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Regression analysis of satellite-derived fire spots and $PM_{2.5}$ levels with respiratory cases in the Philippines

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ABSTRACT

Background and Objectives: Fire events emit pollutants that affect both air quality and respiratory health. This paper analyzed the interrelationship of satellite-derived fire spot density and annual average particulate matter ($PM_{2.5}$) concentrations with the incidence of respiratory diseases.

Methodology: Monthly cases of influenza-like illness (ILI) and pertussis for 2017-2018 in all 17 regions of the Philippines were accessed from the Department of Health (DOH) Epidemiology Bureau. Reported cases per 100,000 population in the Philippines were linked with regional fire spot density and annual mean $PM_{2.5}$ estimates from satellite data, Visible Infrared Imaging Radiometer Suite (VIIRS) active fire data, and Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2), respectively. Linear, logistic, and Poisson models were used to analyze the association between the exposure and outcome variables.

Results and Discussion: The highest $PM_{2.5}$ concentrations were observed in Regions IV-A and NCR but fire spot density was relatively lower. High $PM_{2.5}$ levels can be due to other sources in these largely urbanized regions, such as vehicular emission, among others. Similarly, results showed inconclusive association between atmospheric parameters and incidence of ILI and pertussis. Among the variables, pertussis and $PM_{2.5}$ may have the strongest association, albeit p>0.05. Other factors contributing to the increase of disease counts may be explored including vaccine rates and case reporting.

Conclusion: There is insufficient evidence to show that fire events and higher $PM_{2.5}$ levels at a regional scale increased the risk for ILI and pertussis in 2017-2018. Further studies may be explored on how satellite-derived atmospheric data can be utilized in respiratory health studies.

Keywords: *VIIRS fire spots, MERRA-2 $PM_{2.5}$, influenza-like illness, pertussis*

Introduction

In the Philippines, respiratory illnesses remained in the top leading causes of morbidity with acute respiratory infection as the leading cause since 2008 as soon as it was included in the list of notifiable diseases. Other respiratory cases listed in the top ten by the Department of Health (DOH) include acute lower respiratory tract infections, pneumonia, bronchitis, tuberculosis, and influenza [1-3]. Including various causes, respiratory morbidity is affected by poor air quality from geogenic and anthropogenic hazards.

The slash and burn (*kaingin*) system is common in the Philippines to prepare land for farming. Crop residues are also burned post-harvest. Active fire such as open-field agricultural burning, forest fires, as well as non-biomass burning emit aerosols, such as fine particulate matter ($PM_{2.5}$) that impacts air quality and respiratory health alike [4-7]. Human exposure to particulates ≤ 2.5 µm in aerodynamic diameter is given prime attention because it can penetrate up to the lower respiratory tract. Its impact on health has been directly attributed to its size fraction. Moreover, $PM_{2.5}$ has diverse chemical constituents including elemental and organic carbon, metals, nitrates, sulfates, and organic and biological compounds [8]. A study by Cohen *et al.* (2017) linked approximately 4.2 million deaths globally to $PM_{2.5}$ exposure. This work by Cohen *et al.*

along with other studies utilized estimated ambient or ground-level $PM_{2.5}$ concentrations from secondary sources including satellite data [7,9-13]. But satellite-derived information is not widely employed in health studies in the Philippines. Taking advantage of available data sources will help in the conduct of studies with coarse spatiotemporal scales.

Satellite-derived parameters: $PM_{2.5}$ and fire spots

Since the existing 42 continuous ambient air quality monitoring stations (CAAQMS) for $PM_{2.5}$ measurements in the Philippines are too sparse to cover the entire archipelago, estimates from satellite data augment the need for country-wide $PM_{2.5}$ mass concentrations. The latest of the U.S. National Aeronautics and Space Administration (NASA) aerosol reanalysis products, Modern-Era Retrospective Analysis and Research and Application, version 2 (MERRA-2), provides ground-level $PM_{2.5}$ mass concentration integrated from observations and models in various ground- and space-based remotely sensed measurements. The MERRA-2 update assimilates aerosol optical depth which involves careful cloud screening and the use of a neural net scheme to homogenize observed data from various satellite sensors. The MERRA-2 $PM_{2.5}$ estimates generally compare well with observed data because of these data assimilation systems [14].

