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ESTIMATING TRANSPORTATION COSTS AND EMISSIONS OF RECYCLABLES IN RHODE ISLAND MUNICIPALITIES USING A GIS, ROUTING MACHINE, AND GENETIC ALGORITHM

Luke Norman Martin-Jourdenais
University of Rhode Island, lmartin-jourden@uri.edu

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LUKE NORMAN MARTIN-JOURDENAIS

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LUKE NORMAN MARTIN-JOURDENAIS

APPROVED:

Thesis Committee:

Major Professor

Manbir Sodhi

Valerie Maier-Speredelozzi

Jason Parent

Brenton DeBoef

DEAN OF THE GRADUATE SCHOOL

UNIVERSITY OF RHODE ISLAND

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ABSTRACT

Transportation and logistics of recyclable materials are major cost drivers within recycling systems. In low and medium income countries, the collection costs of municipal solid waste (MSW) respectively can take up to 80-90% and 50-80% of the municipal solid waste management budget. Reducing these costs can significantly improve the viability of recycling systems. A promising approach for cost reduction in this context is improved routing of refuse vehicles, which can be done by developing and using advanced mathematical optimization algorithms and data information systems. Within the optimization research field, vehicle routing is addressed within the capacitated vehicle routing problem (CVRP). The objective is to minimize the total cost of a fleet of vehicles with a designated capacity. The CVRP is stated as an NP-Hard problem in combinatorial optimization problems meaning there is no known algorithm to solve these types of problems within polynomial time. Various heuristics are used to solve the CVRP and this study aims to use a genetic algorithm. The genetic algorithm provides feasible results to the CVRP within reasonable time. Applying the CVRP to a real-world instance requires road network distances compared to euclidean distances. In this thesis, a CVRP is solved using data processed in a geographical information system (GIS), existing local government databases, a routing machine, and a genetic algorithm to estimate recycling costs and emissions for municipalities in the state of Rhode Island.

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DEDICATION

To the Martins and Jourdenaises

Norma Jean Martin-Jourdenais, Claire Jourdenais,
Norman Jourdenais

Paul Martin, Florence Martin,
Dr. Horace Martin

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CHAPTER 1

Introduction

1.1 Residential Recycling

Residential recycling is a relatively new and constantly evolving system. Over 35 years ago, residential recycling programs in the United States had little to no participation [1]. Potential recyclable material followed the same end of life process as all other materials and generally end in a landfill. The world generates roughly 2 billion tons of solid waste annually and only 14% of it is recycled. In 2015, the United States was responsible for 262 million tons of waste and only 26% of it was recycled. This statistic is an improvement compared to the global data but the United States had the ability to recycle 47% of the 262 million tons of solid waste [2]. A major contributing factor is the United States is large and geographically diverse country with various recycling systems performing at different efficiencies. In 2006, there were over 8,000 municipal recycling programs in the United States. A majority of them were residential curbside recycling programs [1]. These programs accounted for over 83,000 jobs, 3.9 billion in wages, and 694 million paid in taxes. For every 1,000 tons of recycled and refused material 1.57 jobs were created. This supports the proposition of residential recycling inside of the United States being a large system [3].

Municipal residential recycling programs are not uniform across the United States. Each individual program contains social, economic, and environmental variables. Social variables may depend on the perceived social norms towards recycling as a whole. This can negatively and positively impact recycling rates [4]. Economic variables may be subject to whether or not the financing comes from local taxpayers, government, or individuals. Along with financing options, market prices for labor, capital, fuel, and disposal fees are also economic variables [5]. An environmental variable example is whether or not the collection system is providing a net positive or negative effect on the environment. Recycling is one of the many methods that promote sustainability. The three fundamental pillars of sustainability: social, economic, and environmental apply to recycling [6]. Therefore, to improve residential recycling systems, it is possible by manipulating these types of variables. This paper aims to estimate the economic and environmental aspects of sustainability related to the transportation of recyclables in local municipalities.

1.2 Municipal Solid Waste Transportation Cost

In municipal solid waste management (MSWM) the most important and costly aspect of the process is that of collection and transportation [7]. The cost of collection significantly varies around the world. It costs, on average, \$3.5 per ton-mile to collect and transport municipal solid waste (MSW) in the United States. Within the United States, Florida estimates an average of \$16.60 per ton is spent on collection alone. In contrast to a worldwide perspective, it can cost between \$2.90 and \$10.40 per ton in Thailand for MSWM [8]. In low income countries, collection costs can take up 80-90% of the MSWM budget and in medium income countries it can take up to 50-80% [7]. The collection process has three different types of implementation. First, the collection process can be privatised, relying on a customer within a municipality to contact a private hauler to collect the waste. The second method is a solely public process. This relies on the municipal government to own and operate the collection system. The third method relies on a hybrid system. This is a cross between a public and private system resulting in ownership and responsibility divided in the municipality in various areas [9]. Identifying the correct collection process for a municipality is extremely complex and can depend on various factors such as distance, labor expenses, quality and quantity of the waste, population, density, and geographical location [8]. In this study, a fully public collection system is assumed for all municipalities regardless of the real-world system. As stated above, with transportation and collection being the most costly parts of the system, an optimised collection method can reduce the overall cost of the system. Therefore, providing an estimation to these costs can be significant for local municipalities and set about positive economic improvements.

1.3 Municipal Solid Waste Transportation Emissions

When a MSWM system is operating at high efficiency, it is known to reduce the economic costs and potentially reduce the transportation emissions. Since MSWM is an extremely energy-consuming activity, it is imperative to improve the efficiency of the system to promote more sustainable life on earth [10]. It is known that MSW collection produces a significant negative impact on the environment because of pollutant emissions and fuel consumption. Various pollutant emissions that come from MSW vehicles are nitrogen oxides, carbon dioxides, and sulfur oxides [11]. These emissions can be detrimental to human health, the environment, and contribute to the worldwide total of greenhouse gas (GHG) emissions. GHG emissions associated with MSWM accounted for 2.6% of global emissions in 2005 [12]. In 1999, landfills accounted for 90% of GHG emissions in the waste sector. This indicates the need for diversion of recyclables from landfills [13]. This paper aims to develop a model to estimate the emissions cost related to the transportation of residential recyclables. Understanding the potential emissions can provide insight to the environmental impact within local municipalities and potentially influence positive environmental change.

1.4 Vehicle Routing Problem

The vehicle routing problem (VRP) was first introduced by Dantzig and Ramser in 1959 [14]. The VRP stems from the traveling salesman problem (TSP).

Both are considered to be NP-hard problems. An NP-hard problem states that using exact optimization methods is difficult to solve within polynomial time but potentially presents an optimal solution [15]. The TSP was one of the first problems to be considered NP-hard in 1972 by Karp [16]. The TSP and VRP problem involves deliveries to a set amount of customers each with a set level of demand. A vehicle departs a depot, visits all nodes and returns to the depot while minimizing the total cost of the route [16]. The main difference between the TSP and VRP, is the TSP is constrained to a single vehicle or route. In the VRP, demand is satisfied by a fleet of vehicles across multiple routes. The TSP vehicle and VRP fleet must satisfy the demand of all customers by visiting each customer a single time with a single vehicle. The VRP can contain more constraints and extensions of the base problem. Some examples are vehicle capacities and route limitations [17]. Figure 1 displays the differences between the TSP and VRP.

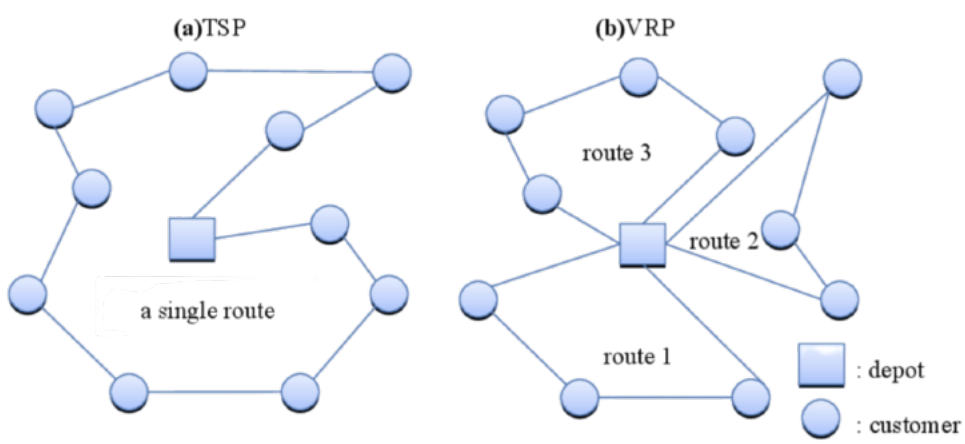


Figure 1. TSP vs. VRP [18]

This paper focuses on the capcitated vehicle route problem (CVRP) extension. The CVRP adds a new constraint where each vehicle is assigned a capacity [19]. The CVRP mathematical formulation is further explored in this paper. This paper aims to solve a CVRP instance for each selected municipality in the study. The results of the CVRP are used to estimate the transportation costs and emissions within the selected municipalities.

1.5 Related Studies

There have been multiple studies performed using VRPs in conjunction with geographical information systems (GIS) and MSWM systems. In 2018, a study in Austin, Texas utilized a GIS program called ArcGIS. The paper used a built-in VRP solver to optimize waste collection routes within a neighborhood [20]. Through the solutions of the solver, the study found that truck capacity, volume ratio of the truck, waste density and collection frequency have significant impacts on truck travel distance. The study also discovered that increasing waste collection frequency and waste density can save 41.9% on travel time and 18.2% on travel distance [20]. In 2020, a second study was performed in the southeast region of Izmir, Turkey using ArcGIS and its incorporated VRP solver [21]. The study aimed to find the optimal location to place transfer stations and provide positive economic outcomes. The solver outcome found that it is not economically feasible to add another transfer station due to landfill proximity, fleet size collection and district level collection. The study did find that additional transfer stations can potentially reduce fuel consumption and truck emissions [21]. In 2018, a study performed in Kerman, Iran aimed to optimize the location of waste sorting centers to limit the environmental impact, overall costs of the process, and improve the service system in relation to the society. The study utilized a GIS software to specify the criteria layers [22]. The study implements the use of a VRP with three main goals of transportation reduction, decreased environmental pollution, and improvement of the service quality. The study concluded that the use of more realistic perceptions of the community and social criteria can bring forth accurate and realistic results [22].

In the city of Mashhad, Iran research was performed to optimize the storage and collection systems in 2017 [23]. A CVRP and GIS system were used in conjunction with each other to determine if the current collection system is efficient. The research indicated that the system is not efficient and the the collection routes can be reduced from 8 to 7. The number of crews can be reduced from 24 to 14. Finally, the combined distances of all the routes is reduced by 53% [23]. A case study performed in Dhanbad City, India in 2016 examined the optimization of collection routes and allocation of MSW bins using a GIS. The study uses the ArcGIS Network Analyst package which contains a built in VRP solver. This is the process used in the Austin, Texas study. The study found that 726 collection bins produced 66 routes serviceable by 22 mechanised trucks. This information is crucial to local MSWM, which can aid decision making to reduce transportation costs, vehicle emissions, and overall route distances [24]. Following a similar approach to the existing studies, this paper also aims to use the GIS program ArcGIS Pro to interpret node and depot locations. However, instead of using the built in ArcGIS Pro Network Analyst Package, this paper uses an open source routing machine, genetic algorithm and programming languages to solve the CVRP and estimate the transportation costs and emissions of residential recycling within select Rhode Island municipalities.

List of References

[1] T. C. Kinnaman, "Policy watch: examining the justification for residential recycling," *Journal of Economic Perspectives*, vol. 20, no. 4, pp. 219–232, 2006.

[2] S. N. Mertens and P. W. Schultz, "Referent group specificity: optimizing normative feedback to increase residential recycling," *Journal of Environmental Psychology*, vol. 73, p. 101541, 2021.

[3] N. Mpafe, "Residential curbside recycle context analysis," Ph.D. dissertation, University of South Florida, 2021.

[4] A. Kirakozian, "The determinants of household recycling: social influence, public policies and environmental preferences," *Applied Economics*, vol. 48, no. 16, pp. 1481–1503, 2016.

[5] R. A. Bohm, D. H. Folz, T. C. Kinnaman, and M. J. Podolsky, "The costs of municipal waste and recycling programs," *Resources, Conservation and Recycling*, vol. 54, no. 11, pp. 864–871, 2010.

[6] G. H. Brundtland and M. Khalid, *Our common future.* Oxford University Press, Oxford, GB, 1987.

[7] S. Das and B. K. Bhattacharyya, "Optimization of municipal solid waste collection and transportation routes," *Waste Management*, vol. 43, pp. 9–18, 2015.

[8] R. Jacobsen, J. Buysse, and X. Gellynck, "Cost comparison between private and public collection of residual household waste: multiple case studies in the flemish region of belgium," *Waste management*, vol. 33, no. 1, pp. 3–11, 2013.

[9] G. Bel and M. Warner, "Does privatization of solid waste and water services reduce costs? a review of empirical studies," *Resources, Conservation and Recycling*, vol. 52, no. 12, pp. 1337–1348, 2008.

[10] Z. Zsigraiova, V. Semiao, and F. Beijoco, "Operation costs and pollutant emissions reduction by definition of new collection scheduling and optimization of msw collection routes using gis. the case study of barreiro, portugal," *Waste management*, vol. 33, no. 4, pp. 793–806, 2013.

[11] C.-Z. Li, Y. Zhang, Z.-H. Liu, X. Meng, and J. Du, "Optimization of msw collection routing system to reduce fuel consumption and pollutant emissions." *Nature Environment & Pollution Technology*, vol. 13, no. 1, 2014.

[12] J. Dong, M. Ni, Y. Chi, D. Zou, and C. Fu, "Life cycle and economic assessment of source-separated msw collection with regard to greenhouse gas

emissions: a case study in china," *Environmental Science and Pollution Research*, vol. 20, no. 8, pp. 5512–5524, 2013.

[13] K. A. Weitz, S. A. Thorneloe, S. R. Nishtala, S. Yarkosky, and M. Zannes, "The impact of municipal solid waste management on greenhouse gas emissions in the united states," *Journal of the Air & Waste Management Association*, vol. 52, no. 9, pp. 1000–1011, 2002.

[14] P. Toth and D. Vigo, *The vehicle routing problem.* SIAM, 2002.

[15] S. N. Kumar and R. Panneerselvam, "A survey on the vehicle routing problem and its variants," 2012.

[16] M. Jünger, G. Reinelt, and G. Rinaldi, "The traveling salesman problem," *Handbooks in operations research and management science*, vol. 7, pp. 225–330, 1995.

[17] B. M. Baker and M. Ayechew, "A genetic algorithm for the vehicle routing problem," *Computers & Operations Research*, vol. 30, no. 5, pp. 787–800, 2003.

[18] W.-Y. Liu, C.-C. Lin, C.-R. Chiu, Y.-S. Tsao, and Q. Wang, "Minimizing the carbon footprint for the time-dependent heterogeneous-fleet vehicle routing problem with alternative paths," *Sustainability*, vol. 6, no. 7, pp. 4658–4684, 2014.

[19] H. Longo, M. P. De Aragao, and E. Uchoa, "Solving capacitated arc routing problems using a transformation to the cvrp," *Computers & Operations Research*, vol. 33, no. 6, pp. 1823–1837, 2006.

[20] H. L. Vu, K. T. W. Ng, and D. Bolingbroke, "Parameter interrelationships in a dual phase gis-based municipal solid waste collection model," *Waste Management*, vol. 78, pp. 258–270, 2018.

[21] M. C. Höke and S. Yalcinkaya, "Municipal solid waste transfer station planning through vehicle routing problem-based scenario analysis," *Waste Management & Research*, vol. 39, no. 1, pp. 185–196, 2021.

[22] A. Farahbakhsh and M. A. Forghani, "Sustainable location and route planning with gis for waste sorting centers, case study: Kerman, iran," *Waste Management & Research*, vol. 37, no. 3, pp. 287–300, 2019.

[23] S. M. H. Erfani, S. Danesh, S. M. Karrabi, and R. Shad, "A novel approach to find and optimize bin locations and collection routes using a geographic information system," *Waste Management & Research*, vol. 35, no. 7, pp. 776–785, 2017.

[24] D. Khan and S. Samadder, "Allocation of solid waste collection bins and route optimisation using geographical information system: A case study of dhanbad city, india," *Waste Management & Research*, vol. 34, no. 7, pp. 666–676, 2016.

CHAPTER 2

Background

2.1 Geographical Information Systems

Using the earths surface as a reference, GIS is a system for data collection, storage, control, processing, integration, analysis, and display [1]. A GIS combines graphical information in the form of spatial data and non-graphical information as descriptive data [1]. The GIS sorts the data into particular layers depending on the information provided to develop digital maps [2]. Displaying the information in the form of a digital map provides the user with the ability to analyze data and to recognize trends, relationships, and patterns [2].

A GIS commonly contains four components with customizable options. The components are spatial data production, data management, cartography and display, and analysis tools [3]. In order to develop spatial data, it requires the capture of data through map scanning, ground base surveying, camera and global positioning systems (GPS). Spatial data development requires data input, quality inspection, and format conversion [3]. The component of data management is used for data queries, maintenance, and data updating where the data can be transferred for cartography and analysis [3]. The component of cartography provides the user with the ability to display the data and apply visual analysis. The final component of analysis tools provides the user with complex and robust tools to examine all aspects of the data to draw conclusions. Since a GIS contains these four customizable components to manipulate spatial and descriptive data, it was identified as one of the necessary aspects of the model. The program of ArcGIS Pro was investigated and considered as the prime GIS software for the model.

2.1.1 ArcGIS Pro

ArcGIS Pro is GIS software designed by a GIS company called ESRI. ArcGIS Pro is a multiple-threaded 64-bit application that provides the user with a project oriented approach, continuous editing, and running multiple projects simultaneously [4]. ArcGIS Pro contains a large number of geoprocessing tools with the ability to manage GIS data and perform spatial analysis. An advantage of ArcGIS Pro is that it contains a ModelBuilder, allowing the user to combine multiple tools for data management processes and create an interactive diagram of the spatial analysis. ArcGIS uses the scripting language Python. The user has the ability to create custom Python scripts. These custom scripts can be used to combine tools and automate ArcGIS Pro workflow processes [5]. In the following sections, each tool used within this model is identified and explained.

2.1.2 ArcGIS Tools

1. **Excel to Table**: Provides the ability to import a Microsoft Excel sheet as an attribute table.

2. **XY Table to Point**: Based on x, y, and z coordinates from an attribute table, it permits the user to create new point feature classes.

3. **Project**: Reclassifies spatial data from one coordinate system to another.

4. **Select Layer By Attribute**: Updates, adds and removes data from a selection determined through an attribute query.

5. **Clip**: Extracts selected input features from the overlying clip features.

6. **Multivariate Clustering**: Finds natural clusters of features around the feature attribute values.

7. **Table to Excel**: Provides the ability to export an attribute table to a Microsoft Excel file.

8. **Split By Attributes**: Splits the dataset by attributes through an attribute query.

9. **Spatially Constrained Multivariate Clustering**: Finds spatially contiguous clusters through a set of feature attribute values and the option of cluster size limitation.

10. **Mean Center**: Determines the geographical center of a set of features.

11. **Merge**: Creates a single output dataset combining multiple input datasets. The tool has the ability to combine point, line, polygon feature classes and tables.

12. **Make Route Analysis Layer**: Creates a route network analysis layer with its intended analysis properties. A route analysis layer is used to determine the best route between a set of nodes along a route network.

13. **Add Locations**: Adds input features to the network analysis layer.

2.1.3 ModelBuilder

ModelBuilder is classified as a geoprocessing environment providing a user the ability to easily and effectively link tools to each other. ModelBuilder can run an operation featuring multiple tools with the click of a button. The ModelBuilder combines multiple advanced capabilities such as if-then statements and looping [5]. ModelBuilder requires an input of map layers, datasets, and the necessary tools to process the information. A legend for all features of a ModelBuilder can be found in Figure 2 and applies to all figures displaying a ModelBuilder in this study. The process is generated visually in the form of a diagram. The model can either be run in selected segments or all at once [6]. Figure 3 shows an example appearance of a ModelBuilder diagram. This study utilizes 4 different ModelBuilder instances and is explained further in this paper.

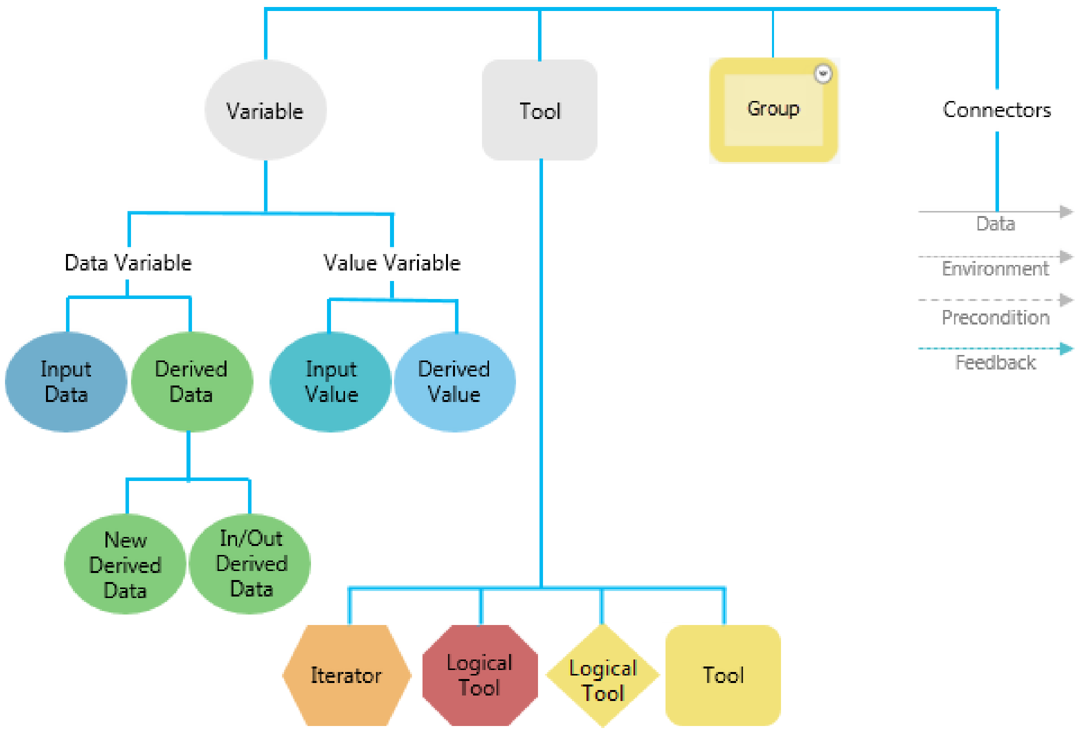


Figure 2. ModelBuilder Legend [7]

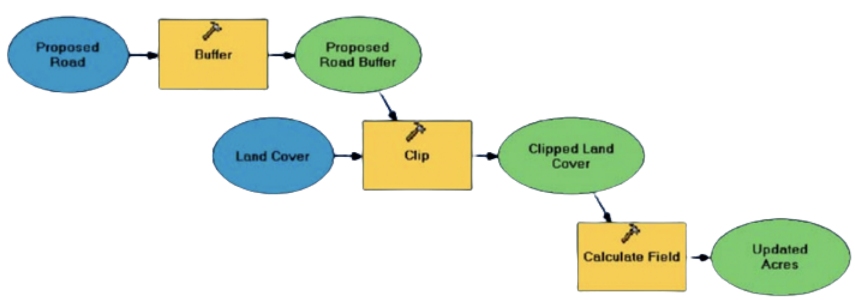


Figure 3. An example of a connected process in ModelBuilder [8]

2.1.4 OpenStreetMaps

OpenStreetMaps (OSM) is considered to be a volunteered geographical information (VGI) project. It is one of the most successful project collaborations over the past 15 years [9]. VGI was forged by Goodchild in 2007 and stated as a voluntary process of collecting spatial data [10]. The data is stored in a database where it must be authenticated by GPS and on occasions released to the general public [9]. This is the fundamental process on how OSM was created and operates today. It was released in 2004 in response to the limits and restrictions on maps around the world. The OSM geospatial database is open access to all and operates under the Open Database License (ODbL). The ODbL provides non-restricting conditions for continued development of the database [11].

Today, OSM is available to all users however, with OSM being VGI, certain areas of the world may not have readily available data. In order to obtain this data, a user can download any area of interest by selecting the area in a bounding box B in terms of latitude and longitude [12].

$$B = (lat_{min}, lon_{min}, lat_{max}, lon_{max})$$

The data from B is extracted in Extensible Markup Language (XML). XML is a markup language and file format used for storing, sending, and repairing data. It was designed for simple usability across the internet, to support numerous applications, be human legible, reasonably clear and easy to create [13]. The file is structured in three primary units of nodes, ways, and relations [14]. Nodes (n) represent GPS coordinates and represented in the form below.

$$n = lat, lon$$

Ways (w)consist of data stored as elements in both linear and area form. It is represented as a collection of nodes and represented below.

$$w = \{n_i\}_{i=1...k}.$$

Relations are represented as r and give previously mentioned geometric entities the ability to create complex structures [12]. Figure 4 displays how an extracted bounding box from OSM can be used to obtain a street network in a selected area.

(a) OSM Map (b) Street Graph

Figure 4. A selected bounding box in OSM is represented in (a) while (b) displays the extracted route network from OSM [12]

With this data from OSM, the purpose of using it in this study is to obtain network road data. This data is used within an Open Source Routing Machine (OSRM). The OSRM section is explained in the next section. OSM is also compatible with ArcGIS. There is the potential to import data from OSM to ArcGIS products and use geoprocessing tools.

2.2 Open Source Routing Machine

OSRM is used to determine the travel distance from point A to B along the shortest route subject to distance and time. OSRM is capable of determining these routes between nodes on large referenced datasets for scientific purposes. OSRM works in an offline method allowing the user to generate an unlimited number of requests. It can perform thousands of requests within seconds due to its multiprocessor capabilities. OSRM runs in C++ and is compatible with OSM [15]. When OSRM is run in an offline mode, it provides three specific advantages. Firstly, if the dataset examined contains sensitive information, OSRM can be performed without exposing information to other parties. Second, an offline mode reduces the risk of various commands becoming obsolete. If OSRM is run mutually with a third party program, there is an increased risk of application programming interface (API) changes, rendering the OSRM obsolete. Finally, OSRM runs on deterministic data compared to real-time data. Often times, real-time data is requested but deterministic data gives OSRM an exact time frame to produce results. This can reduce the potential of misleading information. For example, if real-time results are calculated during peak or non-peak times and not specified, the final output can be misleading [15].

In order to run OSRM, an extract of the selected region is required to be stored on a hard drive disk space. The calculations are performed off an extract from OSM. OSRM requires a system that supports 64-bit architecture such as Windows 7 or later [15]. The OSRM is installed and calculations are performed using the C++ language. A wrapper API can be used to allow scripts written in Python to interact with OSRM.

As stated in the the previous chapter, past studies have opted to use the Network Anaylst package within ArcGIS to solve various routing problems. The Network Analyst package is useful but contains drawbacks. The first is that the Network Analyst package is only as useful as the input network dataset. It was determined that the intended region of study for this paper did not have a regularly available network dataset. ESRI provides its own detailed network dataset through its online servers. Every instance run on the online server requires credits and when processing large datasets it can be costly. Another issue with using the Network Analyst package by ESRI, is that the algorithm used to solve the routing problem is slow. The Network Analyst package uses a heuristic based on Dijkstra's Algorithm [16]. A breakdown of Dijkstra's algorithm is explained in the following sections. Finally, the Network Analyst package does not have a straightforward ability to calculate hundreds of requests [15]. With these drawbacks, this study decided to use OSRM and a heuristic containing a genetic algorithm to solve CVRPs in selected municipalities.

2.2.1 Docker

Docker is an open source container technology that gives a user the ability to run a virtual machine. A container provides a user the potential to run applications reliably and quickly between multiple environments while keeping all code and dependencies packaged [17]. A Docker container image is a standalone and lightweight package containing all code and dependencies [17]. Docker Engine and Docker Hub are the two components of Docker. Docker Engine is a an open source virtualization solution and Docker Hub is a Software-as-a-Service platform intended for the sharing of Docker Images [18]. The Docker Engine is used to turn container images into Docker containers at run time [17]. Docker client is responsible for providing a user interface for all interactions between containers and the user. The Docker client sends the user input to the Docker daemon through RESTful APIs. This allows the docker client to run on the same or different host as the containers [18]. Docker daemon manages and executes all commands for the Docker containers [18]. Listed in Figure 5 is the operating structure of Docker. Docker is used in this paper to create a local instance of OSRM. This is done to reduce dependencies on third parties and is not costly. This paper explains how

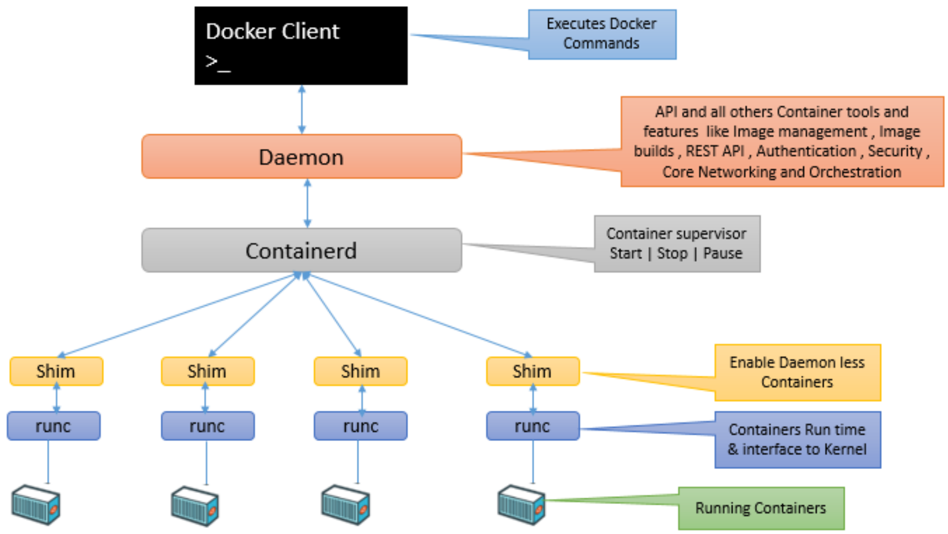


Figure 5. Architecture of Docker [19]

the OSRM instance was initialized using Docker.

2.2.2 GeoFabrik

In order to create a local instance of OSRM with Docker, an OSM base file is required. An online website called GeoFabrik can provide these large datasets. The website contains various parts of the world for download. Since OSM is open source, there are updates by individuals everyday. GeoFabrik states that any changes that are made to the global OSM database are usually reflected and available for download within 24 hours [20]. The website contains three types of downloadable data in PBF file format, Gzip compressed OSM XML, and Bzip2 compressed OSM XML files [21]. A PBF file is known as a Protocol Buffer File. When saved in binary format, it leads to an easy and fast data transfer over the internet due to no overhead [22]. Bzip2 and Gzip are compression schemes. Bzip2 offers better compression than Gzip [23]. This study uses the overlays acquired from GeoFabrik to create an instance of OSRM using Docker. Displayed below in Figure 6, is the process flow of OSM, Geofabrik, and Docker.

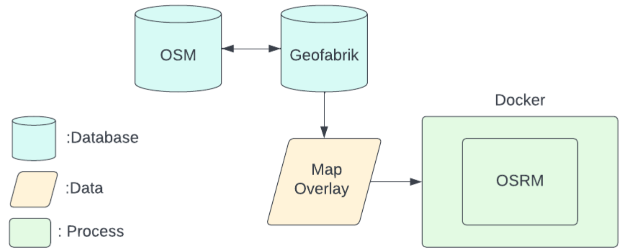


Figure 6. Process flow of OSM, Geofabrik, and Docker

2.3 Capacitated Vehicle Routing Problem

The CVRP was first proposed by Dantzig and Rasmer in 1959 and it was not until five years later that Clark and Wright presented the first heuristics for the CVRP [24]. The CVRP is a focal problem in the field of optimization research. It applies to numerous real-world applications such as logistics, collection methods, and distribution. The CVRP objective is to minimize the total route cost of a fleet of vehicles with an assigned capacity. The fleet is based from a single depot and services all customers with a demand subject to constraints [25]. The first constraint states that each route must begin and end at the depot. All customers must be serviced and each customer can only be visited by a single vehicle. Finally, the total demand of all the customers along the route does not exceeded the capacity of the vehicles [26]. The CVRP is stated as an NP-Hard problem in combinatorial optimization problems. This states that there is no known algorithm to solve these types of problems within polynomial time [27].

This study focuses solely on the symmetric CVRP variation. The CVRP is modeled on a two dimensional graphical plane and the distance between two nodes is symmetrical [28]. Documented throughout the literature [27, 29, 25, 30, 28] are formal definitions and similar information is presented here. A CVRP is modeled upon a two dimensional complete graph. $G = (V,A)$ is specified as an undirected graph. V is equal to the set of nodes $\{0,1, ..., n\}$ also described as customers. Each node has a set position along the graph stated as $(x_i, y_i)\ \forall_i \in V$. A is equal to the edges that connect any two nodes and all edges contain a cost of c_{ij}. Calculating the cost between node i to j is found by determining the euclidean distance between the two nodes for each edge $(i,\ j) \in A$, where $i \neq j$. Listed below is the formula to solve for c_{ij}.

$$c_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

As previously stated, this study focuses solely on a symmetric CVRP stating that $c_{ij} = c_{ji}$. All nodes will be allocated a demand d_i that is greater than 0 and represented mathematically as $d_i > 0\ \forall_i \in V$. A sole depot is modeled and characterized as node 0, which contains no demand. From the depot, a fleet of homogeneous vehicles stated as K, departs to service all nodes. Each vehicle is assigned a maximum service capacity of Q, which is applied uniformly across the fleet and represented as $d_i \leq Q$ for each $i = 1, ..., n$. The primary function of the CVRP is to minimize the overall cost of K vehicle routes that start and end at the depot where the capacity of each vehicle is not violated while the demand of all customers is met.

Figure 7 displays a CVRP illustration where there are 12 customers each with a demand of d_i. The distance costs are represented along the edges between each node. A fleet of four vehicles is available, each with a capacity of $Q = 10$. Figure 7 shows how one feasible solution is calculated. The set $l = \{r_1 \cup r_2 \cup r_3 \cup r_4\}$ is the example solution with a total cost of 114. It is necessary to state that it may not be the optimal solution.

The CVRP is known to have have multiple variations, however the mathematical formulation for the CVRP that is the focus in this paper is listed below [25, 27, 29].

$$min\, z = \sum_{i \in V} \sum_{j \in V} (c_{ij}) * (x_{ij}) \tag{1}$$

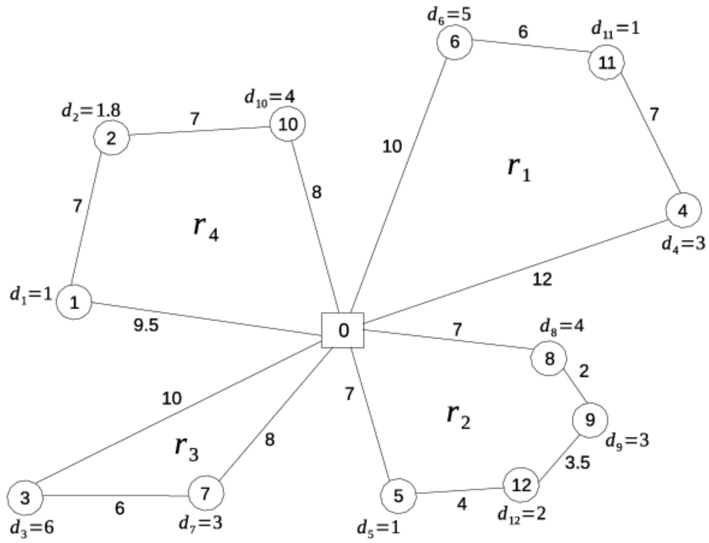


Figure 7. Graphical representation of a CVRP [30]

subject to

$$\sum_{i \in V \setminus \{0\}} x_{ij} = 1 \tag{2}$$

$$\sum_{j \in V \setminus \{0\}} x_{ij} = 1 \tag{3}$$

$$\sum_{j \in V \setminus \{0\}} x_{i0} = K \tag{4}$$

$$\sum_{j \in V \setminus \{0\}} x_{0j} = K \tag{5}$$

$$\sum_{i \notin C} \sum_{j \in C} x_{ij} \geq \lambda(C) \qquad \forall C \subseteq V \setminus \{0\}, \text{where} \quad C \neq \emptyset \tag{6}$$

$$\lambda(C) \geq \frac{\sum d_i}{Q} \qquad \forall_i \in C, \forall C \subseteq V \tag{7}$$

$$x_{ij} \text{ binary} \qquad \forall i, j \in V \tag{8}$$

The primary objective of the CVRP is to minimize the cost of travel between nodes through an edge, as stated in equation 1. Equations 2 and 3 are constraints that guarantee each node is only visited by one vehicle arrival and departure. The constraints from equation 4 and 5 ensure that K vehicles depart and arrive from the depot by setting the values of i and j to 0. C is a subset of nodes, where the purpose of equation 6 ensures that the capacity of the vehicles is not violated and removes the possibility of sub tour formations. Equation 7 determines that $\lambda(C)$ is the number of vehicles required to service the subset of C. In order to ensure that there is no disconnection from $V\backslash\{C\}$ and the minimum condition of service capacity to satisfy all demands of nodes, only an equal or greater number of trucks is allowed to enter the subset. In equation 8, each edge is either selected or not selected by setting the decision variably of x_{ij} to a binary value.

Since the CVRP is considered to be NP-Hard in nature, obtaining an optimal solution using exact methods is not possible. No algorithm exists which can find optimally within polynomial time. There are multiple algorithms that exist which can provide feasible solutions within a reasonable time frame but it can be difficult to prove whether it is the optimal solution. The CVRP is applied to select municipalities and solved to estimate recycling transportation costs and emissions.

2.4 Genetic Algorithm

The genetic algorithm is based on natural selection and principles of genetics. The genetic algorithm includes various advantages such as a large number of variables, compatibility with continuous or discrete variables, and compatibility with numerically generated, experimental data, and analytical functions [31]. The first development is credited to John Holland in 1975. The genetic algorithm generates a group of results specified as chromosomes to evolve under assigned constraints to minimize the overall cost of the function [31]. There are two fundamental operations within a genetic algorithm known as crossover and mutation. The crossover operation takes the two chromosomes with the lowest cost and recombines the genetic aspects of the two chromosomes to create parents. Since these parents will have the highest fitness, they will spread their genes to the next generation

[31]. The primary objective of the mutation operation is to apply diversity to the population by changing genes randomly. These two operations provide the ability to analyze new routes for improved results while concurrently exploring known solutions [31]. Listed in Figure 8 is a flow chart of the processes of a genetic algorithm. In this study, a genetic algorithm that was specifically created to solve

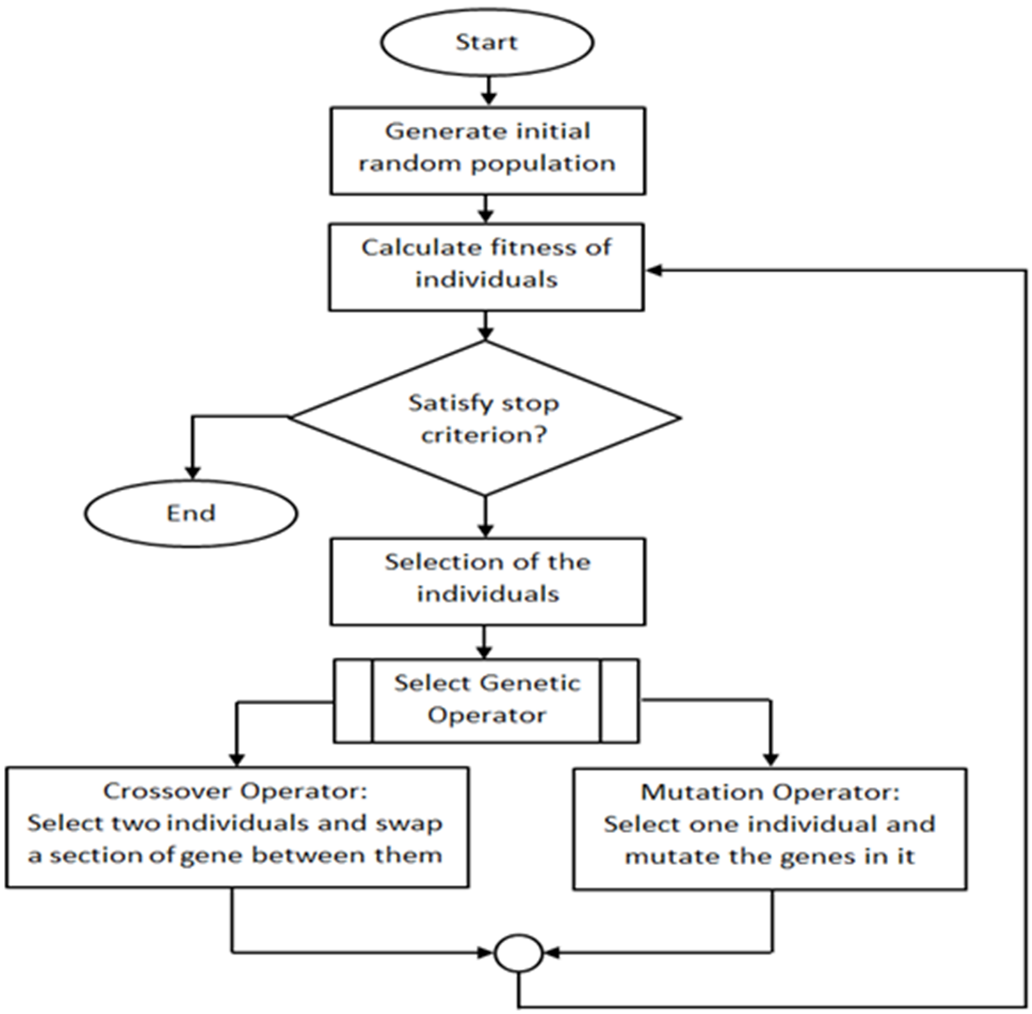


Figure 8. Graphical representation of a genetic algorithm process flow [32]

the symmetric CVRP problem is used. The genetic algorithm was created by doctoral candidates at the University of Rhode Island. The algorithm description, architecture, and implementation can be found in [30].

2.5 ArcGIS and Dijkstra's Algorithm vs. Genetic Algorithm

As stated earlier, various heuristics have been developed to solve the VRP and CVRP. The ArcGIS Network Analyst package uses an algorithm based off of Dijkstra's Algorithm to solve the VRP. A brief overview is explained on how Dijkstra's algorithm works. Also, a comparison of the speed between it and the genetic algorithm is examined. Dijkstra's algorithm is a well known algorithm and is also called the shortest path algorithm. The algorithm determines the shortest path between two nodes on a graph. It was developed by Dijkstra in 1959. The main focus and continued development of the shortest path algorithms is to modify the algorithms to produce results within good time bounds [33]. However, these algorithms may no longer be fast enough to solve problems such as the VRP due to the large network size and node counts. Figure 10 is an illustration of Dijkstra's algorithm.

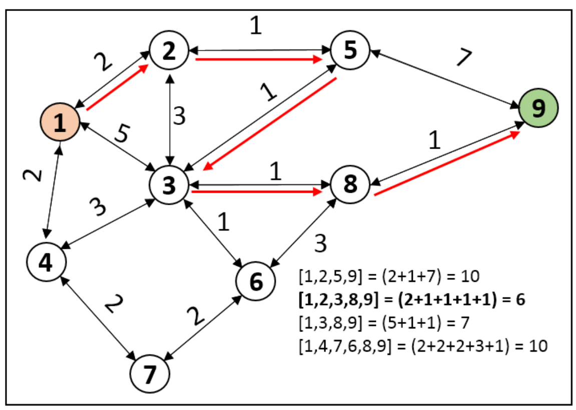


Figure 9. Graphical representation of Dijkstra's algorithm [34]

With both of these algorithms being viable to find a solution for the VRP, the genetic algorithm was identified to be faster than Dijkstra's algorithm. Various studies have shown the speed of using a genetic algorithm instead of Dijkstra's algorithm [31, 35]. One study performed a experiment between both algorithms [31]. Each algorithm was modeled on the same network, with one model using 20 nodes and the other using 80 nodes. In both cases, the genetic algorithm outperformed Dijkstra's algorithm significantly in finding a feasible solution. Displayed in Figure 10 is a chart of the study results.

Approach	Nodes	Size of cost matrix	Elapsed time
GA	20	20*20	260 ms
	80	80*80	390 ms
Dijkstra	20	20*20	1420 ms
	80	80*80	4000 ms

Figure 10. Comparison of a genetic algorithm vs. Dijkstra's algorithm results [31]

As stated earlier, this study opted to utilize the genetic algorithm. The genetic algorithm used in this study is specifically built for a CVRP, while the Network Analyst package can be potentially manipulated to solve CVRPs. Since the Network Anaylst package operates off of an algorithm based on Dijkstra's, it can be expected to be slow and inefficient for this study dataset sizes. It was determined that results will be identified quicker and potentially produce results closer to optimal using the genetic algorithm. With all programs identified, a model was constructed utilizing ArcGIS Pro, OSRM, and a genetic algorithm to estimate the recyclables transportation costs and emissions within municipalities.

List of References

[1] A. Farahbakhsh and M. A. Forghani, "Sustainable location and route planning with gis for waste sorting centers, case study: Kerman, iran," *Waste Management & Research*, vol. 37, no. 3, pp. 287–300, 2019.

[2] M. Hannan, M. A. Al Mamun, A. Hussain, H. Basri, and R. A. Begum, "A review on technologies and their usage in solid waste monitoring and management systems: Issues and challenges," *Waste Management*, vol. 43, pp. 509–523, 2015.

[3] J.-W. Lu, N.-B. Chang, and L. Liao, "Environmental informatics for solid and hazardous waste management: advances, challenges, and perspectives," *Critical reviews in environmental science and technology*, vol. 43, no. 15, pp. 1557–1656, 2013.

[4] "Gis mapping software, location intelligence amp; spatial analytics — esri," 2017. [Online]. Available: https://www.esri.com/content/dam/esrisites/en-us/newsroom/arcuser/summer-2017.pdf

[5] M. Law and A. Collins, *ArcGIS Pro*, 2019.

[6] D. P. Hidayat and S. Andajani, "Development land erosion model using model builder gis (case study: Citepus watershed)," in *MATEC Web of Conferences*, vol. 147. EDP Sciences, 2018, p. 03003.

[7] ESRI, "Modelbuilder vocabulary." [Online]. Available: https://pro.arcgis.com/en/pro-app/2.8/help/analysis/geoprocessing/modelbuilder/modelbuilder-vocabulary.htm

[8] K. Armstrong, "Modelbuilder: An introduction," *ESRI http://gg. usm. edu/kar/GHY418_518/Lectures/ModelBuilder1. pdf [10 Agustus 2011]*, 2009.

[9] P. Neis and D. Zielstra, "Recent developments and future trends in volunteered geographic information research: The case of openstreetmap," *Future Internet*, vol. 6, no. 1, pp. 76–106, 2014.

[10] M. F. Goodchild, "Citizens as sensors: the world of volunteered geography," *GeoJournal*, vol. 69, no. 4, pp. 211–221, 2007.

[11] M. Minghini and F. Frassinelli, "Openstreetmap history for intrinsic quality assessment: Is osm up-to-date?" *Open Geospatial Data, Software and Standards*, vol. 4, no. 1, pp. 1–17, 2019.

[12] G. Floros, B. Van Der Zander, and B. Leibe, "Openstreetslam: Global vehicle localization using openstreetmaps," in *2013 IEEE International Conference on Robotics and Automation*. IEEE, 2013, pp. 1054–1059.

[13] T. Bray, J. Paoli, C. M. Sperberg-McQueen, E. Maler, F. Yergeau, and J. Cowan, "Extensible markup language (xml) 1.0," 2000.

[14] M. Haklay and P. Weber, "Openstreetmap: User-generated street maps," *IEEE Pervasive computing*, vol. 7, no. 4, pp. 12–18, 2008.

[15] S. Huber and C. Rust, "Calculate travel time and distance with openstreetmap data using the open source routing machine (osrm)," *The Stata Journal*, vol. 16, no. 2, pp. 416–423, 2016.

[16] Esri, "Algorithms used by the arcgis network analyst extension," 2016.

[17] J. Ratliff, "What is a container?" Apr 2022. [Online]. Available: https://www.docker.com/resources/what-container/

[18] T. Bui, "Analysis of docker security," *arXiv preprint arXiv:1501.02967*, 2015.

[19] "How docker engine works," Jan 2020. [Online]. Available: https://www.dclessons.com/how-docker-engine-works

[20] P. Mooney and P. Corcoran, "Accessing the history of objects in openstreetmap," in *Proceedings AGILE*, vol. 353, no. 1, 2011, pp. 1–3.

[21] "Our download server," 2020. [Online]. Available: https://www.geofabrik.de/data/download.html

[22] G. Kaur and M. M. Fuad, "An evaluation of protocol buffer," in *Proceedings of the ieee southeastcon 2010 (southeastcon)*. IEEE, 2010, pp. 459–462.

[23] A. El Allali and M. Arshad, "Mzpaq: a fastq data compression tool," *Source code for biology and medicine*, vol. 14, no. 1, pp. 1–13, 2019.

[24] G. Clarke and J. W. Wright, "Scheduling of vehicles from a central depot to a number of delivery points," *Operations research*, vol. 12, no. 4, pp. 568–581, 1964.

[25] Z. Borcinova, "Two models of the capacitated vehicle routing problem," *Croatian Operational Research Review*, pp. 463–469, 2017.

[26] G. Laporte, "What you should know about the vehicle routing problem," *Naval Research Logistics (NRL)*, vol. 54, no. 8, pp. 811–819, 2007.

[27] M. Steinhaus, *The application of the self organizing map to the vehicle routing problem*. University of Rhode Island, 2015.

[28] M. Sajid, J. Singh, R. A. Haidri, M. Prasad, V. Varadarajan, K. Kotecha, and D. Garg, "A novel algorithm for capacitated vehicle routing problem for smart cities," *Symmetry*, vol. 13, no. 10, p. 1923, 2021.

[29] J. C. Fellers, *ALGORITHM SELECTION FOR THE CAPACITATED VEHICLE ROUTING PROBLEM USING MACHINE LEARNING CLASSIFIERS*. University of Rhode Island, 2021.

[30] M. F. Abdelatti and M. S. Sodhi, "An improved gpu-accelerated heuristic technique applied to the capacitated vehicle routing problem," in *Proceedings of the 2020 Genetic and Evolutionary Computation Conference*, 2020, pp. 663–671.

[31] A. Bagheri and M. R. Akbarzadeh Totonchi, "Finding shortest path with learning algorithms," *International Journal of Artificial Intelligence*, vol. 1, 2008.

[32] M. N. A. Wahab, S. Nefti-Meziani, and A. Atyabi, "Flow Chart of Genetic Algorithm with all steps involved from beginning until termination conditions met [6]." 5 2015. [Online]. Available: https://plos.figshare.com/articles/figure/_Flow_Chart_of_Genetic_Algorithm_with_all_steps_involved_from_beginning_until_termination_conditions_met_6_/1418786

[33] R. H. Möhring, H. Schilling, B. Schütz, D. Wagner, and T. Willhalm, "Partitioning graphs to speedup dijkstra's algorithm," *Journal of Experimental Algorithmics (JEA)*, vol. 11, pp. 2–8, 2007.

[34] A. U. Rehman, K. Awuah-Offei, D. BAKER, and D. Bristow, "Emergency evacuation guidance system for underground miners," in *SME Annual Meeting 2019*, 2019, pp. 19–100.

[35] Y. Sharma, S. C. Saini, and M. Bhandhari, "Comparison of dijkstra's shortest path algorithm with genetic algorithm for static and dynamic routing network," *International Journal of Electronics and Computer Science Engineering*, vol. 1, no. 2, pp. 416–425, 2012.

CHAPTER 3

Model Formulation

3.1 Overview of the Model

In order to estimate the recycling transportation costs and emissions within municipalities, the construction of a model using multiple data sets and applications for data processing is required. The basic flow of the model is structured into four sections of node formulation, distance and duration matrix generation, route optimization, and route visualization. Node formulation concentrates on obtaining housing datasets for the target municipality and identifying the coordinates of nodes. These coordinates are to be used within the CVRP and obtain a feasible solution. The distance and duration matrix section focuses on obtaining the distances and duration data between nodes along road networks. The following section of route optimization focuses on using a genetic algorithm to obtain feasible routes within the municipality. The final section of route visualization displays all of the feasible routes graphically. The flow chart of the model can be seen in Figure 11. Each section of the model is examined and individual process flows are available for each section.

3.2 Node Formulation

The first part of the model performs the creation of nodes and their coordinate systems. The overall process requires obtaining housing address, coordinates, road networks, and municipal data. The data is obtained from online databases and the municipalities themselves. The data requires organization and uniformity to flow through the processes. The data is processed and passed through three various ModelBuilders within ArcGIS Pro. The final output of the node formulation process contains all nodes within the selected municipality and their coordinates. This

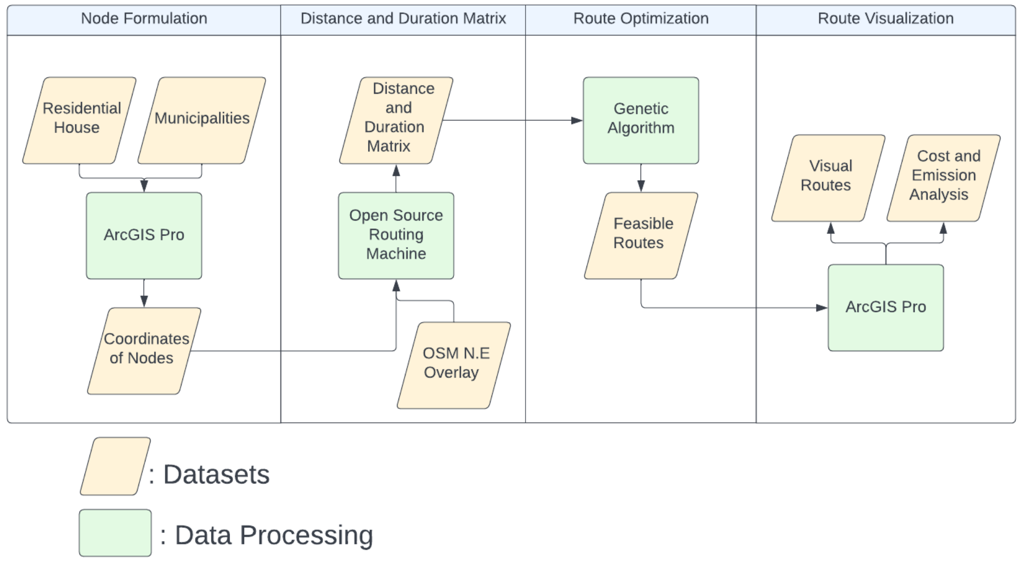


Figure 11. Entire model process flow

data then enters the distance and duration matrix section. Displayed in Figure 12 is a detailed flow chart of the data and processes within the node formulation section.

3.2.1 The Rhode Island Geographic Information System

The first step in the node formulation process requires a collection of the base GIS overlays for the individual municipalities. The place identified to obtain these is through the The Rhode Island Geographic Information System (RIGIS) website. RIGIS provides a diverse set of geographical referenced datasets on topics related to the environment, transportation, and infrastructure [1]. From the RIGIS website, four different shapefiles are obtained to use in the model. Municipalities (1997) is the first dataset acquired and is used for representing the boundary lines for Rhode Island municipalities. The second shapefile called RIDOT Roads (2016) was used for a graphical representation of all transportation highway, roads, and streets within the state of Rhode Island. The third overlay of Active Solid

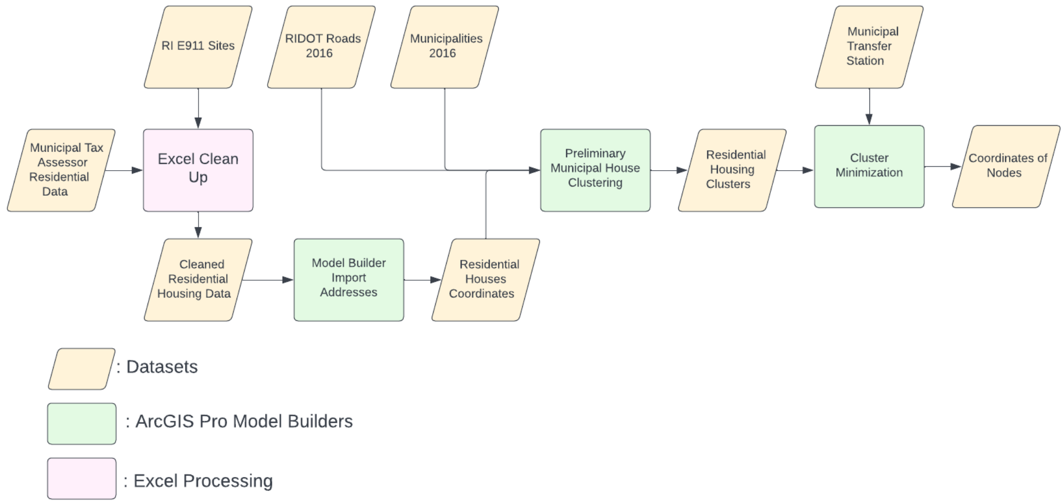


Figure 12. Overview of node formulation section

Waste Facility Sites is used to provide the location of transfer stations within each individual municipality. The final dataset obtained from the RIGIS website is the E-911 Sites dataset, which contains all addressed and unaddressed locations and coordinates in the state of Rhode Island. These four datasets, in combination with data obtained from each municipal tax assessor, provides the foundation of the model.

3.2.2 Municipal Tax Assessor Data

The purpose of obtaining data from various municipal tax assessors in the state of Rhode Island is due to the E-911 Sites dataset not providing a classification field to distinguish residential houses. Each Rhode Island municipality has a database containing all structures and their classifications. This database is contracted through Vision Government Solutions. The databases contains a field distinguishing the type of property [2]. The database allows for a singular property to be examined at once with no option to sort by type of property. An identified solution to obtain the data of all residential houses, is to contact each individual municipality tax assessor. The municipal tax assessor has the ability to sort the requested properties. All municipalities in Rhode Island were contacted. Listed in Table 3.2.2 are the municipalities within the state of Rhode Island who provided acceptable residential housing data. Together with the data obtained from RIGIS, addresses could be assigned coordinates and distinguished as residential houses. In order to standardize the data to proceed into the next step of the model, each individual Excel sheet obtained from a Rhode Island municipality had to be matched with a copy of the E-911 Sites. The process was performed using Excel functions to standardize the data due to the varying formats provided by each tax assessor. Once the data fulfils the criteria to fit into the model, the data can be imported into the first ModelBuilder.

Rhode Island Municipalities			
1. Pawtucket	4. South Kingstown	7. Bristol	10. Westerly
2. Glocester	5. Charlestown	8. Little Compton	11. West Warwick
3. Portsmouth	6. Richmond	9. Scituate	

Table 1. All Rhode Island municipalities that provided residential housing data.

3.2.3 Address Import Model Builder

With all of the data obtained and standardized, the first ModelBuilder is executed in ArcGIS Pro. Displayed in Figure 13 is the ModelBuilder import addresses process flow and the legend can be found in Figure 2. The ModelBuilder begins with selecting the Excel spreadsheet of the chosen municipality. The first tool in the model imports the Excel sheet to a table in ArcGIS Pro. To finish the model, the imported table with the addresses and coordinates is converted to XY points and added to the map. The columns are labeled as X and Y to effortlessly match the input parameters of the X and Y field. The coordinates are applied to the GCS_WGS_1984 coordinate system. The GCS_WGS_1984 is used as the default coordinate system throughout the model. At the conclusion of the first Model-

Builder all residential houses in the selected municipality are added into ArcGIS Pro. The points are further analyzed and manipulated in the next ModelBuilder.

Figure 13. ModelBuilder Import Addresses

3.2.4 Preliminary Municipal House Clustering Model Builder

The second ModelBuilder module starts the preliminary stage of clustering the residential houses. Due to the large amount of residential housing in various municipalities, clustering of residential houses is required to limit the number of nodes. Displayed in the Figure 14 is the preliminary municipal house clustering ModelBuilder and the legend can be found in Figure 2. The first step in the model is importing the three datasets of RIDOT Roads 2016, the imported residential addresses of the selected municipality from the previous ModelBuilder, and the Municipalities 1997. All three of these datasets are projected to ensure that they are on the same coordinate system of GCS_WGS_1984. The residential houses within the municipality are displayed on the map. Next, the select layer by attribute tool are used on the RIDOT Roads 2016 dataset. In order to select and display all of the roads segments within the desired municipality, an expression of "LTWN" = "Selected Town" AND "RTWN" = "Selected Town" is applied. The "Selected Town" field will change to the municipality name of the intended region of study. LTWN stands for left town and RTWN stands for right town. This specifies which municipality is on either side of the road segment. Therefore, the expression only selects roads that are fully within the selected municipality. The clip tool is used to take the original projected road networks as the input and apply the selected roads segments as the clip feature. The same process is performed for the Municipalities 1997 dataset. The select layer by attribute expression "Name" = "Selected Town" is used to identify the desired municipality. Once the municipality is selected, the clip tool is used again by applying Municipalities 1997 as the input dataset and the clip feature is the selected municipality. Once the two processes are preformed, the municipality and road segments are displayed in the maps.

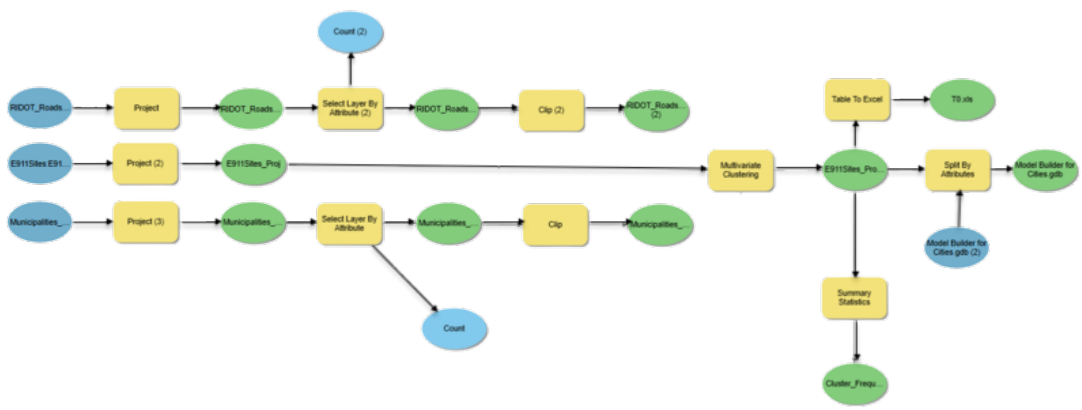


Figure 14. ModelBuilder Preliminary Municipal House Clustering

With all of the residential addresses displayed in the map, the preliminary clustering begins by using the multivariate clustering tool. The input features are the residential houses and the selected analysis fields are the X and Y coordinates. ArcGIS Pro uses k-means algorithm for clustering. The k-means algorithm objective is to find local optimal solutions, while reducing the clustering error [3]. The algorithm will identify a set of centroids specified as k in regards to all of the datapoints X and Y coordinates. The algorithm assigns all datapoints to the nearest centroid. The algorithm looks to minimize the centroid size and provide a feasible solution. ArcGIS Pro limits the number of clusters to 30. The tool provides a second algorithm of k-medoids, which minimizes the sum of dissimilarities of data objects [4]. K-medoids is more sensitive to outliers but k-means is faster than k-medoids and favors large datsets [5]. The tool requires an initialization method for determining the location of the first cluster. The selected method is the optimized seed location. This method randomly selects a location to apply the first cluster. It follows by placing the next clusters in the farthest opposite direction in regards to the X and Y coordinates [5]. Once the process is completed, the table to Excel tool is used to export each residential house, the X and Y coordinate data, and the corresponding cluster ID. Finally, the "split by attributes" tool is used to select all nodes within each individual cluster and create a new feature class for each cluster. Figure 15 displays an example output from the first and second ModelBuilders. The analyzed and created data from the first and second ModelBuilder is used in the final ModelBuilder to complete the node formulation section of the model.

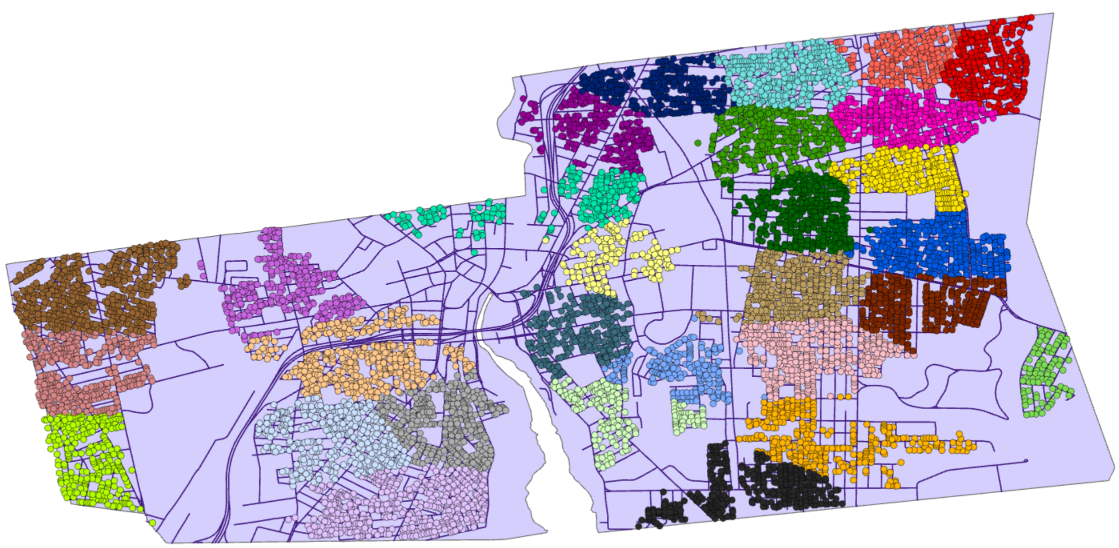


Figure 15. Preliminary municipal house clustering in the municipality of Pawtucket, Rhode Island

3.2.5 Secondary Node Clustering Model Builder

The objective of the final ModelBuilder, cluster minimization, in the node formulation section is to re-cluster within the newly formed clusters. This is done to increase the overall node count. The overall flow of the third ModelBuilder is displayed in Figure 16 and the legend can be found in Figure 2. The first step in the process is to add the new feature class data sets to the model. With the feature classes added to the drawing order, the final ModelBuilder can be validated and run. Figure 16 shows a single instance of a previous feature class being re-clustered. This ModelBuilder contains a total of 30 replications of Figure 16. If the previous ModelBuilder did not generate the potential 30 clusters. The current ModelBuilder will process exactly the number of clusters that were created in the previous ModelBuilder.

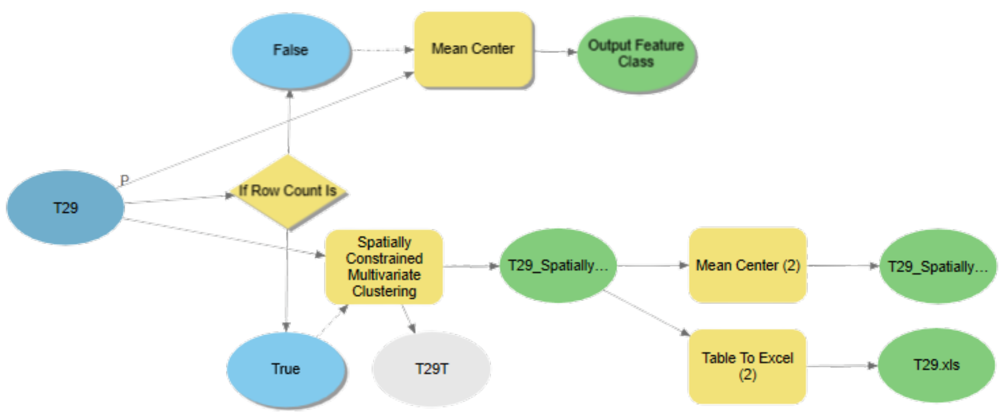


Figure 16. ModelBuilder Cluster Minimization

The cluster minimization begins with a logic tool examining the row count in the attribute table. The objective of this tool is to determine if the cluster needs to be reduced due to the number of houses already assigned to the cluster. If the row count is less than 50, the process flow will move to the mean center tool. The feature class is set as the input feature class and the tool will find the center point of all houses within the cluster. The center point of the cluster is added to the map.

If the row count is greater than 50, the process progresses towards the spatially constrained multivariate clustering tool. Similar to the previous clustering tool, this tool allows for manipulation of the cluster size in relation to the X and Y coordinates of the nodes. The input feature class is the cluster from the previous ModelBuilder and the X and Y coordinates are set in the analysis field. The cluster size constraint field is set to a minimum number of 5 houses per cluster and a maximum of 40. The tool specifies a field for spatial constraints. The tool guarantees that all members of the new cluster are nearby and a feature will only be included in the cluster if it has at least one natural neighbor. The spatial constraint field uses a trimmed Delaunay triangulation method. This creates a mesh of triangles that are non-overlapping and originate from the center of each feature. Nodes that share an edge are considered natural neighbors [6]. The triangles are then clipped with the use of a convex hull. A convex hull is specified as the smallest convex polygon that encloses all of the points in a set [7]. The convex hull is specified by the minimum and maximum cluster size parameters. Displayed in Figure 17 is an output from Delaunay triangulation.

Once the spatially constrained multivariate clustering is complete, the process moves to complete the mean center for each of the new clusters. The case field input is specified as the new cluster ID formed from the previous tools. Once the mean center points are produced, they are displayed on the map. Finally, the table to Excel tool is used to export all of the individual houses within their final nodes and their individual coordinates. Displayed in Figure 18 is an example output of all three ModelBuilders in the node formulation section. The large green circles are the centroids of the final clusters of residential houses. The smaller circles are individual houses and the color represents the cluster they belong to. This applies to all figures that display the preliminary and final clustering of nodes within a

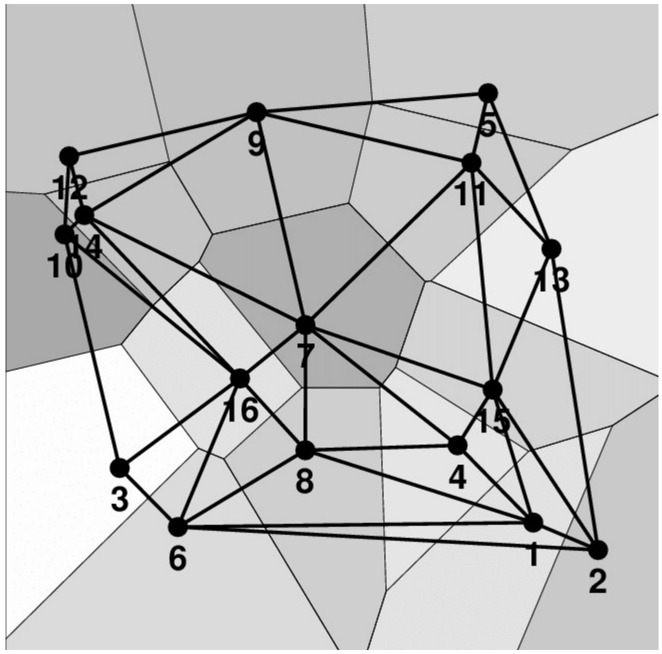


Figure 17. Delaunay Triangulation [8]

municipality in this study.

3.2.6 Node Coordinate Merge and Export

The final component of the node formulation section prepares the nodes for export to the distance and duration matrix generation section. The process begins by selecting the desired transfer station within the selected municipality. Once the transfer station is identified, the merge tool is used to combine all nodes into one table. All nodes produced from the final ModelBuilder are selected and merged with the transfer station. This creates a table with all nodes and their coordinates. Once this is completed, the table to Excel tool is used to export the table for use in the following sections of the model. Once the Excel sheet is generated, the sheet is standardized and the object ID of each node must be reduced by 1. This ensures that the first node (transfer station) is set to 0. Once the process is completed, the data is ready to be implemented in the distance and duration matrix segment.

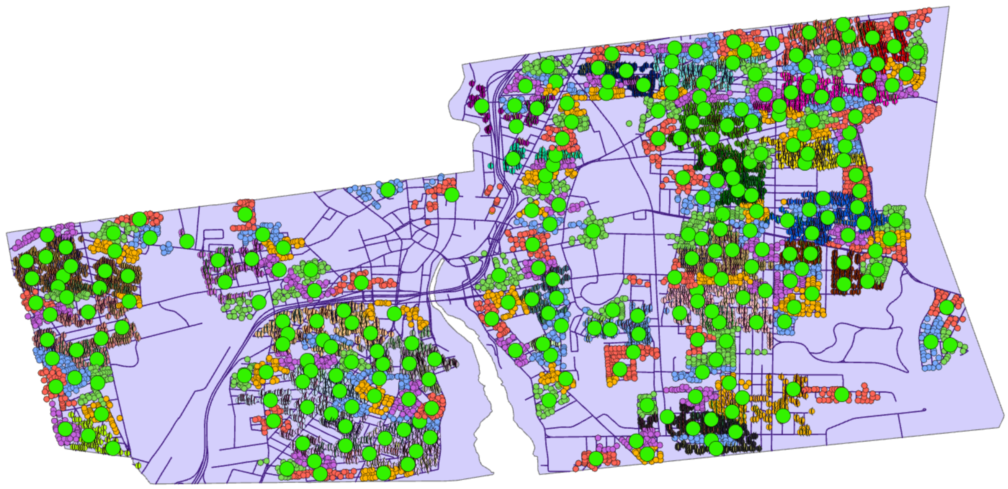


Figure 18. Node formulation final output of clusters within Pawtucket, Rhode Island

3.3 Distance and Duration Matrix

The purpose of the distance and duration matrix segment is to obtain the distances and duration between all nodes following road networks. With the node coordinates available, an instance of OSRM is created. In order to generate the instance of OSRM, the use of Docker is required with overlays obtained from OSM. Once the instance of OSRM is generate, a Python wrapper is used. A Python script is executed to obtain the distance and duration matrices for the selected municipality. Once the matrices are generated, the data moves to the route optimization section. There, the genetic algorithm is run to determine feasible routes within the municipality. Displayed in Figure 19 is the process flow of this segment.

3.3.1 OSRM Initialization

The first step in creating an instance of OSRM backend with Docker is downloading Windows Subsystem for Linux (WSL) and Docker. The process requires an OSRM container to be set up for the backend. The documentation and liter-

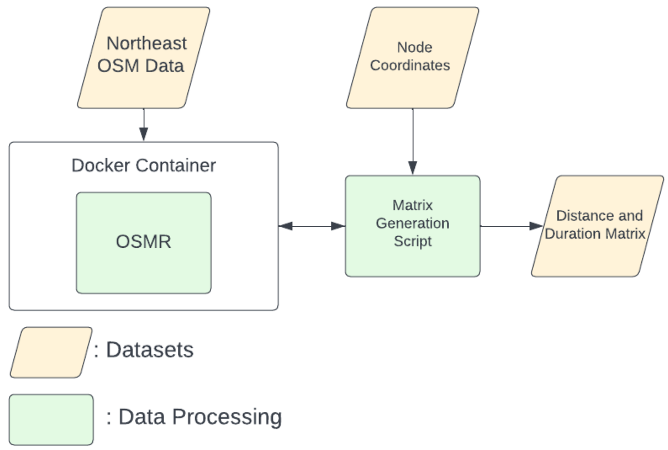


Figure 19. Distance and duration matrix generation model flow

ature can be found in D. Luxen and C. Vetter (2011) [9]. The next step in the process is obtaining the data from Geofabrik for the intended region of this study. This paper focuses on municipalities within the state of Rhode Island. A decision was made to download the U.S latest northeast OSM data. Once the data was obtained, the routing engine was started on a local HTTP server on port 5000. The OSM data can be processed and specifying the mode of transportation by "car" is required. Figure 20 provides the commands required to pre-process the extract. The first line extracts the OSM data. The second line partitions the data. Finally, the third line specifies any customizations related to the OSRM in the selected region. These three lines are the fundamental process of creating an OSRM.

