UNIVERSITY of SOUTH FLORIDA

GIS6306 ENVIRONMENTAL APPLICATIONS OF GIS

SPATIOTEMPORAL VARIATION OF $PM_{2.5}$ CONCENTRATIONS AND ITS RELATIONSHIP TO URBANIZATION PROCESS AND OTHER FACTORS IN CALIFORNIA STATE, U.S.

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1. INTRODUCTION

With the population increase in the last decades, human activity is increasing in populated areas worldwide, resulting in increased air pollution (Meng et al., 2016). Urbanization has accelerated in several major US cities because of modern transportation infrastructure (Baklanov et al., 2016; Popa et al., 2015). The emission caused by the rapid expansion of transportation systems and human activity leads to an upward trend in the concentration of airborne particulate matter (PM) (Martins & Carrilho da Graça, 2017). The diameter of airborne particulate matter (PM) of 2.5 µm or less is known as Fine Particulate matter (Cohen et al., 2017). $PM_{2.5}$ (with a diameter of 2.5 µm) is usually generated from human activities and artificial combustion, i.e., the use of traditional HVAC in both residential and commercial houses (Martins & Carrilho da Graça, 2017; Carrilho da Graça Lic et al., 2012; Oropeza-Perez & Østergaard, 2014; Oropeza-Perez & Ostergaard, 2014). According to EPA Air quality standards, the concentration of $PM_{2.5}$ of more than 12.0 $\mu g/m^3$ annually causes air pollution and deteriorates air quality of an area.

Due to its small size, it is associated with adverse effects on health and chronic diseases, especially asthma (Pope & Dockery, 2006; Xing et al., 2016). It causes more than 200,000 premature deaths annually in the U.S. (Caiazzo et al., 2013). In the past two decades, air quality in the U.S. has deteriorated due to smoke pollution and $PM_{2.5}$ (McClure & Jaffe, 2018; Schwarzman et al., 2021). The high frequency of use of mechanical cooling systems in California has been worsening the air quality day by day (Haves FASHRAE et al., 2004).

Due to spatial complexity, and population exposure, the spatial coverage of air quality monitoring stations from government agencies (Environmental Protection Agency) is very limited in California to predict accurate results (Liu et al., 2009; Lee, 2019). With the development of Geographic Information Systems (GIS) and Remote Sensing techniques, it is now possible to use spatial interpolation methods like Inverse Distance Weighting (IDW) and Kriging to estimate the value of points where data is not available. The Inverse Distance Weighting (IDW) approach is a straightforward technique that computes the weighted average of nearby, closer points based on the value of an unknown point. Compared to the IDW method, kriging is far more advanced because it accounts for the spatial autocorrelation of the data. It is attainable to compare the results of several methods to determine which best addresses the spatial complexity of California.

Additionally, by monitoring the spatiotemporal change of an area, GIS and remote sensing make it easier to handle massive data, which yields more accurate results and enables researchers to identify the causes of the rise in $PM_{2.5}$ levels in the air. It is possible to determine the spatiotemporal variation in urban expansion of a large area, such as a state, using land use and cover data from satellite images with a 30 m resolution. Various statistical models aid in understanding the relationship between the rise in urbanization, population growth, and other issues. The most challenging problem with statistical models is that they require enormous amounts of data in order to predict precise relationships. This study aimed to find out the spatiotemporal variation of the level of $PM_{2.5}$ and the driving factors behind this issue.

2. STUDY AREA

2.1 Area Profile

The study area concerns the state of California, including 58 counties. On the west coast of the United States, California has a diverse topography that includes mountains, deserts, forests, and coastline. With a land area of 163,696 square miles, the state is the third biggest in the U.S. and is populated by more than 39 million people.

