HOTSPOT ANALYSIS AND COMPARISON BETWEEN SATELLITE-DERIVED AEROSOL OPTICAL DEPTH AND GROUND-BASED PARTICULATE MATTER MEASUREMENTS IN METRO MANILA

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ABSTRACT:

Highly urbanized regions such as the Metro Manila area in the Philippines contribute to the deterioration of air quality through overpopulation, excessive vehicle emissions, and industrialization. However, the limited number of ground monitoring stations hinders the detailed estimation of the region's overall air quality. Satellite-derived air pollutant concentrations have been used in several research studies as a substitute or supplementary to ground-based data due to their extensive spatial and temporal coverage. Using the aerosol optical depth (AOD) from the MODIS Multi-Angle Implementation of Atmospheric Correction (MAIAC) algorithm and ground measurements of coarse particulate matter (PM_{10}), this study explores the comparison between satellite-derived and ground-based air pollutant concentrations measured from 2017 to 2020 through trend analysis of monthly average values per city. With 16 stations located in different cities, the monthly average values of AOD vs PM_{10} showed inconsistent results due to significant gaps in the ground data. Through optimized hotspot analysis, it was found that 7.24% of the Metro Manila region are considered hotspots using the MAIAC AOD values from 2017 to 2019 (pre-pandemic). From 2018 to 2020 (pandemic), 23.86% of Metro Manila are counted as hotspots. The AOD derived from satellite imagery and hotspot analysis can be used for future studies that focus on the development of models to predict ground pollutant values and the designation of non-attainment areas.

1. INTRODUCTION

Pollution in the atmosphere is one of the biggest threats to public health in highly urbanized areas. The exponential growth of population, commercial and industrial endeavors, and traffic and vehicle emissions play significant roles in the increase of air pollutants such as carbon monoxide (CO), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), ozone (O_3), and fine particulate matter (PM) (Habibi, et al., 2017).

Air quality is typically measured using ground-based methods such as the use of air filters in established air quality monitoring stations at specific areas in the city that are made to keep track of some air pollutants such as PM, total suspended particles (TSP), NO_2, and SO_2 concentrations. However, these procedures have limited area of observation and do not capture the accurate condition of air quality within a city or a region. Earth-observing satellite systems and imaging sensors have been continuously improved and developed in recent years. This technology, together with image processing techniques, allows a new method of monitoring urban air quality in larger areas (Tulloch & Li, 2004). Another advantage of using satellite imagery in air quality monitoring is its capability to monitor several pollutants more consistently (Wald & Baleynaud, 1999).

PM is a measurement of air pollution created by natural means and human causes. It is described by atmospheric particles with a diameter equal to or less than 100 µm. More specifically, PM_{10} refers to particles with a diameter of less than 10 µm while $PM_{2.5}$ are particles with less than 2.5 µm in diameter (Kim et al., 2014). Moreover, these fine particles can be a possible cause of health problems as it travels in the atmosphere.

Aerosol Optical Depth (AOD) is one of the parameters relevant in monitoring air quality that can be extracted using remote sensing techniques. Li et al. (2019) defined AOD as the amount of incoming solar radiation that is scattered and absorbed by aerosols at a given wavelength. It is also the integrated extinction coefficient over a vertical column of unit cross section (Thi Van et al., 2018). AOD indicates how much sunlight reaches the surface of the planet; with its measurement relating to the amount of aerosol found in the vertical column of the atmosphere. Aerosols are then defined as fine particles found in the atmosphere that are heavily affected by meteorological variables and environmental factors (Li et al., 2017). According to the study of Goldberg et al. (2019), AOD measurements present the total atmospheric column content but not necessarily the equivalent concentration on the earth's surface. A book written by Tomasi et al. (2017) has also stated that aerosols affect the earth's climate through their radiative effect and interactions with the atmosphere.

