Journal of Transport and Supply Chain Management
ISSN: (Online) 1995-5235, (Print) 2310-8789

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Transport network modelling and optimisation for a vaccine delivery system to remote areas using unmanned aerial vehicles

Authors:
Carlos Osorio-Ramírez[1]
Catalina Moreno Castro[2]
Jesus Gonzalez-Feliu[3]
Antonio Comi[4]

Affiliations:
[1]Faculty of Economic Sciences, Universidad Nacional de Colombia, Bogotá, Colombia

[2]Center of Research in Innovation and Intelligence in Management, Faculty of Engineering, Universidad Nacional de Colombia, Bogotá, Colombia

[3]Center of Research in Innovation and Intelligence in Management, Excelia Business School, La Rochelle, France

[4]Department of Enterprise Engineering, University of Rome Tor Vergata, Rome, Italy

Corresponding author:
Jesus Gonzalez-Feliu,
gonzalezfeliuj@excelia-group.com

Dates:
Received: 13 Apr. 2025
Accepted: 22 June 2025
Published: 24 Nov. 2025

How to cite this article:
Osorio-Ramírez, C., Castro, C.M., Gonzalez-Feliu, J. & Comi, A., 2025, 'Transport network modelling and optimisation for a vaccine delivery system to remote areas using unmanned aerial vehicles', *Journal of Transport and Supply Chain Management* 19(0), a1180. https://doi.org/10.4102/jtscm.v19i0.1180

Background: Healthcare supply chains face critical challenges that increase in rural areas due to accessibility restrictions, sparce population and long distances. In Colombia, this situation is mainly reflected in rural food insecurity rates and weaknesses against illnesses. To deal with these issues, public health programmes for poor and vulnerable areas are developed, but need to be efficient and find new logistics and supply chains, taking advantage of new technologies to increase performance.

Objectives: This article proposes a vaccine delivery system using unmanned aerial vehicles (UAVs), commonly known as drones, to access remote areas. It presents a set of optimisation models for distributing vaccines to remote areas with geographical barriers.

Method: To define the vaccine delivery system, an intermodal network design model and a set of delivery options, using realistic data, are proposed.

Results: Results indicate that using an intermodal transport model where aerial transport is combined with UAVs and barges leads to a reduction of about 25% in distribution time as well as improvement in the availability of vaccines to the population in comparison to the existing system.

Conclusion: By using the proposed multimodal network design model where UAVs are used to deliver vaccines to remote areas needs can be better anticipated and healthcare supply chains be improved and supported.

Contribution: This research indicates the interest in using UAVs to access rural, inaccessible areas and its applications in the distribution of vaccines.

Keywords: healthcare transportation systems; unmanned freight transportations; transport network design; combinatorial optimisation; drones; unmanned aerial vehicles; distribution.

Introduction

Across the world, several countries present serious geographical barriers to distributing medicines promptly, specifically to remote or rural areas. Traditionally, these areas are located in poor regions, making the supply chain very difficult to manage as a result of restrictions on access and public order, among others. This is the case in Colombia, with vast rural areas with poor road infrastructure, underpopulated towns and a lack of supply in healthcare and education. In meeting the healthcare demands and delivering efficient healthcare operations, various challenges are encountered, since it is essential to provide both human and material resources at the right place, time and in the right quantities to improve the lives of rural communities (Peña-Orozco et al. 2023). New healthcare logistics and organisations are therefore required to fulfil the needs of rural areas without affecting the rural populations negatively.

To deal with those challenges and needs, the use of unmanned aerial vehicles (UAVs), commonly known as drones, becoming more promising to assist health systems and medical staff in fulfilling their mission of attending to population needs and saving lives (Nyaaba & Ayamga 2021). The use of UAVs has some benefits, including limiting the restrictions on truck transportation as a result of road problems and reducing the delivery time of medical supplies (Shi et al. 2022).

However, there are some unresolved issues regarding managing the UAV fleet for this type of activities, such as the location of the air bases, the management of capacity, the programming of routes and the potential integration with other modes of transportation. In fact, although technologically, UAVs are operational and the organisational issues that allow such a system to be planned and operated still need to be examined in-depth and defined in terms of a planning perspective.

These issues are directly related to the strategic planning phase of freight transportation systems (Tavasszy, Browne & Piecyk 2024), and mainly to the design of the transportation network (Crainic, Gendron & Kazemzadeh 2022). The success of a transportation network, as in industrial and social systems, is based on the capabilities of the design and planning team to address the main needs and problems of the field, therefore defining the most suitable and adapted networks. In the context of healthcare distribution in remote areas, the use of unmanned vehicles seems a potential alternative. However, in the current works, unmanned vehicles are mainly analysed and modelled for urban and regional last-mile applications, or theoretical and conceptual models without a direct real applicability (Ahmed et al. 2022). However, analysing the potential of such systems should provide direct insight into developments on a practical level and can contribute on research level by identifying the main elements that define a healthcare unmanned distribution system as well as the decision-making problems related to the derived transportation network design.

This paper aims to propose a problem-solving methodology for designing and deploying UAVs last-mile distribution networks into medicinal supply networks, and more precisely a vaccine supply chain for a rural municipality in Colombia. This work is therefore considered to be field research, which answers to a set of practical needs using research methods and contributes to creating knowledge and methodological insight from a real problem-solving case. An abductive operations research method composed of a problem instruction phase, a modelling and problem-solving phase, and a solution validation phase is proposed. In this case, it includes a set of mathematical models that is able to support the implementation of the distribution of vaccines to remote areas by using UAVs and exploring other modes of transportation, such as river transport. Those models are solvable, using commercial tools and are allowed to define various vaccine supply scenarios in the considered area (the Municipality of Bahía Solano, Chocó and Colombia) and produce a set of results to validate the proposed solutions and methodology. The structure of this work is organised as follows: Firstly, a literature review related to the research topic is presented. Secondly the methodology and mathematical formulation of the location and distribution models are described. Thirdly, the analysis of the results of the different models and instances is discussed. Finally, the main conclusions are made, and further research suggestions are given.

Background and literature review

In Colombia, there is an important difference between rural and urban areas. Urban areas represent 77% of the population, whereas small towns and rural sparse areas only contain 7% and 16% of the population respectively, according to the 2024 national census.[1] Moreover, rural areas present important deficiencies in infrastructures, with small, poorly maintained roads. In fact, 39% of rural municipalities present important access problems (Así Vamos en Salud 2025). Furthermore, road infrastructures and accessibility are poor (Paz-Orozco et al. 2022), where limited road infrastructure imposes the use of fluvial and air transport that are not always in the best condition (Gonzalez-Feliu et al. 2021). Also, other infrastructures are deficient, as 59% of rural municipalities do not have a sewage system, and 20% of towns that do have, present a sewage coverage lower than 37%, which makes for a very low water sanitation infrastructure (Así Vamos en Salud 2025) and low educational rates (Peña-Orozco et al. 2023).

Another example is food insecurity. In rural areas, food insecurity accounts for more than 40% of the population and in the urban areas for around 25%. According to the Colombian National Department of Statistics (DANE 2025b), food security in Bogotá (the capital city) and its surroundings is lower than 20% and in the rural areas near the Caribbean Sea or the Amazonian region more than 40%. This leads to malnutrition problems, to delays in growth in children and other nutrition issues, which have a direct impact on the general health of populations, making them more prone to illnesses with regard to national means (DANE 2025a).