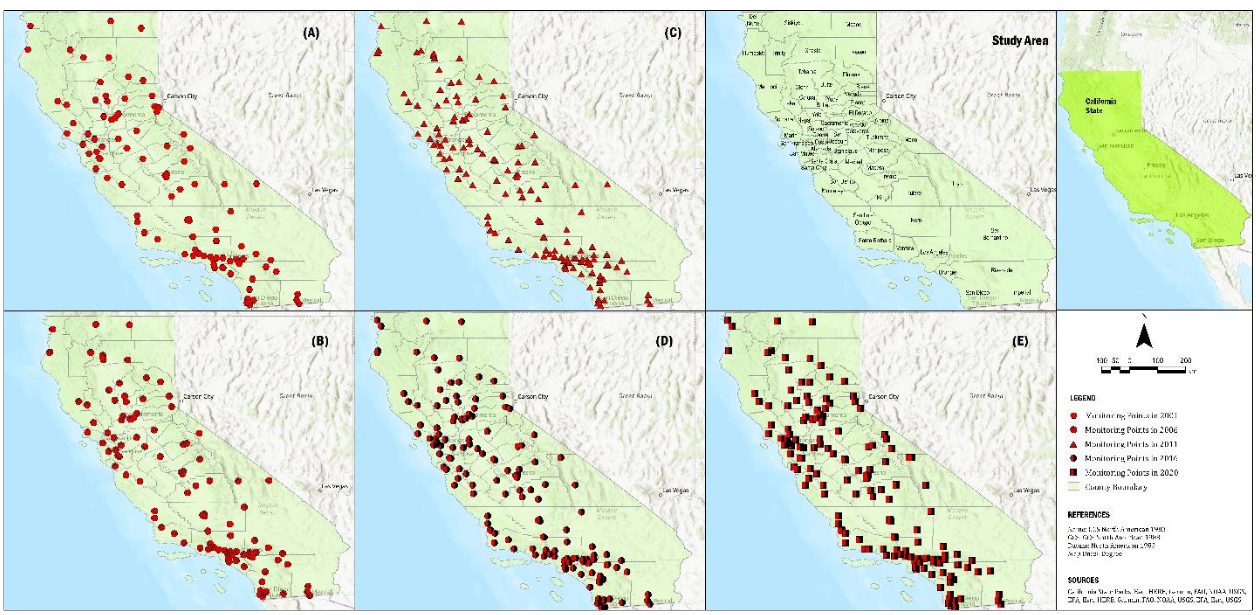

Figure 1. Study Area. (A) $PM_{2.5}$ Monitoring points of 2001 in California State; (B) $PM_{2.5}$ Monitoring points of 2006 in California State; (C) $PM_{2.5}$ Monitoring points of 2011 in California State; (D) $PM_{2.5}$ Monitoring points of 2016 in California State; (E) $PM_{2.5}$ Monitoring points of 2020 in California State

The data used in the daily, county-level estimation covered the period from 2001 to 2020. The number of air quality monitoring stations for recording data has been changed from time to time (Figure 1).

2.2 Data Sources

The objective of the study is to assess the spatiotemporal variation of $PM_{2.5}$ concentrations and its relationship to the urbanization process and other factors in California State, U.S., from 2001 to 2020. Secondary data sources were used to obtain Land use land cover data, demographics data, and air quality data for the study area (Table 1).

Table 1. Data Sources

Parameters	**Data Source**	**Source Location**
Land Cover	Land Cover 2001, Land Cover 2006, Land Cover 2011, Land Cover 2016	https://s3-us-west-2.amazonaws.com/mrlc/NLCD_landcover_2019_release_all_files_20210604.zip
	Land Cover 2020	http://www.cec.org/files/atlas_layers/1_terrestrial_ecosystems/1_01_0_land_cover_2020_30m/land_cover_2020_30m_tif.zip
Administrative	County	https://www2.census.gov/geo/tiger/GENZ2018/shp/cb_2018_us_county_500k.zip
	State	https://www2.census.gov/geo/tiger/GENZ2018/shp/cb_2018_us_state_500k.zip
Demographics	Population Growth Rate	https://usafacts.org/data/topics/people-society/population-and-demographics/our-changing-population/state/california/?endDate=2020-01-01&startDate=2001-01-01
	Migration	https://www.statsamerica.org/downloads/Components-of-Population-Change.zip
Air Quality	$PM_{2.5}$	https://www.epa.gov/outdoor-air-quality-data/download-daily-data
	Monitoring Station	https://epa.maps.arcgis.com/apps/webappviewer/index.html?id=5f239fd3e72f424f98ef3d5def547eb5&extent=-146.2334,13.1913,-46.3896,56.5319

3. METHODS

Spatiotemporal variation of urbanization was calculated from the Land use Land Cover dataset from 2001 to 2020. The satellite image used in the calculation with a resolution of 30m would provide valuable information on the change in urban growth rate over the study period. Land use land cover data was collected in 5 years intervals as the five years interval was suitable for assessing the change in land use land cover of the study area.

