing problem for Indian agri-food supply chain network design. In: 2018 International Conference on Production and Operations Management Society (POMS). Peradeniya, Sri Lanka, Dec 14–16, 2018.

Petersen K., Feldt R., Mujtaba S., Mattsson M. (2008): Systematic mapping studies in software engineering. In: Visaggio G., Baldassarre M.T., Linkman S., Turner M.: Proceedings of the 12th International Conference on Evaluation and Assessment in Software Engineering (EASE). Italy, June 26–27, 2008: 68–77.

Pratap S., Jauhar S.K., Paul S.K., Zhou F. (2022): Stochastic optimization approach for green routing and planning in perishable food production. Journal of Cleaner Production, 333: 130063.

Qin G., Tao F., Li L. (2019:) A vehicle routing optimization problem for cold chain logistics considering customer satisfaction and carbon emissions. International Journal of Environmental Research and Public Health, 16: 576.

Rahim M., Radzuan K., Nadarajan S., Bolaji B.H., Ramli M.F. (2024): Modelling and simulation of the single-period vehicle routing problem in the agriculture industry. JESA, 57: 1445–1451.

Ren Q. (2022): The optimal route selection model of fresh agricultural products transportation based on bee colony algorithm. International Journal of Advanced Computer Science and Applications, 13: 489–499.

Saitone T.L., Sexton R.J. (2017): Agri-food supply chain: Evolution and performance with conflicting consumer and societal demands. European Review of Agricultural Economics, 44: 634–657.

Sánchez-Bravo P., Chambers V.E., Noguera-Artiaga L., Sendra E., Chambers I.V.E., Carbonell-Barrachina Á.A. (2021): Consumer understanding of sustainability concept in agricultural products. Food Quality and Preference, 89: 104136.

Sethanan K., Neungmatcha W. (2016): Multi-objective particle swarm optimization for mechanical harvester route

https://doi.org/10.17221/76/2025-AGRICECON

planning of sugarcane field operations. European Journal of Operational Research, 252: 969–984.

Sethanan K., Pitakaso R. (2016): Differential evolution algorithms for scheduling raw milk transportation. Computers and Electronics in Agriculture, 121: 245–259.

Seyyedhasani H., Dvorak J.S. (2017): Using the vehicle routing problem to reduce field completion times with multiple machines. Computers and Electronics in Agriculture, 134: 142–150.

Seyyedhasani H., Dvorak J.S. (2018): Dynamic rerouting of a fleet of vehicles in agricultural operations through a dynamic multiple depot vehicle routing problem representation. Biosystems Engineering, 171: 63–77.

Singh J., Gupta V. (2017a): A systematic review of text stemming techniques. Artificial Intelligence Review, 48: 157–217.

Singh J., Gupta V. (2017b): Text Stemming: Approached, applications, and challenges. ACM Computing Surveys, 49: 45.

Solomon M.M. (1987): Algorithms for the vehicle routing and scheduling problems with time window constraints. Operations Research, 35: 254–265.

Spekken M., de Bruin S. (2013): Optimized routing on agricultural fields by minimizing maneuvering and servicing time. Precision Agric, 14: 224–244.

Sun M., Pang D. (2017): Vehicle routing optimisation algorithm for agricultural products logistics distribution. International Journal of Applied Decision Sciences, 10: 327–334.

Sun F., Wang X., Zhang R. (2020): Task scheduling system for UAV operations in agricultural plant protection environment. Journal of Ambient Intelligence and Human Computing.

Szabo Ľ., Richnák P., Gubová K. (2021): New dimension of logistics innovations development in agricultural enterprises in Slovakia. Agricultural Economics – Czech, 67: 136–143.

Taherdoost H., Madanchian M. (2023): Multi-criteria decision making (MCDM) methods and concepts. Encyclopedia, 3: 77–87.

Tang J., Liu K., Chen Q. (2013): Study on cold chain logistics of vehicle routing problem for agricultural products. In: Proceedings of 2013 IEEE International Conference on Service Operations and Logistics, and Informatics. Dongguan, P.R. China, July 28–30, 2013: 317–322.

Theeraviriya C., Ruamboon K., Praseeratasang N. (2021): Solving the multi-level location routing problem considering the environmental impact using a hybrid metaheuristic. International Journal of Engineering Business Management, 13.

Utamima A., Reiners T., Ansaripoor A. (2019a): Decision making for Farmers: A case study of agricultural routing planning. In: ACIS 2019 Proceedings. Perth, Australia, Dec 9–11, 2019: 789–799.

Utamima A., Reiners T., Ansaripoor A.H. (2019b): Evolutionary estimation of distribution algorithm for agricultural routing planning in field logistics. Procedia Computer Science, 161: 560–567.

