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A Spatiotemporal Evaluation of Freeway Traffic Demand in Florida During COVID-19 Pandemic

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A SPATIOTEMPORAL EVALUATION OF FREEWAY TRAFFIC DEMAND IN FLORIDA DURING COVID-19 PANDEMIC

by

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ABSTRACT

This thesis contributes to our understanding of the changes in traffic volumes on major roadway facilities in Florida due to COVID-19 pandemic from a spatiotemporal perspective. Three different models were tested in this study- a) Linear regression model, b) Spatial Autoregressive Model (SAR) and c) Spatial Error Model (SEM). For the model estimation, traffic volume data for the year 2019 and 2020 from 3,957 detectors were augmented with independent variables, such as- COVID-19 case information, socioeconomics, land-use and built environment characteristics, roadway characteristics, meteorological information, and spatial locations. Traffic volume data was analyzed separately for weekdays and holidays. SEM models offered good fit and intuitive parameter estimates. The significant value of spatial autocorrelation coefficients in the SEM models support our hypothesis that common unobserved factors affect traffic volumes in neighboring detectors. The model results clearly indicate a disruption in normal traffic demand due to the increased transmission rate of COVID-19. The traffic demand for recreational areas, especially on the holidays, was found to have declined after March 2020. In addition, change in daily COVID-19 cases was found to have larger impact on South Florida (District 6)'s travel demand on weekdays compared to other parts of the state. Further, the gradual increase of traffic demand due to the rapid vaccination was also demonstrated in this study. The model system will help transportation researchers and policy makers understand the changes in traffic volume during the COVID-19 period as well as it's spatiotemporal recovery.

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CHAPTER 1: INTRODUCTION

1.1 Background

As of November 2021, Coronavirus disease 2019 (COVID-19) pandemic, has affected the entire world with reported cases (and fatalities) amounting to 261 million (5 million) (Worldometer, 2021). The pandemic has significantly taxed the social, health and economic systems affecting the mental and physical health of populations (Bhowmik & Eluru, 2021; The World Bank, 2020). United States is one of the significantly affected countries with the highest number of confirmed cases (about 48 million) and deaths (about 776 thousand) in the world (Centers for Disease Control and Prevention, 2021). The emergence of pandemic and the associated social distancing, mask mandates and stay-at-home orders affected nearly every facet of life. The US economy was significantly affected by COVID-19 with an unemployment rate of 14.7% by April 2020. For perspective, the unemployment rate was only as high as 10% during the great recession. The economy also significantly transformed with a rapid shift to teleworking. About 71% of the total workforce moved to teleworking during the pandemic period from the pre-pandemic levels of about 20% (Parker et al., 2020). In recent months, the largely successful vaccination drive in the United States – about 437 million shots delivered by October 2021 – has contributed to reducing cases, and fatalities (Bloomberg, 2021). While public health professionals are wary of potential variants and their impact on unvaccinated populations, there is growing optimism among the public and many communities are emerging into a post-pandemic environment.

As described earlier, the pandemic has delivered a shock to every facet of life and transportation system is no exception. For instance, after the stay-at-home orders were issued the average daily travel distance in the USA has declined by 80% (Hendrickson & Rilett, 2020). Traffic volume detector measurements in Florida for April 2020 indicated a drop of 41% relative to traffic volume measurements in April 2019. Transportation system usage patterns are a complex interaction of employment patterns, demographics, socioeconomics, transportation system attributes and urban regional characteristics. We hypothesize that spatial differences across regions are likely to result in varying evolution patterns across the country. As the country re-emerges from the pandemic, transportation system usage indicators can serve as important proxies for how the various communities were affected and possibly are reemerging from the pandemic.

1.2 Current Study

In our study, employing transportation system usage measures (such as traffic volumes) on major roadways as a surrogate for community mobility, we focus on (a) understanding how local COVID-19 case history, socio-demographics, socioeconomics, transportation system characteristics, and urban form influence system usage and (b) examine disparities across communities in transportation system demand recovery and draw insights on factors contributing to the recovery. Florida serves as an ideal test bed for our analysis with diversity in regional features, population, and COVID-19 spread. The study employs data from 3,957 detectors, across 4 major interstate highways (I-4, I-10, I-75 and I-95) of Florida, sourced from the Regional Integrated Transportation Information System (RITIS) for 2019 and 2020. To analyze the rich database of traffic volumes across the two years for the large number of sites, we employ a spatiotemporal mixed linear regression model. The traffic volume data is augmented with a host of independent variables including detailed COVID-19 information (such as per capita COVID cases), socio-economic characteristics (such as median income, household vehicle availability), land-use characteristics (such as residential, commercial, and recreational area), built environment attributes (such as number of restaurants, and shopping centers), roadway characteristics (such as number of lanes, and maximum speed limit), meteorological information (such as wind speed and precipitation) and spatial locations of the traffic count detectors. The proposed spatiotemporal transportation volume model can offer insights to transportation and economic agencies on factors influencing the recovery process. The performance of the proposed model is further illustrated by predicting traffic volumes for data records not used in the model estimation. The model provides a framework to predict demand recovery as conditions improve across the country.

1.3 Thesis Structure

The rest of the thesis is organized as follows: Chapter 2 provides a brief review of relevant previous research and positions the current study on the evaluation of travel demand during a massive system shock. Chapter 3 provides a detailed summary of the data source and exogenous variables considered for this analysis. Chapter 4 discusses the formulation of the econometric model adopted in this research work. Model estimation results and parameter interpretations are reported in chapter 5. The spatiotemporal analysis of the potential recovery is described in Chapter 6. Finally, a summary of model findings, limitations, and conclusions are presented in Chapter 7.

CHAPTER 2: EARLIER RESEARCH

In this chapter, a detailed summary of research studies relevant to our research and the contribution of the current study is discussed in. The review is organized into two groups of studies. The first group of studies examine approaches to study traffic volumes on roadways. The second group of studies are focused on understanding volume evolution in response to changes/shocks to the system. Finally, the current thesis and its contribution to the literature is described.

2.1 Earlier Research

In this section, the literature across the two groups of studies is presented. The ***first group of studies*** analyze traffic volume data by developing frameworks to (a) identify the factors affecting traffic volumes and (b) predict traffic volumes in the near future. Examining traffic volumes on major transportation roadways is a well-researched objective. Several researchers develop regional models focusing on the drivers of travel using travel demand modeling approaches such as trip-based model and activity-based models (Bowman & Ben-Akiva, 2001; Pendyala et al., 2012; Pinjari et al., 2008; Sider et al., 2013; Ziemke et al., 2019). However, these approaches are focused on capturing regional trends and are not appropriate for modeling traffic volumes on specific facilities. In our review, we focus on research efforts that are developed to study traffic volumes on roadway facilities.

The various traffic volume variables considered in earlier literature include traffic volumes (Kim et al., 2003; Ma et al., 2020), transformed traffic volumes such as natural logarithm or Box-cox transformation (Boonekamp et al., 2018; Faghih-Imani & Eluru, 2016b; Tamin & Willumsen, 1989)

change in traffic volumes over time (Abu-Eisheh & Mannering, 2002). The prevalent approaches for analysis of the volume variable with a focus on identifying important factors include simple linear regression models (Kusam & Pulugurtha, 2016), two stage least squares techniques (Boonekamp et al., 2018), geographically and temporally weighted regression model (Ma et al., 2020), dynamic simultaneous equation systems (Abu-Eisheh & Mannering, 2002), spatial mixed linear model(Faghih-Imani & Eluru, 2016a), autoregressive integrated moving average model (William & Hoel, 2003), and spatial panel mixed multilevel ordered logit model (Faghih-Imani & Eluru, 2016b). Multiple research efforts have also been developed with a focus on improving volume prediction drawing on machine learning and artificial intelligence-based research approaches including artificial neural networks (Yun et al., 1998; Zhu et al., 2014), support vector machines (Xie et al., 2010), gaussian processes (Xie et al., 2010), k-nearest neighbors algorithm (Z. Wang et al., 2019; Zheng & Su, 2014) and CNN-LTSM model (Shao et al., 2021). The most important factors identified in these research as affecting traffic volumes include population density, employment rate, land-use and built environment characteristics (such as number of restaurants, and proportion of commercial area), temperature and rain.

