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A hub-and-spoke design for ultra-cold COVID-19 vaccine distribution

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ABSTRACT

An orderly and effective vaccination campaign is essential in combating the global COVID-19 pandemic. As one of the pioneers, the U.S. Center for Disease Control proposes a phased plan to promote the vaccination process. This plan starts with vaccinating the high-priority population in Phase 1, then turns to the remainder of the public in Phase 2, and ends with a scale-back network in Phase 3. The phased plan not only provides a sense of hope to impacted communities that this global pandemic can be defeated, but can serve as a template for other countries. To enhance this plan, this paper develops a generalizable framework for designing a hub-and-spoke vaccination dispensing network to achieve the goals in the Phase 2, which aims to expand the vaccination coverage for the general public. We introduce a new coverage index to measure the priority of different potential dispensing sites based on geo-data and develop an optimization model for network design. The hub-and-spoke network enhances the accessibility of the vaccines to various communities and helps to overcome the challenges related to ultra-cold storage facility shortage. A case study of Middlesex County in New Jersey is presented to demonstrate the application of the framework and provide insights for the Phase 2. Results from the baseline scenario show that increasing the driving time limit from 10 min to 25 min can improve the total coverage index from 40.8 to 55.9. Additionally, we explore how the changes of parameters impact the network design and discuss potential solutions for some special cases. When we allow 4 outreach nodes per hub, all potential 45 outreach points can be covered in the vaccination network within a 20-minute drive, and the total coverage index reaches its maximum value of 58.3.

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1. Introduction

The COVID-19 pandemic is among the deadliest global public health crises faced by modern society [1]. Scientists, research labs, and governments around the world have raced to find vaccine candidates for this virus, in order to defeat this global pandemic. On December 11, 2020, the U.S. Food and Drug Administration issued its first emergency use authorization (EUA) for the COVID-19 vaccine, which was produced by the Pfizer-BioNTech [2]. At that time, the total global deaths had already topped 1.6 million [3]. The launch of this vaccine, as well as other candidates that have emerged globally, provides a beacon of hope for society to return to normal. Outside the U.S., other countries such as Canada, Japan, Belgium have also placed orders to procure vaccines from various sources [4]. However, along with the first wave vaccinations in the U.S., we find that, while developing a vaccine is a monumental step, it is the first of many key milestones along the journey. Key

challenges in distributing and administering these vaccines to various communities in a timely and equitable fashion still lie ahead.

To promote the vaccination program, the Center for Disease Control (CDC) proposed a phased plan in a playbook ahead of the EUA for the first vaccine [5]. The initial phase of this campaign, Phase 1, starts with vaccinating high-priority population segments, with the remainder of the general public having access to vaccines in Phase 2. However, the Phase 1 vaccine rollout in the U.S. has shed light on numerous challenges that must be overcome for these efforts to be successful. Aside from limited supply challenges, the storage requirements for some vaccine candidates add further complexities to the distribution process. For instance, the recently launched Pfizer vaccines require ultra-cold storage at temperatures between $-80\text{ }^{\circ}\text{C}$ and $-60\text{ }^{\circ}\text{C}$ in order to maintain efficacy [6]. However, most administration sites do not have these capabilities, since these expensive ultra-cold storage resources are usually available in commercial research labs [7]. The lack of appropriate storage facilities will shorten vaccine shelf-life and create difficulty in vaccine rollout.

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In this context, this paper proposes a generic and practical solution to expand the vaccine coverage during the Phase 2 vaccination campaign against the backdrop of the U.S. phased plan. Specifically, we propose a regional hub-and-spoke network design, which includes hub centers and outreach sites as two types of local dispensing sites in the network [8]. This configuration allows public health officials to easily adjust the network configuration in different rollout phases [9,10]. Moreover, the regional hub-and-spoke network design allows us to overcome the difficulties associated with ultra-cold storage without making additional infrastructure investment from two aspects. First, the vicinity of local dispensing sites in the hub-and-spoke network design enables local inventory sharing, thus helping to use up a batch of vaccines within the short shelf-life, reducing the risk of vaccine wastage due to expiration. Second, the short-trip transfers within the regional hub-and-spoke network can help reduce the risk of temperature excursion in transportation.

In order to simultaneously ensure fair and equitable access to vaccines for all communities, we apply a newly proposed vaccination coverage optimization model that seeks to design the optimal configuration for the hub-and-spoke vaccination network. This research serves as a generalized framework that can be adopted in various regions of the globe, especially in low-income countries, with inadequate cold chain infrastructure.

Next, subsection 1.1 presents additional details about the current phased vaccination plan in the U.S. Subsection 1.2 reviews recent works of literature and identifies existing research gaps. Subsequently, in Section 2, we will state the potential advantages of the new configuration and present our model in detail. A case study is presented in Section 3. Finally, we conclude in Section 4.

1.1. Current vaccination plan in the U.S.

As one of the countries in the first vaccine roll-out echelon, the U.S. government proposed a phased vaccination plan [5], as given in Fig. 1. Considering that the supply and demand for vaccines are highly stochastic, the CDC outlines three phases:

Phase 1 focuses on distributing the vaccine to high-priority populations, including the critical infrastructure workforce, and people at increased risk for severe COVID-19 illness.

Phase 2 aims to expand vaccine access to the general public by adding more dispensing sites in the provider network.

Phase 3, upon covering most of the population, CDC plans to scale back these efforts, since the demand for vaccines would be dramatically reduced

This phased vaccination plan streamlines the immunization progress in midst of the pandemic, while also providing a good template for other countries that are mounting a strategy to defeat COVID-19. This plan was made ahead of the EUA of the first vaccine in the U.S., with the CDC providing the strategic framework, and

leaving operational details to the local governments to execute [11]. At the time of writing, most regions of the U.S. are still in Phase 1. Several states announced plans to transition into Phase 2, however, there is a lack of guidance on how to successfully accomplish this task. Our proposed research not only helps to address this gap for the U.S. but may also help other countries to deploy a phased immunization program.

1.2. Previous studies and research gaps

To promote global immunization, various studies have been conducted. This subsection first reviews the existing studies related to common vaccine distribution, then presents recent studies on the COVID-19 vaccination campaign. Research gaps are identified after reviewing from both the problem perspective and the methodology perspective. Lastly, we briefly outline how this paper addresses the current challenge in ultra-cold vaccine distribution and overcomes the drawbacks of existing coverage model.