Satellite data is also useful to monitor fire occurrences at a large scale. The Visible Infrared Imaging Radiometer Suite (VIIRS) sensor aboard the Suomi-National Polar-orbiting Partnership (S-NPP) satellite of the U.S. National Oceanic and Atmospheric Administration (NOAA) and NASA detects both day and nighttime biomass burning and other thermal anomalies up to a 375-m resolution. Fire spots are detected through an algorithm driven by five distinct channels ranging from the visible to the thermal infrared spectral region to discriminate active fires from their fire-free background. For example, the visible, near-infrared, and shortwave infrared regions distinguish clouds, sun glints, and water bodies from the fire spots [15]. The VIIRS 375 m active fire data has higher spatial resolution compared to other Fire Information for Resource Management System (FIRMS) active fire products—VIIRS 750 m and the Moderate Resolution Imaging Spectroradiometer (MODIS) (1-km pixels). Detection of smaller fires is improved which provides a more reliable estimate of fire perimeters. Further, it is better calibrated to detect fires at night [16].

Respiratory illnesses: Influenza-like Illness, Pertussis

The incidence of acute respiratory infections influenza-like illness (ILI) and pertussis was used as proxy data in this study to account for respiratory health.

Influenza-like illness is defined by the World Health Organization (WHO) as an acute respiratory infection with a measured fever of ≥ 38 C° and cough with onset within the last 10 days [17]. This surveillance case definition for ILI has been identified as part of the WHO global influenza surveillance standards. The Philippine Department of Health lists ILI under epidemic-prone diseases [18]. Several studies have also studied ILI with the Coronavirus disease (COVID-19) pandemic [19,20].

Pertussis is a respiratory tract infection caused by the bacterium *Bordetella pertussis* that is easily spread from person to person through droplets when coughing or sneezing. Many children with pertussis or whooping cough experience coughing spells lasting up to 4 – 8 weeks [21]. Pertussis complications may result in pneumonia which is one of the leading morbidity causes in the Philippines. It is a vaccine-preventable disease through the three doses of the diphtheria-tetanus-pertussis (DTP3) vaccine given to infants. The number of reported pertussis cases in the country increased from 88 to 339 in 2017 to 2018, respectively, as the DTP3 immunization coverage declined from 88% to 65% in the Philippines for 2017-2018 [22].

This study analyzed the association between $PM_{2.5}$ and fire spots using the two-year satellite-derived regional data from 2017 to 2018. The study also evaluated the impact of air quality on respiratory health among the 17 regions of the Philippines from 2017 to 2018 using the relationship between (1) Influenza-like illness (ILI) against $PM_{2.5}$ concentration and against fire spot density and (2) pertussis against each of the aforementioned atmospheric parameters.

Methodology

Data Sources

The study utilized secondary respiratory and atmospheric data available from government web sources. Completeness of data for respiratory cases is a significant factor in the identification of the illnesses employed in the study.

Regional respiratory health data was collected from disease surveillance reports by the Public Health Surveillance Division of the Philippine DOH Epidemiology Bureau at www.doh.gov.ph/statistics for 2017-2018. The respiratory diseases used in this study with existing data for all regions were influenza-like illness and pertussis. The total number of cases for each particular year was divided by the regional population. The incidence rate was multiplied by 100,000 to obtain crude rates across the 17 regions.

The surface $PM_{2.5}$ mass concentration (µg/m³) used in the study was retrieved from the Modern-Era Retrospective analysis for Research and Applications, version 2 (MERRA-2) aerosol reanalysis products released by the NASA Goddard Earth Sciences Data and Information Services Center (https://disc.gsfc.nasa.gov/datasets?keywords=merra-2&page=1). The MERRA-2 data is an assimilation of multiple sources including model simulation, satellite data, and ground observations. The spatial resolution is 0.5° latitude by 0.625° longitude. The MERRA-2 surface $PM_{2.5}$ accounts for the cumulative surface mass concentrations of five components: sulfate (SO_4), organic carbon (OC), black carbon (BC), dust (DS), and sea salt particles (SS) [14,23]. The annual mean mass concentration for MERRA-2 $PM_{2.5}$ per region in the Philippines was used in the analysis of the atmospheric and respiratory health variables.

The fire spot data for 2017-2018 in the Philippines was obtained from the Visible Infrared Imaging Radiometer Suite (VIIRS) 375 m active fire data, the latest monitoring product of the Fire Information for Resource Management System (FIRMS) (https://firms.modaps.eosdis.nasa.gov/active_fire/). Fire locations were identified near-real time. Information collected from the VIIRS sensor was processed with a fire detection algorithm to flag active fires. Each dot on the map represented the center of a 375-meter pixel. Its temporal frequency covered the entire globe every 12 hours. Mid-latitudes, including the Philippines, experience 3-4 looks a day due to the ~15% image overlap of the VIIRS swath [16]. Active fire counts per regional land area were used for fire spot density (counts/km²) in the analysis.

