Climate Impacts of Particulate Matter Levels and Land Surface Temperature

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ABSTRACT

In the last three decades, urbanization has rapidly accelerated. The growth of cities has contributed to the increase of resource consumption and air pollution. Current and past studies have shown evidence that most cities around the world are caught in the loop of population growth, urbanization, and increase of air pollution and land surface temperature. With particulate matter (PM 2.5) levels and land surface temperature (LST), they have become important predictors of air pollution and climate change. This study investigates the correlation of PM 2.5 and LST when using Local Climate Zones (WUDAPT) and National Landcover Data (NLCD). I have found that there is a spatial overlap between high values of PM 2.5 and high values of LST in the eastern portion of San Francisco. On the other hand, there was a common pattern of low values of PM 2.5 and LST in areas with green infrastructure, as well as the northwestern part of San Francisco. I also found that the high average values of PM 2.5 and LST belong to the high intensity developed areas and LCZ classes 1-3, which are the compact and open building sites. The findings also suggest that high density-built areas will contribute to high values of PM 2.5 and LST. With these results, it can contribute to improving planning of cities and infrastructure to better the health of the environment for the people inhabiting them.

KEYWORDS

Local Climate Zones, National Landcover Data, Urbanization, ArcGIS, Air Pollution

INTRODUCTION

While urbanization is rapidly increasing around the world, populated cities continue to increase anthropogenic activities, resource consumption, and, most importantly, the increase of surface temperature. Increased urban development, evidently, changes the natural ecosystem and local climate (Ahn et al. 2022). The Urban Heat Island effect confirmed the detrimental effects of pavement and asphalt on the environment (Dutta et al. 2021). By using the Local Climate Zone (LCZ) as a framework to classify different urban environments, PM 2.5 and land surface temperature values can be then analyzed in varieties of urban environments (Shi et al. 2019), such as a site composed of high-density high-rise buildings versus a site composed of high-density open rise buildings.

Related studies on 2D/3D urban morphology land surface temperature also integrates local climate zones to analyze specific urban morphological parameters and remote sensing data for temperature (Zhou et al. 2022). Results showed that temperature showed a distinct characteristic of "high-low-high" across all seasons. Zhou et al. (2022) found that building height was the most influential 3D factor on land surface temperature, while surface fraction was the dominated 2D factor. 2D/3D urban morphology has been compared with local climate zones to analyze specific urban morphological parameters with land surface temperature. Zhou et al. (2022) showed that temperature followed a distinct characteristic "high-low-high" trend across all seasons and found that building height was the most influential 3D factor on land surface temperature, while surface fraction was the dominated 2D factor (Zhou et al. 2022). Furthermore, the spatial arrangement of land use types can influence intra-urban air quality. For instance, Shi et al. (2019) used LCZ to analyze the spatial variation of PM 2.5 with land/use and landscape patterns in Hong Kong. In addition, there was a study on PM 2.5 collected with satellite images to understand air quality at a larger geographic scale (Wang et al. 2013). These studies demonstrate that LCZ can be used as an effective framework to characterize PM2.5 at the intra-urban level; however, there is a need to investigate air quality at a higher resolution.

Shi et al. (2019) investigates the spatial pattern of different land use types on intraurban air quality (PM 2.5) in Hong Kong. The LCZ scheme was also integrated into this study to analyze the landscape of a specific study site. With mobile measurements of PM 2.5 combined with land use/ landscape patterns, Shi et al. (2019) was able to clearly illustrate the spatial variation of PM 2.5 with its landscape pattern. Ahn et al. (2022) presents this study with diurnal patterns of PM concentrations (PM 2.5 and PM 10) and their cluster patterns related to the urban factors in Seoul, Korea. Results showed that higher concentrations of PM concentrations in urban areas without green spaces and that there were low PM concentrations in residential areas. Chen et al. (2022) contributes to the discussion by researching three-dimensional spatial distribution patterns of buildings and uses analysis of variance to prove that certain height indicators of buildings has a greater influence on land surface temperature. Results showed that all indicators of three-dimensional spatial distribution of buildings were factors that have prominent influence on the urban thermal environment. While these studies research the influence of a particular city's urban form on PM 2.5 and land surface temperature, it is important to bridge a connection between PM 2.5 and land surface temperature.

While many current studies research one particular urban environment that the LCZ framework and NLCD classifies, the proposed research compares PM2.5 and land surface temperature in the different LCZ classes. (Zhou et al. 2013, Jung et al. 2021, and Wang et al. 2019) have also included NLCD land cover types as another unit of comparison, but they all do not include the relationship between particulate matter, land surface temperature, and land cover. These studies include NLCD as a simple characteristic framework of the concentrations of vegetation, whereas this study compares LST and PM 2.5 measurements to classification frameworks of urban land cover and local climate zones together to analyze urban environments. Different LCZ classes can potentially model different urban environments all around the world, analyzing land surface temperature at any city. This research presents the spatial urban environments that are negatively impacting the natural ecosystem to employ analysis on improving the disposition of urban infrastructure.