De Boeck et al. [12] provide a review of studies related to the vaccine distribution chain. Based on the review, existing studies can be divided into three categories according to their research scope and decision variables. The first topic is about long-term strategic decisions including the facility location and allocation decisions. For example, Lee et al. [13] use a computational simulation model to re-design the vaccine supply chain in Mozambique by comparing two simulation outputs: the vaccine availability and unit logistics cost. Lim et al. [14] focus on comparing the differences of applying different coverage models in the objective function when optimizing the location of dispensing sites. Hirsh Bar Gai et al. [15] develop a model to find out the optimal locations and capacities for local hub vaccine warehouses to minimize the total traveling distance. Based on the real data of Nigeria, they compare the performance of different scenarios. As for the second topic, some researchers focus on tactical decisions such as shipping policies and transportation modes. Han et al. [16] optimize the routing problem in an existing three-layer supply chain to minimize the total transportation cost for emergency material delivery. Chen et al. [17] propose a planning model for optimizing the vaccine quantities of each delivery trip in a directed WHO-EPI vaccine distribution network in low-income countries. Their model aims to maximize the number of fully immunized children under known demand. Rabta et al. [18] study the last-mile distribution problem by drones in the humanitarian supply chain. An optimization model is presented in their paper to minimize the total traveling distance. Lin et al. [19] discuss the distributor’s transportation decision on using a cold chain for vaccines or not. Meanwhile, they analyze the impact of retailer’s inspections on the aforementioned distributor’s decisions. The third topic is operational decisions including administration policies and inventory policies at the final dispensing sites. A mixed-integer programming model is developed by Proano et al. [20] which focuses on optimizing the number of doses in a combination vaccine. Their model aims to maximize manufacturing profits and customer surplus. Mofrad et al. [21] study the vaccine administration policies considering the non-stationary demand and delayed service. The goal of their work is to reduce the “open vial waste”. Azadi et al. [22] develop a two-stage stochastic programming model to optimize the combination of vaccine vials in a different size, and decide whether to open a new vial or not in face of the uncertain patient arrivals.

Most recently, studies about immunization during COVID-19 have received a lot of attention. Cotfas et al. [23] explore how the COVID-19 vaccination opinions changes in social media network. Risanger et al. [24] present an inventory-location optimization model to optimize the allocation of influenza vaccines during the pandemic. Corey et al. [25] qualitatively discuss possible challenges for both the endpoints and the manufactures in

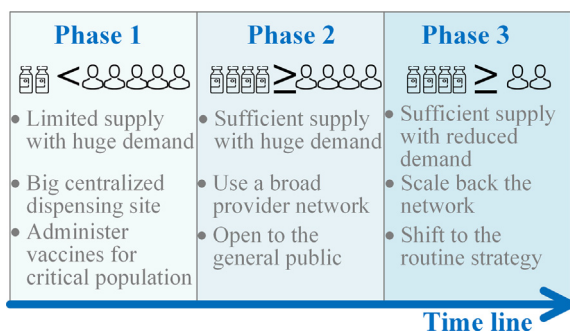


Fig. 1. An illustration of phased vaccination plan in the U.S.

developing COVID-19 vaccines. Similarly, Mills and Salisbury [26] discuss the potential challenges of distributing COVID-19 vaccines. Aruffo et al. [27] introduce a compartmental model to study the vaccination strategy for COVID-19 under scenarios with different vaccine coverage, effectiveness, and waning immunity. Roy et al. [28] use an epidemic model to study the allocation of limited vaccines. Several other studies focus on identifying the population group that has the priority to be vaccinated [29].

With an overview of the previous studies, the following research gaps can be identified:

- (1) Previous studies related to vaccine distribution mostly focus on designing or optimizing networks that minimize cost or traveling distance for permanent routine vaccination. The existing network design models or strategies cannot be used directly in the phased COVID-19 campaign that network changes over time to achieve different goals. Moreover, previous research fails to address the challenges associated with the newly-presented ultra-cold vaccine distribution such as how to facilitate vaccination when most of the sites do not have the appropriate storage facilities for ultra-cold requirement.
- (2) When developing models, there is a lack of a generalized framework that can capture local characteristics (e.g., local transportation accessibility, economics) and be used in different regions of the world. Promoting immunization progress is a global topic. Without loss of generality, there is a clear need for these models to capture the local characteristics to better inform their vaccine distribution strategies.

In addressing these gaps, this paper will develop a network design methodology for the phased vaccination campaign. Considering the very short shelf-life of ultra-cold vaccines, we introduce a hub-and-spoke network configuration in which dispensing sites can share their vaccine inventory, use up the ultra-cold vaccines quickly, and further reduce the vaccine waste. This hub-and-spoke network configuration allows more flexible network expansion or reduction in each vaccination campaign phase when needed. Moreover, to compare the coverage of different dispensing sites, we introduce a coverage index calculation model which considers not only the population lived around a dispensing site, but also the local travel and economic characteristics that impact vaccination wiliness.

2. Framework

2.1. Hub-And-Spoke network for vaccine distribution

Vaccines are strategic stockpiles controlled by a special national division. In general, vaccines are produced by authorized domestic manufacturers and then sent into the vaccine distribution network [13]. For some low-income countries, due to the lack of technology and raw materials, vaccines may be imported from other countries instead of producing locally [17]. In the vaccine distribution system, the specified national division such as the Division of Strategic National Stockpile in the U.S. will manage the allocation and distribution of vaccines. Generally, vaccine distribution involves multiple sectors from the national warehouse to the local warehouse. After vaccines arrive at the local warehouse, local stockpile divisions will take over the vaccines and allocate them to the final dispensing sites where people can be vaccinated [30]. In some cases, vaccine manufactures can directly send vaccines to the final dispensing sites if resources are allowed. In this paper, we focus on the final step of the vaccine distribution network where the vaccines are delivered from manufacturers or local warehouses to the final dispensing sites.