Data Analysis

Data analysis involved linear regression for the following variable combinations: (1) $PM_{2.5}$ concentration and fire spot density; (2) ILI and $PM_{2.5}$ concentration; (3) ILI and fire spot density; (4) pertussis and $PM_{2.5}$ concentration; and (5) pertussis and fire spot density. The linear relationship between each combination was quantified via the coefficient of determination, R^2. The p-value was also determined to test whether fire spot density increases with $PM_{2.5}$ estimates and if disease incidence increases with the density and mass concentration of the air quality variables.

Additionally, logistic regression and Poisson regression models have been included for the analysis of the association between the incidence of diseases with $PM_{2.5}$ levels and fire spot density. The logistic model provides the probability of having ILI/pertussis over the probability of not having the disease. It is expressed by Equation 1, where X_1 represents the annual $PM_{2.5}$ levels/fire spot density, β_0 is the intercept, and β1 is the change with each unit increase of X_1. While the Poisson model, expressed by Equation 2, provides the count of the disease at a fixed monitoring time.

$$ln\left(\frac{case}{population - case}\right) = \beta_0 + \beta_1 X_1 \qquad \text{Equation 1}$$

$$\ln(\text{case}) = \beta_0 + \beta_1 X_1 \qquad \text{Equation 2}$$

Results

Air quality and respiratory health data for the 17 regions in the Philippines in 2017 and 2018 were analyzed. The association between the satellite-derived parameters and respiratory illness crude rates is presented in this section via the following datasets, each for 2017 and 2018: (3.1) annual $PM_{2.5}$ concentration versus fire spot density; (3.2) ILI versus $PM_{2.5}$ concentration and ILI versus fire spot density; and (3.3) pertussis versus $PM_{2.5}$ concentration and pertussis versus fire spot density.

Annual $PM_{2.5}$ Concentration versus Fire Spot Density in 2017-2018

As shown in Figure 1, Regions IV-A and NCR had the highest annual average of $PM_{2.5}$ mass concentrations among all regions in 2017-2018. On the other hand, a relatively low fire spot count per square kilometer was recorded for the two regions. Regions III, IV-B, and CAR, with the highest fire spot density among the regions, had relatively moderate $PM_{2.5}$ concentrations. The annual $PM_{2.5}$ mean mass concentration of the 17 regions ranged from 4.87 to 26.88 µg/m³ while the fire spot density ranged from 0.01 to 0.13 counts/km². Fire spot density in Region XII increased the most among the regions from 0.026 counts/km² in 2017 to 0.079 counts/km² in 2018 but the annual $PM_{2.5}$ levels did not change significantly (5.475 µg/m³ to 5.433 µg/m³) within the succeeding year. The same can be observed for Regions II, X, and CARAGA where the fire spot density increased the most (2nd to 4th) but in $PM_{2.5}$ estimates declined from 2017 to 2018. For the rest of the regions, the $PM_{2.5}$ levels increased in 2017-2018 the highest of which was in Regions I, IV-B, and NCR with 1.074 to 1.571 µg/m³. As seen in Figure 1, the trendline for 2017 and 2018 does not show a positive correlation. R^2 values for the dataset in 2017 and 2018 are 0.0478 and 0.0014, respectively, with p-values 0.399 and 0.888 showing inconclusive association between fire spot density and annual $PM_{2.5}$ mass concentration (Table 1).

