OLDER ADULT MIGRATION, VULNERABILITY, AND TIME-SENSITIVE ACCESSIBILITY IN GEORGIA

by

XUAN ZHANG

(Under the Direction of Lan Mu and Jerry Shannon)

ABSTRACT

With the increasing population and proportion of older adults, the U.S. is facing challenges and opportunities of an aging society. To provide better insights and accommodations to older adults, this dissertation attempts to answer the overarching research question: what are older adult migration choices and living environments, including vulnerability and accessibility, in the aging U.S? New methods are introduced or implemented with GIScience and statistical models to provide new perspectives in older adult related research.

First, for the migration study, a new variable structure describing the destination is proposed to include long-term care facilities, affordable housing, and geriatrician availability, which are rarely considered in previous research. Both linear regression and decision tree models are applied to understand the relationships between the number of older migrants and destination characteristics. Results show that relationships vary for older migrant subgroups of intrastate, interstate, younger, and aged migrants. Second, to understand older adult vulnerability, a new Vulnerability Index of Older adults (VIO) is proposed to consider both environmental and social factors that make older adults more vulnerable than other age groups. The index locates some areas that need more attention for older adults, especially in potential natural hazards or emergencies.

Lastly, accessibility to emergency services is vital for older adults to receive timely treatment. This study implements time series concepts and methods to decompose real-time travel time data collected from Google for over five months. The embedded trend and seasonality (daily and weekly) are detected and used for future travel time prediction. With time series tools, accessibility components can be expressed as functions of time to capture the changing dynamics of travel distance, demand, and supply.

Results of this dissertation contribute to the advancement of integrating both geospatial analysis and statistical methods in older-adult-related research. Future research could follow the same vein to conduct research tailored to the older population and explore older adults' migration and living environments beyond Georgia.

INDEX WORDS: Older adults, Migration, Vulnerability, Accessibility, GIS, Statistical Models

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ACCESSIBILITY IN GEORGIA

by

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DEDICATION

To all my family members, who have shown me how to respect and care for older adults at home and in society.

“老吾老，以及人之老。” -- 孟子

“Honor older adults of other families as we honor our own.”-- Mencius

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CHAPTER 1

INTRODUCTION

1.1 Background

The world population has been growing older rapidly due to the increasing life expectancy and decreasing fertility rates for most regions (He et al. 2016). Globally, a recent report by the United Nations (2019) states that the share of older adults (65 and above) increased from 6% in 1990 to 9% in 2019, reaching 703 million. It is also expected that both the older population and proportion will be twofold by 2050. For both developed and developing counties, population aging has been at unparalleled levels and is expected to continue like this over the next few decades (Northridge 2012; Mather et al. 2015). The U.S. is part of a global trend of countries facing significant aging populations (Glinskaya and Feng 2018), and it is with the largest number of older adults among all developed countries (Ortman et al. 2014). In addition, nearly one-quarter of Americans will be older adults by 2060, and the older population is projected to double from 46 million to 98 million by then (Mather et al. 2015). The related demographic transition will impact all aspects of society (World Health Organization 2020). The increasing older population elicits many challenges, such as the caregiver shortage, social isolation, and potential healthcare system insufficiency (Andrews et al. 2007; Cornwell, E.Y., Waite 2009; Perissinotto et al. 2012). It also highlights some opportunities, including more job openings and economic benefits to the local businesses (Fagan and Longino 1993; Dorfman and Mandich 2016). As one of the goals set by the U.S. National Institute on Aging for 2020-2025, it is important to understand the consequences of an aging society and further inform intervention development and policy decisions (Hodes 2021).

The burgeoning older population comes to the question about where they spend their life after retirement and what factors are related to their quality of life. While some older adults prefer to age in place to stay in their homes and communities, places that they are familiar with, as they age (Binette and Vasold 2018), a proportion of older adults make the efforts to migrate to a new place. Research has found that retirement is one of three key time points that older adults move. Older adults have different considerations than younger generations, whose primary factors are employment opportunities and wages (Rowles 1986; Litwak and Longino Jr 1987; Uhlenberg 2006). The migration ratio differs by age, especially between older individuals and the working population between 18 and 64 (U.S. Census Bureau 2020). Even within older adults themselves, the migration rate is different between younger (65-74) and aged older adults (75+) as well as intrastate and interstate migrants due to unlike health conditions and other considerations (Clark 1986; Jensen and Deller 2007). The significant increase of the older population indicates a growing demand for long-term care (LTC) services, including medical, social, housekeeping, and rehabilitation services, to improve or maintain older adults' function and health (Walker 2002). Kemper et al. (2006) project that 69% of older adults need some LTC in their lifetime and on average for three years. However, it is unclear how the older adult needed service, such as LTC facilities, affordable housing, geriatricians associated with the migration result. This phenomenon generates questions about where older adults move and what destination characteristics are related to the relocation.

While older adults can enjoy the after-retirement life by aging in place or migration, it is unknown how some places may expose them to risks. Due to their health condition and limited mobility, older adults are more vulnerable to natural hazards such as earthquakes, flooding, and extreme weather than younger adults (Gibson and Hayunga 2006; Barusch 2011; Gamble et al.

2013; Carter et al. 2016). The built environment may also present some risks by inadequate primary care physicians, emergency services, nursing homes, intensive care units, and transportation options (Durazo et al. 2011; Shannon et al. 2015; Daly et al. 2018; Davoodi et al. 2020). There are existing vulnerability indexes for the general population (Cutter et al. 2003; Centers for Disease Control and Prevention 2015; KC et al. 2015). However, to our knowledge, none of them are designed for older adults to consider both the social perspective and the environmental risks that make them more vulnerable. To ensure the healthcare and other services they need and be better prepared for potential risks, it is vital to understand the older adult vulnerability and how the vulnerability varies geographically.

An essential component in older adult vulnerability is the inaccessibility to emergency services. Every second is critical, especially for time-sensitive emergencies, such as heart attacks and strokes (Altus Emergency Centers 2021). In addition, with more extreme weather due to climate change, inaccessibility to emergency services can be life-threatening, particularly for people with limited access to immediate medical care (Mastrangelo et al. 2006; Knowlton et al. 2009). Researchers have investigated healthcare accessibility by using the two-step floating catchment area (2SFCA) method considering the supply, demand, and travel impendence (Radke and Mu 2000; Luo and Wang 2003; Wan et al. 2012; Chen and Clark 2016). However, few have considered the temporal dimension of accessibility to incorporate the changing dynamics. Although researchers acknowledge that the travel duration fluctuation follows some daily and weekly rhythms of urban life (Bimpou and Ferguson 2020). no accessibility study uses time-series concepts and methods to identify the rhythm and changing patterns, including trend and seasonality, from the travel time historical data. It will be beneficial to use state-of-art techniques to find the patterns of travel time fluctuation from historical data and then use them in dynamically measuring accessibility.

1.2 Research Objectives and Questions

The overarching research question of this dissertation is what older adult migration choices and living environments, including vulnerability and accessibility, are in the aging society. To provide better insights for both academics and location administrations, this dissertation dives into more detailed explorations on the following three objectives:

1. Investigation of the association between older adult migration and destination characteristics. The following questions are raised to address this objective:
    a. What are the destination characteristics related to the number of older migrants, and what are the magnitudes?
    b. Do the associations vary by subgroups (intrastate, interstate, younger, and aged) of older migrants?
    c. Are LTC facility beds, affordable housing, and geriatrician availability, which are not commonly considered in migration research, associated with older adult migration?
2. Construction of a vulnerability index tailored to the older population. With this objective, I asked three research questions:
    a. What are the environmental and social risks that make older adults more vulnerable than the general population?
    b. Considering both environmental and social risks, how should a vulnerability index of older adults (VIO) be constructed?

   c. How is the newly proposed VIO different from previous widely used vulnerability indexes?

3. Identification of the time series patterns in the travel time data to emergency services. The following questions are asked:
   a. Using time-series theories and methods, are there any temporal patterns (daily and weekly seasonality and trend) detected from the collected data on travel time to emergency services?
   b. If temporal patterns are detected, are patterns identical across the whole study area?
   c. Using historical data, can temporal patterns be better incorporated into accessibility measures?

1.3 Chapter Organization

This dissertation is organized into three manuscripts to understand older adult migration, vulnerability, and accessibility to address the abovementioned research objectives. The first manuscript (Chapter 2) aims to understand older adult migration patterns and relationships between older migrant subgroups (intrastate, interstate, younger, and aged older migrants) and destination characteristics, including the LTC facilities, affordable housing, geriatrician availability, with the commonly used variables. The second manuscript (Chapter 3) introduces a new construction of vulnerability index tailored for older adults by integrating both environmental and social risks at different levels. Lastly, the third manuscript (Chapter 4) explores the travel time variation between selected pairs of the census tract centroid and the closest emergency services. It further decomposes and identifies temporal patterns, including trend and seasonality, by using time series methods. The first two manuscripts take the state of Georgia as the study area and look at the county-level data. The last one zooms into Atlanta Metropolitan Area and focuses on some representative and sampled census tracts. The last chapter (Chapter 5) summarizes the findings of this dissertation and points towards future research in related areas.

In a nutshell, this dissertation investigates older adult migration, vulnerability, and time-sensitive accessibility to emergency services in the state of Georgia. Bringing new considerations into the related topics presents some findings that may guide future adaptations to the aging society.

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CHAPTER 2

THE RELATIONSHIP BETWEEN OLDER ADULT MIGRATION AND DESTINATION CHARACTERISTICS IN GEORGIA[1]

[1] Zhang X, Mu L, Shannon J (2021) The relationship between older adult migration and destination characteristics in Georgia. Appl Geogr 132:. https://doi.org/10.1016/j.apgeog.2021.102464.
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Abstract

Compared with other age groups, older adult migration patterns are shaped by a distinct set of factors. Intrastate and interstate, as well as younger (65-74) and aged (75+) older migrants, have various drivers and constraints. Past research revealed that moving decisions relate to not only individual factors but also the destination's characteristics, including the climate, amenity, and cost of living. However, previous studies have rarely considered destination characteristics such as long-term care (LTC) facilities, affordable housing, or geriatricians. Focusing on Georgia, US, this study addresses this gap by examining older adult migration by age groups and migration types. We proposed a structure of variables describing six living environment categories of destination counties, and further investigated the relationship between the number of migrants and destination characteristics. We identified geographical patterns of migration and used linear regression and decision tree models to analyze the number of migrants with destination variables. Results indicated four subgroups of older migrants have different high-high clusters in or near the Atlanta region, with similar low-low clusters in South Georgia. Linear regression models quantified the relationship and indicated variables including LTC facility bed and affordable housing availability should be considered in older adult migration analysis. Decision tree models revealed that different variables are associated with certain county groups, such as core Atlanta and rural counties. Lastly, our findings highlighted the variety of variables shaping the migration of older adult subgroups.

Keywords: Older adults; migration; long-term care (LTC); linear regression model; decision tree

2.1 Introduction

Facing the worldwide aging phenomena, the U.S. is projected to double its older population by 2060 compared to 2016 with the proportion increasing from 15.2% to 23.4% (Vespa 2018). It is widely recognized that the older population, or older adults, refers to people aged 65 and over (Clark et al. 1996; Lopez-Jornet et al. 2013) although the definition of "old age" changes over time and space (Harper and Laws 1995). For example, some articles define older adults as 55 (Jensen and Deller 2007), 60 (Dou and Liu 2017), or even 70 years and more (Choi 1996). Moreover, a cross-country study states the age cut-offs of older adults may be different because the life expectancy can be 12 years lower for less developed compared to more developed countries (He et al. 2012). Some states are experiencing a significant rise in older adults. Georgia's older population rose by 44.2% reaching 1.4 million, using 2010 and 2019 5-year American Community Survey (ACS) data (U.S. Census Bureau 2021a). The increasing older population highlights many challenges, such as the caregiver shortage, and opportunities, including more job openings (Clark et al. 1996; Dorfman and Mandich 2016). Constrained by the physical condition, older adults migrate at a lower rate and for distinct reasons compared to workforce generations, whose primary considerations are wage and employment opportunities (Rowles 1986; Uhlenberg 2006). This generates questions about where older adults move to and what aspects of the destination are related to the relocation. These questions are relevant to geography, gerontology, economics, and more. While bridging gaps in academic research, a better understanding of relationships between migration and destination characteristics facilitates local governments, healthcare workers, and business owners to accommodate older adults' needs and boost local economies.

Scholars researching migration look at various aspects of the living environment. Jensen and Deller (2007) examined the older adult migration with measures of demographic, economic, and amenity characteristics. They found warmer weather attracts older migrants and different patterns for the four age groups they used. However, the healthcare aspect was beyond the scope of their study. Dorfman and Mandich (2016) investigated amenity and health access measures and found a positive association between health access measures, such as the per capita nursing homes, and the log of older migrants. Nevertheless, nursing-home beds per capita may be more suitable than facility per capita, and other prevalent non-nursing-home LTC facilities were not considered. Although previous research indicates the higher likelihood of moving to LTC facilities when older adults are in declining health (Patrick 1980; Oswald and Rowles 2006), few studies have exhaustively described the destination living environment with the non-nursing-home LTC facility, affordable housing, and geriatrician availability. Older migration boosts economic growth and creates jobs, especially for rural counties (Jensen and Deller 2007). To attract older adults in different age groups and migration types, it is crucial to understand relationships between the exhaustively described destination and the number of migrants. Moreover, it provides insights into how to accommodate older adults and be age-friendly. It also guides future planning and manage regional impacts of the potential migration flow (Patrick 1980).

This project aims to understand older adult migration patterns and relationships between destination characteristics and older migrant subgroups (intrastate, interstate, younger, and aged older migrants). We proposed a comprehensive structure with novel variables, including the LTC facility, affordable housing, and geriatrician availability, along with commonly used ones. Further, we applied linear regression and decision tree models with this structure to analyze the relationship between the number of migrants and destination variables in Georgia. Previous studies challenged the idea of treating older migrants as a generic group and confirmed that migration relationships vary by age groups and migration types (Clark et al. 1996; Dorfman and Mandich 2016). In this case, we grouped migrants by migration type (intrastate and interstate) and age (younger *(65-74)* and aged *(75+)*), and further analyzed by these four subgroups. The term “migrant” denotes various meanings (Moon 1995). Differentiating from the seasonal migrants (Uhlenberg 2006), we look at migrants who change their residential address to Georgia permanently.

This study contributes to the literature in three ways. First, it expands previous work by proposing a new structure of variables that describes six living environments of destination counties. Specifically, the structure considers variables such as LTC facility, affordable housing, and geriatrician availability, which were rarely included in the past. Second, it provides more evidence upon the differences in migration patterns and relationships among older migrant subgroups using the most recent data of Georgia. This evidence can be viewed as a cornerstone for future older adult research. Lastly, it utilizes both linear regression and decision tree models and presents the similarity and nuanced variations. It implies the potential of decision tree models in geographical research.

2.2 Background

2.2.1 The aging society and the need for long-term care

Unprecedented changes are occurring worldwide as populations age in most countries (National Institute on Aging 2018). The U.S. is one of the fastest aging countries (Mather et al. 2015), and the significant increase of older adults indicates a growing demand for LTC services, including medical, social, housekeeping, rehabilitation services. LTC services meet the need of people with functional limitations, including older adults (Harris-Kojetin et al. 2013), and improve or maintain their health (Walker 2002). Kemper et al. (2006) projected that people turning 65 would need LTC for an average of three years. Studies reiterate that older adults are more likely to relocate to LTC facilities for additional or professional care when in declining health or just aging (Patrick 1980; Oswald and Rowles 2006). In a prototypical three-migration trajectory for people in later life, moving to LTC facilities is the last move (Wiseman 1980; Litwak and Longino Jr 1987; Hays 2002). Older adults even migrate to other countries for personalized and affordable LTC (Bender et al. 2014). The LTC decision shapes how they live: in a nursing home or community-based facility, under intensive care or with independence, and how and when the care is given (Rowe and Kahn 2001). It is indispensable to consider LTC facilities with different care levels in migration research.

2.2.2 Migration

Migrants refer to people who travel away from where they previously resided (Moon 1995). While we always consider the space dimension of migration, the time dimension is also important. Seasonal migrants, also called as “snowbirds” or “sunbirds,” are people who relocate for a season to avoid extreme weather (Hogan and Steinnes 1996; Hundsalz 2002). Another group refers to people who permanently change their residential addresses. An alternative way to classify migrants is location-centered. In-migrants and out-migrants describe people who move into or leave a certain location.

The push-pull and life-course models are widely used to analyze migration. Initialed by Lee (1966), the push-pull model assumes decisions are determined by “push” and “pull” factors between the origin and destination based on spatial disequilibria (de Haas 2010). There are three parts: the push, pull, and difference (Clark et al. 1996). The push depicts origin characteristics motivating migration and the pull depicts destination characteristics attracting migration (Bogue 1969; Moon 1995). Lastly, the difference describes improvements by comparing origin and destination. As Clark et al. (1996) put, it captures the spatial variation in locational attributes. Models can be applied at a micro (disaggregated) level for individuals or macro (aggregated) level for a cohort, such as people in the same age group (Champion et al. 1998). Although the micro model leads to richer individual analysis, the difficulty in obtaining detailed data makes the macro model more common (Champion et al. 1998).

Migration patterns follow a life-course rhythm (Champion et al. 1998) where migration is informed by demands and issues along the life course (Bradley and Longino 2009). Life-course transitions, such as marriage, having children, retirement, fluctuate migration rate (Lee 1966; Moon 1995). Champion et al. (1998) studied British migration flows and concluded migration rate changes over people's age, mirroring the life course. Other researches also supported this idea (Fotheringham et al. 2000; Uhlenberg 2006). Meanwhile, migration is motivated by various reasons, including labor market opportunities, beneficial public policies, and recreational choices (Brettell and Hollifield 2014). Migration determinants include personal factors, such as cultural and demographic aspects, along with locational factors, such as the built, physical, or service environment of the origin and destination (McGranahan 1999). Migration motivations also change along the age spectrum. Compared to the working-age generation who prioritize wages and job opportunities, older adults prioritize other factors. Section 2.3 introduces more details about older adult migration.

2.2.3 Older adult migration

Compared to younger generations, older adults encounter different life-course transitions and have varying considerations. Research reveals that later-life migration is related to destination characteristics, which we summarized into six categories (Table 2.1) and used in this study. *Physical and built environment* factors, such as water area, topographic variation, measure the destination attractiveness to older migrants (McGranahan 1999; Dorfman and Mandich 2016). The importance of the *climatic environment* has been confirmed repeatedly for the U.S. and other countries (Jensen and Deller 2007; Schaffar et al. 2018). Scholars found older adult migration is positively associated with *healthcare* measures, including hospital beds and expenditures (Dorfman and Mandich 2016). Destination's *demographic and socioeconomic* environment, such as the employment rate, older population proportion, and more, also matter (Clark and Ballard 1980; Fotheringham et al. 2000). Studies verify that *recreational and cultural* amenities, such as restaurants, museums, or movie theaters, attract older adults' relocation (Litwak and Longino Jr 1987; Dorfman and Mandich 2016). Lastly, the crime rate, cost of living, which includes tax policies, living expenses, and other *residential* environment factors also play an important role (Clark et al. 1996; Conway and Rork 2016).

Within older migrants, scholars repeatedly found that intrastate versus interstate, younger versus aged older migrants have various aspirations statistically despite different age divisions (Champion et al. 1998; Jensen and Deller 2007). Clark et al. (1996) found the density of noxious facilities decreases the likelihood of interstate migration for people between 65 and 74 while the opposite scenario for 75 and above. For these two groups, magnitudes also differ with variables describing nature, amusement, and others (Jensen and Deller 2007). Aging with chronic health conditions, people are becoming vulnerable and likely to be confined by their mobility level. Research indicates that the younger older, who are healthy, financially secure, and seeking amenities, tend to be interstate migrants, and intrastate movers are those who wish to relocate near relatives (Clark and Wolf 1992; Clark et al. 1996). It shows the necessity to consider older adults in finer subgroups.

It is critical to understand the influencing factors of migration decisions to guide future planning and control the local impacts of migration flows (Wiseman and Roseman 1979; Patrick 1980). Additionally, we need recent studies to evaluate whether previously confirmed variables have changed. Despite a large number of analyses regarding the migration decision, researchers have not yet integrated some important variables, such as the LTC facility bed, affordable housing, and geriatrician availability for a comprehensive understanding of the relationship between older migrants and destination characteristics.

While geographical studies of aging are under-researched in human geography (Skinner et al. 2014), this study aims to understand the geographical pattern of older migration and relationships between older migrant subgroups and destination characteristics. We looked at older adult migration in Georgia with two subgroups by age – younger (65-74) and aged (75+) – and two subgroups by type – intrastate and interstate older migrants. Focusing on non-seasonal migrants who are in-migrants to Georgia counties, we proposed a comprehensive structure that contains 28 variables describing the destination in six categories. The proposed structure embraced newly included variables – affordable housing, geriatrician, and two types of LTC facilities' bed availability – along with commonly used ones. We used linear regression and decision tree models to understand the data from different perspectives.

2.3 Methods

2.3.1 Study area

This research focused on Georgia, which is the sixth fast growth of the older population in the last decade (U.S. Census Bureau 2021a). Georgia seems underprepared with worse access to health care for primary care, dental, and mental health care providers than most states based on the American's Health Rankings report (United Health Foundation 2020). The low ranks of quality of life and healthcare make it the 37th best state to retire (Bernardo 2019) although Georgia cities, such as Athens and Savannah, are among Forbes' best places to retire repeatedly (Barrett 2017; Forbes 2019).

2.3.2 The structure of variables and data processing

In this county-level analysis, dependent variables are numbers of older migrants in each subgroup: intrastate, interstate, younger, and aged older adults. We used the migration data from the ACS 2013-2017 estimation (U.S. Census Bureau 2018). Out of four defined migration types, we looked at two: from different counties within the same state (intrastate) and from a different state (interstate), without considering migration within the same county (local), or from abroad (international). Local migrants compare detailed neighborhood-level living improvement and international migrants are bounded by immigration policies and restrictions (de Haas et al. 2019). Both are out of the scope of this research. Beyond subgroups that differ in migration distance, we considered two age subgroups. Younger older adults generally have better health conditions, higher mobility levels, independence, and the probability of employment while the aged are more vulnerable. For independent variables, we proposed a six-category structure of variables (Table 2.1, with more details in Appendix A) to comprehensively describe the destination county, including the *physical and built* (abbreviated as *P*), *climatic* (*C*), *healthcare* (*H*), *demographic and socioeconomic* (*D*), *recreational and cultural* (*Rec*), and *residential* (*Res*) environments. We considered 28 variables, including the rarely considered LTC facility, affordable housing, and geriatrician availability. Older adults in a nursing-home setting need intense care and are more vulnerable, while non-nursing facilities residents are partially or fully independent. Therefore, we categorized LTC facility bed availability variables into the non-nursing-home LTC facility (H_4) and nursing home (H_5).

Table 2.1 Proposed structure of variables in the older adult migration analysis

Category Abbr.	**Independent variable**
1 Physical and Built Environment	
P_1	Elevation variation (s.d.)
P_2	Water area coverage (%)
P_3	Green space coverage (%)
P_4	Road density
2 Climatic Environment	
C_1	Climate zone
C_2	Proximity to the coastline (in miles)
3 Healthcare Environment	
H_1	Hospital availability*
H_2	Physician availability*
H_3	Geriatrician availability#
H_4	Non-nursing-home LTC facility bed availability#
H_5	Nursing home bed availability#
4 Demographic and Socioeconomic Environment	
D_1	Total population (in 1,000)
D_2	Population density
D_3	Older population proportion (%)
D_4	Racial diversity entropy
D_5	Disability proportion (%)
D_6	Wealthy proportion (%)
D_7	Unemployment rate (%)
D_8	Per capita income (in $1,000)
D_9	Real gross domestic product (GDP) per capita (in $1,000)
5 Recreational and Cultural Environment	
Rec_1	Food services and drinking places*
Rec_2	Arts, entertainment, and recreation amenities*
Rec_3	Religious organizations*
Rec_4	Proximity to university (in miles)
6 Residential environment	
Res_1	Cost of living (index)
Res_2	Affordable housing availability#
Res_3	Crime rate (per 100,000)
Res_4	Rurality (%)

(*: per 1,000 people, #: per 1,000 older adults)

We chose categories and variables based on literature reviews (section 2.3). To diminish the time difference, we used the data that best matched the migration data's time frame and processed the data using R and ArcGIS. Due to limited space in this article, we summarize the data processing process just briefly.

In the healthcare environment, hospital data were processed to exclude some hospital types, such as children, to ensure considered hospitals can be used by older adults. Moreover, LTC facilities (n=2720) were geocoded and categorized into nursing-home LTC facilities (nursing home only), and non-nursing-home LTC facilities (assisted living community, community living arrangements, and personal care home) due to different levels of care and independence of older residents. We then spatially joined counties and facilities and calculated the corresponding bed availability.

Using ACS data (U.S. Census Bureau 2018), we calculated demographic and socioeconomic variables. As defined in the MixedMetro project by Holloway et al. (2012), the racial diversity entropy (D_5) was calculated based on the portion of six racial categories and higher entropy means more racial diversity.

2.3.3 Data analysis

2.3.3.1 Migration pattern analysis and statistical summary

We applied choropleth mapping to show patterns of older migration as a whole and four subgroups. We used three measures: the raw count of migrants, the proportion of older migrants in the local older population (Equation 2.1), and the location quotients (LQ). High proportions of older migrants, the second measure, bring impact or even challenges to destination counties due to inadequate care or services. The third measure, LQ, compares the local second measure to the state average. Furthermore, we used the cluster and outlier analysis (Anselin 1995) to pinpoint high-high clusters needing more attention as older migrants' destinations.

$$proportion = \frac{number\ of\ older\ in\text{-}migrants}{older\ population\ in\ the\ destination\ county} \quad (2.1)$$

To understand the distribution of considered variables, we calculated minimum, maximum, mean, and standard deviation as descriptive statistics for dependent and independent variables.

2.3.3.2 Linear regression analysis

To investigate the relationship between the number of migrants and destination characteristics, we created four models for considered subgroups. Each model had the raw number of older migrants in this subgroup as the dependent variable, and the initial independent variable set included all 28 variables. We first zoomed in to the correlation coefficient between independent and dependent variables, then among independent variables alone. We applied the variance inflation factor (VIF) approach to reduce multicollinearity among independent variables. Large VIF values indicate high degrees of multicollinearity and by using a suggested threshold (VIF=4) (Hair, Joseph F. et al. 2010), the variable set was reduced with acceptable multicollinearity. To achieve better prediction accuracy and model interpretability (James et al. 2013), we further applied stepwise variable selection to all VIF-chosen variables. This step narrowed the variable set to the best-practiced one for subgroups and effectively prevented overfitting. For each model, selected variables fitted the following linear regression model:

$$\text{migrants} = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \cdots + \beta_p * x_p \quad (2.2)$$

where β_0 is the intercept, and β_p is the coefficient for x_p, the p_{th} independent variable.