For those reasons, a set of actions based on three pillars, namely nutrition, health and education, was developed as part of a national programme over more than 40 years to support health, growth and social improvement of those sensible populations. Healthcare systems, strongly linked with nutrition, are the basis of rural development, and need to be efficient to sustain inclusive growth and social improvement of populations (Peña-Orozco et al. 2023). Those systems need to be managed and, to achieve viability thresholds, economies of scale are necessary, which benefit populated areas. However, rural areas need minimum service rates, a global management system; a cost-outcome system therefore needs to be deployed to ensure the effectiveness of the entire healthcare network (Espinosa et al. 2022). However, healthcare networks in rural areas are having difficulties: In 2024, about 37% of rural hospitals were in economic deficit in comparison to 17% in 2022 (Así Vamos en Salud 2025). Moreover, the concentration of general practitioners is very low, since only 0.5% of rural municipalities count for more than 100 general practitioners

1. For more information, visit: https://www.dane.gov.co/index.php/estadisticas-por-tema/demografia-y-poblacion/censo-nacional-de-poblacion-y-vivenda-2018/donde-estamos.

per 100 0000 inhabitants. This problem increases if we consider healthcare supply chains and the distribution of medicines and healthcare products to rural regions (Piñan & Bardales 2020).

The population who are mainly affected by this situation are rural inhabitants, and in this case, rural patients, who lack both specialised medicines (with longer times of supplies due to poor road infrastructures) and medical workforce (DANE 2025a). The problem is further enhanced by the need for a reduction in costs of the public healthcare system that needs to find a tradeoff between efficiency, via a centralisation of demand and resources, and service levels, with the overall goal of covering the entire population at national level, and also poses an optimisation problem (Espinosa et al. 2022).

Since the demand is not enough to justify it (on a cost basis), a capillary distribution of capabilities is impossible, and new organisations and logistics networks need to be developed to reach similar service levels, while reducing the overall logistics costs (Piñan & Bardales 2020). In fact, nowadays populations in rural areas are not justified, despite specific programmes and means, as a result of the physical barrier of the Colombian rural areas (lack of road infrastructure) and the sparce demand combined with the limited workforce. To that purpose, the definition of efficient healthcare supply systems based on UAVs could represent a potential solution to increase service levels (and global coverage), while not increasing (and even reducing) logistics costs (Gupta et al. 2021). This can take different forms and be of various natures; the main solutions to improve such systems in the world are related to the optimisation of current operations and the management of current resources (Bradley et al. 2017; Peña-Orozco et al. 2023), the re-design of the transportation (and supply) network (Crainic & Hewitt 2021) and the introduction of unmanned technologies to facilitate economies of scales when dealing with changing demand in small quantities but very frequently.

Healthcare distribution systems present a set of particularities that need specific transportation systems (Ananthakrishnan, Kaplan & Ng 2020). The first is the urgency of products as well as the poor anticipation capabilities of some needs (uncertainty, random nature of some illnesses). The second is the characteristics of healthcare products, which have a high heterogeneity in their availability, value, storage conditions and transport coverage needs, among others. For this reason, planning and optimisation methods that rely on problem solving have been studied for decades (Senna et al. 2023). The most widely used methods for the management of supply networks for medicines and supplies for humanitarian emergencies are mathematical optimisation models, such as linear, mixed, integer, and non-linear programming models; Markov chain models or queuing theory and simulation (Ahmadi-Javid, Seyedi & Syam 2017; Cassidy et al. 2019; Syahrir & Vanany 2015; Zgaya, Hammadi & Renard 2016).

Various examples of models and design methods for healthcare supply networks are seen in literature. Franco (2020) presents a system dynamics simulation model to symbolise the pharmaceutical supply chain in a hospital until delivery to the patient. Gómez, Salazar and Rincón (2019) worked on an optimisation model for reverse logistics of surplus medicines in the shortest period of time. Shi and He (2018) propose an optimisation model for the distribution of medical supplies after natural disasters. It is a two-dimensional model: time and cost. Shishebori and Babadi (2018) present an Mixed Integer Problem (MIP) model for designing a logistics network to supply medicine.

Regarding humanitarian logistics, disaster response and medicine, the implementation of drones or UAV has increased the distribution of supplies to areas that are difficult to access due to natural disasters as well as remote and rural areas where geography prevents the use of other vehicles (Scalea et al. 2018). Sanfridsson et al. (2019), Zègre-Hemsey et al. (2018) and Claesson et al. (2017) propose simulation models to compare the delivery time of automated external defibrillators (AED) using UAVs and emergency medical services completed tests for transporting organs by using UAVs between two hospitals. Mesar, Lessig and King (2018) finished a test to deliver life support medical supplies to a remote area using a multirotor UAV. Amukele et al. (2017) made pilots for the evaluation of the difference in the result of chemical and haematological tests transporting laboratory samples in UAVs.

Liu and You (2020) designed a mobile disaster response system to transport medical supplies by UAV to disaster areas in Puerto Rico. Jeong, Song and Lee (2019) did a multi-objective model to evaluate an airship vehicle, a UAV warehouse, to deliver humanitarian and health supplies in conflict and difficult-to-access areas. Chauhan, Unnikrishnan and Figliozzi (2019) present an integer linear model for UAV base location for humanitarian and medical supply delivery. Boutilier et al. (2017) designed a supply network integrating UAVs to transport AEDs to reduce response time. Pulver, Wei and Mann (2016) show an AED-equipped UAV launch network design. Kim, Jung and Rhim (2017) propose models of base location and the routing of UAVs for delivering and collecting medical supplies. Wen, Zhang and Wong (2016) present a multi-objective problem of routing trained vehicles to reduce distances and the number of UAVs used in the blood supply for areas with limited access.

Furthermore, various works deal with the use of unmanned vehicles in healthcare deliveries (Bridgelall & Tolliver 2024; Ghelichi, Gentili & Mirchandani 2021), mainly in the form of case studies to analyse the needs and main implications of using UAVs to deliver urgent medicines and healthcare supplies, and highlight the potential of such solutions, mainly when facing the lack of accessibility. Regarding unmanned transport systems, various works deal with the optimisation of these systems, but they are more related to urban deliveries and not focusing on healthcare products (Khoufi, Laouiti & Adjih 2019; Thibbotuwawa et al. 2020), and developing vehicle routing variants and algorithms, mostly meta-heuristics because of the non polynomial (NP)-hard complexity of the problem.

The introduction of new vehicles, like unmanned ones, implies a rethinking of the entire transport system. Freight transport systems can be defined as structures which function is to transport freight (Sarder 2020), composed by a demand, a set of vehicles, a network with a layout and a set of constraints (Crainic et al. 2023). To define and plan such systems, various methods can be used, in the function of the characteristics of the system and its planning horizon (Gonzalez-Feliu 2013; Russo & Comi 2023; Tavasszy et al. 2024). The strategic planning phase involves location and network design models and methods (Tavasszy et al. 2024), which have paid little attention in healthcare unmanned systems and are a crucial step in the development and planning of such networks. Moreover, the inclusion of unmanned vehicles changes the nature of the transport system by either changing its layout (Gonzalez-Feliu 2013) or some of its constraints, since unmanned vehicles imply a series of considerations that differ from classical distribution in terms of transport mode, capacities, autonomy and driving and security conditions (Gupta et al. 2021). For that reason, a modelling and optimisation method dealing with network design of unmanned healthcare transport systems will be proposed. It deals with a reality: the needs of vaccine distribution in remote areas of Colombia.

