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MISSION-INFORMED EVACUATION MODELS FOR NAVAL STATION NEWPORT AND AQUIDNECK ISLAND

by

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September 2021

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During major hurricanes, key roads and facilities for military missions can become disrupted and unreachable. This is compounded with local evacuation orders that require nearby communities and military personnel to quickly leave the area. Yet, many military installations and municipalities do not coordinate their evacuation plans, leading to major traffic jams that further disrupt operations on and off base. In this work, we develop a mathematical model and a robust data set of roads, at-risk populations, and evacuation destinations to analyze optimal evacuation for Naval Station (NAVSTA) Newport and surrounding communities on Aquidneck Island. Our work informs possible prioritization of evacuation for all at-risk populations—civilian and military—and identifies critical infrastructure that can assist in minimizing the total evacuation clearance time for Aquidneck Island. Analysis in this thesis was used to advise emergency operations at NAVSTA Newport prior to landfall of Hurricane Henri in New England in August 2021.

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MISSION-INFORMED EVACUATION MODELS FOR NAVAL STATION NEWPORT AND AQUIDNECK ISLAND

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ABSTRACT

During major hurricanes, key roads and facilities for military missions can become disrupted and unreachable. This is compounded with local evacuation orders that require nearby communities and military personnel to quickly leave the area. Yet, many military installations and municipalities do not coordinate their evacuation plans, leading to major traffic jams that further disrupt operations on and off base. In this work, we develop a mathematical model and a robust data set of roads, at-risk populations, and evacuation destinations to analyze optimal evacuation for Naval Station (NAVSTA) Newport and surrounding communities on Aquidneck Island. Our work informs possible prioritization of evacuation for all at-risk populations—civilian and military—and identifies critical infrastructure that can assist in minimizing the total evacuation clearance time for Aquidneck Island. Analysis in this thesis was used to advise emergency operations at NAVSTA Newport prior to landfall of Hurricane Henri in New England in August 2021.

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List of Acronyms and Abbreviations

ADCIRC	Advanced Circulation
BFE	Base Flood Elevation
BPR	Bureau of Public Roads
CERI	Coastal Environmental Risk Index
CRS	Coordinate Reference System
DOD	Department of Defense
DOT	Department of Transportation
DAD	defender-attack-defender
EOP	Emergency Operation Plan
ETIS	Evacuation Traffic Information System
FEMA	Federal Emergency Management Agency
GDAL	Geospatial Data Abstraction Library
HURREVAC	Hurricane Evacuation
KML	Keyhole Markup Language
MCF-CA	minimum cost flow with congestion assignment
MPH	mile per hour
NHC	National Hurricane Center
NOAA	National Oceanic and Atmospheric Administration
NWC	National Weather Center

NWS	National Weather Service
NAVSTA	Naval Station Newport
NUWC	Naval Undersea Warfare Command
NA	nearest allocation
NetCDF	Network Common Data Form
OD	Origin-Destination
RIEMA	Rhode Island Emergency Management Agency
RIGIS	Rhode Island Geographic Information System
Risk MAP	Risk Mapping Assessment and Planning
SLOSH	Sea, Lake, and Overland Surges from Hurricanes
SO	system optimal
SUE	stochastic user equilibrium
SWAN	Simulating Waves Nearshore
TEDSS	transportation evacuation decision support system
USVI	United States Virgin Islands
USGS	United States Geological Survey
UE	user equilibrium
VPH	vehicles per hour

Executive Summary

Evacuation is the withdrawal or removal of people from endangered areas. Successful and timely evacuation during a disaster is a complex problem, one in which transportation infrastructure plays a significant role. Unfortunately, past disasters, both natural and man-made, have highlighted serious shortcomings in current emergency transportation planning and management. Hurricanes that make landfall in the northeastern United States tend to cause more devastation than their southern counterparts because as they track up the East Coast they increase in wind and storm surge. While there are many East Coast communities that are impacted by hurricanes, we focus our analysis on Aquidneck Island, the largest island in Narragansett Bay, Rhode Island, composed of 38 square miles, a population of around 60,000 and an average elevation of only 46 feet above sea level. On Aquidneck Island resides the city of Newport, the municipalities of Middletown and Portsmouth, as well Naval Station (NAVSTA) Newport. Across these civilian and military communities, evacuation plans are not coordinated in terms of who should evacuate first, where they should go and by what route, all of which ultimately places a substantial portion of the island's population at considerable risk.

This thesis focuses on the capacity of Aquidneck Island transportation infrastructure system and its ability to handle the mass departures of its at-risk populations even when faced with the uncertainty surrounding the precise location and potential no-notice of hurricanes. We define the critical components of this transportation system as the at-risk populations that reside in flood and hurricane evacuation zones, the roads and bridges that facilitate movement across the island and to the mainland, as well as designated mass evacuation shelters and off-island evacuation points. Our goal is to use a time-phased network flow model that will produce recommendations for Aquidneck Island's emergency planners on how to improve their emergency evacuation plans over the course of an evacuation period when faced with mass evacuation problems from the city of Newport, municipalities of Portsmouth and Middletown, as well as NAVSTA Newport and her tenant commands.

We achieve this by performing the following modeling and analysis tasks:

1. *Data Processing, Curation and Network Construction.* We construct a data set that

is useful in the analysis of at-risk population evacuation over the surface roads and bridges for Aquidneck Island.

2. *Model Formulation.* We develop a transportation modeling process that measures optimal evacuation clearance times for specific at-risk populations evacuating to assigned inland mass evacuation shelters or off-island.
3. *Evacuation Modeling Analysis.* Using our data set and optimization model, we determine the capability of Aquidneck Island's road and evacuation facility infrastructure systems to enable timely evacuation of all at-risk populations. By doing so, we also identify which city or municipality has the greatest difficulty evacuating its coastal communities.

We consider three evacuation scenarios: Scenario 1 models current evacuation plans, Scenario 2 examines Hurricane Henri, which struck New England in August 2021, and Scenario 3 considers increased shelter capacities. Results for each scenario answer several key questions.

First, what is the optimal clearance time of populations from each installation, city, and township on Aquidneck Island under current evacuation plans? We model Scenario 1 based on the current restrictions and plans provided by the city of Newport, and municipalities of Middletown, and Portsmouth as well as NAVSTA Newport. This baseline scenario results in a total evacuation clearance time of 15 hours, with the city of Newport and NAVSTA Newport resulting in the longest clearance times within their communities.

Second, what is the optimal clearance time of populations if an evacuation route is restricted from use? Additionally, which communities are the most impacted due to increased evacuation restrictions? We model the closure of the Newport Bridge restricting evacuation westward as well as requiring all military personnel to evacuate off-island. This results in an increased clearance time of 30 hours for the entire island, with NAVSTA Newport's clearance time increasing to 19 hours and the city of Newport's clearance time doubling to 30 hours.

Third, if on-island shelter capacities can be increased, what is the resulting optimal clearance time and which shelter allows for the greatest intake of evacuating vehicles? Increasing capacity of the on-island shelters allows for more evacuees to remain on-island versus evacuating off-island. Here, we did not see a change in overall clearance time, which remained

at 15 hours. The two shelters that were determined to be the most beneficial due to the raised capacities were the Florence Grey Shelter in the City of Newport and Portsmouth High School.

Overall, the model formulation and data set requirements are very flexible and can be easily reproduced to analyze the effects of flooding and storm surge inundation from hurricanes on various other military installations and at-risk communities.

This work was performed in collaboration with the Military Installation Resilience Review (MIRR) in Newport led by the University of Rhode Island.

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CHAPTER 1:
Introduction

Evacuation is the withdrawal or removal of people from endangered areas. Successful and timely evacuation during a disaster is a complex problem, one in which transportation infrastructure plays a significant role. Unfortunately, past disasters, both natural and man-made, have highlighted serious shortcomings in current emergency transportation planning and management. Emergency plans based on inadequate representations of a community's transportation network or executed poorly put at risk a significant number of lives. For this reason, development of evacuation models that accurately reflect a community's unique requirements is needed for comprehensive emergency plans. Every year the United States is impacted by a variety of storms, with an increasing number of them declared as major disasters by the president. The Federal Emergency Management Agency (FEMA) is the organization responsible for tracking and reporting on these disasters, which average annually in number between 40 to 80 across the United States (Skinner Jr et al. 2009). Due to such a high number of natural disasters, emergency management planning regarding the evacuation of people to or from critical locations remains of vital interest to homeland security and national defense.

1.1 Thesis Goals

This thesis focuses on the capacity of an urbanized transportation infrastructure system and its ability to handle the mass departures of its inhabitants even when faced with the uncertainty surrounding the precise location and potential no-notice of incidents. A time-phased network flow model enables the analysis of this type of transportation problem by producing recommendations for city planners on how to improve their emergency evacuation plans over the course of an evacuation period (Yuhas 2011; Malveo 2013). In this work, we develop suitable models and analysis for Naval Station Newport (NAVSTA), nearby military and coast guard installations, the city of Newport, and the townships of Middletown and Portsmouth located on Aquidneck Island in Rhode Island. Due to the recent volatile nature of storms that have impacted the Eastern coast of the United States, we seek to develop optimal evacuation plans given future storms and infrastructure impacts based on novel

hurricane simulations and consequence models. Specifically, the purpose of this thesis is to address the following questions:

1. What is the optimal clearance time of populations from each installation, city, and township on Aquidneck Island given future storms?
2. How should current evacuation plans change to accommodate future evacuation needs?
3. Is there critical infrastructure or specific capacity constraints that directly impact evacuation clearance time?

1.2 Background

The 2020 Atlantic hurricane season, which stretched from mid-May to early December, was a season of extreme events; it witnessed the most named storms in a year, the most storms that made landfall in the continental United States, and the most storms to form during the month of September, which is historically the most active month of the Atlantic hurricane season. Even though hurricanes and tropical storms form in both the Atlantic and Pacific Basin, the storms that form in the Pacific basin rarely make landfall. In contrast, nearly every mile of the eastern seaboard experienced high winds and storm surge at some point during 2020. Hurricanes that make landfall in the Northeast tend to cause more devastation than their more southern counterparts because as they track up the east coast they increase in wind and storm surge. When combined with the absence of protected beaches, increased coastal erosion, and high coastal populations of New England, this is the perfect recipe for catastrophe.

Rhode Island, located within the New England region and known for its sandy beaches and historic coastal towns, has a geography that makes it vulnerable to hurricanes and flooding disasters. Rhode Island is only 40 miles wide but has over 400 miles of coastline due to the Narragansett Bay and other inlets (Lemons 2021). In addition to such a vast coastline, the majority of the state's land mass is only 200 feet above sea level, of which 47 square miles (12%) lie within 4.9 vertical feet of sea level, and an additional 24 square miles (6%) between 4.9 and 11.4 feet above sea level (Climate Change Collaborative 2021). This geography makes Rhode Island susceptible to multiple types of coastal and inland flooding, whether from riverine overflow, surface flooding, storm surge, or rising sea levels as a result

of climate change.

Statewide vulnerability to hurricanes and flooding means a significant amount of Rhode Island's commercial and public transportation infrastructure is also susceptible to these disasters. Rhode Island relies on a transportation network consisting of over 6,000 miles of public roads and highways to support its local economy. Many Rhode Island communities rely on tourism, agriculture, and coastal-dependent industries. For example, Rhode Island hosted 26.2 million visitors and generated $1.7 billion in tax revenues in 2019 (Tourism Economics 2019). With the majority of Rhode Island's topography sitting barely above sea level, a storm surge of just one percent has the potential to flood 337 miles of public roads (Morrison et al. 2020). With climate change comes the continued rise in sea level. That same one percent storm surge combined with a seven-foot rise in sea level would flood 573 miles of Rhode Island roads and 163 bridges (Morrison et al. 2020). The combined threat of flooding from storm surge and sea level rise places Rhode Island's coastal transportation systems at a much higher risk of blockage and washout than those further inland.

The risk of storm surge and sea level rise also threatens military installations and federal infrastructure located on the coast of Rhode Island. NAVSTA Newport—located on the West coast of Aquidneck Island in Rhode Island (Figure 1.1) is the Navy's foremost site for training for both officer and enlisted communities as well as the main testing site of various advanced undersea warfare and development systems. Attached to NAVSTA Newport are 50 Navy, Marine Corps, Coast Guard, and U.S. Army Reserve commands and activities whose populations account for approximately 1,000 permanently assigned military members as well as 1,700 students on any given day (MilitaryBases.US 2021).

Sustaining operations on board NAVSTA Newport during storm events as well as withstanding future challenges from sea level rise depend on critical infrastructure both on the installation *and* within the surrounding municipalities. The critical infrastructure systems that support the continued operations within this installation, such as energy, water, and emergency services, are all located within the surrounding city of Newport as well as the nearby townships of Middletown and Portsmouth. Although each of these municipalities have individual emergency response plans, there is no holistic emergency or hazard mitigation plan between them. In particular, flooding of federal and local roadways can impact military missions by preventing access to facilities at NAVSTA Newport and slowing supply

chains required for training and research missions.

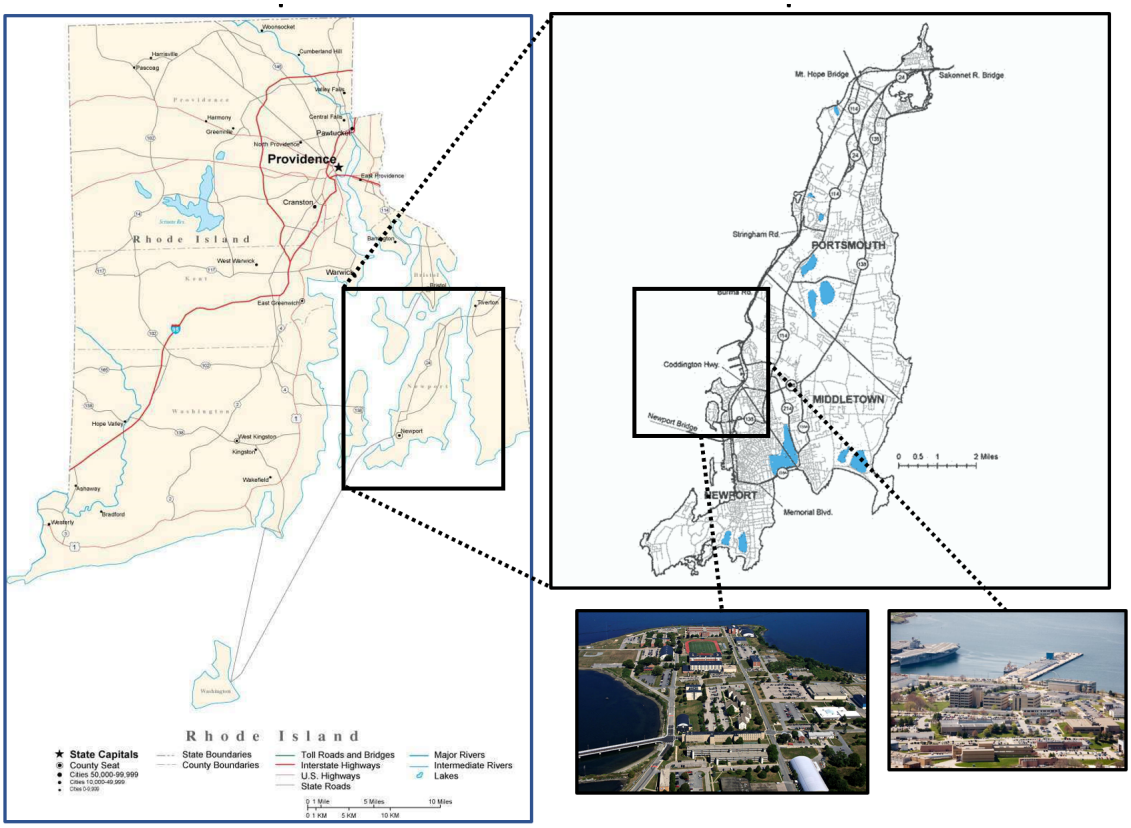

Figure 1.1. Rhode Island, Aquidneck Island and NAVSTA Newport. State of Rhode Island and zoomed in location of Aquidneck Island, which contains the city of Newport and townships of Portsmouth and Middletown as well as NAVSTA Newport. Adapted from Newport Rhode Island (2020).

1.3 Hurricanes in Rhode Island

Hurricanes are complex phenomena that cause a combination of extreme winds, rainfall, and storm surge. Rhode Island has experienced several hurricane-driven disasters that inform future community and military evacuation plans. Notwithstanding the impacts of high winds on buildings and infrastructure, we describe the impacts of extreme rainfall and storm surge to guide evacuation planning.

1.3.1 Past Hurricane Disasters

"The Great New England hurricane of 1938 was one of the most powerful and destructive storms to strike southern New England" (University of Rhode Island 2021). Developing near Cape Verde, this storm tracked for 12 days up the Atlantic coast and made landfall on Long Island on 12 September during a period of high tide (University of Rhode Island 2021). The hurricane maintained its center over the warm gulf stream, sustaining winds of over 100 mile per hour (MPH). Even though Rhode Island escaped most of the rainfall, it experienced the devastation and power of the storm surge. Narragansett Bay experienced 12-to-15 foot waves that destroyed most of the coastal homes, flooded the marinas, blocked roads, and covered Providence in 20 feet of water before continuing inland. In the aftermath of the hurricane, the coastal communities of Rhode Island were devastated with over 8,900 homes and buildings destroyed and 564 lives lost (University of Rhode Island 2021).

Twenty years later in 1954, Hurricane Carol made landfall over Rhode Island, bringing with it sustained winds of 100 mph and the strongest ever recorded wind gusts of 135 MPH (Hurricane Science 2021). Narragansett Bay once again experienced storm surges between 10 to 15 feet, but since Carol made landfall just after high tide, the overall storm tide was lower as it approached inland, and high flood areas like Providence experienced lesser but still devastating flooding of 12 feet. Unlike the Great New England hurricane, Rhode Island experienced more rainfall, but coastal flooding was still the most catastrophic, destroying 4,000 homes. Cascading failures within the power grid also caused the loss of power across the entire state (Hurricane Science 2021).

Just a year later, two storms, Connie and Diane, passed over New England within one week of each other. These storms, unlike those previously mentioned, did not exhibit the same velocity of winds, but instead brought large amounts of rain that caused excessive freshwater flooding across Connecticut and Rhode Island. Record flooding of the Blackstone River in Massachusetts pushed floodwater into the Blackstone River Valley in Rhode Island. Under excessive pressure, the dam north of Woonsocket broke, releasing a 20-foot wall of water down the river. This caused the river to crest 12.8 feet above the tide gauge and spill into Woonsocket (University of Rhode Island, Graduate School of Oceanography 2021). These storms caused devastating floodwaters that spread across Rhode Island before dumping into the Narragansett Bay. The cascading impacts from these storm events still mark the worst flooding in Rhode Island's history.

In 2010, another series of heavy rainstorms over a five-week period saturated much of the soils around Rhode Island's rivers. Unable to properly drain, excessive rainfall brought a majority of the rivers and streams to water levels above their flood gauge, and they crested at heights that broke many of the records set during the Great New England flood of 1938. The waste treatment facility in Warwick Rhode Island was inundated with water and subsequently spilled wastewater into the surrounding region. The state's transportation infrastructure system came to a halt as Interstate 95 in Cranston, a connector airport, railroad tracks in Westerly, and roads all across the state were flooded. More importantly, loss of transportation infrastructure was responsible for the isolation of many of the population centers across Rhode Island.

In October 2012, Hurricane Sandy was the deadliest, strongest, and most devastating hurricane of that year, ripping through eight countries all the way from the Caribbean to Canada, including the entire eastern seaboard of the United States. Although downgraded to a Category 2 hurricane by the time it hit Rhode Island, Hurricane Sandy has remained as the largest Atlantic hurricane on record with tropical storm strength winds stretching over 900 miles (Rafferty 2012). What Hurricane Sandy lacked in intensity she made up with in duration. A low-pressure system off the coast of New England combined with a high-pressure system moving south from Canada prevented Hurricane Sandy from moving quickly back out to sea. Multiple tide cycles combined with Sandy's strong winds created 15- to 30-foot seas that pounded Rhode Island's coast, decimating the protective 6- to 10-foot sand dunes, and inundating many of the state's coastal flood zones with a storm tide that was greater than 9.5 feet (Schubert et al. 2015).

In August 2021, just weeks before the completion of this thesis, Hurricane Henri was the first tropical cyclone to make landfall in Rhode Island in 20 years. The storm resulted in less damage than initially forecast but dropped large amounts of rain that resulted in prolonged flooding and electrical outages (Newman 2021).

1.3.2 Flooding Caused by Hurricanes

Understanding how hurricanes impact communities and evacuation plans requires knowledge of the different kinds of flooding hurricanes cause in Rhode Island. There are three common types of episodic flooding—fluvial, pluvial, and coastal flooding—that cause inun-

dation of the surrounding land. Each type is formed differently and subsequently produces different types and levels of damage and impacts. As a result of permanent sea level rise and increased storm occurrences, all three of these types of flooding have become more persistent across the New England region.

Fluvial floods are river floods, where water levels in a lake, river or stream rise over their banks and flow onto the surrounding terrain. There is a measurable difference between fluvial flooding events and pluvial (rainfall) events in terms of duration as fluvial events "usually occur for duration of days, or even weeks with widespread damages in the floodplains of river systems" (Patra et al. 2016). This excessive rise in water levels is typically caused by heavy, consistent rainstorms or large snow melts. The intensity of the flood is highly dependent on the volume and velocity of the rainfall as well as the size of the corresponding watershed. In flatter regions, water can spill over the banks and remain for long periods of time due to lack of drainage; in more mountainous regions, water can drain very quickly, flooding the areas downhill with large amounts of fast-moving water that is carrying large amounts of debris, causing extensive damage in its wake.