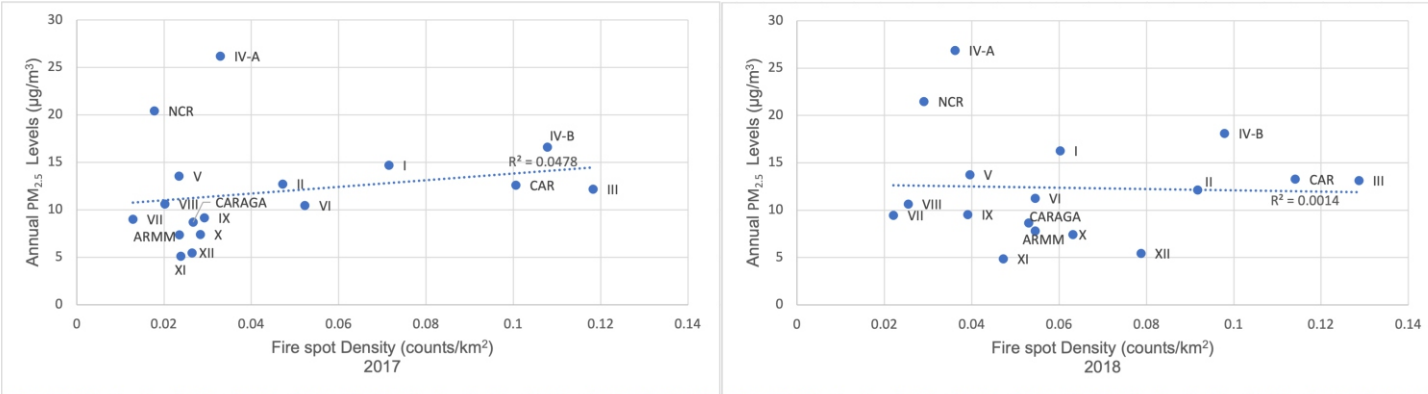

Figure 1. *Average annual $PM_{2.5}$ levels versus fire spot density in 2017-2018 for 17 regions of the Philippines.*

Table 1. *Summary Association between Fire Spot Density and Annual $PM_{2.5}$ Levels in the Philippines*

Year	R^2	p-value	Coefficients		Remarks
			Intercept	X Variable 1	
2017	0.0478	0.399	10.328	34.993	Inconclusive association between annual $PM_{2.5}$ levels and fire spot density
2018	0.0014	0.888	12.774	-6.810	Inconclusive association between annual $PM_{2.5}$ levels and fire spot density (very weak negative association)

ILI versus $PM_{2.5}$ Concentration and ILI versus Fire Spot Density

The number of regional ILI cases in the Philippines ranged from 1.09 to 997.95 cases per 100,000 in 2017 and 1.11 to 1114.92 cases per 100,000 in 2018. For both years, CARAGA and CAR had the highest ILI incidence but their annual $PM_{2.5}$ mean mass concentrations were relatively low compared to the other regions ($PM_{2.5}$ levels for CARAGA: 8.66 µg/m³ and 8.70 µg/m³ in 2017 and 2018; CAR: 13.26 µg/m³ and 12.59 µg/m³) as shown in Figure 2. Region IV-A and NCR with the highest $PM_{2.5}$ levels have relatively low ILI cases. The R^2 values between ILI cases and $PM_{2.5}$ levels in 2017 and 2018 were low at 0.0474 and 0.0312, respectively. The p-values of 0.401 and 0.497 in Table 2 do not reveal a conclusive association between the incidence of ILI and $PM_{2.5}$ levels. In addition, the probability of having ILI may not be directly affected by the increase or decrease of $PM_{2.5}$ concentration for both 2017 and 2018 (p=0.564 and p=0.599 in Table 3). Similarly, determining the counts for ILI cases at a fixed monitoring time may not also be attributed to the change in $PM_{2.5}$ levels (p=0.922 and p=0.971 in Table 4).

Region III had the highest fire spot density (0.12 counts/km² in 2017 and 0.13 counts/km² in 2018) with 43.57 and 35.08 ILI cases per 100,000 reported in 2017 and 2018, respectively. This is low compared to the highest ILI incidence in 2017-2018 in CARAGA and CAR with 1114.92 to 997.95 and 569.66 to 480.58 cases per 100,000 from 2017 to 2018. As shown in Figure 3, there is no substantial trend and the R^2 values were low even in comparison to the $PM_{2.5}$ dataset (0.0028 for 2017 and 0.0174 for 2018). Similar to the association between ILI cases and $PM_{2.5}$ concentrations, the association of ILI cases per 100,000 and fire spot density in 2017-2018 was also inconclusive. The p-values as seen in Table 2 are 0.840 for the 2017 dataset and 0.641 for 2018. The p-values for 2017 are less significant, as similarly observed for the p-values for the logistic and Poisson models in Table 5 and Table 6, respectively.

