Relationship between socio-demographics and COVID-19: a case study in three Texas regions

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Abstract

The COVID-19 is a global pandemic and crisis of public health. Although studies investigate the spatial factors of COVID-19, most of them are based on the macro-level. There is a rising demand to examine the emerging patterns of socio-demographic and COVID-19, especially for preventing the second-peak of COVID-19 outbreaks. This study was based on the recent release of zip code level data of COVID-19 and explore spatial relationships between socio-demographics and COVID-19 density through ordinary least squares (OLS) and geographically weighted regression (GWR). OLS results indicate that rates of poverty, rates of African Americans, and rates of Hispania were influential factors. Results of GWR are complementary to the OLS results. They suggest that associations between socio-demographics and COVID-19 density should be various in different postal areas. We argued that socio-demographics could play significant roles in COVID-19 outbreaks, which may be evidence that socio-demographic disparities happened during the COVID-19 crisis. We suggested that policymakers work on implementations involving interventions and prevention based on different priority levels. Also, it may be more productive for policymakers to implement strategies depending on local situations instead of globally.

Keywords: COVID-19, Geographically Weighted Regression, Socio-demographic disparities, Neighborhood, GIS

1. Background

The emerging disease, COVID-19, is now a pandemic with an overwhelmingly significant impact on the global population and public health. COVID-19, as a new coronavirus with high transmissibility, was originally discovered at the end of 2019. Later, WHO defined it as a global pandemic on March 11 (WHO, 2020).

The first COVID-19 confirmed case in the United States was reported in Washington State on January 19, 2020. Since then, the U.S. has experienced increased COVID-19 cases, especially after March. As of June 15, there were 2,183,892 confirmed cases and 118,283 deaths in the U.S. (WorldMeter, 2020).

Historically, studies have proven that epidemics outbreaks could be associated with socio-demographic factors (Quinn & Kumar, 2014; Credit, 2020). Hence, there is a hypothesis that COVID-19 could disproportionately affect vulnerable communities, including those living in poor, minority individuals, and people living in poverty. Results of exploratory and case studies were consistent with this hypothesis (Chowkwanyun & Reed, 2020; Mollalo, Vahedi, & Rivera, 2020; Kim & Bostwick, 2020; CDC, 2020). Also, most cases in the U.S. gathered in urbanized regions, such as New York City and Houston, where people of minority races and in poverty gather.

Since there could be associations between COVID-19 and socio-demographic, it is worth exploring these associations through spatial modeling, which could provide a spatial perspective on the relationship between explanatory variables and COVID-19. Mollalo, Vahedi, and Rivera (Mollalo, Vahedi, & Rivera, 2020) explored the relationship between environment and socio-demographic and COVID-19 incidence in the U.S based on the county-level dataset and found that income inequality was an influential factor.

Further concerns focused on the spatial bias of observations. Most of them mentioned that the county-level analysis might not be precise enough to provide associations since populations do not distribute equally within counties. Gibson and Rush (Gibson & Rush, 2020) investigated associations between socio-distancing and COVID-19 based on neighborhood-level data in South Africa, provide a precise perspective on this pandemic. Data at a smaller spatial scale in the U.S., however, has not been available in some regions until April, allowing neighborhood-level analysis, which provides the opportunity to explore a precise spatial associations between socio-demographic and economic characteristics and COVID-19.

Since the first confirmed COVID-19 case was reported in Texas on March 4 (The Texas Department of State Health Services, 2020), the number of COVID-19 cases is climbing. As of June 15, there were 91,380 confirmed cases and 2,016 deaths in Texas (WorldMeter, 2020), and the daily confirmed cases were increasing dramatically after June 1 (Texas Medical Center, 2020). Therefore, there is a rising concern that Texas could be the next epicenter of COVID-19 after New York (Kumar, 2020).

In this study, we studied the spatial relationship between socio-demographic factors and COVID-19. Advanced by micro-level (e.g., zip code level) data released, this study provided a micro-level perspective on these spatial relationships, which could assist local governments. Furthermore, precise investigations on these associations could be helpful in implementing plans that aim to help those who are suffering issues caused by OCIVD-19 outbreaks. Since some regions are under risks of the second peak, this study could also contribute to preparations, such as local relief plans, for the subsequent outbreaks.

