The Applications of GIS-based Megaregion Transportation Planning Model: A Case Study on the Impacts of Autonomous Vehicle (AV)

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16. Abstract

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Executive Summary

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Our study finds that (1) AV adoption improves accessibility but increases congestion in urban areas, where capacity benefits are limited by high demand and complex traffic patterns, (2) capacity enhancements outside metro areas effectively reduce congestion and enhance travel efficiency due to lower baseline traffic volumes and less induced demand, (3) AV introduction increases Vehicle Miles Traveled (VMT) and Vehicle Time Traveled (VTT) overall, but combining AV adoption with capacity improvements partially offsets these increases, and, (4) AV introduction has a more significant effect on passenger transportation compared to freight. Policymakers should implement targeted capacity enhancements alongside AV adoption in urban areas to mitigate congestion and optimize travel efficiency.

1. Introduction

The increasing importance of megaregions in transportation planning and infrastructure development has been recognized globally (Amekudzi et al., 2007). According to the United Nations (UN), megaregions are defined as urban areas with populations of 10 million or more, serving as rapidly growing population hubs (Lang & Dhavale, 2005). Economic productivity is a key factor in identifying these regions (Florida et al., 2008), and their competitiveness is further strengthened by the growing interconnectedness of urban areas in the globalization era.

Megaregions consists of clusters of geographic areas connected by similar characteristics and common interests (Hagler, 2009). They feature integrated economic networks, rely on shared natural resources and ecosystems, exhibit consistent settlement and land usage patterns, and share similar cultural and historical backgrounds. Megaregions also collaborate to address common transportation challenges, such as air quality, goods distribution, and road safety, which cross political boundaries. However, planning processes are often confined by these borders. Adopting a megaregional planning perspective offers a way to tackle emerging challenges and capitalize on opportunities around major metropolitan hubs and their surrounding areas, which are linked by existing environmental, economic, cultural, and infrastructural connections (Nelson, 2017).

As of 2016, there were 31 megacities globally with populations exceeding 10 million. Projections indicate that by 2030, this number will increase to 41, with a combined population exceeding 729 million (U.N., 2016). In the United States, approximately 13 megaregions have been identified, some crossing state boundaries and collectively accommodating 80% of the nation's population. The projected 22% increase in the US population to 390 million, along with the expected 115% growth in GDP to $36.7 trillion between 2015 and 2045, highlights the growing importance of megaregions in the US economy (Dewar & Epstein, 2007; G. D. Nelson & Rae, 2016; Woodall et al., 2024). These regions, characterized by dense populations, concentrated employment, and significant economic activities, contribute to around 90% of the country's economic output (Steiner et al., 2022). The rising inter-city commutes, travel, and freight shipments further enhance their economic productivity and highlight their critical role in driving national economic growth.

AVs (autonomous vehicles) and connected and autonomous vehicles (CAVs) have great potential to improve accessibility, enhance in-vehicle travel experiences, increase energy efficiencies, promote car-sharing and ride-sharing services, and reduce traffic congestion, environmental degradation, air pollution, noise disturbances, and social exclusion for individuals currently unable to drive (Nikitas et al., 2020). As a result, AVs and CAVs are expected to become the foundation of intelligent urban transportation systems (Nikitas et al., 2017; Papa & Ferreira, 2018) and are considered a top priority for research and development investments in urban planning (Arakawa et al., 2019; Knowles et al., 2020; Strand et al., 2014). Figure 1 illustrates the six levels of vehicle automation as classified by the Society of automotive engineers (SAE) (Hopkins & Schwanen, 2021).

Leading companies in automobile industry like Toyota, Tesla, Google (Waymo), and Apple have launched extensive pilot testing programs to pave the way for the advent of the AV era. The trend has been subsequently followed by additional automobile manufacturers and entrepreneurial startups in the sector. Projections suggested a 50% rise in AV sales and a 30% increase in the number of AVs on the road by 2040 (Bagloee et al., 2016). According to Global Industry Analysts Inc. (2022), there is a significant rise in the quantity of AVs both in the US and worldwide. The US market was projected to expand from 3,400 to 5,400 AVs, while the global market surged from 6,100 to 13,800 AVs between 2021 and 2022. By 2026, the global AV market was anticipated to reach 110,100 units.

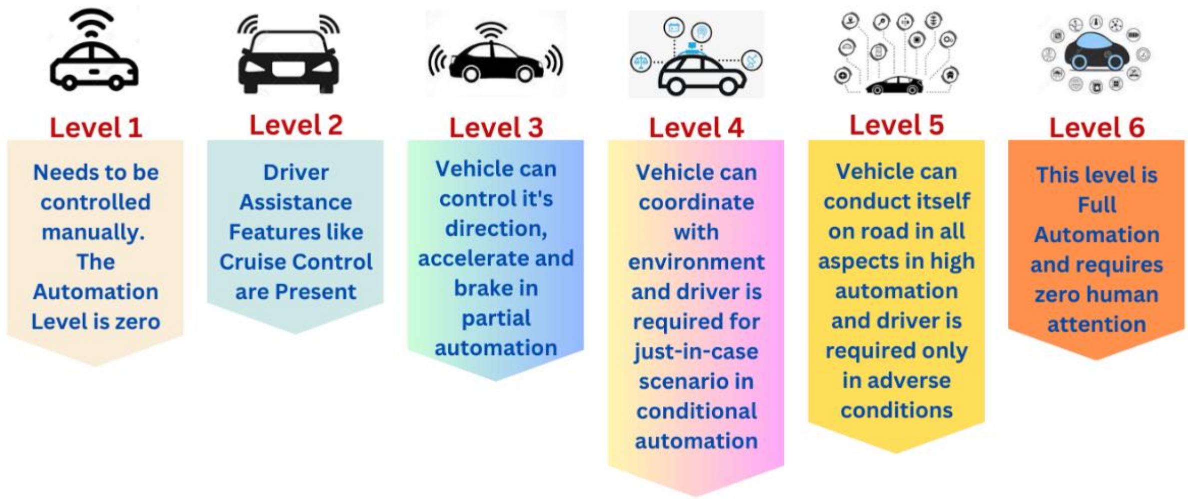


Figure 1. The Levels of Automation for Autonomous Vehicles Proposed by the Society of Automotive Engineers (SAE)

The dramatical increase in the adoption of AVs, particularly in North America, is set to transform urban spatial structures, reshape built environment, and change the design of transportation infrastructure. For example, AVs will require narrower lane widths and create more space-efficient rights-of-way, potentially boosting the capacity of transportation systems (Chapin et al., 2016; Swami & Swami, 2023). Moreover, it will significantly impact travel patterns, transportation efficiency, commuter behavior, and individual lifestyles. This transition will reduce reliance on highly skilled drivers while increasingly leveraging emerging technologies like machine learning in transportation.

As AVs mature and establish themselves as a safer and less risky travel option, their economic viability will increase. AVs are expected to deliver substantial social benefits, including improved fuel efficiency, enhanced accessibility, and greater mobility for marginalized communities, all while maintaining superior safety standards than human-driven vehicles. Given that U.S. transportation infrastructure spans multiple administrative boundaries and has a megaregional scope (Woodall et al., 2024), AVs offer substantial potential to improve mobility and accessibility within densely populated and highly concentrated employment areas (Huang et al., 2020).

Although researchers have thoroughly explored the various impacts of AVs on transportation systems at a regional level, there has been limited focus on the movement of AVs within a megaregion. Most existing studies have measured the mobility impacts of introducing AVs at the megaregion scale, such as VMT, VKT, and mode share (Huang et al., 2020), while largely overlooking the integration of destination accessibility. Additionally, the existing literature on megaregions is primarily driven by academic interests, with limited emphasis on practical application in planning processes. This study aims to fill these gaps by investigating the impact of AVs on various traffic scenarios in the Texas Triangle region, including the metropolitan areas of Dallas/Fort Worth, San Antonio, Austin, and Houston.

The Texas Triangle region has experienced rapid population growth and increasing ethnic diversity, while maintaining strong economic dynamism (Cisneros et al., 2021). As a home to 18.2 million people or 6% of the U.S. population, the Texas Triangle encompasses 66 counties and spans 58,400 square miles. Its thriving economic centers accounted for 7% of the U.S. GDP in 2010 (Todorovich, 2007). With its heavily automobile-dependent urban landscape, more pronounced than in other megaregions, the Texas Triangle provides an ideal setting for examining the implementation and impacts of advanced transportation innovations, such as AVs (Huang et al., 2020).

The research integrates AVs into the GIS-based Megaregion Transportation Planning Model (MTPM) developed in our previous projects, facilitating an evaluation of their effects on transportation system performance. Furthermore, our analysis also accounts for the effect of mixed traffic flows resulting from the integration of AVs and human-driven vehicles (HDVs) in our analysis. Given the uncertainty about the future features of autonomous vehicles (AVs), this study offers one of the initial estimates of the impacts of AV integration on megaregion transportation. It evaluates two primary effects: (i) enhancements in system performance and (ii) changes in travel demands due to traffic growth. These impacts are evaluated for both personal vehicle traffic and freight flows throughout the Texas Triangle region.

2. Studies on AVs in Megaregion Transportation

2.1. The Challenges to Investigate the Effects of AVs in Megaregion Transportation

Urban agglomerations are characterized by their high population density, economic centers, and extensive transportation systems. These features arise from the concentration of attraction and production areas connected by transportation networks. The changing spatial dynamics of megaregions have transformed employment patterns and industrial landscapes, leading to complex travel demands and significant impacts on urban land use development (Monolith Press, 2013). Concurrently, the demographic growth and urban transformation have intensified logistical sprawl, prompting logistics facilities to relocate along highway intersections (Lindsey et al., 2014). This shift worsens negative environmental effects (e.g., noise, air pollution, safety concerns, and congestion) for nearby communities.

These dynamics underscore the intricate relationships between urban spatial structure and the transport systems with passenger and freightflows, highlighting their symbiotic interaction and mutual relationship (Cidell, 2010; Hesse, 2016). Consequently, changes in urban spatial structure can affect both passenger and freight traffic patterns and volumes, driven by various supply and demand factors.

Travel demand models (TDM) are essential for transportation planning at national, state, and local scales. They serve various purposes, such as formulating projects and programs, evaluating and prioritizing plans and policies, and assessing economic and social impacts of transportation investments (Donnelly & Moeckel, 2017; Seedah & Harrison, 2011). However, few TDM extensions have been developed for transportation planning at the megaregion scale, which extends beyond metropolitan areas. Moreover, the intricate interactions between transportation networks, land use configurations, and socio-economic factors further complicate the understanding and modelling of megaregion transportation systems' effectiveness.

TDMs for megaregion planning need to incorporate factors such as rapid technological advancements, socio-economic uncertainties, the necessity for interagency coordination, and the social and equity impacts of transportation policies and investments. However, TDMs developed for megaregion transportation planning often lack important components related to demographic, economic, and environmental factors.

In transportation planning practice, state transportation agencies and Metropolitan Planning Organizations (MPOs) often face challenges due to inadequate data and unsuitable analytical methodologies for gauging travel demands and evaluating how well transportation infrastructure supports the movement of people and goods across megaregions. This hampers collaboration among individual MPOs and cities within a megaregion in developing and implementing megaregion travel demand models. To examine the socio-economic and environmental effects of transportation systems at the megaregion level, it is essential to use integrated urban models (IUMs) specifically designed for megaregions, rather than relying solely on models developed by MPOs or State DOTs (Miller, 2018; M. Zhang et al., 2007).

In September 2017, Senate Bill 2205 was enacted, regulating and legalizing AVs in Texas. Prototypes of highly or fully automated vehicles, specifically classified as SAE Levels 4 and 5, have been extensively tested on public roads in the Texas Triangle region, one of the largest megaregions in the U.S. Recently, Waymo, a California-based AV technology company, began testing its fully autonomous cars in Austin, one of the major cities in Texas Triangle. As vehicle technologies continue to advance, it becomes increasingly important, from both sustainability and equity perspectives, to scrutinize the potential impacts of AVs on road capacity, traffic growth, and accessibility of both personal and freight vehicles across the megaregion.

However, as previously discussed, most existing AV studies focus on municipal, metropolitan, state, and national levels, leaving a significant research gap in understanding the effects of AVs on travel behaviour, congestion, equity, and environmental sustainability at the megaregion scale.

Such research would enable government entities and policymakers to anticipate vital implications and develop proactive strategies to facilitate AV adoption in the megaregion context.

2.2. Potential Benefits of AVs

AVs offer significant potential to improve the capacity of existing roadways and intersections (Guler et al., 2014), leading to reduced congestion and travel times (Duranton & Turner, 2011). They also broaden mobility opportunities for a wider demographic (Truong et al., 2017), reduce vehicular accidents (Papadoulis et al., 2019; Taeihagh and Lim, 2019) and enhance air quality (Rafael et al., 2020). AVs are expected to stimulate travel demand (Soteropoulos et al., 2019), optimize traffic flow, increase lane capacity, enhance speeds, and reduce congestion, even during peak hours. They are also anticipated to lower costs associated with automobile travel, reduce travel time and delays, and enhance network capacities, ultimately resulting in an overall increase in vehicle miles travelled (VMT).

While AV adoption may lead to increased automobile VMT, careful transportation planning and policy interventions can mitigate its negative impacts. Strategies like transit-oriented development, smart growth policies, and shared mobility initiatives can foster high-quality and livable land use (Nadafianshahamabadi et al., 2021). AVs have the potential to extend access to opportunities for individuals who currently lack personal vehicles, including those with physical disabilities, or without driver's licenses or car ownership (Truong et al., 2017). By enabling travelers to engage in other tasks while on the road, AVs are expected to reduce the inconvenience of travel time, potentially making longer trips more tolerable and appealing (Auld et al., 2017).

Beyond their significant impact on automobile transportation, AVs could enhance the efficiency of public transit systems by improving first/last mile connections, potentially increasing transit usage (Levin et al., 2019). Additionally, AVs could reduce the demand for parking spaces in congested urban areas, freeing up land for housing and other uses, potentially contributing to more concentrated urban growth rather than sprawl to suburban and rural areas (Stead & Vaddadi, 2019).

These combined factors could lead to induced demand (Meyer et al., 2017; Soteropoulos et al., 2019), potentially undermining AVs' ability to reduce congestion and potentially leading to increased emissions of greenhouse gases (GHGs) and harmful air pollutants (Brown and Dodder, 2019; Chen et al., 2019; Taiebat et al., 2018; Wadud et al., 2016). These insights into the potential benefits and drawbacks of AV implementation highlight the importance of carefully considering the future integration of AVs into the road network (Anderson et al., 2014; Ashkrof et al., 2019). In this context, it is crucial to adopt land use and transportation policies that promote sustainable urban development while integrating AVs into the planning framework (González-González et al., 2019; Huang Y. et al. 2020; Layzell, et al., 2021; Obaid 2022).

2.3. The Impacts of AVs on Travel Behavior

The effects of AVs can be examined in three stages. The initial stage includes traffic, travel cost, and travel choices. The second stage covers vehicle ownership, sharing, location choices, land use, and transport infrastructure. The third stage addresses energy consumption, air pollution, safety, social equity, economy, and public health (Ashkrof et al., 2019; Milakis et al., 2017).

Evaluating AVs' impacts on travel behavior must include an evaluation of their effects on travel demands. Factors such as driver acceptance, variability in travel time, confidence in efficiency, willingness to own or use shared AVs, and environmental benefits can potentially help mitigate the drawbacks associated with automated driving transport services (ADTS).

Studies exploring the impacts of AVs on travel behavior have revealed varied outcomes concerning VMT, vehicle kilometers travelled (VKT), and mode choice. Research indicates that private AVs may lead to increased VMT, especially in scenarios with reduced value of time and parking costs, resulting in shifts from other transportation modes (Auld et al., 2017; Kim et al., 2015). Similar results were observed for shared autonomous vehicles (SAVs) when the value of time was reduced and costs were low (Hörl et al., 2016; Liu et al., 2017). However, research also indicates that VMT could decrease if a large portion of travelers choose ridesharing (Heilig et al., 2017; Martinez & Viegas, 2017), or if the cost of SAVs is high, leading travelers to select shorter trips (Soteropoulos et al., 2019).

Research assessing the impacts of AVs on Vehicle Hours Traveled (VHT) indicates that VHT generally increases with the use of private AVs, particularly when there are significant reductions in the value of time and parking costs. Conversely, SAVs could lead to a reduction in VHT, especially when costs are high and private vehicle use is not an option (Kim et al., 2015; Soteropoulos et al., 2019).

Similarly, research on the impacts of AVs on mode share suggests that AVs could decrease the use of public transport and slower mode shares when they compete with existing modes. For private AVs, studies indicate larger mode shifts, particularly with significant reductions in the value of time and parking or operating costs, resulting in an increase in the share of private car use (de Almeida Correia & van Arem, 2016; Kim et al., 2015; Kröger et al., 2019). Similarly, studies on SAVs also suggest a decrease in public transport and slower mode shares with high reductions in the value of time and low operating costs (Bösch et al., 2017; Chen & Kockelman, 2016). However, SAVs may reduce the share of private car use. For instance, studies assuming a complete ban on privately owned vehicles and considering specific operating costs report increases in public transport and slower mode shares, as individuals choose these options, particularly for short trips, to avoid expenses (Heilig et al., 2017; Soteropoulos et al., 2019).

2.4. Barriers to Implementing AVs

One major barrier to the widespread adoption of AVs among travelers is their cost. Current LIDAR system prices for AVs range from $30,000 to $85,000 each (Shchetko, 2014), and despite cost reduction efforts, the price may still be $25,000 to $50,000 per AV vehicle with mass production (Dellenback, 2013; Boesler, 2012), posing a challenge for consumer affordability compared to conventional vehicles at a price of $16,000 to $27,000 (Hensley et al., 2009). However, other significant obstacles to implementing AVs encompass multiple facets of individual travelers' experiences, such as comfort, travel time reliability and efficiency, AV certification, liability and public perception, safety and security features, and privacy concerns (Fagnant & Kockelman, 2015). Additional barriers include urban space reallocation, change of design and planning procedures, financial constraints, policy discrepancies, and insufficient research (Ashkrof et al., 2019; Fagnant & Kockelman, 2015).

Many unanswered research questions still remain, such as the potential of vehicle automation systems to decrease travel time variability (Steck et al., 2018), the public's willingness to own or utilize shared Avs (Wang et al., 2020), and the influence of vehicle automation on the volume and spatial distribution of parking demand (W. Zhang & Wang, 2020). Federal, state, and local stakeholders must expand research initiatives in the field of AVs while setting standards related to their liability, security, and data privacy (Wong & Shaheen, 2020). Therefore, further research is needed in the realm of “policy innovation” relating to interventions.

While governments currently have various tools to facilitate the transition of vehicles from human drivers to AVs, additional mechanisms are required. Implementing regional land-use planning measures can help to regulate the potential sprawl associated with the widespread AV adoption. Moreover, authorities will need tools to govern the overall behavior of AVs and ensure the readiness of non-AV drivers to adapt themselves to AVs (Kyriakidis et al., 2015). It is crucial to focus on AV interactions with vulnerable transportation users (Taeihagh & Lim, 2019). This highlights the importance of exploring and developing innovative policies to effectively manage the integration of AVs into our existing transportation systems. Surprisingly, only a small number of planners believe that urban transport planning should be adapted, with the majority viewing it as a concern for the more distant future. This observation contrasts with the strong industry advocacy for AVs (Cohen & Cavoli, 2019; Fraedrich et al., 2019).

The lack of jurisdiction at the megaregion level poses challenges for adopting AVs in terms of government regulation and policy (Addie et al., 2020). Addressing AV implementation at the megaregion scale is inherently more complex compared to enforcement and planning at the metropolitan level. Effectively planning for AVs requires dedicated policy initiatives that must be extensively deliberated and then put into action at the megaregion level.