The Moderate Resolution Imaging Spectroradiometer (MODIS) is an instrument attached in NASA's Terra and Aqua satellites which uses the sun as a natural source of illumination. This detects atmospheric aerosol thickness and other parameters over land and ocean (Remer et al., 2005). Using atmospheric aerosols

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and bidirectional reflectance, the Multi-Angle Implementation of Atmospheric Correction (MAIAC) algorithm is implemented to provide more accurate data. Goldberg, et al. (2019) used MAIAC AOD to estimate the daily $PM_{2.5}$ concentrations in the Eastern United States. The study, which includes the use of regression modeling, Weather Research and Forecasting Model (WRF)-Chem simulation output, and validation using the US Environmental Protection Agency (EPA) Air Quality System (APS) monitors, resulted in a highly accurate estimate ($r^2 = 0.75$ using 10-fold random cross-validation) of the daily $PM_{2.5}$ concentration across the study area. The R-squared statistic (r^2) measures how close the set of data is to a fitted regression line. Its value ranges from 0 to 1, wherein a value of 1 means that the regression predictions perfectly fit the data. MAIAC AOD was also used by Hu et al. (2013) for estimating $PM_{2.5}$ concentrations in the Southeastern region of the United States. A two-stage spatial statistical model utilizing meteorological variables and land use parameters was used to estimate $PM_{2.5}$. A coefficient of determination r^2 of 0.83 in model fitting and r^2 of 0.67 in cross-validation was calculated using the said methodology, which indicates a good correlation between satellite-derived AOD and $PM_{2.5}$. It was concluded by Hu et al. (2014) that MAIAC AOD can be used to estimate $PM_{2.5}$ concentrations. In a study conducted by Kloog et al. in 2015, MAIAC AOD data were used to estimate both $PM_{2.5}$ and PM_{10} daily concentrations in Israel. The three-stage model used in this research resulted in r^2 values of 0.79 and 0.72 for PM_{10} and $PM_{2.5}$, respectively, which are deemed as good fits. Dey et al. (2020) utilized the AOD measurements from the MODIS MAIAC algorithm as $PM_{2.5}$ ground measurements in India are scarce. The daily and annual satellite-derived AOD values were compared against the surface measurements available and resulted in an r^2 value of 0.8 and 0.97, respectively. Moreover, this study found that the annual $PM_{2.5}$ concentration and annual satellite-derived AOD were presenting similar spatial patterns (Dey et al., 2020). The seasonal anomaly and trends in $PM_{2.5}$ concentration were also observed, which can be a consideration for the future of this research as well.

Hot Spot analysis is often applied to location-dependent measurements to describe the spatial characteristics of the data. It is commonly used to detect clusters of data or measurements, in this case, pollutant concentrations, that are surrounded by high or low values of the same measurement and also determines whether these are statistically significant, or the clusters only follow a random distribution pattern. Related studies utilized the spatial statistics approach, one of which is hotspot analysis, to determine spatiotemporal patterns of particulate matter (Wei-Feng et al., 2018) and carbon monoxide and fine particulate matter (Habibi et al., 2017). The patterns are determined based on general and local indices of Moran's I and Getis-Ord Gi* statistics. Moran's I index enables the detection of spatial outliers while Getis-Ord Gi* identifies statistically significant clusters of high values called hotspots or low valuescoldspots. The calculation of the Moran's I and Getis-Ord Gi* values can be executed through GIS tools.

Optimized Hot Spot Analysis (OHSA) makes use of the Hot Spot Analysis Getis-Ord Gi* to determine the settings that will yield the most accurate results depending on the data input. OHSA aggregates the data points and turns them into weighted features. The distribution of these weighted features will be used to identify the most appropriate scale for analysis. (ESRI, 2017). The use of OHSA for different applications can be found on published articles and research. Lu et al. (2019) used OHSA on persistent scatterers and distributed scatterers for the detection of landslides, Zhuang et al. (2018) utilized OHSA for studying the species distribution of *Manglietia insignis* in China, and the use of OHSA in mapping land subsidence in Indonesia using Sentinel-1 SAR data was studied by Hakim et al. in 2021.

2. MATERIALS AND METHODS

2.1 Study Area

Metro Manila, also known as the National Capital Region (NCR) is the Philippines' political and economic center. This megacity is composed of four (4) districts divided into sixteen (16) cities and one (1) municipality with a total land area of around 619.57 km^2 (Chua, et al., 2021). According to the study by Bagtasa (2019), the region experiences two (2) seasons based on temperature and rainfall throughout the year: the wet season, lasting from May to October, and the dry season from November to April.

A study by Oliveros et al. (2018) showed that the urbanization of the region for 11 years from 2000 to 2010, affected the sensible heat flux, temperature, and rainfall in the region. Results from the study showed the occurrence of the urban heat island effect causing a significant minimum and maximum temperature difference in the region. The region's continuous urbanization, poor community planning, and an exponential increase in population over the years make it much more vulnerable to various environmental problems.

