RESEARCH REPORT

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Spatial Modeling of Future Light- and Heavy-Duty Vehicle Travel and Refueling Patterns in California

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16. Abstract
A spatial optimization model was developed for deploying, over the next two decades, hydrogen refueling stations for heavy-duty zero-emission hydrogen vehicles. The model assigns trips to vehicles by applying a routing algorithm to travel demand data derived from another model—the California Statewide Travel Demand Model (developed by the California Department of Transportation). Across a range of adoption levels of hydrogen fuel-cell truck technology, from 2020 through 2030, the results suggest that heterogeneity of travel demand may necessitate an extensive distribution of refueling stations, which may lead to low utilization of stations in the short term. To efficiently employ the capacity of stations, a certain volume of vehicle adoption must be met, and/or truck routes must be planned and committed to specific roadways. Once the number of stations reaches a threshold to meet the principal demand in affected transportation area zones, a small set of smaller "top-off" stations can be built to meet marginal excess demand. The best location of a hydrogen refueling station within a transportation area zone also depends on the criteria such as land cover, slope, and distance from gas stations, truck hubs, and the truck network.

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The University of California Institute of Transportation Studies (UC ITS) is a network of faculty, research and administrative staff, and students dedicated to advancing the state of the art in transportation engineering, planning, and policy for the people of California. Established by the Legislature in 1947, ITS has branches at UC Berkeley, UC Davis, UC Irvine, and UCLA.

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Disclaimer

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Glossary

AB 8	Assembly Bill 8
CSTDM	California Statewide Travel Demand Model
GHG	greenhouse gas
HDRSAM	Heavy-Duty Refueling Station Analysis Model
HRI	Hydrogen Refueling Infrastructure
ITS-Davis	UC Davis Institute of Transportation Studies
LCFS	Low Carbon Fuel Standard
OD	origin-destination
PEV	plug-in electric vehicle
STIEVE	UC Davis Spatial Transportation Infrastructure, Energy, Vehicles, and Emissions
TAZ	transportation analysis zone
ZEV	zero-emission vehicle

Executive Summary

Executive Summary

Reducing carbon emissions from transportation in California will require a better understanding of future fuel demand patterns and infrastructure requirements for zero-emission vehicles (ZEVs). This includes understanding the numbers of vehicles, travel patterns, refueling patterns, refueling station needs, and the implications for the energy system. This information is necessary for planning the location and size of refueling infrastructure, as well as the provision of electric power, renewable natural gas, and other energy systems.

For this project, we developed a spatial model of heavy-duty vehicle travel in California to explore refueling station requirements. The model is framed at the level of “transportation analysis zones” (TAZs) using data from the California Statewide Travel Demand Model (Version 2.0) as the basis of spatial disaggregation (with 5454 such zones across the state including 51 roadway exits). To date, the model development has focused on hydrogen fuel cell heavy-duty trucks. We conducted a first-order estimation of locations of refueling stations, over time, as increasing numbers of fuel cell heavy-duty vehicles travel the roads. The location and size of stations have been estimated in a manner to efficiently provide fuel and minimize the time vehicles spend off-route to a reach a station. We considered a series of cases with increasing numbers of trucks on the road. The resulting station-based hydrogen demand can then be used to provide inputs for other models, such as hydrogen supply models that are also being developed at ITS Davis.

A sense of the results generated so far is provided in the figures below. Figure ES-1 shows a set of cases starting from a low percentage of trucks being fuel-cell trucks (powered by hydrogen), up to 100% of trucks on the road being this type. As more fuel-cell trucks are considered (which could be growth over time or just separate scenarios at a point in time), the need for stations increases, with a choice between the number and size of these stations. The model chooses both, taking into account the need for stations geographically around the state, and with each station sized according to the likely amount of refueling “traffic” it will receive. As shown in the figure, when only 5% of trucks are fuel-cell trucks, there is a mix of station sizes put into service. From that point onward, most additional stations are of the largest possible for this study (5 tons of hydrogen dispensed per day). This remains true until nearly all trucks are fuel-cell trucks, then some additional smaller stations are built in outlying areas and to fill in some final gaps. This finding is considered important: that most stations built as the fuel-cell truck population increases will likely need to be large. Further investigation into this is warranted, as well as seeing how these results change as more types of vehicles are added to the model (e.g., cars and light trucks).

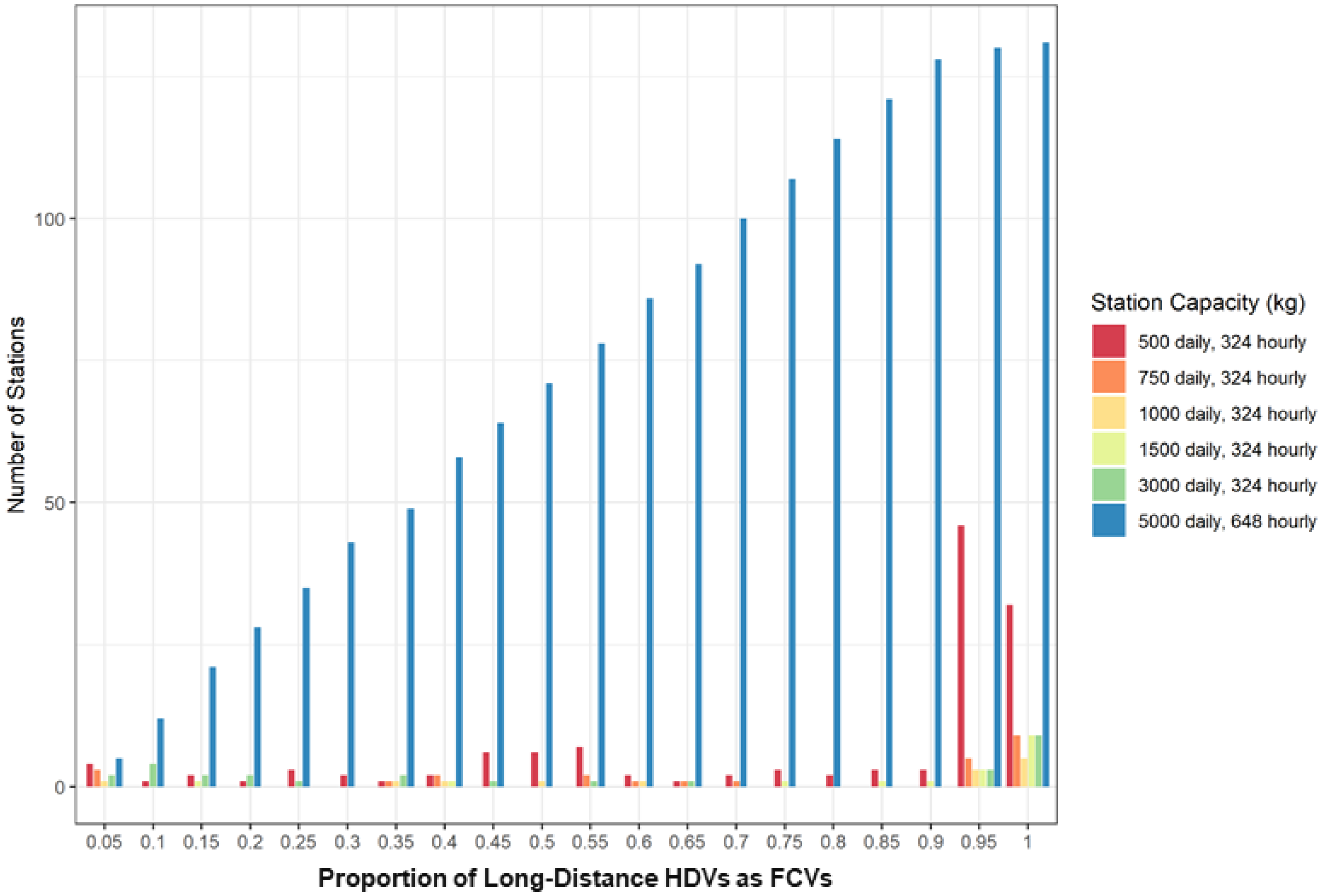
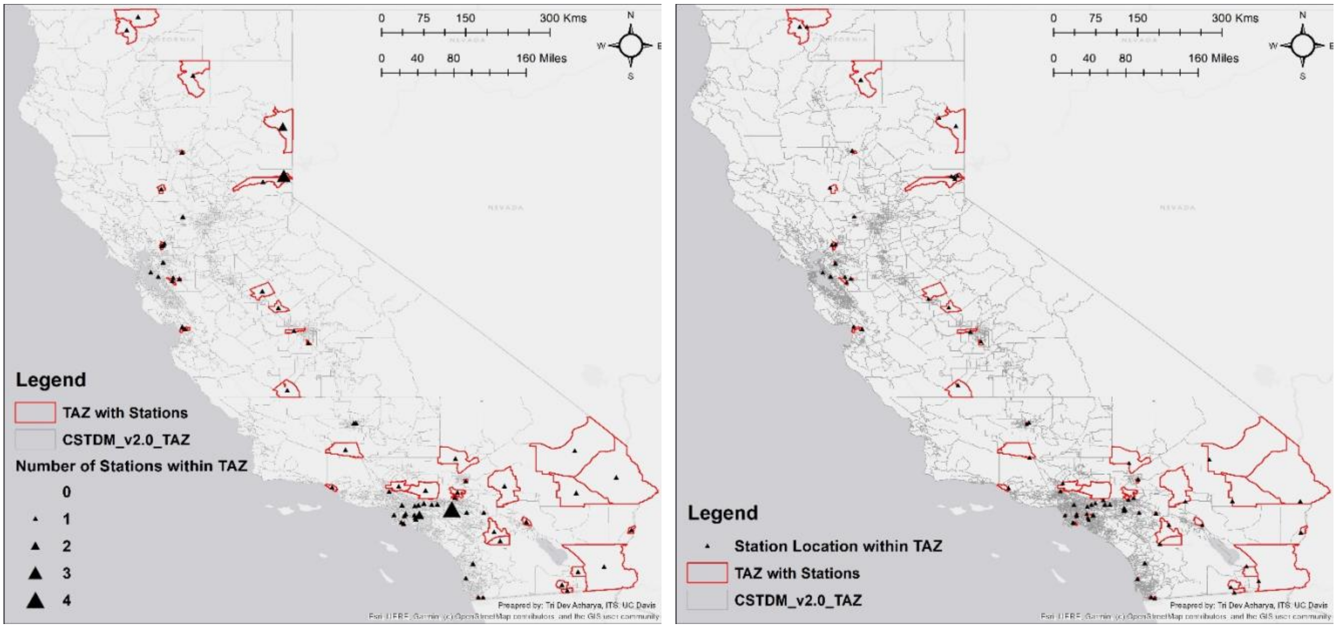