As shown in Fig. 2, the final vaccine delivery in the current point-to-point configuration is from the upstream sector directly to each dispensing site. This configuration is very effective and easy to manage for routine vaccines that can be stored at room temperature or refrigerator. A batch of vaccines is delivered to each dispensing site and stored in the required environment until they are administrated to people. However, when it comes to vaccines that require ultra-cold storage, the point-to-point configuration may cause huge waste. Since ordinary refrigerated trucks cannot reach the required ultra-low temperature, passive refrigerators are widely used along the ultra-cold chain [17,31]. Due to cost reasons, one passive refrigerator container contains a number of vaccine vials. In the point-to-point configuration, upstream sectors ship such containers to each dispensing site. Since there is no ultra-cold freezer in dispensing sites, once a container is opened at the dispensing site, all vaccines in the container start to defrost. Outside the ultra-cold environment, vaccines are only good for a short time once thawed. Hence, the administrations of these vaccines become a race against time. However, it's highly likely that the number of vaccines in one container is more than the amount that most of the dispensing sites could reasonably expect to use. For

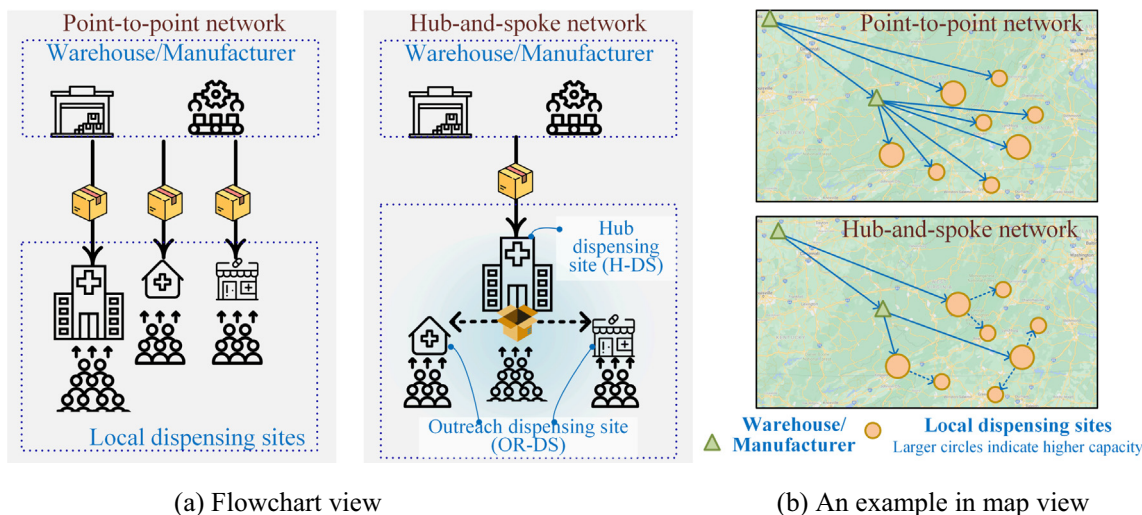


Fig. 2. Point-to-point network versus hub-and-spoke network for vaccine distribution.

example, the current Pfizer’s storage container holds from 1,000 to 5,000 doses of the shot [6]. These vaccines need to be used within five days in standard refrigeration. There are different kinds of dispensing sites such as big hospitals, health care centers, doctor offices, and pharmacies. Based on the data in New Jersey’s vaccination plan published by the New Jersey Department of Health [32], the expected administration capacity per day at one site varies from 50 to 400. That is to say, most of the dispensing sites cannot use up the vaccines in one container before they are out-of-date.

At the time of writing, the U.S. promotes the COVID-19 vaccination rollout process by sending vaccines (point-to-point) to several large, centralized vaccination centers which can rapidly go through all doses. This solution seems to be all right at this phase (Phase 1) whose target is to vaccinate the high-priority population [5]. However, once we step into the second phase aiming to cover as many people as possible, the centralized sites with point-to-point configuration will be unfavorable. These centralized dispensing sites are usually located in densely populated regions and are spread out. People may need to travel a long way to get to an available centralized dispensing site. According to a recent survey conducted in Uganda, one of the most crucial factors determining people’s willingness to be vaccinated is convenience [33]. Long traveling time to a vaccination site will decrease people’s willingness to be vaccinated. So, in addition to using the mega, centralized sites, Phase 2 must expand the provider network by involving more local sites to enhance people’s accessibility to vaccines. By doing so, the aim of stimulating more people to get vaccinated can be achieved.

Considering the aforementioned challenges in COVID-19 vaccine distribution, we propose a hub-and-spoke network configuration for the Phase 2 vaccination campaign. In the proposed configuration, dispensing sites are divided into clusters. Each cluster contains one big hub dispensing site (H-DS) and several outreach dispensing sites (OR-DS). Vaccine containers are shipped from upstream to the H-DSs in each cluster, similar as in Phase 1. The H-DS then shares the vaccines with the OR-DSs in its cluster. This hub-and-spoke network configuration provides three significant advantages over the current point-to-point configuration. First, sharing vaccines within the cluster can help use up the doses within a short time and further reduce the waste caused by unused overdue vaccines. This is particularly important for ultra-cold vaccine rollout since the lack of appropriate storage facilities shortens vaccine shelf-life. Second, the use of outreach dispensing sites enhances the convenience of getting people vaccinated by expanding the geographical coverage area of sites, which will stimulate more people to get vaccinated. Third, the proposed hub-and-spoke configuration can help reduce the temperature excursion risks associated with transporting ultra-cold vaccines, since some of the long-distance shipping trips from upstream to dispensing sites will be replaced by short-distance transfer shipping trips between local dispensing sites within the cluster. With these three strengths, this hub-and-spoke configuration can help us overcome the challenges brought by the lack of ultra-cold freezers in vaccine distribution without having to invest in expensive infrastructure. One question then naturally arises: How to design such a hub-and-spoke network based on the current vaccine distribution system?

2.2. Optimal design of Hub-And-Spoke network

In this section, an optimization model is proposed for designing a hub-and-spoke network for Phase 2 of COVID-19 vaccine distribution. According to the CDC’s vaccine rollout recommendations [5], Phase 2 includes all other persons aged ≥ 16 years not already recommended for vaccination in Phase 1, and any authorized COVID-19 vaccine may be used. Some of the large centralized dispensing sites used in Phase 1 will act as the H-DSs in Phase 2 since

the distribution of vaccines from upstream to these sites is well established. To cover the larger population in Phase 2, OR-DSs will need to be added to the vaccination network. These OR-DSs should be strategically selected from the available local dispensing sites and allocated to the existing H-DSs.

An integer programming problem is formulated with a decision variable $x_{i,j}$ to determine which local sites are selected to be OR-DSs and how the OR-DSs are connected to the H-DSs in the hub-and-spoke network.