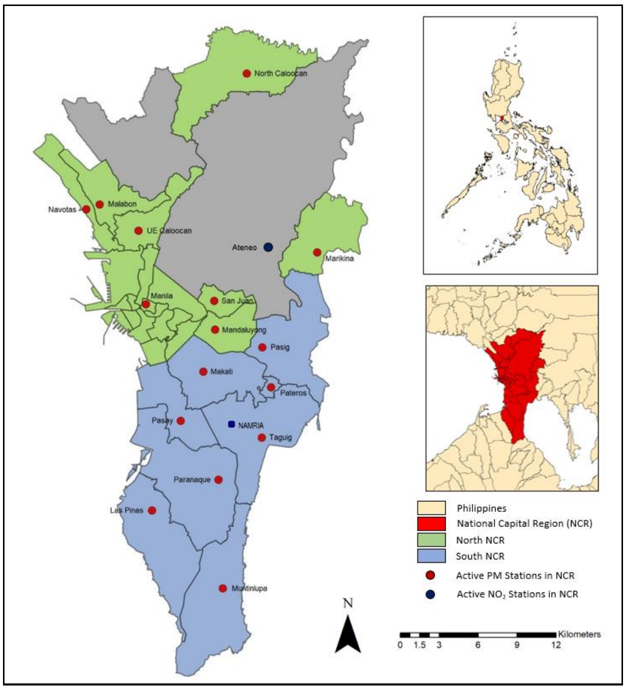

Figure 1. Study area showing NCR boundary along with the available ground monitoring stations provided by the DENR.

2.2 Methodological Framework

2.2.1 Data Acquisition

Google Earth Engine (GEE) is a cloud-based geospatial analysis platform for the analysis of satellite imagery. It provides students and researchers an efficient way of analyzing a large variety of data from its catalog. The platform uses either Python or Javascript to make requests to its servers. A JavaScript-based script was developed to download satellite data from GEE.

The MAIAC Land Aerosol Optical Depth (MCD19) provides users with the AOD values in a 1-km spatial resolution and a daily temporal resolution. There are two bands available for analysis namely: Optical_Depth_47 (Blue Band) and Optical_Depth_55 (Green Band). Related studies have used the green band over the blue band in processing methods due to its better consistency (Ranjan et al., 2020; Lyapustin and Wang, 2018). The satellite images are clipped to the NCR boundary and the period is set from 2017 to 2020. The monthly average of each green band pixel is calculated to generate the image showing the monthly AOD of NCR. Overall, a total of 48 images were acquired.

Available PM data from all sixteen (16) monitoring stations in NCR, together with the station's exact coordinates, were requested from the Department of Environment and Natural Resources Environmental Management Bureau (DENR-EMB).

2.2.2 Comparison between Satellite-Derived AOD and Ground-Based PM Measurements

Monthly average AOD maps from 2017 to 2020 were generated using QGIS, an open-source software that allows the user to visualize geospatial information. According to the MCD19 user guide provided by GEE, MAIAC AOD contains bands that represent the AOD computed from the blue and green bands based on the spectral properties of the regional aerosol model used in retrievals. A total of 48 images were compiled for visual inspection and comparison.

Given the coordinates of the Continuous Air Monitoring Stations (CAMS) in Metro Manila, the monthly spatial average values of PM10 in every station calculated, excluding all measurement entries with no data. This is compared to the satellite-derived monthly average AOD in each city. A similar trend between the two datasets would indicate that the satellite-derived measurements have a possible relationship with the ground-based data.

2.2.3 Hot Spot Analysis

Optimized hotspot analysis was performed in NCR, using the AOD derived from MODIS MAIAC. This process can determine which areas contain a relatively high AOD concentration value and which regions can be classified as significant clusters of interest. The analysis was done at the barangay level, which is the smallest administrative division in the country, as this would allow for a more accurate comparison with the stations given by DENR-EMB.