Pluvial floods, either surface water floods or flash floods, are formed after excessive rainfall and are not specifically linked to the overflow of any body of water. This type of flooding "occurs when the rainfall rate exceeds the capacity of storm water drains to evacuate the water and the capacity of the ground to absorb water" (Houston et al. 2011). What makes this type of flooding dangerous is that it can occur anywhere, urban or rural areas, coastal or inland. Surface water floods are those caused when an independent system such as an urban water or sewage system becomes overwhelmed and spills onto the surrounding areas. This type of flooding typically has slow buildup, and when flooding occurs it is slow and shallow. Surface flooding is more of a nuisance, creating temporary blockage of roadways and intersections versus large-scale property damage or loss of life. Flash floods are another type of pluvial floods. This flooding occurs with little warning and is a high-velocity deluge of water caused by excessive rainfall in a short period of time. These types of floods are very dangerous and can lead to fatalities in addition to extensive damage of the surrounding areas because they occur with little warning, begin in areas of higher terrain, and inundate lower areas with a high flow rate of water.

Coastal flooding is inundation of the shoreline and the surrounding coastal region due to

low- pressure weather systems that form in the ocean, drawing intensity from the warm water and causing the highest level of water surge when they make landfall during periods of high tide. The severity of the storm surge depends on the level of the tide when the storm encroaches the shore in combination with the size, speed, strength, and direction of the storm itself. The surrounding region's topography is also a factor in the level of potential destruction. While natural formations like sand dunes, wetlands, levees, and barrier islands in addition to man-made structures can help reduce the impact of the storm surge, they can also amplify the effects. Levees can break, natural formations can inadvertently create a tunneling effect that channels and intensifies storm destruction, and these combinations combined with high winds and destruction of residences and buildings can lead to very deadly situations.

FEMA has implemented a Risk Mapping Assessment and Planning (Risk MAP) program that works with communities in Rhode Island and across the United States to assess flood risks. The basis of the calculations for determining this floodwater risk is utilization of Base Flood Elevation (BFE). The BFE is the "expected elevation that floodwater will rise during a flooding event that has a 1% chance of occurring", also otherwise known as the 100-year flood (FEMA 2020). FEMA has formulated Special Flood Hazard Areas, which are those areas that are inundated during these surface water floods. Information regarding each zone can be found in Table 1.1.

Further detail on the assignment of these zones across Rhode Island is depicted in Table 1.2. Due to its small size, Rhode Island has only five counties, although there is no active government at that level. Even though Newport County contains the smallest amount of floodplains, totaling just 6%, it does however, contain the largest coastal area, totaling 23%, that is subject to a velocity hazard (wave action).

There is not a single community within Rhode Island that is not vulnerable to some type of flooding, and based on historical events, this state will likely continue to experience one to five flooding events per year. Table 1.3 depicts the number of flooding events that have occurred between 1996 and 2018 (Rhode Island Emergency Management Agency 2018). The cities and townships analyzed in our research reside in Newport County, which according to the figure, has experienced 0.87 annualized flooding events over this period of time. This value can provide a reference that is valuable in predicting the number of future

Table 1.1. FEMA Flood Zones. Description of FEMA flood zones on Aquidneck Island. Adapted from Rhode Island Emergency Management Agency (2013).

Zone	Risk Type	Description
A	high	Areas subject to inundation by the 1% annual-chance flood event generally determined using approximate methodologies.
AE	high	Areas subject to inundation by the 1% annual-chance flood event determined by detailed methods.
AO	high	Areas subject to inundation by the 1% annual-chance shallow flooding (usually sheet flow) where average depths are between 1-3 ft.
AH	high	Areas subject to inundation by the 1% annual-chance shallow flooding (usually areas of ponding) where average depths are between 1-3 ft.
VE	high coastal	Coastal areas subject to inundation by the 1% annual-chance flood event with additional hazards due to storm-induced velocity wave action.

Table 1.2. Rhode Island Flood Zones by County. Adapted from Rhode Island Emergency Management Agency (2018).

County Name	Zone A (sq. mile)	Zone AE (sq. mile)	Zone AO (sq. mile)	Zone AH (sq. mile)	Zone VE (sq. mile)	Zone X 0.2% annual change area (sq. mile)	Zone X Levee (sq. mile)
Bristol	0.080	7.614	0.002	0.000	3.872	3.205	0.000
Kent	6.520	8.255	0.007	0.000	4.066	3.161	0.024
Newport	1.817	5.827	0.000	0.000	23.525	4.289	0.000
Providence	24.853	13.300	0.000	0.008	2.525	5.985	0.652
Washington	30.463	20.673	0.000	0.000	21.205	10.002	0.000

events for this region; however, it does not consider sea level rise or climate change, which undoubtedly will cause this annualized value to increase in years to come.

1.3.3 Impacts of Climate Change

In addition to the damage caused by past events, future storms are expected to have even greater impacts in Rhode Island. Climate change is having an impact on both episodic and persistent flooding. Episodic flooding events are intermittent occurrences of short duration such as storm surge and riverine overflow that can be forecasted to some degree. Analyzing

Table 1.3. Rhode Island Flooding Events 1996-2018. Adapted from Rhode Island Emergency Management Agency (2018).

County Name	Number of Events	Annualized Events	Property Damages	Annualized Damages
Bristol	25	1.09	$6,5234,000	$271,043.48
Kent	49	2.13	$27,872,000	$1,211,826.09
Newport	20	0.07	$6,635,000	$288,478.26
Providence	99	4.3	$32,580,000	$1,416,521.73
Washington	36	1.57	$33,427,000	$1,453,347.83

historic weather patterns and the utilization of advanced storm modeling techniques help identify and track the formation of weather systems that have the potential of impacting the eastern seaboard. However, in conjunction with the rising ocean temperatures, the duration of hurricane seasons is lengthening, and various types of weather systems are concurrently increasing in frequency and intensity. Additionally, a well-accepted consequence to climate change is that sea levels are a continuing to rise, with the average global sea level increasing approximately 8-to-9 inches since 1880 (Lindsay 2021). Sea level in North Eastern United States is in fact rising at a higher rate than the global average with states such as Rhode Island expected to experience a sea level rise of 9.6 feet by 2100 (Coastal Research Management Council 2017).

The National Oceanic and Atmospheric Administration (NOAA) has conducted multiple studies in order to better identify areas of the U.S. coastline that are the most impacted during varying sea level rise scenarios. These studies in conjunction with STORMTOOLS, "a Rhode Island specific coastal mapping software created by the University of Rhode Island, map the extent and water depth for 1-, 2-, 3-, 5-, 7-, 10- and 12-foot sea level rise scenarios" (Council 2021). Rhode Island experiences statewide impacts even within the lowest scenario of 1 foot. Significant impacts really begin to be prevalent within Newport County at the 3-foot sea rise level, with both Washington County and Newport County experiencing significant impacts to over 863 critical residents, facilities, and commercial structures (Rhode Island Emergency Management Agency 2018).

1.4 Evacuation of Aquidneck Island during Hurricanes

Managing future hurricane disasters for NAVSTA Newport and Aquidneck Island requires a combination of protection and emergency response activities. Physical protection options include built and natural systems that attenuate the impacts of flooding. Emergency operations include community and military planning to evacuate and provide disaster relief to flood-impacted communities. Evacuation is particularly important for NAVSTA Newport and Aquidneck Island communities. Aquidneck Island contains the city of Newport, townships Middletown and Portsmouth, as well as NAVSTA Newport. All three of these municipalities with the Naval Base combined encompasses a population of approximately 65K (United States Census Bureau 2019).

Emergency management for Aquidneck Island communities is coordinated by the Rhode Island Emergency Management Agency (RIEMA) and locally implemented by each municipality. RIEMA has established a State Emergency Operation Plan (EOP) that outlines Rhode Island's statewide approach toward coordination and planning during large-scale disasters. This plan is very broad in scope and delegates the creation of specifically tailored EOP to each municipality. The Army Corps of Engineers is responsible for assisting communities in developing maps that outline the various evacuation zones and which communities reside within them. These zones are then activated during specific hurricane events to assist in understanding which at-risk populations should be evacuated. One specific example for Newport is seen in (Figure 1.2).

Different Aquidneck Island communities are required to evacuate for different hurricane events. A culmination of all three evacuation zones (Figure 1.2, 1.3, 1.4) show that the entire perimeter of Aquidneck Island, which includes NAVSTA Newport, is designated as Evacuation Zone A, meaning that it is expected to evacuate prior to a Hurricane Category 1 or 2 event (Nicholson et al. 2017). Newport, Middletown, and Portsmouth also have areas within evacuation Zone B that are recommended to be evacuated during a Category 3 or 4 hurricane (Nicholson et al. 2017). Hurricanes in this region have continued to remain a fairly common occurrence, and those events coupled with the restrictive nature of Aquidneck Islands road network makes evacuation of these population centers quite challenging.

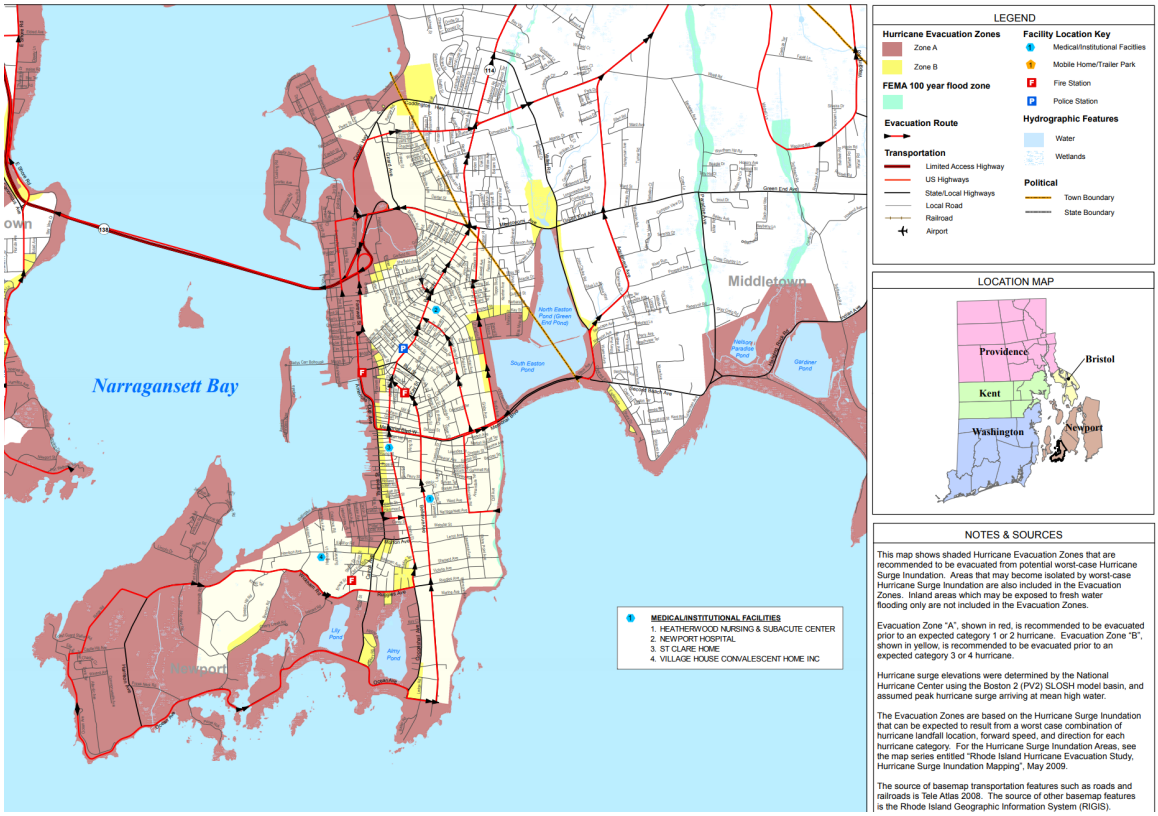

Figure 1.2. Hurricane Emergency Evacuation Zone for city of Newport, Rhode Island. Area in red corresponds to Zone A, which are areas to be evacuated during a Category 1 or 2 hurricane. Region in yellow corresponds to Zone B, areas which are to be evacuated during a Category 3 or 4 hurricane. Source: Rhode Island Emergency Management Agency (2013).

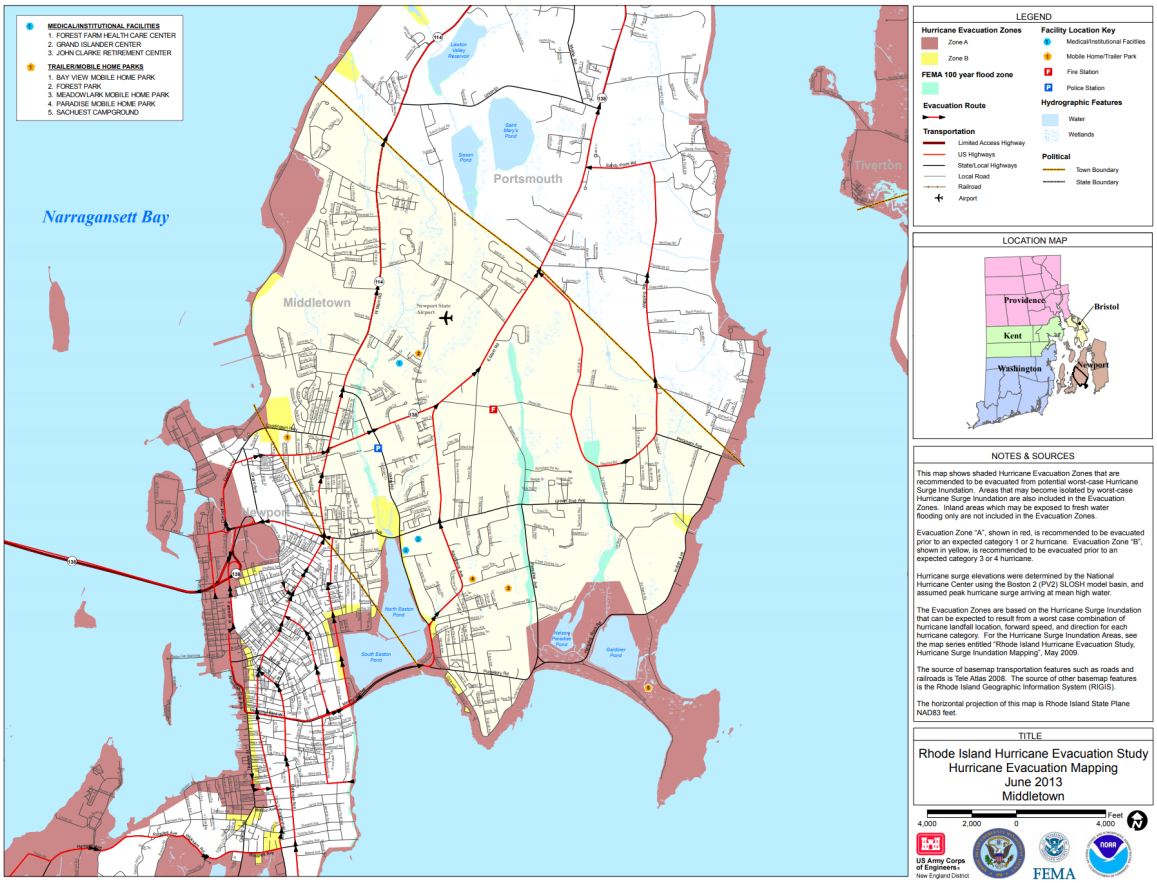

Figure 1.3. Hurricane Emergency Evacuation Zone for Middletown, Rhode Island. Area in red corresponds to Zone A, which are areas to be evacuated during a Category 1 or 2 hurricane. Region in yellow corresponds to Zone B, which are to be evacuated during a Category 3 or 4 hurricane. Source: Rhode Island Emergency Management Agency (2013).

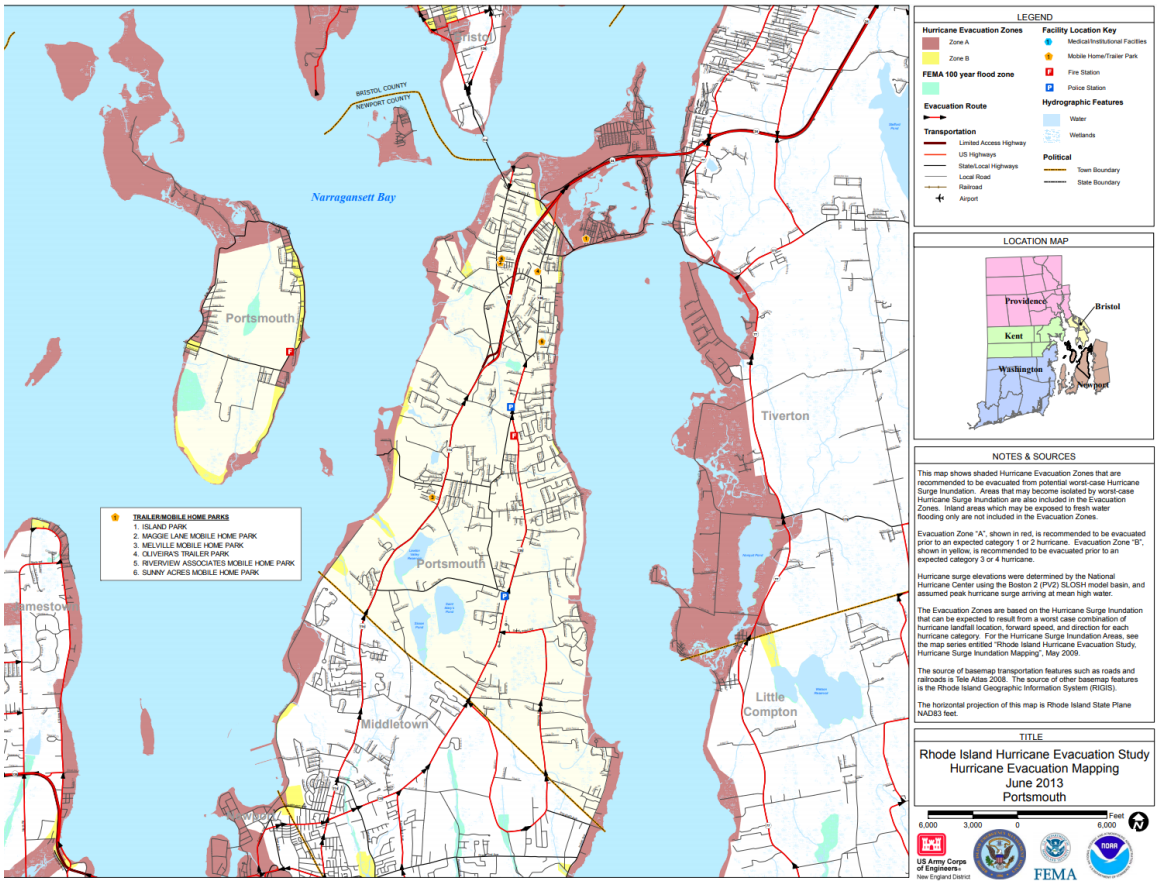

Figure 1.4. Hurricane Emergency Evacuation Zone for Portsmouth, Rhode Island. Region in red corresponds to Zone A, which are areas to be evacuated during a Category 1 or 2 hurricane. Region in yellow corresponds to Zone B, which are to be evacuated during a Category 3 or 4 hurricane. From Rhode Island Emergency Management Agency (2013).

Successful evacuation depends on the functioning of the Aquidneck Island road network and knowing the direction and path civilian and military communities need to travel to escape disaster. Aquidneck Island is a commuter island, with 38,500 jobs but only 26,100 households, meaning a majority of the island's population are daily commuters on and off the island (Town of Middletown Local Hazard Mitigation Committee Town of Middletown Planning Board 2014). However, Aquidneck Island's road network relies heavily on a north to south travel corridor of just two major roads, West Main Road (Routes 114) and East Main Road (Route 138). Another contributor to the Island's congestion is a portion of

cut-through roads that allow drivers who have no origin or destination on the island but instead are crossing the island's bridges as a means to travel to other locations utilizing the states regional highway system. This centralized and restrictive road network combined with the large volume of daily commuters creates heavy traffic volume and major intersection congestion.

The success of evacuation also depends on the capacity to provide safe refuge to evacuees once they reach their final destination. During evacuation orders, as delineated by RIEMA, Rhode Island communities are instructed to open designated shelters in order to accommodate evacuees. In the event that community shelters do not meet the required capacity, other community facilities can be designated to provide temporary, safe refuge to those individuals affected by the hurricane hazards. Each city is responsible for identifying in their EOP pre-designated shelters and their capacities. This does not imply that these specific locations will be used during every evacuation scenario as the choice for evacuation facilities is still an operational decision maintained at the local level and highly scenario dependent. Evacuation needs at the local level are hard to forecast due to uncontrollable behavior of evacuees. Residents can choose to not evacuate, travel to a variety of available shelters or hotels/motels outside of the evacuation zone, or even find safe destinations elsewhere.

Ultimately, emergency management on Aquidneck Island is not handled statewide or even regionally, but exists solely at the local township and city level. Historically, communities have shown a willingness to work together after large-scale flooding events. However, decisions on when to evacuate and, which paths to take are determined at the municipal level and might not be coordinated with other municipalities. Moreover, NAVSTA Newport and Department of Defense (DOD) evacuation decisions and paths might not be coordinated with the municipalities that surround them. As with most disasters, the impetus toward action regarding emergency planning and cross township coordination is typically a massive disruptive event where deficiencies and planning gaps are then discovered.