2.3.3.3 Decision tree analysis

Linear regression analysis demonstrates the numerical relationship, but it had rigorous assumptions, such as linearity and normality. Decision tree analysis, as a widely used data mining technique (Thomas and Galambos 2004), can capture the relationship without strict assumptions on data distribution or format (Tehrany et al. 2013). It provided another perspective to understand data and visualize relations. Decision tree analysis splits the range of a selected independent variable following splitting rules (James et al. 2013). One common rule is the LogWorth statistic, defined as $-log_{10}(p - value)$ (SAS Institute Inc. 2020). A LogWorth bigger than 2 indicates the variable is significant at the 0.01 level and can be included. Based on the biggest LogWorth, each split is conducted at a splitting value and on an independent variable that leads to the most effective binary separation. The splitting creates internal nodes and terminal nodes, or leaves, in the tree structure and maximizes the differences between nodes. Typically, the mean or mode of observations is used to represent the predicted value for the node. Independent variables can be used more than once in the splitting (Rothwell et al. 2008). We split the tree at the optimal splitting point until the LogWorth was smaller than 2 and pruned the worst splits to end up with the best five splits. In JMP, we made the decision tree analysis towards all four subgroups. The raw count of migrants was the response variable, and all 28 independent variables can be splitting factors. The decision tree categorized counties into groups at each node and identified important variables that most differentiated the count of older migrants between nodes. In a nutshell, with better visual interpretability in the hierarchical structure, decision tree analysis categorized counties into groups with different relationships.

The linear model quantifies a numerical relationship with coefficients indicating magnitudes, directions, and significant levels. However, the linear model needs to conduct variable selection based on multicollinearity and then assume an identical relationship to all counties. Conversely, the decision tree approach splits data into nodes without calculating coefficients or removing variables due to multicollinearity. This tree-based model does the binary partition which leads to different relationships for each node. Depending on splitting efficiency, an independent variable can be the splitting variable multiple times. The tree structure illustrates partitions in an easily comprehensible way. The linear model and decision tree are complementary in quantifying one relationship for all counties and differentiating various relationships among counties.

Our research design is introduced in the flowchart (Figure 2.1).

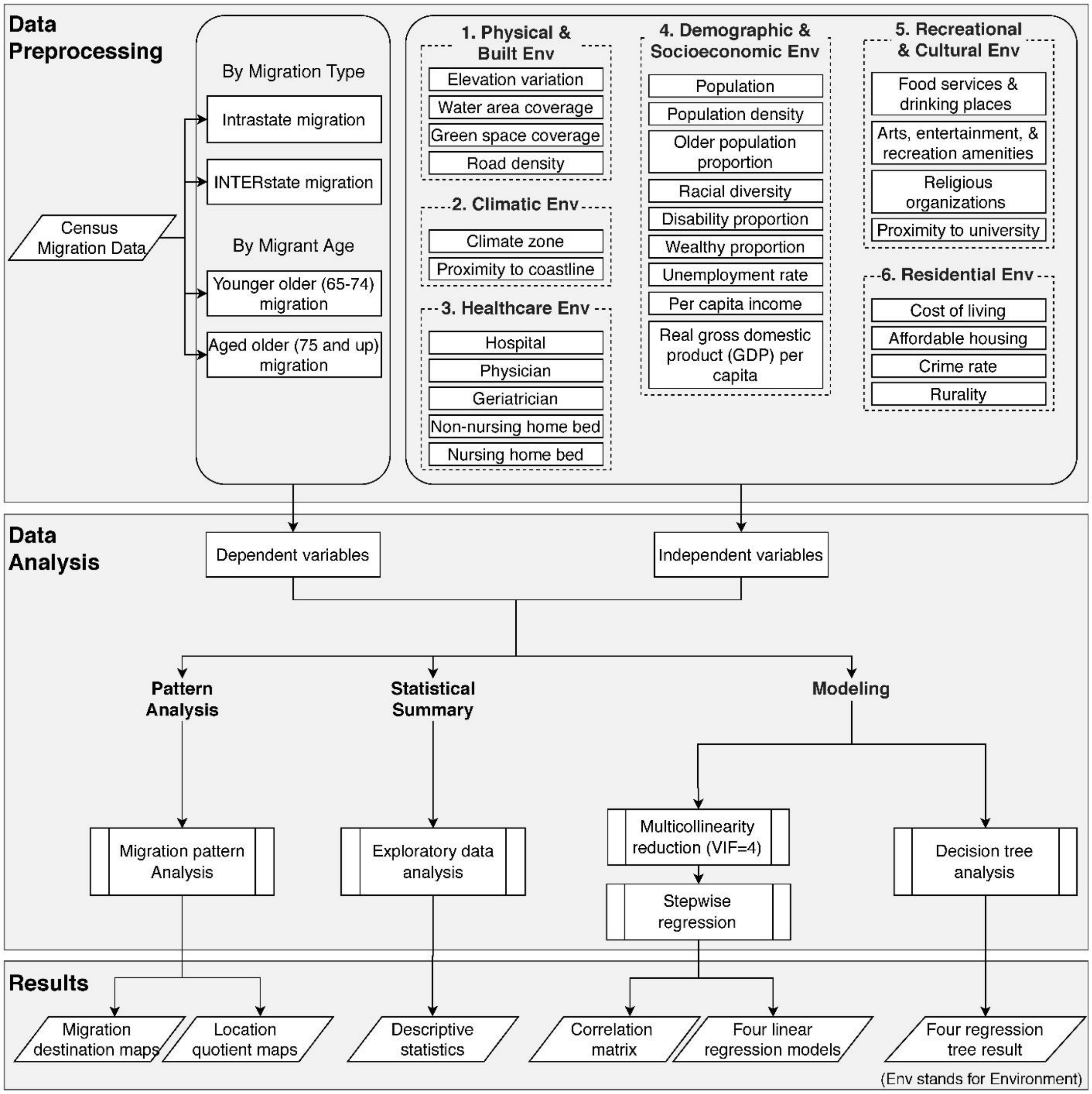

Figure 2.1. Flowchart of research design

2.4 Results

2.4.1 Migration pattern analysis and statistical summary

Figure 2.2 shows maps of older migration by (a-1) the raw count, (b-1) older migrant proportion, (c) LQ of older proportion, and corresponding cluster maps (refers to county names in

Appendix B). Although the core Atlanta region has the highest number of migrants and is a high-high cluster, the older migration may not ripple the local community as much as counties with a high proportion of older migrants (b-1). Counties with high proportions include the fringe of the Atlanta region, especially the northern and southern Atlanta, and coastal Georgia. The LQ map (c) compares the older migrant proportion for a specific county with the statewide average. Counties with bigger than the average value are in pink.

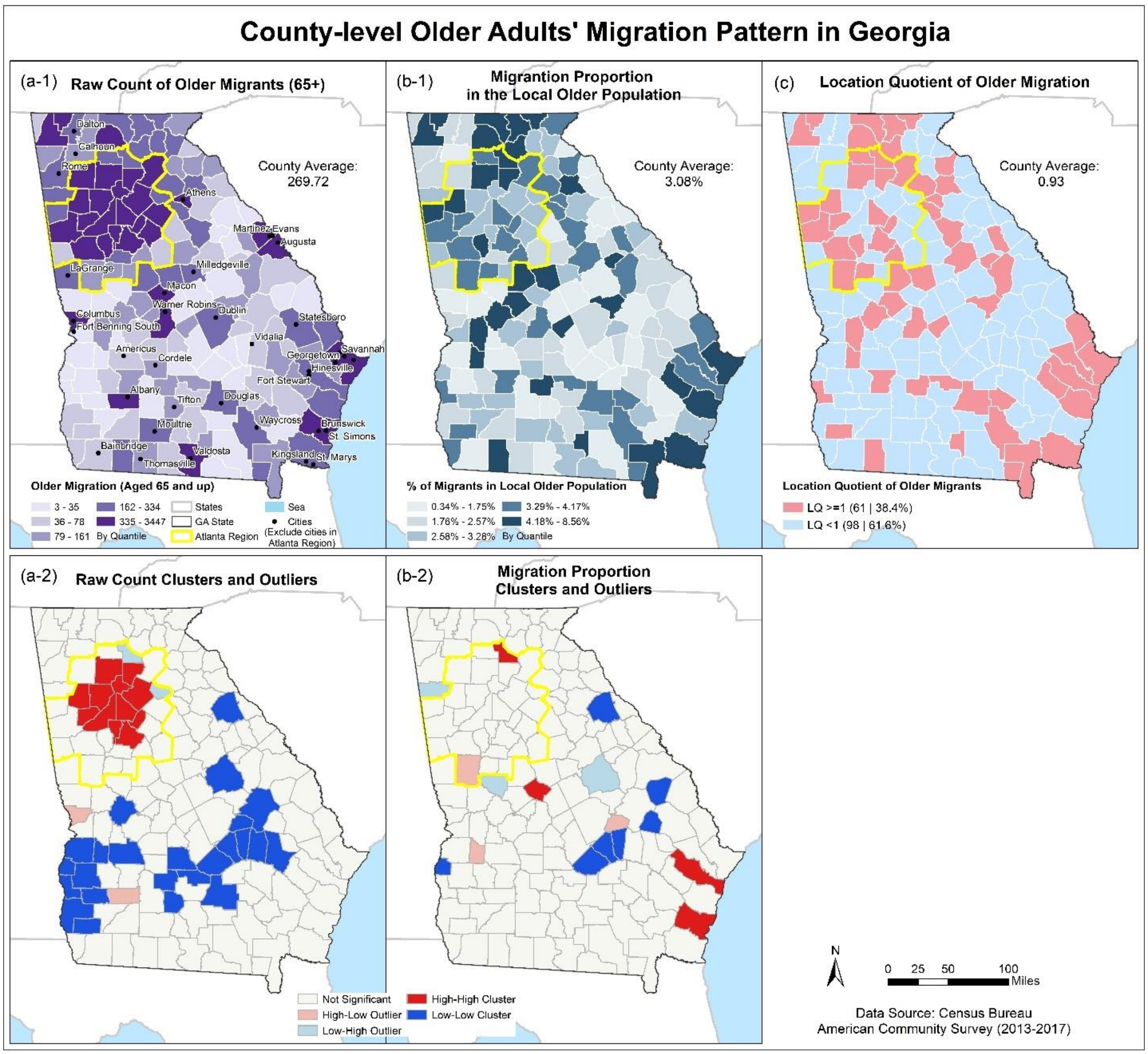

Figure 2.2 Older adult migration patterns

Figure 2.3 shows LQ patterns and clusters for four subgroups. The first-row maps show that 6, 21, 4, and 13 counties do not have intrastate, interstate, younger, or aged older migrants respectively. All of them have different high-high clusters, with similar low-low clusters in the middle part of South Georgia. Most high-value clusters locate in or near the Atlanta region. For example, the intrastate high-high cluster is located at the city of Macon, which is at the fringe of the Atlanta region with a military base. The interstate migration has high LQ clusters near the north state boundary, which is in the Chattahoochee National Forest or near Chattanooga city, the fourth-largest city of Tennessee. In c-2, away from the Atlanta region, younger older adult migration has a cluster in Atkinson County, whose population all live in rural areas, water coverage and racial diversity are above the 75% quantile, and values for most other variables are below the first or second 25% quantile. As for aged older adults (d-2), clusters include Liberty County which is a coastal county in one Metropolitan Statistical Area. Liberty County is near Savannah, which is regarded as one of the best places to retire, and Liberty's water coverage, geriatrician availability, racial diversity, unemployment rate, and GDP are above 75% quantile with only 23.2% of people live in rural areas. Low-low clusters are scattered. The middle low-low clusters all include or near Wheeler County. Wheeler County has an average per-capita-income of $11,192 compared to the national average of $26,040, and it is the third-lowest per-capita-income nationwide according to the 2013-2017 ACS data.

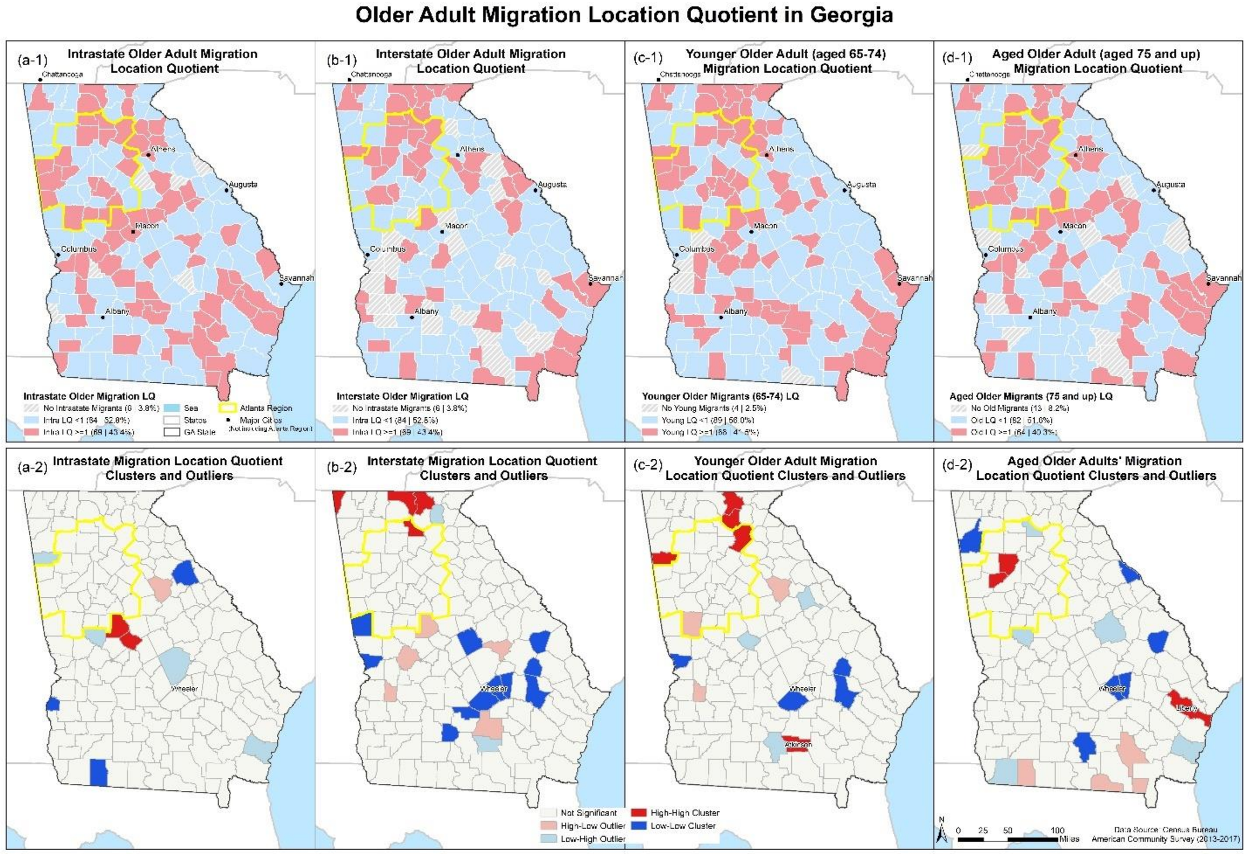

Figure 2.3 Migration pattern and cluster LQ maps

159 Georgia counties had an average total of 42,881 older migrants yearly. 54.11% were intrastate and 45.89% were interstate migrants. Among all, 60.74% were younger and 39.26% were aged older migrants. The summary statistics are in Appendix C.

2.4.2 Linear regression analysis

In the initial variable examination (Appendix D), we found raw counts of migrants are highly correlated [|correlation coefficient| > 0.85] with the total population (D_1) and population density (D_2). Raw counts of migrants are moderately correlated [0.5,0.85] with the road density (P_4), wealthy proportion (D_6), per capita income (D_8), cost of living (Res_1), and rurality (Res_4).

We applied the correlation matrix (Appendix D) to examine the multicollinearity. We set the VIF as 4 to diminish the negative impacts of strong correlation. A subset of 20 variables was derived from the original 28 variables. We further applied the stepwise method to the variable subset. Table 2.2 shows the result of four linear models: (A) intrastate, (B) interstate, (C) younger, and (D) aged older migration with numbers of migrants as dependent variables. We only include variables selected by individual models. For example, model (A) contains H_4, D_1, D_4, D_6, and Res_2 as independent variables for explaining the count of intrastate migrants. Models are statistically significant with different sets of variables at various magnitudes and directions. The aged migration is associated with the least variables, while the interstate is related to the most variables. Except for the recreational and cultural environment, variables from five out of six categories are included in at least one model. The adjusted R-squared ranges from 0.88 to 0.93, meaning that four to six variables explain about 90% of the variation in each model.

Table 2.2 Results of linear regression models

Abbr	Model	A	B	C	D
	Dependent variable	Intrastate	Interstate	Younger	Aged
	Number of included independent variables	5	6	5	4
	Adjusted R^2	0.88	0.91	0.93	0.91
	AIC	1823.21	1780.75	1774.40	1726.00
		Coef sig (S.E.)	Coef sig (S.E.)	Coef sig (S.E.)	Coef sig (S.E.)
	Intercept	3.53 (45.42)	-155.65** (55.27)	-110.28** (25.81)	-165.45** (33.78)
	1 Physical and built environment				
P_1	Elevation variation		0.46* (0.25)	0.55** (0.23)	
P_2	Water area coverage (%)		2.10** (0.51)	1.33** (0.63)	0.95** (0.38)
	2 Climatic environment				
C_1	Climate zone			37.25* (20.12)	
	3 Healthcare environment				
H_4	Non-nursing-home LTC facility bed availability#	0.95 (0.58)			
	4 Demographic and socioeconomic environment				
D_1	Total population (in 1,000)	1.59** (0.07)	1.68** (0.06)	1.81** (0.05)	1.47** (0.05)
D_3	Older population proportion (%)		5.67** (2.14)		3.58** (1.40)
D_4	Racial diversity entropy (*100)	-1.52** (0.72)			
D_5	Disability proportion		-4.65 (2.83)		
D_6	Wealthy proportion (%)	3.65** (0.99)	4.23** (0.96)	4.03** (0.87)	4.15** (0.71)
	6 Residential environment				
Res_2	Affordable housing availability	1.46 (0.91)			

(# : per 1,000 older adults | ** : p<0.05 | * : p<0.1)

We saw interesting findings at both category and variable levels. At the category level, all models are related to the demographic and socioeconomic environment. We further compared intrastate versus interstate, or younger versus aged older migration across models. Intrastate and interstate migrations relate to variables from different categories. Beyond the demographic and socioeconomic, intrastate migration is related to the healthcare environment, while interstate migration is associated with the physical and built environment. Both younger and aged older migration are related to the demographic and socioeconomic environment and the physical and built environment. Moreover, younger older migrants are associated with the climatic environment. The followings are findings at the variable level, given all other variables are fixed.

The physical and built environment: the elevation variation (P_1) is positively related to the number of interstate and younger older migrants at similar magnitudes. Although the water area coverage (P_2) has a positive association in the interstate, younger, and aged older migration models, the association with interstate migration is about twice larger than the younger or aged older. Among 159 counties, a county whose water area coverage (P_2) equals 25.24 (75% quantile) is associated with about 43 more interstate migrants compared with a county whose P_2 equals 4.94 (25% quantile). Such an increase is 34.45% of the average number of interstate migrants.

The climatic environment: the climate zone (C_1) is associated with younger migration. On average, roughly 37 more younger older adults move to a county in the mixed-humid climate zone than to the hot-humid zone where the average number of younger older migrants is 163.81.

The healthcare environment: the non-nursing-home LTC facility bed availability (H_4) is associated with the number of intrastate migrants. Statistically, a county with 28.31 beds per 1,000 older adults (75% quantile) is associated with about 18 more intrastate migrants compared with a county whose H_4 equals 8.86 (25% quantile). Such an increase is 12.66% of the average number of intrastate migrants.

The demographic and socioeconomic environment: all four models are positively associated with the total population (D_1) and wealthy proportion (D_6). An increase of 10,000 people countywide is associated with about 15 to 18 more older migrants in each model when the average of each subgroup is about 106 to 146. When the wealthy proportion (D_6) increases by 10%, there will be 37 to 42 more migrants in each subgroup. The older population proportion (D_3) is positively related to interstate and aged migration. D_3 ranges from 13.83% to 33.62%, and a one percent increase relates to four and six more aged and intrastate migrants. While most coefficients are positive, the racial diversity entropy (D_4) and disability proportion (D_5) are negatively related to intrastate and interstate migrants, respectively.

The residential environment: although not statistically significant, the affordable housing availability (Res_2) is positively related to intrastate migration. A county whose Res_2 equals 5.44 (50% quantile) is associated with about eight more intrastate migrants compared with 100 Georgia counties (62.89%) whose Res_2 equals 0.

2.4.3 Decision tree analysis

Figure 2.4 illustrates the decision trees of four migration subgroups. To describe the node, each node has the average count of migrants and the number of counties in the parentheses. Taking tree (a) as an example, the root node (159 counties with averaging 146 intrastate migrants) is split by the religious organization (Rec_3) at the value of 0.37. The left child node indicates that five counties with a lower value of Rec_3 have a higher mean (1217.6) of migrants than the 154 counties on the right child node. Counties in individual nodes are highlighted in red on the map with the Atlanta region in bold bounding boxes.

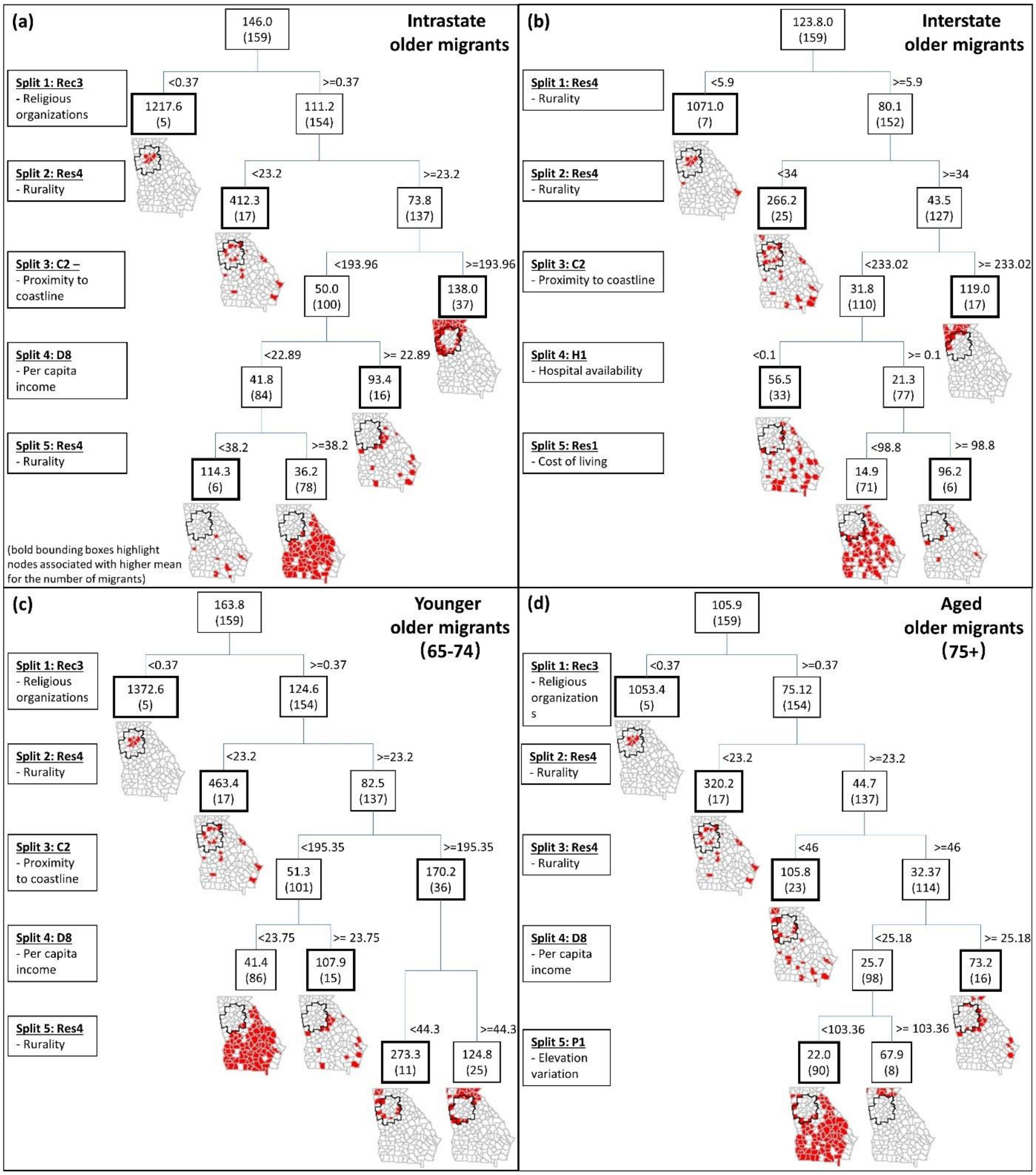

Figure 2.4 Decision trees showing the splitting variables and values

The trees of intrastate and younger migrants are extremely similar. They have the same split variables following the order of religious organizations (Rec_3), rurality (Res_4), proximity to the coastline (C_2), per capita income (D_8), and rurality (Res_4), with similar splitting values.

For individual variables, all trees have rurality (Res_4) which appears twice and indicates that counties with a lower Res_4 relate to more older migrants. Furthermore, three trees have three common splitting variables. The religious organization availability (Rec_3) leads the first split for intrastate, younger, and aged older migrants. This split separates the core Atlanta from the rest of Georgia. Contributing to trees except for the aged one, the proximity to the coastline (C_2) is always the third split separating the northwest part of Georgia, excluding the core Atlanta, from the rest. The further away counties have a higher average of migrants. Those counties are at the outskirt of core Atlanta or neighboring Alabama or Tennessee, some of which are in the Chattahoochee National Forest. For three trees, except for interstate migration, the per capita income (D_8) functions as the fourth split after the rurality (Res_4), religious organization (Rec_3), and for intrastate and young older migrants, proximity to the coastline (C_2). Beyond the abovementioned variables, the cost of living (Res_1) and hospital availability (H_1) appears once in the interstate tree and the elevation variation (P_1) is the last split for the aged older.

To summarize, decision tree models categorized counties into groups in terms of related independent variables. In general, we observed two similar county groups appearing in four trees: the core Atlanta counties (five or seven counties) with an average of 1053.4-1372.6 older migrants from each subgroup, and many rural counties (71-90 counties) in southeast Georgia with average 14.9-41.4 older migrants. The core Atlanta counties are only associated with the religious organizations (Rec_3) in three trees and with the rurality (Res_4) in the interstate tree. Conversely, the large number of rural counties in the further leaf nodes are related to various independent variables for each migrant subgroup.

In the abovementioned decision tree analysis, we excluded the total population (D_1) and population density (D_2). Those two variables dominated the tree for three or four splits which indicated their vital role in determining the number of migrants. To avoid masking other variables' importance, our decision tree was based on the remaining 26 variables.

Results from linear models and decision trees support each other. The total population (D_1) appeared in all linear models and dominated all initial decision trees. Moreover, all linear models had the wealthy proportion (D_6) and three trees had the per capita income (D_8) when they are highly correlated (correlation coefficient=0.92). Linear model and decision tree results provide an additional perspective of the data. Beyond the abovementioned variables and elevation variation (P_1), linear models and decision trees were related to different independent variables. While linear models excluded any recreational and cultural environment variable, religious organization (Rec_3) led the first split for three trees. Additionally, different variables were included despite the same environment categories. For example, among residential environment variables, only the linear model of intrastate migration had affordable housing availability (Res_2) while the rurality (Res_4) appeared twice in all decision trees.

These results demonstrate different views on the data offered by two analysis techniques. Under multiple assumptions, linear models identified the highly significant independent variables and quantified the relationship between independent and dependent variables as coefficients by assuming one relationship worked for all. Meanwhile, non-parametric decision tree models categorized counties into groups that were similar in the association. This categorical perspective of decision trees identified different migration independent variables and relationships for different county groups at each node. Moreover, linear models were based on variable subsets with acceptable multicollinearity while the decision tree models were conducted with the full set of independent variables. With the linear model and decision tree, we understood the data by using parametric and non-parametric methods, treating all counties as a whole and categorizing them into groups, and by using the subset and the full set of independent variables.