3. RESULTS AND DISCUSSION

3.1 Satellite-Derived AOD vs Ground-Based PM Data

Figure 2 presents the summary of monthly average maps of NCR from 2017 to 2020 using MODIS MAIAC AOD measurements with values ranging from 0 to 0.6. Greener areas show minimal AOD values while areas in red show higher AOD. For four years, it can be visually observed that the AOD in the whole region is relatively low from January to April, with values ranging from 0 to 0.2. There is an increase in value starting from May to October in the northern portions of NCR, particularly Quezon City, Valenzuela, Manila, Makati, Mandaluyong, Taguig, and Pasay, with the highest values occurring in August and September of 2018 and 2019. The AOD concentrations in these areas decrease again during December. However, cities from the southern part of NCR particularly Paranaque, Las Pinas and Muntinlupa show the same increasing and decreasing trend as mentioned for the other cities, with values remaining in a constantly low range of 0 to 0.4 throughout the year.

The trend of satellite-derived monthly average AOD values was compared to the acquired PM ground data measurements using the graph as shown in Figure 3. This figure shows that some of the graphs present a similar trend between the two compared datasets. Pasay City in 2017 had no PM data for the first months of the year; however, most of the remaining months show a similar trend to the AOD data. Ground-based and satellite-based data also have the same pattern for most of the months in Paranaque (2018) and Las Pinas City (2020).

Figure 4 exhibits the graphs which show different or opposing trends in some or most months in a city. Pasig City in 2017 experienced two (2) spikes in AOD concentrations during May and July although this does not occur in the PM data. The trend of increasing or decreasing values from one month to another can also be observed to be opposite from February onwards. The same observation is seen in Malabon and Paranaque in the years 2019 and 2020, respectively.

Figure 5 below shows the graphs wherein an observation cannot be made due to the lacking data from ground monitoring stations or the lack of monthly average data for a particular city due to excessive cloud cover. San Juan City, being the smallest city in the Philippines with an area of 5.95 km2, is very likely to be enveloped by clouds or other disturbances in satellite imagery. In 2018, this city only had six (6) months of recorded AOD data with only three (3) consecutive months to analyze the trend: thus, comparison cannot be evaluated. The same goes for the cities of Manila and Muntinlupa in the same year, however, the ground-based PM data for the whole year is not existent instead. Failure to capture data might be caused by a malfunction in the agency's monitoring stations.

3.2 Optimized Hotspot Analysis

3.2.1 Pre-Pandemic Analysis (2017 to 2019)

Using barangay-level analysis, areas are considered AOD hotspots once they are marked as a hotspot for three (3) consecutive years. This was executed by calculating the annual mean of the GI Z-Score and P-value with a requirement of greater than 90 percent confidence level (ESRI, 2017).

There are only 3 out of 16 cities where hotspot areas occurred. Most areas of interest are located in Quezon City and Manila, with a small part in Malabon. 65 barangays out of 897 in the whole NCR, 7.24 percent, are deemed to be hotspots before the pandemic started to spread in the Philippines.

3.2.2 Pandemic Analysis (2018 to 2020)

The COVID-19 pandemic has been a worldwide public health emergency and the use of satellite imagery has provided pictures of the air quality condition in cities since this event occurred. The AOD levels in Southeast Asia, Europe, and the USA amidst the COVID-19 pandemic have been observed by Acharya et al., (2020). It has been found that AOD was significantly reduced by 20% in most areas in the indicated regions while NO2 concentration was reduced by 20 to 40%.

