Potential Benefits of Drones for Vaccine Last-Mile Delivery in Nepal

by

Adriana Lembcke Berninzon
Bachelor of Engineering, Industrial Engineering, Universidad de Lima, 2013

and

Ornipha Vongasemjit
Bachelor of Engineering, Petroleum Engineering, Chulalongkorn University, 2011

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Signature of Author: _____
Adriana Lembcke Berninzon
Department of Supply Chain Management
May 14, 2021

Signature of Author: _____
Ornipha Vongasemjit
Department of Supply Chain Management
May 14, 2021

Certified by: _____
Tim Russell
Research Engineer, Center for Transportation and Logistics
Capstone Advisor

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

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Adriana Lembcke Berninzon

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ABSTRACT

Nepal's immunization coverage hovers around 78%, and 59 out of 77 districts have not yet been fully immunized. The objective of this study is to review the vaccine last-mile distribution to find a cost-efficient solution using a combination of modes of transportation to improve vaccine availability. This study determines which districts could use drones for last-mile delivery, quantifies the benefits from drone implementation, identifies locations for setting drone bases and recommends appropriate drone types. First, a replicable district classification framework was used, from which six potential districts were selected for drone last-mile delivery. Then, an optimization model was created for two of these selected districts, analyzing parameters such as drone payloads and ranges, vaccine shipment sizes, and costs for each mode of transportation. This research demonstrates that implementing drones is suitable mainly in rural service points of the mountainous regions of Nepal. However, the implementation provides cost benefits only when start-up costs are subsidized or when the drone operation is outsourced by lower than $0.10 USD/dose. Addressing the problem of low immunization coverage could help reduce the mortality rate of children. Our solution could be expanded to vaccine distribution during the COVID-19 pandemic or even in disaster relief scenarios, when roads are inaccessible due to flooding or earthquakes.

Capstone Advisor: Tim Russell
Title: Research Engineer, Center for Transportation and Logistics

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LIST OF ABBREVIATIONS

ArcGIS	Arc Geographic Information System
CA	Continuous Aproximation
CCE	Cold Chain Equipment
cMYP	Comprehensive Multi Year Plan
CVRP	Capacitated Vehicle Routing Problem
DVS	District Vaccine Store
EPI	Expanded Program on Immunization
HF1	Health Facility with Cold Chain Equipment
HF2	Health Facility without Cold Chain Equipment
MCV	Measles Second Dose
MILP	Mixed Integer Linear Program
NCO	Nepal Country Office
NHSS	Nepal Health Sector Strategy
PCV3	Pneumococcal conjugate vaccine
PVS	Province Vaccine Store
SCANIT	Supply Chain Analysis and Intelligence Tool
SCGx	Supply Chain Guru X
SCM	Supply Chain Management
TCO	Total Cost of Ownership
TSP	Traveling Salesman Problem
UAV	Unmanned Aerial Vehicle
UNICEF	United Nations Children's Fund
CVS	Central Vaccine Store
VAN	Visibility and Analytics Network
WHO	World Health Organization

1. INTRODUCTION

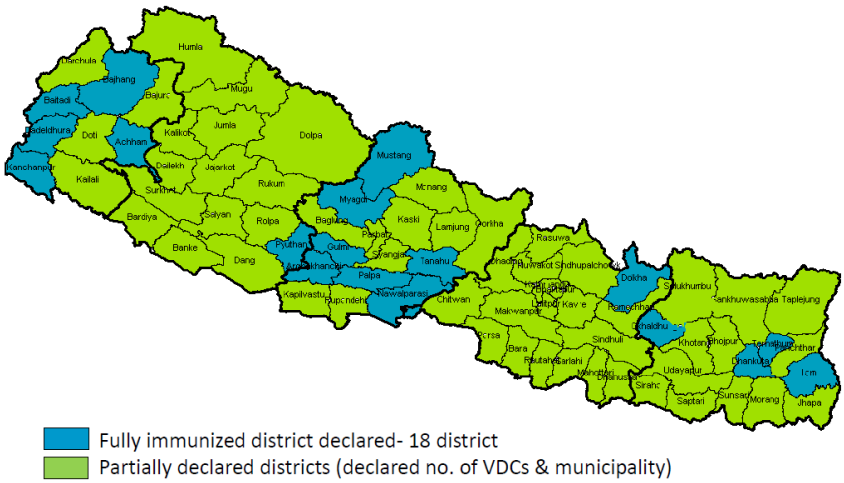
UNICEF is a non-profit organization known worldwide for its humanitarian work saving children's lives. Immunization is one of UNICEF's main pillars for child survival. The current reach of UNICEF's immunization program is astounding. According to their immunization program's record, in 2019 they "reach almost half of the world's children with life-saving vaccines" and save "2 to 3 million lives each year" (UNICEF, 2019). But even though the number of immunized children is high in several vaccine types throughout most countries, some are not reaching full potential due to restrictions in delivery. According to UNICEF's supply chain experts, other factors contributing to not fulfilling total immunization are cold chain storage restrictions, vaccine supply, geographical, and political challenges in some countries.

Nepal is no exception. There are no minor challenges, as Nepal is classified as a least developed country, where the overwhelming majority of the population is rural and with less than 20% of Nepalese living in cities (Bailey, 2019). Topographically, Nepal is divided into three distinct ecological zones: the mountains (*himal*), hills (*pahaad*), and flats (*terai*) (UNICEF et al., 2014). A large part of the population lives in remote, rural, and mountainous regions with difficult access for vaccine delivery. Even in cities, delivery of vaccines can be burdensome because of traffic and lack of cold storage space. Another important characteristic is their health care culture: "Nepalese believe that some illness is caused by spirits. People tend to treat themselves with home remedies, or turn to traditional healers, known as *dhami* or *jhankri*" (Bailey, 2019).

According to information on vaccine coverage in Nepal supplied by UNICEF, coverage for most types of vaccines is 78.5%. Despite this rate, there are still some vaccines like the PCV3 (Pneumococal conjugate vaccine) or MCV (second dose for measles) that fall below the average numbers (UNICEF 2019). Figure 1 also shows that even though a large sector of the population is vaccinated, 59 districts have yet not been fully immunized. For these reasons, finding a more efficient way to make vaccines more accessible by reviewing last-mile delivery is key to improving immunization coverage throughout the whole country.

Figure 1

Map of Nepal Showing Fully Immunized Districts (Nepal Ministry of Health, 2016)



The main motivation for this study is to review a cost efficient strategy to make vaccines more available, offering an increased service level for these life-saving products directly. This will be done by examining in what health facilities it will be feasible to use drones instead of trucks, cars, by-foot delivery or even a mixture of delivery modes. This improvement needs to be aligned with Nepal's Health Strategic Objectives for the next five years that is determined by the Ministry of Health of the Government of Nepal (2017). Considering that drones can improve delivery times,

reach difficult delivery points, and perhaps even in the future reduce cost, it is worthwhile to assess this model (Dubin et al., 2020). At the same time, the proposed approach will have to consider the many challenges of this mode of distribution and the targeted geography, such as the recent devolution of supply chain control at the province level, cold chain storage restrictions, and the maximum payload and volume capacity of drones (including cold chain packaging, etc.), to name a few.

1.1. Problem Statement

Distributing vaccines to mountainous regions and urban areas has been a challenge in Nepal over the past decades, in contrast to other areas of the country. According to research on vaccine coverage conducted by UNICEF, only 18 districts have been fully immunized, while people living in remote rural villages have limited access to vaccines due to an inefficient distribution system, poor quality or even non-existent infrastructure (Nepal Ministry of Health, 2016). Other than the geography challenges in the remote areas, vaccine delivery is also impacted by other obstacles such as shortage of cold chain storage, severe traffic and numerous bridge construction activities. These challenges cause children to lose their lives from a preventable cause.

In the past few years, there has been a lot of dialogue around the possibility of drone delivery services. Some major e-commerce companies are deploying them in their fulfillment operations and distribution centers. Moreover, the technology has already been operating for a greater purpose in the developing world, such as carrying medical supplies to save lives (Winkenbach, 2019).

This capstone project will determine the benefits of drones for last-mile health product delivery in Nepal and identify the most effective strategy for setting drone

bases, specifically for rural districts and urban areas. This project will conduct analyses to understand tradeoffs between different transportation network scenarios using a network design tool that uses optimization. The model will consider adding resources to existing health facilities (such as drone bases or refrigerator/fridges for storing vaccines), studying the shipment size, and including different demand levels. However, the model will not consider the establishment of new fixed health centers.

The main goal is to provide the most efficient cost strategy to increase vaccine availability in Nepal with responsible and efficient use of the budget allocated to last-mile delivery. This increase in vaccine availability should in turn help increase the total immunization coverage, which is not necessarily low because of product availability but for other reasons such as religious believes or lack of information. Although drone technology may increase the cost to deliver the vaccine, it is believed that this application will have advantages over the traditional mode of transportation. Some of those expected advantages are an increase in stock availability, enhancement of immunization coverage, and higher productive hours at health facilities when a smaller number of resources are required to transport product to patients. For this study we will only be considering single-stop trips from drones. Although flight purposes can be multi-stop in the same village, this potential economy of scale is inconsistent and, thus, is not considered in this study.

Addressing the problem of low immunization coverage could help reduce the mortality rate of children who lose their life from a preventable cause. The solution could also potentially be applied outside developing countries, as it can be implemented in disaster relief scenarios, when roads are damaged or are not accessible due to flooding, earthquakes, or other causes.

2. LITERATURE REVIEW

This chapter is organized as follows. Section 2.1 reviews the current vaccination network model in Nepal to understand what are the areas of opportunities and what are the factors relevant for our study. Section 2.2 explores the advantages of drone use in the healthcare sector across both urban and rural geographies, similar to the solution we're evaluating for this study. Section 2.3 covers the literature on other drone network optimization studies to review what can be learned and applied from those cases in our model. Finally, Section 2.4 discusses the methodology used for district classification and selection considering the likelihood of success for drone implementation.

2.1. Vaccine Network

Vaccination is essential to reduce the percentage of world population that dies from preventable illnesses. It remains one of humankind's most important challenges to overcome. Even though today immunization prevents two to three million deaths annually (WHO, 2019), 18.7 million infants throughout the world still do not receive vaccines (Nesson, 2016). The reasons for this problem are twofold.

The first reason, which is not addressed in this capstone, is personal beliefs. Sometimes the media portray rare or unlikely failed cases as the rule or even promote the misconception that vaccines cause autism, although "the mainstream consensus from scientists and the courts has been overwhelmingly against any connection between vaccines and autism" (Kirkland, 2012, p. 49). In Nepal, the setting of our study, most people believe diseases are caused by spirits (Bailey, 2019). There is a cultural barrier to overcome in terms of health education.

The second reason is supply chain coverage, a subject that is covered in this study. Vaccines' specifications demand cold chain storage and distribution; this poses a challenge for health organizations and countries around the world due to capacity and budget, which impacts the coverage and reach of vaccines. In addition, we found that there tends to be a correlation between living in a rural area and low immunization (Hardhantyo & Chuang, 2020), this is relevant in Nepal since there is a wide range of different geographical locations with different immunization coverage that were addressed differently. As another relevant study, we included similar analysis done in 2020 by MIT SCM students, also sponsored by UNICEF. The study they made was on optimizing supply chains considering that "most existing supply chain optimization models aim at minimizing costs or maximizing profit, which do not always fit in the context of humanitarian logistics" (Ribeiro & Hashimoto, 2020, p. 2). They instead also focused first on coverage and as a second priority, cost.

The description of the country's objectives is depicted in the document: Nepal Health Sector Strategy (NHSS). The NHSS's goal is the "improved health status of all people through accountable and equitable health service delivery system. There are 10 national level indicators defined in NHSS to measure the progress toward this goal." (Government of Nepal Ministry of Health, 2017, p. 4) Some of these goals, such as reducing the under-five mortality rate (how many children under 5 years old do not survive for every 100 children), are directly correlated to immunization coverage. Also, a particular goal for the Child Health Division from the Ministry of Health is to declare Nepal a fully immunized country, including a sub-objective of strengthening vaccine storage, stock management and distribution system at all levels.

According to UNICEF's information on vaccine coverage in Nepal, most types of vaccines have a coverage of 78.5%. Nevertheless, some vaccines like the PCV3 (Pneumococcal conjugate vaccine) or MCV (second dose for Measles) reach even lower numbers (UNICEF, 2020). But even though most children may be immunized in a region, because of the highly contagious nature of most viruses, children remain at risk unless a virus is completely eradicated.

One challenge faced by Nepal's vaccine network is its rich geographic complexity. "The mountainous north has eight of the world's ten tallest mountains, including the highest point on Earth, Mount Everest, called Sagarmatha in Nepali" (Nepal Ministry of Health, 2016). Even though the most rural districts are the evident choices for drones, we also strived to include districts with a mix of urban or suburban and rural characteristics districts. We decided to include them because urban and suburban geographic areas have their own set of constraints in supply chain for achieving a higher coverage rate, for example traffic delays and cold chain warehouse capacity limitations.

Next, we used previous studies on vaccine coverage improvement, for example, a study on improvement of immunization supply chains in Nigeria using a Visibility and Analytics Network (VAN) to determine variables to monitor the performance of supply chain (Chibuzo Ottih et al., 2018). In the same way we determined a set of similar variables relevant to our study to perform the two types of analysis that are presented in Sections 3.1 and 3.2 of the methodology chapter. This set of variables discussed in this capstone can provide a guide to identify in which locations or facilities it would make sense to use drones and where it would not. For example, variables like percent of facilities with no stock-outs of vaccines or percent of facilities with adequate cold

chain capacity could suggest a quicker mode of delivery is required or an over dimensioned capacity of cold chain equipment.

Another interesting study conducted in Madagascar talks about immunization inequities, pointing out “service delivery affects poor rural communities more than affluent communities” and findings like “26–33% of the population live beyond 5 km of a health center” (van den Ent et al., 2017, p. 2148). These challenges are similar to what is faced in Nepal. This study proposes to tackle the issue by collecting detailed health facility data at all points in supply chain to identify the disadvantaged facilities and target corrective measures accordingly.

2.2. Drone Use in the Healthcare Sector

Drones (also known as unmanned aerial vehicle or UAVs) have been a prevalent subject in public discussion due to the breadth of its potential applications. The interest in drone use for last-mile parcel delivery has been growing in many companies across industries. According to PricewaterhouseCoopers estimates, the addressable market for drone-powered solutions in the transportation market is $13 billion USD (Mazur et al., 2016). However, multiple factors affect the market adoption, such as airspace regulation, technology capability, and feasibility. There are specific types of cargo that could justify drones for last-mile delivery. In particular, Wang (2016) concludes that ”UAVs are suited for cargo that is small, light, valuable, and time-sensitive, where cost is much less of a factor”. For this study, vaccines meet the specification for suitable cargo for UAVs.

Delivering medical supplies with drones in a remote rural area is an logical application because their technological advantages can aid in delivery performance and coverage, but there’s a trade-off with cost. Some healthcare providers in

partnership with logistics companies already use drones in applications to deliver basic healthcare resources and medical supplies to remote areas around the world. For instance, vaccine and blood samples are delivered over remote areas in Australia and Africa where road infrastructure is poor or there are geographical challenges. In Figure 2 we list six examples where drones have been used for medical supplies before and the key learnings that we have applied for our study in Nepal.

Figure 2

List of Application Examples of Drones in Medical Supply Delivery (Adapted from Otto et al. (2018*), Sowards (2018), and Wright et al. (2018))*

Region		Application	Key Learnings	Application of Key Learnings for Nepal	Source
	Rwanda	Emergency Medical Supply	Drone application decreases the discard due to expiration dates	- Possible wastage cost reduction - Cost structure	Otto et al. (2018)
	Ghana	Transport of blood and medical supplies			Sowards (2018)
	Vanuatu	Vaccine delivery to mountainous areas	Insulation using Styrofoam boxes with doses for up to 13 total vaccinations	- Drone capacity - Cold chain uninterrupted - Cost structure	Sowards (2018)
	Malawi	Transfer of blood samples from hospital to hospital	Helped speed up diagnosis & test for HIV	- Allowed operations up to 400m above ground level	Sowards (2018)
	Papua New Guinea	Transport of blood samples for testing	Determining if there's a resurgence of a desease like TB or Polio	- More agile , quicker supply chain	Sowards (2018)
	Niger	Investigation/Research	Children who live less than 1 hour away from Health facility are 1.8x more likely to be fully immunized at age 1.	- Proximity to Health facility is relevant to determining immunization coverage.	Wright et al. (2018)

Drone technology could be useful in developing countries or remote areas because, unlike cars or motorcycles, drones are not subject to the road network and traffic conditions. An example of this is medicine reaching healthcare workers faster and increasing survival rates from 8% to 80% in patients with heart attack symptoms (Mazur et al., 2016). A real-world example of urban drone express delivery is blood and tissue samples transportation run by Matternet, an autonomous drone technology

firm, and UPS in North Carolina. A UAV could complete a delivery in about three minutes, versus the 30 with drivers in average daily traffic (Eric Adams, 2019). Furthermore, Volansi, in partnership with Merck, is testing in North Carolina drone distribution of vaccines in response to the COVID-19 pandemic. Even though there are several challenges in distributing COVID-19 vaccines via drone, such as security concerns and special specifications of cold box containers, many investors are interested in this initiative. In 2020 alone, over $400 million USD flowed into Volansi's operation (Marc Vartabedian, 2020).

2.3. Drone Network Optimization

In the review paper from Otto et al. (2018), the drone operation that has the most supporting literature is "routing for a set of locations" where drones must visit a discrete set of destinations to perform surveillance and delivery tasks. Some drone operations are modeled as routing problems to find a flight path with the goal of minimizing travel distance. This basic problem is also known as Travelling Salesman Problem (TSP). In the classic TSP, Woods et al. (2017) study the k-neighbor TSP with Hamiltonian cycle to capture a drone's curved tour characteristic. For problems with a given collection of districts nodes that must be visited by exactly one drone, Sathyan et al. (2016) suggest performing clustering using k-mean to group the destinations prior to solving the individual TSPs. Several articles of drone use in the healthcare context consider the Mixed-Integer Linear Programming (MILP) technique or the Capacitated Vehicle Routing Problem (CVRP) and its extension to have multiple objectives. Galvão et al. (2006) introduce the idea of temperature, distance, and payload capacity factors over CVRP in order to guarantee optimal environment conditions for the transported blood. In respect to drone operational requirement, i.e., limited vehicle driving range,

Coelho et al. (2017) formulate MILP for multi-objective routing problem that optimizes drone routes according to charging stations in a city.

Unlike the classic search and routing problem of land transportation mode, drone vehicle routing assumes that each drone make several one-to-one trips until its battery runs out (Chauhan et al., 2019). That approach is consistent with our sponsor company's current ground last-mile transportation focused on single vaccine package delivery from facility location to service point and back.

Another related stream of research focuses on the methodological advancement and applications of continuous approximation (CA). This is a technique for modeling complex logistics problems, such as facility location, vehicle routing, and inventory management (Ansari et al., 2018). We explored this technique to help capture the nature of the vaccine scheduling and delivering that could not be solved with linear programming.

The CA location problem determines the optimal configuration of facility networks to meet a given objective by synchronizing the cost component, demand, and potential facility location points. There are various contexts for CA application from deterministic facility location to districting problems. A Voronoi diagram in combination with CA model can be useful in solving districting in logistics distribution problems in order to find a near-optimal partition of the served region into delivery zones or districts (Okabe & Suzuki, 1997). Further research from Galvão et al., (2006) aims to incorporate more realistic road network and district characteristics by applying multiplicatively weighted Voronoi diagram to smooth district contours. A few years after, Novaes A.G.N. et al. (2010) investigated the application of the power Voronoi diagram in logistics districting problems by capturing physical barriers, such as rivers,

reservoirs, hills, etc., into the vehicle displacement representation. This represented more realistic context with not only physical obstacles from geographical properties of the region but also those due to thoroughfares, municipal boundaries, and regulations.

In addition, building upon work developed by Agatz et al. (2011), CA was used to determine the optimal warehouse density for the served region, assuming its customer density is known. They conduct sensitivity analysis of demand level to warehouse density (Pulido et al., 2015). The methodology proposed by these authors is quite similar to the one followed in this paper, but in our case, warehouse locations are provided.

Recently, several researchers have focused on facility location problems for drone delivery systems that are more closely related to the topic in this research. Several routing and facility location problems are focus on minimizing cost. For example, Chowdhury et al. (2017) used a continuous approximation to recommend drone and truck supply chain during disaster response and relief operation with the objective of also being cost effective. However, the goal of our research is not focused on costs alone, but rather is to maximize vaccine coverage. The following studies focus on maximizing coverage. Chauhan et al. (2019) apply CA to allocate drone units and select drone base locations according to the given set of potential facility location that can maximize the demand coverage. A similar study was conducted by Pulver and Wei (2018) but with considerations of real-world applications, such as capacity constraints at drone launching site as well as battery and weight constraints. The authors also evaluate the performance of CA compared to three different algorithms whereas the model presented in this work is not focused on computational efficiency. The research contains a case study in Portland Metropolitan Area regardless of the geographical

consideration or all building obstacles and, as a result, downtowns are covered as a priority (Chauhan et al., 2019).

2.4. District Classification Method

In order to identify desirable areas for drone development, we started by performing a literature review of pertinent studies in spatial data and then generalize guidelines of drone use case for health product delivery.

We approached this research question the same way in Negi et al., (2020) selected desirable districts in Jaintia Hills in India for turmeric production. They obtained the list of potential sites by overlaying all the thematic maps through weighted overlay methods using ArcGIS software. The ArcGIS platform is a software to manage and analyze spatial data and it allows the user to formulate the data in a spatial dimension using several layers of information.

Part of our research question is similar to what has been proposed by Wright et al. (2018). According to them, there are five indicators of potential value-adding use case for health product delivery drone: (1) High density of health facilities – number of health facilities within the drone range in a particular region; (2) Difficult to access by road – seasonality of the year; (3) High financial or health value; (4) unpredictable demand; and (5) Short product shelf life – indicating the difficulty to store at remote facilities. Although this guideline makes sense, the team undertook a cost-effectiveness analysis to compare various transport options (vs. well-managed traditional modes of last-mile delivery) and the greater level of detail in criteria must be considered for each potential use case. Wurbel (2017) introduced additional factors to guide in decision making, including geographical factors, drone characteristics, the supply chain system in place and the vaccine demand.

There are three sources for drone specification information used in this research. As a primary resource, we use the Drone catalog from UNICEF that has a list of Drone Delivery Service Providers and Manufacturers. Wurbel (2017) also summarizes characteristics for various drones with successful medical delivery pilot projects or planned cargo delivery prototypes. Lastly, Medical Drone Delivery Database is used where information on drone payload capacity is analyzed (UPDWG, 2020). Regarding the drone cost structure, the previously mentioned work from Wright et al. (2018) provides a summary of total fixed and variable costs for determining cost effective use case for drone. According to (GAVI, 2020), there are three drone provider companies that currently use drones as a last-mile solution to deliver vaccines to hard-to-reach areas with information of indicative cost of implementation and infrastructure.