Pertussis versus $PM_{2.5}$ Concentration and Pertussis versus Fire Spot Density

The number of pertussis cases per 100,000 population ranged from 0.03 to 0.77 and 0.03 to 2.04 in 2017 and 2018, respectively. Region XI had the highest incidence of pertussis in 2017 while CAR had the highest incidence in 2018. From 0.22 in 2017, the pertussis cases per 100,000 population in CAR increased to 2.04 in 2018. The R^2 between pertussis and $PM_{2.5}$ concentration in 2017 was higher at 0.088 versus 2018 at 0.001. The pertussis incidence for Regions IV-A and NCR, which has the highest annual mean $PM_{2.5}$ concentrations, dropped in 2018. These two regions were among those with the highest pertussis cases per 100,000 in 2017 along with Regions XI and II. The p-value for the association of pertussis and $PM_{2.5}$ was

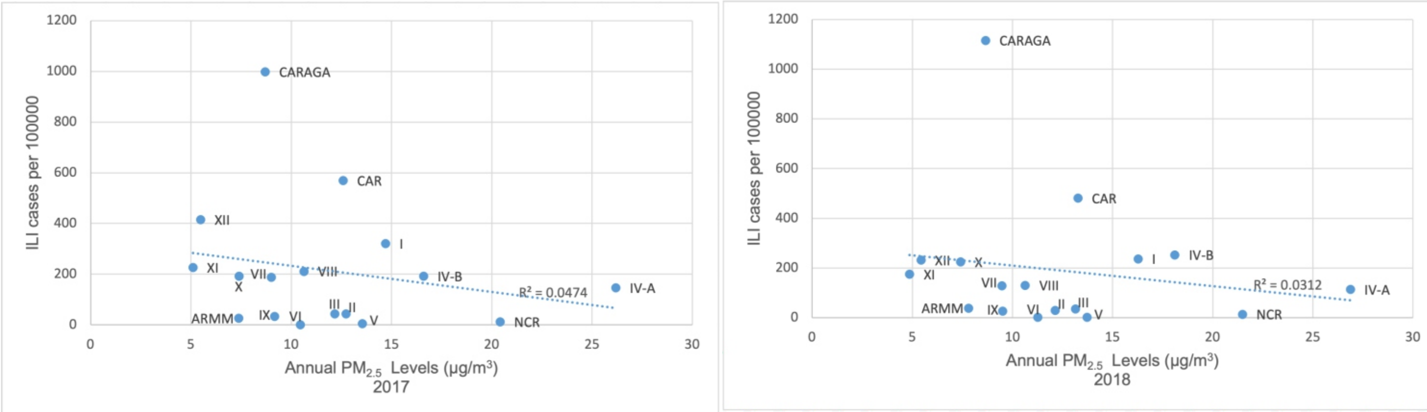

Figure 2. *Influenza-like illness cases per 100,000 versus annual $PM_{2.5}$ levels in 2017-2018*

Table 2. *Summary Association between Influenza-like illness against Annual $PM_{2.5}$ Levels and against Fire Spot Density in the Philippines*

Year	R^2	p-value	Coefficients		Remarks
			Intercept	X Variable 1	
ILI vs. $PM_{2.5}$ concentration					
2017	0.0474	0.401	336.127	-10.334	Inconclusive association between ILI and annual $PM_{2.5}$ levels
2018	0.0312	0.497	292.650	-8.289	
ILI vs. Fire Spot Density					
2017	0.0028	0.840	195.098	403.122	Inconclusive association between ILI and fire spot density
2018	0.0174	0.641	121.164	1133.834	

Table 3. *Logistic Model Results on the Probability of the Case of ILI in Regions vs. $PM_{2.5}$ for 2017-2018*

Logistic Model	Coefficients	Standard Error	t Stat	p-value	Lower 95%	Upper 95%
2017						
Intercept	-6.499	1.109	-5.859	3.14E-05	-8.863	-4.135
X Variable 1	**-0.050**	0.085	-0.589	**0.564**	-0.232	0.131
2018						
Intercept	-6.745	1.140	-5.918	2.82E-05	-9.175	-4.316
X Variable 1	**-0.045**	0.084	-0.537	**0.599**	-0.224	0.134

Table 4. *Poisson Model Results on the Case of ILI in Regions vs. $PM_{2.5}$ for 2017-2018*

Poisson Model	Coefficients	Standard Error	t Stat	p-value	Lower 95%	Upper 95%
2017						
Intercept	8.365	1.016	8.236	6.01E-07	6.200	10.530
X Variable 1	**0.001**	0.078	0.010	**0.992**	-0.166	0.167
2018						
Intercept	8.151	1.043	7.816	1.15E-06	5.928	10.374
X Variable 1	**0.003**	0.077	0.037	**0.971**	-0.161	0.167