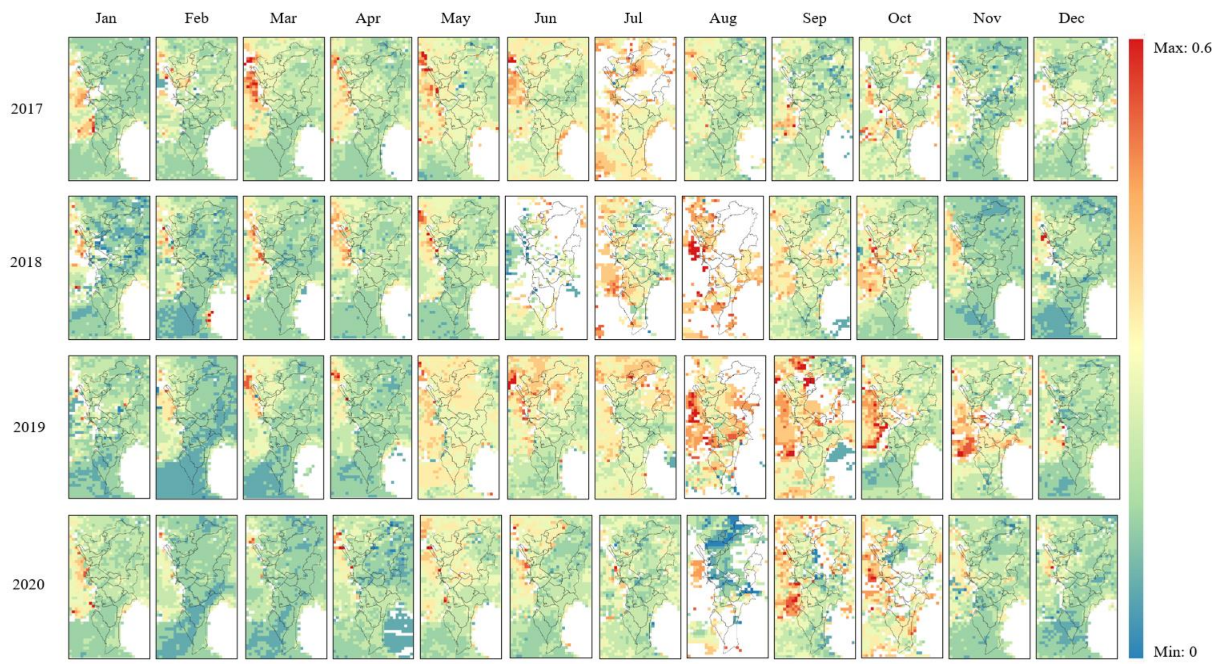

Figure 2. Study area showing NCR boundary along with the available ground monitoring stations provided by the DENR.

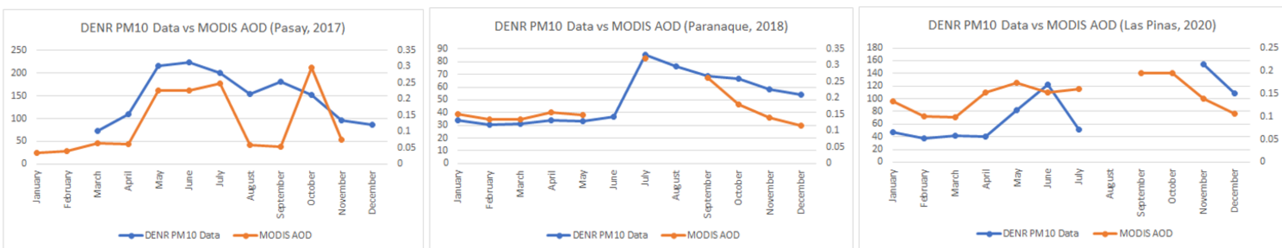

Figure 3. DENR PM10 Ground Data vs Barangay Spatial Average from MODIS AOD (Similar Trends)

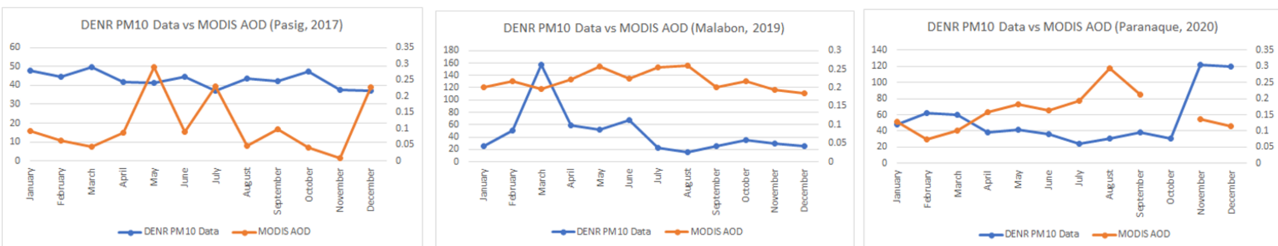

Figure 4. DENR PM10 Ground Data vs Barangay Spatial Average from MODIS AOD (Opposite Trends)