Let

$i =$	local dispensing site; $i = 1, 2, \dots, I$.
$I =$	the number of local dispensing sites being considered as potential out-reach dispensing sites (OR-DSs).
$j =$	hub dispensing site (H-DS); $j = 1, 2, \dots, J$.
$J =$	the number of hubs within the given region.
$c_i =$	the coverage index of local dispensing site i . ($c_i \geq 0$).
$n^{\text{MAX}} =$	the maximum number of OR-DSs that can be connected to H-DS j .
$d_{ij}^{\text{H}} =$	the driving time between site i and hub j .
$d^{\text{MAX}} =$	the upper limit on the allowed driving time from a hub to its OR-DSs considering the ultra-cold vaccine shelf life.
$x_{i,j} =$	$\begin{cases} 1, & \text{if local dispensing site } i \text{ is selected to} \\ & \text{connect with hub } j. \\ 0, & \text{otherwise.} \end{cases}$

Then, the total coverage of the hub-and-spoke network, also the objective function to be maximized is equal to

$$\sum_i (c_i \sum_j x_{i,j}) \tag{1}$$

subject to

$$\sum_j x_{i,j} \leq 1 \quad \forall i \in I \tag{2}$$

$$\sum_i x_{i,j} \leq n^{\text{MAX}} \quad \forall j \in J \tag{3}$$

$$x_{i,j} d_{ij}^{\text{H}} \leq d^{\text{MAX}} \quad \forall j \in J, \forall i \in I \tag{4}$$

Eqs. (2) and (3) together establish the hub-and-spoke configuration. Specifically, Eq. (2) specifies that an OR-DS can only be assigned to at most one H-DS; Eq. (3) specifies that an H-DS is connected with at most n^{MAX} OR-DSs. Frequent vaccine transfers occur between the H-DS and its OR-DS. Thus, it is necessary to limit the travel distance from the H-DS to its OR-DS since a long trip will not only shorten the ultra-cold vaccine’s shelf life in dispensing sites but also increase the temperature excursion risk. Thus, Eq. (4) ensures that OR-DS i can be assigned to H-DS j only if the driving time between i and j is within a predetermined upper limit d^{MAX} .

2.3. Coverage model for Covid-19 vaccine distribution

The most crucial input in the optimization model is the coverage index (CI for short) of each site. The optimal network should consist of high-CI sites to maximize the total coverage. This section presents how we define and estimate the coverage index c_i by extending the basic concept from literature but customizing it for the COVID-19 vaccine.

The original meaning of *vaccination coverage* is the percentage of vaccinated people [34,35]. Lim et al. [14] presented several ways

of measuring coverage: The simplest method is the binary coverage model which assumes all the population within a certain distance radius of the site is covered; Extending from the binary coverage model, the variable single coverage model assumes that the fraction of covered people decreases stepwise as the distance radius increases. Risanger et al. [24] assumed the fraction of covered people decays exponentially as the distance increases. All these models assume straight-line distance when estimating the covered population. Although the straight geographical distance is reasonable in general location selection problems, it does not accurately reflect vaccination coverage. People’s willingness to get vaccinated at a site is directly impacted by how accessible the site is. Transportation accessibility is highly impacted by the conditions of transportation infrastructure (road network, public transportation network, etc.), which may differ significantly in various regions. Straight distance fails to capture the actual transportation accessibility to dispensing sites in different regions, especially in some low-income countries with poor infrastructures.

To remedy the drawback of existing coverage models, we propose a new coverage index that works as a quantitative measure of site selection priority. It’s worthwhile to highlight that the proposed coverage model can also be applied in dispensing site evaluation in different regions regardless of the vaccine types. Our model is derived from the aforementioned variable single coverage model in which a stepwise decreasing function of coverage is assumed. The coverage area is divided into several levels. $\alpha_{i,k}^* \in [0, 1]$ is the fraction of covered people in coverage level k ($k = 1, 2, \dots, K$) of dispensing site i . Fig. 3 illustrates the stepwise coverage model in a simple example with three levels. From the inner level ($k = 1$) to the outer level ($k = 3$), people’s willingness to get vaccinated show a stepwise decrease ($\alpha_{i,1}^* \geq \alpha_{i,2}^* \geq \alpha_{i,3}^*$).

The proposed coverage model improves existing models in three aspects when estimating the total number of covered people. First, we use the driving time instead of the straight distance as the criterion of each coverage level. By doing so, we can grasp the local transportation condition in different regions. Specifically, coverage level k of a dispensing site is the area between t_{k-1} and t_k driving time to the site. For example, people in the first coverage level ($k = 1$) can reach site i within t_1 time by driving; the second coverage level ($k = 2$), shown as the cricoid area in blue in Fig. 3, has its outer boundary as the place from which we need to drive t_2 to the dispensing site. Second, the $\alpha_{i,k}^*$ value in our model adjusts the baseline fraction of covered people by considering public transportation. With public transportation near site i , the site is more convenient and hence will attract more people to come to the site for vaccination. So, we define $\alpha_{i,k}^*$ as

$$\alpha_{i,k}^* = \min(1, \alpha_k + b \times N_i) \tag{5}$$

where α_k is the fixed baseline fraction of covered people in k level area from Lim’s study [14], N_i is the total number of public transportation stops (bus stops, subway stops, etc.) around site i , and b

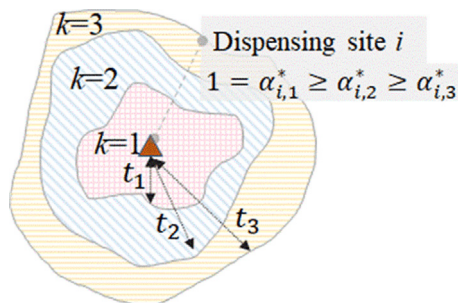


Fig. 3. Illustration of the stepwise coverage model.

is the additional “attractiveness” brought by each transportation stop. So, the fraction of covered people increases from the baseline α_k by bN_i when public transportation is considered. The $\min(\cdot)$ function ensures that $\alpha_{i,k}^*$ does not exceed 1. When $\alpha_{i,k}^* = 1$, the entire population level k of dispensing site i is covered by this site.

Let t_k denote the driving time boundary of coverage level k , and $P_i(t_k)$ denote the total number of residents in the coverage level k of dispensing site i . Considering all K coverage levels for each site, the total number of people covered by site i is calculated by

$$c_i = \sum_k \alpha_{i,k}^* P_i(t_k) \tag{6}$$

Third, we further propose to adjust the coverage index with social vulnerability. This is especially important for COVID-19 vaccination because a more socially vulnerable community is at higher risk of COVID-19 and hence is in more urgent need of vaccines. Let SVI_i denote the social vulnerability index (SVI) of the community that dispensing site i is located in. In order to raise the priority of the more vulnerable regions, we define the final coverage index of site i be

$$c_i = \frac{c_i}{\bar{c}} \times (1 + SVI_i) \tag{7}$$

where c_i is normalized by the average $\bar{c} = \frac{1}{I} \sum_i c_i$, and the site’s final coverage index gets higher if the SVI_i value is higher. The c_i calculated from (7) is then used in the objective function shown in (1).