3. DATA AND METHODOLOGY

This research's key objective is to develop a framework of where in Nepal does it make sense to replace the current mode of last-mile delivery for vaccines with drones. The objective of the new mode of transportation is to find the most cost-efficient strategy in the last-mile to improve vaccine availability, specifically, in the mountainous regions and urban areas of Nepal. The methodology chapter of this research will be divided into two sections.

The first section, also named Phase 1 of the research methodology, is related to the development of District Classification Framework for Drone Application. This is a qualitative approach that provides generalized recommendations as to which factors to consider and which districts are desirable for drone use. This can be found in Section 3.1.

In the second section, named Phase 2, the current supply chain is modeled (Section 3.2.1), the software for modeling is chosen (Section 3.2.2.) and the regions are narrowed down (Section 3.3.3). Once this was completed, analyses was conducted to understand tradeoffs between different modes of transportation using factors, such as vaccine availability, service level and cost. For this, network optimization software was used to formulate a model (Section 3.3.), inputting all the necessary data (Section 3.4.), optimizing it and running different scenarios to determine tradeoffs (Section 3.5).

3.1. Phase 1: District Classification Framework for Drone Application

One way to define the district classification framework for drone application is via a set of rules of thumb. These rules of thumb could also be thought as replicable

criteria to categorize geographical territories based on simple factors and provide a robust top-level direction for further in-depth analysis.

This approach will be used to determine which districts in Nepal are the ones that are more suitable candidates for drone delivery versus the current mode of transportation. As recommended by Wright et al. (2018) there are three rules of comparison to answer the question of whether drones add value in certain cases. The first is to check if drones offer advantage over well-managed transport and not only over the sub optimal current transport. The second is to assess performance holistically across all logistics objectives and not only regular objectives (for example, in vaccines cold chain specifications or speed of response). The third and last rule is to consider not only transportation costs, but also total system costs that may not be directly apparent, like inventory holding costs, expiry and waste, handling costs, etc.).

In our research method, we used a qualitative approach through interviews and implement the district selection using the same weighted overlay technique as Negi et al., 2020 in the ArcGIS platform.

Phase 1 of the research methodology comprises the following five steps:

1. Identify factors
2. Transform values to a normalized scale
3. Weight factors relative to one another
4. Overlay factors
5. Develop Province and District Summary Table

Step 1: Identify factors

According to various sources of information mentioned in the literature review and also interviews conducted with the Nepal Country Office (NCO), we conclude five major aspects to be considered for drone use case in Nepal.

- Geographical Factors

Geography is a key factor and plays an important part in the determination of the performance of different modes of transport. Nepal is topographically divided into three ecological zones: mountains, hills and plains. The first two are currently served by-foot and the last one by motorcycle or car. Evidently, mountain or hills regions have proven to be more difficult to reach areas because of their current mode of transportation, but flats have their own set of difficulties too, such as limited amount of cold storage in associated warehouses or traffic delays due to road construction.

- Demand Factors

The number of vaccine doses needed is closely correlated to the number of births, so this indicator is key to the segmentation of districts where drone delivery can help increase vaccine availability.

- Supply Chain Factors

As this study will not propose changing the existing supply chain facilities, current status of locations in Nepal is another key factor for this study. Health facility density or the number of health facilities per land area will indicate district likelihood to present advantages for drone delivery. The limitation of this measure is that the size of health facilities varies and, therefore, comparisons must be done with care.

- Road Network Quality Factors

Districts with lower quality and quantity of roads are more prone to be good candidates for drone delivery as land delivery can be ultimately constrained. The road density is the key indicator to understand where demand is not being served by current network of roads and understanding where vaccine availability can be augmented.

Another factor to consider will be health facility accessibility which will be catalogued as a qualitative factor. The purpose of this factor is to identify potential districts that have year-round or seasonal problems to deliver vaccines. According to Kumar et al. (2020), “The SRN connecting districts of Karnali Province are relatively unobstructed by landslides. But numerous bridge building activities have diverted roads into small rivulets, which can delay traffic and can be temporarily obstructed during the monsoon season”. Figure 3 provides a visual of a rocky section and the difficulties it presents for delivery. Thus, some of the indicators that will be used to analyze these types of obstruction are:

- Average rainfall per year
- Type and quality of existing road between origin and destination

This health facility accessibility indicator may be hard to procure or not exhaustive for all districts and service points. Some assumptions are made in coordination with UNICEF’s Nepal country office team. For example, an importance of rainfall be lower comparing to the road quality because the quality of road is highly correlated to an accessibility, while rainfall have an impact only on some period of the year.

Figure 3

Rocky Section in Bumramadichaur Joining Nagma to Gamgadhi, Mugu

In addition, the road circuity is a factor that will be included in the categorization as part of road network quality factor. The circuity factor is a number that approximates actual travel distances from straight line distances. Ballou et al. (2002) defined the circuity factor as a ratio of actual travel distance to calculated distance" (Ballou et al., 2002). This factor will help to segment district difficulty of travel and hilliness.

- Performance Factors

Districts with lower performance factors will be prioritized for evaluation of drone delivery. To measure district's performance, the current vaccine availability by district will be the dominant parameter for quantification. Another performance indicator that will be considered is number of cold chain equipment (CCE) in each health facility. Evaluating CCE availability give an insight where an improvement with drone delivery could be effective.

Some of the factors can be used directly in the model, (for example, the vaccine availability, CCE availability, number of doses and elevation). For other factors, the criterion must be derived from the base data (for example, the health facility and road

density must be determined from the health facility location or road network base data). The most complicated layer to develop is the Accessibility because it is determined from a consolidation of road types and rainfall base data.

Step 2: Transform values to a normalized scale

The values of the current factor, whether base data or derived data, are relative to their character and not relative to one another. For example, a 100 may indicate percentage of area that lacking cold chain equipment on a CCE availability map, 8 may represent rainfall volume per land area, and 3,500 may represent an elevation at a particular location. Adding these three layers together results in 3,608 for the location which does not lead to any conclusion of drone applicability.

The original base or derived input values must be transformed to a common scale so the factors can be compared. Thus, all 8 layers from 5 aspects must be transformed to represent the preference for the factor values relative to their proneness to drone relevance and drone applicability. We will use a 1 to 9 scale because this let us have a wider classification range for scoring each factor. For example, higher elevation is assigned a 9 (most preferred on the scale) and flatter land is assigned a lesser value (for example, a one or two) in the elevation layer. This process continues for each factor in each layer. For additional information on preference scales see Table 1.

Table 1

List of factors for district classification and score descriptions

Type of Factor	Factor	Score
Geographical factors	Elevation topographic	1: low elevation level 9: high elevation level
Demand factors	Target number of doses	1: high target doses 9: low target doses
Supply Chain factors	Health facility density	1: high density 9: low density
Road network quality factors	Health facility accessibility and seasonality	1: little rainfall 9: high rainfall
	Road density	1: higher density 9: lower density
	Road circuity	1: circuity close to 1 9: circuity greater than one
Performance factors	Vaccine availability	1: higher availability 9: lower availability rate
	CCE availability	1: CCE Available 9: Lack of CCE

Reclassify is a feature in ArcGIS that is designed to transform categorical input data to a common preference or suitability scale. The output from the Reclassification produces integer output (for example, 1, 2, …, 9). There are two layers, road, and health facility density, that require additional step to transform data prior to an application of Reclassification. Accessibility layer is the most complicated layer that involve both reclassification and preliminary overlay technique to generate the final layer. The overlay technique is discussed in step 4 of this Chapter. An example of

imported layer is shown in Figure 4 and the reclassification of CCE, Health facility and accessibility base data are illustrated in Figures 5, 6 and 7 accordingly.

Figure 4

Imputed Spatial Information of CCE Density by District

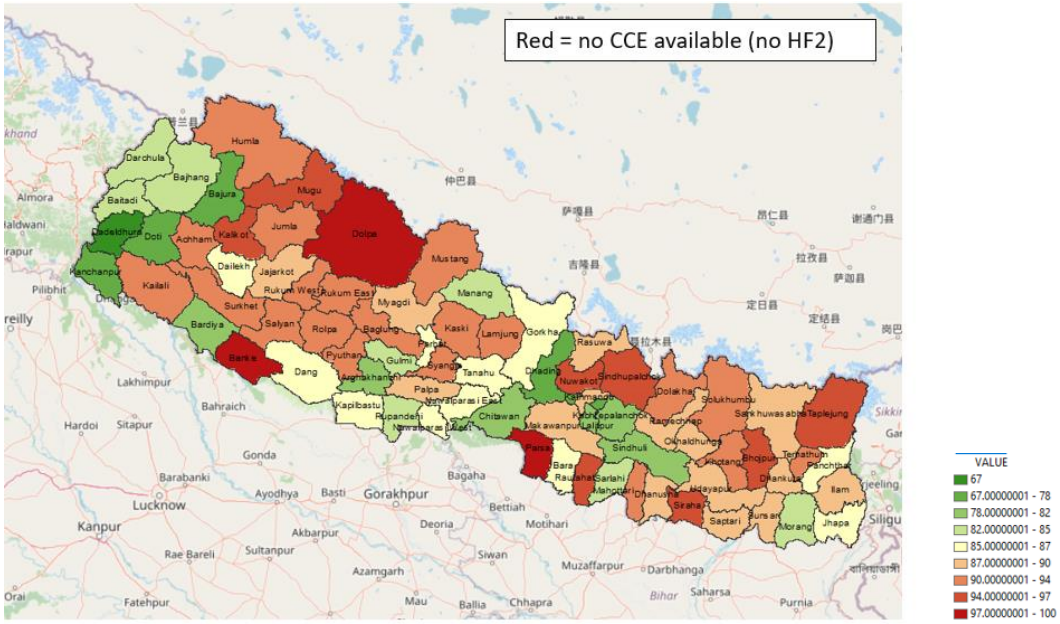


Figure 5

Output Layer for CCE Availability after Reclassification

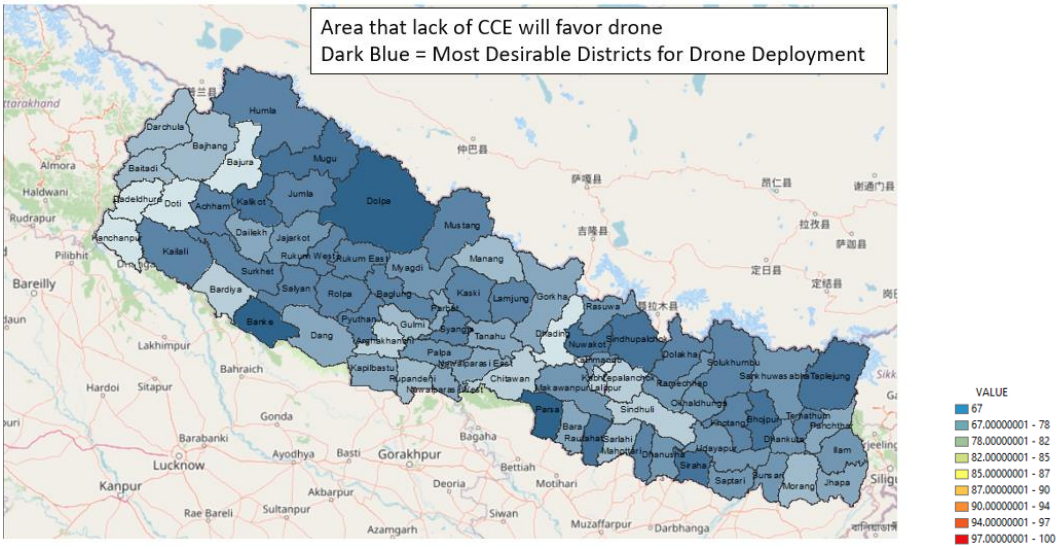


Figure 6

Reclassification Process for Health Facility Layer

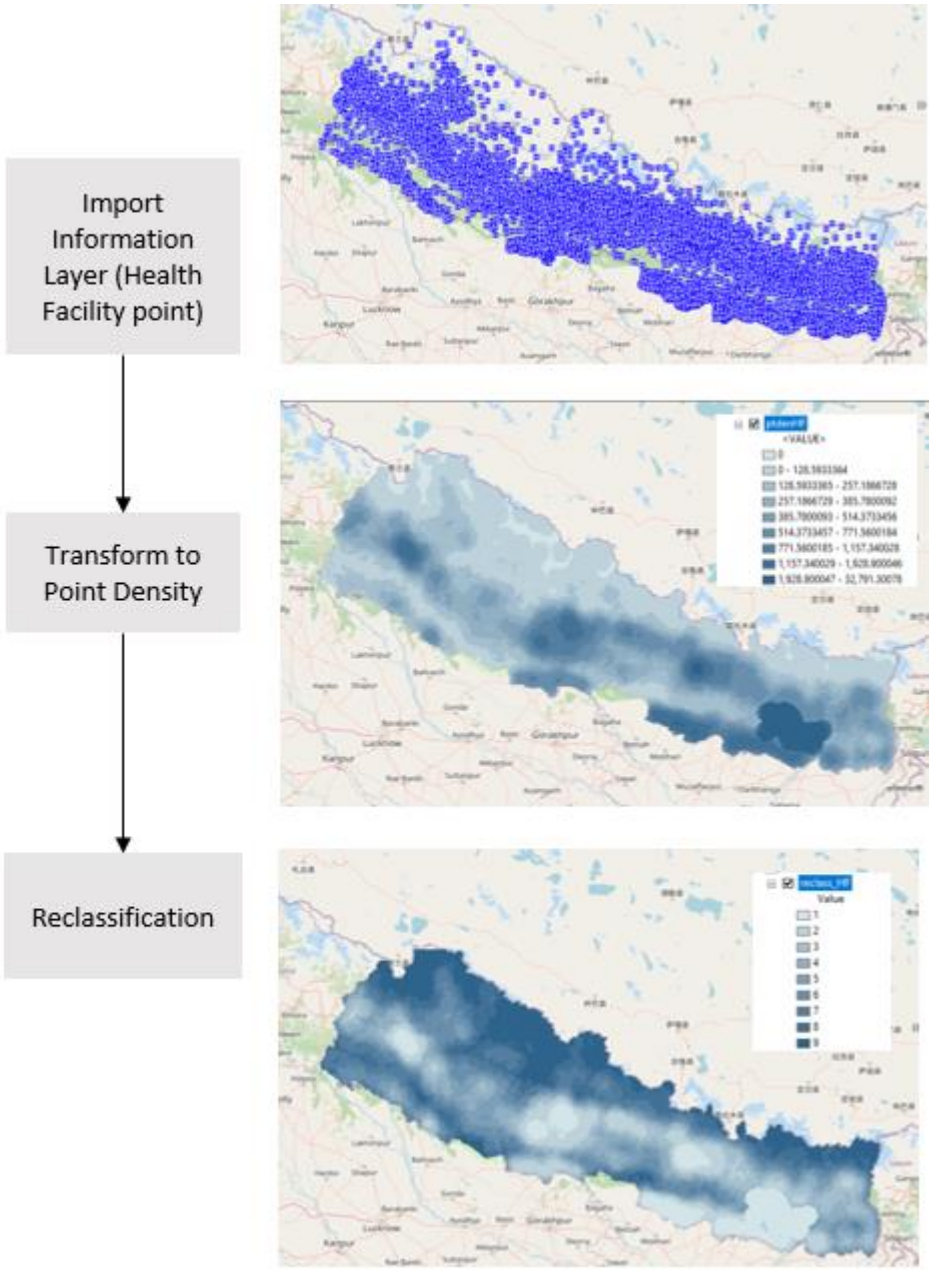
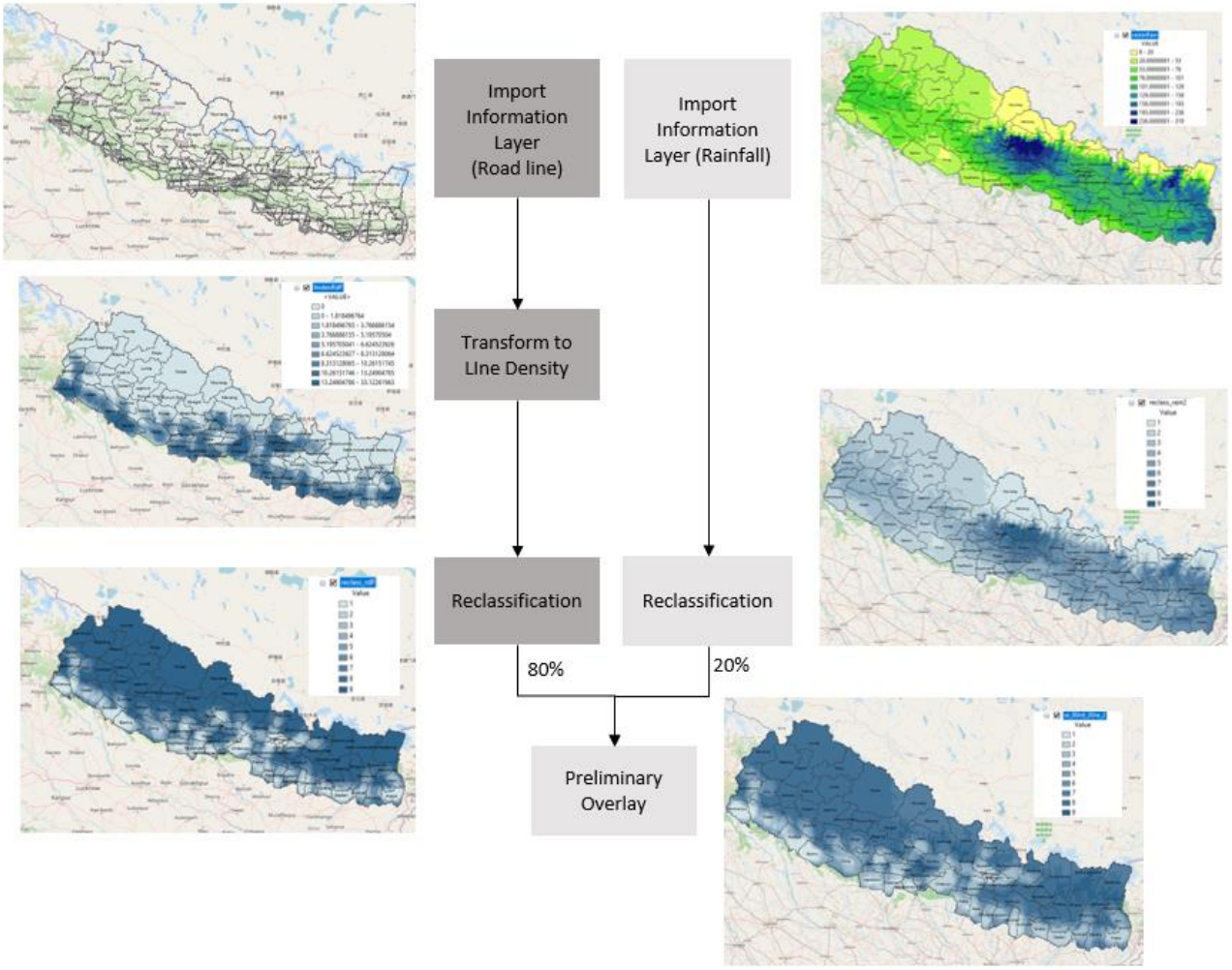


Figure 7

Reclassification Process for Accessibility Layer



<u>Step 3: Weight the factors relative to one another</u>

At this point, each input factor has been identified and placed on a common scale. The factor can now be combined. We create a survey to assess the factor ranking and their contribution as a rule of thumb for drone deployment. The result of this survey will be used as an input for further analysis in ArcGIS. The survey has been sent out to various organization. The participants of the survey include MIT researchers, drone specialist, UNICEF and global health supply chain professional.

An example of survey can be found in Appendix 1, there are two main survey questions:

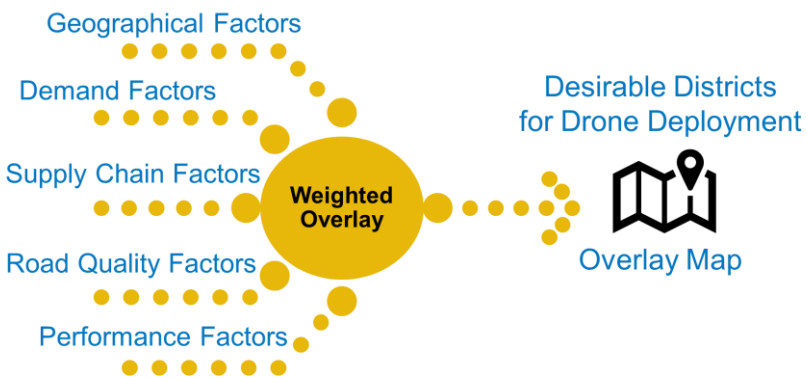
1. In your opinion, what would be the order of importance of the following factors based on their influence on drone applicability? (In descending order, top choice is the most importance factor)
2. According to the ranking of previous question, please assign the percentage of important of each factor to the same order (The percentage of 8 factors must added up to 100%) Input format 50%, 20%, 30%, 10%, etc.

Step 4: Overlay factors

The application of weighted overlay technique is applied using ArcGIS to make recommendations on which regions are suitable for drone development. All layers are given the different weight according to the survey result. Finally, the overlay map is generated and score of 8 is assigned to the most Desirable Districts for Drone Deployment. The complete ArcGIS workflow can be found in Figure 8.

Figure 8

ArcGIS Workflow of Factors for Weighted Overlay



Step 5: Develop Province - District Summary Table

We use the Zonal Statistics toolbox in ArcGIS to obtain insights at district and province health facility level. We intend to provide a table where the tally for each district is classified under it's score ranking by province.

3.2. Phase 2: Optimization Model: Mode Selection and Cost Trade-offs.

The optimization model for mode selection and cost trade-offs, also called Phase 2, will perform a deep dive in two districts picked from Phase 1. This deep dive consists of modelling the complete supply chain in an optimization software, considering all pertinent costs and constraints, and running different sets of scenarios. The output of these scenarios will be the cost associated with each of the proposed supply chain structures, the percentage of volume assigned to each mode of transportation and also the recommended sites were to open drone hubs.

