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Aerosol Optical Depth As a Measure of Particulate Exposure Using Imputed Censored Data, and Relationship with Childhood Asthma Hospital Admissions for 2004 in Athens, Greece

Gary Higgs[1], David A. Sterling[2], Subhash Aryal[3], Abhilash Vemulapalli[3], Kostas N. Priftis[4] and Nicolas I. Sifakis[5,*]

[1]Department of Social and Behavioral Sciences, Harris Stowe State University, St Louis, MO, USA. [2]Department of Environmental and Occupational Health Sciences, School of Public Health, University of North Texas Health Science Center, Fort Worth, TX, USA. [3]Department of Biostatistics and Epidemiology, School of Public Health, University of North Texas Health Science Center, Fort Worth, TX, USA. [4]Pediatric Respiratory and Allergy Unit, 3rd Department of Pediatrics, Athens University, University Hospital "Attikon", Haidari, Athens, Greece. [5]Institute for Astronomy, Astrophysics, Space Applications and Remote Sensing, National Observatory of Athens, Greece. *Currently seconded to the European Research Council, Brussels.

Supplementary Issue: Ambient Air Quality (A)

ABSTRACT: An understanding of human health implications from atmosphere exposure is a priority in both the geographic and the public health domains. The unique properties of geographic tools for remote sensing of the atmosphere offer a distinct ability to characterize and model aerosols in the urban atmosphere for evaluation of impacts on health. Asthma, as a manifestation of upper respiratory disease prevalence, is a good example of the potential interface of geographic and public health interests. The current study focused on Athens, Greece during the year of 2004 and (1) demonstrates a systemized process for aligning data obtained from satellite aerosol optical depth (AOD) with geographic location and time, (2) evaluates the ability to apply imputation methods to censored data, and (3) explores whether AOD data can be used satisfactorily to investigate the association between AOD and health impacts using an example of hospital admission for childhood asthma. This work demonstrates the ability to apply remote sensing data in the evaluation of health outcomes, that the alignment process for remote sensing data is readily feasible, and that missing data can be imputed with a sufficient degree of reliability to develop complete datasets. Individual variables demonstrated small but significant effect levels on hospital admission of children for AOD, nitrogen oxides (NO_x), relative humidity (rH), temperature, smoke, and inversely for ozone. However, when applying a multivari- able model, an association with asthma hospital admissions and air quality could not be demonstrated. This work is promising and will be expanded to include additional years.

KEYWORDS: Aerosol optical depth, AOD, particulate exposure, childhood asthma

SUPPLEMENT: Ambient Air Quality (A)

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CORRESPONDENCE: ghiggs1875@gmail.com

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Introduction

The atmosphere of urban areas is among the most sensitive and dynamically responsive environmental interface between human activities and natural systems. Urban atmospheres influence public health and can be expressed using geographic means. An understanding of human health implications from atmosphere exposure is a priority in both geographic and public health domains. Asthma, as a manifestation of upper respiratory disease prevalence, is a good example of the interface of geographic and public health interests. The unique properties of geographic tools for remote sensing of the atmosphere offer a distinct ability to characterize and model aerosols in the urban atmosphere for evaluation of impacts on health.

Over the last few decades, a large body of literature has become available concerning the nature of the atmosphere and its relationships with asthma in particular.[1–4] However, much of this work has remained within specific disciplines, such as remote sensing in the geospatial literature and health outcomes within the public health literature, while a greater emphasis on interdisciplinary solution-oriented dialog is needed. In Greece, two parallel research endeavors, one focusing on asthma expressed in the form of childhood asthma hospital admissions and another focusing on the remotely sensed aerosol properties of the atmosphere, were conducted during 1978–2006 and 1986–2001 time periods, respectively.[5,6] The first of these studies by Priftis identified long-run trends of increasing prevalence of childhood asthma occurring on a monthly basis over a 22-year period. In a follow-up study by Nastos et al, a relationship between childhood asthma-related admissions and outdoor particulate matter (PM) was observed.[7] At virtually the same time and in the same location, Sifakis identified a trend of increasing aerosol optical thickness (AOT), also frequently referred as aerosol optical depth (AOD), as a representation of the aerosol content of air masses. These studies provide the foundation and the opportunity to merge collected data on AOD measures and asthma hospital admissions. AOD has been demonstrated to have moderate-to-high correlation with atmospheric particulate levels of PM10 and PM2.5.[8–11] Traditionally, atmospheric particulate concentrations are measured at single points, and values obtained are assumed to represent surrounding areas of possibly up to many hundreds of square kilometers. The benefit of using AOD is that large areas are directly measured, with potentially increased reliability of the average measure over a large area.[12] The disadvantage is the potential for censured data because of cloud cover, other atmospheric conditions, or technical issues that limit satellite measurements.[13] The current study is focused on Athens, Greece during the year of 2004 with the overall goal to (1) demonstrate a systemized process for aligning satellite AOD data by geographic location and time, (2) evaluate the ability to apply imputation methods to AOD censored data, and 3) confirm that AOD data can be used satisfactorily to investigate the association between AOD and health impacts using an example of hospital admissions for childhood asthma.