In this study, clusters based on different concentrations of PM 2.5 will be identified using satellite imagery. Three approaches will be used to create this correlation: (1) Utilizing satellite imagery, such as MODIS and Landsat 8, to observe PM 2.5 levels and temperature values in LCZ classes; (2) Comparing NLCD land cover types and LCZ schemes to observe PM 2.5 and temperature values; (3) Analyzing the relationship between population density in San Francisco districts and PM 2.5/LST. Establishing a relationship between PM 2.5 and temperature can illustrate the detrimental impacts of high land surface temperature on human health–as exposure to severe air pollution can pose serious health risks to the population. Once a correlation can be established, global climate change can finally be seen as a threat and action can be taken by implementing green infrastructure where building densities are high.

METHODS

Local Climate Zone Classification

I generated a local climate zone classification map of San Francisco to identify.
which LCZ classes are covering the majority of San Francisco. I generated this map with WUDAPT (the world urban database), which is where a global 100 m spatial resolution local climate zone map can be generated from multiple earth observation datasets (Demuzere et al). Out of the 17 LCZ classes, ten reflect the 'built' environment and the rest of the 7 are 'natural' land cover classes. Google Earth was used to draw digital polygons over the LCZ areas to generate the LCZ map.

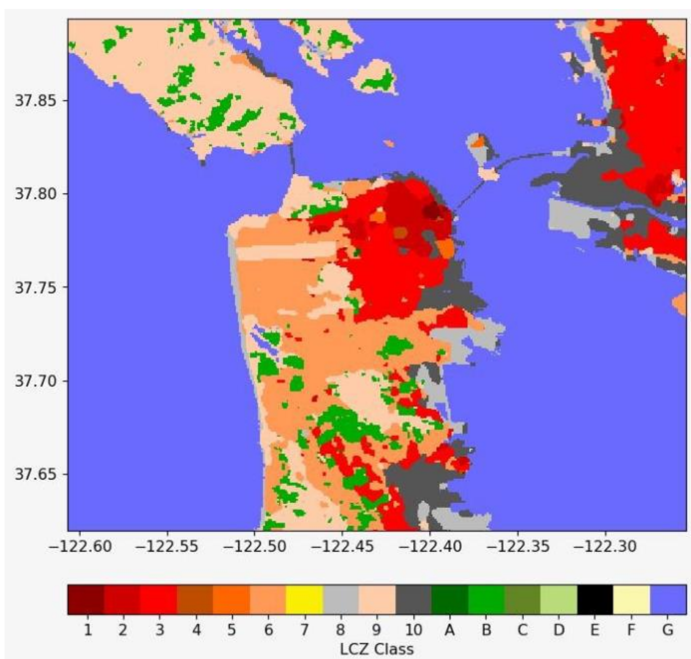


Figure 1. LCZ Classes 1-17

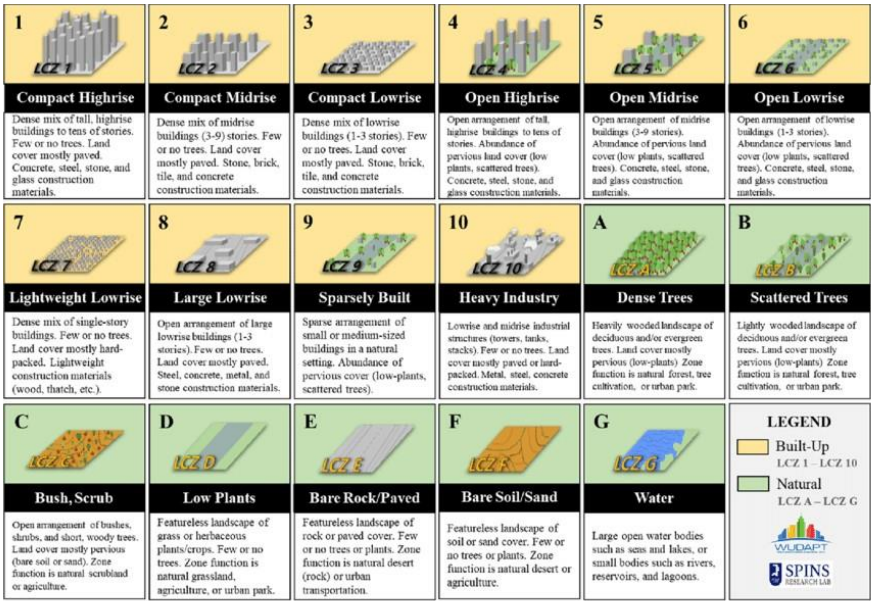


Figure 1a. LCZ Legend

Satellite-Derived Particulate Matter (PM 2.5) and Land Surface Temperature (LST)

Satellite imagery observations were collected from MODIS and Landsat 8 to observe PM 2.5 levels and temperature seasonally. The bands that were used were TIR 10 and TIR 11 bands by using the single-channel method to retrieve LST. I was able to map and calculate LST with (Rosado et al. 2020)'s method. The satellite images of LST were loaded into ArcGIS and then the radiance was calculated with thermal bands 10 and 11 by using the "raster calculator" with the following equations:

(1) $TOA (L) = M_L * Qcal + A_L$

Where:

• ML = Specific multiplicative scaling factor of each band. Value obtained from the MTL metadata file under the name of "RADIANCE_MULT_BAND_X".