In these lines, -v "$PWD:/data" is the flag which creates the directory data located insides of the docker container and makes the user's current directory available. Finally, the first instance is created by running the command in Figure 21.

The –max-table-size 1×10^6 is added to the command to allow OSRM to generate any size matrix with a size constraint of 1×10^6. With an instance of OSRM created and running within the intended region of study, a Python script

```
docker run -t -v "\${PWD}:/data" osrm/osrm-backend osrm-
   extract -p /opt/car.lua /data/us-northeast-latest.osm.
   pbf

docker run -t -v "\${PWD}:/data" osrm/osrm-backend osrm-
   partition /data/us-northeast-latest.osrm

docker run -t -v "\${PWD}:/data" osrm/osrm-backend osrm-
   customize /data/us-northeast-latest.osrm
```

Figure 20. OSRM creation commands

```
docker run -t -i -p 5000:5000 -v "\${PWD}:/data" osrm/
   osrm-backend osrm-routed --algorithm mld --max-table
   -size 1000000 /data/us-northeast-latest.osrm
```

Figure 21. OSRM initialization command

was used to process the data obtained from the previous section.

3.3.2 Python Wrap Around

With an instance of OSRM running on Docker, a Python script is created using the a python wrapper called python-osrm to interact with OSRM. The documentation and dependencies of the wrapper are found in D. Luxen and C. Vetter (2011) [10]. Figure 22 is the script created to generate the distance and duration matrices.

The first process in the script requests configuration of the local host on port 5000, where the docker container is running. Once configured, the script imports the nodes and their coordinates. The data is extracted from the Excel file and turned into a list. Once turned into a list, two OSRM tables are created: one

```
import osrm
osrm.RequestConfig
osrm.RequestConfig.host = "http://localhost:5000"
osrm.RequestConfig
import pandas as pd
list_coord = pd.read_excel('SelectedTownClusterMerge.xls')
list_coord = list_coord.iloc[:,1:3]
list_coord = list_coord.values.tolist()
distance_matrix = osrm.table(list_coord, annotations = "
    distance", output = 'pandas')
duration_matrix = osrm.table(list_coord, annotations = "
    duration", output = 'pandas')
distance_matrix[0].to_csv('locations.csv')
duration_matrix[0].to_csv('location_duration.csv')
```

Figure 22. Distance and duration matrix generation script

specifying the distance between nodes, and, the other specifying the duration between nodes. When generated, the tables will create the values abiding by the OSM overlay specifications such as road network obstacles, one-ways, and speed limits. Once the matrices are generated, they are exported to csv files, where they move to the next section of route optimization.

3.4 Demand Generation

With the distance cost between each node created, the demand data of each node is required for the genetic algorithm. Each node represents a housing cluster. The capacity of each truck was set to a maximum number of nodes a truck could service within an 8 hour period. Listed in Table 2 is the node, recycling, and capacity data for all of the selected Rhode Island municipalities. The data used to generate this table is obtained from the Rhode Island Resource Recovery Co-operation (RIRRC) 2021 Municipal Summary and Charts [11]. The average refuse truck has the ability to hold a total of 31 cubic-yards of recyclables, which roughly equates to 14,000 pounds of recyclables [12]. In this study, all municipalities use a 31 cubic-yard truck.

Town	Population	Households	Square Miles	Nodes	Houses per Nodes	Tons of Recy-clables per Year	Pounds per Week per Node	Truck Capacity
Bristol	22,226	6,758	9.79	215	31.43	2373	435.48	14
Pawtucket	75,387	9,855	8.67	277	32.33	6309	345.33	14
South Kingstown	31,851	8,356	56.37	268	31.18	5792	977.91	14
Charlestown	8,072	4,598	36.54	158	29.10	256	191.31	14
Glocester	10,087	1,342	54.23	53	25.32	936	293.19	14
Little Compton	3,484	1,611	28.9	57	28.26	526	299.77	14
Portsmouth	17,754	5,290	23.03	178	29.72	834	490.63	14
Richmond	8,165	1,860	40.32	66	28.18	718	411.11	14
Scituate	10,404	3,071	48.13	115	26.70	1276	460.8	14
Westerly	23,483	8,616	29.47	283	30.45	5012	807.36	14
West War-wick	31,188	6,223	7.83	208	29.92	2576	391.46	14

Table 2. Demand Matrix

Each node is assigned a demand and each truck a capacity. A cluster of houses represented by a node will be serviced by a truck if it does not violate the vehicles capacity. The vehicle capacity incorporates both the service time and collection space of the vehicle. An Excel sheet with the amount of nodes in the selected municipality is created. A value between .90 and 1.1 was randomly generated for each node. This is used to avoid assigning each node a value of 1. This was used to create diversity between each node without significantly altering the model. Refuse truck models vary between municipalities such as front loading, rear loading, and automated side loading. Each of these truck models vary in service time. An example refuse truck model of a 31 cubic-yard rear loader, performs a cycle time in 21-23 seconds [13]. In this study, all municipalities individual households are assigned a service time of 1 minute. This simulates a potential real-world situation and provides a time buffer of the vehicle performing the service and traveling to the next house. Therefore considering the average amount of households within all municipalities, a truck capacity of 14 is assigned to each vehicle. This determines each truck will not exceed the amount or recyclables collected on a route or the total service time on a route of 8 hours. The depot value is set to 0 because there is no demand. The municipality of South Kingstown provided a monthly breakdown of recyclable collection. The information displayed a peak month increase of recyclables at 28%. Therefore, each town was given an increase of 28% to estimate the maximum potential costs and emissions.

3.5 Route Optimization

This section uses a genetic algorithm to solve the CVRP within the selected municipally and produce a set of feasible routes. As stated earlier, a duration matrix was obtained from the previous segment. It displays the duration of travel between two nodes and takes into account constraints pertaining to the road network. The genetic algorithm documentation relating to the architecture is found in M. F. Abdelatti and M. S. Sodhi (2020) [14]. In order to apply the newly generated duration matrix, the algorithm is modified to read in a duration cost matrix instead of the algorithm calculating one. Since this genetic algorithm is used to solve a symmetric CVRP, a modification to the matrix is required. The OSRM matrix produces an asymmetric matrix due to the constraints along a road network. This means that the CVRP no longer follows an undirected graph but rather a directed graph resulting in $c_{ij} \neq c_{ji}$. In order to use the genetic algorithm, the matrix is modified to become symmetric and follow an undirected graph. The matrix is transposed and added to the original matrix and the average between the two is taken. This produces a symmetric matrix, while still taking into consideration aspects of a road network. Along with the duration matrix, the demands of each municipality are used. Displayed in Figure 23 is the process flow of this section. Once all of the processes are completed, the feasible routes are displayed visually using ArcGIS Pro.

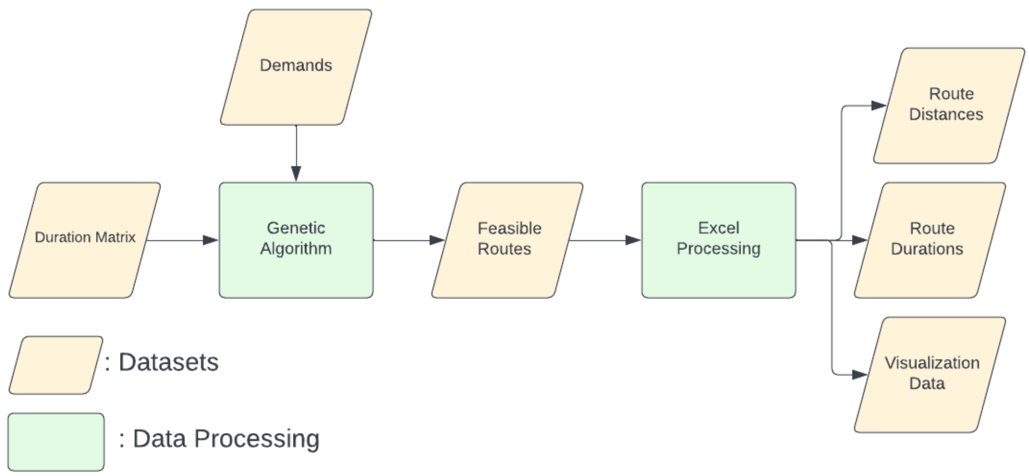


Figure 23. Route optimization process flow

3.5.1 Matrix Read in Modification and Parameter Selection

The first modification applied to the genetic algorithm is within calculation of the cost table. The original cost table was calculated by obtaining the x and y coordinate of each node and determined the shortest path between nodes using euclidean distances. Instead, the algorithm is modified to directly read in a provided cost table. Within the main function of the genetic algorithm, the cost table is added along with the demands. Before executing the genetic algorithm, a series of input parameters are specified. Figure 24 shows all of the parameters requiring specification.

The first parameter, city, requires the user to specify the municipality being observed. The number of nodes is represented by q and signifies the number of nodes within the municipality excluding the depot. The number of nodes is used to

```
#City
city="Pawtucket"
#Number of Nodes
q = 223
#Population Size Multipler
n = 20
# number of generations
generations = 20000
#Truck Capacity
vrp_capacity = 28000
#threshold value
opt = 0
#Crossover Mutation Rate
crossover_prob = 60
#Mutation Prob
mutation_prob = 30
```

Figure 24. Genetic algorithm parameter specifications

generate the population size, which is represented by n. The generations parameter is used to specify the number of generations the problem will run. The vrp_capacity represents the capacity of each truck along a route. The opt variable specifies the optimal solution to the problem, if it exists. If the optimal solution value does not exist or is unknown, a value of 0 is used to obtain a feasible solution. The crossover_prob and mutation_prob state the crossover mutation rate and mutation probability. Theses values are fixed at 60 and 30, respectively, for all cases. This is determined by design of experiments and recommendations from the architect of the genetic algorithm used in this study. Once all of the parameters are specified, the genetic algorithm is run to obtain feasible routes for the intended municipality.

3.5.2 Route Output

Once the genetic algorithm is completed, a text file is produced with feasible routes. An example output is displayed in Figure 25.

```
#City
city="Pawtucket"
#NumbProblem City:  Pawtucket Average
Nodes: 278
Solution Cost: 65857
Population Size: 6000
Generations: 10000
Capacity: 14
Solution: [148, 149, 150, 151, 152, 153, 154, 155, 156,
    ....,0]
```

Figure 25. Sample output from the genetic algorithm

The file displays all of the input parameters specified to obtain the solution. The solution cost displays the time required to service all nodes without violating the capacity constraint of the vehicle. All of the solutions begin at the depot, identified as node 0. The vehicle moves to the first node specified as the first number in the solution list. The vehicle travels between nodes in order corresponding to the numbers in the list. Once the solution list displays 0, the vehicle returns to the depot and a new route is started. All of the route data is processed in Excel to interpret the time and distance of each individual route. Finally, the visualization data is added to a Excel sheet and sent to the route visualization section.

3.6 Route Visualization

With the genetic algorithm providing feasible routes for recycling pickup within Rhode Island municipalities, a visual representation is needed to display the results. The output from the genetic algorithm requires some Excel processing to standardize the data. Once the data is uniform, the data is added back to ArcGIS Pro. Each route is added to an individual Excel sheet that contains an ObjectID. The ObjectID is unique and represents the order of the route. The file also contains the field of node ID and the coordinates. Another ModelBuilder is used to add the routes visually to the map. Multiple routes can be examined at once or individually. Listed in Figure 26 is the process flow for the route visualization segment.

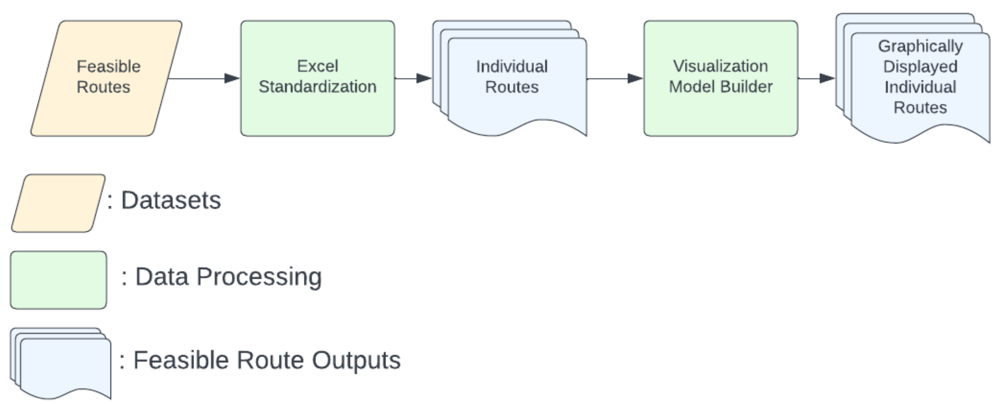


Figure 26. Route visualization process flow

3.6.1 Route Importation Model Builder

Before running the visualization ModelBuilder, the overlay of RIDOT Road 2016 is used to enhance the graphical display of the road network. The default ArcGIS World Topographical Map is used to display the target region. Displayed in Figure 27 is the process flow of the visualization ModelBuilder and the legend can be found in Figure 2.

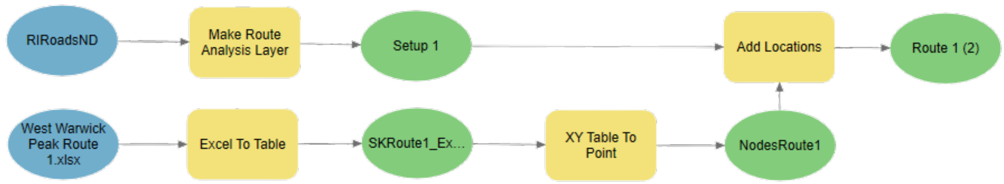


Figure 27. Final output of route visualization in Pawtucket, RI

The process begins with the construction of a network dataset. The network dataset is created using the RIDOT Roads 2016. There is no routing or calculations performed on the network dataset. It is used for a strictly visual purpose. Once the RIRoads network dataset (RIRoadsND) is created, the make route analysis layer tool is used to create the analysis layer. Next, the individual routes are transferred from the Excel sheet to a table in ArcGIS Pro by using the Excel to table tool. The nodes for each route are added to the map by using the XY Table to Point tool. With the network analyst layer created and nodes applied to the map, the network analyst tool, route, is used to display the routes. When using the route tool, it requires all of the nodes to be added as stops. The order is specified by using the ObjectID field, which determines the order of the nodes along the route. Once completed, the nodes are displayed on the map with a number corresponding to the order of pickup. The first node after the depot is displayed as 2 and the highest number of the route is the truck returning to the depot. Each route is represented by a different color. This applies to all figures that display the final output of routes in this paper. Shown in Figure 28 is a completed process of the model graphically displayed. In the following chapter, the routes are examined and the transportation cost and emissions of the recycling hauling is estimated within each municipality.

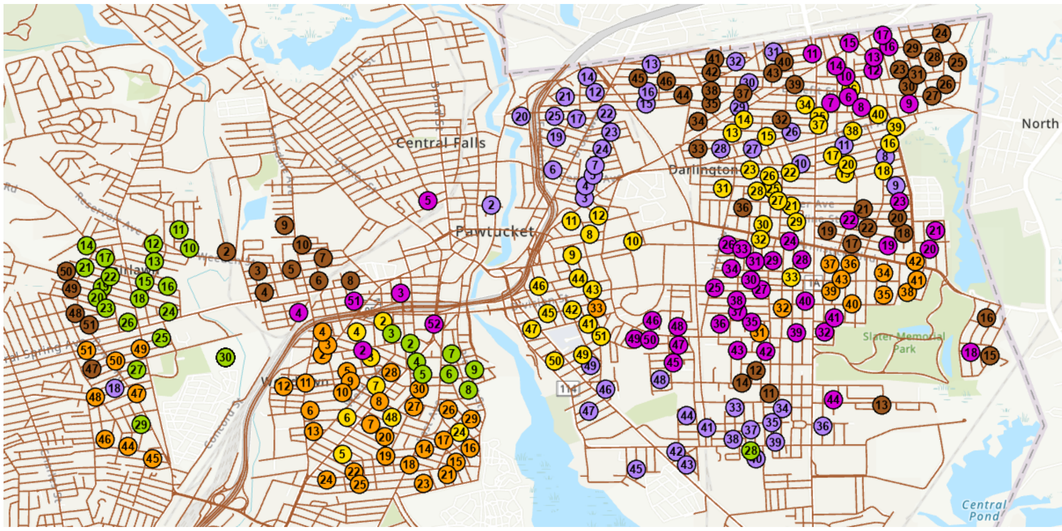


Figure 28. Route visualization flow process

List of References

[1] [Online]. Available: https://www.rigis.org/

[2] "Welcome to the vision government solutions, inc assessor's database for the city of pawtucket, ri." 2016. [Online]. Available: https://gis.vgsi.com/PawtucketRI/

[3] A. Likas, N. Vlassis, and J. J. Verbeek, "The global k-means clustering algorithm," *Pattern recognition*, vol. 36, no. 2, pp. 451–461, 2003.

[4] P. Arora and S. Varshney, "Analysis of k-means and k-medoids algorithm for big data," *Procedia Computer Science*, vol. 78, pp. 507–512, 2016.

[5] "Multivariate clustering (spatial statistics)." [Online]. Available: https://pro.arcgis.com/en/pro-app/2.8/tool-reference/spatial-statistics/multivariate-clustering.htm#:~:text=The%20default%20option%2C%20Optimized%20seed,of%20data%20space%20improves%20performance

[6] "How spatially constrained multivariate clustering works." [Online]. Available: https://pro.arcgis.com/en/pro-app/2.8/tool-reference/spatial-statistics/how-spatially-constrained-multivariate-clustering-works.htm

[7] D. Avis, D. Bremner, and R. Seidel, "How good are convex hull algorithms?" *Computational Geometry*, vol. 7, no. 5-6, pp. 265–301, 1997.

[8] M. Neamtu, "Bivariate simplex b-splines: A new paradigm," in *Proceedings Spring Conference on Computer Graphics*. IEEE, 2001, pp. 71–78.

[9] D. Luxen and C. Vetter, "Real-time routing with openstreetmap data," in *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, ser. GIS '11. New York, NY, USA: ACM, 2011, pp. 513–516. [Online]. Available: http://doi.acm.org/10.1145/2093973.2094062

[10] U. Stroetz, "Ustroetz/python-osrm: A python wrapper around the osrm api." [Online]. Available: https://github.com/ustroetz/python-osrm

[11] "2021 municipal summary (detailed)," Mar 2021. [Online]. Available: https://www.rirrc.org/sites/default/files/2022-04/2021%20Municipal%20Summary%20Detailed%20with%20Charts%2020220331.pdf

[12] "A guide to implementing a cart-based recycling program," Mar 2017. [Online]. Available: https://recyclingpartnership.org/wp-content/uploads/2018/05/implementing-carts-guide.pdf

[13] "New way refuse trucks cobra magnum specification sheet," Apr 2021. [Online]. Available: https://refusetrucks.scrantonmfg.com/

[14] M. F. Abdelatti and M. S. Sodhi, "An improved gpu-accelerated heuristic technique applied to the capacitated vehicle routing problem," in *Proceedings of the 2020 Genetic and Evolutionary Computation Conference*, 2020, pp. 663–671.

CHAPTER 4

Route, Cost, and Emission Results

4.1 Results Overview

Each of the 11 municipalities in the state of Rhode Island are examined. The individual municipalities are examined in two segments of clustering and routing results as well as cost and emission estimations. The results and estimations in each segment are calculated over a weekly period. Within the clustering and routing results the number of nodes, identified houses, total solution cost, longest and shortest routes considering duration and distance, the number of routes reaching maximum capacity, and the number of trucks required to service all routes is examined. To estimate travel distances between nodes along the road network, the inter-node travel distance between houses is taken into account. Due to the geographical diversity of Rhode Island municipalities, determining the inter-node travel distance is complex. To simulate the added distance, a value of 15 feet is added to provide some significance to the inter-node travel distances. This value was used because any new development must be built between 5-15 feet from the existing structure and property line depending on the local zoning requirements [1]. In the future work of this study, this value must be calculated using a sensitivity analysis or geoprocessing tools in ArcGIS Pro. The inter-node travel distance is included within calculations determining travel distance. In order to assign a truck to a route, linear programming is required to determine the greatest amount of routes a truck can perform in a single day without violating an 8 hour work day constraint. This will be further explored in the following sections.

The cost and emission estimations segment examines the total travel distance of all trucks, the estimated required gallons of diesel, estimated diesel cost, estimated wages of workers, estimated amount of recyclables collected, estimated ton-mile of recyclables, and estimated CO2 emissions of each municipality. Since a specific truck model is not identified, an estimated miles per gallon is identified to be 3 from various stuides [2, 3, 4]. The current price of diesel in the state of Rhode Island was found to be \$6.194 [5]. Finally, the hourly worker wages in the 90th percentile of Rhode Island is found to be \$24.91 [6]. Two workers are required for each truck. The wages are estimated by multiplying the total duration by the hourly rate. The amount of recyclables collected is calculated based on data previously stated. The emission factor of a diesel truck is identified as 161.8 grams of CO2 per ton-mile [7]. With these values the total CO2 emissions of an individual truck can be estimated [7]. Due to the complexity of determining the constantly changing emission value between houses, a maximum value of emissions of a truck is used for the entire route.

4.1.1 Bin Packing Problem and Linear Programming

Since the genetic algorithm provides feasible routes within a municipality, the ability to assign multiple routes to a truck arises. In order to assign the maximum amount of routes to the least amount of trucks, the classic bin packing problem (BPP) is used. The BPP has been studied since the early 1970s and is commonly used in production planning and control systems. Similar to the CVRP, the BPP is NP-Hard in nature and is usually solved using custom heuristics [8]. The BPP normally contains m items and n identical bins where the objective function is to assign the maximum items to a bin without breaking the capacity constraint. The overall objective of the problem is to minimize the number of bins [8]. For this paper, instead of using items and bins the BPP is applied to trucks and routes.

The objective of the function is to minimize a set of A trucks represented as n and applying the maximum amount of set B routes represented as m. Each truck n is assigned a capacity c and each route m is assigned a distance cost of d_i. The capacity c is a set value where only a specific amount of routes can be applied to a truck without violating the capacity. The mathematical formulation has been adapted to fit this problem, which is be found below and in equations 1 to 4 and is described as an integer optimization problem [8].

$$min \sum_{j=1}^{n} T_j \tag{1}$$

$$\text{subject to} \quad \sum_{i=1}^{m} d_i * R_{ij} \leq c * T_j \quad \forall j \tag{2}$$

$$\sum_{m}^{i=1} R_{ij} = 1 \quad \forall j \tag{3}$$

$$T_j \in \{0,1\} \tag{4}$$

$$R_{ij} \in \{0,1\} \tag{5}$$

Where T_j and R_ij are binary decision variables described in equation 6 and 7

$$T_j = \begin{cases} 1, & \text{if truck } j \text{ is used} \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

$$R_{ij} = \begin{cases} 1, & \text{if route } i \text{ is assigned to truck } j \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

Equation 1 is the objective function aiming to minimize the amount of trucks. Equation 2 is the first constraint, which states that the routes added to the truck cannot exceed the capacity. The second constraint in equation 3 states that each route must be added to a truck. Finally, equations 4 and 5 represent that the variables musts be binary. If a collection of routes exist whose sum is less than or equal to 8, then without loss of generality, the collection can be assigned to a truck. In Excel, a custom heuristic is recursively defined. If a feasible solution exists, remove a truck and run the algorithm again [9, 10]. This process should be repeated until no feasible solution exists. Upon reaching the infeasible solution, add the previous truck to obtain the preceding feasible solution. The amount of trucks required for the feasible solution should be applied over a 5 day week. If 5 trucks are required to service a municipality, 1 truck can be used over a span of 5 days. In the next sections, results of the model are found for the selected municipalities in the state of Rhode Island.

4.2 Bristol Clustering and Routing Results

Bristol is a coastal municipality located in the eastern part of the state of Rhode Island. The current estimated population of Bristol is 22,226. The population per square mile is 2,297.8. The overall land area of Bristol is 9.79 square miles [11]. Bristol generated 215 nodes after the final clustering stage. The average number of residential households per cluster is 31.43 with a total of 6,758 households being identified within the municipality. The transfer station identified in Bristol is located at 6 Minturn Farm Rd and is used as the depot for this municipality [12]. The output from the genetic algorithm displayed a total solution time of 119,380 seconds and a total of 16 routes are generated. In total, 11 routes fulfilled the maximum capacity of 14 nodes with the longest total duration being route 7. Route 7 duration is found to be 4.58 hours. Route 7 also presented the longest total distance between nodes at 27.286 km. The shortest total duration of a route is route 16, completing the journey in 3.3 hours. The shortest total travel distance between all routes is route 15. It completes the journey within 14.34km but a duration of 4.02 hours is required. The BPP output identified that 3 trucks can be used to service all of the routes within Bristol. Truck 1 must perform route 1 and 6 on the same day and Truck 2 must complete route 13 and 16 on the same day. The clusters and all of the routes are shown in Figures 29, 30, 31. The individual routes of Bristol are displayed in Appendix A.

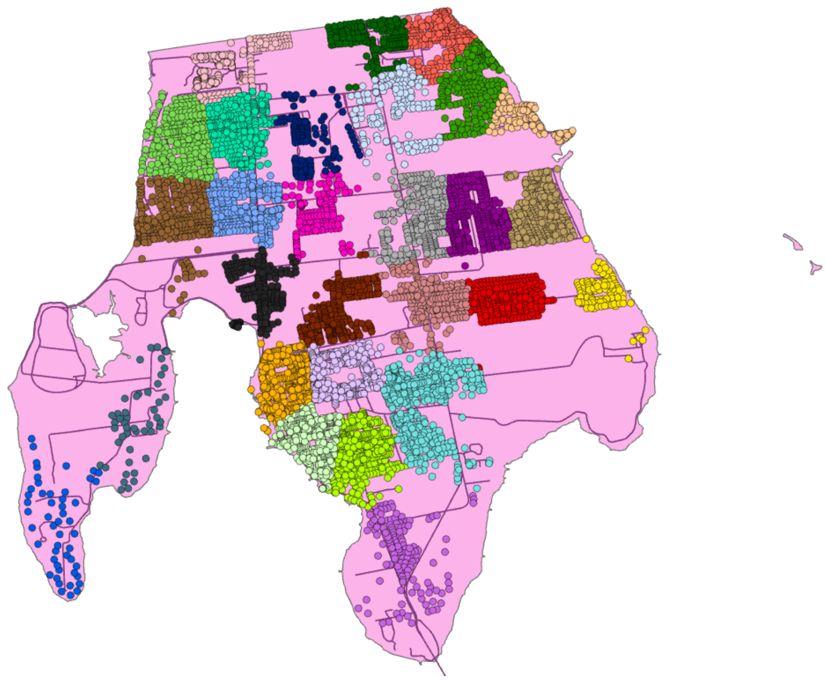


Figure 29. Preliminary clustering results of Bristol, RI

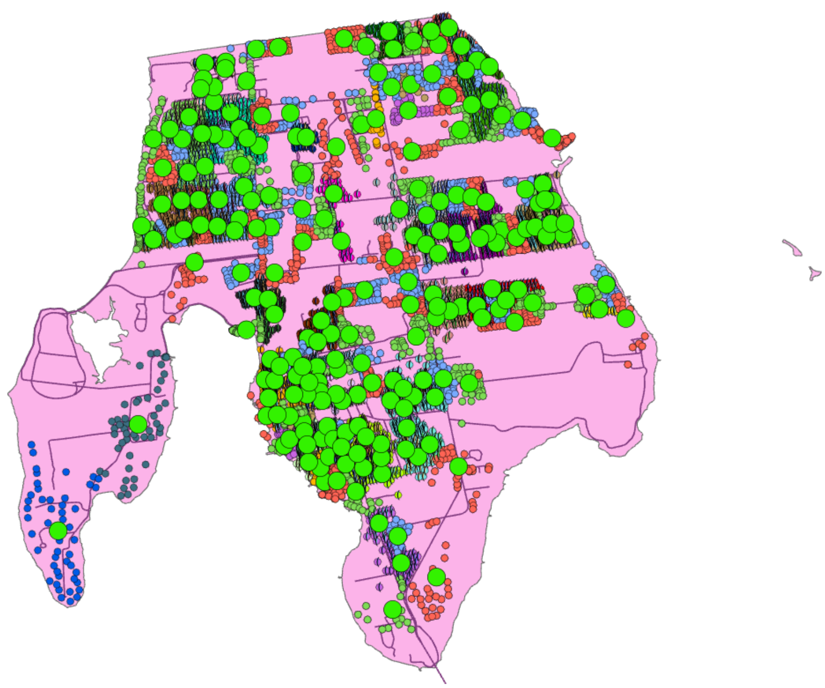


Figure 30. Final clustering results of Bristol, RI

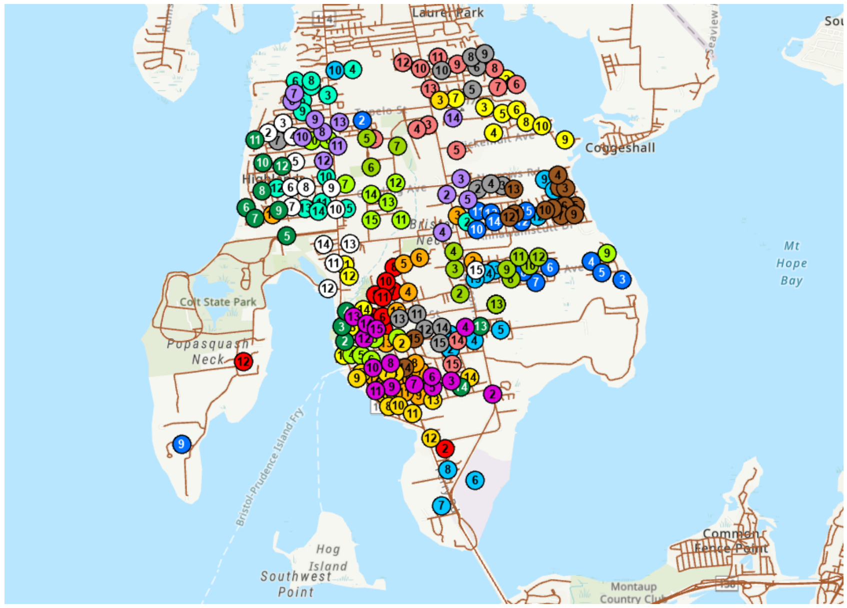


Figure 31. All routes in Bristol, RI

4.3 Bristol Cost and Emission Results

The 3 trucks required to service Bristol complete all of the routes in 229.99 miles and a duration of 65.9 hours. This equates to a total of 76.66 gallons of diesel estimated to service the municipality. The two workers per truck resulted in an estimation of $3,283.14 in wages and a total fuel cost of $474.85. The total weight of recyclables hauled in Bristol is estimated at 46.15 tons with a total ton-mile value of 3,586.23. Finally, the total estimated emission of all trucks in Bristol resulted in 5.80 metric tons of CO_2. Appendix A contains the figures for the costs and emissions of individual trucks.

4.4 Pawtucket Clustering and Routing Results

The city of Pawtucket is located in the northeast of Rhode Island and has a population of 75,387. The land area in square miles is found to be 8.67 with a population per square mile of 8,732 [13]. After processing using the model, a total of 277 nodes was used with approximately 32.33 houses per node and identifying 9,855 houses. The genetic algorithm provided an output of 21 routes and a total solution time of 198,371 seconds. The depot node specified for Pawtucket is the Blackstone Valley transfer station located at 240 Grotto Ave [12]. Pawtucket is one of the municipalities to produce the most amount of routes at 21. The smallest route, 21, contained a total of 9 nodes, or 291 households. Out of the 21 routes, only 10 routes were filled to the max capacity. The shortest route duration was also route 21 taking only 2.76 hours to complete the entire route. Route 21 is the shortest in total travel distance at 13.62 km, however route 16 fulfilled service to 13 nodes within 3.85 hours but only traveled 13.73 kilometers. The route with the longest total duration is route 20 at 4.44 hours and the longest total distance belongs to route 9 at 29.45 km. The custom heuristic for the BPP found that a total of 4 trucks is needed to service Pawtucket. Truck 1 must fulfil routes 3 and 15 on the same day. Truck 2 must complete routes 12 and 21 on the same day and truck 3 must perform route 4 and 16 on the same day. The clusters and all of the routes are shown in Figures 32, 33, 34. The individual routes of Pawtucket are displayed in Appendix B.

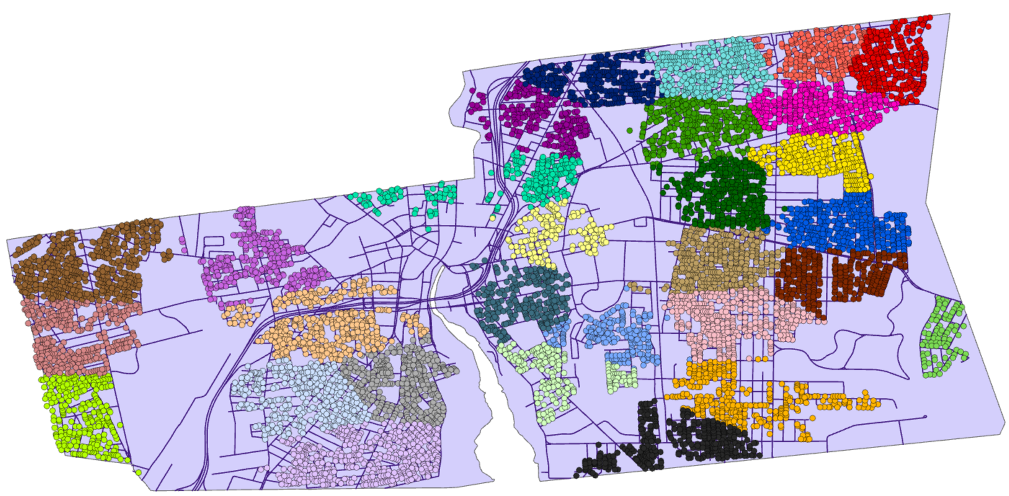


Figure 32. Preliminary clustering results in Pawtucket, RI

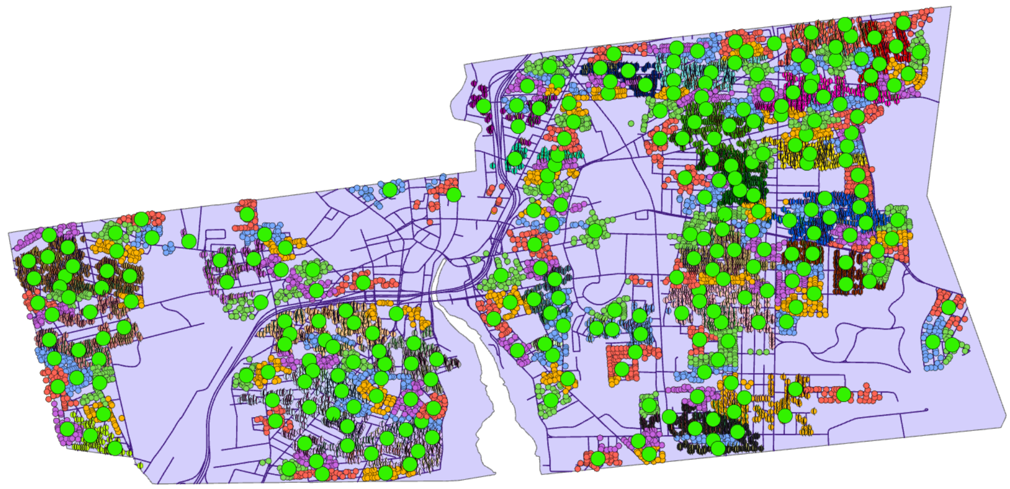


Figure 33. Final clustering results of Pawtucket, RI

4.5 Pawtucket Cost and Emission Results

With a total distance traveled of 283.08 miles and total completion time of 85.93 hours, Pawtucket created a total diesel fuel cost estimation of $584.47 from an estimated 94.36 gallons. Pawtucket totaled $4,281.23 dollars in estimated wages between all the workers and trucks as well as an estimated hauling total of 47.82 tons. The total ton-mile was estimated to be 3,586.39 and estimated totaled emissions were 5.80 metric tons of C02. Displayed below in Appendix B are all of the individual truck estimations.

4.6 South Kingstown Clustering and Routing Results

The city of South Kingstown is located in southern Rhode Island with an approximate land area of 56.37 square miles. The population is estimated to be 31,851 with 566.5 people per square mile [14]. South Kingstown produced a total of 268 nodes, similar to the city of Pawtucket but with only half of the population. This is most likely due to the fact that South Kingstown is a suburban district compared to Pawtucket being an dense urban city. South Kingstown is likely to contain more single family households compared to Pawtucket due to the large

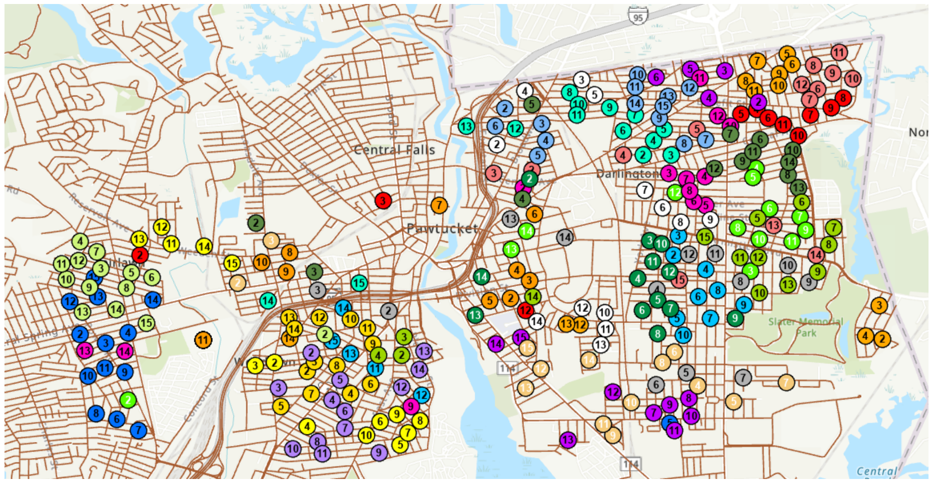


Figure 34. All routes in Pawtucket, RI

land area. From these 268 nodes, an estimated 31.18 houses per node and 8,356 households were identified. The genetic algorithm produced a total solution time of 345,117 seconds and a total of 20 routes. The depot identified for South Kingston is the Rose Hill regional transfer station located at 163 Rose Hill Rd. A total of 11 routes fulfilled the maximum capacity [12]. The shortest route in total duration and distance is route 1, completing all travel in 3.6 hours and 29.29 km. The two longest routes in both duration and distance are routes 13 and 16. While route 13 completes all travel duration at 5.68 hours, it traveled less in total distance at 84.70 km. In comparison, route 16 completes all travel duration within 5.65 hours but travels a total distance of 91.85 km. Once the custom heuristic is performed, a total of 4 trucks is determined to service South Kingstown. Truck 3 is required to perform routes 1 and 18 on the same day. The clusters and all of the routes are shown in Figures 35, 36, 37. The individual routes of South Kingstown are displayed in Appendix C.

4.7 South Kingstown Cost and Emission Results

South Kingstown is estimated to potentially be one of the costliest and highest emitters of CO2. A total of 643.71 miles are completed between all routes in

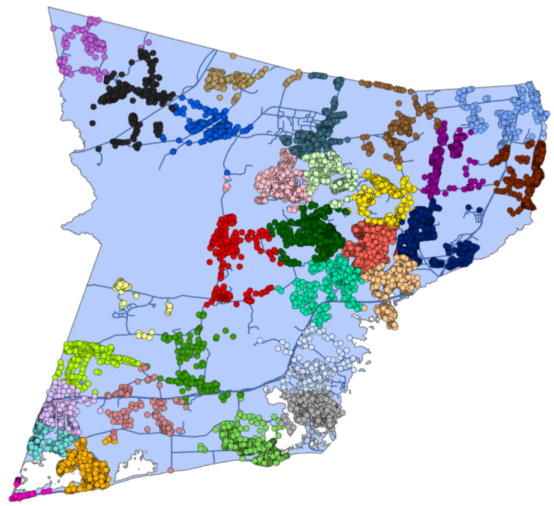


Figure 35. Preliminary clustering results in South Kingstown, RI

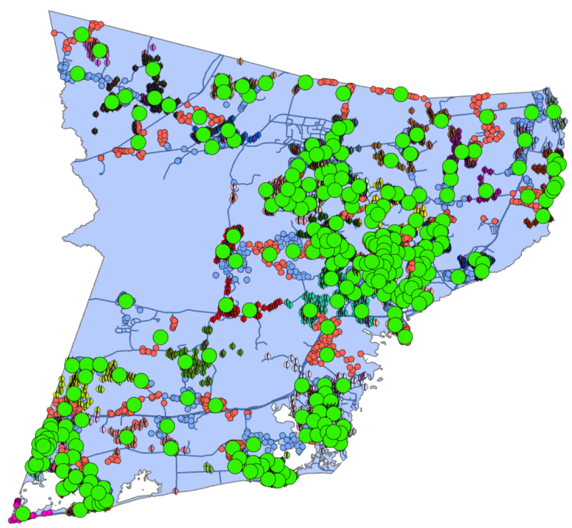


Figure 36. Final clustering results of South Kingstown, RI

South Kingstown requiring an estimated 214.57 gallons of diesel. The estimated fuel required is found to be $1,329.05 and estimated wages are calculated to be $4,722.40. In regards to emissions, a estimated total of 131.04 tons of recyclables are collected with a total ton-mile of 21,393.02. Together, it is determined that the total estimated emissions of CO2 in South Kingstown is 34.61 metric tons. The individual break down of costs and emissions of trucks can be found in Appendix

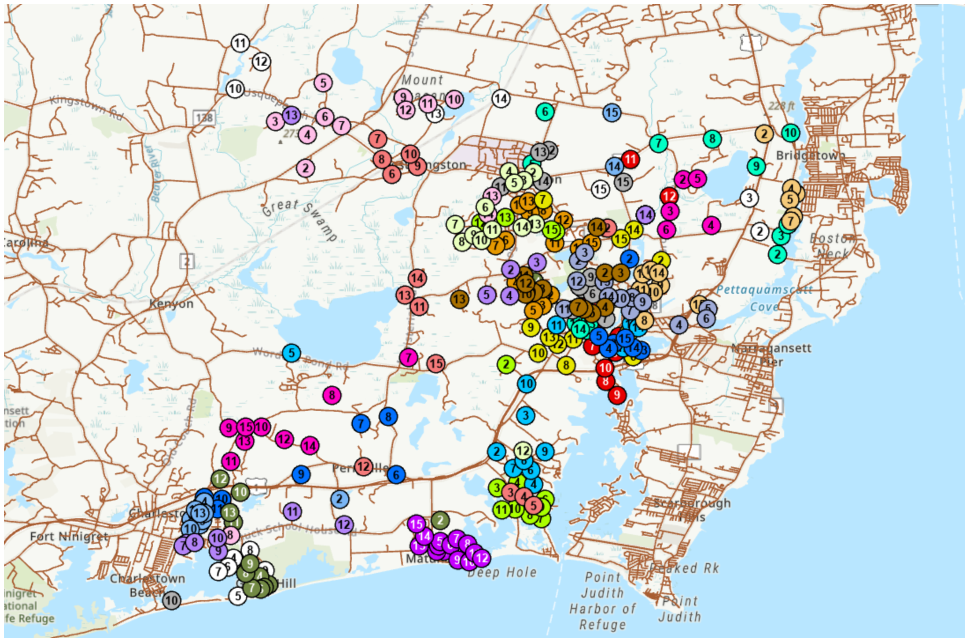


Figure 37. All routes in South Kingstown, RI

C.

4.8 Charlestown Clustering and Routing Results

Charlestown is a coastal municipality in southern Rhode Island. Charlestown has a population estimated to be around 8,072 [15]. The area is determined to be 36.54 square miles and the population per square mile is 218.9. A total of 158 nodes are calculated with an estimated 29.1 households per node and a total of 4,598 households are identified. The transfer station in Charlestown is called the Charlestown Residential Collection Center with an address of 50 Sand Hill Road [12]. The genetic algorithm determined a total of 12 routes within Charlestown and a total solution time of 212,505 seconds. Half of the capacities are filled to the maximum with the lowest being a capacity of 9. The shortest route in total distance and duration is route 9 traveling 34 km within 3.01 hours. The longest route in regards to total duration is route 9 at 4.84 hours while traveling 55.35 km. The longest route in regards to total duration is route 6 which travels 61 km within 4.6 hours. Chalestown is determined to use 3 trucks to complete all routes within a week. In Charlestown, there is no requirement to include multiple routes for a single truck. The clusters and all of the routes are shown in Figures 38, 39, 40. The individual routes of Charlestown are displayed in Appendix D.

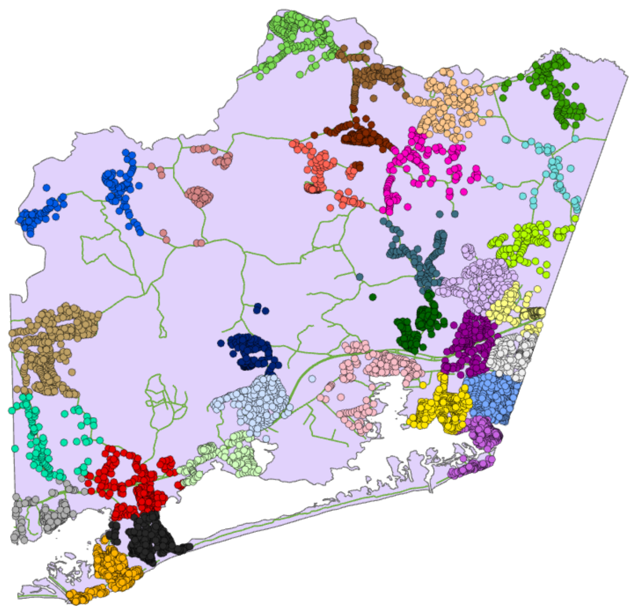


Figure 38. Preliminary clustering results in Charlestown, RI

4.9 Charlestown Cost and Emission Results

In total, 384.29 is the total amount of miles all trucks travel within Charlestown. This results in a total of 128.10 gallons of diesel estimated to service all routes. Chalestown requires an estimated expenditure of $793.42 for diesel and $2,646.37 for wages. Charlestown recycles an estimated total of 15.11 tons resulting in 2,470.29 ton-miles. It is estimated that the CO_2 emissions in Charlestown are 4 metric tons. The low amount of CO_2 emissions is likely related to the amount of recyclables collected within the municipality. The individual break down of costs and emissions of trucks can be found in Appendix D.

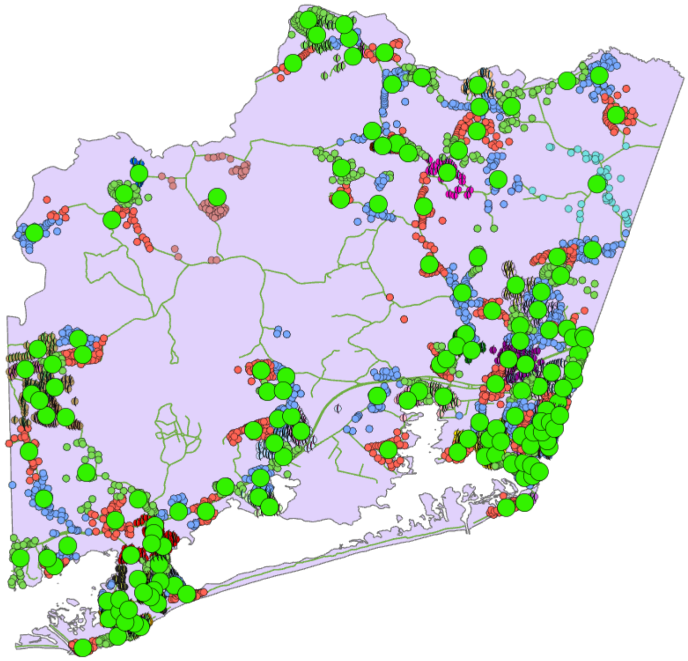


Figure 39. Final clustering results of Charlestown, RI

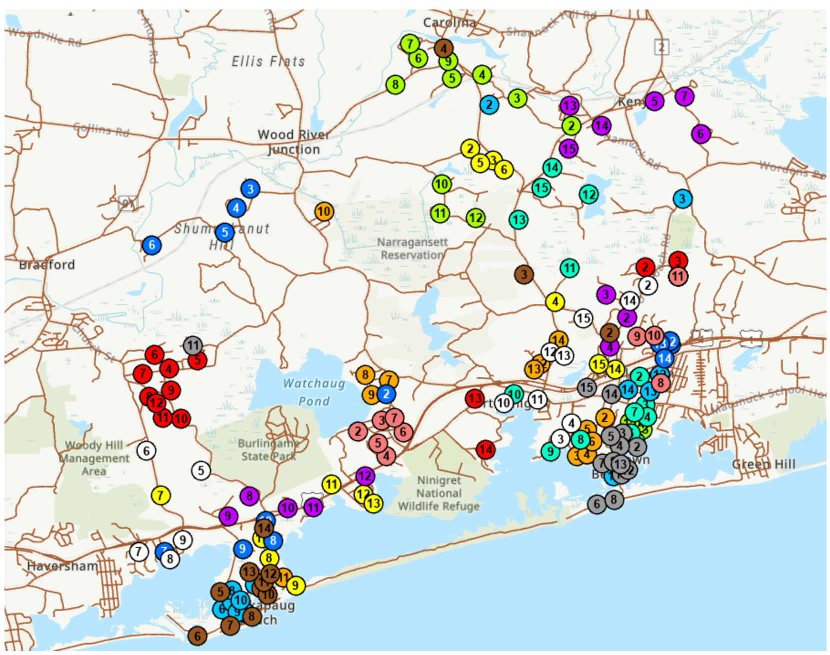


Figure 40. All routes in Charlestown, RI

4.10 Glocester Clustering and Routing Results

The municipality of Glocester is found in the northwest of Rhode Island. Glocester contains an area 54.23 square miles. The estimated population is 10,087 with a population per square mile of 183.9 [16]. The model determined 53 nodes within Glocester making it the smallest in the study. The nodes contained 25.32 houses per node resulting in 1,342 residential households identified. The transfer station identified for Glocester is the transfer station located at 121 Chestnut Hill Road in Chepachet, RI [12]. The genetic algorithm determined a total solution time of 53,865 seconds resulting in 4 routes. Only one of the 4 routes fulfilled the maximum capacity. The lowest total duration was found to be route 1 at 4.26 hours which is the only route to fulfill the capacity. The total distance traveled for route 1 is also the lowest with a value of 56.34 km. The largest route in total duration is route 2 with a value of 5.52 hours and total distance of 99.84 km. The route with the largest total distance is route 3, completing a 102.86 km journey within 5.13 hours. It was determined that only 1 truck is needed for Glocester. The clusters and all of the routes are shown in Figures 41, 42, 43. The individual routes of Glocester are displayed in Appendix E.

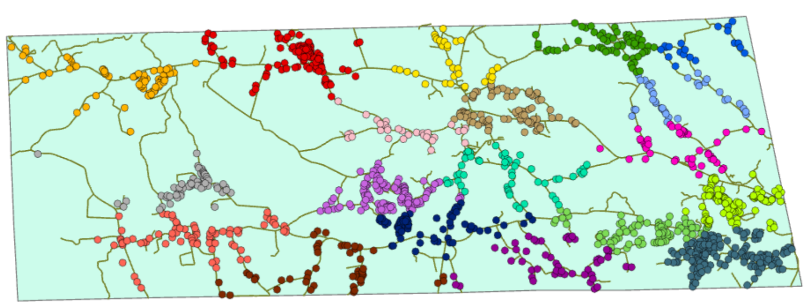


Figure 41. Preliminary clustering results in Glocester, RI

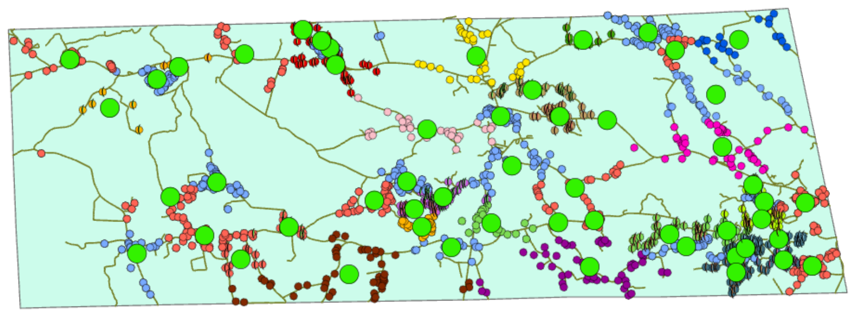


Figure 42. Final clustering results of Glocester, RI

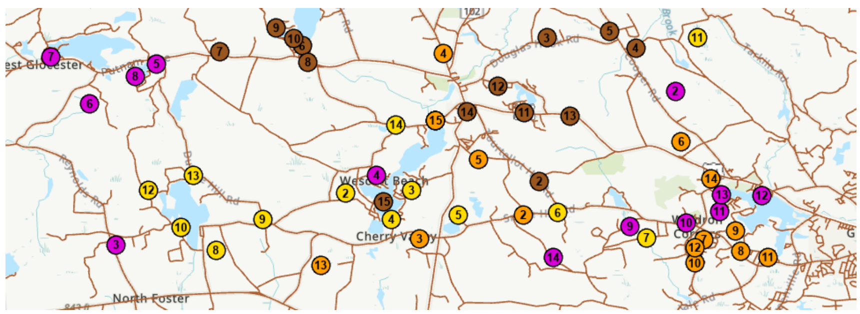


Figure 43. All routes in Glocester, RI

4.11 Glocester Cost and Emission Results

Glocester is one of the lowest emitters of CO2 emissions. It is estimated that Glocester completes a total travel distance of 209.10 miles. There is an estimated need for 69.70 gallons of diesel estimated at $431.73. To complete the routes, wages of $968.51 are estimated for workers. An estimated total of 7.77 tons of recyclables are hauled resulting in 1624.63 ton-miles and an estimated 2.63 metric tons of CO2 emissions.

4.12 Little Compton Clustering and Routing Results

Little Compton is located in the south east of Rhode Island along the coast. The estimated population is 3,484 with a land area of 28.9 square miles as well as 120.55 people per square mile [17]. Little Compton is one of the smallest municipalities in this study resulting in the generation of 57 nodes. A total of 1,611 households are discovered within the 57 nodes and an average of 28.26 households per node. The Little Compton transfer station to be used as the depot within the genetic algorithm is named the Little Compton Transfer Station located at 122 Amy Hart Path [12]. The genetic algorithm created a total of 5 routes within the municipality and a total solution time of 53,352 seconds. A singular route fulfilled the maximum capacity constraint and the lowest amount of nodes per route is 6. Route 1 containing the 6 nodes has the lowest total travel duration and distance at 2.3 hours and 31.2 km, respectively. Route 2 has the largest total travel duration and distance and is the only route with a fulfilled capacity. Route 2 completes the journey within 6.1 hours and a distance of 99.32 km. A single truck is identified to service the 5 routes within Little Compton. The clusters and all of the routes are shown in Figures 44, 45, 46. The individual routes of Little Compton are displayed in Appendix F.

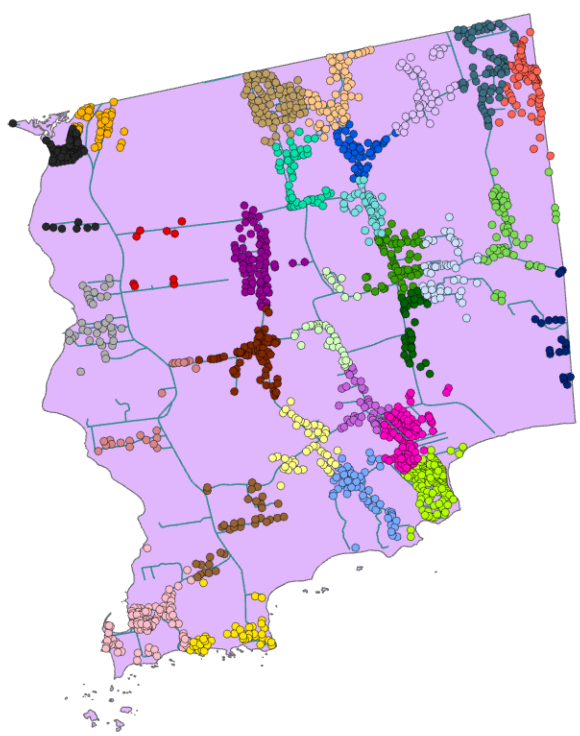


Figure 44. Preliminary clustering results in Little Compton, RI

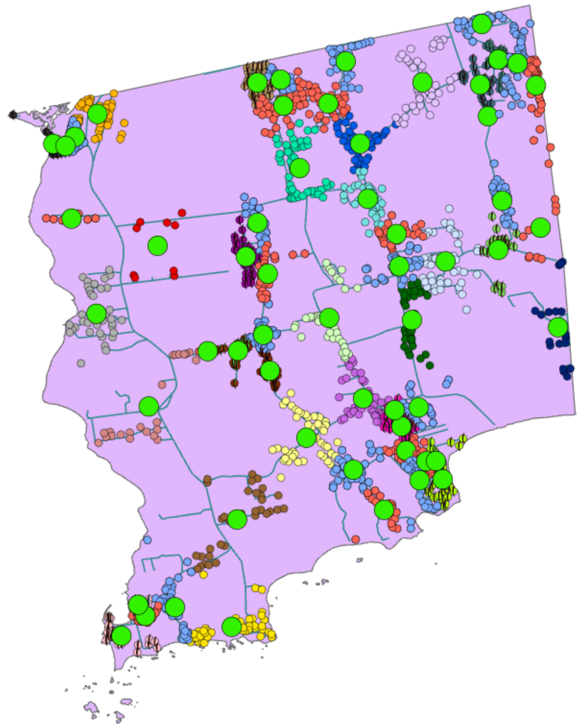


Figure 45. Final clustering results of Little Compton, RI

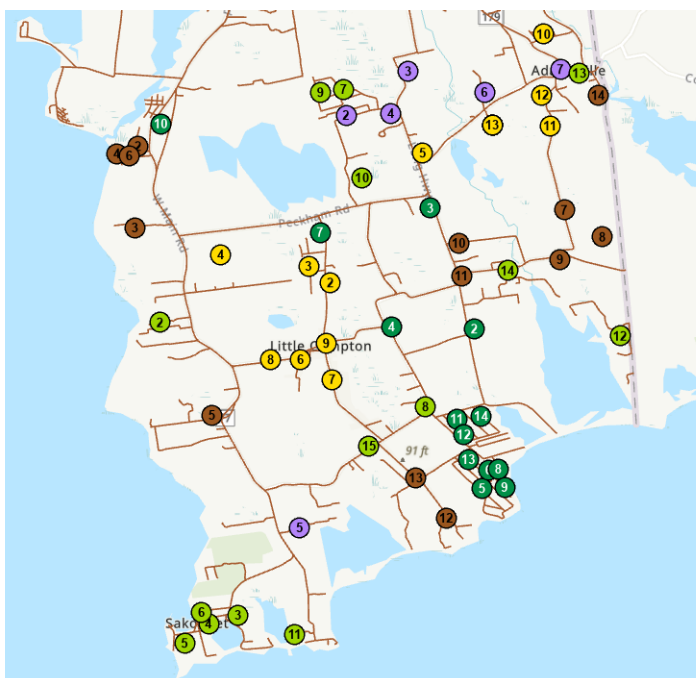


Figure 46. All routes in Little Compton, RI

4.13 Little Compton Cost and Emission Results

With the genetic algorithm providing a total of 5 routes over 5 days, only a singular truck is required to satisfy the total 179.43 mile journey. This journey estimates a total of 59.81 gallons of diesel to complete the routes. The value of the diesel is estimated to be $370.46 ranking the lowest in this study. The weekly wages are estimated to be $1,068.19. An estimated total of 8.54 tons of recyclables are collected which equates to 1,532.94 ton-miles. In total, it is estimated the Little Compton produces 2.48 metric tons of CO_2 emissions from recycling hauling.

4.14 Portsmouth Clustering and Routing Results

Portsmouth is a municipality containing a population of 17,754 along the south coast of Rhode Island. Portsmouth has an land area of 23.03 square miles and population density of 776.2 people per square mile [18]. A total of 178 nodes were calculated in Portsmouth representing 5,290 households within those nodes. An average value 29.72 house per node is determined in Portsmouth. The Portsmouth Transfer Station is located on 800 W Main Rd and designated as the depot in the genetic algorithm [12]. The genetic algorithm determined a total of 13 routes in Portsmouth and a total solution time of 130,044 seconds. A total of 9 out of 13 routes fulfilled the capacity constraint with the lowest route still containing 13 nodes. The total shortest duration was found in route 4 at 3.9 hours and total travel distance at 23.57 km. The shortest total travel distance was found in route 2, which completes the total journey within 18.83 km and a total time of 3.93 hours. The longest total duration and distance belongs to route 5, with a travel time of 4.73 hours and a distance of 58.21 km. Portsmouth requires the use of 3 trucks. Truck 1 must fulfill routes 2 and 10 on the same day as well as routes 4 and 11 on the same day. The clusters and all of the routes are shown in Figures 47, 48, 49. The individual routes of Portsmouth are displayed in Appendix G.

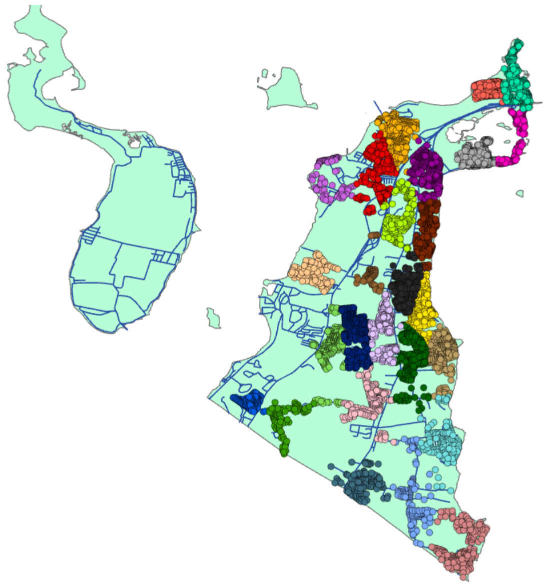


Figure 47. Preliminary clustering rsults in Portsmouth, RI

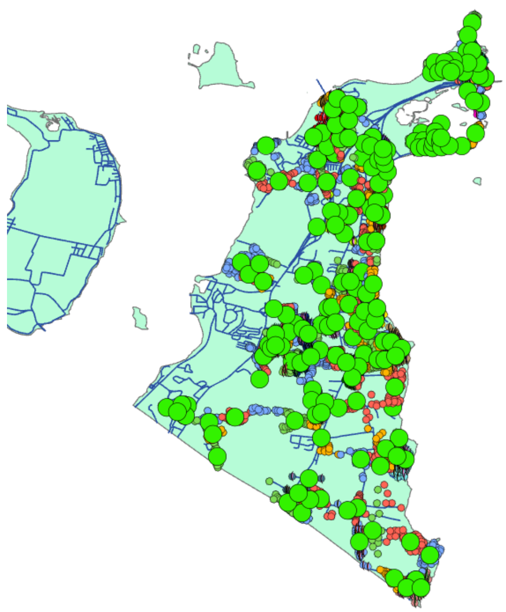


Figure 48. Final clustering results of Portsmouth, RI

4.15 Portsmouth Cost and Emission Results

For Portsmouth, total travel distance of all trucks is found to be 265.33 miles and an estimated total of 88.44 gallons of diesel is required to complete the routes. The estimated price for diesel is \$547.82 and the weekly wages are estimated to

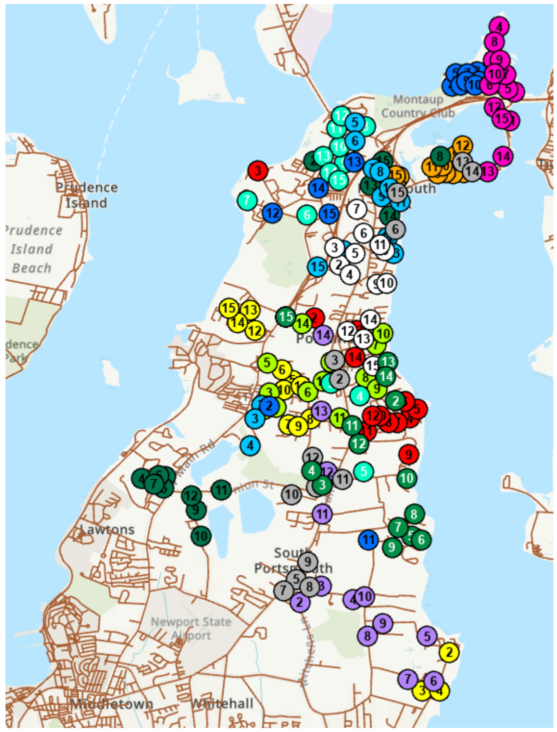


Figure 49. All routes in Portsmouth, RI

be $2,739.12. In total, 43.67 tons of estimated recyclables are hauled resulting in 5178.28 ton-miles a week. The total CO_2 emission estimate for the municipality of Portsmouth is 8.38 metric tons. The individual break down of costs and emissions of trucks can be found in Appendix G.

4.16 Richmond Clustering and Routing Results

Richmond is a small municipality in south western Rhode Island. It has an estimated population of 8,165, a land area of 40.32 square miles and a population per square mile of 198.9 [19]. Richmond is the third smallest municipality in this study resulting in the formation of 66 nodes and a total solution time of 79,949 seconds. A total of 1,860 households are identified with 28.18 households per node in Richmond. The depot location identified for this problem is the Richmond Transfer Station located at 51 Buttonwoods Rd [12]. The genetic algorithm produced a total of 5 routes, similar to Little Compton. Only a singular route fulfilled the capacity and the other 4 determined a capacity of 13. The shortest route in total duration also had the shortest total travel distance and is identified as route 2. The total duration is found to be 4.57 hours with a total route distance of 51.07 km. The longest total duration is found in route 3, which completes the total duration and distance at 5.51 hours and 88.33 km, respectively. The longest total distance is observed in route 5 completing the journey in 99.3 km within 5.42 hours. A single truck is assigned to perform all 5 routes within Richmond. The clusters and all of the routes are shown in Figures 50, 51, 52. The individual routes of Richmond are displayed in Appendix H.

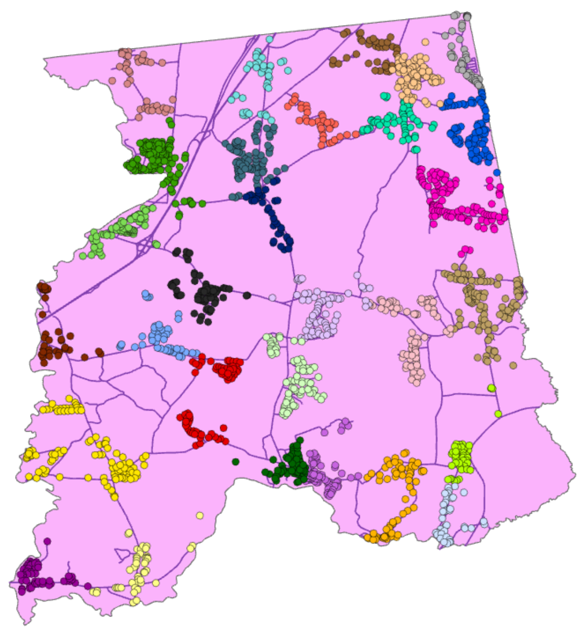


Figure 50. Preliminary Clustering Results in Richmond, RI

4.17 Richmond Cost and Emission Results

With Richmond being one of the smallest municipalities by population, it has lower estimated costs and emissions. In total, 229.59 miles are traversed with a need of 76.53 gallons of diesel estimated. The diesel price estimation is $474.02 and wages are $1255.81. The estimated total recyclables hauled within the munic-

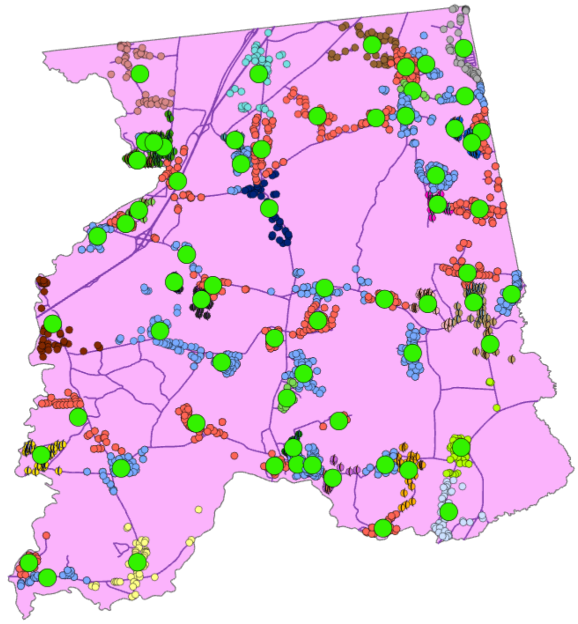


Figure 51. Final clustering results of Richmond, RI

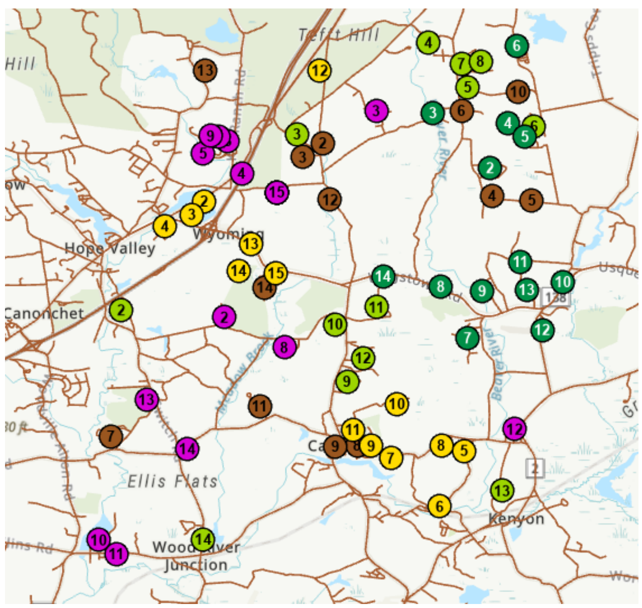


Figure 52. All routes in Richmond, RI

ipality is 13.57 tons and 3114.73 ton-miles. Together, it is estimated the Richmond produces 5.04 metric tons of CO2.

4.18 Scituate Clustering and Routing Results

Scituate is a Rhode Island municipality located in the center of the state. It has an estimated population of 10,404 and land area of 48.13 square miles. It is calculated that the population density is 215.7 people per square mile [20]. Of the 3,071 houses identified in Scituate, 115 nodes are created with an average of 26.7 houses per node. The depot used for Scituate is the transfer station located at 121 Chestnut Hill Road in Chepachet, RI [12]. Scituate uses the same transfer station as Glocester becuase there is no transfer station in Scituate. The genetic algorithm determined a total of 9 routes are needed to service all of the nodes within Scituate at a total solution time of 184,302 seconds. Only 2 of the 9 routes fulfilled a capacity of 14 with the lowest capacity being 10 nodes per route. The shortest total duration and distance is identified in route 9 as 3.52 hours and 54.17 km, respectively. The longest total duration and distance is identified in route 3 as 5.29 hours and 105.75 km, respectively. A total of 2 trucks are assigned to service all of the routes in Scituate. There is no requirement for a truck to service multiple routes within a single day. The clusters and all of the routes are shown in Figures 53, 54, 55. The individual routes of Scituate are displayed in Appendix I.

4.19 Scituate Cost and Emission Results

Scituate requires a total travel distance of 404.3 miles and an estimated 134.77 gallons of diesel to perform all of the routes. The fuel cost of Scituate is estimated to be $404.30 and the wages estimate is $1,974.72. The municipality of Scituate hauls approximately 26.50 tons of recyclables resulting in 5,746.65 ton-miles. Together it is estimated that Scituate recycling hauling produces 9.30 metric tons of CO_2. The individual break down of costs and emissions of trucks can be found in Appendix I.

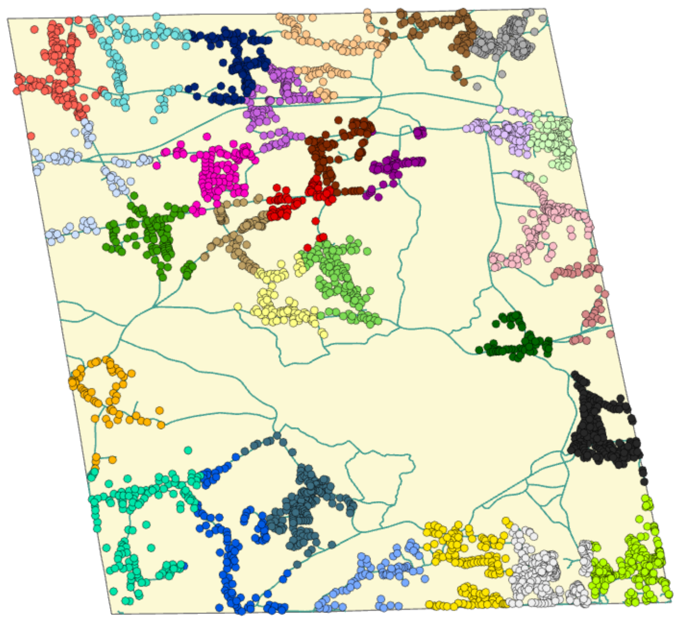


Figure 53. Preliminary clustering results in Scituate, RI

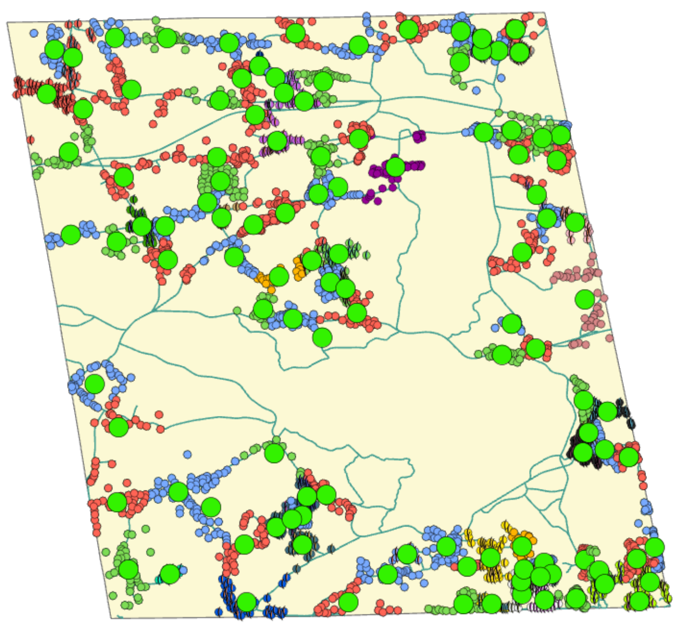


Figure 54. Final clustering results of Scituate, RI

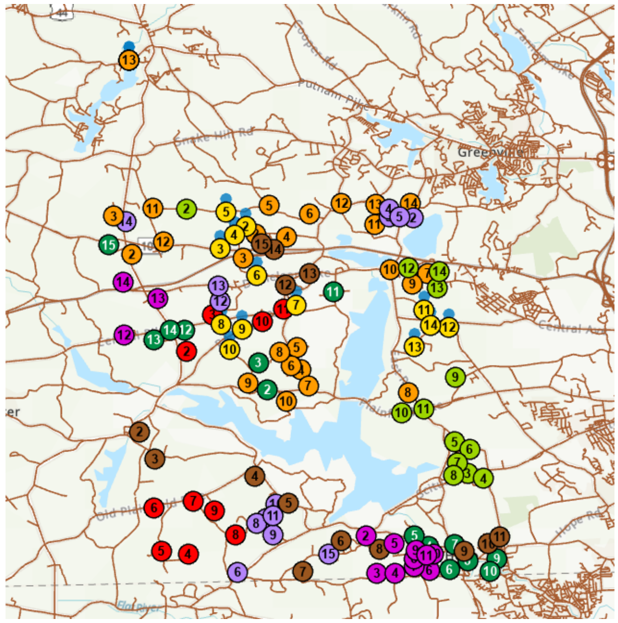


Figure 55. All routes in Scituate, RI

4.20 Westerly Clustering and Routing Results

Westerly is the most south western municipality in the state of Rhode Island. Westerly has a population of 23,483 and a land area of 29.47 square miles. Westerly has a population density of 792.7 people per square mile [21]. Westerly is one of the largest towns with over 8,616 houses identified. The model created 283 nodes making it the largest problem within the study. It was found that there are 30.45 households per cluster in Westerly. The depot identified for this municipality is called the Westerly landfill and transfer station located at 39 Larry Hirsch Lane [12]. The genetic algorithm determined that 21 routes are needed to service all of the households in Westerly, similar to Pawtucket and South Kingstown. A total solution time of 260,673 seconds is provided from the genetic algorithm. It was determined that 13 of the 21 routes fulfilled the maximum capacity constraint. The lowest capacity was found to be 11 but was not the shortest in distance or duration. The total shortest duration and distance is identified in route 1, with a duration of 3.79 hours and distance of 30.5 km. The total longest duration and distance is identified in route 7 with a total duration of 5.72 hours and distance of 113.79 km. It is determined that 4 trucks are required to service the 21 nodes in Westerly. The only truck that is required to service more than one route in a single day is truck 2. Truck 2 is required to service route 1 and 21 on the same day. The clusters and all of the routes are shown in Figures 56, 57, 58. The individual routes of Westerly are displayed in Appendix J.