2.2 Studies on System Changes

The *second stream of studies* are focused on understanding changes to traffic volumes in response to a major transportation system change (such as addition of new lanes, addition of significant public transit facility along the roadway corridor) (Beaudoin et al., 2015; Shams & Zlatkovic, 2020; Slavin et al., 2013) or system level shocks (such as a major economic recession or a pandemic) (Lo & Hall, 2006; Park & Sener, 2019). The reader would note that some studies focused on understanding air quality impacts of COVID-19 and as part of their analysis developed aggregate traffic volume trends/predictions (Elshorbany et al., 2021; Tian et al., 2021; Xiang et al., 2020) and are not directly relevant to our study. A number of research efforts examined how COVID-19 is affecting transportation volumes on multiple roadways. For example, Loske (2020) and Lee et al. (2020) examined COVID-19 data until March 2020 and examined how transport volumes were affected. The studies developed linear regression models with only one variable of interest (COVID-19 cases). Macioszek and Kurek (2021) employed data for 2019 and 2020 from a small number of intersections in an urban region to examine the changes in average daily traffic, changes to traffic at different points of the pandemic using linear combinations of Gaussian functions. Parr et al. (2020) employed data from Florida from more than 200 sites to evaluate the differences in traffic volumes between 2019 and 2020. The study conducted a host of univariate analyses comparing how traffic volumes in 2019 and 2020 changed for (a) specific locations (such as South Florida), (b) between urban and rural locations, (c) between arterials and interstates. Patra et al. (2021) examined changes in traffic volumes using Wi-Fi MAC Scanners (WMS) at two intersections in India in response to the multiple phases of COVID-19 lockdowns and found that traffic initially dropped. However, when enforcement was lax, traffic volumes were closer to normal due to the population ignoring the mandates.

2.3 Current Study

The literature presented clearly illustrates how several researchers have examined traffic volume data in response to COVID-19 pandemic. However, prior research efforts have several limitations, like-

- First, a majority of these research efforts have focused on a short time frame between a few weeks and 3 months to study the impact of COVID-19.

- Second, majority of these studies employed very simple descriptive measures (such as traffic volume percentage change) or linear regression models with only one variable.
- Third, Earlier studies (with the exception of Parr et al. (2020)) focused on less than ten sites to conduct the analysis.
- Fourth, Differences in traffic volumes between weekdays and holidays was not explicitly recognized.
- Finally, all the earlier research that developed statistical models used simple linear regression models without considering for potential spatial correlations between traffic volume sites.

The proposed research addresses these limitations by conducting a detailed spatiotemporal analysis of traffic volumes considering 3,957 detectors processing data for the full 2019 and 2020 years on major Florida interstate facilities. The research develops three model systems: a) Linear regression model, b) Spatial Autoregressive Model (SAR) and c) Spatial Error Model (SEM) (see for earlier work using these methods (Faghih-Imani & Eluru, 2016b; Ferdous et al., 2013; Frazier et al., 2005; X. C. Wang et al., 2012; X. Wang & Kockelman, 2006)). The model development is conducted using a host of independent variables from seven categories: 1) COVID-19 related factors, 2) socioeconomics, 3) land-use characteristics, 4) built environment attributes, 5) roadway characteristics, 6) meteorological variables and 7) spatial factors. The model estimation results are intuitive and highlight various important factors affecting traffic volumes. The results also support our hypothesis that common unobserved factors have a significant impact on traffic volumes.

2.4 Summary

This chapter presented a detailed summary of methodologies employed in earlier research for predicting traffic demand and its response to potential system shocks. A summary of the current study contribution is also presented. The data source along with the descriptions of the dependent and independent variables adopted in this study is described in the subsequent chapter.

CHAPTER 3: DATA PREPARATION

The previous chapter identified the gaps in literature and presented a discussion of the contribution of our thesis. In this chapter, the data source, data preparation procedures employed to compile data for model development and sample data characteristics are described in this chapter.

3.1 Data Source

The data for our analysis is obtained from the Regional Integrated Transportation Information System (RITIS) data archive (RITIS, 2021). The RITIS database is an automated data sharing system with real time data feeds providing information including the hourly traffic count data, detector coordinates and details of the roadway. The traffic count data for the current research effort is obtained for 4 major interstates in the state of Florida from 5,978 detectors for the years 2019 and 2020. The interstates considered include I-4, I-10, I-75, and I-95, within the state of Florida. The number of detectors for each interstate facility range between 910 and 2,061. A spatial map of the interstates along with the detector locations considered for the empirical study is presented in Figure 1**.**

3.2 Dependent Variable

Hourly traffic data for the evening peak period (4PM – 7PM) was the main variable of interest of this study. The dataset obtained from the RITIS data portal contain daily traffic volume at hourly resolution. For evening peak period, traffic volume data of 4PM to 7PM duration have been aggregated.

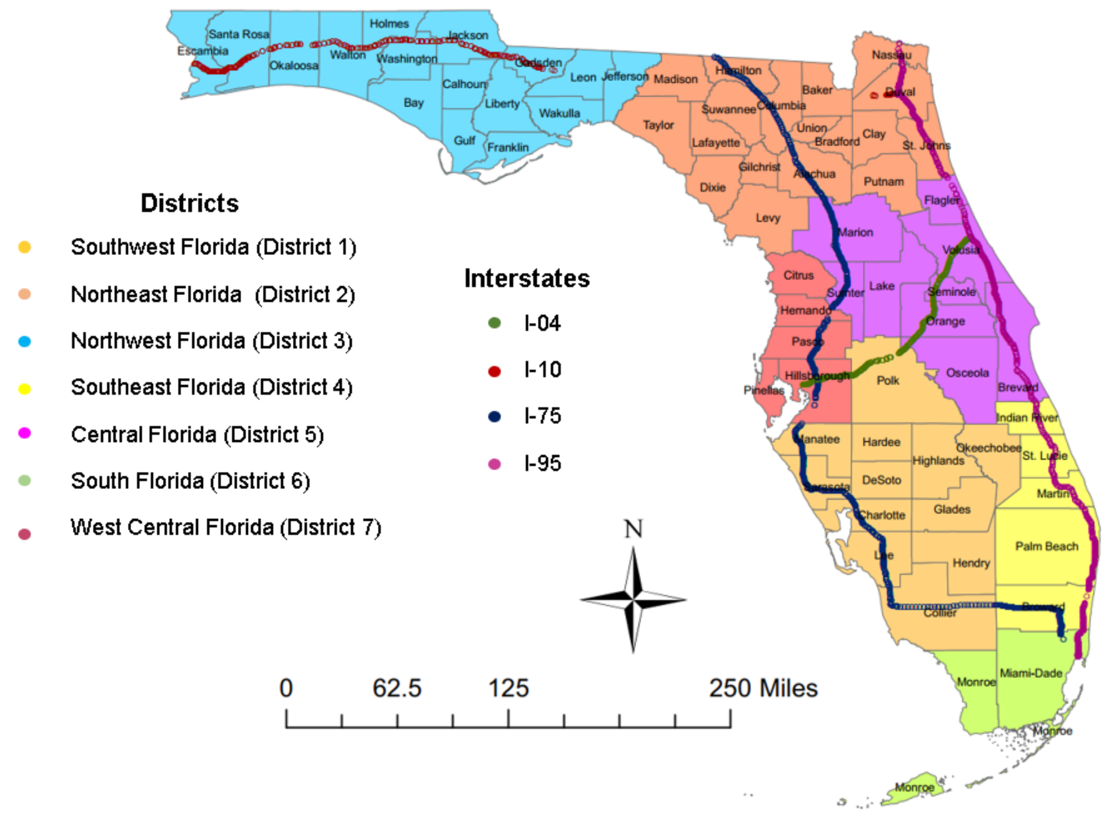

Figure 1. Locations of the traffic count detectors

The daily traffic volume for the peak period was compiled for each day for 2019 and 2020. The data was not available for all 5,978 detectors for the 24 months duration. Hence, to maximize detector coverage and ensure adequate number of records from each detector, we compiled data from 3,957 detectors across the various roadway facilities with traffic volume data available for at least 20 months. The detectors on the east of I-10 corridor were dropped from the model dataset for not having at least 20 months record. The aggregated daily peak volumes dataset was classified into weekdays and holidays (weekends and Florida state holidays). From the weekday and holiday dataset, one record per month for the two-year duration is randomly sampled for our analysis[1]. The

[1] We employed the one day per month randomly to reduce computational complexity. We examined the stability of model estimation by employing multiple random samples following the same process used for the estimation sample. The results of the comparison exercise are documented in the Appendix A.

final weekday and holiday datasets contain a total of 94,373 (Total records = $\sum_{M=20}^{24} M *$ detectors with M records; 20 x 27 + 21 x 36 + 22 x 132 + 23 x 115 + 24 x 3,647) and 94,197 (20 x 34 + 21 x 48 + 22 x 164 + 23 x 163 + 24 x 3548) observations respectively. The reader would note that appropriate modifications were made to ensure the spatial matrix employed always has an order of 3,957 x 3,957 with zero's added in for detectors with missing data for the corresponding time period. As can be seen from the discussion above, the records are missing for a small number of detectors.

3.3 Independent Variables

The traffic volume data compiled was augmented with a host of independent variables from seven categories: 1) COVID-19 related factors, 2) socioeconomics, 3) land-use characteristics, 4) built environment attributes, 5) roadway characteristics, 6) meteorological variables and 7) spatial factors (regional location of the detectors).