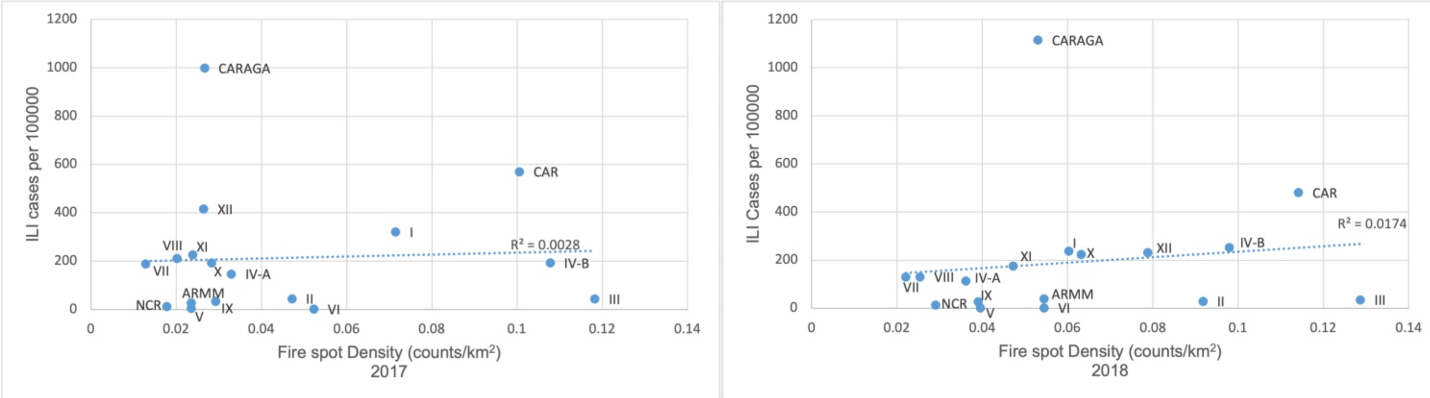

Figure 3. *Influenza-like illness cases per 100,000 versus fire spot density in 2017-2018 in the Philippines*

Table 5. *Logistic Model Results on the Probability of the Case of ILI in Regions vs. Fire Spot Density for 2017-2018*

Logistic Model	Coefficients	Standard Error	t Stat	p-value	Lower 95%	Upper 95%
2017						
Intercept	-7.347	0.763	-9.625	8.24E-08	-8.973	-5.720
X Variable 1	**5.557**	13.739	0.404	**0.692**	-23.726	34.840
2018						
Intercept	-8.060	1.037	-7.773	1.23E-06	-10.271	-5.850
X Variable 1	**12.442**	15.236	0.817	**0.427**	-20.033	44.918

Table 6. *Poisson Model Results on the Case of ILI in Regions vs. Fire Spot Density for 2017-2018*

Logistic Model	Coefficients	Standard Error	t Stat	p-value	Lower 95%	Upper 95%
2017						
Intercept	8.262	0.694	11.910	4.8E-09	6.783	9.7418
X Variable 1	**2.513**	12.487	0.201	**0.843**	-24.104	29.129
2018						
Intercept	-6.745	0.954	8.169	6.65E-07	5.759	9.825
X Variable 1	**6.485**	14.014	0.463	**0.650**	-23.385	36.355

Table 7. *Summary Association between Pertussis Cases per 100,000 against Annual $PM_{2.5}$ Levels and against Fire Spot Density in the Philippines*

Year	R^2	p-value	Coefficients		Remarks
			Intercept	X Variable 1	
Pertussis vs. $PM_{2.5}$ concentration					
2017	0.0881	0.247	0.104	0.013	Inconclusive association between annual $PM_{2.5}$ levels and pertussis cases
2018	0.0011	0.9	0.313	0.003	
Pertussis vs. Fire Spot Density					
2017	0.0309	0.5	0.313	-1.227	Inconclusive association between fire spot density and pertussis cases (no significant negative association)
2018	0.1024	0.21	0.043	5.015	