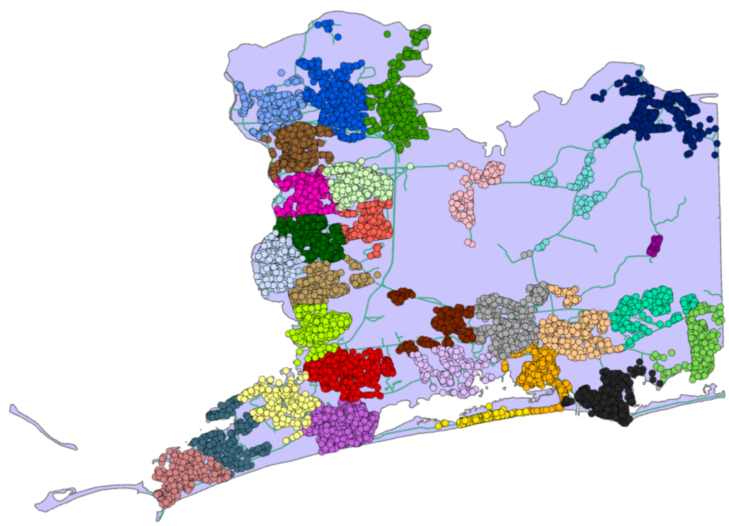


Figure 56. Preliminary clustering results in Westerly, RI

4.21 Westerly Cost and Emission Results

With Westerly being the largest problem set in the study, 730.99 miles is the total travel time to service all of the nodes. An estimated 243.66 gallons of fuel is required to traverse the entire route. The estimated cost of diesel is found to be \$1,509.25 and the estimated wages are \$4,815.90. Overall, Westerly is estimated to collect 114.24 tons of recyclables. The ton-mile value is calculated as 20,879.15. Therefore, it is estimated that Westerly produces 33.78 metric tons of CO_2 on recycling hauling. The individual break down of costs and emissions of trucks can be found in Appendix J.

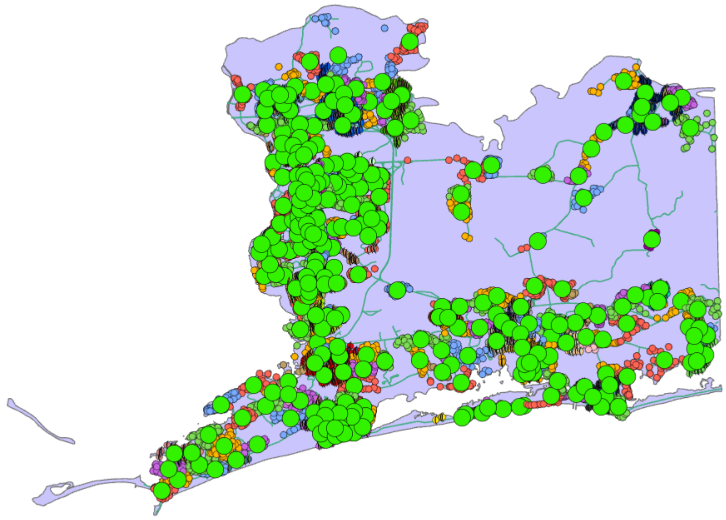


Figure 57. Final clustering results of Westerly, RI

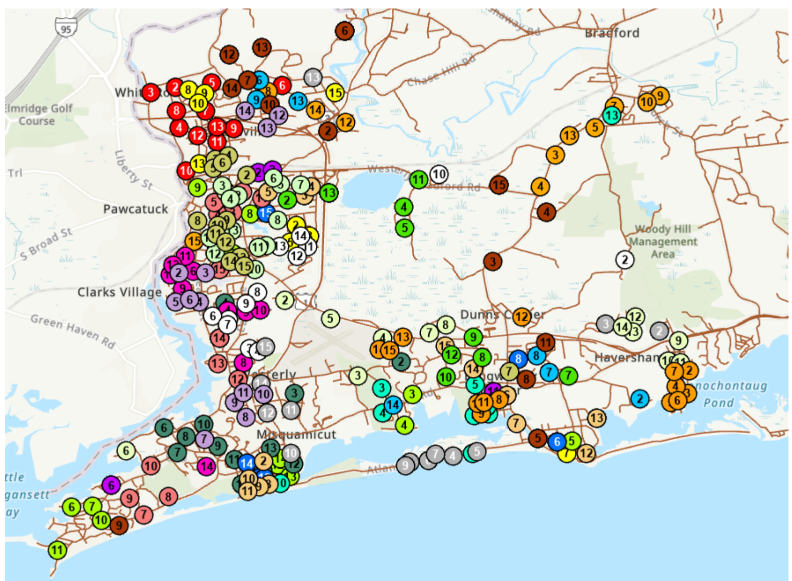


Figure 58. All routes in Westerly, RI

4.22 West Warwick Clustering and Routing Results

The final municipality examined in Rhode Island is West Warwick. West Warwick can be found in the central part of the State of Rhode Island. West Warwick has a population estimate of 31,188, land area of 7.83 square miles and a population density of 3,959.7 [22]. It is a little over half of the size of Pawtucket and is the most similar municipality to Pawtucket. In West Warwick of the 6,223 houses identified, a total of 208 nodes are created with around 29.92 houses per node. There is no transfer station in West Warwick, instead the Warwick transfer station and recycling center on 65 O'Keefe Lane, Warwick is used as the depot [12]. The genetic algorithm created a total of 16 routes, exactly as Bristol, and a total solution time of 277,693 seconds. Half of the routes fulfilled the maximum capacity constraint while the smallest route only contained 5 nodes. The total shortest duration and distance is identified in route 16, which contains only 5 nodes. The total duration is found to be 1.67 hours and total travel distance is found to be 18.74 km. The total longest duration and distance is identified in route 1 with a duration of 4.7 hours and distance of 49.34 km. A total of 3 trucks are assigned to service all of the routes. Truck 2 is required to service routes 5 and 13 on a single day. Truck 3 is also required to service routes 3 and 16 on a single day. The clusters and all of the routes are shown in Figures 59, 60, 61. The individual routes of West Warwick are displayed in Appendix K.

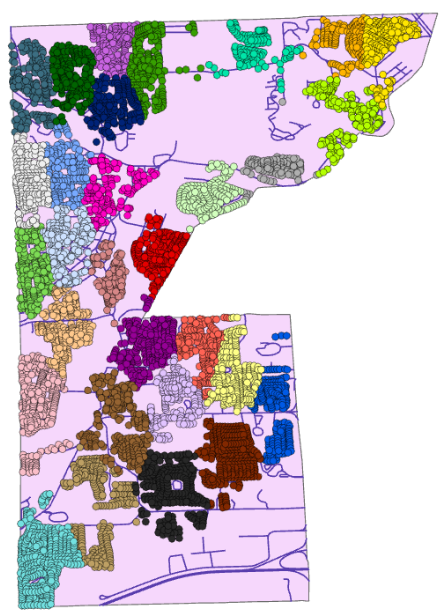


Figure 59. Preliminary clustering results in West Warwick, RI

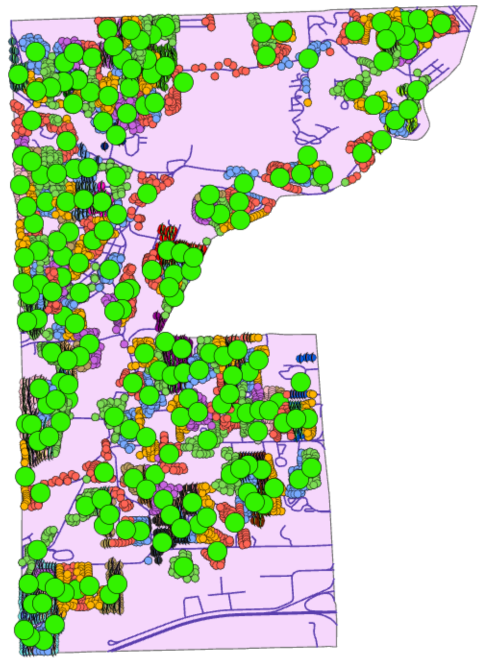


Figure 60. Final clustering results of West Warwick, RI

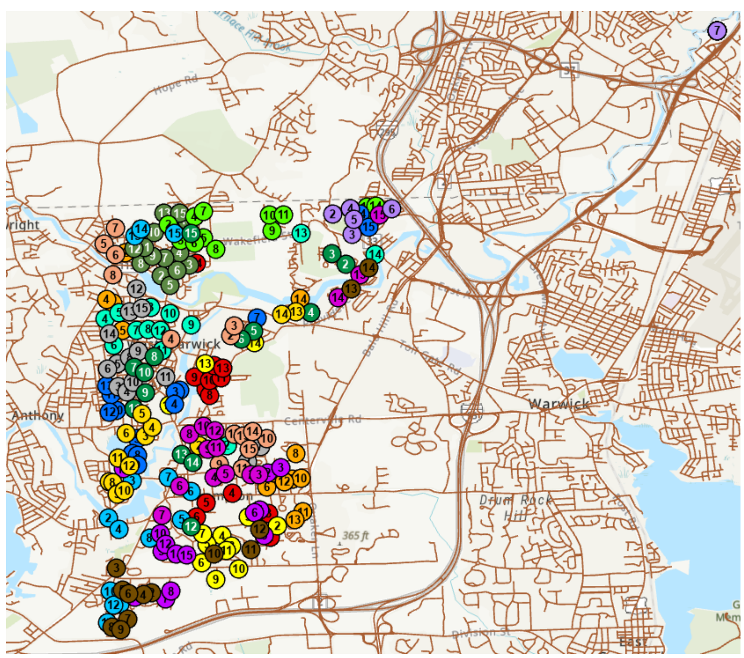


Figure 61. All routes in West Warwick, RI

4.23 West Warwick Cost and Emission Results

The final municipality of West Warwick has a total distance traveled of 379.48 miles. The estimated gallons required is 126.49 spread across the three trucks. The estimated cost of diesel is $783.49 and the wage estimate is $3282.01. In West Warwick the estimated amount of recyclables hauled is 40.71 tons which equates to 5,213.36 ton-miles. With this information the calculated estimation of CO_2 emission within the municipality of West Warwick is 8.44 metric tons. The individual break down of costs and emissions of trucks can be found in Appendix K.

4.24 Comparison of Cities

At the conclusions of the study, two municipalities stood out with the overall traveled distance. The municipalities of Westerly and South Kingstown have the two highest total weekly distances of 643.71 miles and 730.99 miles, respectively. This is mostly likely due to the large land area of the two municipalities along with having similar populations in a low population density area. The two lowest distances of total travel belong to Little Compton and Glocester. These two municipalities have low populations within the State of Rhode and the least amount of nodes and houses. This resulted in fewer trucks being needed to service the municipality, resulting in a total travel distance of 179.43 miles for Little Compton and 209.10 miles for Glocester. West Warwick has similar characteristics to Pawtucket and Bristol, however the total traveled distance is around 100 total miles larger. The main contributing factor to this is likely because of the depot being located in another municipality. Figure 62 is a comparison of all of the total weekly distances.

In regards to fuel, the two largest municipalities are Westerly and South Kingston due to having the highest traveled distances. Scituate has similar land

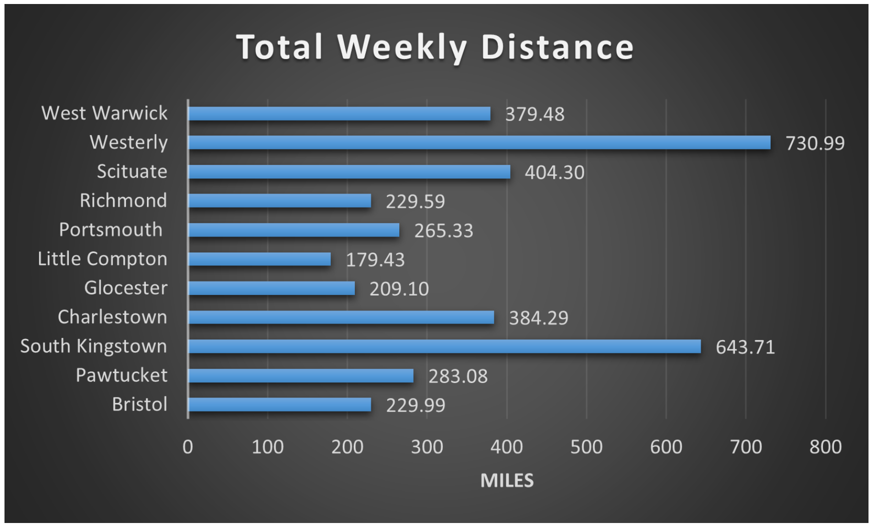


Figure 62. Comparison of total weekly distances in Rhode Island municipalities

area and road network characteristics when compared with Glocester and Richmond, however it contains a significant increase in fuel compared to the two. The main contributing factor is that there are 2 trucks used within Scituate compared to a single truck in Richmond and Glocester. This shows the significant increase in fuel when using multiple trucks in rural areas, which also affects other aspects within the study. Figure 63 is a comparison of the total weekly gallons of diesel consumed.

The total weekly routes of Pawtucket and Westerly produced 21 routes to service the municipality. The likely reason why they are similar in results while having significantly different population and land areas is due to the proximity of nodes. While Pawtucket may have dense clusters of nodes, there is a large populace with many households. Westerly has a smaller population but the sparsity of nodes is greater meaning the truck is constrained to the duration. This requires Westerly to create more routes to stay within the time bound. South Kingston has a similar characteristic to Westerly facing the same challanges. Richmond, Little Compton, and Glocester have some of the lowest populations. The amount of residential

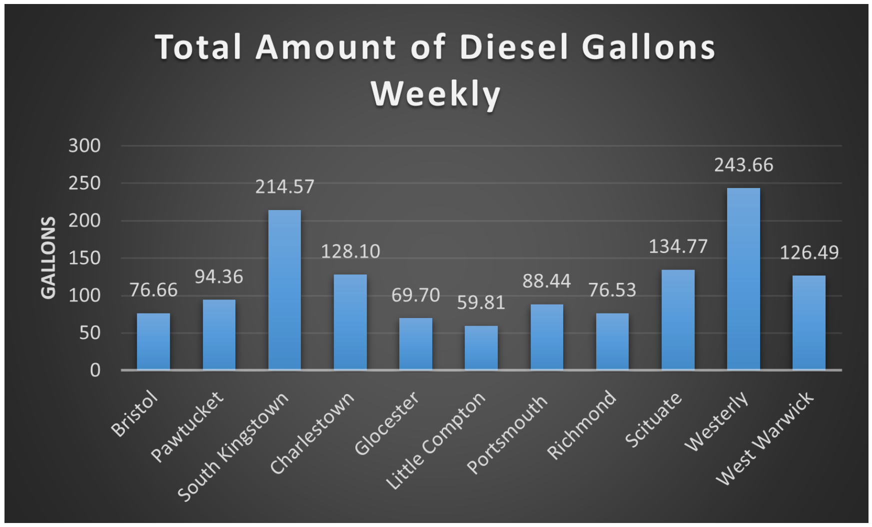


Figure 63. Comparison of total weekly fuel consumption in Rhode Island municipalities

households reflects the low amount of routes required to service the municipality. Displayed in Figure 64 is a comparison of the total weekly routes of municipalities.

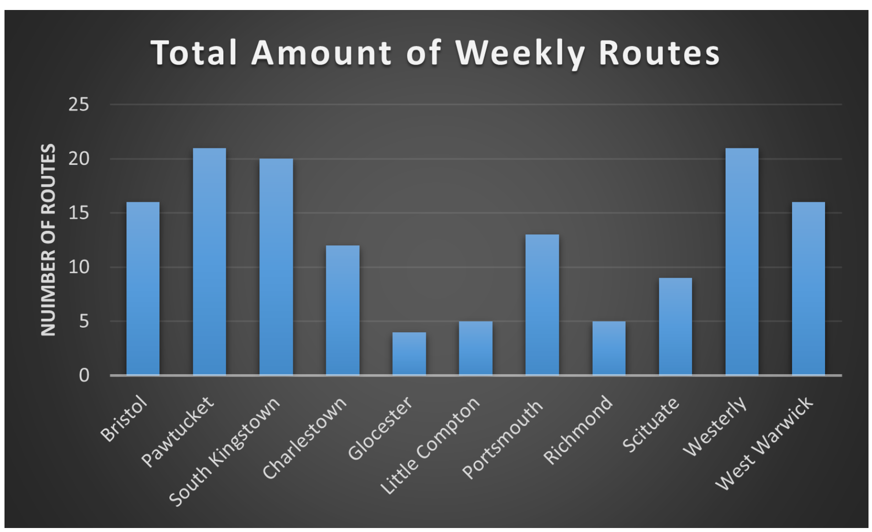


Figure 64. Comparison of total weekly routes in Rhode Island municipalities

Westerly has the highest total fuel cost of $1,509.25 due to the long travel distance and duration between nodes and the large amount of routes to be fulfilled. In comparison, Pawtucket also services a large number of routes but only requires a total fuel cost of $584.47 compared to Westerly. This is significant showing the cost of diesel is favorable to municipalities with high population densities. This is also shown by Pawtucket having a total value slightly higher than municipalities such as Glocester and Richmond, which only service between 50 and 70 nodes compared to Pawtucket that services 277 nodes. Figure 65 is a comparison of the total weekly fuel cost within municipalities.

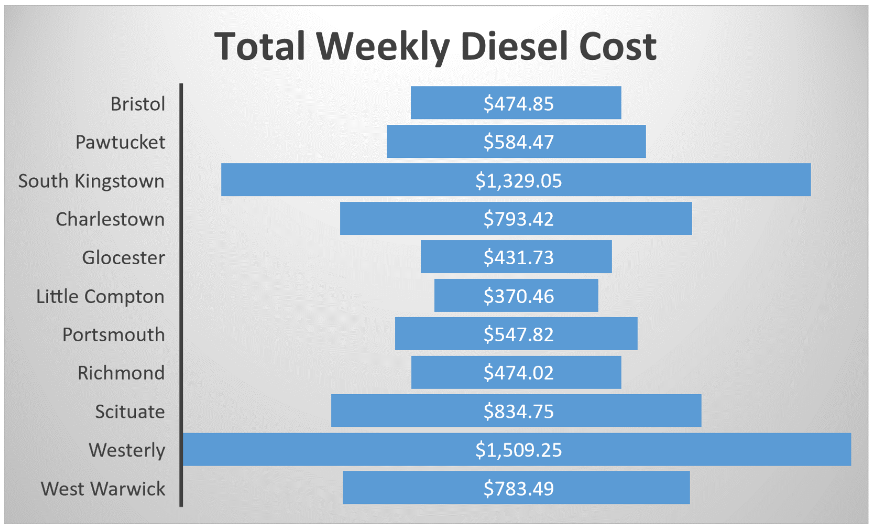


Figure 65. Comparison of total weekly fuel cost in Rhode Island municipalities

Even with densely populated municipalities, the main contributing factor to wages is the amount of trucks required to service the municipality. Pawtucket does not spend as much on fuel, however it is does need a similar value of wages as South Kingston and Westerly. This shows that the amount of trucks and crew members is more significant than the hours actually spent working along the route. Displayed in Figure 66 is a comparison of the total weekly wages required within municipalities.

The largest contributing municipality to CO2 emissions is Westerly and South Kingstown. This is mostly likely due to the amount of nodes within the municipality and the amount of recyclables collected. Displayed earlier in Table 2, these

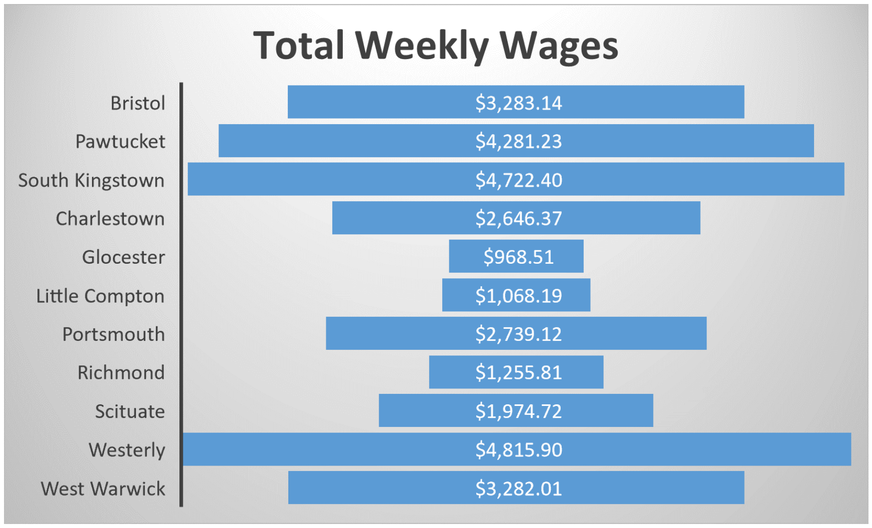


Figure 66. Comparison of total weekly wages in Rhode Island municipalities

two municipalities have large involvement in their recycling program. Along with the hauled tonnage and the large distance traveled between nodes, this results in the large value. This can also be seen between Pawtucket and Scituate. These two municipalities are significantly different in size and land area but even with Scituate having a higher participation in recycling, Scituate displays a higher total CO2 emission than Pawtucket. Displayed in Figure 67 is a comparison of the total weekly CO2 emissions within Rhode Island municipalities. The conclusion chapter summarizes the main findings discovered within this chapter.

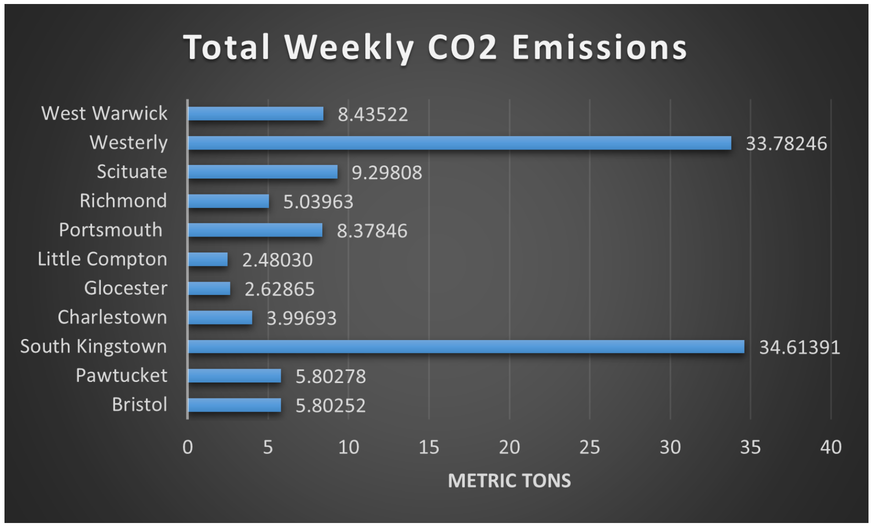


Figure 67. Comparison of total weekly CO2 emissions of recycling hauling in Rhode Island municipalities

List of References

[1] S. Bryant, "How close to your property line can you build?" Dec 2021. [Online]. Available: https://www.rockethomes.com/blog/homeowner-tips/how-close-can-you-build-to-property-line

[2] G. S. Sandhu, H. C. Frey, S. Bartelt-Hunt, and E. Jones, "In-use activity, fuel use, and emissions of heavy-duty diesel roll-off refuse trucks," *Journal of the Air & Waste Management Association*, vol. 65, no. 3, pp. 306–323, 2015.

[3] G. S. Sandhu, H. C. Frey, S. Bartelt-Hunt, and E. Jones, "Real-world activity, fuel use, and emissions of diesel side-loader refuse trucks," *Atmospheric Environment*, vol. 129, pp. 98–104, 2016.

[4] D. C. Vock, "A quiet revolution in trash trucks," Apr 2021. [Online]. Available: https://www.governing.com/archive/gov-to-save-on-trash-trucks-cities-take-a-look-at-the-gas-tank.html

[5] AAA, "R.I. average gas prices," Jun 2022. [Online]. Available: https://gasprices.aaa.com/?state=RI

[6] "Garbage collector salary," Oct 2021. [Online]. Available: https://www.careerexplorer.com/careers/garbage-collector/salary/rhode-island/

[7] J. Mathers, C. Wolfe, M. Norsworthy, and E. Craft, "The green freight handbook," *Environmental Defense Fund*, 2014.

[8] D. Gradišar and M. Glavan, "Material requirements planning using variable-sized bin-packing problem formulation with due date and grouping constraints," *Processes*, vol. 8, no. 10, p. 1246, 2020.

[9] A. Mason, "Opensolver – an open source add-in to solve linear and integer progammes in excel," in *Operations Research Proceedings 2011*, ser. Operations Research Proceedings, D. Klatte, H.-J. Lathi, and K. Schmedders, Eds. Springer Berlin Heidelberg, 2012, pp. 401–406, http://opensolver.org. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-29210-1_64

[10] A. Mason, "Opensolver-an open source add-in to solve linear and integer progammes in excel," in *Operations research proceedings 2011*. Springer, 2012, pp. 401–406.

[11] U. S. C. Bureau, "Quickfacts bristol town, bristol county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/bristoltownbristolcountyrhodeisland

[12] [Online]. Available: https://www.rigis.org/

[13] U. S. C. Bureau, "Quickfacts pawtucket city, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/pawtucketcityrhodeisland/PST045221

[14] U. S. C. Bureau, "Quickfacts south kingstown town, washington county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/southkingstowntownwashingtoncountyrhodeisland/PST045221

[15] U. S. C. Bureau, "Quickfacts charlestown town, washington county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/charlestowntownwashingtoncountyrhodeisland/PST045221

[16] U. S. C. Bureau, "Quickfacts glocester town, providence county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/glocestertownprovidencecountyrhodeisland/PST045221

[17] U. S. C. Bureau, "Little compton town, newport county, rhode island." [Online]. Available: https://www.census.gov/search-results.html?searchType=web&cssp=SERP&q=Little%20Compton%20town,%20Rhode%20Island

[18] U. S. C. Bureau, "Quickfacts portsmouth town, newport county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/portsmouthtownnewportcountyrhodeisland/PST045221

[19] U. S. C. Bureau, "Quickfacts richmond town, washington county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/richmondtownwashingtoncountyrhodeisland/PST045221

[20] U. S. C. Bureau, "Quickfacts scituate town, providence county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/scituatetownprovidencecountyrhodeisland/PST045221

[21] U. S. C. Bureau, "Quickfacts westerly cdp, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/westerlycdprhodeisland/PST045221

[22] U. S. C. Bureau, "Quickfacts west warwick town, kent county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/westwarwicktownkentcountyrhodeisland/PST045221

CHAPTER 5

Conclusion and Future Work

This study aimed to develop a model that can estimate the recycling transportation and emissions cost within Rhode Island municipalities. The model used the GIS program, ArcPro in conjunction with an OSRM and a genetic algorithm. The study found that suburban municipalities with large populations can expect large travel distances. This also contributes to high amounts of diesel fuel consumption and costs. The number of nodes within a municipality and the density of the nodes contributes to a high amount of routes needed to service a municipality. The total diesel cost is sensitive to distances between nodes and can be significantly reduced in high density population areas. The weekly wages are more sensitive to the amount of workers used for trucks, rather than the total working time. Finally, the largest contributing factors to CO2 emissions is the traveled distance along route networks and the amount of participation within recycling programs. Greater contribution to recycling programs can result in higher amounts of CO2 emissions from vehicles due to the weight.

This model is believed to be in its early stages of development and can be expanded in multiple directions. ArcGIS can be used further with its tools to estimate the distance between houses to better understand what value to assign between inter-node travel. ArcGIS Pro has the potential to utilize the iterator tool providing a quicker and more condensed ModelBuilders. Obtaining empirical data of real-world routes can be significant to have baseline data. These real-world routes can be imported to the genetic algorithm to improve the real-world routes. Gathering problem sets with known optimal solutions can be crucial to understand how close the current problem sets are to optimally. An exploration into the social norms of recycling data in Rhode Island presents the possibility of obtaining better model results. The model has the potential to be modified to analyze the differences between a multi-stream and single-stream recycling system. The model can be modified to explore the collection of both MSW and recyclables through the use of a dual compartmentalized truck. The genetic algorithm can be modified to use an asymmetric matrix changing the CVRP to use a directed graph. This allows for the study to be performed on complete road networks. Finally, the model has the potential to be applied to various problems such as logistics, distribution, and collection in various parts of the world.

APPENDIX A

Bristol

A.1 Routes, Individual Trucks, and Charts

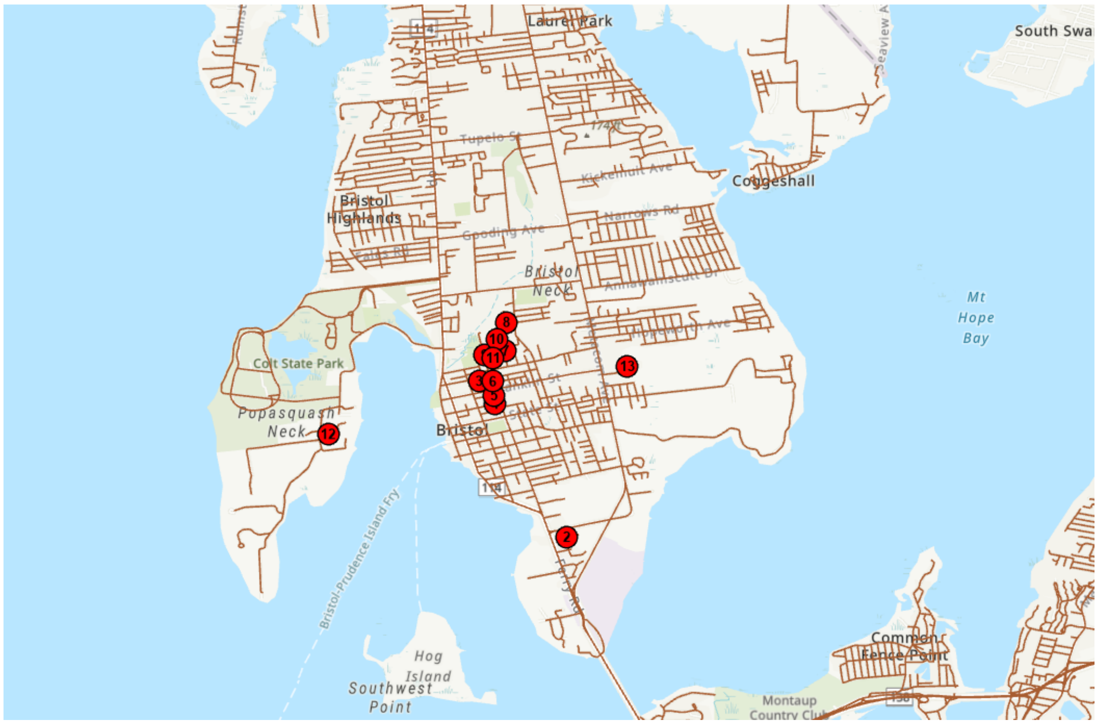


Figure A.68. Bristol Route 1

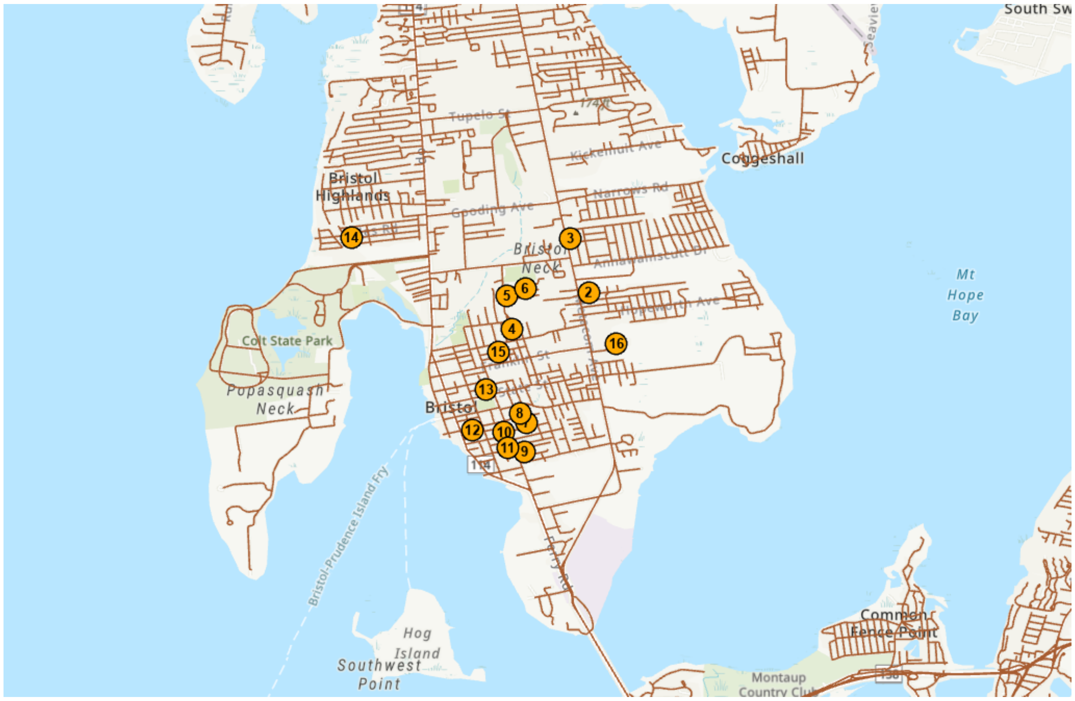
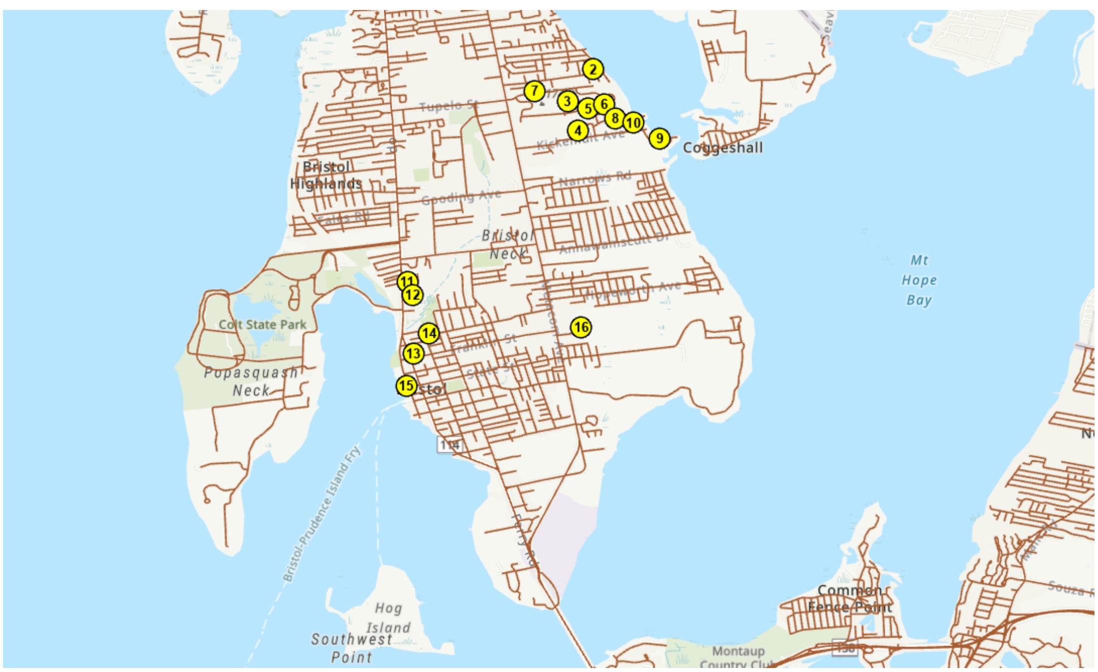


Figure A.69. Bristol Route 2



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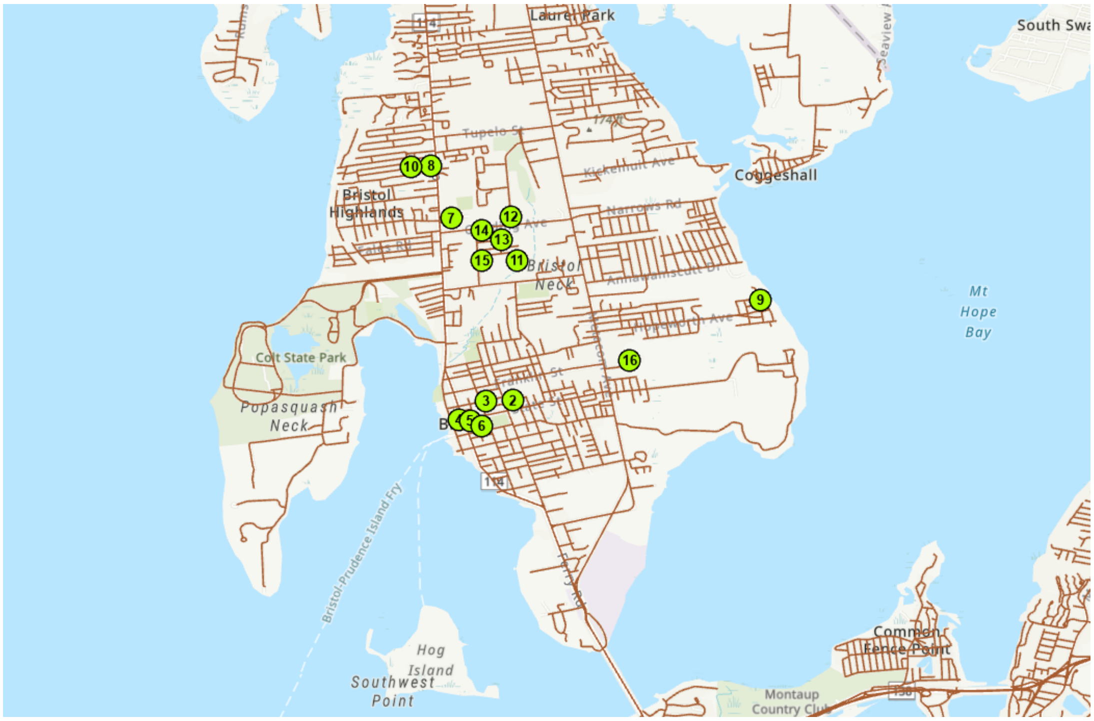

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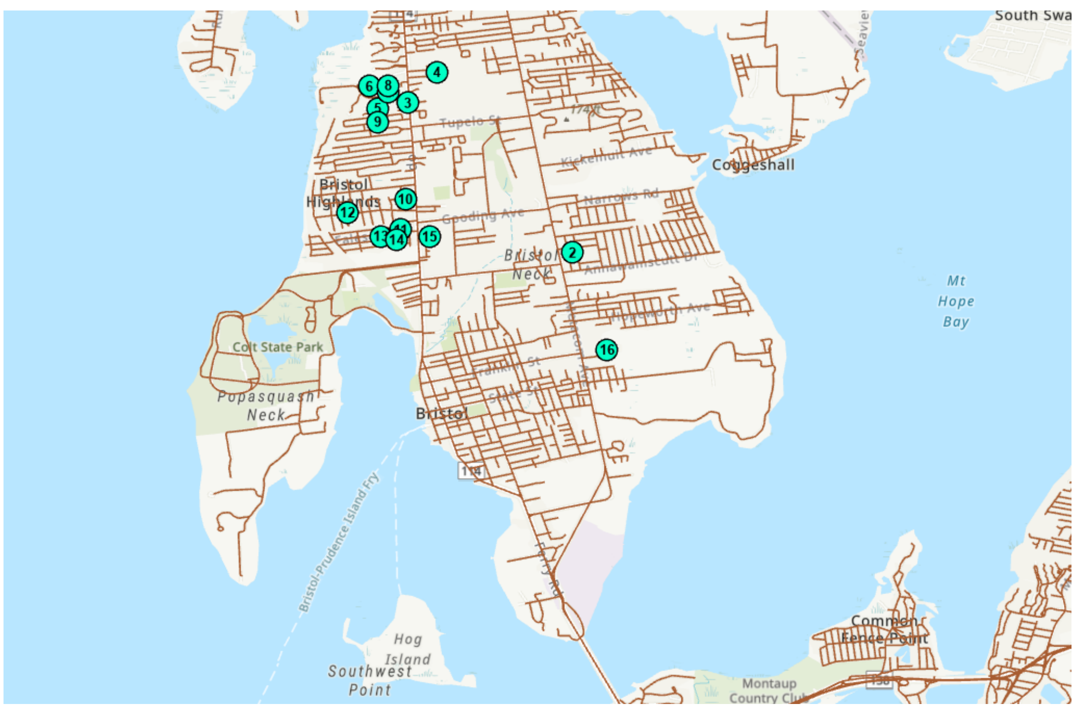

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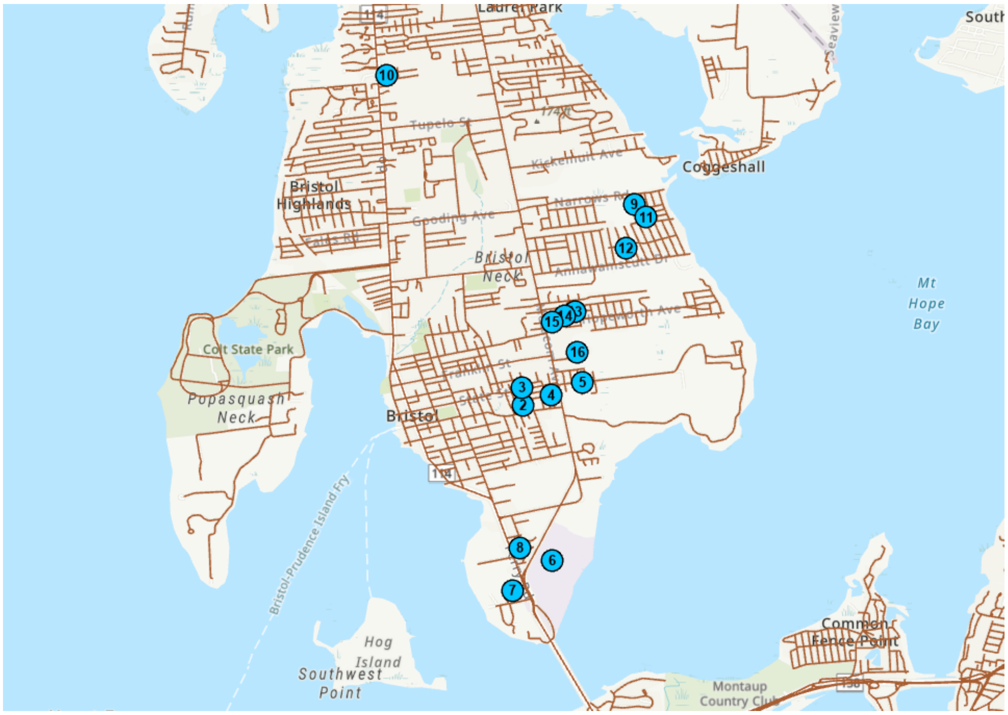


Figure A.73. Bristol Route 6

Figure A.74. Bristol Route 7

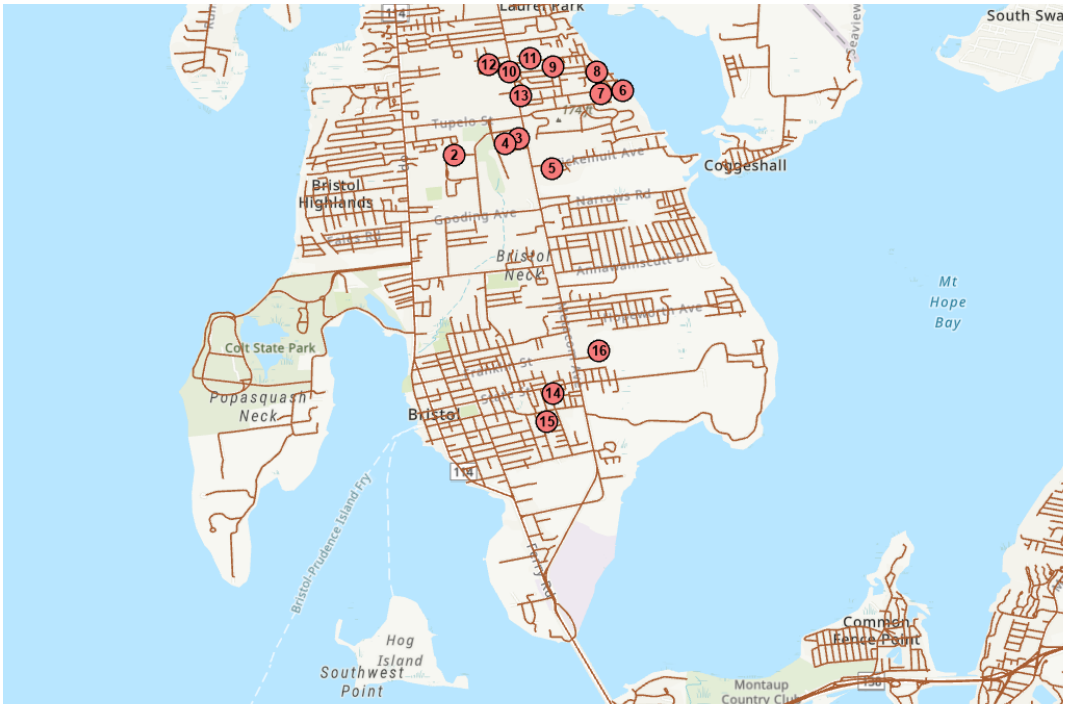


Figure A.75. Bristol Route 8

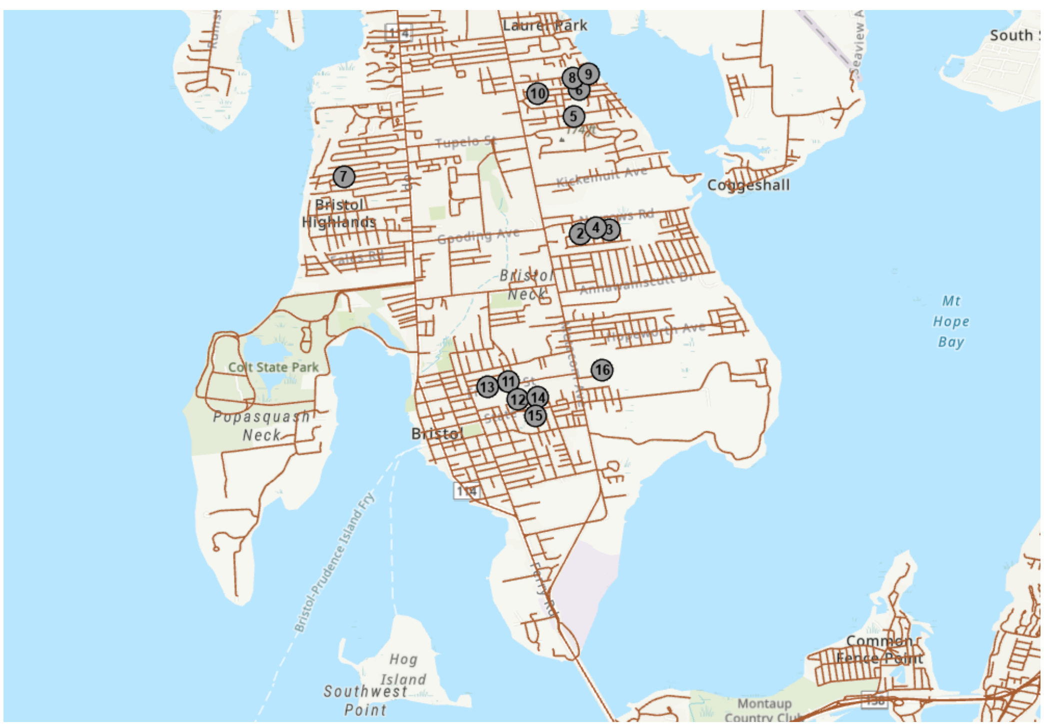


Figure A.76. Bristol Route 9

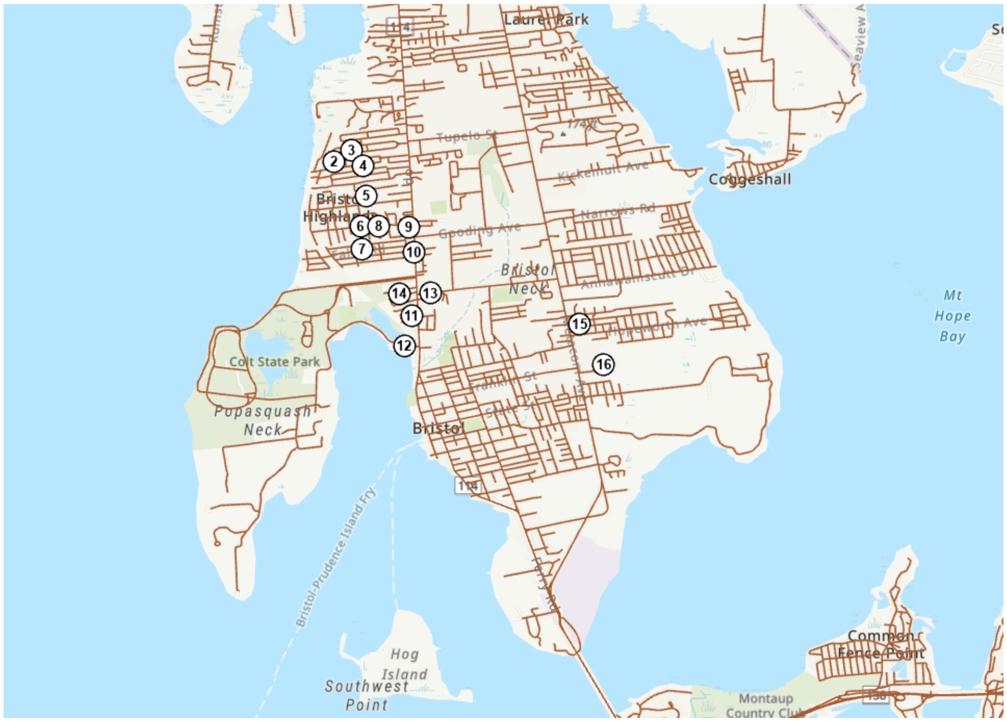
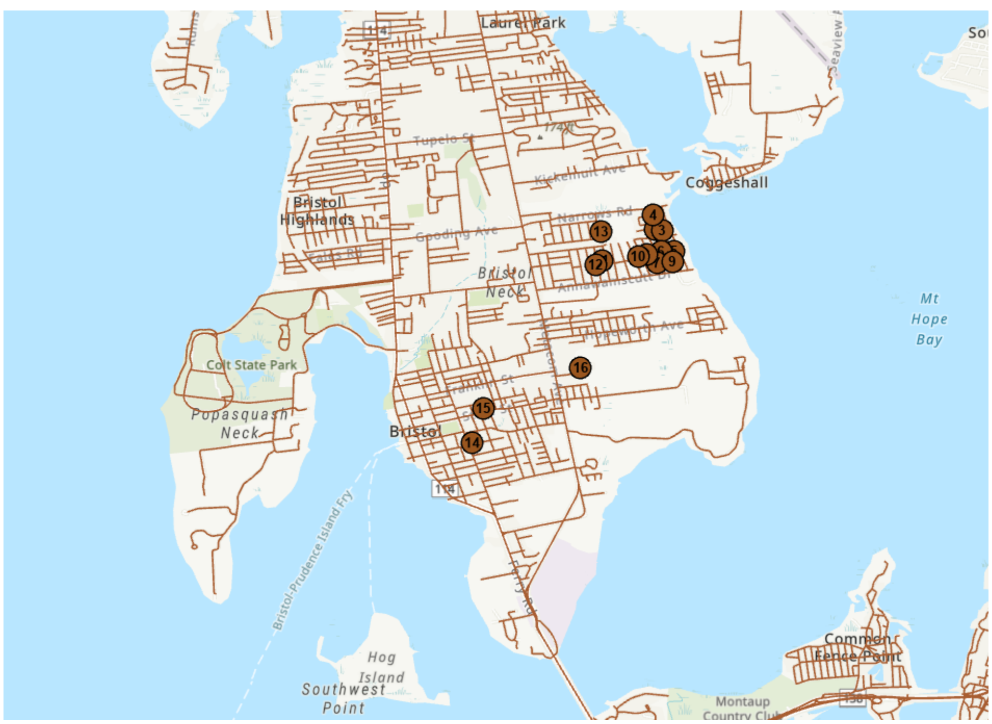


Figure A.77. Bristol Route 10



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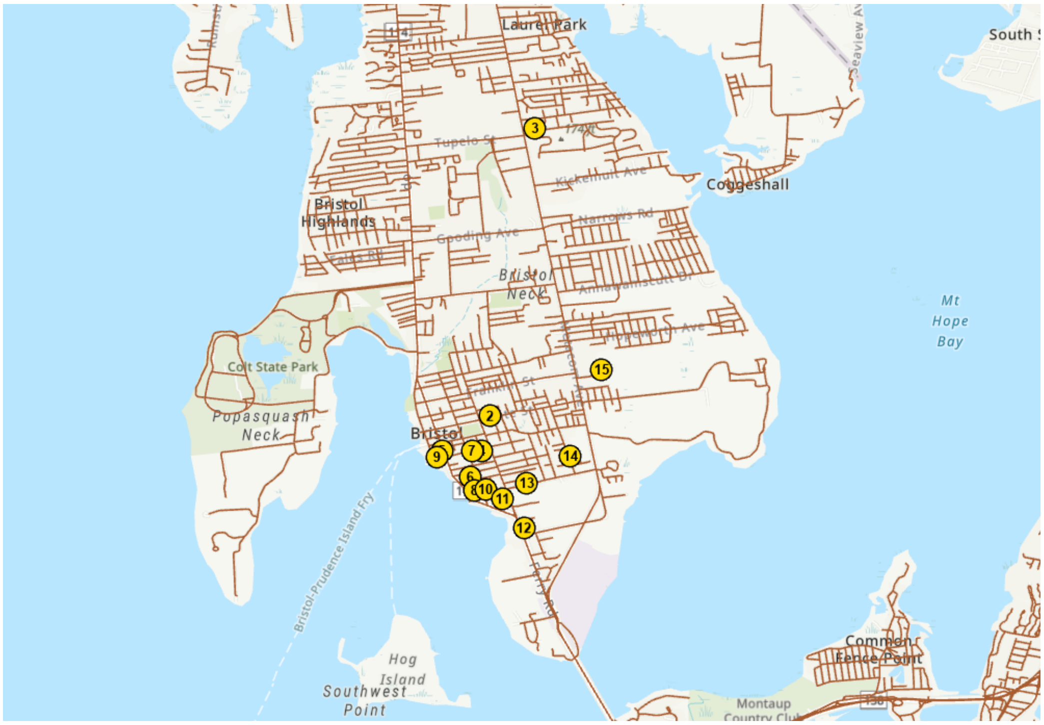

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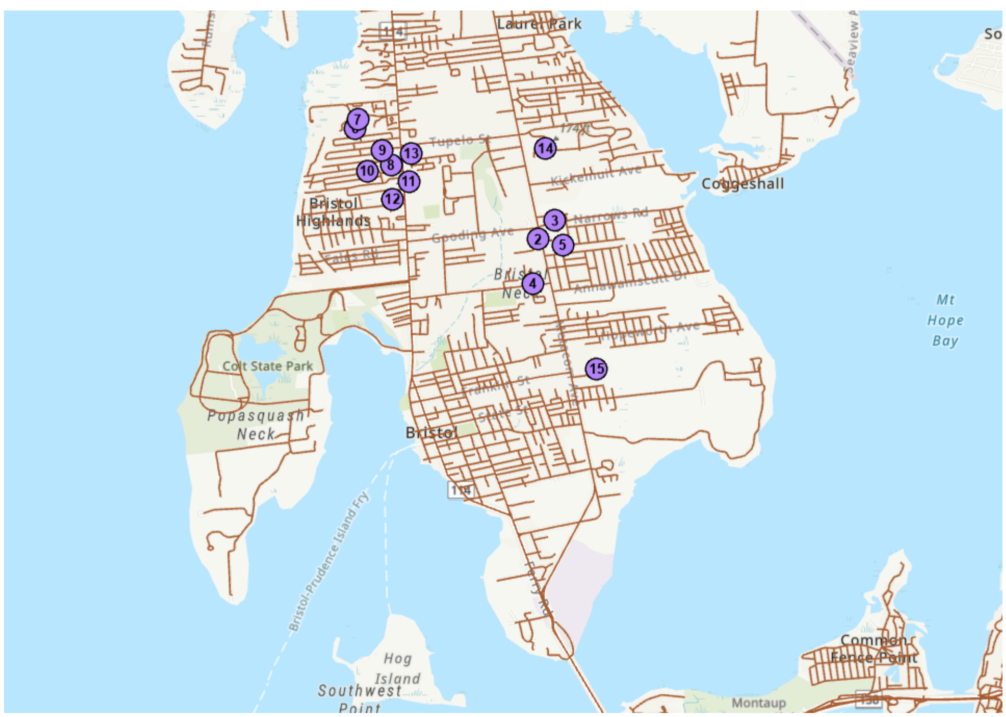

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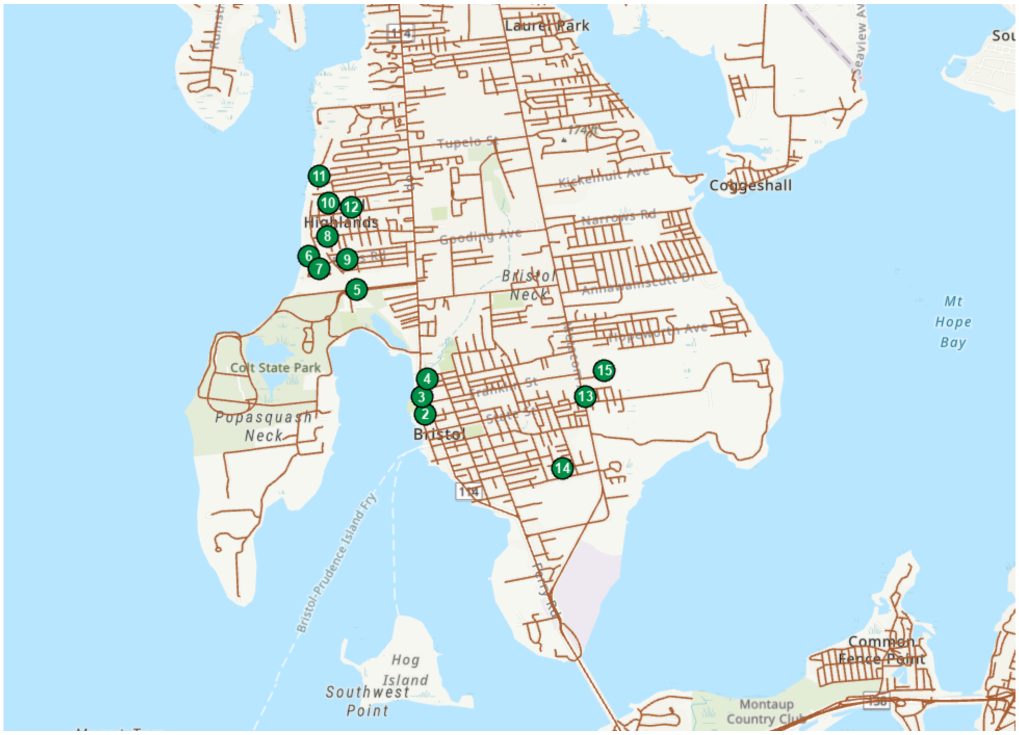

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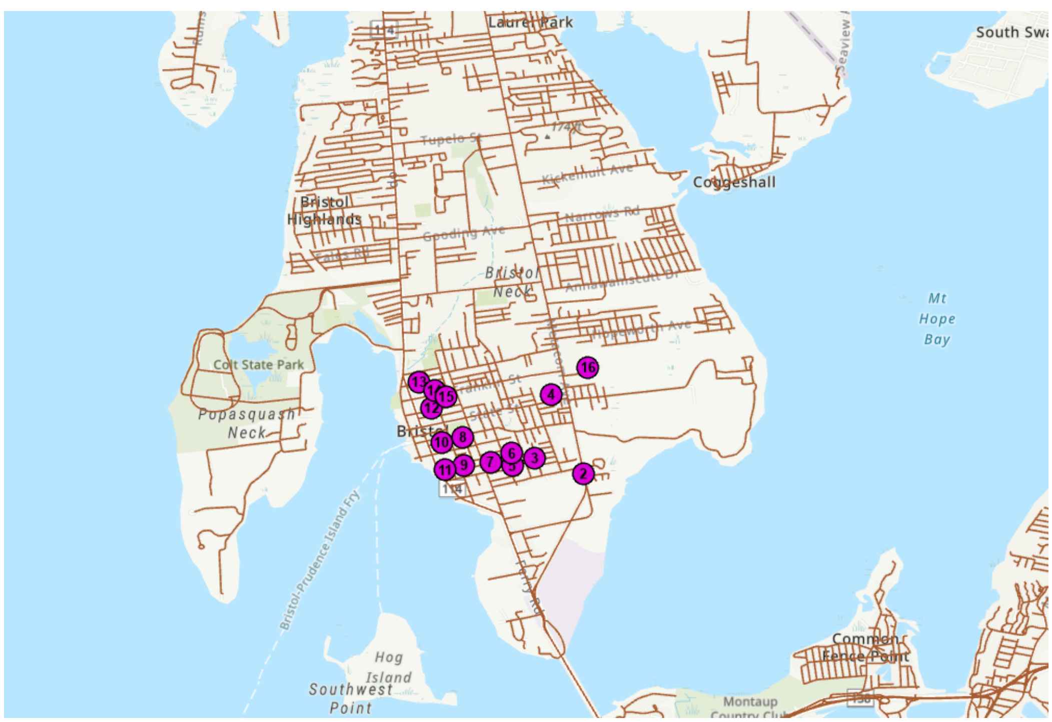


Figure A.82. Bristol Route 15

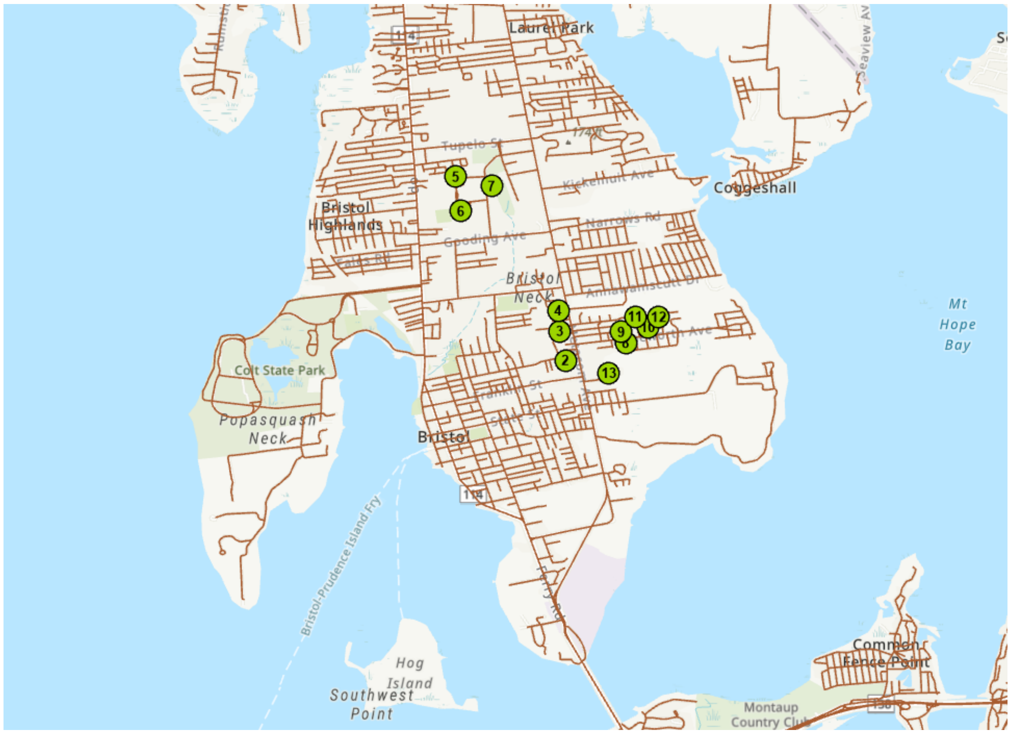


Figure A.83. Bristol Route 16

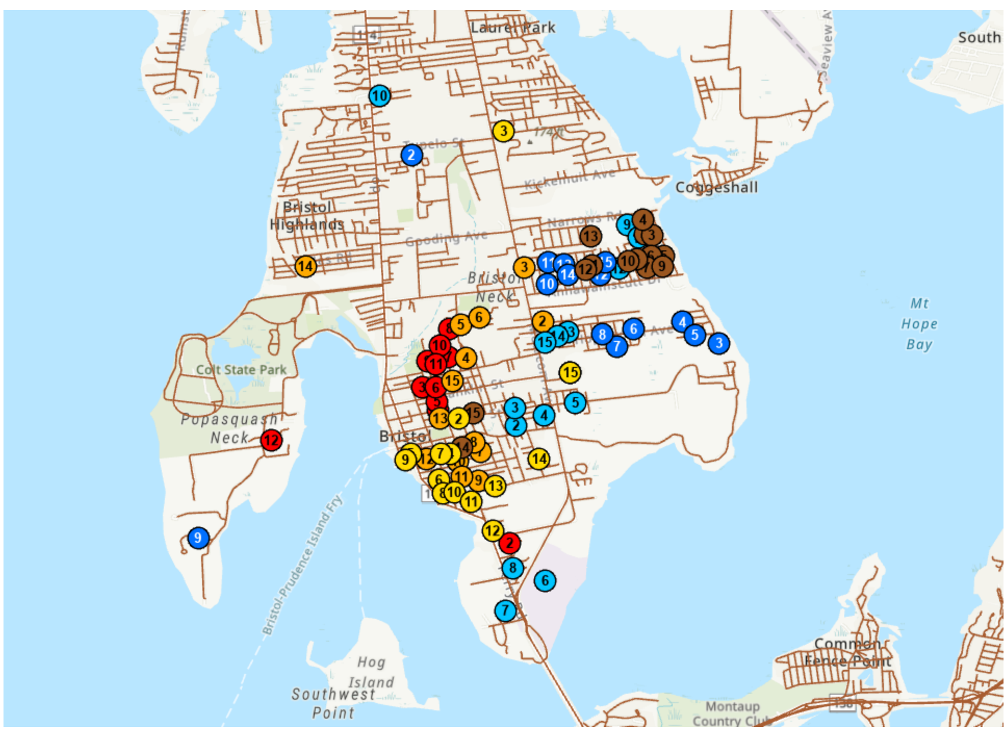


Figure A.84. Bristol Truck 1

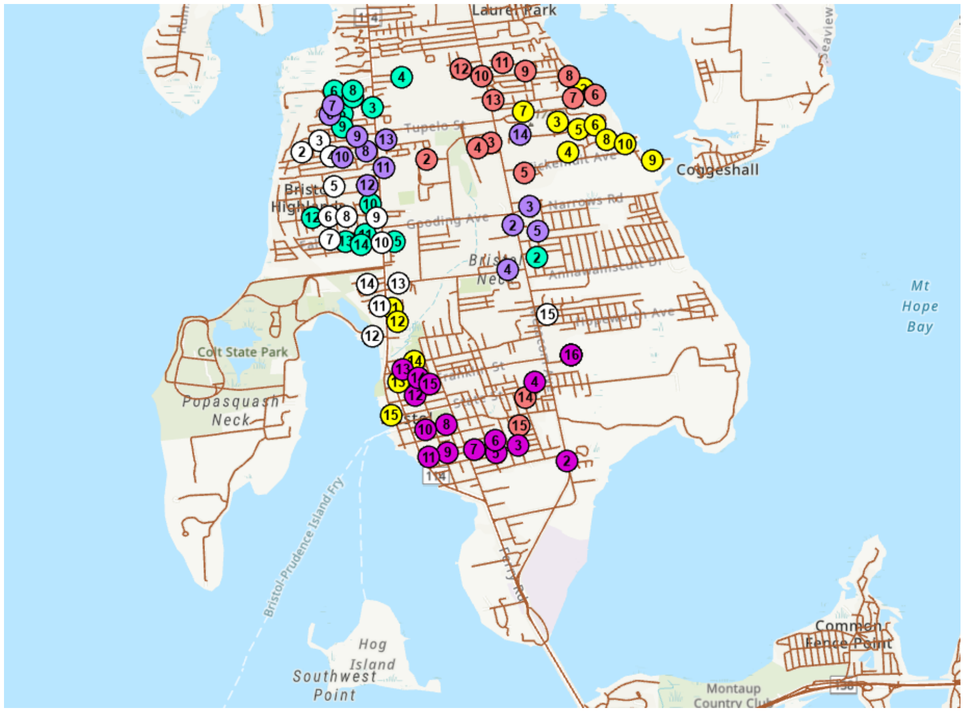


Figure A.85. Bristol Truck 2

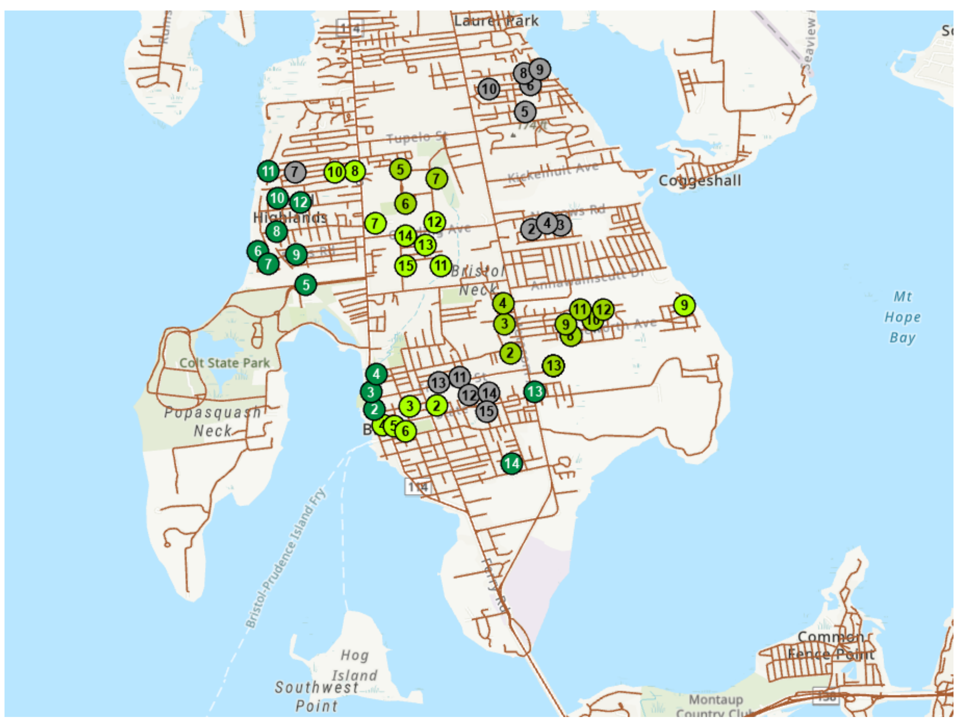


Figure A.86. Bristol Truck 3

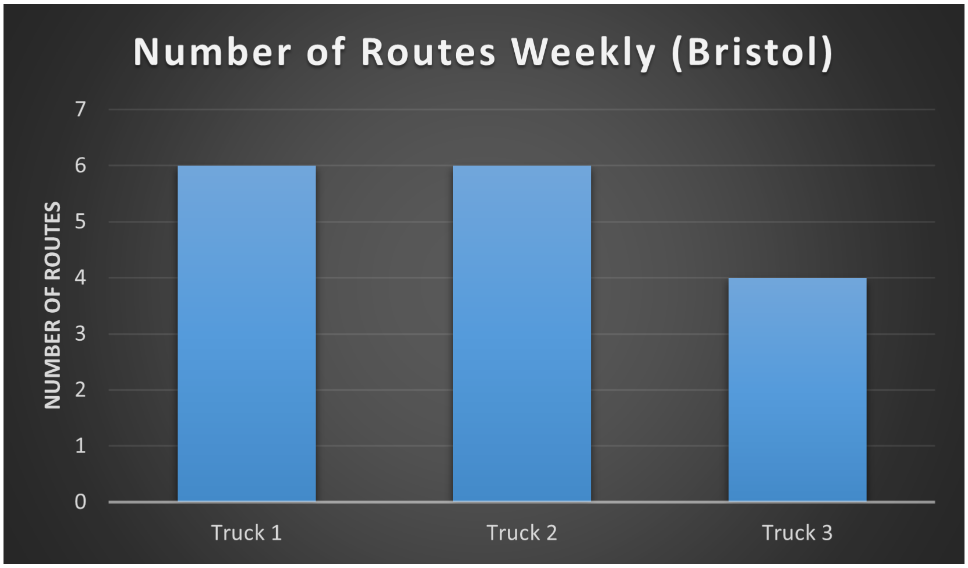


Figure A.87. Number of Routes Weekly (Bristol)

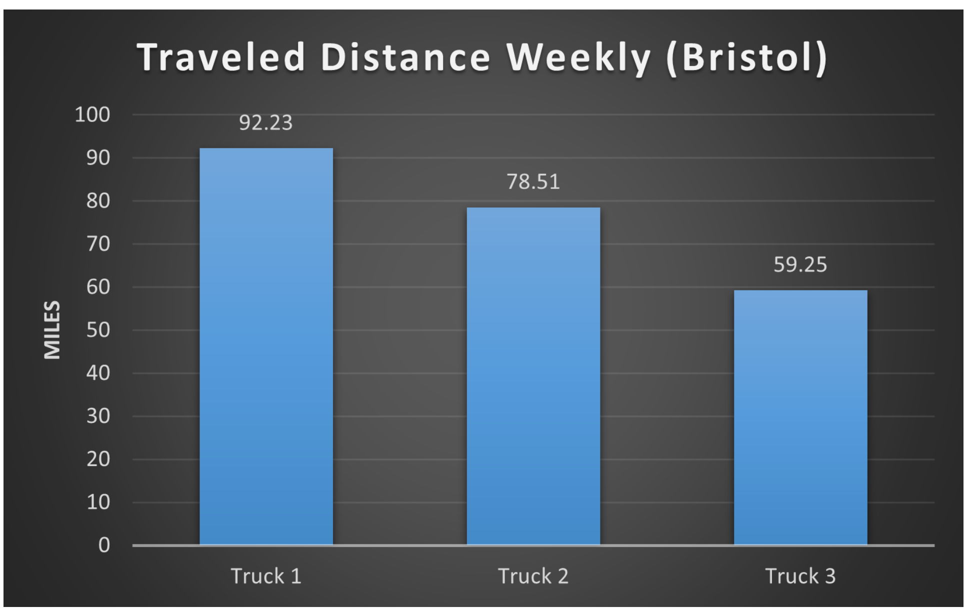


Figure A.88. Traveled Distance Weekly (Bristol)