Methods

Three datasets were the principle resources used in this study: (1) asthma hospital admissions of children collected from Priftis et al[5]; (2) satellite imaging for AOD; and (3) ground-level air monitoring of priority pollutants. Datasets 2 and 3 are publicly available and further described below.

Hospital admissions for asthma. The count of daily hospital admissions per 100,000, age adjusted to the 2001 national census for children aged 0–14 years of age from January 1, 2004 to December 31, 2004, was obtained from Priftis et al as a de-identified data file.[14] These data were derived from three children's hospitals in the city of Athens, which cover approximately 85% of the pediatric admissions in the Athens Metropolitan area, and included all children residing in the area and admitted with the diagnosis of asthma, asthmatic bronchitis, or wheezy bronchitis.

Ground-level air monitoring data. Ground-level air quality data originated from the network of 17 air monitoring stations operated by the Department of Air Quality of the Hellenic Ministry of Environment, Energy and Climate Change. The data consisted of hourly averages of nitrogen dioxide (NO_2), nitrogen oxides (NO_x), carbon monoxide (CO), ozone (O_3), sulfur dioxide (SO_2), relative humidity (rH), wind direction (WD), wind speed (WS), particulate matter 10 μm (PM10), smoke, and daily maximum temperature (T °C). Most stations monitored selected pollutants. Daily averages at each station where each pollutant was monitored were combined to represent the daily mean results for Greater Athens.[15] Figure 1 shows dual images of the Athens basin area. The left image shows a satellite image of Athens with a superimposed major road network and an atmospheric cube as an example of air mass.[16] The right image illustrates the topography of the basin, urban land cover, and air monitoring stations.

AOD data. The remote sensing approach of this paper was modeled after that of Sifakis, who derived AOD from a series of MERIS image sources over the Athens area.[17,18] This approach relies on MODIS imagery. MODIS is a NASA satellite mission named after the Moderate Resolution Imaging Spectroradiometer, which is the primary sensor on the program satellites. The MODIS project and its sensor systems were designed to gather information about the atmosphere and its aerosol properties. NASA has especially enhanced and leveraged the capability of the MODIS system to extract atmospheric information relating to aerosols and atmospheric thickness from MODIS data.[19]

The MODIS satellites Terra and Aqua are in polar orbits at approximately 700 km above the surface, with 14–15 orbits a day and a view field across a scan of 2330 km with wavelength sensitivity in the visible to infrared spectrum range of 0.41–14.235 μm.[15] Daily AOD was recorded one time each 24-hour period, approximately between 8:30 am and 10:20 am local time, with up to four pixels within the Athens area, for up to a possible total measurement of four. The raw data are organized into different levels. For example, Level 1A data are data input into the geophysical and aerosol retrieval algorithms, while Level 1B data are the calibrated and geolocated radiance or reflectance products of the data input.