Figure ES-1. The number of stations with different hydrogen capacities that will be needed as an increasing proportion of long-distance heavy-duty vehicles (HDVs) are fuel-cell vehicles (FCVs)

An example of the spatial results of the model is shown in Figure ES-2. For different levels of fuel-cell truck adoption, the model determines which of the 5454 transportation analysis zones (TAZs) in California will need one or more hydrogen refueling stations, and how many will be needed in each TAZ (Figure ES-2a). The model then determines the precise location of those stations within each TAZ (Figure ES-2b), which depends upon factors such as station footprint and site attributes.



(**a**) (**b**)

Figure ES-2. Spatial outputs of the model. (a) The red boundaries and black triangles (at the centroids of transportation analysis zones [TAZs]) indicate those TAZs that contain one to four hydrogen refueling stations; (b) the triangles indicate the precise location of those stations within TAZs, assuming a station area of 400 × 400 m^2.

The results to date and descriptions of the model provided in this report reflect a work in progress; the spatial model is currently being expanded to include more vehicle categories (such as medium-duty trucks and light-duty vehicles, as well as electric vehicles, with tracking for both electric and hydrogen infrastructure). The study will also be updated and enhanced to project endogenously (i.e., based on other variables within the model) the numbers of vehicles, travel patterns, and locations of refueling stations. The modeling tool could also be used to evaluate the geographic distribution of truck pollutant emissions, geofencing strategies, and regional air quality impacts, by incorporating emissions-sensitive area information into the model. A separate report on the initial findings using the full model will be prepared during late 2021 or 2022. This current report focuses on a reporting of methodology and the results to date, as funded under this SB1 project.

This work will assist state agencies in prioritizing a combination of programs and investments for electric recharging and hydrogen refueling infrastructure to align with the likely future transportation system (particularly in terms of fuel demands) in the state.

Contents

Introduction

Globally, heavy-duty freight transport represents a major source of greenhouse gas (GHG) emissions. In California alone, $2.8 trillion in goods are shipped to and from the state annually, mostly by trucks. On any given day, tractor-trailers and large commercial trucks move more than 5 million tons of freight through California, with San Bernardino, Riverside, and Los Angeles counties experiencing the most traffic. The transportation sector accounts for roughly 40% of the total GHGs emissions in California, with heavy-duty trucks accounting for roughly 20% of transportation GHGs and contributing significantly to local pollution (*1*). To reduce these environmental damages, California has aggressively been promoting the deployment of zero-emission vehicles (ZEVs) through both legislative and regulatory efforts spanning several agencies, including the California Air Resources Board, the California Energy Commission, and the California Public Utilities Commission.

Light-duty vehicles have enjoyed regulatory support in the market for over a decade, via policies such as the California Air Resources Board's ZEV Program (*2*) and the Center for Sustainable Energy's Clean Vehicle Rebate Project (*3*). However, the same cannot be said for medium- and heavy-duty trucks. Medium- and heavy-duty ZEVs are eligible for financial incentives through the Hybrid and Zero-Emission Truck and Bus Voucher Incentive Project (*4*). In June 2020, the California Air Resources Board passed the landmark Advanced Clean Truck (*5*) regulation, which will drive the transition of medium- and heavy-duty vehicles to ZEVs, starting in 2024 and extending till 2035. Several technologies—including plug-in electric vehicles (PEVs) and hydrogen fuel cell vehicles—would allow automakers to meet the requirements of the Advanced Clean Truck regulation. Studies have shown that hydrogen-based fuel-cell trucks are more attractive than pure electric trucks, because the former have longer ranges between refueling and shorter refueling times (*6*). Most medium- and heavy-duty vehicles have sufficient space for hydrogen storage tanks to accommodate 90 percent of each vehicle's daily range of operation, although identifying a standard size, design, and placement of these components may be challenging (*7*, *8*). Furthermore, fuel-cell trucks running on renewable hydrogen produce near-zero life-cycle GHG emissions, and even with a mix of hydrogen feedstocks produce significantly lower GHGs than do conventional, internal combustion engine trucks (*9–11*).

A transition to new technologies will require infrastructure for refueling the heavy-duty ZEVs. In California, the number of public retail hydrogen stations has increased gradually and their dispensing capacity has increased by up to four times annually since 2015 (*12*). However, there are many challenges in scaling them up due to high capital and operational costs (*12*). Identifying the optimum number of hydrogen stations, their size, and locations in consideration of current and future vehicle volume could assist investors in the deployment of these infrastructures. In general, infrastructure planning and deployment for hydrogen supply chains are done using three approaches: system optimization methods; geographical information systems (GIS)-based approaches; and assessment of broader GHG targets and plans towards the transition to hydrogen structure (*13*, *14*). Various studies from around the world have used either one or a combination of these approaches(*15–18*). Recent studies are more focused on regional and national level infrastructure deployment for various scenarios for the hydrogen supply chain (*19–28*).

California's hydrogen fueling station network is one of the first in the world to demonstrate the feasibility of hydrogen fuel sales. The strategy for developing this network has evolved since the publication of the California Hydrogen Blueprint Plan in 2005 *(29*). California has recently revived its focus on developing retail hydrogen refueling stations through legislation such as Assembly Bill 8 (AB 8) and amendments to the Low Carbon Fuel Standard (LCFS). AB 8 dedicates up to $20 million per year to support the construction of the first 100 hydrogen fuel stations in the state. The 2018 LCFS amendments allow for Hydrogen Refueling Infrastructure (HRI) credits, intended to help support up to 200 hydrogen stations by 2025. This allows eligible hydrogen station operators to apply for LCFS credits based on the difference between the station's installed capacity and the actual hydrogen throughput. Stations are eligible to generate these credits for 15 years. The combination of grant programs through AB 8 and the LCFS HRI credit provides station developers with opportunities to receive consistent support for the capital-intensive expenses of establishing a hydrogen refueling station.

To facilitate the deployment of the refueling stations, we first need to understand: travel behavior; demand patterns within California, including the numbers of vehicles, travel patterns, refueling patterns, and refueling station needs; and implications for the energy system. In the ongoing development of the UC Davis Spatial Transportation Infrastructure, Energy, Vehicles, and Emissions (STIEVE) model, we have focused on the development of an optimization model to deploy stations for heavy-duty vehicles based on the characteristics of travel and attributes of the stations. We are evaluating our STIEVE model in California based on a subset of empirical origin-destination (OD) data and route network data from the California Statewide Travel Demand Model (CSTDM).