In this study, $PM_{2.5}$ recorded data for 2001, 2006. 2011, 2016, and 2020 were collected from Environmental Protection Agency, and then it was projected using geolocation of monitoring points in ArcGIS Pro. As the spatial coverage of monitoring stations is somewhat limited in some locations, the Inverse Distance Weighting (IDW) and Kriging method were used for estimating air pollution at any unknown locations where monitoring stations were unavailable with the following parameters:

IDW

Power: 2
Output Cell Size: 0.005

Krigging

Kriging Method: Ordinary
Semi-variogram model: Exponential
Cell size: 0.005
Search radius: variable

The power value of 2 in the IDW method was used, which referred to the monitoring station data as inversely proportional to the squared Distance between the monitoring station point and the unknown point where there was no data. In the Kriging method, ordinary method was used with exponential diagram where the spatial correlation was modeled between data points using an exponential function as follows:

$$\gamma(h) = \sigma\hat{}2 \exp(-h/\varphi)$$

where

γ(h) = Semi-variance, which measures the spatial correlation between pairs of data points separated by a distance h,
σ^2 = Variance of the data,
h = Distance between data points,
φ = Range parameter, which represents the Distance beyond which the correlation between data points is negligible

County-wise Population data and Migration data were collected from the U.S. census dataset to determine the relationship between the level of PM2.5 and urbanization, population growth and migration rate over time using a linear regression model on Rstudio. This model would establish a linear relationship between the level of $PM_{2.5}$ and other factors.

4. RESULTS

Massive land use and cover changes have occurred in the study area over the past 20 years, from 2001 to 2020, due to urbanization, population expansion, and migration rates.

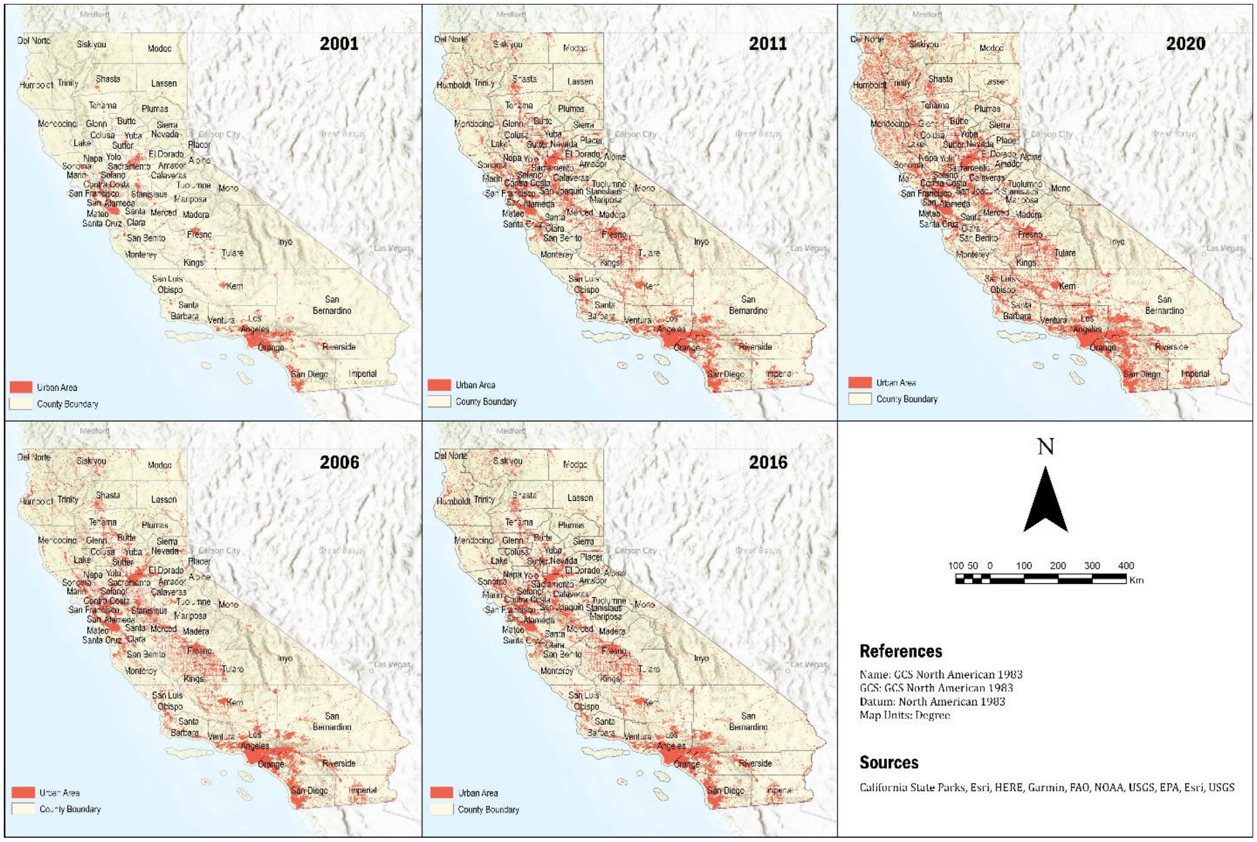

Figure 2. Urbanization in Study Area (2001-2020)

San Bernardino County had the most significant average urban growth rate among the 58 counties, at 61.869, followed by Kern County at 55.201. Alpine County and San Francisco County experienced low urban growth rates of 0.575 and 0.687, respectively, in contrast to other counties that experienced the fastest rates of urban expansion (Figure 2).