COVID-19 data compiled from the Johns Hopkins University COVID-19 data archive (GitHub, 2021), was employed to identify county level COVID case information for each day in 2020 data (excluding January and February). The detectors were assigned to the corresponding county data based on their location. The data sources for other independent variables include the United States Census Bureau (for demographics and socio-economics) (US Census Bureau), Florida Department of Revenue parcel level data (for land-use and built environment data) (Florida Department of Revenue), Florida Department of Transportation website (for roadway characteristics and spatial factors) (Florida Department of Transportation) and Florida Automated Weather Network (FAWN) data portal (2019 and 2020 meteorological data) (Florida Automated Weather Network). The data for socioeconomics, land-use, built environment and roadway information were aggregated within a one-mile buffer for each detector for our analysis. The literature hosts the use of different buffer size for predicting several transportation modal demand and crash analysis. For instance, Chakour & Eluru (2016), and Rahman et al. (2020) examined various buffer size and found 800m or 0.5 mile giving the best model fit for predicting city traffic. Further, for predicting toll road or freeways' traffic behavior Mathew et al. (2021), and Pulugurtha & Sambhara (2011) considered 1-mile buffer area. These directed us to use 0.5-, and 1-mile radius buffer area. However, the estimation results of 1-mile buffer have been shown because it gave the best fitted model. Some of the 1-mile buffer areas of the detectors crossed multiple census tracts. In that case, we took the weighted average of the variables based on the census tract area coverage. The meteorological data from 27 weather stations across the state of Florida have been assigned to the 3,957 traffic detectors considered in this study. The near table tool in ArcGIS software was used to assign the weather information of the nearest weather station to each of the detector. The descriptive statistics of the distance between the traffic detectors and the weather station has been shown in Table 1. For spatial factors, based on the detector's location binary variables were created for each of the seven districts in Florida.

3.4 Sample Characteristics

A descriptive summary of the dependent and independent variables is provided in Table 1. An illustration of the sudden impact of COVID-19 emergence and its continuing influence on weekly traffic volumes is presented in Figure 2. From the Figure 2, we can observe the sudden drop in traffic volumes in March 2020. The figure also overlays the weekly count of COVID-19 cases in the state. The traffic volume data indicates a reasonable recovery from middle of 2020 with traffic volumes very close to 2019 traffic volumes as we get to the end of 2020. Surprisingly, the August surge in COVID-19 cases results in a minor dip in traffic volumes. Further, it is interesting to note that the December surge in COVID-19 cases did not influence the weekly traffic volumes.

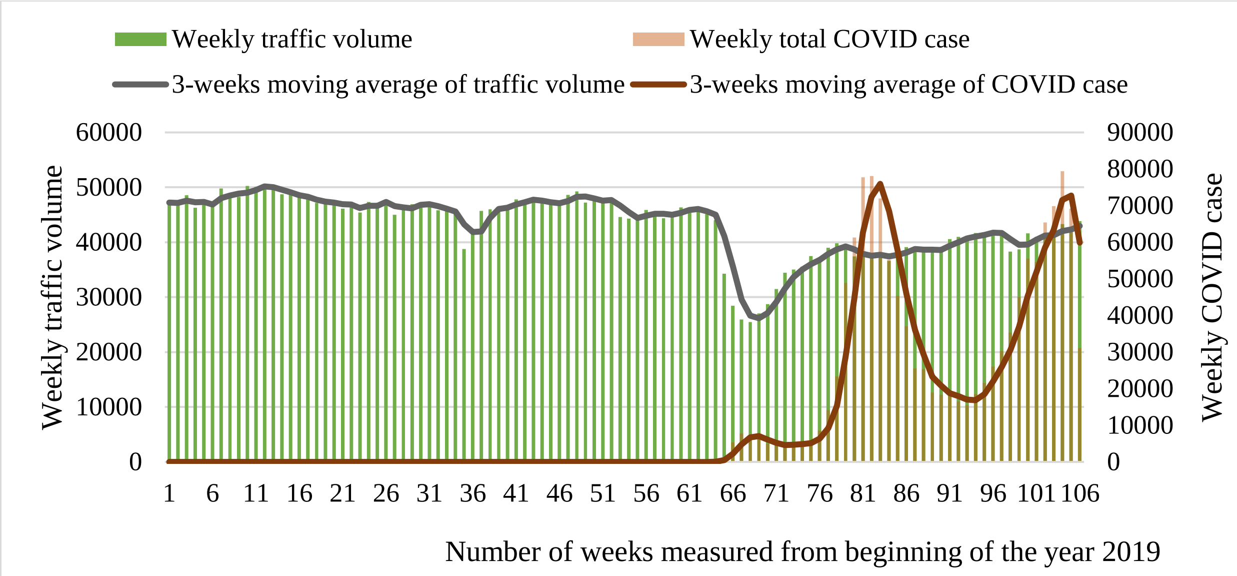

Figure 2. Weekly COVID-19 transmission rate and traffic volume in Florida 2019 and 2020

3.5 Summary

The data source, data compilation procedures adopted for this study were discussed in this section. The summary statistics of the compiled variables are reported. The next chapter will describe the details of the mathematical model employed in this research.

Table 1: Descriptive Summary of Sample Characteristics

Variables with same values in both models (N = 3,957)				
Variable	**Variable Description**	**Min.**	**Max.**	**Mean**
Socioeconomics				
Low median income	Annual median income ≤ $35,200	0.00	1.00	0.04
Proportion of no vehicle household	Number of no vehicle household/ Total number of households in 1-mile buffer	0.00	0.33	0.07
Employment population ratio	Total number of employed population/ Total population in 1-mile buffer	0.00	85.60	58.92
Land use characteristics				
Distance from the nearest CBD	Distance of the detectors from the nearest CBD in miles	0.27	186.85	45.19
Proportion of commercial area	Commercial area/ Total land-use area in 1-mile buffer zone	0.00	1.00	0.14
Proportion of industrial areas	Industrial area/ Total land-use area in 1-mile buffer zone	0.00	0.88	0.05
Proportion of recreational area	Recreational area/ Total land-use area in 1-mile buffer zone	0.00	1.00	0.13
Proportion of institutional area	Institutional area/ Total land-use area in 1-mile buffer zone	0.00	0.79	0.07
Proportion of residential area	Residential area/ Total land-use area in 1-mile buffer zone	0.00	1.00	0.58

Built environment attributes				
Number of shopping center	Total number of shopping centers in 1-mile buffer zone	0.00	279.00	18.30
Number of restaurants	Total number of restaurants in 1-mile buffer zone	0.00	321.00	13.13
Roadway characteristics				
Number of Lanes	Average number of lanes in 1-mile buffer zone	2.00	7.00	3.53
Maximum speed limit	Maximum speed limit within 1-mile buffer zone	50.00	70.00	67.94
Spatial factors				
Central region	Detectors in Central region	0.00	1.00	0.22
South region	Detectors in South region	0.00	1.00	0.08
Southeast region	Detectors in Southeast region	0.00	1.00	0.19
Southwest region	Detectors in Southwest region	0.00	1.00	0.16
Northeast region	Detectors in Northeast region	0.00	1.00	0.16
Northwest region	Detectors in Northwest region	0.00	1.00	0.08
West central region	Detectors in West central region	0.00	1.00	0.09
Distance to nearest weather station	Distance of the detectors from the nearest weather station (miles)	0.43	42.47	17.15

Variables varies in weekday and holiday models							
Variables	**Variable Description**	**Weekday (N = 94,373)**			**Holiday (N = 94,197)**		
		Min.	**Max.**	**Mean**	**Min.**	**Max.**	**Mean**
Covid-19 transmission Factors							
2-weeks lag average COVID case per 1M population	Number of average COVID cases of 2-weeks lag per 1 million population	0.00	19,235.00	511.98	0.00	19,235.00	518.68
Difference with the 3-weeks moving average	Moving average = (Sum of 1-, 2-, 3-weeks lag average COVID case)/3 Diff. with 3-week moving average = ((1 week lag case - moving average)/moving average) *100	-1.00	2.00	0.07	-1.00	2.00	0.08
Meteorological variables							
Precipitation	Average precipitation ≥ 0.25 inch during the PM peak period	0.00	1.00	0.02	0.00	1.00	0.01
Average wind speed	Average wind speed of the corresponding date in PM peak period	0.00	67.52	5.93	0.00	21.15	5.79
Temporal Factors							
1 week lag traffic volume	Traffic volume of 1 week lag of the corresponding date in PM peak period	0.00	20091.00	6255.80	0.00	20085.00	5795.80
Dependent variable							
Traffic volume	Traffic volume of the corresponding date in PM peak period	0.00	20091.00	6281.37	0.00	20089.00	5748.17

CHAPTER 4: METHODOLOGY

The econometric model structure employed in the thesis is described in this chapter. The model systems employed in the research explicitly recognize the presence of repeated observations across detectors - panel data – in developing our models. The presence of repeated measures necessitates the consideration of the influence of unobserved factors on the prediction. Specifically, two types of advanced linear regression models are considered in our analysis:

- Spatial Lag or Autoregressive Model (SAR)
- Spatial Error Model (SEM)

The formulations of these models are described in the subsequent sections.