Data Used

California Statewide Travel Demand Model Data

The California Statewide Travel Demand Model, Version 2.0 (CSTDMv2.0) forecasts all personal travel made by every California resident, plus all commercial vehicle travel, made on a typical weekday in the fall/spring (when schools are in session). It has five demand models as summarized in Figure 1**.** It is trip-based (recently updated to an activity-based model), which includes passenger trips, as well as a heavy-duty truck model. The model then distributes these trips through the internal and external zones, resulting in several origin-destination (OD) matrices. Our study uses the 2040 calibrated OD matrices to estimate the aggregate energy demand.

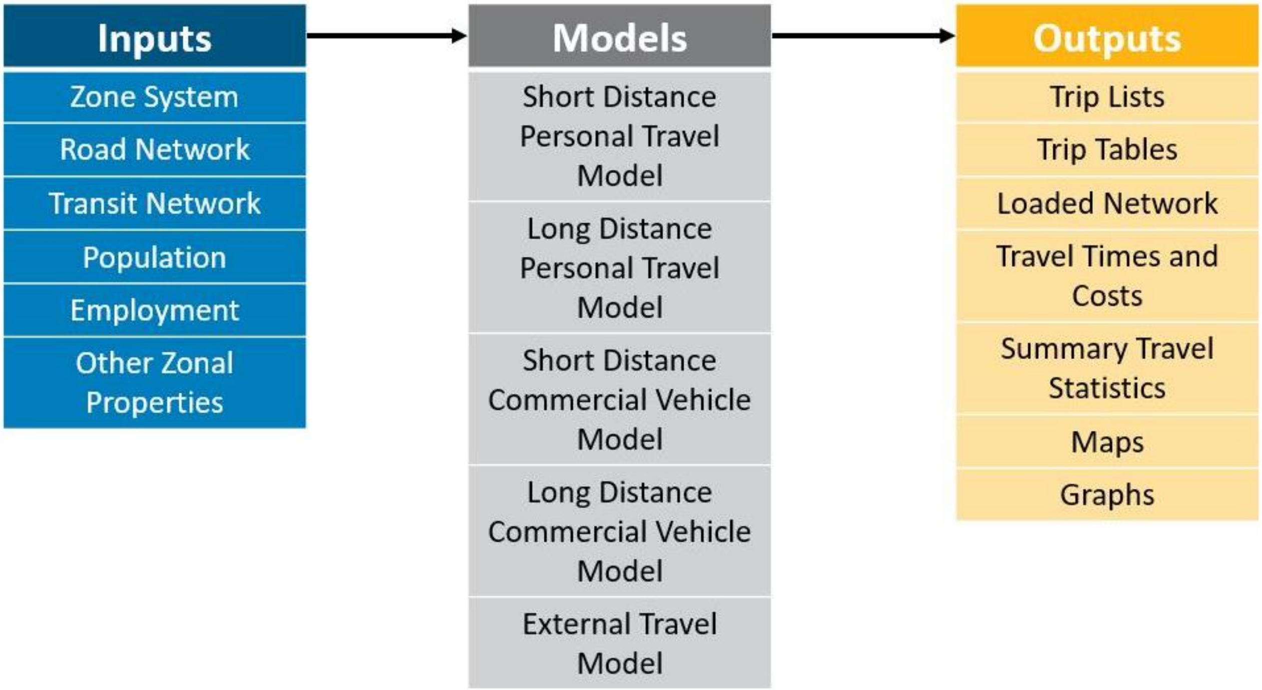
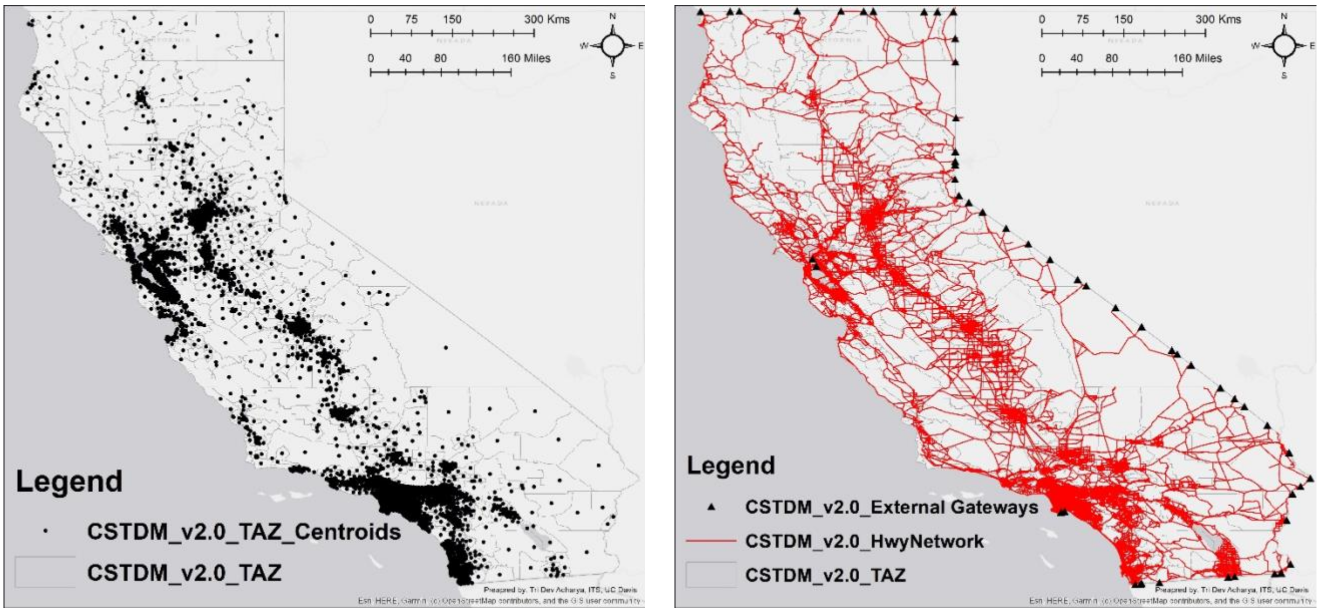


Figure 1. CSTDM v2.0 model system operation *(30)*

Statewide Spatial Data

The CSTDM uses a traffic analysis zone (TAZ) system of 5,474 zones. TAZ boundaries were split and adjusted to accommodate the 2010 Federal Census zone system, to match California Air Resources Board air zone boundaries, and to accommodate areas of major growth to ensure reasonable zone sizes. The road and transit networks for the base year were updated to reflect 2010 conditions. The CSTDM road network includes over 125,000 nodes and 325,000 links and its transit network was developed using the Google Transit platform. The synthetic population was generated with the US Census, American Community Survey, and other sources of data. Also, there are 48 external zone vehicle entry/exit points on roads on the state boundary, plus three external zone seaports (Long Beach, Los Angeles, and Oakland) whose import/export activities generate significant truck activity, making 51 total existing external zones. The zones nest both within the 58 California counties and the 524 land use zone system used in the California Production, Exchange, and Consumption Allocation System spatial economic model. Figure 2 illustrates the CSTDM v2.0 TAZ system with external exiting zones. In our study, we have used 5454 TAZs across the state.



(**a**) (**b**)

Figure 2. CSTDM v2.0: (a) 5454 TAZs with Centroids and (b) highway network with 53 external gateways

To find suitable land for the station deployment, we use base criteria such as land cover, slope, truck hubs, and network, and existing gas stations. Land cover data are extracted from the National Land Cover Database (NLCD) 2016, which is a legacy product of the United States Geological Survey in partnership with various federal agencies. It utilizes multi-source integrated training data and decision-tree-based classifications of Landsat imagery. The slope was derived from the National Aeronautics and Space Administration's (NASA's) improved Digital Elevation Model. The truck network, hub, and CSTDM TAZs were downloaded from the Caltrans GIS website. These spatial features are shown in Figure 3.