2.5. The Integration of AVs into Transportation models

Levin & Boyles (2015) present a four-step model that categorizes demand based on the time value and AV ownership by treating AVs as private vehicles. Their nested logit approach, which assesses choices between parking, repositioning, and transit, incorporates a generalized cost function with factors including time, fuel, and tolls in static traffic assignment. Levin (2015) advanced the model by integrating dynamic traffic assignment (DTA) with endogenous departure time choices, offering a more realistic depiction of traffic flow and intersection control. Their research reveals that while AVs enhance intersection capacity, they do not significantly alleviate overall congestion.

Similarly, Auld et al. (2017) utilized the so-called POLARIS simulation model, which merges the activity-based model ADAPTS with a traffic simulation model. Their adjustment of road capacity to regulate market penetration regionally underscores the significant influence of both capacity and time value on VKT. Likewise, Kloostra & Roorda (2019) focused on the impact of adaptive cruise control (ACC) technology of AVs on road capacity. They modified road link capacities to simulate the potential throughput increase from AV driving behavior, differentiating between freeways and arterial roads. Their static assignment using Emme 4 also includes an analysis of parking operations, indicating the broader implications of AV technology on urban infrastructure.

Jordan (2012) analyzed the utility of SAVs, considering trip length, speed, fleet size, and vehicle costs. Their findings confirm the economic benefits of SAVs in cities like Ann Arbor, Babcock Ranch, and Manhattan. Fagnant & Kockelman (2014) employed MATSim to simulate SAVs in Austin, highlighting the crucial role of effective fleet management and relocation strategies. Their subsequent study on electric SAVs (Fagnant & Kockelman, 2015) uncovers range limitations, a challenge further addressed by Chen et al. (2016) through the incorporation of charging stations in their model.

Zhang et al. (2015) extended Fagnant & Kockelman (2014)'s model by adding user income and dynamic ridesharing (DRS); they explored parking strategies, demonstrating that DRS can reduce VKT and waiting times. Boesch et al. (2016) modelled the relationship between AV fleet size and demand, finding it non-linear. Levin et al. (2017) developed an event-based SAV framework with first-come, first-served vehicle assignment and limitless parking capacity, emphasizing the need for efficient vehicle distribution strategies. Shen et al. (2017) used SimMobility to enhance first/last-mile connectivity in Singapore, achieving positive outcomes with shared vehicles and balanced fleet availability.

In Texas, Kuhr et al. (2017) proposed multiple planning scenarios and developed approaches to examine the effects of AVs and connected autonomous vehicles (CAVs) on society and economics in the North Central Texas Council of Governments (NCTCOG) region. Employing an agent-based land use and transportation model, Kuhr et al. (2017) simulated the impacts of AVs on household relocation. They assumed that households commuting with AVs would be less sensitive to parking availability and less focused on proximity to work, resulting in a decrease in transit ridership. The presence of AVs in urban cores, leading to a decreased demand for parking, might offset the urban sprawl caused by longer commutes (Llorca et al., 2022).

Although these studies provide valuable insights into the potential benefits and challenges of AVs and SAVs, none have specifically focused on the development and implementation of transportation models at the megaregion level. This gap presents an opportunity for further research to explore the impacts of AV and SAV integration on a larger, interconnected scale. Addressing this gap could significantly enhance our understanding of how AVs and SAVs might transform transportation systems across broader, more complex regions, ultimately contributing to more efficient and sustainable urban mobility solutions.

2.6. Operational Megaregion Transportation Models and AV Integration

Improving accessibility and mobility for both passengers and freight emerged as key factors in the regional long-range planning framework (Read et al., 2017). Existing studies have pointed out a lack of clear guidance for planning agencies in dealing with megaregional issues. They also highlight a growing trend of interregional collaboration across jurisdictional borders concerning transportation, air and water quality, and resilience. Some researchers examined publicly available data to study commute and truck flows, although they developed a conceptual and descriptive approach, lacking quantitative analysis (Dewar & Epstein, 2007). Researchers from the University of Texas, Austin conducted a study that examines mode choices, congestion levels, and trip distances before and after assuming an increase of trip generation rates in Texas Triangle region (Huang et al., 2020). However, these studies have not considered the adoption of AVs into their framework.

Various aspects of the transportation system in large planning areas are often under the purview of different public agencies. MPOs are responsible for developing transportation improvement plans (TIPs) and maintaining regional transportation plans (RTPs). State transportation agencies also have their statewide transportation improvement programs (STIPs) and State Long-Range Transportation Plans (SLRTPs). The necessity of travel forecasting models has grown to evaluate policies, plans, and projects at regional and state levels. Donnelly & Moeckel (2017) have highlighted the blurred distinction between regional and state models as their level of resolution converges, with an increasing demand for fine-grained analyses.

The study of megaregion transportation is a complex and relatively unexplored topic, partly due to the heterogeneity of data sources and variations in spatial and temporal definitions. The delineation of megaregion boundaries is challenging because these conceptual areas are defined by interconnected transportation networks, geographies, socio-economic activities, and demographic characteristics. As a result, many studies rely on qualitative descriptions and case study research, primarily emphasizing policy issues and governance frameworks for megaregions. However, there is a significant lack of academic research and professional programs that specifically explore the development and applications of operational megaregion transportation models. There are even fewer studies exploring both passenger and freight movement within megaregions. Moeckel et al. (2015) emphasized the limited research conducted on modelling megaregions, despite an extensive body of literature available on megaregion analysis. Moeckel et al. (2015) also pointed out the lack of operational megaregion models in a synthesis report for the National Cooperative Highway Research Program (NCHRP). It stated that the Chesapeake Bay Megaregional Model is currently the only operational travel demand model for megaregions, yet it has not been extensively used.

Integrated Urban Models (IUMs) offer potential for extending spatial analysis from metropolitan to megaregion level. They can evaluate transportation performance for both passenger and freight traffic in megaregions, assisting in decision-making and policy analysis for megaregion transportation planning. The substantial progress in computer software and hardware, along with advanced GIS techniques, large urban spatial databases, and advanced model estimation software, has made it possible to develop and implement operational Integrated Urban Models (IUMs). This progress has in turn facilitated the creation and use of operational transportation models for megaregions (Miller, 2018).

Recognizing the limitations of existing models and the potential of IUMs, Pan & Chun (2018) built an analytical model for estimating spatial and temporal patterns of megaregion truck flows based on the available datasets. They selected Texas Triangle as an empirical case to implement the megaregion truck flow model. They also emphasized several limitations of their study, including the design of virtual network centroids using highway intersections rather than traffic analysis zones (TAZs) and the indirect estimate of temporal patterns of megaregion truck flows through nighttime light data.

To gain a better understanding of the movement of both people and goods within megaregions, Pan & Chun (2020) developed a GIS-based operational transportation model with an analytical framework for personal and freight flows in megaregions. Their model intended to improve personal access to various opportunities and facilitate truck access to freight facilities. It also aimed to strike a balance between academic research priorities and the needs of operational planning agencies, providing insights into decision-making on socio-economic and environmental issues related to megaregion transportation. The Texas Triangle was selected as an empirical case to demonstrate the application of the megaregion transportation model for both passenger and truck flows.

Based on Pan and Chun's (2018, 2020) foundational models for the integration of AVs within megaregions, this study focuses on examining the effects of AVs on transportation system in the Texas Triangle region using the GIS-based megaregion transportation model developed by Pan and Chun (2020). It utilizes a scenario-based approach, considering assumptions about possible transportation system alterations resulting from AV integration. The findings demonstrate how varying levels of AV penetration rates impact mobility, accessibility, and other key transportation performance metrics.

3. Methodology

Analyzing passenger and freight movement within megaregions using integrated models presents a substantial challenge (Moeckel et al., 2015). This is because integrated models must demonstrate robust theoretical foundations and methodological soundness to meet both academic and practical standards, while also fulfilling public agencies' expectations for efficiency, reliability, and user-friendliness (Pan and Chun 2020). To tackle these issues, Pan and Chun (2020) developed a transportation model at the megaregion scale. Their model builds on the transportation module from the Southern California Planning Model (SCPM), a Lowry-type regional planning model (Pan & Richardson, 2015).

The SCPM was first developed by researchers at the University of South California (USC) in the early 1990s to analyze spatial economic impacts within the five-county Los Angeles area (Richardson et al., 1993). Since then, SCPM has been implemented in Los Angeles, Houston and some other regions (Cho et al., 2001; Gordon et al., 2007; Pan et al., 2008), to evaluate the effects of natural and manmade disasters on the performance of the transportation system (Pan & Richardson, 2015). Over the years, the model been consistently updated with the new and updated data sources to include more advanced functionalities (Richardson et al., 2015).

The SCPM model has seen significant development, evolving into a spatial input-output model. Originally labeled SCPM1, it employed various origin-destination (OD) matrices to study both local and regional passenger movements and freight transport. While it incorporated detailed sectoral and geographical data, SCPM1 fell short in incorporating transportation networks and travel demand functions effectively (Pan, 2020).

In the late 1990s, SCPM 2 emerged as a later iteration, coded in C and C++. Notably, it improved upon its predecessor by internalizing traffic flows and freight movements, integrating a transportation network model alongside gravity models to allocate indirect and induced impacts on Traffic Analysis Zones (TAZs) from the input-output model. This enhancement facilitated the dynamic adjustment of the transportation network in response to economic shifts, thereby influencing both travel behavior and freight movement. SCPM 2 seamlessly integrated the freight database into the regional transportation model, advancing its capabilities further to analyze changes in traffic patterns, shifts in travel behavior, and alterations in freight movement within the affected zones (Pan et al., 2011). However, this version was limited to modeling traffic solely during the 3-hour morning peak period and employing static user equilibrium assignment (Cho et al., 2001; Gordon et al., 2007; Pan et al., 2008).

Unlike SCPM2, the latest version, SCPM3, inherits all capabilities from its predecessors while advancing the model with the addition of time-of-day functions. This upgrade enables the modeling of traffic not only during the AM peak period but also during the PM peak and off-peak periods. SCPM3 can analyze the effects of peak-load pricing on transportation network performance at the link level and evaluate activity effects at the TAZ level (Pan et al., 2011).

Expanding the SCPM transportation module from the regional level to a megaregion necessitates the integration of passenger and freight trips between metropolitan areas into the modeling process. Building on the framework of intraregional and interregional data processing outlined by Pan (2006) and Giuliano et al. (2010), as well as the two-layer structure of the Chesapeake Bay Megaregion Model described by Moeckel et al. (2015), Pan and Chun (2020) adopted a framework of two geographic layers to examine intra-metropolitan and inter-metropolitan transportation flows (Figure 2).

Unlike passenger flows, freight movement poses a significantly more complex and relatively unexplored challenge. This complexity primarily stems from the costs associated with data collection, the heterogeneous nature of data sources, the ambiguity surrounding classifications, and the absence of adequate methodologies (Pan, 2006). Giuliano et al. (2010) addressed this challenge by leveraging reliable secondary data sources, such as small-area employment data, to derive estimates of commodity flows when vehicle (trip)-based freight data were unavailable. However, in the past decade, there has been a notable increase in the availability of truck movement data, including origin-destination trip matrices, at various local, state, and federal transportation agencies.

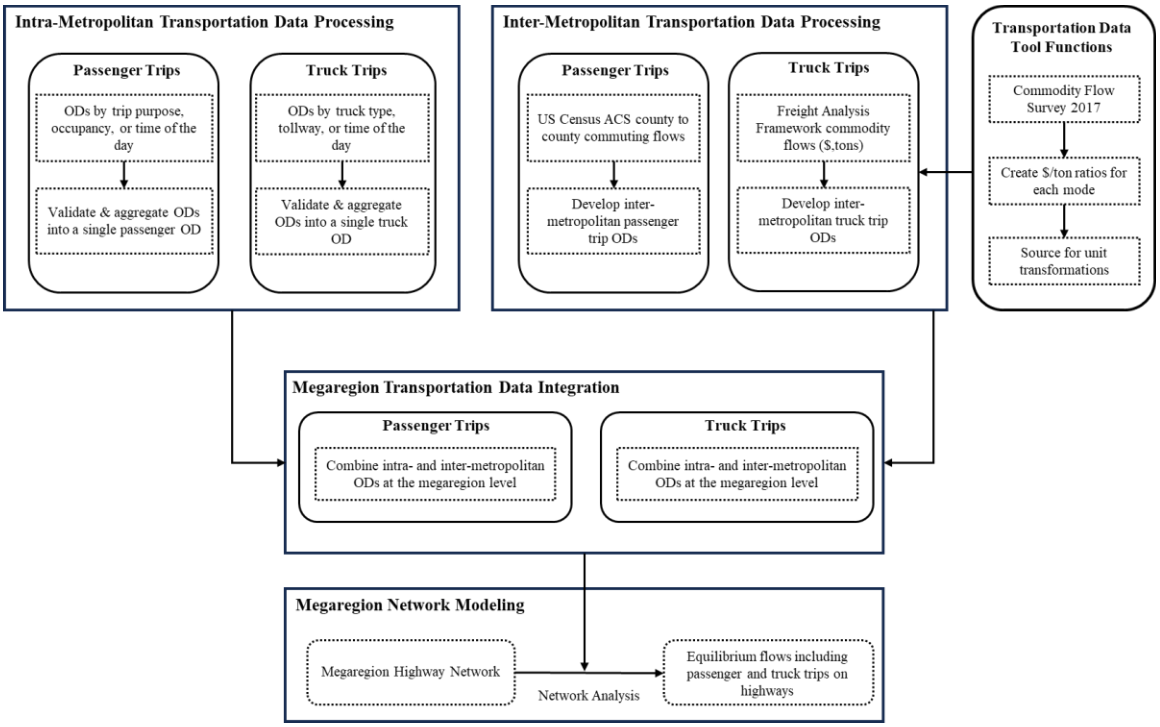


Figure 2. An analytical framework of the megaregion transportation model.

Pan and Chun (2020) took advantage of this opportunity and developed an analytical framework for the megaregion transportation model. Their approach builds upon the foundation of previous SCPM models while integrating newly available freight datasets. Their framework consists of four key components: (1) Megaregion transportation data processing, which includes processing of intra-metropolitan and inter-metropolitan transportation data, (2) Megaregion transportation data tool functions, (3) Megaregion transportation data integration, including the combination of intra-metropolitan and inter-metropolitan personal trips and the combination of intra-metropolitan and inter-metropolitan truck trips, and (4) Megaregion network modeling.

As depicted in Figure 2, the analytical framework divides megaregion transportation into two spatial layers: intra-metropolitan and inter-metropolitan layers, for both passenger and truck trips.

Intra-metropolitan transportation pertains to the movement of passengers and trucks between traffic analysis zones (TAZs) within a single metropolitan area of a megaregion. Conversely, inter-metropolitan transportation involves the movement of passengers and trucks where either the starting point or the destination (or both) of their trips are located outside the boundaries of the same metropolitan area within the megaregion.

The local MPOs within a megaregion can provide intra-metropolitan transportation data for their respective regions. These datasets typically includes origin-destination (OD) pairs for personal trips across various trip purposes, as well as OD pairs for different truck types, along with traffic analysis zones (TAZs) and network link files (Pan, 2006).

The inter-metropolitan transportation component focuses on capturing passenger and truck movements between different metropolitan areas within a megaregion. This includes collecting data on trips that either originate from or are destined for areas outside a specific metropolitan area within the megaregion, as well as those that extend beyond the megaregion itself. State or federal transportation agencies typically provide datasets relevant to inter-metropolitan transportation (Donnelly & Moeckel, 2017; Pan & Chun, 2018).

The Bureau of Transportation Statistics (BTS) and the Federal Highway Administration (FHWA) utilize various data sources like the Commodity Flow Survey (CFS) for inter-metropolitan freight transportation. These datasets are crucial for building the Freight Analysis Framework (FAF), which provides a comprehensive view of freight movement between states and major metropolitan areas across different transportation modes[1]. The FAF provides data on freight shipments, including tonnage, value, and ton-miles, categorized by origin and destination, commodity type, and transportation mode (Giuliano et al., 2018). To facilitate analysis, tool functions are needed for data conversion, such as transforming tons into dollars, jobs, trucks, or passenger-car-equivalents (PCEs). Pan and Chun (2018) have developed essential tool functions for this purpose. For inter-metropolitan personal trips, the US Census Bureau's American Community Survey (ACS) offers data on commuting trips between workers' residences and workplaces at the county level[2]. The dataset includes information on commuters' workplace locations, trip start times, chosen

[1] https://ops.fhwa.dot.gov/freight/freight_analysis/faf/
[2] https://www.census.gov/topics/employment/commuting/guidance/flows.html

transportation modes, and trip durations. The most recent available datasets are the 2016-2020 5-Year ACS commuting flows.

Pan and Chun (2020) outline a procedure for integrating intra-metropolitan and inter-metropolitan transportation data into the megaregion transportation system using a GIS-based platform (Figure 2). This method utilizes GIS functions to create Traffic Analysis Zones (TAZs) within metropolitan areas and zones beyond, such as county boundaries, to establish Megaregion Analysis Zones (MAZs). These MAZs serve as the primary units for analyzing the megaregion transportation system, including both personal and truck trips that originate from or are destined for the MAZs, as well as their movement through the megaregion's transportation networks.

After integrating megaregion transportation data, Pan and Chun (2020) proceed with developing megaregion network models. Their model incorporates megaregion personal and truck trip Origin-Destination (OD) data into the megaregion highway networks using capacity constraint network assignment functions. During this process, both passenger and truck trips are simultaneously considered within an equilibrium-based model, addressing the network's overloading condition. This approach ensures a comprehensive evaluation of the network's performance and capacity utilization through the following equations:

$$\text{Min} \sum_a \int_0^{x_a} C_a(x)dx \tag{3.1}$$

$$\text{subject to } x_a = \sum_o \sum_d \sum_p \delta_{a,p}^{od} h_p^{od} \quad \forall a \tag{3.2}$$

$$\sum_p h_p^{od} = T_{od} \qquad \forall o,d \tag{3.3}$$

$$h_p^{od} = P_p^{od} + F_p^{od} \qquad \forall o,d \tag{3.4}$$

$$h_p^{od},\ \ P_p^{od},\ \ F_p^{od} \geq 0 \quad \forall p,o,d \tag{3.5}$$

where x_a is the total flow on link a,

$C_a(t)$ is the cost-flow function which calculates the average travel cost on link *a*,

$\delta_{a,p}^{od}$ is the link-path incidence variable; it equals one if link *a* belongs to path *p* connecting OD pair *o* and *d* ,

h_p^{od} represents the flow on path *p* connecting OD pair *o* and *d*, including both passenger flow P_p^{od} and truck flow F_p^{od},

T_{od} represents the total trips between origin node *o* and destination node *d*, encompassing both passenger and truck trips,

p refers to a network path, while *o* and *d* denote two end nodes on the network.

The assignment models for both passenger and truck flows are based on the functions outlined by Sheffi (1985). These functions were derived from the mathematical model formulated by Beckman et al. (1956) to represent Wardrop's first principle, which states that no traveler can lower their travel costs by changing routes. This modeling approach, with the objective function (3.1) aiming to minimize travel costs while treating link flows and zonal demands as constraints, was previously employed by Giuliano et al. (2010) to load freight traffic onto regional highway networks. Similarly, Pan (2003, 2006) applied this approach to assign both passenger and truck trips in regional transportation models.

To implement the model, it's essential to iteratively generate all feasible values. The objective is to minimize travel costs to satisfy the objective function (3.1) until the model reaches convergence. The procedure is outlined as follows,

Step 0: **Initialization**. Conduct an all-or-nothing approach to simultaneously assign both passenger and truck trips, utilizing free flow travel costs, $C_a = C_a(0)$, for each link, *a*, on the empty network. Link flows x_a are obtained.

Step 1: **Update link travel times**. The travel time on link a is updated as $C_a = C_a(x_a)$.