Methodology

To conduct this study, a mixed-methods research approach is designed. For the initial qualitative phase, surveys, semi-structured interviews, and field observation are used to collect the information in order to understand the operation of the drug supply network in the study region. In the second quantitative phase, data analysis techniques and mathematical modelling are used to design the distribution network.

Type of research, choice of the field, local background and general methodology

This research stems from a field project where community needs are examined and their decision problems are dealt with by means of research methods. In fact, it is a case of problem-solving field research (Ackoff 2004). This type of research, which was very popular in the 1980s–1990s, has in recent years become popular once again since companies and institutions face more incertitude, unexpected events and specificities for which decision problems need to be analysed case by case, and standard decision problems and models are not always adapted to the real field (Treffinger, Isaksen & Stead-Dorval 2023).

The field of research is the Municipality of Bahía Solano, Colombia. This municipality, located in the coastal region of Chocó on the Pacific side of the country, has an area of 1667 km² and has about 10 000 inhabitants, which makes for a very low population density (about 7 inhabitants per km²).[2] In terms of infrastructure and services, according to the Rural Health Index 2024 (Así Vamos en Salud 2025), sewage networks cover 53% of the built environment (close to the national mean, which is 57%), water supply and waste collection remain almost the same as the national means (82% and 60% respectively) but lacks important internet and gas infrastructures (18% and 1% respectively of the total number of deserved households). Mortality rates in children are about 2% (three times higher than the national mean) and vaccination coverage is about 90% with respect to the national mean (DNP 2022).

Although vaccination rates remain high, they are lower than the national means. Moreover, public authorities, in an attempt to reduce the children mortality rate, want to increase the vaccination supply in order to improve the podiatry healthcare system in the area. Since the area has a very low population density, it is important to find a solution to bring vaccines to most remote areas on time while the overall logistics costs are also contained. However, the decision problem is not simple and needs an abductive analysis (Gonzalez-Feliu & Gatica 2022), that is, a combination of problem structuring and instruction methods to well-identify the problem to be solved, and modelling and optimisation methods once the problem is defined in order to solve the problem.

To do this, a problem-structuring phase was firstly defined to identify, with the involved stakeholders, the main needs, issues and constraints related to the implementation of UAVs to deliver vaccines within the area. To structure the problem, a semi-structured interview campaign was carried out (Moreno Castro 2021). Those interviews were aimed at defining, for health institutions and public authorities, their current needs and supply schemes for vaccination up to childhood, and examining, according to the Corporate Planning Framework (Peña-Orozco et al. 2025), which identifies on the one side the needs and goals, and on the other side the resources (physical, informational, human, financial), the means (know-how), implementation (organisational issues) and control or evaluation elements. Those interviews also enquired on the current bottlenecks and constraints of the vaccine supply chain and the objectives that the new distribution network should have. In total, 40 interviews were conducted, which allowed for a statistical representativeness of the answers and is regarded as a high volume of interviews for a qualitative characterisation (Qu & Dumay 2011).

Secondly, with the results of those interviews, an objective function and a set of needs and constraints were defined, and then confirmed with a narrow set of selected stakeholders (the Municipality of Bahía Solano, the region of Chocó, the Central and Regional Department of Health and the main hospitals of the Municipality of Bahía Solano), which are the

2. Data for the characterization of the Municipality of Bahía Solano has been obtained from the Colombian National Department of Statistics (DANE), census 2020: https://www.dane.gov.co/.

core decision makers regarding the distribution of vaccines and are mobilised to validate and problematise the various outputs of the research to deal with abduction cycles in problem solving (Gonzalez-Feliu & Gatica 2022). Once the main components of the problem are defined and confirmed, the decision problem is modelled, with an aim to be closer to the field's needs and expectations. This was made possible by confirming the main elements of decision (objective function, decision variables and constraints) as well as via a second confirmation phase once the model was defined (Gonzalez-Feliu & Gatica 2022).

Thirdly, once the model was validated by the core key stakeholders, it was solved using a commercial tool. In fact, in order to deal with a practice problem, the use of commercial tools was preferred to the deployment of an ad hoc algorithm. According to Ackoff (2004), finding the right problem gives better results than solving a wrong problem optimally, since, if the solution to the right problem is not optimal, it can be further improved, but the main issues are identified; the solution is therefore suitable although non-optimal. Finally, and following the cycle of problem solving (Gonzalez-Feliu 2024), the obtained solution was verified and confirmed by the core key stakeholders and the model adapted, to be sure it represented their decision problem reality. With this three-phase methodology, it was possible to propose a solution for planning and managing vaccine deliveries by means of UAV's to the Bahía Solano municipal area.

Decision problem and network design mathematical formulation

This section presents the decision problem and its consequent model, related to the distribution of vaccines to the remote areas of the Municipality of Bahía Solano in the coastal region of Chocó, Colombia. For the first time, a description of the system and the main issues in the distribution of vaccines are presented on the basis of the collection of qualitative data and the analysis of the data in the context of the problem instruction phase. In the national healthcare system, the region of Chocó is serviced from a unique warehouse located at Quibdó (which is very accessible by road and well-integrated in the national healthcare logistics network). The distance between Quibdó and Bahía Solano is not far (about 100 km[3]), but Bahía Solano is not connected to the national road network (only very narrow roads, mainly for internal connections, are present in the area); therefore, vaccine distribution needs to take place by means of air transport (Moreno Castro 2021). At the main centre of Bahía Solano, final distribution has traditionally been made by means of road transport, but this type of transport takes nearly a day to reach remote regions due to the lack of suitable road infrastructure. The main urban centre of the area also does not have the necessary infrastructure (mainly in the form of controlled temperature facilities) to store vaccines. The municipality therefore aimed to examine the possibility of implementing UAVs for the final deliveries of vaccines to the different populated centres of the area.

The distribution network resulting from the considerations for the delivery of vaccines via UAV in the transport network with distances that were calculated by using DANE's geoportal (https://geoportal.dane.gov.co).

The vaccine delivery starts from Quibdó (considered as the unique depot for the distribution system) and reaches the Municipality of Bahía Solano by plane. At this location, a consolidation hub is defined to split the shipment of planes into final deliveries in order to supply the populations in inaccessible zones. This hub has low to no inventory capabilities, that is, it is aimed at transshipping goods (Gonzalez-Feliu 2012). Then, from the hub in Bahía Solano, the vaccines are delivered to the remote areas (townships and villages) by means of UAVs. The system is a three-echelon distribution system (Diks, De Kok & Lagodimos 1996) with a single depot, a single hub and a two-stage plain-UAV transport network, being one of the rare origin-to-destination pure air transport systems.

The first issue regarding the decision problem is to identify the goal of the involved stakeholders and then define a suitable objective function. The focus of the Colombian Department of Health and its regional division is mainly to reduce the overall duration of the distribution of vaccines, following the guidelines of the Expanded Immunisation Programme (PAI in Spanish) of the public health programme (García et al. 2014). This aims to reduce the suffering of the populations involved. In fact, the PAI establishes a vaccination scheme that mainly includes boys and girls up to 9 years old, pregnant women and women of childbearing age as well as adults aged 60 years and older representing the demand to be met. The programme covers 14 different types of vaccines that, in turn, have other presentations.