4.1 Model Formulation

The formulation of the different spatial panel models considered in our analysis are described in Elhorst (2003). Let $i\ (= 1 \dots \dots \dots, N)$ be an index to represent each detector (N = 3,957), and $t\ (= 1 \dots \dots \dots, 24)$ be an index to represent the time period of data collection. The general form of the pooled linear regression model considering spatial effects has the following structure:

$$y_{it} = \beta' X_{it} + \varepsilon_{it} + \delta_i \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots (1)$$

where, y_{it} is the natural logarithm of traffic volume incremented by 1, $X_{it}$is a matrix of variables at detector i and time t, β is the model coefficients to be estimated and ε_{it} are independently and identically distributed error terms for all i and t, with zero mean and variance σ^2. The δ_i represents the spatial effect to account for all the detector-specific time-invariant unobserved attributes. Now, conditional on the specification, this δ_i can be treated as fixed or random effect in the model estimation. However, a fixed effect model is not suitable in the presence of time-invariant exogenous variables (Faghih-Imani & Eluru, 2016b). In our analysis, socioeconomics and land use patterns did not change over the months for any detector. Hence, we adopt the spatial random effect model formulation for our study context.

Several specifications are used for accounting spatial dependence in the literature including Spatial Lag or Autoregressive Model (SAR), Spatial Error Model (SEM), and Geographically Weighted Regression Model (GWRM). In the current study, we restrict ourselves to the use of SAR and SEM models. The SAR accommodates for the spatial dependency by adding a spatial lagged dependent variable in the model while the SEM model considers a spatial lagged error structure for incorporating spatial correlation.

The general form of the SAR (see equation 2) and SEM (see equation 3 and 4) are as follows (Elhorst, 2003):

$$y_{it} = \alpha \sum_{j=1}^{N} W_{ij} y_{jt} + \beta' X_{it} + \varepsilon_{it} + \delta_i \quad \ldots\ldots\ldots \quad (2)$$

$$y_{it} = \beta' X_{it} + \delta_i + \vartheta_{it} \quad \ldots\ldots\ldots \quad (3)$$

$$\vartheta_{it} = \gamma \sum_{j=1}^{N} W_{ij} \vartheta_{jt} + \varepsilon_{it} \quad \ldots\ldots\ldots \quad (4)$$

where, α represent the spatial autoregressive coefficient; γ indicates the spatial autocorrelation coefficient, ϑ_{it} is the spatial autocorrelated error term and W is the spatial weight matrix. To be specific, W_{ij} depicts the element of the weight matrix between detector i and j. In spatial econometrics, several functional forms of the weight matrix are commonly adopted including neighboring units, inverse of distance square, inverse of distance or different threshold values (such as unit within 500meters, 1mile, 5 miles, 10 miles and 20 miles). In our empirical study, we considered several weight matrices and a correlation structure representing reducing correlation as a function of the squared distance that dissipates to 0 beyond 10 miles offered the best results in terms of statistical data fit and interpretation. The reader should note that, the diagonal of Weight matrix is set to be zero to prevent the use of y_{it} to model itself. Further, the W matrix is normalized across rows to increase the model estimation stability (Elhorst, 2003). The models are estimated in Matlab using the routines provided by (Elhorst, 2003, 2014b). All the parameters are estimated using the maximum likelihood approaches (see (Elhorst, 2014a) for details on likelihood functions).

4.2 Summary

The formulation of the spatial lag model and spatial error model along with the description of weight matrix employed in this study have been reported in this section. The next section will describe the model selection process for identifying the fitted model and present the interpretation of the estimation results.

CHAPTER 5: MODEL ESTIMATION RESULTS

This chapter is organized in two parts. The first part describes the selection of the best fitted models among the 3 models described in the previous section for weekdays and holidays. In the second part, the parameter interpretations of the selected models are explained.

5.1 Model Fit Measures

In our empirical analysis, we estimated the following models: (a) traditional linear regression model, (b) Spatial Autoregressive Model (SAR) and (c) Spatial Error Model (SEM). These models were estimated for weekday and holiday datasets separately. The performance of these models are compared on the basis of the log-likelihood (LL) at convergence, Bayesian Information Criterion (BIC) (Burnham & Anderson, 2004) and overall interpretability of the model. The model goodness of fit measures is presented in Table 2. Two observations can be made from the model fit results. First, models considering spatial correlation (SAR and SEM) significantly outperform the simple linear regression model in terms of statistical data fit. This result clearly highlights the importance of accommodating spatial unobserved heterogeneity in regression approaches. Second, we observe that SEM model offered marginal improvement in terms of data fit compared to the SAR model for both weekday and holiday model. Further, the variable interpretations for SAR model were less intuitive and hence we preferred the SEM model that offers an improved interpretation with a good fit.

Table 2: Goodness of Fit Measures

Model	Weekday Model		Holiday Model	
	Log-likelihood (LL)	**Bayesian Information Criterion (BIC)**	**Log-likelihood (LL)**	**Bayesian Information Criterion (BIC)**
Ordinary Least Squares Linear Regression Model	-126,400.01	252,983.38	-132,300.03	264,783.38
Spatial Autoregressive Model (SAR)	-88,145.05	176,484.95	-92,552.26	185,299.36
Spatial Error Model (SEM)	-87,925.71	176,034.81	-92,357.22	184,897.82

5.2 Variable Effects

The SEM estimates for weekdays and holidays are shown in Table 3. For both the models, only the statistically significant variables (at 90% significance level) are included in the model estimation. A positive (negative) sign in the Table 3 indicates the increased (decreased) traffic volume corresponding to the temporal period (weekday and holiday). The model results are discussed by variable group for the two datasets.

Table 3: Model Estimation Results

Variable	Weekdays		Holidays	
	Coefficient	**T-value**	**Coefficient**	**T-value**
Intercept	7.31	132.11	6.72	105.11
Covid-19 transmission Factors				
Ln (number of Covid case per 1M people, 2 weeks lag +1)	-0.74×10^{-2}	-8.78	-0.57×10^{-2}	-5.86
% Difference with the preceding 3 weeks moving average	-0.07	-10.32	-0.12	-19.09
x Effect in the South region	-0.05	-2.19	----	----
Socioeconomics				
Low median income	-0.46	-7.79	----	----
x COVID effect after March 2020	-0.07	-3.02		
Proportion of Zero vehicle household	-3.17	-11.84	-3.40	-12.31
Land use characteristics				
Distance from the nearest CBD	-0.07×10^{-2}	-2.31	0.13×10^{-2}	4.04
Proportion of commercial area	----	----	-0.28	-3.75
Proportion of industrial areas	0.33	3.04	----	----
Proportion of recreational area	----	----	0.21	4.15
x COVID effect after March 2020	----	----	-0.05	-2.89
Built environment attributes				
Number of shopping centers	0.18×10^{-2}	3.69	0.19×10^{-2}	3.56
x Covid effect after March 2020	-0.04×10^{-2}	-2.67	-0.03×10^{-2}	-1.81
Roadway Characteristics				
Number of Lanes	0.16	11.64	0.21	14.65
Meteorological variables				
Precipitation	-0.05	-2.92	-0.03	-1.69
Average wind speed	-0.20×10^{-2}	-2.65	-0.21×10^{-2}	-2.51
Spatial Factors				
Base: Other regions in Florida				
Central Region	----	----	0.49	16.93
South Region	-0.57	-8.52	-0.48	-6.67
Temporal Factors				
1 week lag traffic volume/1000	0.12	125.48	0.14	135.95
Correlations				
Spatial auto correlation	0.25	32.27	0.27	36.49

5.2.1 COVID-19 Related Factors

The inclusion of these variables depicts the relation between the transmission of COVID-19 and travel demand on interstates. As case rates change across the county, the impact on traffic volumes is likely to vary over time. Therefore, in our models COVID-19 transmission variables with 1, 2 and 3-week lag have been tested. Among these variables, 'log transformation of COVID-19 cases with a 2-week lag per 1M population' was found to offer the best model fit. The sign of this variable in both the models indicates a decrease in travel demand with the increase of the COVID-19 transmission rate two weeks prior. In addition, for capturing the impact of the increasing and decreasing COVID-19 transmission rates on traffic volume, we included a percentage difference variable which represents the change in weekly cases relative to the 3-week moving average. This variable indicates that, the percentage change in the COVID-19 transmission rate has a significant impact on traffic volume. The model results also indicate a higher impact of percentage difference in COVID-19 cases for the South Florida region (District 6) on weekdays. It indicates a reduction in traffic in this region due to a gradual increase in COVID-19 cases.

5.2.2 Socioeconomics

Several socio-economic variables were tested in our model. The detector locations in neighborhoods with low median household income (≤ $35,200) are likely to have lower volumes for weekdays. Interestingly, the weekday traffic volumes in these locations are substantially lower after the pandemic started. The result highlights the disproportionate impact of the pandemic on the vulnerable population. The variable proportion of zero vehicle households in the vicinity of the detector provides an expected reduction in traffic volumes for both weekdays and holidays.