2. Materials and methods

2.1. Data collection and preparation

Local departments of health are working on monitor cases by zip code areas. We chose three regions, Travis/Austin, Bexar/San Antonio, and Harris and Fort Bend, as the study area since they are significant cities in Texas state and local government of Dallas-Fort Worth Metropolitan Area did not release the number of COVID-19 cases by zip code. We captured the number of COVID-19 cases in the study area on June 5 (City of Austin, 2020; City of San Antonio, 2020; Fort Bend County, 2020; Harris County, 2020). Notably, different regions have different measures, which could be a stumbling block for across regions research. For instance, Travis/Austin and Harris and Fort Bend publish the actual number of COVID-19 cases by zip code while Bexar/San Antonio releases the number of cases by 1,000,000 people. Also, none of these three regions distribute the number of COVID-19 tests by zip code. To unify the outcome variable and eliminate possible biases of tests, we calculated the density of COVID-19, which refers to the number of COVID-19 confirmed cases by 1000 people, as the outcome variable in this study. Figure 1 presents the spatial distribution of COVID-19 density in the study area.

Socio-demographic variables and timely travel behavior variables were considered as explanatory variables in this study. Eight socio-demographic variables were retrieved from the 2018 American Community Survey at the census block group level. Two variables, measuring appropriate travel behaviors, were also at the census block group level from SafeGraph that is a data company providing real-time measures of travel behavior situations across the whole U.S. (SafeGraph, 2020).

There were spatial mismatches between the outcome variable (at zip code level) and explanatory variables (at the census block group level), and the boundaries of postal areas differed from those of census block groups. We integrated all explanatory variables into the zip code level based on the spatial weights. For instance, we assumed that population/workers/households were equally distributed in each census block group. If there are overlaps of census block groups by two postal areas, each postal area will aggregate portions of factors based on the area within. Table 1 provides final descriptions of explanatory variables at the zip code level in the study area.

Table 1. Explanatory variables description in this study

Variable Name	Description	Source
Percentage of males	Assumed proportion to the fraction of population living in each census block group	2018 American Community Survey
Percentage of 65 years and over		
Median household income		
Percentage of African American		
Percentage of Hispania		
Percentage of educated equal or higher than college levels.		
Percentage of household in poverty	Assumed proportion to households in poverty in each census block group	
Percentage of workers commuting through public transit	Assumed proportion of workers through public transit in each census block group	
Median distance traveled	Median distance (1000 meters) traveled from the home by the devices during the period	SafeGraph updated in May 30
Percentage of participants totally at home	Proportion of participants who dwelled at home totally during the period	