It was found that the urbanization rate had been steadily increasing until 2016. Most of the counties were found with extreme urbanization processes in the study period of 2016-2022. The urbanization growth rate was 11.637 in San Bernardino County from 2001 to 2006, which increased to 218.565, following Kern County, San Diego County, and Los Angeles County (Figure 3).

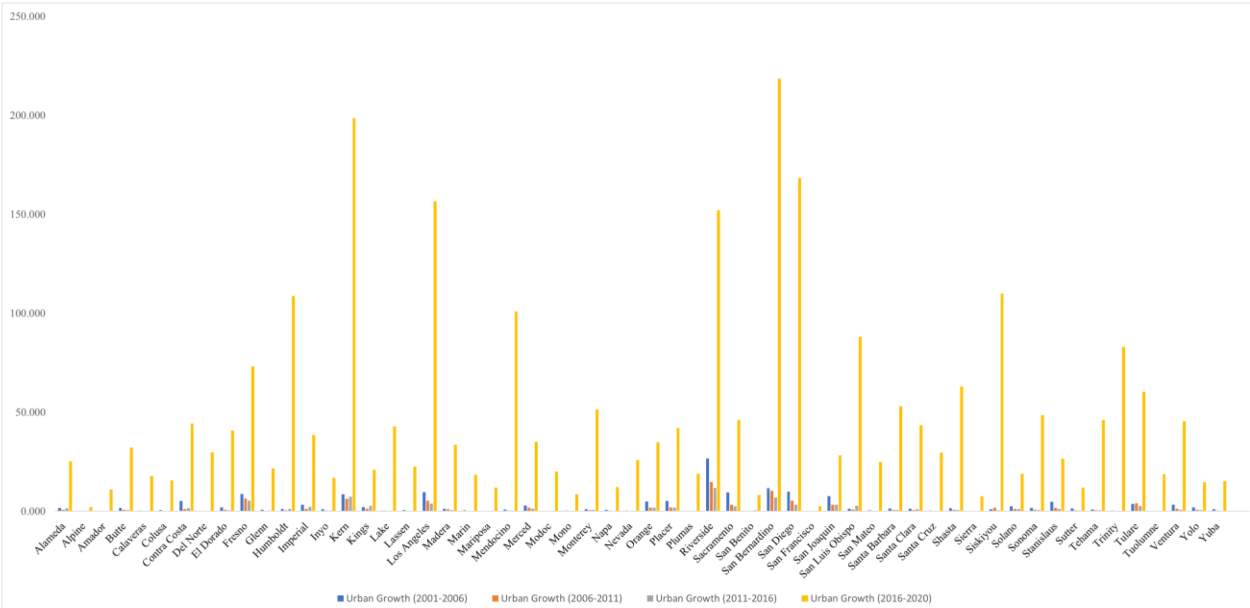

Figure 3. Urban Growth Rate in Study Area (2001-2020)

In reference to the migration rate from 2001 to 2020, it was found that Yuba County was found with the highest average migration rate of 36.763, including both domestic and international migration, following San Benito County, with an average migration rate of 26.988.