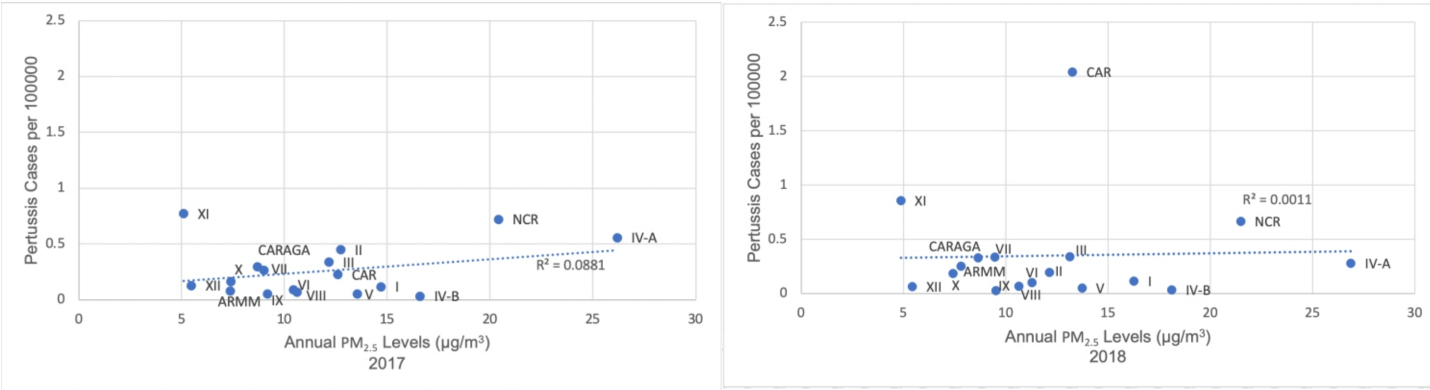

Figure 4. *Pertussis cases per 100,000 versus annual $PM_{2.5}$ levels in 2017-2018*

Table 8. *Logistic Model Results on the Probability of the Case of Pertussis in Regions vs. $PM_{2.5}$ for 2017-2018*

Logistic Model	Coefficients	Standard Error	t Stat	p-value	Lower 95%	Upper 95%
2017						
Intercept	-13.724	0.599	-22.924	4.33E-13	-15.001	-12.449
X Variable 1	**0.0366**	0.046	0.795	**0.439**	-0.062	0.135
2018						
Intercept	-13.356	0.722	-18.491	9.8E-12	-14.895	-11.816
X Variable 1	**0.001**	0.053	0.186	**0.855**	-0.104	0.123

Table 9. *Poisson Model Results on the Case of Pertussis in Regions vs. $PM_{2.5}$ for 2017-2018*

Logistic Model	Coefficients	Standard Error	t Stat	p-value	Lower 95%	Upper 95%
2017						
Intercept	1.143	0.760	1.504	0.153	-0.477	2.764
X Variable 1	**0.088**	0.058	1.497	**0.155**	-0.037	0.212
2018						
Intercept	1.544	0.794	1.944	0.071	-0.149	3.237
X Variable 1	**0.058**	0.059	0.987	**0.339**	-0.067	0.183

Table 10. *Logistic Model Results on the Probability of the Case of Pertussis in Regions versus Fire Spot Density for 2017-2018*

Logistic Model	Coefficients	Standard Error	t Stat	p-value	Lower 95%	Upper 95%
2017						
Intercept	-13.724	0.414	-31.654	3.76E-15	-14.002	-12.234
X Variable 1	**-3.809**	7.460	-0.511	**0.617**	-19.710	12.090
2018						
Intercept	-13.611	0.657	-20.718	1.89E-12	-15.011	-12.211
X Variable 1	**6.207**	9.653	0.643	**0.530**	-14.367	26.781

Table 11. *Poisson Model Results on the Case of Pertussis in Regions versus Fire Spot Density for 2017-2018*

Logistic Model	Coefficients	Standard Error	t Stat	p-value	Lower 95%	Upper 95%
2017						
Intercept	2.492	0.549	4.541	0.0004	1.322	3.662
X Variable 1	**-6.850**	9.877	-0.694	**0.499**	-27.903	14.203
2018						
Intercept	2.242	0.755	2.970	0.010	0.633	3.851
X Variable 1	**0.261**	11.091	0.024	**0.982**	-23.379	23.901

less significant in 2018 with 0.9 compared to 2017 with 0.247 (Table 7). The probability of having pertussis due to the increase in $PM_{2.5}$ concentrations was also less significant for 2017 (p=0.439 in 2017; p=0.855 in 2018). Based on the results of the Poisson model (Table 9), the recorded pertussis cases may not be attributable to the change in $PM_{2.5}$ levels.

Region XI and NCR with the highest pertussis incidence rates in 2017 had low fire spot density. CAR, on the other hand, had the highest pertussis cases per 100,000 in 2018 but with high fire spot density. There was no clear association between pertussis incidence and fire spot density for 2017 and 2018. Contrary to the association of the satellite-derived $PM_{2.5}$ with pertussis, the p-value in 2017 for the association between fire spot density and pertussis was less significant than in 2018. There is inconclusive association between the two variables. Likewise, the results of the logistic and Poisson models (Table 10 and Table 11) did not show conclusive trends for the association between pertussis and fire spot density.