5.2.3 Land-use Characteristics

Traffic volumes on interstates are potentially affected by surrounding land-use characteristics. In our analysis, several land use variables were tested. Of these variables, distance from the nearest Central Business Domain (CBD), proportion of commercial, industrial, and recreational area, interaction of these variables with COVID-19 after March 2020 have been found to be significant. For the weekday model, distance of the detectors from the nearest CBD is found to have a negative impact on the traffic volume, whereas for the holiday model the impact is positive. The result indicates that peak traffic volume is higher (lower) closer to the CBD areas in the weekdays (holidays). Further, a positive sign for the variable proportion of industrial areas within the 1-mile buffer zone of the detectors in the weekday model indicates traffic volume is positively associated in industrial areas on the weekdays. On the contrary, the proportion of commercial area within the same buffer zone has a negative association with traffic volume in the holiday model. Finally, proportion of recreational areas in one-mile vicinity of the detector has a positive impact on traffic volumes on holidays. Further, the impact of recreational areas has lowered after COVID-19 emergence. The reader would note that recreational areas still contribute to traffic volumes on holiday, but the magnitude is lower during the pandemic.

5.2.4 Built Environment Attributes

In terms of built environment attributes, number of shopping centers within the one-mile buffer zone is found to have a positive impact on traffic volume in weekday and holiday models. However, the contribution to traffic volume has lowered, yet remains positive, after the emergence of the pandemic.

5.2.5 Roadway Characteristics

Only one variable – number of lanes– offered statistically significant parameters in either the weekday or the holiday model. As expected, number of lanes is positively associated with traffic volume in both models.

5.2.6 Meteorological Variables

Meteorological variables such as average wind speed, rainy day (=1, if average precipitation is ≥ 0.25 inch) were considered in our study to capture the effect of weather on traffic volume. The weather impacts are found to follow the expected trends. The negative sign of both variables in both models indicates a lowering of traffic volume in high wind and heavy rainy conditions.

5.2.7 Spatial Factors

To capture the influence of detector locations, we incorporated the district categorization for the Florida region (see Fig. 1 for districts). These variables represent the fixed effects of the locations and are not interpretable after adding other variables.

5.2.8 Temporal Variables

We also considered traffic volume history in modeling future volumes including 1-, 7-, 14-, 21- and 28-days lag volumes. In both models 7-days lag traffic volume was found to be positive and offered the best fit.

5.2.9 Correlation Factors

The reader would note that the weight matrix in our study follows the inverse of distance within 10 miles and 0 outside 10 miles relationship. As hypothesized, for this relationship, spatial correlation was significant in the two models. The result highlights the role of common unobserved factors affecting volumes across detectors that are spatially close.

5.3 Summary

In our research, for weekdays and holidays, Spatial Error Model has been selected as the model with the best fit. The impact of several categories of variables on travel demand has also been reported. The spatial correlation factors are found to be significant in both weekday and holiday model, supporting our hypothesis that common unobserved factors across the spatially proximal detectors needs to be considered. The next chapter will describe the model validation and prediction of recovery rate of traffic volume from a spatiotemporal perspective.

CHAPTER 6: PREDICTION ANALYSIS

In the preceding chapter model estimation results are summarized. The validation of the models will be described in this chapter. Specifically, this chapter reports on travel demand recovery rate after the post-pandemic period.

6.1 Prediction of Recovery Rate

One of the principal objectives of this study is providing insight on spatiotemporal changes in future traffic demand while accommodating for the uncertainty of future COVID-19 transmission rate. In early 2021, mass vaccination efforts across the entire US have resulted in sharp reduction in cases encouraging more travel. However, COVID-19 transmission rate increased substantially after the month of May 2021. To evaluate the impact of this sudden rise, the spatial and temporal changes in traffic volume for the months of June, August and October has been presented in Figure 3 and 4 for weekdays and holidays respectively. In order to determine the model applicability in predicting traffic recovery rate after COVID-19, true and predicted recovery rates have been calculated as follows in equation (5) and (6),

$$\boldsymbol{T}rue\ recovery\ rate = \frac{Observed\ traffic\ volume\ of\ the\ year\ 2021}{Observed\ traffic\ volume\ of\ the\ year\ 2019} \dots\dots\dots\dots\dots\dots\dots..\dots (5)$$

$$Predicted\ recovery\ rate = \frac{Predicted\ traffic\ volume\ of\ the\ year\ 2021}{Observed\ traffic\ volume\ of\ the\ year\ 2019} \dots\dots\dots\dots\dots\dots (6)$$

A value greater than 0.95 would imply either similar (0.95 to 1) or higher (>1) volume in 2021 relative to 2019, representing a near to full recovery of traffic volumes. Traffic volume data from January through October of the year 2019 and 2021 have been used for this purpose. Since all the 3,957 detectors does not have 10-months data, this analysis was done over 31,250 (28,354) cases for weekday (holiday) model. The confusion matrix for weekday and holiday model have been shown in Table 4.

It has been found that, the weekday model predicts ((418+809+20010)/31250) =0.68 or 68% of the true prediction, where holiday model can predict ((276+879+14314)/28354) =0.546or 54.6%. It should be noted that, mass vaccination started at the beginning of 2021. Since we used 2019 and 2020 data for modelling, the impact of mass vaccination was not estimated, which results in the above disparity between the observed and the predicted traffic recovery rate.

Table 4: Confusion matrix for weekday (holiday) model

	Predicted traffic volume recovery					
		Less than 0.81	0.81 to 0.90	0.90 to 0.95	More than 0.95	Total
Observed traffic volume recovery	Less than 0.81	-- (--)	-- (--)	-- (--)	-- (--)	-- (--)
	0.81 to 0.90	35 (28)	418 (276)	64 (67)	65 (164)	58 (535)
	0.90 to 0.95	4 (36)	673 (1056)	809 (879)	175 (475)	1,661 (2,446)
	More than 0.95	23 (51)	1,690 (3,023)	7,284 (7,985)	20,010 (14,314)	29,007 (25,373)
	Total	62 (115)	2,781 (4,355)	8,157 (8,931)	20,250 (14,953)	31,250 (28,354)

Several observations can be made from these figures. First, weekday traffic volumes present varying spatial patterns across the state. Traffic volumes in Central Florida (District 5) and West Central Florida (District 7) regions are well into the recovery while parts of the southwest (District 1), northeast (District 2) and northwest (District 3) regions are away from a full recovery.

Central Florida is a tourist attraction for several amusement parks in Orlando and sea beaches on the east coast. Therefore, the recovery is quite faster in that region. On the contrary, northeast, and northwest regions are more of a commercial area than a recreational area. Since work-from-home trend was practiced in most of the places even in 2021, the recovery was comparatively slower in those regions. Second, for holidays, the trend is slightly different. The results indicate an overall slower pattern of recovery across the state potentially highlighting how COVID-19 has reduced discretionary travel. Interestingly, for holiday travel, the Southeast (District 4) and Central Florida (District 5) region appears to be recovering at a faster rate compared to the rest of the state. Like Central Florida, Southeast part is also a big tourist attraction and thus experiencing a faster travel recovery. Overall, the result indicates a faster recovery on the coastal sides of Florida due to being a tourist destination. Third, the results also illustrate changing traffic volumes over time. As we move from June through August the number of detectors that experienced recovery of traffic volume closer to 2019 levels have declined (in particular for weekdays). For instance, 1,718 detectors indicate a full recovery (> 95%) with respect to weekday traffic volume in August 2021, a decrease of around 13.5% from June 2021. On the contrary, in holidays the recovery rate is found to remain almost constant from June through August with a full recovery in 40% of the total detectors. However, in October, traffic volume for weekdays and holidays begins to be recover. Overall, the figures clearly illustrate how the proposed model can be utilized to examine the spatiotemporal traffic trends at a high resolution[2].

[2] A representation of traffic volumes in earlier months of 2021 are included in the Appendix B (Figure 7 and 8) for interested readers.

6.2 Summary

From the aforementioned discussion it is noticeable that traffic volume recovery during the post-pandemic period varies across different districts in Florida. Regions with high incidence of commercial areas and amusement parks in the vicinity are more likely to recover compared to other detector locations. In addition, a temporal change in recovery rate across different months of 2021 is also noticeable, indicating the impact of vaccination rates on travel demand.