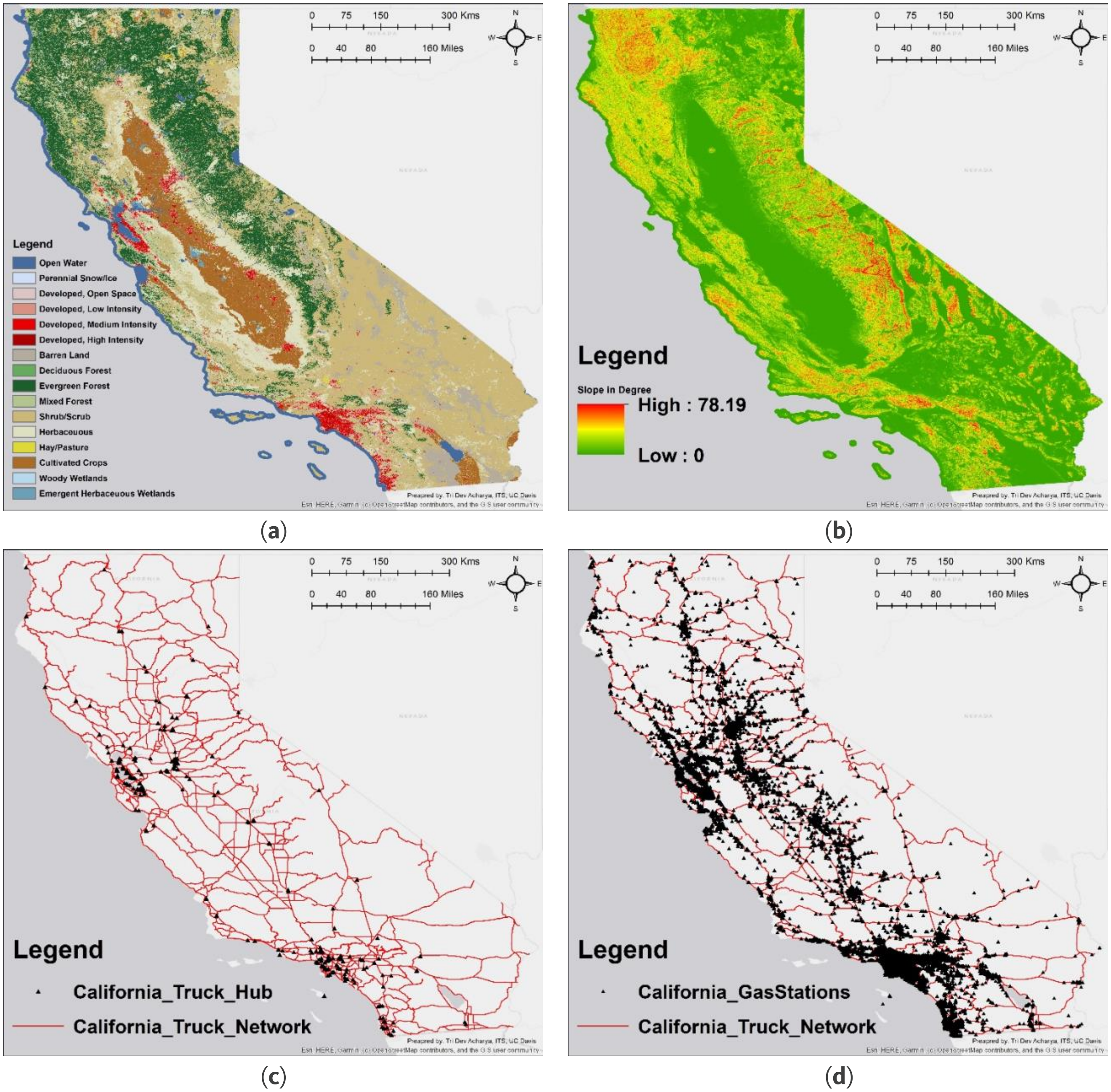


Figure 3. Spatial data for suitability analysis: (a) land cover, (b) slope, (c) truck network and hubs, and (d) existing gas stations

Hydrogen Fueling Station Attribute Data

The Heavy-Duty Refueling Station Analysis Model (HDRSAM) was used to analyze station characteristics and generate refueling station costs. HDRSAM is an Excel-based bottom-up tool that Argonne National Laboratory has been developing since 2005, for simulating the costs of hydrogen refueling stations. (*31*).

The HDRSAM optimizes the cost of hydrogen refueling for various station configurations and demand profiles. The key assumptions are the cost of capital, depreciation and labor rates, land requirements based on National Fire Protection Association codes, and technical information on the process and equipment. User-defined inputs include fueling demand parameters, cost, and performance data of refueling components as a function of throughput and manufacturing volume, and other financial inputs. The key outputs include levelized cost [$/kg] of hydrogen refueling, capital, operating, and maintenance costs of station components, along with annual cash flows and land and energy use (*31*, *32*).

The study uses the following station configuration for gaseous and liquid refueling, for different station capacities such as 3 ton/day, 5 ton/day, etc.:

1. Gaseous Hydrogen from Supply → High-Pressure Compressor → High-Pressure Buffer Storage→ Pre-Cooling Unit→ Dispenser
2. Liquid Hydrogen from Supply → Heat Exchanger → High-Pressure Compressor → High-Pressure Buffer Storage → Pre-Cooling Unit → Dispenser.

The assumptions and inputs of the refueling model are corroborated in Table 1.

Table 1. Parameterization in the HDRSAM model *(33, 34)*

Parameter	Value
Station utilization rates (%)	25,50,100
Lifetime (years)	30
Location of station	Urban, Rural
Electricity rates ($/kwh)	0.10,0.06, 0 .02
Hydrogen dispensing pressure (bar)	700
Number of dispensers	3,5,10
Hose occupied fraction during peak hour (%)	50
Filling rate for urban and highway/base refueling (kg/min)	7.2,3.6,1.8
Maximum dispensed amount per vehicle for urban and highway/base refueling (kg)	80
Vehicle lingering time (min)	2
Discount rate (%)	8
Dollar year	2016
Total federal and state tax (%)	39

The outputs of HDRSAM are critical inputs to the spatial model. The impact of varying critical refueling parameters (station size, filling rate, number of dispensers, etc.) can be analyzed and these serve as inputs to the spatial model while selecting the optimal combination of station subsystems (dispensers, number of vehicles filled, etc.) to cater to the demand from trucks in the CA region.

Methodology

Our STIEVE model requires several key pieces of information: how vehicles move on routes through our region of interest, the origin and destination of vehicles on the network, attributes of refueling stations, and characteristics and availability of the land. Figure 4 shows the data inputs for our model. The first step is to find the shortest route between origin and destination TAZs; these routes, combined with the CSTDM travel demand between OD pairs, act as the major component of energy demand for vehicles. The HDRSAM provides important attributes such as cost and footprint for the refueling station. These two modules are major inputs in determining the optimal TAZs and the number of refueling stations in each of them. The final suitability analysis is the spatial analysis that indicates the actual location of stations within the selected TAZs. This analysis uses as inputs the number of stations, the footprint of each station, and the distance between two stations.

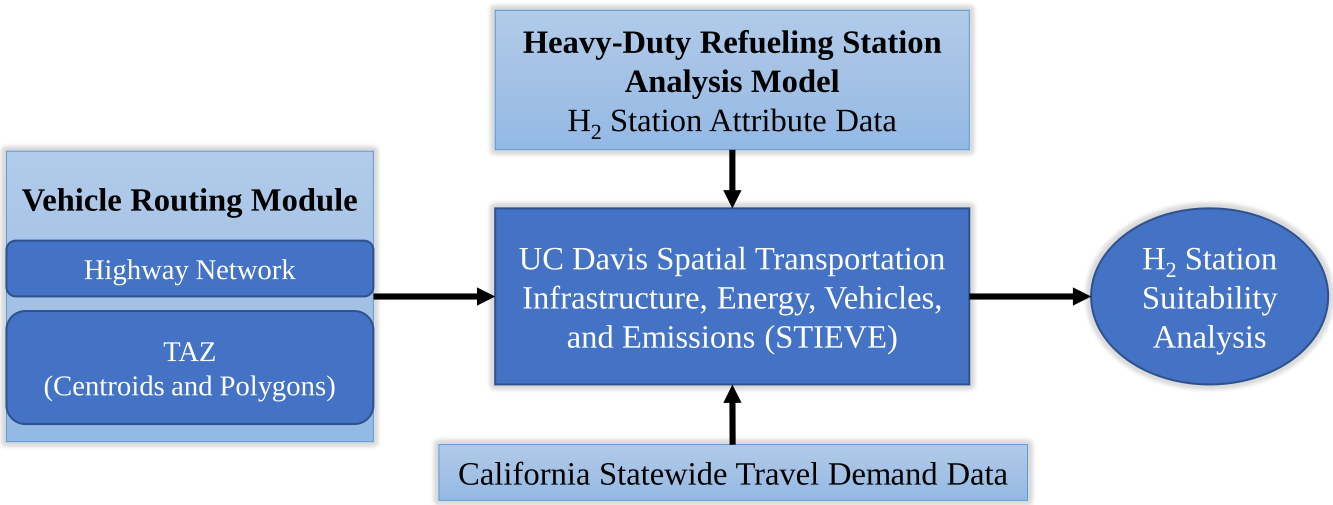


Figure 4. A diagram displaying general data input requirements for the UC Davis STIEVE model

In the remainder of this section, we describe the data used in this study, as well as the modeling approach employed to generate the result. All the preprocessing and visualization were done in ArcGIS Pro 2.6 and the optimization and data parsing were conducted in GAMS 25.1.2 and R 4.0.2 respectively.