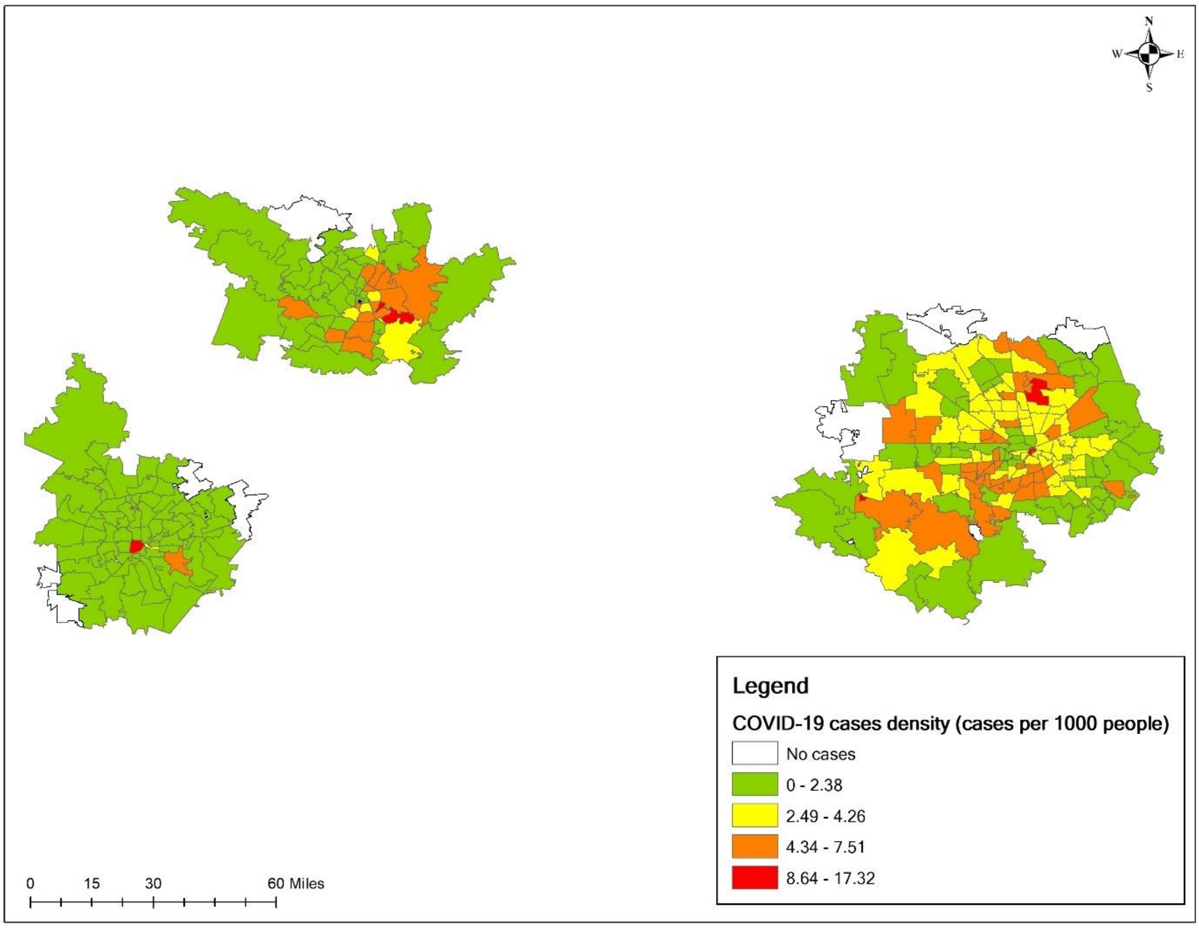

Fig 1. Density of COVID-19 by zip code areas

2.2. Methods

2.2.1. Global model

Two types of associations between socio-demographic and COVID-19, including global associations and spatial associations, were investigated in this study through two types of models. One was the global model, ordinary least squares (OLS) regression, and the other was the local model, geographic weighted regression (GWR) regression.

The OLS regression is used to examine the relationship between multiple explanatory variables and a dependent variable. The equation in this study is given by:

$$Y = \beta_0 + \beta_i * X_i + \varepsilon$$

where Y is the COVID-19 density, β_0 is the intercept, X_i refers the explanatory variables, β_i refers related coefficients, and ε is the random error term.

Since the OLS lacks for testing spatial effects among observations and does not consider spatial autocorrelation (Beale, Lennon, Yearsley, Brewer, & Elston, 2010), this method may not be a prefect tool to investigate effects on COVID-19. Given previous studies that these outbreaks should be spatially correlated (Mollalo, Vahedi, & Rivera, 2020), we introduced local models to examine spatial associations.

2.2.2. Local model

We first applied Moran's I, measuring spatial autocorrelation. If it were significant, we would use GWR to study the spatial associations. If it were significant, we would use GWR to study spatial associations. It could deal with issues involving spatial autocorrelation. Besides, this method allows us to measure various coefficients over observations instead of estimating global coefficients like OLS (Brunsdon, Fotheringham, & Charlton, 1996). In this study, the GWR equation is given by:

$$Y_i = \beta_{i0} + \sum_{j=1}^{n} \beta_{ij} * X_{ij} + \varepsilon_i$$

where at postal areas i, Y_i is the value for the COVID-19 density. β_{i0} is the intercept for postal areas i. β_{ij} refers the coefficients of different explanatory variables in different postal areas, and X_{ij} is the related explanatory variable. ε_i is the random error.

2.3. Analysis framework

There were ten possible explanatory variables in this study (Table 1), while a small set of observations (e.g., 58 postal areas of Travis/Austin) limited the number of explanatory variables. We first applied Pearson's correlation analysis and Variance inflation factor (VIF), as the data selection process, to eliminate the multicollinearity risk.

All global models and local models were implemented with the same selected variables. The global model was run in R 3.6.2, and the local model was implemented in ArcGIS 10.6 (Esri, 2020). We set optimal bandwidth as the adaptive kernel and Akaike Information Criterion (Mollalo, Vahedi, & Rivera, 2020). The adjusted R^2 was used to measure the performance of models.