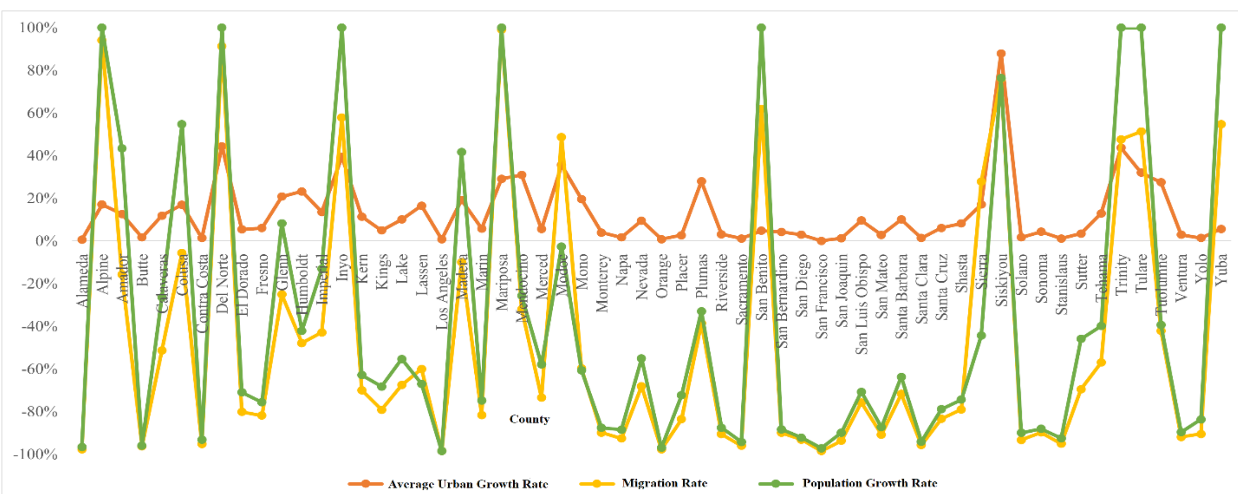

Figure 4. Urbanization and Demographic Profile of the Study Area

On the other hand, the average migration rate had been recorded as lowest in Los Angelos County, following San Diego County over time. Placer County and Riverside County had the highest population growth rate of 53.900 and 49.900, whereas Sierra County, and Modoc County had the lowest population growth rate of -8.200 and -7.400, accordingly (Figure 4).

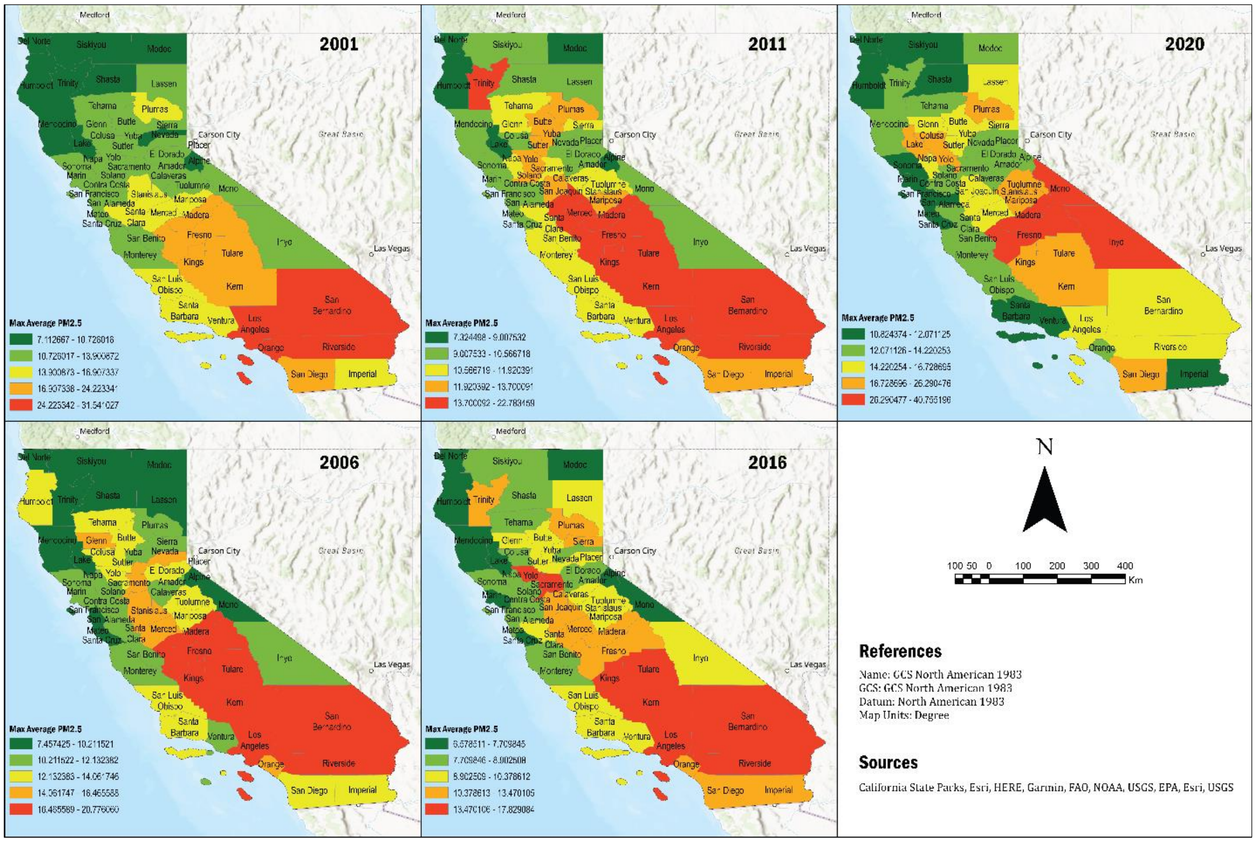

Figure 5. Maximum Average Concentration Level of PM2.5 (IDW Method) in the Study Area

From the analysis of IDW interpolation, it was found that the level of $PM_{2.5}$ had increased over time with the increase in population, migration, and built-up area. In the last 20 years, San Bernardino County was found with the highest average level of concentration of $PM_{2.5}$ (21.240) though the level of $PM_{2.5}$ had been decreasing from 2016 to 2020 (16.338) (Figure 5). In 2020, Inyo County, Mono County, Madera County, and Freson County were at the top in terms of the concentration level of $PM_{2.5}$ where the value was 40.755, 34.985, 30.957, and 29.852, accordingly. On the other hand, Del Norte County, San Francisco County, and San Mateo County were at the bottom of the list, indicating comparatively good air quality compared to other states. The overall scenario showed an increase in the concentration of $PM_{2.5}$, which was concentrated in a few states over time in the study area.