Vehicle Routing Module

For the TAZ centroids, the shortest route was calculated using the 'stplanr' package in R. First, the CSTDM Highway SpatialLines were converted to SpatialLinesNetwork. For the provided OD pair in CSTDM, nodes in the network were searched using the 'find_network_nodes' function that finds the node ID of the closest point to a single coordinate pair (or a set of coordinates) from a SpatialLinesNetwork. Then 'sum_network_links' function was used to find the shortest path on the network between the searched nodes. The process was used for a multiple-origin, multiple-destination algorithm to summarize the shortest link between the OD pairs. The shortest route was later used to extract the list of TAZ that it passes over. The list for each route is one of the key inputs for optimization.

Optimization Algorithm

The station deployment optimization model is a mixed-integer linear program that attempts to minimize total system costs for an operator based on installation cost, $c^{\text{stationCost}}$, of a particular station *i* along with the fuel cost, c^{fuelCost}. The model decides how many stations to install, x^{station}, of each type of station *i* in each region *r* alongside how much hydrogen fuel is dispensed in each region x^{fueled}. This can be represented in the following objective function:

$$\min_{w.r.t: x_{ir}^{\text{station}}, x_{rvt}^{\text{fueled}}} \sum_{i} \sum_{r} x_{ir}^{\text{station}} c_{i}^{\text{stationCost}} + \sum_{r} \sum_{v} \sum_{t} x_{rvt}^{\text{fueled}} c^{fuelCost} \quad (1)$$

Additionally, the optimization is subject to the following operational constraints that ensure that station deployment will meet the demand for fuel along the route that trucks are traveling while simultaneously following capacity constraints (both at the dispenser and overall daily fuel limits).

Constraint 1: Vehicle fueling must be greater than energy demand

$$\sum_{t} \sum_{r \in vtor_{vr}} x_{rvt}^{\text{fueled}} - c_{v}^{\text{demand}} \geq 0; \forall v \quad (2)$$

Where c^{demand} represents the total demand for trips made from a specific origin to destination. The fueling can be distributed from a mapping of regions to this origin-destination route via a two-dimensional set, $vtor_{v,r}$, that maps the O-D from the *v* set to a set of routes *r*.

Constraint 2: Daily fueling capacity must exceed the amount of fuel dispensed

$$\sum_{i} x_{ir}^{\text{station}} c_{i}^{\text{dailyCap}} - \sum_{v} \sum_{t} x_{rvt}^{\text{fueled}} \geq 0; \forall r \quad (3)$$

The daily fueling capacity constraint ensures that the total fueling amount in each day can be fulfilled in every region given all the stations installed within that region. There are two primary values of daily station capacity, c^{dailyCap}, chosen from the HDRSAM model with maximum fueling rates of 3000 kg H_2 or 5000 kg of H_2 per day.

Constraint 3: Hourly fueling capacity must exceed the amount of fuel dispensed every hour

$$\sum_{i} x_{ir}^{\text{station}} c_{i}^{\text{hourlyCap}} - \sum_{v} x_{rvt}^{\text{fueled}} \geq 0; \forall r, t \quad (4)$$

Lastly, we also enforce an hourly fueling capacity constraint to ensure that congestion at the level of dispensers is accounted for. The maximum amount that a particular station can dispense in an hour, $c^{hourlyCap}$, is also a function of the station. The constraint is similar in form to Constraint 2, but it is enforced every hour. The inputs for HDRSAM are based on the dispensing rate and number of dispensers, resulting in 9 unique configurations of hourly limits ranging from as low as 324 kg H_2/hour to as high as 4,320 kg H_2/hour.

Our station deployment model is uniquely designed to be able to capture large-scale transportation systems at very high spatial resolution. Ordinarily, system design at high spatial resolution would require careful tracking of individual vehicles—which quickly becomes intractable at larger volumes. Instead, our approach aggregates demand from all OD pairs. This method, unfortunately, sacrifices resolution on the heterogeneity of demand (e.g., a non-uniform pattern of arriving at refueling stations), but the tradeoff is that computational complexity is strictly a function of the size of the network and not of the number of trucks. This means that the model can operate at *any* level of fuel-cell truck adoption without increasing the complexity of the system. This approach is particularly useful in exploring a broad array of scenarios of adoption.

Suitability Analysis

In the ArcGIS environment, suitability analysis is used to rank and score sites based on multiple weighted criteria. Suitability can be ranked based on data variables related to the site attributes. First, the problem is defined, the criteria for solving it are identified, and the required input datasets are prepared. These variables might include raster datasets (slope, for example), site attributes, proximity to point/line features, etc. Once the criteria are selected, weights can be assigned to them, weighted scores assigned to each potential site, and final site score ranks—from most to least suitable—can be reviewed. The suitability analysis can be run on a set of point location sites, polygon areas, standard geographies, or any combination thereof.

After the optimization model provides the number and size of hydrogen stations in each TAZ, suitability analysis will be carried out to identify the optimal siting of the individual station(s). Figure 5 shows the overall workflow, which can have more base criteria in the future.

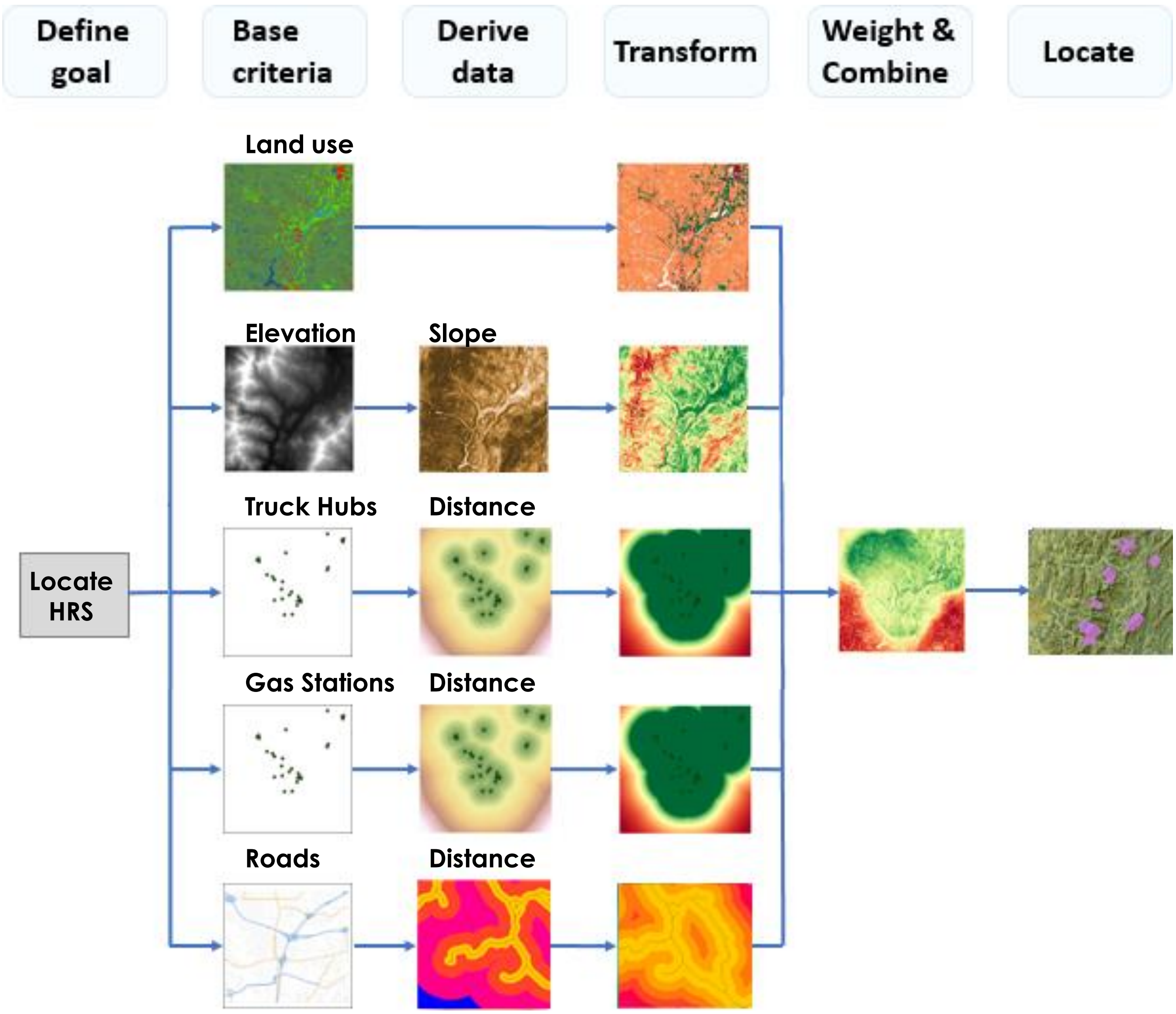


Figure 5. Suitability analysis workflow for the HRI deployment (modified from ESRI)

Model Scenarios

CSTDM-based Travel Pattern

Figure 6 reflects the travel patterns of heavy-duty vehicles based on the CSTDM. These show the TAZs, color-coded to reflect the frequency at which the origins, destinations, and shortest routes between origins and destinations occur within the TAZs. As most origins and destinations lie in the central region (along the north-south axis) and the western/coastal region (along the east-west axis), the TAZs including sections of I-5 and state highway 99 show the highest frequency of travel.