Each individual image, of 1 km resolution, for 2004 was searched and evaluated visually for each day of the year to confirm place and alignment over the study area using an available visualization tool from NASA.[20] These datasets/images were sorted by location, date, and time, and reviewed for coverage using NASA-supplied image statistics. The best candidate images for each day in 2004 were selected, based on the center of the image being over the Athens area and having limited

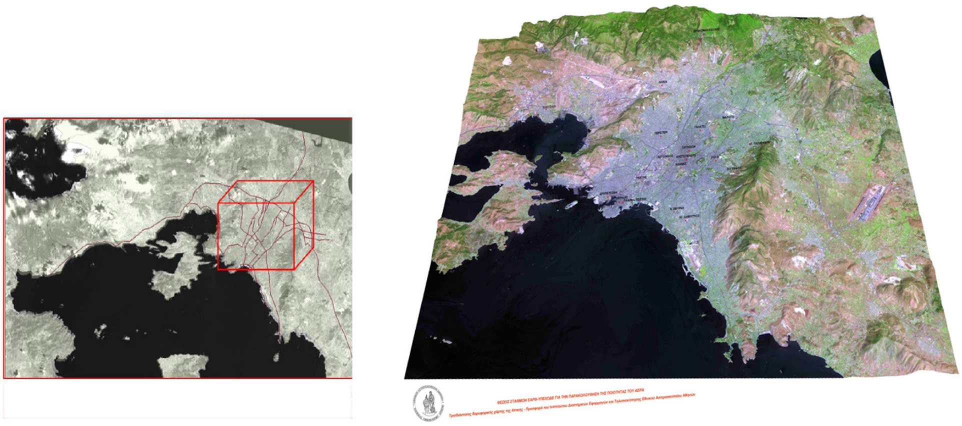

Figure 1. The left image shows a satellite image of Athens with a superimposed major road network and an atmospheric cube as references for the air mass over the Athens basin. The right image illustrates the topography of the basin, urban land cover, and the Department of Air Quality of the Hellenic Ministry of Environment, Energy and Climate Change's air monitoring stations.

image obstruction. These selected images were downloaded from a publicly available source.[21]

Although 366 days occurred during 2004, only 99 images and corresponding datasets were found to be suitable because of days of no images availability and no AOD observation or the MODIS satellite was not at an appropriate attitudinal aspect to the study area of Athens to provide good image data. In remote sensing observations, the list of useful images is often less than the number of theoretically possible observations for a variety of technical and physical reasons. For example, such factors as technical problems with sensor systems, characteristics of the air mass itself, and intervening media such as cloud cover have traditionally contributed to limitations on the completeness of remotely sensed data. Additionally, the computer-based algorithms used to interpret the images may limit or enhance the information available, depending on the resolution of interest, area of coverage, and computation power available. As the evolution of processing algorithms continues, this limitation will be reduced.[22]

To address these missing data, a data imputation method was employed utilizing the Markov chain Monte Carlo (MCMC) approach to generate data, and is further discussed below.[23]

Alignment of data sources. The MODIS dataset images used in this study are the Level 2 data products or aerosol products. The files exist in an HDF (heretical data file) format designed to encompass a variety of materials. The MODIS .hdf files contained 59 data subsets covering a variety of atmospheric properties and image information. These subdatasets in the .hdf files are referred to in HDF parlance as scientific datasets (SDS).

After study and consultation, SDS 5 {203 × 135] Cloud_Mask_QA mod04 (8 bit integer) and SDS 7 (203 × 135) Optical_Depth_Land_And_Ocean mod04 (16 bit integer) were selected for this analysis because SDS 5 contains a configuration of the land and water masses of the image necessary for geopositioning of the data, and SDS 7 contains the pixel values representing AOD measurements. Thus, SDS 7 contains data that represent properties of the air masses. These properties effectively characterize or model the atmosphere according to aerosol type, aerosol optical density, particle size distribution, aerosol mass concentration, and related optical properties.[24–26] These data products contain information on the ambient aerosol optical density of air mass over any area of the earth and are considered to be Level 2 products because they are derived products that are produced at the spatial resolution of 10 km^2.[27]

The images for each day were synchronized with the Priftis asthma admissions data by Julian date. Both subdatasets 5 and 7 include latitude and longitude information, enabling automatic geopositioning given reliable reference coordinates. However, in this instance, classical cartographic techniques of georeferencing were implemented to ensure as close a spatial correspondence as possible between the MODIS image subdataset 7 and the hospital admissions data.[28] The positioning task was necessary to ensure that the AOD values of each pixel represented their corresponding correct locations in the study area. The process of geopositioning of the MODIS data over the study area was considered to be the most critical step, as a misalignment could be a significant source of potential error. A spatial mismatch could produce either false positive observations of AOD over Athens or prevent the actual observations of a truly existing AOD.