The calculation of SVI_i depends on the available data of the target area. For example, in the U.S., the CDC has an open and well-established measuring system to calculate the SVI based on the census variables. The value of CDC’s SVI is between 0 and 1. Up to 15 social factors are considered in the SVI including poverty, aged 65, diploma, etc. These factors are also the key risk factors for COVID-19. CDC ranks tracts within each state based on the value of these social factors. Tracts in the top 10% are given a value of 1 to indicate high vulnerability, while 0 is given to the tracts in the bottom 10%. For other countries that have no ready-to-use SVI, they can apply a similar calculation and use important social factors with available data for ranking the local regions.

3. Case Study

To demonstrate our framework and gain insights on the Phase 2 vaccination campaign, a case study is conducted in this section. We take Middlesex County in central New Jersey, U.S., as the case area. Also known as the “Heart of New Jersey,” Middlesex County is located squarely in the center of New Jersey [36]. As part of the New York metropolitan area, Middlesex has an estimated population of over 825,000 in 2019 and 523 census block groups [37]. The County is 318 square miles in size, has 25 municipalities ranging from quiet rural towns to vibrant city centers [36]. The case study will develop a hub-and-spoke vaccination network at the county level based on real data. Section 3.1 describes the data collection process. Section 3.2 provides results of the case study. The optimization model in this case study is solved by the CPLEX Optimizer.

3.1. Data Collection

Two types of data are needed for the optimization model: location of the potential dispensing sites and geographic data and information (also known as geo-data) on local demographics, transportation facilities, economics, etc.

The vaccination plan published by NJDOH in October 2020 provides a list of potential local dispensing sites for each county [32]. According to NJDOH, potential dispensing sites include hospitals,

Federally Qualified Health Centers (FQHC), and chain retail pharmacies. The NJDOH’s vaccination plan lists a total of 58 potential dispensing sites in Middlesex County, including 6 hospitals, 7 health centers, and 45 retail pharmacies. For convenience, we reasonably assume that all 13 hospitals and health centers (numbered 101 to 113) are already included in the Phase 1 vaccination plan and will serve as H-DSs in Phase 2. The remaining 45 chain retail pharmacies (numbered 201 to 245) are potential OR-DSs for Phase 2. For further mapping and analytics, we import the longitude and latitude information of all 58 sites into the ArcGIS Online platform [38]. By doing so, a map layer with the location information of all dispensing sites can be generated in the ArcGIS Online platform.

Geo-data on Middlesex are retrieved from ArcGIS Online’s geoportal. This geoportal pulls data from various sources such as the CDC, the American Community Survey, and the U.S. Department of Transportation into an open database for users to generate maps showing the geo-data. The geo-data used in the case study include the demographic data at the block level, public transportation routes and stops, social vulnerability index at the tract level, and live traffic data. The demographic data and live traffic data are used to calculate $P_i(t_k)$, the total residents that live in the coverage level k of dispensing site i . We use the *Summarize Nearby* function in ArcGIS Online to calculate the total population within a specified distance of a dispensing site. As stated in Section 2, to better capture the local transportation accessibility, we define that distance is measured by driving time. The live speed in a typical peak hour (Monday 8 a.m.) is used to estimate the driving time. Public transportation data are used to obtain the number of nearby bus stops (N_i). The SVI data layer enables us to calculate the SVI_i .

Table 1 lists the input data to the case study. The $K = 3$ coverage levels and the values of α_k ’s are adopted from Lim’s work [14]. According to the 2017 person trips statistics data released by the U.S. Department of Transportation [39], about 2% of personal trips use public transportation. So, we assume that the estimated additional attractiveness brought to a dispensing site per public transportation stop is 0.02.

The maximum number of OR-DSs that can connect to a H-DS (n^{MAX}) and the upper limit on the allowed driving time from a H-DS to its OR-DSs (d^{MAX}) vary in different scenarios. As stated in Section 2, d^{MAX} is introduced to limit the travel distance from H-DS to its OR-DS for reducing the on-trip time and the long-trip temperature excursion risks during ultra-cold vaccine delivery. It’s reported that the ultra-cold COVID-19 vaccine allows at most 30 min under room temperature considering some local transfers may not use refrigerated trucks [6]. So, we let the d^{MAX} values range between 10 and 30 min. As for n^{MAX} , the baseline scenario allows each hub to be connected with at most 3 OR-DSs ($n^{MAX} = 3$), since a

Table 1
Input of the case study.

Symbol	Definition	Value
K	The number of coverage levels being considered	3
α_1	The baseline fraction of level 1 coverage	1
α_2	The baseline fraction of level 2 coverage	0.5
α_3	The baseline fraction of level 3 coverage	0.2
t_1	The driving time limit (minutes) of level 1 coverage	5
t_2	The driving time limit (minutes) of level 2 coverage	8
t_3	The driving time limit (minutes) of level 3 coverage	10
b	The additional attractiveness brought to a dispensing site per public transportation stop	0.02
n^{MAX}	The maximum number of out-reach dispensing sites that one hub dispensing site can connected with	{3, 4, 5} ^a
d^{MAX}	The upper limit on allowed driving time from a hub dispensing site to its out-reach dispensing sites (minutes)	{10, 15, 20, 25, 30} ^a

^a Value differs in different scenarios.

cluster with 4 sites (1 hub and 3 outreach sites) is expected to administer 1,000 doses per day according to NJDOH’s estimation [32], which is the minimum quantity in one Pfizer’s container. To investigate how n^{MAX} impacts vaccine distribution, we increase n^{MAX} to 4 and 5, respectively, in sensitivity analysis, allowing more OR-DSs to be connected to a hub. For convenience, we name each scenario by its n^{MAX} and d^{MAX} values. For example, “4OR15DT” represents the scenario with $n^{MAX} = 4$ and $d^{MAX} = 15$ min.

3.2. Results Analysis

(1) Baseline Scenarios

This section analyzes the results of the 5 baseline scenarios. Table 2 presents the total coverage index (TCI, objective function value) and the total number of OR-DSs included in the optimal hub-and-spoke network. As shown in Table 2, when d^{MAX} is less than 20 min, several H-DSs do not reach the maximum number of out-reach dispensing sites that one hub can connect with, due to a lack of available sites within the allowed distance of the H-DS. The TCI increases as d^{MAX} increases until d^{MAX} reaches 25 and then TCI stays at 55.9. We can then conclude that there is a threshold d^{MAX} value that below the threshold, increasing d^{MAX} can improve the TCI. Once d^{MAX} reaches the threshold, the TCI can no longer be improved.