• Qcal = Is the band or the cut of it.

• AL = Value included in the MTL metadata "Radiance_Add_Band_X", where X corresponds to the number of the band

(2) $BT = (K_2 / (\ln (K_1 / L) + 1)) - 273.15$

Where:

• K1 and K2 = Conversion constants, included in the metadata (K1_CONSTANT_BAND_x and K2_CONSTANT_BAND_x) apply to each band, 10 and 11.

• ln (natural logarithm) = Function in the raster calculator.

(3) NDVI = (Band 5 - Band 4) / (Band 5 + Band 4)

(4) Pv = Square ((NDVI - NDVImin) / (NDVImax - NDVImin))

Where:

• Square = Corresponds to squaring the formula

• NDVImax = Maximum values visible in the "table of contents"

• NDVImin = Minimum values visible in the "table of contents"

(5) e = m Pv + n (5)

Where:

• m = value of emissivity of vegetation, in this case 0.004 was used

• Pv = corresponds to the percentage of vegetation

• n = Soil emissivity value, in this case 0.986 was used

• Substituting remains:

• LSE = 0.004 * Pv + 0.986

(6) LST = BT / 1 + w (BT / p) * Ln (ε)

Where:

• BT = Brightness temperature (band 10 or 11 depending on the case)

• w = Length of the emitted radiation (band 10 or 11 as the case may be)

• p = Constant value obtained by the formula h * c / s that when substituting the values is 1.438 * 10^ -34Js and results in 14,380 and ε is LSE obtained previously, this equation should be applied in bands 10 and 11 separately for later unify the results with the tool (cell statistics)

For PM 2.5, monthly ground-level fine particulate matter is combined with Aerosol Optical Depth (AOD) retrievals from the MODIS instruments with the GEOS-Chem chemical transport model and is then calibrated to global ground-based observations using Geographically Weighted Regression (GWR) (Donkelaar et al. 2021). PM 2.5 datasets that were used in this study were provided by the ("Surface PM2.5 Atmospheric Composition Analysis Group | Washington University in St. Louis" 2021). Data collection results after data preprocessing can be seen in Figure 3 and 4. Optimized Hot Spot Analysis for PM 2.5 and LST was performed to find statistically significant hot and cold spots of PM 2.5 and LST.