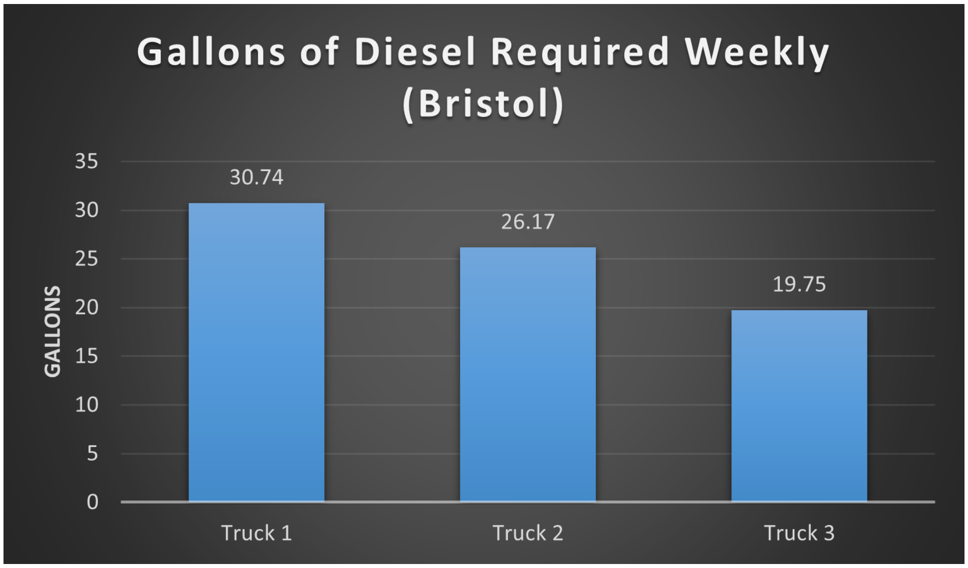


Figure A.89. Gallons of Diesel Required Weekly (Bristol)

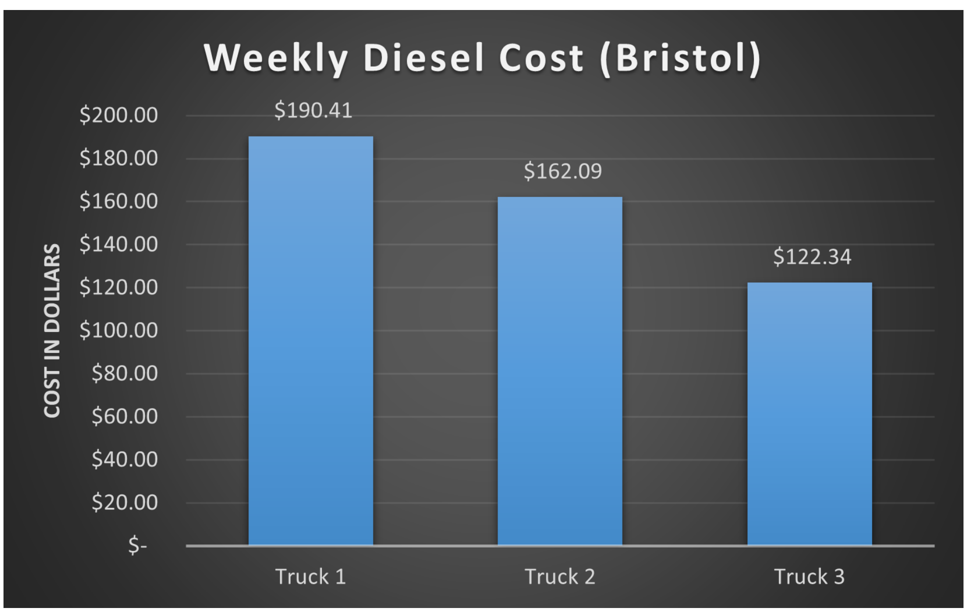


Figure A.90. Weekly Diesel Cost (Bristol)

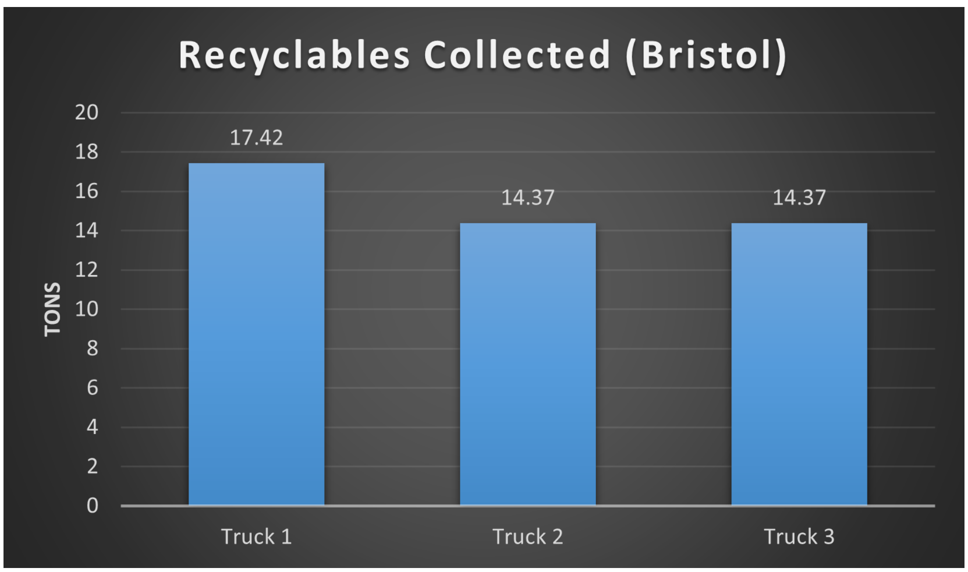


Figure A.91. Recyclables Collected (Bristol)

APPENDIX B

Pawtucket

B.1 Routes, Individual Trucks, and Charts

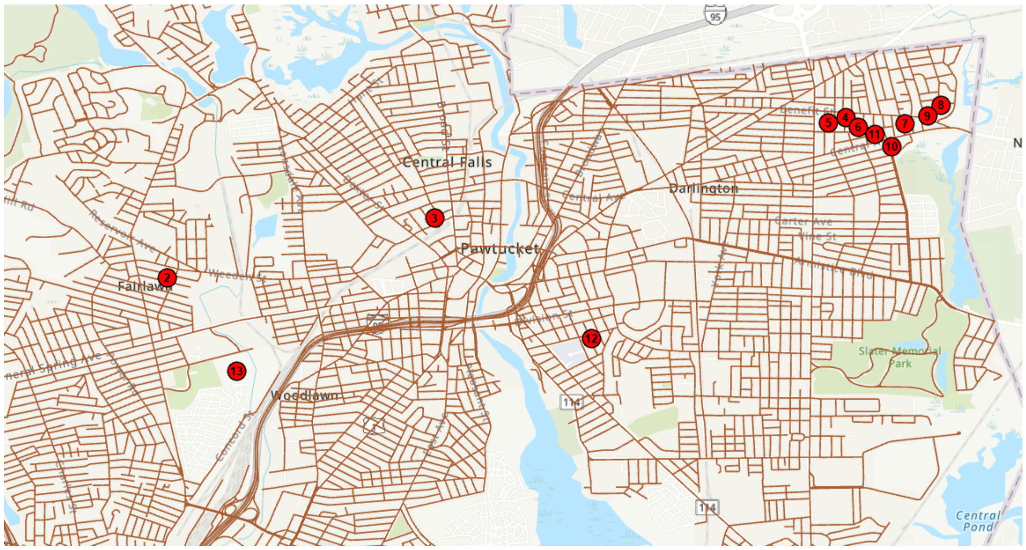


Figure B.92. Pawtucket Route 1

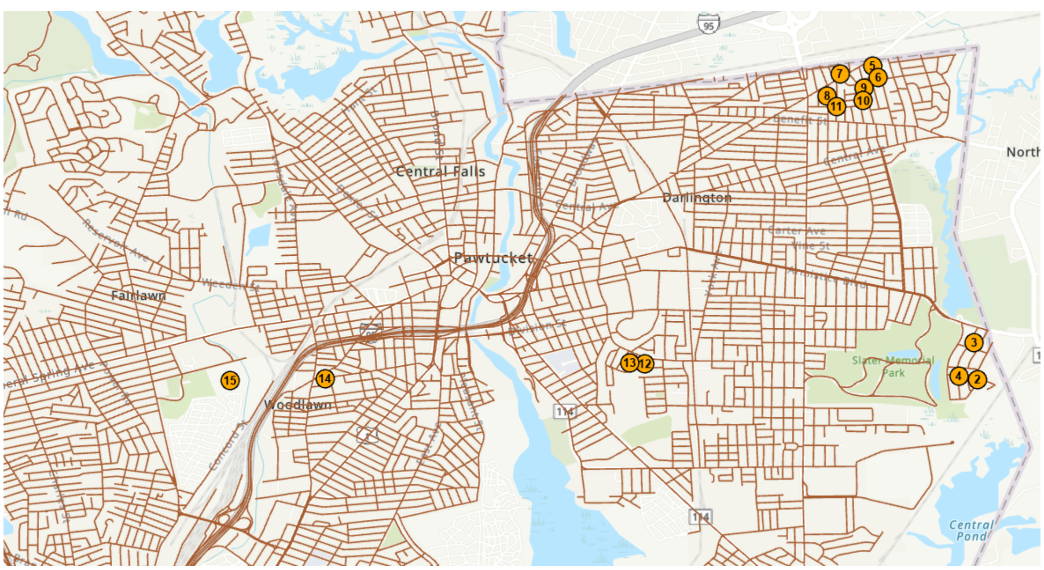


Figure B.93. Pawtucket Route 2

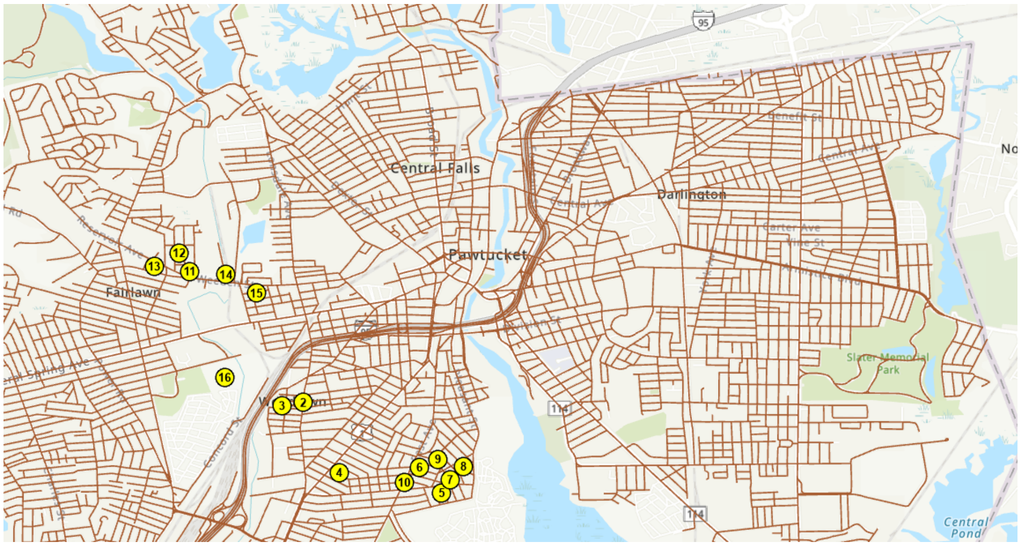


Figure B.94. Pawtucket Route 3

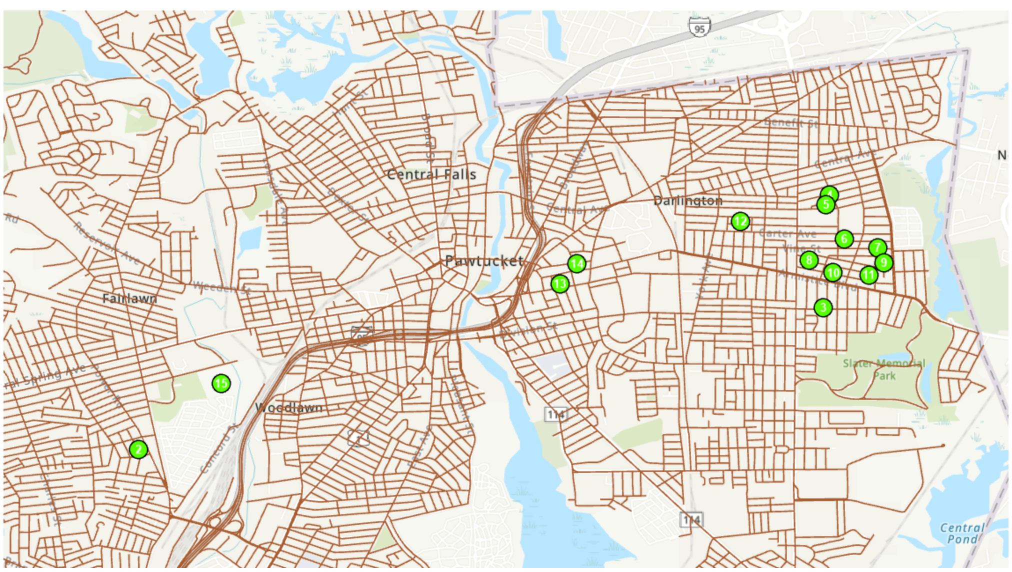


Figure B.95. Pawtucket Route 4

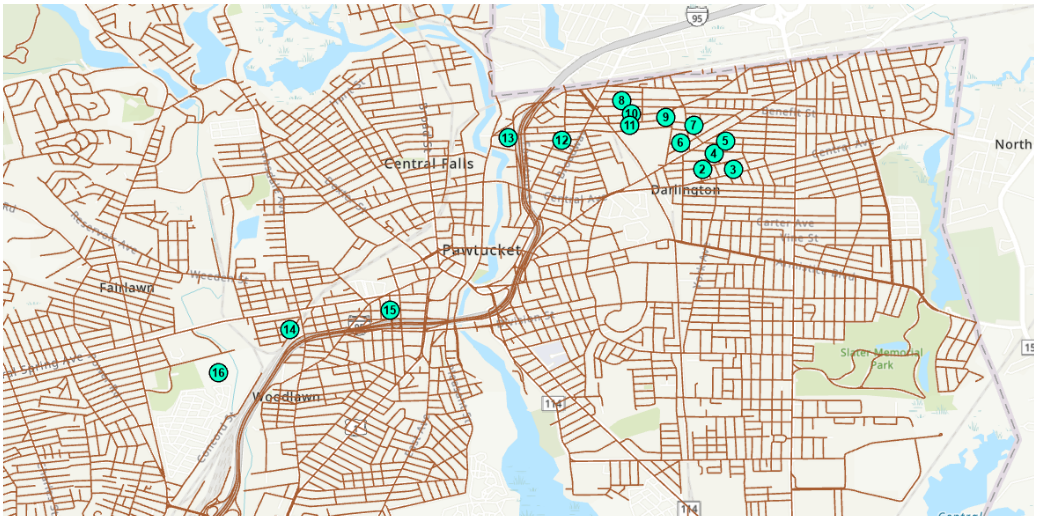


Figure B.96. Pawtucket Route 5

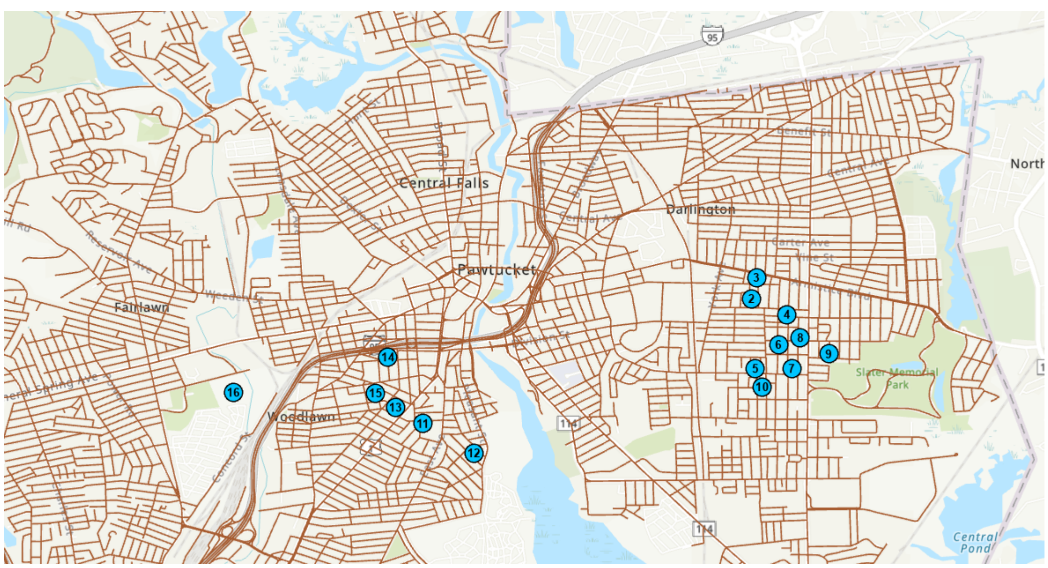
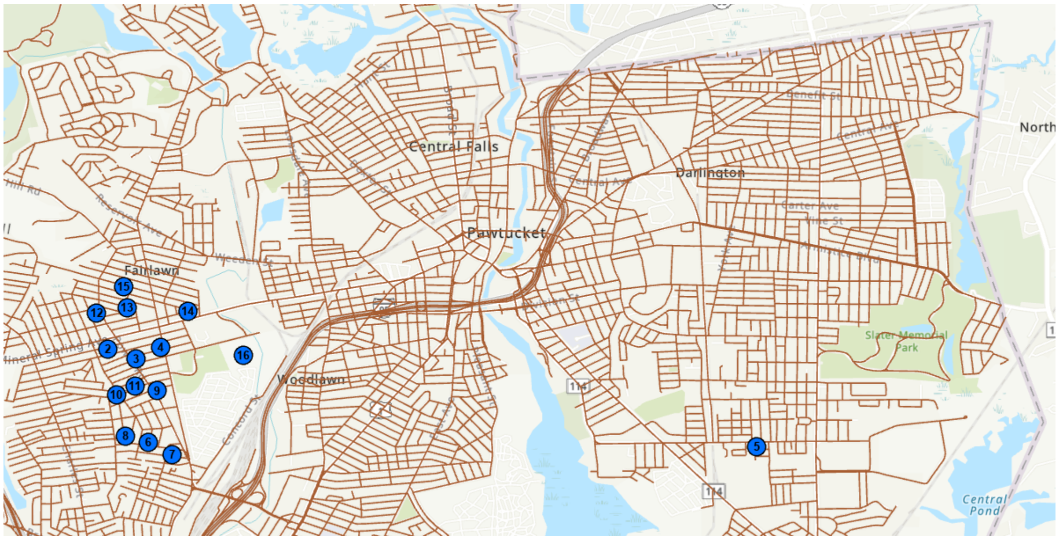


Figure B.97. Pawtucket Route 6



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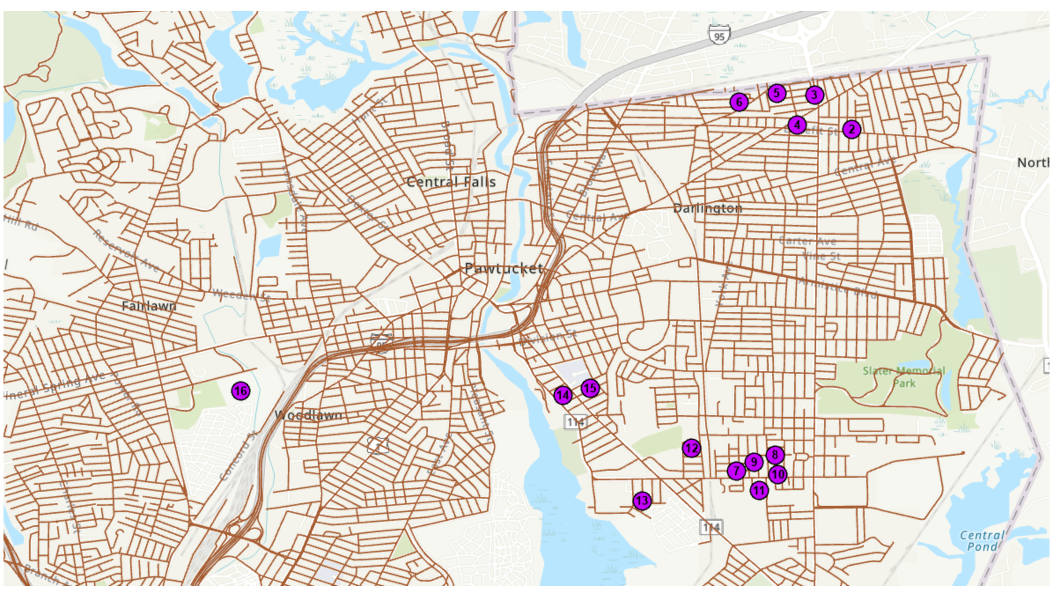


Figure B.99. Pawtucket Route 8

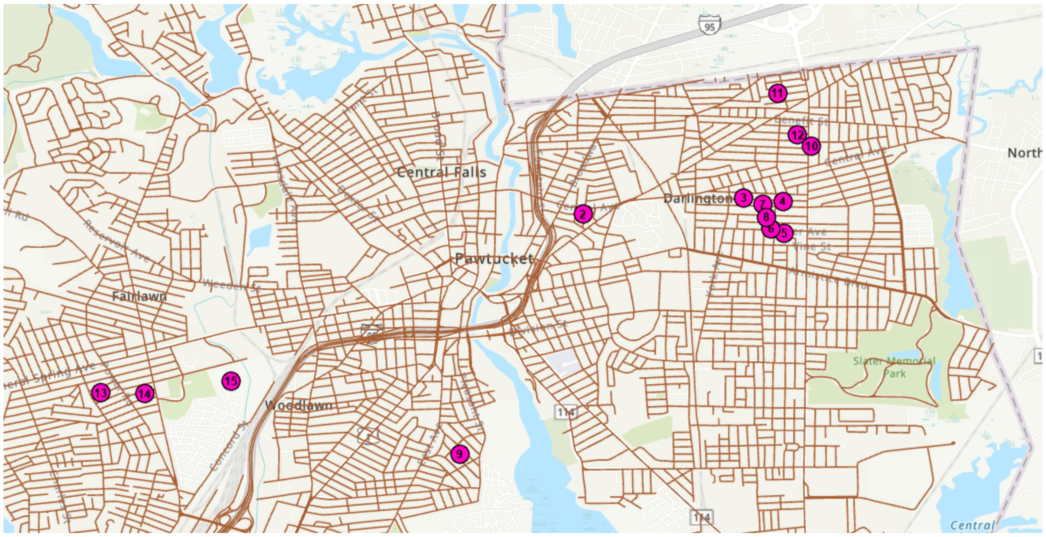
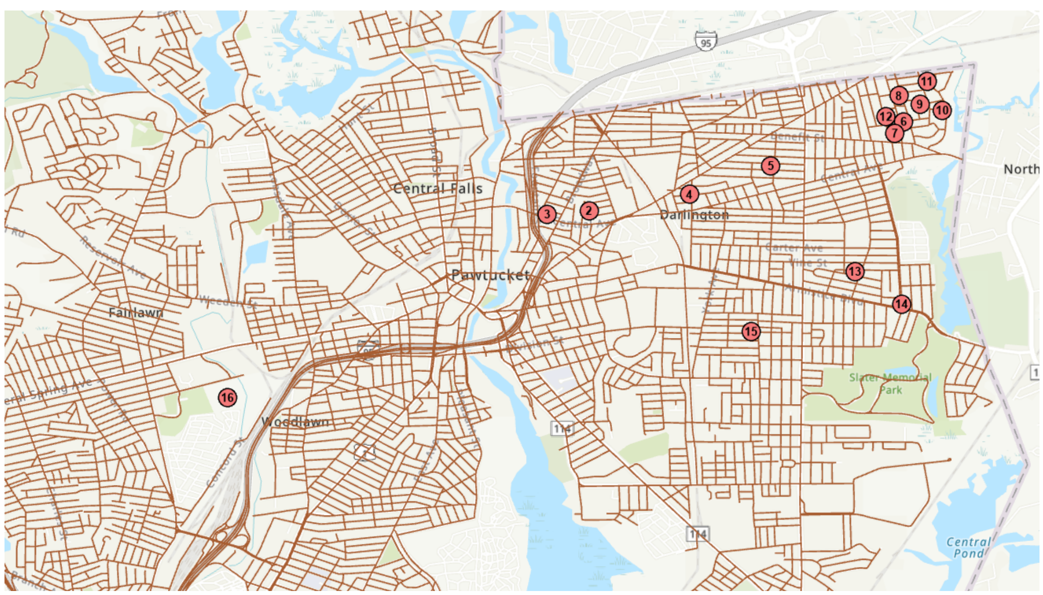


Figure B.100. Pawtucket Route 9



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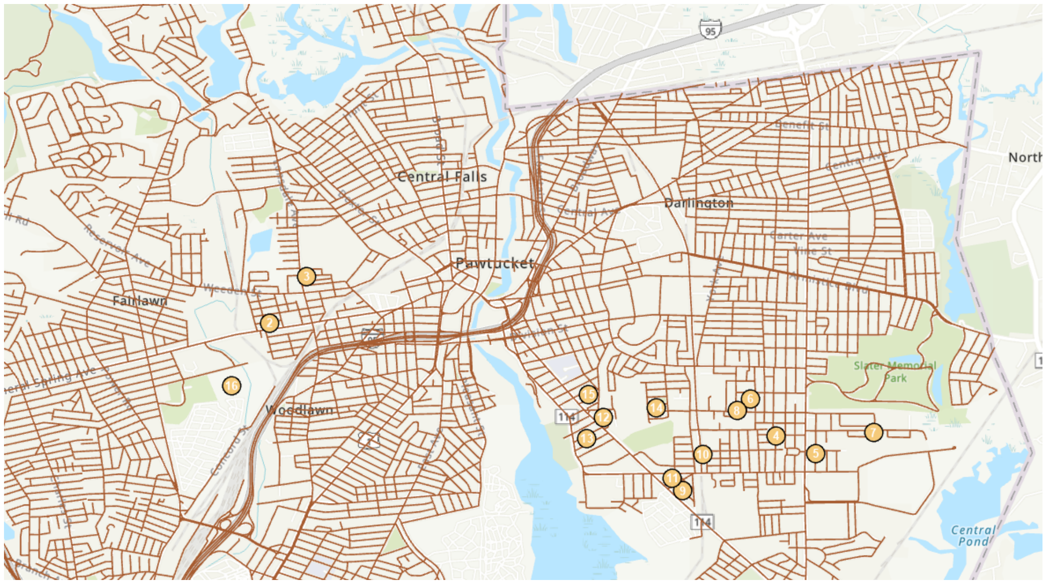

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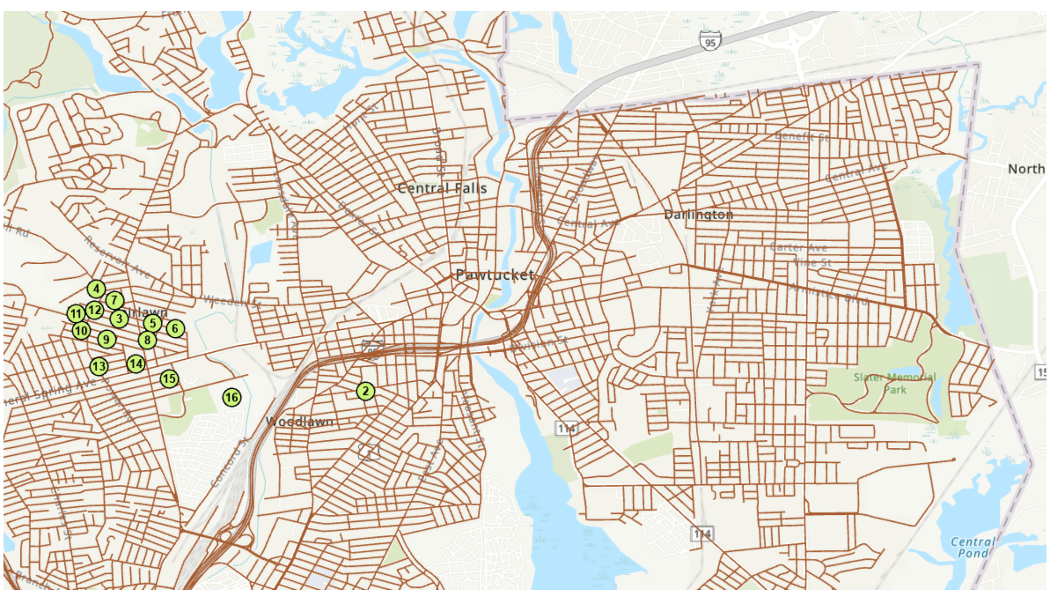
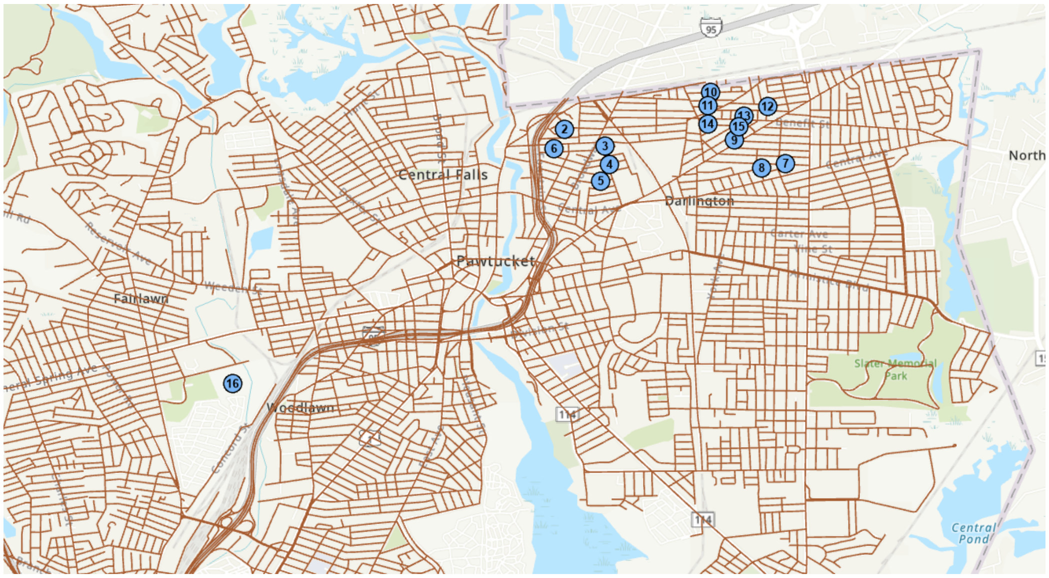


Figure B.103. Pawtucket Route 12



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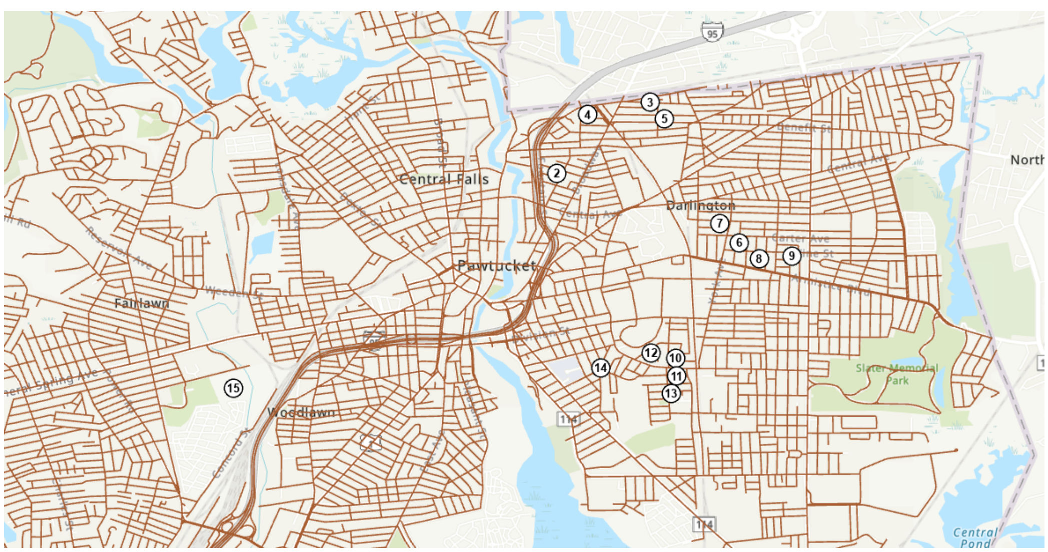


Figure B.105. Pawtucket Route 14

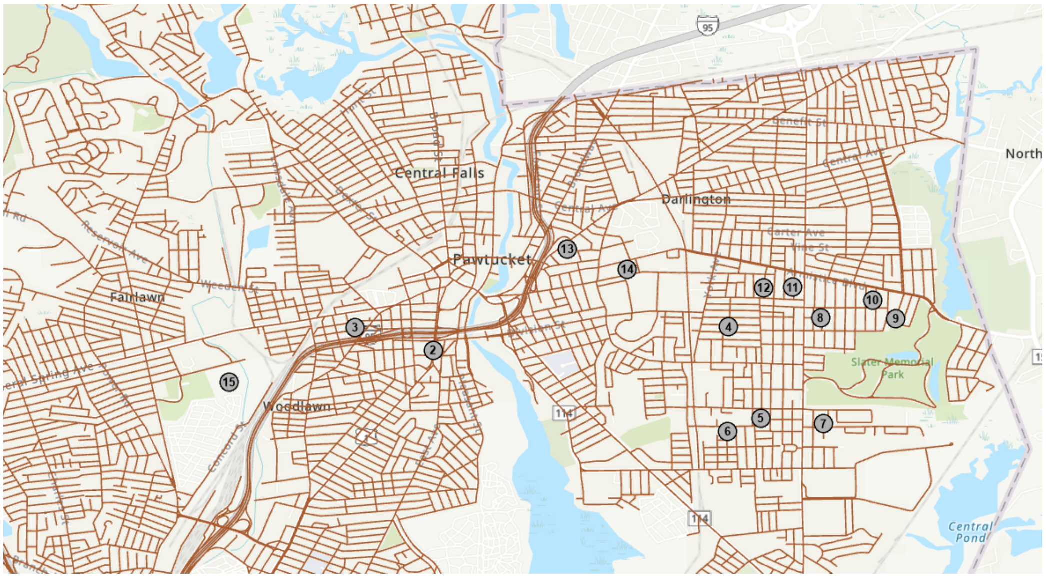


Figure B.106. Pawtucket Route 15

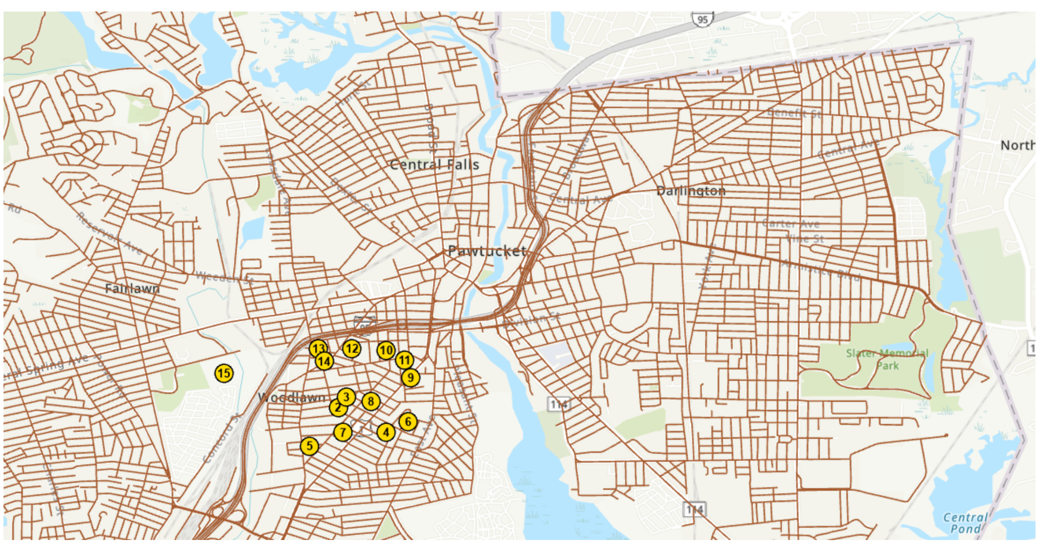
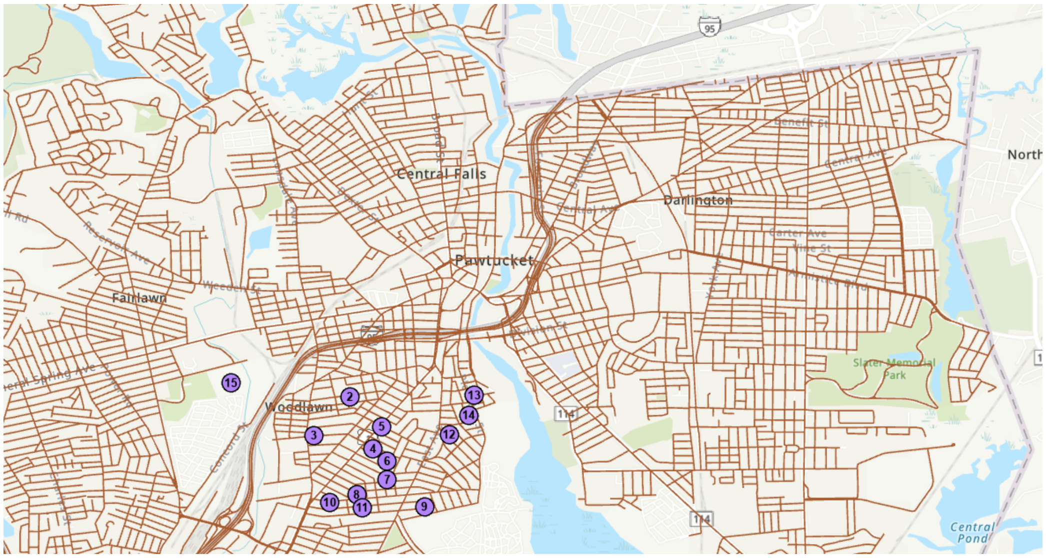


Figure B.107. Pawtucket Route 16



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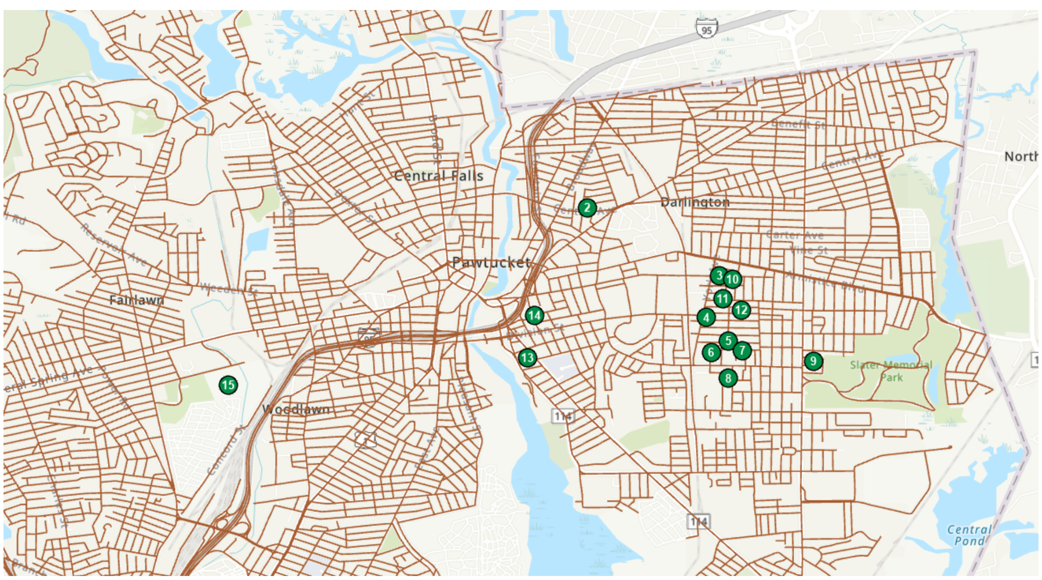

Figure B.109. Pawtucket Route 18

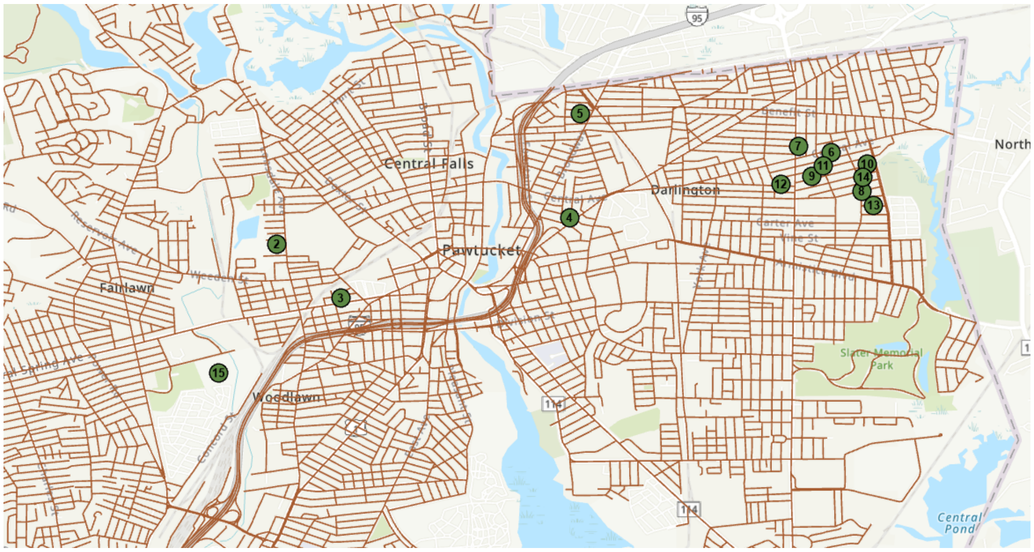

Figure B.110. Pawtucket Route 19

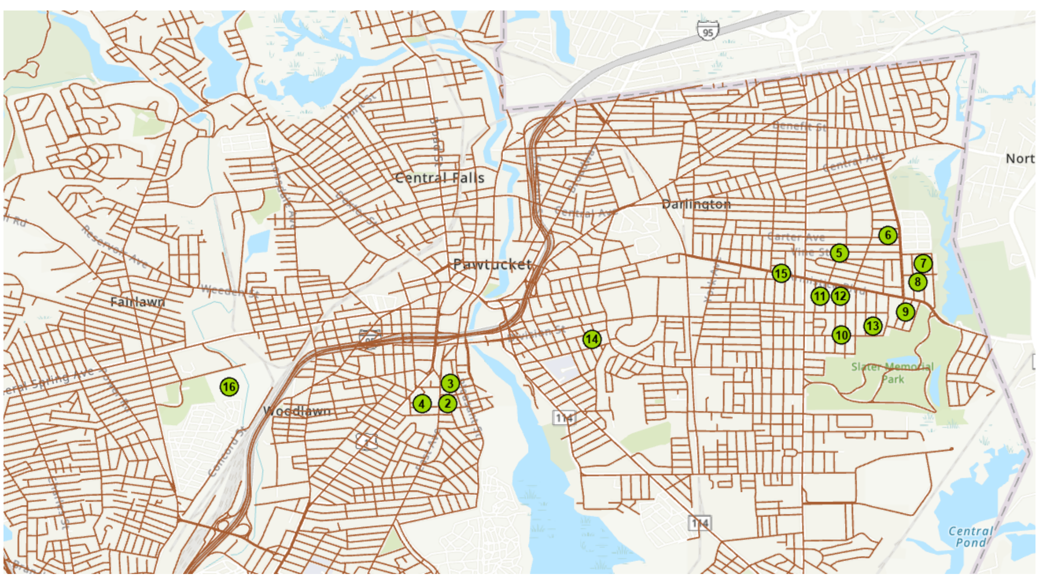

Figure B.111. Pawtucket Route 20

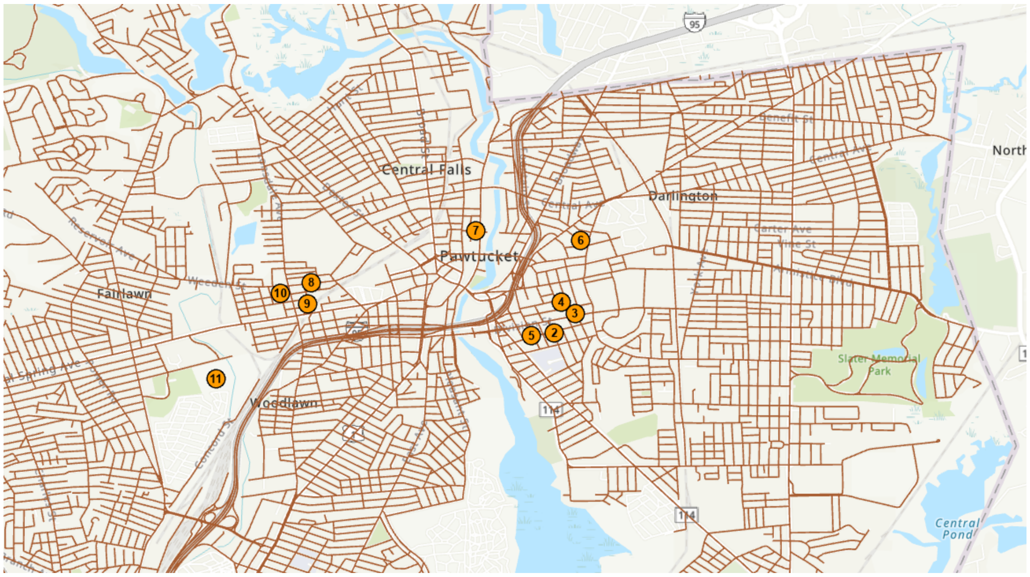

Figure B.112. Pawtucket Route 21

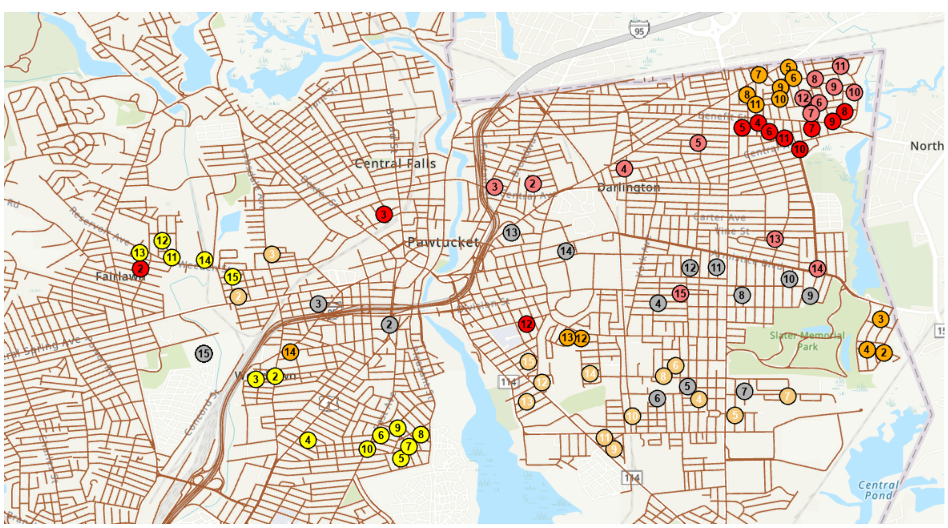

Figure B.113. Pawtucket Truck 1

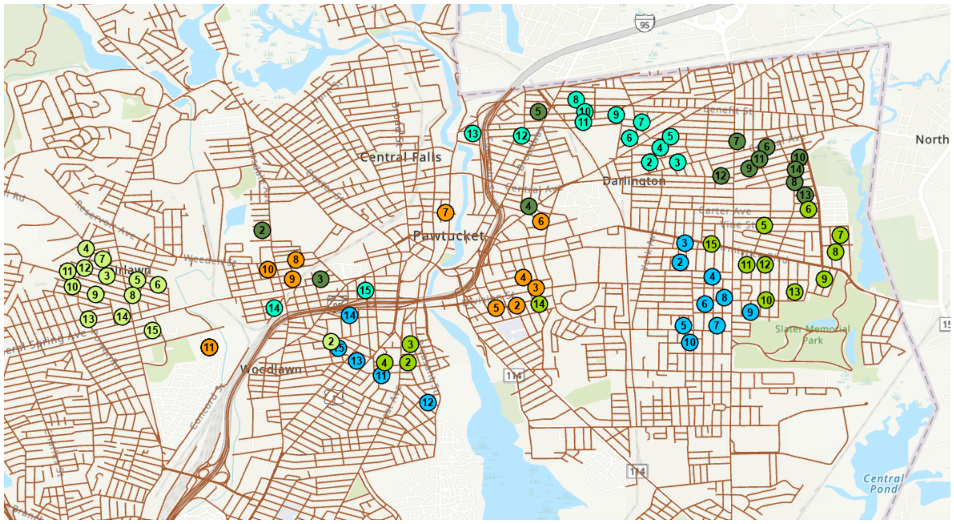

Figure B.114. Pawtucket Truck 2

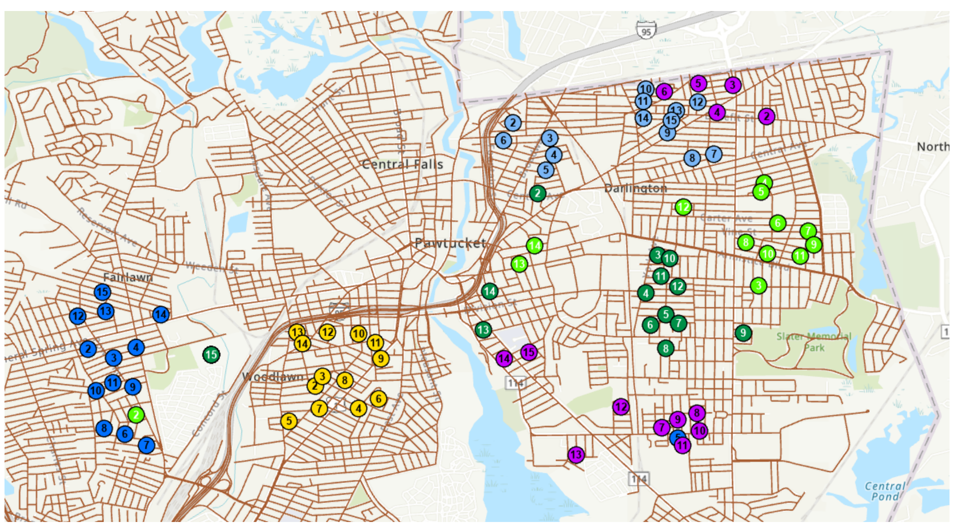

Figure B.115. Pawtucket Truck 3

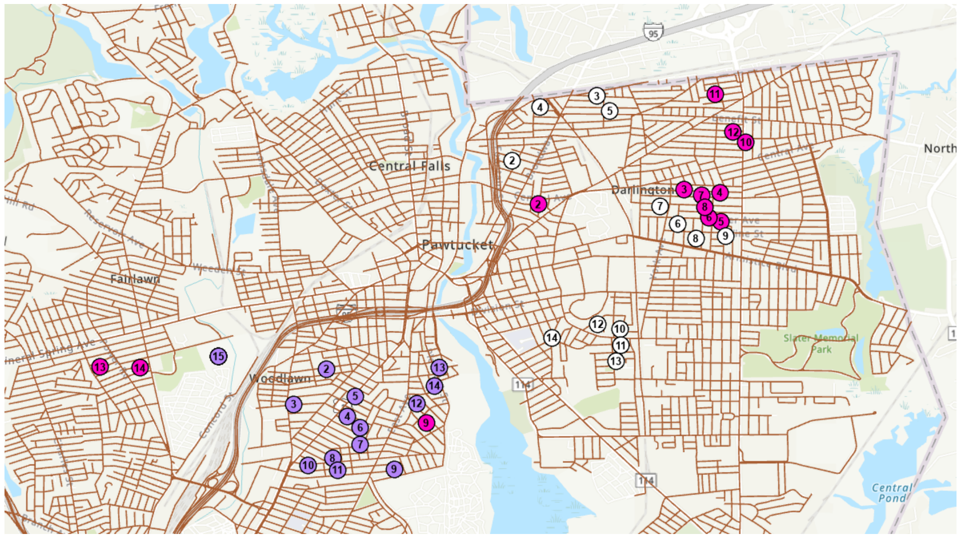

Figure B.116. Pawtucket Truck 4

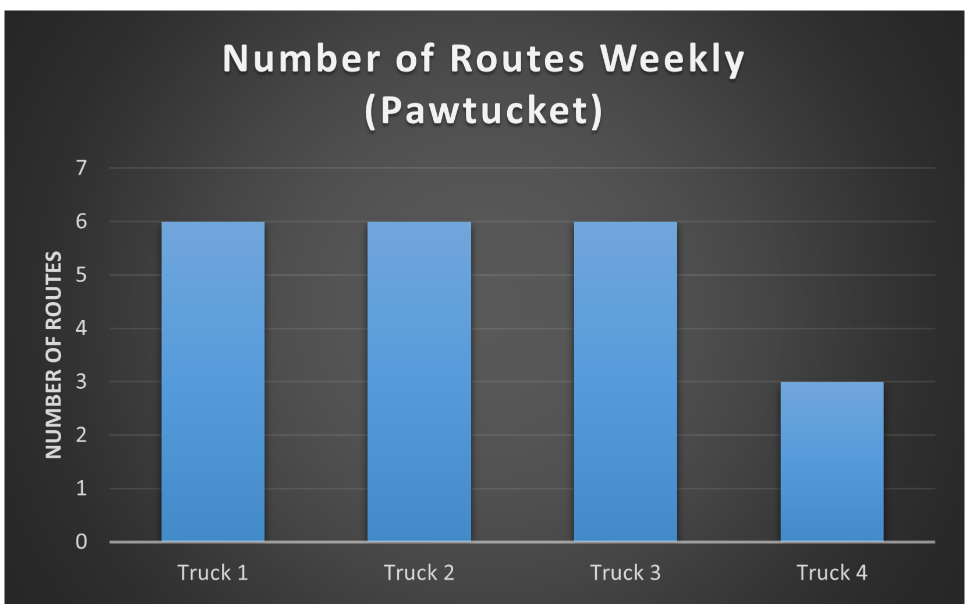

Figure B.117. Number of Routes Weekly (Pawtucket)

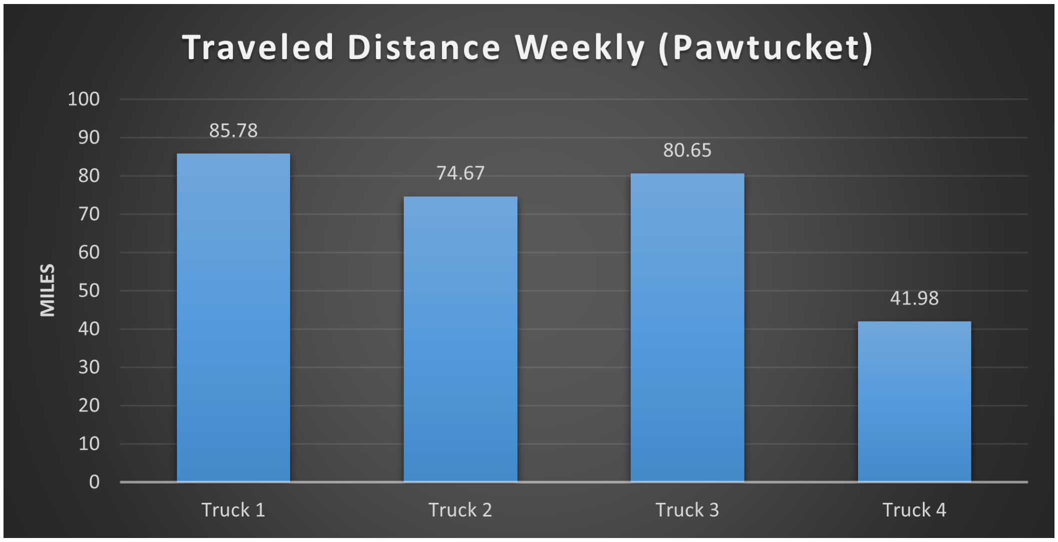

Figure B.118. Traveled Distance Weekly (Pawtucket)

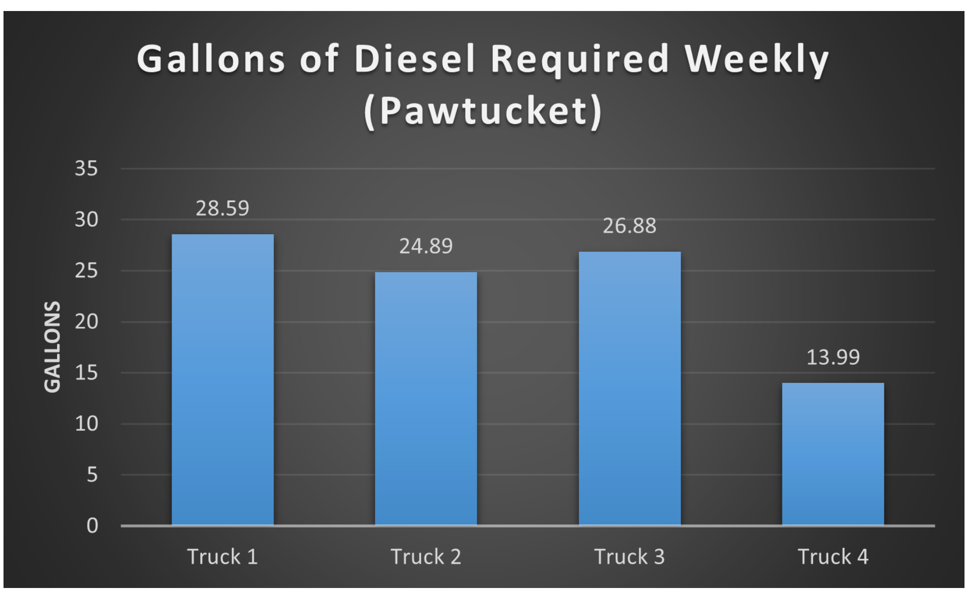

Figure B.119. Gallons of Diesel Required Weekly (Pawtucket)

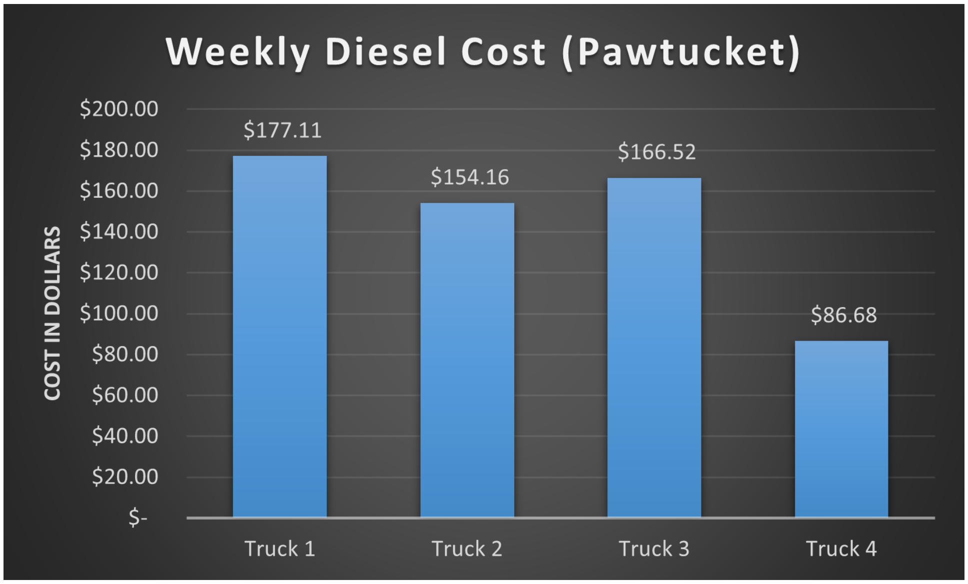

Figure B.120. Weekly Diesel Cost (Pawtucket)

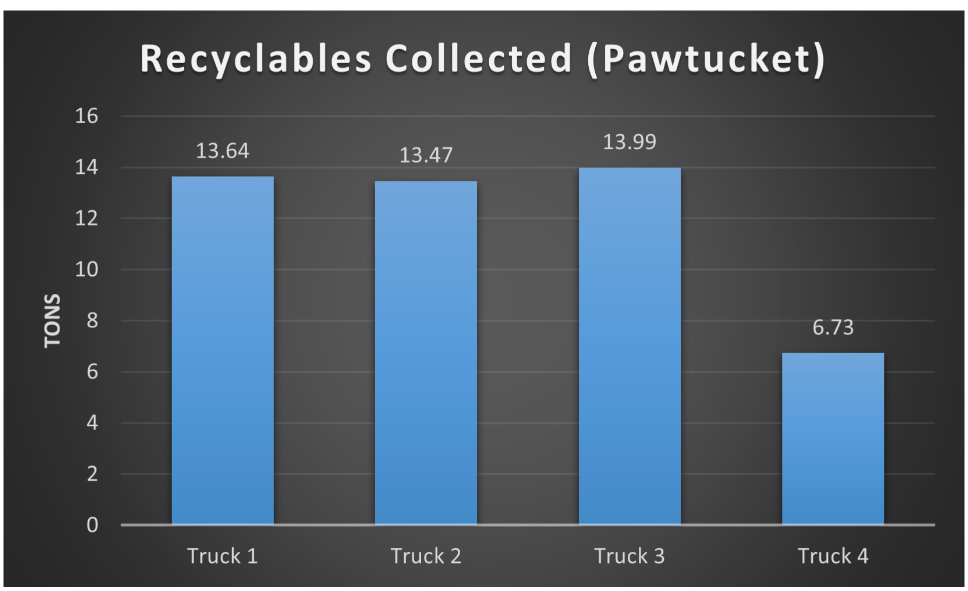

Figure B.121. Recyclables Collected (Pawtucket)