Step 2: **Find a feasible descent direction**. Use the updated travel time $\{C_a\}$ for an all-or-nothing assignment for passenger and truck trips, resulting in a set of auxiliary link flows $\{u_a\}$ combining passenger trips with truck trips in PCEs.

Step 3: **Find optimal parameter**. Apply a linear approximation algorithm (LPA), such as the Golden section or Bisection method outlined in Sheffi (1985), to determine the optimal parameter, α , that satisfies the following equation:

$$\text{Min} \sum_a \int_0^{x_a+\alpha(u_a-x_a)} C_a(x)dx$$

Step 4: **Update link flows**. Link flows x_a is changed to be $x_a+\alpha(u_a - x_a)$

Step 5: **Test Convergence.** The process concludes when a convergence criterion is met, and the link flows reach optimal equilibrium conditions. If the criterion is not satisfied, return to Step 1 and repeat the process.

Pan (2003, 2006) employed this methodology to assign passenger and truck flows together onto a congested regional highway network while maintaining a user equilibrium condition. Similarly, Pan and Chun (2020) applied this approach to load both passenger and truck trips onto megaregion highway networks under congested conditions.

Our study builds on the extensive framework developed by Pan and Chun (2020) to examine the impact of AVs on megaregion transportation performance across various scenarios.

4. Analysis

4.1. Study Area

A megaregion transportation model, developed by following the analytical framework shown in Figure 2, has been implemented to examine the impacts of AVs on passenger and truck flows in the Texas Triangle, one of the largest megaregions in the U.S. identified by the Regional Planning Association (RPA) (2006, 2017).

The Texas Triangle consists of the state's four largest cities and metropolitan areas, i.e. Austin, Dallas, Houston, and San Antonio, connected by major interstate highways including I-10, I-45, and I-35. According to the US Census Bureau, the combined population of these four metropolitan areas within the Texas Triangle grew significantly by 19.7% between 2010 and 2019, increasing from 16.2 million to 19.4 million. This significant population increase reinforces its status as one of the fastest-growing megaregions in the United States. By comparison, the population of Texas was recorded at 29.1 million in 2020 and estimated to be 30.2 million in 2022 by the US Census Bureau.

It should be noted that the boundaries of the four major metropolitan areas within the Texas Triangle differ from the freight analysis zones defined by freight analysis framework version 4 (FAF4) and utilized in the commodity flow survey (CFS). Figure 3 illustrates the broader areas covered by the FAF4 zones compared to the traffic analysis zones (TAZs) defined by the respective local MPOs for the metropolitan areas. Additionally, the figure shows the extent of the Texas Triangle as determined by the personal job accessibility calculations from the study conducted by Pan and Chun (2020).

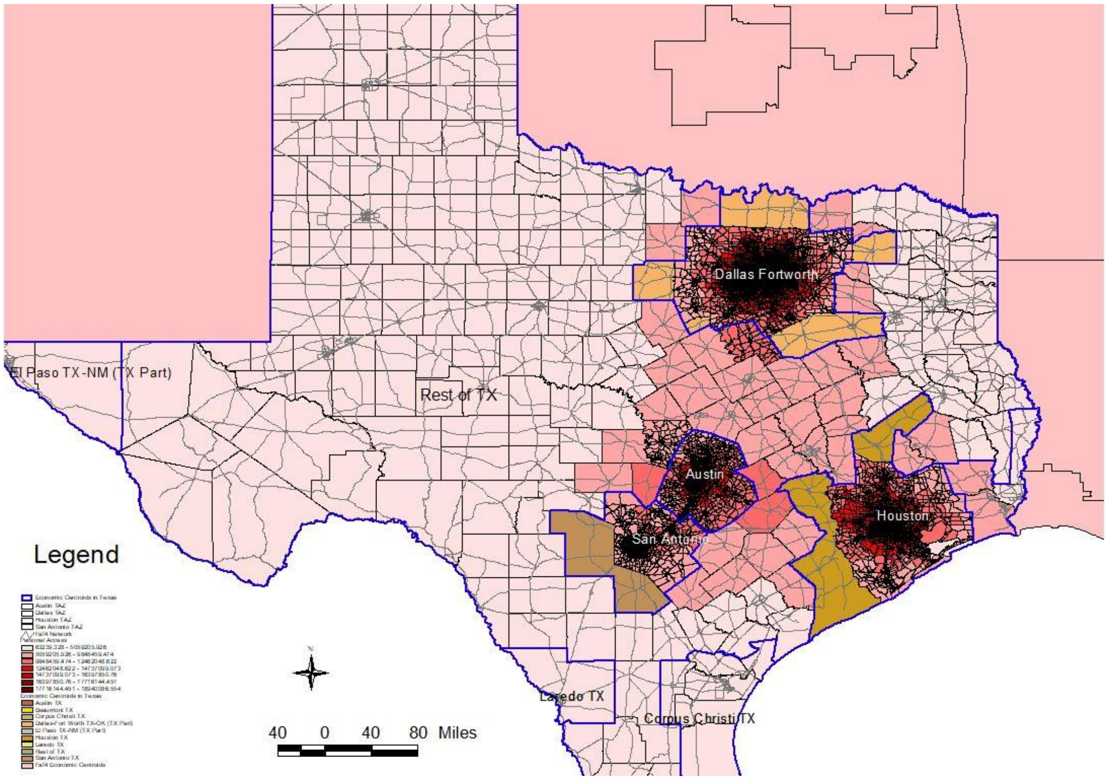


Figure 3. The study area - Texas Triangle with its megaregion analysis zones (MAZs)

Note: This figure was adopted from Figure 2 in Pan and Chun (2020)

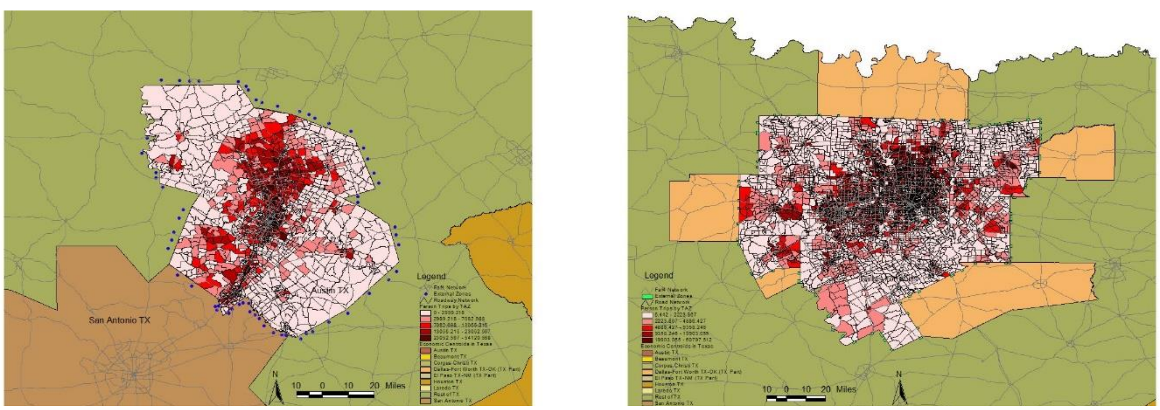
4.2. Data Collection

Our data has been collected from various agencies at two different geographic levels: the intra-metropolitan level and the inter-metropolitan level. Key data sources at the metropolitan level include MPOs. These federally mandated and funded organizations are responsible for developing transportation plans and policies for regions with a population of 50,000 or more. They are required to create a Regional Transportation Plan (RTP), a long-term transportation plan, as well as a Transportation Improvement Program (TIP), a four-year plan. Our traffic analysis zones, original-destination matrix, and transportation network data for metropolitan areas were obtained from the respective local MPOs.

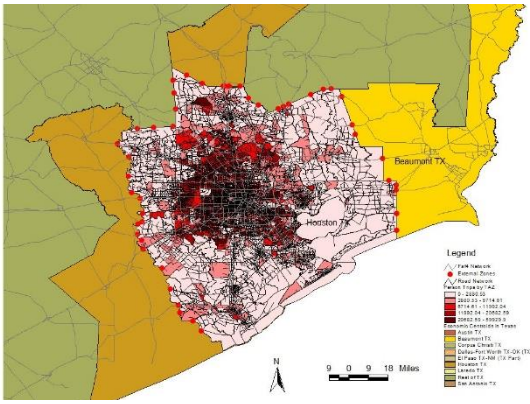
The Austin MPO, also known as the Capital Area Metropolitan Planning Organization (CAMPO), is responsible for transportation planning in Bastrop, Burnet, Caldwell, Hays, Travis, and

Williamson Counties. In our study, we obtained transportation modeling data from CAMPO (2018)'s 2040 regional transportation plan. This dataset included origin-destination (OD) information for passenger and truck trips across 2,102 internal traffic analysis zones (TAZs) and 59 external zones, a detailed road network consisting of 17,169 links covering 6,533 miles, and 396 existing and planned transit routes. In the metropolitan areas, a total of 11,678,748 daily passenger vehicle trips and 1,031,178 truck trips were recorded. Of these trips, 320,610 passenger vehicle trips and 51,333 truck trips had one end outside the CAMPO region (see Table 1). Passenger trip tables were provided for various trip purposes, occupancy levels, and times of day. The TAZ system covered the entire six-county CAMPO region, corresponding with the FAF4 zone designation for the Austin metropolitan area (see Figure 4a).

a. Austin b. Dallas



c. Houston



d. San Antonio

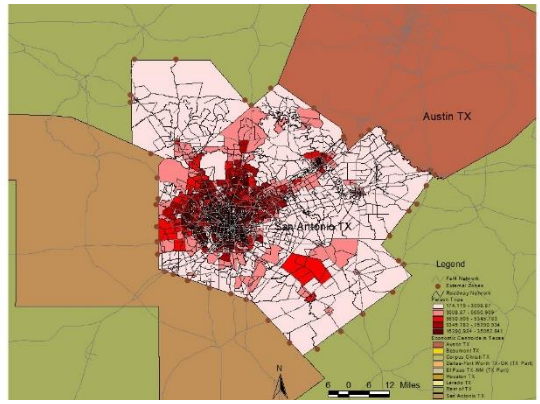


Figure 4. Transportation data collected for Austin, Dallas, Houston, and San Antonio

Table 2. Passenger and truck trips in the four metropolitan areas of Texas Triangle

Metropolitan area	Passenger Trips			Truck Trips		
	Intra-metropolitan	External	Total	Intra-metropolitan	External	Total
Austin	11,358,138	320,610	11,678,748	979,844	51,333	1,031,178
Dallas	19,511,249	331,914	19,843,163	662,478	95,528	758,006
Houston	15,545,394	181,121	15,726,515	1,122,215	31,924	1,154,140
San Antonio	6,435,229	175,658	6,610,887	590,453	31,509	621,961

Source: Author calculation based on the data from local MPOs.

The North Central Texas Council of Governments (NCTCOG) serves as the Metropolitan Planning Organization (MPO) for the Dallas-Fort Worth region. They provided us with transportation data for Collin, Dallas, Denton, Ellis, Hill, Hood, Hunt, Johnson, Kaufman, Parker, Rockwall, Tarrant, and Wise Counties. The NCTCOG data includes passenger and truck trip origin-destination (OD) information for 5,386 traffic analysis zones (TAZs), consisting of 5,303 internal and 83 external zones. The road network data includes 41,454 links covering 19,404 miles. Passenger trip tables are categorized by time of day and occupancy, while truck trip tables are available for various times of day. A total of 19,843,163 passenger trips and 758,006 truck trips are generated within the NCTCOG area every day. This includes 331,914 external passenger trips and 95,528 external truck trips (see Table 2). The NCTCOG's TAZs cover a smaller area compared to the FAF4 zone designated for the Dallas metropolitan area, which extends to additional counties such as Cooke, Henderson, Hopkins, Grayson, Palo Pinto, Navarro, and Somervell (see Figure 4b).

The Houston-Galveston Area Council (H-GAC) works with local governments in the Houston metropolitan area to address regional planning challenges. Their transportation plans cover eight counties: Brazoria, Chambers, Fort Bend, Galveston, Harris, Liberty, Montgomery, and Waller. We obtained ODs for passenger and truck trips across 2,954 internal TAZs and 46 external zones, as well as a road network consisting of 68,314 links covering 30,167 miles. Passenger trip tables are available for various trip purposes. A total of 15,726,515 passenger trips and 1,154,140 truck trips are generated daily within the eight-county H-GAC region. This includes 181,121 passenger trips and 31,924 truck trips that enter or exit the region through its external zones (see Table 1). The FAF4 zone designated for the Houston metropolitan area includes Austin, Matagorda, Walker, Washington, and Wharton Counties, which are included in the eight-county H-GAC region (see Figure 4c).

The Alamo Area Metropolitan Planning Organization (AAMPO) develops transportation plans and programs for the greater San Antonio area, which includes Bexar, Comal, Kendall, Guadalupe, and Wilson Counties. This area is smaller than the FAF4 zone designated for the San Antonio metropolitan area. Atascosa, Bandera, and Medina Counties are part of the FAF4 zone but are not included in the AAMPO transportation plans (see Figure 4d). We obtained the ODs for passenger and truck trips across 1,248 internal zones and 42 external zones, as well as a road network consisting of 16,140 links covering 6,256 miles. Overall, 6,610,887 passenger trips and 621,961 truck trips are generated, including 175,658 passenger trips and 31,509 truck trips classified as external trips (see Table 2).

Along with the metropolitan-level transportation data, we also obtained inter-metropolitan data from federal agencies. The US Census Bureau provided us with passenger commuting data through their 2011-2015 5-Year ACS Commuting Flows dataset, which offers information on commuting trips from workers' residence county to workplace county. We also obtained freight transportation data from the Freight Analysis Framework version 4 (FAF4). The FAF4 offers an origin-destination matrix for commodity flow, including tonnage and dollar value, across 132 pre-defined domestic regions referred to as economic centroids. In Texas, there are nine FAF4 economic centroids: Austin, San Antonio, Dallas-Fort Worth, Houston, Laredo, Beaumont, Corpus Christi, El Paso, and the rest of Texas. Among these economic centroids, Austin, Dallas-Fort Worth, Houston, and San Antonio are located within the Texas Triangle. By utilizing the Census ACS commuting flow data and the FAF4 commodity flow data, we were able to address the gaps in passenger and freight trips that involve at least one end outside of the four metropolitan areas of the megaregion.

One advantage of this research is that the diverse transportation data we collected from various sources are in a similar format and nearly based on the same year. For instance, the H-GAC provided us with data from their 2015 base year model, while the US Census commuting tables cover the 2011-2015 5-Year ACS commuting flows.

4.3. Analysis Results and Discussions

Following the data collection phase, we utilized the analytical framework shown in Figure 2 to analyze both intra-megaregion and inter-megaregion data on passenger and freight flows. The initial step has data validation, which includes multiple checks. We compared passenger trips with population and employment data at the Traffic Analysis Zone (TAZ) or county level, examined calculated truck ratios within the total vehicle fleet, compared truck trip data obtained from MPOs and FAF4, and evaluated passenger and truck trip densities to ensure their distribution patterns matched urban forms. Additionally, we converted the dollar value or tonnage of inter-metropolitan commodity flows into the number of trucks and further into Personal Consumption Expenditures (PCEs) using ratios estimated from transportation data tool functions.

In parallel to data validation, we aggregated passenger trip OD data by trip purpose, occupancy, or time of day to establish daily passenger trip ODs for each of the four metropolitan areas: Austin, Dallas, Houston, and San Antonio. Similarly, we combined truck trip ODs categorized by truck type, highway type, or time-of-day to create daily truck trip ODs for each of the four metropolitan areas.

Regarding inter-metropolitan transportation data, we encountered a discrepancy between the geographic locations of county-level passenger commuting data and truck flow data within the FAF4 zonal system. To address this issue, we created a comprehensive zonal system for the megaregion using a Geographic Information System (GIS) platform. This system integrates the intra-metropolitan zonal systems from MPOs, counties outside of metropolitan areas but within the state, and external zones outside of the state. Altogether, it includes 12,436 Megaregion Area Zones (MAZs) for the Texas Triangle, as outlined in Table 3.

Table 3. The megaregion transportation analysis zones (MAZs) for Texas Triangle

Name	TAZs	Internal Zones	External Zones	Descriptions
Ext-Tex	391	N/A	N/A	External zones located out of Texas
Austin	2,161	2,102	59	TAZs in Austin
Dallas	5,386	5,303	83	TAZs in Dallas
Houston	3,000	2,954	46	TAZs in Houston
San Antonio	1,290	1,248	42	TAZs in San Antonio
TexCounty-OutMetro	208	N/A	N/A	Texas counties out of the four metropolitan areas defined by FAF4
SUM	12,436	N/A	N/A	Total number of zones for the megaregion

Source: Author preparation using the data from local MPOs and FAF4

The zonal system for the Texas Triangle megaregion encompasses 391 external stations designed for the state of Texas. These stations are identified through the FAF4 zonal system, border entries, and other geographic information. Additionally, the zonal system incorporates both internal and external zones of the four metropolitan areas within the megaregion, aligning with the TAZ systems defined by their respective MPOs. It also includes the counties located outside the four metropolitan areas, with their boundaries defined by FAF4. Similar to the development of TAZ systems in regional transportation analysis or census tracts in socio-demographic studies, the design principle of the megaregion zonal system features smaller-sized zones in areas with higher population density. Figure 3 displays the megaregion zonal system, while Figure 4 shows the internal and external zones for each individual metropolitan area within the megaregion.

Following the analytical framework outlined in Figure 2, the intra-metropolitan passenger trip tables for the four metropolitan areas in the Texas Triangle are combined with inter-metropolitan passenger trip ODs to create a megaregion passenger trip OD. Similarly, the intra-metropolitan truck trip tables for the Texas Triangle's metropolitan areas are combined with inter-metropolitan truck trip tables to create a megaregion truck trip OD.

To facilitate the network analysis of passenger and truck movement within the megaregion, we use the transportation network provided by FAF4, which includes 39,160 network links in Texas.

Assuming all network links are bidirectional, the total number of network links in the FAF4 dataset amounts to 78,320. Additionally, we include two-way centroid connectors to each of the 12,436 network centroids. As a result, the megaregion transportation system includes a total of 103,192 network links, combining 24,872 centroid connectors with the 78,320 FAF4 network links.

In our study, the 103,192 highway network links are organized in the forward star data structure, as described by Sheffi (1985), to optimize computer memory usage and manage the sequence list of links effectively. "In addition to the from-node, to-node, length, and lanes attributes, the network link attributes also include link capacity, speed, and link type. Link capacity is derived from the FAF4 dataset, which estimates capacity using the methodology outlined in the Highway Capacity Manual (HCM). Link speed is estimated based on the link type.

Once the megaregion passenger and truck trip ODs are prepared and the network links are developed, we use a user-equilibrium-based model with capacity constraints. This approach, following the iterative procedure outlined in the methodology section, allocates both passenger and truck flows onto the megaregion transportation network.

To align with passenger trips, truck trips are measured in Personal Consumption Expenditures (PCE). This is derived from freight tonnage in the FAF4 database using the ton-per-PCE ratio estimated by Giuliano et al. (2010). Figure 5a and Figure 5b display the link volumes estimated by the user equilibrium assignment with link capacity constraints, showing passenger flows and truck flows, respectively. They clearly show that passenger and truck flows have similar distributions within the Texas Triangle, with intra-metropolitan trips displaying significantly higher volumes compared to inter-metropolitan trips.