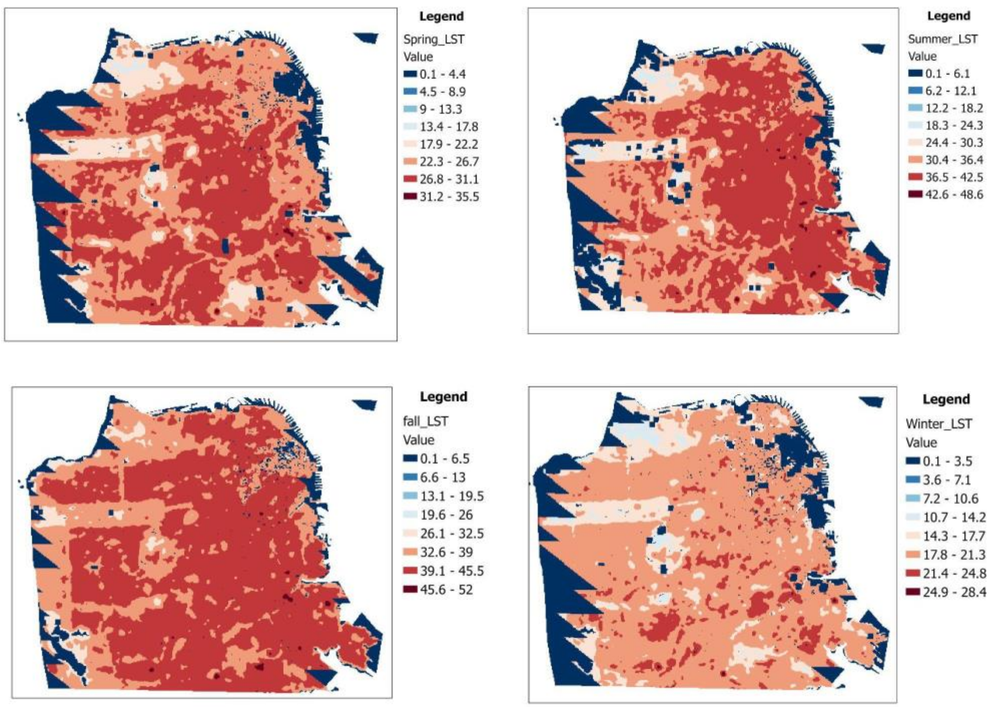


Figure 2a. LST maps across the four seasons

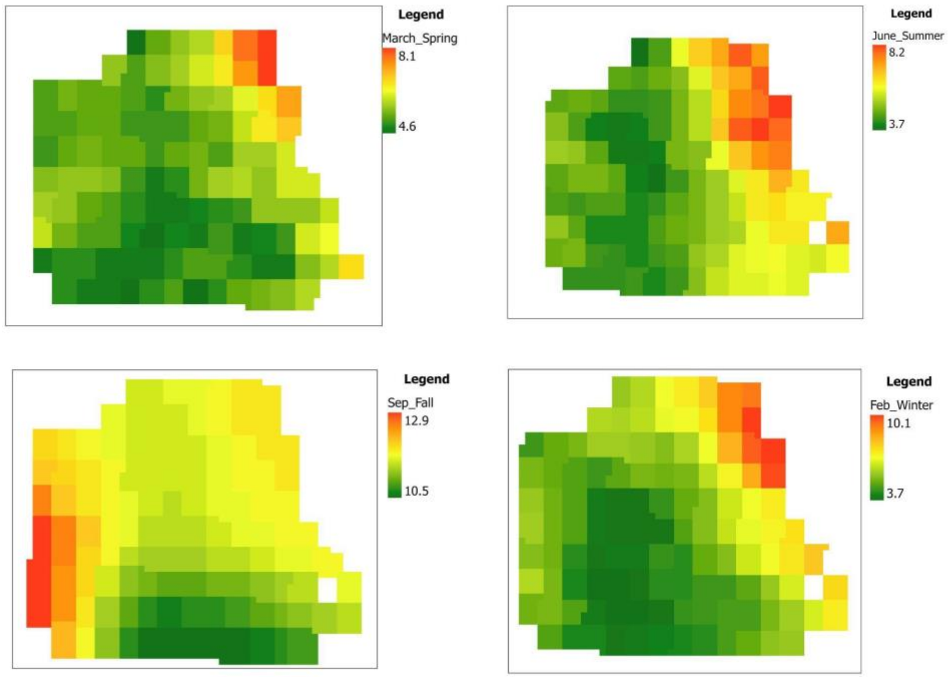


Figure 2b. PM 2.5 maps across the four seasons

National Land Cover Database (NLCD)

To establish a relationship with landcover and PM 2.5/LST, a NLCD map is generated for the LCZ areas for comparison to support the claim that developed, high intensity areas. In terms of developed, high intensity, NLCD defines this as highly developed areas where people reside or work in high numbers (Xian et al. 2009). There are classes within the developed classification, which I also analyzed. The NLCD dataset was collected from the USGS National Landcover Database. It was then resampled and reprojected for data preprocessing. Zonal statistics was used in ArcGIS Pro to determine the average values of PM 2.5 and LST within the NLCD developed areas.

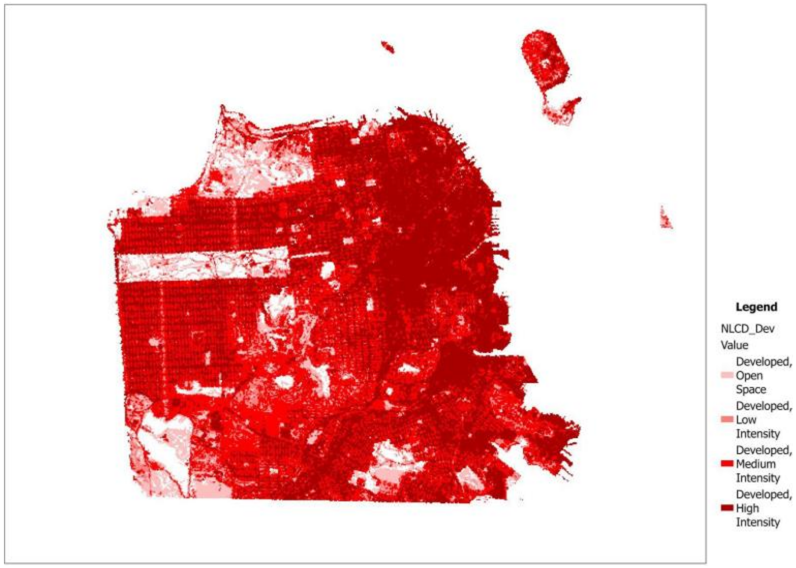


Figure 3. NLCD map of developed areas

San Francisco Districts and Population

San Francisco population numbers within districts was collected from the San Francisco Government database. I acquired the shapefile and loaded it into ArcGIS to perform zonal statistics to find the high average values of PM 2.5 and LST within each San Francisco District.

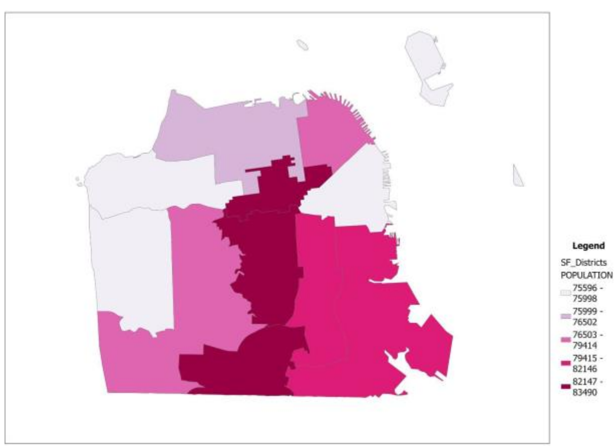


Figure 4. San Francisco Districts map with their corresponding population numbers