1.5 Purpose

As shown in this chapter, there is a vast history of hurricane disasters in Rhode Island and existing plans and efforts to improve disaster resilience for Aquidneck Island. Moreover, there has been extensive research done on the impact of flooding and climate change on

transportation networks in Rhode Island. These past studies help emergency planners for Newport, Middletown, and Portsmouth produce viable emergency disaster plans for each of their individual areas, respectively.

However, coordination among DOD installations and local communities has yet to take place, and no disaster plan for local municipalities has included NAVSTA Newport or considers how military operations must continue even during an evacuation. This work focuses on understanding these relationships inside and outside the fence line to support both community and military installation resilience. Specifically, we develop a model that determines the capacity of the existing road system to support civilian and military evacuation given future hurricane disasters.

The next chapter reviews research on the resilience of transportation systems during various storm phases and the methods used to create various evacuation plans. Chapter 3 presents our proposed model and our selected case study location of Aquidneck Island in Rhode Island, followed by our analysis in Chapter 4. Finally, after the analysis, we provide our recommendations for best practices as well as opportunities for future research.

CHAPTER 2:
Literature Review

Globalization, increased urbanization and climate change are all factors that have increased not only the occurrence of disasters, but also ones that now affect much larger centralized populations. Communities like those on Aquidneck Island in conjunction with military installations are becoming increasingly more complex, and therefore so are the challenges they face. This chapter discusses current research on various evacuation modeling methods that lay a foundation for our analysis into understanding and quantifying the resilience of Aquidneck Island communities and NAVSTA to evacuate when faced with a disaster.

There is extensive literature that discusses many impacting factors on traffic congestion and resilience of a transportation network. Areas that have been studied are routing behavior, evacuation of populations by various means when disaster locations are known versus unknown, as well as storm modeling and the impact of storm surge and sea level rise. There is, however, limited research that looks at these factors in combination with each other. Here, we review key studies done in each of these areas and then conclude with our contributions to this area of analysis.

2.1 Basic Tenets of Transportation Modeling

As our population increases, so does the number of vehicles on the roadways. Traffic congestion has become a normal phenomenon within our urbanized transportation networks. Literature suggests ways to alleviate this congestion are to use models that utilize macro or micro methodologies in order to better understand the dynamics of traffic flow, which continue to be influenced by route choices, capacity, and most importantly disruptions. Reviewing specific models can provide insight into the methods for analyzing and predicting traffic.

2.1.1 Micro and Macro Traffic Models

Traffic models are typically classified based on the scale and level of detail, as either *micro* or *macro* models. Micro models afford the user the most amount of traffic flow detail, focusing

on the single vehicular unit and effects of travel during various types of disruptions. Gazis et al. (1960) proposed an early use of this methodology in their follow-the-leader model where traffic speed was determined based on the spacing between the lead vehicle and the vehicle behind it, assuming the vehicle in tow keeps safe distance. The optimal velocity model proposed by Bando et al. (1995) analyzes speed of an individual vehicle not only based on the vehicle in front but also the influence that comes from the neighboring vehicles. Both of these models imply that the speed it takes to get from an origin to a destination is determined based on the velocity of the lead vehicle. The leading difference between the two models is how vehicle velocity is determined by which stimulus the driver of the vehicle responds to.

Macro models are inherently less detailed because they are conducted on a much larger scale, analyzing vehicles in such a sufficiently large quantity that they are analyzed as more of a flow or a stream. This approach "estimates the efficiency of a road network's density" using the averages of a large quantity of vehicles combined with the variables of flow, speed, and density and has less computational time than micro models (Jan et al. 2009). Jan et al. (2009) looked at freeway flow and congestion in the San Francisco Bay area using a modified version of the macroscopic model developed by Kurzhanskiy (2007) called the LinkNode Cell Transmission Model. In this model the freeway is a unidirectional network with vertices and edges, where every edge is a road segment, and the vertices represent junctions between these edges (Jan et al. 2009). Road density, flow, and congestion was determined by the number of vehicles per lane of traffic moving from node to node. This traffic flow research was narrowly focused on a single segment of the I-80 East freeway in the San Francisco Bay area, and the only disruptions analyzed were those caused by increased vehicular capacity.

2.1.2 Four-Step Travel Models

All the model methodologies described above follow a basic formulation of mobility modeling called the four-step traffic assignment model, (Figure 2.1). There are slight naming variations of the basic formulation steps by different researchers. Those four steps as described by Ahmed (2012) are (1) trip generation; (2) trip distribution; (3) mode choice; and (4) trip assignment.

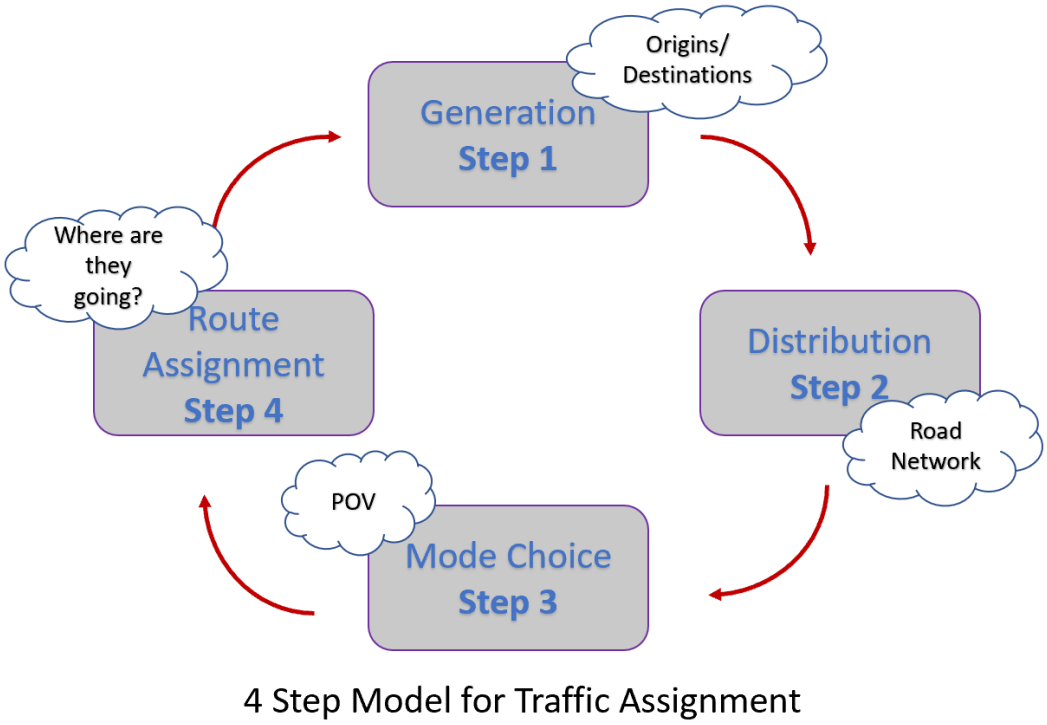

Figure 2.1. Four-Step Traffic Assignment Model. Adapted from Ahmed (2012).

Step 1. Trip Generation: Trip generation estimates the number of trips within a particular region. Regions have common characteristics with regard to demographic and land use similarities, meaning assumptions can be made regarding the fact that population centers will generate primarily trip productions (i.e., origins) while nonresidential zones will be utilized for trip attractions (i.e., destinations). Trip generation starts with the reason behind travel is calculated as trips per household from a specified origin to a destination.

This stage in the four-step travel model determines the *frequency* that individuals may travel from a given origin to a destination. Trip generation does not specify when trips occur within a day or over which transportation mode (e.g., car, bus, etc.).

Trip generation in previous work by Good (2019) and Routley (2020) identified ports and

population centers (representing entire communities) as origins and supply centers for food, fuel and construction material as destinations. Both traffic models focused on whether or not the United States Virgin Islands (USVI) transportation network, in the aftermath of a disaster, was resilient enough to handle the required round trips individuals needed to perform within a specific time frame (Good 2019; Routley 2020).

Step 2. Trip Distribution: Trip generation then feeds into the trip distribution step, which is where the number of trips between one identified location and all other locations is determined. Traffic and mobility is time-based, such that two vehicles traveling on the same road at different times of day may not interact with each other. The purpose of the trip distribution step is to model the choice of when and where to travel given origin-destination pairs. The output is an Origin-Destination (OD) matrix for a given time period, indicating total travel demands for the transportation network.

Trip distribution is important when attempting to balance traffic flow and reduce congestion because it considers issues affecting actual mobility choices, such as the distance between the origin and the desired destination within the transportation network and the volume of drivers desiring to go to each location. Ideally, all generated trips will be accomplished utilizing the most direct path. However, as capacity increases and disruptions occur, a varied number of desired trips may go unaccomplished.

In practice, an OD matrix need not be predefined when designating travel. For example, Good (2019) and Routley (2020) conduct analysis using models that are both non-specific when it comes to their origin-destination matrix. Instead of assigning a specific destination to a specific origin, both models analyze whether or not a specific traveler can achieve a round trip between origin and destination given a specific time window. Within the model, the authors include rules such as commodity desired (e.g., food) that dictate how travelers may choose one route over another and allow these distribution rules to affect travel model results. Both models utilize a 40/40/20 numerical split when determining how many vehicles from each population origin would travel to gas stations, grocery stores and hardware stores, respectively.

Good (2019) and Routley (2020) also consider ports and the last-mile delivery of supplies from them. Ports are designated as origins, and instead of calculating individual trips for the supply trucks leaving the ports, each port has to make a single round trip to all gas

stations, grocery stores, and hardware stores. As long as a vehicle from a household or port completes a round trip to their destination(s) within their category (i.e., any gas station or any grocery store), then the model records it as successful. Vehicles unable to reach their final destination within the given time window do not travel and incur a penalty cost for the network, where the travel objective is to reduce this penalty as much as possible.

Step 3. Mode Choice: In general, neither Steps 1 or 2 make assumptions about mode of travel. According to Xuedong et al. (2012), "a traveler's decision on transportation mode is generally influenced by a combination of travel time and other factors." Once a mode choice has been chosen, the individual's next goal is to minimize their travel time to their intended destination by choice of route.

While many cities and towns have multi-modal transportation systems, the majority of the research focuses on personal use vehicles. This is partly due to additional difficulty simulating a multi-modal system than that of a private car roadway system. For example, only a small population within the USVI uses public transportation. For this reason, Good (2019) and Routley (2020) use the same assumption within their traffic models, which is that all trips are exercised by the maximum number of personal vehicles leaving from each origin.

Step 4. Traffic Assignment: The traffic assignment step is used to calculate performance measures within the network being modeled. This step identifies the percentages of populations that actually transit between selected origin and destination locations based on mode choice and trip distribution. The selection of traffic assignment is usually selected using mathematical models, which are based upon Wardrop's principle (Wardrop 1952), which states "that capacity of the network is defined by its flow, which is the minimum acceptable speed between mean speed and journey time." Flows are therefore assigned to the shortest path that subsequently also demonstrates the smallest travel delays. But due to the randomness in traffic behavior there are many factors that can cause congestion, making perhaps the shortest path not necessarily the one that has the most minimum delay.

A classic approach to assigning traffic to a transportation model assumes that all traffic flow moving across the network remains in a constant state of equilibrium. This assumption correlates to a static traffic assignment, which while helpful in some modeling contexts, neglects important traffic flow phenomena. More accurately, when traffic flow is modeled

this way, it ignores a realistic tendency, which is that increased flow on the roads commonly results in increased travel time. It is this increased travel time, that when used as a penalty, forces route changes that produce the cheapest cost (less total time to travel to destination) for each vehicle. Since our research is focused on population clearing times as well as the effects of zone-based evacuation, we utilize the Bureau of Public Roads (BPR) power function to induce these types of realistic capacity constraints. This BPR formula (2.1) expresses travel time T as a function of flow q over each road segment (Maerivoet and De Moor 2005).

$$T = T_{ff}\left(1 + \alpha(q/q_{pc})\right)^{\beta} \tag{2.1}$$

Here, T_{ff} is the travel time under free flow conditions, q_{pc} is the practical capacity of the road segment under consideration, and α, β are parameters that change the shape of the function. When flow is low, the BPR function remains rather flat, and the travel time reflects what is typically seen under free-flow conditions (T_{ff}) where no traffic congestion occurs. As the flow approaches the capacity of the road segment (q_{pc}), the total travel time increases nonlinearly (see Figure 2.2).

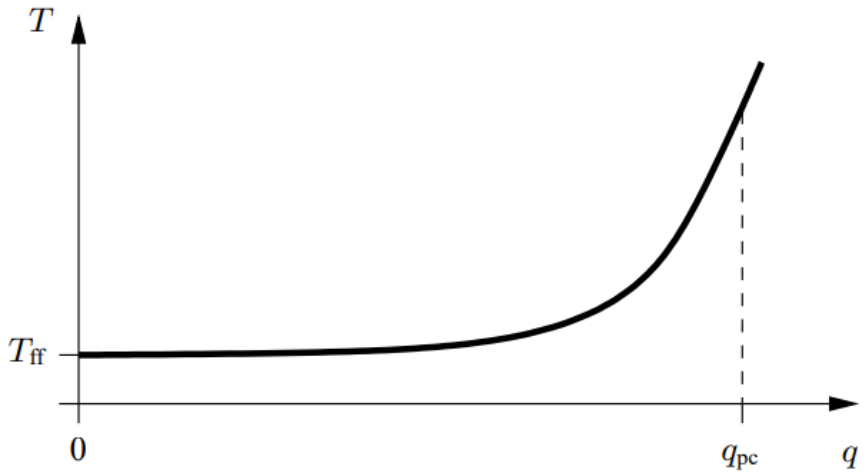

Figure 2.2. The Bureau of Public Roads BPR Function. Relates travel time to vehicle flow across road segments under free flow conditions and the capacity of the road segment being analyzed. Source: Maerivoet and De Moor (2005)

Good (2019) and Routley (2020) consider "selfish" and "coordinated" routing behaviors to determine the destinations to which vehicles choose to travel. A "selfish" decision is a destination that brings the most gain to the individual at the expense of what is best for the group as a whole; individuals choose to travel to the closest location to them despite travel time or congestion. A "coordinated" decision is one that incorporates shared information and produces benefits that are applied to the whole group even though the individual might experience a loss. Individuals are routed to locations that might be inconvenient for the traveler (e.g., by increasing that person's travel time), but enabling better traffic flow throughout the entire road network. Ultimately, one must recognize that even when individuals are provided a coordinated and individualized traffic route that ensures the network achieves a global optimal solution regarding travel time, in reality some travelers will still choose sub-optimal alternative routes that are most optimal for them as individuals, thus, the selfish decision.

Po et al. (2020) implemented such a transportation model, which they called the cavity method, where users were given globally optimal solutions based on their origin-destination selection, but some users in fact chose not to follow the recommendation but instead choose their route. This cavity method showed that within uncoordinated transportation networks, small quantities of selfish route-choices can actually improve the networks performance locally, but overall, the efficiency of the network is degraded, producing results far from optimal (Po et al. 2020). Even with a slight improvement in network performance, this research also confirmed that when the fraction of selfish users increases, the level of congestion produced also subsequently increases, which produced an overall decreased performance over the entire network.

2.1.3 Use of Travel Models

Transportation modeling and simulation have become the foundation for many types of network research. The micro and macro four-step travel models are used for numerous real-world decisions, such as predicting travel time of a route given current traffic and long-term planning of new routes in road networks. We focus attention on the use of these models for supporting emergency response and evacuation planning before a disaster happens.

2.2 Evacuation Models Under Both Certain and Uncertain Disaster Locations

Evacuation is one of the cornerstones of emergency management, and even with advances made in current technology and storm tracking, it's still nearly impossible to determine with precision where a flooding or hurricane event might occur, when it might occur and to what degree of severity might be experienced. The strategy then becomes to protect people during times of disaster, which is controllable. Evacuation can be limited in scope, such as escaping from a burning structure, or extremely complex, such as a city-wide evacuation due to a man-made or natural disaster. Evacuation plans are typically tailored in relation to the scope and nature of the emergency. In this study, we focus on establishing an optimal evacuation plan given large-scale disaster on an island region restricted by water on all sides, multiple independently managed cities and towns, a condensed road network, and few avenues for egress.

The main purpose of any evacuation plan is to identify optimal evacuation routes as well as determine the time needed to fully evacuate an at-risk population. Many after-action reviews for past disasters, like the one conducted by the Office of Homeland Security following Hurricane Katrina, conclude that a major contributor to the number of deaths was an ineffective evacuation plans and/or insufficient time to evacuate (United States. Executive Office of the President and United States. 2006). Evacuation plans require the integration of many variables, like defining appropriate evacuation regions, identifying shelter locations, and providing optimally configured evacuation routes. Some of the earliest examples of using transportation modeling to make informed decisions involves mass evacuations for areas surrounding nuclear power stations (Hardy and Wunderlich 2009). More recently, studies have considered natural disasters that lead to evacuation, like hurricanes, wildfires, and tsunami. We review several of these studies to present the current state of methods and models for evacuation planning using transportation models.

2.2.1 Evacuation Models and Methodology When Disaster Locations are Known

To achieve a controlled evacuation, an understanding of the traffic patterns within an urbanized region is required. Many traffic assignment models are based on solving stochastic location-allocation problems. Common models of this type are the stochastic user equilib-

rium (SUE), user equilibrium (UE), system optimal (SO), and nearest allocation (NA). The SUE and UE methodologies model the most selfish of evacuee behavior where evacuees choose the shortest travel time path based on either perceived travel time or the assumption that they have perfect information about every route (Bayram and Yaman 2018). These models are limited in that although they mostly minimize individual travel times, the total evacuation time within the evacuation network is not equally minimized. This is counter-productive to the goal of emergency management, which is to evacuate everyone as safely and quickly as possible.

The evacuation management objective is more readily achieved using the SO or NA models, which are structured more in line with coordinated behavior. The SO model chooses to send some evacuees to shelter locations much farther away than where they would individually choose in order to maximize the benefit for all other evacuees. One problem with the SO model however is that asking evacuees to accept traveling longer distances while trying to flee a danger zone is not typically accepted by the majority of the population. The slight difference in the NA model is that shelter location is chosen based on either the shortest geographical distance or shortest travel time to reach the destination. This approach has the advantage of being readily accepted by most evacuees but does still have the potential to lead to poor overall network performance.

Hobeika et al. (1994) created a software package called the transportation evacuation decision support system (TEDSS) that enabled users to "prepare detailed evacuation plans, including evacuation times, best routes, expected bottlenecks and allocation of evacuees to different shelters." A cornerstone of this model, similar to those in Good (2019) and Routley (2020), are the characteristics of the highway network such as the identification of nodes, the distances between them, and the speed of road types as well as their capacity. Socio-economic similarities also include determining population and auto availability needed to produce the number of trips per evacuation zone. TEDSS is advanced in the ways that it also takes inputs such as tourists, special facility data, school attendees and size of labor force (Hobeika et al. 1994). This information is important because unlike Good and Routley, this model analyzes three time categories and two different evacuation scenarios: weekday, weeknight and weekend time phases combined with evacuations purely coming from home locations and another where evacuations come from both home and from work. A similar assumption between the models discussed so far is that in the supply chain models of Good

(2019) and Routley (2020), vehicles travel to their closest designated destination and return, and in TEDSS, evacuees strive to evacuate thru their closest exit point. Closeness in both scenarios is measured in terms of shortest travel time, not necessarily shortest path.

Unlike other models requiring extensive detail, TEDSS is an example of a macroscopic model. While comprehensive in what it is intended to do, it does however still have its limitations. TEDSS was created to help inform planners faced with evacuations due to nuclear disasters. Unlike floods and hurricanes, nuclear disasters have a fixed location with a well-defined region of impact making the evacuation routes that TEDSS identifies quite fixed and relatively stable, only requiring moderate updates in the future once established.

Bayram and Yaman (2018) extended these basic modeling methodologies and proposed a two-staged scenario-based stochastic evacuation model that optimally assigned evacuees to shelter locations while also minimizing total evacuation time. This bi-level model brought together the benefits from both SO and UE models. Shelter locations were identified by SO methodology, and the assignment of evacuees to shelters and the routes provided were determined using UE methodology.

So far all of these traffic flow models produce optimal evacuation routes for networks constrained only by road congestion, in other words, the relationship between traffic speed and traffic volume. These studies lack an analysis into how those road networks would be impacted and whether or not population evacuations remain feasible if specific portions became unusable. There is ambiguity in evacuation that stems from the uncertainties inherent to disasters and the resulting impacts caused by the degradation of a road network structure such as loss of a road, a bridge, or a tunnel. Understanding the impacts of disruption and interdependencies is critical to assess and improve the resiliency of any transportation network.

Alderson et al. (2018) developed a defender-attack-defender (DAD) model to identify where to apply limited resources in order to maximize performance within a highway network when impacted by a worst-case loss of its physical components such as a road, bridge, or tunnel. This model was applied to a study of a major bridge and tunnel highway system within the San Francisco Bay Area that is impacted by a targeted terrorist attack. Alderson et al. (2018) still applied the BPR function for congestion with the SO methodology for traffic assignment, but instead of presenting a single level or even bi-level model similar to Bayram

and Yaman (2018), they solved a tri-level DAD model using nested Bender's decomposition. Another unique aspect of this DAD model was implementation of time epochs, in fact a multi-period model that evaluated traffic patterns after given time periods, allowing for infrastructure recovery after damages to one or more targets after the attack.