To summarize, the linear regression and decision tree models provide different perspectives to interpret the data and, due to varying procedures, they concluded with different sets of variables. In combination, these two approaches offer greater insight into the associations of older migration than either does alone.

2.5 Discussion, Conclusions, and Future Studies

Although most older adults prefer to “age in place” (Wiles et al., 2012), there are interesting questions related to post-retirement migration (Bradley and Longino 2009). This study focused on answering the question about the county-level relationships between the number of older migrants and destination characteristics in six environment categories. As prior researchers, we acknowledged differences among older migrant subgroups, intrastate, interstate, younger (65-74), and aged (75+) older migrants. Beyond commonly used variables in the older migration literature, we proposed a six-category structure of variables to include LTC facility bed, affordable housing, and geriatrician availability, which were rarely considered.

Linear regression and decision tree models provided specific findings as follows. Collectively, results indicate populous and wealthy counties are associated with more migrants in all older subgroups. Separately, two models provide their unique perspectives on older migration in four aspects. First, across linear models, relations between dependent and independent variables are in the same direction consistently and coefficients have similar magnitudes for shared variables, such as total population, and wealthy proportion. Second, linear model results show older subgroups are related to distinct sets of independent variables with the least variables for the aged and most for the interstate. Specifically, more non-nursing home LTC facility bed availability, less racial diversity, and more affordable housing availability are associated with more intrastate migrants. More elevation variation, higher water area coverage, higher older population proportion, and lower disability proportion relate to more interstate migrants. The number of younger migrants is positively related to the elevation variation, water coverage, and climate zone. Counties with higher water area coverage and older population proportion have more aged older migrants. Third, decision trees have variables from all six categories while linear models include variables from five categories (except the recreational and cultural environment). Even for overlapping categories, linear and decision tree models have very different variable sets. Lastly, decision trees delineate different relationships and various independent variable sets for categorized county groups. All subgroups have county groups for the core Atlanta and rural counties in southeast Georgia.

Collectively from these two models, we see the bigger picture of older adult migration in Georgia. First, our proposed structure of variables is suitable to analyze older population migration since decision trees include all categories and linear models include five out of six. Particularly, linear model results show variables such as LTC facility bed and affordable housing availability should be considered in the older migration analysis. Second, although our results echo that intrastate, interstate, younger, and aged older migration are with different relationships, our findings are different from previous studies, which found recreational amenities and hospital access are statistically significant with migration. Third, our study shows linear regression and decision tree models can be used together to offer greater insight into the data. Lastly, four subgroups of older migrants have different high-high clusters, with similar low-low clusters in the middle part of South Georgia. Most of the high-high clusters are in or near the Atlanta region.

Our findings potentially provide insights for policymakers to know how to attract certain types of older migrants in future planning. For example, when the climatic environment or elevation variation cannot be changed, linear regression models indicate more water area coverage is associated with more interstate, younger, and aged older migrants. For intrastate migrants, affordable housing and non-nursing-home LTC facility bed availability are important factors. Decision trees visualized the variable hierarchy and categorized counties into groups with different relationships. This helps policymakers know counties that they can learn from and the variable priority in attracting older migrants. Moreover, to accommodate the high proportion of migration flow, counties at the fringe of the Atlanta region and coastal Georgia may need more attention for older adults' service and amenities.

This study has limitations that can be addressed in future studies. First, due to the size of the study area, the influence of some variables may be hidden. For example, Georgia only has two climate zones. By extending to a larger area, differences between climate zones can be tested. A clearer trend may be revealed when the data includes a higher variation. Similarly, the size of our analysis unit, county, may mask internal variation. Future studies can use smaller units, such as census tracts, or local zoning units, such as Neighborhood Planning Units in Atlanta (Shelton and Poorthuis 2019; Wang et al. 2020a), which are more homogenous in demographics and others. However, the small area estimation problem (Rao and Molina 2015), small number problem (Jones and Moon 1991), modifiable areal unit problem (MAUP) (Kwan 2012), and data availability may be the challenge. Second, this research only looks at destination characteristics to understand the pull side. More analysis can be done with individuals' migration trajectories to examine the push and different parts of the migration. Forth, some variables can be added to embrace micro-level migration analysis. For example, whether their offspring are living nearby (Champion et al. 1998), whether there is a cultural cluster, such as an Asian community with Asian stores and churches, and more. Third, since the destination characteristics, such as older proportion, reflects the cumulative effect of past migration (Clark and Ballard 1980), time series analysis can be used to investigate long-term and dynamic relationships between migration and destination characteristics. Lastly, some diagnoses can be conducted to linear model results when the sample size is bigger. For 159 counties in Georgia, we cannot easily exclude outliers from the diagnosis. Additionally, the decision tree method is highly sensitive to outliers, so enhanced methods, such as boosting and random forest, can be used to increase the liability with a larger sample size.

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CHAPTER 3

OLDER ADULT VULNERABILITY ANALYSIS IN GEORGIA: AN INTEGRATION OF ENVIRONMENTAL AND SOCIAL FACTORS[2]

[2] Zhang X, Mu L, Shannon J To be submitted to Applied Geography.

Abstract

While it is a consensus that older adults are among the most vulnerable populations, there is no vulnerability index specifically for older adults considering both environmental and social considerations. With the rapidly growing older population and more frequent hazards due to climate change, it is vital to understand older adult vulnerability to better prepare, cope with, and mitigate potential risks. Following the idea of the hazards-of-place model of vulnerability, this paper proposed a Vulnerability Index of Older Adults (VIO) for assessing place vulnerability using both environmental and social factors related to older adults as a peer group and as a part of the society at large. Based on the historical hazard events data, service site locations, as well as demographic and socioeconomic data, I measure older adults' vulnerability by quantifying risks from the environment, built environment, peer group, and society. There is some spatial variation of VIO in Georgia, with the most vulnerable counties in the Atlanta Region and near other Georgia cities, such as Savannah, Columbus, and Albany. By using hypothesis testing, I found statistically different levels of vulnerability between rural and urban counties.

Keywords: vulnerability, older adult, risk, accessibility, GIScience

3.1 Introduction

The older population (>= 65) in the U.S. is proliferating, and comparing to 2016 data, it will double its size with increasing proportion by 2060 (Vespa 2018). Older adults, as well as children, are more vulnerable than young adults (Fernandez et al. 2019). For example, more than half of the fatalities in hurricanes, earthquakes, and flooding, are older adults (Gibson and Hayunga 2006; Barusch 2011; Gamble et al. 2013). The direct and indirect consequences of intensified climate change present even more stressors, such as extreme heat, to older adults' vulnerability (Gamble et al. 2013). Due to their relatively frail physical conditions, they are also among the first to be affected by infectious diseases. For instance, they are at the highest risks for severe illness and hospitalization with coronavirus disease 2019 (COVID-19) and take eight out of ten related deaths in the U.S. (CDC 2021). There are multiple vulnerability indexes measuring for specific hazards and populations. However, to our knowledge, no index for older adults considering the risks from the environmental, built environment, peer group, and society level risks. With four out of five older adults having chronic conditions, they need extra assistance outside their household during and after a disaster (Aldrich and Benson 2008). Understanding older adult vulnerability can guide hazard preparation, management, and mitigation at different levels.

Following the same vein of the widely used hazards-of-place model (Cutter et al. 2003), this paper introduces a Vulnerability Index of Older Adults (VIO) to assess their place vulnerability as an integration of potential risks and societal resilience using both environmental and social factors. I used historical hazard event records, various types of service sites, and demographic and socioeconomic data to measure the different perspectives of older adult vulnerability. The proposed VIO synthesized all considered factors and was visualized to capture the spatial variation.

This analysis was designed to strengthen the understanding of older adult vulnerability and its contributing factors through the combination of both environmental and social risks.

3.2 Background

3.2.1 Vulnerability

Vulnerability measures the potential for loss (Cutter 1996) which varies geographically, over time, and among different social groups (Cutter et al. 2003; Smith 2003). A population's vulnerability level not only depends on proximity to potential hazard sources but also relates to social factors that contribute to greater vulnerability (Cutter et al. 2003). The hazards-of-place model is a classic model in the domain. Cutter and Solecki (1989) proposed their initial hazards-of-place model by following the fundamental concept from the original work of Hewitt and Burton on the hazardousness of places (1971). Then the hazards-of-place model (Figure 3.1) (Cutter 1996; Cutter et al. 2003) was refined based on other literature. In the words of Cutter et al. (2003), risk (measures of the likelihood of a hazard event) interacts with mitigation (measures to lessen risks or reduce their impact) to produce the hazard potential. The hazard potential is moderated or enhanced by a geographic context and the social fabric of the place. The geographic context mainly considers the proximity to the natural hazards, incident frequency or probability, magnitude, and more (Cutter 1996). More than the community's experience and perceptions of hazards, the social fabric includes the community's ability to cope with, recover from, and adapt to hazards, which are influenced by socioeconomic, built environment infrastructure, and other characteristics. The biophysical and social vulnerabilities interact to produce the overall place vulnerability. To assess the place vulnerability, this study adapted the biophysical and social vulnerability. The biophysical portion was renamed as environmental vulnerability to distinguish from the biophysics and refer to the natural environmental aspect of the place.

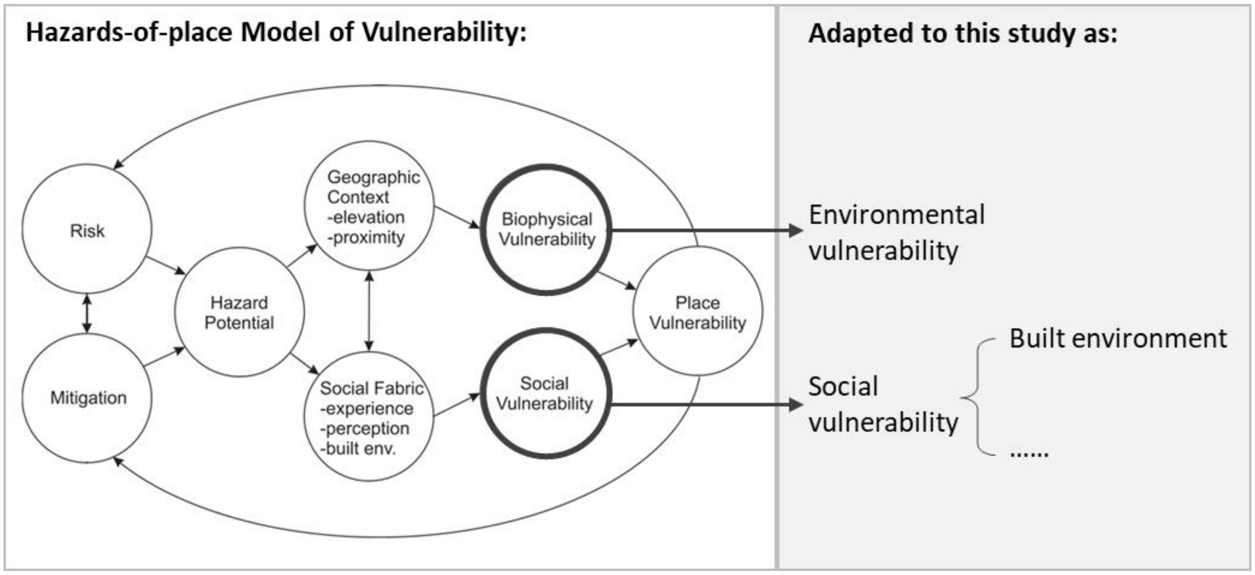

Figure 3.1 Adapted Parts from the Hazards-of-place Model of Vulnerability (Cutter et al. 2003)[3]

Social vulnerability defines the susceptibility to potential losses from hazard events or resistance and resilience to hazards of social groups or the whole society (Cutter et al. 2000). Cutter et al. (2003) stated that social vulnerability is partially the product of social inequalities, which influence people's susceptibility and their ability to deal with hazards. They also pointed out that social vulnerability also includes place inequalities, such as the characteristics of the communities and the built environment. Andrew and Keefe (2014) further applied the social ecology framework to social vulnerability. They illustrated it with seven spheres across levels from individuals, family and friends, peer groups, institutions, neighborhoods and community, to the society at large. This structure provides a different perspective to understand social vulnerability from various scales. I am particularly interested in the spheres of peer group, neighborhoods & community, and society at large. By merging the neighborhood & community and society at large into one group called society, I analyzed two levels - peer group and society (Figure 3.2).

[3] With permission of the Journal Social Science Quarterly

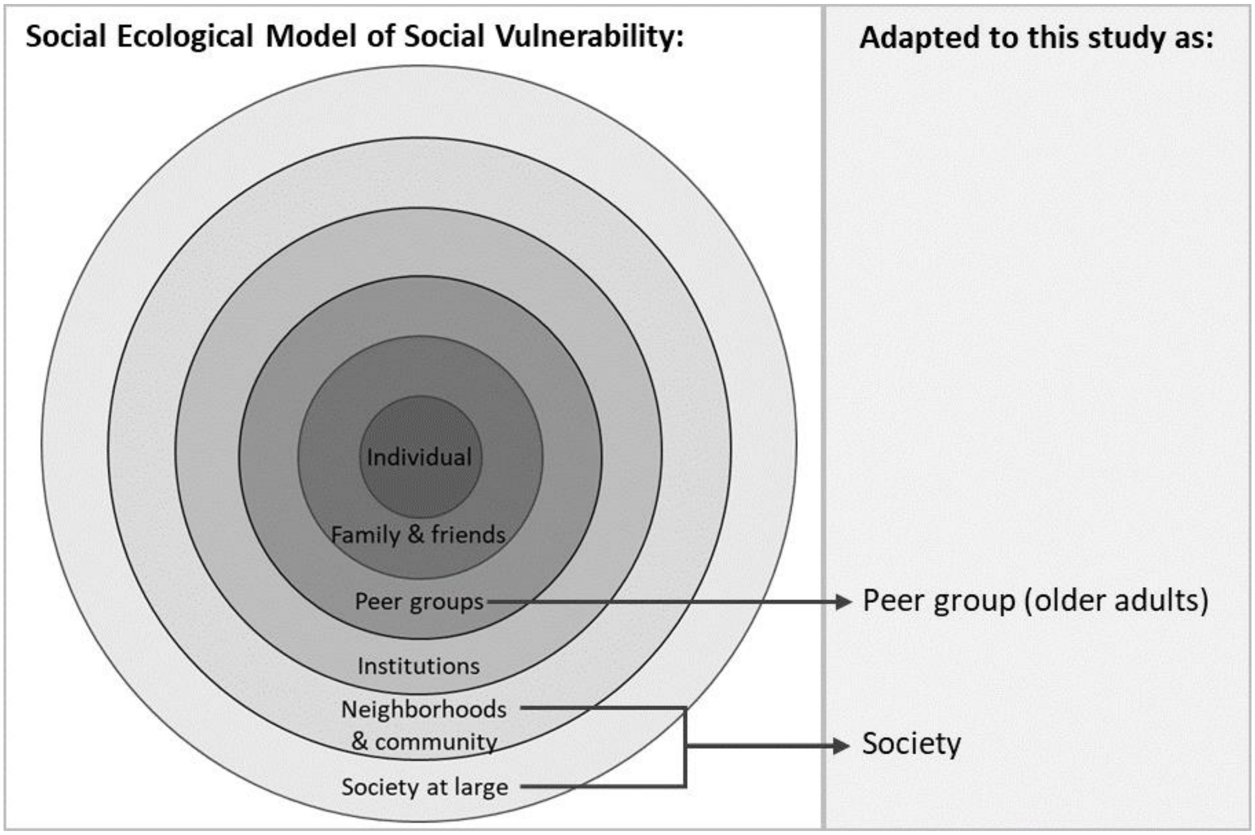

Figure 3.2 Adapted Parts from the Social Ecological Model of Social Vulnerability (modified from (Andrew and Keefe 2014))

3.2.2 Measuring vulnerability

Scholars measure vulnerability for specific locations, different subgroups, and/or specific hazards in mind. Cutter et al. (2000) integrated environmental and social indicators into a vulnerability index and took Georgetown County, South Carolina as a case study. Focusing on children younger than 18-year-old, researchers examined children's vulnerability in disasters from psychological, physical, and educational aspects. A group of scholars investigated flood vulnerability and assessed the vulnerability of different age groups (Lee and Vink 2015). Looking at air pollution vulnerability, Makri and Stilianakis (2008) examined past publications to identify related population characteristics. Reid et al. (2009) propose a heat-related vulnerability index that includes specific variables such as vegetation coverage, and percent households without any air conditioning. Some researchers looked at climate change vulnerability by combining climatic, social, land cover, and hydrological components together as an overall index (KC et al. 2015).

While studies may have different emphases, two widely acknowledged vulnerability indexes, SoVI by Dr. Cutter and her colleagues and SVI by the U.S. Centers for Disease Control and Prevention (CDC), stand for the same name - Social Vulnerability Index. Both focus on the social half of vulnerability. SoVI is a publicly available tool for assessing social vulnerability based on the socioeconomic and demographic profile (Cutter and Finch 2008). SoVI was initially developed in 1996 (Cutter 1996; Cutter et al. 2003). Currently, the data are compiled and processed by the Hazards and Vulnerability Research Institute at the University of South Carolina ([CSL STYLE ERROR: reference with no printed form.]; Cutter 1996; Cutter et al. 2003). Using the five-year American Community Survey (ACS) data, the index synthesizes a few dozen (29 to 41) socioeconomic variables and applied principal component analysis to capture the major components, such as age, gender, race, and more. It measures the social vulnerability to environmental hazards at the county level for the general population (Hazards & Vulnerability Research Institute 2013).

Another widely used vulnerability measure is CDC's SVI, which is developed by the Geospatial Research, Analysis, & Services Program (GRASP) and Agency for Toxic Substances and Disease Registry (ATSDR) (Flanagan et al. 2011). SVI refers to the resilience of communities when confronted by external stresses such as natural or human-caused disasters, or disease outbreaks. Using census data at the tract level, SVI includes 15 variables, which fit into four themes: socioeconomic status, household composition & disability, minority status & language, and housing & transportation. Methodologically, it generates percentile rank among all census tracts/counties from zero to one for individual variables, four themes, and eventually, the overall vulnerability based on five-year ACS data (Centers for Disease Control and Prevention 2020). The higher the ranks, the more vulnerable. This index has been used to map the vulnerabilities within communities, understand adult physical inactivity, study hazard mitigation planning, and more at different levels (Horney et al. 2014; An and Xiang 2015; Gay et al. 2016; Lue et al. 2017; Tarling 2017).

Both indexes focus on social vulnerability with the majority or all variables from ACS data. While they are very efficient to apply to large-scale analysis, such as for the whole country or region, the environmental vulnerability is out of the scope of their investigation. Describing the likelihood of exposure, environmental vulnerability refers to the physical attributes of hazards and the environment (Hazards & Vulnerability Research Institute; Cutter 1996). The difficulty lies in that variables related to environmental vulnerability are not always available and ready to use for large-scale analysis. Assessing environmental vulnerability involves data collection, preprocessing (term matching, geocoding, etc.), and calculation. Despite that, it is vital, especially for older adults who are among the most vulnerable populations, to understand and quantify environmental vulnerability along with social vulnerability to prepare for potential hazards. There is a need for a place vulnerability index for older adults to capture the whole picture of vulnerability considering the risks related to environmental and built environment factors.

3.2.3 Older adult vulnerability

Vulnerability is highly associated with disadvantages (Joseph and Cloutier-Fisher 2005). As Cutter et al. put it (2000), "special needs" locations or populations require some extra consideration for hazard and emergency response to ensure safety. Older adults are more affected by disasters than the general population in the middle of the age spectrum due to mobility, diminished sensory awareness, and other limitations (Cutter et al. 2000, 2003; Barusch 2011; Fernandez et al. 2019).

In addition, older adults will be more vulnerable and have increased risks, in nutrition, mobility, and more while getting older, and will have limited regenerative abilities and become more susceptible to disease, syndromes, and sickness than younger adults (Slaets 2006; Lopez-Jornet et al. 2013). The older population is more susceptible to disease and disability (World Health Organization). Moreover, living in some areas may make them even more vulnerable to reaching specific resources, such as health care facilities (Joseph and Cloutier-Fisher 2005) or facing emergency cases such as natural hazards.

Disasters of all kinds disproportionately affect older adults, especially those that require extra assistance (Aldrich 2007). Moreover, some socioeconomic and psychological factors, such as less stable financial status and increased social isolation, also contribute to their vulnerability (Gamble et al. 2013). Since 80% of older adults have chronic conditions, they need extra assistance outside their household during and after a disaster (Aldrich and Benson 2008). In Japan's earthquake and the following tsunami, about two-thirds of the deaths were people aged over 60 years (Barusch 2011). In the New Orleans area, the U.S., almost three-quarters of Hurricane Katrina-related deaths were among people aged 60 and over, although they comprised only 15 percent of the local population (Gibson and Hayunga 2006). Researchers found the dispositional death among the decedents in the Alabama tornado outbreak as well. 34% were older adults, while the older population was only 13% of the general population (Chiu et al. 2013). In summary, older adults are a special-needs population and specific strategies are needed to meet their needs during an emergency (Aldrich 2007).

Compared to 2016, the U.S. is predicted to double its older population with an increasing proportion by 2060 (Vespa 2018). Understanding older adult vulnerability helps us better prepare for potential emergencies and hazards, especially the ones related to climate change. I identified factors contributing to environmental and social vulnerability specifically related to older adult vulnerability based on the literature. The structure consists of four categories (A. Environmental risks, B. built environment risks, C. peer-group risks, and D. society risks). The environmental and built environment categories refer to the sources of vulnerability, and the peer group category depicts the vulnerable populations in the older population. The remaining society risks describe the vulnerable populations from the whole population. Vulnerability can also be considered as a function of sensitivity, exposure, and adaptive capacity (resilience) (Gamble et al. 2013; KC et al. 2015). From this perspective, the environmental and built environment factors are focusing on hazard exposure. Peer group and society factors are for the sensitivity and adaptive capacity.

3.2.3.1 Environmental risks

Older adults are more vulnerable to a range of weather-related hazards such as heat waves, cold periods, flooding, hurricane, air pollution, and more. Weather- and climate-related programs identify older adults as vulnerable to climate change stressors (U.S. Climate Change Science Program 2008; U.S. Global Change Research Program 2009; Gamble et al. 2013). Older adults are among the most vulnerable in the general population to weather-related disasters' direct and indirect impacts (Pekovic et al. 2007).

Compared to young adults, older adults are also more vulnerable to storm and flood-related events due to impaired mobility and pre-existing health conditions (Aldrich and Benson 2008). For example, a study in the Philippines found that people aged 70 showed a remarkably high number of flood fatalities than their proportional population size. In the U.S., among the flooding-related fatalities after Hurricane Katrina, nearly 60% were older adults (Jonkman et al. 2009; Gamble et al. 2013). A similar situation happened for a tornado in China, with more than half of the injuries and about 64% of the deaths occurred to older adults (Wang et al. 2017).

Extreme cold or hot weather also strikes older adults the most. Using the 1968-1994 data, researchers found that half of the heat-stroke death cases occurred in the 4-year-old-and-under and over-70-year-old age group (Nakai et al. 1999). Hajat et al. (2007) used the mortality data between 1993 and 2003 for all ages with the weather data and concluded that older adults were most vulnerable to both hot and cold weather. Based on the CDC report on 2006-2010 weather events, the cold- and the heat-related death rate of older adults was higher than other age groups, especially for the people >= 75-year-old (Berko et al. 2014). A review about how heatwave impacts in the older population indicated that studies have consistently reported increases in cardiovascular and respiratory mortality during hot days and heatwaves (Åströma et al. 2011).

The risk of wildfires increases after drought (Cannon and DeGraff 2009), and older adults are more sensitive and at risk from wildfire smoke (U.S. Environmental Protection Agency (EPA) 2020; Center for Disease Control and Prevention 2021). National Academies of Sciences, Engineering, and Medicine (2020) also pointed out that the older population, along with the migrant population and others, are especially vulnerable to wildfires.

There is also a group of researchers looking at how air toxics affects older adults. Controlling for the season, weather, and other factors, Saldiva et al. (1995) found a solid association between the increase in respirable particles and the mortality cases of older adults. Moreover, some results suggested that air pollution has significant associations with older adult cardiovascular hospital admissions, even when the air pollution concentrations are below the health guidelines (Barnett et al. 2006). Studies found that the air pollution particles, such as particulate matter 10 micrometers or less in diameter (PM_{10}) and particulate matter 2.5 micrometers or less in diameter ($PM_{2.5}$), have decreased heart rate variability, which may further lead to mortality risk in the older adults (Tsuji et al. 1994; Devlin et al. 2003).

There is a consensus about some major factors contributing to social vulnerability (National Research Council 2001; Cutter et al. 2003). These include lack of access to resources, frail and physically limited individuals, and the type and density of infrastructure and lifelines. Here I categorize social vulnerability as the built environment risks to quantifying the lack of access to resources, and social risks influencing other peer groups and society at large.

3.2.3.2 Built environment risks

The built environment risk was often overlooked in past research despite their importance. Emergency service inaccessibility can have severe consequences. For example, some stressors can rapidly become life-threatening, and the situation can be especially dangerous for people with limited access to immediate medical resources (McLeod 2000; Knowlton et al. 2009). People with severe symptoms, such as stroke, have little time to seek treatment from emergency services, and older adults are at most significant risk for their preconditions and hazards such as heat waves (Knowlton et al. 2009).

The primary care physicians (PCPs) that older adults can visit are physicians whose specialties are in family medicine, general practice, geriatric medicine, and internal medicine. Researchers found that higher geographic access to PCPs is related to lower rates of potentially avoidable hospitalization of older adults (Daly et al. 2018). Some studies have projected a large shortage of PCPs with the increasing aging population and the waning interests in primary care in US medical school graduates (Colwill et al. 2008; Chang et al. 2011). While the PCP per 100,000 population is 39.8 in rural areas, the PCP-to-people ratio is as high as 53.3 in large central metropolitan areas (Hing and Hsiao 2014). This spatial disparity of PCP presents rural older adults with barriers to obtaining medical care (Nemet and Bailey 2000). Moreover, compared to urban PCPs, their rural counterparts are expected to more various care even though they are paid less by Medicare (Rosenthal and Fox 2000). This may intensify the PCP accessibility disparity in the future.

Studies have found that many rural communities have a dearth of grocery stores due to low population density (Durazo et al. 2011). Food insecurity in older adults is related to not only their economic circumstances and functional limitations but also the physical and social environment (Carter et al. 2014; Shannon et al. 2015).

For both urban and rural low-income older adults, access to transportation is a challenge (Durazo et al. 2011). Transportation availability has been a major determinant of accessibility, particularly to specialty care (Rosenthal and Fox 2000). Driving a personal vehicle is the preferred method for older adults, but when driving is not feasible, there is a demand to meet the transportation needs, especially for the suburban and rural areas (Georgia Health Policy Center 2018; Dickerson et al. 2019). For these areas, many older adults lack alternative forms of transportation other than driving (Georgia Health Policy Center 2018). Although older adults usually prefer to age in place, in the same homes and communities as they age (Durazo et al. 2011), the transportation issue is among the five major risks of taking this route (Butas 2018).