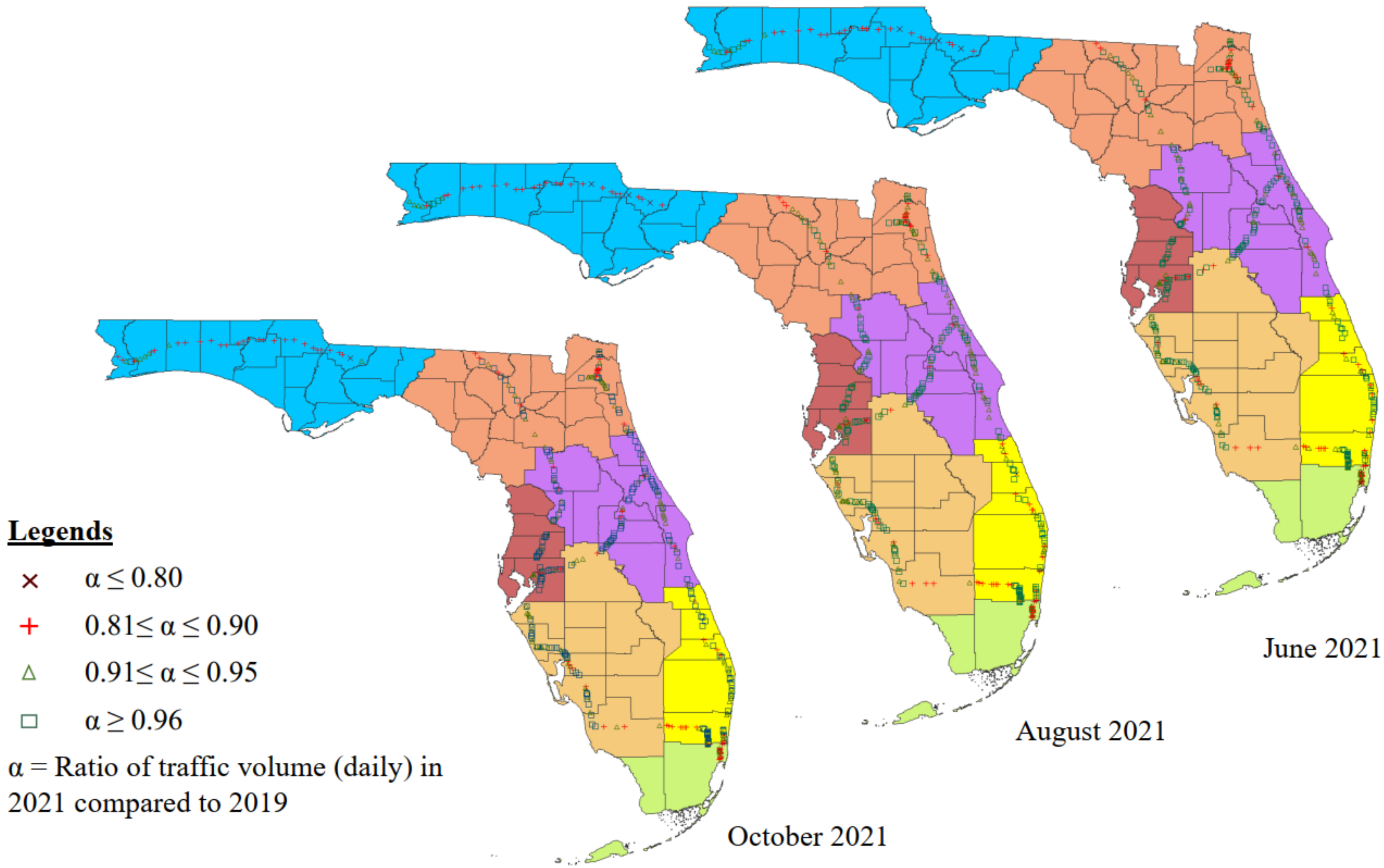

Figure 3. Spatial and temporal changes in weekday's traffic volume

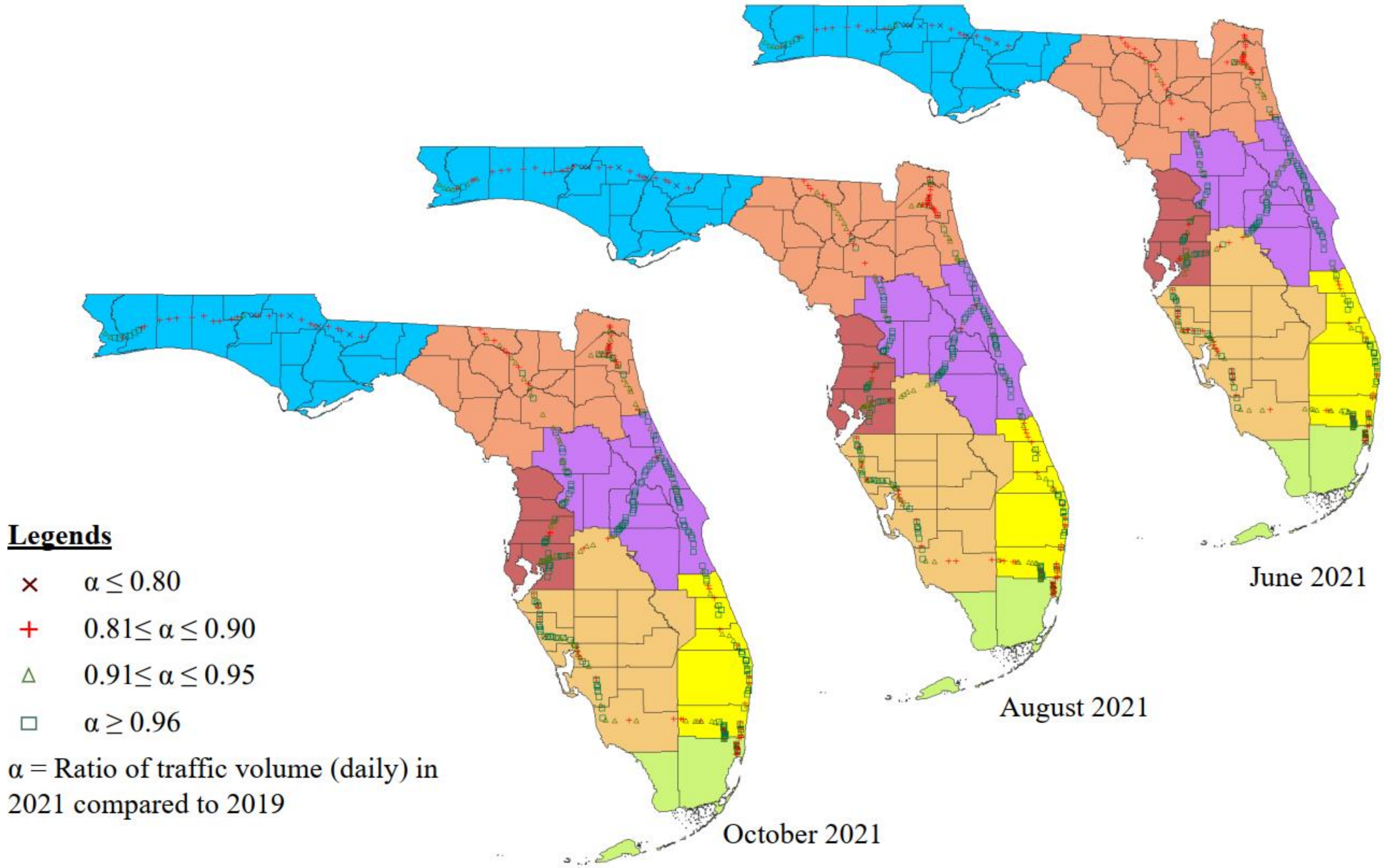

Figure 4. Spatial and temporal changes in holiday's traffic volume

CHAPTER 7: CONCLUSION

Several earlier research efforts have examined the impact of COVID-19 on traffic volumes. However, these efforts were either limited to a very short time frame and/or examine data from a small number of locations. Further, earlier work employed simple descriptive comparisons or statistical models that do not control for a host of factors that affect traffic volumes. In our current study, using traffic volume data for 2019 and 2020 from 3,957 detectors on four interstate facilities in Florida, an econometric framework for traffic volume spatiotemporal analysis is developed. Recognizing the presence of multiple repeated datapoints for each detector and the presence of common unobserved factors affecting traffic volumes at neighboring detectors, a comprehensive set of panel spatial models are estimated. The dataset was also partitioned for weekdays and holidays to capture intrinsic differences in traffic volumes on weekdays and holidays. The model estimation process considered an exhaustive set of independent variables including detailed COVID-19 information (such as per capita COVID cases), socioeconomic characteristics (such as employment rate, median income), land-use characteristics (such as residential, commercial, and recreational area), built environment attributes (such as number of restaurants, and shopping centers), roadway characteristics (such as number of lanes, and maximum speed limit), meteorological information (such as wind speed and precipitation) and spatial factors (district-wise detectors location). Among the spatial models, Spatial Error Model offered the best fit for weekdays and holidays.

The model estimates clearly highlight the impact on COVID-19 on traffic volumes. The model also recovered several important associations with other independent variables. The findings from the model highlight the inequity in the impact of pandemic on lower income households. The model for holidays indicates that traffic volumes during the pandemic are lower for recreational areas (relative to pre-pandemic conditions). The model estimation results are further augmented with a policy analysis exercise to illustrate the value of the proposed model system. The policy analysis clearly identifies spatiotemporal variations across the state in terms of traffic volume recovery. Further, the recovery patterns are quite different for weekdays and holidays. For weekdays, Central Florida region (District 5) appears to have recovered close to pre-pandemic traffic volumes while the northwest (District 3), northeast (District 2) and southwest region (District 1) are below the pre-pandemic levels. For holidays, the trends are quite different with both Central (District 5) and southeast region (District 4) are closer to recovery than rest of the state. Further, across the state, holidays have lower traffic volumes highlighting the impact of COVID-19 on discretionary travel.

The proposed model system has wide application for understanding traffic volume patterns as well as traffic volume prediction. With the number of cases increasing rapidly across the country, it is possible that increased measures to reduce COVID-19 spread might be instituted affecting traffic volume recovery. Employing the growing case numbers the proposed model system can offer guidelines on future recovery paths for traffic volumes on weekdays and holidays. The model developed can be enhanced by incorporating vaccination data at the county level in future research to incorporate spatiotemporal variations in vaccination rates across Florida.