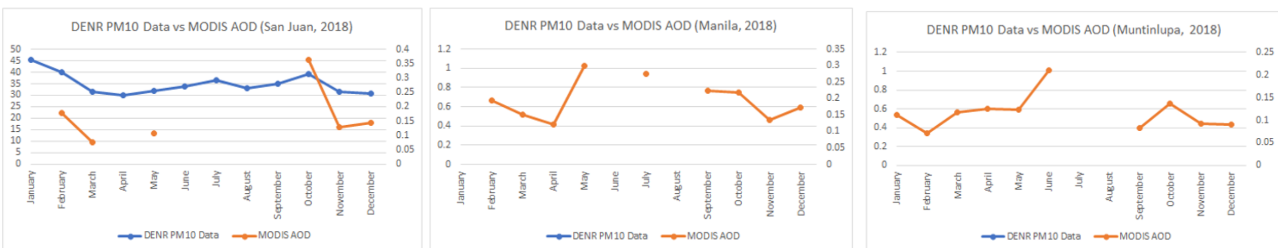

Figure 5. DENR PM10 Ground Data vs Barangay Spatial Average from MODIS AOD (Inconclusive Trends due to Data Gaps)

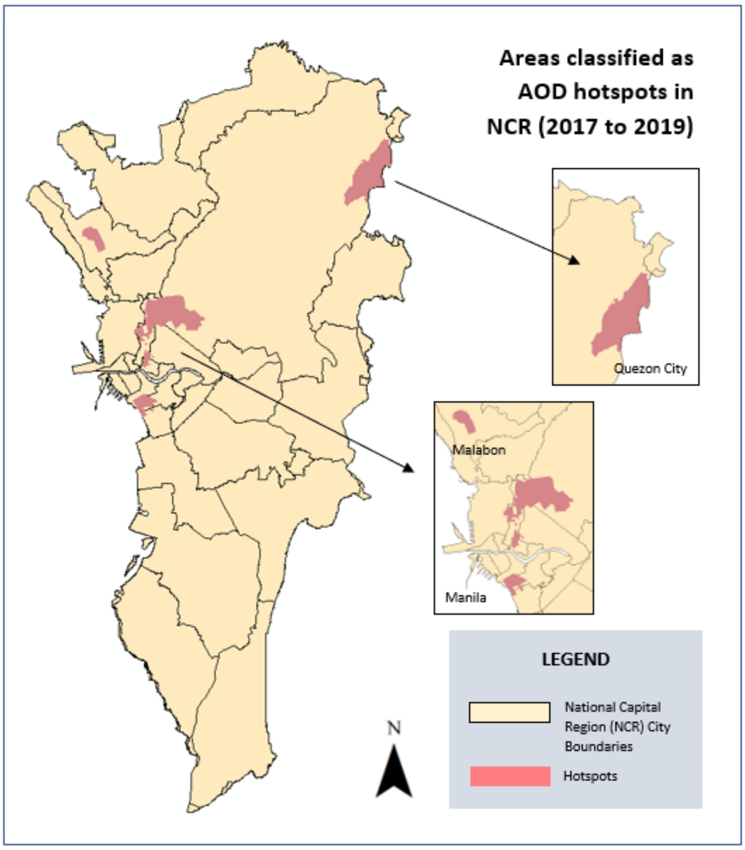

Figure 6. Map of the areas in NCR classified as hotspots over 3 years (2017 to 2019)