The procedures for positioning the MODIS images were performed first by locating the identifiable points of the corresponding image on a geographic map and counterpart points on the MODIS subdataset 5. The image on day 32 of 2004 (obtained at 10:10 am) was used to represent the frame of reference for the atmospheric mass over the populated area of Athens (Fig. 2). This file was allocated into its correct geographical position. The ArcMap identify tool, an icon on the ArcMap tool bar, was used to read the values from the subdataset 7 pixels over the Athens basin for each day. Typically,

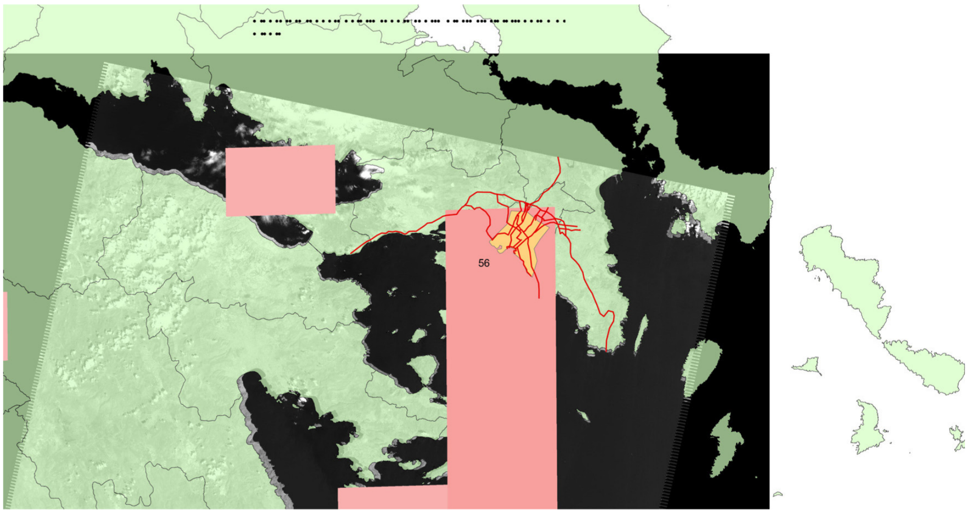

Figure 2. A representation of the land and water contrast of the Athens basin and a bowl ringed by mountains and opened to the southwest. Superimposed on this is the outline of the urban built-up area of city in yellow and the regional arterial transportation system in red. The pink polygons represent MODIS pixels on day 32 of 2004, and the label 56 on the polygon over Athens is the AOD value for that particular air mass. Using the corrected AOD values, this reading would be 0.0056.

AOD values are considered to range from 0.0 to 0.4, with a value of 0.01 representing an extremely clear atmosphere and a value of 0.4 a very hazy atmosphere.[29]

Data Management and Analysis

Imputation of censured MODIS data. Several approaches are available in the statistical literature for analyzing data in the presence of missingness, including complete case analysis, weighted analysis, and multiple imputation (MI). The most common approach is complete case analysis, which ignores missing values and only the observed data are analyzed. This approach is often suitable when the percentage of missing values is small and the statistical inference methods do not rely heavily on large sample approximation. A serious drawback of this approach is that the results can be biased.[30] To correct the bias, an inverse probability weighting (IPW) approach is often used. This approach requires weighting each complete case by the inverse of its probability of being a complete case. The cases with higher weights essentially represent themselves and other cases with missing values, hence reducing or eliminating bias from complete case analysis. IPW methods are most appropriate when missingness occurs for multiple variables of each subject, such as in longitudinal studies where a subject misses a visit and no measurement can be obtained. An alternative to complete case analysis-based approaches is MI.[31] When the missing data pattern is arbitrary, Schafer and Olsen recommend using an MCMC method that is based upon assumption of multivariate normality to impute the missing values.[32] This method can be used to impute all missing values or impute some missing values to create a monotone missing pattern and employ other imputation models. In this approach, first each missing value is replaced by a series of $m > 1$ plausible values. Next, each m complete datum is analyzed and parameter estimates and standard errors are obtained using standard complete data approaches. Finally, results from m separate analysis are combined. Next, we provide brief detail of the MI approach.