In the definition of the vaccine distribution network, it became evident from the interviews that the main needs of this system are to define suitably a good set of vehicles to ensure the operations, and to locate the operation bases, which will in turn define a network. Once the network is defined, it is possible to construct the delivery routes. Therefore, three different models are proposed for the distribution of vaccines. Firstly, a transportation model that determines the number of vehicles or routes needed to meet the total demand in the shortest period of time. This model is similar to a resource allocation problem but needs to consider the specificities of the network in terms of demand density and the main strategic decisions of the stakeholders involved. Secondly, a UAV launch base localisation model that maximises demand coverage, which derives from well-known facility location problems but is adapted for the context of UAVs. Finally, a UAV launch base localisation model that minimises the distance travelled from the bases to the demand points. This second model complements the first, since it starts from an ensured demand coverage and adapts the network to reduce the distances travelled, which being aerial distances, are directly transformable in times since no road traffic is considered. Loading and unloading

3. For more information, visit: https://atlas.co/explore/countries/colombia/.

times are considered to be very similar for each vehicle; they therefore do not impact the overall optimisation.

Since the main focus at this stage is to define the assignment of transport flows between each origin and its destination, the proposed model is derived from the well-known transportation problem in its two-stage version (Gonzalez-Feliu & Gatica 2022). This model can be defined as follows: In a healthcare supply system, since it is a logistics system, needs are directly related to demand. Demand, as shown in the interviews, is uncertain and sparse, although it follows some patterns and, regarding vaccination, can be periodically planned. This demand leads to vaccine needs in quantities, locations and times. To supply the vaccines, the supply system has a set of capacities (related to the vehicles but also to the warehouses and platforms used for the supply). Consequently, the following parameters are defined; see below, specifying the symbols and notations being used.

General model parameters

The general model parameters are as follows:

1. OFQ_j be the vaccine supply capacity at type *j* provider,
2. CBA_k be the vaccine storage capacity in type *k* intermediary,
3. TTR_{jkv} the travel time from supplier in location *j* to intermediary in location *k* by vehicle type *v*,
4. VE_v be the load capacity of vehicle type *v*,
5. D_{lm} be the vaccine demand in the remote areas *l* and of vaccines of type *m*;

Unmanned aerial vehicle transport parameters

The unmanned aerial vehicle transport parameters are as follows:

1. CV_t be the load capacity of the UAV vehicle of type *t*,
2. AT_t be the autonomy of flight of the vehicle UAV of the type *t*,
3. TR_{klt} be the travel time from the intermediary in location *k* to the remote area *l* by the UAV vehicle type *t*,
4. *B* be the number of bases for UAV to locate,
5. *M* be the maximum number of UAV,
6. COV_{kl} be the binary coverage matrix from remote area *k* to remote area *l*;

Current means of transportation parameters

The current means of transportation parameters are as follows:

1. TR_{klt} be the travel time from the intermediary in location *k* to the remote area *l* by the boat vehicle type *t*,
2. CV_t be the load capacity of the boat vehicle of type *t*,
3. AT_t be the autonomy of navigation of the boat vehicle of the type *t*.

Transportation model formulation

After defining the main parameters, the distribution network is defined, which is represented by a directed graph with various types of nodes, grouped in different sets. The referential sets are:

1. $J = \{J1, J2 \ldots Jn\}$, the set of providers of type *j* vaccines;
2. $K = \{K1, K2 \ldots Km\}$, the set of intermediate nodes where vaccines of type k are stored;
3. $L = \{L1, L2 \ldots Lo\}$, the set of townships, communities or villages that demand type *l* vaccines;
4. $T = \{T1, T2 \ldots Tq\}$, the set of means of transport of type *t* to distribute vaccines in the last mile;
5. $V = \{V1, V2 \ldots Vs\}$, the set of means of transport of type *v* to distribute vaccines from the supplier to the intermediary;
6. $M = \{M1, M2 \ldots Pr\}$, the set of the type of vaccines that must be supplied to meet the demand for type *m*;
7. $P = \{P1, P2 \ldots Pu\}$, the set of periods in which the UAV vehicles are launched to distribute vaccines in the last mile of type *p*.

The decision variables defined with the key stakeholders are two types since the distribution network has three echelons; therefore, two transport stages are indicated. Each variable relates to a number of trips for each of the transport stages, as follows:

1. RQ_{jkv}, the number of trips from supplier type *j* to intermediary type *k* by vehicle type *v*;
2. RC_{kltp}, the number of journeys from the intermediary type *k* to the remote areas type *l* by vehicle type *t* in the period *p*.

Optimisation model

Once the different parameters, sets and variables of the decision problem (represented as a directed graph) are defined, the optimisation model can be constructed. This leads to the definition of an objective function and a set of constraints, as detailed below. Although different objective functions can be defined, the key stakeholders agreed that the main goal with this problem was to reduce the waiting time of the patients; therefore, decreasing the overall distribution time was the most suitable objective function. In the discussion that follows, there will be possibilities of extending this objective function but in the first version of the model, and according to key stakeholders' feedback, time minimisation was consensually chosen as the most suitable objective for the decision problem.

Objective function:
See Equation 1:

$$Min \sum_{j=1}^{n}\sum_{k=1}^{m}\sum_{v=1}^{s} RQ_{jkv} * TTR_{jkv} + \sum_{k=1}^{m}\sum_{l=1}^{o}\sum_{t=1}^{q}\sum_{p=1}^{u} RC_{kltp} * TR_{klt} \qquad \text{[Eqn 1]}$$

Subject to (see Equations 2, 3, 4, 5, 6, 7 and 8):

$$\sum_{j=1}^{n}\sum_{v=1}^{s} RQ_{jkv} * VE_v \geq \sum_{l=1}^{o}\sum_{m=1}^{r} D_{lm} \qquad \forall k \in K \qquad \text{[Eqn 2]}$$

$$\sum_{k=1}^{m}\sum_{v=1}^{s} RQ_{jkv} * VE_v \leq OFQ_j \qquad \forall j \in J \qquad \text{[Eqn 3]}$$

$$\sum_{j=1}^{n}\sum_{v=1}^{s} RQ_{jkv} * VE_v \le CBA_k \qquad \forall k \in K \qquad \text{[Eqn 4]}$$

$$\sum_{k=1}^{m}\sum_{t=1}^{q}\sum_{p=1}^{u} RC_{kltp} * CV_t \ge D_{lm} \qquad \forall l \in L \qquad \text{[Eqn 5]}$$

$$\sum_{k=1}^{m}\sum_{l=1}^{o} RC_{ktlp} * TR_{klt} \le AT_t \qquad \forall t \in T, \forall p \in P \qquad \text{[Eqn 6]}$$

$$RC_{kltp} \in \mathbb{Z}^+ \qquad \forall k \in K, \forall l \in L \quad \forall t \in T \quad \forall p \in P \qquad \text{[Eqn 7]}$$

$$RQ_{jkv} \in \mathbb{Z}^+ \quad \forall k \in K, \ \forall l \in L \quad \forall t \in T \qquad \text{[Eqn 8]}$$

The objective function (Equation 1) minimises the total transport time between all nodes to meet the area demand. In Equation 2, the model is forced to activate the link from Quibdó to Bahía Solano. Equation 3 limits the supply of vaccines found in Quibdó (facility for the vaccines's production and storage). Equation 4 complements the previous one and guarantees that the units shipped to Bahía Solano (where the main hub is situated) are less than their storage capacity. Equation 5 guarantees that the tours cover all the demands for each vaccine. Equation 6 limits the routes of UAVs according to their maximum flight autonomy, and Equation 7 and Equation 8 are integer constraints of the variables.