APPENDIX C

South Kingstown

C.1 Routes, Individual Trucks, and Charts

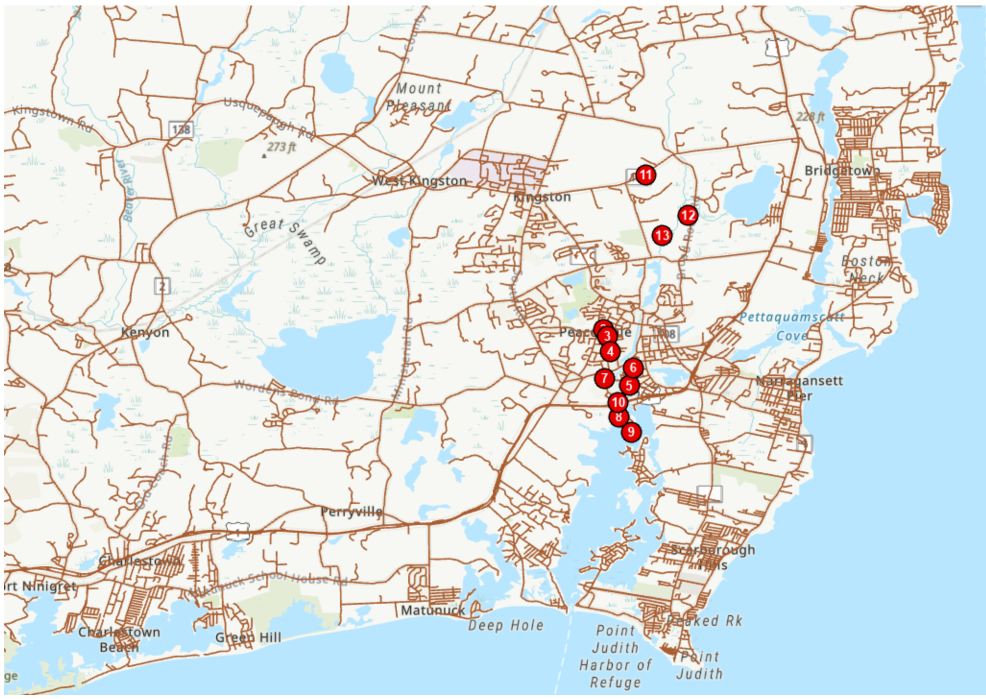

Figure C.122. South Kingstown Route 1

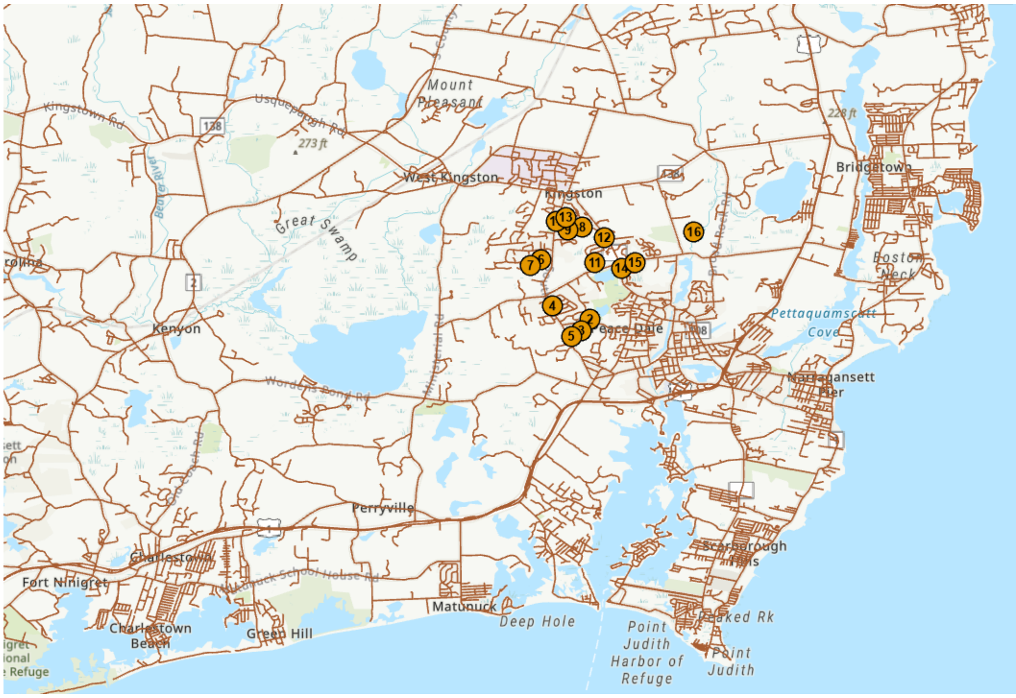

Figure C.123. South Kingstown Route 2

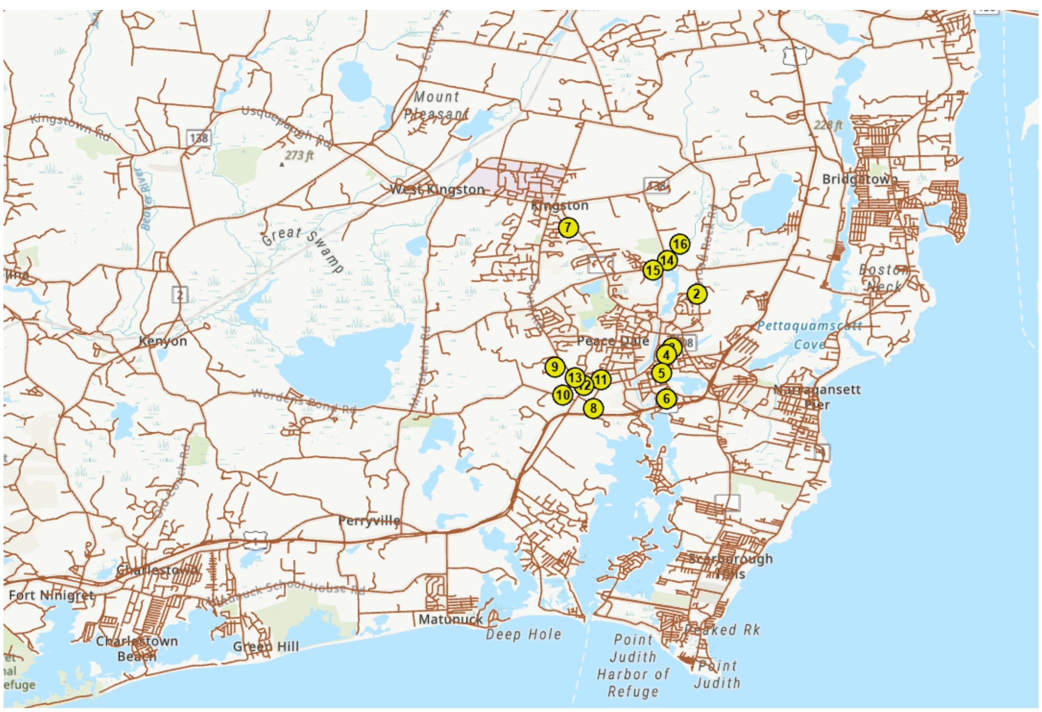

Figure C.124. South Kingstown Route 3

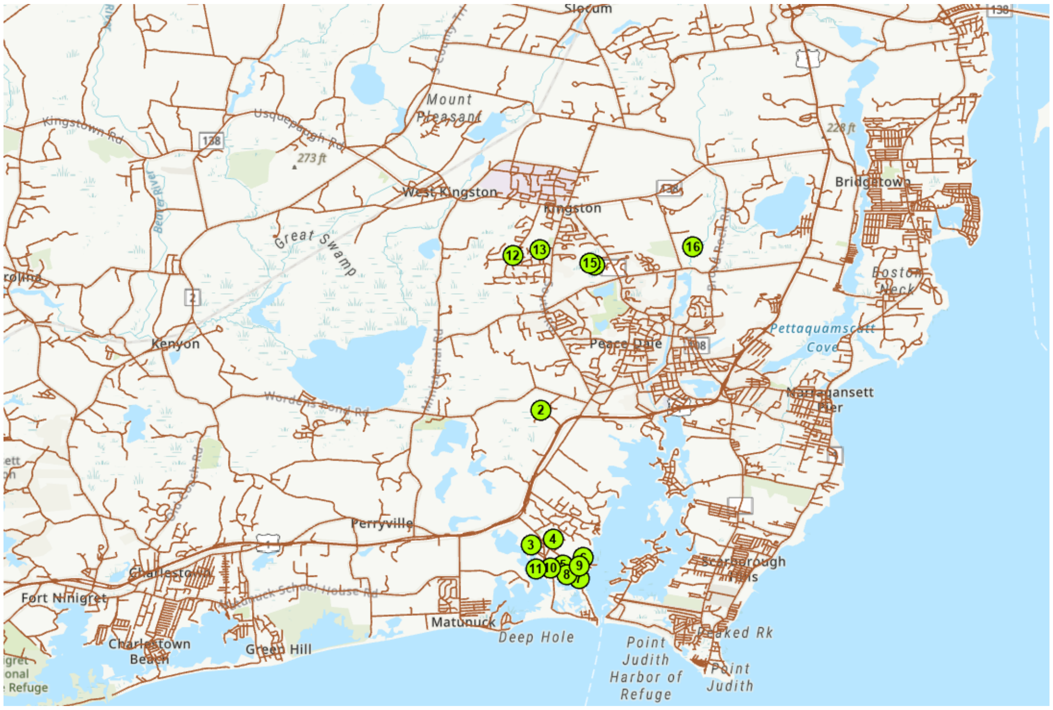

Figure C.125. South Kingstown Route 4

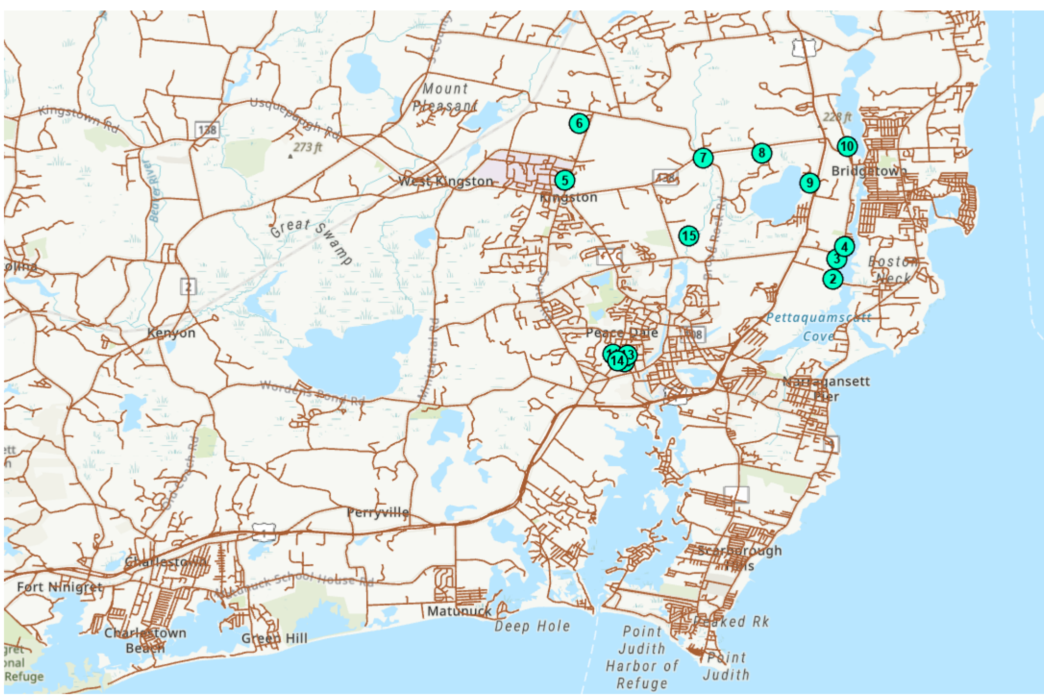

Figure C.126. South Kingstown Route 5

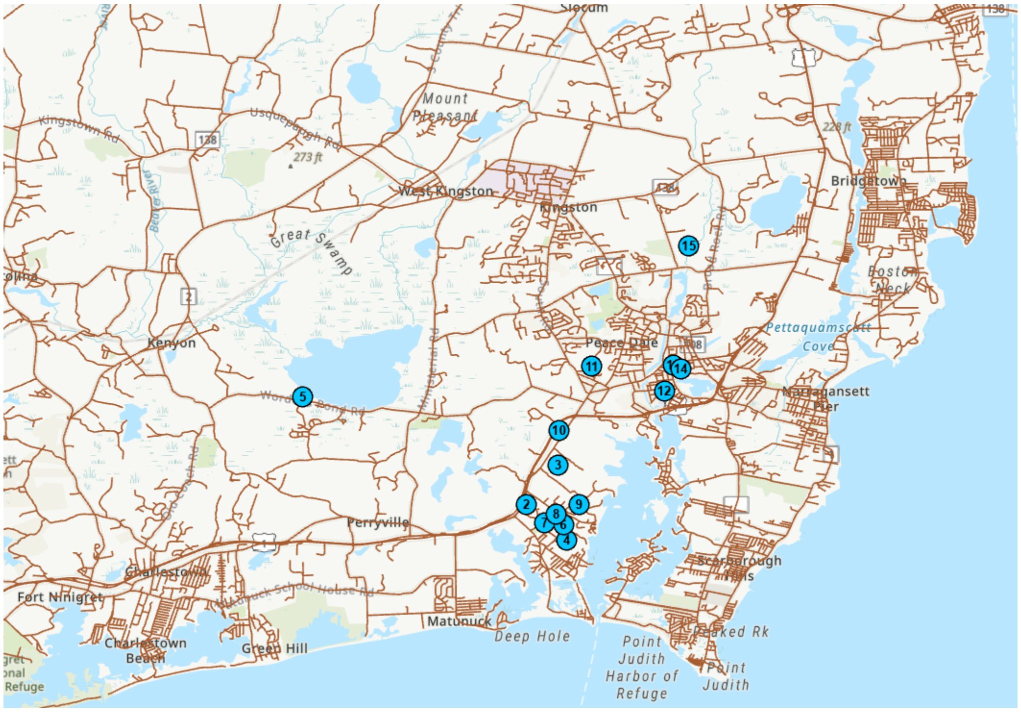

Figure C.127. South Kingstown Route 6

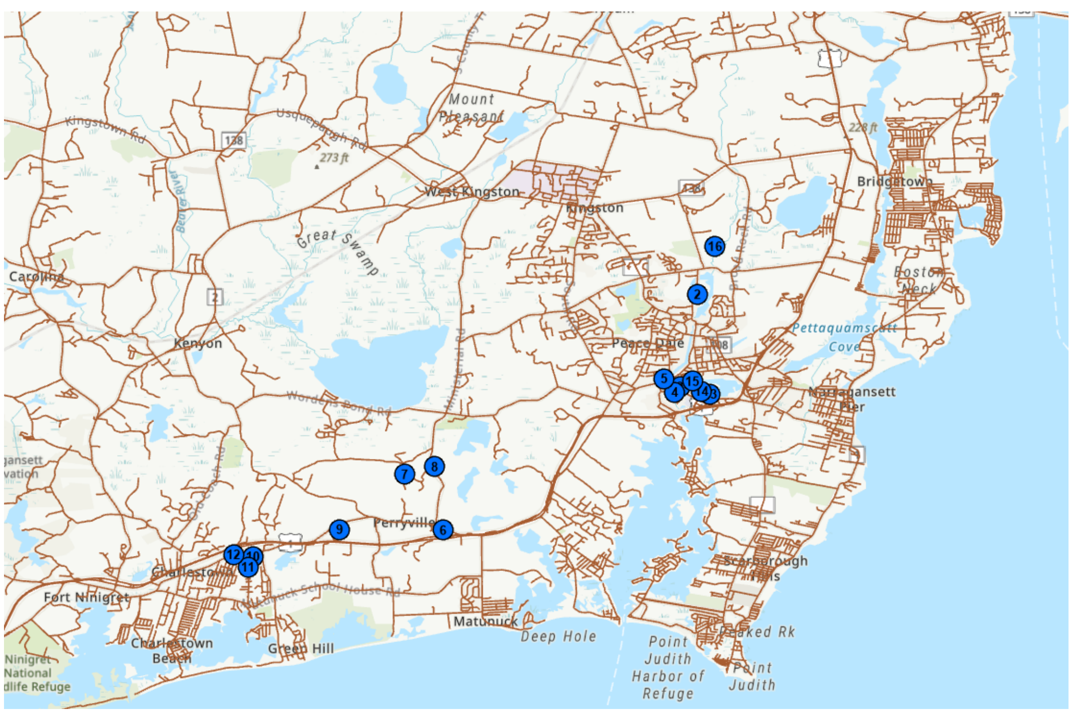

Figure C.128. South Kingstown Route 7

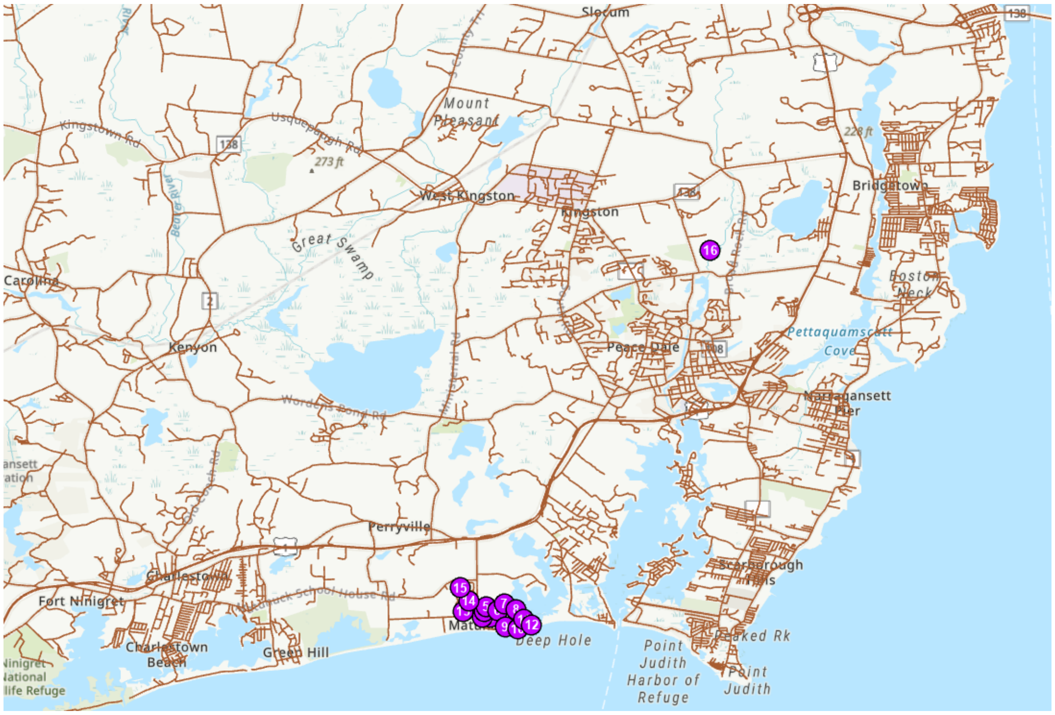

Figure C.129. South Kingstown Route 8

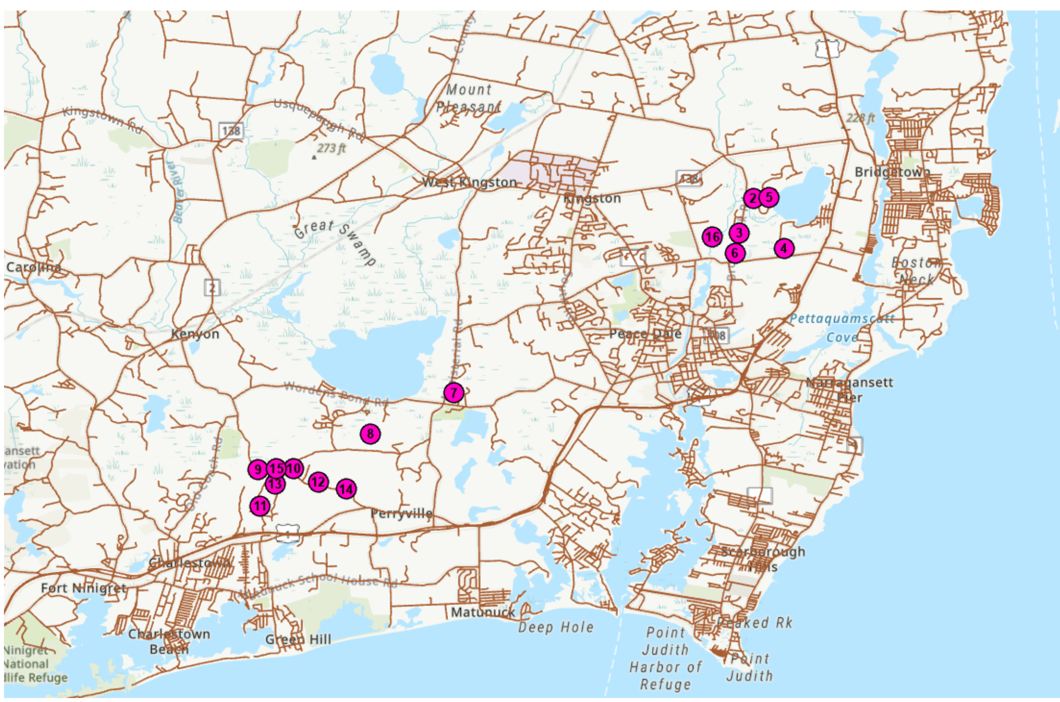

Figure C.130. South Kingstown Route 9

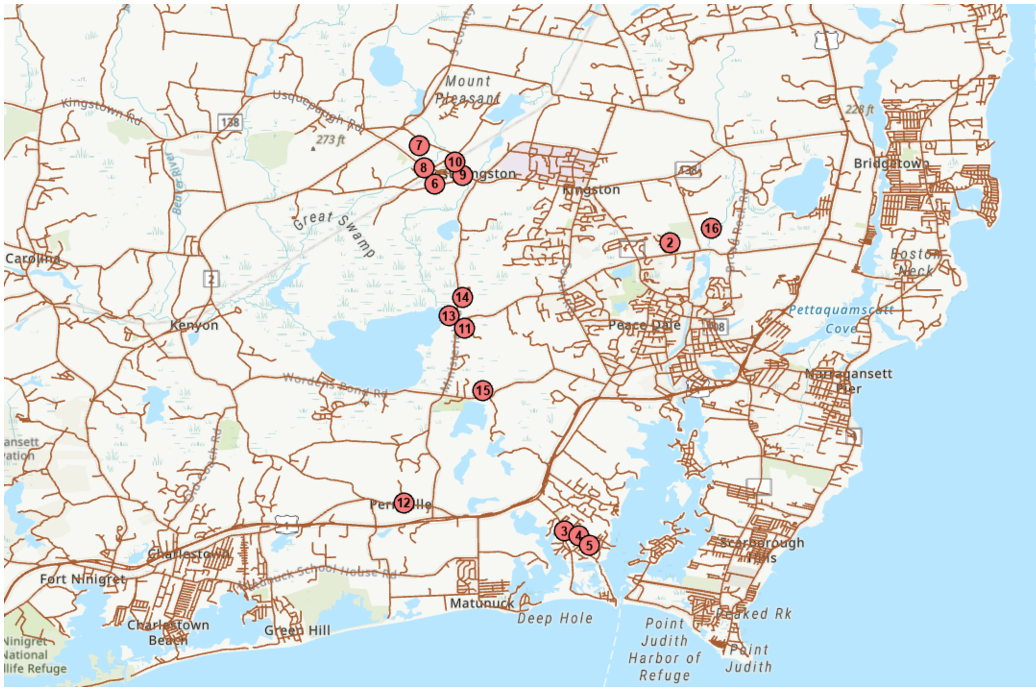

Figure C.131. South Kingstown Route 10

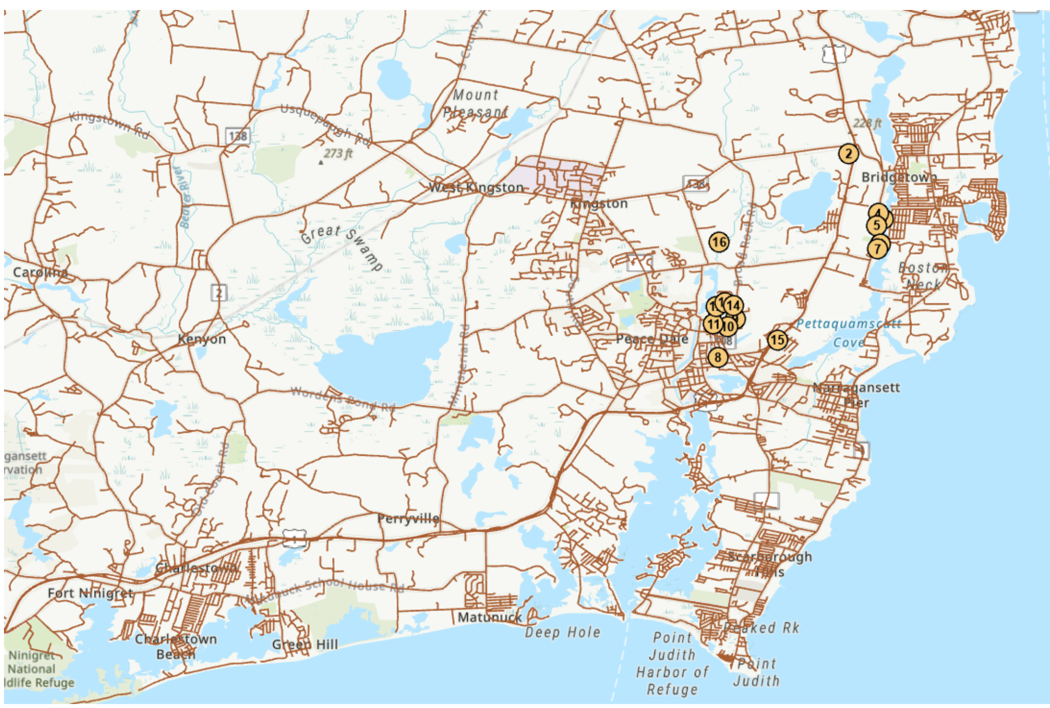

Figure C.132. South Kingstown Route 11

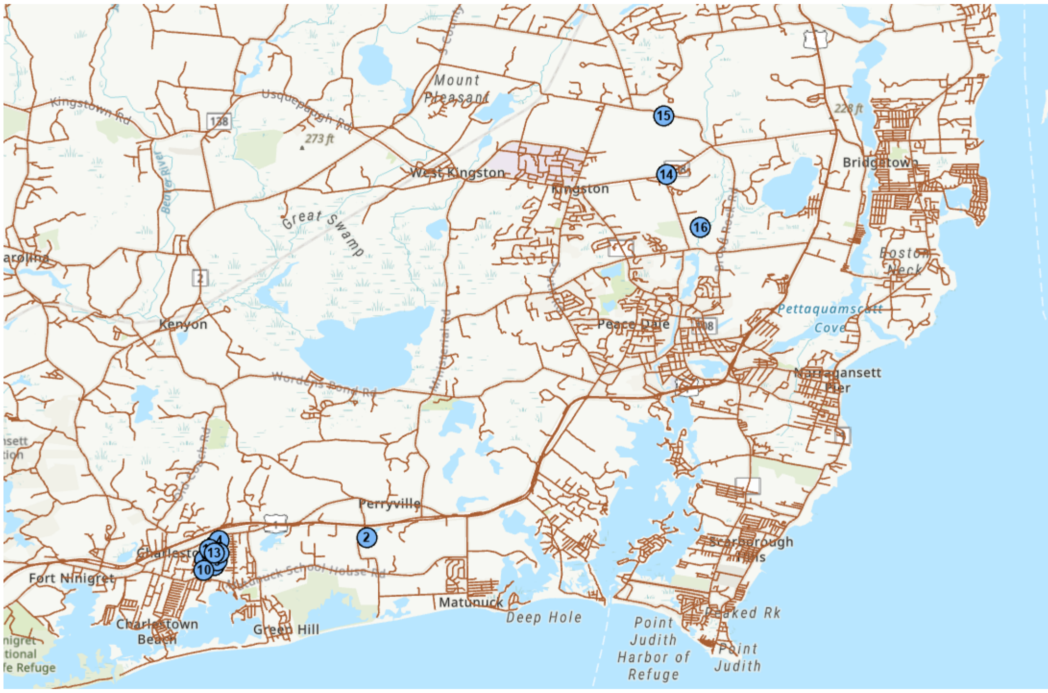

Figure C.133. South Kingstown Route 12

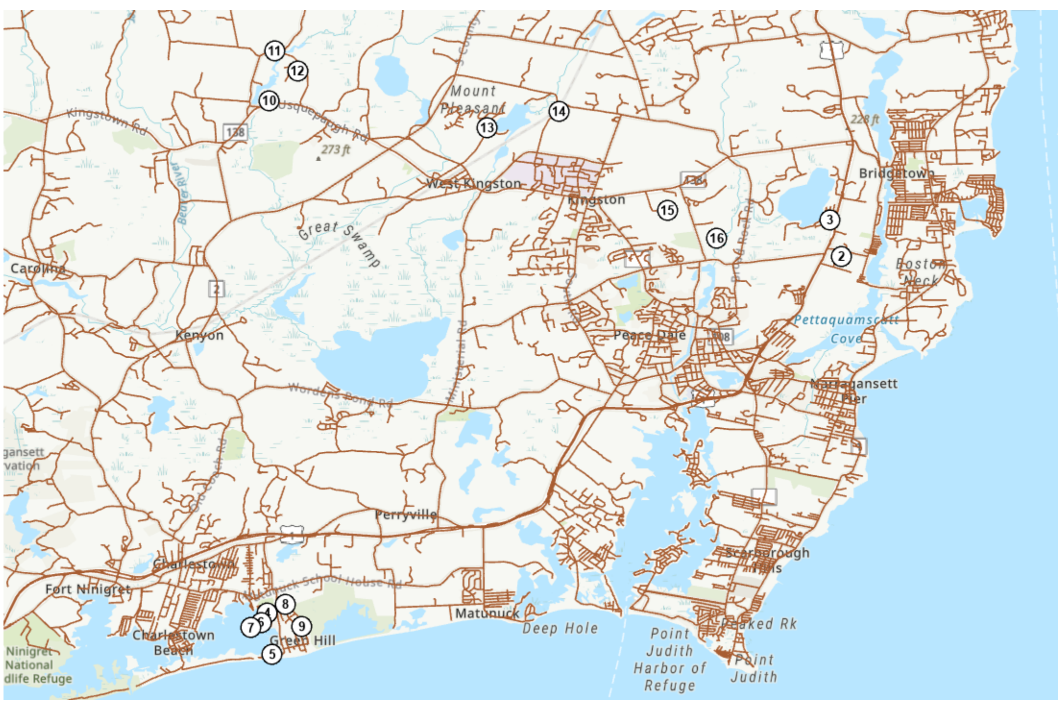

Figure C.134. South Kingstown Route 13

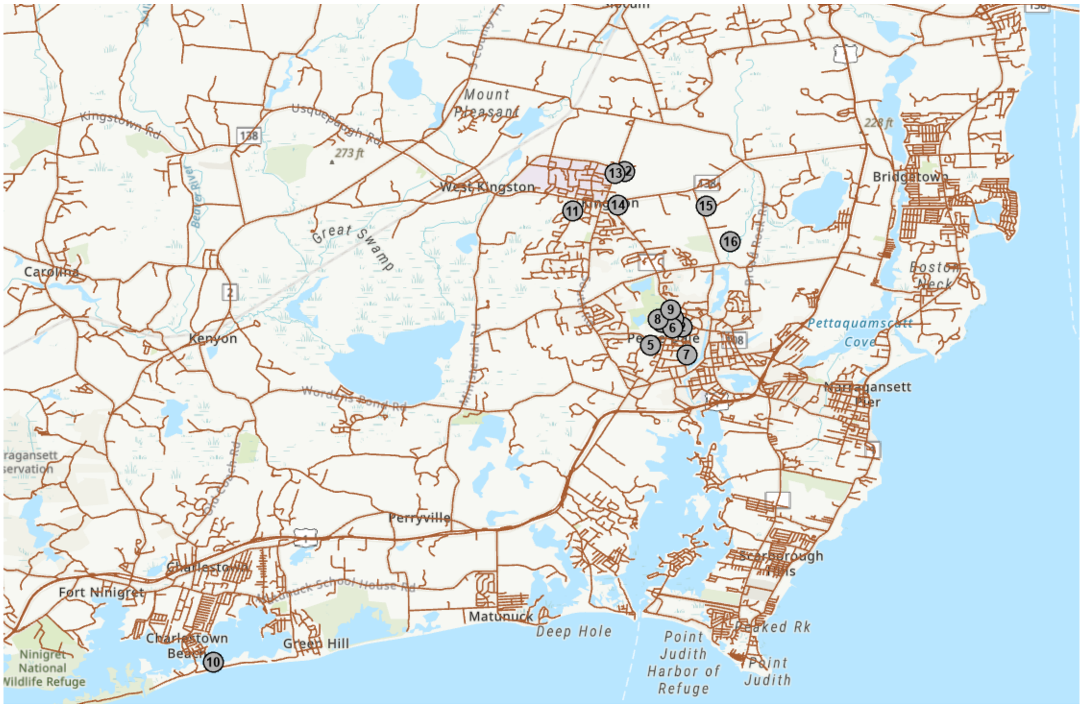

Figure C.135. South Kingstown Route 14

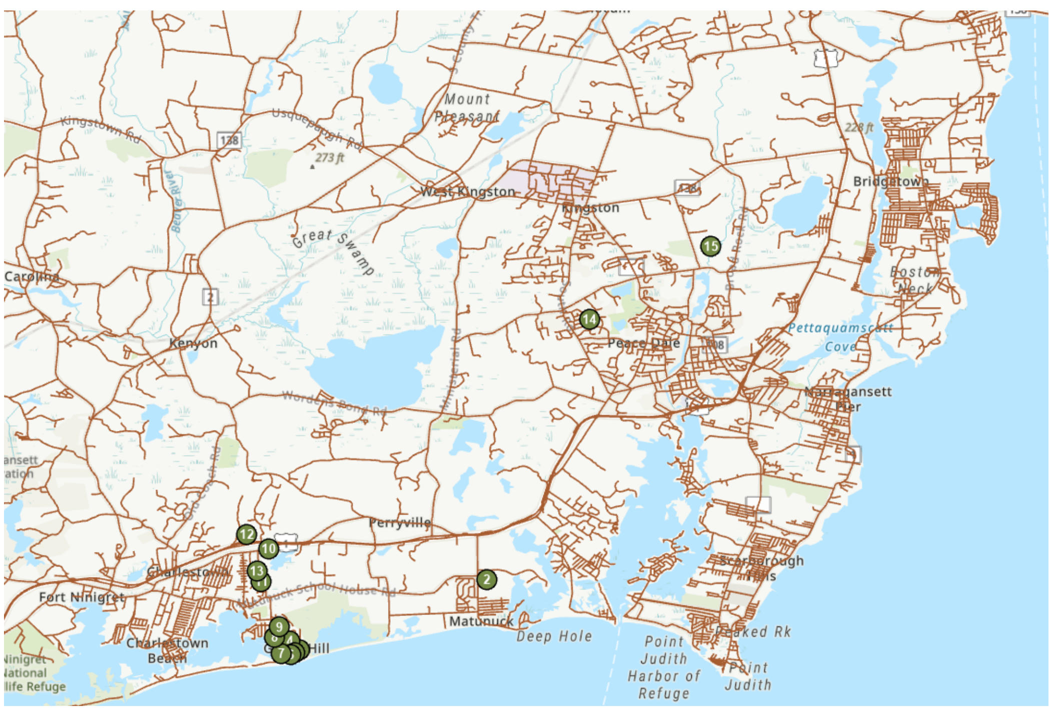

Figure C.136. South Kingstown Route 15

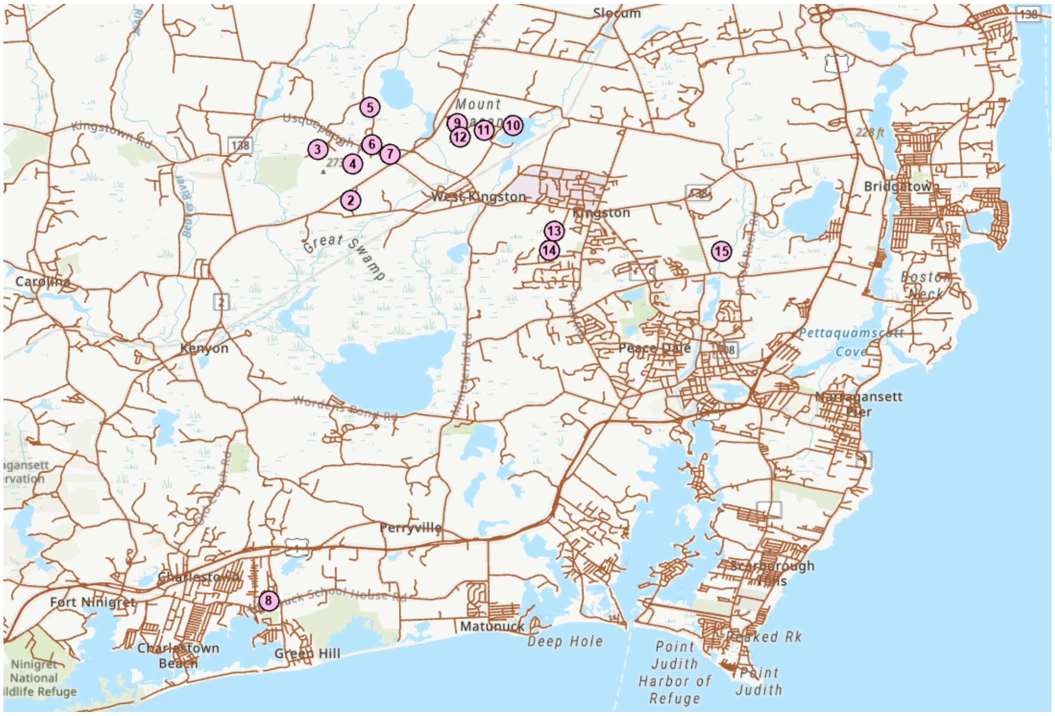

Figure C.137. South Kingstown Route 16

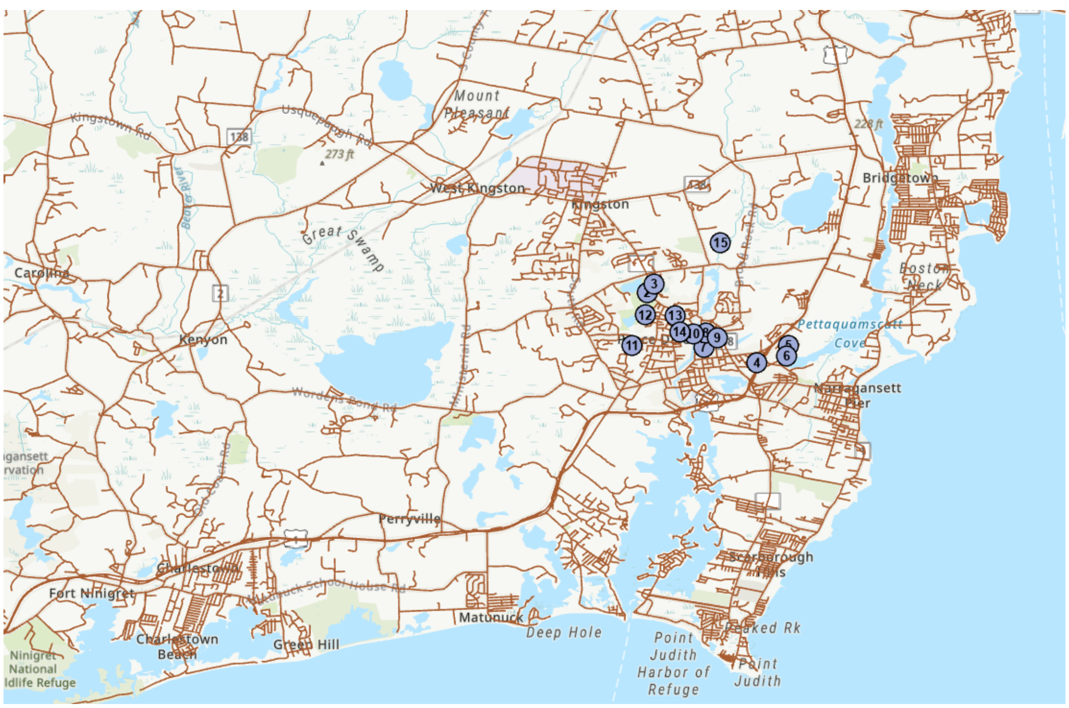

Figure C.138. South Kingstown Route 17

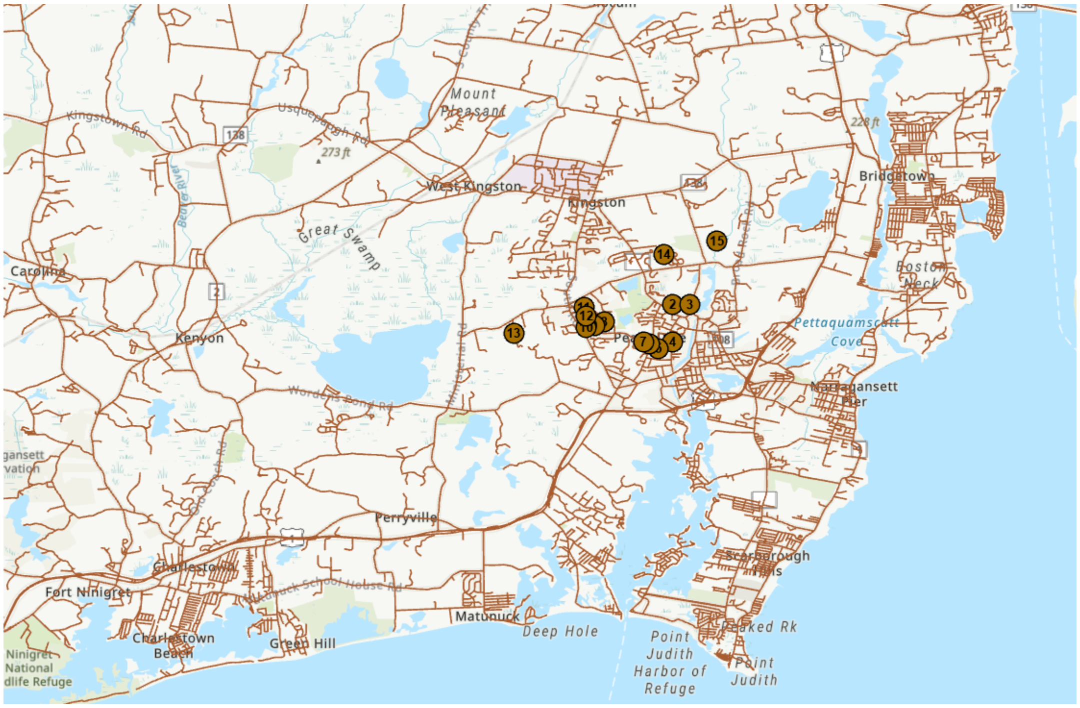

Figure C.139. South Kingstown Route 18

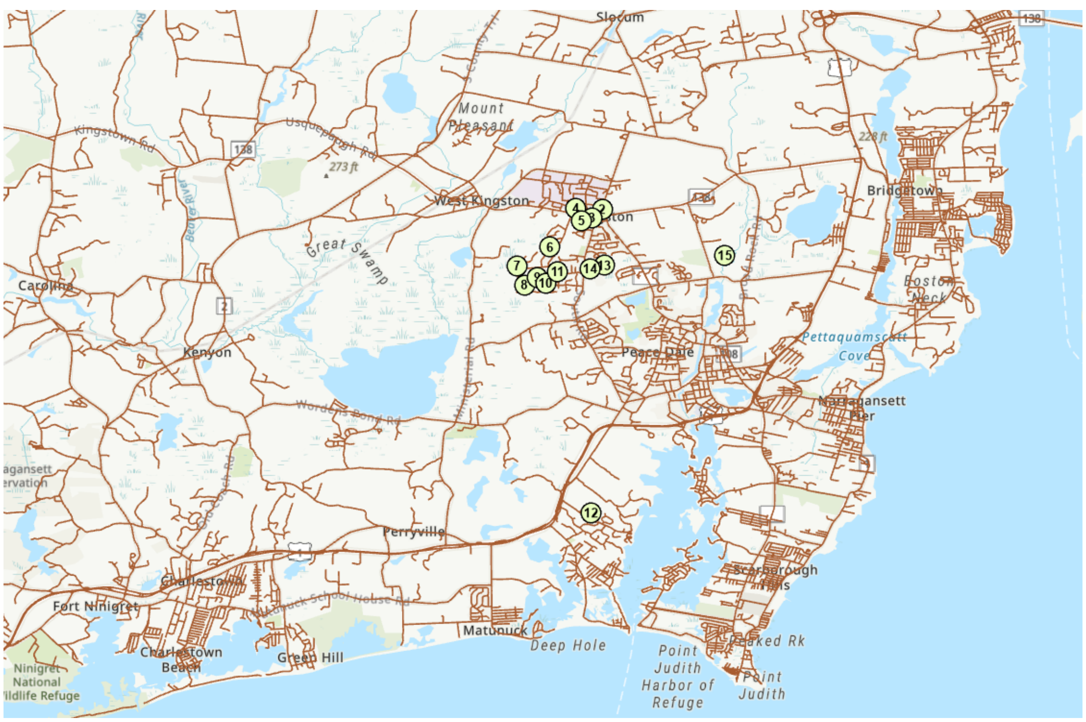

Figure C.140. South Kingstown Route 19

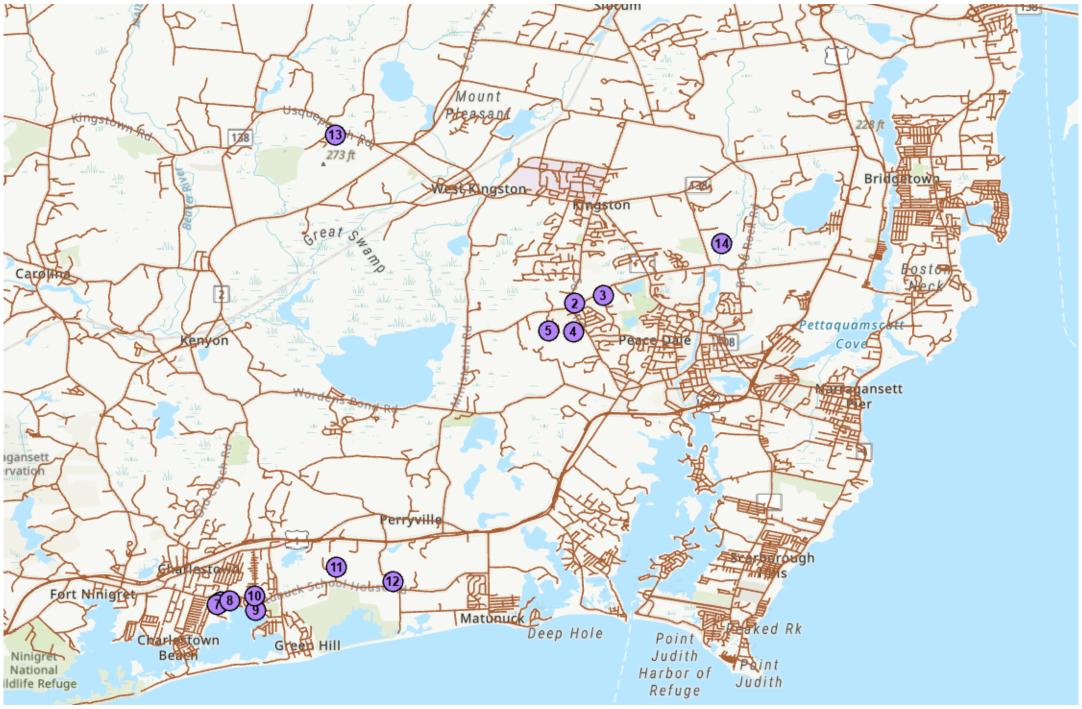

Figure C.141. South Kingstown Route 20

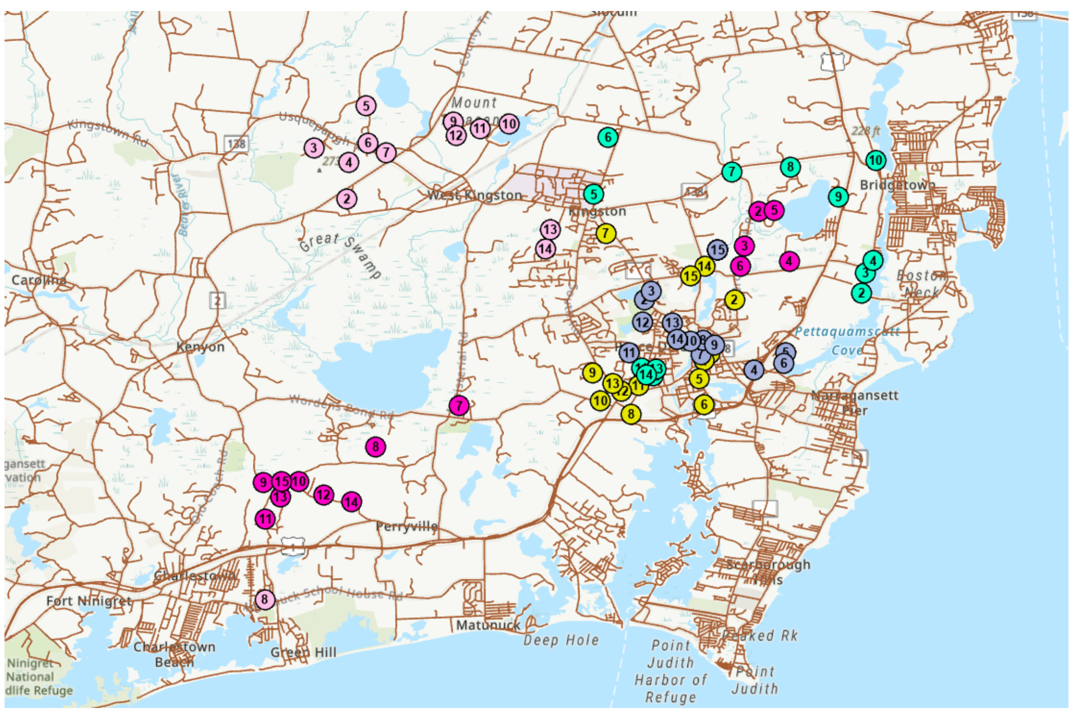

Figure C.142. South Kingstown Truck 1

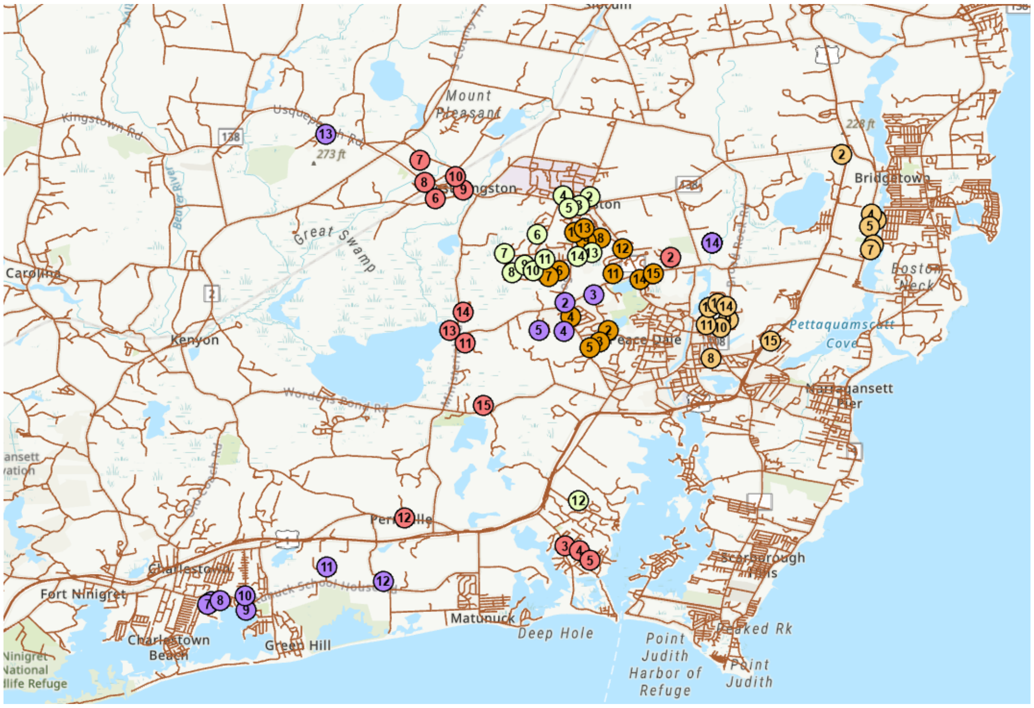

Figure C.143. South Kingstown Truck 2

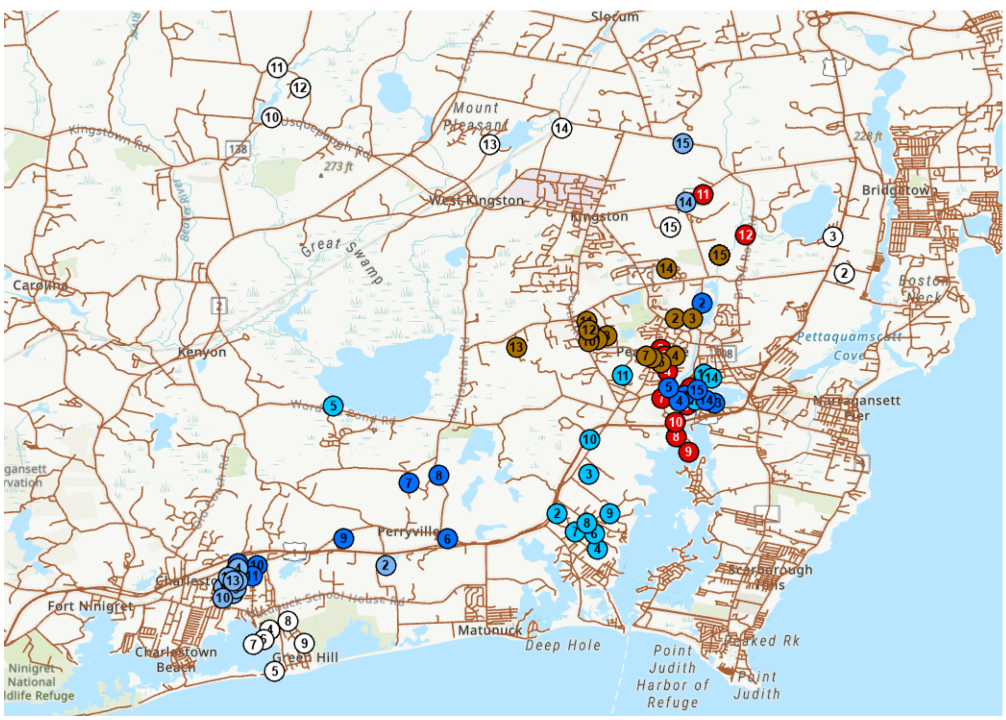

Figure C.144. South Kingstown Truck 3

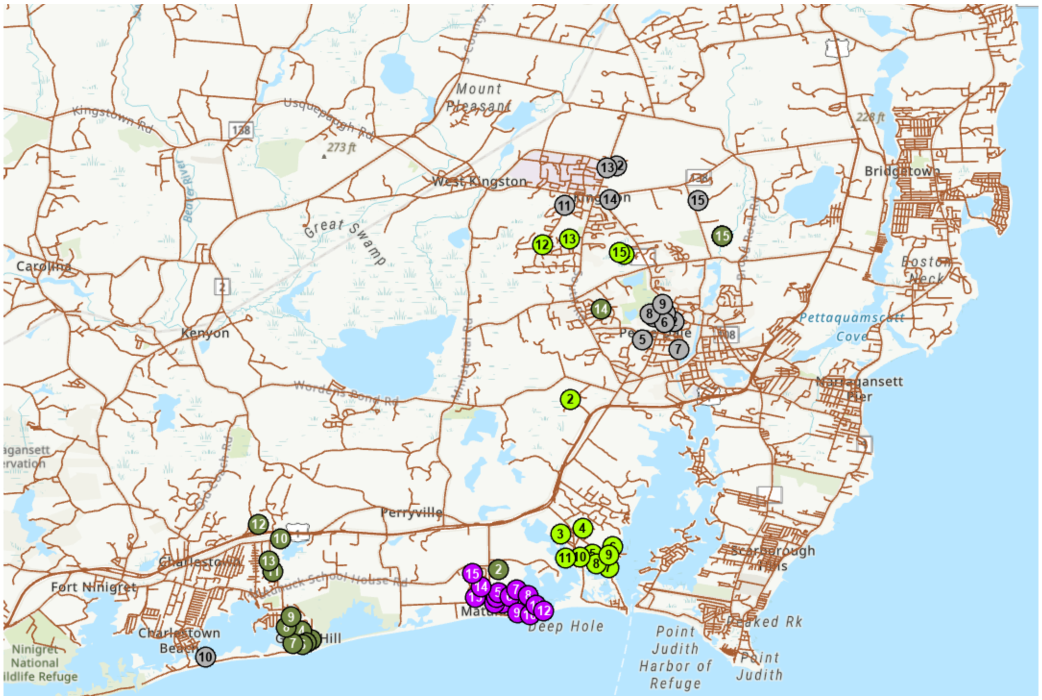

Figure C.145. South Kingstown Truck 4

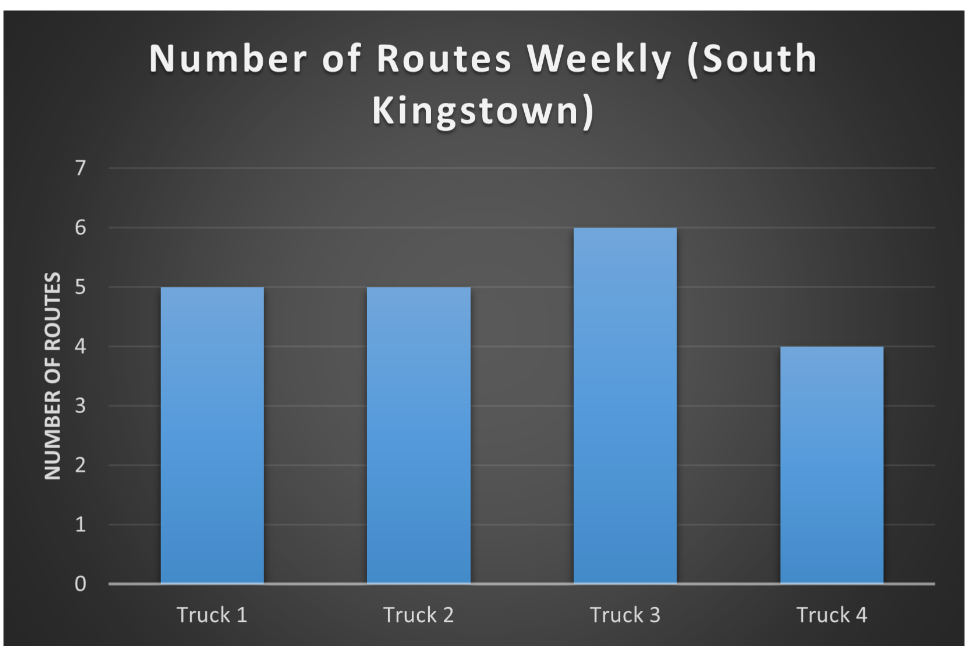

Figure C.146. Number of Routes Weekly (South Kingstown)

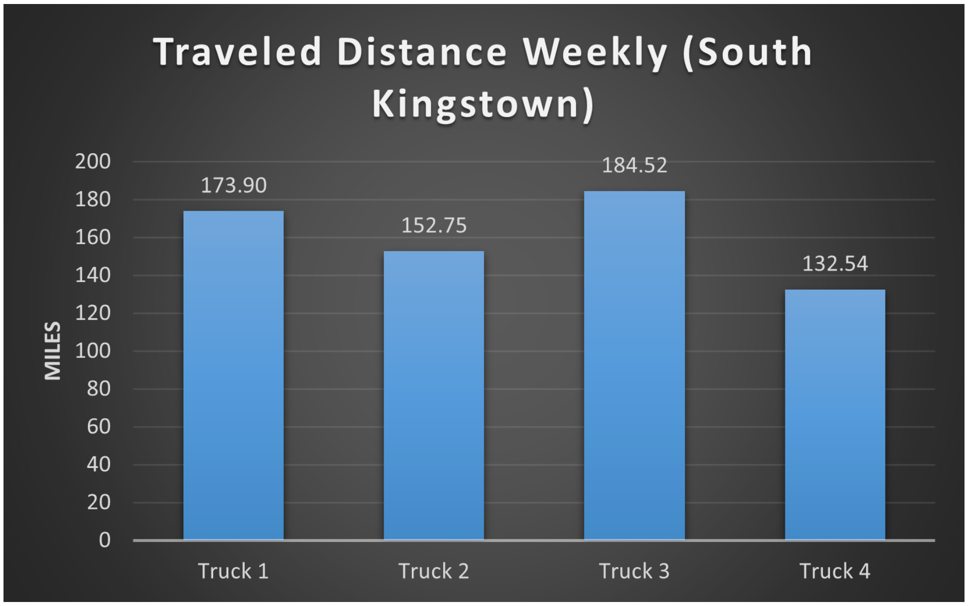

Figure C.147. Traveled Distance Weekly (South Kingstown)

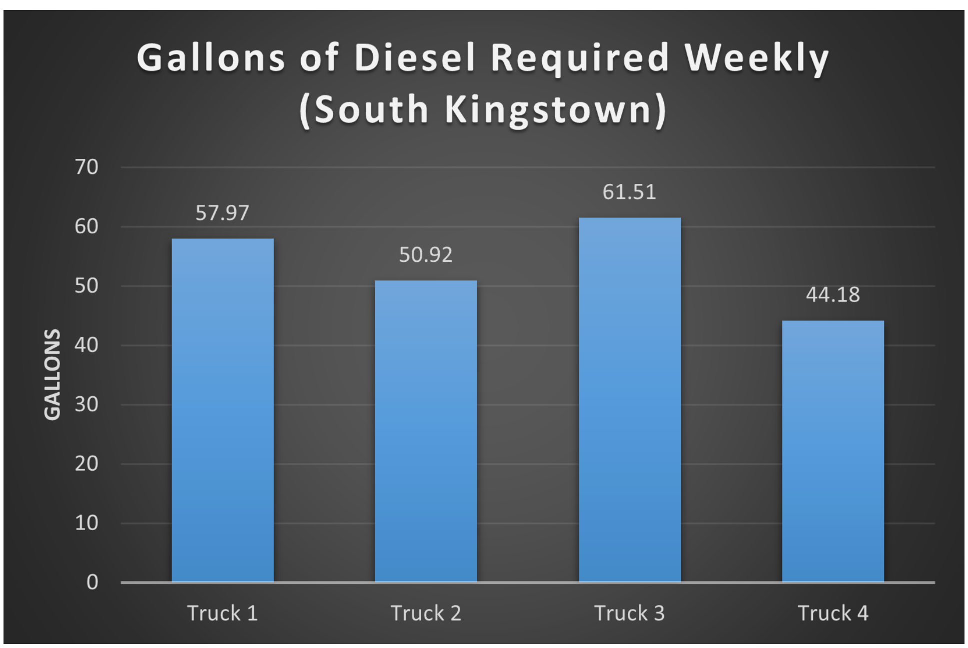

Figure C.148. Gallons of Diesel Required Weekly (South Kingstown)

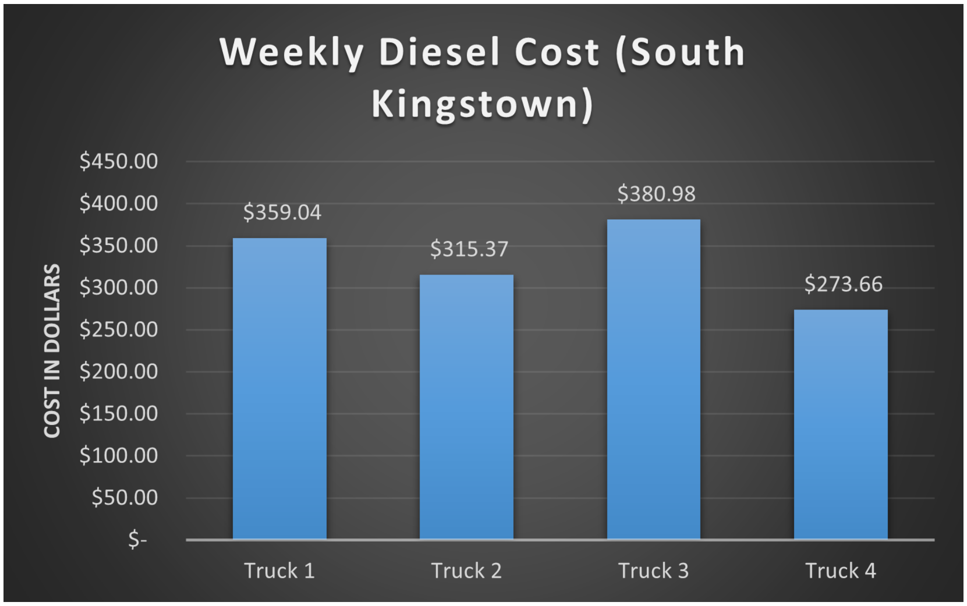

Figure C.149. Weekly Diesel Cost (South Kingstown)

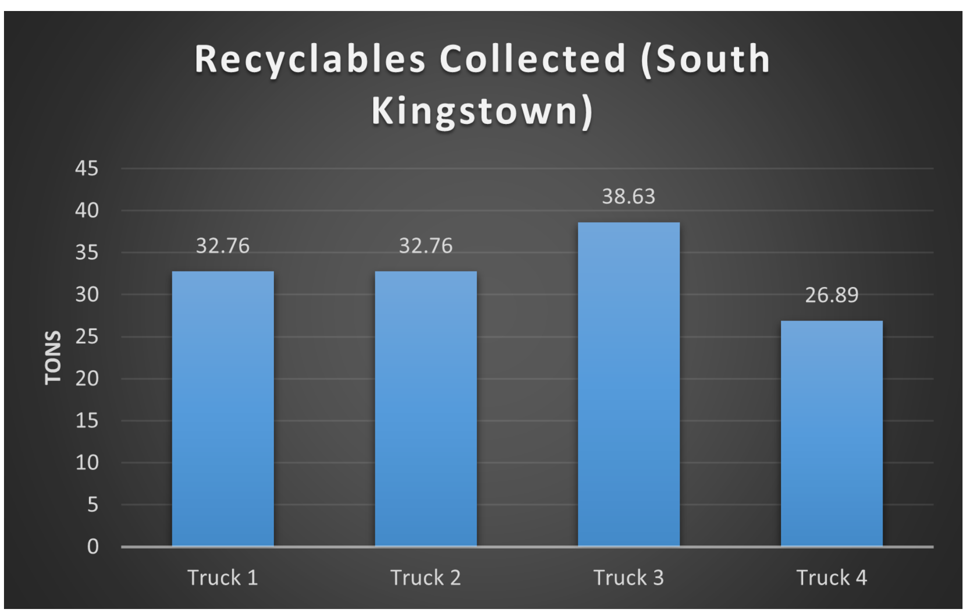

Figure C.150. Recyclables Collected (South Kingstown)

APPENDIX D

Charlestown

D.1 Routes, Individual Trucks, and Charts

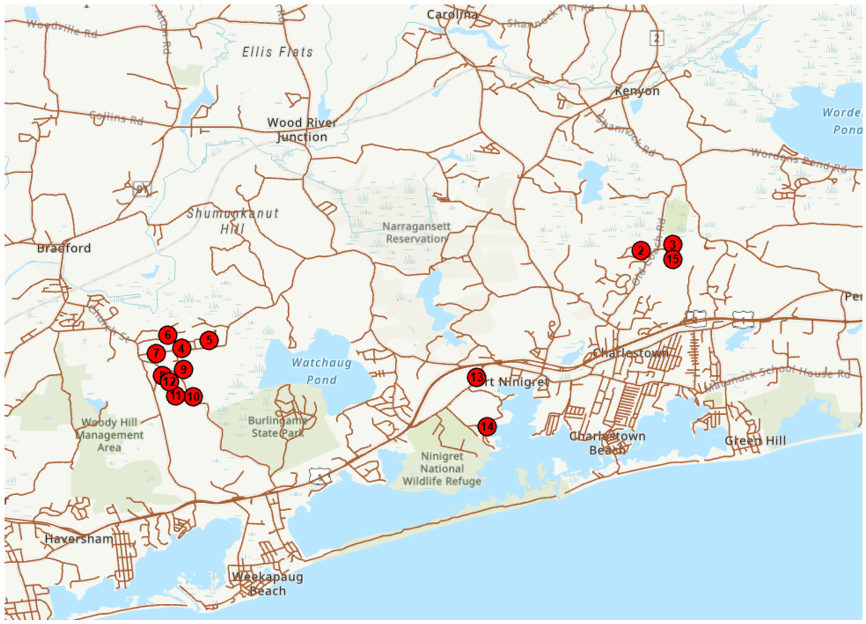

Figure D.151. Charlestown Route 1

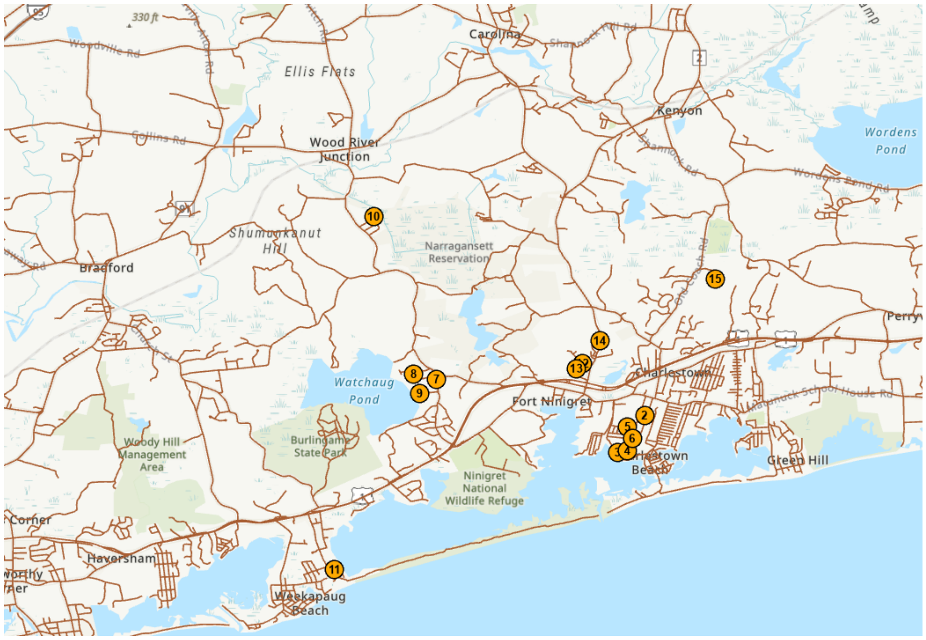

Figure D.152. Charlestown Route 2

Figure D.153. Charlestown Route 3

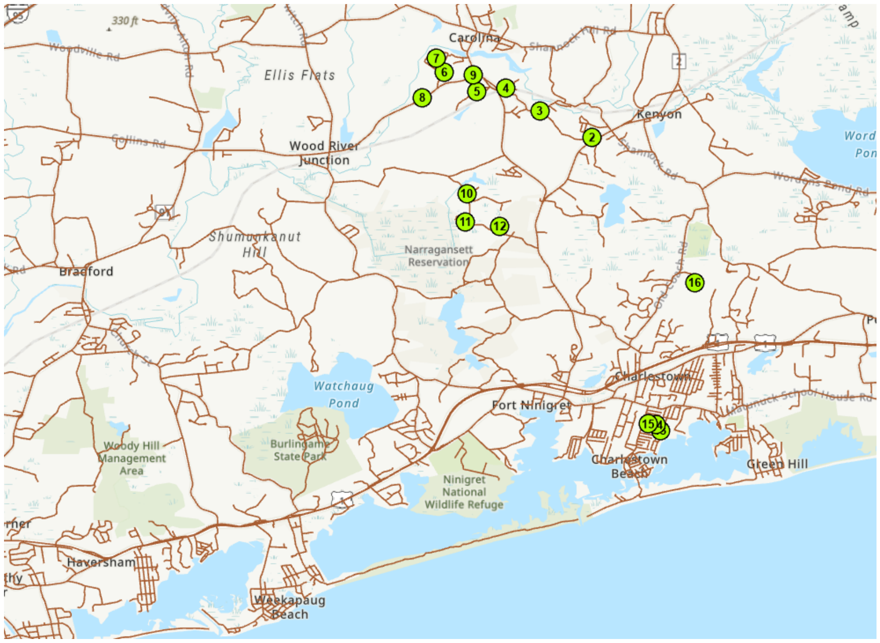

Figure D.154. Charlestown Route 4

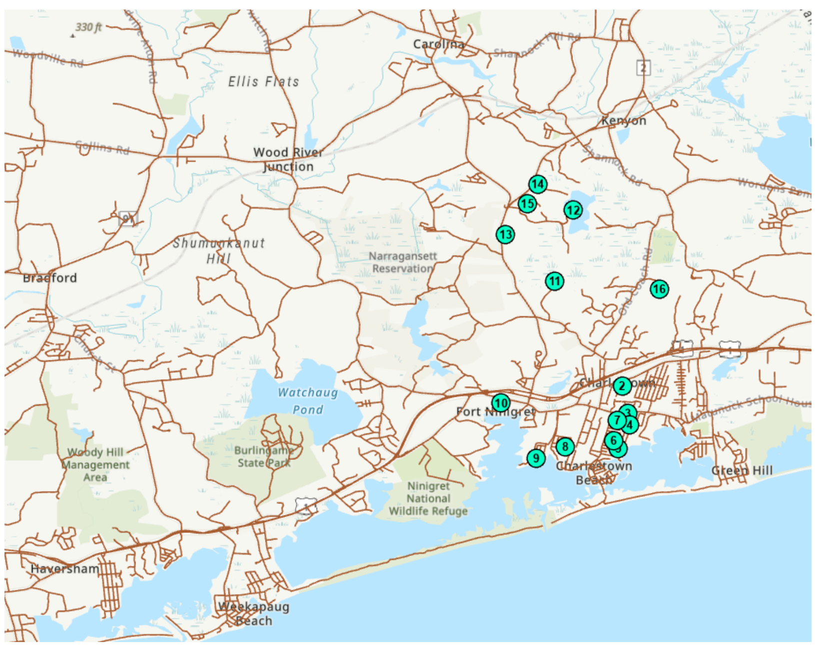

Figure D.155. Charlestown Route 5

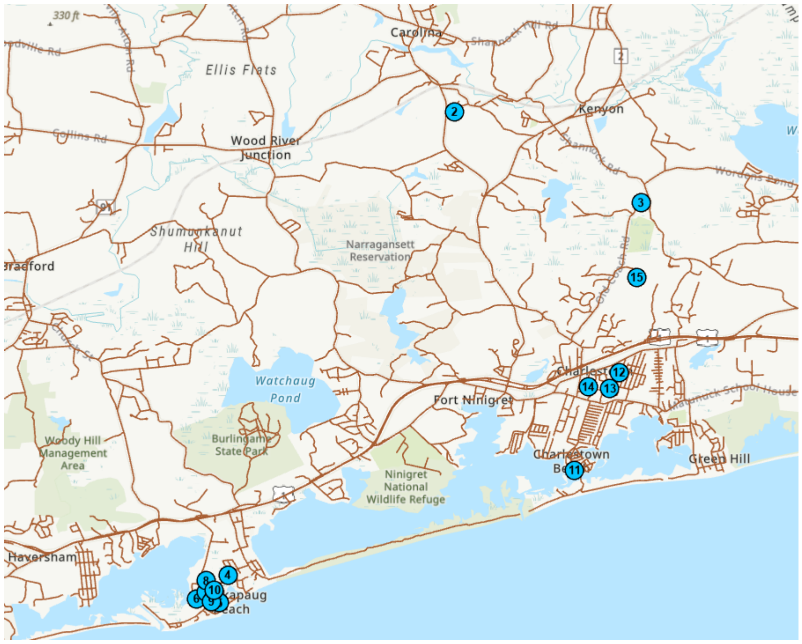

Figure D.156. Charlestown Route 6

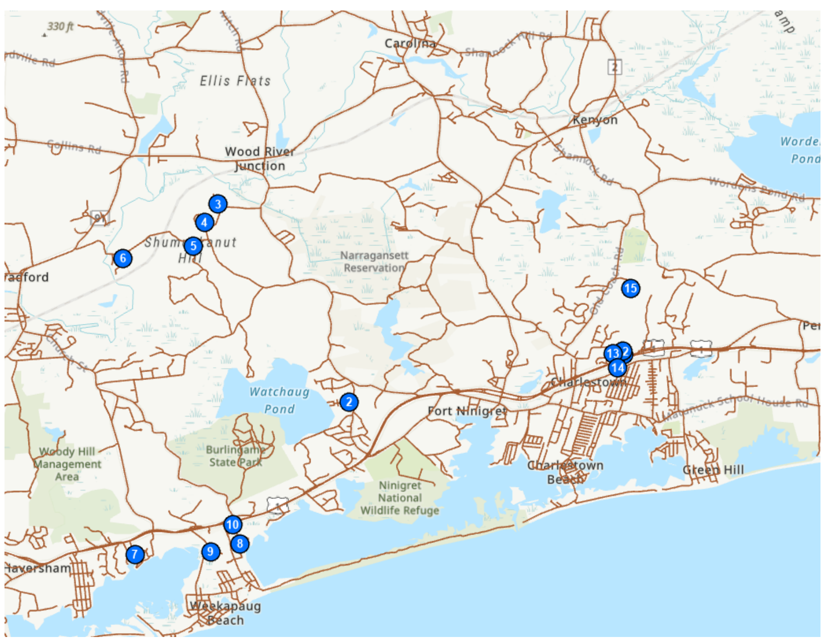

Figure D.157. Charlestown Route 7

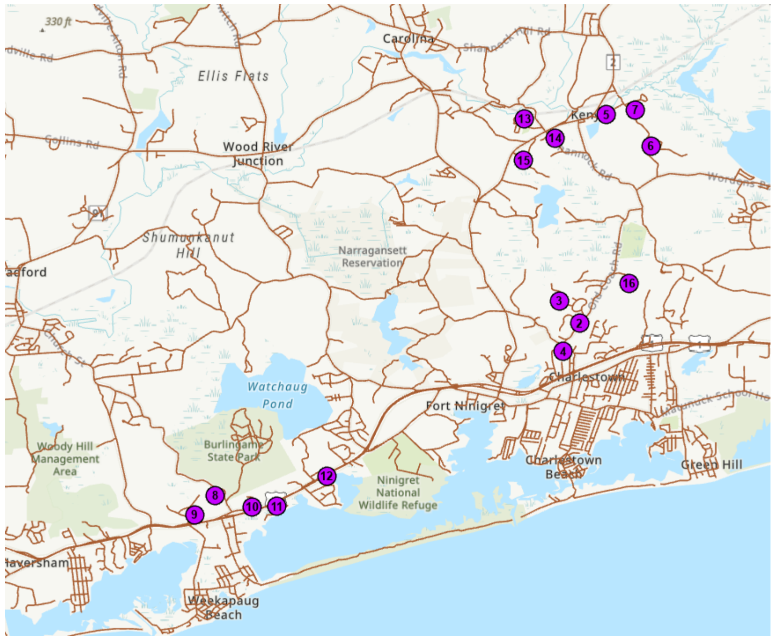

Figure D.158. Charlestown Route 8

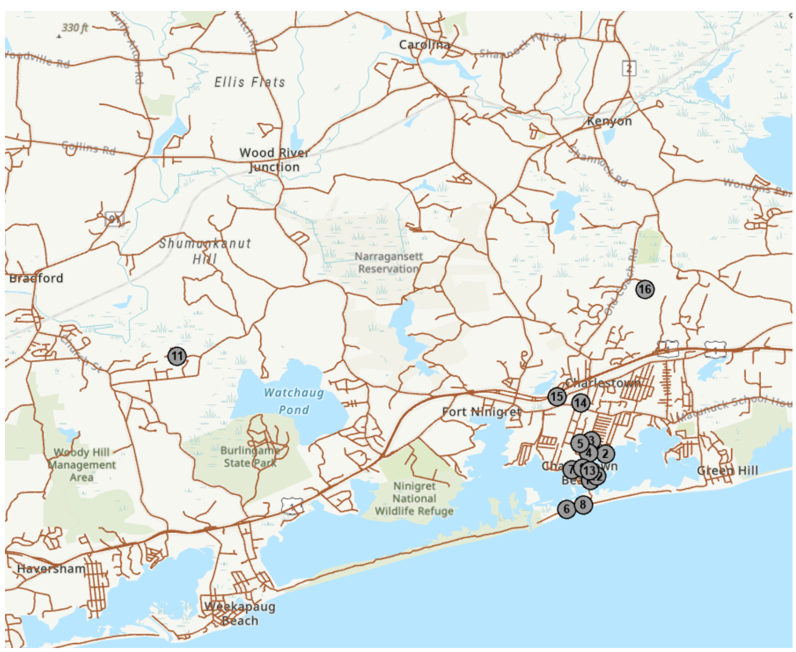

Figure D.159. Charlestown Route 9

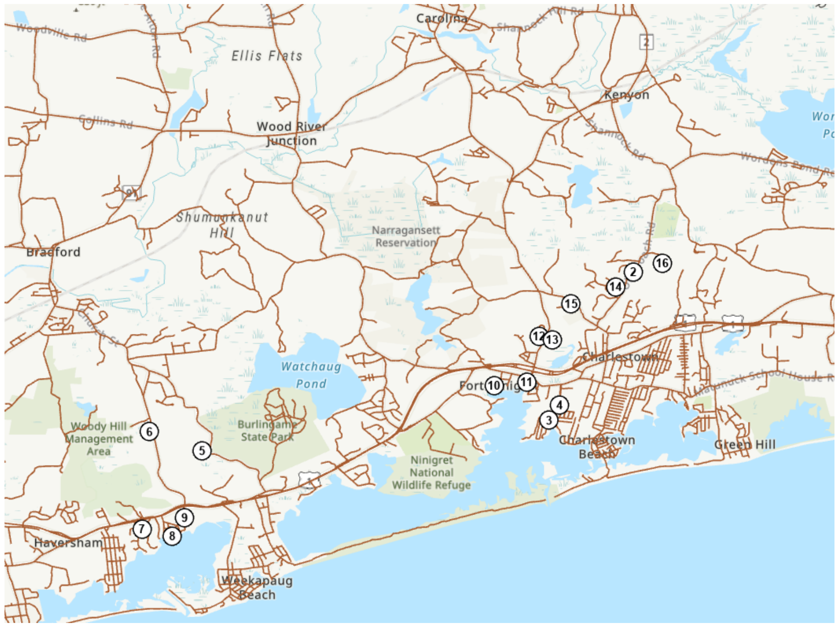

Figure D.160. Charlestown Route 10

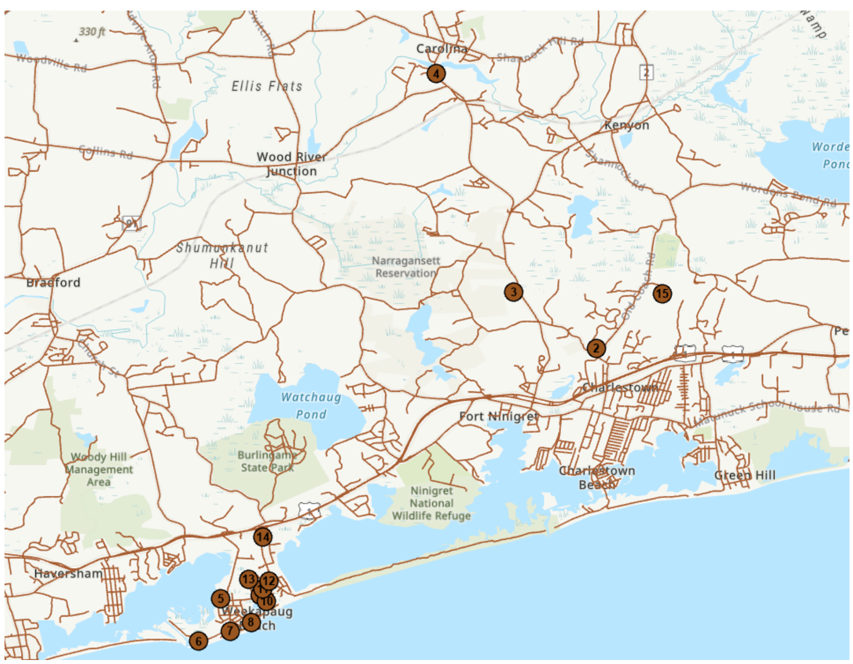

Figure D.161. Charlestown Route 11

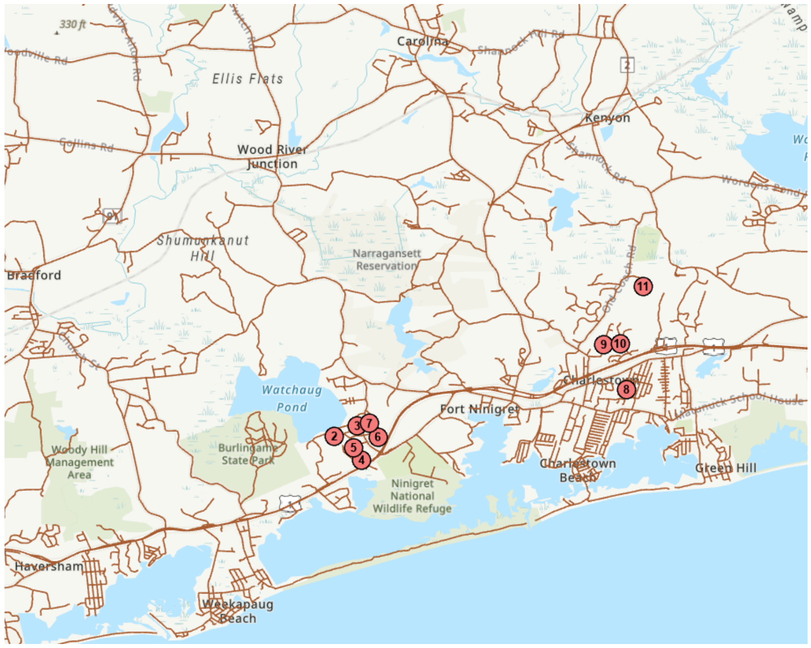

Figure D.162. Charlestown Route 12

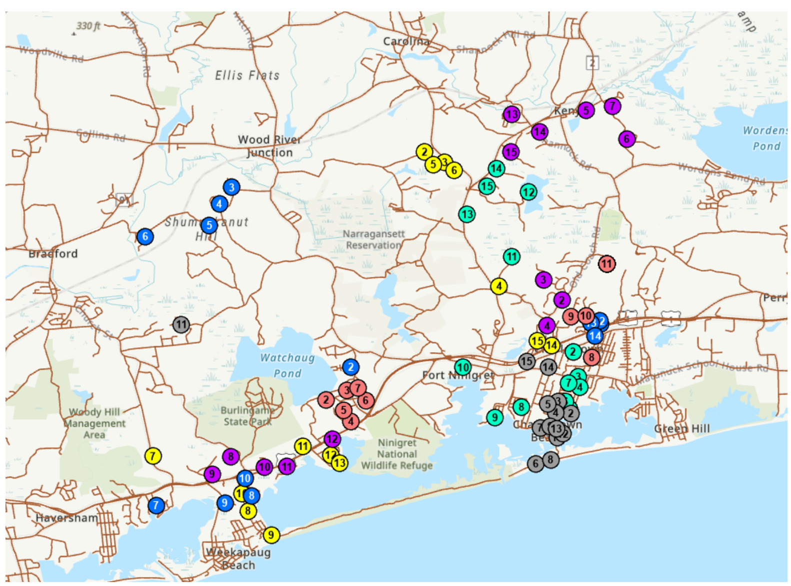

Figure D.163. Charlestown Truck 1

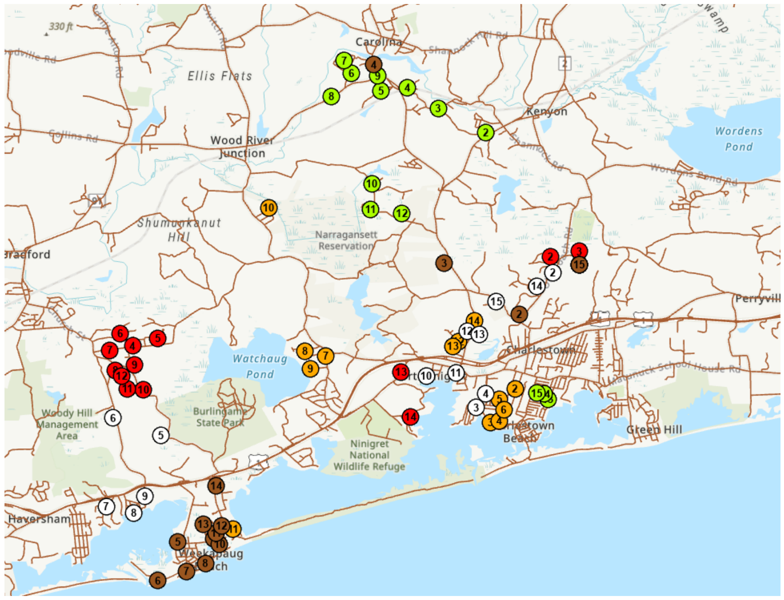

Figure D.164. Charlestown Truck 2

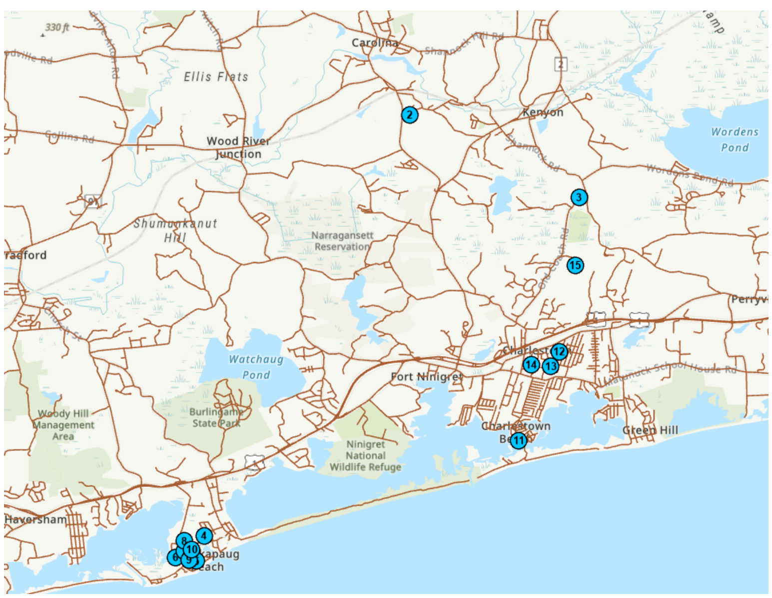

Figure D.165. Charlestown Truck 3

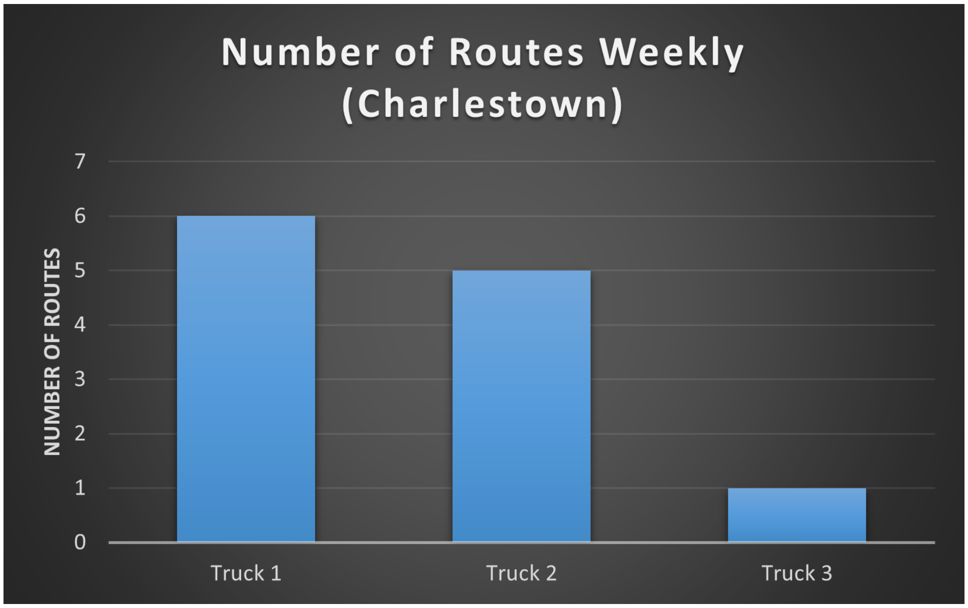

Figure D.166. Number of Routes Weekly (Charlestown)