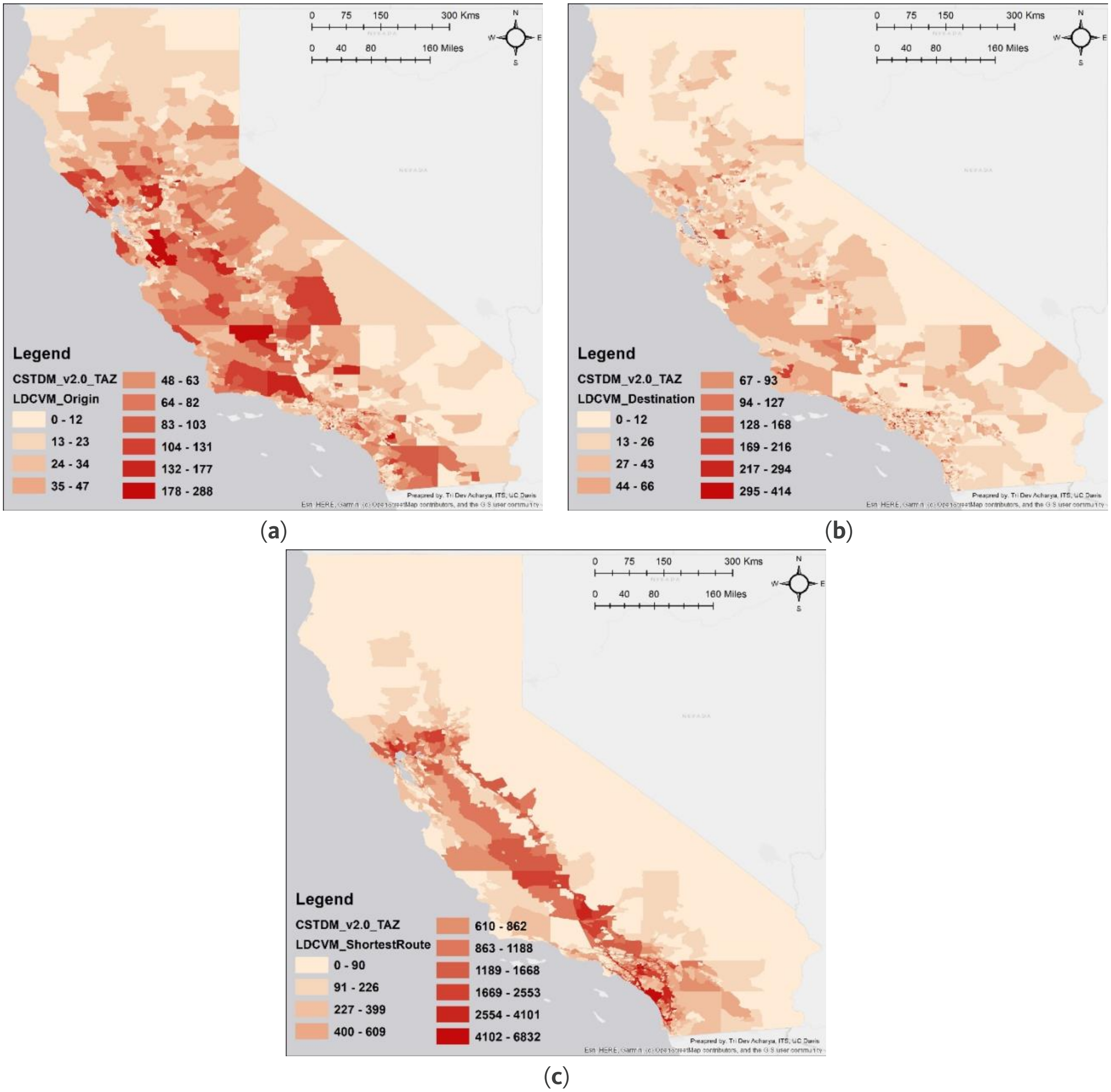


Figure 6. CSTDM based travel patterns. The maps show the number of (a) origins, (b) destinations, and (c) routes (between each origin-destination pair) contained within each transportation analysis zone (TAZ). To generate panel (c), we assume that, for each trip, a truck would take the shortest possible route between an origin and destination in a given origin-destination pair.

Station Deployment Spatial Results

Figure 7 and Figure 8 show results from our station deployment model. Each map superimposes several layers, each of which contains distinct types of information, as follows. The state is divided into TAZs, and those with observed demand from fuel-cell vehicles are outlined in black. The results of the infrastructure deployment are displayed both as a function of the energy demand (in terms of kg of hydrogen fulfilled) and the location and type of station deployed. It should be noted that the location of the stations indicated on this map reflect only which TAZs should contain stations and how many stations, but not the location of these stations within the TAZs; thus, the station icons are placed at the centroid of the relevant TAZ. The subsequent suitability analysis, described below, localizes stations more precisely within TAZs.

As shown in Figure 7, the placement of stations tends to occur in regions that intersect with multiple road networks (not shown here but superimposable on this map), in the densest travel areas (particularly near the major cities: Los Angeles, San Francisco, and San Diego), and near borders to Nevada and Mexico (since we track truck traffic crossing those borders). With 10% of heavy-duty vehicles switching to hydrogen power, hydrogen demand varies between 1,000 to upwards of 5,000 kg per day. As adoption continues to increase to 50% of the travel by heavy-duty vehicles, hydrogen demand throughout eastern California increases correspondingly (Figure 8). As expected, with a similar number of stations, the overall demand is about four times higher, with some stations fueling nearly 20,000 kg of hydrogen per day. Even in a 100% adoption scenario, the sizing of stations is more than sufficient to meet all the demand. One note of interest is that the aggregate demand in any single region does not exceed 30,000 kg of hydrogen per day—this indicates that the distribution of stations does not simply scale linearly at the same stations. In other words, as demand increases, stations are deployed over a wider area of the network, so that the added demand is focused at stations that serve fewer fuel-cell trucks. We observe slight variations across scenarios of fuel-cell truck adoption in the placement of refueling stations in specific TAZs. This is likely a flexible difference with multiple solutions where stations are placed in locations that can be fulfilled in other corresponding locations.

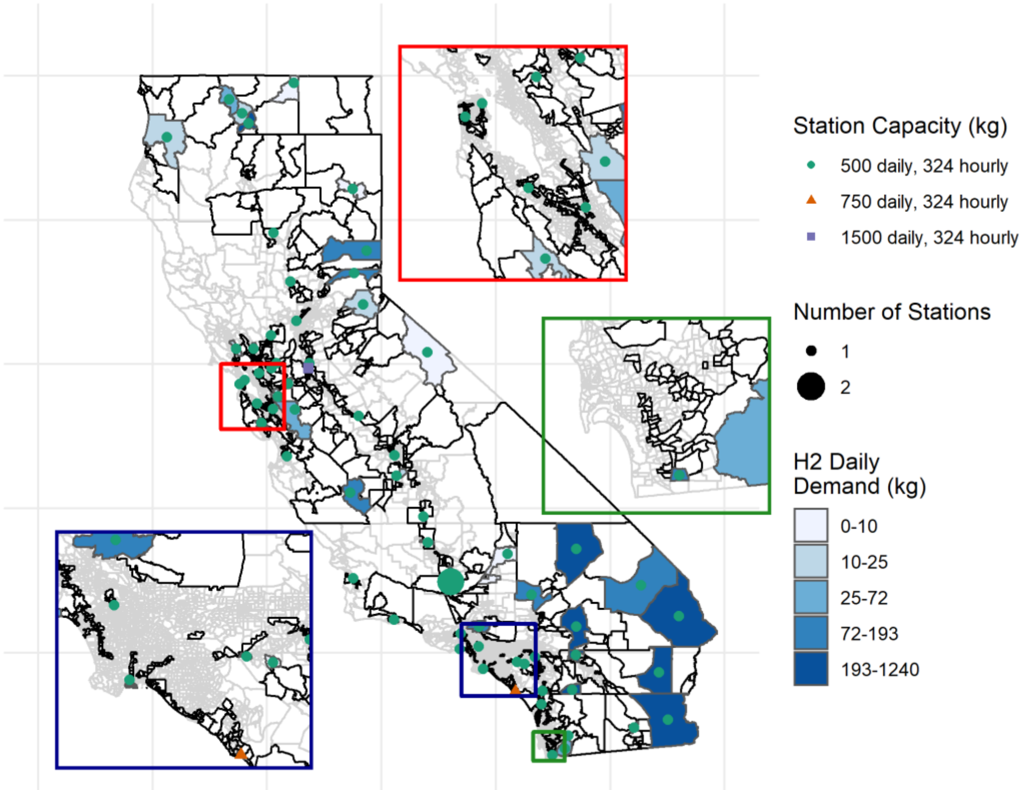


Figure 7. California Hydrogen station deployment for long-distance trips for heavy-duty vehicles in 2025. Zones outlined in black indicate zones with observed demand.