The multi-period model in Alderson et al. (2018) was important because it looked at more than just the performance of a road network immediately following an attack. Their model revealed longer term impacts to traffic flow and the interdependencies that were created from not only the disruption of combinations of highway segments but also varying restoration time. A few assumptions applied to this body of work was that mass transit was not accounted for as an option to help alleviate traffic flow, the model did not account for random events like traffic accidents, and the attacker was resource constrained as far as how many attacks could be made. Alderson et al. (2018) presented a valid method to assess a system's resilience when faced with component loss as well as provide planners with recommendations for how to maximize resilience under a resource constrained environment. This analysis, however, was conducted with an awareness of where the attacks would occur. The next phase would be testing the effectiveness of this multi-phased time-based model to random events like natural disasters.

2.2.2 Time-Phased Modeling Approaches and the Impacts on Evacuation within Congested Transportation Networks

Traffic congestion is a common phenomenon within road transportation networks and thus far the traffic flow evacuation centric models have all been analyzed under static, predetermined, post-disaster conditions. Traffic flow patterns are however dynamic in nature, responding uniquely to disruptions that are caused over the course of the disaster. Time phased approaches to traffic modelling investigates the dynamic evolution of traffic flows on individual roads and the propagation of interactions that affect population clearing times within arbitrarily selected time moments.

Yuhas (2011) created a single-commodity, multi-period minimum cost network flow model that focused on the evacuation routes and clearance times of residents within the California counties of Yolo, Sacramento, San Joaquin, and Stanislaus on a macroscopic, strategic level where vehicles were modeled as aggregate flows. The model assumed travelers had "perfect

knowledge" of road conditions before evacuation, that roads were devoid of vehicles until the evacuation order was given, that only highways were used for evacuation routes, and the only constraint to vehicular flow was traffic capacity (Yuhas 2011). Yuhas analyzed whether or not residents had enough time during any single time period to reach a safe destination point. If unable to achieve this goal due to road capacity, then the resident remained stranded until the next time epoch. Yuhas incorporated contra-flow methodology and pre-defined road capacities to assess the potential to improve evacuation times by minimizing both highway inundations and the number of permanently stranded residents within this road network.

Malveo (2013) also studied clearing times but alternatively used a minimum cost flow with congestion assignment (MCF-CA) model to analyze the evacuation times of residents in Mobile County and Baldwin County in Alabama and Escambia County in Florida. Congestion assignment was based on the number of vehicles driving on each road segment and the maximum speed at which those vehicles were able to travel across that same road segment. Unique to Malveo (2013), the model considered three congestion levels (none, moderate and high) for each highway segment during each time epoch and incorporated similar assumptions as Yuhas (2011) that evacuation would only be conducted using highways, that all roads within the network were available for evacuation and that roads were empty until the evacuation order was given.

The mesoscopic transportation analysis of evacuation clearance times in Malveo (2013) is similar to that from Yuhas (2011) in that is it a multi-period evacuation model. However, the model in Malveo (2013) used the time-dependent speed flow function from Akçelik (2003) and limited the number of vehicles allowed to transverse each segment due to congestion level within the MCF-CA model during each time period. Implementation of MCF-CA in a rolling horizon fashion limited residents' prior knowledge of traffic conditions and allowed for studies to be conducted on how this limited knowledge impacted evacuation patterns once the order to evacuate was given. Malveo (2013) also modeled the impact of sub-optimal routing decisions when residents exhibit selfish behaviors by choosing their own shortest path rather than the globally optimal route.

Just like in Yuhas (2011), the MCF-CA model's main constraint on clearing times was purely traffic congestion. This study did not investigate accidents that might occur during evacuation or roads that were either impeded to begin with or became unusable during the

time phases, which has the potential to cause important secondary effects on the clearing times.

2.2.3 Mass Evacuation Utilizing Public Transportation

Evacuating the maximum number of people that reside within an disaster risk zone before a hurricane makes landfall is extremely important. Once a disaster occurs, due to stranded individuals or those who simply choose not to evacuate, place an additional burden on emergency personnel when it comes to now needing to provide assistance and distribute relief materials. This additional surge of demand inevitably further impedes and complicates resident evacuation. Existing research focuses on the available capacity within the road networks to reduce congestion and allow for the maximum number of evacuees to travel to safe destinations.

One common assumption that can be found in many evacuation models is that the at-risk population will utilize their personal vehicles to evacuate vice multi-modal transportation assets. This assumption can be misleading when trying to analyze how quickly an at-risk population can evacuate pre-disaster if the car-less population in the affected area tends to be much higher due to the fact that public transportation is the main vehicle for daily commute.

Swamy et al. (2017) presented a framework to address the issue of the evacuation of people who solely depend on public transportation. They "developed a simulation tool to model the dispatching of buses, the stochastic arrival of evacuees at pickup locations, and the transportation of those individuals to designated safety locations" (Swamy et al. 2017). This multi-stage heuristic model was employed on a targeted area of New York City, specifically Brooklyn, using historical data collected from Hurricane Sandy to evaluate the effectiveness of using mass transportation as an approach to alleviate road congestion and enable quicker clearing times during times of mass evacuation. Although this work is beneficial in determining new ways to influence routing design within a traffic network during times of disaster by utilizing public transportation, our research utilizes the base assumption that all residents will evacuate using their own vehicle.

2.3 Storm Modeling and Flooding Impacts to Transportation Networks

Transportation infrastructure has expanded immensely over the past four decades and as a result of disasters like 9/11 as well as recent hurricanes, emergency management personnel continue to develop storm tracking models to enable a better understanding and prediction of the characteristics of evacuations. Some of the most current and widely used macroscopic models are discussed in this section.

2.3.1 SLOSH Model

The National Weather Service (NWS) has developed a widely accepted flooding model called Sea, Lake, and Overland Surges from Hurricanes (SLOSH) that predicts storm surge and estimates of geographic locations that could be flooded based on a given set of conditions. After recent model updates in 2013, Forbes et al. (2014) applied this new SLOSH model to those conditions recorded from Hurricane Sandy in order to validate its predictions of storm surge threat against what was predicted by the SLOSH model in 2012. The goal was to "quantify its ability to replicate the height, timing, evolution and extent of the water that was driven ashore by this large, destructive storm" (Forbes et al. 2014).

Within 48 hours of identification of any tropical disturbance that has the potential of developing into a tropical cyclone in the Atlantic Ocean, Caribbean Sea, or the Gulf of Mexico, NWS uses SLOSH to begin generating storm surge forecast simulations(Forbes et al. 2014). This was the case in 2012 with Hurricane Sandy, where in surge-only mode, SLOSH was used to run simulations to help National Weather Center (NWC) identify where the greatest storm surge threats were expected to appear. In the aftermath of Hurricane Sandy, it appears that the predictions from SLOSH at that time produced an error of approximately 20%-30%. However, at that time SLOSH simulations did not account for tide data; this numerical enhancement was introduced during the 2013 upgrade.

Analysis of an upgraded SLOSH version modeled in (Forbes et al. 2014) produced a root mean squared error within a 10%–20% range between water levels at all of the NOAA tidal gauges, United States Geological Survey (USGS) storm surge sensors and High-Water Marks compared against the SLOSH model-simulated maximum water levels (Forbes et al. 2014). Even with this overall high level of accuracy, the SLOSH model did underestimate

water levels in some areas, mainly in Connecticut, Massachusetts, and Rhode Island, which Forbes et al. (2014) attributed to factors such as lack of grid resolution as well as tidal waves in those regions within the simulations. The highly complex nature of Sandy with regard to her wind speeds and erratic forward movement caused minor prediction errors within the SLOSH model, and because of this there is a plan to upgrade this parametric wind model in the future.

Ultimately, Forbes et al. (2014) concluded that this newer model "was able to simulate the height, timing, evolution, and extent of the water that was driven ashore by Hurricane Sandy (2012) with a high degree of fidelity", and that by including tide data increased the accuracy of the model, and can subsequently enable forecasters in better predicting the extent of water level and storm surge inundation.

2.3.2 HURREVAC

The Hurricane Evacuation (HURREVAC) software program was developed by FEMA specifically to assist with hurricane evacuations. The main purpose of this forecasting tool is to identify the approach path of a hurricane, as well as its speed and intensity, and then produce a graphic display to help visualize evacuation timing. Additionally, it can take inundation estimates from the SLOSH model as well as a variety of other inputs to provide estimates on flooding potential to better inform evacuation timing. This makes the combination of both this software program and the SLOSH model a very powerful resource. Emergency planners can therefore better identify who is at risk, when decisions need to be made to ensure the safety of impacted populations, and how the risk changes as the dynamics of the hurricane change.

HURREVAC still has some inconsistencies that emergency planners need to be aware of (Kirlik 2007). There is an increased error in track and intensity during the early stages of the hurricane formation when the storm is still quite a distance from shore. To account for this increased error, it is important that emergency planners place a larger region of the shoreline under the hurricane watch and warning than what will most likely be impacted. There are also many other factors that go into the decision-making calculus to evacuate that HURREVAC estimates do not account for, such as tourist population, special events, road closures, and time of day.

Despite its inconsistencies, this computer-based decision support tool has in fact been shown to be successful. For example, it was used during Hurricane Katrina (2005) in determining when to evacuate New Orleans. It is widely purported that the emergency response failed during Hurricane Katrina, and while that assessment might be true, one must remember that there is more to an evacuation decision than just what a computer program recommends. When it comes to the validity of this tracking tool and what it was created to do, according to the National Hurricane Center (NHC), "the forecasts were timely and effective and within about two and half days before landfall were exceptionally accurate and consistent. Errors were considerably less that than the average official track errors for the 10-year period from 1995-2004" (Kirlik 2007).

2.3.3 ETIS Model

Another web-based modeling program used in conjunction with other storm tracking tools is the Evacuation Traffic Information System (ETIS). ETIS is a program that allows states and FEMA to monitor the entire evacuation process as it is occurring. It was deployed for the first time by the Department of Transportation (DOT) for the coastal areas of Louisiana and Texas, which were issued evacuation orders during the approach of Hurricane Lili in 2002. After Hurricane Floyd in 1999, it became very evident that there was much improvement needed in interstate communication. ETIS incorporated many of the lessons learned from significant traffic problems that occurred during the Hurricane Floyd evacuation in addition to real-time data such as weather information, evacuation percentages and tourist occupancy rates in affected areas and successfully helped manage the evacuation of over 500,000 people (Post and Buckley and Schuh and Jernigan, Inc. 2003).

This macroscopic standalone model was developed to primarily assist with forecasting large cross-state traffic volume in the event of large-scale evacuations. Implementation of future hurricane studies, road closures, close to real-time information regarding vehicular accidents and increased linkage with traffic sensors at strategic locations that better identify traffic congestion will aid emergency planners in identifying better evacuation routes as well as staging evacuation times in order to moderate traffic flow as much as possible.

2.4 Past Storm Modeling Studies and Analysis into Infrastructure Resilience Specific to Rhode Island

Most of the literature found regarding prior studies done in Rhode Island of impacts from storm surge and increasing sea level rise are more qualitative in nature and focus mainly on Providence, Rhode Island. Not only does "the length and orientation of Rhode Island's Narragansett Bay, and its proximity to the Atlantic hurricane zone, make it susceptible to extreme storm surges", but Providence is also referred to by FEMA as the "Achilles's heel of the Northeast" (Rubinoff 2007; Becker et al. 2015).

Many ports had suffered extensive damage from past hurricanes even before climate change and its associated sea level rise. Due to the economic importance of the Port of Providence for the state of Rhode Island, Becker et al. (2015) conducted a fine-grained analysis of the impact from future hurricanes as well as the inclusion of anticipated sea level rise on that seaport. Their research simulated multiple category 3 and 4 storm scenarios together with storm surge overlays and 3D modeling that was constructed to represent the structures of the Port of Providence. Their study focused on conducting key stakeholder interviews, reviewing port planning and policy documents to evaluate the current level of resiliency within the Port of Providence and identifying which stakeholders were best positioned to implement specific recommended improvement strategies (Becker et al. 2015). This exploratory analysis was not a quantitative detailed assessment like the evacuation and traffic studies reviewed above, as it did not focus on the magnitude, linkage, or probability of the various impacts between storm surge and rising sea level on the Port of Providence nor the transportation system it feeds into.

Witkop et al. (2019) shifted the focus from resilience of port infrastructure and supply chain to assisting in developing consequence thresholds for combinations of hydrodynamic, wind and precipitation-based storm models. Westerly Rhode Island was chosen because the small number of critical facilities located in this area were found to have a higher degree of exposure to hazards than other surrounding areas. This high degree of connection between facilities and hazards better enabled researchers to uncover any critical inter dependencies and cascading consequences (Witkop et al. 2019). Becker et al. (2015) recognized a knowledge gap between the community emergency planners and the creators of storm models. Storm models employ high resolution simulations that draw data from historic events such

as track, intensity, and size parameters in order to try to quantify potential implications of future hazards. Becker et al. (2015) analyzed interviews conducted with multiple emergency responders and facility managers and identified individual pieces of infrastructure and facilities that were then fed into existing storm models and discovered 193 "consequences" that were impacted by storm hazards in either a hydrodynamic, wind or precipitation model that had not been originally identified (Witkop et al. 2019). The storm impact model and its underlying simulations increased both in accuracy and applicability. This study proved that many of the storm models being utilized today lack the specificity that is understood by those emergency responders at the community level, and failing to incorporate this knowledge into a hazard model has an increased potential to lead to an underestimation of future hazards.

STORMTOOLs is a specific model used by researchers that takes wind and sea level data from the SLOSH model and calculates various levels of storm inundation over specific time periods, and under conditions of both sea level rise and without for all of Rhode Island's coastal waters. At its most basic level, the model can provide flood estimates for coastal planners and homeowners. At a more sophisticated level, it is used by emergency planners to perform regional studies that support future coastal planning and emergency preparedness planning. STORMTOOLs continues to be enhanced. One such enhancement is the creation of the Coastal Environmental Risk Index (CERI) in 2016, which was first tested on areas in Warwick and Charleston Rhode Island (Spaulding et al. 2019). It has since been expanded to all of the southern coastline of Rhode Island and the combined results are presented in Spaulding et al. (2019).

The building blocks of CERI are surge and waves specified in terms of the BFE, which is the combination of inundation depth and the associated wave height. These BFEs are used to characterize the flooding risk and damage functions from both waves and inundation are estimated from Guise et al. (2015). Spaulding et al. (2019) focused on using CERI within STORMTOOLs to visualize the BFE for specific 100-year flooding scenarios and estimate the worst-case damage to structures along the coastline, however, using different base maps that exist within STORMTOOLS, these same flooding scenarios can be used to identify the inundation impact on roads and the transportation network within selected locations.

Advanced Circulation (ADCIRC) models have been utilized by Rhode Island emergency

planners in the past for vulnerability analysis of specific geographic points impacted by natural disasters. These models combined with the Simulating Waves Nearshore (SWAN) model can calculate storm surge hazard impacts for specific time epochs, and then displays the chronological effects of those hazards (Stempel et al. 2018). Incorporating weather data into these models then provides emergency managers the ability to adjust and improve evacuation orders once they assess the potential storm impacts before it ever makes landfall.

A majority of storm surge hazard modeling requires the integration of modeling platforms. The transformation of ocean modeling data types and geographical data is required to properly combine the ADCIRC and SWAN models. This reconfiguration can lead to inaccuracies and undermine the legitimacy of the results. To improve computational efficiency and reduce the air gap that is created during this integration, Stempel et al. (2018) introduced an all-numerical approach that instead allowed for both models to be run on the same platform. This approach was tested in areas around Galilee, Rhode Island and validated against historical data from Hurricane Carol. The results, when compared, did indicate an accurate simulation of the maximum water level that was seen during the storm surge, but the duration modeled was too short relative to what was actually observed (Stempel et al. 2018). Even with the time duration inaccuracies, this all-numerical approach did demonstrate the ability to accurately model the potential hazard impacts of a hurricane strike.

2.5 Our Contribution

Like much previous work, we also analyze a transportation network but, with a variety of road types and various disruptions. We incorporate the major steps commonly used for the transportation model described below, as well as implementing a hybrid transportation model based on micro variables on a macro scale. We use the basic formulation of transportation used by Good (2019) and Routley (2020) with some enhancements regarding flexible origins, destinations, and traffic trip choices. Models like Alderson et al. (2015) that evaluated the operational resilience of critical infrastructure systems as well as some of the earlier transportation models from Good (2019), Routley (2020) focused on a single time period post disaster. Our research instead mirrors the time-phased modeling approaches studied in Yuhas (2011) and Malveo (2013) that investigated cascading impacts to the road network and evacuation clearing times before, during and after the hurricane. We provide storm surge data on specific road inundations using time phased data outputs from the

ADCIRC model.

Our research similarly studies individual trips of vehicles, but we do so on a macro level regarding how the entire transportation network responds to the fast-acting stimulus of population evacuations and emergency responders during periods of times during a natural disaster.

CHAPTER 3:
Methodology

The City of Newport and the townships of Middletown and Portsmouth have each identified evacuation routes all utilizing the same internal state roadway system that traverse Aquidneck Island north to south. These evacuation routes are assumed to be best case, but when combined with time-phased storm surge data from various hurricane scenarios, the opportunity arises to discover optional routes that are in fact better suited for timely evacuation when the road network is congested and constrained by flooding. Central to our research, we construct an optimization model that overlays climate-induced hazards like sea-level rise, storm surge, and inland flooding from the ADCIRC model on top of a constructed road network of Aquidneck Island. Together, this allows us to provide city planners with alternative routes as well as a better understanding of population clearing times and identification of higher at-risk populations given future disasters.

Overall, we develop methods to perform three main analysis tasks:

1. Data collection and Network Construction: We collect and combine datasets from various sites in order to analyze the movement of vehicles across surface roads on Aquidneck Island.
2. Formulation and Implementation of Model: We develop a four-stage traffic model (refer to Figure 2.1 in Chapter 2) that measures evacuation clearing times from affected coastal populations to reach mass evacuation locations both inland and off-island during normal and degraded road conditions.
3. Evacuation Analysis: We utilize the curated datasets and traffic model to determine the capability of Aquidneck Island surface roads to enable timely evacuation of all at-risk populations that reside within the City of Newport, Middletown, Portsmouth, as well as NAVSTA Newport. We identify which Aquidneck Island coastal populations have the highest clearing times and those populations with the highest risk of isolation during normal and worst-case flooding situations.

3.1 Data Collection, Curation, and Analysis

The development of our model requires new data sets derived from diverse primary sources and modified using open-source software. The overall process used in this thesis is presented in Figure 3.1. First, we collect data from three sources. We pull data files of the local and state road networks from an Rhode Island's online open-source geospatial repository Rhode Island Geographic Information System (RIGIS) (Rhode Island Geographic Information System (RIGIS) Data Distribution System 2017). Collaboration with Dr. Austin Becker's team from the University of Rhode Island provided consequence and impact data that is collected using Survey 1-2-3 (Environmental Systems Research Institute 2021) as well as hourly storm surge/flooding data for three specific hurricane scenarios generated within ADCIRC (Luettich and Westerink 2004).

Data curation of these files is then done using open source Python-based tools to include QGIS (QGIS Development Team 2021) and GeoPandas (Jordahl et al. 2020) for viewing, editing, and analysis of geospatial data. We also use Geospatial Data Abstraction Library (GDAL) (GDAL/OGR contributors 2021) for data conversion and management of ADCIRC data, as the data sets are provided as irregular grids in Network Common Data Form (NetCDF) file formats and converted to raster files for analysis. Our time phased evacuation routing is analyzed using a network model built with the Pyomo optimization modeling language (Hart et al. 2011). We visualize our results using Plotly, the java-script library LEAFLET (Plotly Technologies Inc. 2015), and QGIS.

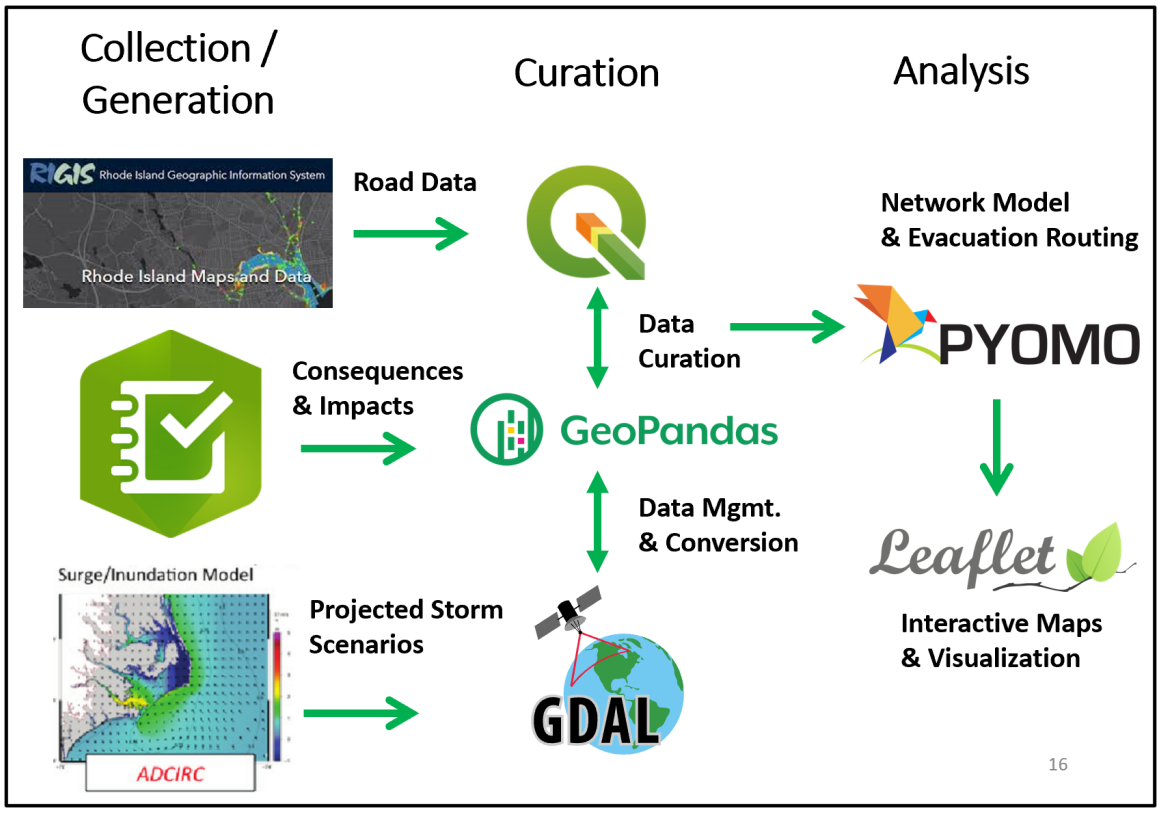

Figure 3.1. Data Collection, Curation, and Analysis. Steps depicting the data collection and generation process, how the data is curated as well as then analyzed.