3. Results

3.1. Results of global models

After the data selection, six variables were selected as the final explanatory variables in following models. The final explanatory variables include the percentage of households in poverty, the percentage of African Americans, the percentage of Hispania, the percentage of educated equal or higher than college levels, the percentage of workers commuting through public transit, and median distance traveled at the zip code level. Table 2 presents the result of all three regions through OLS. It indicates that rates of poverty and rates of African Americans were significantly associated with the density of COVID-19 in the study area. There could be 7.382 more and 4.401 more in COVID-19 density because one percentage increases in poverty rates and rates of African Americans.

The separate results of each region were different from the results of the whole study area. In Travis/Austin, only the percentage of Hispania was significantly and positively associated with the density of COVID-19. For every percentage increasing in the rate of Hispania, there could be 4.369 more cases per 1000 people in Travis/Austin. The results of Bexar/San Antonio, the third column of Table 2, indicate that only the percentage of poverty was significantly and positively associated with the density of COVID-19. For every percentage increase in the poverty rate, there could be 9.681 more cases per 1000 people in Bexar/San Antonio. Moreover, the OLS results of Harris and Fort Bend presents that the percentage of African American and public transit workers were significantly and positively associated with COVID-19 density. For every percentage increasing in the rate of African Americans, there could be 3.575 more cases per 1000 people in Harris and Fort Bend.

Table 2. OLS results for all three regions

	Dependent variable*:* COVID-19 density			
	All three regions (1)	Travis/ Austin (2)	Bexar/San Antonio (3)	Harris and Fort Bend (4)
Percentage of household in poverty	7.382***	6.472	9.681***	2.625
	(2.579)	(7.144)	(3.265)	(3.735)
Percentage of African American	4.401***	6.815	-0.910	3.575***
	(0.895)	(5.140)	(1.860)	(1.112)
Percentage of Hispania	-0.616	4.369*	-0.953	0.922
	(0.831)	(2.192)	(1.025)	(1.343)
Percentage of educated equal or higher than college levels	-1.382	-1.695	0.274	0.011
	(1.488)	(1.873)	(3.820)	(5.200)
Percentage of workers commuting through public transit	7.015	17.072	-0.878	18.170*
	(5.743)	(11.260)	(8.140)	(10.088)
Median distance traveled	-0.028	-0.204	-0.016	-0.111
	(0.082)	(0.205)	(0.092)	(0.124)
Constant	1.352***	0.530	0.789	1.644**
	(0.407)	(0.675)	(0.763)	(0.745)
Observations	301	58	77	166
Adjusted R^2	0.225	0.352	0.262	0.188
Note*:*				*p<0.1; **p<0.05; ***p<0.01

3.2. Local models

We investigated positive spatial relations among the distributions of COVID-19 density in the study area, Travis/Austin (Moran's I = 0.185, $p < 0.01$), Bexar/San Antonio (Moran's I = 0.176, $p < 0.01$), and Harris and Fort Bend (Moran's I = 0.088, $p < 0.01$). Compared the adjunct R^2, local models performed better than global models of each region. In detail, Figures 2, 3, and 4 present local coefficient and p-values of explanatory variables by zip code.

3.2.1 Travis/Austin results

In the Travis/Austin region, the poverty rate was not significant in most areas, while it was significant in the southwest corner, as a positive effect, and the south part of this region, as a negative effect. Higher rates of African Americans could be associated with higher COVID-19 density in the east and south parts while it could be reversed in the northwest areas of Travis/Austin.

The rate of Hispania was a significant factor in predicting the density of COVID-19 across the north part of the Travis/Austin region, which is consistent with OLS's results. For most areas of Travis/Austin, excluding northwest and southwest, higher rates of Hispania were significantly and positively correlated with COVID-19 density.

Higher rates of educated with college or higher degrees were significantly and negatively related to COVID-19 in the east and south parts, while rates of workers commuting through public transit could play a reversed role in these areas. Finally, the median distance traveled was significantly negative in the north and south parts, which means that areas with more long-distance traveling could be associated with less COVID-19 density.

3.2.2 Bexar/San Antonio results

The rate of poverty was globally significant and positive in Bexar/San Antonio region, consistent with the OLS results. It indicates that the poverty rate could be an influential and positive factor in predicting COVID-19 density in this region. Areas with higher rates of poverty could also be with more significant COVID-19 density. Also, the positive effect of the poverty percentage in the northwest part of this region could be larger, as shown in Figure 3 (a).