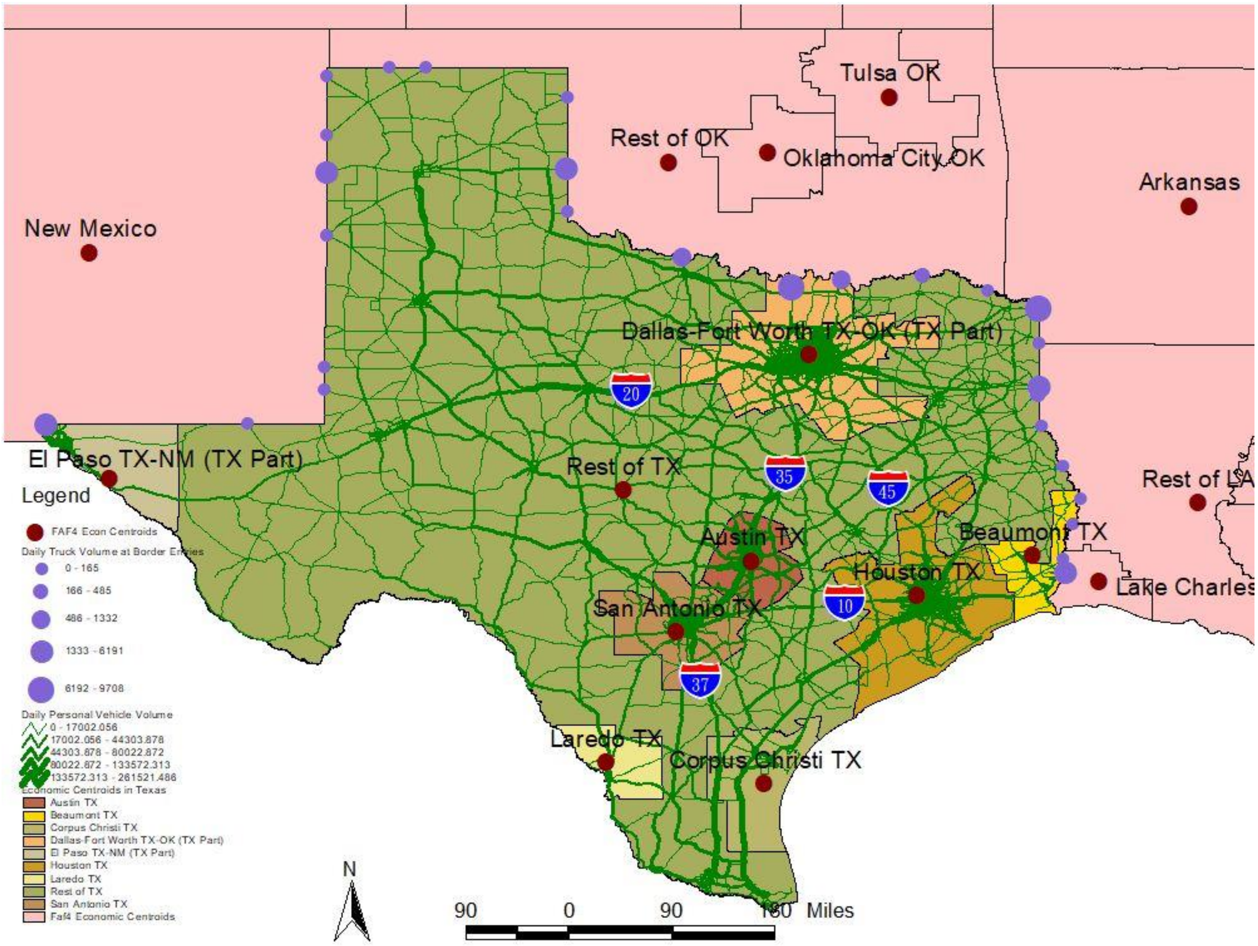


Figure 5(a). Passenger Flows in Texas Triangle

Major highways such as I-20, I-35, I-45, I-10, and I-37 experience high volumes of inter-metropolitan trips. There are fewer trips crossing the state boundary compared to those crossing the boundaries of metropolitan areas within the Texas Triangle.

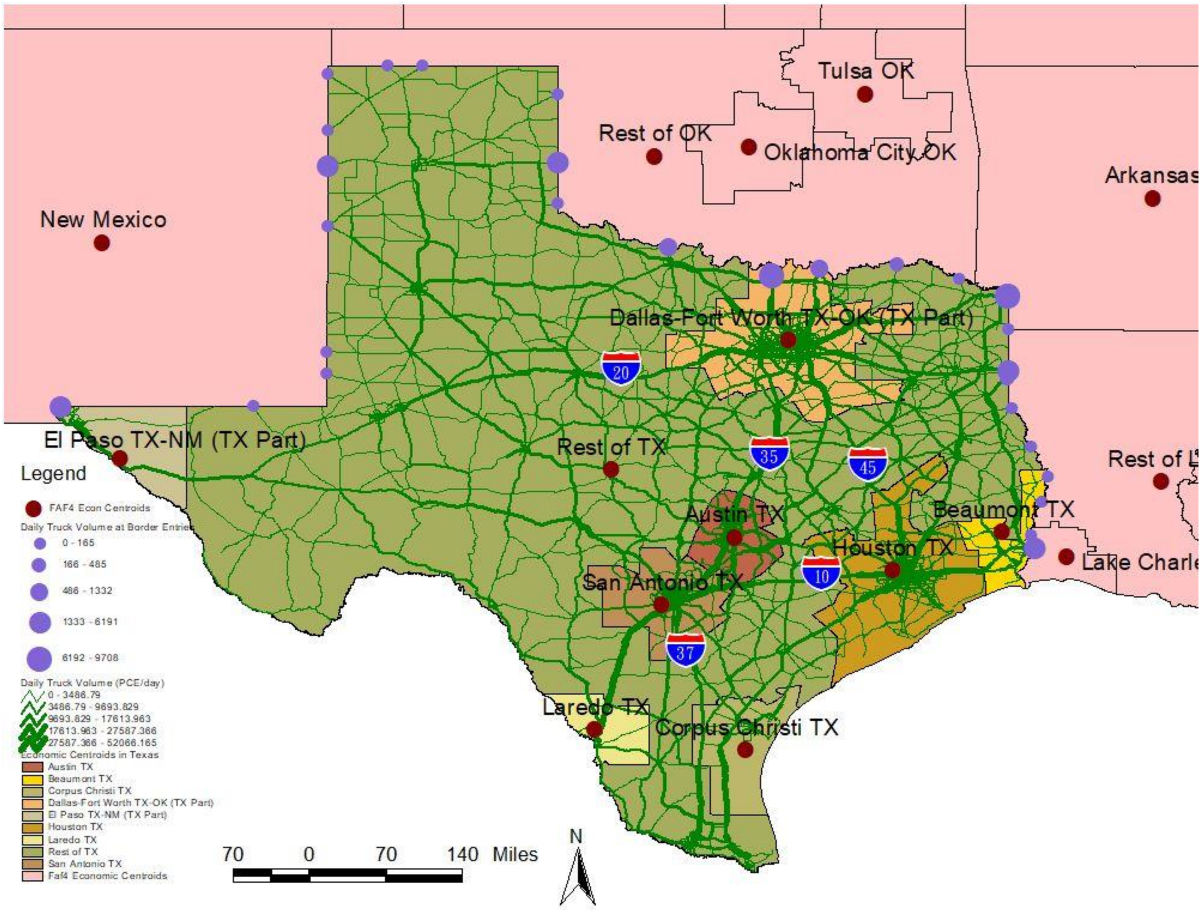


Figure 5(b) Truck Flows in Texas Triangle

Traffic volume trends were projected for future years, and growth rates were predicted for both the lower bound and upper bound scenarios as shown in Table 4.

Table 4. Vehicle Growth rates for year 2015-2035

Projected for Years	Lower bound		Upper bound	
2015	1%	2%	3%	7%
2015-2035	122%	149%	181%	387%
2020-2035	116%	135%	156%	276%

Source: Author calculation.

Additionally, traffic growth scenarios are based on 1% and 3% growth rates. The analysis includes separate scenarios for capacity increases of 50% and 100%. Combined scenarios of traffic growth and capacity increase are also considered to assess the impact of AVs on the traffic stream.

Table 5. Analysis Results

Region	Variables	Modes	Scenarios							
			Volume + 1%	Volume + 3%	Capacity + 50%	Capacity - 100%	Volume + 1% & Capacity + 50%	Volume + 1% & Capacity + 100%	Volume + 3% & Capacity + 50%	Volume + 3% & Capacity + 100%
Entire Texas	Accessibility	Passenger	12.84%	25.03%	9.60%	13.09%	29.03%	13.09%	68.28%	86.53%
		Freight	12.02%	20.95%	10.61%	14.50%	29.68%	14.50%	67.11%	87.03%
	VMT	Passenger	22.07%	83.09%	0.14%	0.27%	22.00%	22.19%	80.81%	80.81%
		Freight	22.01%	83.12%	0.11%	0.24%	21.89%	22.10%	80.57%	80.57%
	VTT	Passenger	34.86%	210.84%	-8.83%	-11.17%	14.88%	10.10%	74.86%	74.86%
		Freight	36.00%	220.24%	-9.95%	-12.60%	14.07%	8.53%	74.06%	74.06%
	Volume	Passenger	21.94%	80.78%	0.00%	0.00%	21.94%	21.94%	80.78%	80.78%
		Freight	21.89%	80.59%	0.00%	0.00%	21.89%	21.89%	80.59%	80.59%
Texas Triangle	Accessibility	Passenger	13.13%	26.53%	9.15%	12.42%	28.76%	12.42%	68.67%	86.33%
		Freight	12.10%	21.35%	10.47%	14.26%	29.60%	14.26%	67.21%	86.98%
	VMT	Passenger	22.02%	82.73%	0.20%	0.32%	22.05%	22.25%	80.86%	80.86%
		Freight	21.99%	82.82%	0.18%	0.31%	21.97%	22.19%	80.70%	80.70%
	VTT	Passenger	33.59%	195.24%	-8.13%	-10.34%	15.46%	11.03%	75.36%	75.36%
		Freight	34.80%	205.14%	-9.32%	-11.85%	14.62%	9.39%	74.60%	74.60%
	Volume	Passenger	21.94%	80.77%	0.00%	0.00%	21.94%	21.94%	80.77%	80.77%
		Freight	21.91%	80.65%	0.00%	0.00%	21.91%	21.91%	80.65%	80.65%

Source: Author calculation.

As anticipated, our study confirms that increasing capacity by 50% and 100% does not lead to any changes in traffic volumes across both the Texas Triangle and the entire state of Texas. However, the introduction of AVs at 1% and 3% penetration rates leads to an increase in traffic volume in both regional contexts, with a slightly higher rate observed at 3% compared to 1%. Surprisingly, this trend continues even when AV penetration is coupled with capacity increases. These findings suggest that while expanding infrastructure capacity has no effects on congestion, the additional traffic generated by AVs negates these benefits. Our findings show that combining AV adoption with capacity enhancements does not reduce the rise in traffic volume, highlighting the complexities of integrating AVs into existing transportation systems. These consistent results for both freight and passenger transportation in Texas and the Texas Triangle regions emphasize the urgent need for careful planning to manage potential congestion and optimize infrastructure utilization as AV technology advances.

Our findings show that increasing capacity has minimal impact on VMT for both freight and passenger transportation in Texas and the Triangle regions. However, with autonomous vehicle (AV) penetration rates of 1% and 3%, we observe substantial increases in VMT—around 22% and 83%, respectively, across both regions. Notably, the combination of AV adoption and capacity enhancements did not lead to a significant reduction in VMT for either passenger or freight traffic in these regions. Similar to the previous results, these findings highlight the significant impact of AV adoption on increasing travel distances. This suggests that effectively managing the integration of AVs into transportation systems will require strategic planning to optimize infrastructure use while addressing potential increases in traffic volume.

As expected, our analysis demonstrates that increasing capacity by 50% and 100% leads to reduced travel times for both passenger and freight transportation in both Texas and the Triangle regions, with decreases of approximately -9% and -12%, respectively. In contrast, at AV penetration rates of 1% and 3%, travel times increase significantly—at approximately 34% and 220%, respectively, across both regions. Interestingly, in combined scenarios with 1% AV penetration and capacity increases of 50% and 100%, the VTT decreases from approximately 35% to 10% for both passenger and freight traffic across both regions. These results highlight the importance of integrating AV adoption with concurrent increases in infrastructure capacity. Doing so is essential to manage the potential increases in travel times associated with AVs effectively, while also optimizing overall transportation efficiency and reducing congestion.

Next, we analyze changes in passenger and freight accessibility across different scenarios. As expected, both AV penetration and capacity enhancements contribute to increased accessibility. At AV penetration rates of 1% and 3%, accessibility increases by approximately 12% and 25%, respectively, compared to the baseline. Similarly, with capacity increases of 50% and 100%, accessibility rises by approximately 9% and 13%, respectively. In combined scenarios for both regions, with 1% AV penetration and capacity increases of 50% and 100%, accessibility improves by 29% and 13%, respectively. Similarly, with 3% AV penetration and capacity enhancements of 50% and 100%, accessibility increases by 69% and 87%, respectively, compared to the baseline. These findings highlight the combined benefits of AV adoption and capacity improvements in enhancing accessibility for both passenger and freight transportation. Planning and policy efforts should aim to harness these synergies to maximize accessibility benefits while addressing the complexities introduced by increased presence of AVs in transportation networks.

We now present maps that show how the introduction of AVs under different scenarios affects accessibility, VMT, and VTT. These visualizations enhance our understanding of how AV adoption, coupled with various levels of capacity improvements, affects these key transportation parameters.

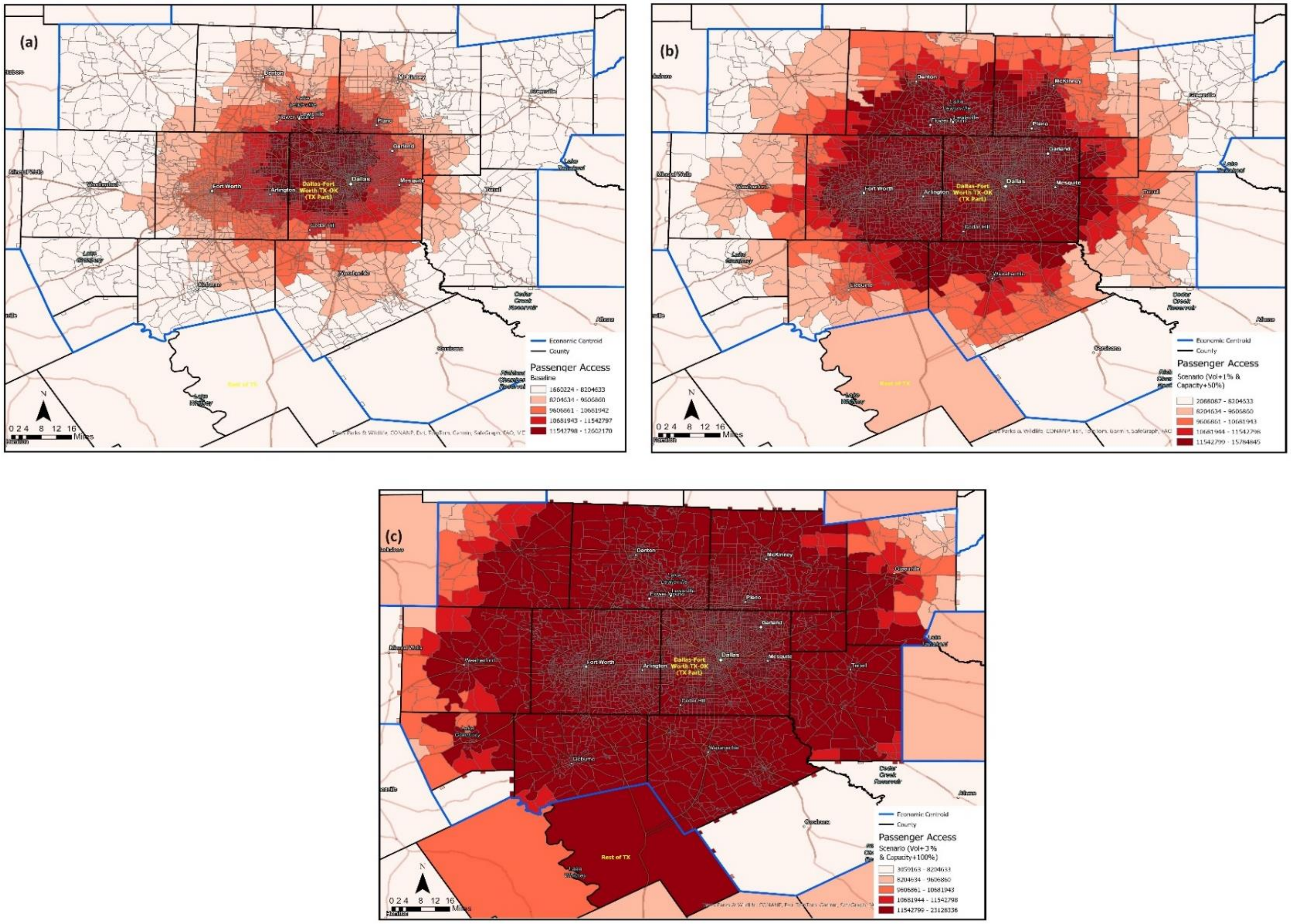


Figure 6. Personal Vehicle Accessibility for the (a) Baseline, (b) a 50% increase in capacity with a 1% growth in traffic, and (c) a 100% increase in capacity with a 3% growth in traffic scenarios in Northern Texas

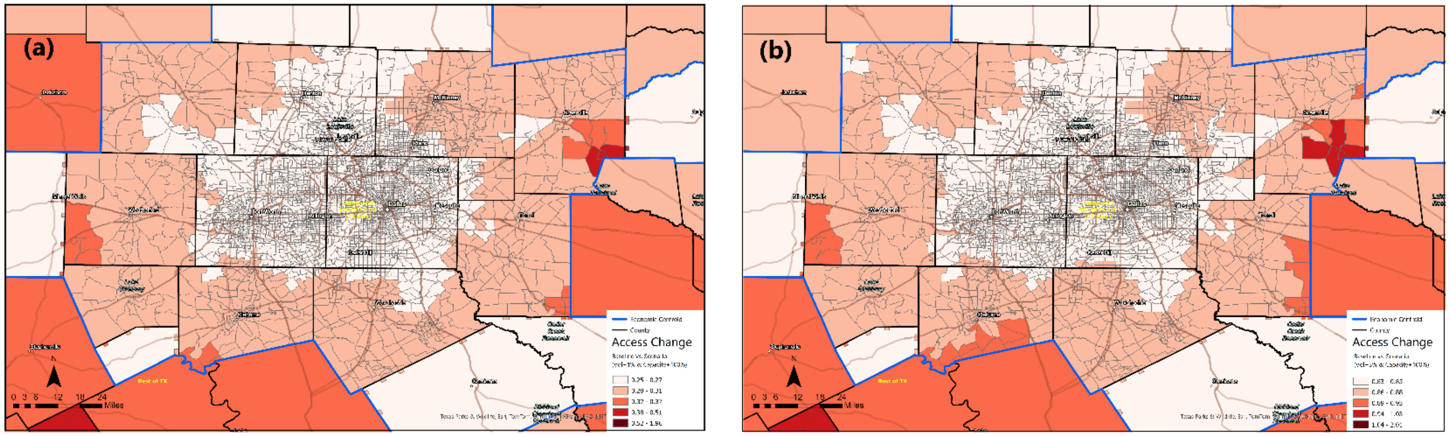


Figure 7. Change in passenger accessibility when (a) traffic growth is 1% and capacity is increased by 50%, and (b) traffic growth is 3% and capacity is increased by 100% in Northern Texas

Figures 6 and 7 illustrate passenger accessibility in the Northern Texas region under three scenarios: (a) Baseline, (b) a 50% increase in capacity with 1% traffic growth, and (c) a 100% increase in capacity with 3% traffic growth. Figure 6 presents the accessibility levels for each scenario, while Figure 7 illustrates the changes in accessibility compared to the baseline for scenarios (b) and (c). The figures reveal a notable improvement in both scenarios (b) and (c) compared to the baseline, with scenario (c) demonstrating the most substantial increase.