Location models

After defining the first model for identifying the main transport flows and volumes, and the dimension of the distribution network, the service parameters and settings of this network need to be defined. This leads mainly to locating the different infrastructures and transshipment points, since both vehicles and flows are defined in the first model; two models of discrete facility location will therefore be considered. The first is coverage maximisation, that is, aiming (as defined as main goal for this stage) to maximise the total territorial coverage by vehicles in order to vaccinate the maximum number of households as this point was the major one highlighted in the interviews. To be more precise, a maximum coverage location problem (MCLP) model has been proposed (Güneş, Melo & Nickel 2019), with the number of maximum UAV launch bases to be established as a constraint. The second model is a distance reduction model and is designed as the P-Centre Location Problem (PCLP) model in such a way as to minimise the maximum distance between any user and their assigned facility (Laporte, Nickel & Saldanha-da-Gama 2019), where the number is also restricted. These models are described from Equation 9–22.

The referential sets are:

1. $K = \{K1, 12 \dots Km\}$, set of townships that can be selected as K-type UAV launch bases;
2. $L = \{L1, L2 \dots Lo\}$, the set of townships, communities, and/or villages that demand type l vaccines;
3. $T = \{T1, T2 \dots Tq\}$, the set of UAV means of transport of type t to distribute vaccines in the last mile;
4. $M = \{M1, M2 \dots Pr\}$, the set of the type of vaccines of type m that must be supplied to meet the demand;
5. $P = \{P1, P2 \dots Pu\}$, the set of periods in which the UAV vehicles are launched to distribute vaccines in the last mile.

The decision variables are:

1. $X_k = \left\{\dfrac{1 \ \text{if the remote area } k \text{ is selected as a base}}{0 \ \text{otherwise}}\right\}$
2. $Y_{lk} = \left\{\dfrac{1 \ \text{if the area } k \text{ covers the area l}}{0 \ \text{otherwise}}\right\}$
3. ND_{tk}, the number of UAV vehicles of type t that must be in each selected base in the district k,
4. RC_{kltp} the number of journeys from the selected base in the type k district to the type l districts in the vehicle type t in the period type p.

Optimisation model of maximum coverage

After defining the various parameters, sets and variables of the decision problem, the set covering maximisation model is proposed. This leads to the definition of an objective function and a set of constraints, as detailed below. Regarding the objective function, since the aim is to cover the maximum territory possible, a set of transport paths that reach the maximum number of delivery points is proposed, as indicated in Equation 9.

Objective function:

$$Max \sum_{k=1}^{m}\sum_{l=1}^{o}\sum_{m=1}^{r} Y_{lk} * D_{lm} \qquad \text{[Eqn 9]}$$

Subject to (see Equations 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21 and 22):

$$\sum_{k=1}^{m} X_k \le B \qquad \text{[Eqn 10]}$$

$$Y_{lk} \le X_k * COV_{kl} \qquad \forall k \in K \quad \forall l \in L \qquad \text{[Eqn 11]}$$

$$\sum_{k=1}^{m} Y_{lk} \le 1 \qquad \forall l \in L \qquad \text{[Eqn 12]}$$

$$\sum_{k=1}^{m} X_k * COV_{kl} \ge 1 \qquad \forall l \in L \qquad \text{[Eqn 13]}$$

$$\sum_{m=1}^{r}\sum_{l=1}^{o} D_{lm} * Y_{lk} \le \sum_{t=1}^{q} ND_{tk} * CV_t \qquad \forall k \in K, \forall p \in P \qquad \text{[Eqn 14]}$$

$$\sum_{t=1}^{q} ND_{tk} \le M * X_k \qquad \forall k \in K \qquad \text{[Eqn 15]}$$

$$\sum_{k=1}^{m}\sum_{t=1}^{q}\sum_{p=1}^{u} RC_{kltp} * CV_t \geq \sum_{k=1}^{m}\sum_{m=1}^{r} D_{lm} * Y_{lk} \qquad \forall\, l \in L \qquad \text{[Eqn 16]}$$

$$\sum_{l=1}^{o} RC_{kltp} * CV_t \leq ND_{tk} * CV_t \qquad \begin{matrix}\forall\, k \in K\\ \forall\, t \in T\\ \forall\, p \in P\end{matrix} \qquad \text{[Eqn 17]}$$

$$\sum_{k=1}^{m}\sum_{l=1}^{o} RC_{ktlp} * TR_{klt} \leq AT_t \qquad \begin{matrix}\forall\, t \in T\\ \forall\, p \in P\end{matrix} \qquad \text{[Eqn 18]}$$

$$X_k \in \begin{Bmatrix} 1 \\ 0 \end{Bmatrix} \qquad \forall\, k \in K \qquad \text{[Eqn 19]}$$

$$Y_{lk} \in \begin{Bmatrix} 1 \\ 0 \end{Bmatrix} \qquad \begin{matrix}\forall\, k \in K\\ \forall\, l \in L\end{matrix} \qquad \text{[Eqn 20]}$$

$$RC_{kltp} \in \mathbb{Z}^+ \qquad \begin{matrix}\forall\, k \in K\\ \forall\, l \in L\\ \forall\, t \in T,\\ \forall\, p \in P\end{matrix} \qquad \text{[Eqn 21]}$$

$$ND_{tk}\ \varepsilon\ \mathbb{Z}^+ \qquad \begin{matrix}\forall\, k \in K\\ \forall\, t \in T\end{matrix} \qquad \text{[Eqn 22]}$$

The objective function (Equation 9) maximises the demand covered by the selected bases. Equation 10 limits the number of bases to open. Equation 11 establishes that district l is covered by district *k* if and only if district *k* is selected to locate a base and is within the defined coverage range. Constraint (Equation 12) assigns or does not assign type 1 demand districts to some selected districts as a base; Equation 13 defines that all the opened bases have set at least one demand point. Equation 14 limits the attention capacity of each base to be selected, given the number of UAV vehicles available in the base. In Equation 15, the maximum number of UAV vehicles for the operation is restricted, keeping in mind that they are a limited resource. Equation 16 guarantees that if the demand type *l* is assigned to some bases, all its demands will be met with the routes to be carried out. Equation 17 verifies that the capacity of each base is not exceeded, and Equation 18 limits the routes to be carried out by each UAV according to its flight range. Equations 19–22 are integrality constraints of the variables.

Optimisation model of minimum distance

For this model, the same referential sets of the previous model are handled; similarly, the parameters are kept constant, since it remains the same type of model (a location model) but with a different objective function (Saldanha-da-Gama 2022). In fact, in this final model, the main goal is difference, since it aims at reducing costs. The objective function is regarded by the interviewees as a cost reduction function; therefore, the main goal in the final model for planning the routes once the levels of services are set is reducing costs. The transport costs are directly linked to the distance travelled, mainly when dealing with interurban or rural transport systems (Russo & Rindone 2007). The distance parameter must therefore be included for this case, and the objective function and one of the system constraints must be modified, as presented below. As stated above, other objective functions can be defined but the current practices as well as the needs and goals of the stakeholders involved (evident in the interviews) highlight cost reduction as priority above other objectives. However, other possibilities of objective function will be discussed in the conclusion.

Let DIS_{kl} be the distance in kilometers from the township *k* to the township *l*.