We present additional detail regarding the curation of all data sets developed in this thesis. Specifically, we determine at-risk populations that will need to evacuate in future storms, develop a road network data set for Aquidneck Island, and develop an evacuation model that optimizes evacuation routing and timing.

3.1.1 At-Risk Populations

We identify which locations and how many people will evacuate during a future storm. Not all populations should evacuate during a hurricane. If it is considered safe, sheltering in place is generally the best option. In contrast, communities that experience significant flooding can experience isolation and death if they do not evacuate. For this reason, we determine

community locations and the quantity of people and vehicles expected at these locations. We then identify which of these communities will flood in future storms. The combination of this data develops a data set of just the at-risk populations that are recommended to evacuate.

The U.S. Census Bureau maintains census tract shapefiles with associated population and housing counts for each state. As census tracts are polygons representing a jurisdictional area, they do not easily relate to road data used for evacuation that is generally a network of nodes and arcs. We convert this data into population nodes representing contiguous houses to more easily support evacuation analysis.

To establish the population nodes on Aquidneck Island, the most current census tract shapefile for Rhode Island is downloaded and plotted in QGIS utilizing the Coordinate Reference System (CRS) EPSG:4326. Rhode Island has 244 census tracts, which we filtered down to just the census tracts for Aquidneck Island. Each census tract can be further separated into blocks that contain detailed population and housing counts. Using this block data, centroids were plotted for each census tract shape utilizing geometry tools available in QGIS. Initially, 1104 centroids were plotted. In order to reduce the number of centroids, we overlay these points over a Google Sat Hybrid layer and merge the centroids that were very closely clustered and contained very small population counts. Locations of these centroids were also inspected to ensure they were placed in locations that accurately reflected surface road access. Final count of population centroids was 309 and can be seen in Figure 3.2 below.

In the event of an evacuation on Aquidneck Island, prior storm surge inundation studies have highlighted at-risk areas along the entire coastline of the island for varying categories of hurricanes. We take the historical probabilistic data from the STORMTOOLS model and merge it with max flood storm surge inundation data from the ADCIRC model for the most extreme Hurricane Sandy storm scenario combined with 5 ft of sea level rise (Spaulding et al. 2016; Luettich and Westerink 2004). We overlay this combination of flooding data on top of our population nodes and merge them by location, which highlights 55 population centroids. We define the at-risk communities as these 55 population nodes that would need to be evacuated in the event of a storm. The high risk flood areas and impacted populations are shown in Figure 3.3.

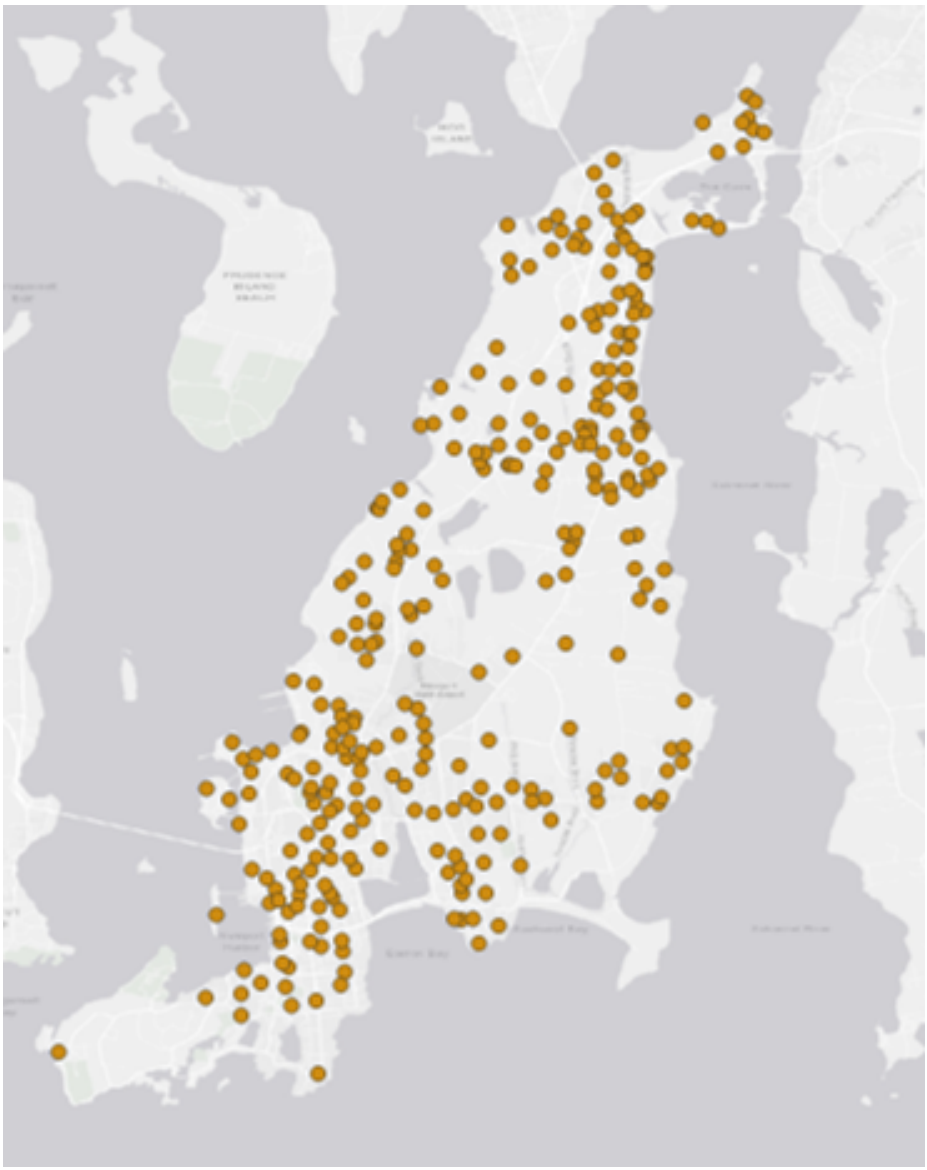

Figure 3.2. Population centroids on Aquidneck Island using census tracts from 2010 census data plotted in QGIS.

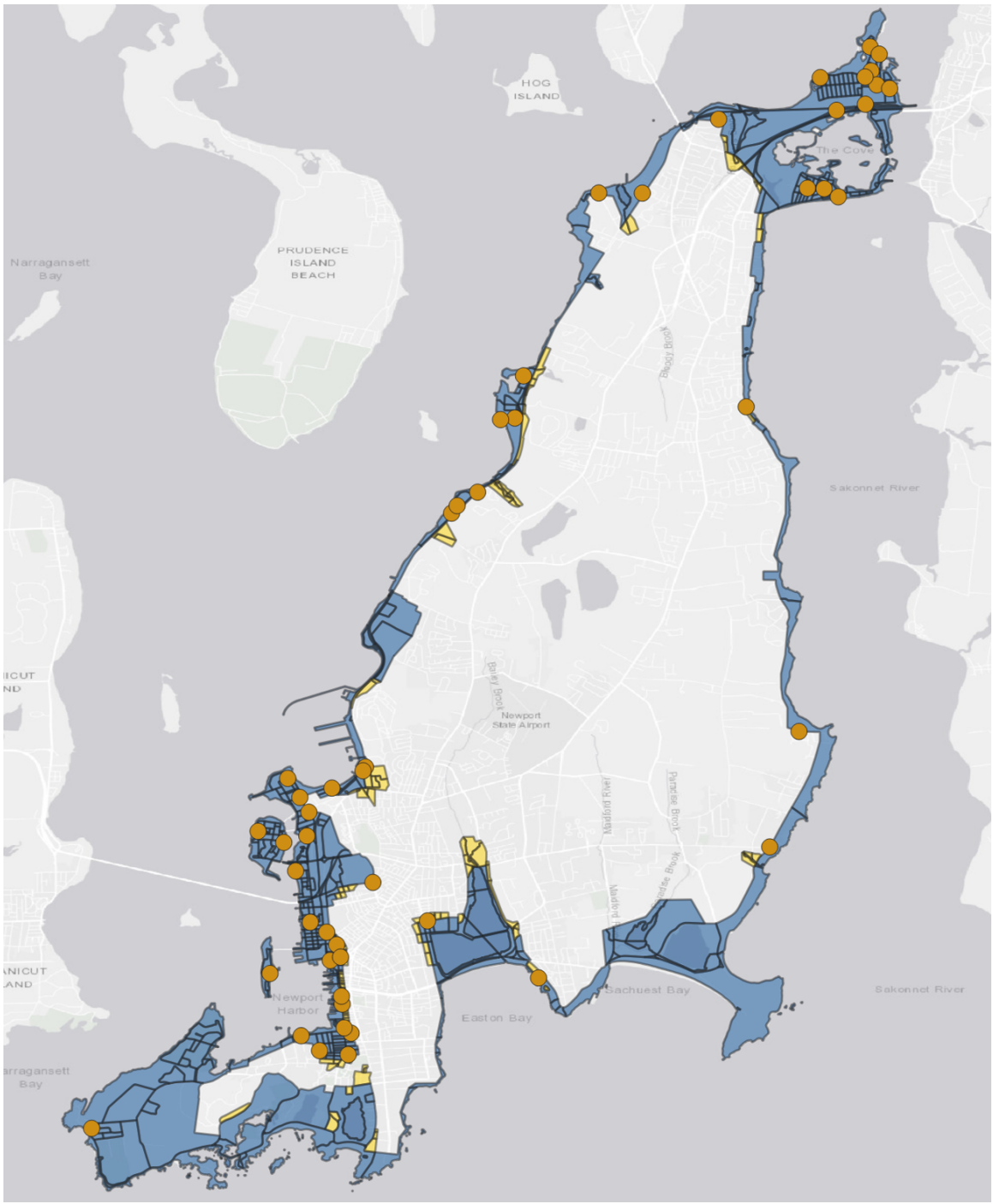

Figure 3.3. At-Risk Populations under Evacuation Zones. Identified population nodes that fall within Evacuation Zones A & B based on STORMTOOLS and ADCIRC flooding data. Population nodes highlighted in gold, Evacuation Zone A highlighted in blue and Evacuation Zone B highlighted in yellow.

Finally, we aggregate at-risk populations by city and Navy installation for evacuation planning. The breakdown of the 55 at-risk populations by city, township and the naval installation is provided in Table 3.1 and the location of each node is presented in Figure 3.4. The city of Newport has the largest impacted population that falls within the storm surge inundation areas. According to the United States Census Bureau (2019), the average number of vehicles per household in Newport County is two. When calculating the total number of vehicles, we expect to see on the road, total number of households is multiplied by two. These vehicle values are listed in Table 3.1. The exception to this, is for number of vehicles assumed to be departing NAVSTA Newport and Naval Undersea Warfare Command (NUWC). Due to the transient nature of the personnel stationed on NAVSTA Newport and NUWC, and the majority residing in barracks and other lodgings, it is assumed that in the event of an evacuation each individual will depart using their own vehicle and will not aggregate within shared vehicles.

Table 3.1. At-Risk Population, Household, and Vehicle Data by City. Population count, number of evacuees and vehicles by city (assuming 2 ppl/vehicle except NAVSTA Newport and NUWC, which is 1 ppl/vehicle). Adapted from United States Census Bureau (2019).

City	Population Nodes By City	Total Population	Total Households	Total Vehicles
Newport	16	2326	1542	3084
Portsmouth	16	1582	785	1570
Middletown	2	605	232	464
NAVSTA Newport	13	1496	276	1496
NUWC	8	308	188	308

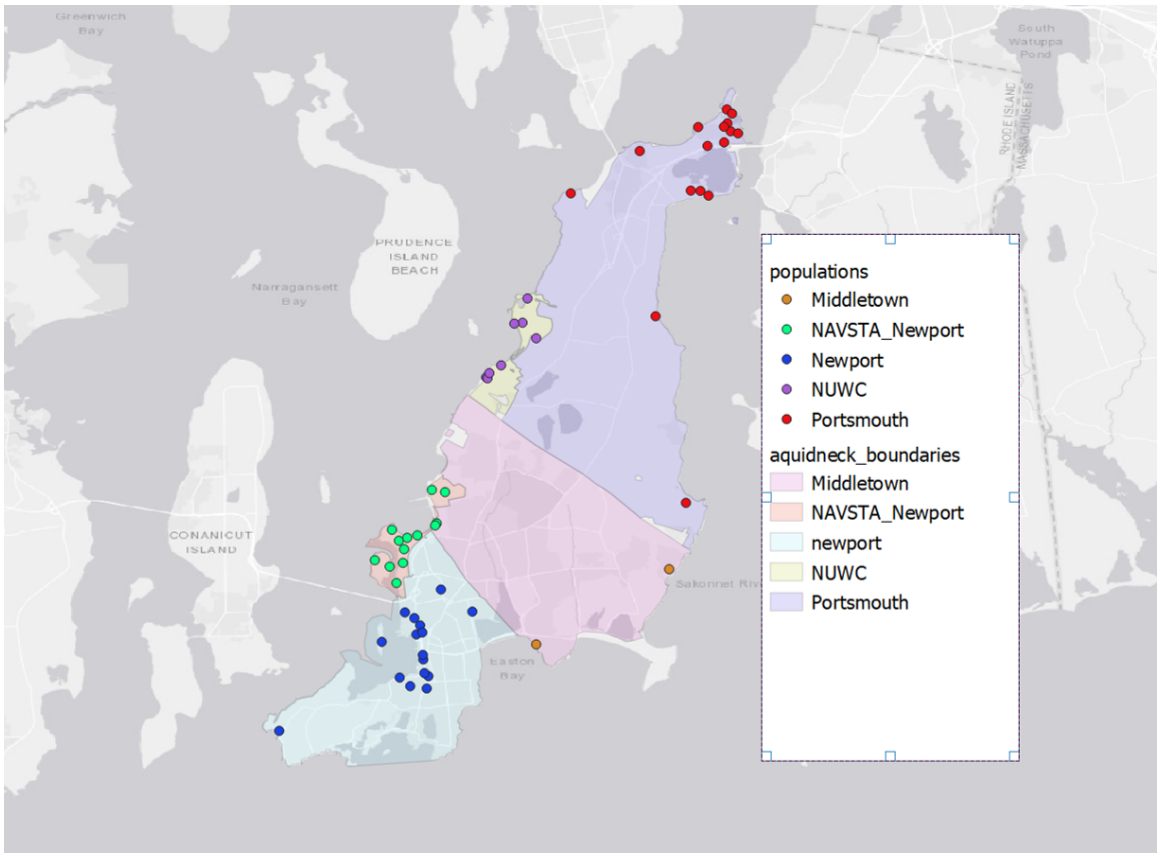

Figure 3.4. At-Risk Population Locations. At-risk populations located within each of the city boundary lines and military installations located on Aquidneck Island.

3.1.2 Road Network Construction

We use primary data sets from RIGIS with QGIS software to construct a road network for evacuation modeling of Aquidneck Island. Within RIGIS is a database of road network shapefiles that is maintained by the Department of Transportation. The Rhode Island shapefile includes all of the highways and local roads for vehicular traffic across Rhode Island. We filter this dataset to just the road network for Aquidneck Island and plot it in QGIS using CRS EPG:4326 using OpenStreetMap as the base layer. Using geometry tools available in QGIS, transshipment nodes are created by placing points along each intersection where a local road connects to the main state roads that traverse the island as well as intersections be-

tween local roads. This increases the fidelity of the road network and previously established population, shelter, and evacuation nodes. Figure 3.5 displays the transshipment nodes for Aquidneck Island.

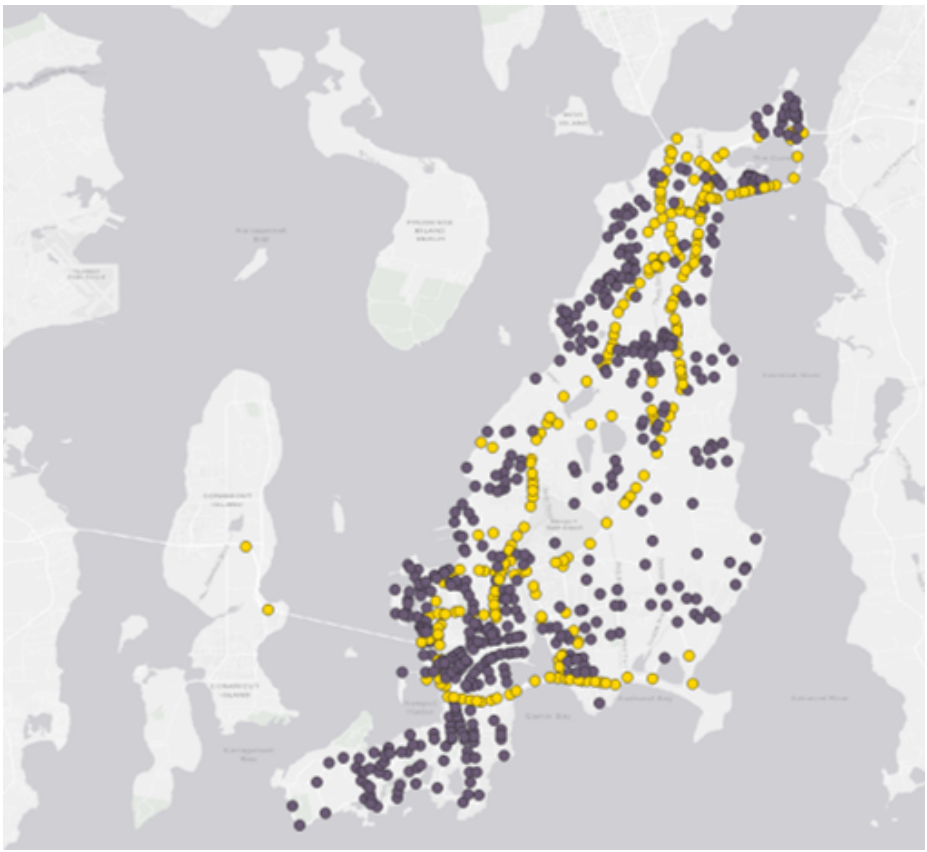

Figure 3.5. Transshipment Nodes Plotted on Aquidneck Island. Highway and local Transshipment nodes on Aquidneck Island plotted in QGIS. Highway nodes displayed in yellow, local nodes displayed in purple.

Then, we use a process that is very similar to the one performed by Routley (2020) to develop a road network connecting transshipment nodes. The road network is first constructed by plotting all transshipment nodes on top of an OpenStreetMap overlay within QGIS. The data within this overlay is the real road network we obtain from the RIGIS website for Aquidneck Island. Using a new linestring layer, we draw lines between each node using the line snapping tool that closely mirrors the road network outlined on the OpenStreetMap overlay. Once the road network is constructed, we create the first "from-to" arc layer using

the QGIS “merge by location (summary)” tool where vertices are designated as minimum and maximum. A second layer is generated in the same way, but with the vertices reversed. These two layers are then merged to create one final “from-to” arc layer that contains every arc required for the network. The road network of Aquidneck Island is displayed in Figure 3.6.