3.2.1. Current Supply Chain Network

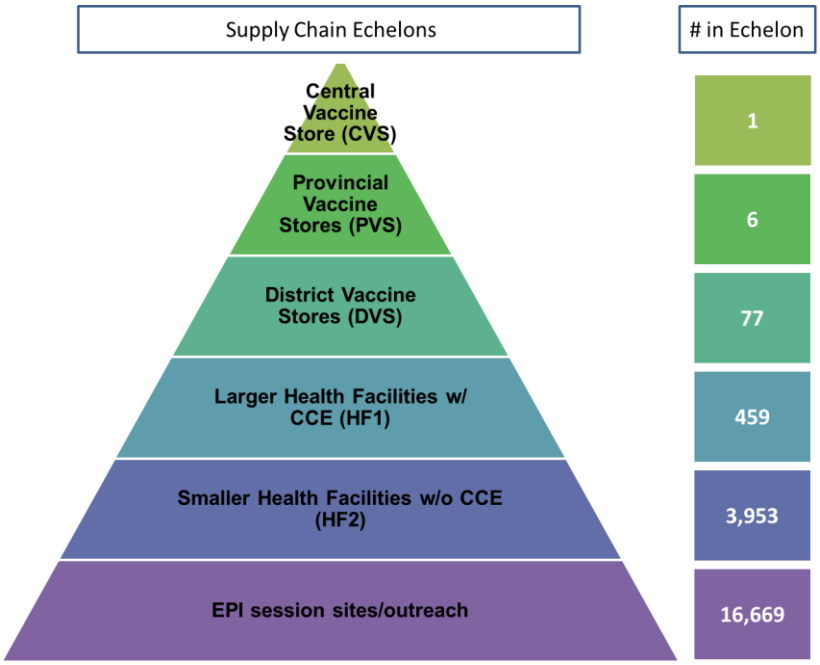
To begin with the tradeoff analysis, we first need to define the current supply chain network of vaccines in Nepal, as a baseline. A graphic description of the different supply chain echelons is shown in the triangle diagram in Figure 9. The information for this diagram was provided by UNICEF's Nepal country office.

Vaccines arrive by air to Nepal through main airport in Kathmandu and are directly transported to main central vaccine store (CVS) in Teku. The next level are provincial vaccine stores (PVS), these are served approximately every three months from CVS. Following, there are 77 District Vaccine Stores (DVS) that are served every month either from CVS (67 of total) or PVS (10 of total). Next, health facilities are served from the DVS. In Nepal, currently there exist 4,412 health facilities, but only 459

of them currently are equipped with the CCE needed to handle vaccines. That first group of larger health facilities are served directly by the DVS and will be called HF1 in this study for easier referral. The rest of those HF are 3,953 smaller distribution points that are served from the larger HF1 and do not have the CCE necessary to hold more than one day of supply of vaccines. Finally, from those HFs (large and small) around 16,700 EPI session/outreach sites are reached. When this study refers to last-mile, it means the leg that starts at the DVS and flows through larger HF to smaller ones and finally to EPI sessions/outreach sites. This is the last-mile that will be explored in this study.

Figure 9

Triangle Diagram of Supply Chain Echelons for Vaccine Delivery in Nepal (Nepal Ministry of Health, 2016)



3.2.2. LLamasoft Supply Chain Guru X Model Application

Next, we will describe the platform chosen to model Nepal's supply chain and evaluate the different outcomes in cost and transportation modes for different vaccine availability levels. We explored and compared the different features and scope of 2 different software platforms: Supply Chain Analysis & Intelligence Tool (SCANIT) and LLamasoft's Supply Chain Guru X software (SCGx).

SCANIT, jointly developed by UNICEF and Llamasoft, is a system design tool that uses readily available data to model supply chain alternatives. With this collaboration and integration, the tool is designed to retrieve inputs from already existing standardized data sources such as cMYP costing tool, Cold Chain Inventory spreadsheets, etc. The tool generates maps, graphs and tables that illustrate the impacts of network design scenarios for decision-making. SCANIT can support 5 alternative system design analyses which are: new product introduction, inventory holding points, stock levels, distribution flow network, and transport operations. The transport operations option is used to calculate the impact of the change in delivery frequency or direct delivery which are not the main objective of this project. Looking at the distribution flow network option, this is used to model potential supply points and generate optimal flow routing based on the primary transportation method, however, SCANIT does not optimize across transportation modes. In addition, the tool does not include CCE costs in the total cost equation while some CCE infrastructures could be removed if drones were to be used. The benefit of drones regarding the supply chain flexibility could not be modeled using SCANIT.

LLamasoft's SCGx allows the user to model, optimize, and simulate networks using complex real-world data. The model derives quantified insights and solutions to

answer questions about viability, comparisons between scenarios, and optimizations. We concluded that SCGx is the more suitable modelling software for this project and, in this study, SCGx is used to create a digital twin of Nepal's current vaccine network. By creating this digital twin, one can add or loosen constraints in order to assess viability and obtain and compare different results by visualization or quantified outputs. These constraints can be of different natures: cost, modes of transportation, demand, supply restrictions, etc. In neither of the software mentioned, coverage couldn't be modeled as a target variable, this is why we were forced to include it as a constraint.

The main benefit from SCGx in this study is the quantification of the benefits derived from changing delivery modes of transportation, including drones, for each of the proposed scenarios discussed in a further subsection of this chapter.

3.2.3. Surkhet and Rukum West Districts

For the trade-off analysis the recommendation from the sponsoring entity was to choose two districts, one rural and one urban, as suggested by the sponsor organization. For this, the first two districts discussed were Dolpa and Surkhet. Dolpa being one of the districts with a probable high score in Phase 1 and Surkhet with a middle score due to its mixed topography. Unfortunately, the availability of the data for detailed geolocation of facilities and CCE per facility in Dolpa district, was scarce. So Rukum West was proposed as a replacement. Finally, both Surkhet and Rukum West were agreed upon to further analysis in Phase 2.

3.2.3.1. Surkhet District

Surkhet is one of the flat (*terai*) districts in Nepal. It is located at about 600 km of Kathmandu, the nation's capital. The district's area is about 2,500 square km. In Figure 10. the location of Surkhet in Nepal is shown.

Figure 10

Map of Nepal Showing Surkhet District Location

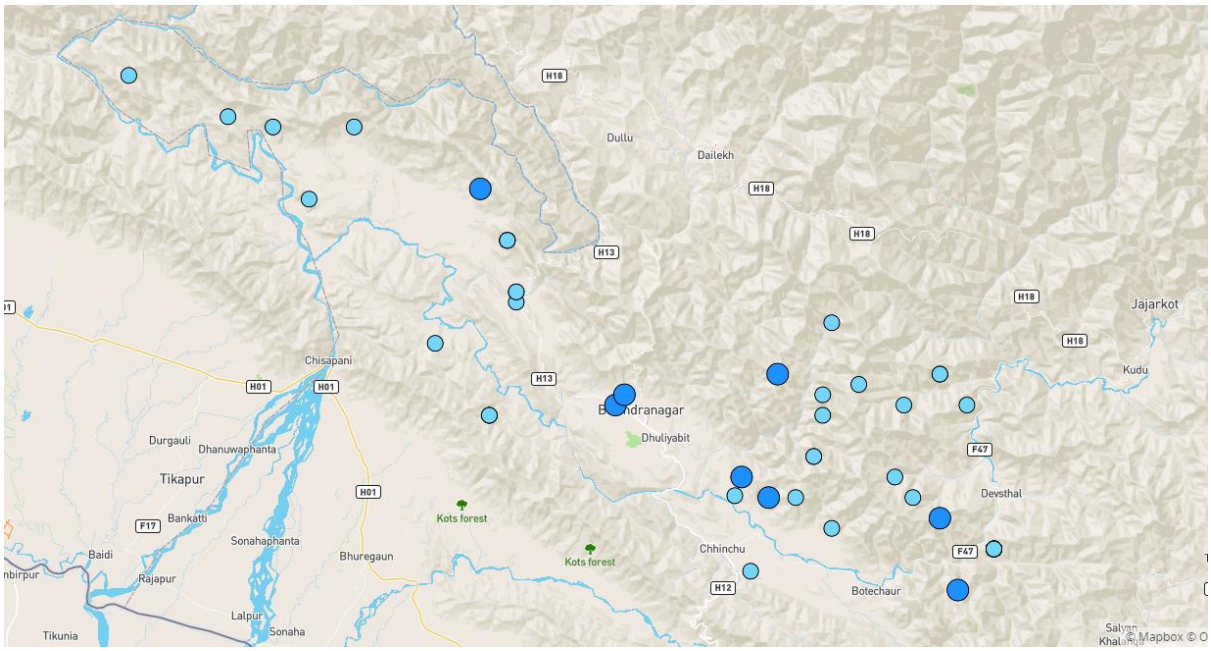
This district was chosen because it is considered as semi urban – semi rural, so rich insights could be gathered from a topographic blended district. UNICEF was interested in getting recommendations not only for districts where drone implementation was more evident, but also from districts like Surkhet, where the decision is not as clear.

Also, according to UNICEF's NCO experts, Surkhet is a relatively new explored district in terms of health facility capacity and vaccine network. This implies that any knowledge gathered from this study could help quickly improve decision making in Surkhet.

It also has a population of over 415,000, so it is a large enough district to be attractive for analysis but not too large as to make the modelling more complex.

Figure 11

Surkhet District's Health Facility Nodes Schematic View



In Figure 11 we show the different health facilities that currently exist in Surkhet. The larger, darker blue dots represent HF1 (larger health facilities that do have CCE). The smaller, lighter blue dots represent HF2 (smaller health facilities that do not have CCE and are supplied by HF1).

The hypothesis for this district it that due to its blended topography, difficult to reach areas and recently managed vaccine network it could make sense to implement drones to improve vaccine availability, albeit at a higher cost.

3.2.3.2. Rukum West District

Rukum West is one of the hill districts (*pahaad*) in Nepal. It is located at about 600 km of Kathmandu, the nation's capital, similar to Surkhet in distance. The district's area is about 1,200 km^2. In Figure 12 the location of Rukum West in Nepal is shown.

Figure 12

Map of Nepal Showing Rukum West District Location

This district was chosen because it is considered as a rural district, and it is the part on the main hypothesis that this are the districts that are more prone to be favorable for drone implementation. It has a population of over 170,000. Being a hillier and more rural district, it is less population dense.

The prior alternative for selection of a rural district and more attractive option for modeling was the Dolpa district, but as mentioned before, the data for this district was scarce, so Rukum West was chosen as the next best alternative.

3.3. Model Formulation

In this section, we present the entire mathematical formulation of the problem that derived based on a literature review and discussion with UNICEF. We defined sets, variables parameters, objective function, and constraints.

3.3.1. Sets

Our network problem consists of three types of nodes: the fixed health centers, outreach sites and discrete populations. Their nomenclatures are listed as follows:

- F = set of fixed health facilities with CCE f
- P = set of fixed health facilities with passive device* p
- O = set of potential outreach sites o
- D = set of fixed health facilities that set up as drone base d
- I = set of population i within the district that is served by fixed health facilities with CCE f or drone base d
- J = set of population j within the district that is served by fixed health facilities with passive device p or drone base d
- K = set of population k within the district that is served by potential outreach sites o or drone base d
- V = set of all vehicle type v used to transport vaccine in Nepal

*Passive device is the non-electric device in substitution of cold chain such as a cold box and refrigerator.

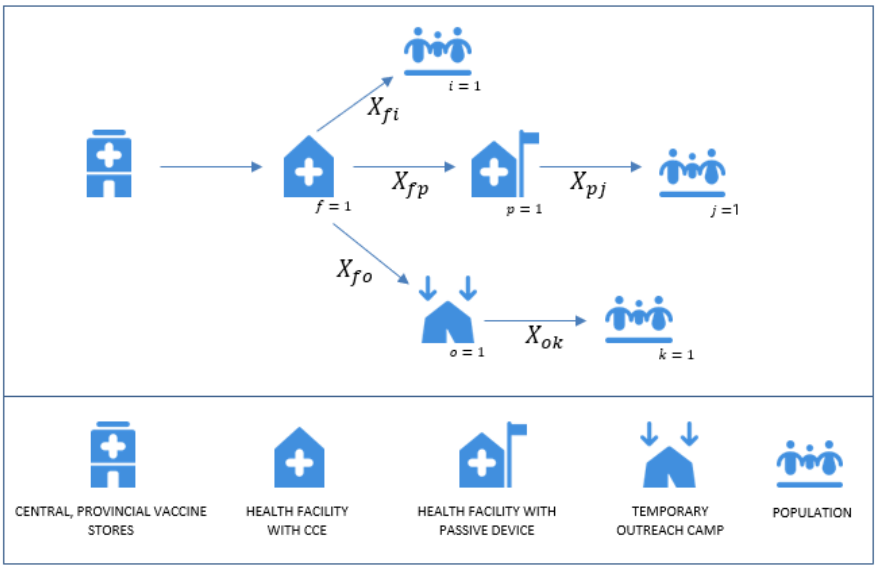
3.3.2. Variables

The variables are the mathematical representation of the decision being made by the model. There are three key decisions in the model: (1) which facilities with CCE will be responsible directly to population; (2) how many doses will be supplied to each health facility with passive device; and (3) how many doses will be sent from each health center to each outreach site. The decision of sending supply to health facility with passive device and an outreach site indirectly defines whether the candidate drone location is used or not. Figure 13 illustrated how each of these variables is positioned in the network flow.

- X_{fi} = number of doses supplied to population in the district by fixed health facilities f
- X_{fp} = number of doses supplied to health facilities with passive device by fixed health facilities f
- X_{fo} = number of doses supplied to outreach sites by fixed health facilities f
- X_{di} = number of doses supplied to population in district by drone base d
- X_{dp} = number of doses supplied to health facilities with passive device by drone base d
- X_{do} = number of doses supplied to outreach sites by drone base d
- Y_d = 1, if drone base d is established; 0 otherwise.
- N_f = number of CCE at fixed health facilities f

Figure 13

Network Modeling using Variables Used



3.3.3. Parameters

The parameters used for constraints and objective function are presented below and are grouped in three categories.

Cost

- C_t = Total Transportation cost in USD
- G_d = Drone facility set up cost in USD
- C_c = Operating expense of CCE in USD/CCE/year (constant)
- CE = Employee cost per day or Per Diem cost in USD/day
- C_m = Motorbike fuel cost in USD/km
- C_c = Car fuel cost in USD/km
- C_d = Drone cost in USD/km

Distance

- $Dist_{fp}$ = Distance between f and p in km
- $Dist_{fo}$ = Distance between f and o in km
- $Dist_{dp}$ = Distance between d and p in km
- $Dist_{do}$ = Distance between d and o in km

General

- PE = Employee productivity in transportation in km/day
- Q_v = Vaccine carrying capacity of vehicle v in doses/trip
- D_v = Maximum travel distance of vehicle v in km or maximum drone radius in km (constant)
- V_c = Maximum number of doses per CCE (constant)
- V_f = Maximum throughput at fixed health facilities f or total CCE capacities

3.3.4. Objective function

Our objective function is to minimize the total logistics cost for the district, this is shown in Equation 1. Due to the complexity of this equation, in order to simplify its explanation, the total Logistics Cost is broken down into 2 factors (A) the transportation costs modeled in Equation 2; (B) the CCE cost at fixed health centers modeled in Equation 5.

$$\min \left(\sum_{f\in F}\sum_{p\in P} X_{fp} * C_{fp} + \sum_{f\in F}\sum_{o\in O} X_{fo} * C_{fo} + C_d * \sum_{p\in P}\sum_{d\in D} Dist_{dp} + C_d * \sum_{o\in O}\sum_{d\in D} Dist_{do} + G_d * \sum_{d\in D} Y_d + \sum_{f\in F} C_c * N_f\right)$$

A. Total transportation cost

The total transportation cost equation shown in Equation 2 is the sum of the current mode of transportation cost modeled in Equation 3, the drone cost equation modeled in Equation 4.

$$\sum_{f\in F}\sum_{p\in P} X_{fp} * C_{fp} + \sum_{f\in F}\sum_{o\in O} X_{fo} * C_{fo} + C_d * \sum_{p\in P}\sum_{d\in D} Dist_{dp} + C_d * \sum_{o\in O}\sum_{d\in D} Dist_{do} + G_d * \sum_{d\in D} Y_d \tag{2}$$

a. Current mode of transportation

Mode of transportation for population that is served via current available modes (car, motorbike and by-foot)

$$\sum_{f\in F}\sum_{p\in P} X_{fp} * C_{fp} + \sum_{f\in F}\sum_{o\in O} X_{fo} * C_{fo} \tag{3}$$

Where:

$$C_{fp} = \begin{cases} \frac{CE}{PE} * 2 * Dist_{fp} : By\ foot \\ C_m * 2 * Dist_{fp} + \frac{CE}{PE} : \ Motorbike \\ C_c * 2 * Dist_{fp} + \frac{CE}{PE} : Car \end{cases}$$

$$C_{fo} = \begin{cases} \frac{CE}{PE} * 2 * Dist_{fo} : By\ foot \\ C_m * 2 * Dist_{fo} + \frac{CE}{PE} : \ Motorbike \\ C_c * 2 * Dist_{fo} + \frac{CE}{PE} : Car \end{cases}$$

b. Drone cost equation

Cost equation for population that is served via drones

$$C_d * \sum_{p \in P} \sum_{d \in D} Dist_{dp} + C_d * \sum_{o \in O} \sum_{d \in D} Dist_{do} + G_d * \sum_{d \epsilon D} Y_d \quad (4)$$

B. CCE cost at fixed health centers

$$\sum_{f \in F} C_c * N_f \quad (5)$$

These equations excluded new health facility capital expenses as the project scope only included existing facilities. Also, employee costs at outreach sites and health facilities with passive devices are excluded. We would require additional information on number of employees needed for each outreach site and health facility with passive devices.

3.3.5. Constraints

The model has 4 constraints: (1) the demand for vaccine doses; (2) the vaccine storage capacity of each fixed site is limited by the CCE capacities; (3) the number of doses distributed and travelling distance must be lower than the vehicle capacities; and (4) the flow conservation of vaccine through each fixed health facilities.

1. Demand constraint

This constraint will model the number of doses distributed. The total amount of doses presented in Equation 6 is obtained through the sum of the doses distributed from fixed health centers $X_{pj}$and X_{fi} plus the ones from outreach sites X_{ok}. There is an additional term to sum of the doses distributed from drone base X_{di}, X_{dj}, and X_{dk} if drone base is established, added in Equation 7.

$$\sum_{k\epsilon K}\sum_{j\epsilon J}\sum_{i\epsilon I}(\sum_{f\epsilon F}X_{fi}+\sum_{p\epsilon P}X_{pj}+\sum_{o\epsilon O}X_{ok}) \tag{6}$$

$$\sum_{k\epsilon K}\sum_{j\epsilon J}\sum_{i\epsilon I}(\sum_{f\epsilon F}X_{fi}+\sum_{p\epsilon P}X_{pj}+\sum_{o\epsilon O}X_{ok}+\sum_{d\epsilon D}(X_{di}Y_d+X_{dj}Y_d+X_{dk}Y_d)) \tag{7}$$

2. CCE capacities

CCE capacity constraints, in Equations 8 and 9, control that the number of doses distributed to fixed health facilities f from district vaccine store must be lower than the amount of vaccine that these facilities can store.

$$(\sum_{i\epsilon I}X_{fi}+\sum_{p\epsilon P}X_{fp}+\sum_{o\epsilon O}X_{fo})-V_f\leq 0, f\in F \tag{8}$$

$$V_f=V_c\times N_f \tag{9}$$

3. Vehicle capacities

The following constraints guarantees that the number of vaccines transported at each mode of transportation does not exceed the vehicle shipment size capacity as shown in Equation 10. Also, Equation 11 is defined to ensure the distance traveled by each vehicle does not exceed their maximum range specification.

$$X_{fiv}\leq Q_v, v\in V, f\in F, i\in I \tag{10}$$

$$Dist_{fiv}\leq D_v, v\in V, f\in F, i\in I \tag{11}$$

4. **Flow conservation**

The last constraint, presented in Equations 12 and 13, guarantee the flow conservation at each health facilities with passive device and outreach site accordingly.

$$\sum_{f \epsilon F} X_{fp} - \sum_{j \epsilon J} X_{pj} = 0, p \in P \tag{12}$$

$$\sum_{f \epsilon F} X_{fo} - \sum_{k \epsilon K} X_{ok} = 0, o \in O \tag{13}$$

3.4. Model Inputs

One of the most challenging tasks in any network design project is to derive the necessary data required for the optimization model. Simplifying assumptions were made when deriving the input data for our model. Some of these assumptions may seem simplistic. However, our main objective with this exercise is not to reproduce or provide a specific number for the cost and vaccine availability of the supply chain network. Rather, the purpose is to determine whether there are benefits of drone implementation or not through a real scale scenario. All costs and parameters are proportional to each other and overall were derived from reasonable assumptions. However, the exercise will be successful if it provides the capacity to derive insights and suggestions that allow the vaccination network structure to achieve greater vaccine availability. We derived as much data as possible from publicly available sources. We also thoroughly detail the data extraction procedure. This enables the model to be easily reproduced in any district of Nepal, even if limited data are available.

As a next step, this section discusses a detailed view of how the optimization model inputs were derived, including what data sources were used, how they were cleaned, and what assumptions were made. In general terms, a network design

problem has inputs that can be associated to three elements: nodes, arcs, and costs. Accordingly, this section is organized based on those three elements:

- The nodes in our model are derived from the following subsections: the target population, vaccine schedule, vaccination doses demand and current vaccine availability. Data is presented in Sections 3.4.1., 3.4.2., 3.4.3 and 3.4.4.

- The arcs are derived from following subsections: road distance, choice of transportation, cold box capacity and drone specifications. These are presented in Sections 3.4.5., 3.4.6., 3.4.7., and 3.4.8.

- The costs that depend on distance are presented in Section 3.4.9., together with CCE cost in Section 3.4.10., and the fixed and variable drone costs in Section 3.4.11.

Concluding this section, the actual real-world cost is presented for later comparison to model cost as to verify the model, this is presented in Section 3.4.12.

3.4.1. Target Population

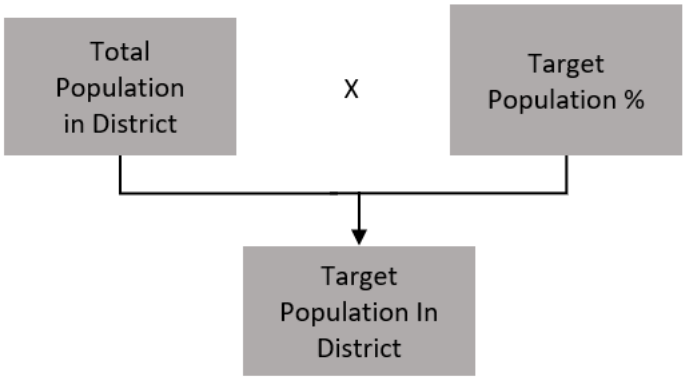
The target population input was derived by a combination of the total population per district and the target segments of the population that vaccines are mostly used for. Specially for UNICEF, the target demographics are children.

This target demographic refers to three groups: Children under 12 months, children from 12 to 24 months and expected pregnancies. The % of the population that belongs to these three groups was derived using information sent by UNICEF on Rukum West district and then extrapolated for Surkhet as well. The percentage of those three groups compared to the total population in Rukum West adds up to 7.1%. This number was then validated also for Surkhet and was a sound number for the rest of

the country as well. For next steps, target doses will be calculated in the next subsections of this chapter based on the target population. In case of Surkhet and Rukum West, the target population calculated is approximately 30,000 and 12,000, respectively. In Figure 14 a graphical description of the derivation for target population is shown.

Figure 14

Target Population Data Derivation



3.4.2. Vaccine Schedule

The recommended vaccine schedule for the target population was acquired from the Nepal Country Office from UNICEF and cross validated with the CDC's recommended child and adolescent immunization schedule for ages 18 years and younger (CDC, 2021). The main difference between those two sources of information is the Japanese Encephalitis vaccine. Japanese Encephalitis is a disease only found in Asia and the West Pacific, and this is the reason why it is included in the Nepal vaccine schedule in this study. The final vaccine schedule is shown in the Table 2.