Overall, other variables did not perform well in Bexar/San Antonio region. Figure 3 (b) indicates that the relations between rates of African Americans and COVID-19 density were significantly negative in a few areas, like rates of Hispania, which was significant only in a few areas of west. Higher rates of educated with college or higher degrees were significantly and negatively related to COVID-19 in the southwest part, as shown in Figure 3 (d), which is inconsistent with common sense that people educated may know how to prevent COVID-19 individually.

Rates of workers commuting through public transit were significantly negative in the northwest part. In these areas, higher rates of commuting through public transit were associated with smaller COVID-19 density. It is not consistent with a statement that public transit could be the hotbed for COVID-19 (Naka, 2020). Surprisingly, we found that the median distance traveled did not play a significant role in this region.

3.2.3 Harris and Fort Bend results

Figure 4 demonstrates the results of the GWR model in Harris and Fort Bend. Although rates of poverty are not significant in this region, it does not indicate that the association between rates of poverty and COVID-19 is unworthy noting. It indicates that controlling by other effects, the influence of poverty rates may not be critical in this study.

Consistent with OLS results, rates of African Americans were significantly positive in most areas of this region, excluding Houston's downtown. Besides, this effect was larger in the northeast part. For rates of Hispania, it was significantly positive in the west part of this region, which indicates that higher rates of Hispania may be associated with higher rates of COVID-19. The education factor seemed to be various. In the south part of the region, its effect was significantly negative, higher rates of college, and higher leading to smaller COVID-19 density. In reverse, the effect of education was positive in a few areas of the north part.

The rates of commuting through public transit were significantly positive in central areas, which indicates that higher rates of public transit could be associated with more significant COVID-19 density. While the median distance traveled was only significant and negative in the southwest part of this region where could be defined as Fort Bend County.