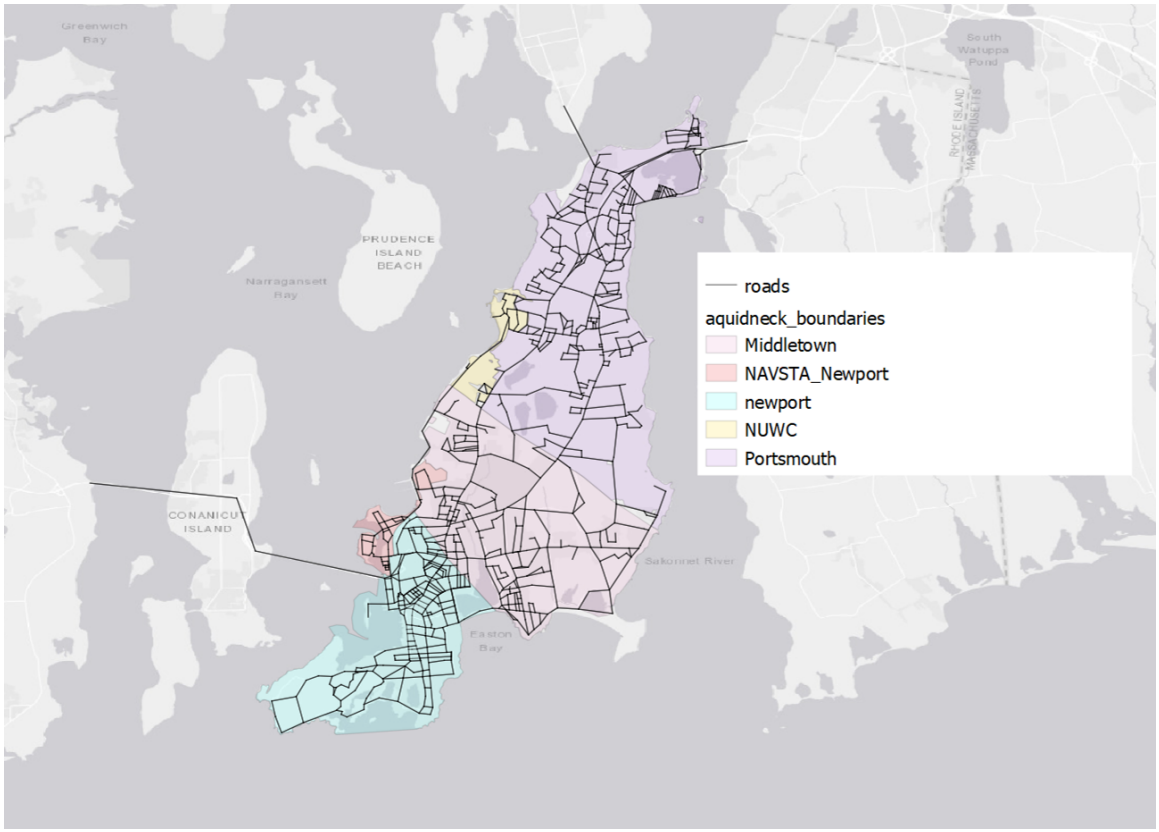

Figure 3.6. Road Network on Aquidneck Island. Road network overlayed on city census boundaries.

Finally, we add real road data to the simplified road network developed in QGIS for road capacity and speed. RIGIS has several data sets that inform the capacity of roads on Aquidneck Island. We use this data to classify roads as arterial other, freeway, local, major collector, minor arterial, minor collector, and dirt. The Rhode Island Department of Administration Division of Planning (2016) publishes data on non-congested road capacities based on road type for the state of Rhode Island, and we utilize these capacities within our

network. We combine this data to determine road capacity for our simplified network. Speed limits within the network are also assigned based on road classification that is obtained from a Rhode Island road network file published by the Rhode Island Department of Transportation, and made available on the RIGIS website (Rhode Island Geographic Information System (RIGIS) Data Distribution System 2017).

3.1.3 Evacuation Locations

The final data set we create is for the evacuation destinations—on-island shelters and off-island routes—that at-risk populations will travel to if an evacuation is declared. We build on evacuation locations already identified in existing plans and policies. In response to the Disaster Mitigation Act of 2000, the City of Newport and townships of Middletown and Portsmouth produced and maintain hazard mitigation plans that list on-island shelter locations for evacuations. We identify the geospatial locations of these shelters on Google Maps and export them as a Keyhole Markup Language (KML) file. This KML file is then read into GeoPandas where its geospatial data is further manipulated using Shapely and then exported as a GeoJSON file. Using QGIS and the full CRS EPSG:4326, this GeoJSON file is plotted on top of an OpenStreetMap base layer.

In addition to on-island shelters, we identify three evacuation locations off-island, which represent the main routes evacuating vehicles will use once they are outside Aquidneck Island jurisdictions. We determine evacuation routes based on bridges originating on Aquidneck Island and leading to Jamestown, Tiverton, and Bristol cities. Once an evacuee reaches any of these locations, it is considered to have safely evacuated to the mainland. Figure 3.7 shows the resulting data set of on-island shelters and off-island evacuation locations.

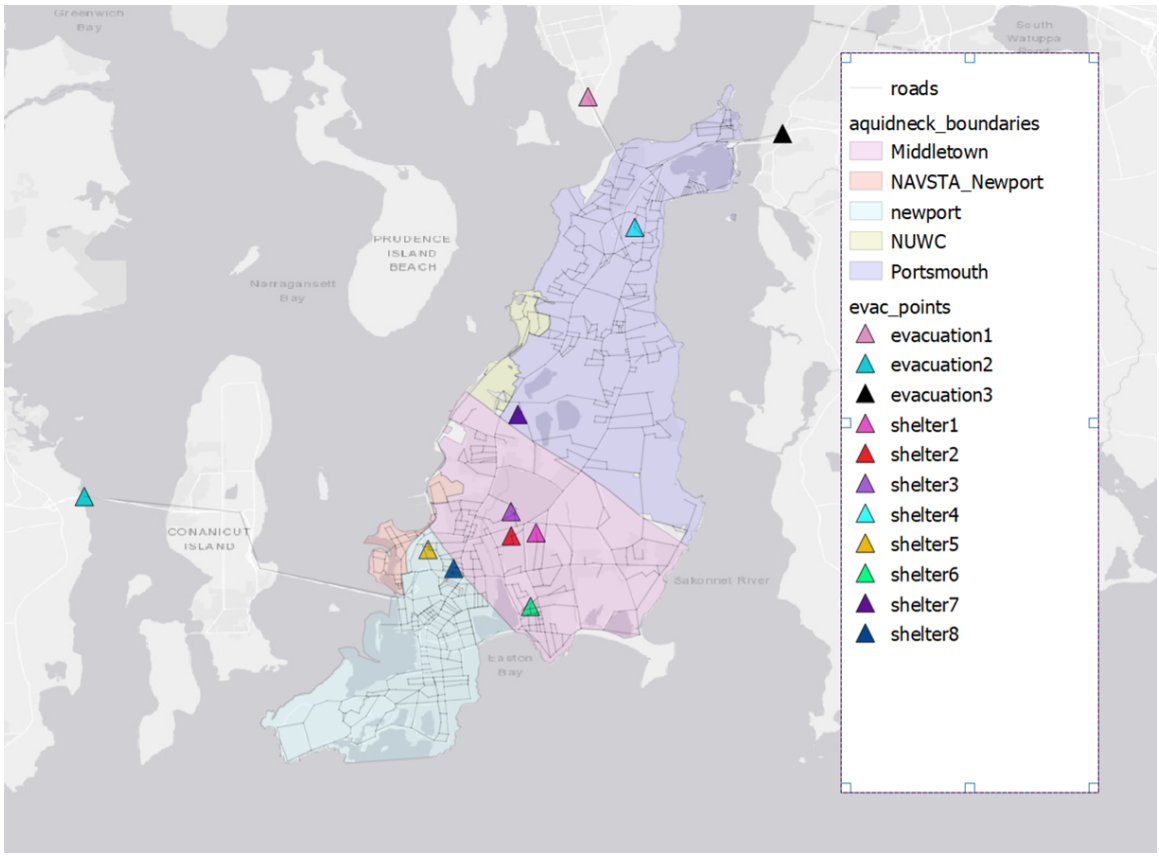

Figure 3.7. Evacuation Points and Shelter Locations. Off-Island Evacuation points within the nearby mainland areas and inland shelters identified within each municipalities hazard mitigation plan. Refer to Table 3.2 for specific shelter names and locations.

We annotate this data set with information derived on the capacity for each shelter to accept evacuees. Table 3.2 details the evacuee capacity and vehicle capacity for each of the shelters. Shelter locations and evacuee capacities are based on an Army Corps of Engineers New England Hurricane Evacuation study that provided analysis on the capacities of various identified American Red Cross shelters (U.S. Army Corps of Engineers, New England District 2016). Most of these shelters are also identified in the hazard mitigation plans for Newport, Middletown, and Portsmouth. Vehicle capacity is determined using the 2021 Codification of the General Ordinances of the City of Newport, Rhode Island and calculations are extended to the cities of the Middletown and Portsmouth (Municipal

Code Corporation 2021). Under the parking and loading standards contained within this ordnance, all schools must have 1 parking spot per every 5 seats in a classroom. We obtain the classroom ratios for each school as well as the number of teachers. An assumption is made that each teacher is assigned to a classroom. The number of seats per class is then multiplied by the number of teachers to determine the number of parking spots, a.k.a vehicle capacity for each shelter. Resulting evacuee and vehicle capacities for each shelter is presented in Table 3.2.

Overall, shelters are more constrained by parking than by capacity to shelter individuals. For this reason, we use vehicle capacities to determine the total number of evacuees that can be accepted at a shelter for all analyses.

Table 3.2. Shelter Capacity Analysis. Shelter capacity based on evacuee and parking space availability. capacities not listed by the American Red Cross are labeled as UNK. Off-island evacuation points have infinite capacity, listed as INF. Adapted from U.S. Army Corps of Engineers, New England District (2016).

City	Shelter Type	Designator	Shelter Name	Evacuee Capacity	Vehicle Capacity
Middletown	Regional	shelter1	Gaudet Middle School	1098	138
Middletown	Local	shelter2	Middletown High School	1000	123
Middletown	Local	shelter3	Forest Ave. Elementary	UNK	73
Middletown	Local	shelter6	Aquidneck Elementary	UNK	68
Newport	Local	shelter5	Florence Gray Center	0	60
Newport	Local	shelter8	Sullivan Elementary	UNK	48
Portsmouth	Local	shelter4	Portsmouth High School	297	173
Portsmouth	Local	shelter7	Portsmouth Middle School	500	148
Bristol	N/A	evacuation1	Mt Hope Bridge	INF	INF
Jamestown	N/A	evacuation2	Newport Bridge	INF	INF
Tiverton	N/A	evacuation3	RT 24 Bridge	INF	INF

Given the new data sets curated for this study, we construct an network model built with the open-source mathematical modeling program called Pyomo (Hart et al. 2011) in order to analyze the Aquidneck Island network. Pyomo offers an avenue to explore various constraints in order to discover solutions that optimize our objective. Our formulated mathematical model is detailed in the next section.

3.2 Model Formulation

With the identified at-risk populations, road network, and evacuation locations, we use a network optimization process to determine the best combinations of at-risk populations and their destination assignment under various Aquidneck Island evacuation scenarios. For this purpose, we develop a mathematical model that assigns evacuation routes to at-risk populations while minimizing total evacuation travel time from at-risk population centers to evacuation locations.

Indices and Sets

$n \in N$	nodes (alias i, j)
$s \in S \subset N$	set of all source nodes
$e \in E \subset N$	set of all evacuation destination nodes
$(i, j) \in A \subseteq N \times N$	arcs
$\tau \in T$	number of time steps [0,96]
	($\bar{\tau}$ = total time period)
$k \in K_s$	set of all evacuation paths starting at given source node $s \in S$

Data [units]

$c_{ij\tau}$	capacity of arc (i, j) in time period τ [vehicles per hour (VPH)]
$d_{ij\tau}$	distance of arc (i, j) in time period τ [miles]
$\rho_{ij\tau}$	speed of arc (i, j) in time period τ [mph]
z_s	number of evacuating vehicles (i.e., supply) at source node s
v_e	shelter capacity for evacuees at node e
λ_{sek}	= 1 if evacuation node e is included in path k for source node s, 0 otherwise [Binary]
w_{sijk}	= 1 if arc i, j is included in path k for source node s, 0 otherwise [Binary]

Decision Variables [units]

σ_{sk}	= 1 if path $k \in K_s$ chosen for source node $s \in S$; 0 otherwise [Binary]
$\beta_{s\tau k}$	flow rate of evacuating vehicles leaving node s in time period τ along path k [VPH]
$\mu_{s\tau}$	the number of evacuating vehicles remaining at node s in time period τ [VPH]

Formulation

$$\min_{\sigma,\beta,\mu} \sum_{s} \sum_{\tau} \mu_{s\tau} \tag{3.1}$$

$$\text{s.t.} \sum_{s} \sum_{k} \beta_{s\tau k} w_{sijk} \leq \left(\frac{60 \cdot d_{ij\tau}}{\rho_{ij\tau}} c_{ij\tau} \right) \quad \forall (i,j) \in A, \forall \tau \in T \tag{3.2}$$

$$\sum_{k} \sigma_{sk} = 1 \qquad \forall s \in S \tag{3.3}$$

$$\sum_{\tau} \beta_{s\tau k} \leq \sigma_{sk} z_s \qquad \forall s \in S, \forall k \in K_s \tag{3.4}$$

$$\mu_{s0} = z_s \qquad \forall s \in S \tag{3.5}$$

$$\mu_{s,\tau+1} = \mu_{s\tau} - \sum_{k} \beta_{s\tau k} \qquad \forall s \in S, \forall \tau \in T-1 \tag{3.6}$$

$$\sum_{s} z_s \left[\sum_{k} \sigma_{sk} \lambda_{sek} \right] \leq v_e \qquad \forall e \in E \tag{3.7}$$

$$\sigma_{sk} \in \{0,1\} \qquad \forall s \in S, k \in K_s \tag{3.8}$$

$$\beta_{s\tau} \geq 0 \qquad \forall s \in S, \tau \in T \tag{3.9}$$

$$\mu_{s\tau} \geq 0 \qquad \forall s \in S, \tau \in T \tag{3.10}$$

Discussion

This model analyzes the flow of evacuating vehicles departing from source nodes located within flooding regions toward inland shelters and off-island evacuation points. The model assumes that evacuees will depart from their source nodes at the earliest time period based on available road capacity within their assigned route to their assigned destination. Additional model assumptions are that each source node will be assigned one route and one destination node. This assigned route and destination will be utilized by all of the population evacuees throughout the entire duration of their trip. Evacuating populations as early as possible also provides a best case total clearance time of all evacuating vehicles when road congestion and flooding restricts usage of impacted road segments and inland shelters.

The objective function value (3.1) of the formulation minimizes the number of vehicles waiting to depart, summed over each time period. This creates an incentive for vehicles to leave as soon as possible. Constraint (3.2) enforces the capacity on each arc (i,j) given

nonlinear congestion. Constraint (3.3) enforces that only one evacuation path is selected for each source node$s$. Constraint (3.4) enforces the total flow of vehicles out of source node s along the selected evacuation path to be less than or equal to the number of evacuees initially at that node. Constraint (3.5) enforces that at time period $\tau = 0$, the remaining number of evacuees equals the initial number of evacuees at each source node s. Constraint (3.6) calculates the number of evacuees remaining at source node s for all remaining time periods τ and is equal to the prior time period's number of evacuees remaining minus the number of vehicles that were able to evacuate during that prior time period τ. Constraint (3.7) enforces that the total number of evacuees from all source nodes that arrive at a destination node e be less than or equal to its total shelter capacity. Stipulations (3.8), (3.9) and (3.10) enforce the binary and non-negativity requirements for the decision variables.

3.3 Application of Our Network and Optimization Model

Summarizing the above data curation and model development integrates our methods for evacuation analysis. We begin our network construction with 309 population centroids. Using historical flooding data as well as current ADCIRC storm and sea level rise modeling data, we identify only those at-risk populations that lay within these Aquidneck Island flooding areas. The end result is 55 at-risk populations that serve as our origins. We also have 8 inland shelters and three mainland evacuation points that serve as our destinations. We apply in-land shelter capacity values that reflect individual upper limits on vehicle capacity, as well as vehicle values for each at-risk population that reflect the total vehicle count evacuating from each origin.

Additional assumptions are required for applying our model. We assume that each household in Newport, Middletown, and Portsmouth will utilize two vehicles per household, and those individuals on NAVSTA Newport and NUWC due to their transient nature will each utilize their individual vehicle. We assume all evacuations take place by car, and multi-modal evacuation is not analyzed. Additionally, We analyze multiple shortest paths for each population node to each destination, and our model assigns all evacuees from each of the at-risk population nodes to just one available path.

Given our data, model, and assumptions, we can test various disaster scenarios and evacuation plans. Together, the results produce evacuating clearance times, destination assignment

and vehicular flow. We develop three key scenarios demonstrating our methods in Chapter 4.

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CHAPTER 4:
Analysis

We apply the model discussed in Chapter 3 to specific scenarios on Aquidneck Island in order to analyze impacts of evacuation of at-risk populations under both clear day conditions and flooding scenarios where specific road segments are impacted by worst case flooding levels. We consider our previously identified at-risk populations, which consist of 55 origin nodes representing local communities of houses. Each origin node must evacuate to one of 11 destinations, 8 of which are inland shelters and three represent the off-island evacuation points that are all connected over a network that consists of 2744 road segments.

When considering the evacuation times presented within each scenario, as a point of reference Aquidneck Island is approximately 15 miles from its most southern point to its most northern, and on average takes 30-40 minutes to traverse on a clear day without significant traffic.

We consider the following scenarios for evacuation.

Scenario 1: Clear Day with Realistic Shelter Capacities
Scenario 2: Hurricane Henri (August 2021)
Scenario 3: Increased Capacities at All Shelters

For each of these scenarios, we address the following questions:

1. What is the total evacuation clearance time for the at-risk populations that reside within the city of Newport, each of the municipalities as well as the military installations?
2. To which on-island shelter or mainland evacuation point is each at-risk population being evacuated?
3. What is the number of vehicles arriving at each mainland evacuation point during each time period, as well as the total number of vehicles being directed off-island?
4. What is the vehicle flow into each of the shelters assigned over each time period, as well as is the final capacity level reached at each shelter?

4.1 Scenario 1: Clear day with Realistic Shelter Capacities

The first scenario we model takes place on a clear, "blue sky" day where road congestion and destination capacity constraints are the only constraints that impact vehicle flow, path, and destination selection.

According to the hazard mitigation plans for Newport, Middletown, and Portsmouth, each town or municipality has outlined designated shelters to which their at-risk populations should evacuate in the event that evacuation is required due to a natural disaster (Nicholson et al. 2017; Town of Middletown Local Hazard Mitigation Committee Town of Middletown Planning Board 2014; Rhode Island Emergency Management Agency 2018). We apply the realistic capacities of each of these inland shelters as well as allowing for traffic flow off-island in order to determine the total clearance time to fully evacuate all at-risk populations and the optimal destination assignments when a coordinated traffic routing algorithm is applied.

Figure 4.1 shows the flow of vehicles exiting the city of Newport, municipalities of Middletown and Portsmouth, NAVSTA Newport, and NUWC during each time period. Each of the lines represent the origin groupings. Total evacuation clearance time for all at-risk populations is 15 hours. The city of Newport and NAVSTA Newport take the longest amount of time to fully evacuate all of their at-risk populations.

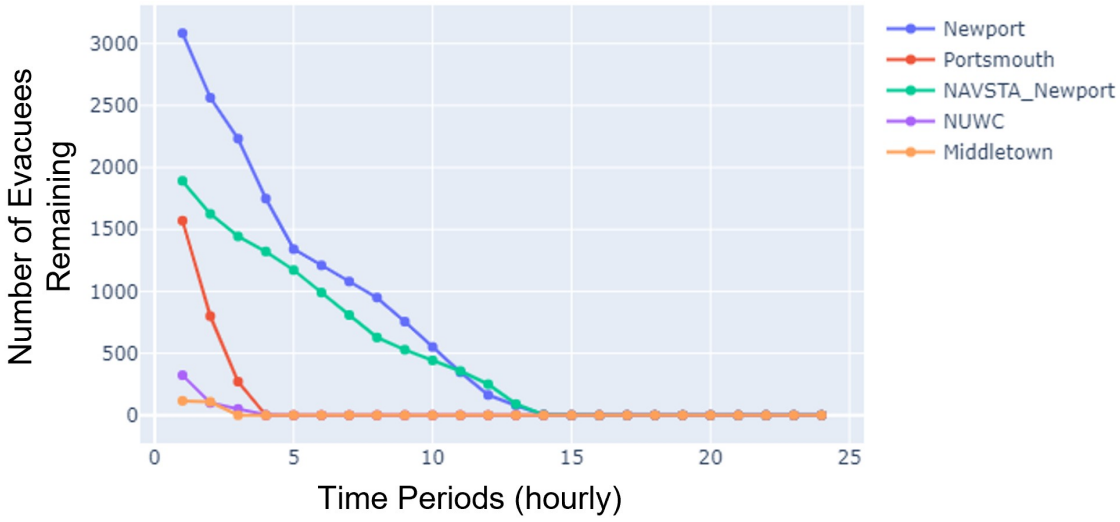

Figure 4.1. Scenario 1—Vehicle Evacuation Flow Over Time. Flow of vehicles evacuating from the city of Newport, municipalities of Middletown and Portsmouth, NAVSTA Newport and NUWC. Total time period analyzed is 24 hours.

The model assigns evacuation destinations to each population in order to establish the most optimal evacuation route and flow of vehicles based on the constraints of road and individual capacity. These population-destination assignments can be seen in Figure 4.2.