In order to take a closer look at the optimal hub-and-spoke network, Table 3 lists the selection results of the 15 potential OR-DSs with smallest coverage index. Symbol “○” in Table 3 indicates the OR-DS is selected into the optimal hub-and-spoke network, whereas symbol “-” indicates the OR-DS is not selected. In 3OR25DT and 3OR30DT, unselected OR-DSs are the sites with the top 6 smallest coverage indices. This observation explains why the system’s TCI stays the same in 3OR25DT and 3OR30DT: under the limitation of 3 OR-DSs per hub, the system achieves its maximum TCI in 3OR25DT and 3OR30DT. Another observation is that sites No.239 and No.238 are not selected in any of the baseline scenarios. This observation can be explained by further analysis of the results in a map view.

Fig. 4 is a map view of the Middlesex County, NJ. All local dispensing sites are marked at their locations in Fig. 4. The green cross markers represent H-DSs. The circles represent potential OR-DSs, and the gradient colors correspond to the CI values (c_i) of the sites. Deeper colors indicate higher CI values. The size of a circular object shows the preference of the OR-DS. Preference here is defined as the number of times out of the 5 baseline scenarios that a site is selected into the optimal hub-and-spoke network. A larger circle indicates the site receives higher preference and that the site is selected into the optimal design more. CI is an input attribute of a site, while preference is an output from optimization. Intuitively, the preference of a site should depend on its CI.

It can be seen from Fig. 4 that the geographical distribution of dispensing sites in the case area shows an obvious imbalance: 11 of the 13H-DSs and nearly all high-CI OR-DSs are located in the northern half of the county. Moreover, the locations of the H-DSs are bunched up in big cities. This imbalance in geographical distribution impacts the preference of each site. The results show that high-CI OR-DSs in the northern part of the county indeed have high preferences since they are usually located in big cities with H-DSs nearby. However, for those low-CI OR-DSs, their preferences are highly impacted by their geographical location. For example, although sites No.239 and No.238 have CIs higher than that of site No.244, it takes more than 20 min of driving between No.239 or No.238 and their closest H-DS (No.106). So, sites No.239 and No.238 are not selected in 3OR10DT, -15DT, and -20DT scenarios.

Table 2
Input and optimal results in baseline scenario.

n^{MAX}	d^{MAX} (minutes)	Scenario Name	Total Number of Selected OR-DSs	Total Coverage Index (TCI)
3	10	3OR10DT	27	40.8
	15	3OR15DT	38	51.5
	20	3OR20DT	39	55.4
	25	3OR25DT	39	55.9
	30	3OR30DT	39	55.9

Table 3
Selection of the 15 OR-DSs with smallest coverage index

Scenario Site ID	3OR10DT	3OR15DT	3OR20DT	3OR25DT	3OR30DT	c_i^b
244	○	○	-	-	-	0.326
239	-	-	-	-	-	0.380
238	-	-	-	-	-	0.397
241	-	○	○	-	-	0.413
243	-	○	○	-	-	0.432
245	○	○	○	-	-	0.437
230	-	-	-	○	○	0.481
227	-	○	-	○	○	0.586
207	-	○	-	○	○	0.716
217	-	○	○	○	○	0.738
205	○	○	○	○	○	0.843
214	-	○	○	○	○	0.934
229	-	○	○	○	○	0.955
221	○	○	○	○	○	0.960
219	○	○	○	○	○	0.993

○ indicates the node is selected.
- indicates the node is excluded.

^b Sites are sorted in ascending order of the coverage index.

If we increase d^{MAX} to 25 or 30 so that No.106 can be connected with No.239 and No.238, additional potential sites can be considered and some of them have a higher CI than No.239 and No.238. Therefore, sites No.239 and No.238 are not selected into the optimal design in any of the baseline scenarios.

Fig. 5 shows the area covered by the optimal hub-and-spoke network in the baseline scenarios. The innermost covered areas ($k = 1$) are filled with deep green color, while the outmost covered areas ($k = 3$) are filled with light yellow-green. We highlight the three main differences in the results by red dashed boxes (I), (II), and (III). In 3OR10DT, the covered areas wrap tightly around the H-DSs. Areas (I) and (II) are both underpopulated areas, but Area (I) is not covered at all in 3OR10DT since there is no H-DS in this area. When d^{MAX} is increased from 10 min to 15 min, an obvious expansion of the covered area can be observed in both Areas (II) and (III), showing greener in these areas. More OR-DSs in these two areas are involved in the vaccination plan. In 3OR20DT, a further expansion can be seen in Area (III). At this point, the northern half of the county is almost completely covered. Scenarios 3OR25DT and 3OR30DT have identical results. The case county achieves its largest possible TCI under the limitation of 3 OR-DSs per hub. Compared with 3OR20DT, No.245, No.244, and No.243 in Area (II) are now replaced by No.230, No.227, and No.207 in Area (I). Unselected sites in the last two scenarios are the sites with the smallest CI. In combination with the findings provided by Fig. 4, we can conclude that a big enough d^{MAX} can mitigate the negative effect brought by the geographical imbalance of H-DSs.

(2) Sensitivity analysis on the maximum number of out-reach dispensing sites per hub

The previous baseline scenarios allow up to 3 OR-DSs to be connected to one H-DS ($n^{MAX} = 3$). This section conducts a sensitivity analysis on n^{MAX} to investigate its impact on the vaccine distribution network. Fig. 6 compares the results of the baseline scenarios

with additional 10 scenarios ($n^{MAX} = \{4, 5\}$, $d^{MAX} = \{10, 15, 20, 25, 30\}$). Compared with the baseline scenarios, allowing 4 OR-DSs per H-DS can improve the TCI. However, when further increasing n^{MAX} from 4 to 5, the TCI stays the same. Scenarios 3OR15DT, 4OR15DT, and 5OR15DT have identical results since there are only 38 OR-DSs within the 15 min driving time limit and all of them have been selected into the optimal vaccine distribution network at $d^{MAX} = 15$. A threshold of d^{MAX} can also be observed in the scenarios with a higher n^{MAX} : once d^{MAX} reaches 20 min, any further increase in d^{MAX} can no longer improve the TCI. At $d^{MAX} \geq 20$, all 45 potential OR-DSs are selected into the optimal hub-and-spoke network for vaccine distribution. In other words, when the hub-and-spoke network configuration is implemented, ultra-cold vaccines can be delivered to all local dispensing sites from the hubs within its 30-min restriction under room temperature after opening the vaccine container.