RESULTS

Optimized Hot Spot Analysis of PM 2.5 and LST

Satellite-derived PM 2.5 values and LST values are used in ArcGIS to perform an Optimized Hot Spot Analysis to establish statistically significant hot spots (high values) and cold spots (low values) in San Francisco. Throughout the seasons, a significant trend can evidently be seen in the east side of San Francisco for PM 2.5 and LST. Some of the corresponding neighborhoods include: Chinatown, Financial District, Civic Center, South of Market, Mission District, Potero Hill, and Bayview Hunters Point. In the LCZ classification scheme, these neighborhoods lie within LCZ classes 1-3 and 10. Bayview Hunters Point was classified as a heavy industrial site (LCZ 10). Therefore, a geographical significance can be deducted from the Optimized Hot Spot Analysis. Hot spots of PM 2.5 and LST correspond to compact building environments as well as heavy industrial environments. On the other hand, cold spots (low values) has a significant trend of appearing on the west side of San Francisco–with the exception of fall. On the west side of San Francisco, there is significantly greater square footages of parks and open areas. According to the LCZ classification scheme, LCZ 4-6 and high vegetations= sites lie within the majority of the west side of San Francisco. For example, Golden Gate Park, Presidio Park, Sunset District, Twin Peaks, and Parkside District. Residential areas would also emit less PM 2.5 and LST because of less activity and less crowded spaces. Parks, evidently, are cold spots because vegetation is known to cool the Earth and clean the atmosphere. Cold spots were also seen to lie in the middle of the SF to the southern parts. This is an important distinction because high and low concentrations of PM 2.5 and LST relate to a specific microclimate within San Francisco.

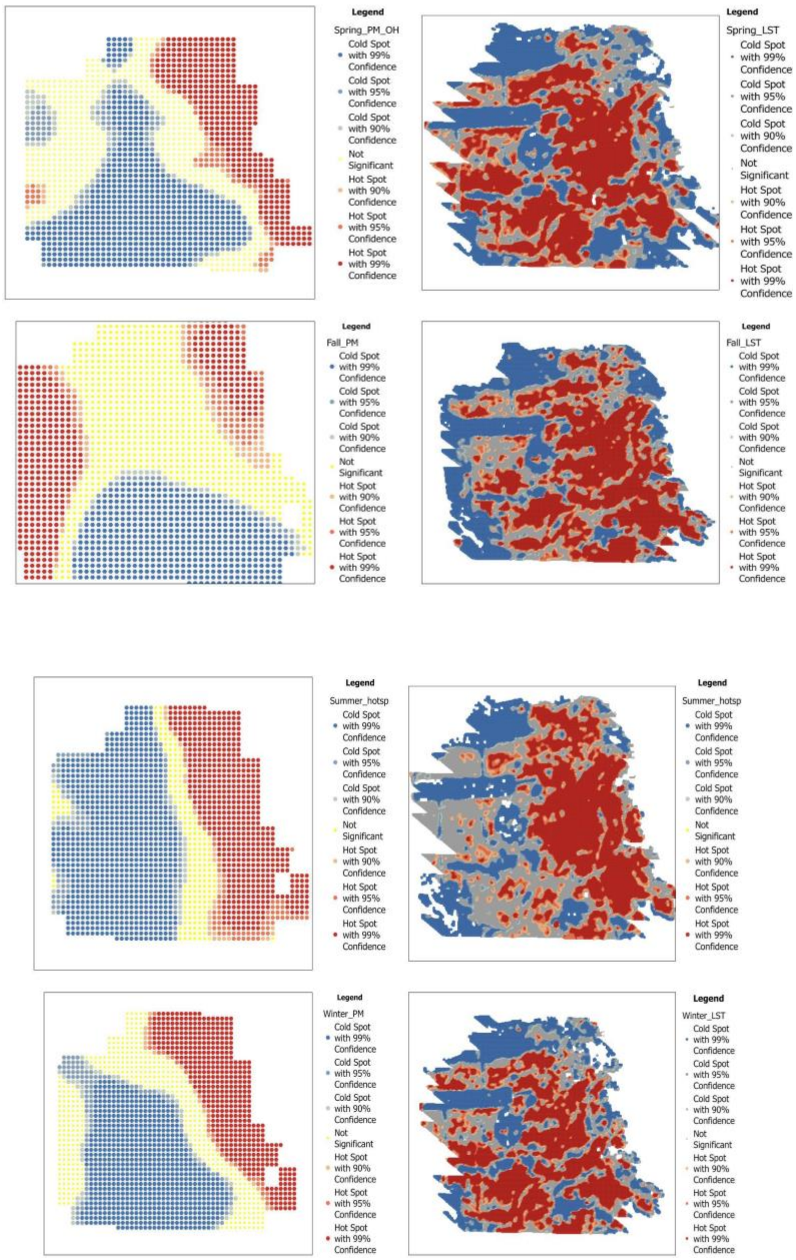


Figure 5. Optimized Hot Spot Analysis across the four seasons

Results of PM 2.5/LST and NLCD/LCZ Classes

With the results of Zonal statistics, Figure 8 shows the average cell values of PM 2.5/LST across all seasons that lie within the zones of NLCD and LCZ on the y-axis and LCZ/NLCD classes on the x-axis. There is a positive linear relationship between the variables for NLCD (line charts in red) because the intensity of developed areas increases on the x-axis. Therefore, high averages of PM 2.5/LST that fall within NLCD classes fall within the developed, high intensity zones. For LCZ's relationship with PM 2.5/LST, there is a negative linear relationship because the higher we go up in the LCZ scheme, we transition from urban building types to vegetated areas. High PM 2.5/LST values will decrease as we go further along the x-axis. To further support the central research question, we can see that majority of the high averages of PM 2.5/LST lie within LCZ classes 1-6.