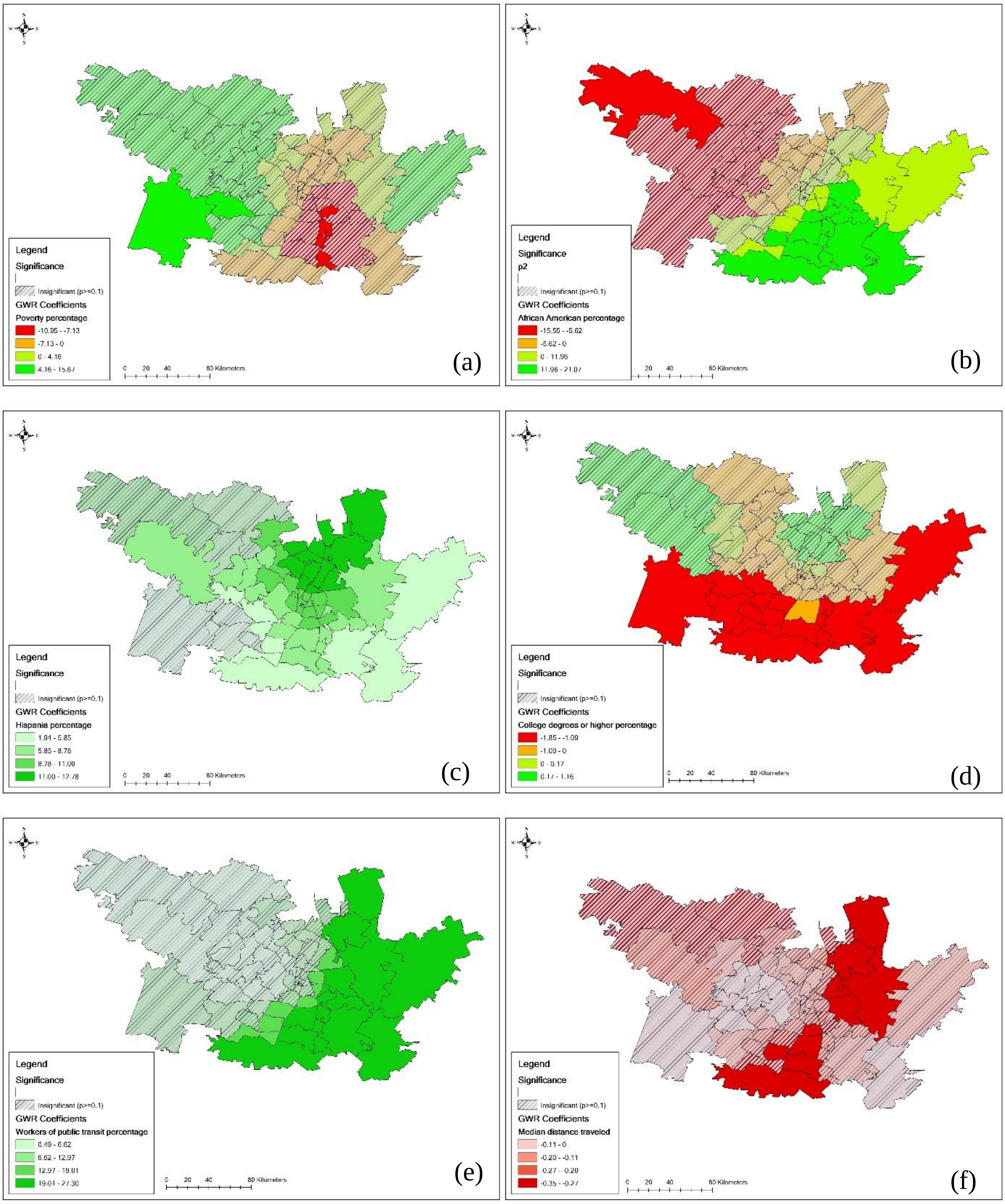

Figure 2. GWR results for Travis/Austin (Adjusted R2 = 0.494)