3.3. Insights and lessons learned

Using our analytical framework, we have demonstrated the process of utilizing a geographical information system to determine and improve the coverage index of each dispensing site. Furthermore, within this framework, we adopt a hub-and-spoke design to support vaccination efforts, and apply it to the Phase 2 vaccination campaign in Middlesex County, NJ, the U.S. After evaluating 15 scenarios with varying constraints and parameters, we observe the following key takeaways:

- (1) There is a maximum threshold level for the distance limitation which restricts the acceptable driving time from a H-DS to its OR-DSs. While we can expand coverage by increasing the distance limitation, once this threshold is met, any further increases in the distance limitation would not result in expanded coverage.

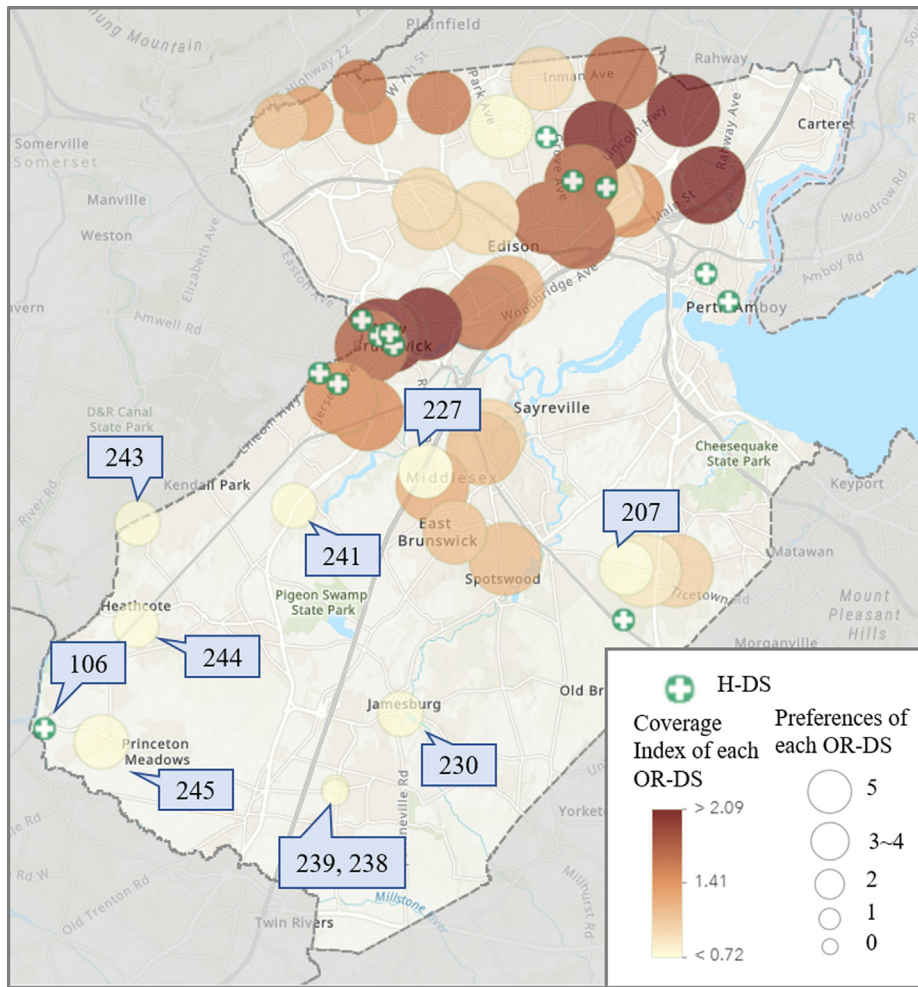


Fig. 4. Coverage index and preference of each OR-DS in the baseline scenarios.

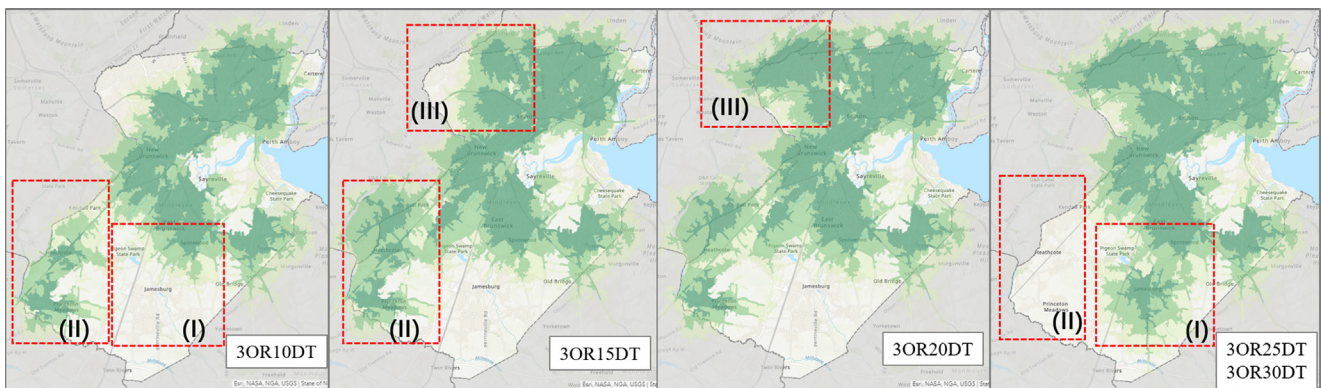


Fig. 5. Area covered by the optimal hub-and-spoke network in the baseline scenarios.

- (2) Increasing the number of OR-DSs per H-DS will not always lead to expanded coverage. To determine an upper bound on the number of OR-DSs per H-DS, public health officials and local government should assess the current state of the pandemic in conjunction with demographic information and guidance from the Federal Government.
- (3) Our framework serves as a decision support tool, which can aid state and local governments in designing vaccination campaigns in the face of a public health crisis. While this framework can be applied to many regions and countries

to obtain generalizable insights, we observe that rural and underpopulated areas are at risk of limited coverage under the current assumptions of this framework. For example, Fig. 7 shows the potential dispensing sites in New Jersey's Cape May County. Pharmacies in the highlighted area are far from the county's hub centers. In order to ensure fair and equitable access to vaccines in such cases, public health officials may need to consider alternative options, establishing partnerships with neighboring counties or deploying pop-up vaccine administration sites.