Table 2

Vaccine Schedule for Nepal children under 18-24 months

Abbreviation	Description	Dose #
BCG	Tuberculosis	1
DPT Hep B Hip 1	Hepatitis B, Diphtheria, Tetanus, Pertussis,	1
DPT Hep B Hip 2	Hepatitis B, Diphtheria, Tetanus, Pertussis,	2
DPT Hep B Hip 3	Hepatitis B, Diphtheria, Tetanus, Pertussis,	3
OPV 1	Oral Polio Vaccine	1
OPV 2	Oral Polio Vaccine	2
OPV 3	Oral Polio Vaccine	3
PCV1	Pneumococcal Conjugate Vaccine	1
PCV2	Pneumococcal Conjugate Vaccine	2
PCV 3	Pneumococcal Conjugate Vaccine	3
MMR 1	Measles, Mumps and Rubella	1
MMR 2	Measles, Mumps and Rubella	2
JE	Japanese Encephalitis	1
TD 1	Tetanus and diphtheria	1
TD 2	Tetanus and diphtheria	2
TD 2+	Tetanus and diphtheria	3
RV1	Rotavirus vaccine	1
RV2	Rotavirus vaccine	2
RV2	Rotavirus vaccine	3
VAR 1	Varicella	1

According to this schedule, there are 20 doses of vaccines needed for the target population. From those 20 doses, two types of vaccines segments were created due to its different cold chain requirements: Refrigerated (2-8°C) and Frozen (-20°C). Most types of vaccines require only refrigeration, so 17 doses per person were classified in the first segment that will need 2-8°C temperature for storage. The only type of vaccine

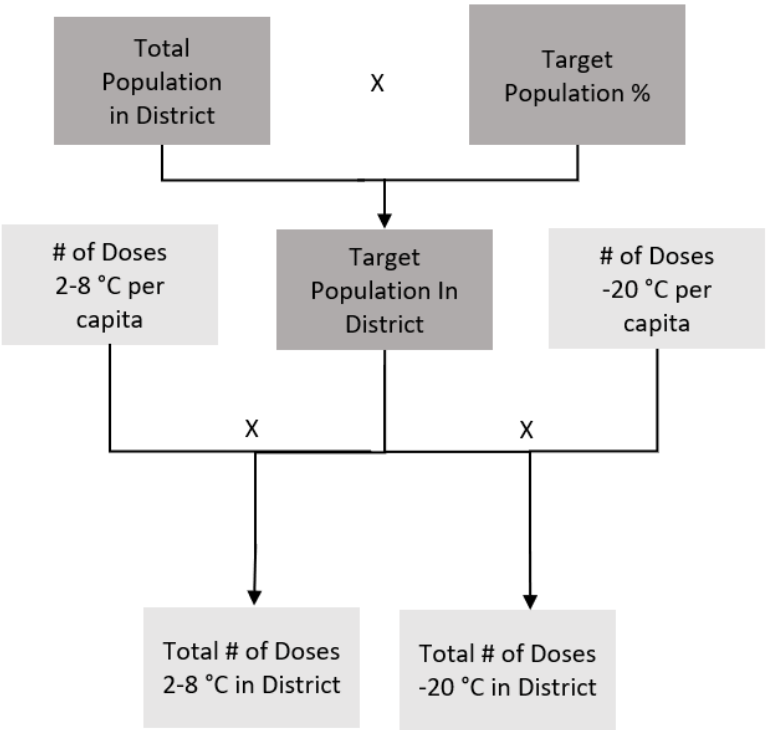
that requires a different sub-zero storage is the Polio vaccine, so three doses were classified in the second segment that needs -20°C temperature for storage.

3.4.3. Vaccine Doses Demand

To calculate the demand for each district in the model, several assumptions had to be made as the exact requirement could not be procured. Figure 15 shows the standard procedure to calculate the number of doses needed for each of the cold chain requirement groups per district.

Figure 15

Calculation from Population to Vaccine Doses. (Adapted from Interviews with UNICEF Experts and CDC Vaccine Schedule)



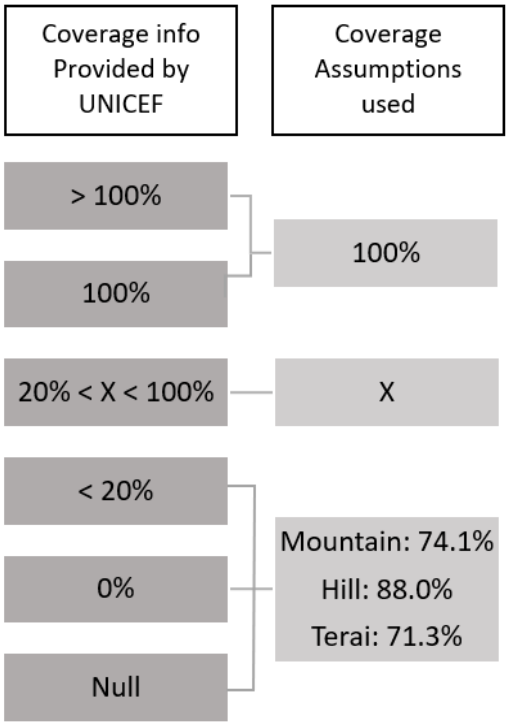
In Figure 15, the total population in each district is multiplied by the target population derived in 3.3.1 (7.1%) to calculate the target population in each district. Subsequently, this target population number is multiplied by the number of doses in the 2-8 °C group classification (17 doses) to arrive at the total number of doses that have a 2-8 °C cold chain requirement. In parallel, the same multiplication is done using the target population times the number of doses in the -20 °C group classification (3 doses) to derive the total number of doses that require a -20 °C cold chain storage.

3.4.4. Current Vaccine Availability

To model the current vaccine availability for the baseline scenario at the subdistrict level needed for the simulation, different sources were used. The first was a collection of data for the penta-3 vaccine at health facility level, but as some of the data collected from this source was not correct (some values exceeded 100% and some values were null or 0 or inconsistent), we crossed check with another source from the Biomed Central Coverage Report by eco region and assigned an ecoregion to each health facility: 74.1% to mountain regions, 88% to hill regions and 71.3% to flat regions (Acharya et al., 2019). Finally, as shown in Figure 16 we used those values for the inconsistent or null information to complete filling the initial UNICEF report. This was verified by experts from UNICEF's NCO.

Figure 16

Immunization Coverage Assumptions and Data Cleaning



3.4.5. Road Distance

In the model, the definition for the method for measuring road distances was needed. For this model, the distance between sites will be calculated as a straight line using Euclidean distance plus a circuity factor. In the case of Nepal, we will be using a circuity of 17%.

3.4.6. Choice of Mode of Transportation

For modelling the current mode of transportation on the baseline model, the NCO from UNICEF was interviewed. From the information gathered, three main modes were defined for last-mile delivery: Car, motorcycle, and by-foot. All of these modes of transportation are currently used for last-mile distribution from the health facilities with CCE to the health facilities that do not have CCE. In this interview, a few other details

were gathered: In plain (flat) areas, motorcycles are mostly used. In hill areas, they transport the vaccines by-foot, unless there are paved roads, where they could also mix with motorbikes and or car. An approximation was used where for the Surkhet district 55% of all last-mile delivery transportation was done by motorcycle, 35% by-foot, and the remaining 10% by car and for Rukum West district 25% of all last-mile delivery was done by motorcycle, 70% by-foot and the remaining 5% by car. The difference in Rukum West is because the majority of the last-mile has low vehicle accessible roads. This previous approximation was validated by the Nepal country office based on empirical observation.

3.4.7. Cold Box Capacity

Cold boxes are the principal way that vaccines are delivered in last-mile in Nepal. Either they are carried by-foot, transported in the back of a motorcycle, or transported by car, they are transported in a cold box. To calculate how many vaccines could fit in a cold box and consequently in a single trip, the capacity for cold boxes translated in number of doses needed to be derived.

Tables 3 and 4 show the conversion units used to make these assumptions. For example, each vial can hold on average 8 doses of vaccines (that have a 2 – 8 °C storage requirement). These vials have and approximate capacity of 30 cm^3. Next, vials come in boxes of 27 vials on average. Finally, for cold boxes we picked the most commonly used one of 7 liters capacity. This cold box has an internal volume capacity of 7,000 cm^3, so it can hold 179 vials equivalent to 1,433 doses of vaccines (that have a 2 – 8 °C storage requirement).

The same procedure was calculated for the other segmentation of vaccines (that have a - 20 °C storage requirement) and the cold boxes can hold 379 vials equivalent to 3,787 doses of vaccines.

Table 3

Conversion Factor for Cold Boxes' Capacity in Vaccine Doses for 2-8 °C

For Vaccines Stored at 2-8 °C			
Measure Unit	**Volume Capacity (in cm^3)**	**Conversion factor**	**Conversion unit**
Doses	3.7	N/A	
Vials	30	8	Doses
Secondary Packaging Box	879	27	Vials
Cold Boxes (7L)	7,000	7	Secondary Packaging Box

Table 4

Conversion Factor for Cold Boxes' Capacity in Vaccine Doses for -20 °C

For Vaccines Stored at -20 °C			
Measure Unit	**Volume Capacity (in cm^3)**	**Conversion factor**	**Conversion unit**
Doses	1.4	N/A	
Vials	14	10	Doses
Secondary Packaging Box	879	57.1	Vials
Cold Boxes (7L)	7000	6.64	Secondary Packaging Box

3.4.8. Drone Specifications

UNICEF's drone catalog lists two main propulsion types, Electric and Fuel, each with a different payload capacity and flying range. Each propulsion type drone can be categorized into small and large payloads. Small payload drones can be provided by various company and are often used to transport blood, medical supplies, and

vaccines. Large payload drones are new to the healthcare context, but we included in the scope to understand their benefits and limitations and possibly recommend them for future applications in health supplies. We used the triangular distribution (a continuous probability distribution that is defined by a minimum, a mode and a maximum value) on the drone data for payload and range and confirmed outcomes with other resources (mentioned in the literature chapter). Finally, we calculated the drone capacity in doses by interpolating with the cold box specifications. We also found that the drone carrying capacity is limited by weight not the volume. In Table 5 all the different types of drones considered in this study are categorized.

Table 5

Drone Classification by Type

Characteristic	Propulsion Type	Small Payload		Large Payload	
Drone Payload (kg)	Electric Propulsion:	Min:	0.7	Min:	100
		Mode:	2	Avg:	162.5
		Max:	11.3	Max:	225
	Fuel / Gas:	Min:	3	Min:	100
		Avg:	13	Avg:	612.5
		Max:	40	Max:	1850
Drone Range (km)	Electric Propulsion:	Min:	11	Min:	500
		Mode:	100	Mode:	500
		Max:	200	Max:	500
	Fuel / Gas:	Min:	300	Min:	250
		Avg:	400	Avg:	1375
		Max:	1000	Max:	2500
Drone Payload (doses)	Electric Propulsion:	Min:	86	Min:	n/a
		Mode:	245	Avg:	n/a
		Max:	1384	Max:	n/a
	Fuel / Gas:	Min:	345	Min:	n/a
		Avg:	1592	Avg:	n/a
		Max:	4899	Max:	n/a

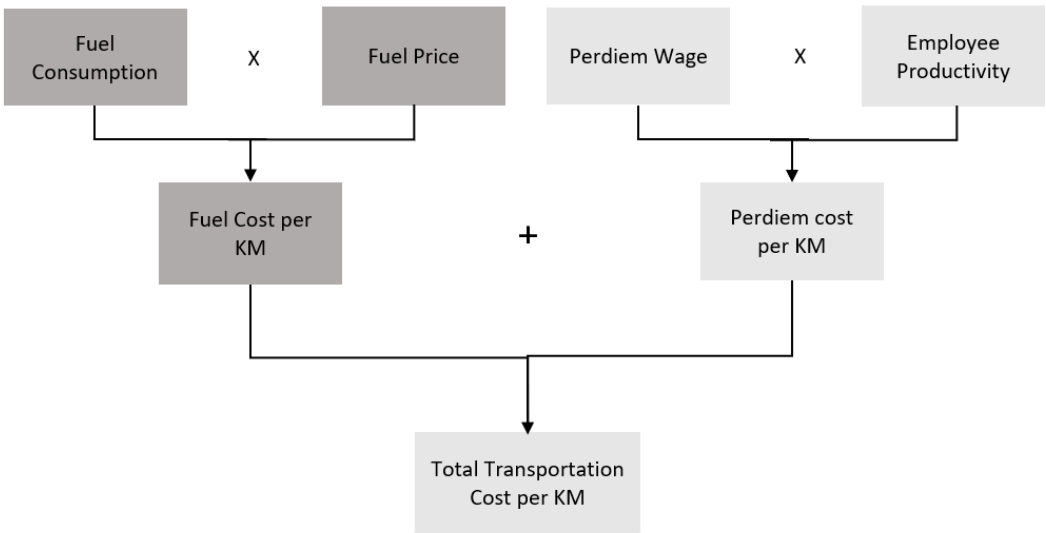
From now on we will name the different min, mode and max drones type 1, type 2 and type 3 respectively for easier recognition.

3.4.9. Transportation Costs

There are three modes of last-mile transportation between each health facilities: car, motorcycle, and by-foot. As described in the model formulation subchapter, the total transportation cost is including the fuel cost per distance and per diem cost. The fuel cost is calculated from fuel consumption and fuel price for each vehicle type. The per diem cost that is associated to the delivery is derived from productivity rate and the standard Nepal wage procured from DLCA assessment (DLCA, 2020) and productivity. Base on the interview of the NCO, we conclude that it is reasonable to assume that each of the employees will have capability to perform delivery for 20 km per day. It is also important to mention that the costs of incremental vehicles such as cars and motorcycles, are not considered in this study. The calculation and assumption of variable cost is described in Figure 17.

Figure 17

Diagram of Total Transportation Cost Calculation Assumptions



3.4.10. Cold Chain Equipment Costs

The total cost of ownership (TCO) tool for CCE, used by Gavi (2020), is the key resource for the CCE cost estimation for this Capstone. The tool models capital and operating expenses of World Health Organization Performance, Quality and Safety prequalified CCE via interactive worksheets.

The information gathered corresponds to the average of all CCE (8 model types) with the following characteristics:

- Energy Source: Electric Mains
- Equipment Type: Refrigerator
- Capacity segmentation: 60-89
- WICR FR type CCE data is considered an outlier
- 10 years of depreciation for CCE

The total cost of ownership is $2,100 USD per refrigerator as an average across the different models of equipment.

3.4.11. Fixed and Variable Drone Costs

According to the literature review and resources provided by UNICEF Drone specialize, we have concluded that drone variable cost per distance assumptions are the best representative among all information sources for small and large fixed wing drone type. However, an infrastructure component is missing from the white paper from Wright et at. (2018). This is due to an assumption that their operation has its own funders. Thus, the set-up cost from GAVI Innovation Catalogue has been leveraged. (GAVI, 2020) mentions about $2 million USD set-up cost for both, Swoop and Wingcopter operation in Tanzania, and Democratic Republic of the Congo. In this

paper, they also add 2 years of operations within that total set-up amount and the breakdown of infrastructure set-up and operational cost is ambiguous. In the result and discussion chapter, we summarize our observation and discuss how to capture that set-up cost breakdown and how to structure cost for future adapter to set up and run the operations. The summary for this section can be found in Table 6.

Table 6

Fixed and variable costs for drones

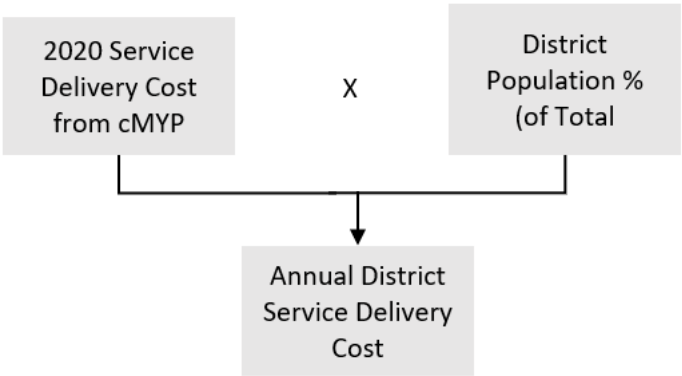
Cost Description	Electric Propulsion	Fuel Propulsion
Total Fixed and Variable Costs per KM	$0.19	$0.54
Total Infrastructure Set up Cost	$2 million	$2 million

3.4.12. Current Total Network Cost Allocation by District

The Comprehensive Multi-Year Plan (cMYP) is a document from Nepal's Ministry of Health with the detailed strategy for the national immunization program. In this document, cost information was provided in an aggregated level. This is the real cost information to which we compared our baseline model costs to check if correct. The allocation assumption, to breakdown cost per district, was made using the population number. Figure 18 depicts allocation method of current total transportation cost from cMYP expenditure.

Figure 18

Calculation for Current Total Cost Allocated by District



3.5. Scenario Runs

Eight different scenarios were run in order to assess the effectiveness of the developed model and to reflect several changes that would help quantify decisions regarding changes in the modes of distributions in the vaccine network of Nepal.

In the baseline, the model baseline is defined by running the network with the current CCE capacity constraints, the base mode distribution derived in 3.4.5, the costs for each mode and not including any drone lanes or facilities. This will be the model which next scenarios will be compared to.

In the first scenario, the cold chain capacity constraint is eliminated. The next two scenarios are introduced the drone option into the model with a sensitivity analysis. The fourth and fifth scenarios are to simulate different drone cost structure. Finally, sensitivity analyses are performed on demand and cost in sixth and seventh scenario. Table 7 shows the summary list for all scenarios to be run.

Table 7

Overview of the Differences Between the Eight Optimization Scenarios

#	Scenario Name	Transportation Mode	Drone Type	Major Cost
0	Baseline	-Current distribution **-Decision Variable**	N/A	Current
1	100% Vaccine Availability	-Current distribution **-Decision Variable**	N/A	CCE Depreciation
2	Drone use over Baseline (0)	-Current distribution **-Decision Variable**	A. Fuel-Propulsion B. Electric-Propulsion	-1x Drone Set Up Cost & OPEX -2x Drone Set Up Cost & OPEX
3	Drone use over 100% Vaccine Availability (1)	-Current distribution **-Decision Variable**	A. Fuel-Propulsion B. Electric-Propulsion	-1x Drone Set Up Cost & OPEX -2x Drone Set Up Cost & OPEX
4	Outside Funding of Drone Facilities Set-up Costs	-Current distribution **-Decision Variable**	A. Fuel-Propulsion B. Electric-Propulsion	Drone OPEX
5	Outsource Drone Operation	Current distribution	Electric-Propulsion (max payload)	Higher Drone OPEX per dose (include maintenance cost)
6	Demand Sensitivity Analysis	Current distribution	Electric-Propulsion (max payload)	Drone Set Up Cost & OPEX
7	Fuel and Per-diem Cost Sensitivity Analysis	Current distribution	Electric-Propulsion (max payload)	Higher Transportation and Holding Costs

Scenario 0: Baseline

This is to simulate the current vaccination network in particular district for the baseline of future scenarios. The model is created according to the assumptions in chapter 3.4, actual demand served and shipment size from micro planning information from the NCO. We validate the model using the allocated cost by District, described in Section 3.4.10, to match the total transportation and CCE cost from the model.

Scenario 1: 100% Vaccine Availability

The 100% vaccine availability scenario has the objective to evaluate whether the current health facility can be used in more efficient way if the cold chain capacity is unconstrained. For this scenario we considered that the district in question had 100% vaccine availability, so the demand was modifying to reflect this. This scenariois the basis which the further optimized scenarios will be compare to.

Scenario 2: Drone Use Over Baseline (Scenario 0)

The drone scenario has the objective to evaluate the change in transportation mode selection, cost impact to the current vaccination network, and to provide a recommendation on the best drone type for Nepal. For the purpose of the model, total cost to serve the current 78.5% coverage is compared across different drone specifications (Section 3.4.8) and different number of drone facility.

Scenario 3: Drone Use over 100% Vaccine Availability (Scenario 1)

The model objective for scenario 3 is similar to scenario 2, however, the comparison of total cost will be performed against optimized baseline. The network will have unconstrained CCE capacity and serve 100% demand.

Scenario 4: Outside Funding of Drone Facilities Set-up Costs

We create this scenario to evaluate the change in decision if the drone set-up cost is funded by the government or other organization. Scenario 4 does not require additional model runs, the result from scenarios 2 and 3 are utilized without considering start-up cost for drone bases.

Scenario 5: Outsource Drone Operation

When outsourcing the drone operation, the drone provider is responsible for the infrastructure set-up cost, but they will charge the operating cost per dose with a margin. Typically, this margin includes the maintenance cost which the drone service provider spreads across multiple customers. Because of the uncertainty of the number of customers, we conducted a sensitivity analysis for the total operating cost per dose proposed by the drone operator. The outcome of this scenario includes the recommendation of a reasonable total operating cost per dose for outsourcing the drone operation.

Scenario 6: Demand sensitivity analysis

We hypothesize that the drone application will provide more flexibility to overall vaccination network. Thus, additional demand sensitivity scenarios are conducted to assess whether drone have benefit over current mode of transportation when there is high uncertainty involve.

Scenario 7: Fuel and per diem sensitivity analysis

For the last scenario, additional fuel and per diem sensitivity scenarios are performed to assess the drone benefit when the cost structure of current transportation mode change.

4. RESULTS AND DISCUSSION

In this chapter, we will discuss the results of our qualitative and quantitative approach, which are the ArcGIS and Llamasoft analyses, respectively.

4.1. Phase 1 Results: District Classification Framework for Drone Application

The first stage of our problem-solving methodology is the district classification analysis. Eight factors that derived from 5 aspects are preprocessed to have common scale via ArcGIS, as described in Section 3.1 of the methodology chapter. These 8 layers are overlaid with assigned weight from survey results.

4.1.1. Survey Results

The survey objective was to assess the ranking of factors and their contribution as a rule of thumb for drone deployment. We sought to identify areas where the use of drones could make the greatest contribution for vaccine availability (regardless of feasibility and cost efficiency). This survey requests the following:

- Ranking of the factors based on order of importance.
- Assigning percentages for each factor adding up to 100%

The survey was conducted in January 2021 and the survey response rate was 86%.

Initially, the weight percentages were concluded based on all participants' responses, however, we found the values in the data set were widely scattered. We conducted an interview and a meeting to discuss the outliers and found that people outside the UNICEF organization were not properly informed about the project scope and the real implication of each factor. Concluding, we created a new data set of the weight percentages from the internal team's responses and compared measures of

dispersion for the two data sets. The standard deviation is double for “All Participants” compared to “Project Team” data set in some factors. Figures 19 and 20 show the variation of average and median weights for both data sets.