Objective function (see Equation 23):

$$Min \sum_{k=1}^{m}\sum_{l=1}^{o}\sum_{p=1}^{u}\sum_{t=1}^{q} RC_{kltp} * DIS_{kl} \qquad \text{[Eqn 23]}$$

Finally, Equation 14 is modified by Equation 24, and the coverage model for other equations remain the same.

$$\sum_{k=1}^{m} Y_{lk} = 1 \qquad \forall\, l \in L \forall \qquad \text{[Eqn 24]}$$

The objective function (Equation 23) seeks to minimise the total distances travelled that are necessary to meet the township demand from the townships selected as the UAV launch base. Equation (6–24) guarantees that all demand points are covered by one of the established bases.

Additional definitions:

- A route (Re) refers to the round trip in which a UAV leaves the launch base in Bahía Solano, goes to one of the townships to supply the vaccine demand, and returns to the base of operation.
- A launch (La) is when a UAV takes off from the base.
- A base departure (SB) is when the boat leaves the operation.
- The flight time (TV) is the total sum of the time that all UAVs operate on all the necessary routes.
- The navigation time (TN) is the total sum of the time that all the boats operate on all the necessary routes to meet all demands (active navigation hours).
- The setup time (TA) includes loading the routes in the GPS, the programming of the vehicles for each launch, and the loading and unloading time of the vehicles.
- The launch time (TL) is determined by the vehicle that makes the largest number of trips and covers the largest distance.
- The recharge time (TR) takes about 1 h (60 min). For models with motorboats, this time corresponds to the refuelling time.
- The operation time (TO) for vaccine distribution is defined as the total real-time (calendar days) necessary to deliver all vaccines in all townships. (TO = TA + TL + TR)

- Total supply time (TS): This time represents the total time for the distribution of vaccines in the entire supply (TS = TO + TBQ).

Results and discussion

The model description is shown in Table 1. Initially, the transport model that simulates the current distribution scheme in the Municipality of Bahía Solano for extramural vaccination days is shown. This model presents the results with the existing and proposed means of transport in the municipality.

Likewise, a sensitivity analysis is carried out to reduce the uncertainty of the model input information and evaluate the system performance and behaviour under these different conditions.

The sensitivity analysis is based on a second instance of the previous models, where one of the parameters is modified, but the formulation stays the same. This analysis only applies to UAV models since they can be changed and optimised according to the goals of this work. The sensitivity analysis is done by changing the autonomy parameter of UAVs.

Table 2 shows a summary of the results obtained in each of the models presented above, where the flight time (TV) or navigation time (TN) and the total operating time (TO) are compared.

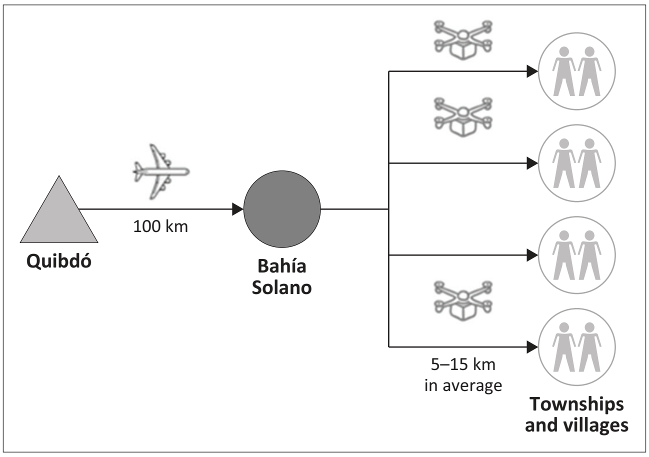
The analysis of results is presented in two steps. The first step compares the models in which UAVs are used, starting with the two locations, and then transport Model 2 is included. The second step considers the model with UAV that has the best performance. The results are compared with the model that considers the use of motorboats and represents the current distribution situation. The section from Quibdó to Bahía Solano cannot be modified because the only connection is by air, and the time is similar for all cases.

When prioritising broad demand coverage and minimized distances by selecting Ciudad Mutis (the nearest township to Bahía Solano) as the UAV launching base, Models 3 and 4 show no significant difference from the current vaccine distribution model in the municipality.

Additionally, Model 4, which aims to reduce the total travel distances, reduces the TO, TV, La and Re necessary to supply the demand, as seen in Figure 1. In contrast, Model 3 does not seek to optimise the routes only to meet the demand. Model 4 reduces the distance by 7.86% and reduces the total operating time (TO) by 11.1% compared to Model 3. About La and Re, Model 4 needs 5 LA and 9 Re less than Model 3 because Model 4 looks for the best combination of routes to reduce the distances in total.

Model 2 is the only one that uses the 3 UAVs and is the model that generates longer trips since it travels 177 km more than Model 3 and 296 km more than Model 4.

Although these three models are based in Ciudad Mutis, which is the central point for all the townships, Model 2 is the model that generates the shortest operating time (TO), as seen in Figure 2. The shorter operating time is the result of the model



Source: Adapted from Moreno Castro, C., 2021, *Modelo para la distribución de medicamentos a comunidades en zonas apartadas de la región costera del departamento del Chocó, Colombia*, Tesis de Maestría, Universidad Nacional de Colombia, Bogotá; distances were estimated with the assistance of the regional Department of Health and official Colombian data

Note: Distances were calculated by using DANE's geoportal: https://geoportal.dane.govco/#gsc.tab=0.

FIGURE 1: The proposed distribution network.

TABLE 1: Proposed models for vaccine distribution.

Models set	Instance description
Transport model	Model 1, Instance 1: Non-dedicated transport model that reduces the navigation time of motorboat-type vehicles
	Model 2, Instance 1: Non-dedicated transport model that reduces the total flight time of UAV vehicles
	Model 2, Instance 2: Non-dedicated transport model with maximum flight autonomy that reduces the total flight time of UAVs
Localisation model max coverage	Model 3, Instance 1: UAV vehicle base location model that maximises demand coverage with non-dedicated transport
	Model 3, Instance 2: UAV vehicle base location model with maximum flight autonomy, which maximises demand coverage with non-dedicated transport
Localisation model min distance	Model 4, Instance 1: UAV vehicle base location model that minimises the distance travelled with non-dedicated transport
	Model 4, Instance 2: UAV vehicle base location model with maximum flight autonomy that minimises the distance travelled with non-dedicated transport

UAV, unmanned aerial vehicles.

TABLE 2: Results for Models 1, 2, 3, 4, Instance 1.

Model	Base	#launches (La)	#Routes (Re)	#vehicles 2nd stage	TV/TN (h)	TO (h)	TS (day)	Distance (km)
1	Mutis airport	5	17	1 boat	12	18.6	2	272
2	Mutis airport	16	83	3 UAV	45	59	5	1690
3	Mutis airport	39	84	2 UAV	40.2	99.2	9	1513
4	Mutis airport	34	75	2 UAV	37.1	87.7	8	1394

Source: Moreno Castro, C., 2021, *Modelo para la distribución de medicamentos a comunidades en zonas apartadas de la región costera del departamento del Chocó, Colombia*, Tesis de Maestría, Universidad Nacional de Colombia, Bogotá

Note: The base of each model was the José Celestino Mutis Airport of Ciudad Solano.