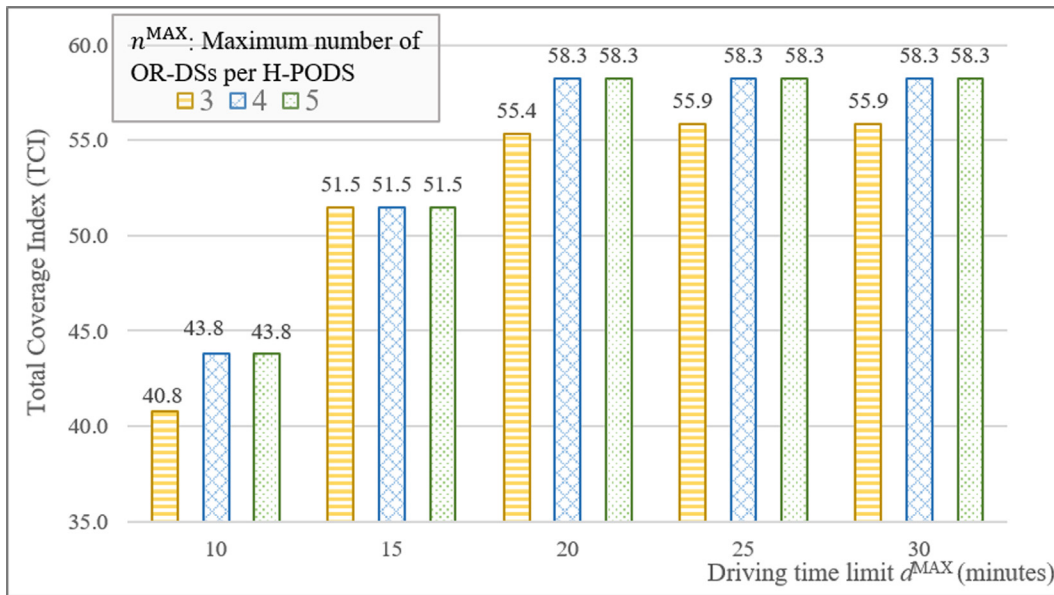


Fig. 6. Comparison of the total coverage index (TCI) in all scenarios.

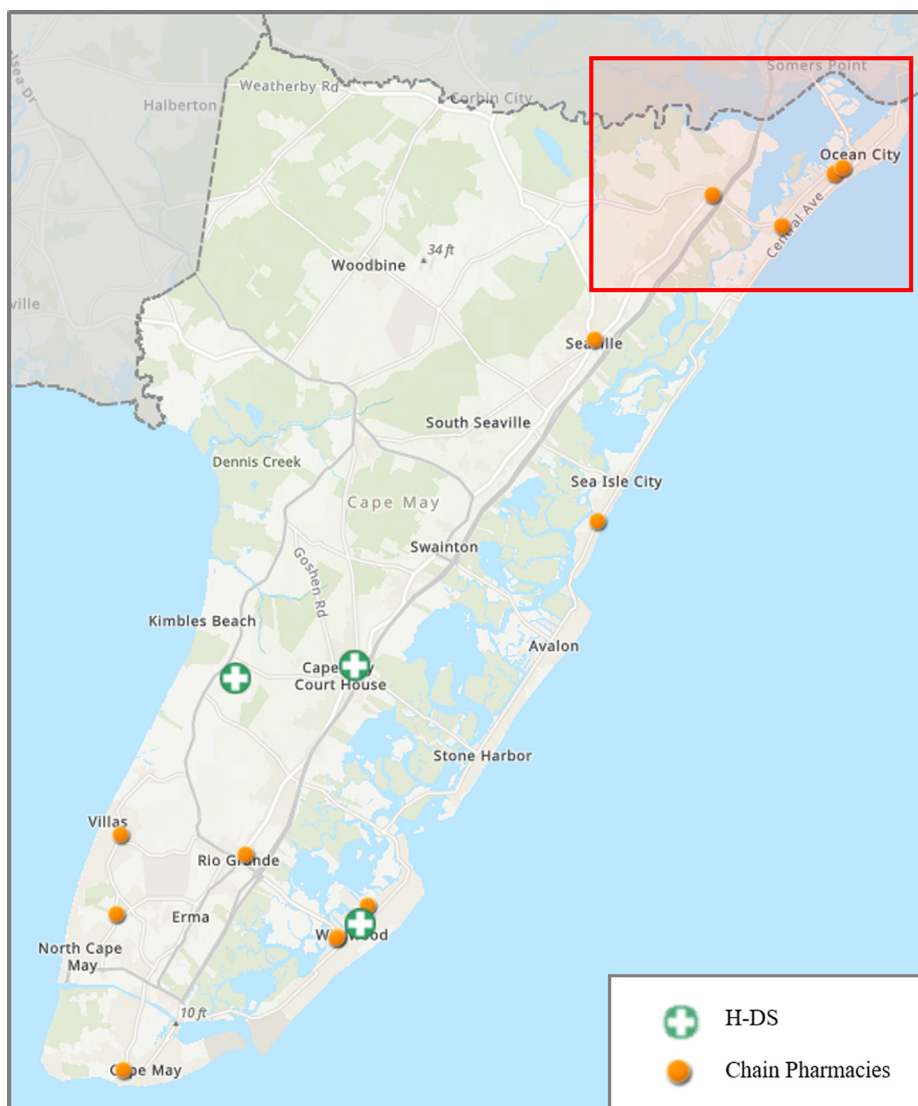


Fig. 7. Locations of potential dispensing sites in the Cape May County in New Jersey.

4. Conclusion

This paper focuses on expanding the COVID-19 vaccination coverage against the backdrop of the phased vaccination campaign in the U.S. In face of the challenges brought by ultra-cold storage requirements, we propose a framework to design a regional hub-and-spoke vaccine distribution network that can be generalized to support different communities in a public health crisis by enhancing the access to the vaccines. This network configuration is expected to reduce vaccine waste without making infrastructure investments by sharing inventory within each region. Furthermore, we introduce an improved coverage index in the optimization model to measure the priority of each dispensing site. This newly proposed coverage index utilizes a geographical information system to capture local characteristics and demographics. We demonstrate our framework by evaluating 15 different scenarios based on real data, which yields actionable strategies for the upcoming Phase 2 vaccination campaign.

Additionally, our newly proposed framework can be further generalized to support other countries deploying a vaccination campaign in the face of a public health crisis. To accomplish this, our work may be further expanded by considering site-specific demands, flexible administration policies, and new opportunities for secondary distribution such as using drones or smaller containers. Though our solution provides a way to improve vaccine access, it must be noted that enhancing vaccine awareness and acceptance are also essential for a successful vaccination program [40]. Further actions such as funding support and media promotion should be taken simultaneously to improve vaccine acceptance. Future research is required on a case-by-case basis to evaluate individual challenges faced by other regions or countries, and how to combine the framework with other opportunities.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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