Utamima A., Reiners T., Ansaripoor A. (2019c): Optimisation of agricultural routing planning in field logistics with evolutionary hybrid neighbourhood search. Biosystems Engineering, 184: 166–180.

Utamima A., Reiners T., Ansaripoor A. (2020): Automation in agriculture: A case study of route planning using an evolutionary lovebird algorithm. In: Proceedings of the 2020 12th International Conference on Computer and Automation Engineering. Sydney, Australia, Feb 14–16, 2020: 13–17.

Uyar A. (2009): Google stemming mechanisms. Journal of Information Science, 35: 499–514.

Valente J., Del Cerro J., Barrientos A., Sanz D. (2013): Aerial coverage optimization in precision agriculture management: A musical harmony inspired approach. Computers and Electronics in Agriculture, 99: 153–159.

Wang Y., Xie M. (2024): Analysis on path optimization of agricultural warehouse logistics handling robot based on potential field ant colony algorithm. INMATEH – Agricultural Engineering, 73: 784–795.

Wu D., Wu C. (2021): TDGVRPSTW of Fresh agricultural products distribution: Considering both economic cost and environmental cost. Applied Sciences, 11: **1**0579.

Wu D., Wu C. (2022): Research on the time-dependent split delivery green vehicle routing problem for fresh agricultural products with multiple time windows. Agriculture, 12: 793.

Wu D., Zhu Z., Hu D., Mansour R.F. (2022): Optimizing fresh logistics distribution route based on improved ant colony algorithm. Computer, Materials & Continua, 73: 2079–2095.

Wu D., Yan R., Jin H., Cai F. (2023a): An Adaptive nutcracker optimization approach for distribution of fresh agricultural products with dynamic demands. Agriculture, 13: 1430.

Wu D., Li J., Cui J., Hu D. (2023b): Research on the time-dependent vehicle routing problem for fresh agricultural products based on customer value. Agriculture, 13: 681.

Xiong H. (2021): Research on cold chain logistics distribution route based on ant colony optimization algorithm. Discrete Dynamics in Nature and Society, 2021: 6623563.

Xu S. (2011): Tactics on the development of modern agricultural logistics in central China. Advanced Materials Research, 219–220: 366–369.

Xu Y. (2024): Research on agricultural logistics distribution path planning considering uav endurance mileage limit. INMATEH – Agricultural Engineering, 73: 688–701.

Yang W., Xu J., Li Y. (2017): Multi-variety fresh agricultural products distribution optimization based on an improved

https://doi.org/10.17221/76/2025-AGRICECON

cuckoo search algorithm. In: Fei M., Ma S., Yue D., Peng C., Li K., Xue Y. (eds): International Conference on Life System Modeling and Simulation, LSMS 2017 and International Conference on Intelligent Computing for Sustainable Energy and Environment, ICSEE 2017. Nanjing, P.R. China, Sept 22–24, 2017: 294–302.

Yao Q., Zhu S., Li Y. (2022): Green vehicle-routing problem of fresh agricultural products considering carbon emission. International Journal of Environmental Research and Public Health, 19: 8675.

Yazdani M., Torkayesh A.E., Chatterjee P., Fallahpour A., Montero-Simo M.J., Araque-Padilla R.A., Wong K.Y. (2022): A fuzzy group decision-making model to measure resiliency in a food supply chain: A case study in Spain. Socio-Economic Planning Sciences, 82: 101257.

Yu K., Liu Y., Sharma A. (2021): Analyze the effectiveness of the algorithm for agricultural product delivery vehicle routing problem based on mathematical model. International Journal of Agricultural and Environmental Information Systems, 12: 26–38.

Zavala-Alcívar A., Verdecho M.-J., Alfaro-Saiz J.-J. (2021): Resilient strategies and sustainability in agri-food supply chains in the face of high-risk events. In: Camarinha-Matos L.M., Afsarmanesh H., Ortiz A. (eds): Boosting Collaborative Networks 4.0: PRO-VE 2020. Valencia, Spain, Nov 23–25, 2020: 560–570.

Zhang S., Lee C., Choy K.L., Ho W., Ip W.H. (2014): Design and development of a hybrid artificial bee colony algorithm for the environmental vehicle routing problem. Transportation Research Part D: Transport and Environment, 31: 85–99.

Zhou L., Hou G., Rao W. (2024): Collaborative logistics for agricultural products of 'farmer + consumer integration purchase' under platform empowerment. Expert Systems with Applications, 255: 124521.

Received: February 20, 2025
Accepted: December 2, 2025
Published online: April 14, 2026