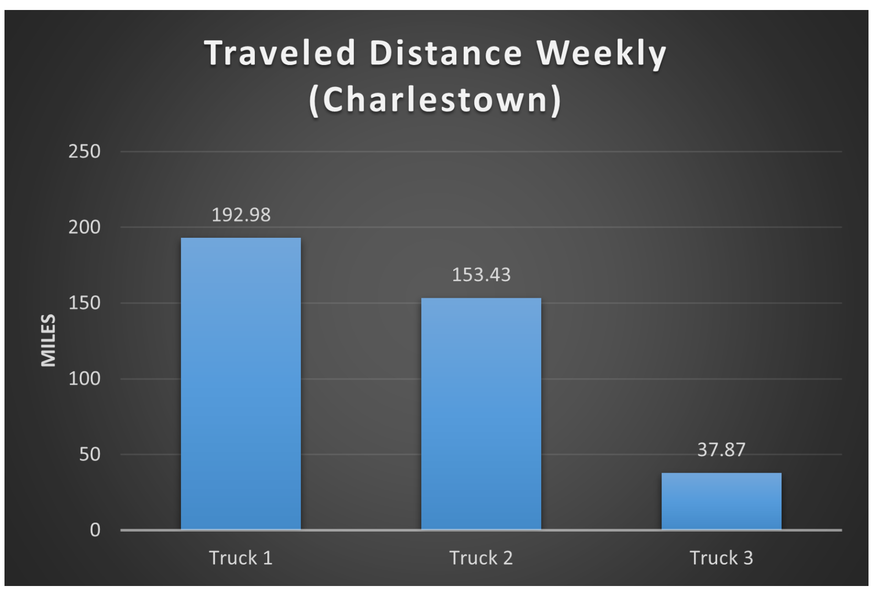

Figure D.167. Traveled Distance Weekly (Charlestown)

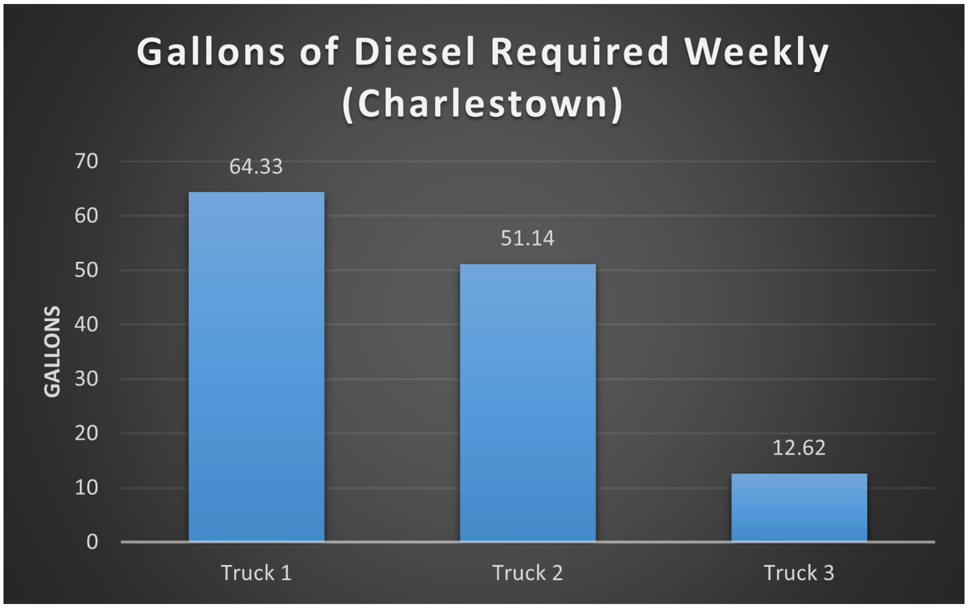

Figure D.168. Gallons of Diesel Required Weekly (Charlestown)

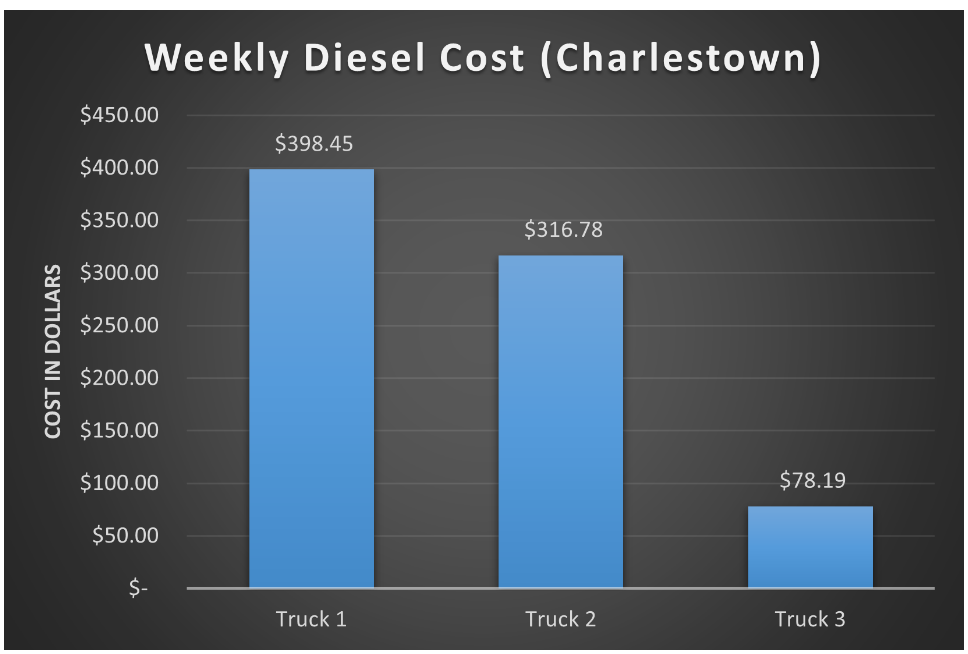

Figure D.169. Weekly Diesel Cost (Charlestown)

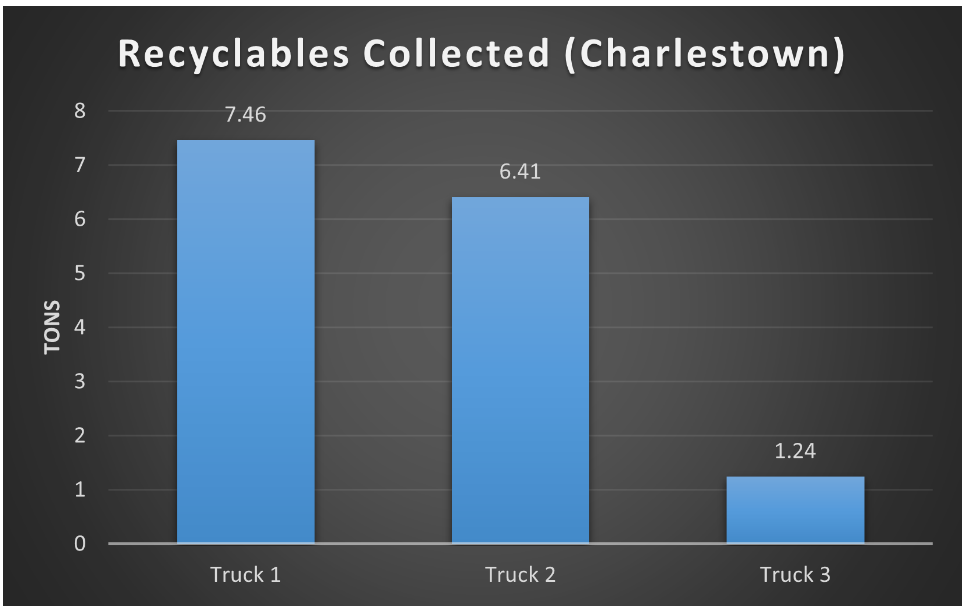

Figure D.170. Recyclables Collected (Charlestown)

APPENDIX E

Glocester

E.1 Routes, Individual Trucks, and Charts

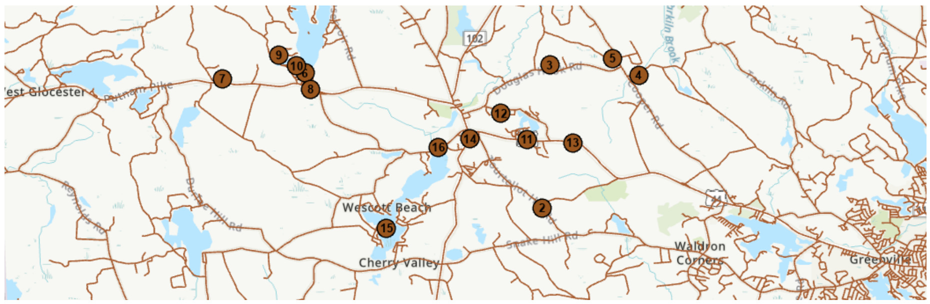

Figure E.171. Glocester Route 1

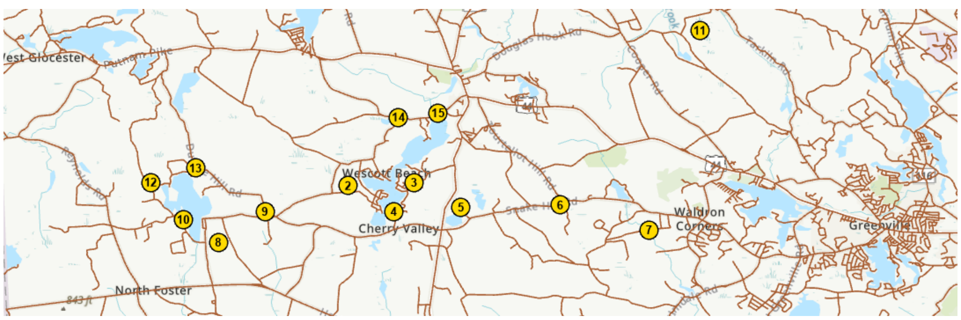

Figure E.172. Glocester Route 2

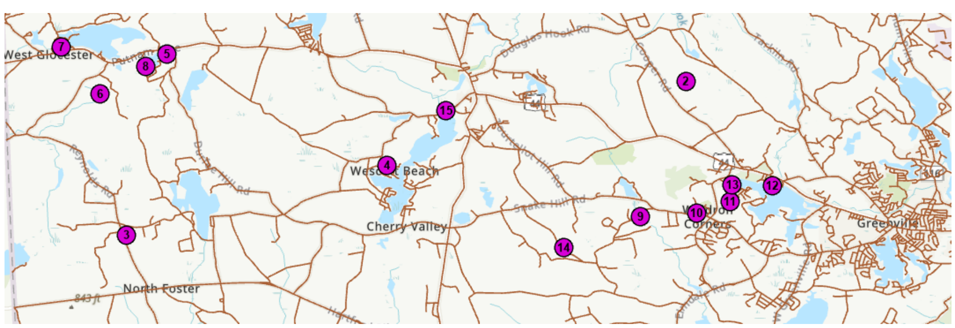

Figure E.173. Glocester Route 3

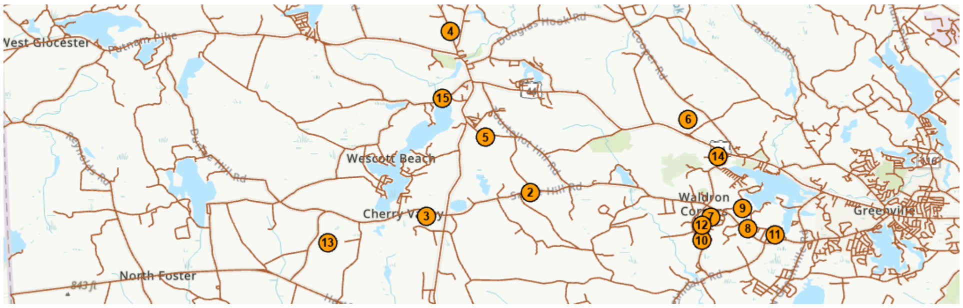

Figure E.174. Glocester Route 4

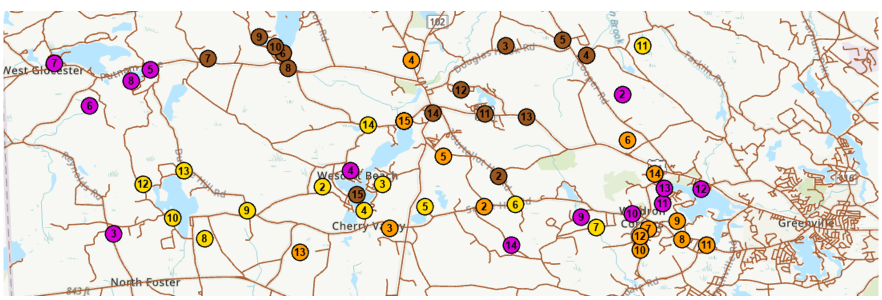

Figure E.175. Glocester Truck 1

APPENDIX F

Little Compton

F.1 Routes, Individual Trucks, and Charts

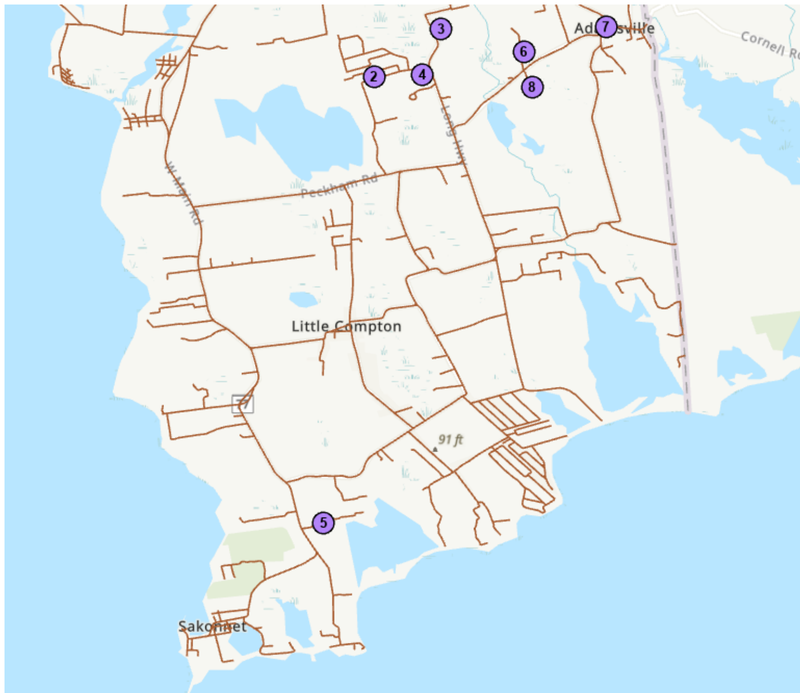

Figure F.176. Little Compton Route 1

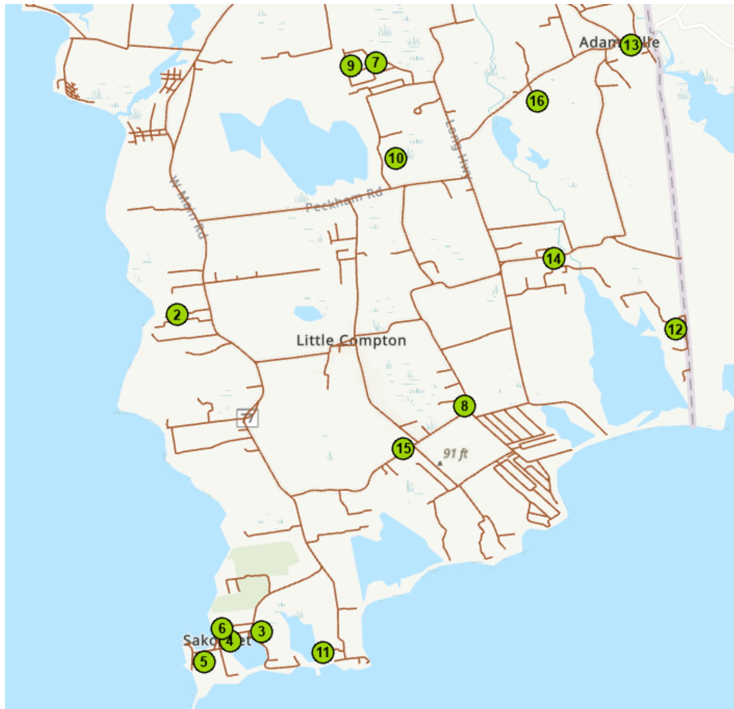

Figure F.177. Little Compton Route 2

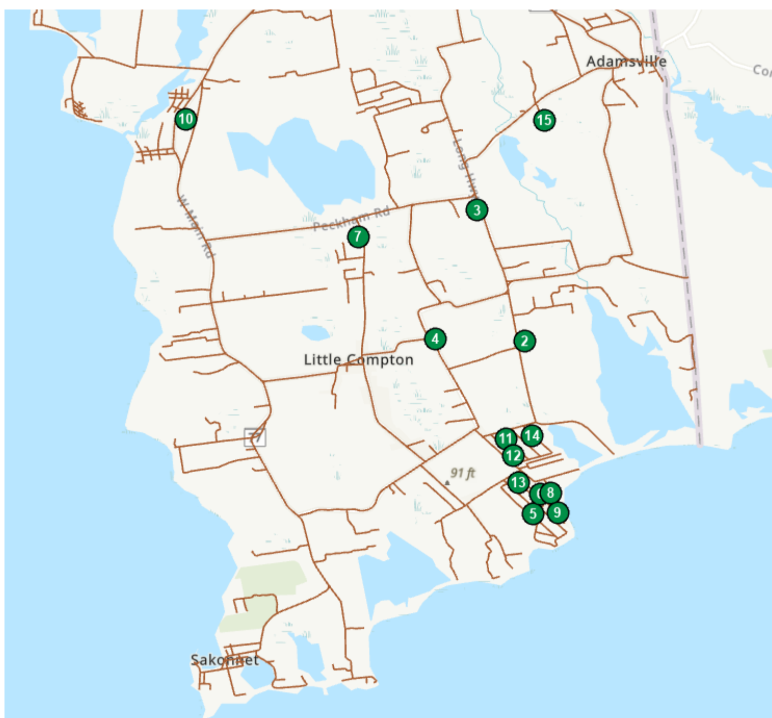

Figure F.178. Little Compton Route 3

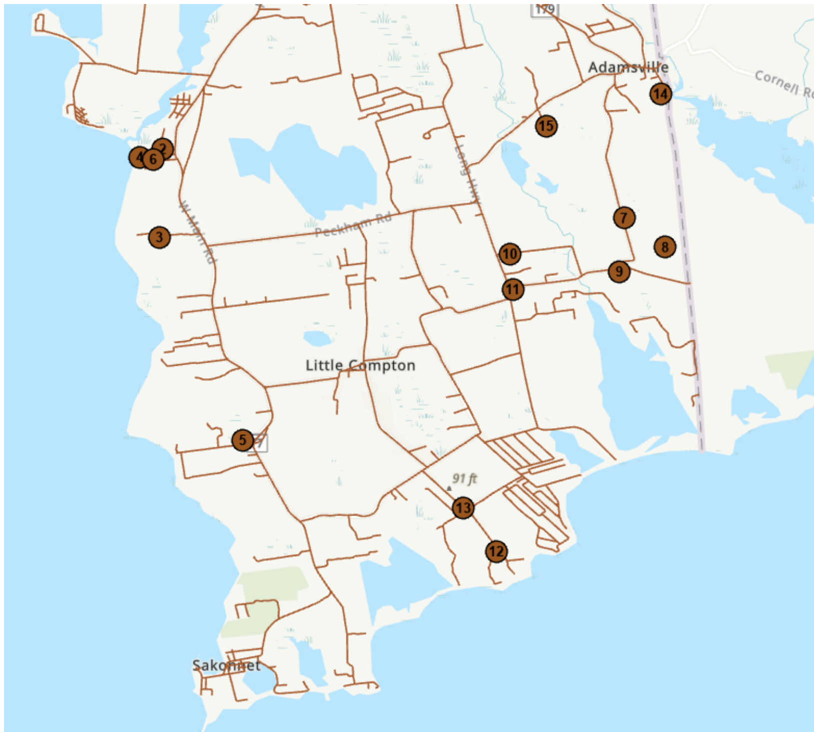

Figure F.179. Little Compton Route 4

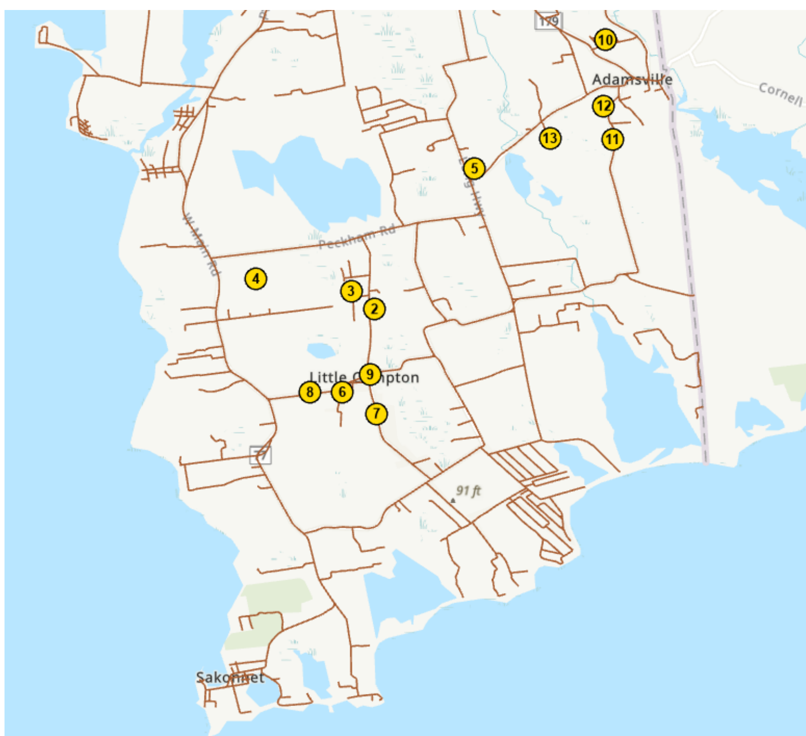

Figure F.180. Little Compton Route 5

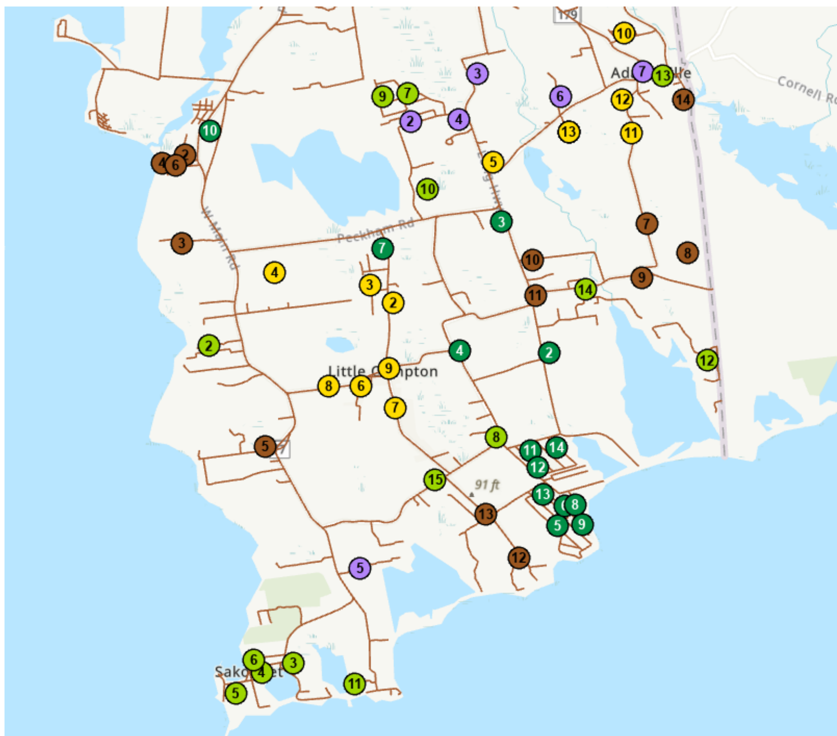

Figure F.181. Little Compton Truck 1

APPENDIX G

Portsmouth

G.1 Routes, Individual Trucks, and Charts

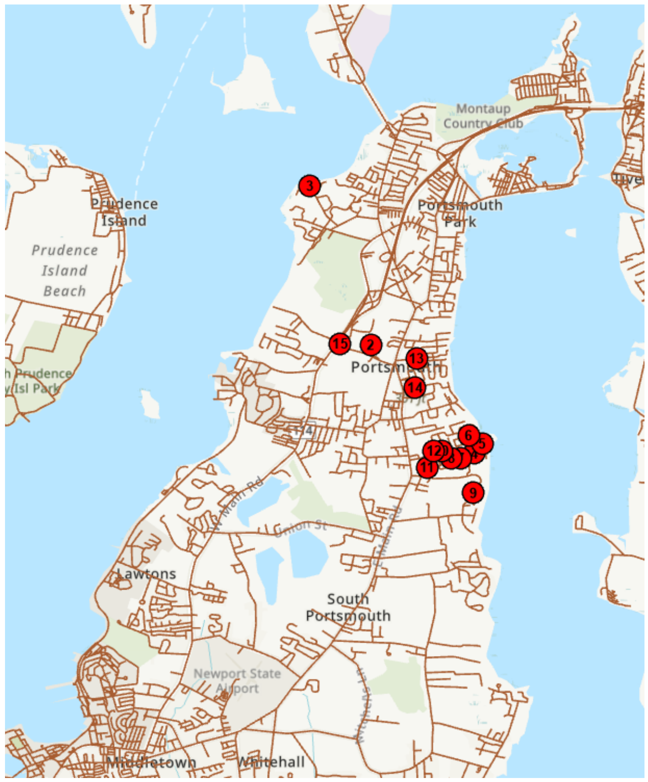

Figure G.182. Portsmouth Route 1

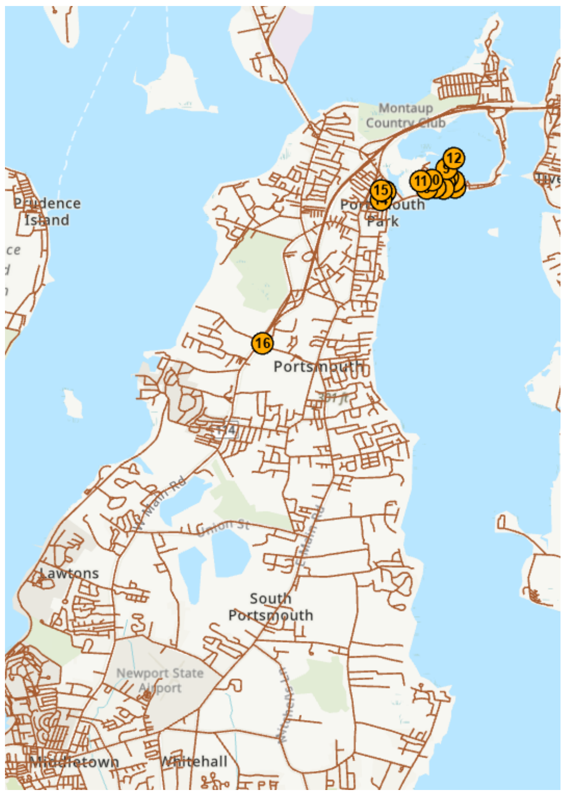

Figure G.183. Portsmouth Route 2

Figure G.184. Portsmouth Route 3

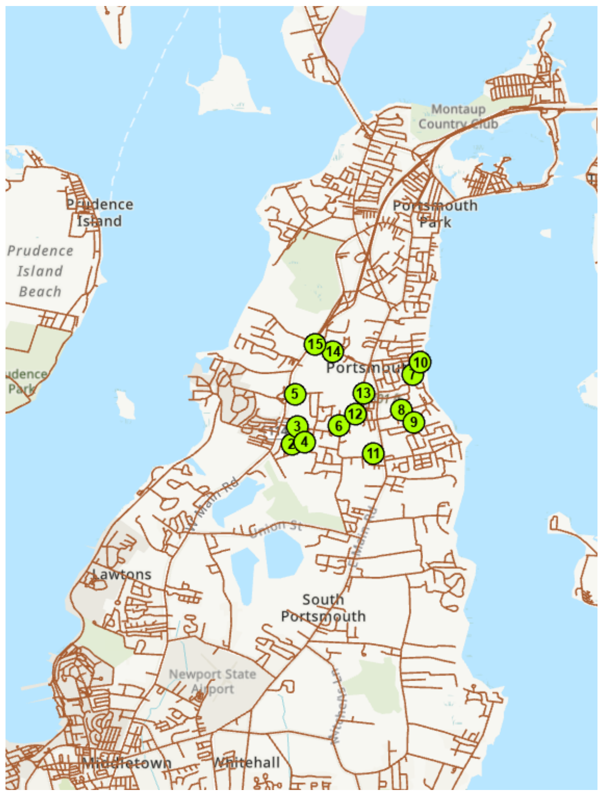

Figure G.185. Portsmouth Route 4

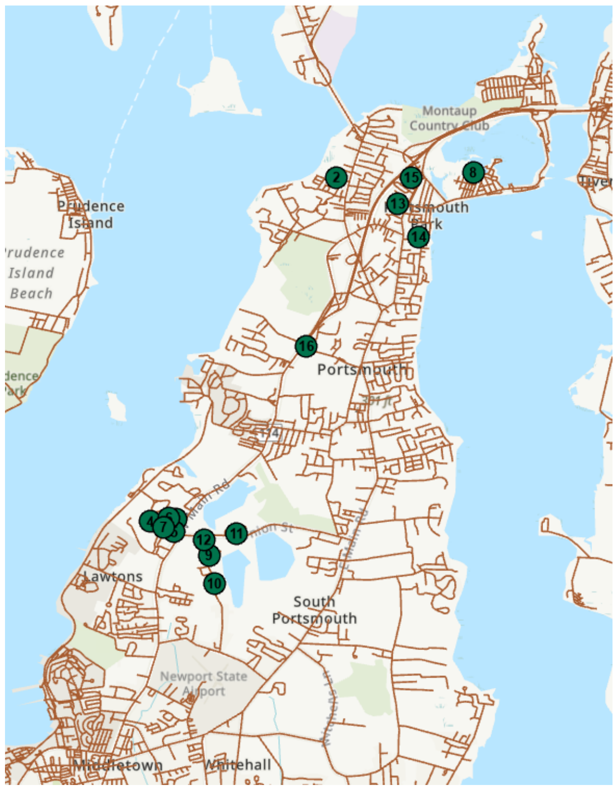

Figure G.186. Portsmouth Route 5

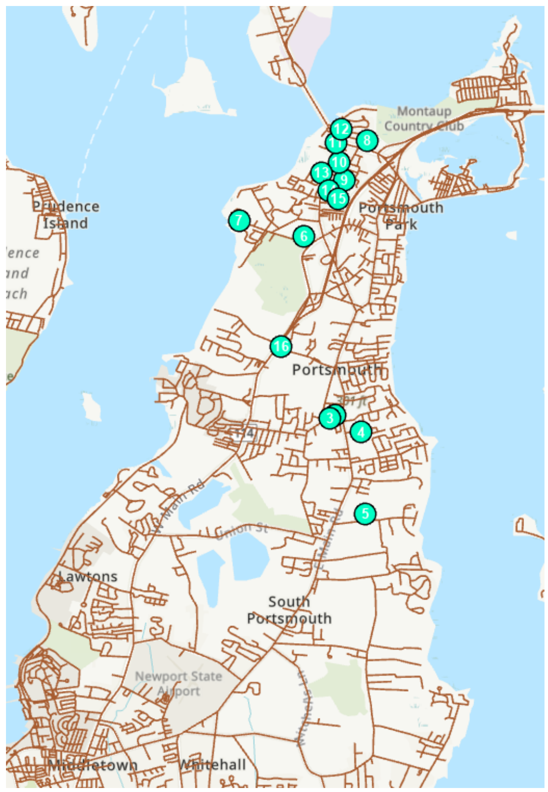

Figure G.187. Portsmouth Route 6

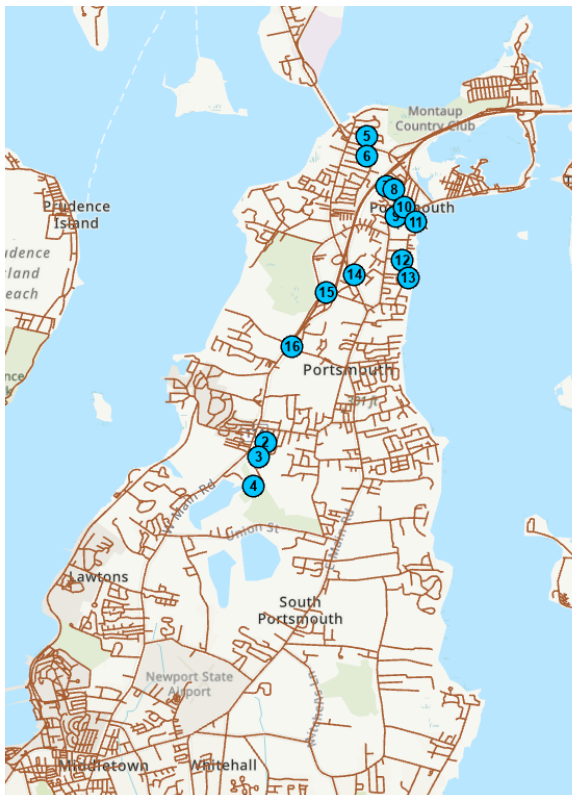

Figure G.188. Portsmouth Route 7

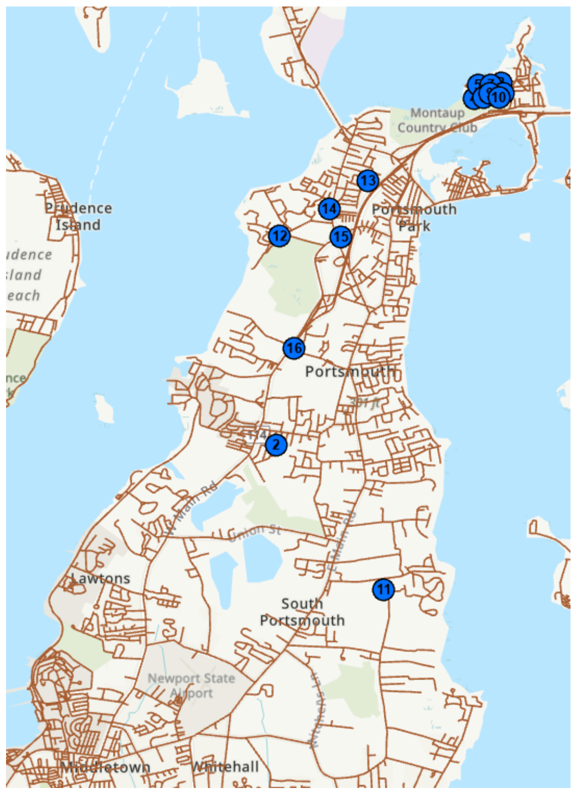

Figure G.189. Portsmouth Route 8

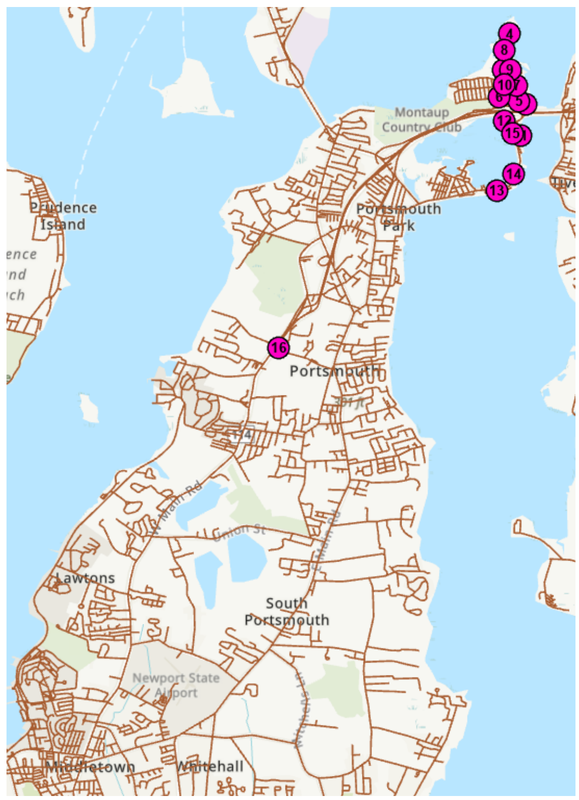

Figure G.190. Portsmouth Route 9

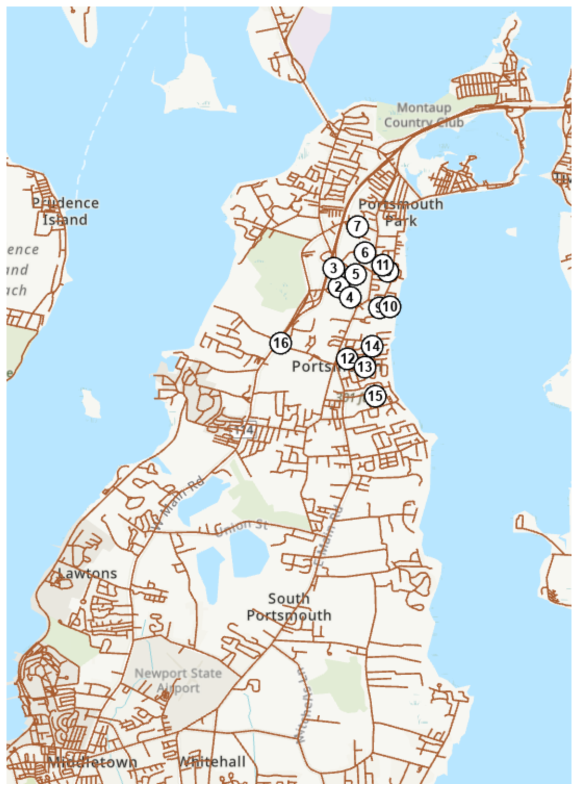

Figure G.191. Portsmouth Route 10

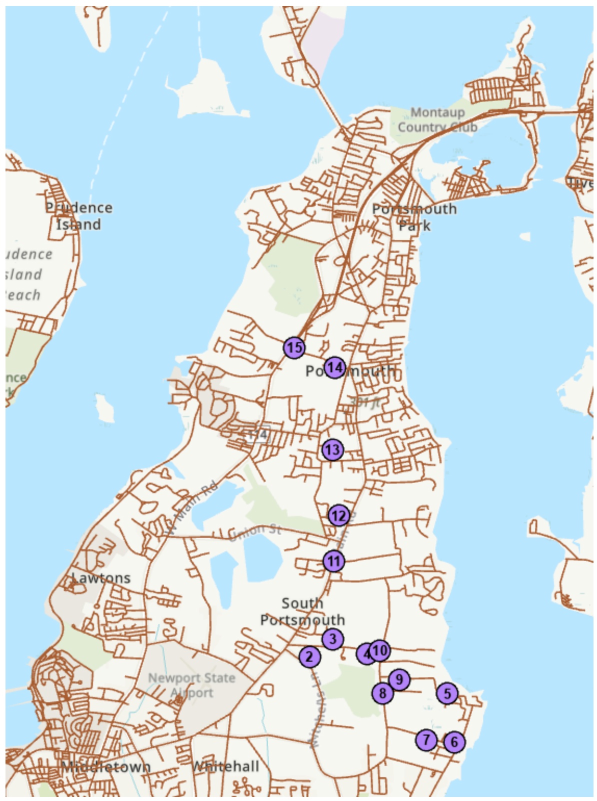

Figure G.192. Portsmouth Route 11

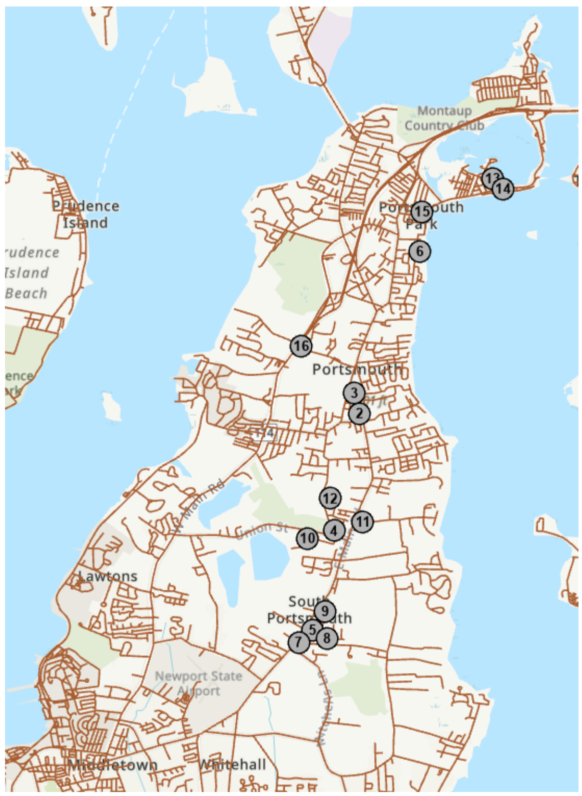

Figure G.193. Portsmouth Route 12

Figure G.194. Portsmouth Route 13

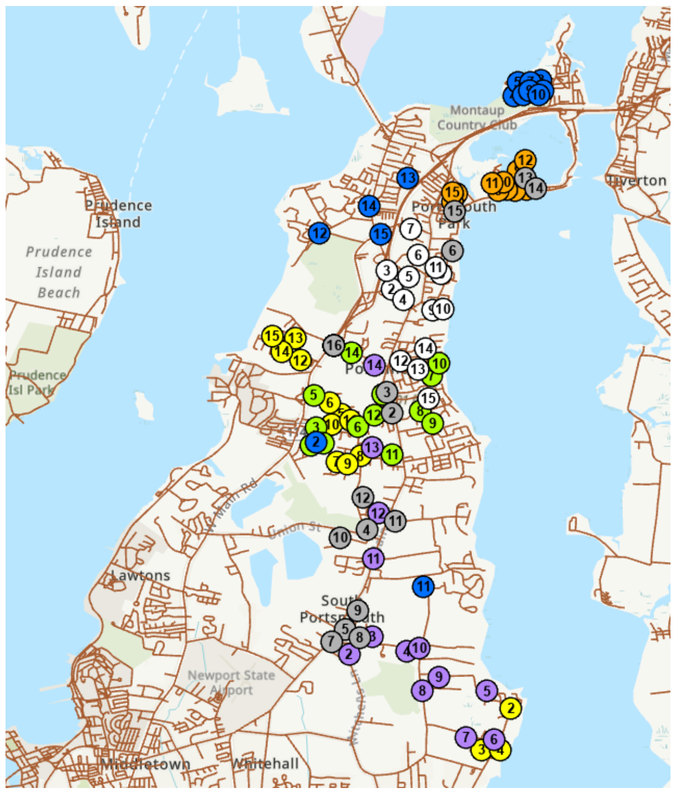

Figure G.195. Portsmouth Truck 1

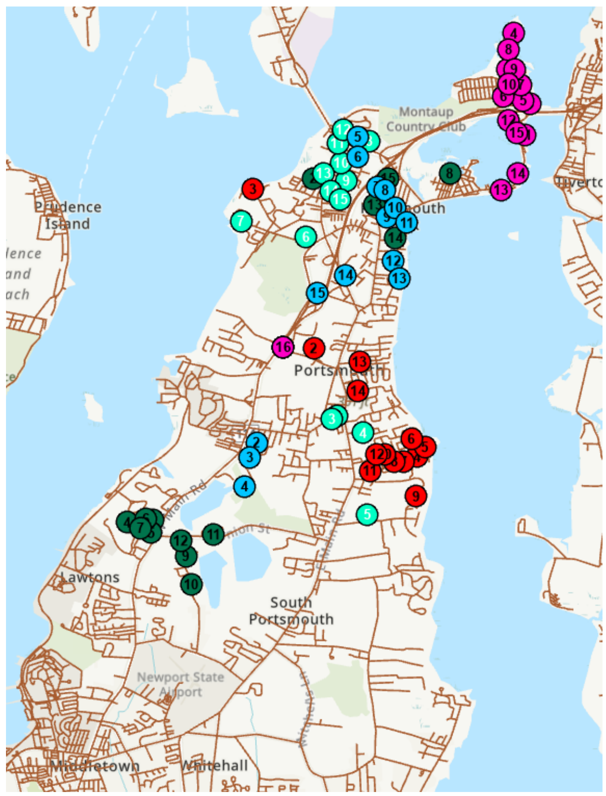

Figure G.196. Portsmouth Truck 2

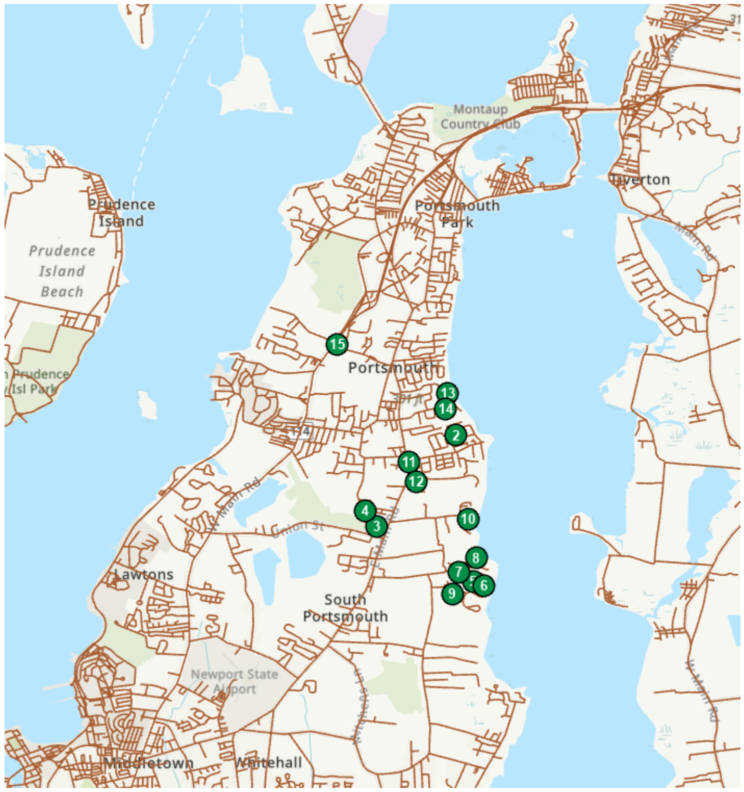

Figure G.197. Portsmouth Truck 3

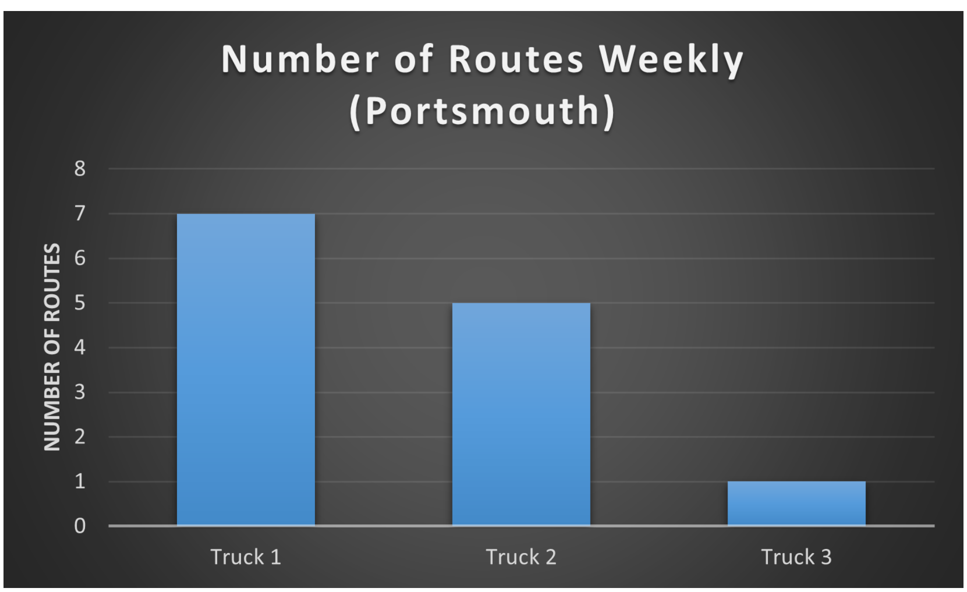

Figure G.198. Number of Routes Weekly (Portsmouth)

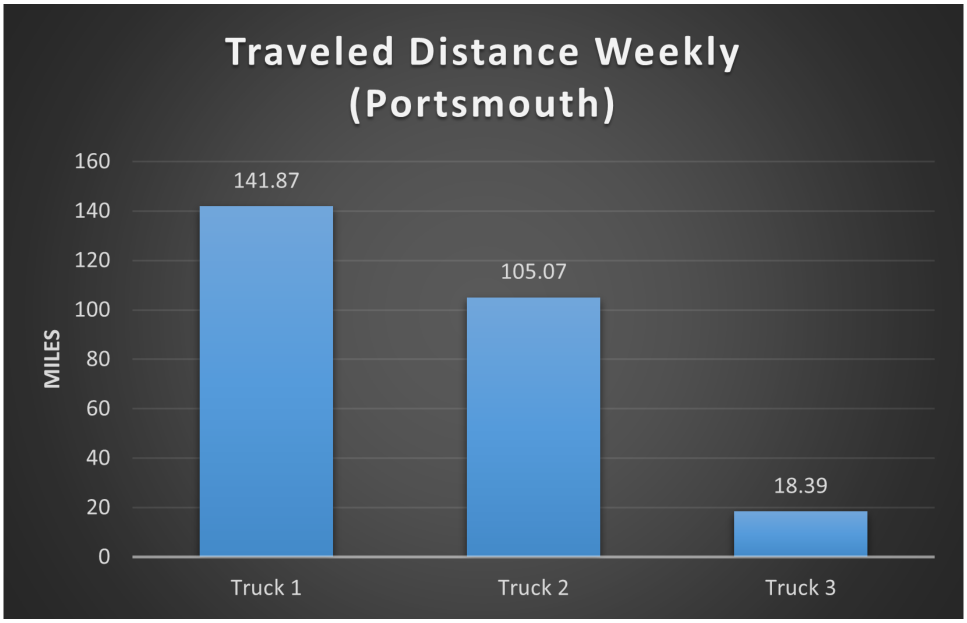

Figure G.199. Traveled Distance Weekly (Portsmouth)

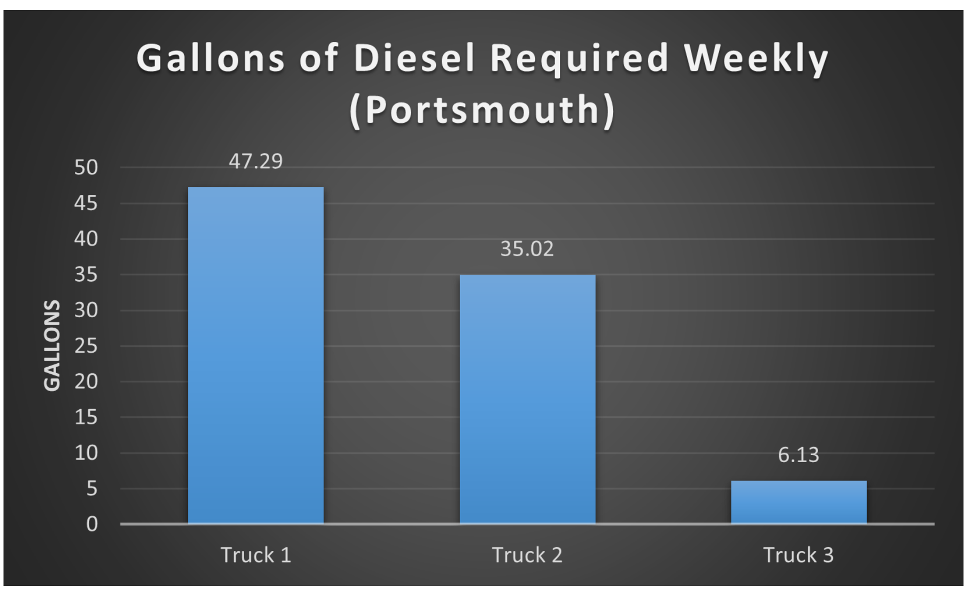

Figure G.200. Gallons of Diesel Required Weekly (Portsmouth)

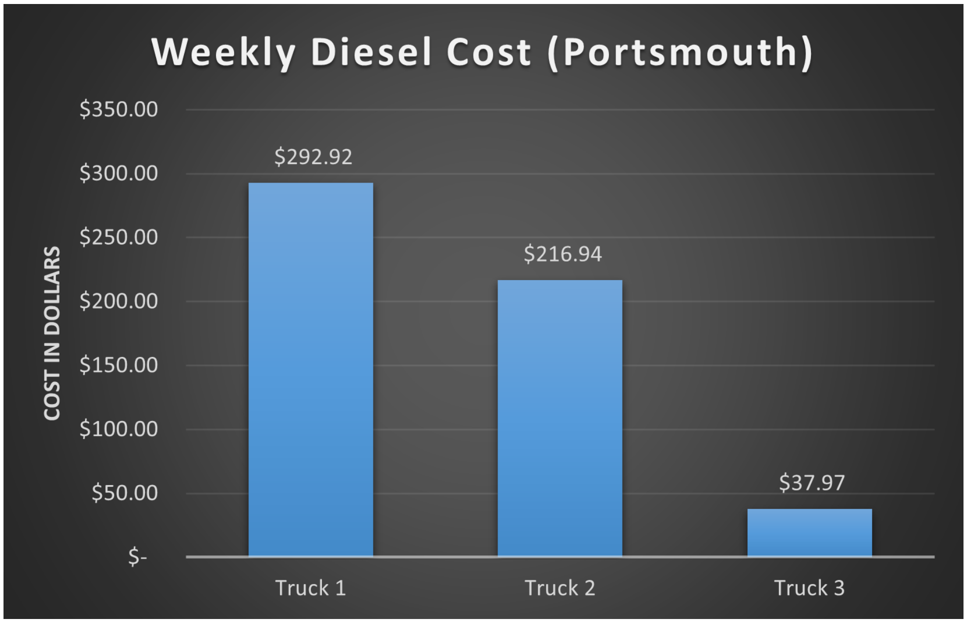

Figure G.201. Weekly Diesel Cost (Portsmouth)

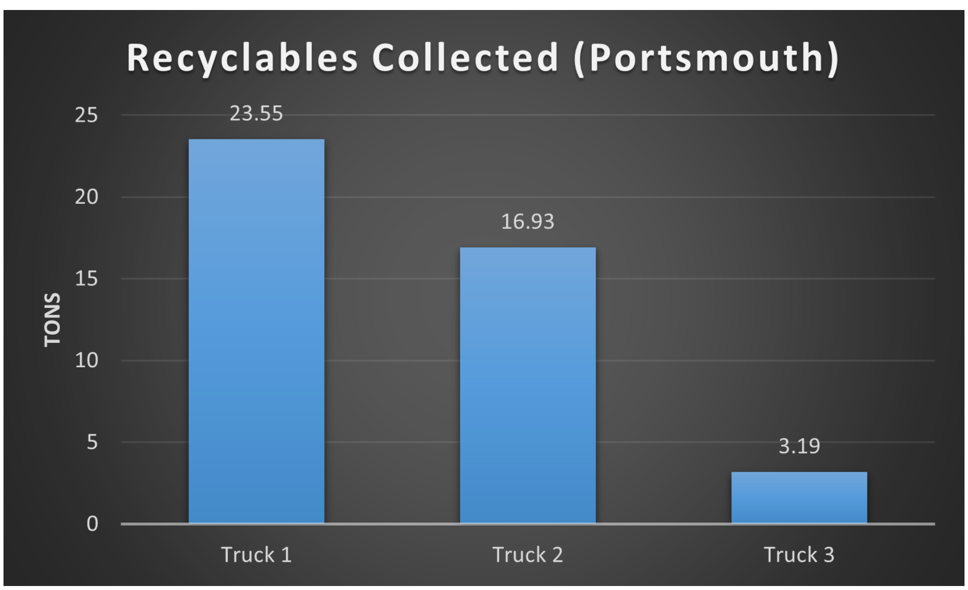

Figure G.202. Recyclables Collected (Portsmouth)

APPENDIX H

Richmond

H.1 Routes, Individual Trucks, and Charts

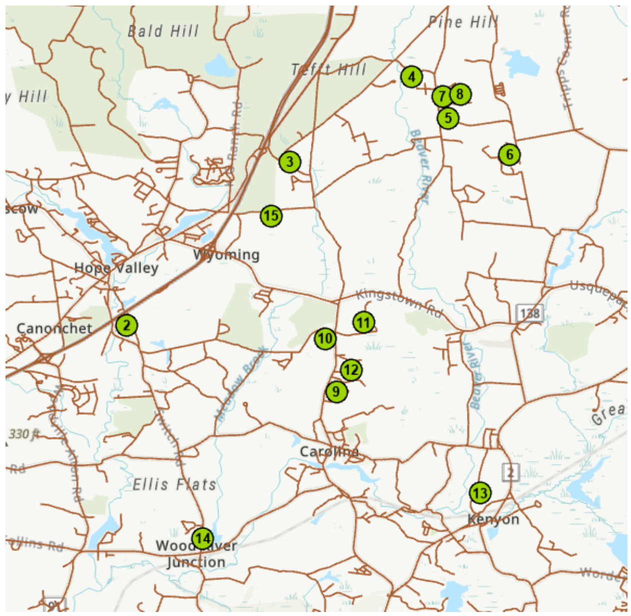

Figure H.203. Richmond Route 1

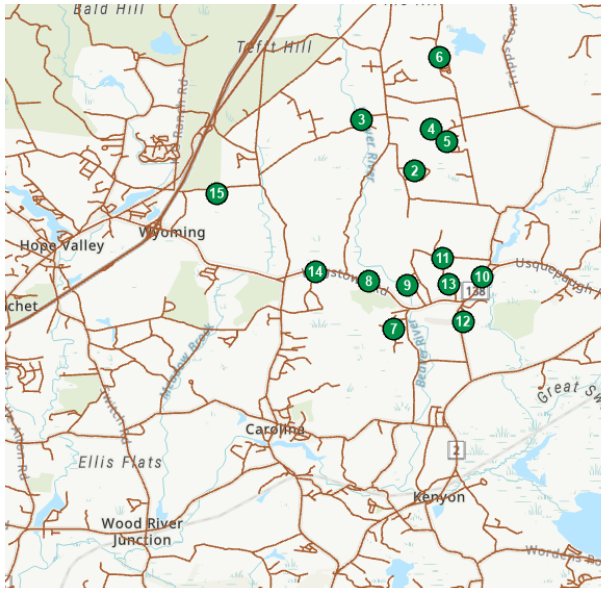

Figure H.204. Richmond Route 2

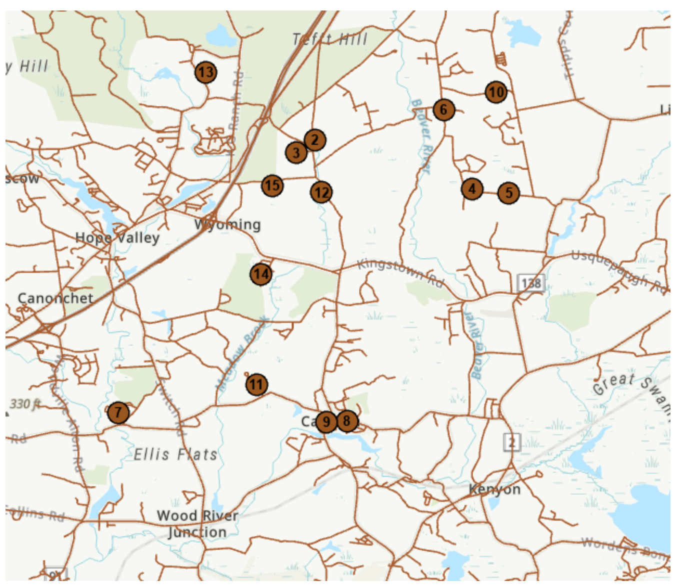

Figure H.205. Richmond Route 3

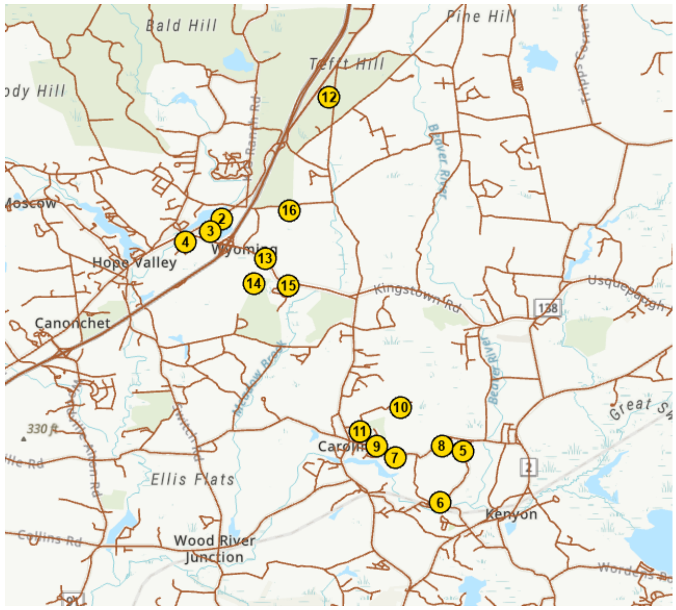

Figure H.206. Richmond Route 4

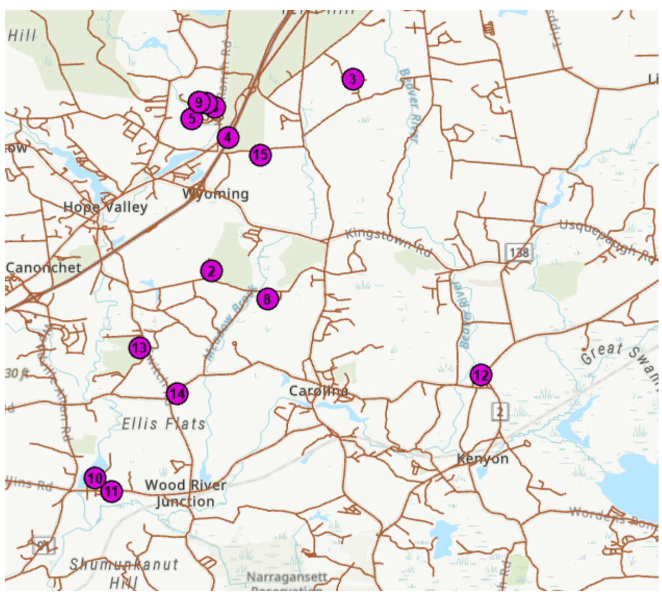

Figure H.207. Richmond Route 5

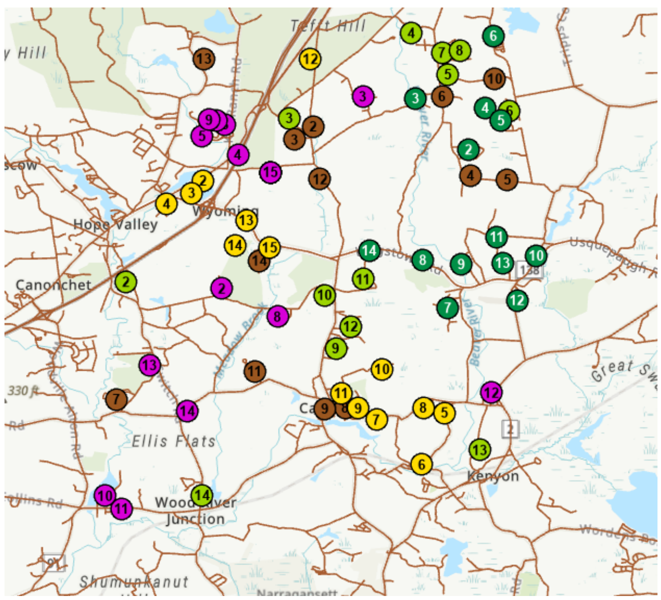

Figure H.208. Richmond Truck 1

APPENDIX I

Scituate

I.1 Routes, Individual Trucks, and Charts

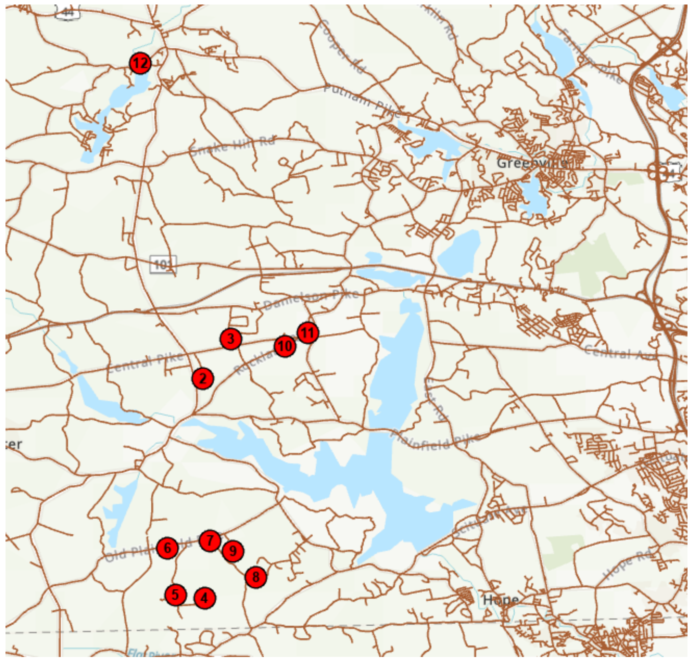

Figure I.209. Scituate Route 1

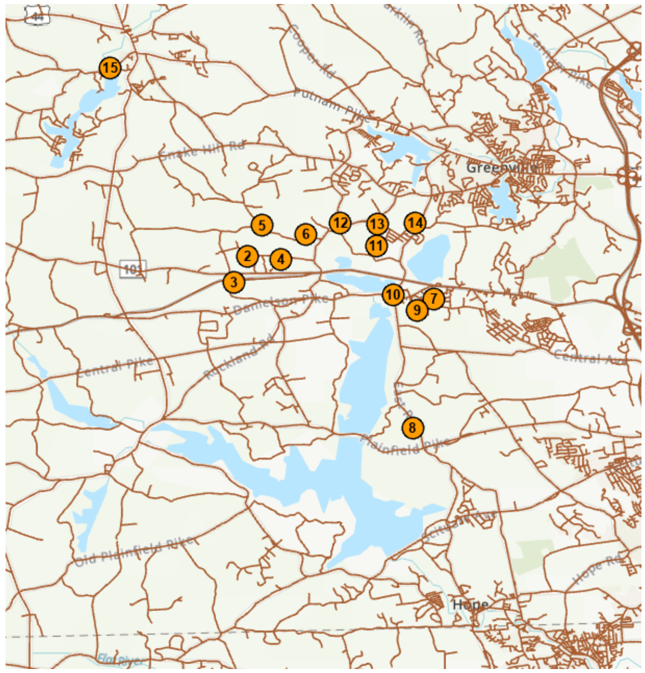

Figure I.210. Scituate Route 2

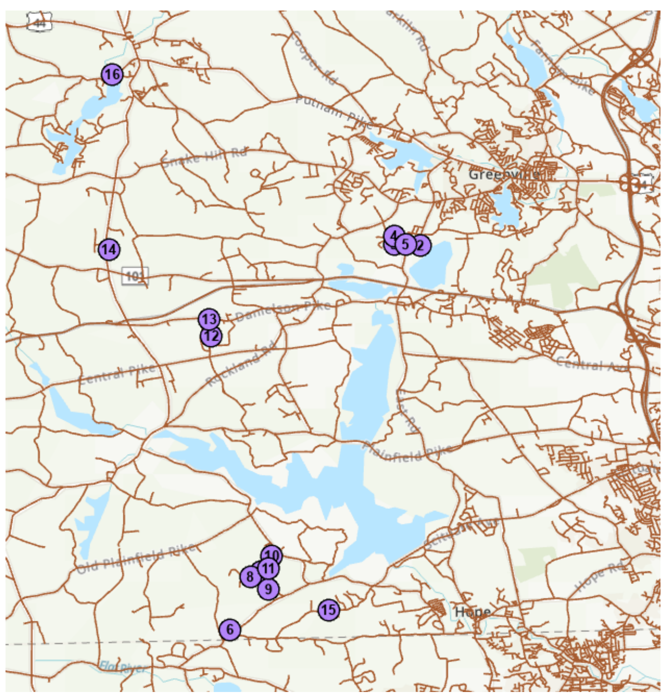

Figure I.211. Scituate Route 3

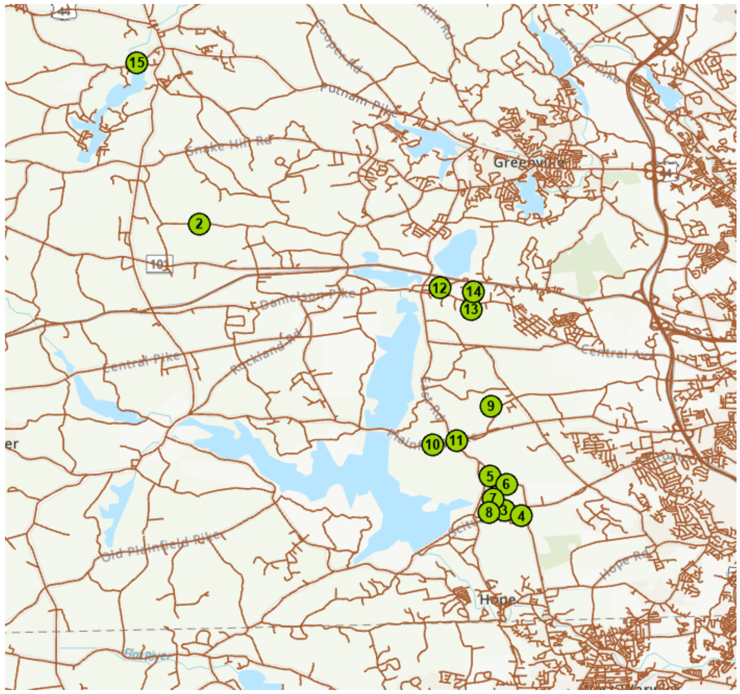

Figure I.212. Scituate Route 4

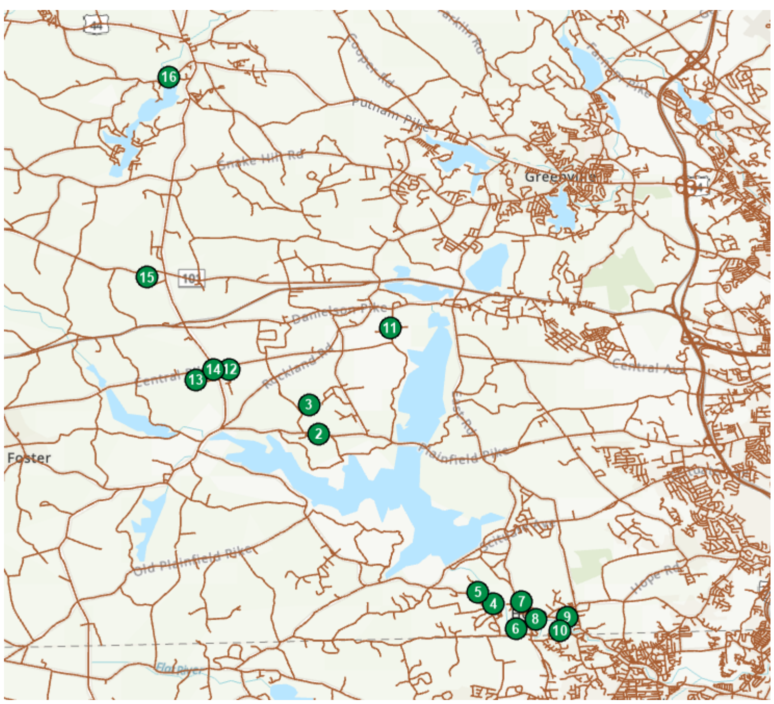

Figure I.213. Scituate Route 5

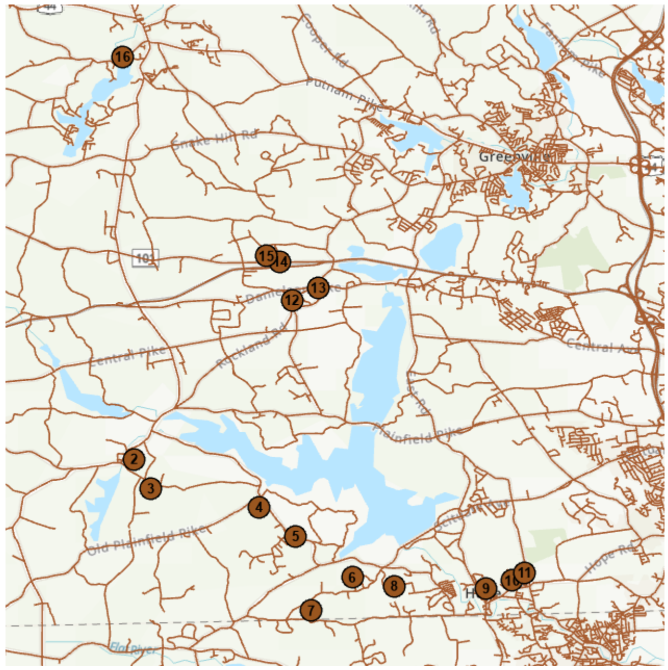

Figure I.214. Scituate Route 6

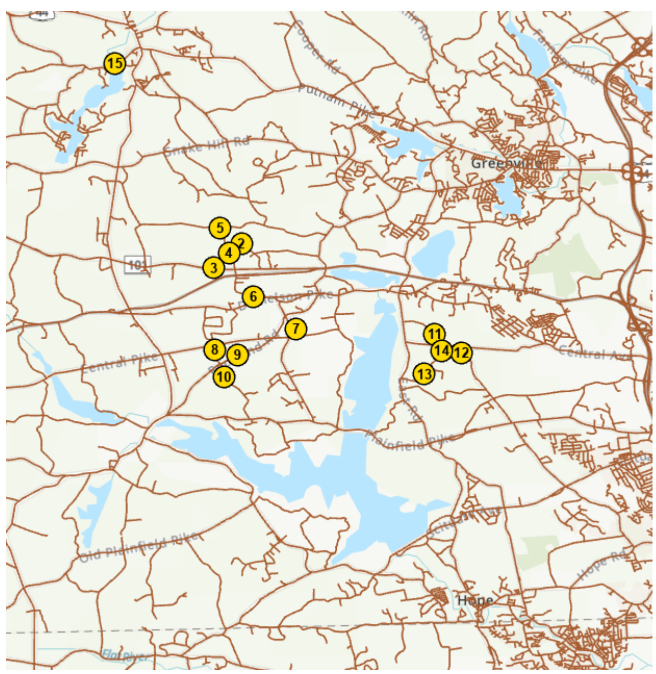

Figure I.215. Scituate Route 7

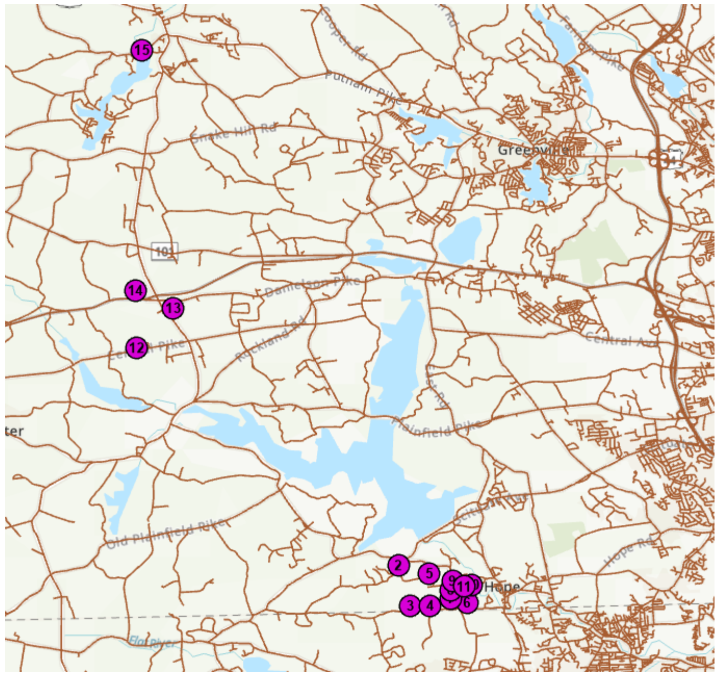

Figure I.216. Scituate Route 8

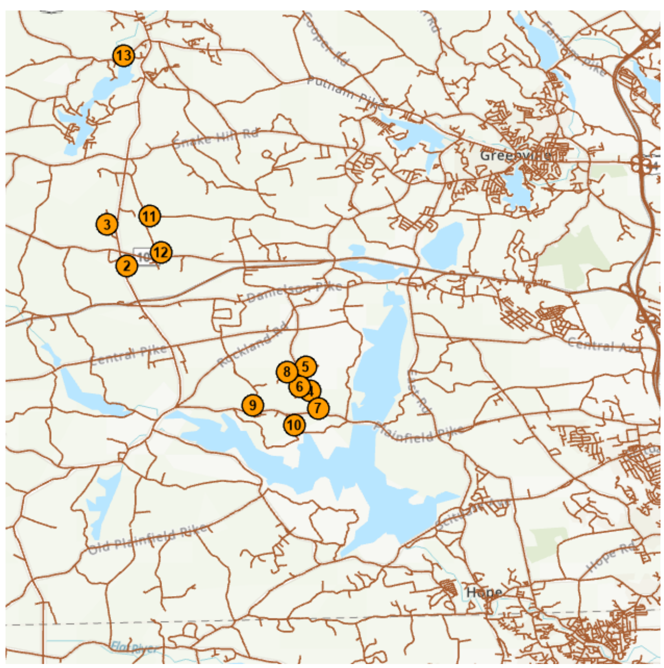

Figure I.217. Scituate Route 9

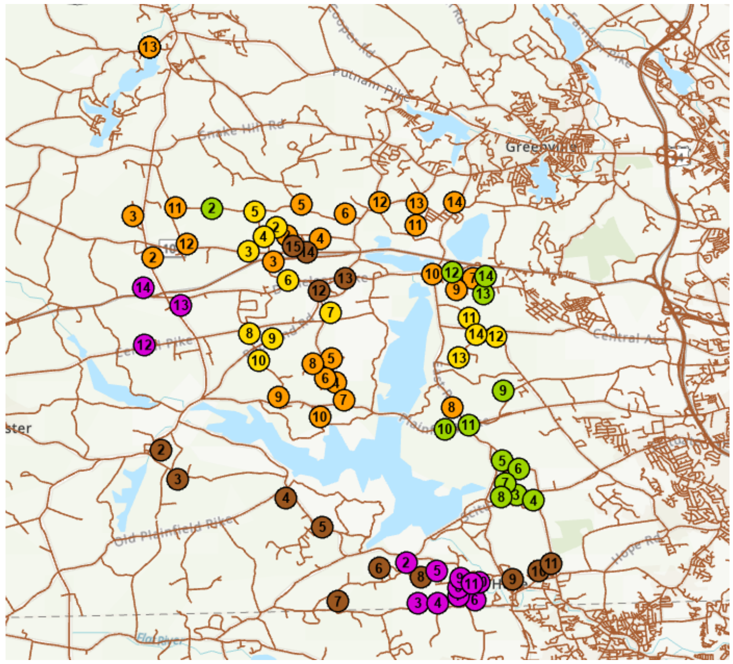

Figure I.218. Scituate Truck 1

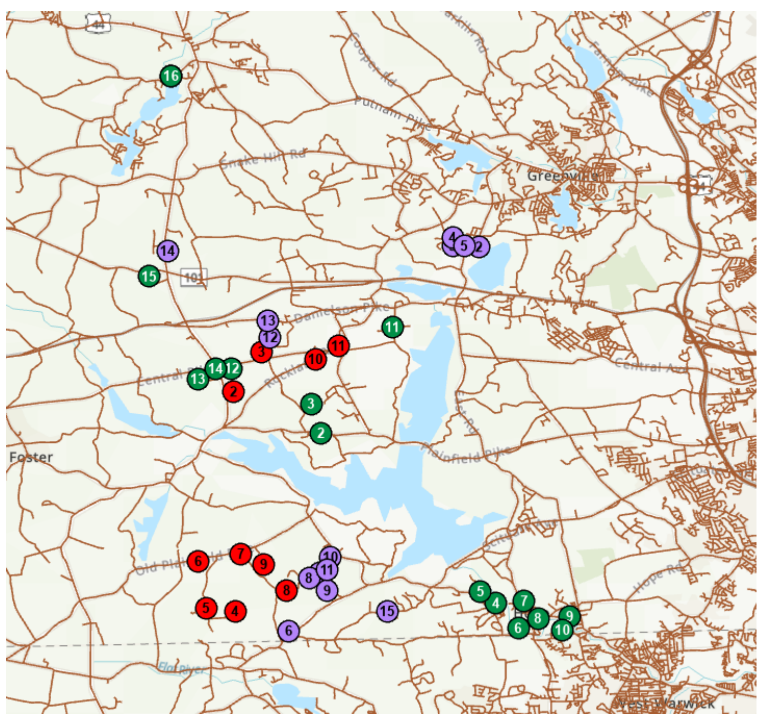

Figure I.219. Scituate Truck 2

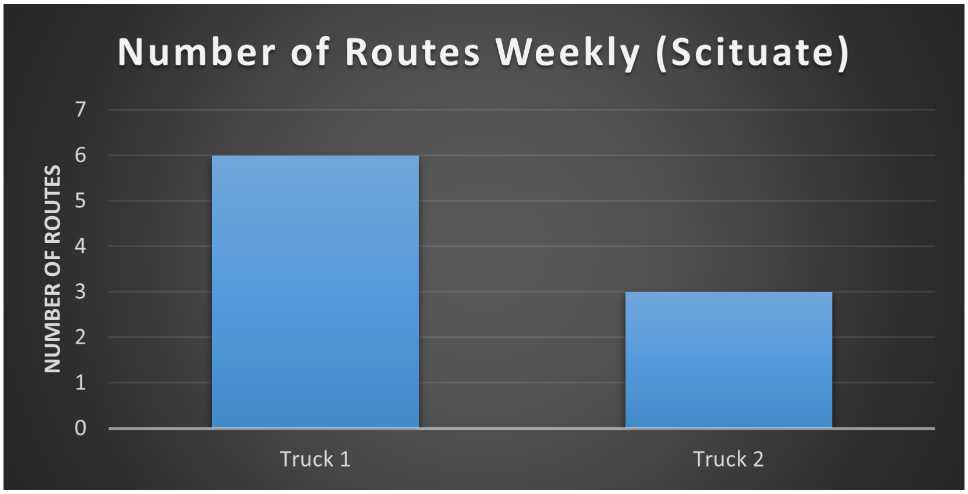

Figure I.220. Number of Routes Weekly (Scituate)