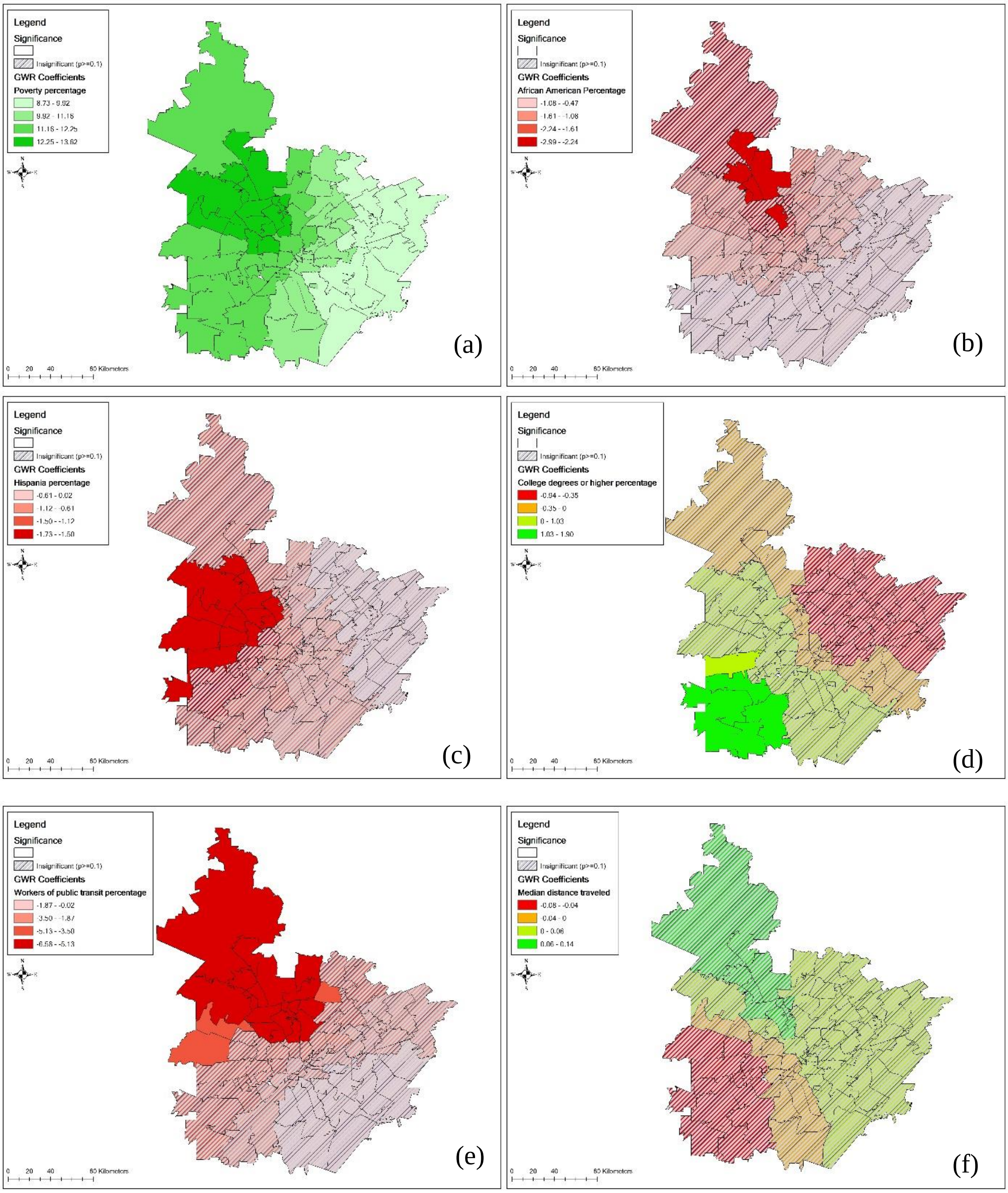

Figure 3. GWR results for Bexar/San Antonio (Adjusted R2 = 0.302)