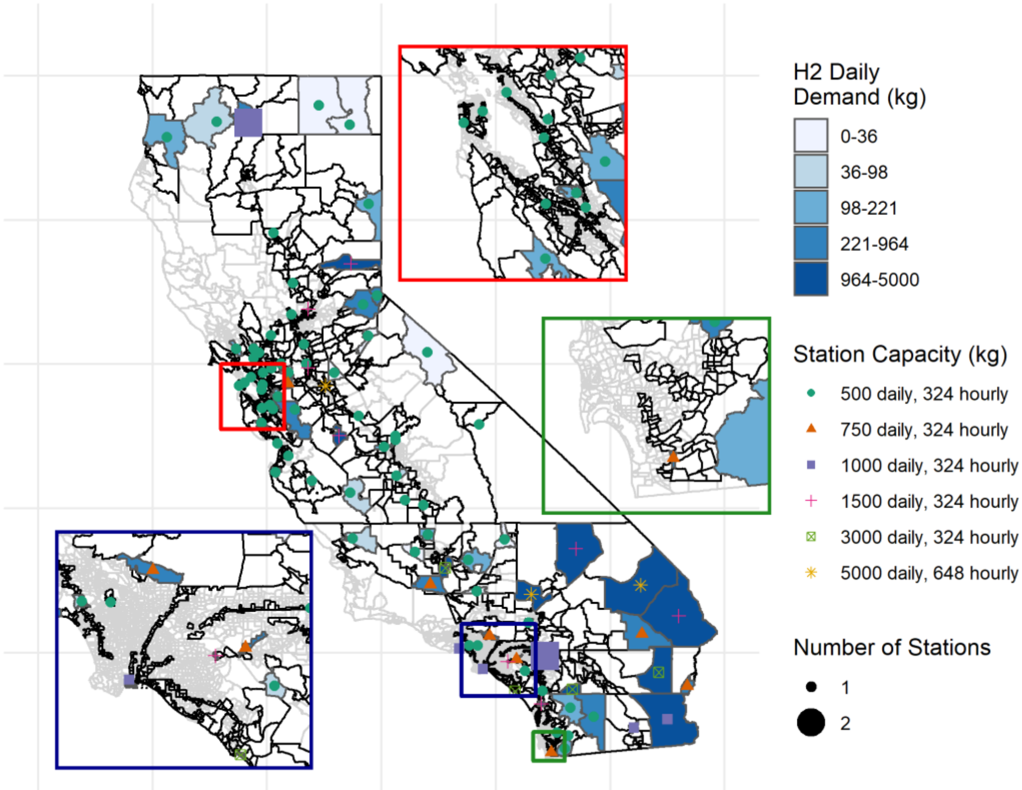


Figure 8. California hydrogen station deployment for long-distance trips for heavy-duty vehicles in 2030. Zones outlined in black indicate zones with observed demand. (The dots in the legend representing "Number of Stations" do not actually appear as dots on the map, but they indicate the information encoded by the size of the geometric icons listed under "Station Capacity (kg)".)

Figure 9 shows station deployment as technology adoption increases. After the creation of some smaller stations in the early stages of deployment, station size shifts to the maximum allowable under the model (a capacity of 5 tons per day), in order to meet the expected demand from a growing fuel cell vehicle fleet. This phenomenon occurs as the demands from year to year are satisfied independently, therefore, we assume that small to large station transitions are upgrades of existing infrastructure. Once fuel-cell trucks begin reaching saturation in the fleet, some smaller stations will again be needed to fill in final gaps in the system.

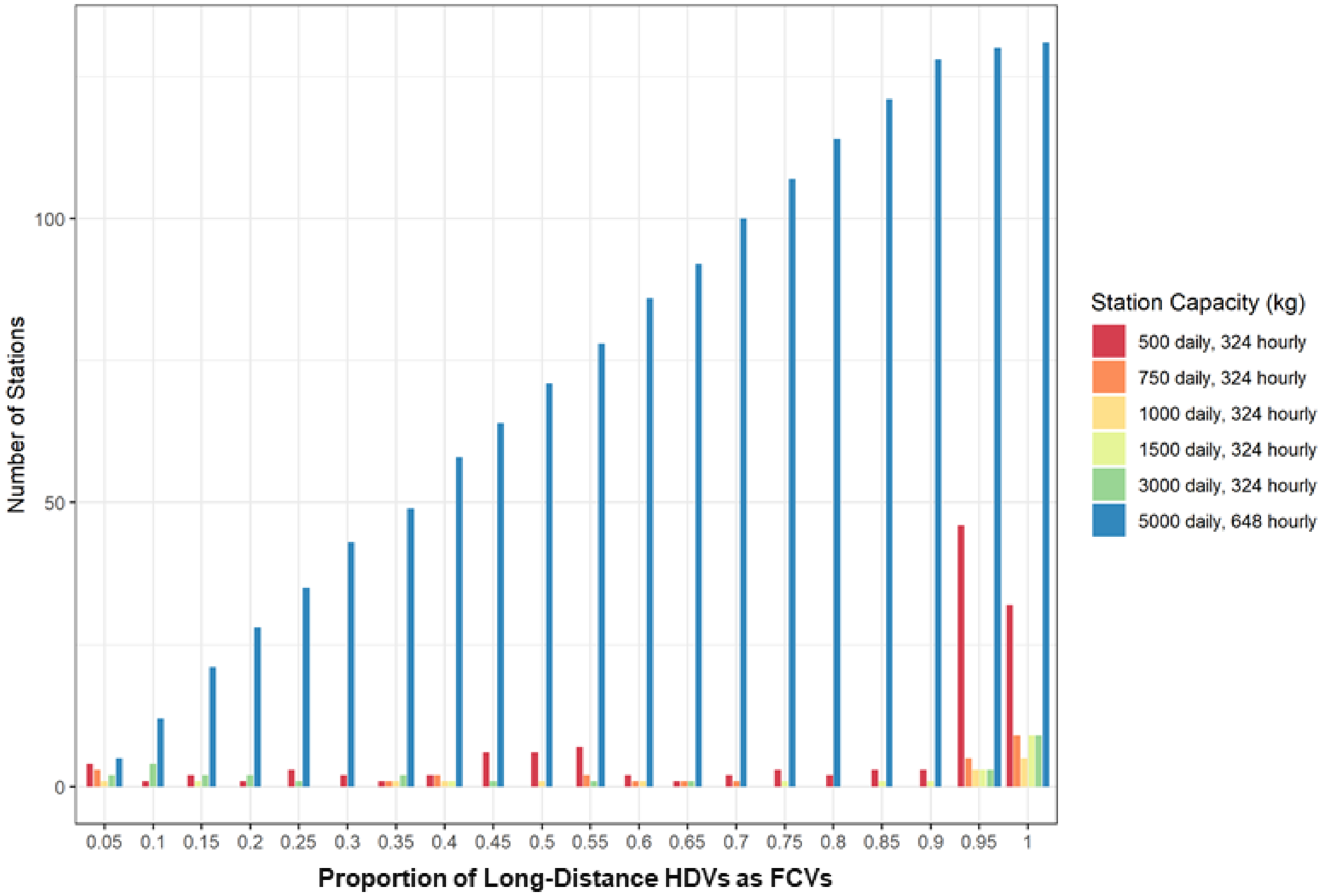


Figure 9. The number of stations with different hydrogen capacities that will be needed as an increasing proportion of hydrogen-powered long-distance heavy-duty vehicles (HDVs) are fuel-cell vehicles (FCVs).