While previous vulnerability literature rarely touches on the accessibility of intensive care units (ICU), nursing homes, or affordable housing in older vulnerability, they are important in older adults' lives regarding receiving timely and long-term health care and housing. In a review article of COVID-19 effects, researchers pointed out that rural communities, whose older populations are predominant, are especially vulnerable to poor outcomes due to lacking ICU capacity (Davoodi et al. 2020). Hames et al. (2017) have investigated the older population's medical vulnerability, driven by the availability of nursing home beds. In a housing report, López

(2017) noted that on average, older adults spend more than one-third of their income on housing, and creating more affordable housing can mitigate the situation.

Following the ecological model of social vulnerability (Andrew and Keefe 2014), I also assess older adult vulnerability from peer group and society levels.

3.2.3.3 Peer group risks

The peer group risks look at the group of older adults, and the following three factors are the proportion of the older population that would need extra assistance due to even higher vulnerability than the rest in their group. As a cause of death, Alzheimer's disease and related dementia (ADRD) have increased substantially over time (Uhlenberg 2009), with an 89% increase between 2000 and 2004 (Alzheimer's Association 2017). A report by the American Association of Retired Persons (AARP) stated that 10 percent of American older adults, or 4.5 million, are with dementia and would need to be paid more attention to their needs in evacuation (Gibson and Hayunga 2006). It also pointed out that living alone and not speaking English would make older adults even more vulnerable, for both evacuation and medical treatment. Living alone in later life is also associated with higher risks of falling, lower physical activity, poorer diet, and more (Kharicha et al. 2007). A longitudinal aging study in Singapore found that living alone was associated with a higher mortality rate, independent of health, marital, and other variables (Ng et al. 2015).

3.2.3.4 Society risks

From a higher level of community and the society at large, less attention and resources can be allocated to older adults if other populations need extra assistance. I looked at various factors that past literature justified the association with vulnerability. In emergency preparedness literature, the special need population refers to people with disabilities, minority groups, children, older persons, and those who do not speak English (Cutter et al. 2003; Gibson and Hayunga 2006). Beyond that, KC et al. (2015) also found that female-headed households, poverty, unemployment, education, among others, play an important role in the sensitivity and resilience of the population. Previous vulnerability literature also used the abovementioned variables and referred to some of them as social dependence (Cutter et al. 2000). When responding to an emergency, families with disabled members, either physically or mentally, are likely facing greater obstacles and more vulnerable to hazards (Morrow 1999; Flanagan et al. 2011). In addition, households without a vehicle are also among the at-risk groups, and identifying them ahead of time can help plan more effective evacuation in an emergency (Centers for Disease Control and Prevention 2015).

Despite a burgeoning body of vulnerability assessment and analysis, to our knowledge, there lacks a vulnerability index specifically for older adults that consider not only the social side of the place vulnerability using socioeconomic data, but also the built environment and environmental risks. While the social vulnerability part is essential in evaluating the resilience to potential hazards, environmental and built environment risks present the potential exposure of hazards. Moreover, environmental risks should consider historical hazard events, including flooding, heat wave, extreme cold, and more, which older adults are susceptible to. For the built environment, some service sites are vital to older adults, and inaccessibility may lead to a dangerous situation. As for the peer group risks, the prevalence of ADRD, living alone, and not speaking English are posing the older adult group with more needs. For the whole society, the proportion of children, minorities, poverty, and more, also influences the allocation of resources. A general vulnerability index may not mirror the risk scenario that older adults will encounter. Following the same vein of the Hazard-of-Place model and the ecological model of social vulnerability, this paper assesses older adult place vulnerability using both environmental and social indicators as an integration of potential exposures and societal resilience (Cutter et al. 2003). Our proposed Vulnerability Index of Older adults (VIO) was further used to analyze the state of Georgia. The spatial variations of VIO and the underlying categories were visualized using GIScience, a handy analysis and mapping science.

3.3 Methods

3.3.1 Study area

This study focuses on Georgia, whose older adults make up 13.5% of the state's population compared to 15.7% for the whole U.S. (U.S. Census Bureau 2021a). There are 39.8% of the non-white population in Georgia which ranked as the fourth state with the most minority proportion after Hawaii, Maryland, and Mississippi (U.S. Census Bureau 2021b). With a 13.3% poverty rate, Georgia ranked as the fifteenth among all the states (U.S. Census Bureau 2021c). The following considerations drove the selection. First, Georgia's older population rose by 44.2% reaching 1.4 million, comparing 2010 and 2019 five-year American Community Survey (ACS) data (U.S. Census Bureau 2021a). Second, a national report indicates Georgia's overall older adult health ranks 41st among 50 states. It is the third from the bottom from the community and environment perspective, considering the nursing home quality, poverty, and food insecurity (America's Health Rankings 2019). Third, Georgia has been exposed to several types of natural hazards historically, including floods, hurricanes, extreme cold, and wildfires. Lastly, it is diverse in its social structure and service site distribution across the state.

3.3.2 Data and preprocessing

The considered categories and factors are listed in Table 3.1. To minimize the impact of outliers and scale the data into comparable ranges, I calculated standardized variates, or z-score (with mean as zero and variance as a unit) (Borden et al. 2007) for each variable. Then the average z-score was calculated for each category. I will briefly introduce how the data was processed. The environmental risks were derived from NOAA Storm Events Database. I first selected events that have been identified to make older adults more vulnerable and used the record from 2010-2019 to obtain a decade-long event profile. The details of considered hazards are listed in Appendix E, and a full description can be retrieved from the original data instruction. Then for each event type that occurred in Georgia, the sum occurrence was calculated at the county level. The event types were categorized into four groups: storm/flood-, cold-, heat-, and drought-related. I calculated the z-score for each event type and calculated the mean z-score to represent the summarized occurrence for each event group. The air toxics risk was also scaled to a z-score from the original respiratory hazard index, which summarizes health risks posed by air toxics from fires, biogenics, mobile, and more (U.S. Environmental Protection Agency (EPA) 2018).

Table 3.1 Considered Categories and Factors

Category Factor	Factor definition
A. Environmental risks	
Storm/flood-related risk	Occurrence of a flash flood, flood, heavy rain, hurricane (typhoon), tornado, tropical storm
Cold-related risk	Occurrence of cold/wind chill, extreme cold/wind chill, frost/freeze, hail, heavy snow, ice storm, winter storm, winter weather
Heat-related risk	Occurrence of excessive heat, heat
Drought-related risk	Occurrence of drought, wildfire
Air toxics risk	Respiratory hazard index
B. Built environment risks	
Emergency service inaccessibility	Inaccessibility to hospitals with emergency services (with overall rating)
PCP (taking Medicare) inaccessibility	Inaccessibility to primary care physicians (family medicine, general practice, geriatric medicine, and internal medicine) who take Medicare
Nursing home inaccessibility	Inaccessibility to nursing homes (with number of beds)
ICU bed inaccessibility	Inaccessibility to hospitals with ICU beds (with number of total beds and ICU beds)
Supermarket inaccessibility	Inaccessibility to supermarkets
Affordable housing inaccessibility	Inaccessibility to affordable housing (with capacity)
Public transit availability	Without public transit
C. Peer group risks	
ADRD prevalence in older adults	The percentage of ADRD patients among 65 years and older
Non-English speaking in older adults	The percentage of older adults who speak English not well or not at all
Living alone in older adults	The percentage of older adults who live alone by county
D. Society risks	
Age group < 18	The percentage of adults who are <18
Age group >= 65	The percentage of adults who are > =65

Racial/ethnic minorities	The percentage of the nonwhite population
Female householder	The percentage of the female householder
Education	The percentage of population less than high school graduate
Poverty	The percentage of adults who are under the poverty line
Unemployment	The percentage of adults who are unemployed
Disability	The percentage of adults who are disabled
No vehicle ownership	The percentage of adults who have no vehicle

Since the factors in built-environment risks consider services sites within a catchment area, I collected services site data in Georgia and surrounding states, including South Carolina, North Carolina, Tennessee, Alabama, and Florida. For the emergency service data, I used the hospital dataset, which includes all hospitals that have been registered with Medicare (Centers for Medicare & Medicaid Services (CMS) 2020a). I excluded hospitals that do not have emergency services or ordinary older adults cannot visit, such as children's hospitals or hospitals operated by the Department of Defense. The data has an overall rating column which can be used as attractiveness in further accessibility measures. As some hospitals do not have the rating value, I used the median value of the overall rating of Georgia hospitals to fill the missing value. For the physician dataset (Centers for Medicare & Medicaid Services (CMS) 2020b), I processed the data into a subset of physicians who take Medicare and specialize in family medicine, general practice, geriatric medicine, and internal medicine. The ICU data came from the CovidCareMap team, who compiled data from various sources, including CMS Healthcare Cost Report Information System, Florida Agency for Health Care Administration, and others (Su et al. 2020). The data also includes capacity, such as total beds and ICU beds. The nursing home data was compiled using CMS COVID-19 Nursing home dataset and GaMap2Care with the capacity information (Centers for Medicare & Medicaid Services (CMS) 2020c; Georgia Department of Community Health 2020). The supermarket data was preprocessed from the Supplemental Nutrition Assistance Program (SNAP) Retailers Database (Shannon et al. 2018a), based on the USDA listing of authorized retailers. I obtained the affordable housing data from the U.S. Department of Housing and Urban

Development (2010). Lastly, the public transit availability was processed from a statewide transit plan by the Georgia Department of Transportation (2019). Most of the data were in tabular format and were geocoded using ESRI ArcGIS 10.6.

As for the factors in the peer group and society categories, most of the variables were obtained from ACS 2014-2018 data (U.S. Census Bureau 2020) using Census Data Application Programming Interface (U.S. Census Bureau 2017), R 4.0.1, and RStudio 1.3. The county-level Alzheimer's disease or related dementia (ADRD) data was requested from the Georgia Department of Public Health (2021). The collected data were further normalized using the scale function using Python 3.8 in Jupyter Notebook.

3.3.3 Methods

As mentioned above, the environmental, peer group, and society's social risks were all represented using z-scores. Accessibility was measured using the 2-step floating catchment area (2SFCA), which considers both the supply of the service site and the demand of the population (Radke and Mu 2000; Luo and Wang 2003). It involves two steps. The first is finding all population locations within a threshold travel time/distance, catchment, for each service site location, computing the site-to-population ratio. The second step finds all the sites within the catchment and sums up the site-to-population ratios for each population location. This method has been enhanced by different approaches, including using variable catchment sizes and different weighting for catchment subzones (Luo and Qi 2009; Schuurman et al. 2010; Luo and Whippo 2012; Wan et al. 2012). Based on the abovementioned literature, Luo (2014) proposed a three-step floating catchment method by integrating the Huff model, which quantifies the probability of people's selection on a service site out of multiple available options based on both travel cost and capacity/attractiveness (Huff 1964). The proposed method by Luo applies the negative power distance impedance function continuously within the catchment, and therefore the effects of arbitrarily defined subzones can be avoided. Taking the ICU bed accessibility for instance, I will introduce the method details here and how it is applied in this study.

The first step (Eq. 3.1) is to calculate the probability of people selection on a certain hospital for its ICU service out of multiple available hospitals with ICU:

$$Prob_{ij} = \frac{C_j d_{ij}^{-\beta}}{\sum_{(s \in D_0)} C_s d_{is}^{-\beta}} \tag{3.1}$$

where $Prob_{ij}$ is the probability of population location i visiting service site j; d_{ij} is the travel time between i and j, and β is the distance impedance coefficient; C_j is the capacity/attractiveness of service site, hospital j. In our case, C_j is the capacity, total available beds, of the hospital. s is any qualified hospital within the catchment D_0 of i.

The second step (Eq. 3.2) involves calculating the supply to population ratio, ICU-bed-to-population ratio, for each service site j:

$$R_j = \frac{S_j}{\sum_{(k \in D_0)} Prob_{kj} Pop_k W_{kj}} \tag{3.2}$$

$Prob_{kj}$ is the Huff Model-based selection probability of population at k visiting service site j. W_{kj} is the inverse-power distance weight between population location k and service site j, and it can be equivalent to $d_{ij}^{-\beta}$. This method uses the continuous impedance weight instead of the predefined subzone-based impedance weight compared to previous accessibility measures. D_0 is the catchment size of j.

The last step (Eq. 3.3) summarizes the supply to population ratio of all service sites within the catchment of a population location:

$$A_i^F = \sum_{(j \in D_0)} Prob_{ij} R_j W_{ij} \tag{3.3}$$

where R_j is the ICU-bed-to-population ratio of service site j within the catchment D_0 of population location i. W_{ij} is the inverse power impedance weight between i and j.

Using ArcGIS 10.6, I calculated the county population centroid based on the older population at the block group level and ensured the weighted centroids were inside each county[4]. The centroids were further applied in the accessibility calculation. Although some of the service sites, such as supermarkets, can be utilized by all populations, the older population centroid is used here to emphasize the accessibility situation of the older. While the catchment size depends on the characteristics of the service site, there is rare literature about how to determine it. A Washington state survey specifically asked about the distance that older adults are willing to travel for routine and urgent care (Yen 2013), and the results are 18.1 miles (29.1 km) and 17.7 miles (28.5 km). Here I rounded the numbers up to 20 miles (32.2 km) as our catchment size (D_0) for the accessibility calculation. Since I was interested in the inaccessibility of the service sites, the calculated accessibility (by Eq. 3) was first standardized. Then its additive inverse was calculated to represent the inaccessibility z-score.

After standardizing the calculated value for each factor with Python 3.8 in Jupyter Notebook, I used the mean value for each risk category to represent the risk level of this category. Then I created choropleth maps to visualize the results by the standard deviation.

Finally, I calculated the overall place Vulnerability Index of Older adults (VIO) using an additive model to summarize the considered categories to an overall and averaged value (Eq. 3.4).

[4] Occasionally, if the calculated centroid is outside the polygon, a label point (inside the polygon) is returned to function as centroid.

As previous research states (Cutter et al. 2003; Borden et al. 2007), there is no defensible method for assigning weights differently, so each category, and each factor within a given category, were considered an equal contribution to the county's place vulnerability. To locate the most vulnerable counties in both category and overall vulnerability level, choropleth maps (by standard deviation, or S.D.) were used to visualize vulnerability variation.

$$\text{VIO} = \frac{1}{4} * (\text{Environmental risks} + \text{Built environment risks} + \text{Peer group risks} + \text{Society risks}) \tag{3.4}$$

I used boxplots to visualize the risks of overall VIO and each category to compare rural and urban counties. I also used hypothesis testing by Kolmogorov-Smirnov (K-S) test, which can test whether two underlaying distributions differ. K-S test is a non-parametric test without assumptions of data normality. The null hypothesis is that two samples/populations follow the same distribution. The alternative hypothesis is that they follow different distributions. It was used on overall VIO and individual categories between rural and urban counties.

To understand the differences between existing vulnerability indexes, VIO was compared with SOVI and SVI to pinpoint the various spatial variation visualized by three different indexes.

3.4 Results

Figure 3.3 shows the category result of environmental risks (left) and risk of individual factors (right). In the following figures, high risks counties whose category risk >= 2 SD are labeled in Italic, and the county name reference map is in Appendix A. In general, western Georgia is more vulnerable than the rest part of the state. Fulton County and Chatham County, where Savannah sits, are the most vulnerable two counties in this category. We can also see the variation of vulnerability for each factor. For example, Chatham County is extremely vulnerable (z-score >= 2) to storm/flood-, cold-, and heat-related hazards. Atlanta region is susceptible to storm/flood, and northern Georgia, in general, is facing more cold-related risk. The core Atlanta (Fulton, DeKalb, and Clayton) and counties near Columbus are having a higher risk for air toxics.

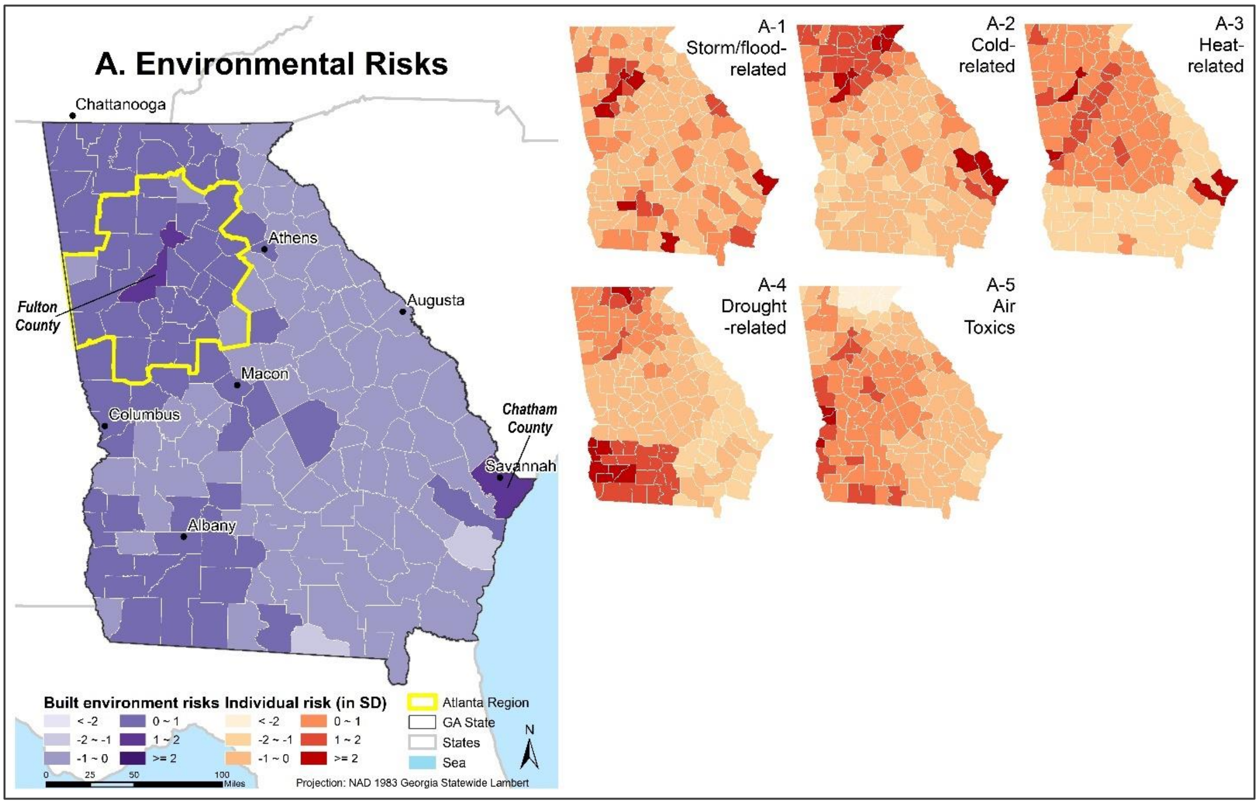

Figure 3.3 Environmental Risks

Comparing to the environmental risk, the built environment risks (Figure 3.4) have fewer extreme cases. There is no noticeable pattern after considering the population and service site capacity. In general, the periphery Atlanta region has better accessibility than the core Atlanta. As for individual factors, some counties in the Atlanta region and South Georgia have nursing home inaccessibility issues. For the public transit, the vulnerable counties are without local transportation systems.

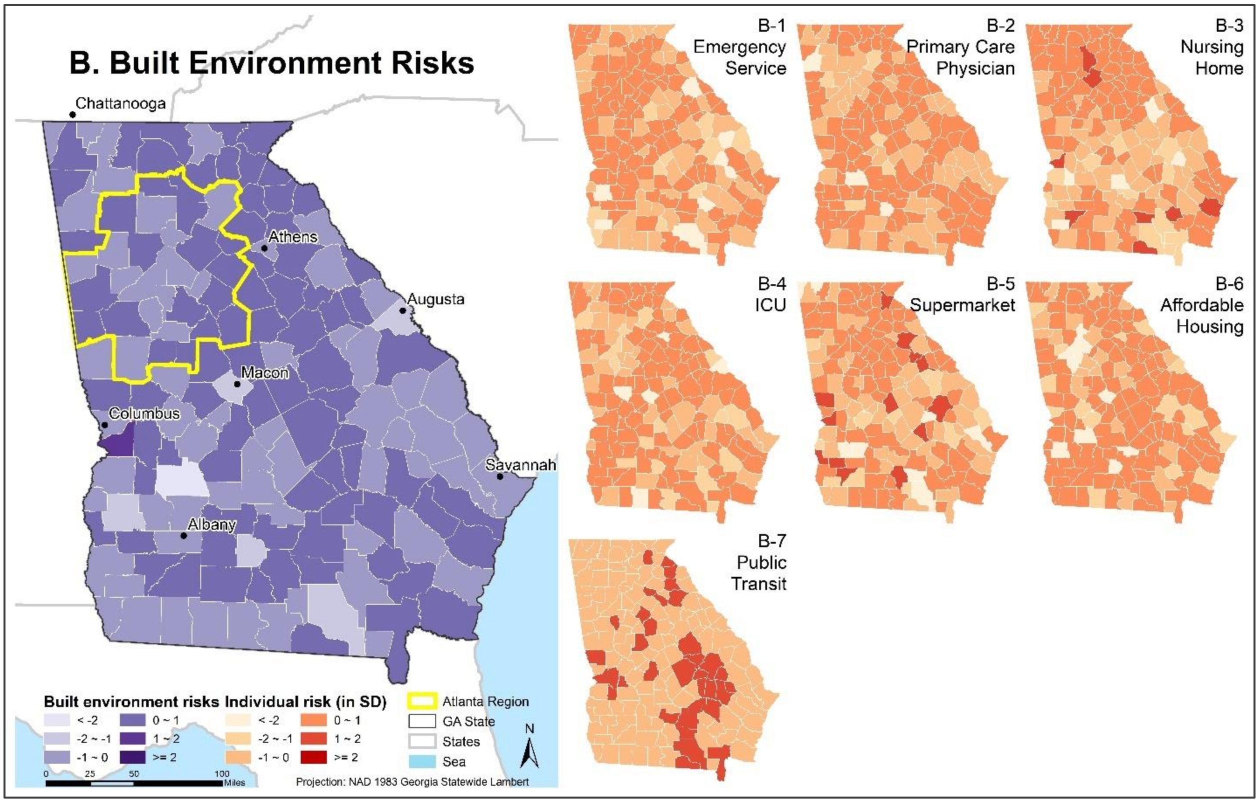

Figure 3.4 Built Environment Risk

For the peer group category (Figure 3.5), Whitfield, Gwinnett, Bleckley, Sumter, and Brooks have more risks due to different underlying factors. For example, Bleckley and Brooks are the top two counties with the highest prevalence of older adults with ADRD (more than 13%). Atlanta region, Whitfield, along with Habersham, and Banks, have a high portion of the older not speak English (4.07% - 12.21%) comparing to 0% in more than one-third of the counties (57). For Georgia counties, at least 14.84% of older adults live alone. As the third-lowest per-capita-income nationwide (U.S. Census Bureau 2020), Wheeler County has 40.65% of its older adults live by themselves.

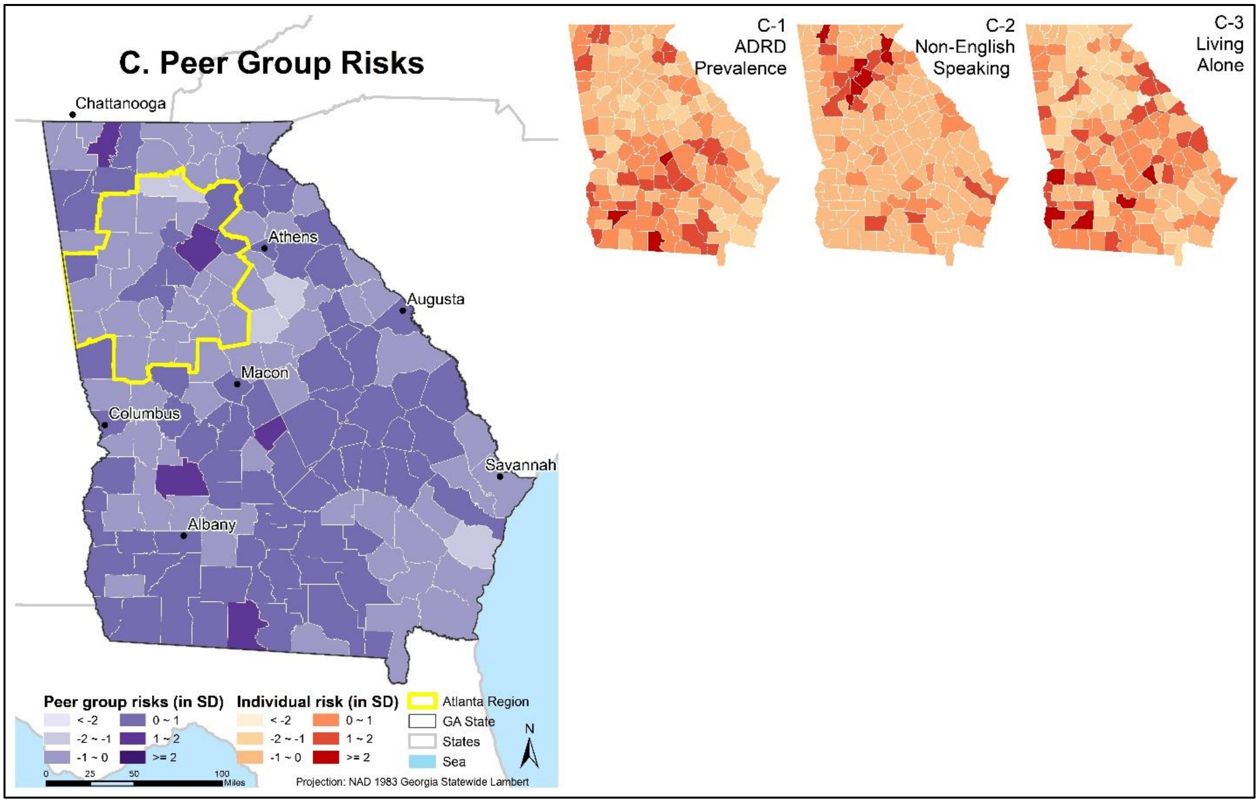

Figure 3.5 Peer Group Risks

For society risks (Figure 3.6), counties between Columbus and Albany and Taliaferro County are relatively more vulnerable. Factors such as the minority groups, female householders, poverty, unemployment, and no vehicle ownership stand out in these counties. Among the individual factors, there are significant variations across Georgia. Counties with a high proportion of older adults (D-2) cluster on the state's northwest corner, near the Chattahoochee National Forest. The Atlanta regions are generally with a lower proportion of disabled people (D-8).