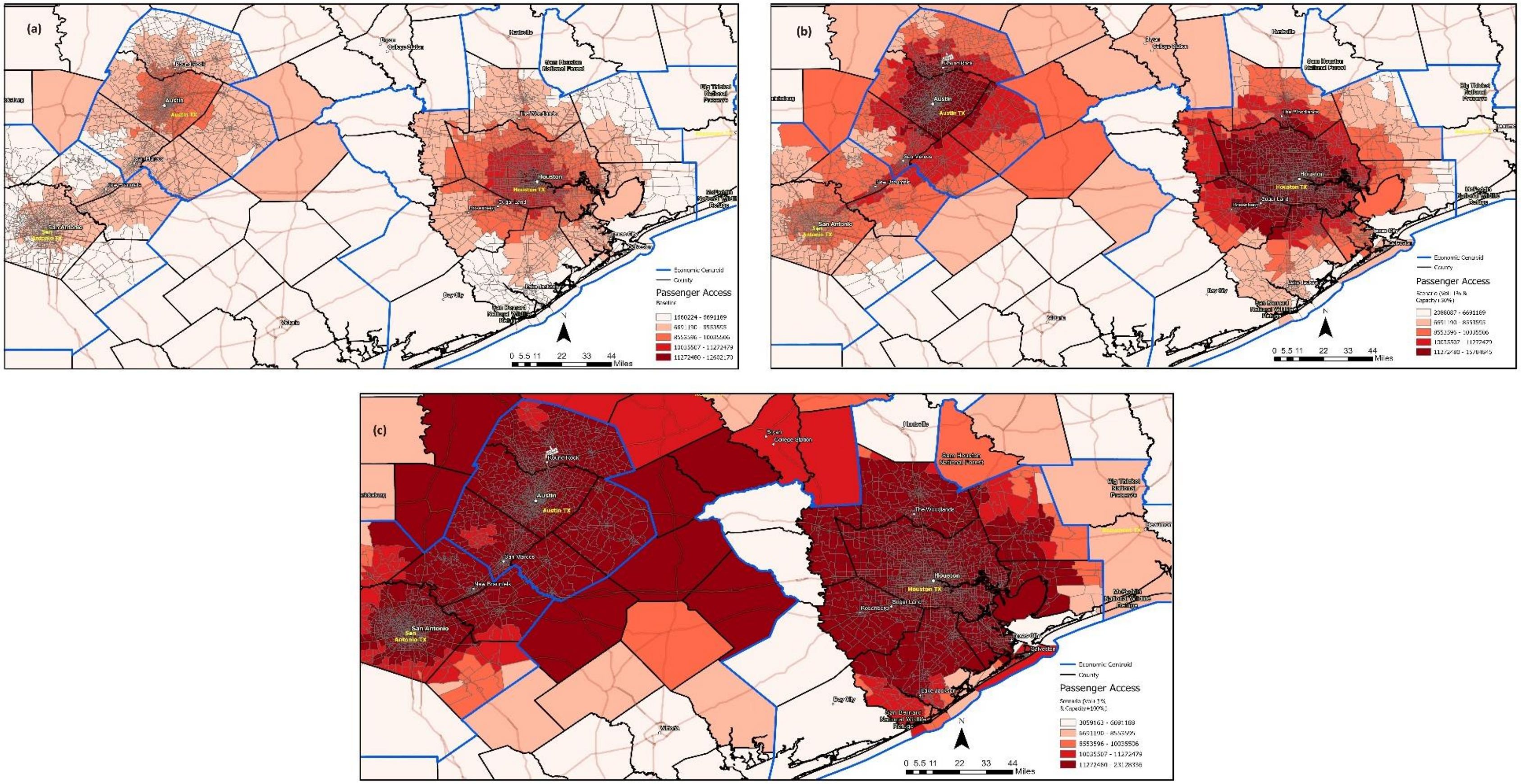


Figure 8. Personal Vehicle Accessibility for the (a) Baseline, (b) a 50% increase in capacity with a 1% growth in traffic, and (c) a 100% increase in capacity with a 3% growth in traffic scenarios in Southern Texas

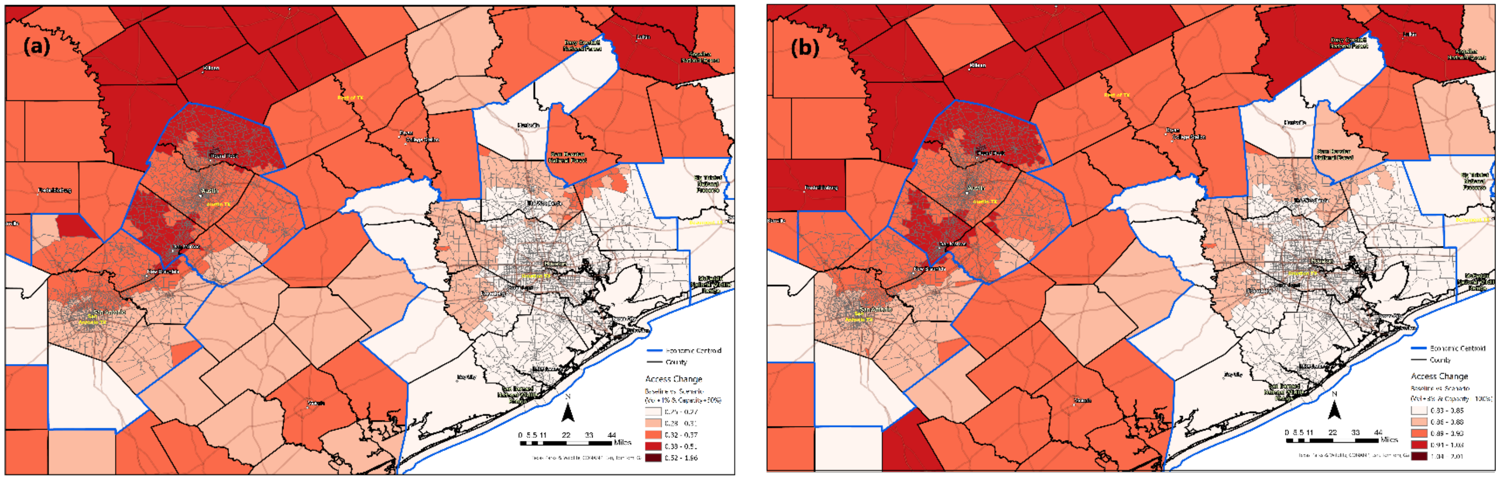


Figure 9. Change in passenger accessibility when (a) traffic growth is 1% and capacity is increased by 50%, and (b) traffic growth is 3% and capacity is increased by 100% in Southern Texas

Similarly, Figures 8 and 9 present the same scenarios and changes for Southern Texas, including Houston, San Antonio, and Austin. Figure 8 shows passenger accessibility levels for three different scenarios: (a) Baseline, (b) a 50% increase in capacity coupled with 1% growth in traffic, and (c) a 100% increase in capacity along with a 3% growth in traffic. Figure 9 highlights the changes in accessibility relative to the baseline for scenarios (b) and (c). Much like in Northern Texas, passenger accessibility significantly improves in both scenarios (b) and (c) compared to the baseline, with scenario (c) demonstrating the greatest enhancement. It's evident that both increased AV penetration and capacity enhancements lead to improved accessibility. It is noteworthy that Austin and San Antonio experience greater changes in passenger accessibility compared to other metropolitan areas. This may be due to several factors that were not explored in this study and warrant further investigation.

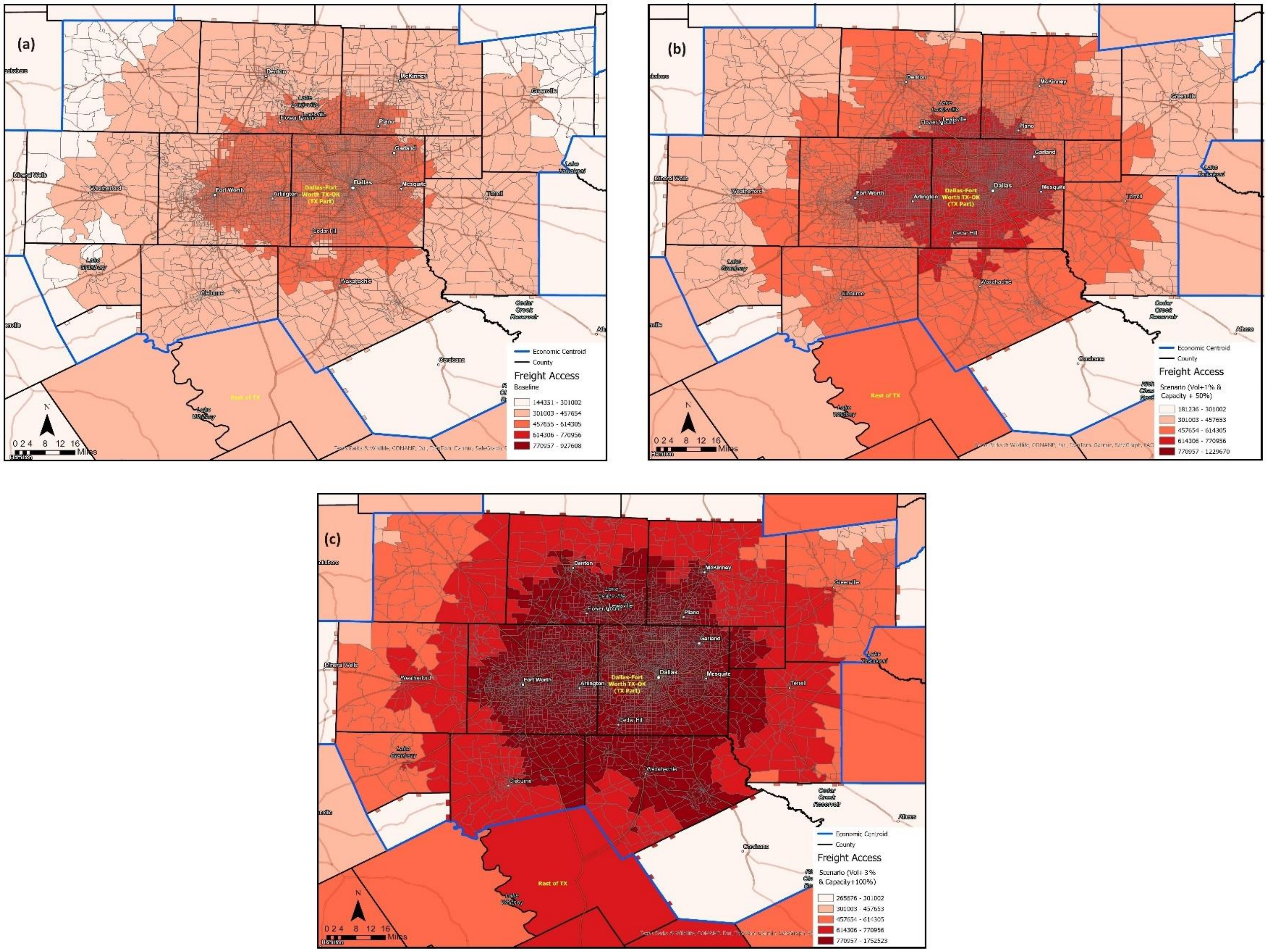


Figure 10. Freight Vehicle Accessibility for the (a) Baseline, (b) a 50% increase in capacity with a 1% growth in traffic, and (c) a 100% increase in capacity with a 3% growth in traffic scenarios in Northern Texas

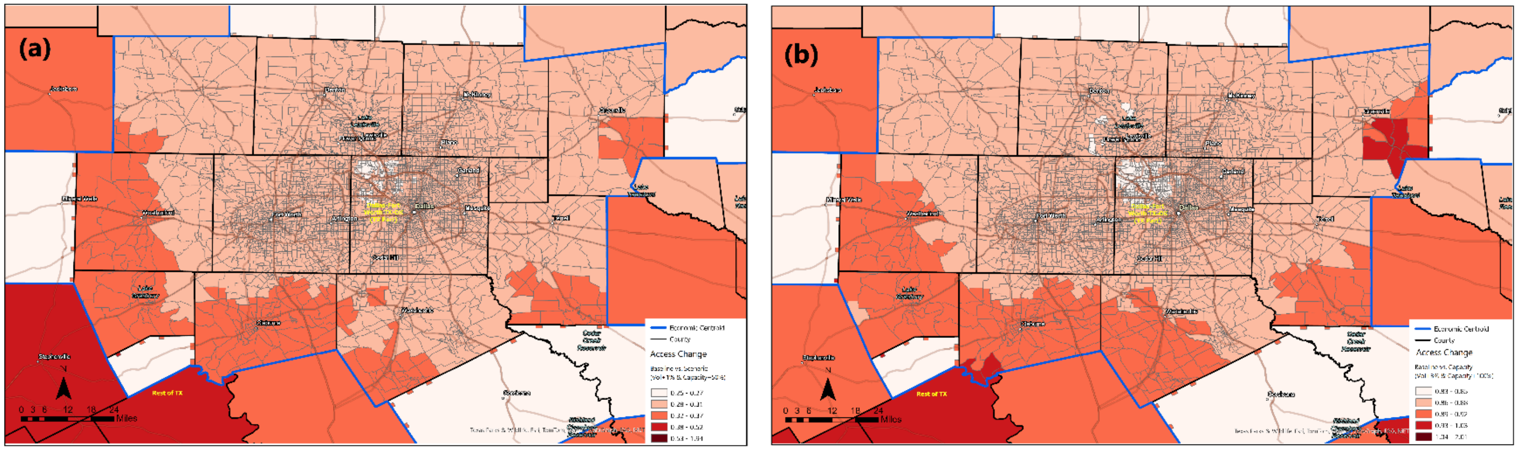


Figure 11. Change in freight accessibility when (a) traffic growth is 1% and capacity is increased by 50%, and (b) traffic growth is 3% and capacity is increased by 100% in Northern Texas

Figures 10 and 11 illustrate freight accessibility and its changes in the Northern Texas region across three scenarios: (a) Baseline, (b) a 50% increase in capacity with a 1% growth in traffic, and (c) a 100% increase in capacity with a 3% growth in traffic. Figure 10 shows the accessibility levels for each scenario, whereas Figure 11 compares the changes in accessibility relative to the baseline for scenarios (b) and (c). These figures show that freight accessibility significantly improves in both scenarios (b) and (c) compared to the baseline, with scenario (c) exhibiting the most significant enhancement. However, freight accessibility catchments are substantially lower compared to passenger accessibility in North Texas.

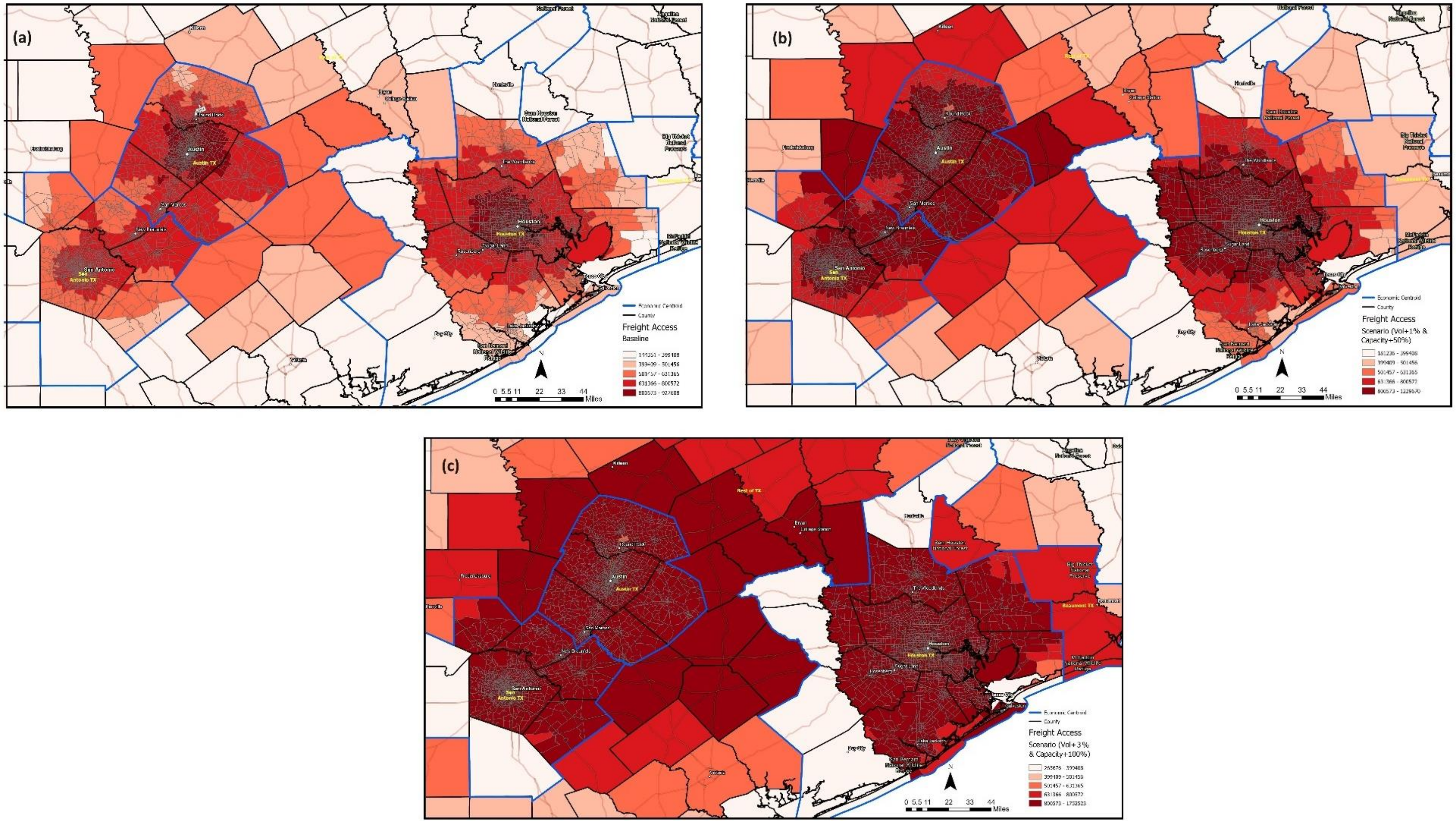


Figure 12. Freight Vehicle Accessibility for the (a) Baseline, (b) a 50% increase in capacity with a 1% growth in traffic, and (c) a 100% increase in capacity with a 3% growth in traffic scenarios in Southern Texas

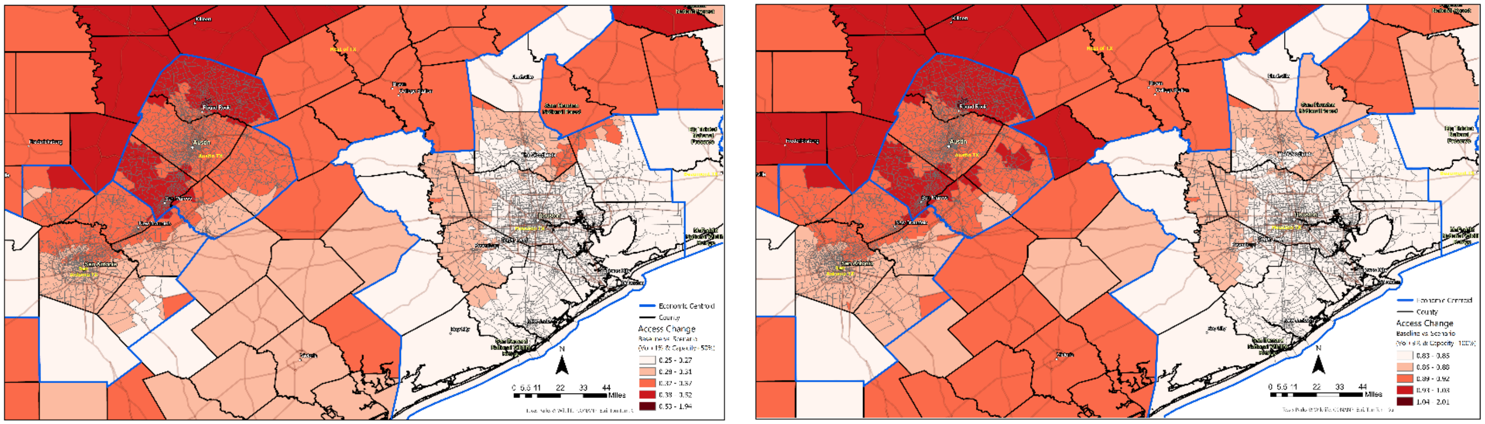


Figure 13. Change in freight accessibility when (a) traffic growth is 1% and capacity is increased by 50%, and (b) traffic growth is 3% and capacity is increased by 100% in Southern Texas

Figures 12 and 13 illustrate freight accessibility and its changes in the Southern Texas region across the same scenarios: (a) Baseline, (b) a 50% increase in capacity with a 1% growth in traffic, and (c) a 100% increase in capacity with a 3% growth in traffic. Figure 12 shows the accessibility levels for each scenario, whereas Figure 13 contrasts the changes in accessibility relative to the baseline for scenarios (b) and (c). These figures show that freight accessibility markedly improves in both scenarios (b) and (c) compared to the baseline, with scenario (c) showing the greatest improvement. These scenarios indicate that integrating AVs into the traffic flow and increasing capacity are likely to enhance accessibility for both passengers and freight traffic. Freight accessibility in Austin and San Antonio has risen significantly compared to Dallas and Houston. Additionally, the South Texas region has seen a more substantial increase in freight accessibility under the two scenarios compared to the North Texas region, surpassing the improvements observed in passenger access. Due to the close proximity of the three major metro areas—Houston, San Antonio, and Austin—freight movement is expected to be higher in these areas, leading to improved accessibility.