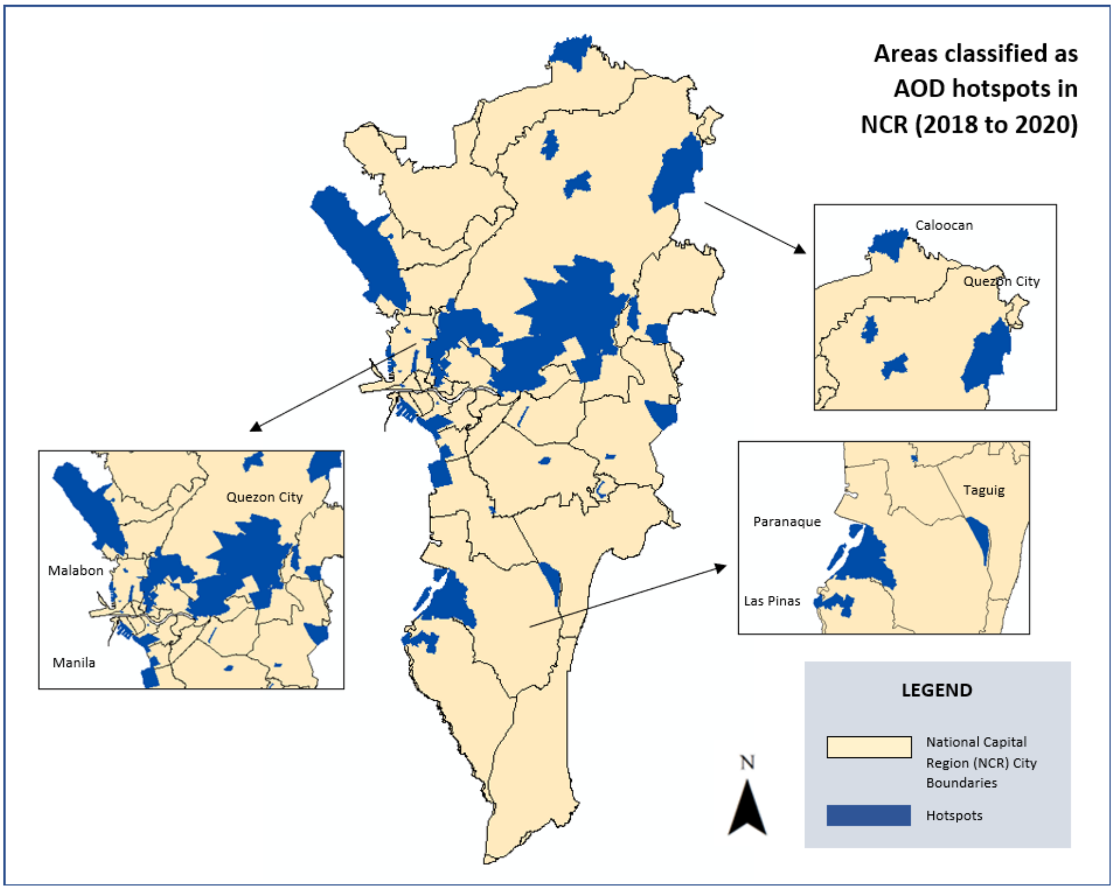

Figure 7. Map of the areas in NCR classified as hotspots over 3 years (2018 to 2020)

AOD values derived from the green band of the MODIS Terra and Aqua satellite and NO2 concentration from Sentinel-5P TROPOMI were also used in the study by Li et al. (2020) for the investigation of aerosol significance in determining the COVID-19 fatality rate in Germany, Italy, and Spain. By the start of 2020, this infectious disease has already made its way into the Philippines, affecting several Filipinos. Establishments and outdoor recreational activities were closed and going out for leisure is prohibited. Due to this, air quality is expected to show more improvement.

As seen in Figure 7, there are more areas considered hotspots compared to the map in Figure 6. Since this was derived from a 3-year period, several factors could have contributed to this result such as the unencoded data due to cloud covers or errors in the satellite images. In this period, 214 out of 897 barangays in NCR, equivalent to 23.86 percent, are considered hotspots in the years including 2020, the year COVID-19 occurred.

4. CONCLUSIONS

This study focused on the comparison between the satellite-derived AOD and the PM values measured from local monitoring stations. Graphs were created for each of the existing sixteen (16) stations in NCR for every year (2017 to 2020). Some graphs showed similar patterns, yet there are also graphs which presented opposite trends, specifically in the increase or decrease in pollutant values from one month to another. Due to the lack of ground measurement data, it was inevitable to have inconsistent results, thus, proper analysis cannot be given.

Moreover, optimized hotspot analysis was performed at the barangay level to determine the areas which have relatively high AOD values during a 3-year period. Two sets were analyzed: pre-pandemic (2017 to 2019) and pandemic (2018 to 2020). For the pre-pandemic years, 7.24 percent or 65 out of 897 barangays were labelled as hotspots while the analysis which included year 2020 resulted to 23.86 percent or 214 out of 897 barangays as hotspots. Since the satellite-derived AOD measurements does not entirely represent the situation on the earth's surface, thus may have caused the theoretically inaccurate and unexpected increase in number of hostpots between the two study periods.

Future works can consider filling the gaps in the data from air monitoring ground stations which can be accomplished using appropriate mathematical models. This procedure can significantly help the validation of the satellite-derived measurements. The relationship between AOD and PM can also be evaluated better using models. Linear and multiple regression methods are commonly used in studies for estimating PM_{10} concentrations from AOD values (Liu et al., 2005; Gupta & Christopher, 2009; Gupta et al., 2006). Other publications have also explored the use of more complex mathematical models such as artificial neural networks to achieve better and more accurate results (Zhang et al., 2019). The process of determining the PM concentration on the ground through the use of satellite imagery is a great way to accurately picture the air quality in a specific location. With this. proper community planning and awareness follow.

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