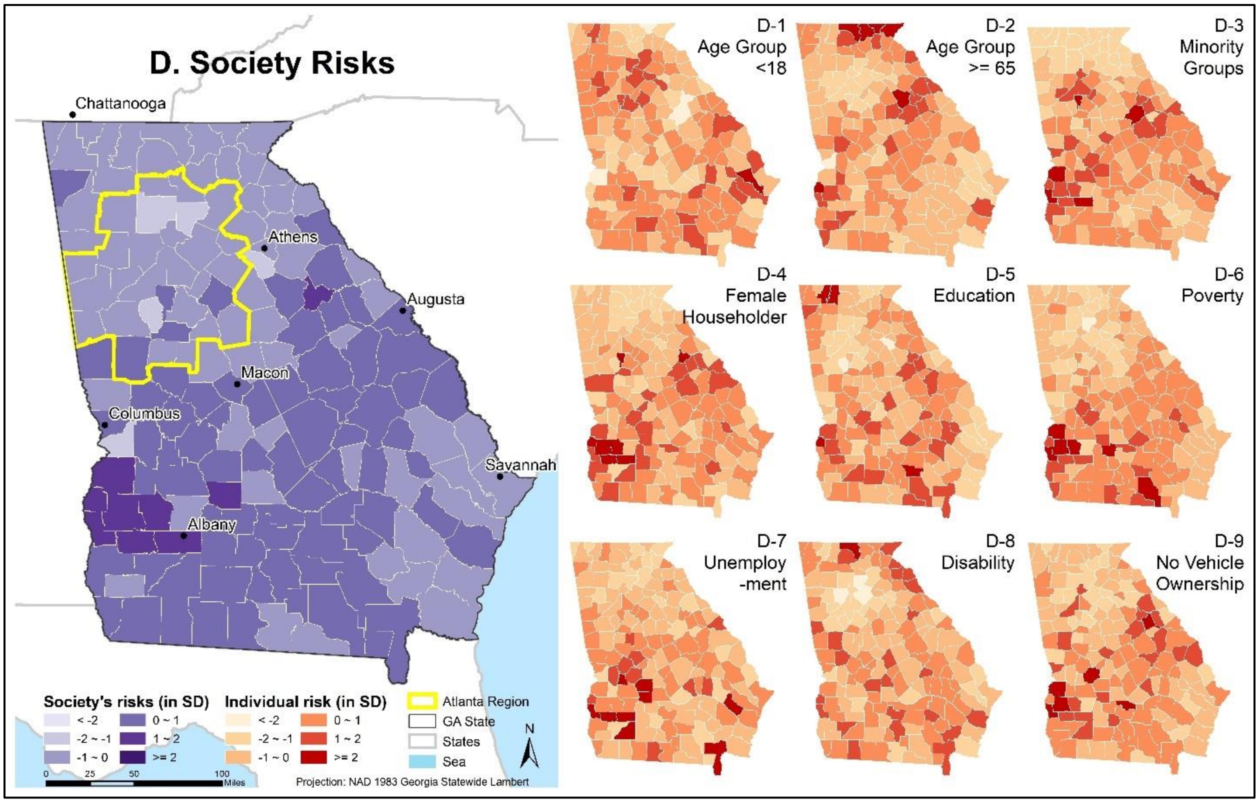

Figure 3.6 Society Risks

Figure 3.7 illustrates Georgia's overall place vulnerability by quintiles. The high VIO counties are across Georgia. The top two vulnerable counties, Fulton and Gwinnett, are both within the Atlanta Region. Counties near cities, such as Savannah, Columbus, and Albany, are also relatively more vulnerable than others.

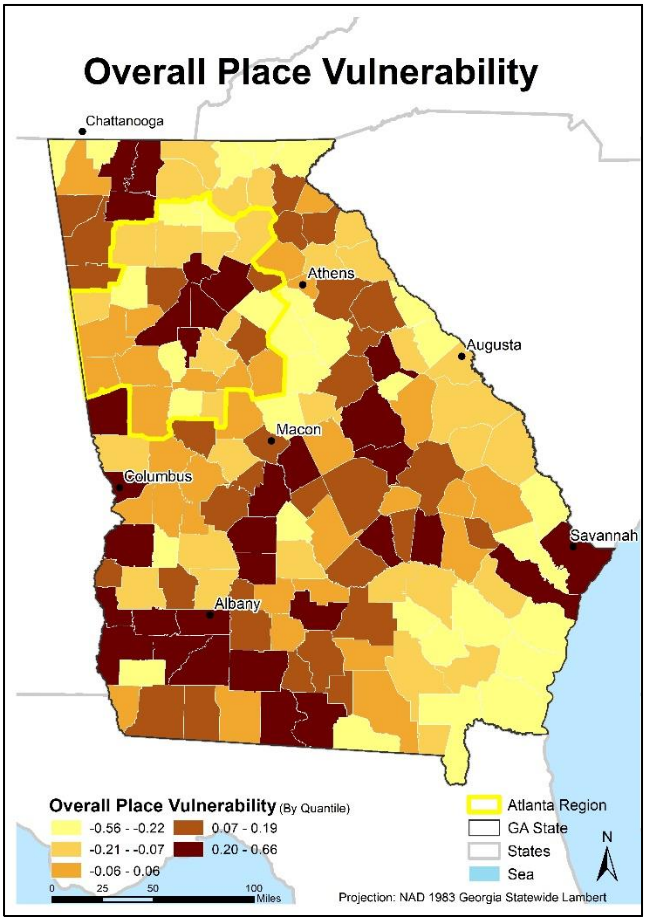

Figure 3.7 Overall Place Vulnerability

Figure 3.8 presents the vulnerability differences between rural and urban counties. There are 74 (46.54%) urban and 85 (53.46%) rural counties. For the overall VIO, the value distributions of urban and rural counties are not statistically significantly different (p-value = 0.052). At the category level, the distributions of the environmental, peer group, and society categories are different between the urban and rural counties at significant levels (p-value << 0.05).

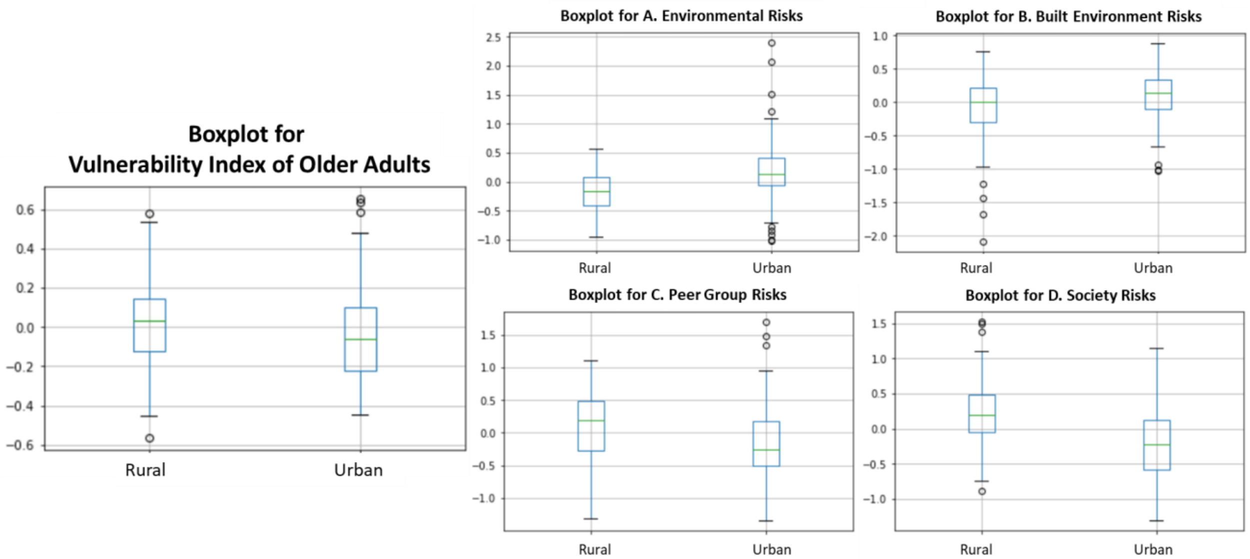

Figure 3.8 Boxplots for VIO and Individual Vulnerability Categories for Rural and Urban

Comparing the VIO with SOVI and SVI (Figure 3.9), there are noticeable differences between the spatial variation of high and low vulnerability. Based on VIO, the counties in Atlanta Region, Fulton, Gwinnett, Clayton, and Dekalb, are among the top 10% most vulnerable counties. Beyond that, Chatham and Liberty County on the coast are also with high VIO (top 20%). Other than that, counties in the southwest, middle part, and north of Atlanta Region that are with high VIO. As for SOVI, it also has a high vulnerability cluster in southwest Georgia, but also near the northern border where the Chattahoochee National Forest. Richmond County, where the City of Augusta locates, and Glynn County along the coast, are also with high SoVI. For the CDC SVI, the high vulnerability counties sit in the south of the state and show clear cluster patterns. It also clusters in the southwest part and has a line-shaped cluster from Taliaferro County to Clinch County. The differences are derived from the variable set that has been used in each vulnerability index. As their names indicate, SOVI and SVI emphasize social vulnerability. They consider socioeconomic variables from census data while VIO further integrates environmental and built environment factors as environmental vulnerability into the index. Moreover, SOVI and SVI are synthetic indexes for the general population, while the VIO focuses on older adults. Therefore, factors in VIO are selected based on a literature review to ensure that the considered factors make older adults even more vulnerable than other populations.

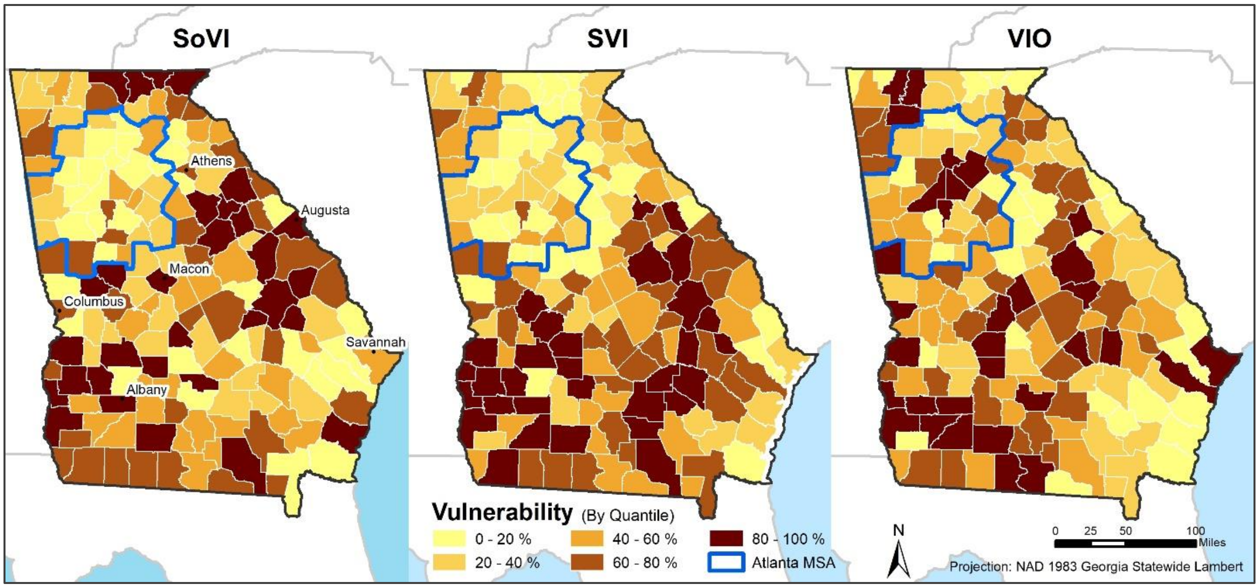

Figure 3.9 Comparison of VIO with SOVI and SVI by Quantile

3.5 Discussion, Conclusions, and Future Studies

Focusing on older adults and the state of Georgia, this study examined risks in both environmental and social vulnerability, including the environmental, built environment, peer group, and society risks. I further proposed a Vulnerability Index for Older adults (VIO). This synthetic index considered selected risk factors that make older adults more vulnerable. VIO pinpoints the location of the most vulnerable counties for the overall result as well as individual categories. While there are extremely vulnerable counties (S.D. >= 2) for environmental, peer group, and society risks, there is minimal variation in built environment risks. Fulton and Gwinnett County are most vulnerable for the overall VIO, along with counties near cities, such as Savannah, Columbus, and Albany.

This study may provide insights for future research and planning about older adult vulnerability and disaster management, preparation, mitigation, and more. While the peer group and society risks are hard to address or mitigate, this index can pinpoint location and factors that local governments should reduce the potential hazards. For example, suppose a county has high air toxics risk. In that case, the local planning department may work with Environment Protection Agency to reduce the toxics release from factories or provide more supports on carpooling and public transportation. In addition, local government and business sections can alleviate built environment risks if they ensure accessibility to facilities and services. Moreover, the peer group and society risks illustrate the older adult sensitivity as well as the resilience of all the residents. This index may also be a guidebook for local older adults and older migrants to acknowledge the potential hazards.

VIO is a new construct focusing on related vulnerability variables to older adults. Like many other vulnerability indexes which are not perfect (Cutter et al. 2003), it has some limitations and future directions. First, this project used an addictive model and weighed all factors in the same way due to the deficiency of related literature or survey result. It will be ideal for refining the index by knowing how the relative importance of selected factors from some domain exports, emergency management specialists, and older adults themselves collectively. Second, the selected variables may have some underlying multicollinearity between them. For example, the proportion of people below the poverty line and unemployed are among others are correlated although they describe the vulnerability from different perspectives. Third, the mitigation and hazard perception parts were not included in the index. Based on numerous local considerations, mitigation policies can help better prepare and recover from hazards. However, they are hard to include in a state or regional level assessment. Future small-scale vulnerability analysis may include the local mitigation part for more precise estimation. Fourth, our risk factor list may not be a full list. For instance, some technical hazards, such as power outages, are not included due to data availability. Moreover, the environmental hazards only list the hazard events which happened in Georgia before. There is a need to reevaluate the environmental hazards if applying this to other locations. Fifth, I set the search radius as 20 mile (32.2 km) Euclidean distance for all built-environment factors when measuring accessibility. Different searching radii make more sense as people's ideal travel distance would be different for these service sites. Lastly, using county-level variables may not be ideal for urban areas with a lot of internal heterogeneity. If data is available at smaller units, such as census tracts, it can reveal detailed spatial variations.

Future studies can also work on the validation, personalization, and maintenance of this index. A longitudinal study can be conducted to trace the change in health conditions among randomly sampled older adults and further validate the VIO. In addition, qualitative approaches, such as surveys or interviews, can also obtain older adults' views on their vulnerability, and reflect on the accuracy of this index. At the individual factor level, they can be validated with related data. For example, ICUs are highly critical to the COVID-19 pandemic. The older adults' mortality data can be used to validate the ICU inaccessibility. Another future direction for VIO would be personalized vulnerability assessment where older adults can weigh factors differently based on their needs and preferences, and then a newly calculated vulnerability will be illustrated as an online map. The same idea can be used to dynamically evaluate VIO by comparing the importance of the considered factors. For instance, during the current pandemic, emergency service and ICU bed inaccessibility are much more fatal than other risks. The ideal situation will be updating the result whenever a new dataset is available to maintain the timeliness of this index. If the whole process can be automated, the VIO can be scalable. It can be extended to the entire U.S. to allow national-level comparison of vulnerability or at a refined scale for tract-level comparison.

While this index focuses on measurable county-level factors, it may not capture the risks of information inaccessibility as well as social isolation. According to the Pew Research Center (Elisa Shearer 2021), 86% of Americans get news from digital devices and older adults. Moreover, access to the internet is critical for information retrieval, access to services, connectivity to friends and family, among others that influence health results (Yang and Chen 2015). Moreover, the lack of social activities which may cripple older adult psychological or mental health. Older adults are at risk for social isolation and following consequences, such as depression (Cornwell, E.Y., Waite 2009; He et al. 2012). Although now there are online social programs, such as Senior Center Without Walls, it is still good to have physical senior centers nearby to interact with other fellows and enjoy the nutritious meals and entertainment classes designed for them. However, the differences in admission requirements, fees, available activities, and services (with transportation services or not) make it hard to measure accessibility.

This study builds on growing research on how social and environmental vulnerability can be integrated to place vulnerability for a certain population. Understanding vulnerability from refined categories, including the environmental, built environment, peer group, and society risks, helps us better prepare for potential disasters. Despite we can hardly mitigate some risks, such as environmental, peer group, and society risks, it is beneficial to acknowledge the risks by the older adults themselves, their families, as well as local governments. VIO can pinpoint the service types and locations that need more attention for the built environment risks, especially in potential natural hazards or emergencies. We might better intervene through such research and index to mitigate the older adult vulnerability in the future.

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CHAPTER 4

INTEGRATING TIME-SERIES THEORIES AND METHODS INTO ACCESSIBILITY RESEARCH: A CASE STUDY FOR OLDER ADULTS[5]

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Abstract

Time is sensitive in health emergencies, especially for vulnerable older adults. Despite the efforts of considering time dimension in measuring accessibility, few researchers have attempted to find patterns, such as trend and seasonality, in the travel time, which influences the assessment of accessibility. Using the theories and methods of time series, this study presents the results of a time series analysis of travel time from selected census tracts to the nearest hospital (origin-destination, or OD pairs) in Atlanta Metropolitan Area. Using Prophet, a time series model, on the collected driving durations from Google API, I detected trend and seasonality for weekly and daily patterns in travel times. I also proposed a new form of assessing accessibility that can possibly embed the time impact in the catchment area, as well as other components of the measure. Through the analysis, I observed various trends and seasonality between OD pairs, and some tracts have difficulties accessing hospitals within the recommended Door-to-MD time. While some OD pairs have very consistent travel time throughout the study time frame, others show seasonality, including an increase for weekdays and two daily rush-hour peaks. This study also illustrates the potential of applying time series theory and methods to accessibility measures or in geography research in general.

Keywords: accessibility, time series, older adults, Atlanta, travel time

4.1 Introduction

In health-related scenarios, time is often critical, especially for conditions such as heart attacks and strokes, which are considered top time-sensitive emergencies (Altus Emergency Centers 2021). People with heatstroke symptoms have little time to seek treatment in emergency departments or hospitals (Kovats et al. 2004; Knowlton et al. 2009). The sooner the patient receives the medical care, the greater chance of surviving the emergency (Mayer 1979). Despite the fact that 10 minutes is recommended as Door-to-MD time in the National Institute of Health National Symposium (Jauch 2002), health disparities make it hard to ensure timely treatment, especially for low-income neighborhoods (Johnson 2018). In the climate change era, extreme weather has become more and more common (Gamble et al. 2013). Heat stress can become life-threatening rapidly, particularly for those with limited access to immediate medical care (Mastrangelo et al. 2006; Knowlton et al. 2009). Older adults (65-year-old and above) are more vulnerable to medical emergencies as well as climate change stressors due to their impaired health condition (Gamble et al. 2013). Although the travel duration varies a lot within a day or a week, it can describe the changing dynamics of the accessibility, such as the accessibility from a certain location to emergency care. The accessibility research is burgeoning with two major directions of place-based accessibility and personal-based accessibility. While the place-based methods attempt to include the time dimension in assessing the accessibility, few researchers have investigated the fluctuation and temporal patterns in travel time, not to mention integrating them into accessibility measures.

This paper conducts a time series analysis of travel time from selected census tracts to the nearest hospital (origin-destination, or OD pairs) in Atlanta Metropolitan Area. By applying time series methods on collected driving durations from Google Directions API from Dec. 24, 2020, to June 7, 2021, I detected trend and seasonality, for both weekly and daily patterns, along with holiday effects, in travel times. I also proposed a new form of assessing accessibility that can possibly embed the time impact in the distance decay function, as well as other components of the measure. Through the analysis, I observed various trends and seasonality between OD pairs, and some tracts have difficulties accessing hospitals within the recommended Door-to-MD time. By presenting the theories and methods of time series, this study demonstrated the potentials of integrating machine learning techniques and travel time big data to dynamic accessibility measures or the general geography field.

4.2 Background

4.2.1 Spatiotemporal accessibility

Research on accessibility has been one booming area of GIScience for promoting equality in the interdisciplinary community of geography with transportation, public health, and planning. It has touched different aspects of life, such as health care, job opportunities, food environment, and greenspace (Comber et al. 2008; Mao and Nekorchuk 2013; Cheng and Bertolini 2013; Shannon et al. 2018b). Despite the definitions with nuanced differences, access, the bigger umbrella of accessibility, refers to the relationship between the demand and supply, from multiple dimensions. Under the healthcare context, Penchansky and Thomas (1981) have decomposed access into five dimensions: availability, accessibility, accommodation, affordability, and acceptability, emphasizing different aspects of the relationship and are not easily separated. Table 4.1 provides the detailed definitions in the frame of healthcare access.

Table 4.1 Five Dimensions of Access in Healthcare

Dimension	Definition
Availability	The relationship of the volume and type of existing services/resources to the clients' volume and types of needs.
Accessibility	The relationship between the location of supply and the location of clients, taking account of client transportation resources and travel time, distance, and cost.
Accommodation	The relationship between the manner in which the supply resources are organized to accept clients and the clients' ability to accommodate to these factors and the clients' perception of their appropriateness.
Affordability	The relationship of prices of services and providers' insurance or deposit requirements to the clients' income, ability to pay, and existing health insurance.
Acceptability	The relationship of clients' attitudes about personal and practice characteristics of providers to the actual characteristics of existing providers, as well as to provider attitudes about acceptable personal characteristics of clients.

In general, there are two major threads of accessibility measures: one is individual- or people-based, and the other is place-based. The individual-based accessibility can be traced back to Hägerstrand's (1970) work which introduced the space-time path, space-time prism–also known as the Fish Tank model, and constraints under the frame of time geography. Scholars apply multiple methods to visualize the space-time component, such as the space-time path, space-time prism, potential path area, and space-time cube (aquarium) to illustrate the real travel path or the potential reachable areas (Kwan 2000; Kraak 2003; Jacquez et al. 2015). The widely used space-time prism (Figure 4.1) delimits the space that individuals can physically reach during a given time interval (Miller 1991), and the idea was enhanced greatly with GIScience due to the computational and visualization power (Neutens et al. 2010a; Miller 2017).

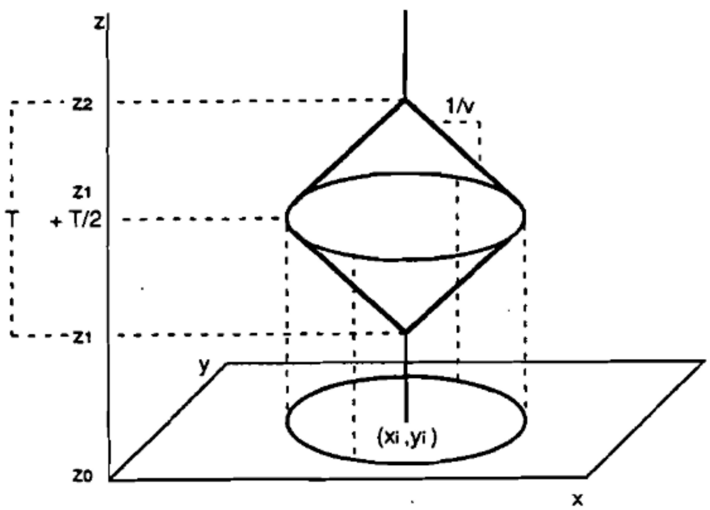

Figure 4.1 Schematic Representation of the Space-Time Prism (Miller 1991)[6]

Human activities have three major classes of constraints: capability constraints (such as the distance limit that people can cover within a given time-span), coupling constraints (such as the time and space limit that individual must join others), and authority constraints (such as time and space that individual cannot visit) (Hägerstrand 1970; Pred 1977). Time geography is a constraints-oriented approach to understanding human activities in space and time (Miller 2017). Time geography framework has been widely applied in the interdisciplinary areas for transportation modeling, behavior modeling, and accessibility analysis (Timmermans et al. 2002; Delafontaine et al. 2011). Various individual-based measures have been proposed considering an individual's travel behavior, space-time environment, travel mode, and interactions (Kwan 1998; Neutens et al. 2010a). For instance, travel diary (Kwan 1998) and GPS data (Kraak 2003) have added more evidence of travel behavior to refine space-time prism.

The other thread of accessibility measures, place-based accessibility, focuses on some demand location, such as home or workplace. With the understanding of spatial mismatches between the

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supply and demand, we can apply location-allocation models to find the optional location for the new service site (Clarke et al. 1984; Gregory et al. 2009). As an integral assessment, it evaluates the degree of accessibility based on the density or proximity of surrounding service sites by using various models, including cumulative-opportunity, gravity-type, and kernel density models (Neutens et al. 2010a; Wan et al. 2012; Chen and Jia 2019).

Wan et al. (2012) generalized three critical factors for measuring accessibility: supply capacity, population demand, and geographic impedance. The recent two decades have witnessed a thriving development of the place-based measure family, especially around the initial two-step floating catchment area (2SFCA) method which included all the abovementioned three critical factors (Radke and Mu 2000; Luo and Wang 2003). Based on the gravity model, the original 2SFCA method involves two steps. The first step (Eq. 4.1) is to estimate the demand for each service site by identifying all population locations within a catchment D_0 (defined by a distance or driving time zone) for each service site j, and calculating the supply-to-demand ratio for each service site, R_j , by

$$R_j = \frac{S_j}{\sum_{(k \in D_0)} Pop_k} \tag{4.1}$$

where Pop_k is the population of any unit k, such as census tract, within the catchment, and S_j is the capacity of service site j. The second step (Eq. 4.2) is to identify all service sites within the catchment for each population location i and sum up the supply-to-demand ratios of the considered service sites as the accessibility of population location i:

$$A_i^F = \sum_{(j \in D_0)} R_j \tag{4.2}$$

where R_j is the supply-to-demand ratio of service site j within the catchment D_0 of population location i.

2SFCA has limitations of assuming all population locations within the catchment with equal access, not considering the competition among services sites, and overlooking the attractiveness aspect of the service site (Tao and Cheng 2016). To overcome them, scholars proposed enhanced and modified models. Accounting for distance decay, Luo and Qi (2009) introduced an enhanced 2SFCA, which applies different weights to subzones instead of one homogeneous catchment. Wan et al. (2012) proposed a three-step floating catchment area (3SFCA) method which generates selection weight to consider the service competition. Luo (2014) further integrated the Huff model, which quantifies the probability of people's selection on a service site based on distance and capacity/attractiveness. The original 2SFCA and its extended family have been widely used in healthcare, food environment, and green space research (Dai 2011; Luo and Whippo 2012; Chen 2019). While there is no consensus about the best formulation of the distance decay effect, people have agreed on the influence of distance (Wang 2012; Chen and Jia 2019). The 2SFCA can be modified as follows (Luo and Whippo 2012):

$$R_j = \frac{S_j}{\sum_{(k \in D_0)} Pop_k * f(d_{kj})} \tag{4.3}$$

$$A_i^F = \sum_{(j \in D_0)} R_j * f(d_{ij}) \tag{4.4}$$

Although accessibility measures have included travel time to delineate accessible areas, the time dimension is still statically considered. Researchers have attempted to add more time components to the accessibility analysis. One direction is considering the temporal variation of the service sites, such as the hours of operation for supermarkets. Weber and Kwan (2002) investigated the influence of facility opening hours on travel time variations and individual accessibility. Chen and Clark (2016) incorporated the operation time of food retailers to measure the space-time access with time constraints. Another group of scholars assessed the public service accessibility by including operation hours of the government offices (Neutens et al. 2010b).