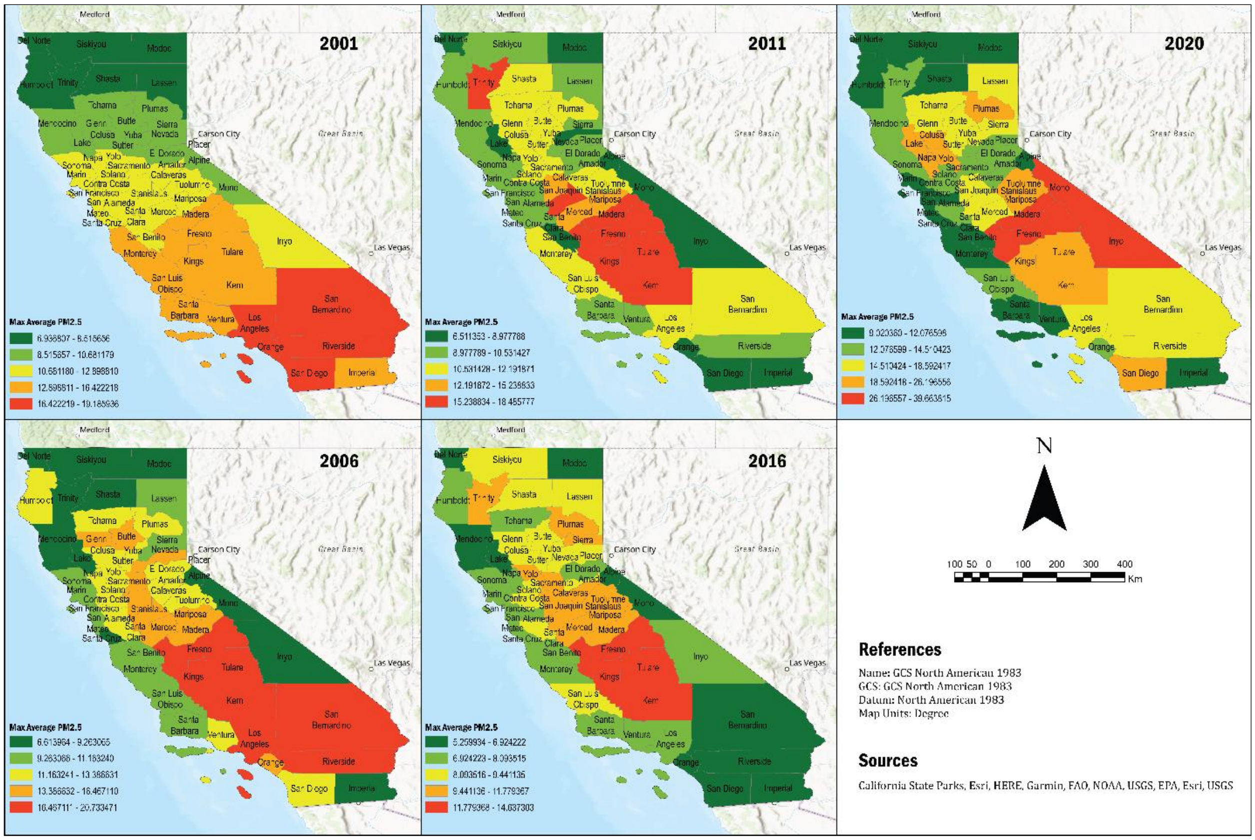

Figure 6. Maximum Average Concentration level of $PM_{2.5}$ (Kriging Method) in the Study Area

In contrast to the results of IDW interpolation, Fresno County was found with the highest average level of concentration of $PM_{2.5}$ (19.363). The concentration level of $PM_{2.5}$ had been increasing over time; it was 13.854 in 2006 but 31.329 in 2020, followed by Madera County, where it was 13.845 in 2006 but 30.967 in 2020 (Figure 6). On the other hand, Alpine County, San Benito County, and Del Norte County were at the bottom of the list with good air quality in terms of concentration of $PM_{2.5}$ where the value was 9.020, 10.218, and 10.823 accordingly. The overall scenario indicated the same results of concentration of $PM_{2.5}$ in the study area as the results from IDW Method.