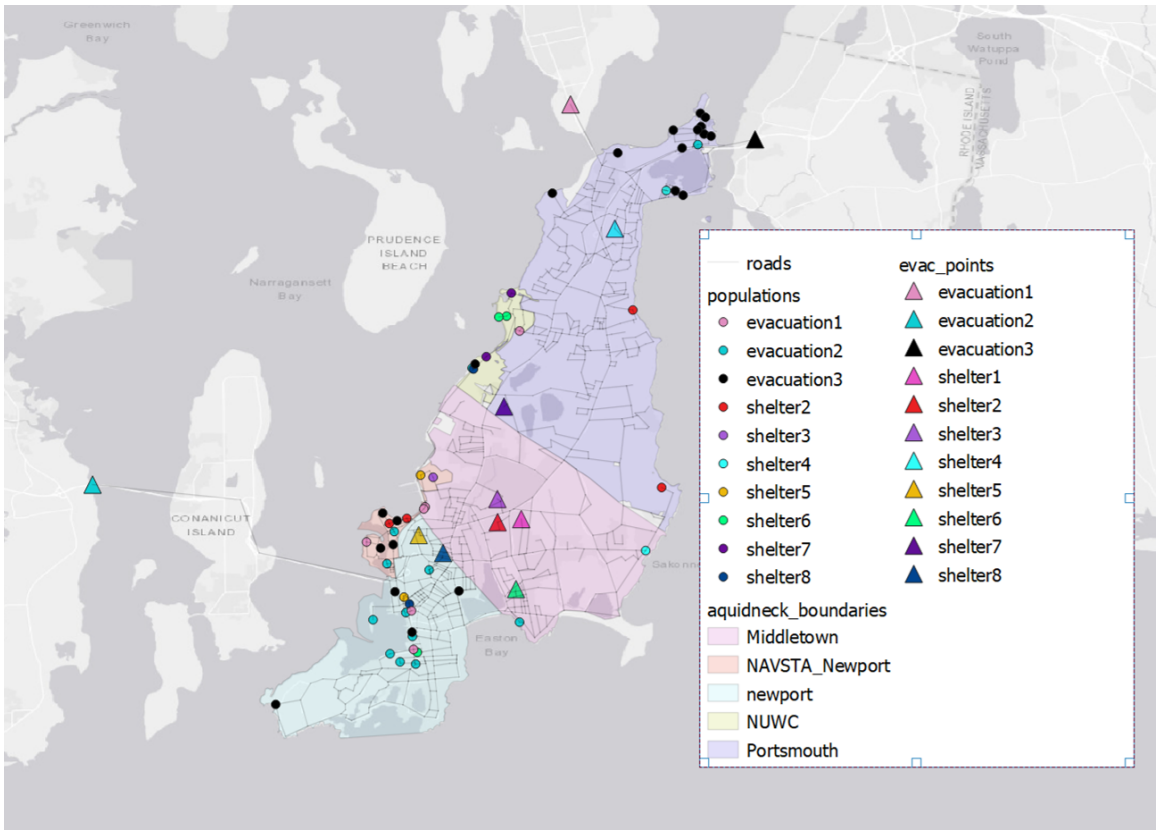

Figure 4.2. Scenario 1—Shelter Assignment. Populations and their assigned evacuation destinations from coordinated routing model. Each population is color coded to match its assigned destination. Refer to Table 3.2 for specific shelter names and locations.

Figure 4.3 shows the flow of vehicles entering each of the inland shelters as well as the mainland evacuation points. Due to limited capacity within the inland shelters, many of the shelters are full by approximately hour two. Additionally, the shelter capacity constraints ultimately force a majority of evacuees off-island so that all of the at-risk populations can completely evacuate to safety in the time period analyzed. Evacuation point 3, which is the northeastern evacuation point to Bristol via RT 24, has the largest number of arriving vehicles out of all destinations. This coincides with very at-risk large populations in Northern Portsmouth that fall within FEMA identified hurricane evacuation zones whose shortest and quickest path off-island is via evacuation point 3.

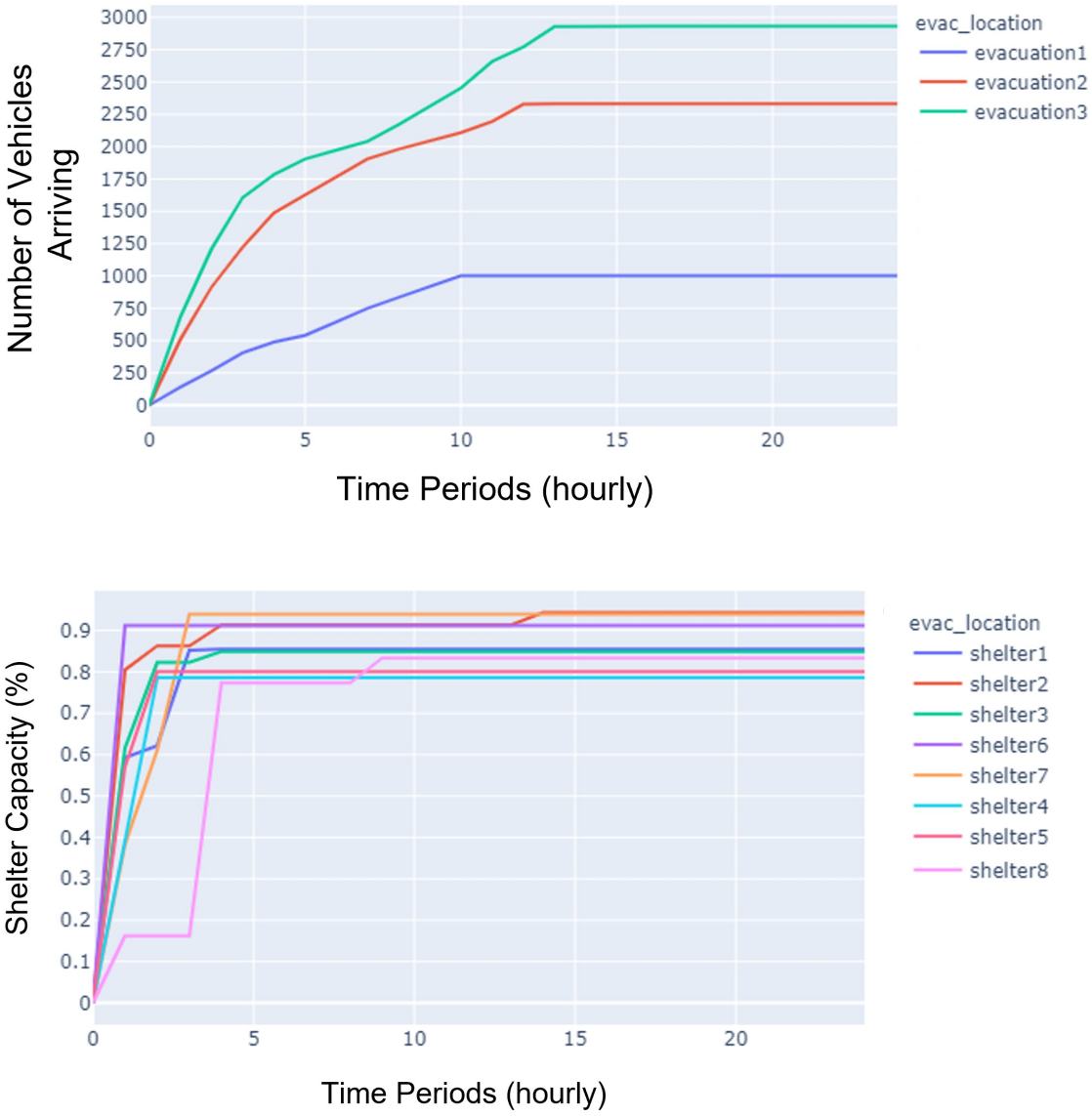

Figure 4.3. Scenario 1—Vehicle Flow to Evacuation Locations Over Time. Top: Map of vehicle flow off-island to the off-island evacuation points. Y axis represents number of vehicles arriving off-island during each time period. Bottom: Flow of vehicles into each inland shelter. Y axis represents the % filled to capacity as vehicles arrive. Total time period analyzed is 24 hours. Refer to Table 3.2 for specific shelter names and locations.

4.2 Scenario 2: Hurricane Henri

During the course of this thesis, Hurricane Henri, which weakened from a hurricane category 1 to a tropical storm, made landfall in Westerly, Rhode Island. On 22 August 2021, this slow moving storm brought wind speeds of 70mph, heavy rains and heavy inland and coastal flooding. With an anticipated landfall occurring west of Aquidneck Island, on the evening of 20 August, we began coordination with NAVSTA Newport emergency planners. Within a few hours, we identified their concerns, ran our model and prepared a brief for the NAVSTA Newport base installation commander. This brief was presented on Saturday morning the 21st of August to all pertinent stakeholders, the day prior to Hurricane Henri making landfall. In less than 48 hours, we produced results from a critical evacuation scenario and provided information that assisted in NAVSTA Newport's time critical evacuation planning process.

Despite the projected weakening of this storm, NAVSTA Newport requested information regarding evacuation clearance times for their resident population if an evacuation order was implemented. After discussion with the installation's emergency planners, we were requested to model this evacuation with the following constraints: evacuation to the west across the Newport Bridge was prohibited due to the projected storm track, and all NAVSTA Newport personnel had to evacuate off-island. Additionally, NUWC employs a large number of civilian employees, and because Hurricane Henri was making landfall over the weekend, a majority of these employees were not at work during this time period. Therefore, we adjusted the number of vehicles evacuating NUWC in Scenario 3 to better represent only the essential military personnel that would be at NUWC if the evacuation order was given. Even though the local shelters were available, local emergency planners from Newport, Middletown, and Portsmouth in the past have requested that all military personnel who are evacuating leave Aquidneck Island in order to allow for the local population to use the inland shelters. Another considering factor in this decision is that the Navy pays for the lodging of all personnel required to evacuate, while many in the civilian population require the ability to shelter in locations free of charge.

This Hurricane Henri scenario is analyzed using the coordinated algorithm. We apply the planning requirements from NAVSTA Newport and assume that all of the at-risk populations located on Aquidneck Island would also be ordered to evacuate at the same time. Total clearance time for all at-risk populations on Aquidneck Island is found to take 30 hours.

However, the populations located on NAVSTA Newport are able to completely evacuate off-island within 19 hours using northern evacuation routes toward mainland cities of Tiverton and Bristol. The flow of vehicles leaving the city of Newport, municipalities of Middletown and Portsmouth as well as the military installations can be seen in Figure 4.4. With the exception of Newport's at-risk populations, all other locations are able to evacuate within approximately five hours.

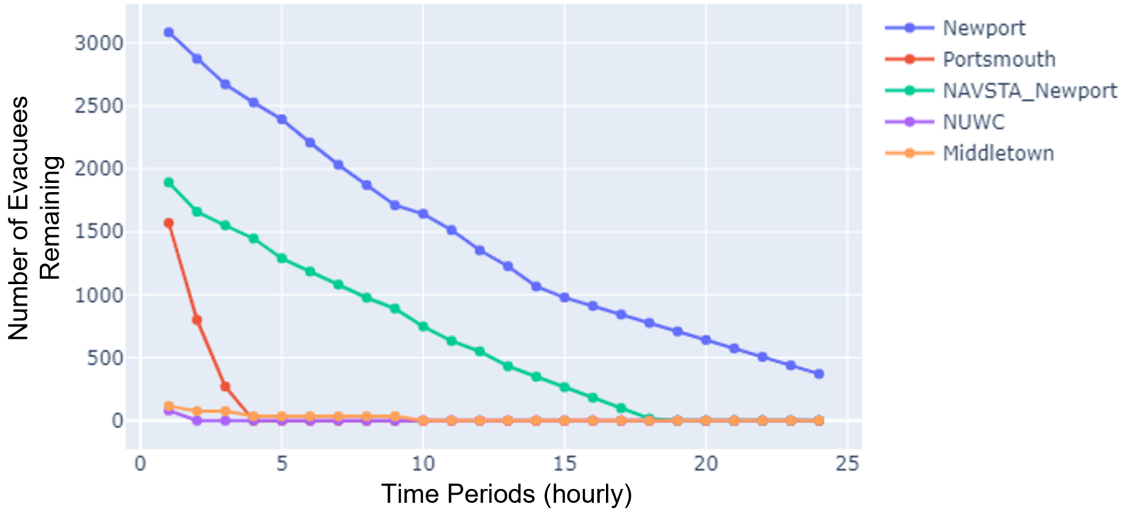

Figure 4.4. Scenario 2—Vehicle Evacuation Flow Over Time. Flow of vehicles out of the city of Newport, the municipalities of Middletown and Portsmouth, as well as NAVSTA Newport and NUWC during each time period during Hurricane Henri scenario. Total time period analyzed was 24 hours.

Closing of one of the major bridges in Newport and prohibiting evacuation westward is more restrictive than Scenario 1. This restriction causes a large impact on evacuation travel times as road capacities cannot handle the additional flow. The result is that full evacuation of all at-risk populations is not possible within a 24-hr period, particularly for large Newport populations that reside in the southern portion of Aquidneck Island. These evacuees would, if allowed, evacuate much quicker westward over the Newport Bridge versus having to

traverse the entire Aquidneck Island in order to use the two northern bridges to reach the mainland.

In Scenario 2, the model assigns new evacuation destinations to each population in order to establish the most optimal evacuation route and flow of vehicles. New routing is driven by the additional constraints of no evacuation westward and all NAVSTA Newport personnel being required to evacuate off-island. The population-destination assignments can be seen in Figure 4.5.

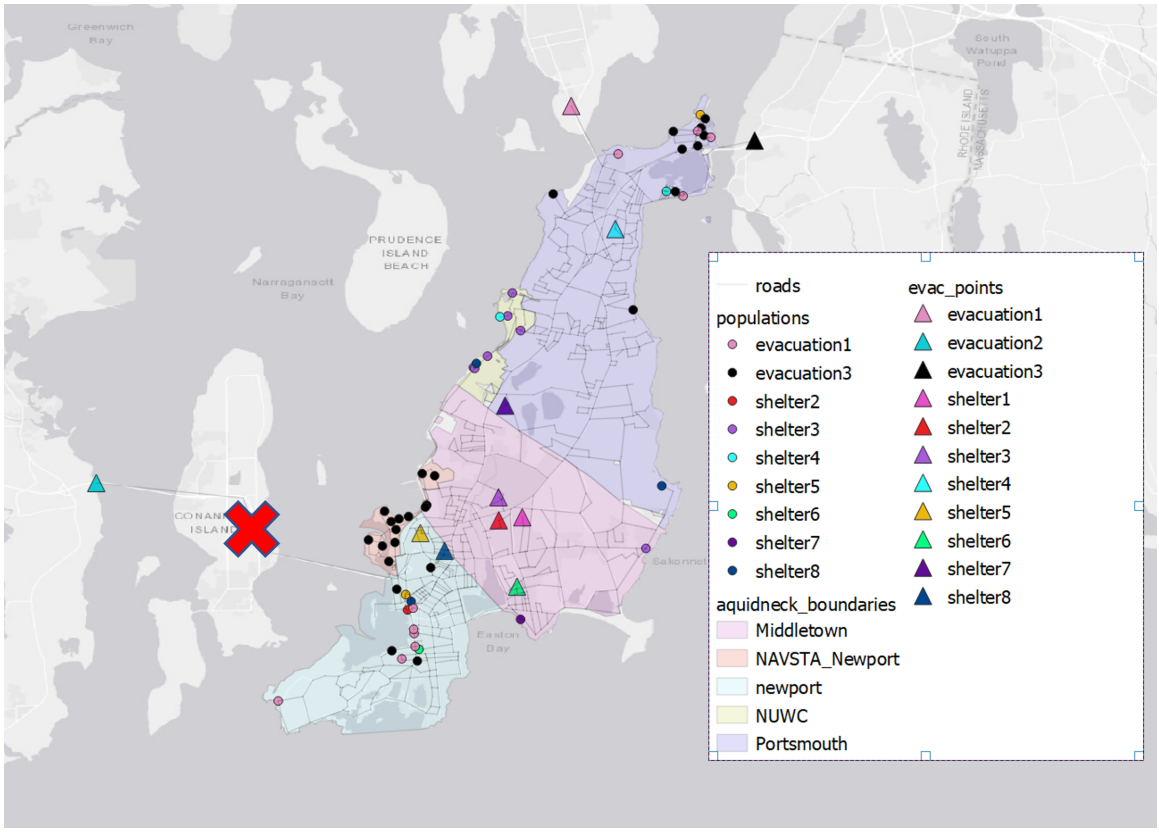

Figure 4.5. Scenario 2—Shelter Assignment. Populations and their assigned evacuation destinations from coordinated routing model within the Hurricane Henri scenario. Each population is color coded to match its assigned destination. Refer to Table 3.2 for specific shelter names and locations.

Due to the limited capacities of the inland shelters, they are all at their maximum limit by approximately hour ten, In fact with the exception of shelter one and shelter seven, all

other inland shelters are full by approximately hour two of the evacuation. Additionally, a majority of the evacuation population are still routed off-island. The flow into the inland shelters as well as the off-island evacuation points can be seen in Figure 4.6.

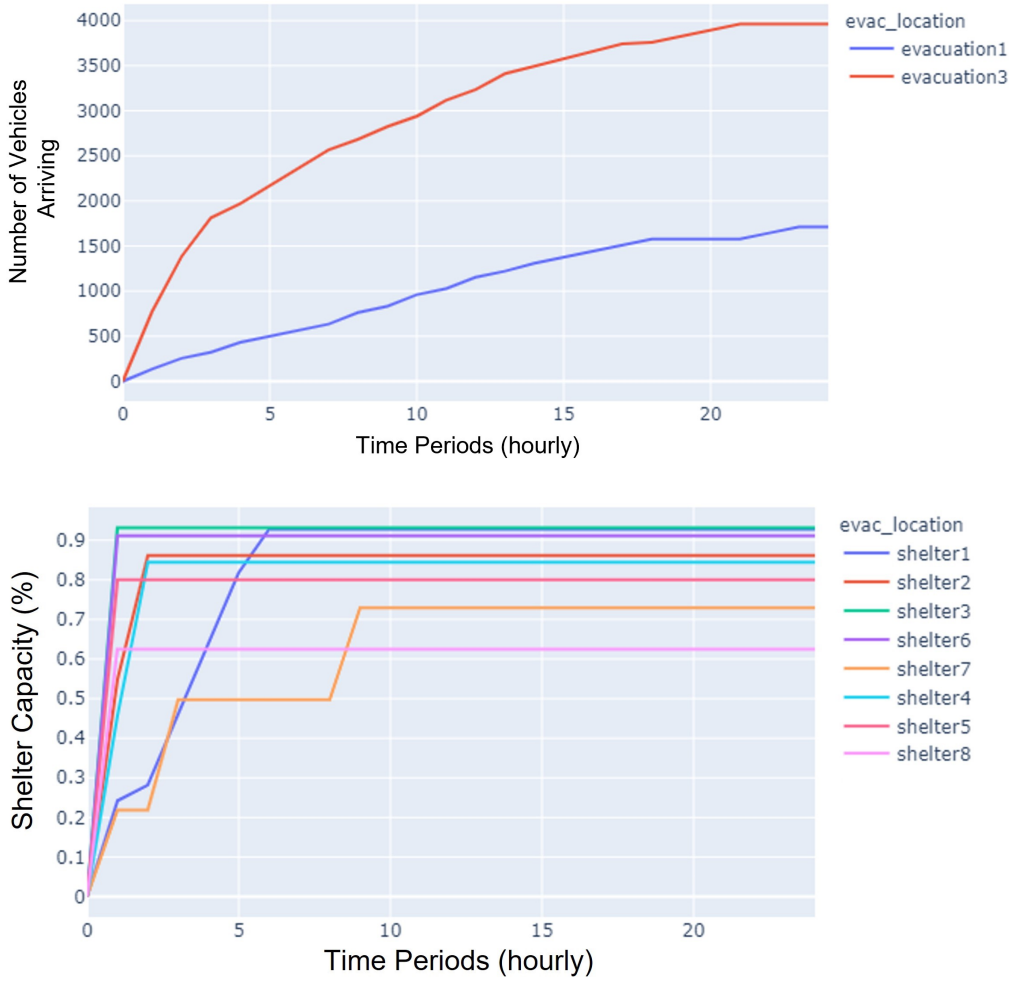

Figure 4.6. Scenario 2—Vehicle Flow to Evacuation Locations Over Time. Top: Map of vehicle flow off-island to the off-island evacuation points. Y axis represents number of vehicles arriving off-island during each time period. Bottom: Flow of vehicles into each inland shelter. Y axis represents the % filled to capacity as vehicles arrive. Total time period analyzed was 24 hours. Refer to Table 3.2 for specific shelter names and locations.

4.3 Scenario 3: Increased Capacities at All Shelters

As demonstrated in Table 3.2 in Chapter 3, the total vehicular capacity at inland shelters is far less than the anticipated number of evacuating vehicles. This is why in Scenarios 1 & 2, a majority of the at-risk population is routed off-island. In total, inland shelters can only support approximately 1/6 of those evacuees. Scenario 3 is developed to test the benefits of additional shelter capacity on island. Specifically, we test optimal evacuation given an increased capacity for each shelter as 8000 vehicles. We also include off-island evacuation in all three directions. This scenario's parameters are the least restrictive, and assume that if shelter capacity is not a constraint, then evacuees will most likely choose the closest shelter available.

For Scenario 3, total evacuation clearance time is again 15 hours. Vehicle flow can be seen in Figure 4.7. Scenario 3 vehicle flow is similar to what was seen in Scenario 1, but with a noticeable difference in evacuation clearance for some populations. Specifically, a majority of Newport's at-risk populations reach shelter destinations by hour five of evacuation. This vehicle flow makes sense because out of the eight inland shelters, six of them are situated either within the city of Newport, or on the border between between Newport and Middletown. Thus, increased shelter capacity has the greatest impact on Newport communities.