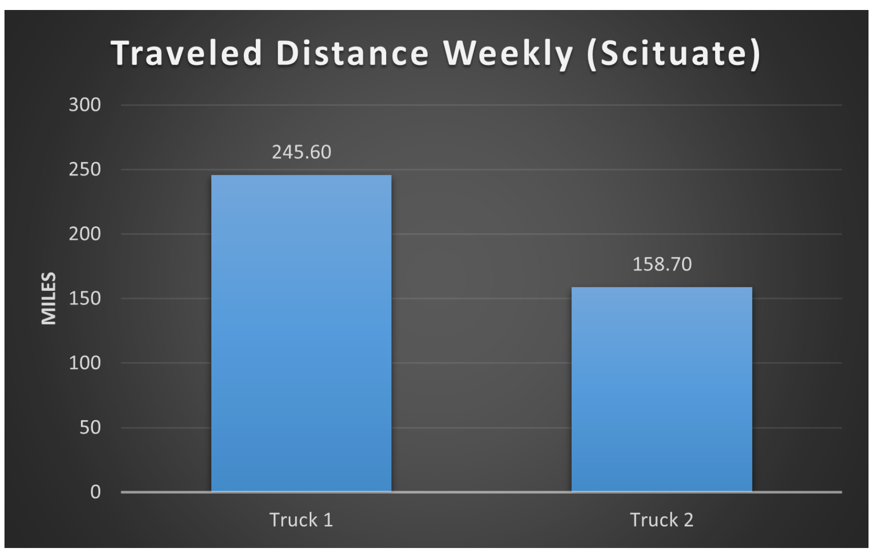

Figure I.221. Traveled Distance Weekly (Scituate)

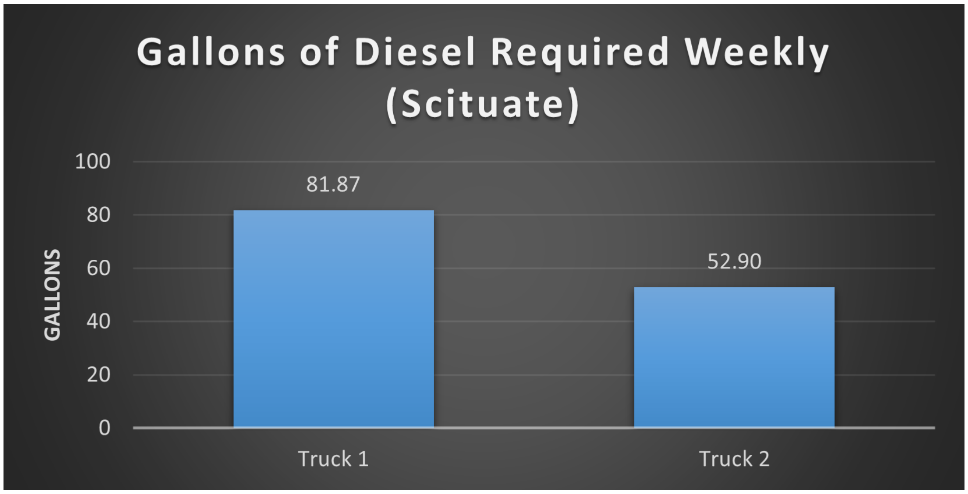

Figure I.222. Gallons of Diesel Required Weekly (Scituate)

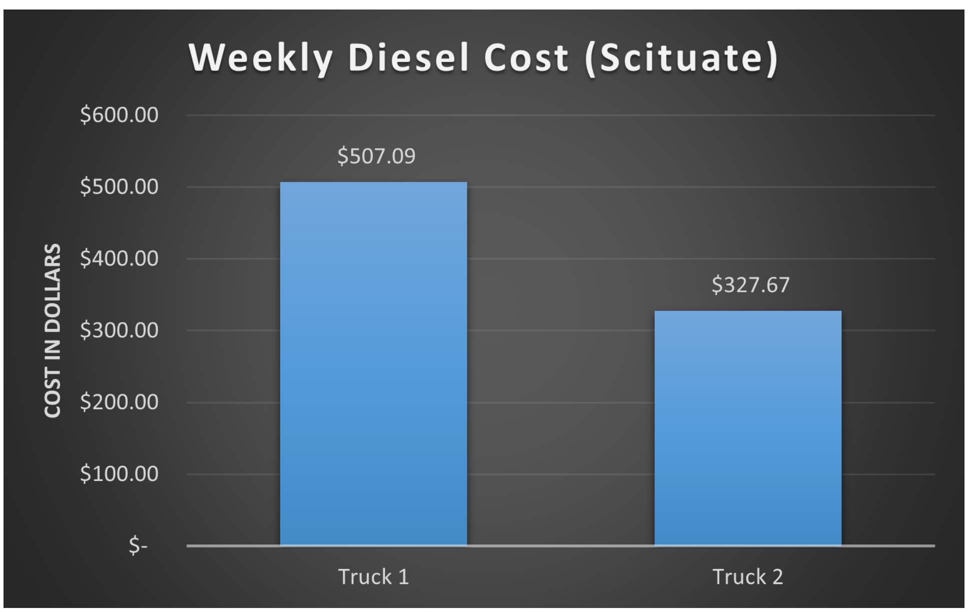

Figure I.223. Weekly Diesel Cost (Scituate)

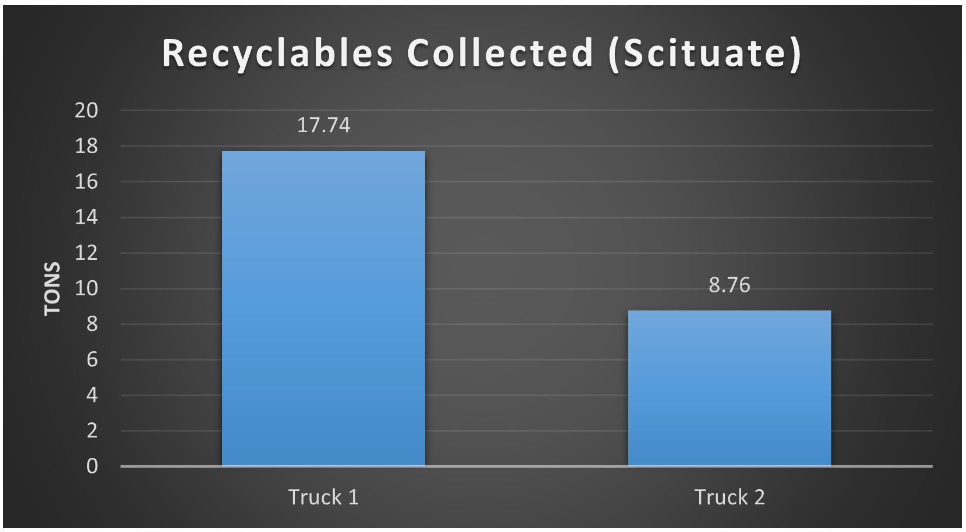

Figure I.224. Recyclables Collected (Scituate)

APPENDIX J

Westerly

J.1 Routes, Individual Trucks, and Charts

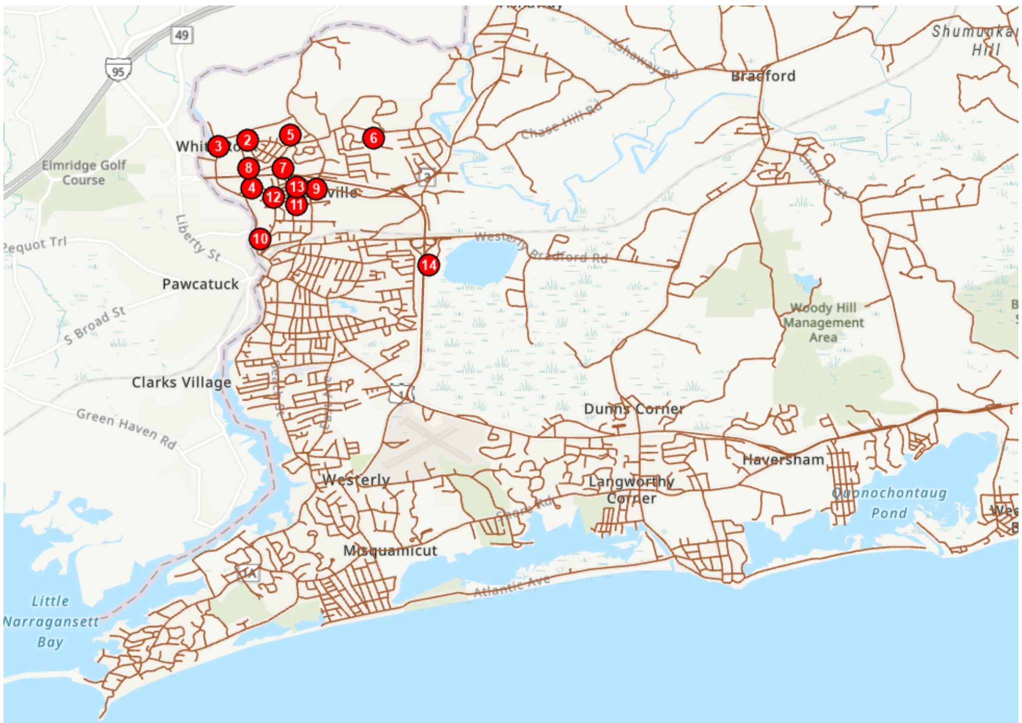

Figure J.225. Westerly Route 1

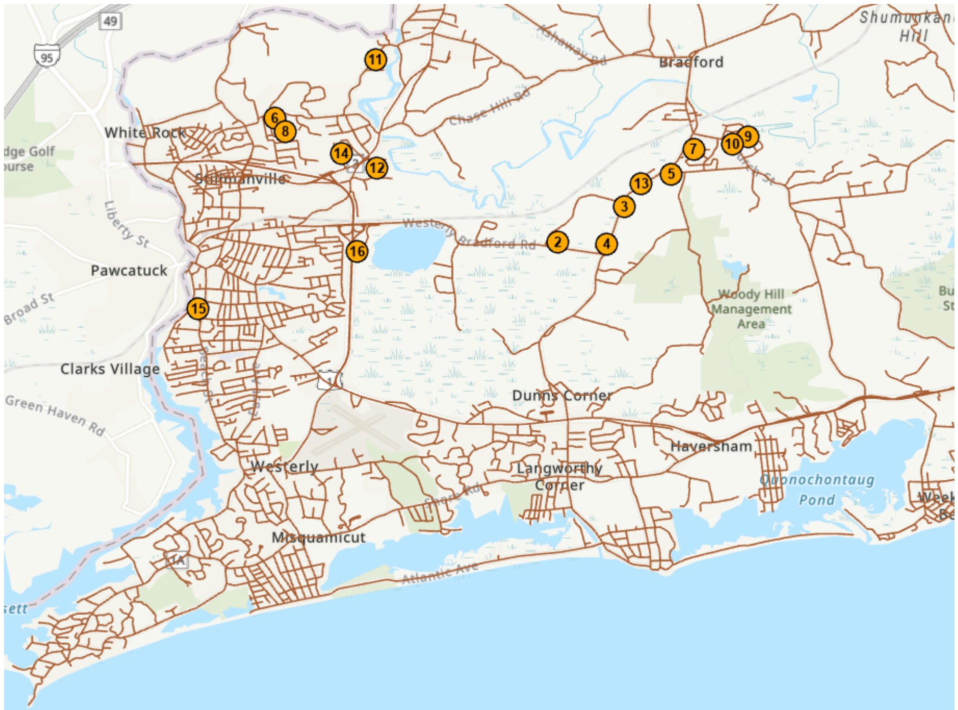

Figure J.226. Westerly Route 2

Figure J.227. Westerly Route 3

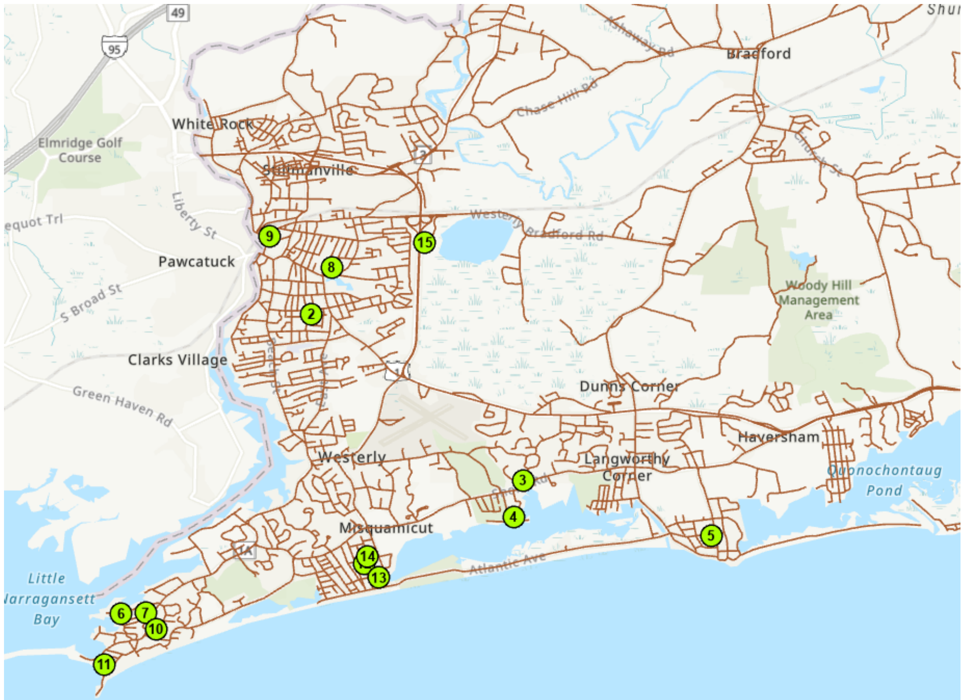

Figure J.228. Westerly Route 4

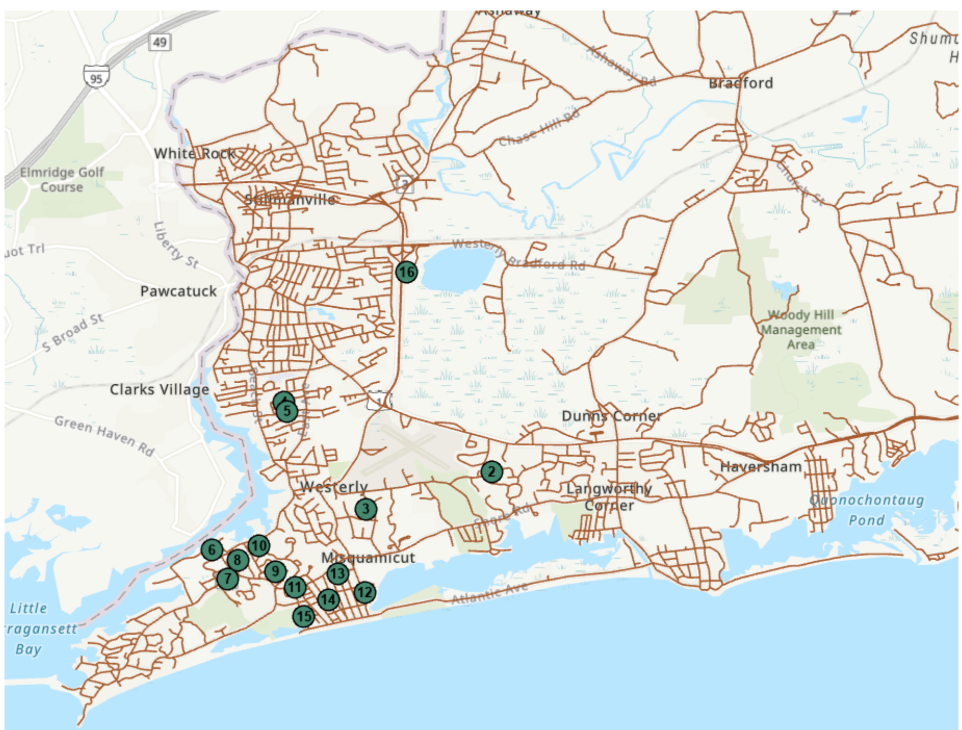

Figure J.229. Westerly Route 5

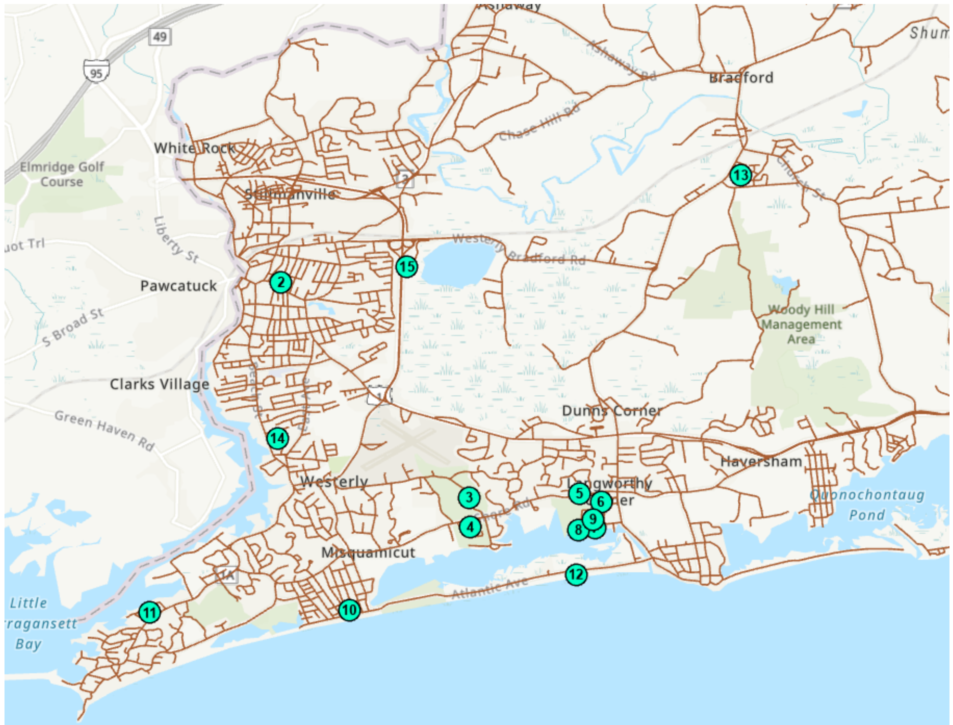

Figure J.230. Westerly Route 6

Figure J.231. Westerly Route 7

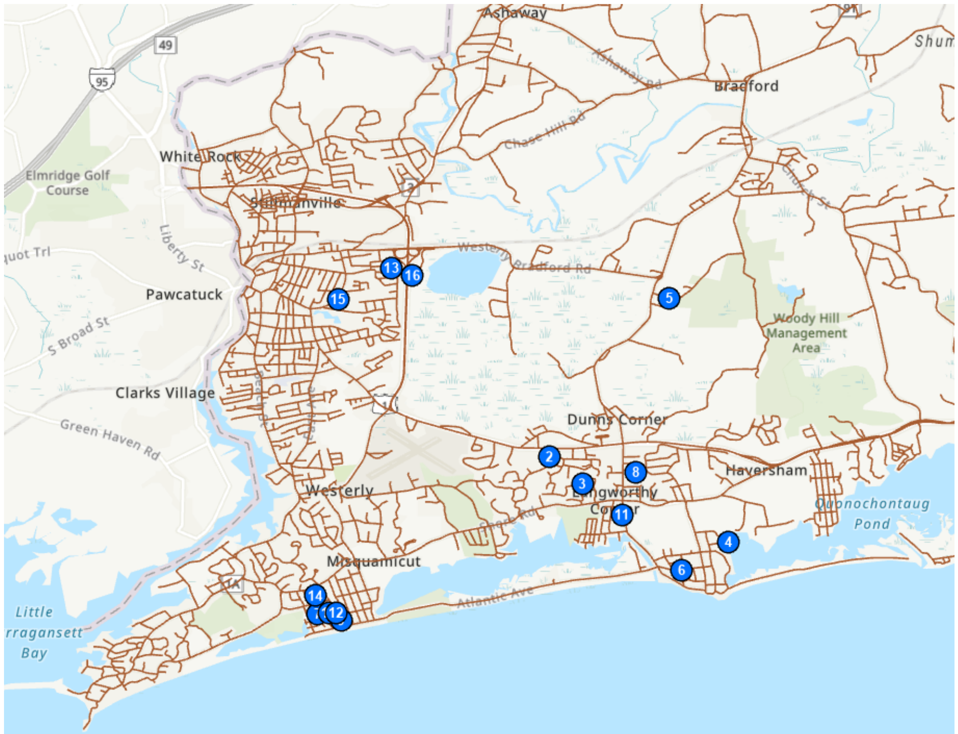

Figure J.232. Westerly Route 8

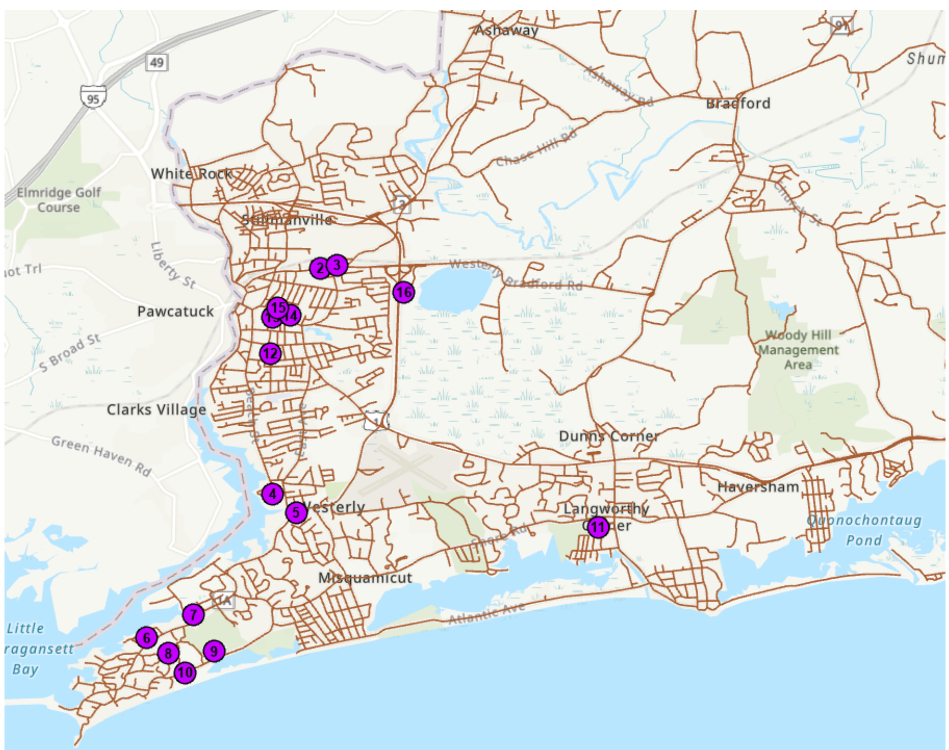

Figure J.233. Westerly Route 9

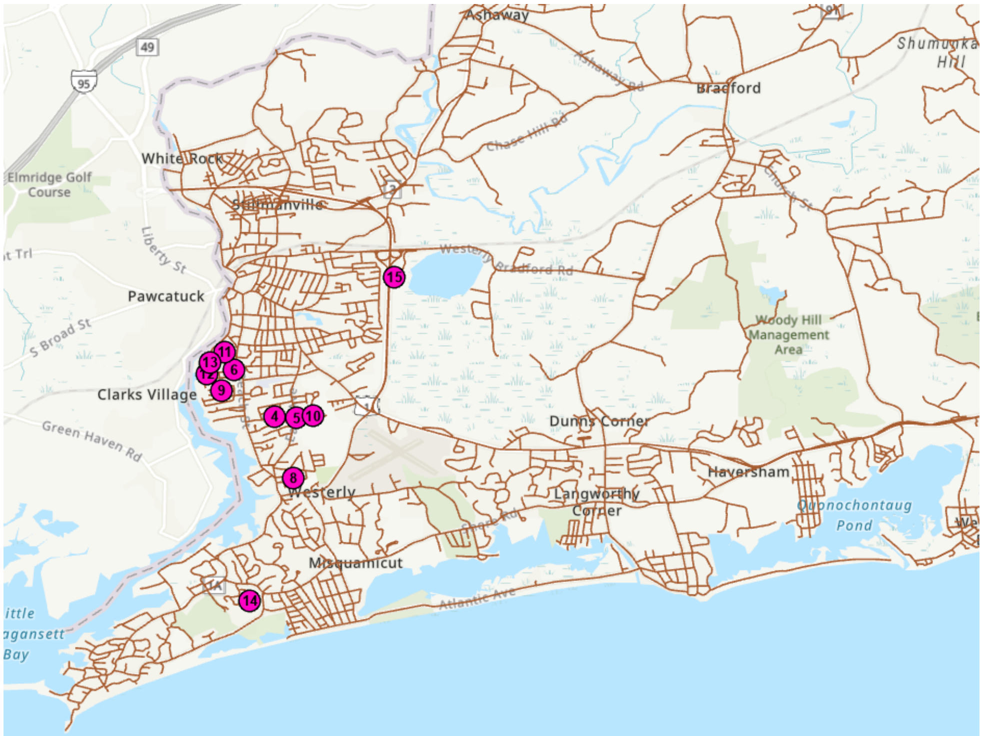

Figure J.234. Westerly Route 10

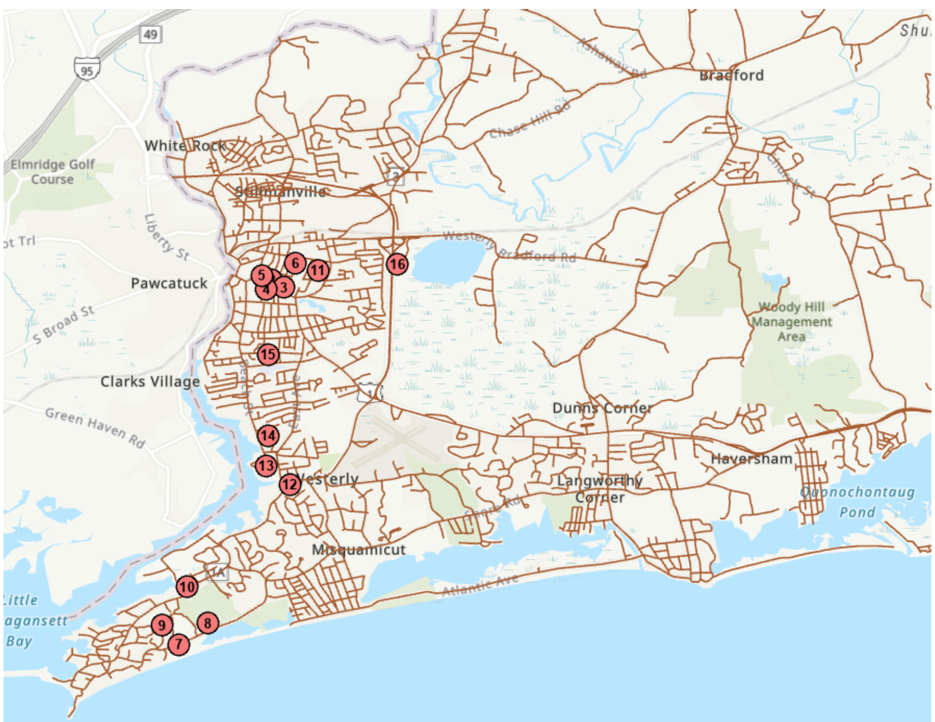

Figure J.235. Westerly Route 11

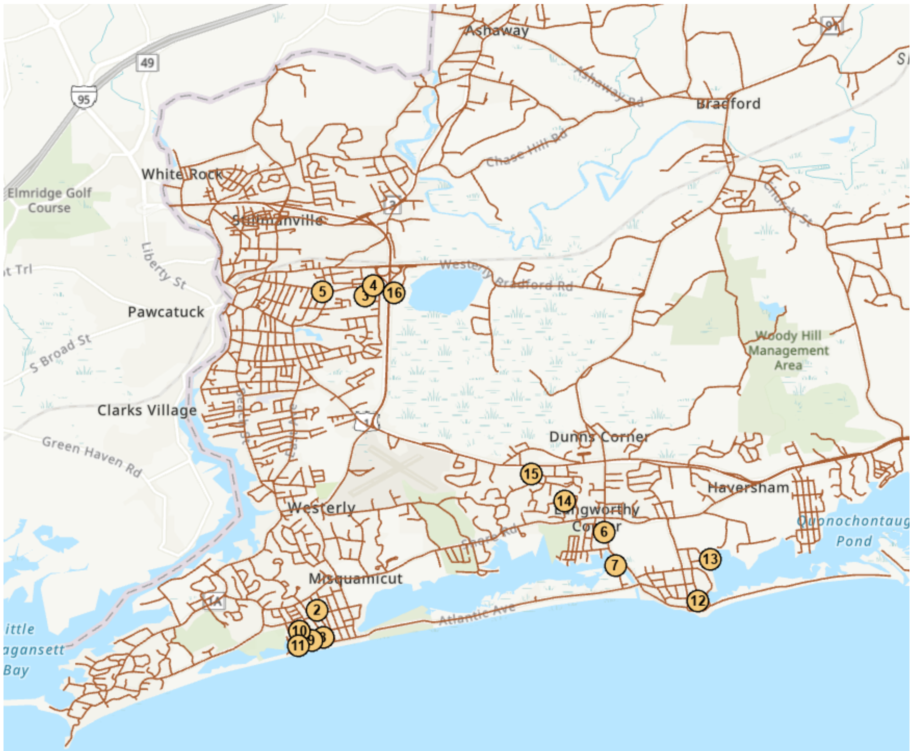

Figure J.236. Westerly Route 12

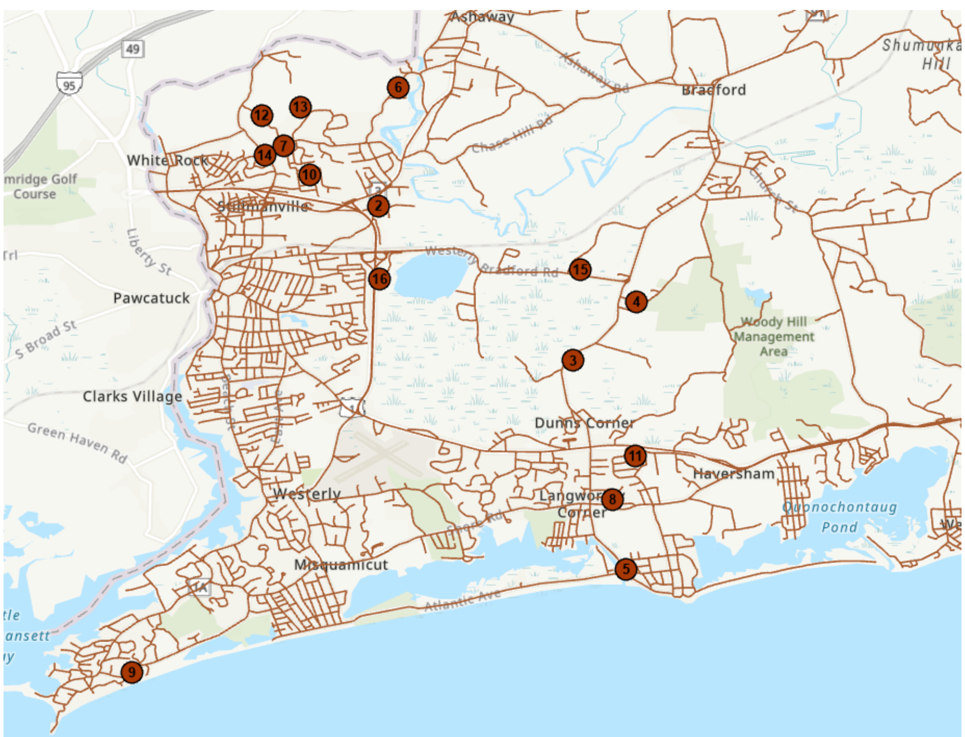

Figure J.237. Westerly Route 13

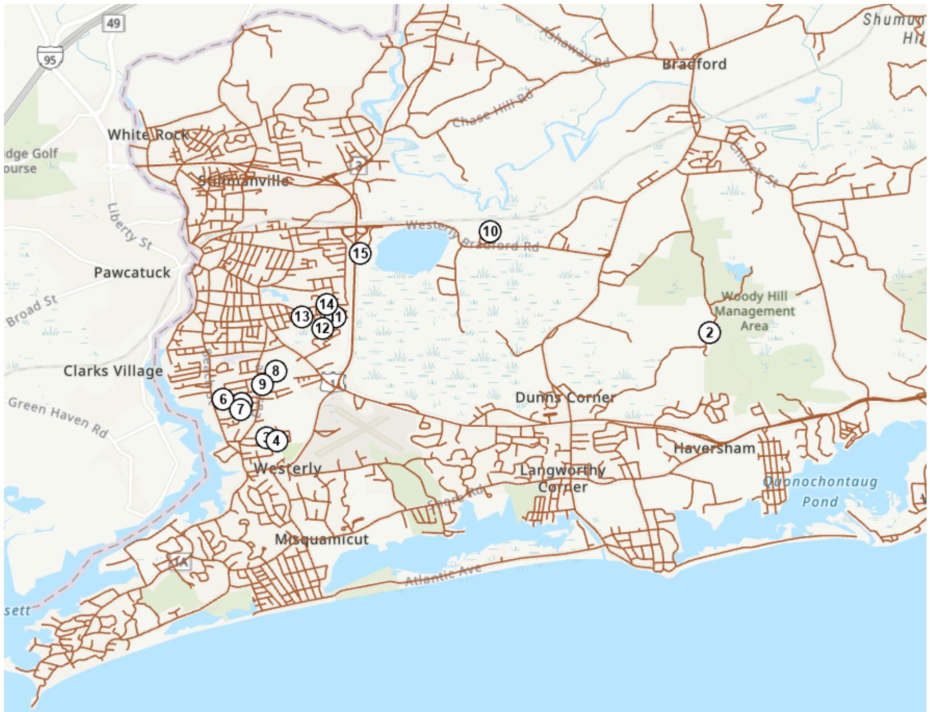

Figure J.238. Westerly Route 14

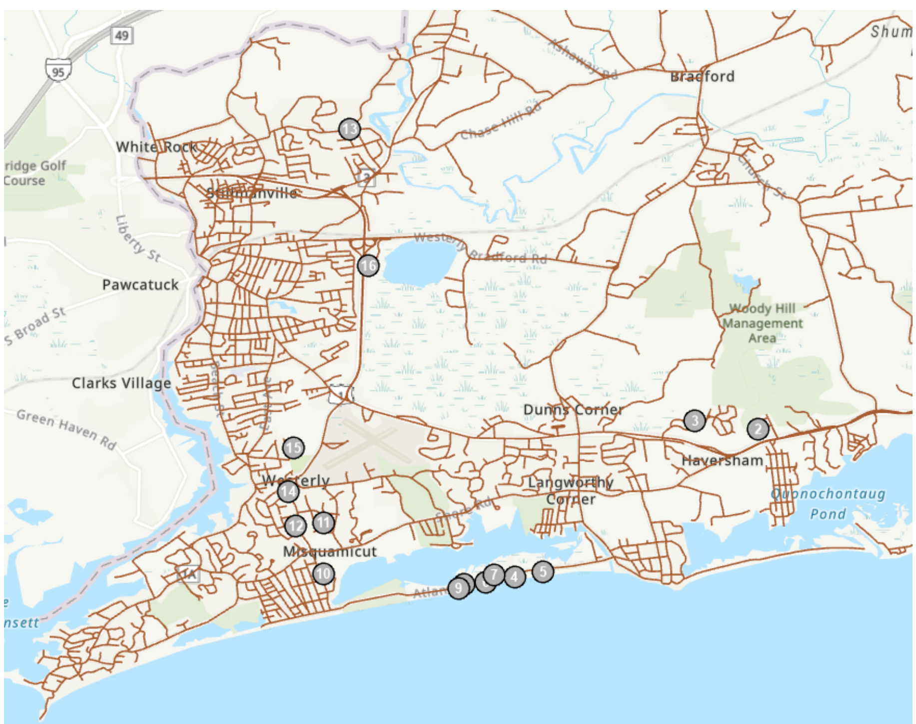

Figure J.239. Westerly Route 15

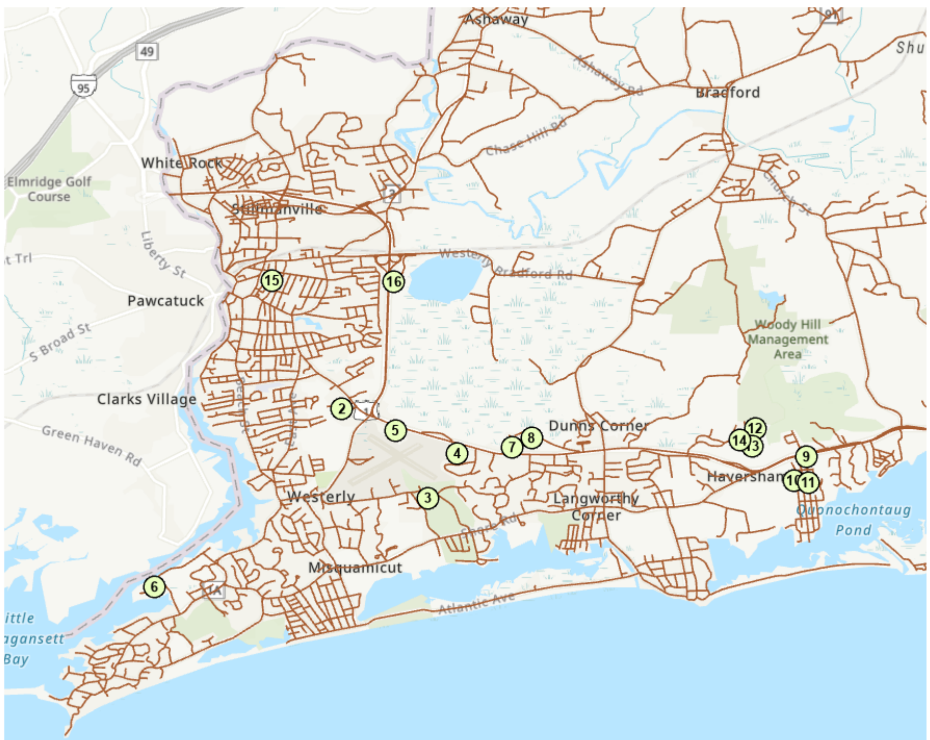

Figure J.240. Westerly Route 16

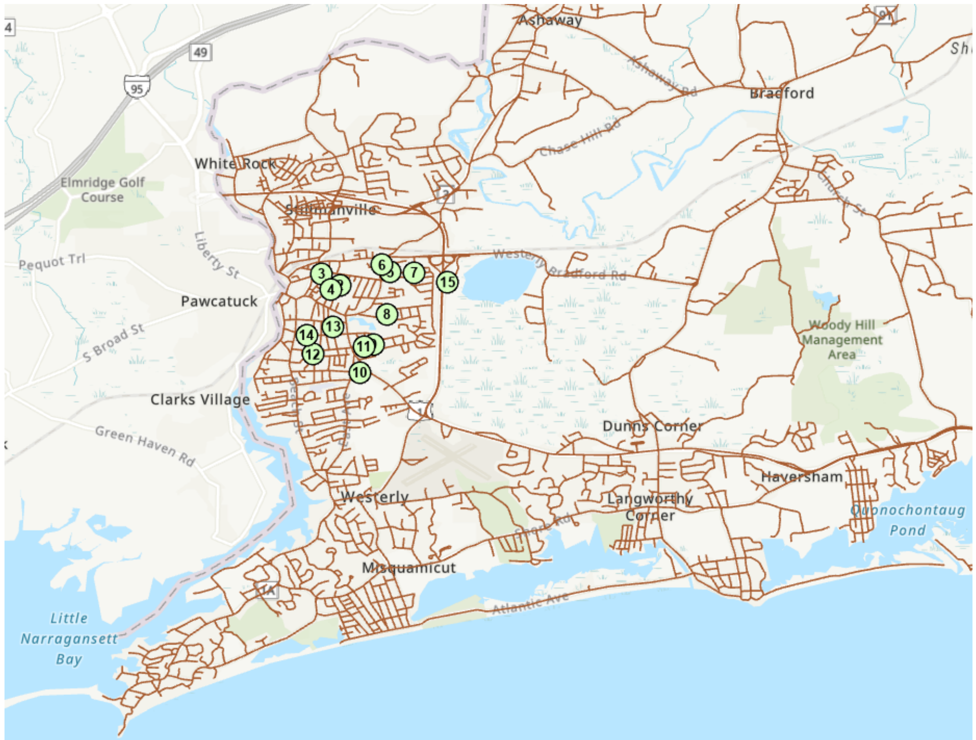

Figure J.241. Westerly Route 17

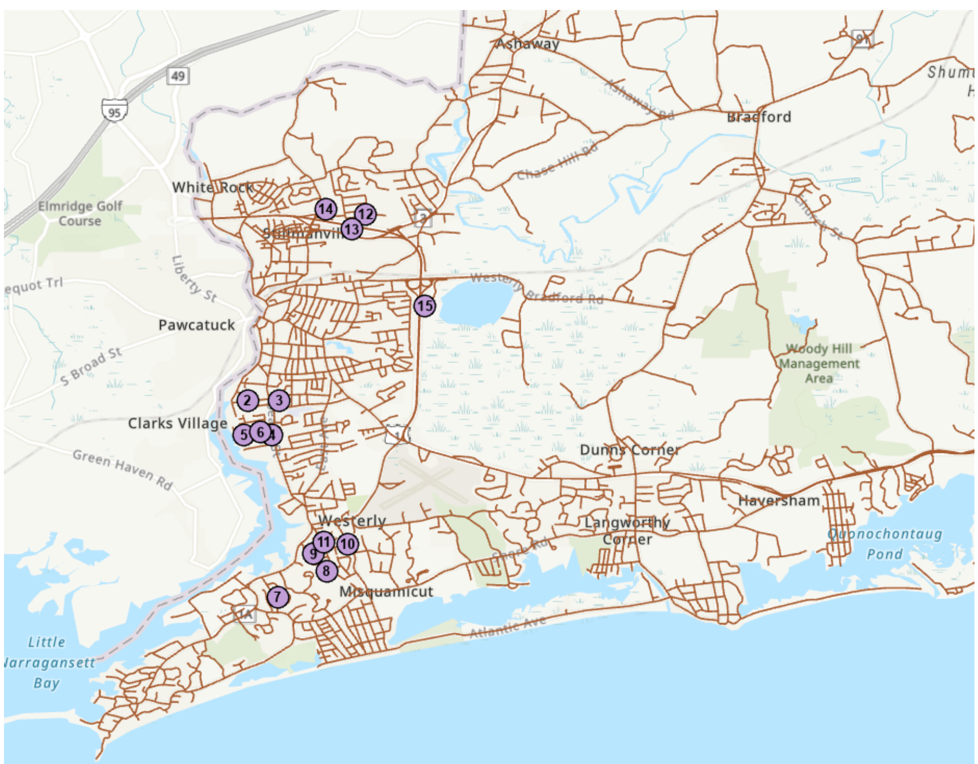

Figure J.242. Westerly Route 18

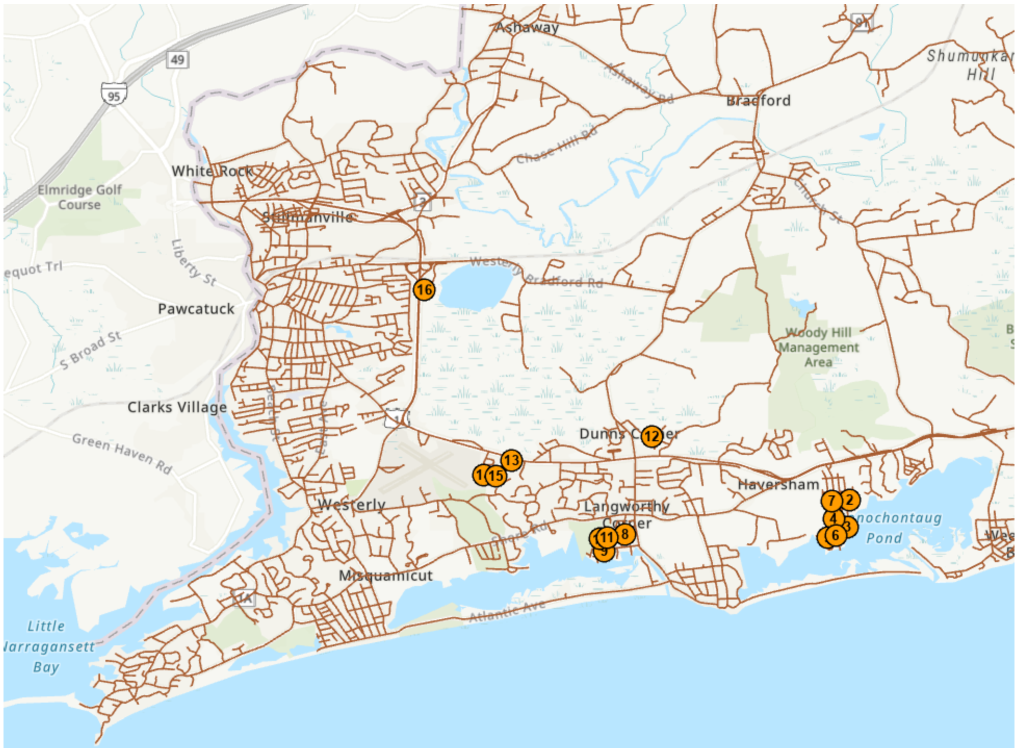

Figure J.243. Westerly Route 19

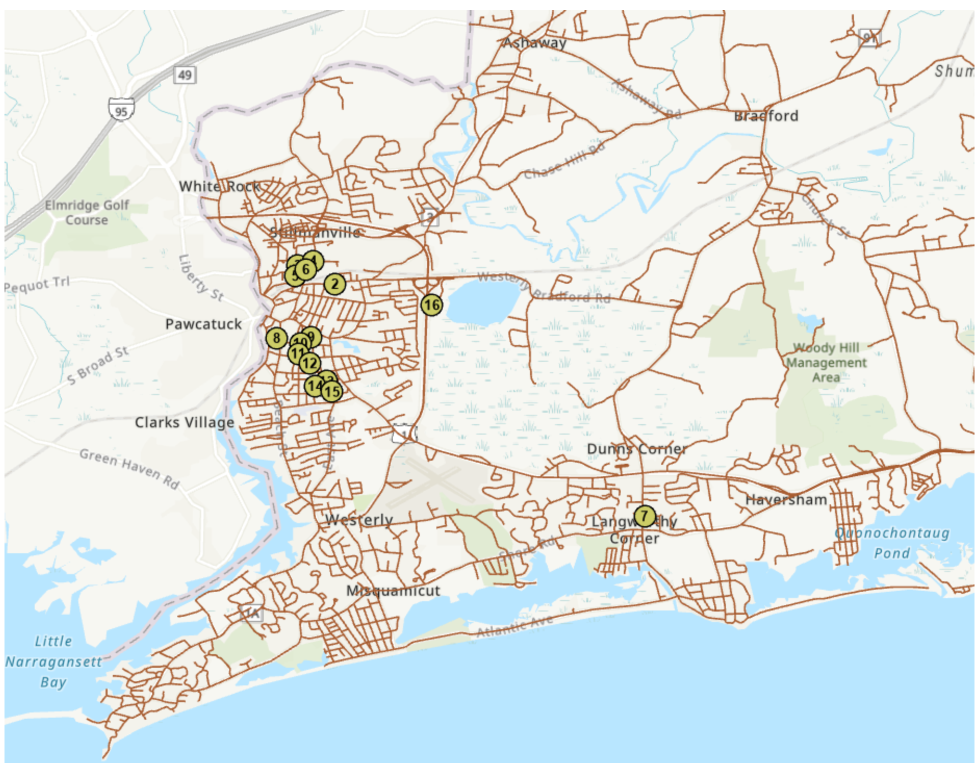

Figure J.244. Westerly Route 20

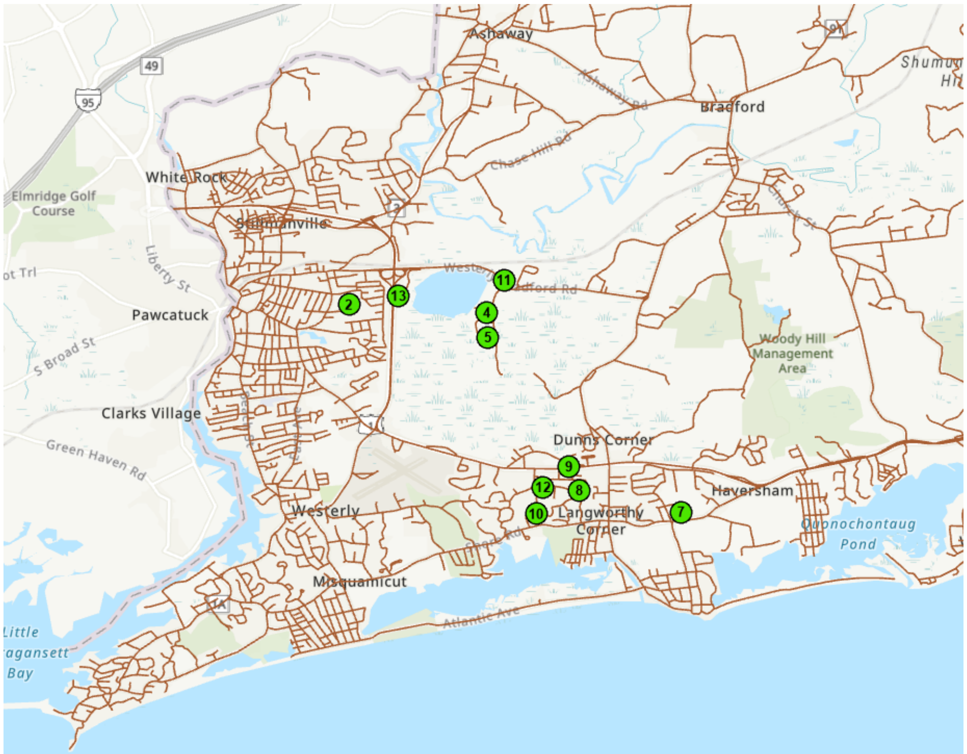

Figure J.245. Westerly Route 21

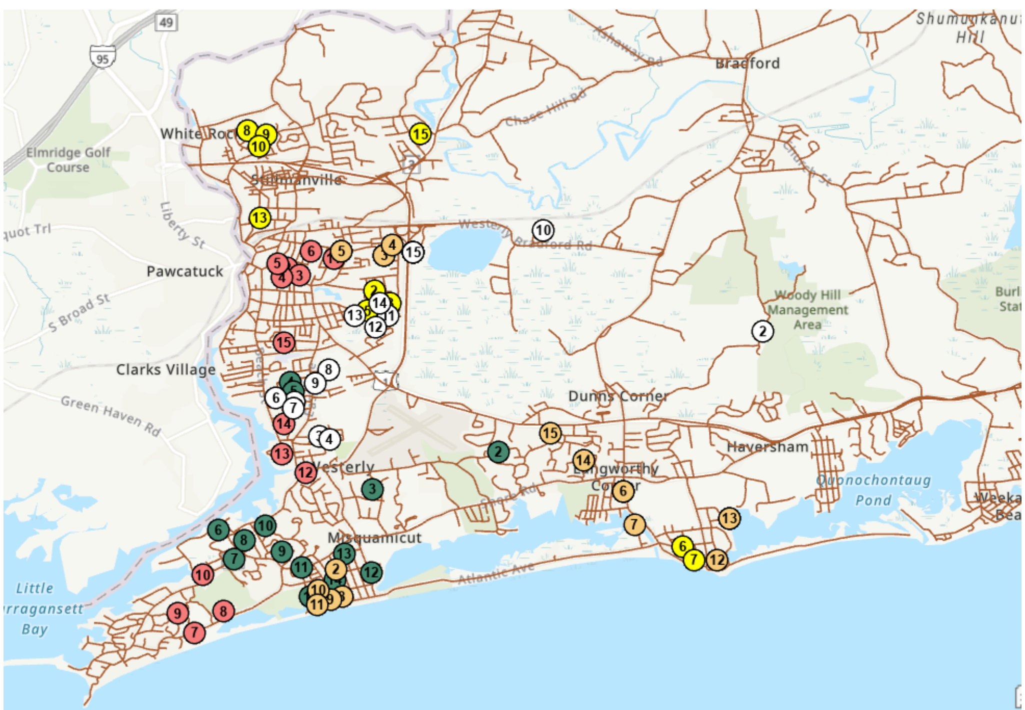

Figure J.246. Westerly Truck 1

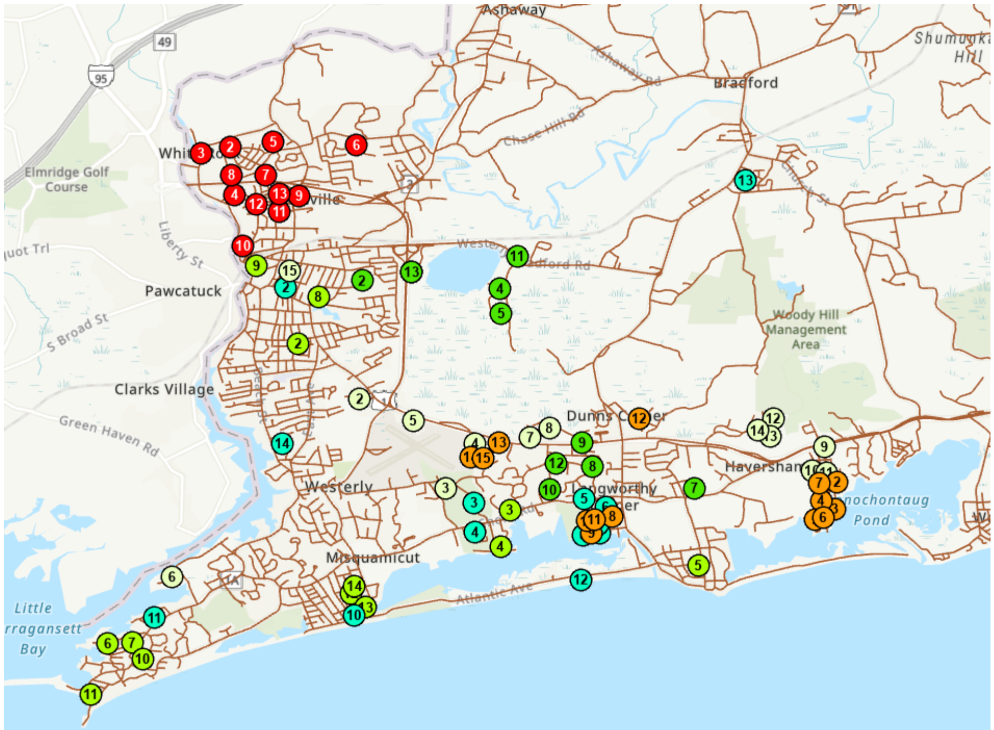

Figure J.247. Westerly Truck 2

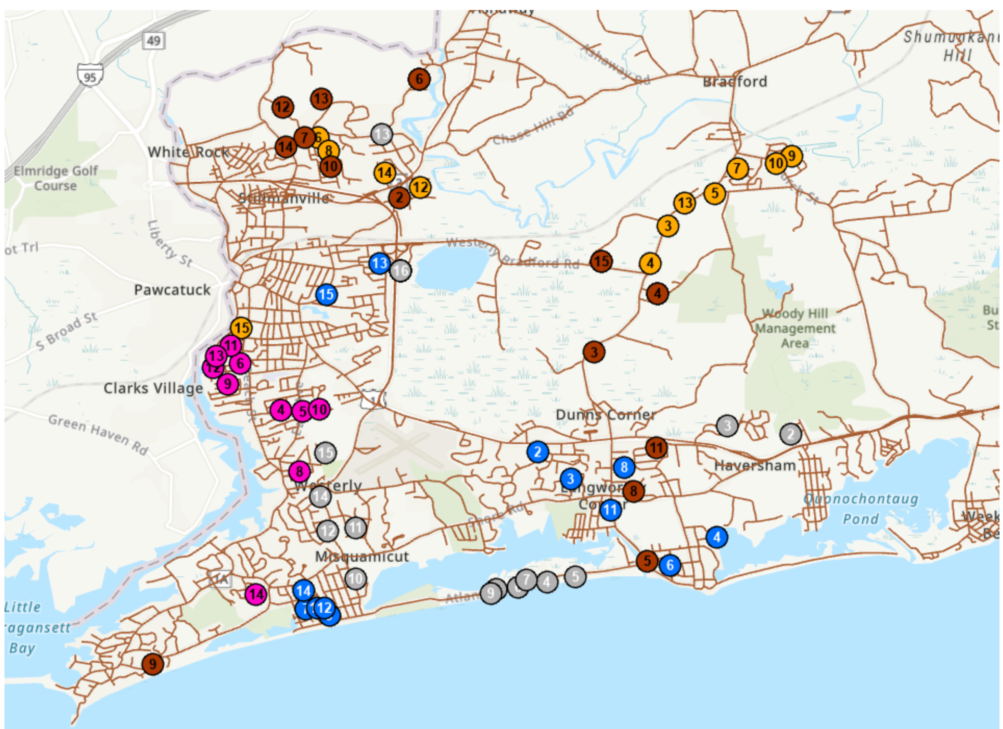

Figure J.248. Westerly Truck 3

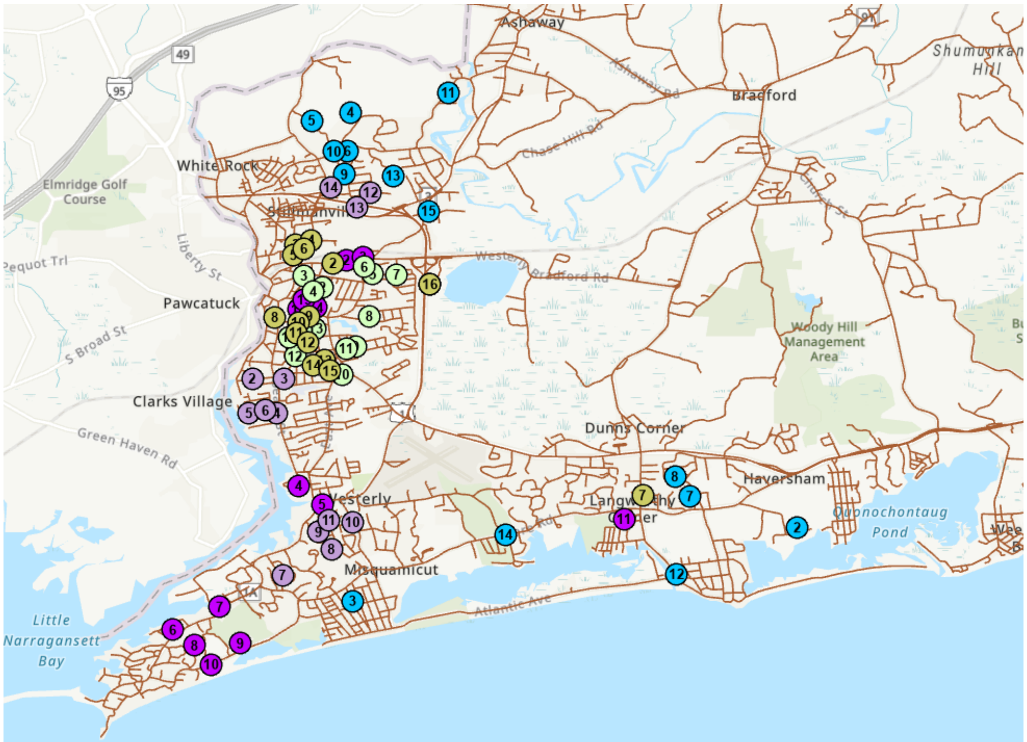

Figure J.249. Westerly Truck 4

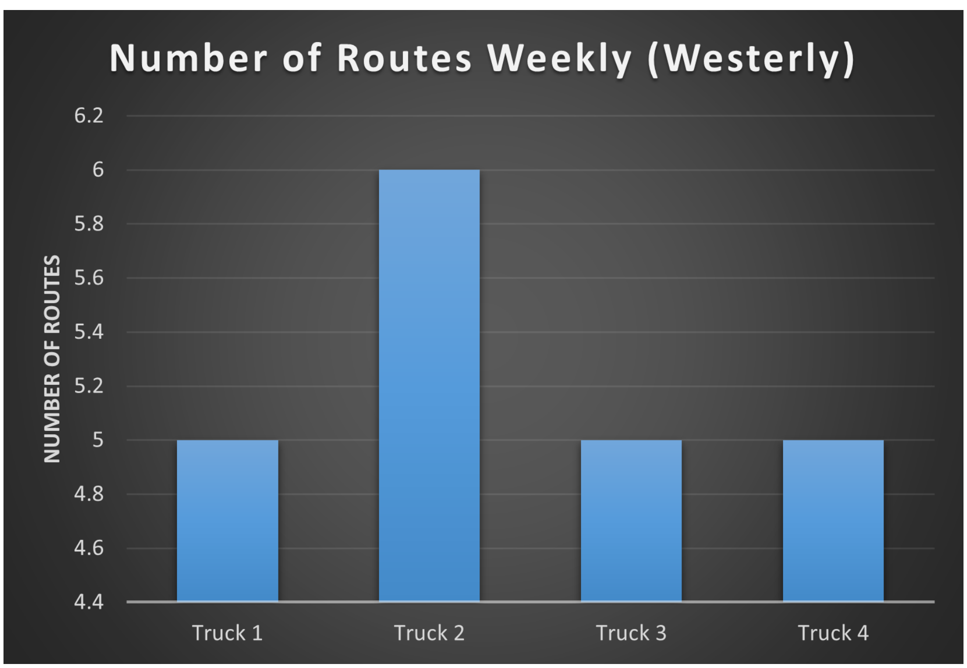

Figure J.250. Number of Routes Weekly (Westerly)

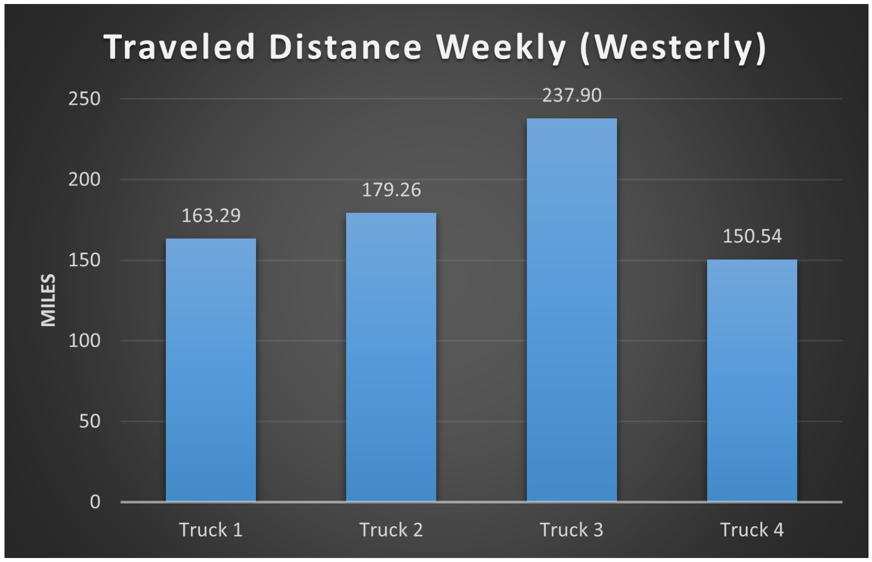

Figure J.251. Traveled Distance Weekly (Westerly)

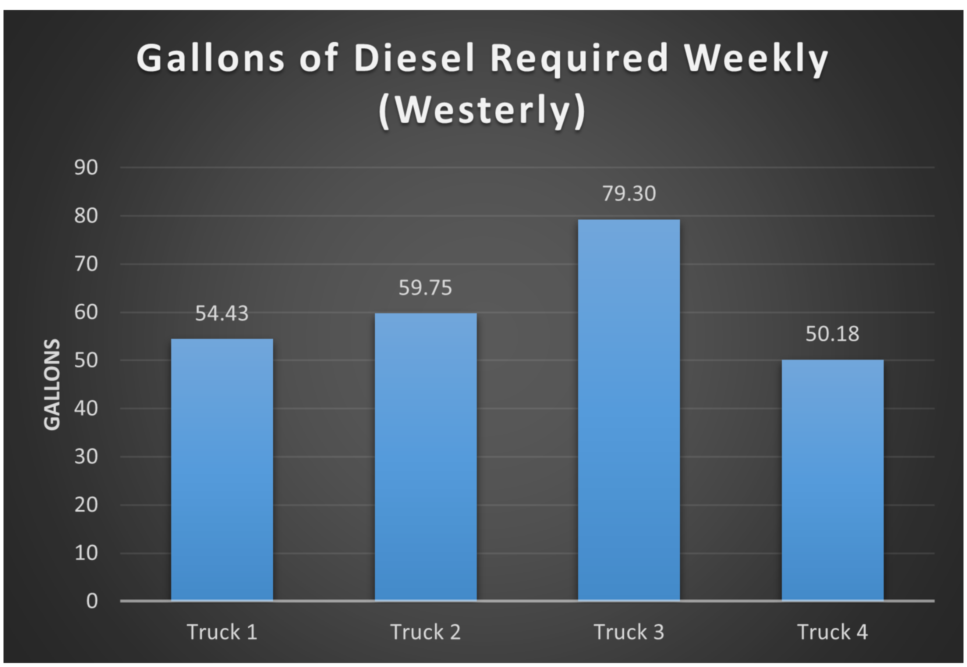

Figure J.252. Gallons of Diesel Required Weekly (Westerly)

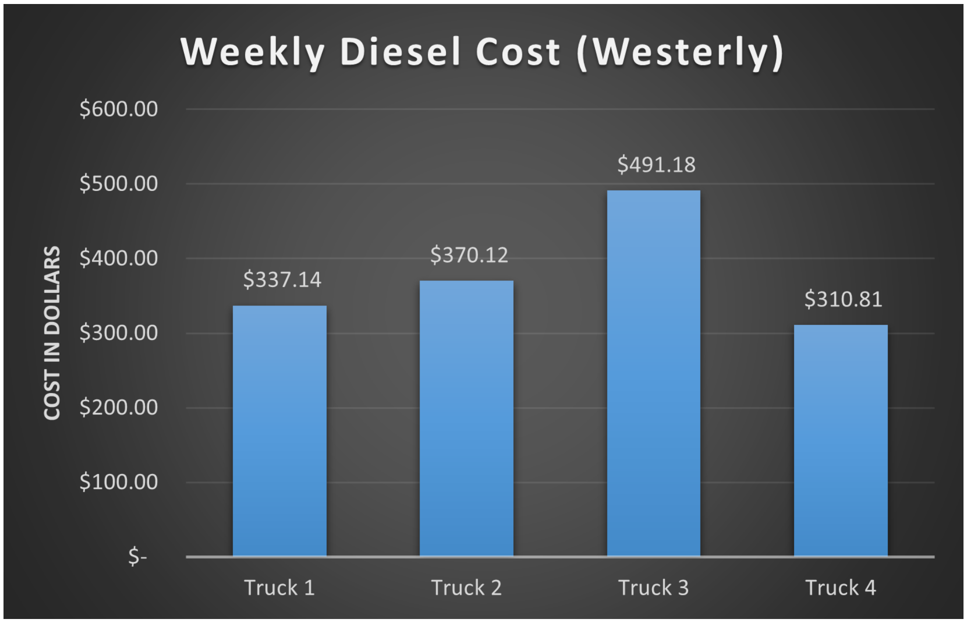

Figure J.253. Weekly Diesel Cost (Westerly)