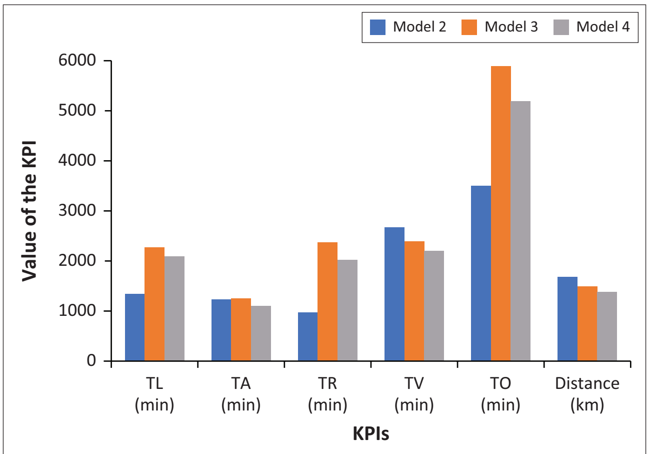
TV, flight time; TN, navigation time; TO, total operating time; TS, total supply time; UAV, unmanned aerial vehicle.

having an objective function of time reduction and using all the resources (3 UAVs) that are available for the operation. For these reasons, it needs to perform fewer launches, which significantly reduce the recharging time of the vehicle batteries (TR). The configuration of the routes also makes the launch time (TL) shorter. In this way, the total operation time (TO) for the distribution of vaccines is the minimum.

The TL in Model 2 is reduced by 40.4% compared to Model 3, and 35% to Model 4. The TR decreases by 60% and 53% in Model 2, in comparison to Models 3 and 4 respectively. The TO reduces by 40.5% and 33% in Model 2, in comparison to Models 3 and 4 respectively. These results indicate that Model 2 is the best scheme to distribute vaccines in Bahía Solano among the models presented using UAVs.

When comparing the results of Models 1 and 2, which represent the current vaccine distribution scheme, it is evident that it is more efficient to continue using the existing means of transport in the municipality. Since motorboats have a considerably greater transport capacity than UAVs, they generate fewer trips, making them more efficient for operation in terms of time and distance.

In this instance, time and distance are directly related to the number of trips being made. Similarly, there are significant reductions in the operation time. Model 1, in comparison to



TL, launch time; TA, setup time; TR, recharge time; TV, flight time; TO, total operating time; KPI, key performance indicators.

FIGURE 2: A comparison of results between Models 2, 3 and 4.

Model 2, reduces the total time of the distribution day (TO) by 67.7%, the total time in which the vehicles are in motion (TN, TV) by 73.3%, and the distance travelled by 83.9%.

Table 3 compares the results between Instances 1 and 2 of Models 3 and 4. Here, it is evident that, by increasing the autonomy of UAVs, the time of the operation is reduced by 22% (TO) and 36% of the distance travelled.

Regarding Model 3, despite having the same number of UAVs in operation, the total operating time (TO) is reduced by 14% by increasing the autonomy of UAVs. In this regard, the distance being travelled increases by 11%. However, in Instance 2, the TV increases by 23% because longer trips can be made by increasing their autonomy.

Regarding Model 4, by increasing the autonomy of UAVs, the total operating time (TO) is reduced by 33% and the distance travelled by 23%.

In terms of TO and distances travelled, Instance 2 of Model 2 is the model that performs best, which makes it the best model for vaccine distribution in the municipality. However, the difference in the performance between Instance 2 of Model 2 and Instance 2 of Model 4 is not very huge. Also, Instance 2 of Model 4 reduces the distance travelled and days of operation by 37%, in comparison to Instance 2 of Model 3, which seeks to maximise coverage. In Instance 2 of Model 4, the total operating time is reduced by 2 days and 36% of the distance travelled in comparison to Instance 2 of Model 3, as seen in Figure 3, due to the difference in operating times.

When comparing these results with the initial instances of the models, it is notable that performance measures are reduced by increasing the autonomy of the UAVs. Model 2 is the model that performs the best with Instance 2 being the model that reduces the OT for the distribution of vaccines in the municipality the most.

However, despite the significant reductions in time, it is still better for the municipality to continue distributing vaccines by means of transport by boat.

TABLE 3: A comparison between Instances 1 and 2 of Models 2 and 3.

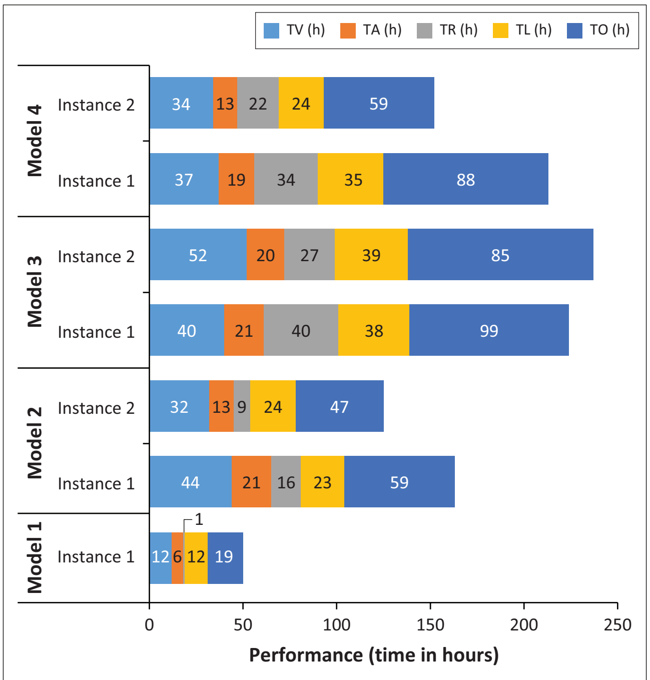
Indicator	Model 2		Model 3		Model 4	
	Instance 1	Instance 2	Instance 1	Instance 2	Instance 1	Instance 2
Base	Mutis airport	Mutis	Mutis	Mecana	Mutis	Mutis
La	16	9	39	27	34	22
Re	83	53	84	78	75	52
Vehicles	3 UAV	3 UAV	2 UAV	2 UAV	2 UAV	2 UAV
TV (min)	2662	1936	2412	3130	2226	2040
TA (min)	1245	795	1260	1170	1125	780
TR (min)	960	540	2400	1620	2 40	1320
TL (min)	1364	1460	2292	2316	2102	1440
TO (min)	3569	2795	5952	5106	5267	3540
Distance (km)	1690	1086	1513	1699	1394	1075

TV, flight time; TA, setup time; TR, recharge time; TL, launch time; TO, total operating time; UAV, unmanned aerial vehicle; La, launch; Re, route.

Finally, we have Instance 3 of Model 2, where intermodal transport is accepted. The results of this instance show that the total operating time (TO) is significantly reduced. This finding agrees with Gunaratne et al. (2022), where intermodality shows essential benefits in transportation costs and higher utilisation. In this instance, for the last-mile transportation, one UAV and a boat must do three launches and departures from the base located in Ciudad Mutis to meet the demand.

During these launches, 19 corresponding trips are made to each township. In this model, the UAV is used for 83% of its flight autonomy, while the boat is used for between 80% and 97% of its navigation autonomy. Instance 3 is the model that generates the best total operating time (TO) among the instances of Model 2, as seen in Table 4.

According to these results, the best way to distribute vaccines in the Municipality of Bahía Solano is through intermodal transport, that is, by river, the maritime mode,



UAV, unmanned aerial vehicle; TV, flight time; TA, setup time; TR, recharge time; TL, launch time; TO, operation time.

FIGURE 3: A comparison of results between all unmanned aerial vehicle models.

TABLE 4: A comparison between Instances 1, 2 and 3.