In this study, the IDW method was found very effective compared to the Kriging method in identifying the hotspots of $PM_{2.5}$. It indicated that the IDW method was comparatively suitable in terms of the geographical context of the study area. The Kriging method failed to predict the maximum concentration of $PM_{2.5}$ in some years, especially in 2011, i.e., Riverside County was found with the maximum average concentration of $PM_{2.5}$ of 18.990 in IDW ordinary method but it was 9.883 using the Kriging method. The comparison of results from the IDW and Kriging methods indicated that the IDW method predicted the maximum concentration of $PM_{2.5}$ value more accurately than the Kriging method (Figure 7).

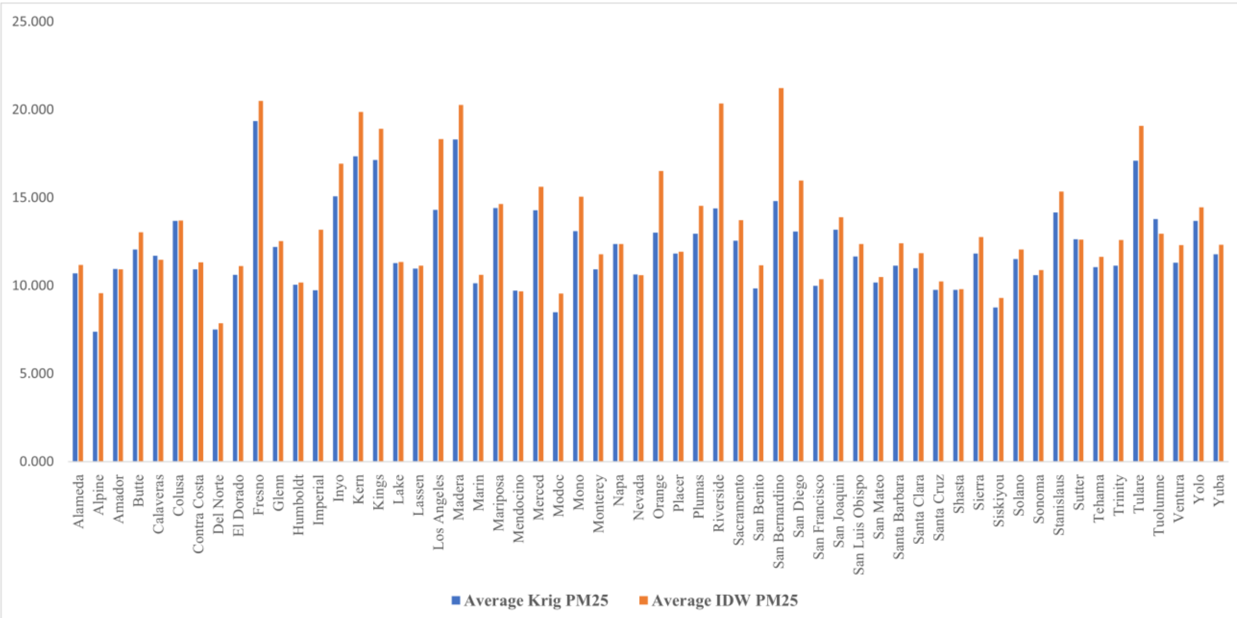

Figure 7. Average Maximum Concentration Level of $PM_{2.5}$ in IDW and Kriging Method

The graph of migration rate referred to the negative relationship between the average maximum concentration level of $PM_{2.5}$ and, as with the increase in migration, average maximum concentration level of $PM_{2.5}$ decreased (Figure 8). No significant relationship was found with migration rate and the average maximum concentration level of $PM_{2.5}$ after running a linear regression model. The graph of urban growth rate and population growth rate represented the positive relationship between urban growth rate, population growth rate, and the average maximum concentration level of $PM_{2.5}$ as with the increase in population and built-up area, the concentration level of $PM_{2.5}$ had been increased. The slope of the regression line in the graph of urban growth rate and population growth rate was relatively higher, representing the magnitude of the estimated effect of these predictors on the concentration level of $PM_{2.5}$. The linear regression model found a significant relationship between population growth rate and the concentration of $PM_{2.5}$ (where the "p" value was 0.000737), which indicated the strong effect of population growth rate on the concentration of $PM_{2.5}$ following urban growth rate.