Figure 14. Personal Vehicle Travel Time for the (a) Baseline, (b) a 50% increase in capacity with a 1% growth in traffic, and (c) a 100% increase in capacity with a 3% growth in traffic scenarios in Northern Texas

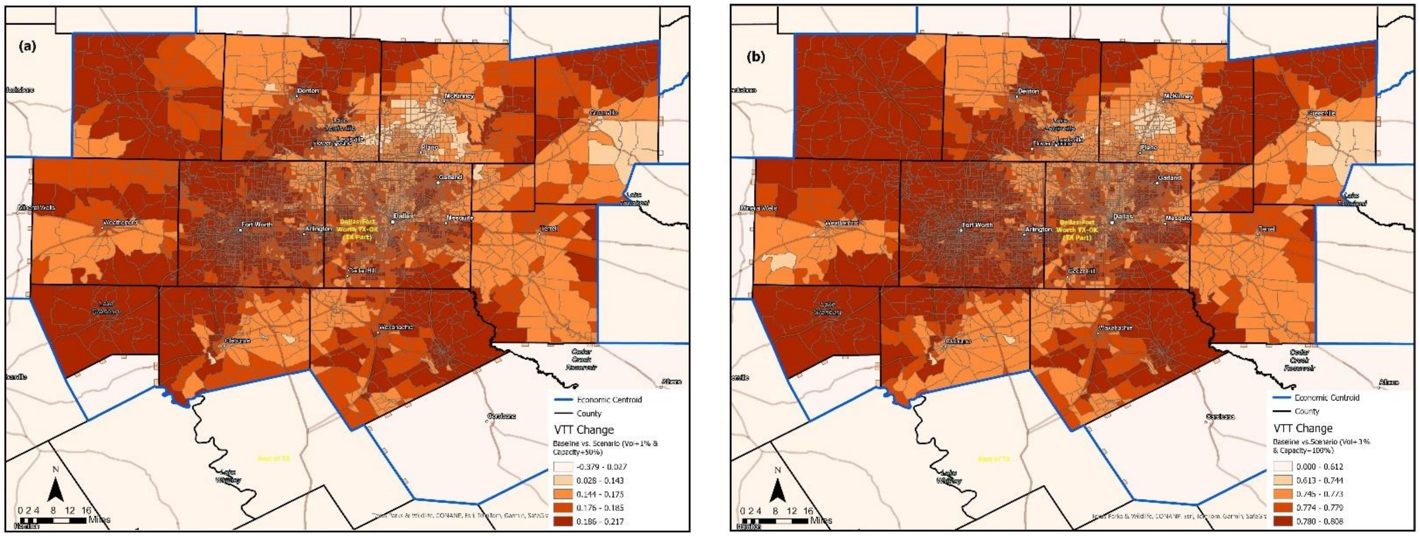


Figure 15. Change in passenger vehicle travel time when (a) traffic growth is 1% and capacity is increased by 50%, and (b) traffic growth is 3% and capacity is increased by 100% in Northern Texas

Figures 14 and 15 evaluate the same scenarios in terms of passenger vehicle travel time. These figures show that the integration of AVs into the traffic stream, along with increased capacity, is projected to significantly impact passenger vehicle travel time. Figure 14 presents the travel time for each scenario, while Figure 15 highlights the changes in travel time relative to the baseline for scenarios (b) and (c). These figures indicate that the adjustments in capacity and traffic growth can lead to a notable increase in total vehicle travel time. Scenario (c) shows the greatest increase in travel time compared to the baseline. However, it is important to note that with the integration of AVs into traffic streams, capacity enhancements are essential to alleviate congestion, as indicated by our descriptive analysis results.

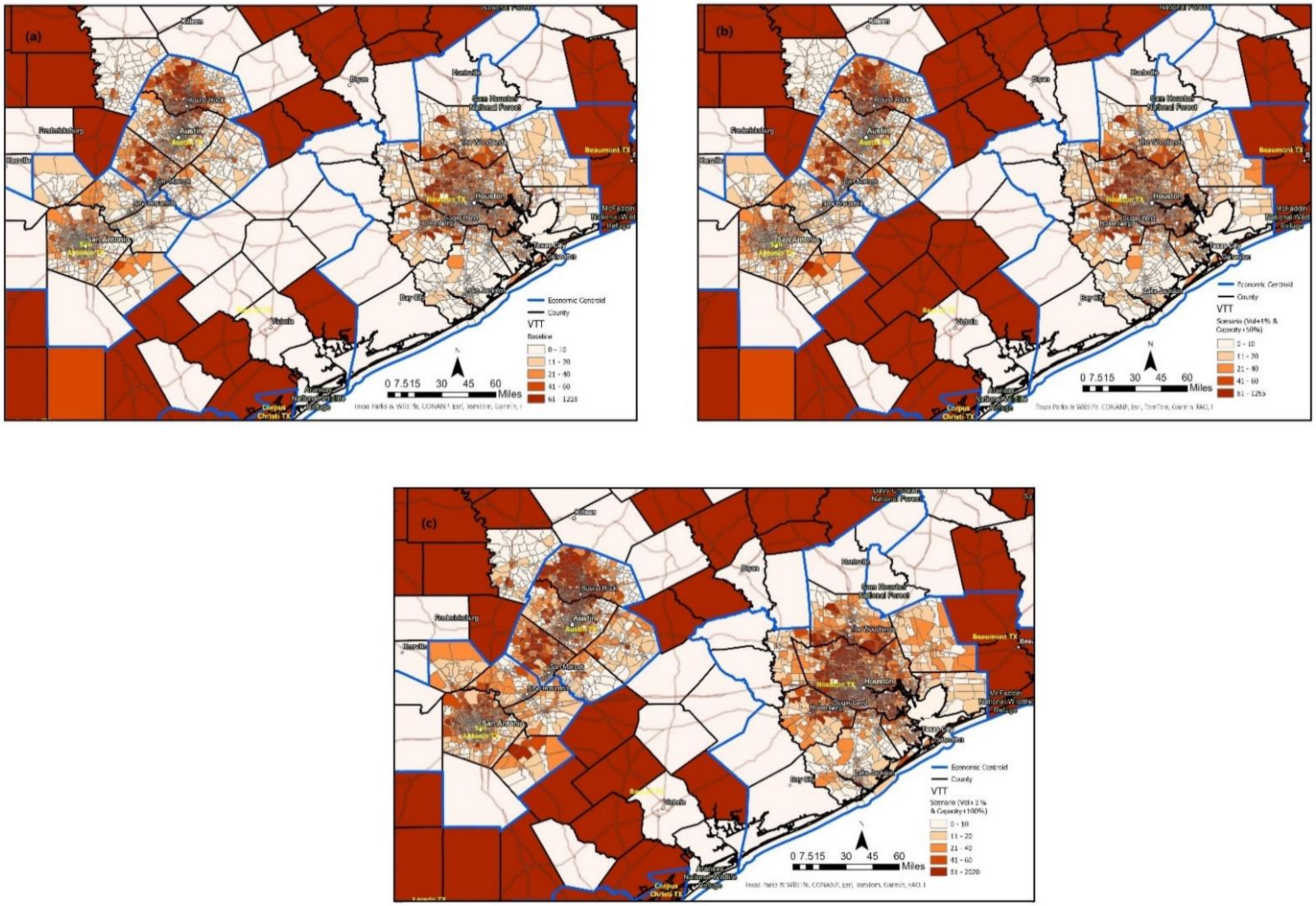


Figure 16. Personal Vehicle Travel Time for the (a) Baseline, (b) a 50% increase in capacity with a 1% growth in traffic, and (c) a 100% increase in capacity with a 3% growth in traffic scenarios in Southern Texas

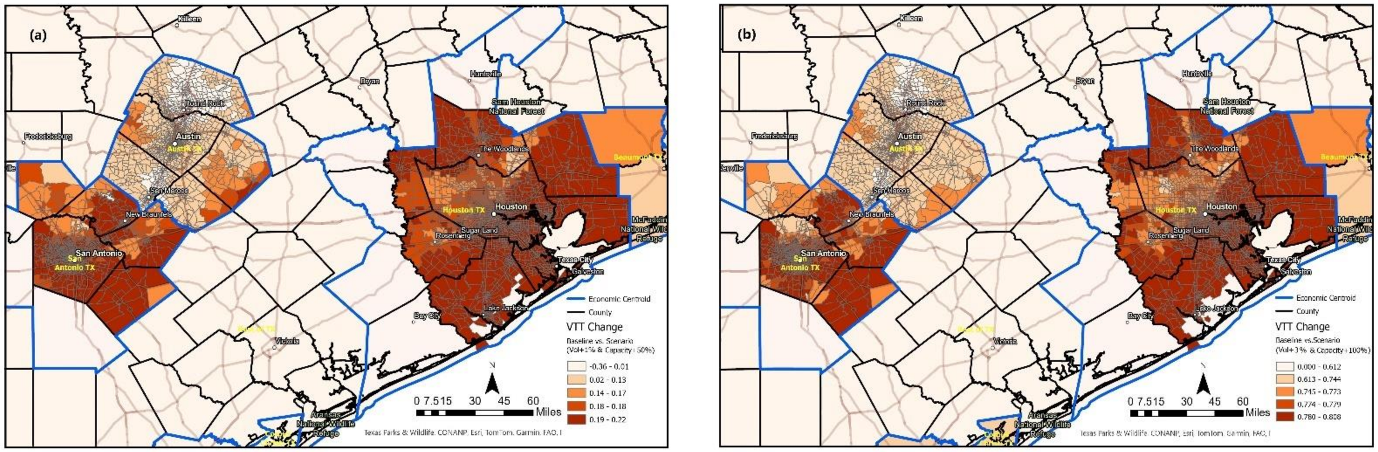


Figure 17. Change in passenger vehicle travel time when (a) traffic growth is 1% and capacity is increased by 50%, and (b) traffic growth is 3% and capacity is increased by 100% in Southern Texas

Figures 16 and 17 evaluate the same scenarios for passenger vehicle travel time in Southern Texas. These figures illustrate the expected changes resulting from the integration of AVs into the traffic stream and increased capacity. Figure 16 details the travel times for each scenario, while Figure 17 highlights the changes in travel time compared to the baseline for scenarios (b) and (c). These figures suggest that adjustments in capacity and traffic growth can lead to a significant increase in total vehicle travel time. Once again, scenario (c) shows the greatest increase in travel time compared to the baseline. Austin stands out in these scenarios, with some areas of the city experiencing reduced travel times compared to the baseline in scenario (a) and minimal travel times in scenario (b), in contrast to other metropolitan areas in the Texas Triangle region. Additionally, we observe reduced travel times outside metropolitan areas, while travel times within the metro areas tend to increase.

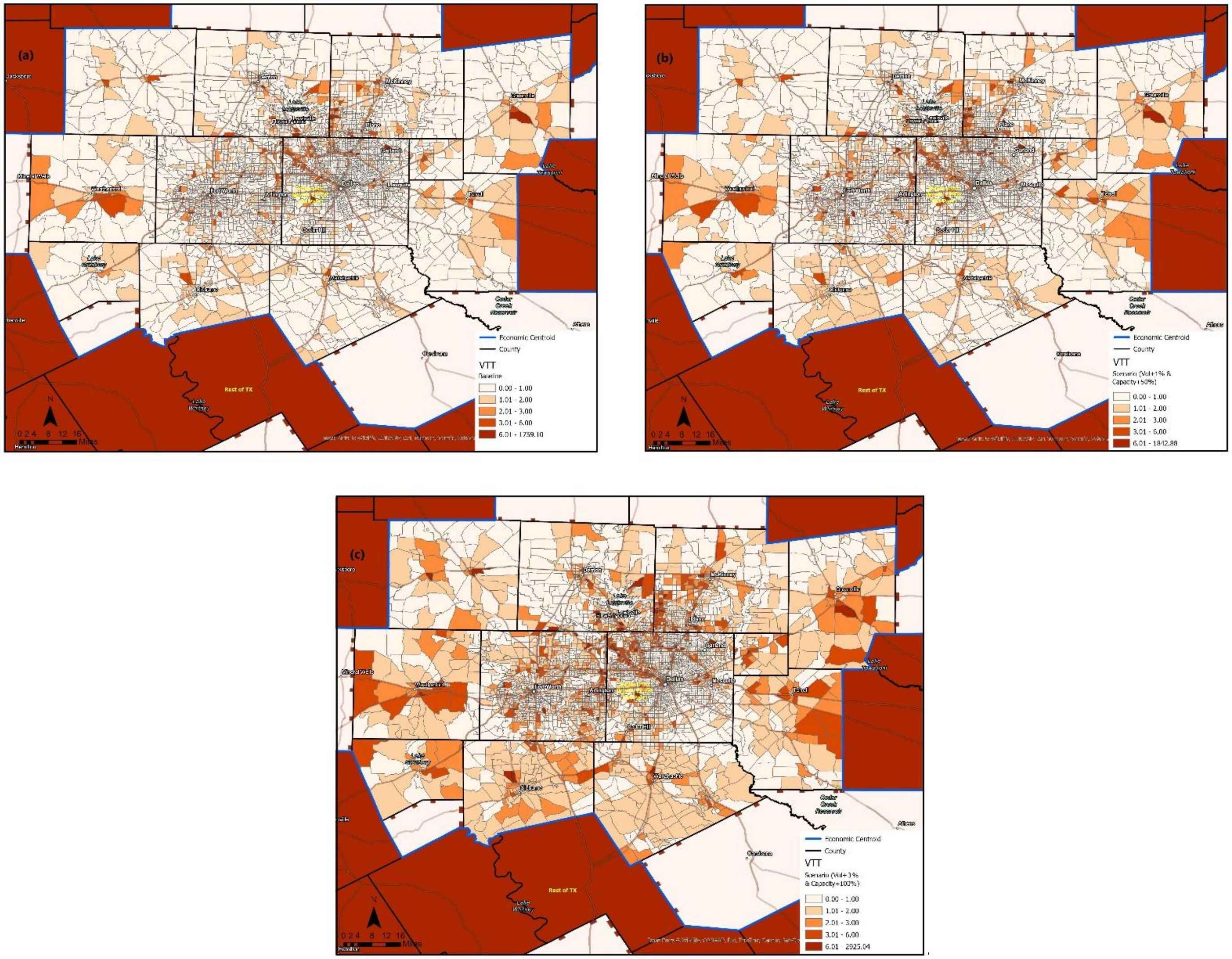


Figure 18. Freight Vehicle Travel Time for the (a) Baseline, (b) a 50% increase in capacity with a 1% growth in traffic, and (c) a 100% increase in capacity with a 3% growth in traffic scenarios in Northern Texas

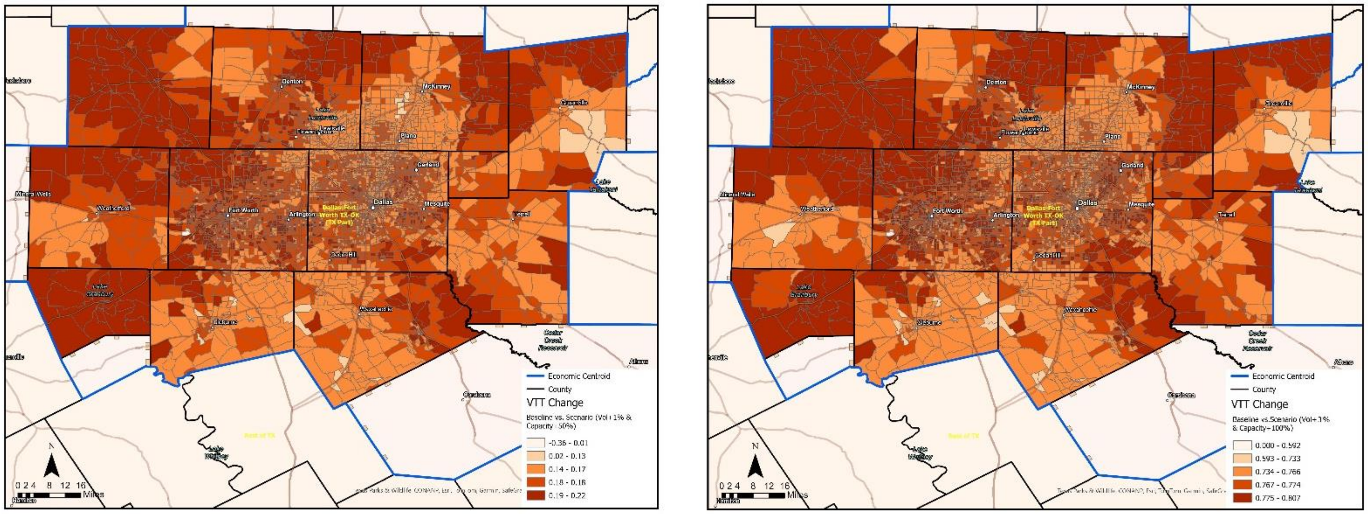


Figure 19. Change in freight vehicle travel time when (a) traffic growth is 1% and capacity is increased by 50%, and (b) traffic growth is 3% and capacity is increased by 100% in Northern Texas

Figures 18 and 19 evaluate the same scenarios for freight transportation in Northern Texas. These figures illustrate the expected changes of freight transportation resulting from integrating AVs into the traffic stream and increasing capacity. Figure 18 provides details on freight travel times for each scenario, while Figure 19 highlights the changes in travel time compared to the baseline for scenarios (b) and (c). These figures suggest that changes in capacity and traffic growth can lead to a significant increase in total freight vehicle travel time. Once again, scenario (c) shows the greatest increase in travel time compared to the baseline.