Discussion

The hypothesis meant to be tested in this study was that atmospheric pollution, represented by the increase in $PM_{2.5}$ concentrations and fire spot density, may lead to an increase in respiratory cases, using ILI and pertussis as proxy for respiratory diseases. In addition, the spread in fire spot density may contribute to the increase in $PM_{2.5}$ levels, which in turn, may affect respiratory health.

From the results of the study, there was no specific association observed between satellite-derived parameters, specifically the annual mean ground-level $PM_{2.5}$ mass concentration and fire spot counts per km², and incidence of respiratory diseases ILI and pertussis for 2017 to 2018 in the Philippine regions. Regions IV-A (CALABARZON) and NCR (Metro Manila) had the highest $PM_{2.5}$ levels but had low fire spot counts, contrasting to the expected emission increase from rising active fire density. These regions are highly populated urban areas. The high $PM_{2.5}$ mean mass concentrations may be due to sources other than active fire—such sources may be carbon emissions from vehicles, dust from construction activities, and other anthropogenic activities coupled by the meteorological factors active at the time of data acquisition. The annual $PM_{2.5}$ mass concentration of IV-A (26.18 μg/m³ in 2017 and 26.88 μg/m³ in 2018) and NCR (20.41 μg/m³ in 2017 and 21.49 μg/m³ in 2018) is more than double compared to the 10 μg/m³ WHO standard for annual $PM_{2.5}$ levels [24]. For both 2017-2018, more than 10 Philippine regions exceeded the WHO guidelines.

Datasets for ILI and the atmospheric variables did not show a conclusive relationship. The causes of influenza-like illness involve a number of viruses including influenza and the new SARS-CoV-2 among others [19,20]. These can be carried by aerosols such as $PM_{2.5}$ and can be affected by seasonal changes. A study in Beijing reported strong positive relationships between $PM_{2.5}$ and ILI during highly polluted days of the flu season, which includes the months of October to April but no significant association was found in the non-flu months [25]. Another study in Tucson, Arizona in 2020 did not find an association between ILI activity and $PM_{2.5}$ concentration under lightly to moderately polluted atmospheric environment [11]. Comparing the values for ILI association with $PM_{2.5}$ mean mass concentration and fire spot density (Table 2), it is nearer for $PM_{2.5}$ to have possible relation with ILI as compared to fire spot density.

Pertussis incidence was the highest in Region XI for 2017 regardless of low $PM_{2.5}$ levels. This inverse relationship for pertussis and $PM_{2.5}$ remained for Region XI in 2018. This region has the highest population and the second-highest population density in Mindanao. The cause for the high disease incidence cannot be easily pinpointed with the absence of onsite verification. The causative agents may be multi-factorial and wide-ranging from health causes for high transmission rates to perhaps gaps in case reporting and surveillance. For 2018, CAR reported the highest pertussis incidence. Pertussis is vaccine-preventable with the aid of DTP3 vaccine. There was a decline in the DTP3 vaccine coverage in the Philippines (88% to 65%) from 2017 to 2018, which may probably have affected the increase in pertussis cases in some of the regions, including CAR [21]. It may be worthy to note that the Poisson model for the association of $PM_{2.5}$ concentrations to pertussis counts at a given monitoring time resulted in the smallest p-value (0.155) compared to the other datasets and models in this study.

Furthermore, there was also no conclusive association found between fire spot density and the respiratory health variables. Since fire spot density in this study are regional datasets, the fire spots detected by the VIIRS sensor might be far from the populated areas where the ILI and pertussis cases have been reported. The relationship between the variables showed that these respiratory illnesses could not have been mainly caused by fire occurrences in the regions.

Conclusion

There was no statistically significant correlation found between the exposure and outcome variables. Between the satellite-derived atmospheric variables, no direct association was observed. Fire spot density did not directly contribute to $PM_{2.5}$ concentrations looking at the regional level. In addition, the increase in $PM_{2.5}$ concentrations, as well as fire spot density, did not directly affect both ILI and pertussis. Hence, fire may not have been a significant cause for these respiratory illnesses in 2017-2018 in the Philippine regions. Apart from ILI and pertussis, further studies can use the incidence of other respiratory diseases. Furthermore, limitations from satellite-derived data may be explored and how these readily available data can be utilized in other facets of respiratory health. Ground truthing for verification of both satellite data and respiratory health data can also be conducted when possible. Coordination with the local health community workers can also be crucial.

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