The other direction considers the temporal variation of the travel time by acknowledging that accessibility is dynamically changing as the travel time and speed are susceptible to traffic disruption caused by congestion, traffic accidents, and roadworks (Bimpou and Ferguson 2020). With the same travel duration allowance, the accessibility will be different for rush hour and midnight or for rural and urban areas due to the traffic volume and speed limit. Studies attempted to address it as an unreal assumption that travel times are static (Farber et al. 2014; Fransen et al. 2015; Kaza 2015). A group of researchers in the transportation and planning domain have investigated the travel time distribution to understand the travel time reliability and variation (Taylor 2013; Cui and Levinson 2018). Following the same vein, Bimpou and Ferguson (2020) introduced a dynamic accessibility measure with the integration of travel time reliability by considering travel time variability on weekdays using travel durations collected from Google API. They defined travel time reliability ($TTRel$) (Eq. 4.5) as the difference between the m^{th} and k^{th} percentiles of travel time divided by the m^{th} percentile of travel time:

$$TTRel_{ij,t} = \frac{TT_{m,t} - TT_{k,t}}{TT_{m,t}} \tag{4.5}$$

where $TTRel_{ij,t}$ expresses the degree of uncertainty in the travel time between point i and point j at a specific time t. Focusing on the transit-dependent population and food environment, Farber et al., (2014) used a pedestrian network file, transit-related data, and Esri OD Cost Matrix tool to calculate transit-based travel times from the census block to its nearest supermarkets at different times of the day. They further estimated transit-based accessibility. This study advanced the accessibility to a dynamic version by showing the spatiotemporal variation of travel time throughout the day. However, it still used computed travel time rather than real travel duration which is influenced by not only the time of the day, but also car accidents, weather, the day of the week, and the day of the year. There is some general understanding of what affects the travel time reliability. Scholars state the disruptions that influencing travel time reliability, or the transportation system in general, can be categorized based on the sources' frequency, severity, and recurrence (Kwon et al. 2011; Wang 2015). Integrating the existing literature (Kwon et al. 2011; Wang 2015), I summarize the disruption sources into three parts: short-term changes (such as earthquakes or other disasters), medium-term changes (changes related to the day-to-day variations in demand and capacity with a rhythm), and long-term changes (such as climate change).

The choice of accessibility measure has a significant effect on assessing spatial equity (Talen and Anselin 1998; Neutens et al. 2010a). It is important to address the temporal variation is not only about the operation hours of service sites but also the travel duration. As the travel time fluctuates regularly due to congestion, the accessibility is inherently dynamic (Farber et al. 2014). Atemporal measures, which are static in the time dimension, are overly generalized indicators that may not represent the actual changing nature and time dependence of accessibility. It is beneficial to understand the fluctuation and predict the future travel times and estimate the spatiotemporal accessibility. Despite the growing attention to the temporal aspect of accessibility (Chen and Clark 2016; Bimpou and Ferguson 2020), very few dynamic measures have been put forward (Farber et al. 2014) and the literature on accessibility temporal variation is limited (Bimpou and Ferguson 2020). Although some research considered the traffic volume's influence on accessibility by using different velocities for rush hours (Miller 1991), the temporal variation of accessibility has not been addressed extensively by the research community. In addition, while accessibility research often uses Euclidean or road network distances to delimit reachable services areas, it is necessary to call for more advanced methods of delimiting service areas, or assessing accessibility in general, to capture the dynamically changing travel time and effort. There is a need to carefully exam the travel time variations and to have refined time-varying measurements.

Since most existing measures assess accessibility using static distance measures, such as the geographical impedance and catchment size, they describe accessibility as the ease of traveling in the geographical dimension without considering the time expense. While the travel distance between the supply and demand is fixed, the travel effort in time will fluctuate. The three critical factors can be extended as supply capacity as a function of time, population demand as a function of time, and geographic impedance as a function of time.

4.2.2 Time series data and methods

A time series is a time-oriented or chronological sequence of observations on some variables of interest (Montgomery et al. 2016). It adds an explicit order dependence between observations as a time dimension. Without being explicitly called in this way, time-series data are indeed widely used in geography and related disciplines to visualize and detect the temporal changes over space. For example, scholars examined the 1960 to 2010 socioeconomic status to understand the spatial and temporal changes in social vulnerability to natural hazards (Cutter and Finch 2008). Researchers used 2008 to 2013 demographic and retailer data to understand the changes in proximity to selected food retailers in the Atlanta urban area (Shannon et al. 2018a). Conway and Rork (2016) investigated 1980-2010 older adult migration data from different data sources. However, few researchers in geography have attempted to go beyond visualization to find the rhythms/patterns in the time dimension.

In statistics or the new trending machine learning, practitioners scrutinize the time series data to find the pattern and forecast future values. In general, there are three patterns in time series data: trend, seasonality, and a cycle (Hyndman and Athanasopoulos 2021a). A trend exists when there is a long-term increase or decrease in the data, such as the slowly increasing temperature in the global warming era. A seasonality is always of a fixed and known period and it occurs when a time series is affected by seasonal factors such as the time of the year or the day of the week. For example, daily temperature follows a pattern of increasing and decreasing. A cycle occurs when the data exhibit rises and falls that are not of a fixed frequency. These fluctuations in a cycle are usually due to economic conditions, such as financial crises. In the decomposition process, the trend and cycle are usually combined into a single trend-cycle component, called a trend for simplicity. Thus, we can think of a time series as comprising three components: a trend(-cycle) component, a seasonal component, and a remainder component (containing anything else in the time series). The whole idea is very similar to the disruption I summarized from the transportation literature: long-term changes (trend), day-to-day variations (seasonality), and short-term changes (remainder).

The time-series data can be decomposed in an additive (Eq. 4.6) or multiplicative way (Eq. 4.7). If we assume an additive decomposition, then we can write:

$$y_t = S_t + T_t + R_t \tag{4.6}$$

where y_t is the data, S_t is the seasonal component, T_t is the trend component, and R_t is the remainder component, all at period t. The additive way is the most appropriate if the magnitude of the seasonal fluctuations does not vary with the trend. A classic example of the additive model is the total U.S. retail employment (Hyndman and Athanasopoulos 2021b). When the variation is proportional to the trend of the time series data, a multiplicative decomposition (Eq. 7) would be the choice:

$$y_t = S_t * T_t * R_t \tag{4.7}$$

For example, monthly air passenger traffic data is a classic dataset to be decomposed using a multiplicative model (Hyndman and Athanasopoulos 2021b). Despite the different methods of decomposing the data, the idea is similar: tracing the trend, seasonality, and remainder. The remainder could be further addressed using adjustments to events such as holidays, extreme weathers, sports events, pandemics, accidents, and more.

There are many classic methods for detecting patterns and forecasting future data (Hyndman and Athanasopoulos 2021a). Here introduce two prestigious ones: exponential smoothing and AutoRegressive Integrated Moving Average (ARIMA). Exponential smoothing assumes that the more recent the observation, the higher the association to the current value. It uses weighted averages of past observations, with the weights decaying exponentially for older observations. The Holt-Winters' seasonal method is an example of exponential smoothing data by capturing the level, trend, seasonality. By describing the autocorrelations in the data, ARIMA forecasts the variable of interest using an autoregressive model (linear combination) of past values of the variable itself, and a moving average model of past forecast errors. As it is defined in terms of lagged variables, it requires data points without missing values. For instance, Shuvo et al. (2021) applied exponential smoothing and ARIMA, among others, to forecast traffic volume. Some research has also adapted both to predict the air quality index in Beijing, China (Zhu et al. 2015).

Recently, researchers in Facebook have proposed Prophet, a new time series forecasting method that automates the process of pattern detection (Taylor and Letham 2018). Following the idea of Harvey and Peters (1990), they decompose the time series data by considering the holiday effect using an additive or multiplicative model (Eq. 4.8):

$$y_t = S_t + T_t + H_t + \epsilon_t \qquad \text{OR} \qquad y_t = S_t * T_t * H_t * \epsilon_t \tag{4.8}$$

where H_t represents the effects of holidays which occur potentially irregularly over one or more days, and ϵ_t is the error term representing any changes that the model does not accommodate. A huge advantage of this method is the measurements do not need to be regularly spaced or to interpolate missing values (Taylor and Letham 2018). The authors applied Prophet to conduct forecasting at scale for Facebook event data and found better results on accuracy and weekly seasonality after considering the effects of holidays. Zhao et al. (2018) has applied Prophet to find weekly and seasonal patterns of air quality indicators in the U.S. Researchers have also used it for COVID-19 cases prediction (Papastefanopoulos et al. 2020; Wang et al. 2020b).

After finding the trend and seasonality through a time series model, the fitted model is used to forecast future values. The forecasting result is evaluated by comparing the predicted with the observed values for a selected time range of unseen data. There are a few groups of metrics for evaluating accuracy. The first one is scale-dependent, which means errors are on the same unit scale as the data and cannot be compared between series if in different units. As a common measure in this group, mean absolute error (MAE) (Eq. 4.9) is the average magnitude of error produced in the forecast, and it equals the average of the absolute value of errors for individual time points. An alternative group calculates the percentage error, which eliminates the influence of the unit. Mean absolute percentage error (MAPE) (Eq. 4.10) calculates the average absolute percentage change between the predicted value and the observed value. It shows how far (in percentage) the predictions are off from the real values.

$$\text{Mean absolute error: } MAE = \frac{\sum_1^n |y_i - \hat{y}_i|}{n} = \frac{\sum_1^n |e_i|}{n} \tag{4.9}$$

$$\text{Mean absolute percentage error: } MAPE = \sum_1^n \left|\frac{y_i - \hat{y}_i}{\hat{y}_i}\right| * \frac{100}{n} = \sum_1^n \left|\frac{e_i}{\hat{y}_i}\right| * \frac{100}{n} \tag{4.10}$$

where y_i and $\hat{y}_i$ are the predicted and observed values of the variable of interest, e_i is the error for the i prediction, and n is the number of observations in the forecasting.

While a lot of geographical features have time attributes, they are used in visualization and representation of the temporal changes following the foundation work of Monmonier (1990). There is a potential to unveil patterns in the time dimension for further applications. Nevertheless, only a few studies have used real-time travel data from Google. Some researchers queried travel time every 15 minutes from Google and used the percentile to help understand the travel time reliability and apply it to accessibility (Bimpou and Ferguson 2020). Wang and Xu (2011) developed a tool to obtain a reliable estimate of OD travel time matrix from Google which has updated road network data. However, to our knowledge, none of the Google travel duration data has been analyzed using concepts of time series analysis. In addition, only a few time-related data have been used in measuring accessibility and demonstrating the volatility. Some researchers have embedded transit schedules into the accessibility measure (Farber et al. 2014; Kaza 2015). Others incorporated the operation time of the selected service sites to have more refined accessibility (Neutens et al. 2010b; Chen and Clark 2016). As the impedance between two locations, real-time travel data would be one step further than the Euclidean or network distance. Moreover, time series methods can provide a better idea of how travel time may change along the time dimension, and further guide works on accessibility measures.

4.3 Methods

4.3.1 Study area and data collection

Our study area (Figure 4.2) is the 29-county Atlanta Metropolitan Area, or Atlanta–Sandy Springs–Alpharetta metropolitan statistical area (MSA), which is the ninth largest in the U.S. With about 6 million people, its population takes 57.85% of the Georgia population (U.S. Census Bureau 2020). Due to the costs of repeated API queries, I used a stratified random sample of 60 tracts, out of a total of 982 census tracts in Atlanta MSA, to represent the general scenarios. Since the travel time to the closest hospital determines the bottom line of travel time, I simplified our question as the travel time to the closest hospital instead of finding the shortest travel time among all nearby hospitals. Focusing on the older adults, I first calculated the older proportion in each census tract and excluded those with less than average proportion. This step reduced our pool to 447 (45.52%) tracts. Second, I created quartiles based on older adult density (by area) and randomly sampled 15 tracts from each quartile. Lastly, I used Google Maps during the non-rush hour to find the nearest hospital, that has been registered with Medicare and with emergency services (Centers for Medicare & Medicaid Services (CMS) 2020a), in terms of travel time.

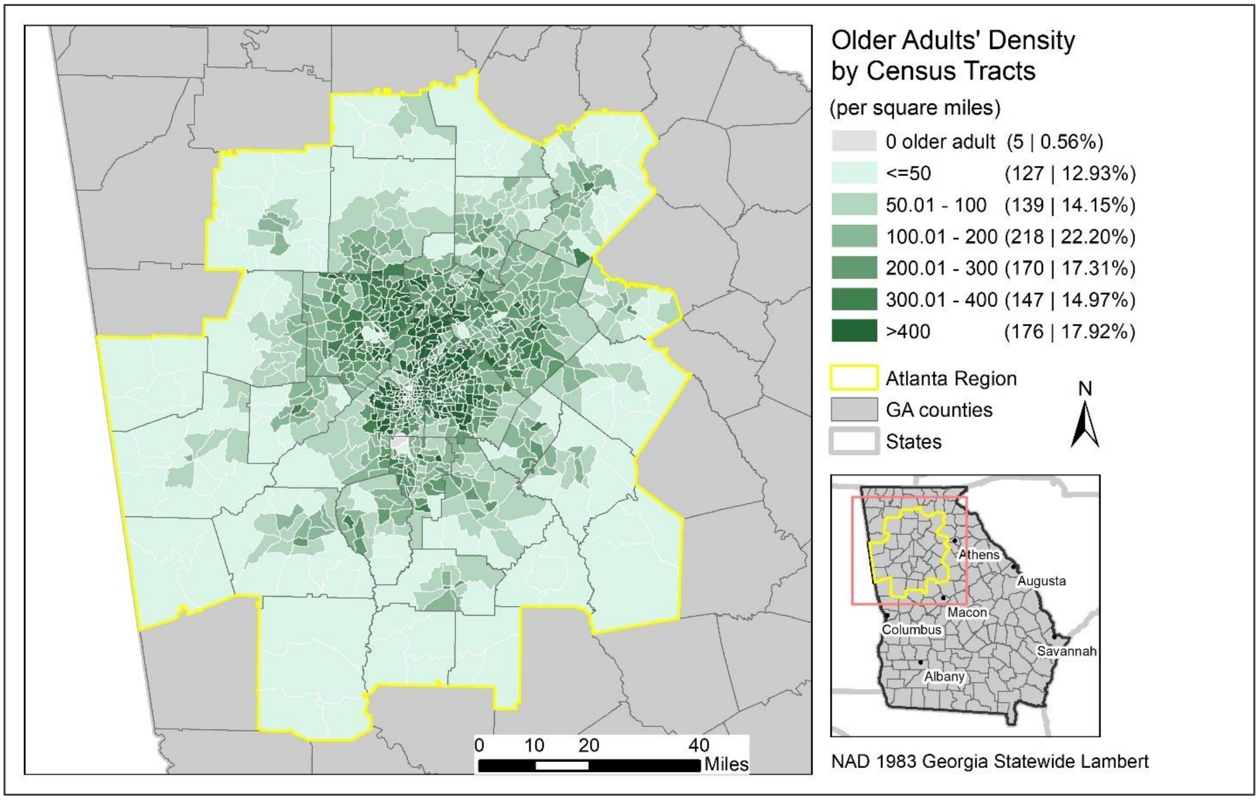


Figure 4.2 Study Area

I wrote a Python script to collect the real-time driving durations for the selected 60 tract-hospital OD pairs from the Google Directions API (Google Maps Platform 2020). Based on a pilot study, I found that travel duration was constant between 12:00 am – 6 am, so I decided to collect travel duration only for 6 am – 12:00 am (19-time points) with hourly granularity. The script automated the data collection from Dec. 24, 2020, to June 7, 2021, to cover multiple major holidays in the U.S.

4.3.2 Accessibility with time series consideration

To bring the time series concepts into accessibility, I propose to make the accessibility components a function of time. To take the modified 2SFCA as an example:

$$R_j(t) = \frac{S_j(t)}{\sum_{(k \in D_0(t))} Pop_k(t) * f(d_{kj}, t)} \tag{4.11}$$

where $D_0(t)$ is the catchment size for time t, $Pop_k(t)$ is the population of any population unit k within $D_0(t)$, $S_j(t)$ is the capacity of service site j at time t, and $f(d_{kj}, t)$ refers to the distance decay function between population and service site at time t. As a function of t, the supply, population, and feasible catchment sizes change throughout the day and week. For example, the catchment size can be considered in terms of the reachable distance at time t, for which a function of t using time series concepts can be beneficial. This can also help capture the dynamic changes in demand, especially considering the people who commute for work or schools. The second step equation also has some modifications on the equation:

$$A_i(t) = \sum_{(j \in D_0(t))} R_j(t) * f(d_{ij}, t) \quad (4.12)$$

where $R_j(t)$ is the supply-to-demand ratio of service site j at time t.

4.3.3 Analysis

I used Python 3.8 and Jupyter Notebook to calculate the proportion of travel time that was smaller or equal to 10 minutes to provide a general picture of traveling to the hospital from the collected data. The result was further visualized by ESRI ArcGIS 10.6. I applied the time series method to the selected OD pairs to detect the trend seasonality. Further, I chose two OD pairs to compare how the travel time fluctuated differently between them.

After exploratory data analysis, I found data gaps caused by technical issues or non-response from API. Further, I used the data from Dec. 24, 2020, to May 31, 2021, as the training data to fit the Prophet model and find inherent patterns in the data. Although I did not collect data for 1:00 am to 5 am, filling values of this time range with the neighboring values can provide a better picture of the consecutive data. I used forward filling (Moahmed et al. 2014) to fill the missing values between midnight to early morning with previously available data (travel time collected at 12:00 am).

To visualize the travel time divergence in the training data, I plotted the travel times of each OD pair as a boxplot in the order of median travel time. Following the idea of Bimpou and Ferguson (2020), I defined travel time variation as the difference between the 95th and 5th percentiles of travel time divided by the median, 50th percentile, of travel time:

$$TTVar_{ij} = \frac{TT_{95} - TT_{5}}{TT_{50}} \tag{4.13}$$

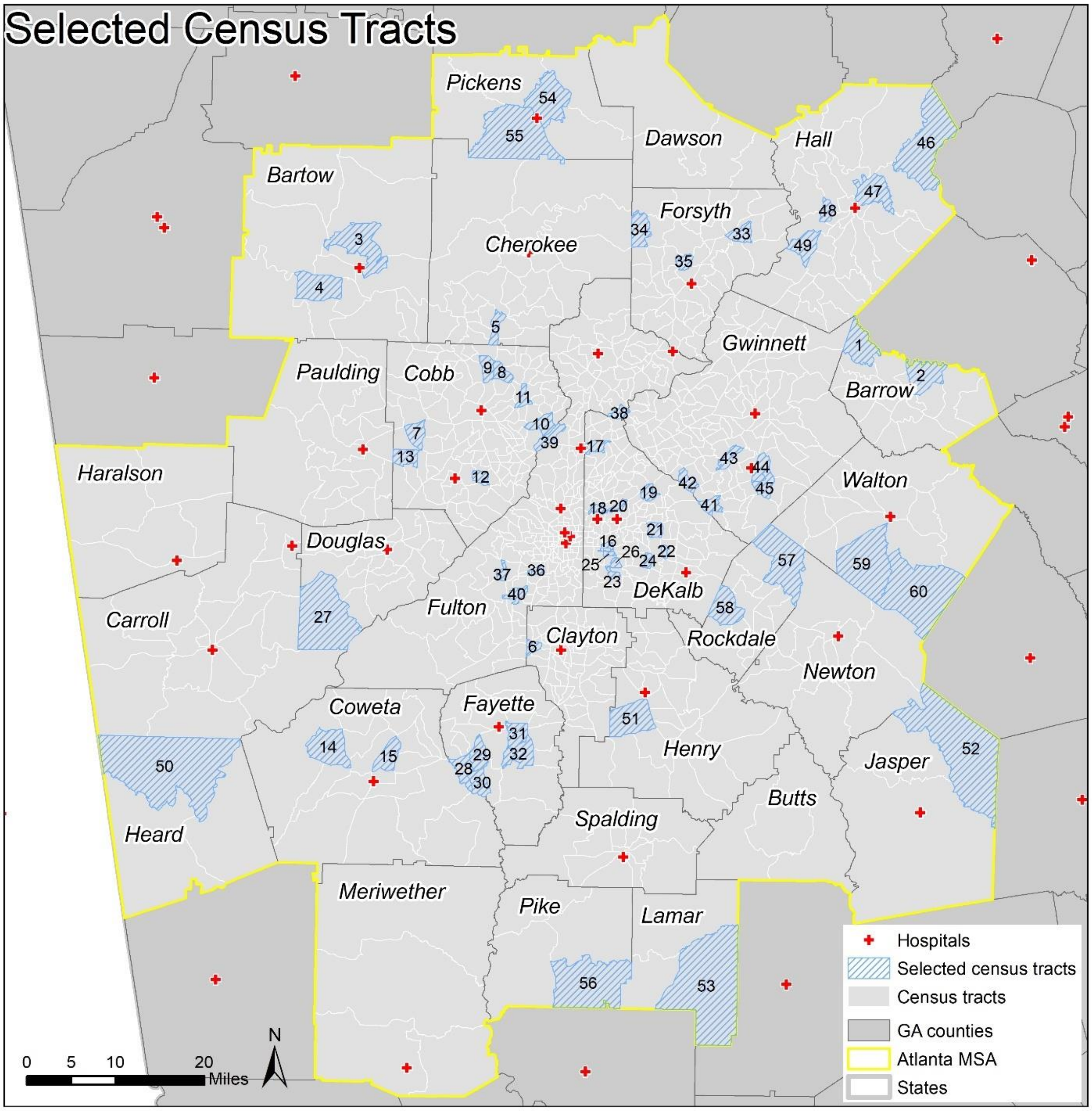
Using 95th and 5th percentiles can eliminate some extreme outliers but also retain the range that travel time fluctuated. By dividing the difference calculated in the nominator to the 50th percentile, the travel time variation reflects the changing range compared with the median of the collected travel time. I further understand how the variation is different for the selected OD pairs and found the pairs with the smallest and biggest variance.

Before fitting the collected travel duration to the Prophet model, I wrote Python scripts to preprocess the collected data into individual files with two columns, the time and travel duration, for each OD pair. Then I fitted the Prophet model to the individual travel duration file. The fitted model was used further to predict future travel times. To be more specific, the week (June 1 – 7, 2021) following the training data was used as the test data to test whether the travel time follows the same pattern that the model found and tested the accuracy on unseen data by using metrics such as MAPE.

4.4 Results

Figure 4.3 shows the selected census tracts for data collection. To collect the real-time travel durations for 60 OD pairs, a total of 173,940 (60 x 2,899) travel time queries to the Google

Directions API were carried out over the training data period from Dec. 24, 2020, to May 31, 2021, which are in total 159 calendar days. Out of 3021 (159 days * 19 hours/day) query time points, 2,899 were valid, and 122 (4.04%) were missing due to internet or other technical issues. The missing time points included two full days, May 12 (Wednesday) and 13 (Thursday). The missing data was forward filled and fit into Prophet additive models.



County Name *ID* Tract Name						
Barrow County	**Cobb County**	**DeKalb County**	**Fayette County**	**Fulton County**	**Hall County**	**Pickens County**
1 Tract 1801.03	*9* Tract 303.13	*18* Tract 215.04	*28* Tract 1403.03	*37* Tract 77.03	*46* Tract 1.01	*54* Tract 502
2 Tract 1803.02	*10* Tract 303.18	*19* Tract 218.05	*29* Tract 1403.04	*38* Tract 101.08	*47* Tract 6	*55* Tract 505
3 Tract 9604.02	*11* Tract 303.30	*20* Tract 223.02	*30* Tract 1403.06	*39* Tract 102.04	*48* Tract 10.04	**Pike County**
4 Tract 9609.02	*12* Tract 311.17	*21* Tract 232.04	*31* Tract 1404.04	*40* Tract 113.03	*49* Tract 14.02	*56* Tract 104
Cherokee County	*13* Tract 315.08	*22* Tract 232.11	*32* Tract 1404.05	**Gwinnett County**	**Heard County**	*57* Tract 601.02
5 Tract 910.01	**Coweta County**	*23* Tract 234.11	**Forsyth County**	*41* Tract 504.15	*50* Tract 9702	**Rockdale County**
Clayton County	*14* Tract 1702	*24* Tract 235.07	*33* Tract 1301.05	*42* Tract 504.26	**Henry County**	*57* Tract 601.02
6 Tract 405.09	*15* Tract 1703.06	*25* Tract 236.01	*34* Tract 1303.03	*43* Tract 507.12	*51* Tract 703.05	*58* Tract 602.02
Cobb County	**DeKalb County**	*26* Tract 236.03	*35* Tract 1304.08	*44* Tract 507.20	**Jasper County**	**Walton County**
7 Tract 302.35	*16* Tract 208.02	**Douglas County**	**Fulton County**	*45* Tract 507.21	*52* Tract 101	*59* Tract 1106.02
8 Tract 303.12	*17* Tract 212.02	*27* Tract 804.02	*36* Tract 76.03		**Lamar County**	*60* Tract 1108
					53 Tract 9702	

Figure 4.3 Selected Census Tracts for Travel Time Collection

Compared to the recommended door-to-MD time, there are five census tracts (8.33%) where the closest hospital was within 10 minutes all the time, and 37 tracts (61.67%) had that were always greater than 10 minutes. Based on the percentage of time reaching the hospital within 10 minutes, the spatial distribution of the tracts is showed in Figure 4.4.

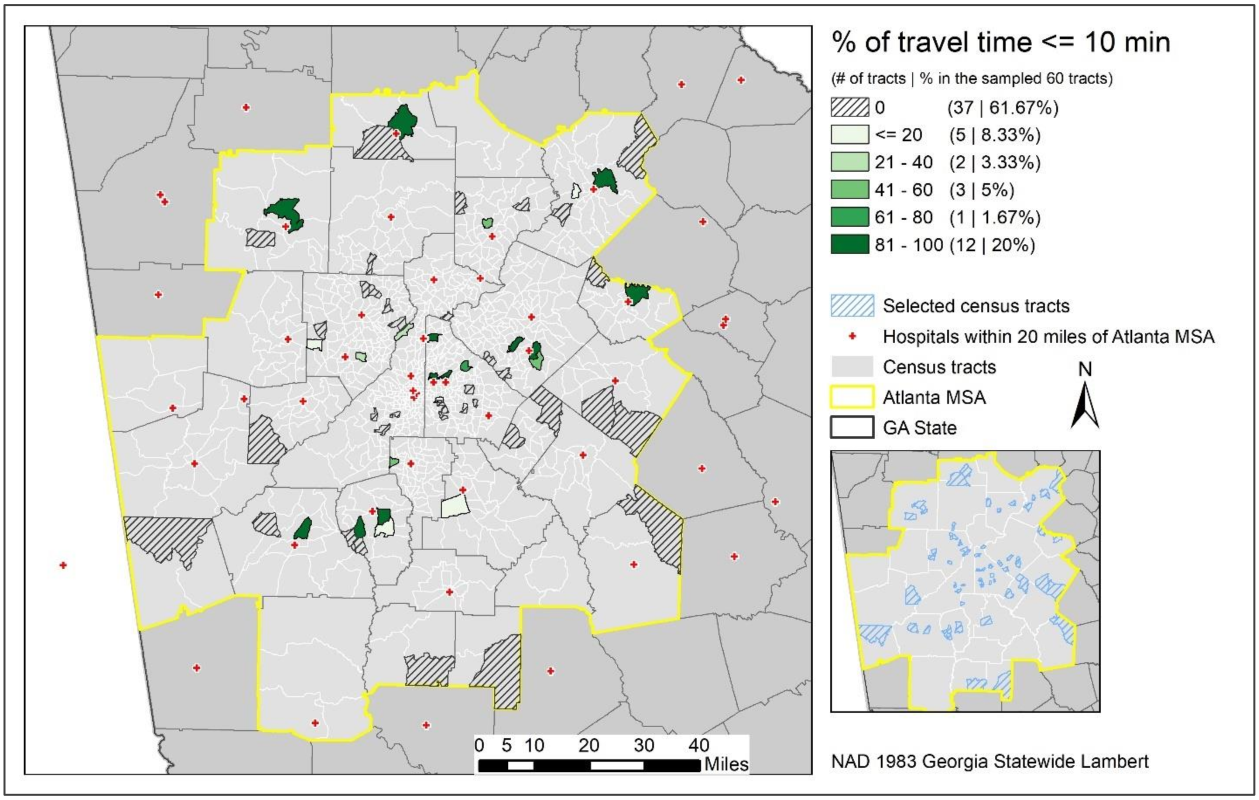


Figure 4.4 Spatial Distribution of Tracts Travel Time to the Nearest Hospital

Figure 4.5 shows the travel time variation for all OD pairs, ordered by the mean travel time. Some OD pairs are with very constant travel times while the others have a few high-value outliers. There is a trend of having higher variance when the mean travel time increases.