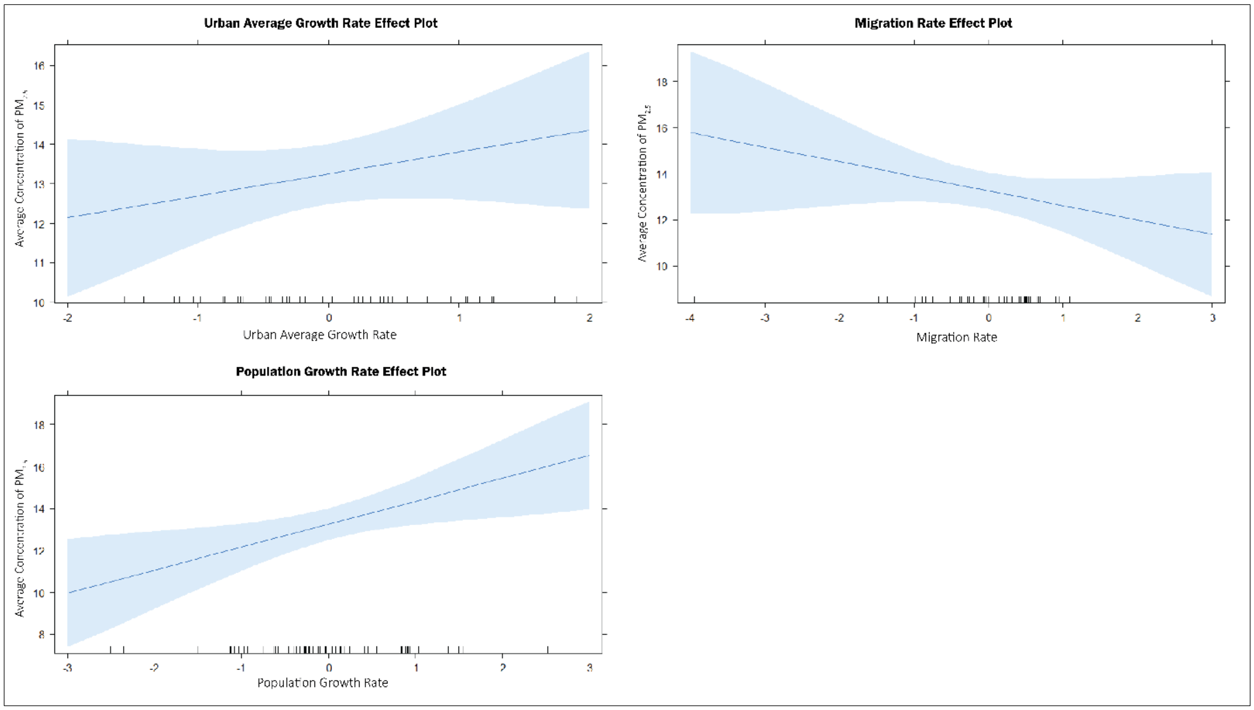

Figure 8. Effect Plots of Urban Average Growth Rate, Population Growth Rate, and Migration Rate

5. DISCUSSION & CONCLUSION

Urbanization is one of the major concerns in terms of air pollution. Rapid urbanization process leads to population growth and migration rate in major states and counties of the U.S. The consequence of the urbanization process gives rise to the concentration level of $PM_{2.5}$ day by day in California state. It has adverse health effects on the inhabitants of counties with a high concentration level of $PM_{2.5}$. This study was conducted on the assessment of average maximum concentration level of $PM_{2.5}$ from 2001 to 2020 with five years intervals. The results showed that the concentration level of $PM_{2.5}$ had been increasing among all counties of California state during the study period. It was evident that the growing concentration of $PM_{2.5}$ had been becoming a concern in a few counties with poor air quality and unhealthy environments for children and adults, especially Inyo County, Mono County, Madera County, Fresno County, and Colusa County.

On the other hand, Del Norte County, San Francisco County, San Mateo County, Santa Cruz County was found to be a comparatively healthy environment with good air quality as population exposure was less compared to other counties with high concentrations of $PM_{2.5}$. The statistical model indicated a significant relationship between the population growth rate and the average maximum concentration level of $PM_{2.5}$. The statistical results didn't show a significant relationship between urban growth rate, migration rate, and concentration of $PM_{2.5}$ due to less frequency of data. Otherwise, there should be a significant relationship between these predictors and the concentration of $PM_{2.5.}$ Moreover, the urbanization process wasn't even in every place with the progress of time. The fluctuations in urban growth need to be cross-validated with an extensive dataset which could establish a significant relationship with the concentration of $PM_{2.5.}$ Due to the absence of any air quality organization, no evidence supports current air quality responsible for acute deaths in California (You et al., 2018). The concerned authority, i.e., decision makers, city planners, and policymakers, should take some strategies to control the growth of urban development and promote natural ventilation instead of using air conditioning systems. However, if urban and population growth rates increase in the coming decades, their impact on the concentration of $PM_{2.5}$ could be a serious threat to California.

6. REFERENCES

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