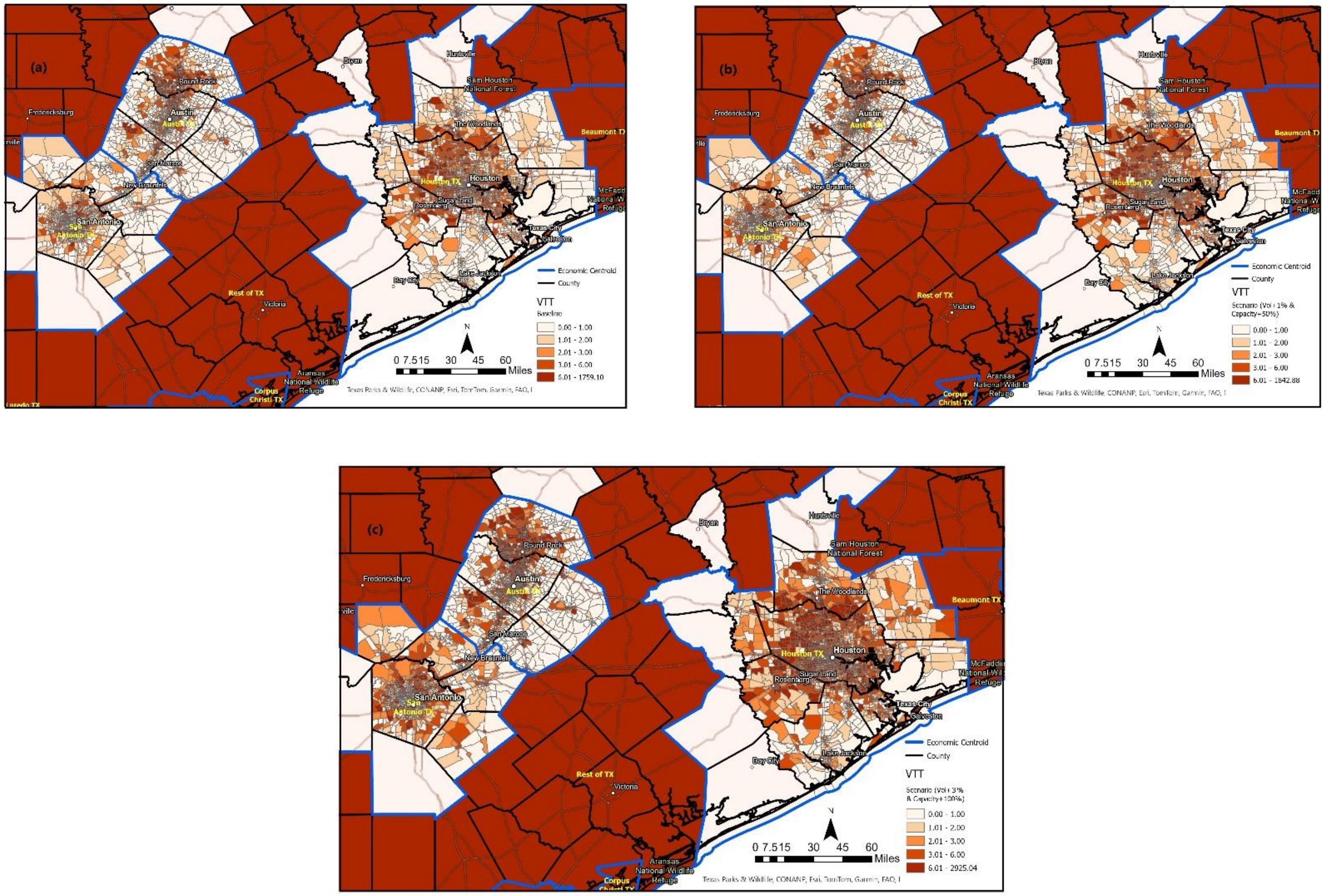


Figure 20. Freight Vehicle Travel Time for the (a) Baseline, (b) a 50% increase in capacity with a 1% growth in traffic, and (c) a 100% increase in capacity with a 3% growth in traffic scenarios in Southern Texas

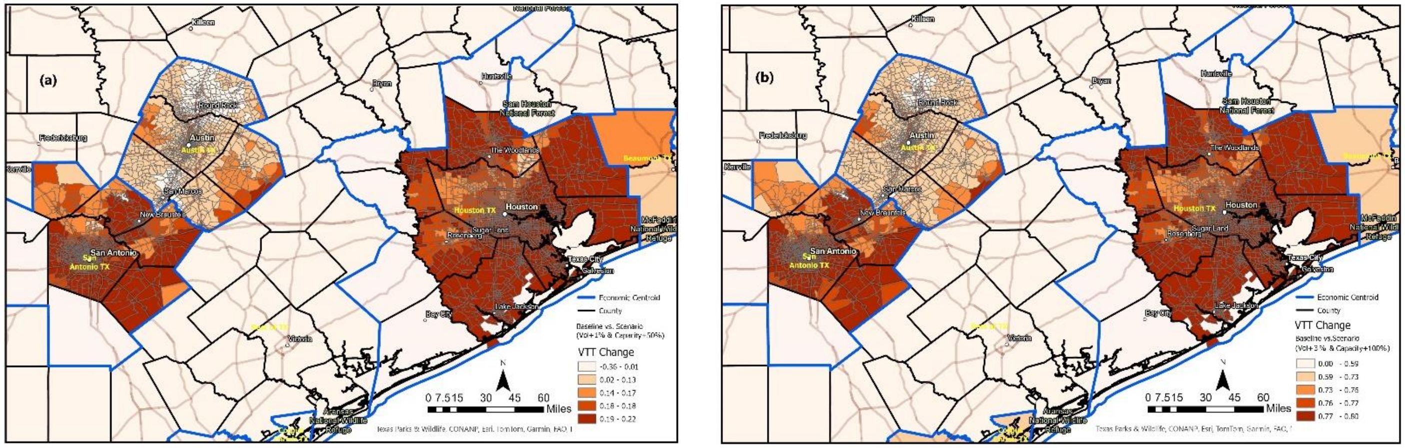


Figure 21. Change in freight vehicle travel time when (a) traffic growth is 1% and capacity is increased by 50%, and (b) traffic growth is 3% and capacity is increased by 100% in Southern Texas

Figures 20 and 21 evaluate the same scenarios for freight transportation in Southern Texas. These figures illustrate the expected changes resulting from the integration of AVs into the traffic stream and increased capacity. Figure 20 outlines the freight travel times for each scenario, while Figure 21 highlights the changes in travel time compared to the baseline for scenarios (b) and (c). These figures indicate that changes in capacity and traffic growth can lead to a significant increase in total freight vehicle travel time. Once again, scenario (c) shows the greatest increase in travel time compared to the baseline. Austin continues to demonstrate significant reductions in travel times compared to the baseline in scenario (a) and minimal travel times in scenario (b), for both passenger and freight transportation. Outside metropolitan areas, travel times decrease noticeably, whereas within metro areas, they tend to increase. This highlights that the integration of AVs into the traffic stream has a more pronounced effect than capacity enhancements in metro regions, whereas the opposite is observed outside metro areas. Overall, the maps of vehicle travel time suggest that integrating AVs into the traffic stream, even with increased capacity, will lead to an increase in total vehicle travel time. This is likely due to induced demand, where improved conditions attract more freight traffic, counteracting the initial congestion reductions.

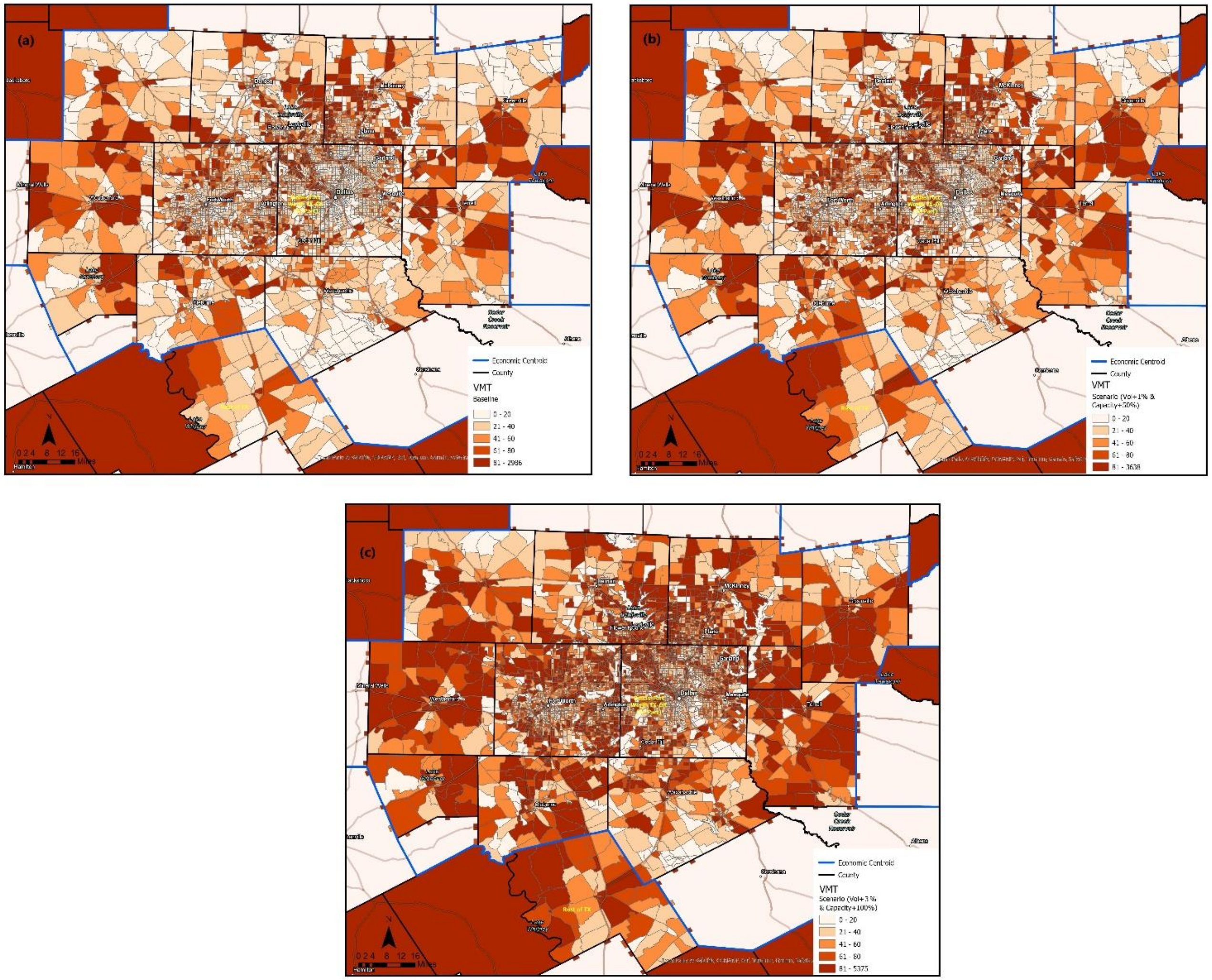


Figure 22. Personal VMT for the (a) Baseline, (b) a 50% increase in capacity with a 1% growth in traffic, and (c) a 100% increase in capacity with a 3% growth in traffic scenarios in Northern Texas

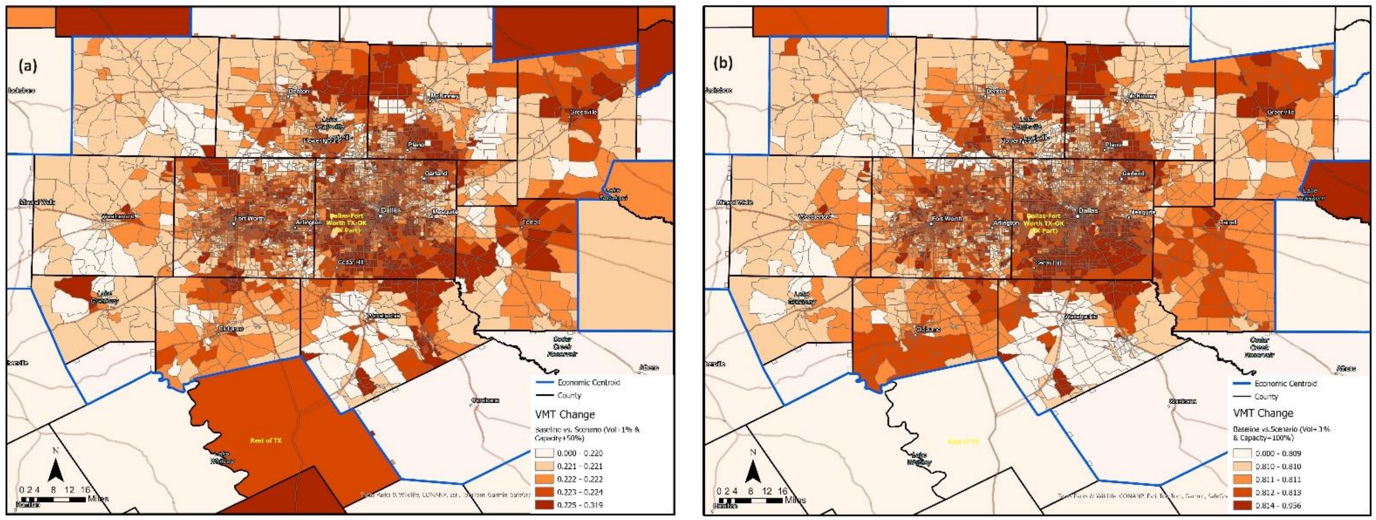


Figure 23. Change in personal VMT when (a) growth in AV is 1% and capacity is increased by 50%, and (b) growth in AV is 3% and capacity is increased by 100% in Northern Texas

Next, Figures 22 and 23 present personal VMT and its changes in Northern Texas. These figures illustrate the expected changes resulting from integrating AVs into the traffic stream and increasing capacity. Figure 22 provides details on Personal VMT for each scenario, while Figure 23 highlights the changes in VMT compared to the baseline for scenarios (b) and (c). These figures suggest that changes in capacity and traffic growth can lead to a significant increase in total personal VMT. Once again, scenario (c) shows the largest increase in VMT compared to the baseline.

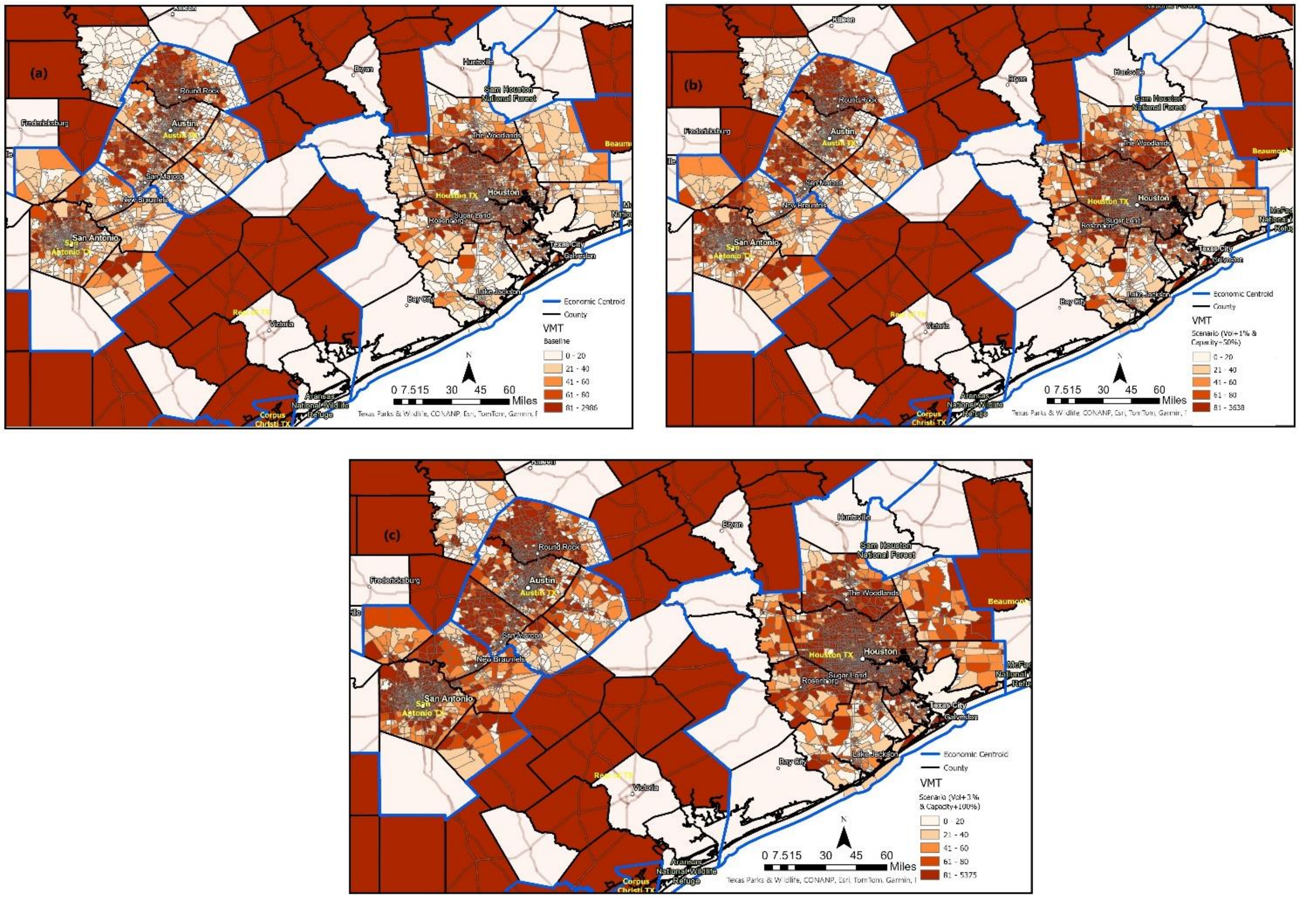


Figure 24. Personal VMT for the (a) Baseline, (b) a 50% increase in capacity with a 1% growth in traffic, and (c) a 100% increase in capacity with a 3% growth in traffic scenarios in Southern Texas

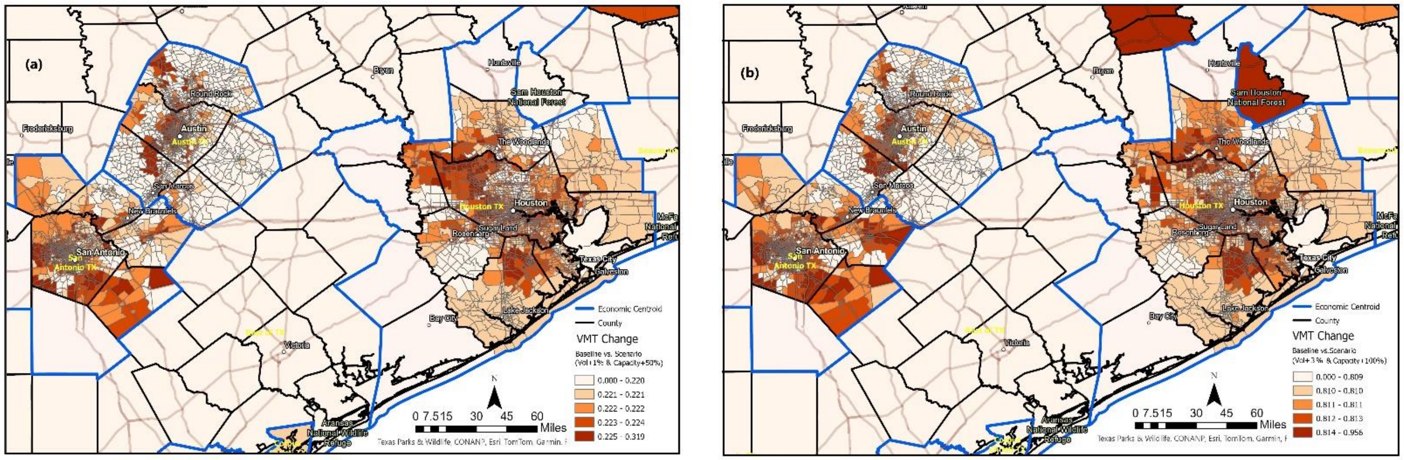


Figure 25. Change in personal VMT when (a) growth in AV is 1% and capacity is increased by 50%, and (b) growth in AV is 3% and capacity is increased by 100% in Southern Texas

Similarly, Figures 24 and 25 evaluate personal VMT and its changes in Southern Texas. Figure 24 presents the personal VMT for each scenario, while Figure 25 highlights the changes in VMT compared to the baseline for scenarios (b) and (c). These figures also indicate that changes in capacity and traffic growth lead to a significant increase in total personal VMT. Scenario (c) again shows the largest increase in personal VMT compared to the baseline.