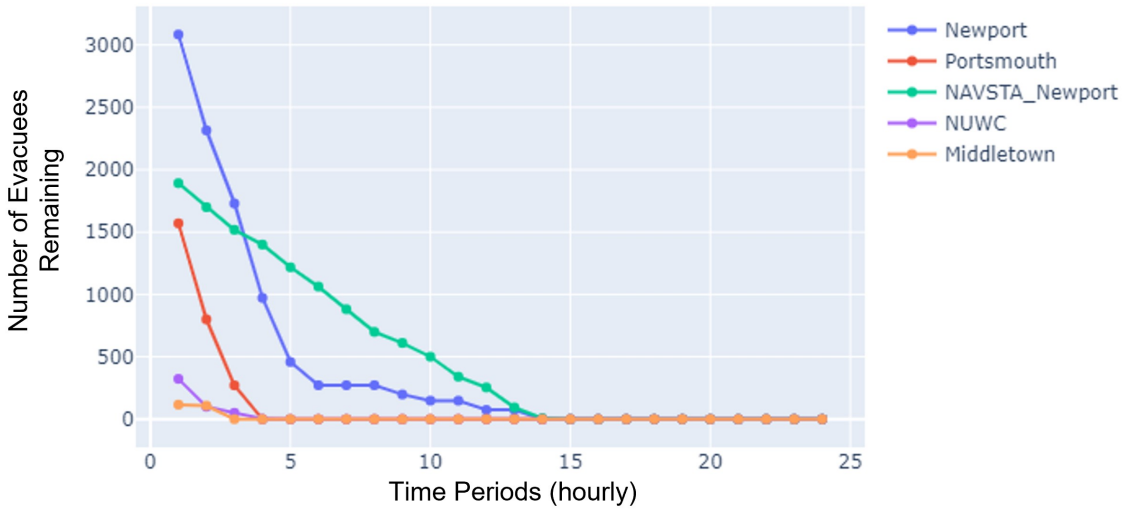

Figure 4.7. Scenario 3—Vehicle Evacuation Flow Over Time. Flow of vehicles out of the city of Newport, the municipalities of Middletown and Portsmouth, as well as NAVSTA Newport and NUWC during each time period. Total time period analyzed is 24 hours.

In Scenario 3, the model assigns new evacuation destinations to each population in order to establish the most optimal evacuation route and flow of vehicles based on road capacity constraints only. This is a relaxation of Scenario 1. Resulting population-destination assignments can be seen in Figure 4.8.

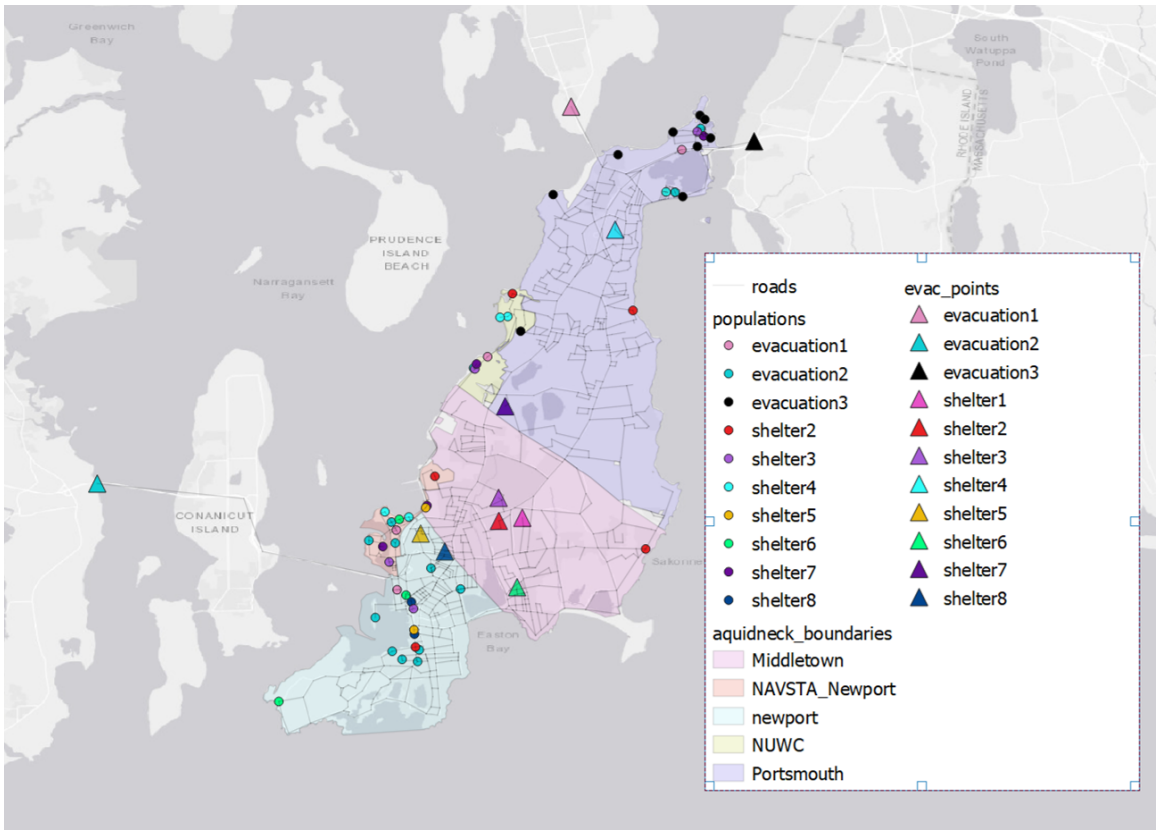

Figure 4.8. Scenario 3—Shelter Assignment. Populations and their assigned evacuation destinations from coordinated routing model within the increased shelter capacity scenario. Each population is color coded to match its assigned destination. Refer to Table 3.2 for specific shelter names and locations.

Figure 4.9 details the vehicle flow into each of the shelters as well as off-island. The top figure details the number of vehicles that are flowing off-island, while the bottom figure gives insight into how much of the shelter's capacity is being consumed as the time periods progress. In Scenario 3, because the shelter capacities have all been increased to 8000, each shelter has a large amount of capacity remaining at the end of the evacuation period. Shelters two, six, seven and eight receive all of their evacuees by hour 5, while the remaining four shelters continue to receive evacuees until hour 13. Off-island vehicle flow continues until hour 15. Interestingly, when all three off-island evacuation points are available, the optimal choices made by the model are to send evacuees westward across the Newport Bridge and northeast across RT 24 into Tiverton. The largest percentage of at-risk populations

on Aquidneck Island resides very near to these two off-island exit points. This scenario clearly shows that available road capacity and short distance to the mainland allow for the evacuation of large amounts of people in a short time.

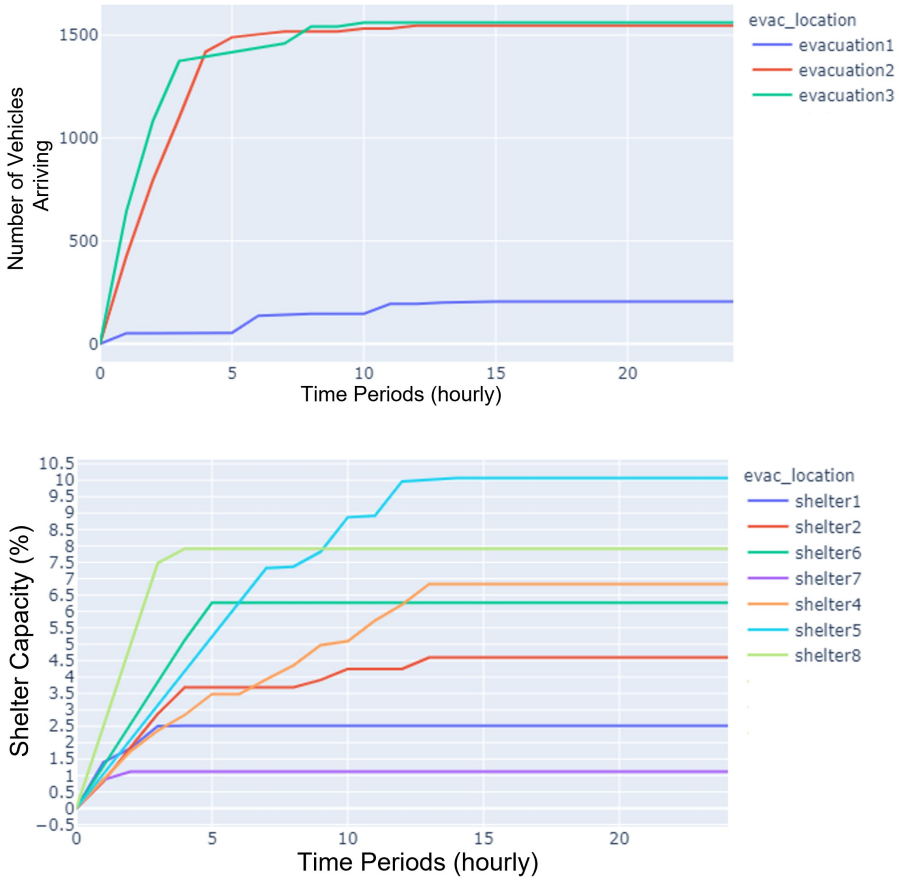

Figure 4.9. Scenario 3—Vehicle Flow To Evacuation Locations Over Time. Top: Vehicle flow off-island to the off-island evacuation points during each time period. Bottom: Flow of vehicles into each on-island shelter during each time period. When normalized shelter utilization $= 1$, then the number of vehicles arriving at the shelter $=$ the true shelter capacity. Utilization > 1 implies the arrival of more vehicles than true capacity. For example, after evacuation, shelter 7 is utilized near its true capacity (utilization $\sim \ 1$), where shelter 5 is utilized by 10.5 times more vehicles than its true capacity. Total time period analyzed is 24 hours. Refer to Table 3.2 for specific shelter names and locations.

4.4 Scenario Comparison and Discussion

The three scenarios above highlight distinctly different environments for potential evacuation from Aquidneck Island.

Evacuation on a clear, blue sky day (Scenario 1) provides the baseline best case scenario of evacuation of all at-risk populations according to the current plans developed by the city of Newport, Middletown, and Portsmouth. Additionally, this scenario also includes the coordination required for evacuation of NAVSTA Newport and her tenant commands, which to date is not something that has been included in the city of Newport, Middletown, or Portsmouth's planning process. In other words, this this the first evacuation plan for Aquidneck Island that optimally routes both civilian and military evacuees.

Consideration of Hurricane Henri (Scenario 2) allows us to model a realistic evacuation scenario with constraints that would be imposed in the event of an actual disaster. Due to Hurricane Henri's storm track, the westward evacuation route was deemed to be dangerous and therefore we model that evacuation point being restricted from any use. We also learned from the Emergency Management Officer for NAVSTA Newport that, in the event of an evacuation order, local emergency planners request that all military personnel leave the island and reserve shelter space for the local civilian populations. In order to fully model the constraints within this scenario, we slightly modify our model to ensure that during the optimization, the solver does not assign any local shelters as destinations for any military personnel.

We consider Scenario 3 to provide insight into the most effective locations for a potential expansion in shelter capacity. Shelter capacity expansion could be adding increased space to the shelters already being utilized, or the designation of more shelters in the same generalized area.

The total clearance times for all civilian and military communities differ across scenarios. In Scenario 1, when evacuating conditions are perfect and all off-island evacuation routes are available, as well as the only constraints restricting timely traffic flow are available road and shelter capacity, it takes 15 hours for the entire island to evacuate. In Scenario 2, when additional constraints are applied, we observe that evacuation clearance time for NAVSTA Newport increases by 21%, going from 15 hours to 19 hours. Additionally, total island

clearance time goes from 15 hours to 30 hours, an increase of 50%. In Scenario 3, even with the increase in shelter capacity, total evacuation time is the original baseline evacuation time seen in Scenario 1, which is 15 hours.

Each scenario imposed specific constraints that impact the clearance time for sub-populations in the city of Newport, the municipalities of Middletown and Portsmouth, as well as NAVSTA Newport and NUWC. The clearance times for each of these locations is listed in Table 4.1. Portsmouth is the one location whose clearance time was unchanged during each scenario, which can be attributed to the fact that there are two main evacuation points, one northeast and one northwest that are very close and easily accessible to Portsmouth's at-risk populations. This accessibility allows them a quicker evacuation to the mainland, even under the same restrictive conditions that impact the other locations. The city of Newport experiences the biggest impact under Scenario 2 with the closing of the Newport Bridge combined with the limited capacity of the nearby shelters. These conditions force their large at-risk populations to have to compete with traffic flow from all of the other evacuation locations, as they traverse the entire island to the two northern exits.

Table 4.1. City of Newport, the Municipalities of Middletown and Portsmouth, NAVSTA Newport and NUWC Evacuation Clearance Time Scenario Comparison in hours.

Location	Scenario 1	Scenario 2	Scenario 3
NAVSTA Newport	15	19	15
NUWC	5	2	4
City of Newport	15	30	14
Middletown	4	10	5
Portsmouth	5	5	5

The constraints of road capacity, available shelter capacity, and blockage of certain access points also impacts the number of vehicles chosen to evacuate off-island in each scenario. The number of evacuees leaving the island under these various constraints is listed in Table 4.2.

In Scenario 1, 90% of the population is routed off-island, while in Scenario 2, when the military population is required to leave the island, only 80% of the total population is

Table 4.2. Vehicle Flow Off-Island Scenario Comparison. For reference, total number of evacuees is 6923 for Scenario 1 and Scenario 3. Total number of evacuees for Scenario 2 is reduced to 6695 because of reduction in number of evacuees located on NUWC within this scenario. Refer to Table 3.2 for specific evacuation locations.

Evacuation location	Scenario 1	Scenario 2	Scenario 3
Evacuation1	1001	1713	205
Evacuation2	2331	N/A	1547
Evacuation3	2932	3963	1561
Totals	6264/6923	5675/6695	3313/6923

routed off-island, which implies that in Scenario 1, large portions of NAVSTA Newport personnel were being evacuated to nearby shelters in the city of Newport, which required larger portions of the local population to have to leave the island. In Scenario 3 where shelter capacity constraints are relaxed, only 47% of at-risk populations are routed off-island, which implies that if the local shelters had the available capacity, an optimal solution is that shelters across the island become primary evacuation points for many of the at-risk populations vice off-island evacuation.

Another area of analysis is the vehicle flow towards inland shelters and the capacity to which they are utilized. This information is listed in Table 4.3 and Table 4.4. Due to limited capacity within each shelter, a majority of all shelters fill within the first few hours in each evacuation scenario. In Scenario 1, shelter 2 (Middletown High School) remains open the longest receiving evacuees until hour 14 of the evacuation. This location also fills to approximately 94% of its available capacity in Scenario 1. In Scenario 2, shelter 7 (Portsmouth Middle School) remains open the longest receiving evacuees until hour 9, however even by remaining open the longest it ultimately only fills to approximately 73% of its available capacity. In Scenario 3 with the increased capacity of the inland shelters, more shelters remain open longer. Interestingly in Scenario 3, shelter 3 (Forest Ave. Elementary) is not even utilized, while in Scenarios 1 and 2 it is filled to 85% and 93% of its capacity.

With expanded capacity capabilities provided in Scenario 3, the shelter that experiences the largest increase in evacuees is shelter 5 (Florence Grey shelter), located within the

city of Newport, which is the city on Aquidneck Island that has the largest number of at-risk populations that need to be evacuated. It is interesting that shelter 4 (Portsmouth High School) does see a large increase in capacity, but if you refer back to Figure 4.8, the increased number of evacuees to that shelter are from outside Portsmouth. This implies that even with the increased shelter capacity at two nearby shelters, the optimal solution for evacuation for Portsmouth at-risk populations is to still be routed off-island.

Table 4.3. On-Island Shelter Fill Time Scenario Comparison in hours. Refer to Table 3.2 for specific on-island shelter names and locations.

Shelter location	Scenario 1	Scenario 2	Scenario 3
Shelter1	4	6	4
Shelter2	14	2	13
Shelter3	4	1	0
Shelter4	2	2	13
Shelter5	2	1	14
Shelter6	1	1	5
Shelter7	3	9	2
Shelter8	9	1	3

Table 4.4. On-Island Shelter Capacity Scenario Comparison in %. Refer to Table 3.2 for specific shelter names and locations.

Shelter location	Scenario 1	Scenario 2	Scenario 3
Shelter1	0.85	0.93	2.52
Shelter2	0.94	0.86	4.59
Shelter3	0.85	0.93	0.00
Shelter4	0.79	0.84	6.83
Shelter5	0.80	0.80	10.06
Shelter6	0.91	0.91	6.26
Shelter7	0.94	0.73	1.12
Shelter8	0.83	0.63	7.91

The results across all three scenarios outline the current applicability of our model and its capability to perform under a range of constraints. The use of our optimization model is a

tool for analysis that provides insights into possible evacuation plans. Optimization models like it are not considered in current evacuation practices and hazard mitigation plans in many municipalities.

While our model supports optimal evacuation routing and minimizes evacuation time, the results may be difficult to implement. For example, across all three scenarios, our model assigns co-located or nearby communities to different shelters or off-island evacuation locations. This means nearby houses may need to travel to entirely different parts of Aquidneck Island for optimal evacuation. Such nuance is hard to implement in practice as municipalities generally only get to choose "go" or "no-go" evacuation decisions and may have limited capacity to direct traffic on a house-by-house basis.

There is also the inherent factor of human decision making that can't be controlled. Even if told where to go, how to get there and when to leave, the final decision resides with the evacuee. Ultimately, some evacuation plans might be easy for emergency planners to implement, but are overall inefficient when it comes to clearance time. Or conversely, evacuation plans that produce optimal clearance times, may be to difficult to implement in practice.

Thus, this thesis is only a starting point for a broader discussion with Aquidneck Island's emergency managers and planners to answer the questions: what is possible for evacuation, and how long will it take? Answering these questions requires additional information beyond the optimization model. Thus, this work is also supporting a tabletop exercise to be conducted by Dr. Austin Becker's team to identify real decision-making needs. This supports a much larger Military Installation Resilience Review project.

CHAPTER 5:
Summary And Conclusions

This chapter concludes with a brief summary of our work as well as current limitations and potential future work.

5.1 Summary

In this thesis, we construct a data set of nodes including at-risk populations (origins) and evacuation points (destinations), a road network with real capacities and travel times, and an optimization model for analysis. We implement our new data and model to measure evacuation clearance times for individual at-risk populations as well total island clearance times. We use our data and methods to determine optimal evacuation in several key scenarios, including a real evacuation plan for a recent storm. Together, our approach proved capable of analyzing traffic flow of evacuating vehicles under a variety of contexts, including "clear sky" days and situations with reduced capacities imposed by a natural disaster.

We provide insight into how the current hazard mitigation plans can be modified to ensure a more successful evacuation when cross city/municipality and NAVSTA Newport coordination is required. Furthermore, we identify critical infrastructure that has direct impacts on clearance times, of which includes the Newport Bridge and the individual shelter capacities located on-island.

Ultimately, we suggest that the current road network of Aquidneck Island is in fact able to support full evacuation of the currently identified at-risk populations within varying time frames. The current limitations to evacuations seems to not come from capacity constraints of the roads themselves, but the limited number of vehicle capacity available at each of the shelters on-island.

5.2 Limitations

Our analysis relies on a number of assumptions, whose validity would impact the applicability of our results. We impose a requirement that all evacuating vehicles from a single

at-risk population are assigned the same evacuation destination and travel route (i.e., choice of roads used to reach the destination). Additionally, vehicles remain on this assigned path for the entire evacuation, this means that we do not account for blockages that might occur along this path that could result in the requirement to reroute traffic. Destination selection is also only assigned to a specific population if it has the capacity to accept all of the population's evacuees. In other words, we do not model the splitting of an at-risk population to multiple destinations. Additionally, we make an assumption that each household will be evacuating using two cars with the exception of NAVSTA Newport and NUWC where every evacuee uses their own personal vehicle. In reality, many households might use more or less than what we have approximated, which would impact road capacity levels during each time period and clearance times.

Within this thesis, we use the ADCIRC model's flooding and storm surge inundation data to identify the 55 at-risk populations, and we model the restricted use of the Newport Bridge in Scenario 2 as though flooding and high winds prevent evacuation along that route. However, even though the pre-processing of the data is constructed in such a way to calculate changes in road capacity and speed along specific arcs that could be impacted by road flooding, we do not incorporate time-phased flooding constraints within the current analysis.

Although storm surge inundation and road flooding is a severe consequence of hurricanes, these storms tend to also produce high winds that impact at-risk communities that reside both along the coast as well as inland. These high winds have the potential to restrict the use of bridges hours before any flooding occurs. The impacts of high wind speeds on the three mainland evacuation points leaving from Aquidneck Island, which all happen to be via the use of a bridge, is not considered in this study.

When analyzing vehicle flow from each at-risk population over each of the time epochs, there are periods of time where flow of vehicles exiting an at-risk population is paused or delayed in travel from the start of the evacuation. The current objective function within our model does seek to minimize the number of vehicles waiting to depart summed over each time period, but a future modification of this objective function that applies a stronger penalty for delay in vehicle flow might produce even quicker evacuation clearance times.

5.3 Future Work

The next phase of this work should be to incorporate different traffic conditions, such as car accidents and power outages. Integration of specific infrastructure systems such as power and water, will allow for a deeper analysis into the cascading impacts that occur due to the interdependencies between these systems. Both of these systems are highly impacted by natural disasters, causing major disruptive events like power outages at intersections and storm water inundation to sewer and water drainage systems, leading to additional dangerous overflow onto the roads.

We conduct evacuation analysis under an implied assumption that all populations are evacuating using their own personal vehicles. There are opportunities to expand our model to better reflect communities that rely more on multi-modal forms of transportation such as buses, street cars, or the subway.

The road network and node data set conducted for the analysis on Aquidneck Island can easily be reconstructed for other isolated and vulnerable locations important to the United States Navy such as Guam, Hawaii, Norfolk, and San Diego.

We recommend that these areas should be further researched and incorporated within our current model, and that the results are built upon to help inform emergency planners in the creation of successful, integrated, time-phased, and feasible hazard mitigation and evacuation plans for their communities.

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