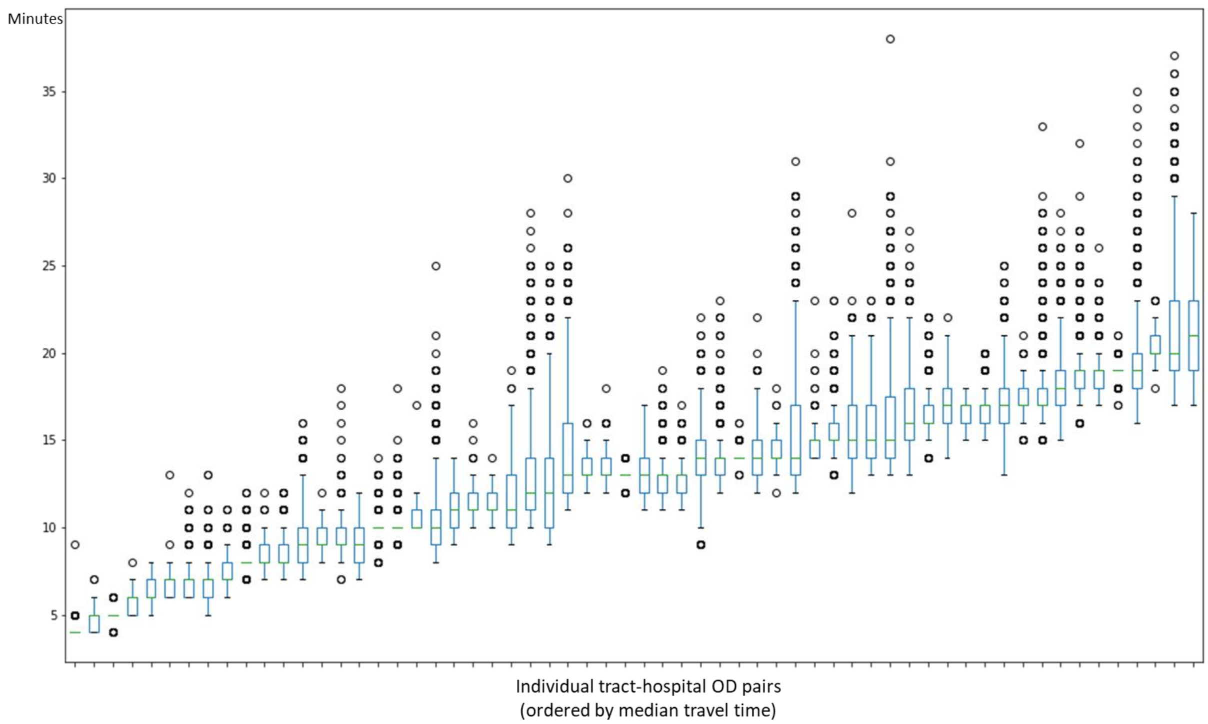


Figure 4.5 Travel Time Variation Boxplot of Tract- Hospital OD Pairs

For each OD pair, I calculated its travel time standard deviation and travel time variation (Eq. 13). Figure 4.6 displays the histograms showing the distribution. Out of 60 OD pairs, the maximum travel time standard deviation is 3.32 minutes, which is from tract 40 (Fulton County tract 113.03). 51 (85%) pairs have a standard deviation smaller than 2 minutes. As defined in Eq. 4.13, travel time variation compares the travel time fluctuation to its own median, which makes it in the scale of its median and is comparable between OD pairs. The travel time variation (Figure 4.6, A), ranges from 0 to 0.77, referring to the ratio of the difference between the 95th and 5th percentiles and its median travel time. The largest variation is also in Fulton County (tract 76.03), whose travel time ranges from 11 to 30 minutes to the nearest hospital, which is 9.3 miles (15.0 km) away in the road network. The smallest variation happens in Gwinnet County (tract 507.20), and the tract is only 1.6 miles (2.6 km) from the hospital and 96.79% of its collected travel time is 5 minutes. 52 (86.67%) pairs have travel time variations smaller than 0.5. Among the eight tracts whose variation equals to or more than 0.5, seven are in Fulton or Dekalb County, where the majority of Atlanta city is in Fulton and a small portion is in Dekalb. Six have the Emory University Hospital Midtown as their closest hospital and they are all tracts in the sample that take this hospital as their destination. Moreover, their routes all involve I-85, a major interstate highway in the Southeastern U.S. serving multiple major metropolitan areas and stretching through Alabama, Georgia, South Carolina, North Carolina, and Virginia.

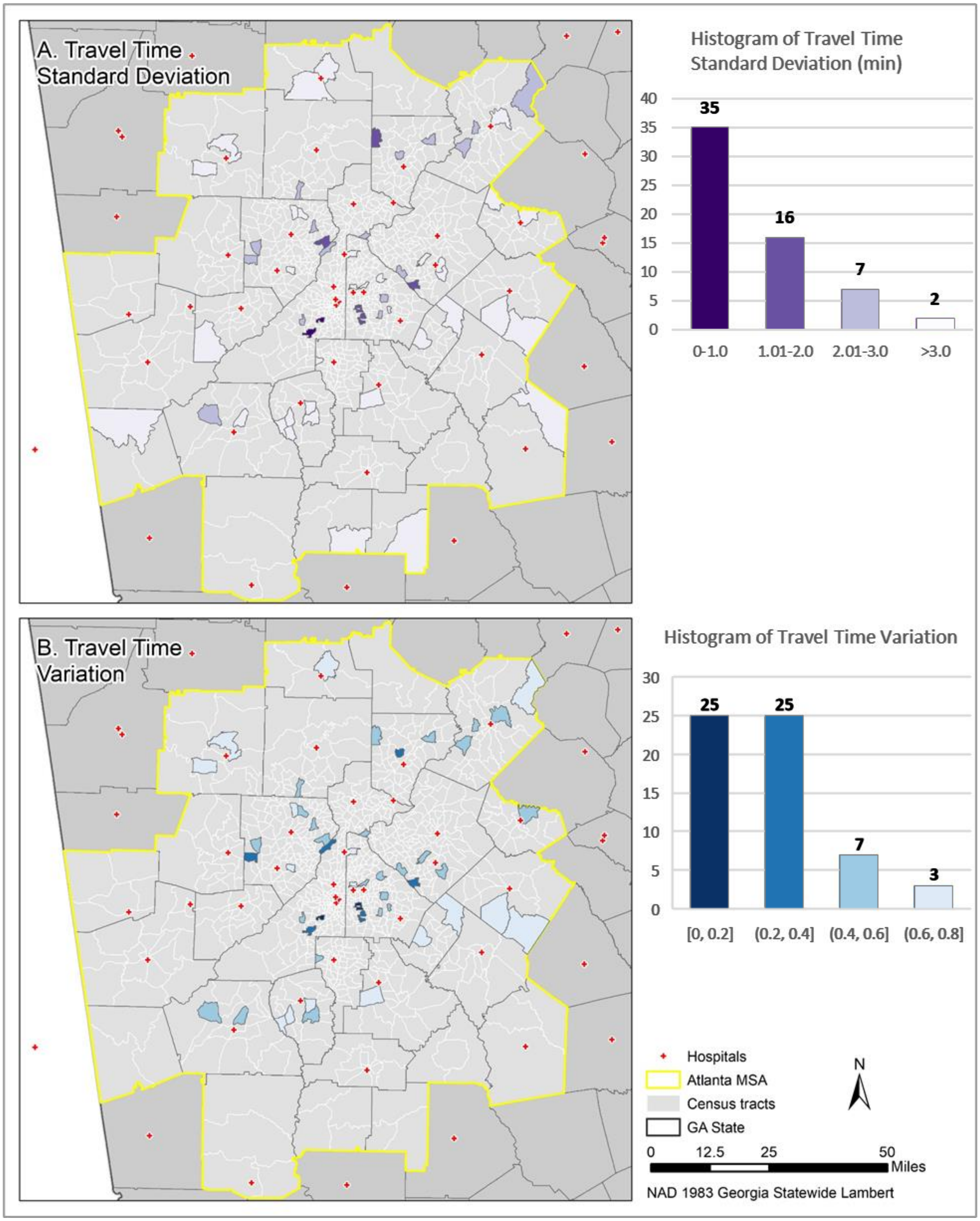


Figure 4.6 Maps and Histograms of Travel Time Standard Deviation and Variation

There are some findings when grouping the travel time variations by the destination hospital. 60 OD pairs have 26 hospitals as their destinations, and each hospital serves one to six sampled tracts. With the highest (0.62) averaged travel time variation, Emory University Hospital Midtown is the destination for most (six) tracts, and the travel distance ranges from 7.2 to 13.5 miles (11.6 to 21.7 km). Located in Carroll County, which is at the edge of our study area, Tanner Medical Center/Villa Rica serves one sampled tract, which is 9.9 miles (16.0 km) away and has the lowest travel time variation (0.06) with more than 98% of collected travel times are 16 or 17 minutes.

Two of the sampled tracts illustrate the travel time variation of individual OD pairs and detected patterns by Prophet model: tract 39 (102.04, Fulton County) to Northside Hospital (Figure 4.7), and tract 53 (9702, Lamar County), to the Monroe County Hospital (Figure 4.8). In both figures, penal A is the line chart of travel time from late December to June. Penal B presents the extracted trends in the collected data, and penal C shows the effects of holidays on travel time. Panel D and E are the weekly and daily seasonality observed in the data. The y-axis of panel A and B shows the real travel time in minutes. For panel C, D, and E, the values on the y-axis can be seen as the incremental effect on y from the considered component, holiday, or seasonality (Letham 2019). In other words, it measures the change compared to the baseline.

For the Fulton County tract 39 in Figure 4.7, the shortest road distance of a regular trip is 4.6 miles (7.4 km), half of which is on I-285. The minimum travel time is 9 minutes with some outlier cases at 5 pm (19 min) and 6 pm (21 min) on Jan. 6, and especially 5 pm (25 min) on Feb. 25. On Feb. 25, a man was shot and killed inside a car on I-20 in Downtown Atlanta and I-20 was shut down for hours (King 2021; Prince and Spink 2021), which may detour some traffic to I-285. For this tract, 29.85% of the collected travel time (before filling in the missing values) is smaller or equal to 10 minutes. Although the trend change (the difference between maximum and minimum in panel B) is not tremendous (about 0.8 min), we can see a decrease in travel time from Dec. to late Jan., an increase till the end of Apr., and a decrease in May. There is a noticeable dip in early Apr., which was the Metro Area Spring Break, Apr. 5-9, for Atlanta public schools (Atlanta Public Schools 2020). For the holiday consideration, I assumed the holiday can influence three days before and after, and included Christmas (Dec. 25) of 2020, New Year (Jan. 1), Martin Luther King Jr. Day (Jan. 18), Washington's Birthday or Presidents' Day (Feb. 15), and lastly, Memorial Day (May 31) of 2021. Compared to non-holidays, we noticed in panel C that, for most of the time, holidays had negative effects (shorter travel time) for this OD pair, especially for Christmas. However, it instead had a longer travel time before Memorial Day. For the weekly and daily seasonality, there is an increase for weekdays (with the difference as big as 150% between the valley and peak - Sunday noon and Friday night) in panel D and two rush-hour peaks (with the difference as big as 300% between midnight and afternoon) in panel E.

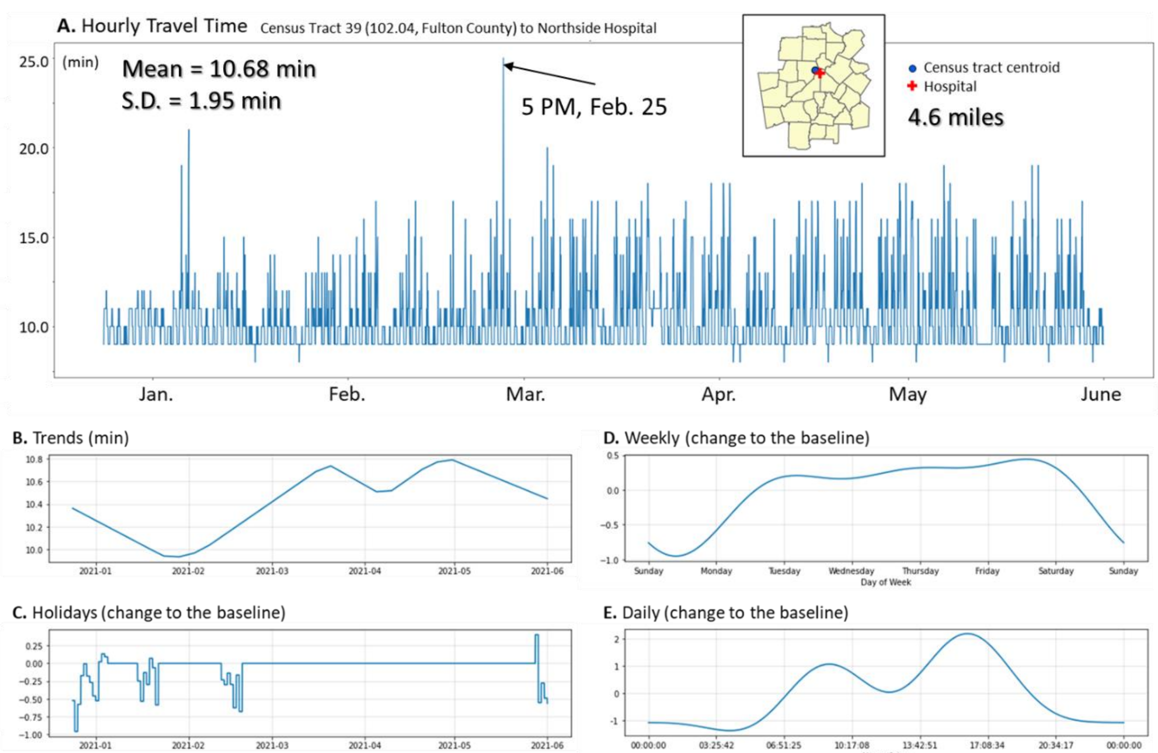


Figure 4.7 Travel-Time Line Chart and Detected Patterns for Tract 39 (102.04, Fulton County)

For the Lamar County case (tract 53), the shortest road distance is 12.0 miles (19.3 km), most of which is on US-41. While the minimum and maximum travel times are 13 and 16 minutes, 94.17% of the queries returned 14 minutes, which are quite consistent (Figure 4.8, panel A). The trend change in panel B is minor again for only about 0.3 min, with an increase till mid-March. Unlike the Fulton case, holidays positively impacted this OD pair (increasing travel time), especially for Martin Luther King Jr. Day and Washington's Birthday. Although it has weekly and daily seasonality as well, the differences between the valley and peak are only 10% and 12.5%, respectively.

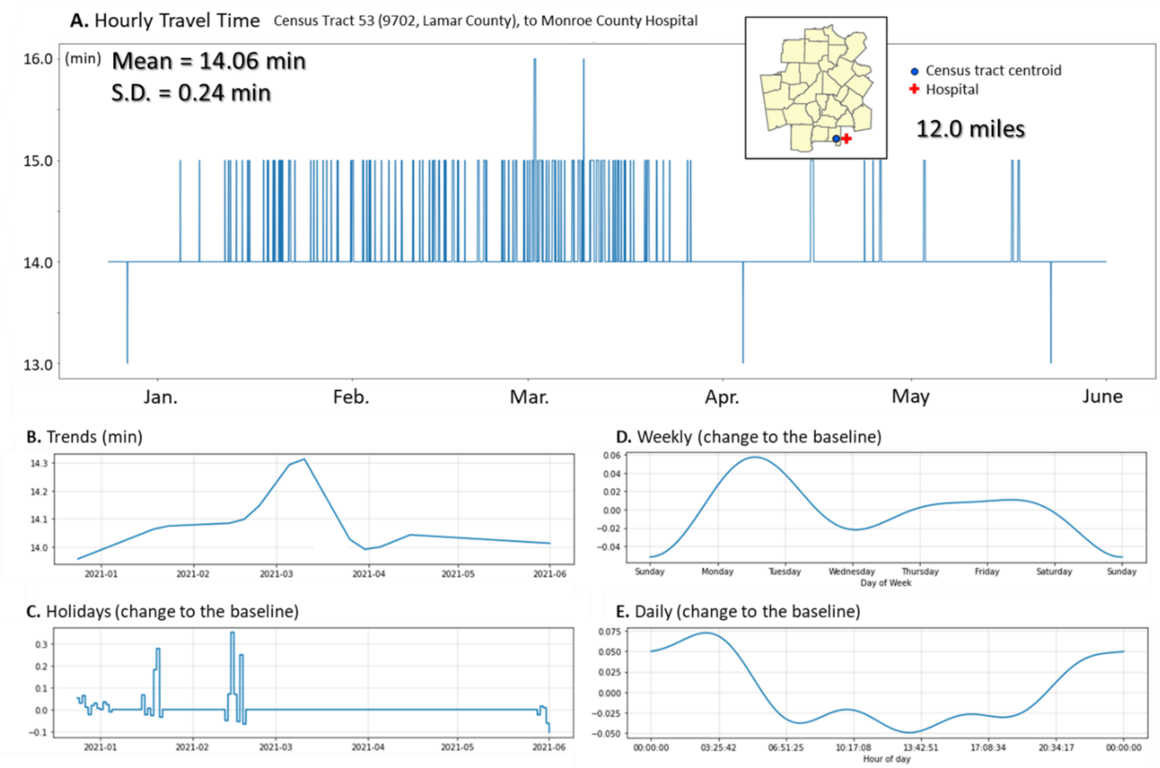


Figure 4.8 Travel-Time Line Chart and Detected Patterns for Tract 53 (9702, Lamar County)

Using the Prophet model to predict June 1-7, I calculated MAPE for each OD pair by comparing the predicted values to the collected travel time from Google. MAPE (Eq. 4.10) is a measure of how accurate a forecast model is. As a measure in percentage of the actual value, the smaller the value, the more accurate the model predicts unseen values. For example, close to zero means the predicted values are very close to the actual values. The median MAPE is 7.60% which means the percentage difference between the predicted and real travel time is 7.60%. The range of the MAPEs is 1.60% (Census Tract 101, Jasper County to Jasper Memorial Hospital) to 22.81% (Census Tract 208.02, DeKalb County to Emory University Hospital Midtown). For the tract with the highest MAPE, it shows that, on average, the predicted value is 22.81% off (bigger or smaller) than the actual travel time.

By applying the time series results, we can update the catchment size $D_0(t)$ in the accessibility equations (Eq. 10 and 11). Take the June. 7th as an example, Figure 4.9 shows how the catchment size varies throughout the selected time points of the day. Panel A shows the forecasted travel time based on the Prophet model, with the lowest travel time stays almost the same from 0 to around 5:00 and two peaks at 9:00 and 16:00. The change points at 0:00, 9:00, 12:00, and 16:00 are used for illustrating changes in average travel speed (panel B) and catchment size (panel C). The Average travel speed can be calculated using the distance between the OD and the travel time. Then the speed is applied in drawing the catchment in panel C (for illustration purposes, the catchment is based on Euclidean distance instead of road network distance). The change in the catchment size will influence how many population units (demand) and service sites (supply) are considered in Eq. 10 and 11, and further impact the value of accessibility.

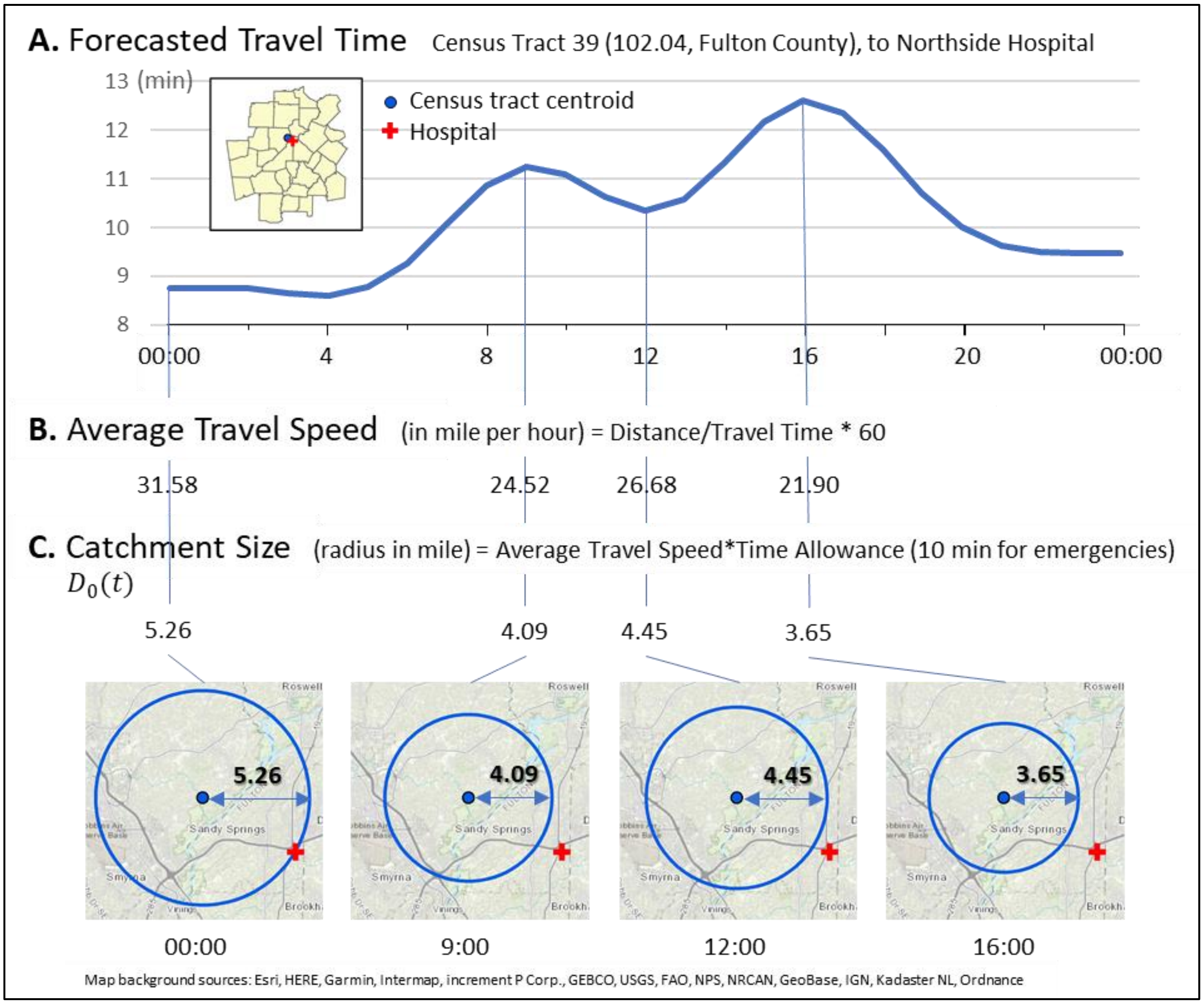


Figure 4.9 Accessibility Catchment Size Variation by Using Time Series Results

4.5 Discussion and Conclusions

Using driving as an example, I demonstrate the volatility of travel times for the older adult weighted centroid of 60 selected tracts to their nearest hospital pairs in Metro Atlanta. While every second counts for medical emergencies, especially for older adults, I found that 37 out of 60 sampled tract centroids (more than 60%) can never reach a hospital within recommended door-to-MD time while five can always ensure timely arrival. For 18 sampled tract centroids (30%), they are vulnerable to changing travel conditions. Their chance of reaching hospitals within 10 minutes spans from 0.23% to 99.97% throughout the study timeframe. By applying time series concepts and methods to the collected driving duration from Google, I observed significant differences in trend, both weekly and daily seasonality of travel times, as well as the holiday effects, and further illustrated with two examples. Using the detected patterns, I predicted travel time for the following week and compared it with the actual travel time. The median of the percentage difference between the predicted and real travel time is 7.60% for considered OD pairs. However, travel time variation can be significant (as 0.8 of its median travel time) for tracts that route via an important interstate highway. Understanding the trend and seasonality at different temporal scales (daily, weekly, and possibly yearly) with holiday impact can help us capture the dynamic nature of accessibility. Otherwise, atemporal accessibility measures can be oversimplified for the real scenario by looking over the influence of ever-changing travel time, demand, and supply. Hence, I proposed the idea of making every component of accessibility a function of time after detecting the inherent patterns by time series theory and methods. The idea can be easily applied to 2SFCA and its extended methods and other travel modes, especially transit, which is highly influenced by traffic and its schedule.

This study has several limitations. First, the data were collected during the COVID-19 pandemic, which may have impacted travel patterns due to factors such as working/studying from home, related restrictions, vaccination rollout process, among others. Second, this project assumes that the travel time equals the driving duration queried from Google. However, since the collected driving duration is still an estimation at that time point, there may be some changes for a real driving trip (a longer trip due to car accidents that happened after the query time). Moreover, in the scenario of medical emergencies, the driving time of an ambulance may be shorter than the queried time, but it is also hard to consider the response time for the ambulance to arrive at the patients' location. Third, in our case, the test week (June 1 to June 7) tailed the long weekend of

Memorial Day, which may impact the result of forecasting. The performance of the model may be more robust if data for a longer period is included. In addition, there is an option to customize the holiday list by adding local events, such as sports games and school calendars, to the model.

Building on time series concepts and methods, this study applied them to real-world travel data. It provided more evidence on the dynamics, such as trend and seasonality, of travel time and further accessibility. Future studies can use a similar framework to collect data without sampling and query the *n* closest service sites instead of only the closest one. This can help to create a series of maps showing the spatiotemporal variation in travel times. Besides, a longer data collection time of a whole year or even multiple years can unveil yearly patterns. In addition, to incorporate the time-series aspect to other components of accessibility, such as demand population ($Pop_k(t)$), future studies can refine accessibility measures to capture the changing pattern of population demand due to commuters, such as employees and students. The same idea can be used for the capacity ($S_j(t)$), which may have a seasonality embedded due to operation hours, staffing plan, and others.

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CHAPTER 5

CONCLUSION

The United Nations General Assembly stated that "Health is central to our experience of older age and the opportunities that aging brings" and declared 2021-2030 the Decade of Healthy Ageing (World Health Organization 2020). By focusing on older adults, this dissertation aims to understand their migration, vulnerability, and accessibility to emergency services to better accommodate their needs in the aging era. To embrace aging as individuals and the whole society, three specific objectives were addressed here: (1) investigation of the relationship between older adult migration and destination characteristics, (2) construction of a vulnerability index tailored to the older population to assess the potential risks, and (3) identification of the time series patterns in the data of travel time from weighted tract centroid to emergency services. These objectives were at different scales: the first two investigated statewide migration and vulnerability at the county level and for Georgia, while the last one took a closer look at Atlanta Metropolitan Area at the census tract level. More and more researchers have tried to understand related topics in geography, public health, and economics (Jensen and Deller 2007; Wiles et al. 2012; Shannon et al. 2015). This research builds upon the previous literature and highlights some new considerations in older adult studies.