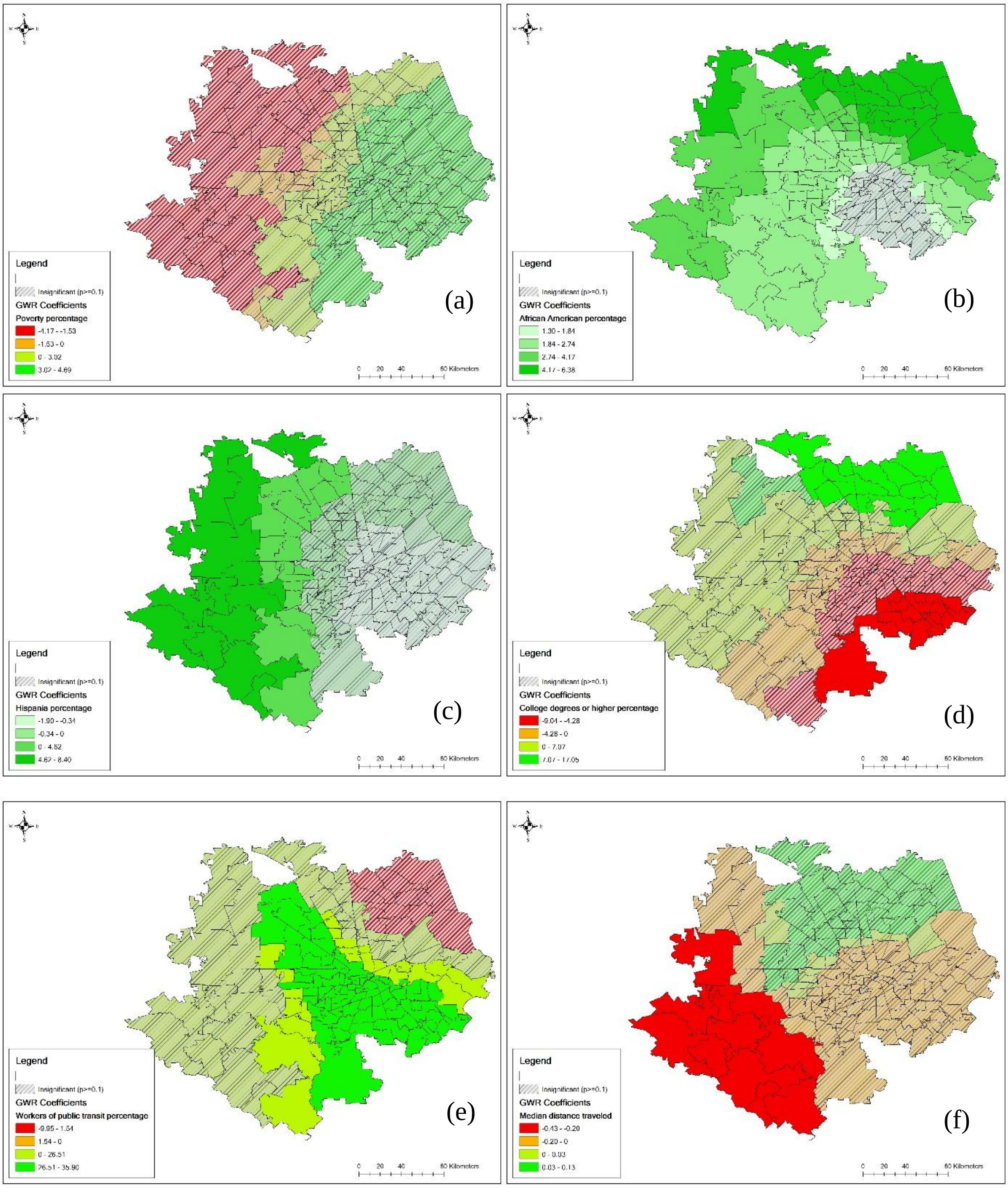

Figure 4. GWR results for Harris and Fort Bend (Adjusted R2 = 0.361)

4. Discussion

This study was an exploratory study that explored the relationships between socio-demographic and COVID-19 density based on the zip code level data. In general, results of OLS indicate that vulnerable groups (people in poverty, African Americans, and Hispania) were positively associated with COVID-19 density, but the significances of these associations were different among regions. Besides, rates of commuting through public transit were significantly positive in Harris and Fort Bend region. Results of GWR were complementary to the OLS results. They further examined the local models' various local coefficients for each postal area and suggested that these associations be different for each zip code in the study area.

Limitations of this study could be worth further research. First, since we chose COVID-19 density, the number of COVID-19 cases per 1,000 people, it could be biased. For future studies, we suggested that researchers choose rates of positive COVID-19 cases, which refers to the number of confirmed COVID-19 cases divided by the number of tests if this data is accessible. Also, the study area was not connected, which leads to information missing. We suggested that the local department of health release this data so that system-wide research of COVID-19 could be appliable for all metropolitan areas or regions. Moreover, although we pre-selected the variables from 10 candidate explanatory variables, there could be some overlaps among selected explanatory variables. We considered applying the principal component analysis to conduct indexes in further analysis.

Albeit the limitations, this study could be meaningful for policymakers who are working on interventions and preparation for the post-pandemic period. Since each region's results were different, there might not be general interventions or preventions for all cities. In Travis/Austin, the east part was regarded as areas of vulnerable group gathering. At the same time, coefficients of minority races and workers commuting through public transit were significantly positive. Policymakers have already noted this situation (DuPree, 2020; The Austin Monitor, 2020). The local government and state government are working on addressing COVID-19 issues in East Austin. Based on the results, we suggested the City of Austin to pay more attention to minority groups in these areas, as complementary. Furthermore, since there are around 35% of the population is Hispanic in this region (City of Austin, 2020), and rates of Hispania were an influential factor. The priority task for future inventions and preventions of COVID-19 could be implemented in Hispanic communities of East Austin.

Poverty seemed to be an influential factor in Bexar/San Antonio. It was a significant positive predictor in all zip codes of this region. Also, the San Antonio metro had a high poverty rate compared to other areas across the U.S, as the second-highest poverty rate in 2017 (Phillips, 2019). Policymakers may implement a rescue plan for those in poverty in this region. It should be critical and necessary since most low-income people might not get paid during this pandemic. Besides, the priority of this rescue plan may start with the poor living in the northwest part of Bexar/San Antonio.

Minority groups and workers through public transit could be at a higher risk of COVID-19 in this region. In peripheral areas, especially the north and west parts of this region, policymakers could be worth noting the minority groups. For instance, African American communities in the north part and Hispanic communities in the west part could be priorities for interventions and preventions. Also, areas with significant effects of workers through public transit distributed like banded, which could be ascribed particular origin and destination patterns of working. Bus routes connecting to these areas need sanitations in priority.

5. Conclusion

This study aimed to investigate the spatial relations between socio-demographic and COVID-19 density by zip code through OLS and GWR. Results indicate that vulnerable groups, including people in poverty and minority, could be at high risk of COVID-19. It may be more efficient for local governments to implement strategies of interventions and preventions depending on the local situation.

Future research may be worth addressing the limitations of this study. First, the number of tests by zip code could be helpful to eliminate the possible bias of the outcome variables. Second, larger study areas could be worth for future research, providing a system-wide analysis for COVID-19 outbreaks. Third, complex indexes, instead of individual variables, should be better metrics in predicting COVID-19 outbreaks.

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