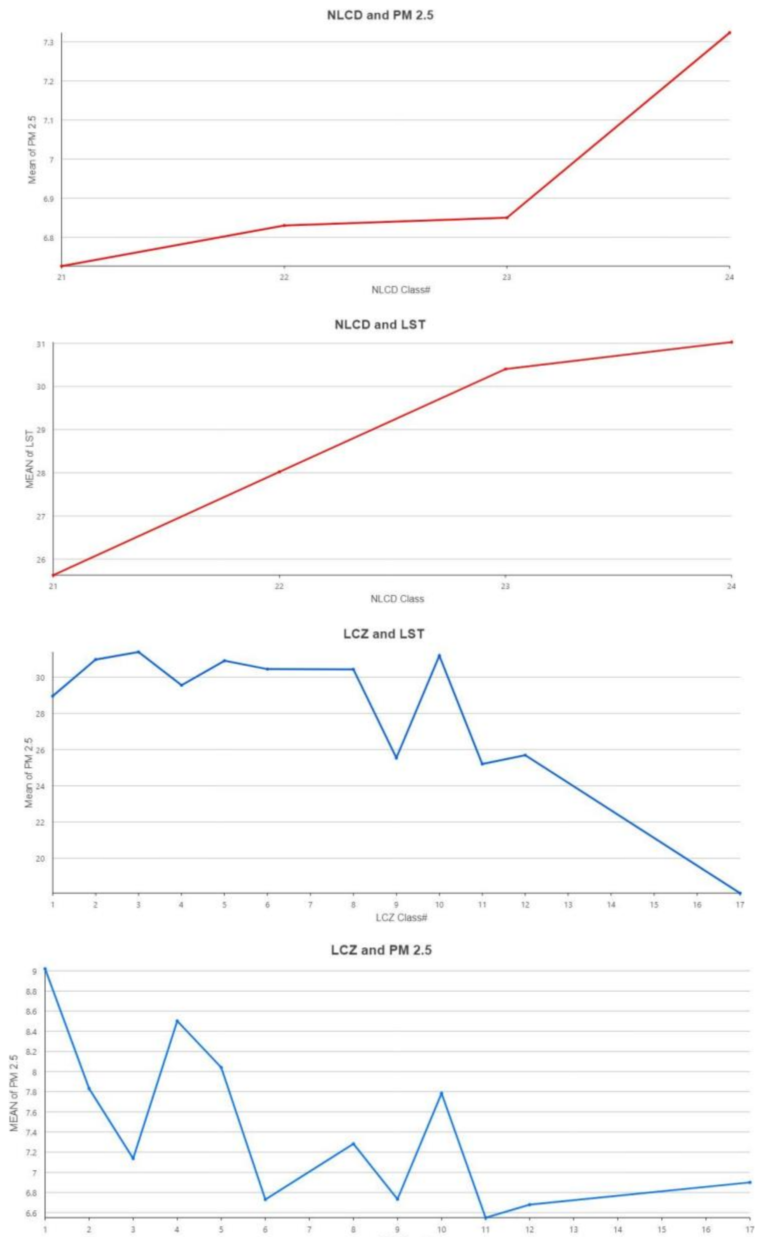
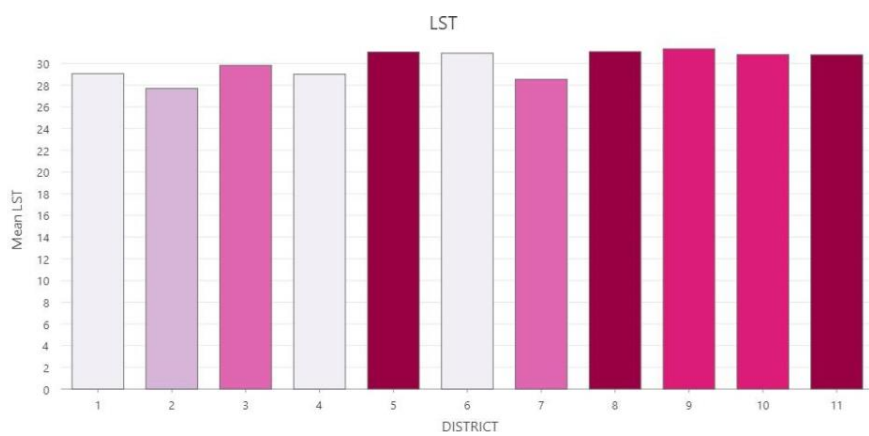


Figure 6. Line Plots from Zonal Statics

To establish a relationship with land cover and PM 2.5/LST, a National Land Cover Data (NLCD) map is generated for the LCZ areas for comparison to support the claim that developed high-intensity areas.