Figure 19

Radar Plot of Average and Median Weight Values over Eight factors of “All Participants” vs “Project Team” Data Sets

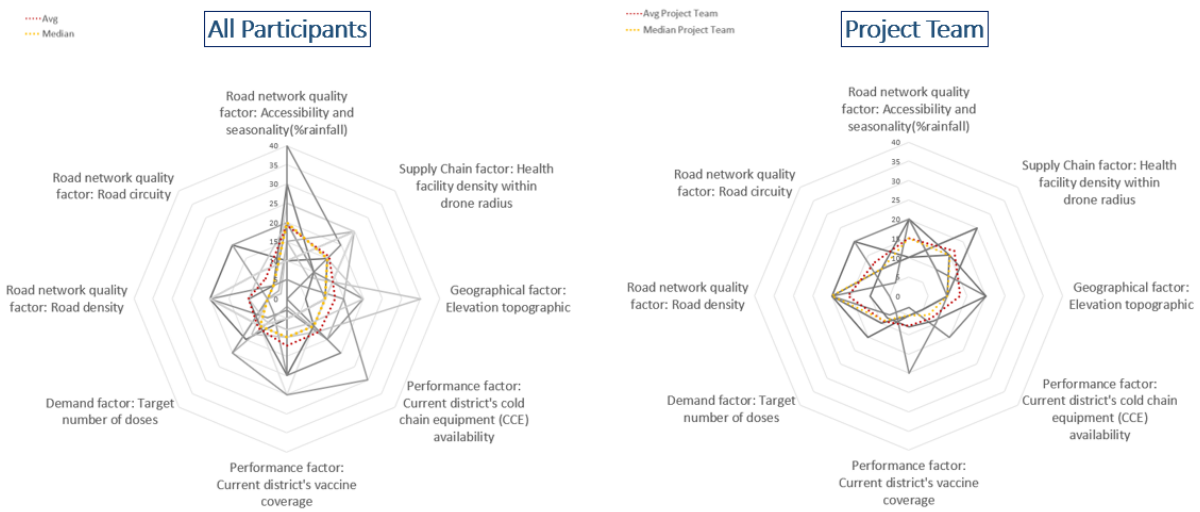
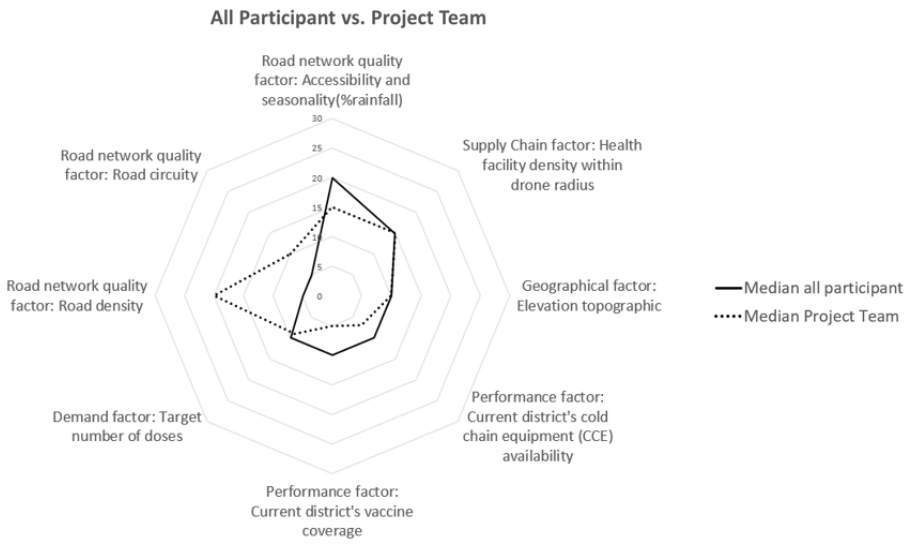


Figure 20

Radar Plot of Median Weight values over Eight Factors of “All Participants” and “Project Team” Data Sets.



Finally, we proposed to remove the outliers from the analysis to avoid survey selection bias. The summary of weight for each factor is presented in Table 8 and the variation of weights is visualized in radar plot Figure 21.

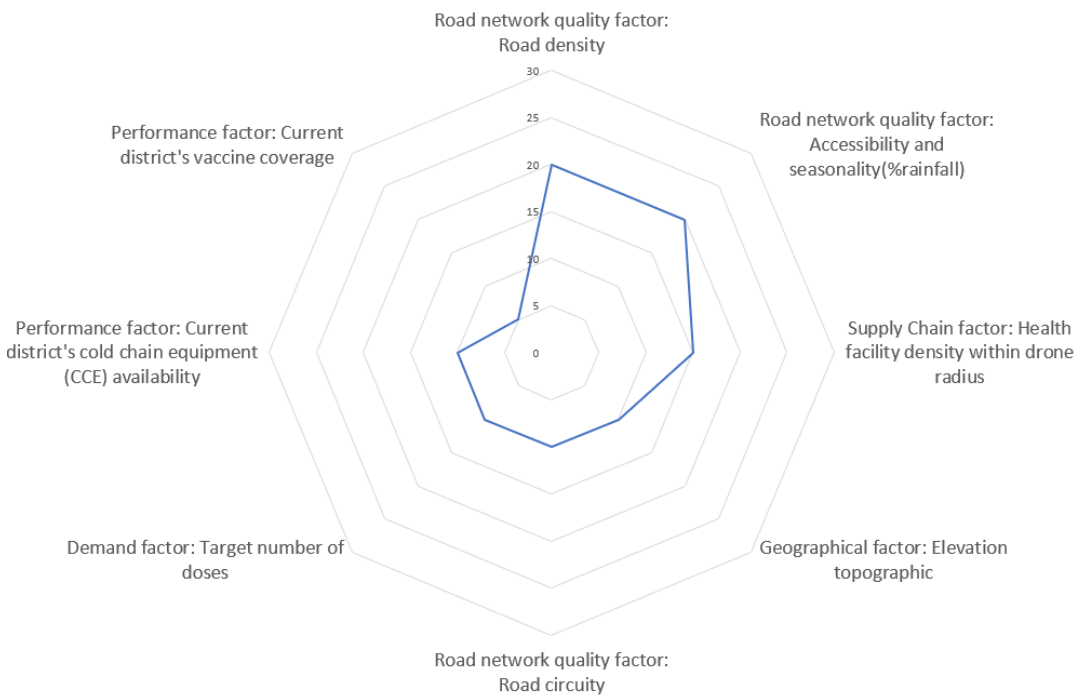
Table 8

Weight allocation for each factor

Weight, %	Factor
20	Road network quality factor: Road density
20	Road network quality factor: Accessibility and seasonality(%rainfall)
15	Supply Chain factor: Health facility density within drone radius
10	Geographical factor: Elevation topographic
10	Road network quality factor: Road circuity
10	Demand factor: Target number of doses
10	Performance factor: Current district's CCE availability
5	Performance factor: Current district's vaccine coverage

Figure 21

Radar Plot of Proposed Weight Values over Eight Factors



There were three major findings among the eight factors:

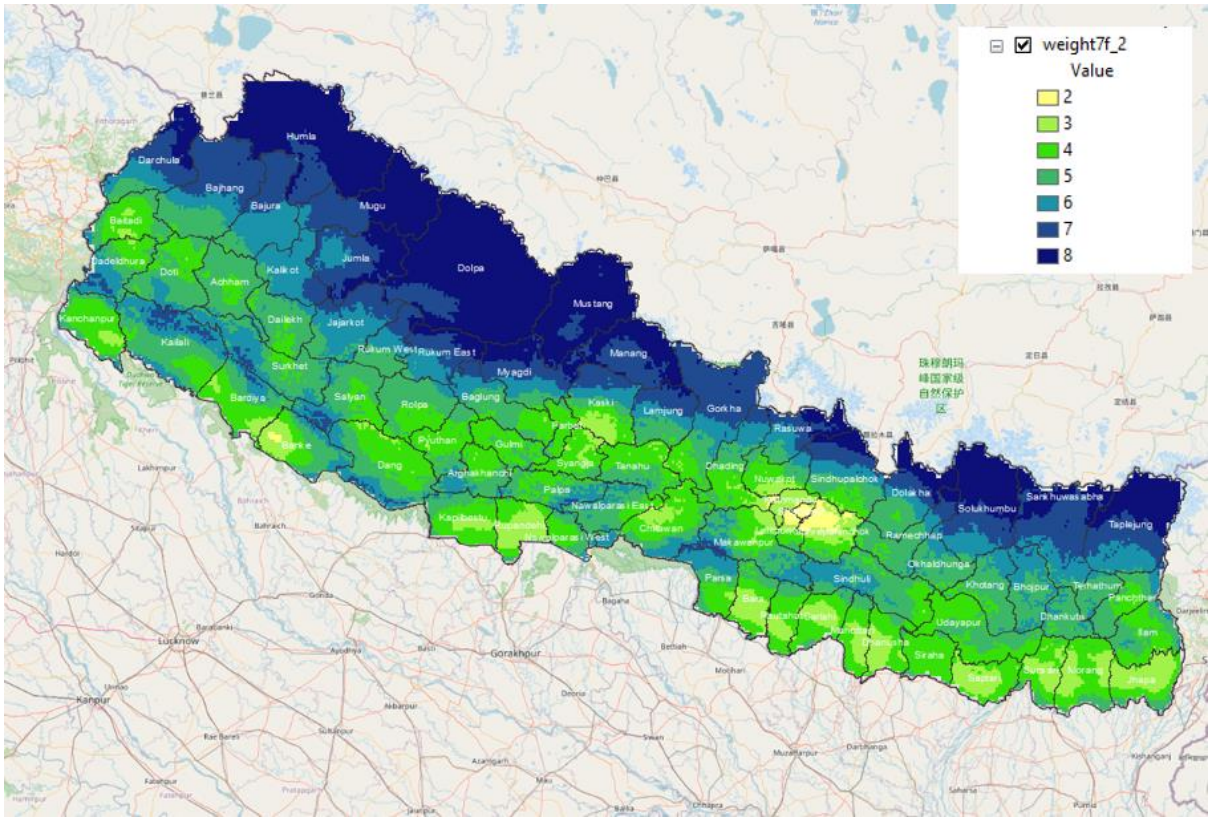
- The road network quality factor (Accessibility and seasonality) is ranked with the highest score, with a 20% weight. Results are consistent between participants, which indicates that drones should be recommended primarily for 'hard-to-reach' facilities, rather than for all facilities.
- The performance factor is ranked with the lowest score. The districts' vaccine availability is ranked with a 5% weight. There could be many reasons for low vaccine availability, such as lack of communication between echelons, replenishment frequency problems, etc. The current vaccine availability does not necessarily point to a need for a new mode of transportation. It is an important criterion for prioritization when more than one district is ranked with the same score and resources are limited.
- The demand factor was very significant in the ranking. The target number of doses matters greatly in commercial drone projects when the focus is the cost of delivery efficiency. On the contrary, it does not matter much if the goal is to reach isolated communities.

4.1.2. Overlaid Map

The result of the survey is used as an input for weight overlay analysis in ArcGIS. The overlaid map depicts the most suitable location for drone development, as shown in Figure 22, where a score of 8 is the most Desirable Districts for Drone Deployment and 2 indicates Less Desirable Districts for Drone Deployment.

Figure 22

Final Overlaid Map Showing Geographic Areas Colored by Drone Applicability



From the result, it is evident that the most favorable area for drone use in Nepal is formed around the mountain area that borders Tibet in the north. This is due to the domination of both Road network quality factors: Road density and Accessibility, which have a 40% weight combined (20% for each factor). These top 2 layers offset each other and are shown in Figures 23 and 24. Even though there are low road densities in some districts along the Nepal-India border in the South, these roads are paved and have good accessibility throughout the year. According to the overlay map, there is lower attractiveness for drone implementation in the districts of Bagmati, Karnali, and Lumbini Province compared to the same scenario but considering the complete road density factor.

Figure 23

Road Network Quality Factor Map: Road Density

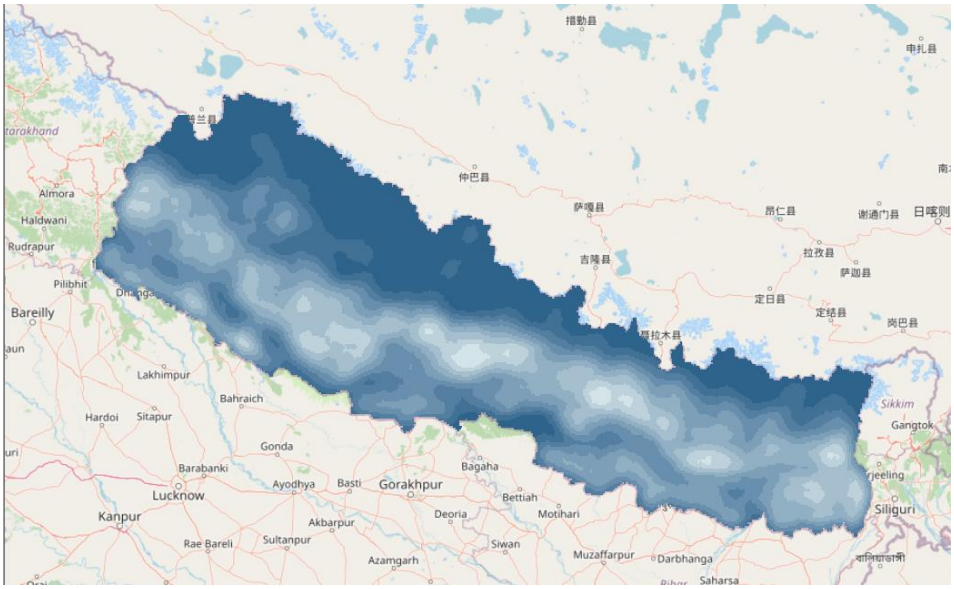
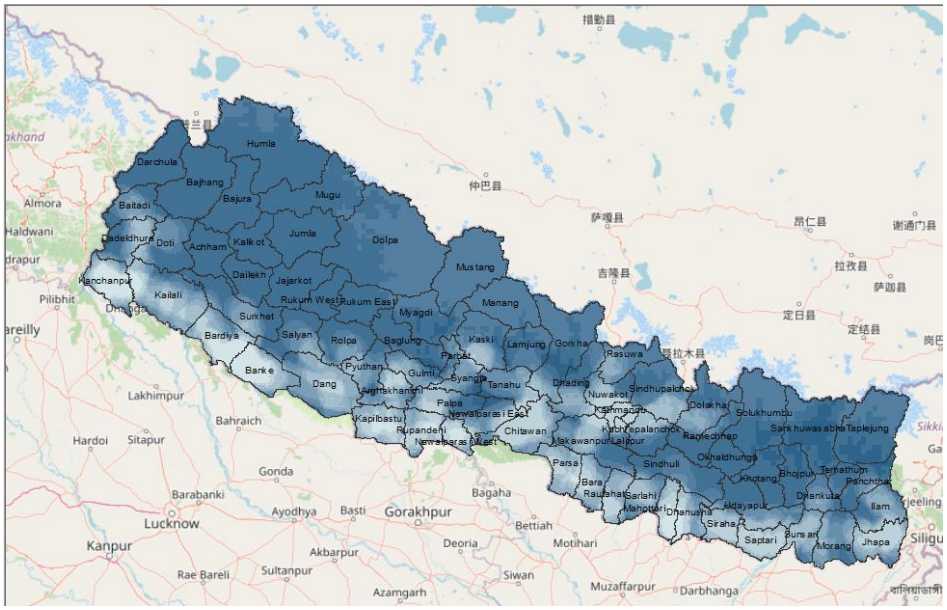


Figure 24

Road Network Quality Factor Map: Accessibility



Even though we have accounted for the rainfall in the accessibility layer, due to the fact that this factor only affects travel during the monsoon season, the factor has less influence on the overall accessibility to health facilities layer.

One important comment is that this is a reusable framework that is scalable to a more granular detail in Nepal or adoptable for other geographies that have similar characteristics. For example, the aggregation level for Phase 1 was at district and provincial level, the same framework could be applied to data at the health facility level in Nepal or other geographies.

4.1.3. District Summary Table

Finally, a Zonal Statistics toolbox was utilized to obtain an insight at the district and province health facility level. Zonal Statistics toolbox is a feature in ArcGIS that calculates statistics on values of a raster within the zones. The chart in Figure 25 is the classification of districts by overlay score. Districts with a score of 8 are the most favorable ones for drone implementation, while districts with a score of 2 are the least. We discovered that the district classification result has followed the normal distribution where most of the districts occur in the middle of the curve at score 5. There are six districts (two from Gandaki province, three from Karnali province, and two from Province 1) that rated at score 8, which is the most desirable for drone development range. The list of districts that were identified as high potential for drone use case (score 8) can be found in Table 9.

Figure 25

Classification of Districts by Overlaid Score

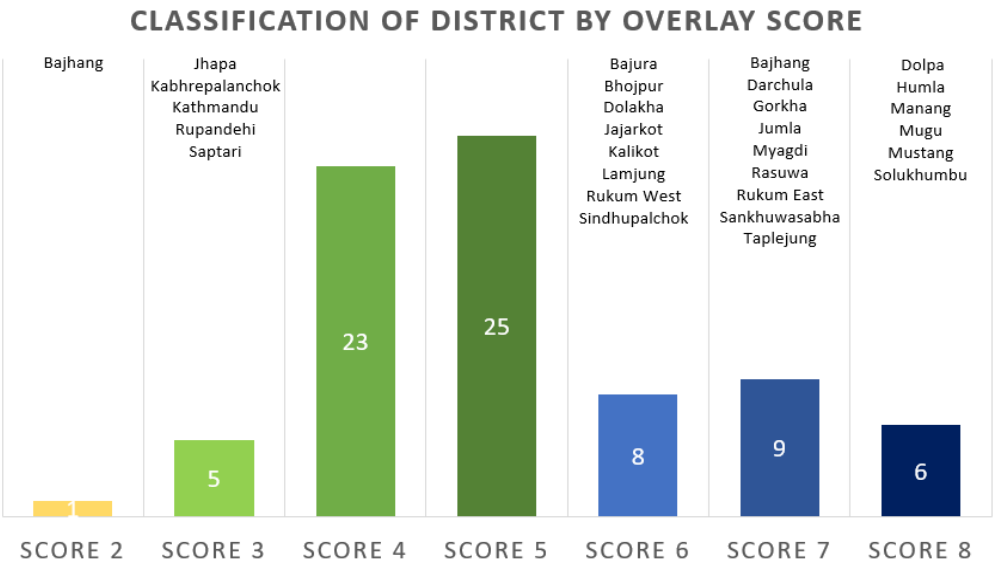


Table 9

List of Districts with Highest Potential for Drone Application

District	Province
Dolpa	Karnali Province
Humla	Karnali Province
Manang	Gandaki Province
Mugu	Karnali Province
Mustang	Gandaki Province
Solukhumbu	Province 1

With this classification result, the sponsoring organization can review only the districts that fall between scores 6 and 8 and conduct further studies on it. Other considerations to select the districts are the location, the existing drone hub locations and data availability. Districts that are located close to the country's capital can be inferred to have better infrastructure and be more adequate for constructing and operating a drone facility. This district classification framework is derived based on a greenfield analysis, which means that any point could be selected even though there was no previous operation on it. If drone hubs had already existed in the country, further

information of existing drone's ranges would be critical for district selection. Finally, in Section 3.4, we highlighted the importance of having exhaustive data for each outreach site and health facility in the district to perform a drone network optimization. Thus, the selected district needs to have all necessary data required to be used in the optimization model.

The results at the province level indicate that the Karnali Province has the highest score and Province 2 has the lowest score for drone development. In Figure 26, we can quickly identify any province in the map of Nepal, locating Karnali in the northeastern part of Nepal and Province 2 in the southwestern part.

Figure 26

Nepal's geopolitical regional division

In Table 10 the number of districts per province and overlay score is shown. The information on this table matched the previously commented result, the Karnali

province has the most likelihood of success for drone implementation, it has 3 districts that scored 8, and all the other districts except for one with scores over 5. After, comes the Sudurpashchim province, followed by Gandaki, Province 1, Bagmati, Lumbini, and finally Province 2, with the least likelihood of success for drone implementation.

Table 10

Distribution of Districts by Province and Overlay Score

		Overlay Score							Weight Avg. Score
		Score 2	Score 3	Score 4	Score 5	Score 6	Score 7	Score 8	
District count by Province	Bagmati Province	1	1	3	4	2	1		5
	Gandaki Province			4	2	1	2	2	6
	Karnali Province		1		3	2	1	3	6
	Lumbini Province		1	5	5		1		5
	Province 1		1	4	5	1	2	1	5
	Province 2		1	6	2				4
	SPP			1	4	2	2		6

Due to the time constraint of the project, the circuity factor layer has not been incorporated to the overlaid map as planned. The health facility point density calculation could also be improved by using the total number of health facility per district instead of using it per land area. Suggestion for future work can focus on either applying this framework to the different geography to test its robustness or improving the input layer's quality, especially for the circuity and the health facility density.

4.2. Phase 2 Results: Optimization Model

The objective for Phase 2 was to select two districts from Phase 1 and perform a trade-off analysis to determine the differences in cost for implementing drones vs the current model and to recommend where to set drone bases and what type of drone would be appropriate for the implementation. According to the allocation method in Section 3.4.12, the total annual spend of Surkhet district is approximately $100,000 USD. UNICEF also shared a benchmark value for Uganda, where district level cost is

approximately $80,000 USD per year, this further confirmed our baseline calculations. The first validation we did before starting all other scenarios was to check that our baseline matched the real-life cost and vaccine availability provided by UNICEF. In the case of Surkhet, these numbers are depicted in Table 11, which shows that they are within 10% of the true figures, so we had a good estimation as baseline. In the case of Rukum West, these numbers are depicted in Table 12, which shows that they are within 6% of the true figures, so also confirmed a correct estimation of the baseline. The only difference is that for Rukum West the CCE cost had to be adjusted because the real numbers did not match the fact that there is only one refrigerator in the one HF1.

Table 11

Comparison of real-life costs and baseline model for Surkhet result costs

Surkhet District	2020 Actual	Model Result
Vaccine Availability, %	78.5%	78.5%
Transportation Cost, USD	30,893	27,008 (-8%)
CCE Cost, USD	75,154	69,300 (-10%)

Table 12

Comparison of real-life costs and baseline model for Rukum West result costs

Rukum West District	2020 Actual	Model Result
Vaccine Availability, %	86%	86%
Transportation Cost, USD	12,600	13,418 (+6%)
CCE Cost, USD	2,100	2,100 (0%)

In Figures 27 and 28, the current flow of vaccines from the HF1s to HF2s is shown for the Surkhet and Rukum West districts, respectively. This illustrates the different current

network flows for each of the districts. While both districts' networks consist of the CVS serving the PVS, which serves the DVS, which in turn serve the HF1s that finally serve HF2s, Rukum West is rather smaller in size and population. In Surkhet there are several health facilities with CCE that serve different smaller health facilities with no CCE. For Rukum West, there is only one big health facility, other than the district vaccine store, that serves the smaller health facilities that do not have cold chain equipment.