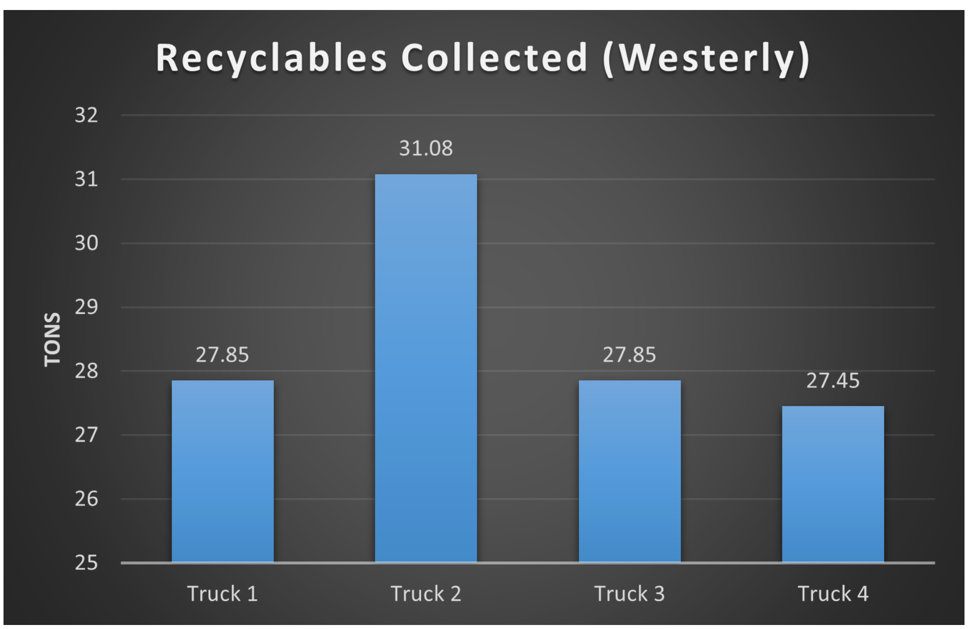

Figure J.254. Recyclables Collected (Westerly)

APPENDIX K

West Warwick

K.1 Routes, Individual Trucks, and Charts

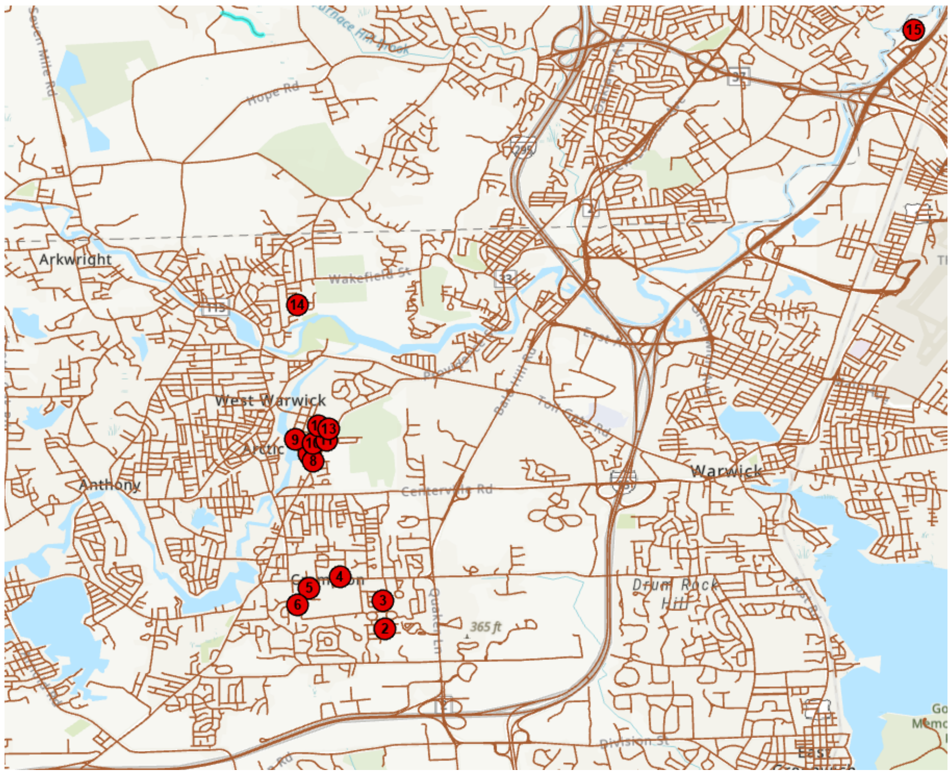

Figure K.255. West Warwick Route 1

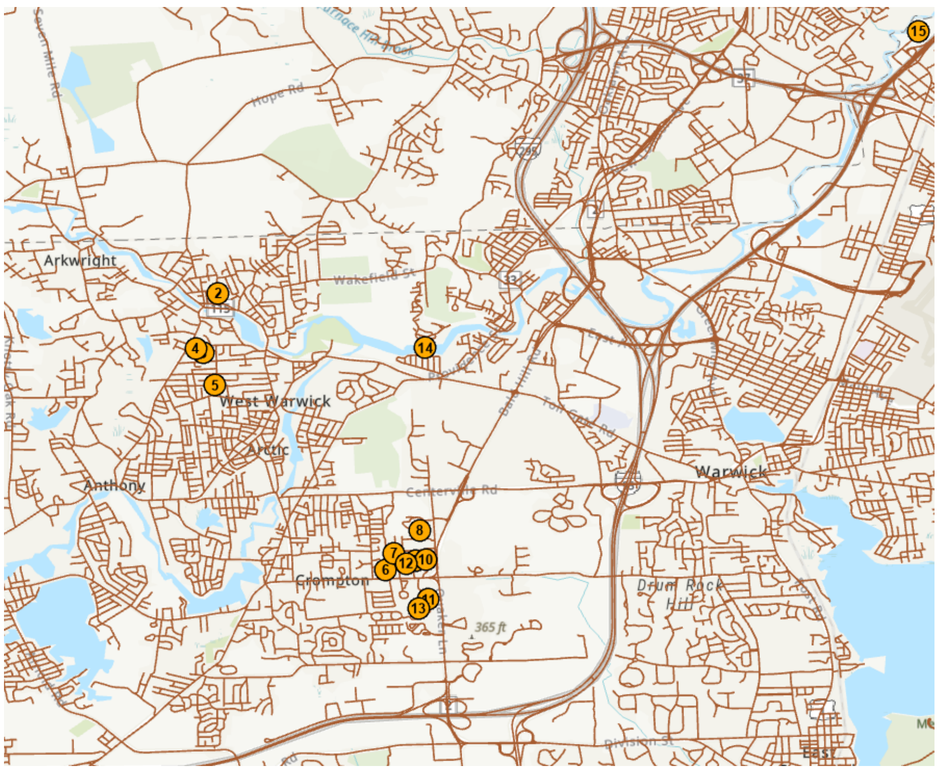

Figure K.256. West Warwick Route 2

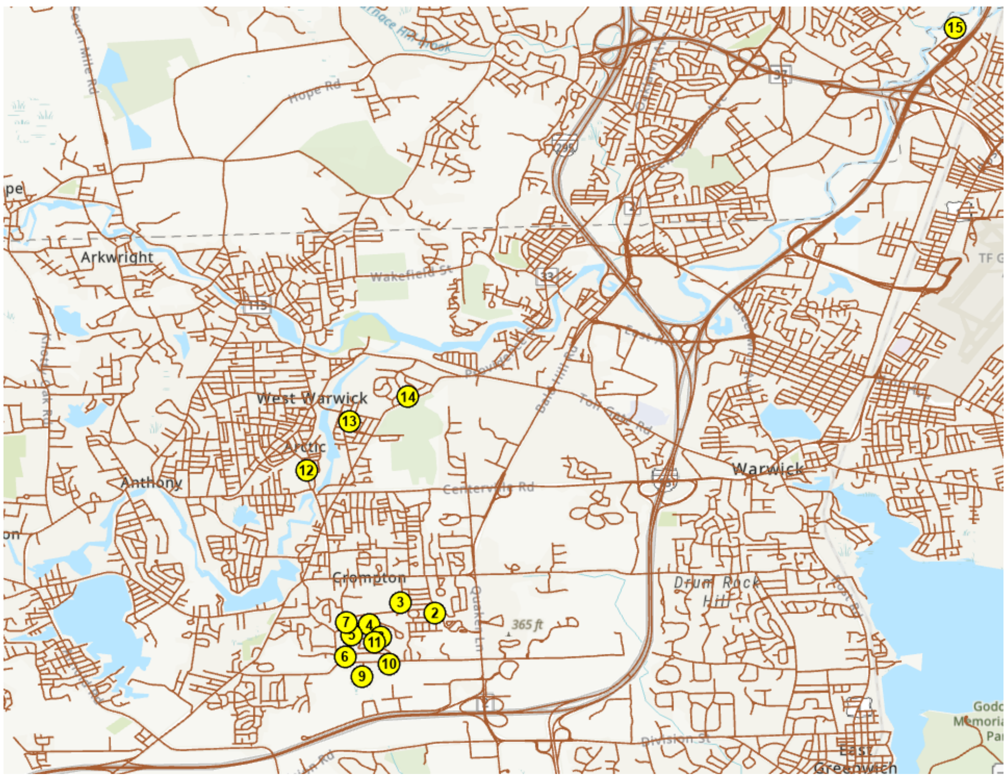

Figure K.257. West Warwick Route 3

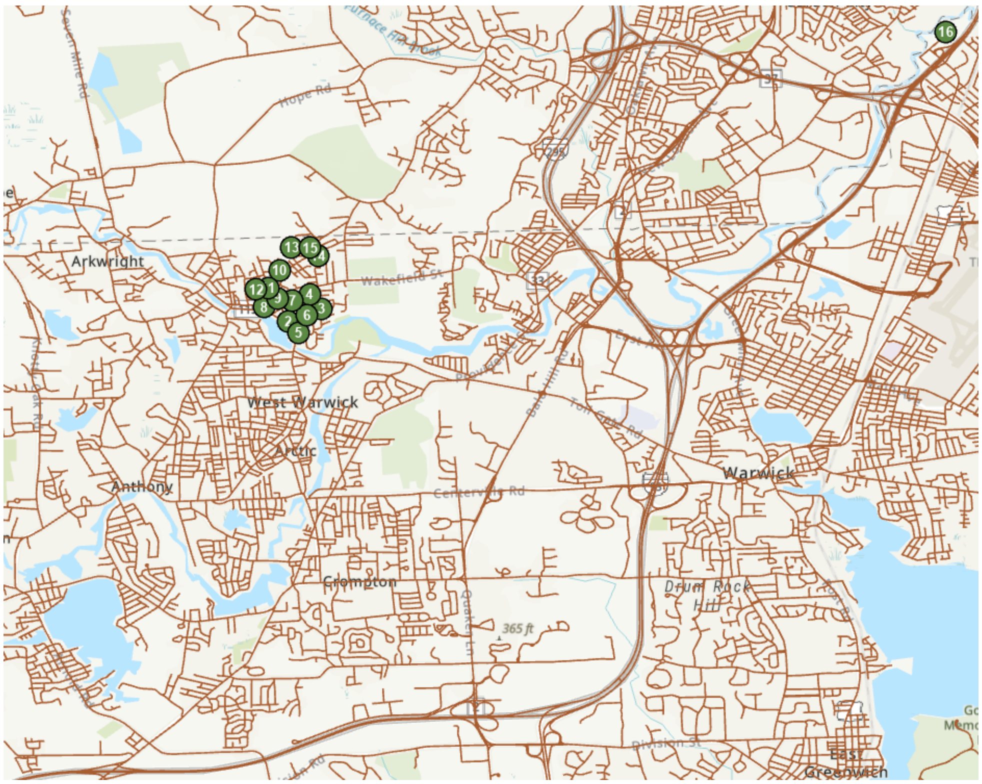

Figure K.258. West Warwick Route 4

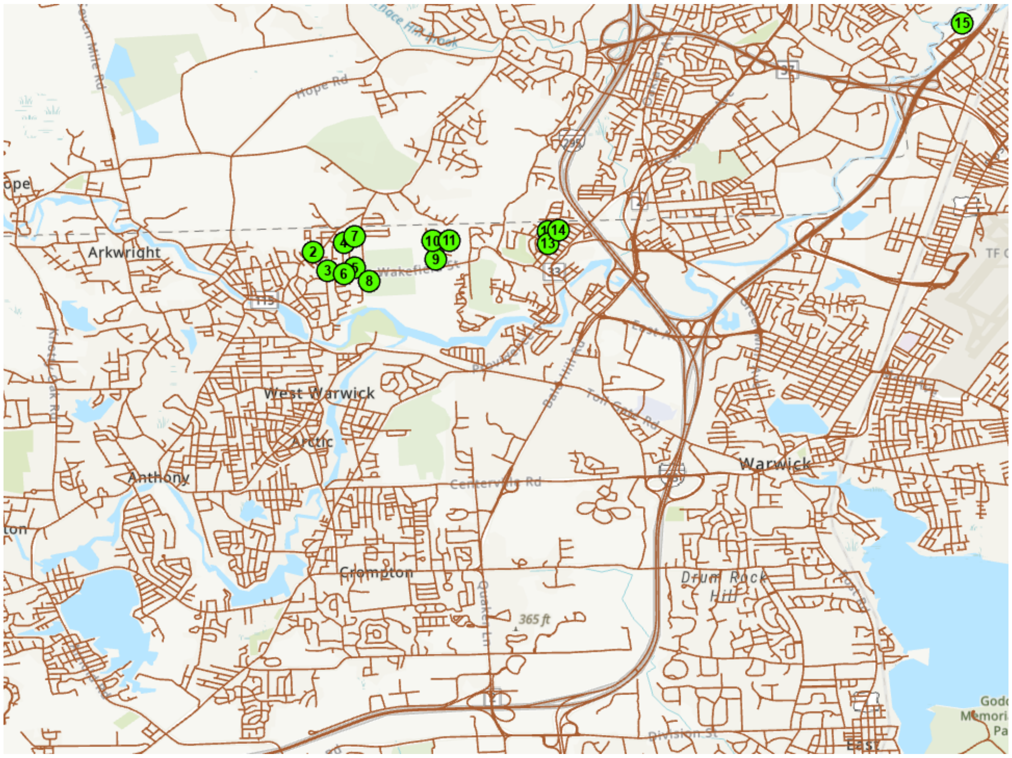

Figure K.259. West Warwick Route 5

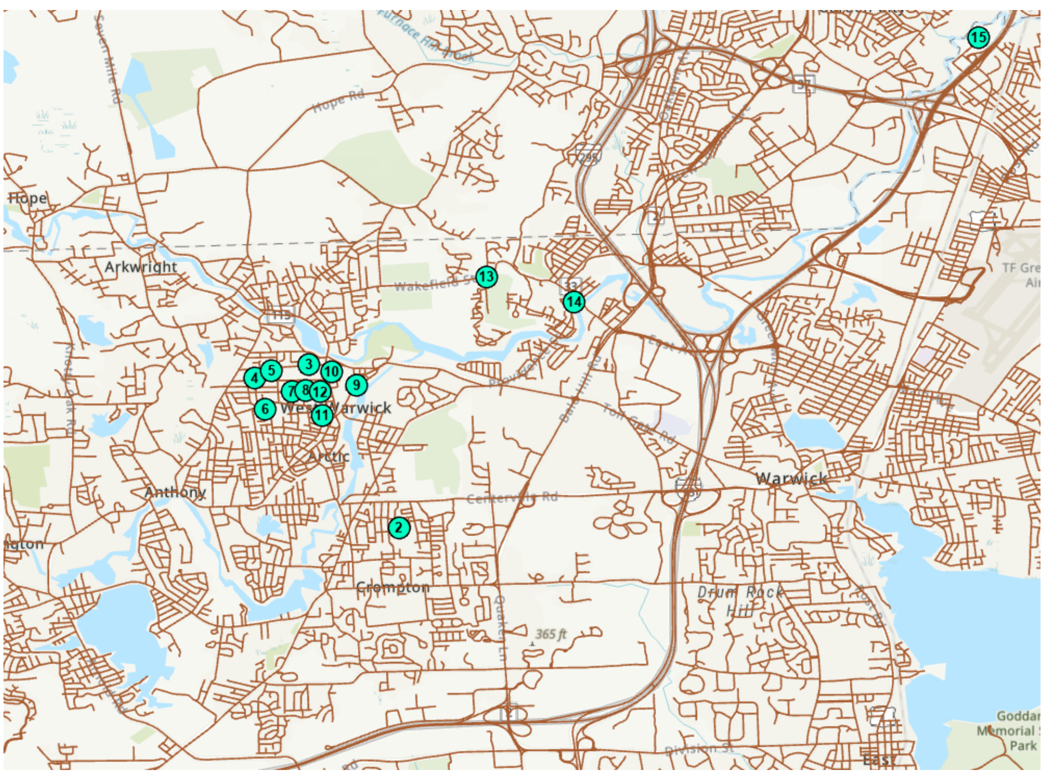

Figure K.260. West Warwick Route 6

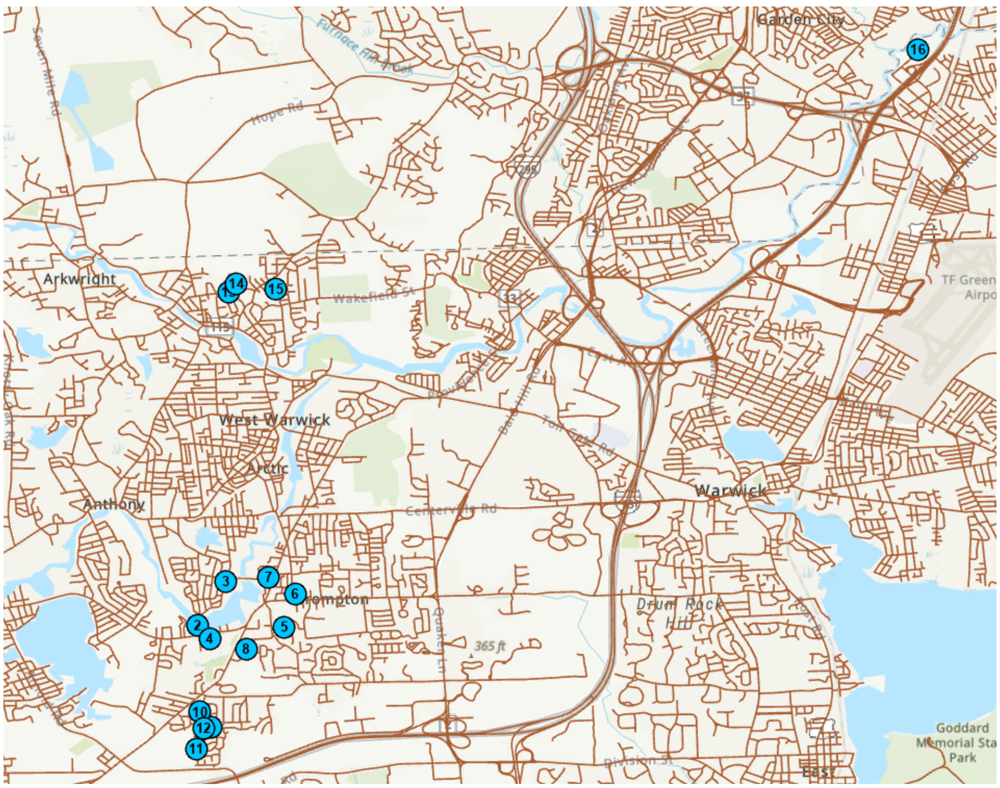

Figure K.261. West Warwick Route 7

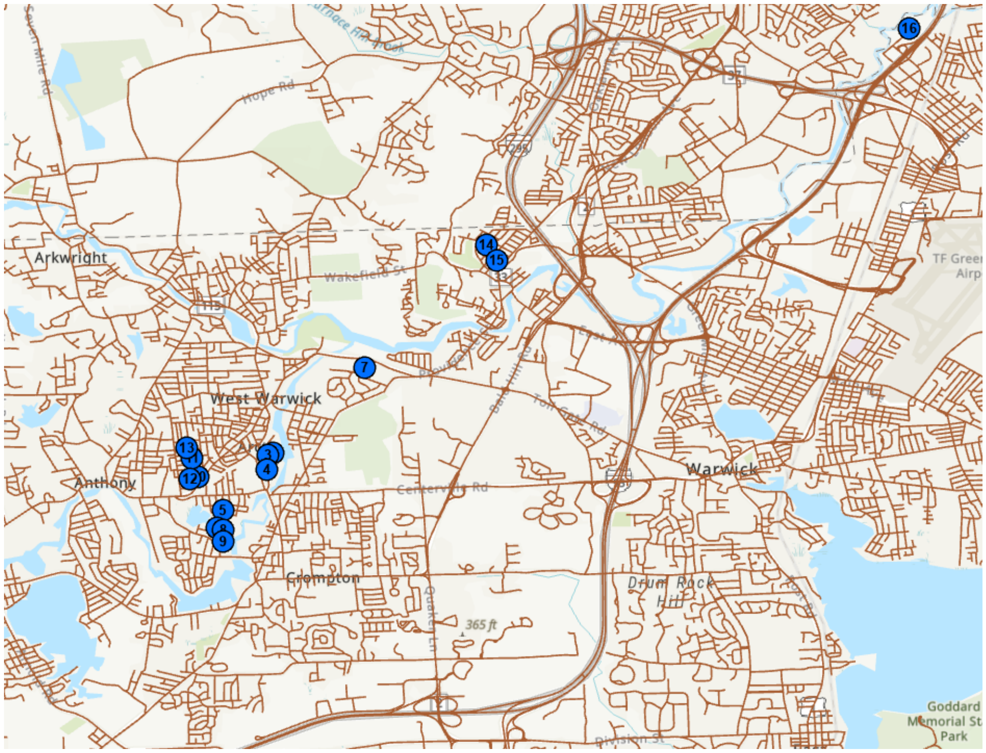

Figure K.262. West Warwick Route 8

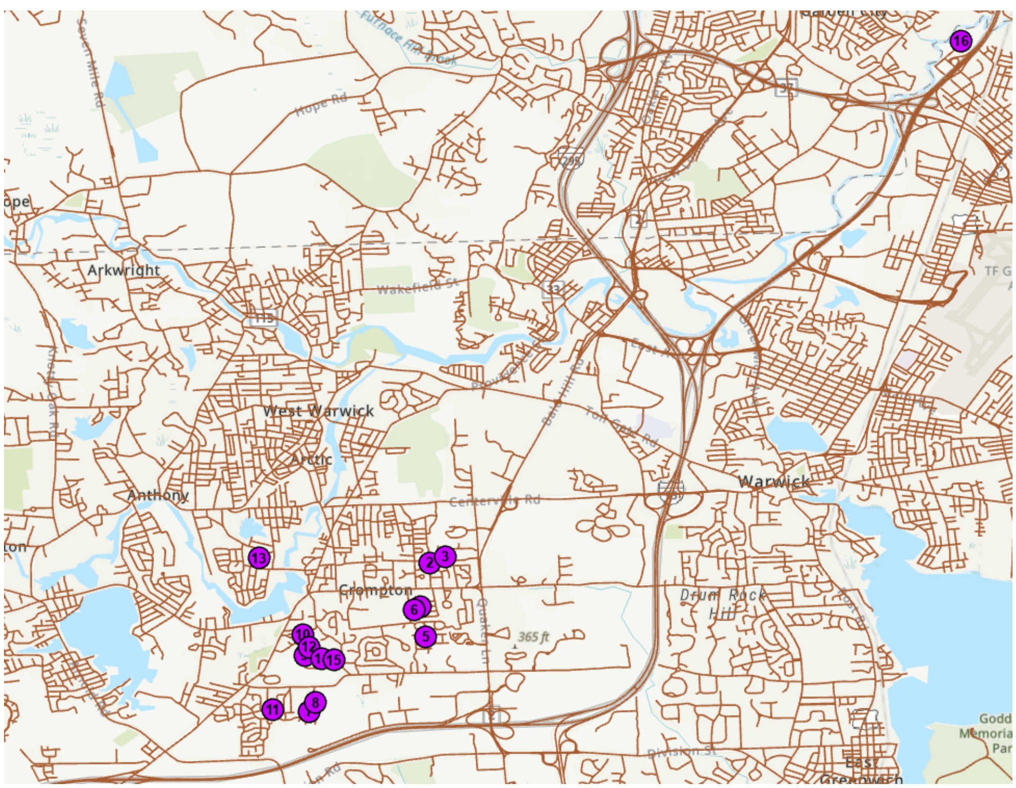

Figure K.263. West Warwick Route 9

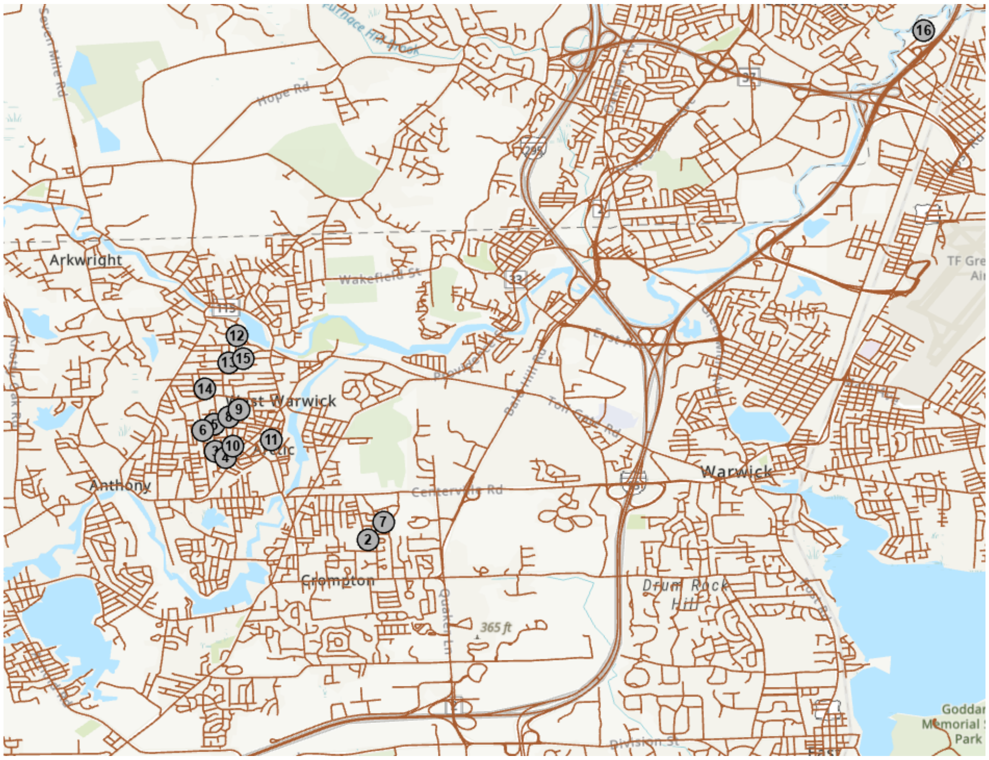

Figure K.264. West Warwick Route 10

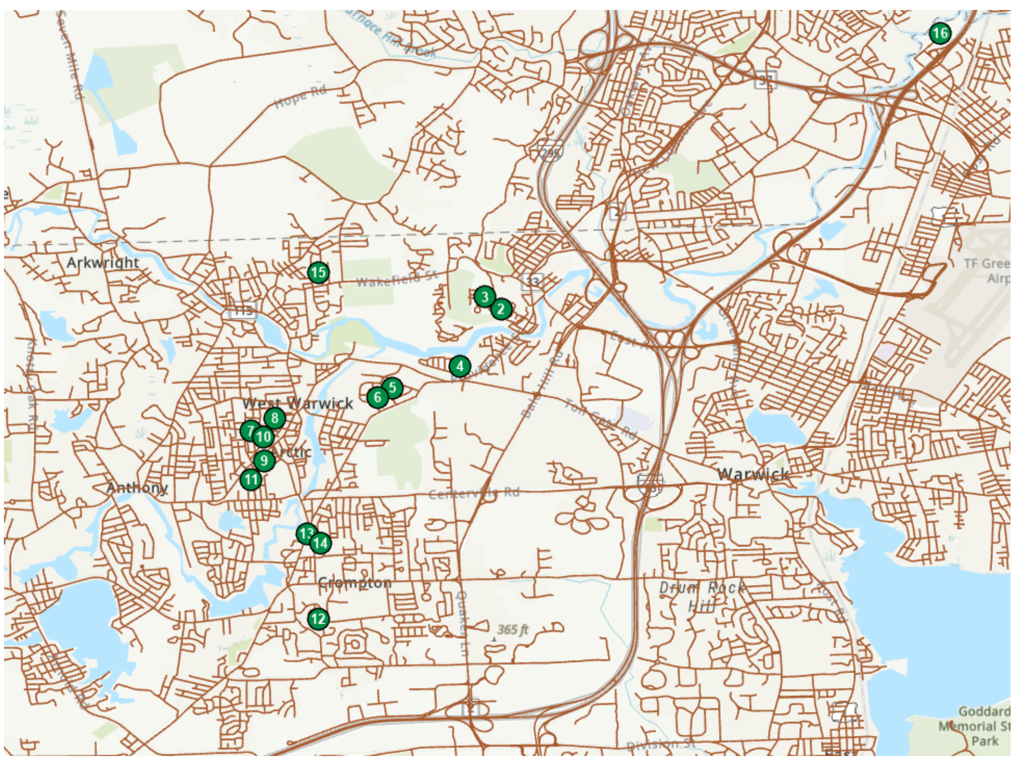

Figure K.265. West Warwick Route 11

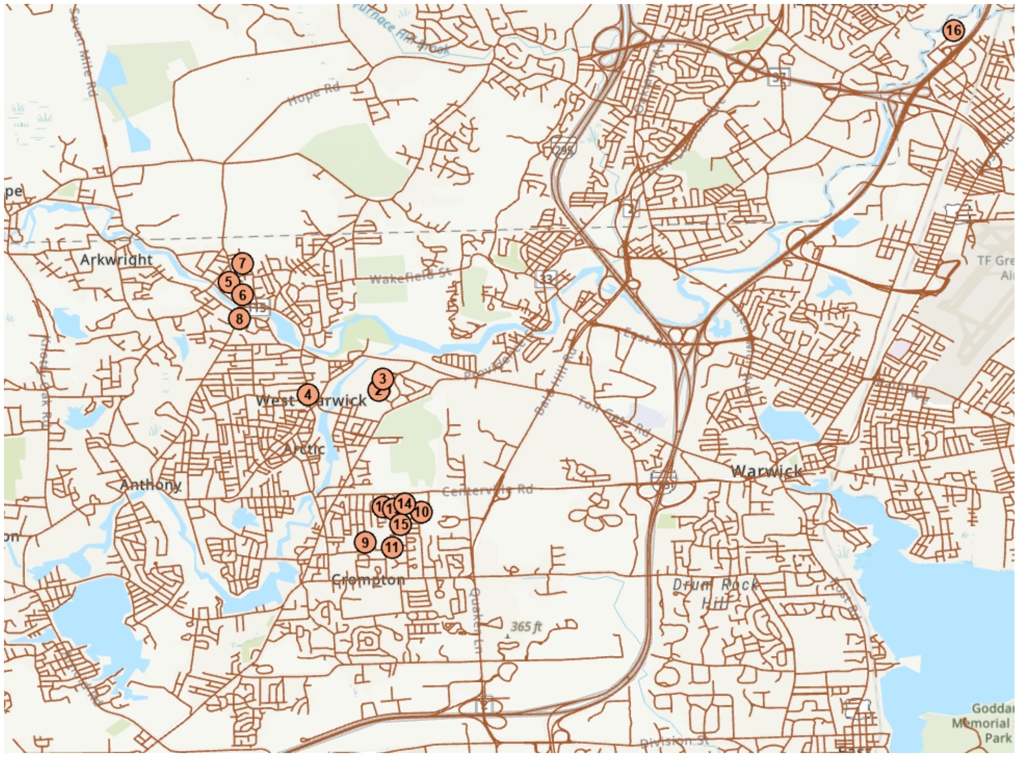

Figure K.266. West Warwick Route 12

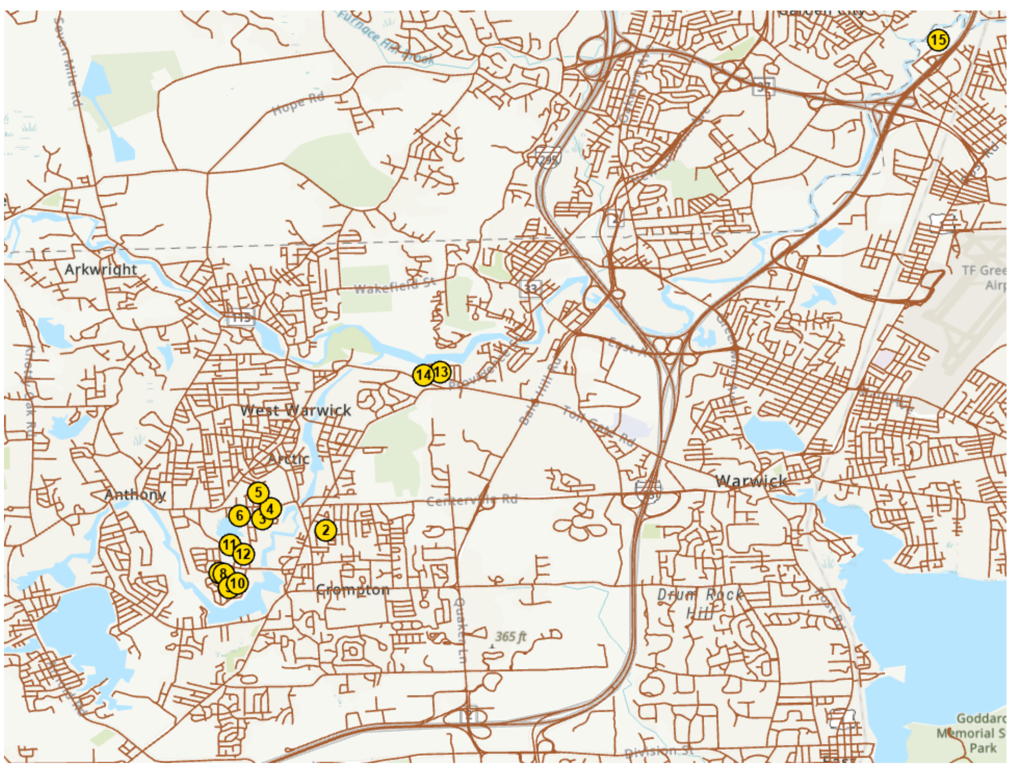

Figure K.267. West Warwick Route 13

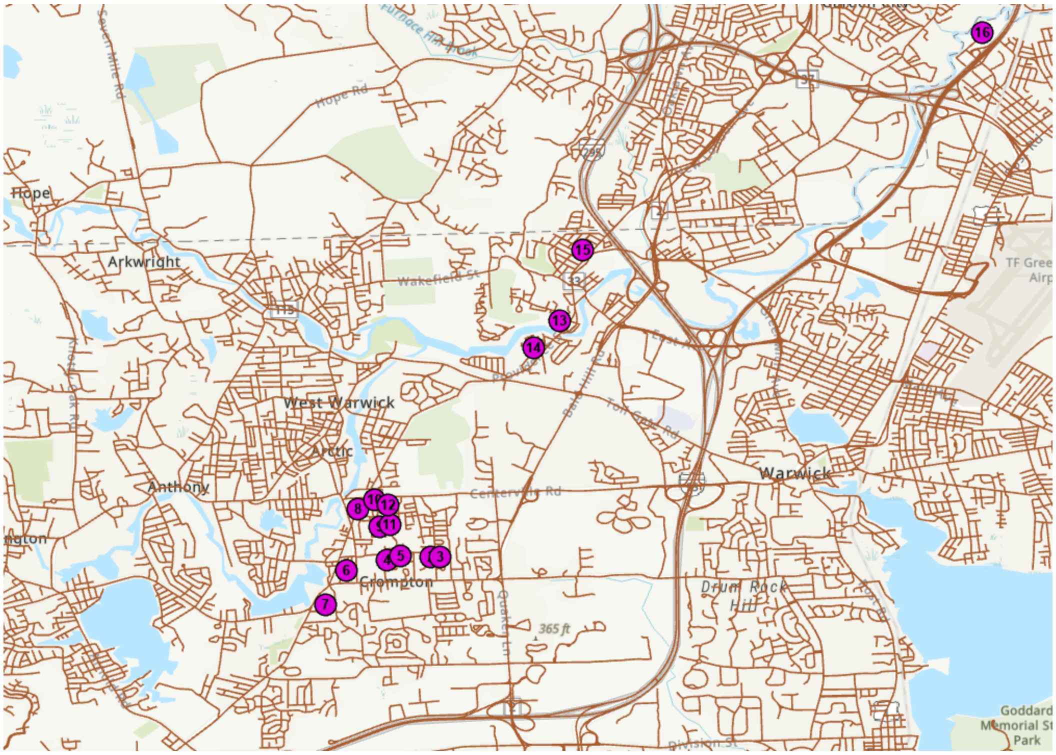

Figure K.268. West Warwick Route 14

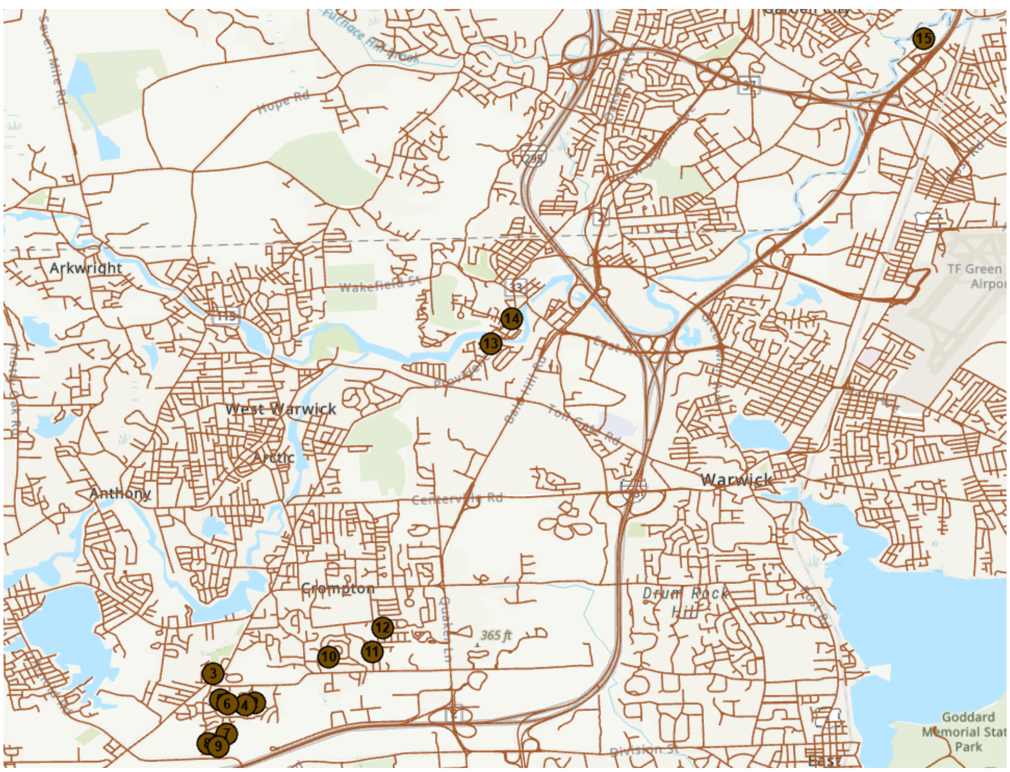

Figure K.269. West Warwick Route 15

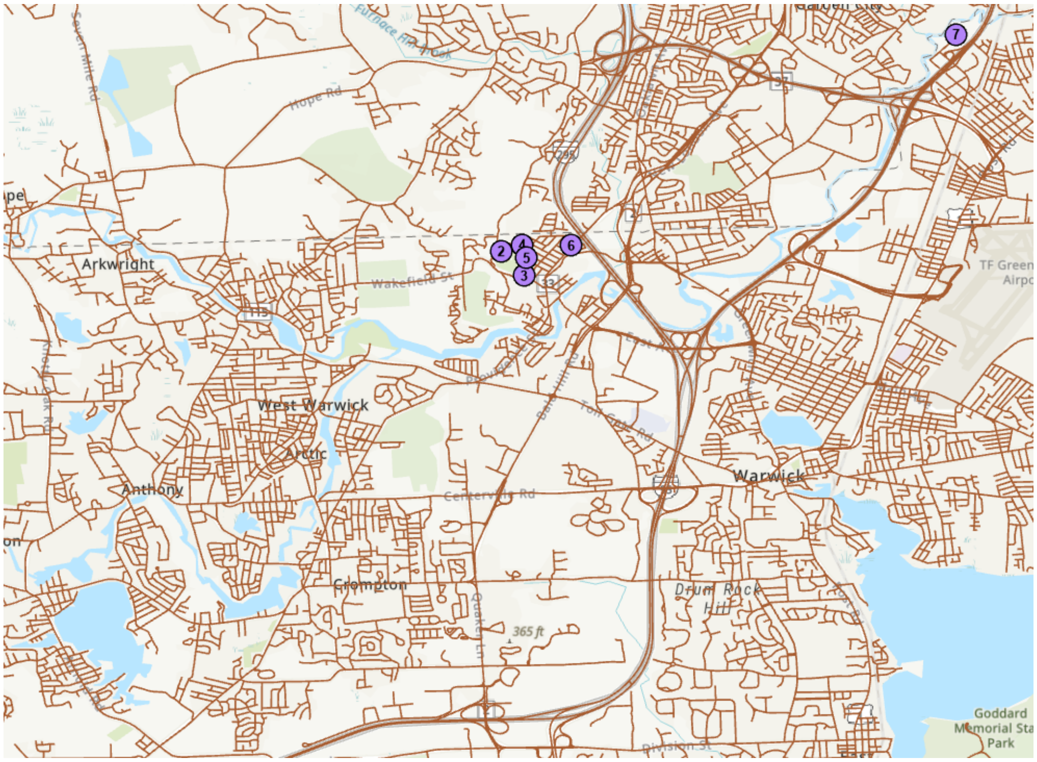

Figure K.270. West Warwick Route 16

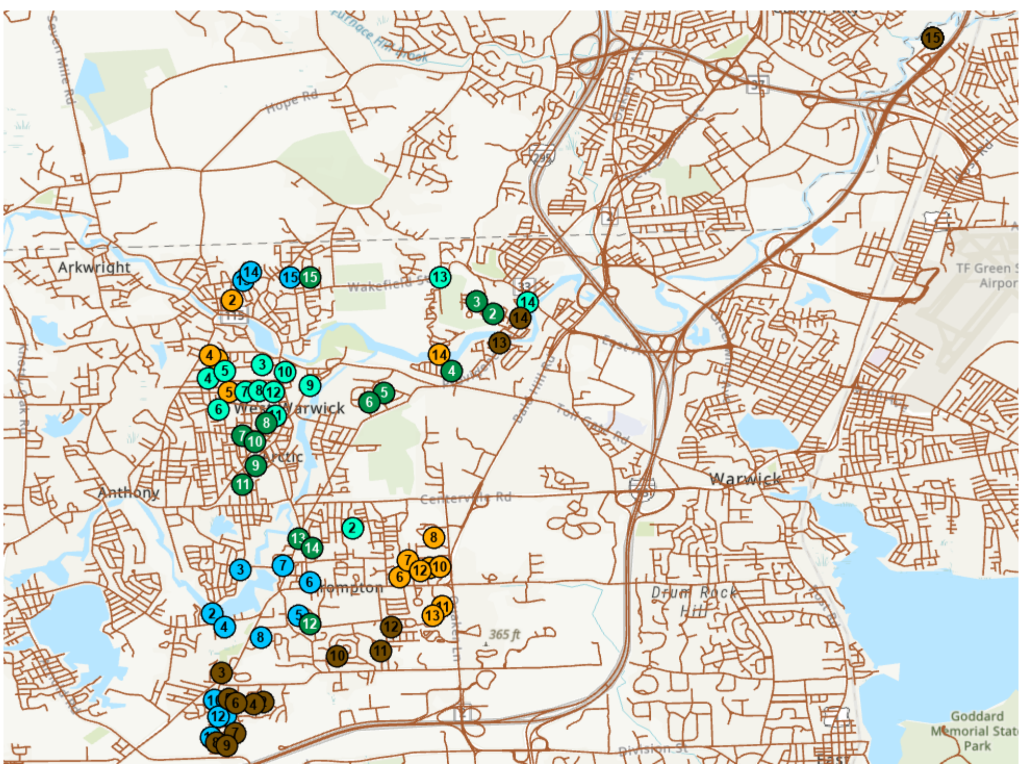

Figure K.271. West Warwick Truck 1

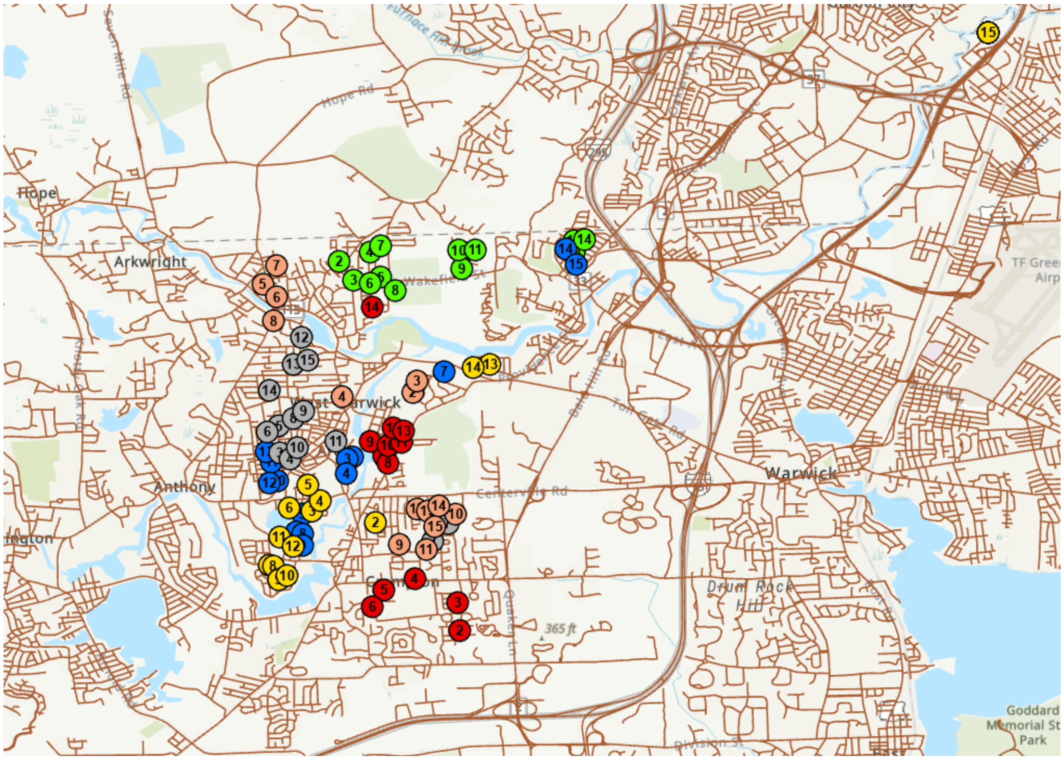

Figure K.272. West Warwick Truck 2

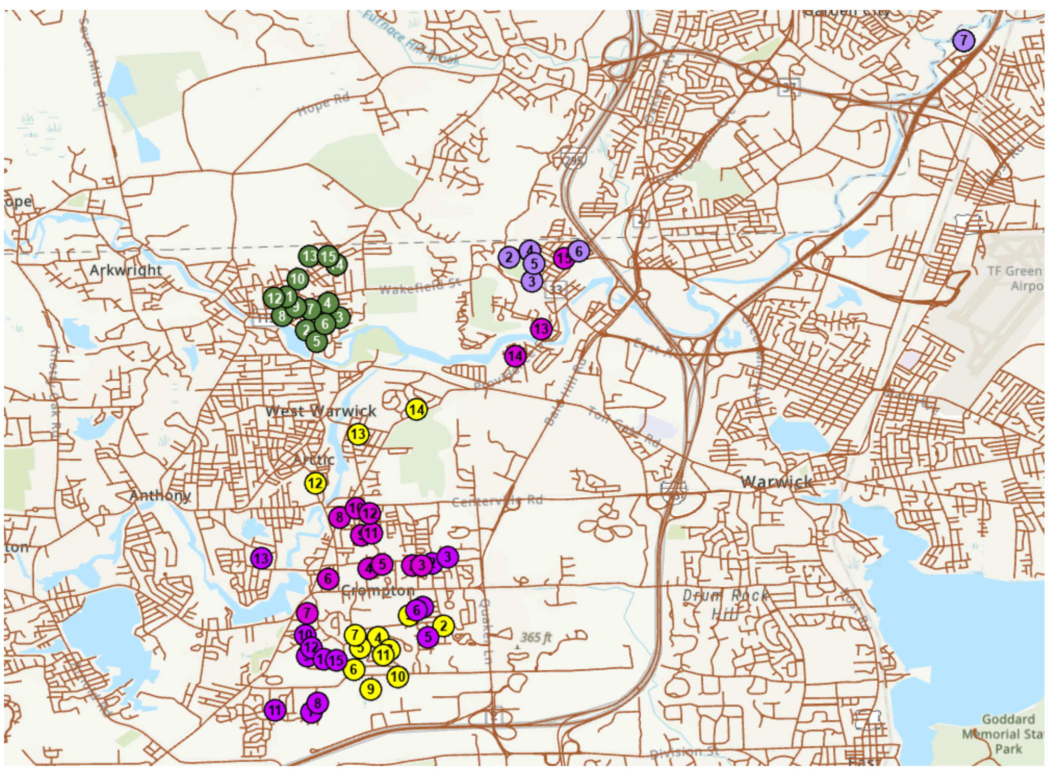

Figure K.273. West Warwick Truck 3

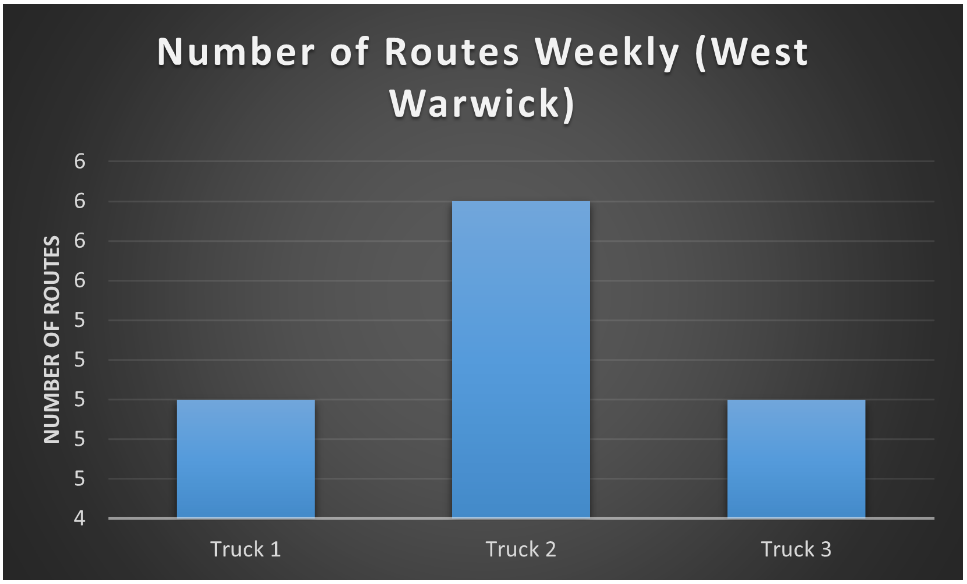

Figure K.274. Number of Routes Weekly (West Warwick)

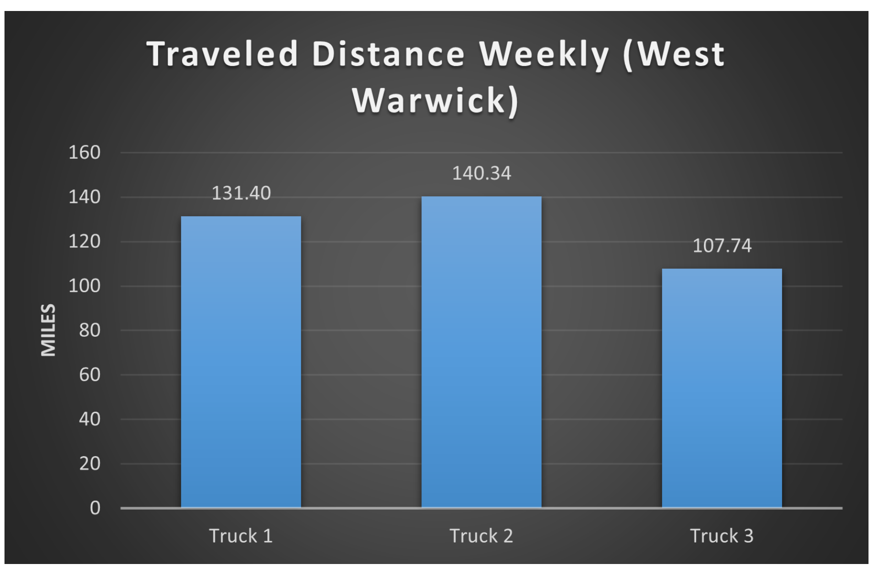

Figure K.275. Traveled Distance Weekly (West Warwick)

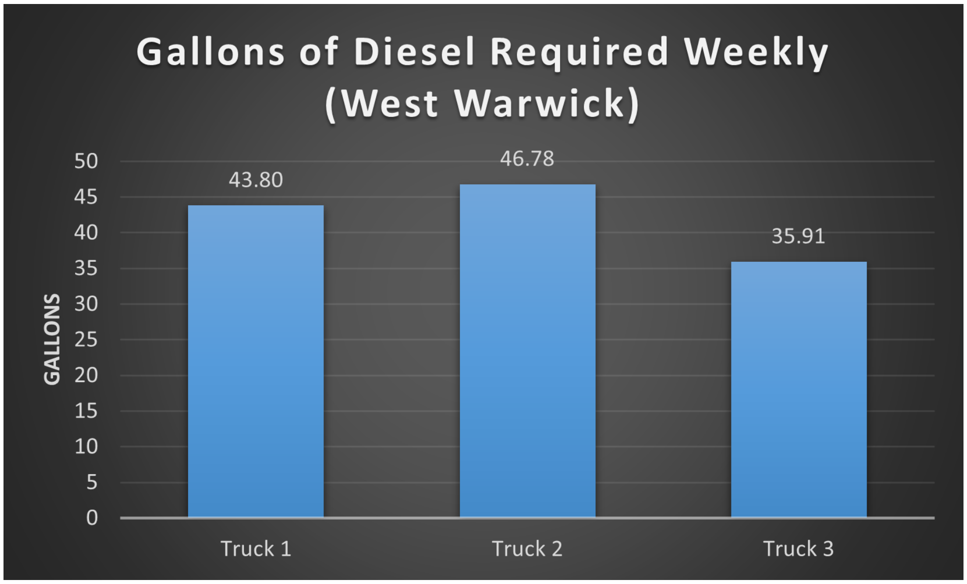

Figure K.276. Gallons of Diesel Required Weekly (West Warwick)

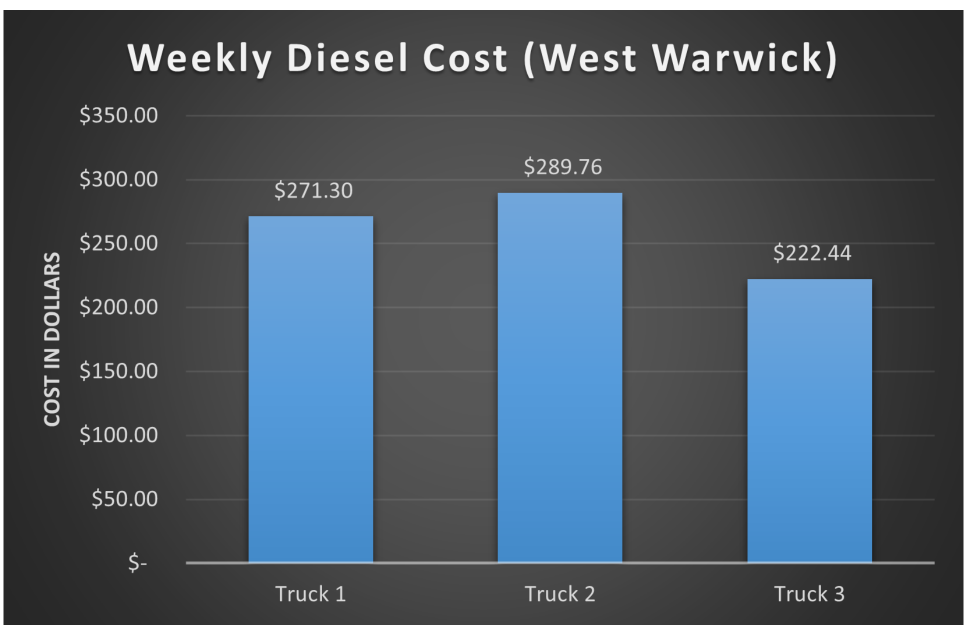

Figure K.277. Weekly Diesel Cost (West Warwick)

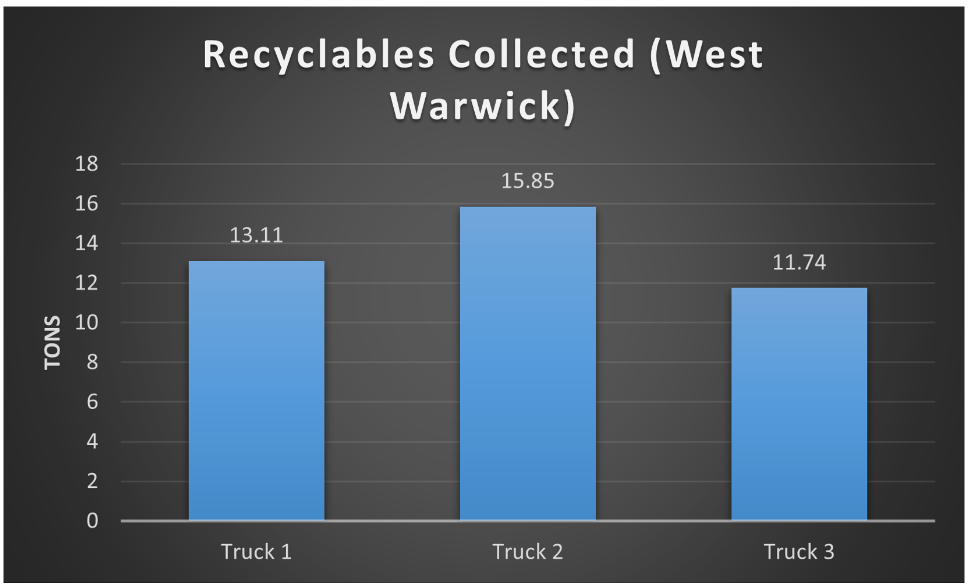

Figure K.278. Recyclables Collected (West Warwick)

BIBLIOGRAPHY

[Online]. Available: https://www.rigis.org/

"How spatially constrained multivariate clustering works." [Online]. Available: https://pro.arcgis.com/en/pro-app/2.8/tool-reference/spatial-statistics/how-spatially-constrained-multivariate-clustering-works.htm

"Multivariate clustering (spatial statistics)." [Online]. Available: https://pro.arcgis.com/en/pro-app/2.8/tool-reference/spatial-statistics/multivariate-clustering.htm#:~:text=The%20default%20option%2C%20Optimized%20seed,of%20data%20space%20improves%20performance

"Welcome to the vision government solutions, inc assessor's database for the city of pawtucket, ri." 2016. [Online]. Available: https://gis.vgsi.com/PawtucketRI/

"Gis mapping software, location intelligence amp; spatial analytics — esri," 2017. [Online]. Available: https://www.esri.com/content/dam/esrisites/en-us/newsroom/arcuser/summer-2017.pdf

"A guide to implementing a cart-based recycling program," Mar 2017. [Online]. Available: https://recyclingpartnership.org/wp-content/uploads/2018/05/implementing-carts-guide.pdf

"How docker engine works," Jan 2020. [Online]. Available: https://www.dclessons.com/how-docker-engine-works

"Our download server," 2020. [Online]. Available: https://www.geofabrik.de/data/download.html

"2021 municipal summary (detailed)," Mar 2021. [Online]. Available: https://www.rirrc.org/sites/default/files/2022-04/2021%20Municipal%20Summary%20Detailed%20with%20Charts%2020220331.pdf

"Garbage collector salary," Oct 2021. [Online]. Available: https://www.careerexplorer.com/careers/garbage-collector/salary/rhode-island/

"New way refuse trucks cobra magnum specification sheet," Apr 2021. [Online]. Available: https://refusetrucks.scrantonmfg.com/

AAA, "R.I. average gas prices," Jun 2022. [Online]. Available: https://gasprices.aaa.com/?state=RI

Abdelatti, M. F. and Sodhi, M. S., "An improved gpu-accelerated heuristic technique applied to the capacitated vehicle routing problem," in *Proceedings of the 2020 Genetic and Evolutionary Computation Conference*, 2020, pp. 663–671.

Armstrong, K., "Modelbuilder: An introduction," *ESRI http://gg. usm. edu/kar/GHY418_518/Lectures/ModelBuilder1. pdf [10 Agustus 2011]*, 2009.

Arora, P. and Varshney, S., "Analysis of k-means and k-medoids algorithm for big data," *Procedia Computer Science*, vol. 78, pp. 507–512, 2016.

Avis, D., Bremner, D., and Seidel, R., "How good are convex hull algorithms?" *Computational Geometry*, vol. 7, no. 5-6, pp. 265–301, 1997.

Bagheri, A. and Akbarzadeh Totonchi, M. R., "Finding shortest path with learning algorithms," *International Journal of Artificial Intelligence*, vol. 1, 2008.

Baker, B. M. and Ayechew, M., "A genetic algorithm for the vehicle routing problem," *Computers & Operations Research*, vol. 30, no. 5, pp. 787–800, 2003.

Bel, G. and Warner, M., "Does privatization of solid waste and water services reduce costs? a review of empirical studies," *Resources, Conservation and Recycling*, vol. 52, no. 12, pp. 1337–1348, 2008.

Bohm, R. A., Folz, D. H., Kinnaman, T. C., and Podolsky, M. J., "The costs of municipal waste and recycling programs," *Resources, Conservation and Recycling*, vol. 54, no. 11, pp. 864–871, 2010.

Borcinova, Z., "Two models of the capacitated vehicle routing problem," *Croatian Operational Research Review*, pp. 463–469, 2017.

Bray, T., Paoli, J., Sperberg-McQueen, C. M., Maler, E., Yergeau, F., and Cowan, J., "Extensible markup language (xml) 1.0," 2000.

Brundtland, G. H. and Khalid, M., *Our common future*. Oxford University Press, Oxford, GB, 1987.

Bryant, S., "How close to your property line can you build?" Dec 2021. [Online]. Available: https://www.rockethomes.com/blog/homeowner-tips/how-close-can-you-build-to-property-line

Bui, T., "Analysis of docker security," *arXiv preprint arXiv:1501.02967*, 2015.

Bureau, U. S. C., "Little compton town, newport county, rhode island." [Online]. Available: https://www.census.gov/search-results.html?searchType=web&cssp=SERP&q=Little%20Compton%20town,%20Rhode%20Island

Bureau, U. S. C., "Quickfacts bristol town, bristol county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/bristoltownbristolcountyrhodeisland

Bureau, U. S. C., "Quickfacts charlestown town, washington county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/charlestowntownwashingtoncountyrhodeisland/PST045221

Bureau, U. S. C., "Quickfacts glocester town, providence county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/glocestertownprovidencecountyrhodeisland/PST045221

Bureau, U. S. C., "Quickfacts pawtucket city, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/pawtucketcityrhodeisland/PST045221

Bureau, U. S. C., "Quickfacts portsmouth town, newport county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/portsmouthtownnewportcountyrhodeisland/PST045221

Bureau, U. S. C., "Quickfacts richmond town, washington county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/richmondtownwashingtoncountyrhodeisland/PST045221

Bureau, U. S. C., "Quickfacts scituate town, providence county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/scituatetownprovidencecountyrhodeisland/PST045221

Bureau, U. S. C., "Quickfacts south kingstown town, washington county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/southkingstowntownwashingtoncountyrhodeisland/PST045221

Bureau, U. S. C., "Quickfacts west warwick town, kent county, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/westwarwicktownkentcountyrhodeisland/PST045221

Bureau, U. S. C., "Quickfacts westerly cdp, rhode island." [Online]. Available: https://www.census.gov/quickfacts/fact/table/westerlycdprhodeisland/PST045221

Clarke, G. and Wright, J. W., "Scheduling of vehicles from a central depot to a number of delivery points," *Operations research*, vol. 12, no. 4, pp. 568–581, 1964.

Das, S. and Bhattacharyya, B. K., "Optimization of municipal solid waste collection and transportation routes," *Waste Management*, vol. 43, pp. 9–18, 2015.

Dong, J., Ni, M., Chi, Y., Zou, D., and Fu, C., "Life cycle and economic assessment of source-separated msw collection with regard to greenhouse gas emissions: a case study in china," *Environmental Science and Pollution Research*, vol. 20, no. 8, pp. 5512–5524, 2013.

El Allali, A. and Arshad, M., "Mzpaq: a fastq data compression tool," *Source code for biology and medicine*, vol. 14, no. 1, pp. 1–13, 2019.

Erfani, S. M. H., Danesh, S., Karrabi, S. M., and Shad, R., "A novel approach to find and optimize bin locations and collection routes using a geographic information system," *Waste Management & Research*, vol. 35, no. 7, pp. 776–785, 2017.

ESRI, "Modelbuilder vocabulary." [Online]. Available: https://pro.arcgis.com/en/pro-app/2.8/help/analysis/geoprocessing/modelbuilder/modelbuilder-vocabulary.htm

Esri, "Algorithms used by the arcgis network analyst extension," 2016.

Farahbakhsh, A. and Forghani, M. A., "Sustainable location and route planning with gis for waste sorting centers, case study: Kerman, iran," *Waste Management & Research*, vol. 37, no. 3, pp. 287–300, 2019.

Fellers, J. C., *ALGORITHM SELECTION FOR THE CAPACITATED VEHICLE ROUTING PROBLEM USING MACHINE LEARNING CLASSIFIERS*. University of Rhode Island, 2021.

Floros, G., Van Der Zander, B., and Leibe, B., "Openstreetslam: Global vehicle localization using openstreetmaps," in *2013 IEEE International Conference on Robotics and Automation*. IEEE, 2013, pp. 1054–1059.

Goodchild, M. F., "Citizens as sensors: the world of volunteered geography," *GeoJournal*, vol. 69, no. 4, pp. 211–221, 2007.

Gradišar, D. and Glavan, M., "Material requirements planning using variable-sized bin-packing problem formulation with due date and grouping constraints," *Processes*, vol. 8, no. 10, p. 1246, 2020.

Haklay, M. and Weber, P., "Openstreetmap: User-generated street maps," *IEEE Pervasive computing*, vol. 7, no. 4, pp. 12–18, 2008.

Hannan, M., Al Mamun, M. A., Hussain, A., Basri, H., and Begum, R. A., "A review on technologies and their usage in solid waste monitoring and management systems: Issues and challenges," *Waste Management*, vol. 43, pp. 509–523, 2015.

Hidayat, D. P. and Andajani, S., "Development land erosion model using model builder gis (case study: Citepus watershed)," in *MATEC Web of Conferences*, vol. 147. EDP Sciences, 2018, p. 03003.

Höke, M. C. and Yalcinkaya, S., "Municipal solid waste transfer station planning through vehicle routing problem-based scenario analysis," *Waste Management & Research*, vol. 39, no. 1, pp. 185–196, 2021.

Huber, S. and Rust, C., “Calculate travel time and distance with openstreetmap data using the open source routing machine (osrm),” *The Stata Journal*, vol. 16, no. 2, pp. 416–423, 2016.

Jacobsen, R., Buysse, J., and Gellynck, X., “Cost comparison between private and public collection of residual household waste: multiple case studies in the flemish region of belgium,” *Waste management*, vol. 33, no. 1, pp. 3–11, 2013.

Jünger, M., Reinelt, G., and Rinaldi, G., “The traveling salesman problem,” *Handbooks in operations research and management science*, vol. 7, pp. 225–330, 1995.

Kaur, G. and Fuad, M. M., “An evaluation of protocol buffer,” in *Proceedings of the ieee southeastcon 2010 (southeastcon)*. IEEE, 2010, pp. 459–462.

Khan, D. and Samadder, S., “Allocation of solid waste collection bins and route optimisation using geographical information system: A case study of dhanbad city, india,” *Waste Management & Research*, vol. 34, no. 7, pp. 666–676, 2016.

Kinnaman, T. C., “Policy watch: examining the justification for residential recycling,” *Journal of Economic Perspectives*, vol. 20, no. 4, pp. 219–232, 2006.

Kirakozian, A., “The determinants of household recycling: social influence, public policies and environmental preferences,” *Applied Economics*, vol. 48, no. 16, pp. 1481–1503, 2016.

Kumar, S. N. and Panneerselvam, R., “A survey on the vehicle routing problem and its variants,” 2012.

Laporte, G., “What you should know about the vehicle routing problem,” *Naval Research Logistics (NRL)*, vol. 54, no. 8, pp. 811–819, 2007.

Law, M. and Collins, A., *ArcGIS Pro*, 2019.

Li, C.-Z., Zhang, Y., Liu, Z.-H., Meng, X., and Du, J., “Optimization of msw collection routing system to reduce fuel consumption and pollutant emissions.” *Nature Environment & Pollution Technology*, vol. 13, no. 1, 2014.

Likas, A., Vlassis, N., and Verbeek, J. J., “The global k-means clustering algorithm,” *Pattern recognition*, vol. 36, no. 2, pp. 451–461, 2003.

Liu, W.-Y., Lin, C.-C., Chiu, C.-R., Tsao, Y.-S., and Wang, Q., “Minimizing the carbon footprint for the time-dependent heterogeneous-fleet vehicle routing problem with alternative paths,” *Sustainability*, vol. 6, no. 7, pp. 4658–4684, 2014.

Longo, H., De Aragao, M. P., and Uchoa, E., “Solving capacitated arc routing problems using a transformation to the cvrp,” *Computers & Operations Research*, vol. 33, no. 6, pp. 1823–1837, 2006.

Lu, J.-W., Chang, N.-B., and Liao, L., “Environmental informatics for solid and hazardous waste management: advances, challenges, and perspectives,” *Critical reviews in environmental science and technology*, vol. 43, no. 15, pp. 1557–1656, 2013.

Luxen, D. and Vetter, C., “Real-time routing with openstreetmap data,” in *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, ser. GIS ’11. New York, NY, USA: ACM, 2011, pp. 513–516. [Online]. Available: http://doi.acm.org/10.1145/2093973.2094062

Mason, A., “Opensolver-an open source add-in to solve linear and integer progammes in excel,” in *Operations research proceedings 2011.* Springer, 2012, pp. 401–406.

Mason, A., “Opensolver – an open source add-in to solve linear and integer progammes in excel,” in *Operations Research Proceedings 2011*, ser. Operations Research Proceedings, Klatte, D., Lathi, H.-J., and Schmedders, K., Eds. Springer Berlin Heidelberg, 2012, pp. 401–406, http://opensolver.org. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-29210-1_64

Mathers, J., Wolfe, C., Norsworthy, M., and Craft, E., “The green freight handbook,” *Environmental Defense Fund*, 2014.

Mertens, S. N. and Schultz, P. W., “Referent group specificity: optimizing normative feedback to increase residential recycling,” *Journal of Environmental Psychology*, vol. 73, p. 101541, 2021.

Minghini, M. and Frassinelli, F., “Openstreetmap history for intrinsic quality assessment: Is osm up-to-date?” *Open Geospatial Data, Software and Standards*, vol. 4, no. 1, pp. 1–17, 2019.

Möhring, R. H., Schilling, H., Schütz, B., Wagner, D., and Willhalm, T., “Partitioning graphs to speedup dijkstra’s algorithm,” *Journal of Experimental Algorithmics (JEA)*, vol. 11, pp. 2–8, 2007.

Mooney, P. and Corcoran, P., “Accessing the history of objects in openstreetmap,” in *Proceedings AGILE*, vol. 353, no. 1, 2011, pp. 1–3.

Mpafe, N., “Residential curbside recycle context analysis,” Ph.D. dissertation, University of South Florida, 2021.

Neamtu, M., “Bivariate simplex b-splines: A new paradigm,” in *Proceedings Spring Conference on Computer Graphics.* IEEE, 2001, pp. 71–78.

Neis, P. and Zielstra, D., "Recent developments and future trends in volunteered geographic information research: The case of openstreetmap," *Future Internet*, vol. 6, no. 1, pp. 76–106, 2014.

Ratliff, J., "What is a container?" Apr 2022. [Online]. Available: https://www.docker.com/resources/what-container/

Rehman, A. U., Awuah-Offei, K., BAKER, D., and Bristow, D., "Emergency evacuation guidance system for underground miners," in *SME Annual Meeting 2019*, 2019, pp. 19–100.

Sajid, M., Singh, J., Haidri, R. A., Prasad, M., Varadarajan, V., Kotecha, K., and Garg, D., "A novel algorithm for capacitated vehicle routing problem for smart cities," *Symmetry*, vol. 13, no. 10, p. 1923, 2021.

Sandhu, G. S., Frey, H. C., Bartelt-Hunt, S., and Jones, E., "In-use activity, fuel use, and emissions of heavy-duty diesel roll-off refuse trucks," *Journal of the Air & Waste Management Association*, vol. 65, no. 3, pp. 306–323, 2015.

Sandhu, G. S., Frey, H. C., Bartelt-Hunt, S., and Jones, E., "Real-world activity, fuel use, and emissions of diesel side-loader refuse trucks," *Atmospheric Environment*, vol. 129, pp. 98–104, 2016.

Sharma, Y., Saini, S. C., and Bhandhari, M., "Comparison of dijkstra's shortest path algorithm with genetic algorithm for static and dynamic routing network," *International Journal of Electronics and Computer Science Engineering*, vol. 1, no. 2, pp. 416–425, 2012.

Steinhaus, M., *The application of the self organizing map to the vehicle routing problem.* University of Rhode Island, 2015.

Stroetz, U., "Ustroetz/python-osrm: A python wrapper around the osrm api." [Online]. Available: https://github.com/ustroetz/python-osrm

Toth, P. and Vigo, D., *The vehicle routing problem.* SIAM, 2002.

Vock, D. C., "A quiet revolution in trash trucks," Apr 2021. [Online]. Available: https://www.governing.com/archive/gov-to-save-on-trash-trucks-cities-take-a-look-at-the-gas-tank.html

Vu, H. L., Ng, K. T. W., and Bolingbroke, D., "Parameter interrelationships in a dual phase gis-based municipal solid waste collection model," *Waste Management*, vol. 78, pp. 258–270, 2018.

Wahab, M. N. A., Nefti-Meziani, S., and Atyabi, A., "Flow Chart of Genetic Algorithm with all steps involved from beginning until termination conditions met [6]." 5 2015. [Online]. Available: https://plos.figshare.com/articles/figure/_Flow_Chart_of_Genetic_Algorithm_with_all_steps_involved_from_beginning_until_termination_conditions_met_6_/1418786

Weitz, K. A., Thorneloe, S. A., Nishtala, S. R., Yarkosky, S., and Zannes, M., “The impact of municipal solid waste management on greenhouse gas emissions in the united states,” *Journal of the Air & Waste Management Association*, vol. 52, no. 9, pp. 1000–1011, 2002.

Zsigraiova, Z., Semiao, V., and Beijoco, F., “Operation costs and pollutant emissions reduction by definition of new collection scheduling and optimization of msw collection routes using gis. the case study of barreiro, portugal,” *Waste management*, vol. 33, no. 4, pp. 793–806, 2013.