Results of PM 2.5/LST in Correlation with Population Numbers

The bar graphs show high averages of PM 2.5/LST in each district in San Francisco. Because there is not much differentiation of population numbers within each district, the bar graph results are relatively close when looking at PM 2.5/LST values. However, we can see which districts fall in the high spectrum of PM 2.5/LST values. For PM 2.5, districts 3 and 6 are clearly greater than the rest. This is due to the fact that districts 3 and 6 fall in the north east corner of San Francisco, where the hot spot of PM 2.5 is also located. This is also where Chinatown and Financial District are located. For LST, districts 5, 6 and 8-11 are greater compared to the other districts. These districts are also located in the east portion of San Francisco. With zonal statistics of population numbers and PM 2.5/LST, a relationship can be said when looking at the two variables.



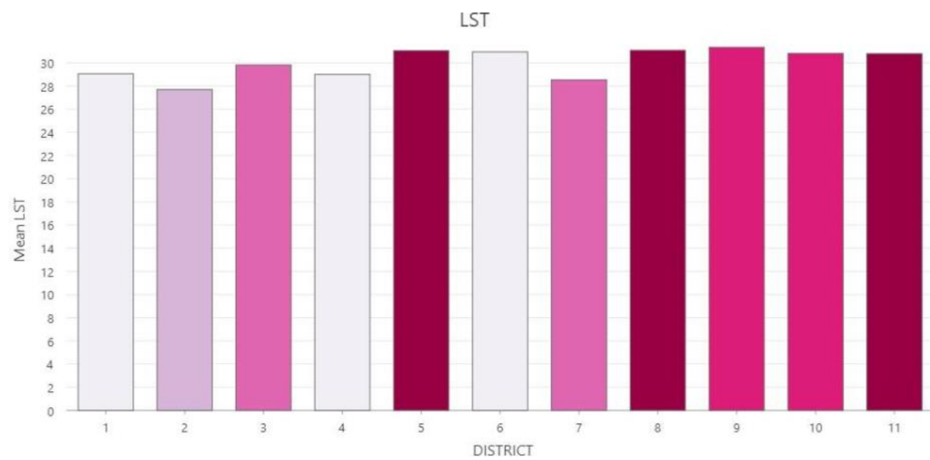


Figure 7. Bar graphs of each district's high average LST values

DISCUSSION

Analyzing the relationship between PM 2.5 and LST with Local Climate Zones and National Landcover Data will support the fact that cities are contributing to climate change and global warming. It draws awareness to how specific urban climates are affecting levels of PM 2.5 and land surface temperature. By classifying San Francisco into different LCZ and NLCD classes, we are able to identify areas that are the high emitters of particle pollution and temperature. A growing population within a city also contributes to PM 2.5/LST as well. With district population numbers, a relationship can be established between population growth and PM 2.5/LST. Highly densely populated areas can contribute to the urban activity classified in the NLCD scheme.

PM 2.5, LST, and Local Climate Zones

Results showed that San Francisco is approximately divided in the middle when it comes to the high and low value clusters of PM 2.5 across all seasons. The western portion of San Francisco is majority residential areas, where the cold spots are displayed. Sunset District, a neighbor hood covering most of the cold spot clusters, is the largest residential neighborhood in the city–covering an area of 5.709 mi². Lakeside, Richmond, and Presidio are also some of the residential areas within the low value PM 2.5 clusters. Most of the LCZ classes located there were also LCZ 6 (open low-rise), 9 (sparsely built), B (scattered trees), and G (water). According to Yang et al. (2022), low concentrations of PM 2.5 are in more open areas compared to compact, and there will always be less PM 2.5 in the natural categories. High PM 2.5 clusters were identified in the northeast to the east in the city. Neighborhoods in these areas were Financial District, Downtown, South of Market, Mission, Potero Hill, and Bayview. I hypothesized correctly that these are the districts with high concentrations of PM 2.5 because they fall in LCZ 1-3 (compact high-rise, compact mid-rise, compact low-rise) and 10 (heavy industrial). (Yang et al. 2022) had also found that LCZ 1, 2, and 10 possess high PM 2.5 across the seasons within a city. Other studies that compare PM 2.5 and the LCZ scheme will be different due to the fact that every city around the world is different. PM 2.5 in the LCZ scheme will vary based on how each city is classified. Fall and winter had the highest PM 2.5 concentrations while spring and summer had the lowest. Fall had high concentrations of PM 2.5 in the northeast and in the south to the southwest of the city. Cold spots were in the south. This could be due to the fact that there is an abundance of sea spray aerosol in coastal areas. Sea spray aerosol is when tiny particles from the ocean scatter into the atmosphere. Particles from the sea spray aerosol can stay in the atmosphere for a period of time if weather conditions are windy. Another reason could be the two wastewater discharge facilities along the Great Highway. Fall had also the highest PM 2.5 concentrations compared to the rest of the seasons. (Huang et al. 2018) had also discovered mirroring results in PM 2.5 across the seasons, mentioning that related studies have stated that coal combustion is the main reason for this seasonal disparity.