Figure 27

Map of Surkhet showing baseline flow for Health Facilities with and without CCE

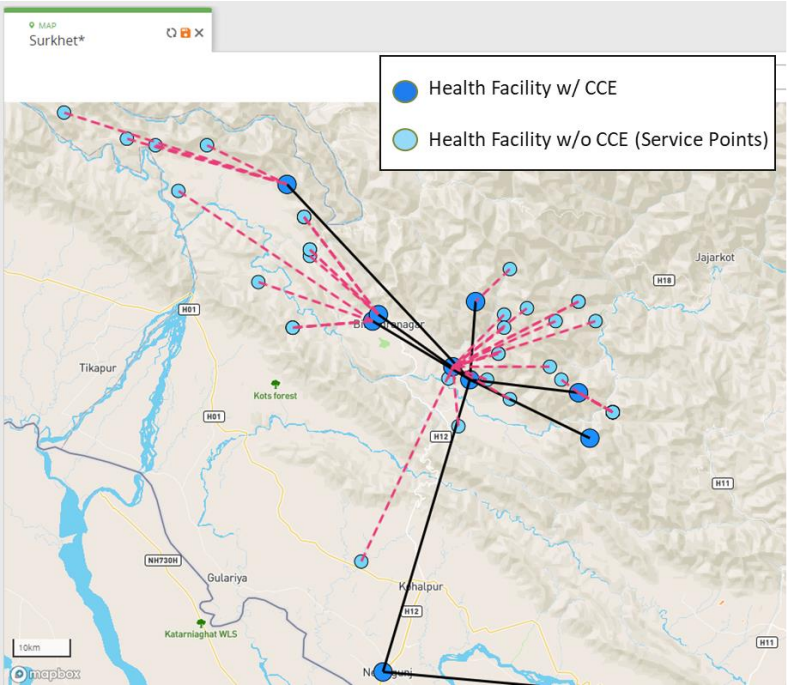
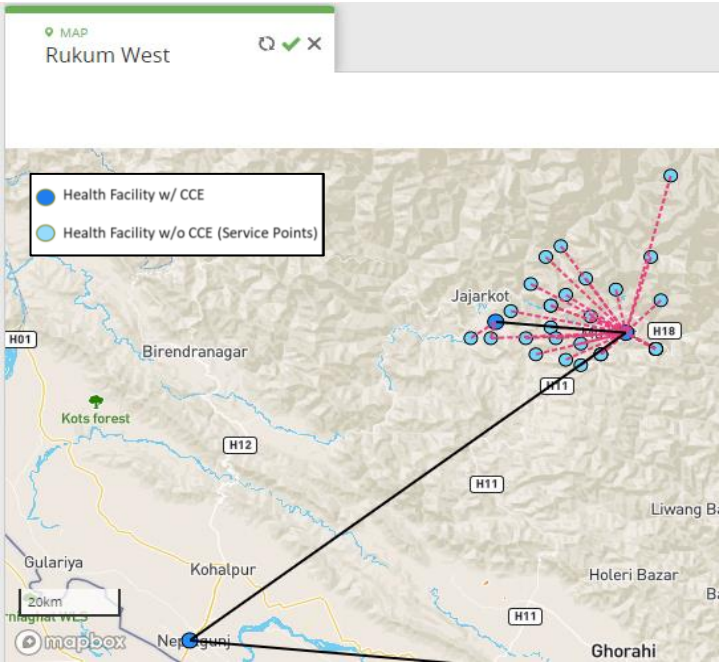


Figure 28

Map of Rukum West showing baseline flow for Health Facilities with and without CCE



After validating the baseline in contrast with the real-world data, we could confidently start building the rest of the scenarios. For each of the scenarios, a series of iterations were run in order to capture different characteristics and the result for the various inputs, these iterations are displayed in Table 13.

Table 13

List of Iterations Run for Each Scenario

#	Scenario Name	# of Iterations	Iteration Number	Comments
0	Baseline	2	17, 17.5	One for each transportation mode constraint
1	100% Vaccine Availability	2	20, 20.5	One for each transportation mode constraint
2	Drone Over Baseline (0)	24	23 - 46	Combination of 2 transportation mode constrains, 2 drone propulsion types, 3 types of drones, 2 number of drone hubs
3	Drone Over 100% Vaccine Availability (1)	24	51 - 74	Combination of 2 transportation mode constraints, 2 drone propulsion Types, 3 Types of Drones, 2 number of drone hubs
4	Outside Funding of Drone Facilities Set-up Costs	0	0	Used the results from Scenarios 2 and 3 without considering set-up costs
5	Outsource Drone Operation	10	75 - 84	10 different costs per km for outsourced operation
6	Demand Sensitivity Analysis	8	85 - 88	4 different demand levels over Scenario 1 and Scenario 4
7	Fuel and Per-diem Cost Sensitivity Analysis	4	89 - 92	4 different fuel & per-diem costs
		74		

For example, for the baseline (Scenario 0), we run the first iteration (#17) as close to reality as we could to validate the real-world costs, but also run another iteration (#17.5) to analyze what would happen if we removed the transportation mode distribution constraint. For Scenario 1, with 100% vaccine availability, we also run 2 iterations, the first with the transportation mode distribution constraint (#20) and a second one without that same constraint (#20.5). Twenty-four iterations were run for both Scenarios 2 and 3 (#23 - #46 and #51 - #73, respectively): one iteration for each combination of drone propulsion type (electric and fuel), 3 types of drones (type 1, 2, and 3), opening 1 and 2 drone hubs and with or without the transportation mode

distribution constraint. For Scenario 4, no new iterations were needed because we could just use the cost information derived from Scenarios 2 and 3 and remove the start-up costs. For Scenario 5, we run 10 different iterations (#75 - #84) considering different transportation costs for the recommended drone after previous scenarios' analysis — a type 3 electric propulsion drone. For Scenarios 6 and 7, sensitivity analysis was conducted changing demand, fuel costs, and per-diem costs. In Scenario 6 we run 8 different iterations using demand at 25%, 50%, 150% and 200% over both the 100% availability model and the recommended drone with 1 hub iteration. For Scenario 7 we run 4 more iterations over the recommended drone with 1 hub iteration using 50%, 110%, 120% and 150% of the logistics cost.

After this, we began drawing some results from a comparison of the different iterations of the scenario runs. For this we created several figures for better understanding.

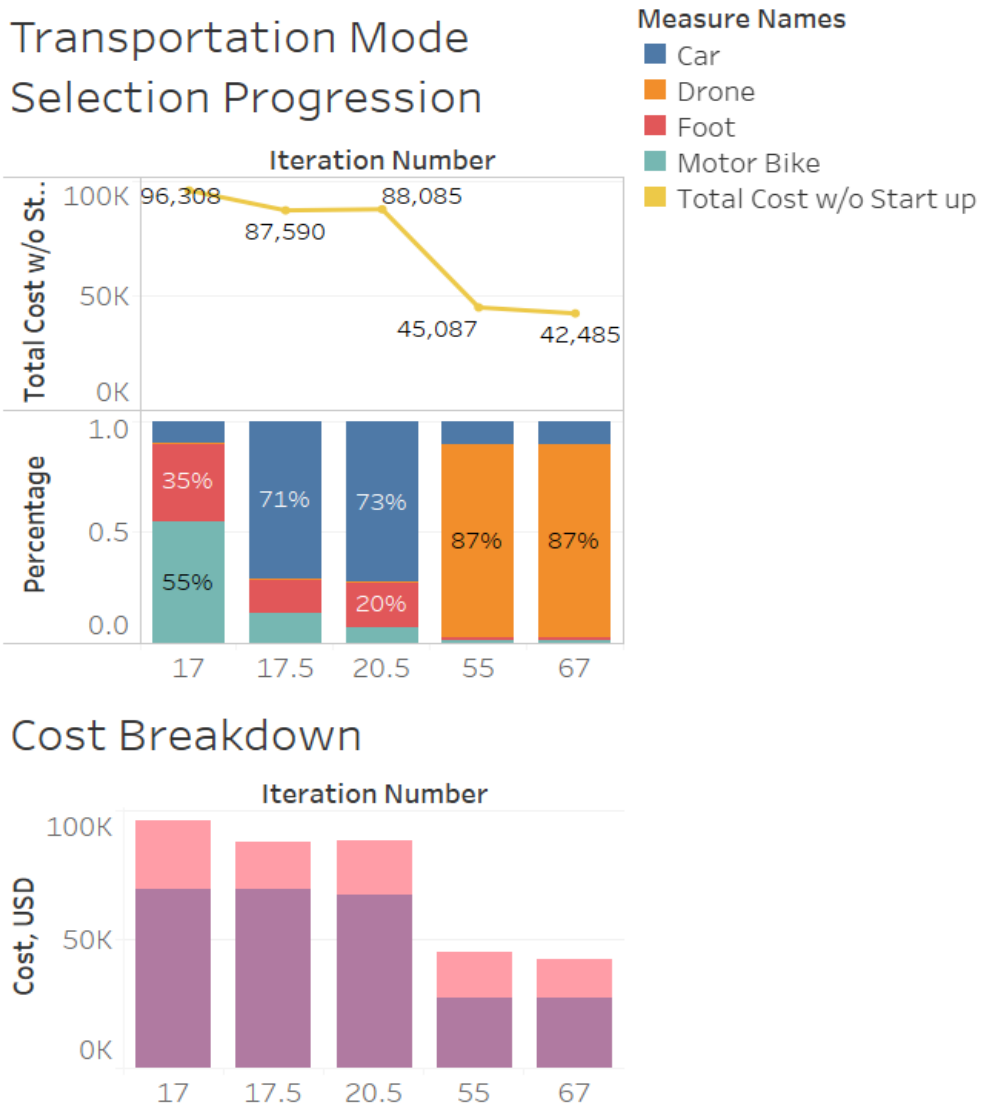
The first set of charts, Figures 29 and 30, shows the cost and mode selection progression of 5 iterations:

- Iteration #17: The baseline model
- Iteration #17.5: The baseline model without forcing the transportation mode to the baseline distribution (55% by motorcycle, 35% by-foot and 10% by car for Surkhet and 25% by motorcycle, 70% by-foot and 5% by car for Rukum West as described in Section 3.4.6)
- Iteration #20.5: Iteration with 100% vaccine availability and without forcing the transportation mode to the baseline distribution (same as described in last bullet)

- Iteration #55: Based on Iteration #20.5 but including electric type 2 drone and 1 drone hub
- Iteration #67: Based on Iteration #33 but opening 2 drone hubs

Figure 29

Transportation Mode Selection Progression for Surkhet District



The results for Surkhet derived from Figure 29 are:

- When we freed up the constraint that forces the mode distribution to be 55%-35%-10%, the model chooses car first because it can hold double capacity, thus, the cost per dose lowers.

- When we include 100% vaccine availability, the model includes more flow of vaccines. The transportation cost goes up because there are more doses. The CCE cost drops slightly because the CCE capacity is better distributed.

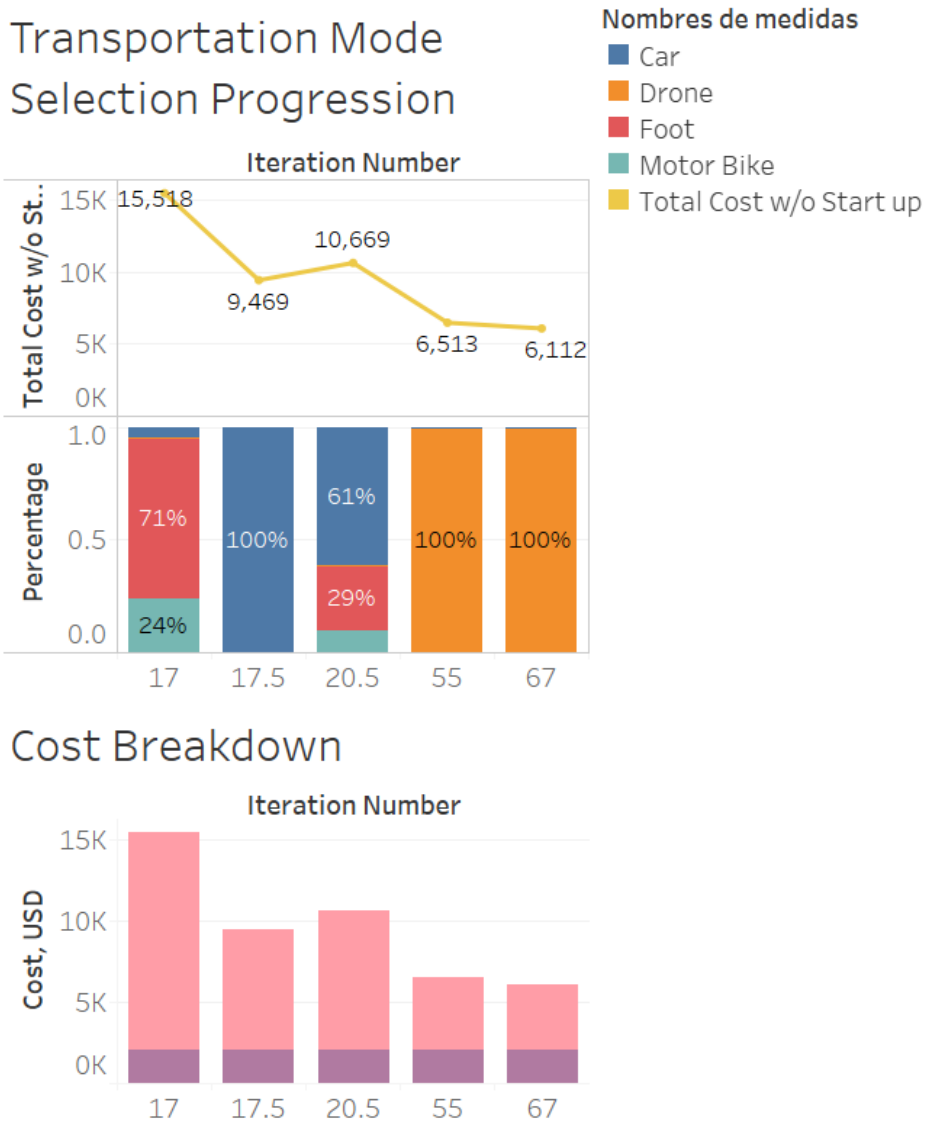
- In the final two iterations, drones are selected. The variable cost per km for drones is lower than the other modes, so the model prefers it by far (87%). The difference between the last two iterations is opening either 1 or 2 drone facilities. When 2 hubs are opened, the transportation cost goes down because the model can choose a better hub that is closer to the service area.

The results for Rukum West derived from Figure 30 are:

- Similar to the analysis in Surkhet, the total cost per dose lowers when the constraint that forces the mode distribution to be 25%-75%-5% is loosened. In Rukum West case, when the distribution constrain is freed, the model chooses 100% flow by car. Although this option would be the most cost efficient, it is not viable due to the lack of vehicle accessible roads in the district.
- Another difference in this district is that as there is only one HF1 with CCE, there is no possibility to redistribute the flow to optimize the use of several refrigerators' capacities across health facilities.

Figure 30

Transportation Mode Selection Progression for Rukum West District



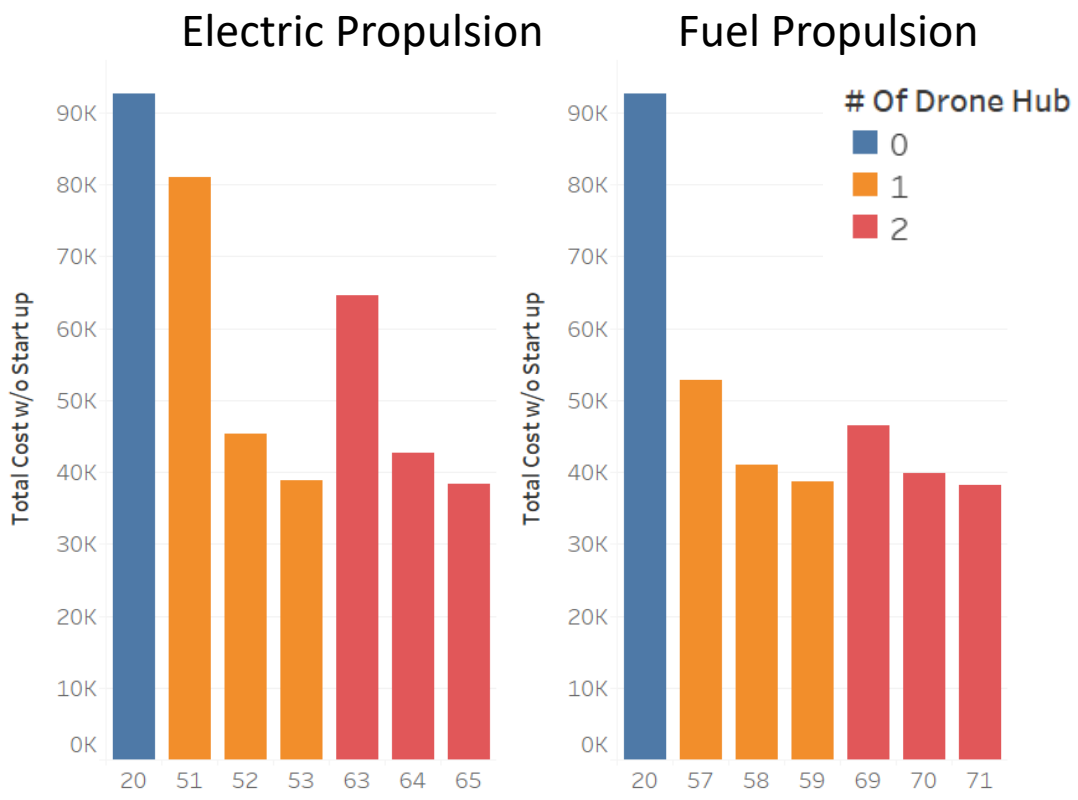
The second analysis, shown in Figures 31 and 32 for Surkhet and Rukum West, respectively, compares scenarios which offer 100% vaccine availability and do force a mode selection to reflect real-life constraints or availability of resources. The iterations used in this analysis were:

- Iteration #20: Iteration with 100% vaccine availability and constraint forcing the transportation mode to the baseline distribution (55%-35%-10%)

- Iterations #51, #52, #53: Using an electric propulsion drone model for Type 1, Type 2 and Type 3 and opening 1 drone hub
- Iteration #63, #64, #65: Using an electric propulsion drone model for Type 1, Type 2 and Type 3 and opening 2 drone hubs
- Iteration #57, #58, #59: Using a fuel propulsion drone model for Type 1, Type 2 and Type 3 and opening 1 drone hub
- Iteration #69, #70, #71: Using a fuel propulsion drone model for Type 1, Type 2 and Type 3 and opening 2 drone hubs

Figure 31

Drone Type Selection Without Including Start-up Costs for Surkhet District



The insights that we concluded from the Surkhet analysis are:

- The choice of the best type of drone was based on the lowest transportation and CCE costs. This did not consider the start-up costs for drone bases, which we assume are similar between types.

- The best option is the biggest drone in terms of payload and range, the type 3 electric propulsion drone.

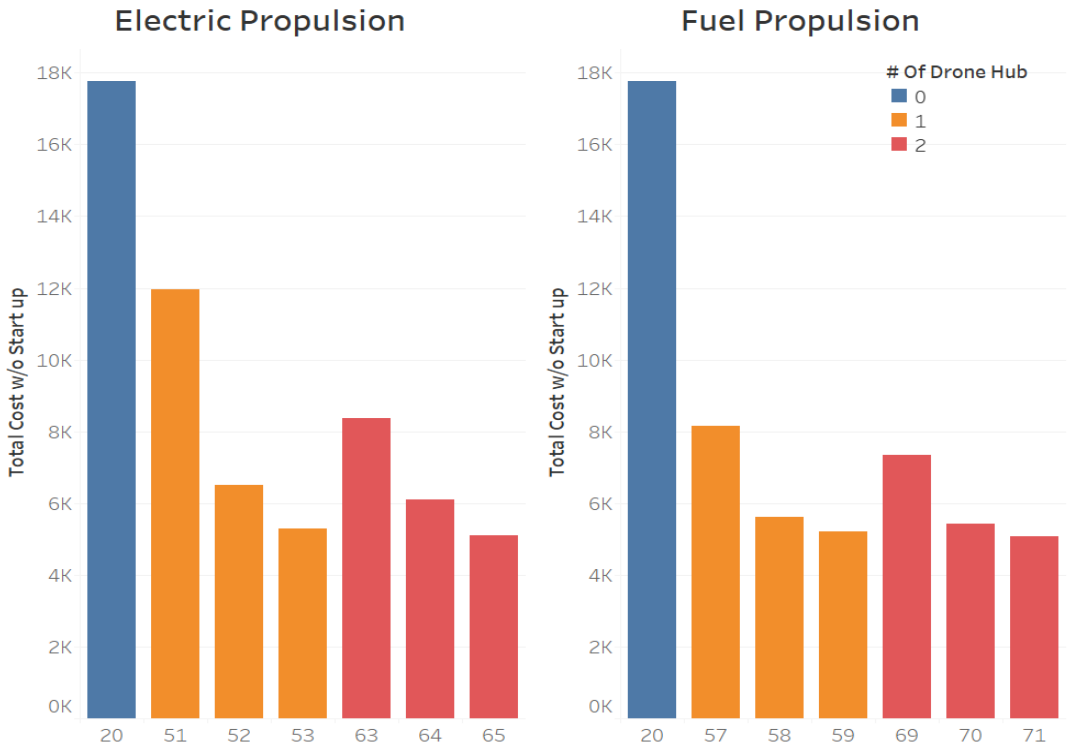
- Another insight is that the type 2 drone is very close in cost to the type 3 drone. If the cost to acquire type 3 drones compared to the cost of type 2 drones is larger than the difference in delivery cost between them, then type 2 drones could be chosen.

- The total cost of smaller drone declines significantly when opening more hubs closer to demand points. So, we can assume that when opening more facilities, the smaller drone becomes a more attractive option.

- In the case of the electric propulsion drone, the range for the type 2 drone is 10 times bigger than the type 1 drone. In the case of the fuel propulsion drones, the range for type 2 drones is only 1.3 times bigger type 1 drones. Therefore, the difference in cost becomes smaller in the fuel propulsion chart.

Figure 32

Drone Type Selection Without Including Start-up Costs for Rukum West District



In case of Rukum West for the same analysis:

- The results confirm that the type 3 electric type drone is the recommended one considering cost and sustainability.
- The cost also decreases when increasing the number of drone hubs opened in this district.
- If only opening one single drone hub, the range of the type 1 drone cannot cover the whole district, and fewer doses (43%) could be served from the opened drone facility.
- For type 2 and 3 drones, the drone range is enough to serve the whole district as its distribution network is not very large. The only change is the selected geolocation for opening the drone hub.

In Figures 33 and 34, we present the results from adding the start-up costs to the previous analysis on Surkhet and Rukum West districts, using the same model iterations.