Overall, this paper gives an insight about the travel demand to the transportation planner while planning any transport infrastructure. Firstly, this paper has shown the impact of different categories of variables as well as changes of these impacts due to a shock in the system, like-COVID-19, on traffic demand. This output will help the policy planners to predict future travel demand considering the surrounding characteristics and potential future system shock. Secondly, the spatial variability in travel recovery suggests that regions hosting recreational areas are more likely to have a faster travel recovery after COVID-19, which would help the planners while planning such types of establishments.

This study is not without limitations. Passenger cars and trucks were considered in the same category due to data unavailability. In future research, it might be useful to consider them separately. Further, the interruption of the regular traffic demand due to any types of major traffic incidents has been ignored in this study because of the absence of crash related information in the RITIS data. In addition, due to the absence of origin and destination of the trips, it has not been possible to differentiate the pass-through traffic from the local traffic in the interstate system. These might be also considered in the future research based on data availability.

APPENDIX A: PARAMETER TEST

In our analysis, we employed the one day per month randomly to reduce computational complexity. To ensure the random sampling does not affect the stability of estimates, we conducted model estimation by employing multiple random samples following the same process used for the estimation sample. For all of these samples the linear regression model specifications described were estimated. The reader would note that across the samples, it is not likely that the parameters estimates remain identical. However, the focus is on examining if the parameters across these multiple samples exhibit statistically significant variability. For this purpose, we consider the mean of the parameters across the 11 samples as the population estimate. Subsequently, a revised Wald test statistic is generated for each sample parameter relative to population mean parameter as follows (see Hoover et al. (2021) for a similar approach):

$$\text{Parameter test statistics} = abs\left[\frac{Sample\ parameter - Population\ benchmark}{\sqrt{SE_{sample}^2 + SE_{population}^2}}\right] \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (7)$$

If the parameter test statistic is less than critical t statistic value (1.65) for 90% confidence interval, the result indicates that the parameter is not significantly different from the population mean. Using the parameters estimates for 10 data samples, revised t-statistics for all variables were computed. From the comparison, both weekday and holiday model test statistics values for all the variables are less than 1.65, indicating that sample selection does not cause a significant change in the model. The detailed comparison results are included in supplementary materials (Figure 5 and 6).

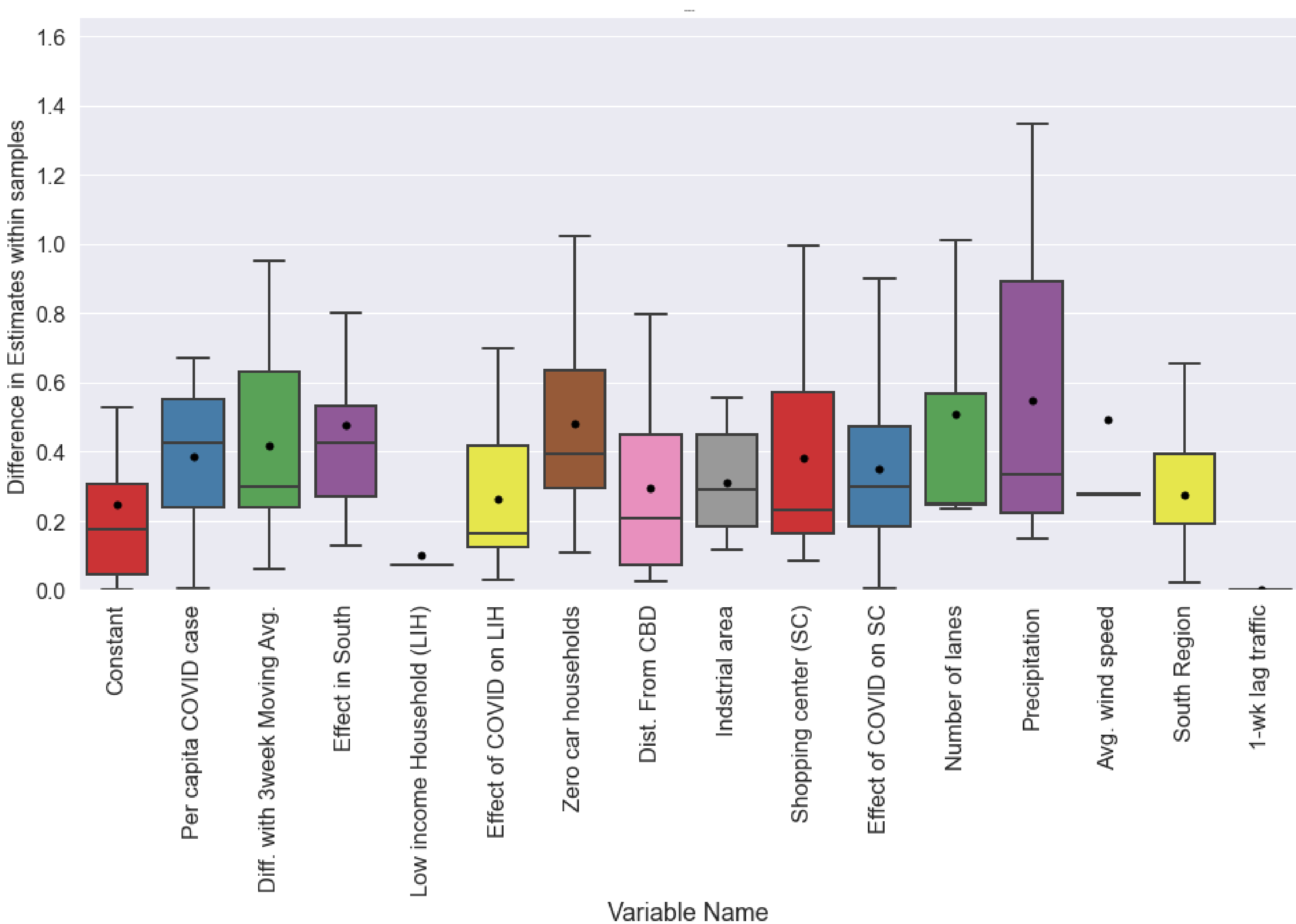

Figure 5. Variation of the coefficients of linear regression model for different random samples (Weekday Model)

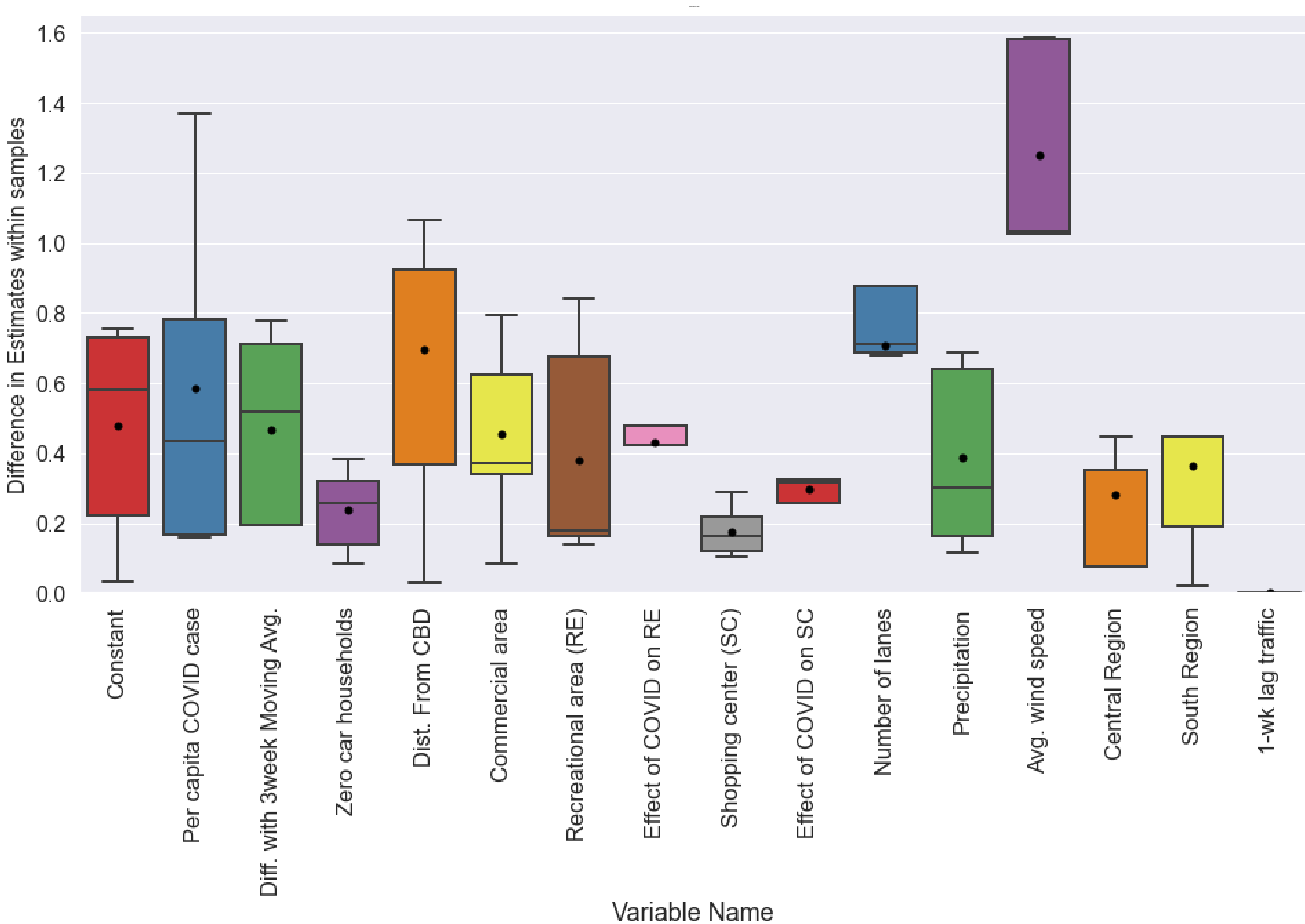

Figure 6. Variation of the coefficients of linear regression model for different random samples (Holiday Model)