Findings for LST showed a consistent trend of high values in the eastern portion of San Francisco. Fall and summer had the highest LST values out of the seasons, while spring and winter had the lowest. The three significant hot spots that can be seen across the seasons is in the South of Market District, Mission District, Potero Hill, and Bayview District. The corresponding LCZ classes for those hot spots include: LCZ 1-3 and 10. This furthers supports my hypothesis that high LST correlates to the compact LCZ classes, as well as industrial sites. (Zhou et al. 2022) had also used local climate zones to understand how urban morphology effects land surface temperature in a study site. The study found that spatial distributions of seasonal LSTs were displayed in a circle-like pattern, showing a characteristic of “high, low, high.” City centers displayed high LST while low LST was in the fringe areas. My results had displayed something similar. Due to the fact my study area was bigger than (Zhou et al. 2022)’s, a circle-like pattern could not be seen with my

LST results. However, my hot-spot analysis identified hot urban cores, like (Zhou et al. 2022)'s study. LST studies, such as, (Zhou et al. 2022, Dutta et al. 2021, Middel et al. 2014, etc.) have found that heavily built areas contribute to the increasing LST temperatures in a given study area, whereas low-density built areas have lower LST values. This can be confirmed in my study as well.

NLCD, LCZ, and PM 2.5/LST

Findings exhibited high average values of PM 2.5 and LST in high intensity, developed areas from NLCD and LCZ 1-6. This proved my hypothesis that most of the high values PM 2.5 and LST were found in those particular NLCD and LCZ classes. To my knowledge, there has been limited studies comparing all of these four variables together. Most studies, like, (Shi et al. 2019, Ke et al. 2022, Geletic et al. 2016, etc.) has compared PM 2.5 and LST separately with LCZ or NLCD. My study connects all four variables to establish a spatial relationship between PM 2.5 and LST. Although other studies researched different relationships with the variables, a common conclusion from these findings is that highly developed and built areas will always mostly likely contribute to the dispersion of PM 2.5 and high values of LST, which is what I have found in my study. For example, (Zhou et al. 2013) had found that the percent of impervious surfaces was the best predictor of LST for the seasons. Another important pattern that was identified across all seasons was that majority of the PM 2.5 hotspots identified in the hot spot analysis was also where the LST hot spots were located. Therefore, addressing the spatial relationship between all of these variables positively contributes to the discussion that increasing urban development causes an increase in climate change and global warming.

San Francisco Districts and Population Numbers

District population numbers showed a significant relationship between PM 2.5/LST, but results between each district in San Francisco was not as strong as I predicted in terms of their differentiation. Nonetheless, a relationship could still be made between population density and PM 2.5/LST. There were still districts in San Francisco that still had higher PM 2.5/LST compared to other districts. For example, district 3 and 6 had the highest average PM 2.5 values, while the average LST values for all the districts were all relatively close. But a slight differentiation could still be made for districts 5, 6, 8, and 9. For PM 2.5, the districts with the highest average values did not have the highest population. For LST, the districts with the highest average LST values did include the districts with higher population numbers. This was a significant finding because even though an area has a higher population density, it doesn't necessarily mean that would affect PM 2.5/LST values. However, this also confirmed that a more developed area with high intensity levels has an impact on PM 2.5/LST. Urbanization could also be characterized by the level of activity that is being taken place in a given area, not necessarily population density.

Limitations and Future Directions

The study design of my research, I believe, has achieved the initial objectives and motivations for this research. My findings show there is a spatial correlation between PM 2.5/LST when being compared to LCZ and NLCD within San Francisco. Thus, discovering that specific landcover types and urban climates affect PM 2.5/LST. However, a possible limitation in my study could be that I only performed these analyses on San Francisco only. If this research framework was done on another city, evidently, the values of PM 2.5/LST would be different because the environment would also be different. A place with more trees in their landscape would potentially have cooler LST values. Therefore, the landscape of San Francisco cannot be applied globally. Another limitation could be that the PM 2.5 data used in this study was a lot courser than intended. Courser satellite data limits an area to a specific PM 2.5 value, which means the data is not that detailed compared to the LST data.

Given these limitations, I would include different cities with differentiating landscapes form one another to compare PM 2.5/LST across different environments. I believe this would make my research framework more inclusive of different types of urban landscapes. I would also attempt to find satellite-derived PM 2.5 at a higher resolution–that way data analysis would be more detailed for PM 2.5. My findings can be important information for environmentalists and planners, allowing for further research to be done on how we can use these types of data analysis as predictors of PM 2.5/LST globally.

From the perspective of environmentalists and planners, the theme of sustainable development has been a common theme throughout the field to solve climate change and global warming issues. Especially in metropolitan areas, where urbanization and development has been seen as a catalyst for environmental issues. With my research, findings clearly illustrate the impact that buildings and developed areas have on PM 2.5/LST. Future studies in this field would also exhibit the gravity of climate change and how that can negatively impact human health, as well as the environment around us. PM 2.5 showed a stronger correlation with population density compared to LST, which is significant in the sense that PM 2.5 is caused by emissions from oil, fuel, and gasoline in the atmosphere—all of which is from urban development and city activity. Returning to the central research question, can a correlation be made between PM 2.5 and LST when using local climate zones and national land cover data. Findings have addressed the CRQ and the following sub questions. With this research framework, environmental scientists and planners would be able to utilize the tools mentioned to further improve the sustainable development in urban areas.

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