Figure 33

Drone Type Selection Including Start-up Costs for Surkhet District

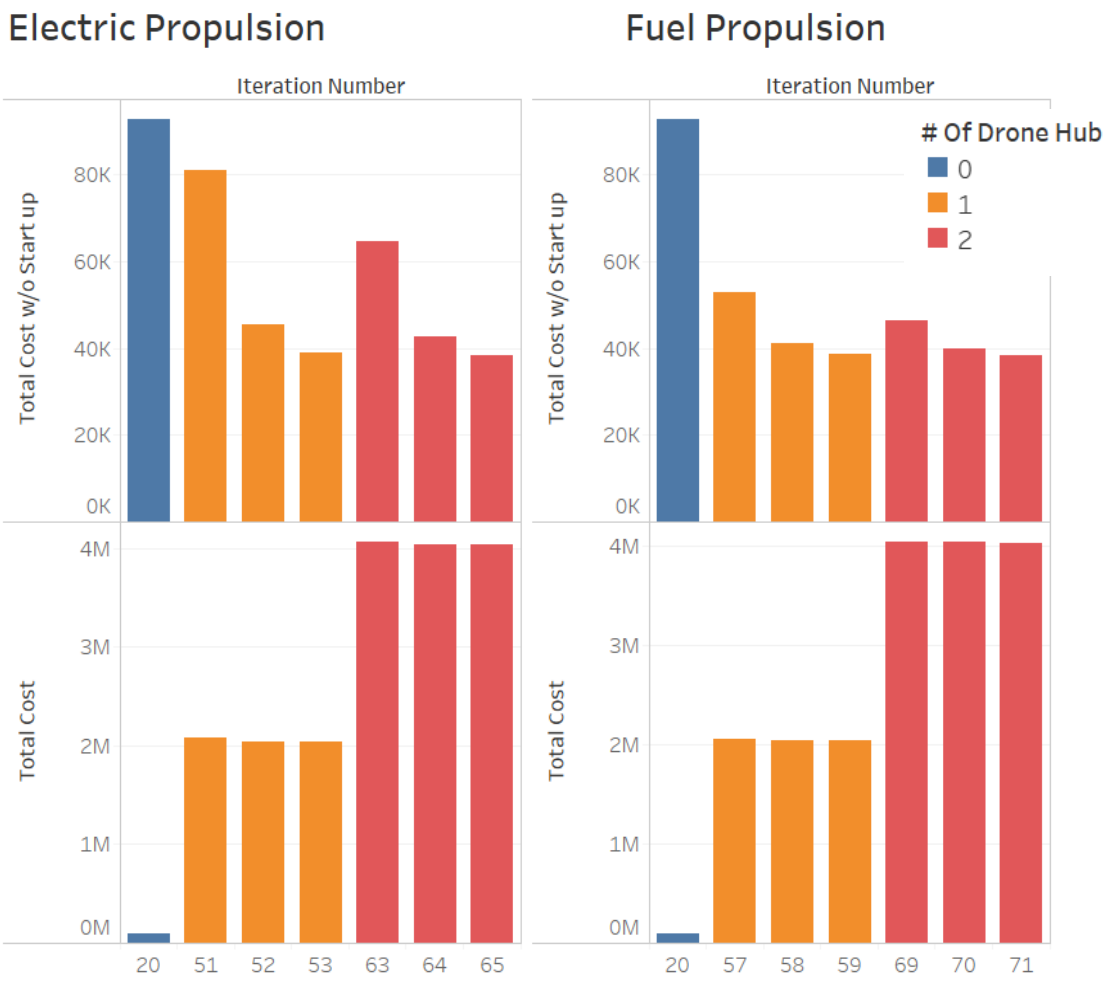
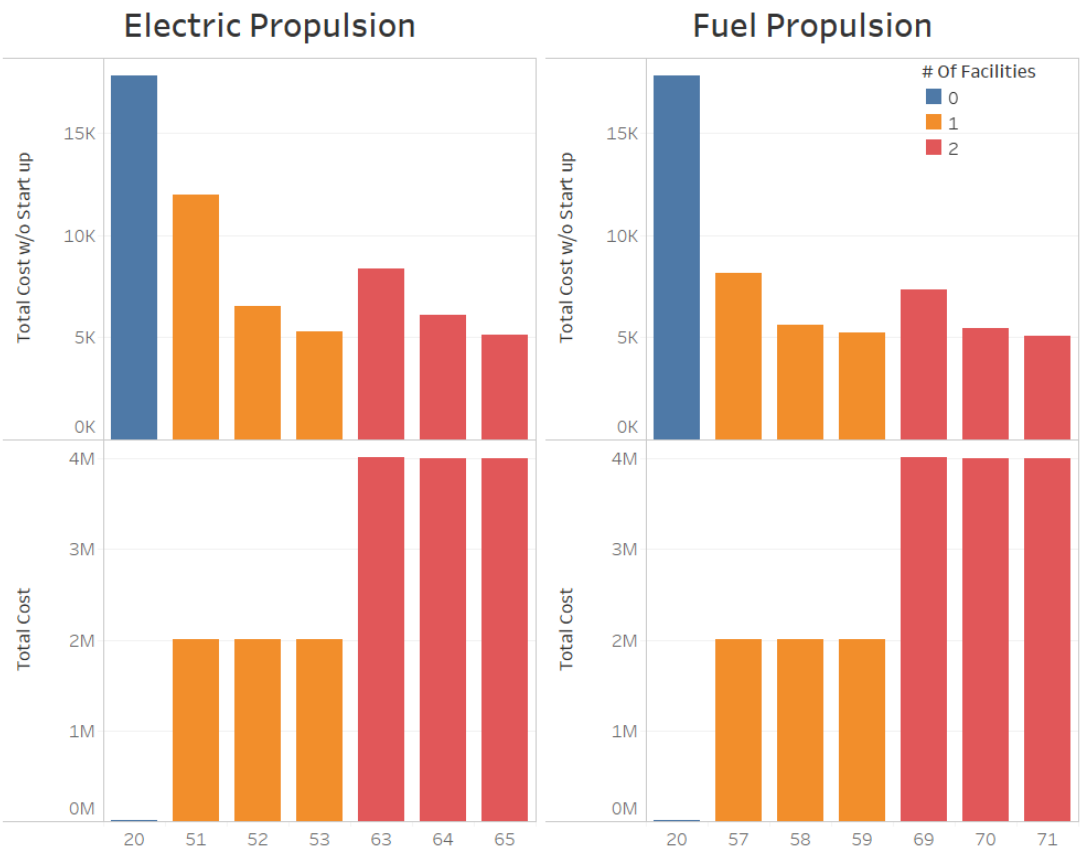


Figure 34

Drone Type Selection Including Start-up Costs for Rukum West District



With this analysis, we can conclude that when adding start-up costs, the drone type becomes irrelevant. Even looking at districts as different as Surkhet and Rukum West, startup costs become the main component of total cost and the variation among types is negligible. The main difference stands out when incrementing the number of drone facilities.

Next, we performed a cost sensitivity analysis that considers outsourcing the drone operation and its inherent variation in transportation costs, as shown in Table 14 and Figure 35 for Surkhet District and Table 15 and Figure 40 for Rukum West. For both districts, the analysis considers opening a single drone hub, using the electric propulsion type 3 drone (recommended drone type from the previous analyses).

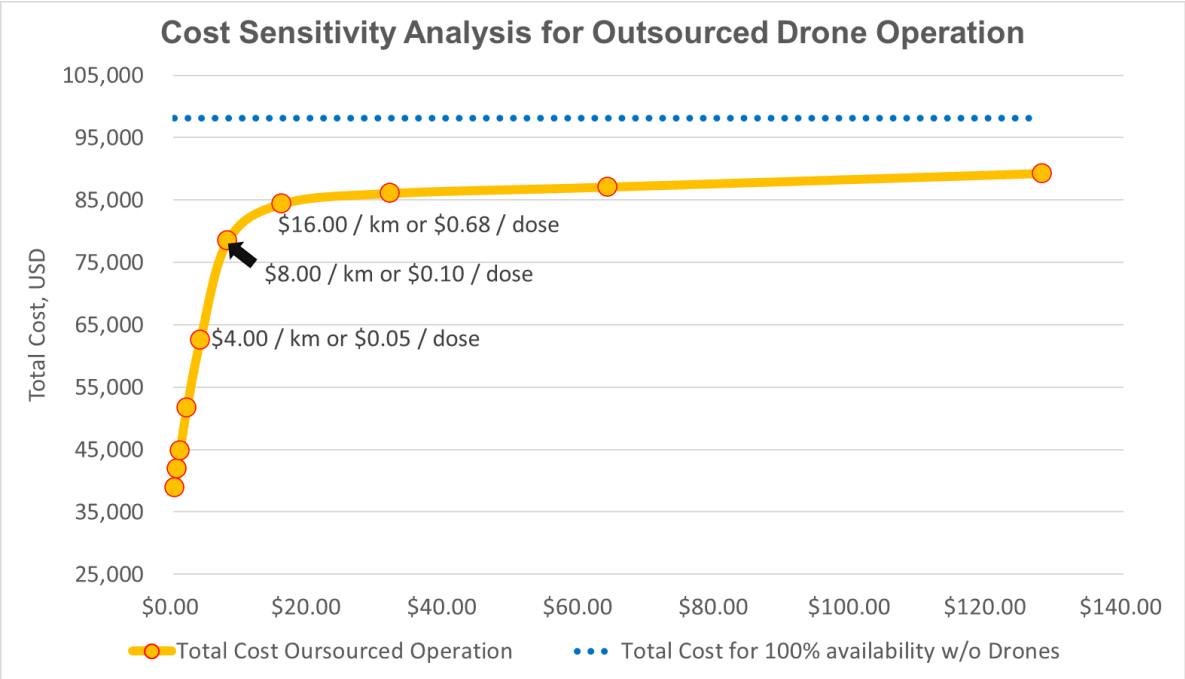
Table 14

Cost Sensitivity Analysis for Outsourced Drone Operation in Surkhet District

Iteration #	Variable Costs per KM	Outbound Transportation Cost	CCE cost	Total Logistics Costs	Flow % by Foot	Flow % by Motor bike	Flow % by Car	Flow % by Drone
75	$0.19	11,596	27,300	38,896	1%	2%	0%	**96%**
76	$0.60	14,610	27,300	41,910	2%	3%	0%	**95%**
77	$1.00	17,540	27,300	44,840	2%	3%	0%	**95%**
78	$2.00	24,373	27,300	51,673	4%	7%	1%	**87%**
79	$4.00	35,335	27,300	62,635	11%	17%	3%	**69%**
80	$8.00	51,153	27,300	78,453	11%	17%	3%	**69%**
81	$16.00	31,899	52,500	84,399	26%	41%	8%	**25%**
82	$32.00	33,603	52,500	86,103	26%	41%	8%	**25%**
83	$64.00	32,518	54,600	87,118	27%	42%	8%	**24%**
84	$128.00	34,702	54,600	89,302	27%	42%	8%	**24%**

Figure 35

Cost Sensitivity Graph for Outsourced Drone Operation in Surkhet District



Outsourcing the drone operation means a third-party vendor provides service and is responsible for capital costs, maintenance of equipment, etc. The variable transportation cost per dose will increase due to the mark-up from the vendor. The findings from the Surkhet cost sensitivity analysis shown in Table 14 and Figure 35 are the following:

- The total logistics costs are lower than the scenarios using an in-house operation when selecting scenarios with a cost per km lower than $16 USD. However, the $16 USD per km realistically does not make sense because the model selects a single route in the district to fly drones and only 25% of the vaccine doses flow would use drones (Figure 36). For this reason, we selected $8 USD per km as the recommended scenario because it serves 69% of the vaccine doses flow using drones.
- The threshold for selecting a vendor for the outsourced operation determined by the model is $8 USD per km or $0.10 USD per dose.
- The total cost for the outsourced drone operation is less expensive than the scenario considering 100% vaccine availability.
- There is a change in transportation mode selection at different drone transportation operating costs. For lower costs, the model selects drone as the preferred mode of transportation (95% of doses are transported using drones), while for higher costs the model switches to the other three modes (motorbike, by-foot and car) and drones are not preferred (around 24% of doses are transported using drones).
- When increasing costs, the model selects different locations for opening hubs in the Surkhet District, as seen in Figures 36, 37, 38 and 39.

Figure 36

Map of Surkhet District Vaccine Flow using Outsourced Operation at $2 USD / km

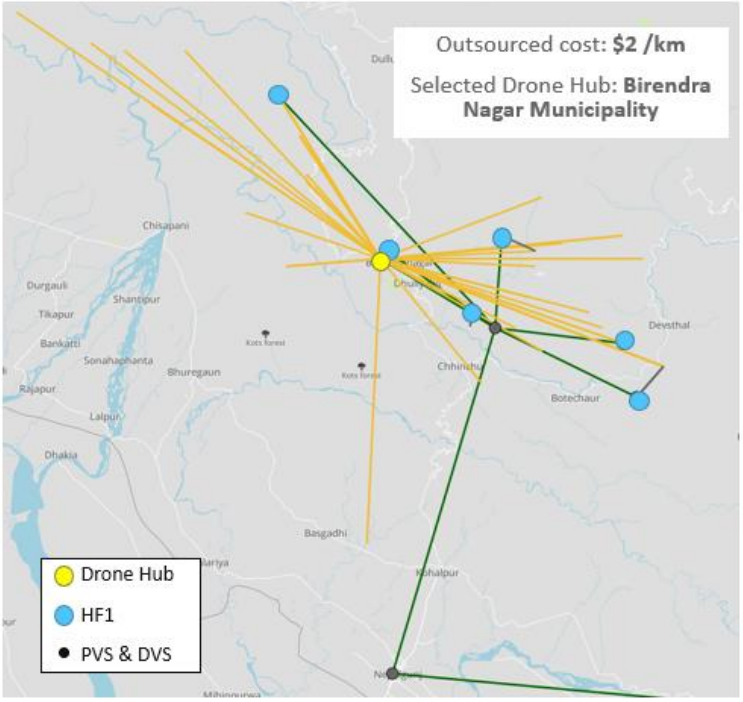


Figure 37

Map of Surkhet District Vaccine Flow using Outsourced Operation at $4 USD / km

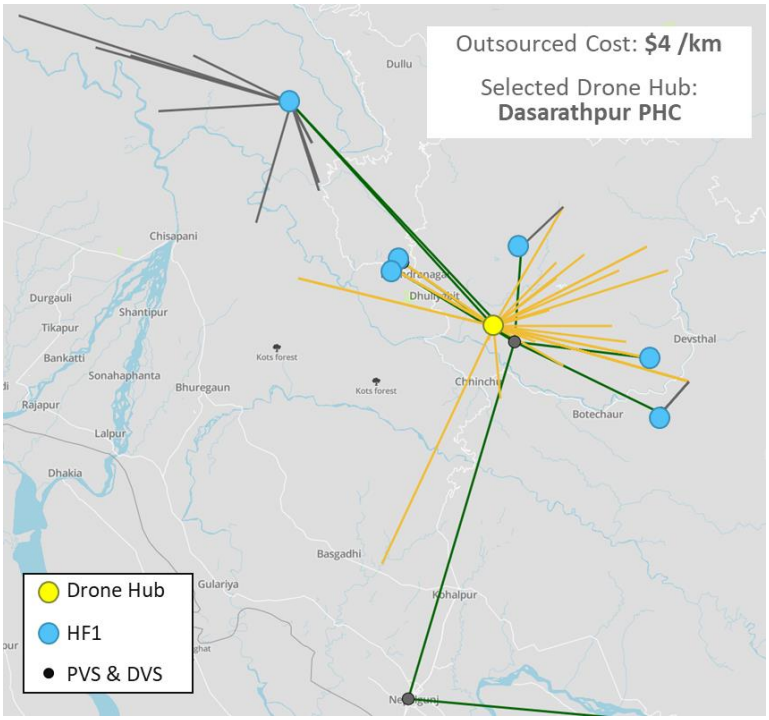


Figure 38

Map of Surkhet District Vaccine Flow using Outsourced Operation at $8 USD / km

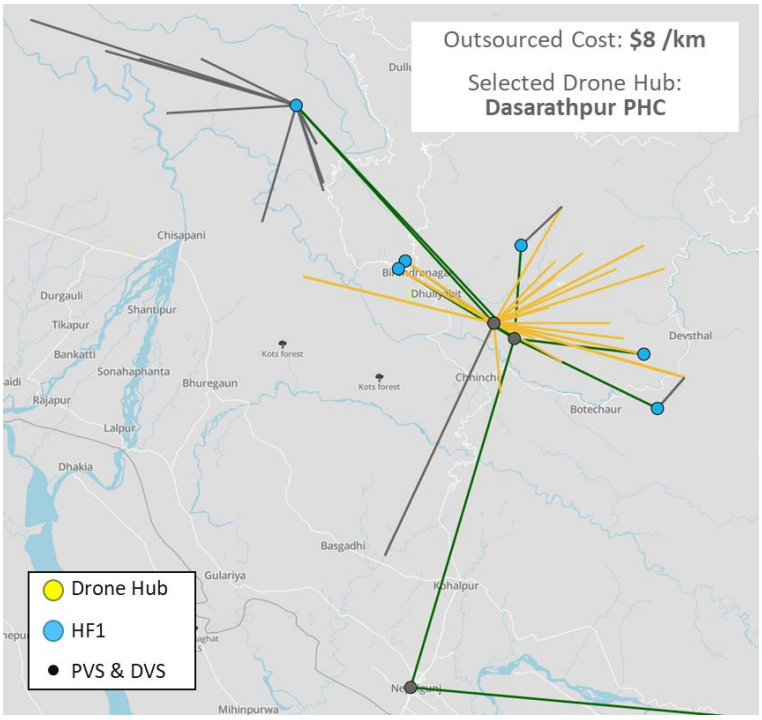
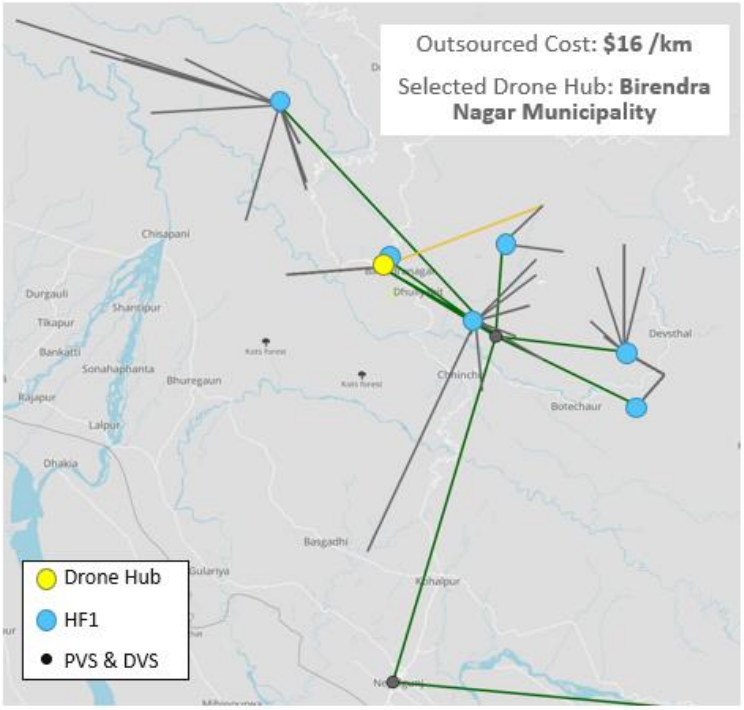


Figure 39

Map of Surkhet District Vaccine Flow using Outsourced Operation at $16 USD / km



The same cost sensitivity analysis was performed for an outsourced drone operation in the Rukum West district, as shown in Table 15 and Figure 40

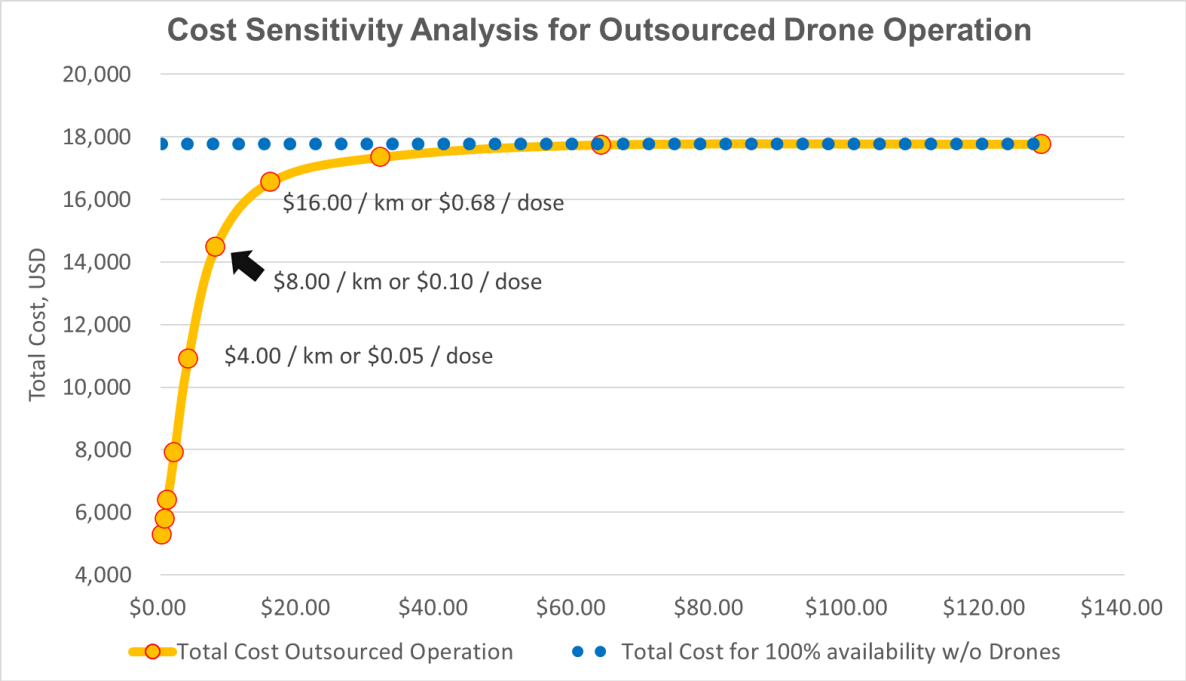
Table 15

Cost Sensitivity Analysis for Outsourced Drone Operation in Rukum West District

Iteration #	Variable Costs per KM	Outbound Transportation Cost	CCE cost	Total Logistics Costs	Flow % by Foot	Flow % by Motor bike	Flow % by Car	Flow % by Drone
75	$0.19	3,193	2,100	5,293	0%	0%	0%	**100%**
76	$0.60	3,700	2,100	5,800	0%	0%	0%	**100%**
77	$1.00	4,302	2,100	6,402	0%	0%	0%	**100%**
78	$2.00	5,807	2,100	7,907	0%	0%	0%	**100%**
79	$4.00	8,817	2,100	10,917	0%	0%	0%	**100%**
80	$8.00	12,381	2,100	14,481	40%	14%	3%	**44%**
81	$16.00	14,460	2,100	16,560	60%	21%	4%	**15%**
82	$32.00	15,249	2,100	17,349	68%	23%	5%	**4%**
83	$64.00	15,643	2,100	17,743	69%	23%	5%	**2%**
84	$128.00	15,668	2,100	17,768	71%	24%	5%	**0%**

Figure 40

Cost Sensitivity Graph for Outsourced Drone Operation in Rukum West District



From the mirroring cost sensitivity analysis for outsourced operation in Rukum West, we can deduct the following:

- The cost threshold for selecting a vendor for the outsourced operation of Rukum West is the same as Surkhet at $8 USD per km or $0.10 USD per dose.
- Compared to Surkhet, Rukum West has less supply chain network complexity because it only serves from one HF1. For this model we included the district's vaccine store (DVS) as a possible drone hub.
- When increasing cost, the model selects different locations for opening hubs in the Rukum West District, as seen in Figures 41, 42, 43 and 44.
- If the cost is below $8 USD/km or $0.10 USD/dose, the DVS is selected as the only drone hub for the whole district.
- If the cost is $8 USD/km or $0.10 USD/dose, the model suggests using the Kotjahari HF1 as a drone hub and the percentage of vaccine flow by drone is reduced significantly from 100% to 44%.
- At above $8 USD/km or $0.10 USD/dose, the more expensive the operation cost, the less percentage of vaccine flow is served using drones. This is due to the fact that as the model picks the other modes of transportation for being cheaper.
- Finally, at $32/km, the model selects drone as a mode of transportation for less than 5% of the vaccine flow. Also, the main cost driver is the current mode of transportation. As a result, Figure 40 shows an interception between both the outsourced operation cost curve and the 100% availability without drones cost curve. This was not observed in the Surkhet model.