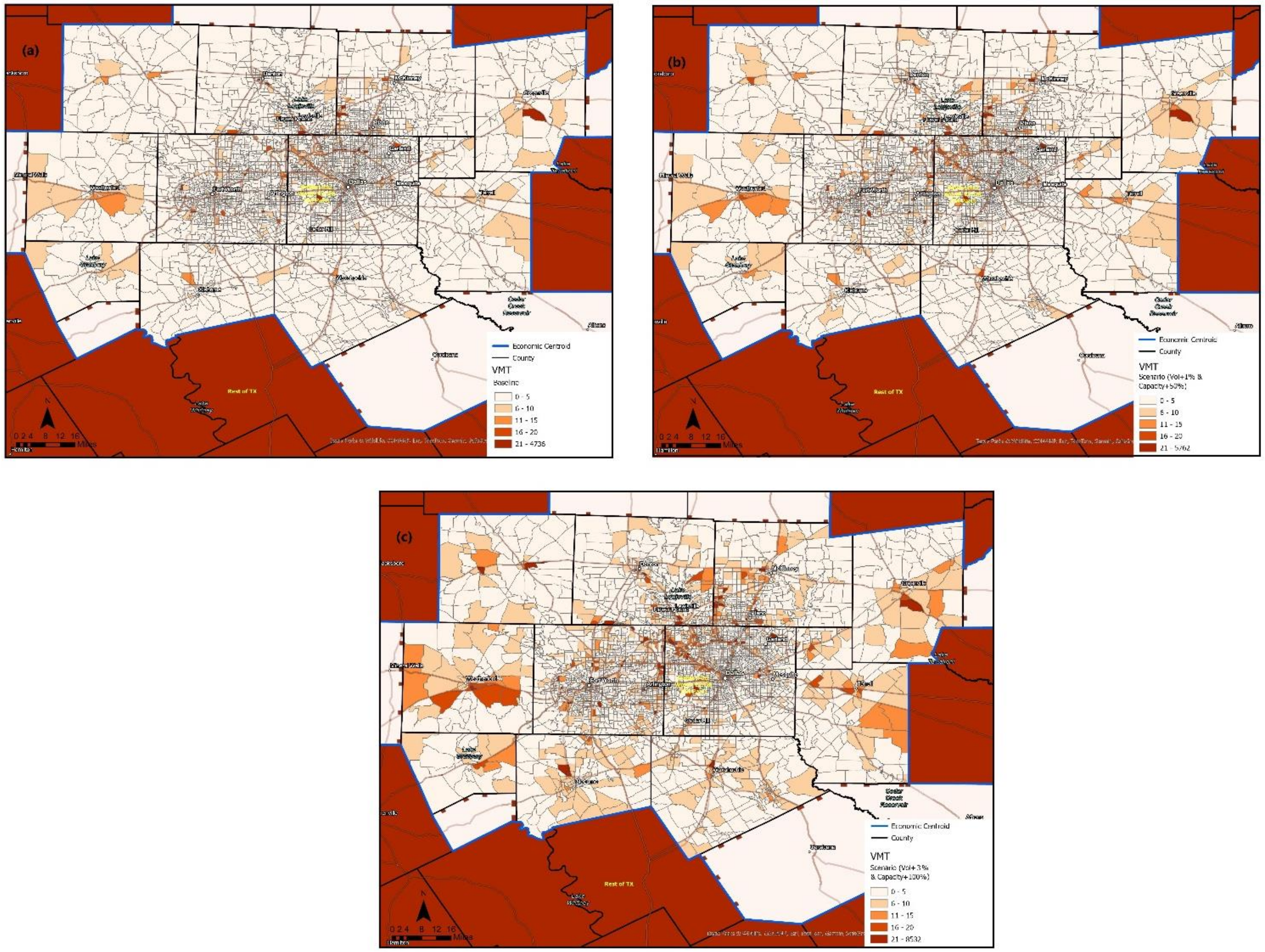


Figure 26. Freight VMT for the (a) Baseline, (b) a 50% increase in capacity with a 1% growth in traffic, and (c) a 100% increase in capacity with a 3% growth in traffic scenarios in Northern Texas

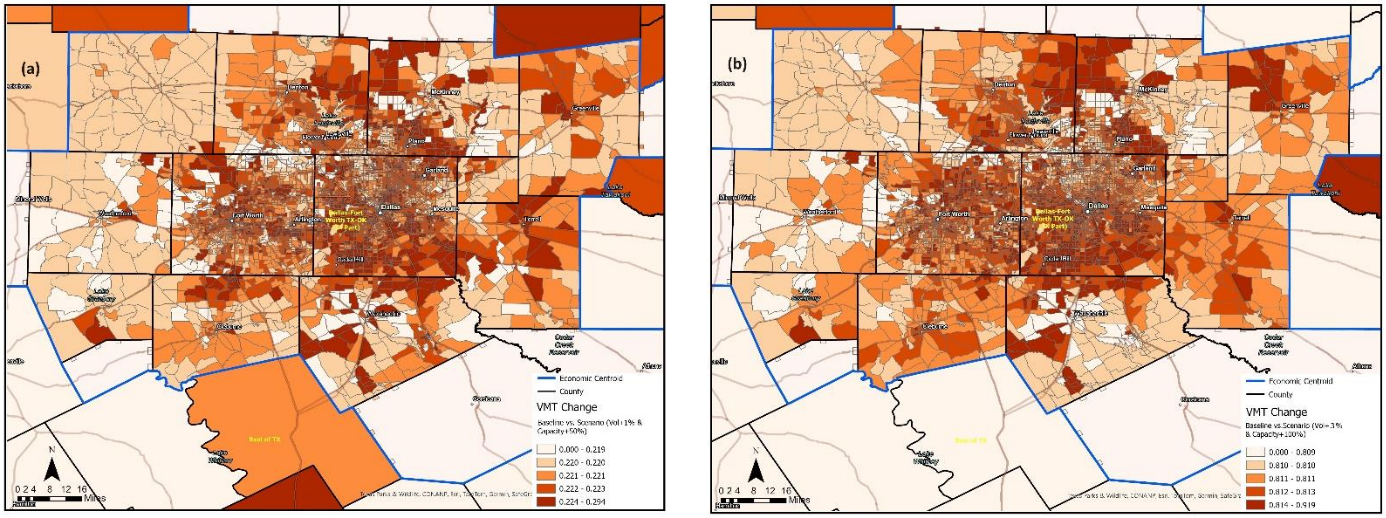


Figure 27. Change in freight VMT when (a) growth in AV is 1% and capacity is increased by 50%, and (b) growth in AV is 3% and capacity is increased by 100% in Northern Texas

Figures 26 and 27 show freight VMT and its changes in Northern Texas. These figures illustrate the expected changes resulting from integrating AVs into the traffic stream and increasing capacity. Figure 26 provides details on freight VMT for each scenario, while Figure 27 highlights the changes in VMT compared to the baseline for scenarios (b) and (c). These figures suggest that changes in capacity and traffic growth can lead to a significant increase in total freight VMT. Once again, scenario (c) shows the largest increase in VMT compared to the baseline.

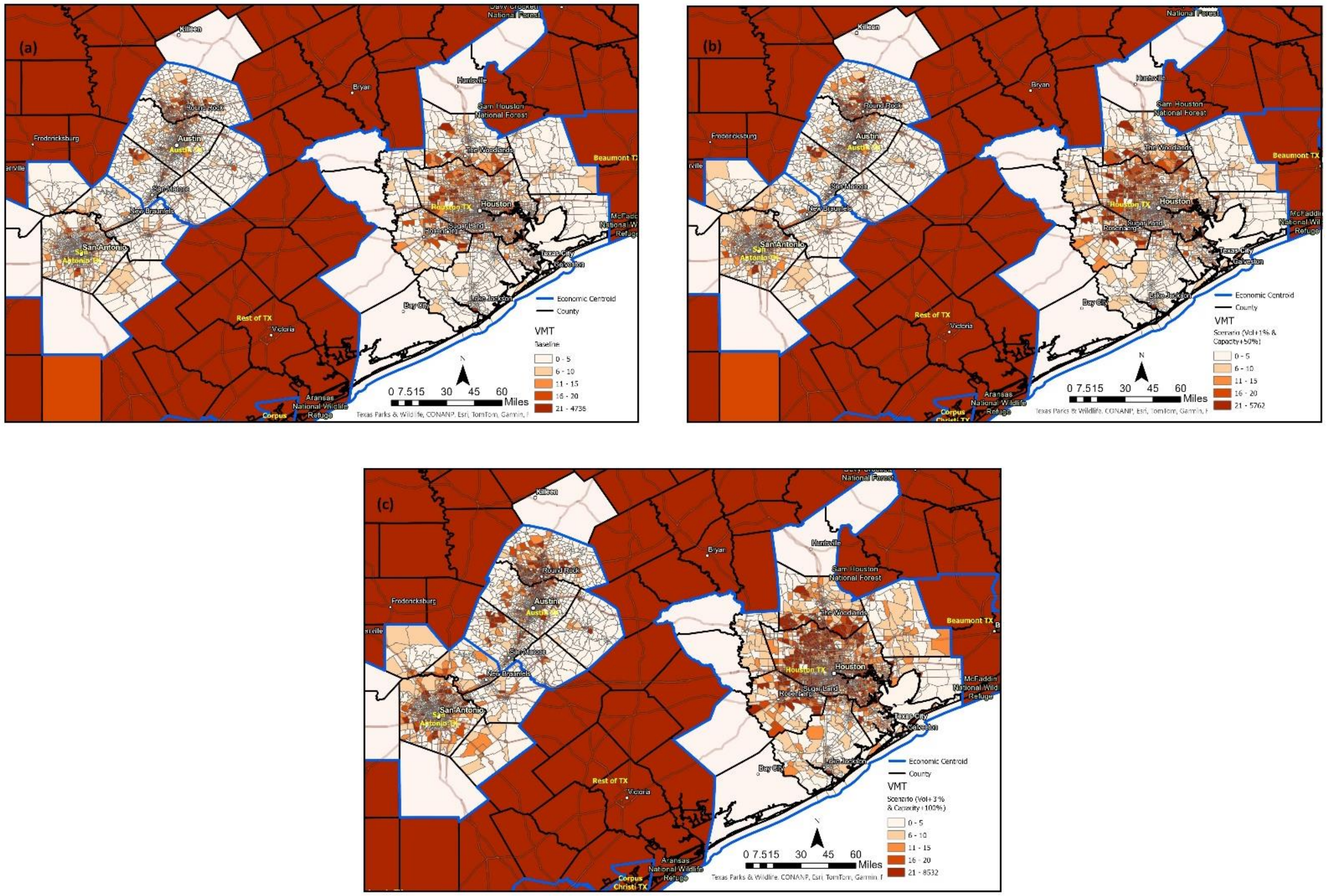


Figure 28. Freight VMT for the (a) Baseline, (b) a 50% increase in capacity with a 1% growth in traffic, and (c) a 100% increase in capacity with a 3% growth in traffic scenarios in Southern Texas

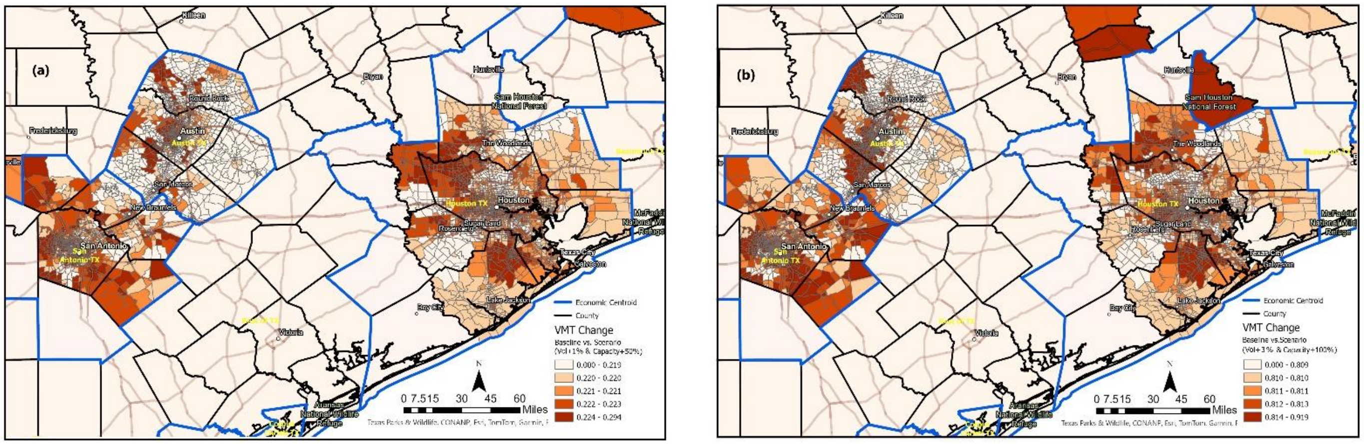


Figure 29. Change in freight VMT when (a) growth in AV is 1% and capacity is increased by 50%, and (b) growth in AV is 3% and capacity is increased by 100% in Southern Texas

Finally, Figures 28 and 29 present freight VMT and its changes in Southern Texas. These figures illustrate the expected changes resulting from the integration of AVs into the traffic stream and increased capacity. Figure 28 presents details on freight VMT for each scenario, while Figure 29 highlights the changes in VMT compared to the baseline for scenarios (b) and (c). These figures again suggest that changes in capacity and traffic growth can lead to a significant increase in total freight VMT. Once again, scenario (c) shows the greatest increase in VMT compared to the baseline.

Collectively, our findings show that the introduction of AVs, combined with increased capacity, enhances accessibility, reduces VTT, and increases VMT for both freight and passenger transportation. AVs improve transportation efficiency and reliability, making travel more appealing. At the same time, increased capacity mitigates initial congestion, leading to smoother and faster trips. This combined effect encourages more frequent and longer trips throughout the network, resulting in overall increases in accessibility, VTT, and VMT.

In Austin, the integration of AVs along with capacity enhancements provides distinct benefits compared to other metropolitan areas. The city experiences significant reductions in travel times when AVs are introduced alongside increased capacity, a trend that highlights Austin's unique transportation infrastructure. Unlike many other cities, Austin does not have primary interstate highways running east-west, which likely affects how AVs and capacity improvements influence travel efficiency within the city.

Moreover, as previously discussed, these patterns indicate that AV adoption significantly affects travel metrics, often surpassing the impact of capacity enhancements in metropolitan areas. However, outside of these urban centers, the benefits of increased capacity in reducing congestion become more apparent. This nuanced understanding highlights the need for tailored planning strategies that address both AV integration and infrastructure improvements to optimize transportation systems effectively.

5. Conclusions and Policy Recommendations

With the U.S. transportation infrastructure spanning multiple administrative boundaries and featuring megaregional connectivity, the introduction of AVs holds the potential to revolutionize mobility and accessibility within these densely populated economic hubs. In this context, we examine how AVs influence transportation networks across the Texas Triangle megaregion. Using a GIS-based Megaregion Transportation Planning Model (MTPM), we analyze various scenarios to evaluate the impact of AV integration on the region's transportation dynamics. Our study specially investigates how the penetration of AVs into the traffic stream interacts with traditional motorized vehicles and affects transportation patterns within the Texas Triangle megaregion.

Our findings show significant improvements in accessibility and increased travel times in urban areas for both passenger and freight traffic. Meanwhile, capacity enhancements are more effective at reducing congestion outside metropolitan regions. This suggests that while AV adoption may exacerbate congestion in cities, where the benefits of increased capacity are less noticeable due to higher demand and more complex traffic patterns. Conversely, outside metropolitan areas, capacity improvements are more successful in alleviating congestion and improving travel efficiency in less densely populated areas, where baseline traffic volumes are lower and induced demand is reduced..

Additionally, our findings show that increasing infrastructure capacity does not affect traffic volumes in Texas or the Texas Triangle, whereas the introduction of AVs leads to higher traffic volumes, VMT, and VTT. Notably, combining AV adoption with capacity enhancements does not reduce the increase in VMT and VTT. However, AV penetration significantly improves accessibility for both passenger and freight transportation, especially when combined with increased capacity. Our maps indicate that VTT for both passenger and freight vehicles increase significantly with higher AV penetration, even with enhanced capacity. Nonetheless, capacity improvements can partially offset these increases. This suggests that while AVs lead to longer travel times due to induced demand, increased capacity can help manage the effects of congestion.

In Austin, the integration of AVs along with capacity enhancements demonstrates unique and significant benefits compared to other metropolitan areas. Notably, the city experiences considerable reductions in travel times and improved accessibility when AVs are introduced alongside increased capacity. These trends are likely notable due to Austin's unique transportation infrastructure, especially its reliance on Interstate 35 (I-35) as the primary north-south corridor connecting the city with Dallas to the north and San Antonio to the south. Unlike many other cities, Austin lacks major interstate highways running east-west, which likely affects how AVs and capacity improvements affect travel efficiency within the city. Future research should test this hypothesis to gain more insights into this issue.

Based on these findings, several policy implications could be drawn. First, since AV adoption tends to exacerbate congestion in urban areas due to induced demand, this congestion can disproportionately affect lower-income communities, who may rely more on public transportation or have limited access to AV technology. Meanwhile, capacity enhancements outside metropolitan areas improve travel efficiency, potentially benefiting rural communities by increasing accessibility and reducing travel times.

Policymakers should consider implementing dynamic toll rates based on real-time traffic conditions and vehicle occupancy. This approach could incentivize shared AV usage and off-peak travel, effectively alleviating peak-hour congestion. This strategy can help mitigate the increased congestion in urban areas caused by AV adoption, which disproportionately affects lower-income communities that rely more on public transportation. At the same time, these policies can leverage capacity enhancements outside metropolitan regions to improve travel efficiency for rural communities, thereby enhancing accessibility and reducing travel times. By encouraging shared AV usage and optimizing toll rates based on traffic conditions, policymakers can promote more equitable and sustainable transportation solutions across the Texas Triangle megaregion. This approach can address urban congestion challenges while also improving mobility in rural areas.

Second, to maximize the benefits of AVs without increasing VMT and VTT, policymakers should encourage shared mobility solutions. This includes supporting AV fleets operated under ride-sharing models and promoting shared AV services for freight transport. Such measures can reduce the total number of vehicles on the road and mitigate the effects of induced demand. These strategies will enhance transportation access for lower-income communities that rely on public transit, helping to address mobility barriers. Moreover, prioritizing shared mobility models can help reduce environmental disparities by lowering overall vehicle emissions and alleviating pollution burdens in marginalized neighborhoods.

Additionally, to ensure safe and efficient AV operations across the Texas Triangle megaregion, policymakers should develop robust regulatory frameworks supported by continuous data monitoring and analysis. This involves working with AV manufacturers and operators to share data on performance, traffic patterns, and user behavior. This ensures that safety standards are consistently maintained across regions, enhancing equitable access to safe transportation options.

Our study also has several limitations. First, while we evaluated the impact of introducing AVs on accessibility, VMT, and VTT in the Texas Triangle region, we did not examine the social equity implications of these findings. This will require exploring how AVs interact with current and future transit systems and their users, as well as their role in addressing the first mile/last-mile challenges for various population groups. Secondly, while our analysis explores changes in transportation dynamics, we did not conduct cost-benefit analyses to evaluate the economic viability of AV adoption. This would involve evaluating infrastructure investments, operational costs, and the potential economic benefits from reduced congestion and enhanced mobility.

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