Figure 10 shows an example of determining the location of a refueling station in a TAZ. First, the optimization module determines how many, if any, stations a TAZ should contain. For each station in a TAZ, we input a minimum footprint or range of possible footprints. Then the suitability analysis in ArcGIS uses various spatial factors to localize the station(s) within the TAZ. In this example, the suitability analysis factors in land cover, slope, distance from gas stations, truck hubs, and the truck network. As the lower right panel in Figure 10 shows, the station locations within the TAZ changes depending on the footprint.

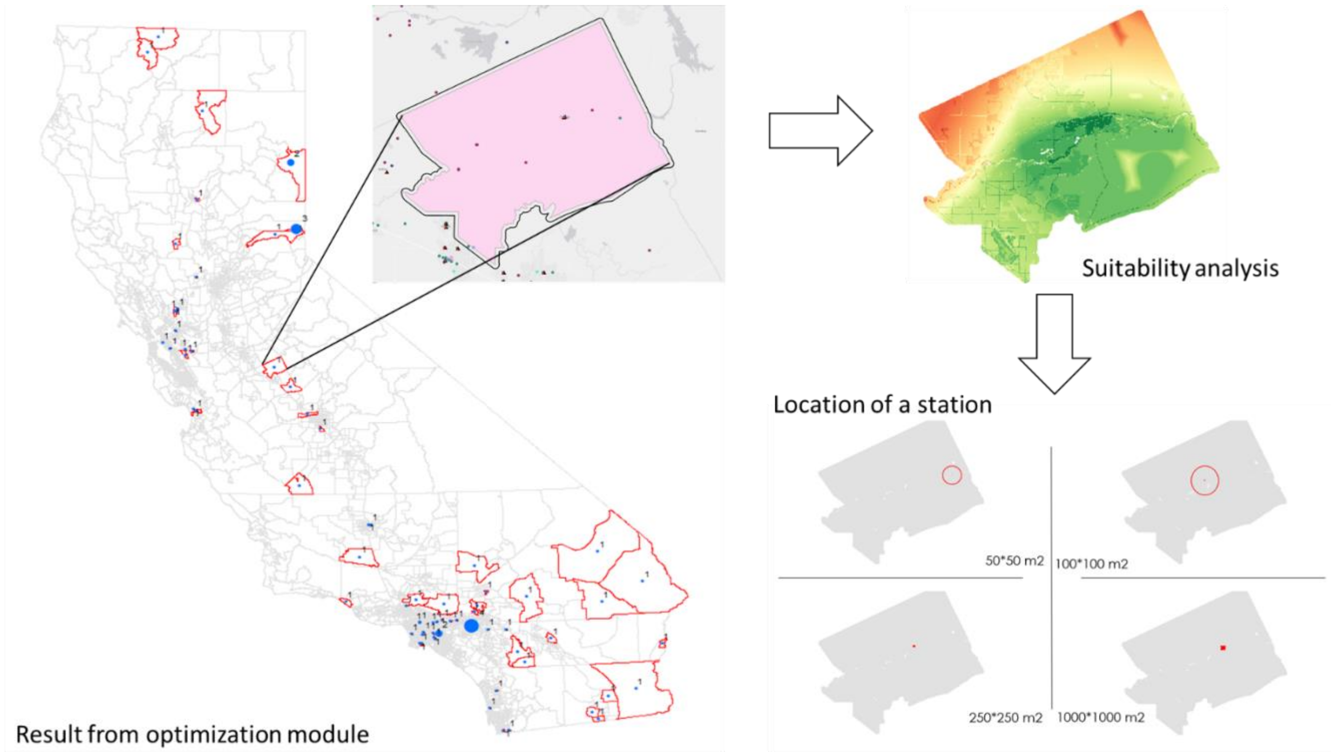
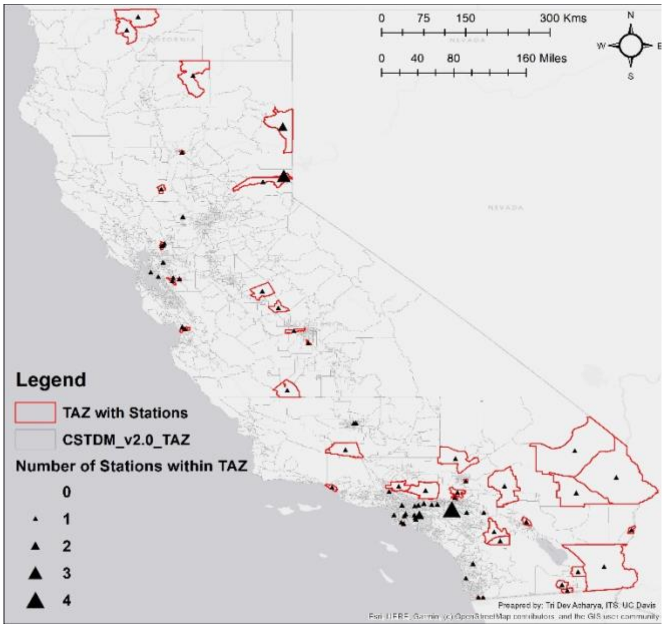
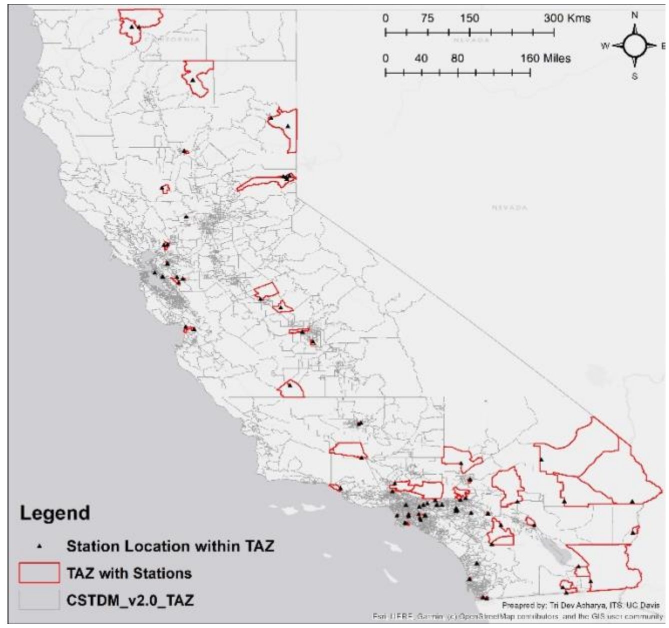


Figure 10. An example of suitability analysis to site a hydrogen station within a TAZ depending upon the station footprint

Figure 11 shows the preliminary results from the model at 50% penetration for long-distance heavy-duty truck trips. Out of 5454 TAZs in the state, 71 were selected by the optimization module as those that should contain a total of 78 refueling stations. Of these 71 TAZs, 67 had one station, 2 had two stations, 1 (near a Nevada exit) had three stations, and 1 (in Riverside County) had four stations. Figure 11b shows the precise locations of all stations within each TAZ, based on the suitability analysis and a station footprint of 400 × 400 m^2. Most stations were in relatively large TAZs with plenty of land that was suitable for locating stations. However, some stations were in smaller TAZs, such as those around Los Angeles, where many areas are not suitable for siting stations. The border for each of these smaller TAZs was expanded by a buffer of 500 m in each direction to allow the model to identify a more suitable station site.





(**a**) (**b**)

Figure 11. Outputs of (a) the optimization model and (b) suitability analysis. (a) The red boundaries and black triangles (at the centroids of TAZs) indicate those TAZs that contain one to four hydrogen refueling stations; (b) the triangles indicate the precise location of those stations within TAZs, assuming a station area of 400 × 400 m².

Limitations and Future Work

The current model is our first iteration. These preliminary results are limited in being based only on heavy-duty vehicles and their shortest routes from origin to destination. The model's output in terms of fuel demand will likely vary as we add mid- and light-duty vehicles. In addition, the precise localization of stations, provided in the suitability analysis, can be refined to prioritize the use of renewable energy, such as solar, wind, electricity, or renewable natural gas. Furthermore, land parcel sizes could also be used to select station sites. Finally, adding electric vehicles to the model will allow localization of both charging and hydrogen refueling stations, with the possibility of co-siting if that makes sense. Connections to the grid will be an important part of that future analysis.

In the next development phase, a travel model for light- and medium-duty commercial vehicles will be used, and the routing will be either passed through the CSTDM Highway Network or TIGER Road Network. A more detailed criteria evaluation will be required to determine the deployment of hydrogen refueling stations in an urban and dense neighborhood with a high volume of personal vehicles.

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