Figure 41

Map of Rukum West District Vaccine Flow using Outsourced Operation at $2 USD / km

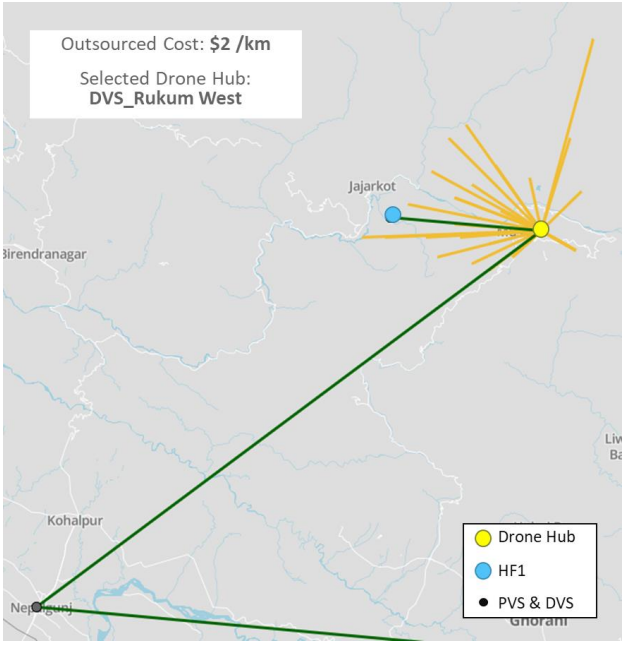


Figure 42

Map of Rukum West District Vaccine Flow using Outsourced Operation at $4 USD / km

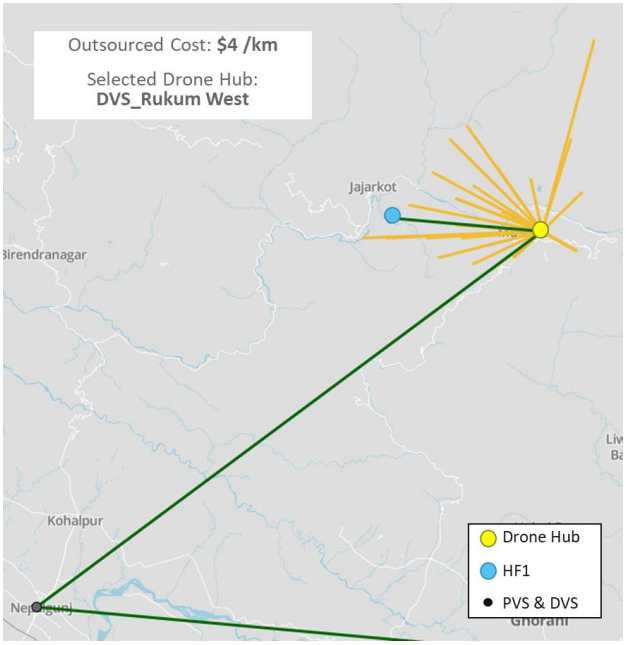


Figure 43

Map of Rukum West District Vaccine Flow using Outsourced Operation at $8 USD / km

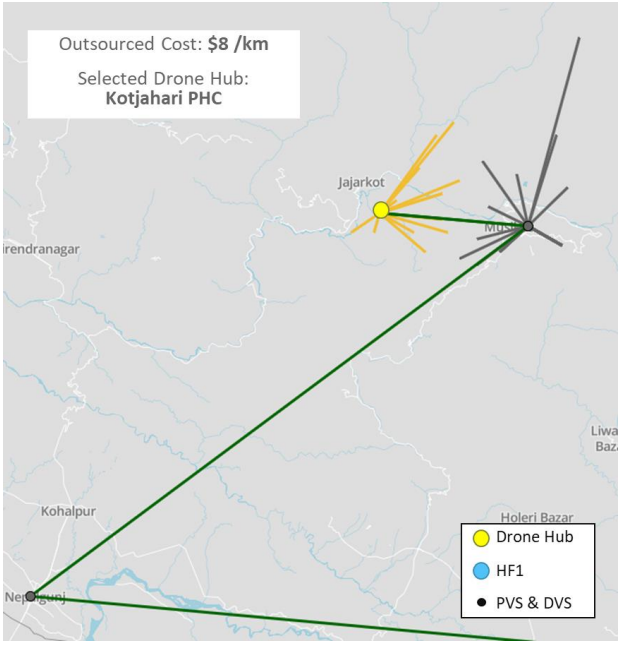
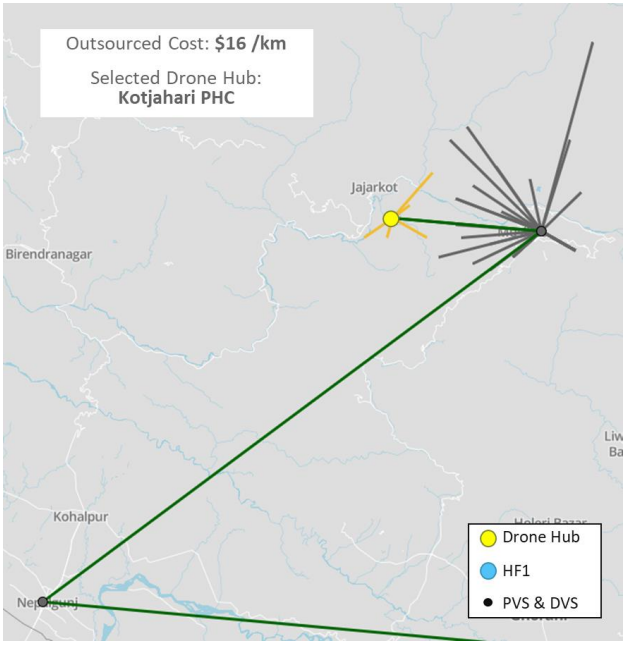


Figure 44

Map of Rukum West District Vaccine Flow using Outsourced Operation at $16 USD / km



Following, we calculated the variation of the cost to serve per child using drones through different scenarios. This calculation is shown in Table 16 for Surkhet and in Table 17 for Rukum West.

Table 16

Comparison of Logistic Cost per Child Immunized for Different Scenarios in Surkhet District

	Baseline Scenario (Iteration #17)	**100% Vaccine Availability (Iteration #20)**	**100% Vaccine Availability, Drone Type 3 w/Start-up Costs (Iteration #53)**	**100% Vaccine Availability, Drone Type 3 w/o Start-up Costs (Iteration #53)**	**Outsourcing Drone Operation, 100% Vaccine Availability w/ Drone Type 3 (Iteration #80)**
Total Cost, USD	96,308	98,079	2,038,896	38,896	78,453
Number of doses, #	517,587	589,409	589,409	589,409	589,409
Cost per dose, USD/dose	0.19	0.17	3.46	0.07	0.13
Cost per child, USD/child	**3.70**	**3.30**	**69.20**	**1.30**	**2.70**

Table 17

Comparison of Logistic Cost per Child Immunized for Different Scenarios in Rukum West District

	Baseline Scenario (Iteration #17)	**100% Vaccine Availability (Iteration #20)**	**100% Vaccine Availability, Drone Type 3 w/Start-up Costs (Iteration #53)**	**100% Vaccine Availability, Drone Type 3 w/o Start-up Costs (Iteration #53)**	**Outsourcing Drone Operation, 100% Vaccine Availability w/ Drone Type 3 (Iteration #80)**
Total Cost, USD	15,518	17,768	2,005,293	5,293	14,481
Number of doses, #	106,033	123,296	123,296	123,296	123,296
Cost per dose, USD/dose	0.15	0.14	16.26	0.04	0.12
Cost per child, USD/child	**2.93**	**2.88**	**325.28**	**0.86**	**2.35**

The key insights we can derive from these calculations are:

- If we do not include drones in the model but increase throughput to match 100% vaccine availability and consider the same mode distribution, the cost to serve per child decreases by $0.40 USD and $0.04 USD for Surkhet and Rukum West respectively, compared to the baseline scenario (from $3.70 to $3.30 USD for Surkhet and from $2.93 to $2.88 USD for Rukum West). This decrease is due to the more efficient use of the CCE capacities. However, this scenario is not realistic due to the constraints for modes of transportation that are inherent to the mountainous and undeveloped regions of Nepal.

- If we do include drones and their set-up costs, the cost to serve per child increases by $65.50 USD in Surkhet and by $322.35 USD in Rukum West, each compared to their baseline scenarios (from $3.70 to $69.20 USD in Surkhet and from $2.93 to $325.28 USD in Rukum West). The main drivers for this cost increment is the $2 million USD cost for each drone base. The elevated cost in Rukum West is due to the fact that there are fewer doses to be served thus the unit cost is higher.

- If the drone base set-up costs are subsidized by the government of Nepal or another organization, the cost to serve one child will be reduced by $2.40 USD in Surkhet and by $2.07 USD in Rukum West compared to the each of their baseline scenarios (from $3.70 to $1.30 USD in Surkhet and from $2.93 to $0.86 USD in Rukum West).

- Finally, when comparing the outsourced drone operation to the baseline using the recommended threshold for variable cost per dose, the cost to serve one

child will be reduced by $1.00 USD in Surkhet (from $3.70 to $2.70 USD) and by $0.58 in Rukum West (from $2.93 to $2.35 USD)

Next, for Scenario 6, the demand sensitivity analysis, we compared what would happen if the demand for vaccines increased or decreased. This scenario is currently very relevant because COVID-19 cases have spiked in Nepal, this requires a larger number of vaccines to be delivered more quickly. We performed eight iterations for each model of the Surkhet and Rukum West districts. We used different levels of demand, four for the 100% vaccine availability scenario, and four for Scenario 53, which uses the recommended type 3 electric drone and 1 hub opened in the district. For the demand levels, the iterations considered two very different situations: demand plummeting by 75% and 50% and demand increasing by 50% and 100%. Although the step-size for demand variation between iterations is not proportional for the first point, we included a 75% decline as a worst-case-scenario. These iterations are shown and compared in Figure 45 for Surkhet and Figure 46 for Rukum West.

Figure 45

Demand Sensitivity Analysis for Surkhet Logistics Cost

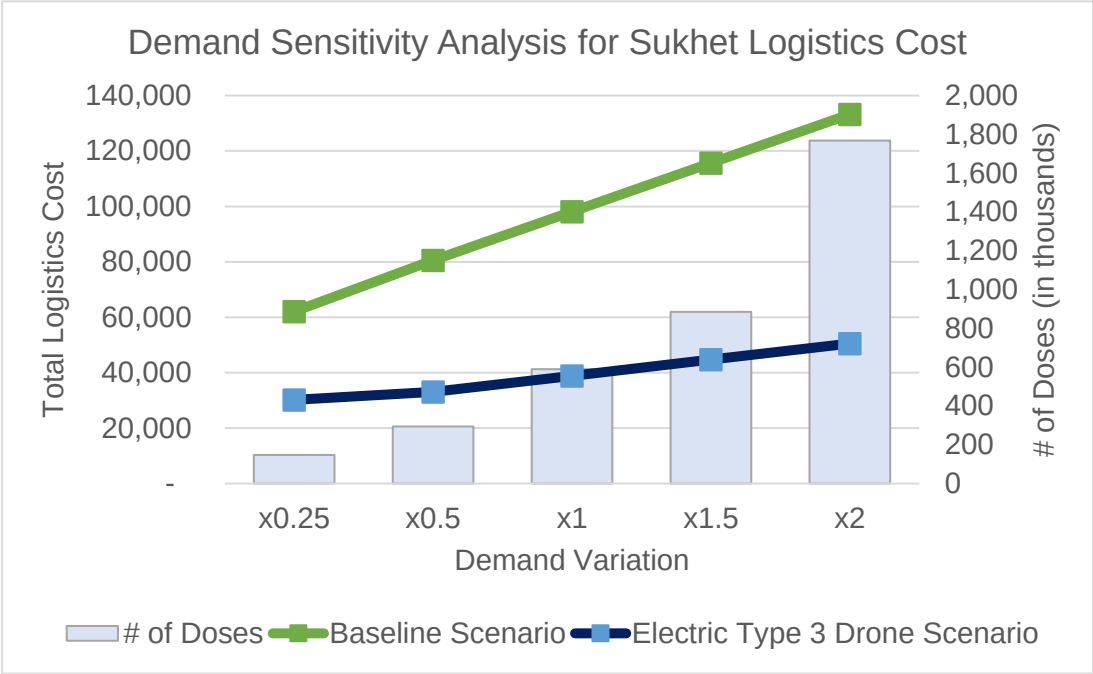
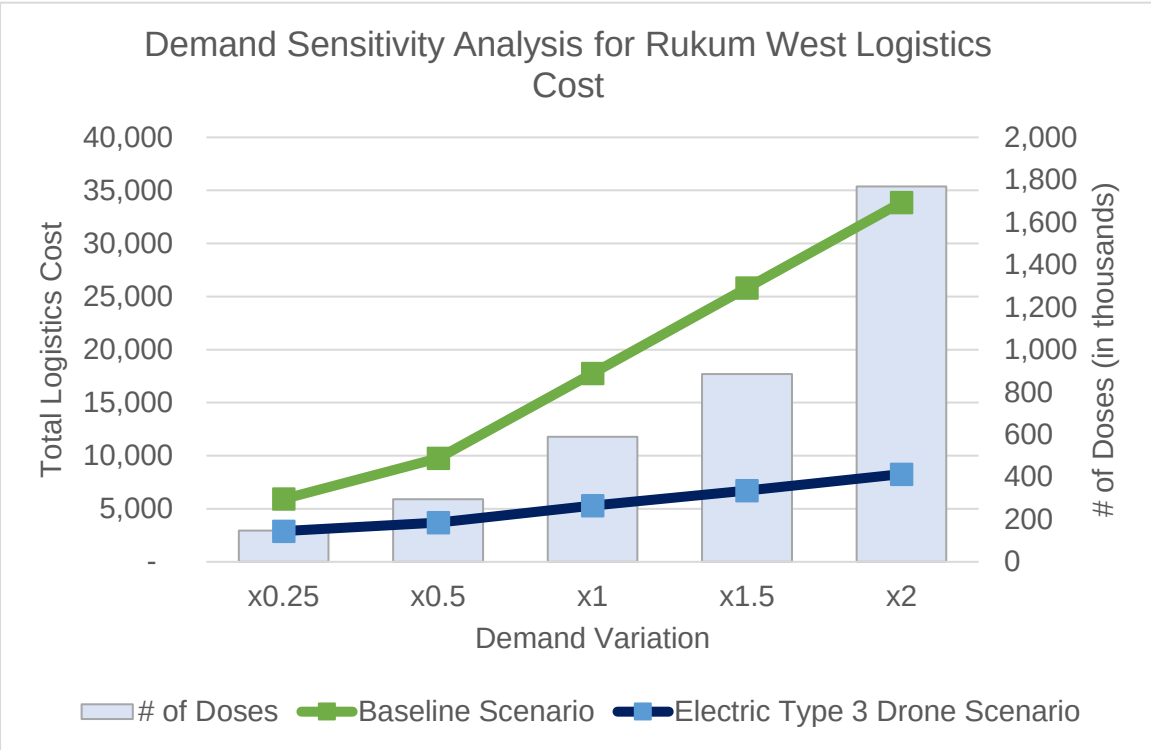


Figure 46

Demand Sensitivity Analysis for Rukum West Logistics Cost



From Figure 45, the Surkhet demand sensitivity chart, we can see that the baseline scenario cost curve for demand variations is steeper than for the drone scenario. This means that the baseline scenario is more sensitive to demand changes and cost varies more rapidly. If drones were implemented, vaccine demand changes would not affect the logistics costs so drastically and the increases would not be as abrupt. Similar behavior has been observed in Rukum West. In addition, we notice that the Rukum West district's cost curve for demand variations is steeper than Surkhet district's curve, this means that the baseline scenario of Rukum West is more sensitive to demand changes than Surkhet. It can be concluded that, when demand variation occurs, the drones yield higher benefits in the district that have lower number of target doses.

The final scenario run is Scenario 7, the per diem and fuel cost sensitivity analysis. For this scenario we performed 4 more iterations using Iteration 53 as a base case (1 drone hub opened, electric type 3 drone selected). We modeled what would happen if per-diem and fuel costs are decreased by 50%, and are increased by 10%, 20% and 50% vs Iteration 53. As in Iteration 53, 96% of the vaccine doses flow was already served by drones, as a result for this Scenario was a cost variation lower than 2% in all cases. With this experiment, we proved that drone application is a robust solution when fuel or labor cost variations occurs.

5. CONCLUSIONS

This capstone project determines which districts in Nepal could utilize drones for vaccine last-mile delivery. This is done by determining the best cost-effective strategy to improve vaccine availability, quantifying the benefits from this implementation, identifying the best facilities for setting drone bases and selecting the appropriate drone type.

Through a series of discussions with UNICEF, their drone expert, an MIT researcher, and information from the literature review, we created a district classification framework that uses quantitative and qualitative data to provide a recommendation of where to deploy drones. This framework includes steps that are repeatable and scalable, thus, this is a “thought experiment” that can be replicated for other geographies to help organizations such as UNICEF or Ministries of Health when approaching the question of where to implement drone last-mile delivery.

Using the district classification framework for Nepal’s vaccine supply chain, six out of 77 districts were selected. These six districts were recommended to UNICEF for application of drones in last-mile delivery. These districts are mostly located around the mountainous area that borders Tibet in the north, where the road network quality and accessibility factors are weighted the heaviest. In addition, the results at the province level indicate that the Karnali Province has the highest score for drone application, and Province 2 has the lowest score.

After selecting two districts from the previous classification, a baseline model was created for each district. The necessary parameters for this baseline model were derived though the structured approach shown in Sections 3.3 and 3.4. Afterwards, a series of scenarios were run varying the input parameters. These scenarios showed

that there is an opportunity in the current network to redistribute the flow of vaccines between modes to efficiently use Cold Chain Equipment (CCE) and to avoid additional capital and/or operational expenditures.

We highlight the importance of analyzing two other strategies for drone operations to be cost-effective. The first is using outside funding to cover the start-up cost for drone bases, and the second is outsourcing the drone operation to a third-party operator. For the outside funding scenario, the logistics costs can be improved dramatically by including one or two drone hubs in the same district. And if UNICEF were to consider outsourcing the complete drone operation, we would recommend that the operating cost per dose for should not exceed $0.10 USD/dose.

Another inference made from this study is that smaller electric drones are not recommended; this is because they present no significant cost benefit over current mode of transportation due to their limited range and payload. Larger drones should be considered for vaccine last-mile delivery. Specifically, the recommended drone specification for execution in Nepal's is an electric propulsion type with an 11 kg maximum payload and 200 km range. However, smaller drones become more attractive when opening more hubs in the same district, but this assumption will depend on whether the district is big enough to sustain more than 2 hubs.

Using the Phase 2 methodology for the Surkhet and Rukum West districts, it was shown that the incremental costs to serve one more child using drones with one single hub in the district are $65.50 USD/child and $322.35 USD/child accordingly. If start-up costs were to be subsidized, the total cost could be reduced by $2.40 USD/child for Surkhet and $2.07 USD/child for Rukum West, comparing to their corresponding baselines (from $3.70 USD/child to $1.30 USD/child in Surkhet, and

from $2.93 USD/child to $0.86 USD/child in Rukum West). Finally, according to the sensitivity analysis, we conclude that drones are a less sensitive solution when demand variation occurs, compared to the other ground modes of transportation.

Future research on this topic could focus on procuring more granular data, such as the demand for each outreach location, when selecting a drone facility location. Although we highlighted that there are more benefits using bigger drones for vaccine delivery, in this study we only included the category of smaller payload drones defined in Table 5, due to their market availability in the short term. Larger payload drones outline as a promising area for future research when considering larger demand geographies. Another opportunity for future research is to get more precise data on vaccination rates within the districts to better inform how drones may improve the vaccination rates. For lack of better data for our model, most health facilities within a district have been modeled using the overall coverage number of the district itself. Finally, one last recommendation for future research is to study drone applications to enable more outreach sessions in targeted areas considering the vaccines arrive just in time inside of a cold box.

Using drones to address the problem of low immunization coverage could help reduce the mortality rate of children. The solution presented in this study could also potentially be expanded outside of developing countries like Nepal, as it can be implemented in disaster relief scenarios. These scenarios include roads being damaged or blocked due to floods, earthquakes, or other causes. Furthermore, at the time this report was written, the world was witnessing the tremendous impact of the COVID-19 pandemic and the urgent need for innovative and efficient new ways for

vaccine distribution. Perhaps these difficult times will reinforce the contact-free and fast distribution benefits that drones offer.

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APPENDIX A

Survey for Phase 1

As part of Phase 1 research methodology, we create a survey to assess the factor ranking and their contribution as a rule of thumb for drone deployment. There are 2 main survey questions in the form.

UNICEF Drones for Health Product Delivery in Nepal

Supply Chain Management Capstone Research

Survey objectives: To assess the factor ranking and their contribution as a rules of thumb for drone deployment. The result of this survey will be used as an input for further analysis in ArcMAP.

* Required

1. Name *

Enter your answer

2. In your opinion, what would be the order of importance of the following factors based on their influence on drone applicability? (In descending order, top choice is the most importance factor) *

Geographical factor: Elevation topographic

Demand factor: Target number of doses

Supply Chain factor: Health facility density within drone radius

Road network quality factor: Road density

Road network quality factor: Road circuity

Road network quality factor: Accessibility and seasonality(%rainfall)

Performance factor: Current district's vaccine coverage

Performance factor: Current district's cold chain equipment (CCE) availability

3. According to the ranking of previous question, please assign the percentage of important of each factor to the same order (The percentage of 8 factors must added up to 100%)
Input format 50%,20%,30%,10%,etc. *

Enter your answer

You can print a copy of your answer after you submit

Submit