To archive the first objective, I examined the county-level relationship between the number of older migrants and destination characteristics in six environment categories (physical and built, climatic, healthcare, demographic and socioeconomic, recreational, and lastly, residential environment) in the state of Georgia. The proposed six-category structure of variables includes

LTC facility bed, affordable housing, and geriatrician availability, which were rarely considered in the migration literature but are vital to older adults. Both linear regression and decision tree models were applied here to understand the relationship using parametric and non-parametric methods. Despite some common variables, our finding echoes with previous researchers that there are different relationships among older migrant subgroups, intrastate, interstate, younger (65–74), and aged (75+) older migrants. For example, linear regression results show that the intrastate migration is not related to the physical and built environment, while all the other three subgroups are related to elevation variation and/or water area coverage. The combination of linear regression and decision tree models explored the potential to apply different models to capture various data perspectives. Despite the different subset of selected variables among models of older migrant subgroups, the shared variables are in the same direction (positive or negative impact) and with similar magnitudes. In addition, only younger migration is statistically significant with the climatic environment. The result also indicates that intrastate migration is associated with the bed availability of non-nursing-home LTC facilities, one of the variables that have not been considered in previous research. Understanding the relationship between older adult migration and destination characteristics provides insights into accommodating older adults and building age-friendly communities. It can also guide future planning and manages regional impacts of the potential migration flow (Patrick, 1980).

While the first piece investigated the questions about where older adults migrate and why, the second study aimed to assess and understand where may make older residents more vulnerable. Although existing vulnerability indexes, such as the Social Vulnerability Index (SoVI and SVI), have been widely adapted to assess the vulnerability level for the general population (Cutter et al. 2003; Centers for Disease Control and Prevention 2020), but there is a need for constructing an older adult vulnerability index to outline the risk factors that make the older more susceptible than other age groups. Based on the existing literature, risks that impair older adults more than other subpopulations can be summarized into four categories: the environmental, built environment, peer group, and social risks. Refined categories were used here to consider the risks from natural disasters, extreme weathers, air toxics, service inaccessibility, and other socioeconomic variables describing older adults peer group and other populations in need. The four categories are further integrated as the Vulnerability Index of Older Adults (VIO). Results show that the proposed VIO has very varying geographical variation compared to widely used social vulnerability by Dr. Cutter (SOVI) or by CDC (SVI), both focusing on the social part of vulnerability and are designed for the general population. VIO can be useful to understand potential risks facing by older adults, plan for resource allocation, and disaster preparation by integrating both environmental and social risks. This index can also pinpoint the locations that need more attention, especially in potential natural hazards or emergencies and related factors that may vary geographically. It is also beneficial to acknowledge the risks by older adults themselves, their families, as well as local governments to better intervene and mitigate the older adult vulnerability in the future.

Lastly, the third study dived the accessibility measure by applying time-series concepts and methods to real-world travel time data. Despite numerous versions and a wave of development of accessibility measures, few have incorporated changing dynamics of travel time into assessing accessibility. As a popular subdomain in statistics, time series analysis has the advantage of decomposing the temporal data to detect the trend (the level of increasing or decreasing) and seasonality at different granularity (daily, weekly, or yearly patterns). Hourly travel duration time was collected using Google Directions API from late Dec. 2020 to the end of June 2021for selected pairs of the census tract centroid (weighted by older population) and nearest hospital in the Atlanta

Metropolitan Area. The collected data helped identify the census tracts that could not reach the emergency services within recommended door-to-MD time for life-threatening conditions. The time series model decomposed the travel time data to unveil the embedded patterns, including trend, seasonality, and holiday impact for each census tract to hospital pair. The trend, daily and weekly seasonality, and holiday effects were visualized and compared between two examples of the tract to hospital pairs. The patterns were unlike across the study area because of various involved routes and distance. The model was further used to predict future travel times and using the accuracy metric in time series. The prediction was with high accuracy. In addition, the idea can further apply to refine accessibility measures to incorporate the patterns to dynamic accessibility measures. A new way of assessing accessibility was introduced to make every component of accessibility measures as a function of time, so the population demand, supply capacity, and geographic impedance all fluctuate with the time of the day, the day of the week, and whether it is a holiday or not. Future studies can refine accessibility measures to capture the changing dynamics of demand due to commuters, as well as supply which is related to operation hours, staffing plan, and others.

Future studies may take steps further from this research to better understand older adults' needs and their geographical variation. For example, the migration study used climatic variables such as climate zones, but there are only two zones in Georgia. Future studies may extend the idea to a larger area, such as the region or the whole U.S., so that differences among climate zones can be tested. A more evident trend may be revealed when the data includes a higher variation. As for the vulnerability study, the selection of analysis unit, county, may not be ideal, especially for urban areas with a lot of internal heterogeneity. Future research may use smaller units, such as census tracts, when the data is available, and it can reveal the masked spatial variations. In addition, for the accessibility study, future studies can use a similar framework to collect data without sampling and query the n closest service sites instead of only the closest one. This approach can help to create a series of maps or interactive maps showing the spatiotemporal variation in travel times. Additionally, with more data available, it can be observed that what are the characteristics of census tract and hospital pairs that have similar patterns in trend and seasonality. This finding can be helpful to estimate the trend and seasonality for the unseen origin and destination pairs.

This dissertation sets out to better understand the older adults' migration choices and living environments, including vulnerability and accessibility, to provide some insights for both academics and local administrations in preparing for the aging society. Using GIS analysis, statistical models, and time series methods, this research presents some findings and directions that future studies may work on to ensure accommodations for older adults at different levels. Through similar research efforts tailored to this population, older adults will have drawn more attention they need to lead to an enjoyable after-retirement life.

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APPENDICES

Appendix A. Proposed structure of variables considered in the county-level analysis (with description and data source)

Category Abbr.	Predictor variable	Description	Data source
1 Physical and Built Environment			
P_1	Elevation variation (s.d.)	The standard deviation of elevation (feet) of the county	National Elevation Dataset (USGS)
P_2	Water area coverage (%)	Water area as a proportion of the total county area	National Land Cover Data (USGS)
P_3	Green space coverage (%)	Green space as a proportion of the total county area	National Land Cover Data (USGS)
P_4	Road density	Road density (miles per square mile) of the county	TIGER (U.S. Census Bureau)
2 Climatic Environment			
C_1	Climate zone	Climate zone (0 denotes hot-humid, 1 denotes mixed-humid)	U.S. Department of Energy
C_2	Proximity to the coastline	Distance (in miles) to the closest coastline	TIGER (U.S. Census Bureau)
3 Healthcare Environment			
H_1	Hospital availability*	Hospital availability per 1,000 people within 10 miles of the county	HIFLD (U.S. Department of Homeland Security)
H_2	Physician availability*	Physicians (pediatricians excluded) availability per 1,000 people in the county	GA Board of Health Care Workforce
H_3	Geriatrician availability#	Geriatrician availability per 1,000 older adults in the county	U.S. News
H_4	Non-nursing-home LTC facility bed availability#	Non-nursing-home LTC facility beds per 1,000 older adults in the county	GaMap2Care (Georgia Department of Community Health)
H_5	Nursing home bed availability#	Nursing home facility beds per 1,000 older adults in the county	
4 Demographic and Socioeconomic Environment			
D_1	Total population (in 1,000)	Total population in the county	County-level 2013-2017 ACS (U.S. Census Bureau)
D_2	Population density	The population density in a square mile	
D_3	Older population proportion (%)	Older population proportion in the total population	
D_4	Racial diversity entropy	County's racial diversity entropy. High value demotes higher diversity.	
D_5	Disability proportion (%)	The proportion of people with disability	
D_6	Wealthy proportion (%)	The proportion of people with income at or above 400% of the poverty threshold	
D_7	Unemployment rate (%)	The unemployment rate in the civilian noninstitutional population	
D_8	Per capita income (in $1,000)	The per capita income by county	
D_9	Real gross domestic product (GDP) per capita (in $1,000)	The average of the real GDP per capita (2013-2017) in $1,000 of chained 2012 dollars by county	Bureau of Economic Analysis

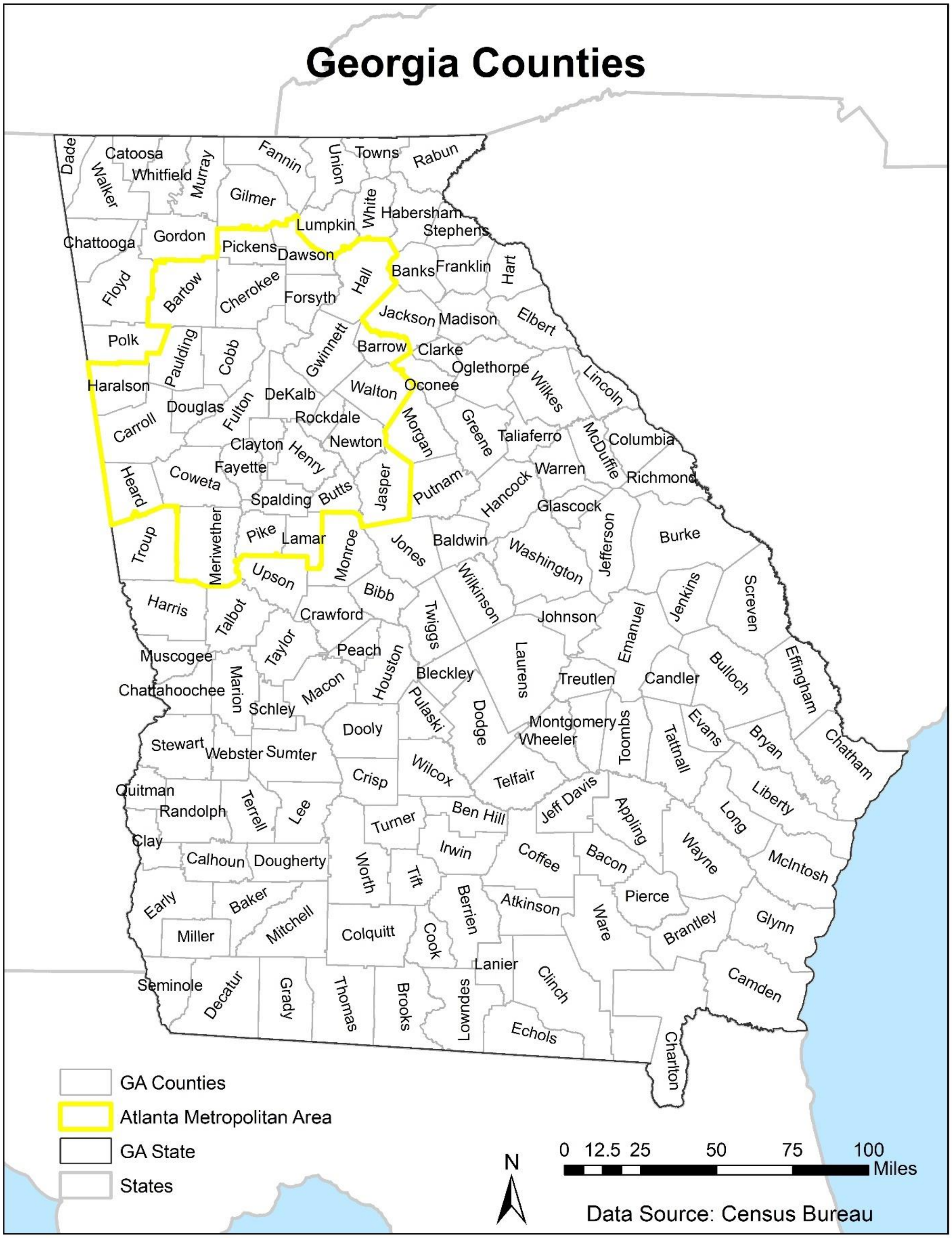
Appendix A continued

Category Abbr.	**Predictor variable**	**Description**	**Data source**
5 Recreational and Cultural Environment			
Rec_1	Food services & drinking places*	Smoothed availability* of food services and drinking places in the county	County Business Patterns and Nonemployer Statistics Combined Report (U.S. Census Bureau) and North American Industry Classification System (NAICS)
Rec_2	Arts, entertainment, & recreation amenities*	Smoothed availability* of arts, entertainment, and recreation amenities in the county	
Rec_3	Religious organizations	Smoothed availability* of religious organizations, such as churches, in the county	
Rec_4	Proximity to university	Distance (miles) to the closest university in the University System of Georgia	University System of Georgia

Category Abbr.	**Predictor variable**	**Description**	**Data source**
6 Residential environment			
Res_1	Cost of living (index)	Cost of living index for 2016	The Council for Community and Economic Research
Res_2	Affordable housing availability#	Affordable housing unit availability within the county	U.S. Department of Housing and Urban Development
Res_3	Crime rate (per 100,000)	Crime rate per 100,000 people	Uniform Crime Reporting Program Data (U.S. Department of Justice)
Res_4	Rurality (%)	Percent (%) of population living in rural areas	2010 Percent Rural table (U.S. Census Bureau)

(* - per 1,000 people, # - per 1,000 older adults)
USGS -
TIGER - Topologically Integrated Geographic Encoding and Referencing
HIFLD - Homeland Infrastructure Foundation-Level Data

Appendix B. Georgia county names

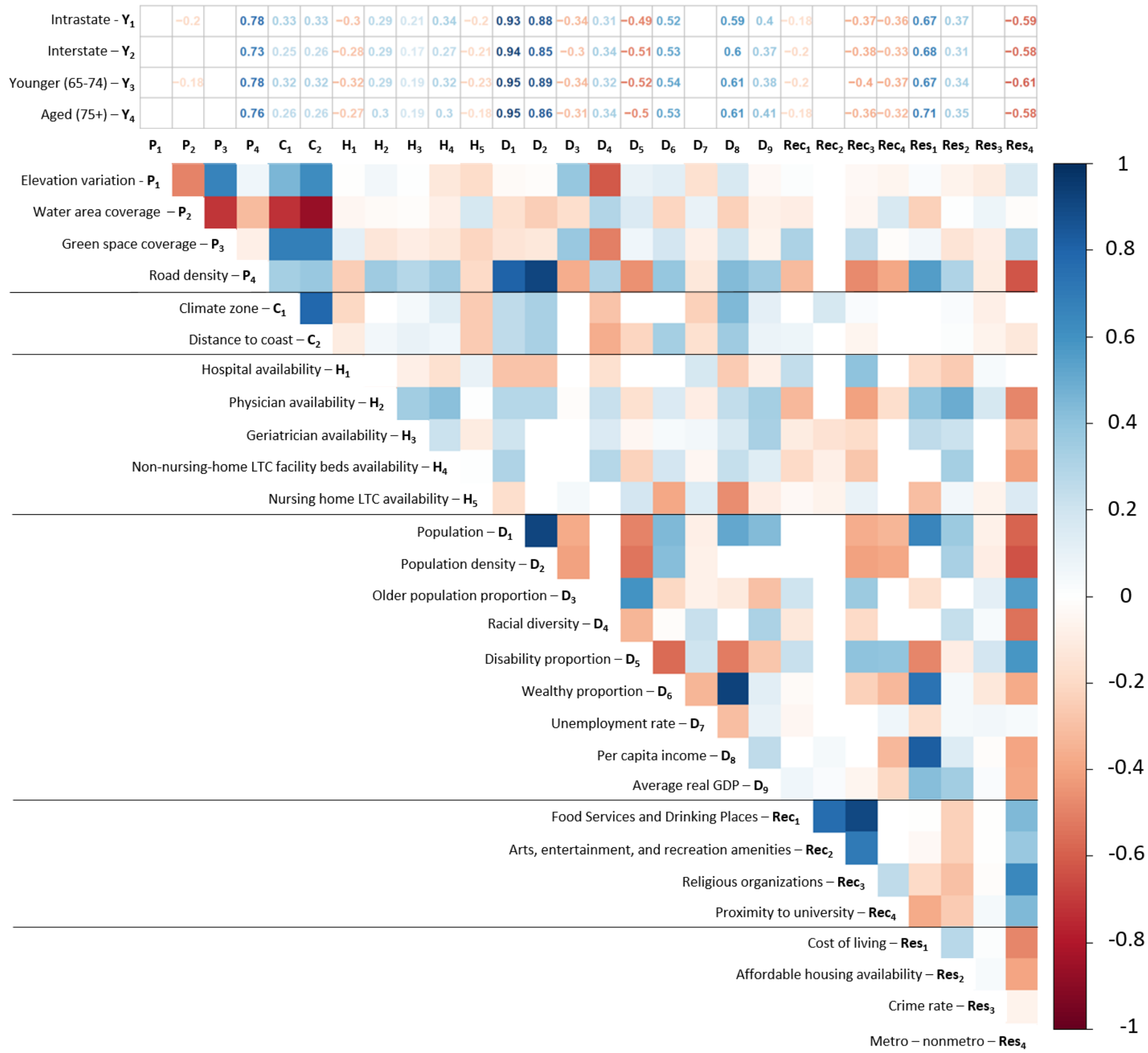


Appendix C. Descriptive statistics of variables (by county).

Abbr.	Variable	Min	Max	Mean	Std.dev
Y					
	Total migration	3	3447	269.69	496.24
Y_1	Intrastate migration	0	1911	145.96	255.09
Y_2	INTERstate migration	0	1575	123.76	258.25
Y_3	Younger older migration	0	1794	163.81	281.02
Y_4	Aged older migration	0	1653	105.88	223.23
X					
1 Physical and Built Environment					
P_1	Elevation variation (sd)	2.46	173.54	30.84	35.23
P_2	Water area coverage (%)	0.33	68.76	16.73	15.12
P_3	Green space coverage (%)	11.82	86.28	45.37	17.87
P_4	Road density	2.03	15.25	4.08	1.98
2 Climatic Environment					
C_1	Climate zone	0	1	0.52	0.50
C_2	Distance to the coastline (in mile)	7.17	312.72	148.55	74.26
3 Healthcare Environment					
H_1	Hospital availability (per 1,000 people in the county)	0	0.99	0.15	0.15
H_2	Physician availability (per 1,000)	0	2.37	0.62	0.43
H_3	Geriatrician availability[#]	0	2.44	0.12	0.26
H_4	Non-nursing-home LTC facility beds availability[#]	0	75.40	18.99	14.01
H_5	Nursing home beds availability[#]	0	209.80	41.83	33.28
4 Demographic Environment					
D_1	Total population (in 1,000)	1.84	1010.42	64.16	138.36
D_2	Population density (people/square mile)	8.23	2715.36	197.59	399.01
D_3	Older population proportion (%)	3.69	33.62	16.18	4.31
D_4	Racial diversity	0.16	0.81	0.49	0.12
D_5	Disability proportion (%)	7.23	27.10	16.15	3.52
D_6	Wealthy proportion (%)	10.68	59.12	24.82	8.63
D_7	Unemployment rate (%)	2.52	21.40	7.79	3.01
D_8	Per capita income (in $1,000)	11.19	41.04	22.31	5.11
D_9	Average real GDP (in $1,000)	6.39	150.65	30.08	18.60
5 Recreational and Cultural Environment					
Rec_1	Food Services and Drinking Places (per 1,000)	0.81	9.09	2.40	1.56
Rec_2	Arts, entertainment, and recreation amenities (per 1,000)	0.05	1.97	0.39	0.29
Rec_3	Religious organizations (per 1,000)	0.31	4.09	1.21	0.71
Rec_4	Proximity to university (in mile)	0.63	61.31	23.21	12.76
6 Residential Environment					
Res_1	Cost of living (index)	84.00	111.40	95.44	3.50
Res_2	Affordable housing availability [#]	0	43.90	4.82	9.06
Res_3	Crime rate (per 100)	0	9.98	3.15	1.57
Res_4	Rurality	0.2	100	60.48	28.87

([#] per 1,000 older adults)

Appendix D. Correlation matrix for the considered variables



Appendix E. Descriptions of Considered Hazards of the Environmental Risks from NOAA Storm Data Instruction (National Weather Service 2016)

Factor	Hazard	Description from the NOAA Storm Data instruction
Storm/flood -related risk	Flash Flood	A Flash Flood event begins within minutes to multiple hours of the causative event such as moderate to heavy rain, dam break, or ice jam release. Ongoing flooding can intensify to the shorter term flash flooding in cases where intense rainfall results in a rapid surge of rising flood waters. Flash flooding, such as dangerous small stream or urban flooding and dam or levee failures, requires immediate action to protect life and property. Conversely, flash flooding can transition into flooding as rapidly rising waters abate. The Storm Data preparer uses professional judgment in determining when the event is no longer characteristic of a Flash Flood and becomes a Flood.
	Flood	Any high flow, overflow, or inundation by water which causes damage. In general, this would mean the inundation of a normally dry area caused by an increased water level in an established watercourse, or ponding of water, that poses a threat to life or property. If the event is considered significant, it should be entered into Storm Data, even if it only affected a small area.
	Heavy Rain	Unusually large amount of rain which does not cause a Flash Flood or Flood event, but causes damage, e.g., roof collapse or other human/economic impact. Urban and small stream flooding commonly occurs in poorly drained or low lying areas. These are types of areal flooding and are to be recorded as Flood events, not Heavy Rain.
	Hurricane (Typhoon)	A tropical cyclone in which the maximum 1-minute sustained surface wind is 64 knots (74 mph) or greater. In the Atlantic Ocean or the North Pacific Ocean east of the International Date Line, this event would be labeled a Hurricane, and in the North Pacific Ocean west of the International Dateline, this event would be classified as a Typhoon.
	Tornado	A violently rotating column of air, extending to or from a cumuliform cloud or underneath a cumuliform cloud, to the ground, and often (but not always) visible as a condensation funnel. For a vortex to be classified as a tornado, it must be in contact with the ground and extend to/from the cloud base, and there should be some semblance of ground-based visual effects such as dust/dirt rotational markings/swirls, or structural or vegetative damage or disturbance.
	Tropical Storm	A tropical cyclone in which the 1-minute sustained surface wind ranges from 34 to 63 knots (39 to 73 mph) inclusive. The tropical storm should be included as an entry when its effects, such as wind, storm tide, freshwater flooding, and tornadoes, are experienced in the WFO's CWA. Terrain (elevation) features, in addition to the storm tide/run- up height, will determine how far inland the coastal flooding extends.
Cold-related risk	Cold/Wind Chill	Period of low temperatures or wind chill temperatures reaching or exceeding locally/regionally defined advisory (typical value is -180F or colder) conditions. If the event that occurred is considered significant, even though it affected a small area, it should be entered into Storm Data. There can be situations where advisory criteria are not met, but the combination of seasonably cold temperatures and low wind chill values (roughly 150F below normal) may result in a fatality. In these situations, a cold/wind chill event may be documented if the weather conditions were the primary cause of death as determined by a medical examiner or coroner. Normally, cold/wind chill conditions should cause human and/or economic impact.
	Extreme Cold/Wind Chill	A period of extremely low temperatures or wind chill temperatures reaching or exceeding locally/regionally defined warning criteria (typical value around -350F or colder). If the event that occurred is considered significant, even though it affected a small area, it should be entered into Storm Data. Normally these conditions should cause significant human and/or economic impact. However, if fatalities occur with cold temperatures/wind chills but extreme cold/wind chill

		criteria are not met, the event should also be included in Storm Data as a Cold/Wind Chill event and the fatalities are direct.
	Frost/Freeze	A surface air temperature of 32 degrees Fahrenheit (F) or lower, or the formation of ice crystals on the ground or other surfaces, for a period of time long enough to cause human or economic impact, during the locally defined growing season. If the event that occurred is considered significant, even though it affected a small area, it should be entered into Storm Data.
	Hail	Frozen precipitation in the form of balls or irregular lumps of ice. Hail 3/4 of an inch or larger in diameter will be entered. Hail accumulations of smaller size, which cause property and/or crop damage or casualties, should be entered. Maximum hail size will be encoded for all hail reports entered.
	Heavy Snow	Snow accumulation meeting or exceeding locally/regionally defined 12 and/or 24 hour warning criteria. This could mean values such as 4, 6, or 8 inches or more in 12 hours or less; or 6, 8, or 10 inches in 24 hours or less. If the event that occurred is considered significant, even if it affected a small area, it should be entered into Storm Data. In some heavy snow events, structural damage, due to the excessive weight of snow accumulations, may occur in the few days following the meteorological end of the event. The preparer should include this damage as part of the original event and give details in the narrative. Normally, strong winds or other precipitation types are not present in a Heavy Snow event. If they were, then the Winter Storm event should be used.
	Ice Storm	Ice accretion meeting or exceeding locally/regionally defined warning criteria (typical value is 1/4 or 1/2 inch or more). If the event that occurred is considered significant, even though it affected a small area, it should be entered into Storm Data. The Storm Data preparer should include the times that ice accretion began, met criteria, and accretion ended. If the freezing rain was mixed with other precipitation types, then a Winter Storm event should be used.
	Winter Storm	A winter weather event that has more than one significant hazard (i.e., heavy snow and blowing snow; snow and ice; snow and sleet; sleet and ice; or snow, sleet and ice) and meets or exceeds locally/regionally defined 12 and/or 24 hour warning criteria for at least one of the precipitation elements. If the event that occurred is considered significant, even though it affected a small area, it should be entered into Storm Data. Normally, a Winter Storm would pose a threat to life or property.
	Winter Weather	A winter precipitation event that causes a death, injury, or a significant impact to commerce or transportation, but does not meet locally/regionally defined warning criteria. A Winter Weather event could result from one or more winter precipitation types (snow, or blowing/drifting snow, or freezing rain/drizzle). The Winter Weather event can also be used to document out-of-season and other unusual or rare occurrences of snow, or blowing/drifting snow, or freezing rain/drizzle. If the event that occurred is considered significant, even though it affected a small area, it should be entered into Storm Data.
Heat-related risk	Excessive Heat	Excessive Heat results from a combination of high temperatures (well above normal) and high humidity. An Excessive Heat event occurs and is reported in Storm Data whenever heat index values meet or exceed locally/regionally established excessive heat warning thresholds. Fatalities (directly-related) or major impacts to human health that occur during excessive heat warning conditions are reported using this event category. If the event that occurred is considered significant, even though it affected a small area, it should be entered into Storm Data.
	Heat	A period of heat resulting from the combination of high temperatures (above normal) and relative humidity. A Heat event occurs and is reported in Storm Data whenever heat index values meet or exceed locally/regionally established advisory thresholds. Fatalities or major impacts on human health occurring when ambient weather conditions meet heat advisory criteria are reported using the Heat event. If the ambient weather conditions are below heat advisory criteria, a Heat event entry

		is permissible only if a directly-related fatality occurred due to unseasonably warm weather, and not man-made environments.
Drought-related risk	Drought	Drought is a deficiency of moisture that results in adverse impacts on people, animals, or vegetation over a sizeable area. Conceptually, drought is a protracted period of deficient precipitation resulting in extensive damage to crops, resulting in loss of yield. There are different kinds of drought: meteorological, agricultural, hydrological, and social-economic. Each kind of drought starts and ends at different times. Additional information can be obtained at this web address: http://drought.unl.edu/DroughtBasics/WhatisDrought.aspx. A drought event should be included in Storm Data in relation to the drought classification system which is the foundation of the Drought Monitor, a multi-agency effort. Droughts are rated as Abnormally Dry (D0), Moderate (D1), Severe (D2), Extreme (D3), or Exceptional (D4). Details on the Drought Monitor can be found at the following web address: http://droughtmonitor.unl.edu/.
	Wildfire	Any significant forest fire, grassland fire, rangeland fire, or wildland-urban interface fire that consumes the natural fuels and spreads in response to its environment. "Significant" is defined as a wildfire that causes one or more fatalities, one or more significant injuries, and/or property damage (optional: include significant damages to firefighting equipment if loss estimates are available). Professional judgment should be used in deciding to include a Wildfire in Storm Data. In general, forest fires smaller than 100 acres, grassland or rangeland fires smaller than 300 acres, and wildland use fires not actively managed as wildfires should not be included. This is consistent with the definitions for significant and/or large fires utilized by most land use agencies.