Indicator	Instance 1	Instance 2	Instance 3
Base	Mutis airport	Mutis	Mutis
La	16	9	3
Re	83	53	19
Vehicles	3 UAV	3 UAV	1 UAV – 1 boat
TV (min)	2662	1936	616
TA (min)	1245	795	345
TR (min)	960	540	30
TL (min)	1364	1460	466
TO (min)	3569	2795	841
Distance (km)	1690	1086	268

TV, flight time; TA, setup time; TR, recharge time; TL, launch time; TO, total operating time; UAV, unmanned aerial vehicle; La, launch; Re, route.

and UAVs. Combining these two modes makes it possible to significantly reduce the total operating time by configuring distribution times only with boats or UAVs. This study corroborates the benefits of intermodality when designing UAV-based distribution systems as a result of the potential to significantly improve healthcare supply chain performance, as shown in Gunaratne et al. (2022) and Javaid et al. (2022).

Conclusions and further research

General conclusion

This research proposes a set of models for distributing drugs that are of interest in public health (vaccines) through mathematical formulation to optimise resources and reduce distribution times. Unmanned aerial vehicles are included for last-mile transportation to remote regions of the Municipality of Bahía Solano. Similarly, intermodality with boats, currently the region's most used means of transport, is allowed. The research regards the decision problem of inserting UAVs in a rural vaccine supply system as a sequence of three independent, but connected decision problems, which derives from three proposed models: a transportation model to define the vehicle needs, a set covering a maximisation model to define the service levels of the supply chain and a cost optimisation location problem for the strategic and tactical planning of deliveries.

Of all the models presented using UAVs for transport, the transport model performs the best, measured by the total time of distribution of the vaccines to all the townships and indigenous reservations of the municipality. Instance 3 of this model, which allows intermodality, shows results that reduce the total distribution time between 70% and 76% compared to the exclusive use of UAVs.

These results are compared with the simile of the current operation, where the only means of transport in the municipality takes place by boat. Intermodality reduces the distribution time by 25% and the total distance by 20% travelled, improving accessibility and availability of medicines to remote and rural populations. In this way, it is assumed that intermodality could also reduce supply costs and increase coverage rates on each vaccination day.

Contributions to theory and practice

The contribution to theory and methodology arises from the deployment of abductive reasoning in operations research, which can establish the bases of what is conceptually advocated in Gonzalez-Feliu and Gatica (2022) and partially developed in Peña-Orozco et al. (2025). By combining a problem instruction method (based on a qualitative analysis using interviews) and a model validation method, it was possible to identify and define the planning problem of the field of study, which can then be generalised to healthcare logistics but also to a more general topic, namely the inclusion of UAVs into existing transportation networks. The inclusion of these vehicles into existing networks implies a reorganisation of the entire network. In this regard, this work defines three main decision problems (and not only one), which are interconnected. This makes an important contribution to the theories on purposeful decision systems (Ackoff & Emery 2005): A first decision is related to the identification of needs in terms of vehicles for each transport stage, a second concerns the covering of the territory followed by a first systemic organization of the network, and finally the optimisation of this network, which leads to a third decision concerning the service parameters of the network. In this context, the resulting three models compose a network design problem in three stages, which completes existing literature in the subject (Crainic & Hewitt 2021).

The contribution to practice is direct, since the research is field-based and problem-solving in nature, and was developed to deal with a real decision problem: the optimisation and improvement of a rural healthcare supply system. By deploying a problem-solving method that starts from a field and responds to a decision problem, which is identified and validated within the field, the resulting methods and solutions can directly be applied in practice. In fact, the stakeholders involved in the solution validation phase remained satisfied with the models and results proposed, and currently, the deployment of this type of vehicles is being investigated and considered.

This method and the resulting network can also be generalised to other healthcare systems, not only when responding to an emergency but also as a result of its reduced costs and relatively easy management, and has good results with high efficiency in extreme rural conditions (Paz-Orozco et al. 2022; Peña-Orozco et al. 2023) where there is a need for new methods and schemes, and shows how technologies Comi and Russo (2022) can be used in synergy to increase the efficiency of integrated freight transport systems.

Recommendations

In this work, the objective functions used need to be examined. Here, the objective of each model is fixed and validated with the involved stakeholders according to their current needs and goals, but it could evolve to include possible other scenarios or the impacts could be analysed to consider other goals, such as increasing equity, minimising environmental impacts, increasing social value or employment opportunities, or valorising territorial competencies, among others. Although the definition of generalised cost functions is a popular issue, it has an important limitation: generalised costs are in general weighted sums where weights are difficult to be obtained in an objective way; similarly, quantitative and rigorous data to fix and validate those weights is just as difficult to obtain. Instead of generalised cost functions, multi-objective or goal programming approaches (which do not sum weight but respectively aim to optimise each objective separately while not penalising the other objectives and reach the maximum number of goals) seem more appropriate for the real decision problem in our abductive operations research perspective.

Another recommendation refers to the application of the abductive reasoning of operations research, which leads to defining the right problems in order to have problem-solving methods that are context and field based. This does not mean that objective function types or standard unitary constraints cannot be defined, but when trying to solve a problem, the characterisation of the context and the definition of the right problem in terms of goals, needs, resources, means (and then constraints) are essential to achieve a suitable solution in order for the decision makers to make the right choices.

Future research

For future research, it is recommended that a pilot study of the use of UAVs is carried out in the study area, which allows for refining the parameterisation of the models since the calculation of speed, autonomy, transport capacities and flight time may vary.

It is also recommended that the transportation of health personnel, who carry out vaccinations and carry other supplies that may be required, be included. In these cases, the proposed models can be modified by using multi-criteria optimisation techniques and methods to achieve several objectives in a single model. Similarly, future research is expected to consider models that involve all levels of the supply chain in the country.

Acknowledgements

This article includes content that overlaps with research originally conducted as part of Catalina Moreno Castro's master's thesis entitled 'Modelo *para la distribución de medicamentos a comunidades en zonas apartadas de la región costera del departamento del Chocó, Colombia*', submitted to the Universidad Nacional de Colombia, Faculty of Engineering, Department of Systems and Industrial Engineering, SEPRO in 2021. The thesis was supervised by Carlos Osorio-Ramírez. Portions of the data, analysis and/or discussion have been revised, updated and adapted for journal publication. The original thesis is publicly available at: https://repositorio.unal.edu.co/bitstream/handle/unal/79712/1018474048.2021.pdf?isAllowed=y&sequence=6. The author affirms that this submission complies with ethical standards for secondary publication, and appropriate acknowledgement has been given to the original work.

Competing interests

The funding mentioned was granted by the Colombian Ministry of Science and Technology and Innovation to finance the broader research project that provided the framework and resources for Catalina's thesis work. While the thesis was a key output of this funded project, the financial support was

not designated for: (1) this specific journal publication nor (2) exclusively to Catalina in a personal capacity.

Authors' contributions

C.O-R. is the corresponding author. He has written the main part of the manuscript, managed the research and supervised C.M.C.'s work. C.M.C. has done most of the research for her Master's degree. This Spanish document forms the basis of this article. J.G.F.'s contribution focused mainly on methodological conceptualisation and guidance, model and data collection validation processes and data analysis. He also wrote part of the methodology section and reviewed the final manuscript critically. A.C.'s contribution is reflected in his knowledge of and expertise in UAV transportation and distribution, the validation of the results, the literature and critical review of the paper and the general improvement of the manuscript.

Ethical considerations

Ethical clearance to conduct this study was obtained from the SEPRO, Universidad Nacional de Columbia.

Funding information

This work was funded by the Ministry of Science, Technology and Innovation of Colombia (grant number 110180763723).

Data availability

The data supporting the findings of this study are available on request from the corresponding author, J.G-F.

Disclaimer

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