APPENDIX B: SPATIOTEMPORAL VARIATION

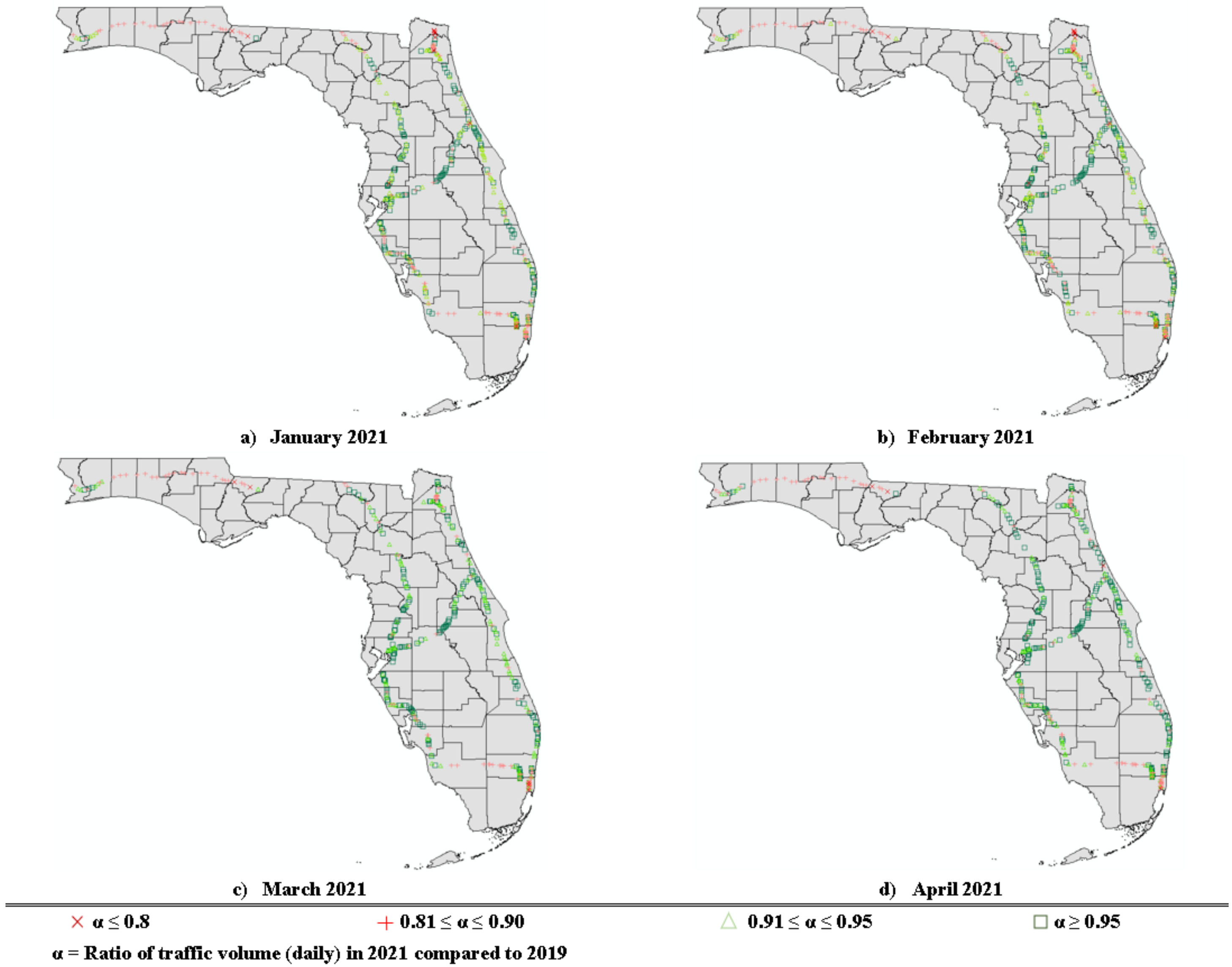

Figure 7. Spatial and temporal changes in weekday's traffic volume (January 2021 through April 2021)

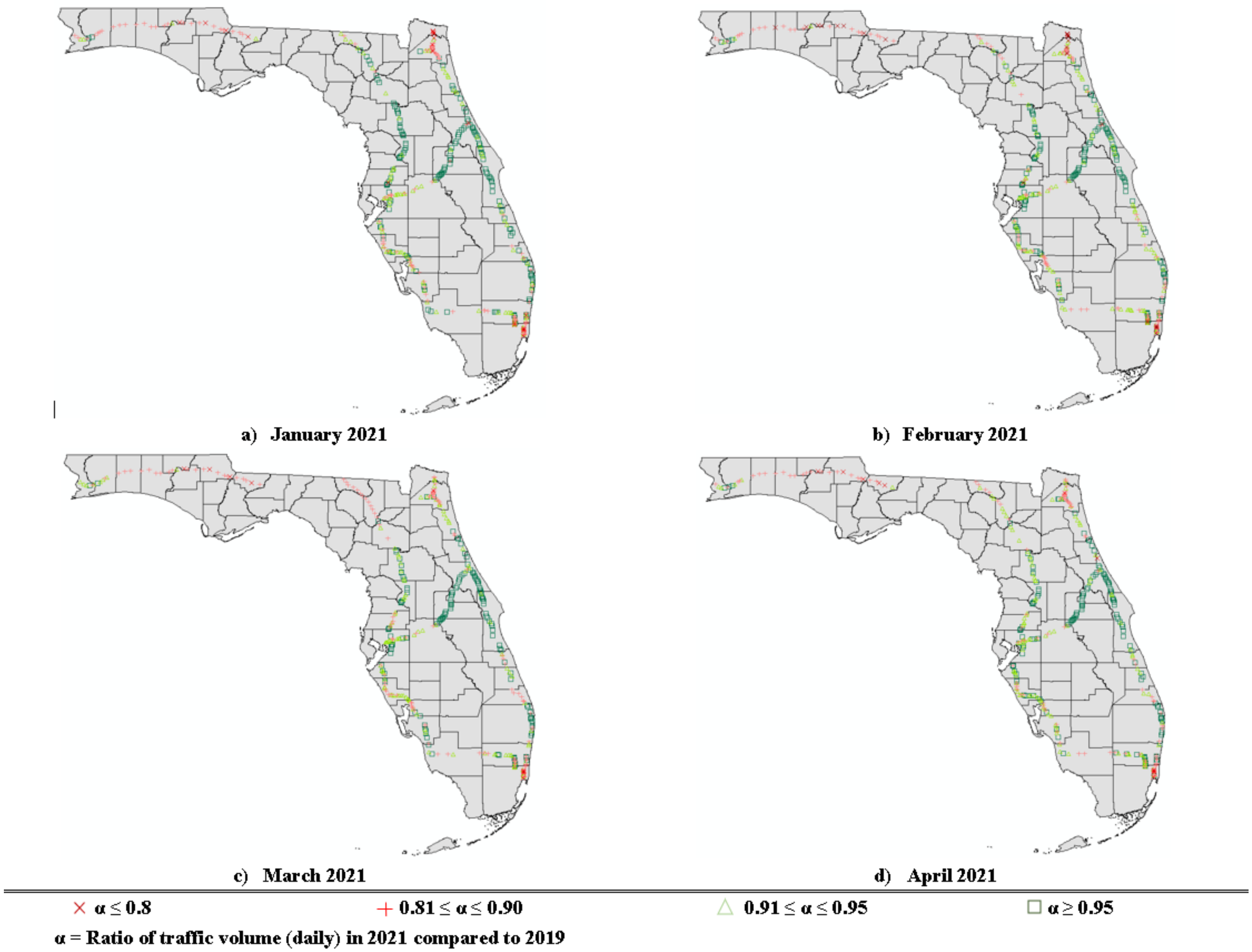

Figure 8. Spatial and temporal changes in holiday's traffic volume (January 2021 through April 2021)

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