Let $Y = (Y_{obs}, Y_{mis})$ denote the intended data, where Y_{obs} is the observed part and Y_{mis} is the missing part. Let Q denote a parameter of interest such as the mean. An estimate of Q denoted by $\hat{Q}$ could be obtained in the presence of complete data along with the standard error U. Let us assume we imputed m dataset. We can now obtain a point estimate for Q as $\bar{Q} = \frac{1}{m}\sum_{i=1}^{m} \hat{Q}i$. Next, we obtain the standard error for $\bar{Q}$. There are two sources of variance, the between-imputation variance $B = \frac{1}{m-1}\sum_{i=1}^{m} (\hat{Q}_i - \bar{Q})^2$ and the within-imputation variance $\bar{U} = \frac{1}{m}\sum_{i=1}^{m} \hat{U}_i$. The total variance $T = \bar{U} + \left(1 + \frac{1}{m}\right) B$. We can now construct a test statistics or confidence interval using t-approximation as follows: $\frac{(\bar{Q} - Q)}{\sqrt{T}} \sim t_{\vartheta}$ with $\vartheta = (m-1)\left[1 + \frac{\bar{U}}{\left(1 + \frac{1}{m}\right) B}\right]^2$. The validity of this approach depends heavily on how the imputed data are generated.

As discussed above, we obtained a number of daily admissions because of asthma symptoms from various hospitals in Athens, Greece from January 1, 2004 to December 31, 2004. Similarly, daily AOD was recorded via satellite one time each 24-hour period, with up to four pixels within the Athens area, for up to a possible total measurement of four. rH and daily maximum temperature in the city were also recorded.

A major drawback of AOD data collection via satellite is that when measurements cannot be recorded because of cloud

Table 1. Number of days data are available and the overall mean.

VARIABLE	SAMPLE SIZE (*N*)	PERCENT AVAILABLE DAYS OF DATA	MEAN (STD. DEV)
Daily Asthma Admits	272	73.3	3.07 (2.43)
AOD (1)	98	26.77	223.88 (140.79)
AOD (2)	81	22.13	217.34 (136.44)
AOD (3)	51	13.93	233.80 (149.90)
AOD (4)	20	5.46	210.87 (125.94)
Daily Max Temperature (˚C)	366	100	18.24 (7.36)
Relative Humidity (%)	366	100	68.73 (8.72)

cover and other factors indicated above, the result is missing data. Degree of missingness (eg, 20% versus 80%) needs to be taken into account while determining an appropriate statistical method for analyzing data. From Table 1, we observe that only 26.77%, 22.13%, 13.93%, and 5.46% of measurements are available for the four possible pixels within the Athens area each day, and 74.3% of measurements are available for daily asthma admissions. Such a high degree of missing values complicates data analysis, and conclusions drawn from such data can be misleading. For our work, we used the MCMC approach to impute data. Details of MCMC are provided in Schafer.[23]

Results of evaluation of AOD and asthma hospital admissions. For each air pollutant shown in Table 2, we applied a two-day measurement lag. This decision was based on the results of similar studies and prior experience of the study team. Our primary outcome variable, which is number of admissions because of asthma, was recorded beginning January 1, 2004 and ending December 31, 2004. Time series data generally exhibit strong day-to-day correlation, and statistical methods that account for autocorrelation are appropriate for analysis of such data. To evaluate autocorrelation, we plotted the time series for a number of admissions because of asthma, shown in Figure 3.

A visual inspection of Figure 3 indicates no observable trend in our data. In order to confirm our findings, we used the Durbin–Watson test for autocorrelation in time series data, which indicated that autocorrelation was unlikely (P-value > 0.05). As a result, we chose to fit a negative binomial regression model with a log link. Generally, counts of events such as number of hospital admissions are modeled using Poisson or negative binomial regression models. The negative binomial model includes an extra parameter to account for overdispersion, which often occurs in counting-type data. Our model exhibited significant overdispersion (estimate = 0.0992, 95% CI 0.0568, 0.1732), thus rendering a more simple Poisson model inappropriate.

In our preliminary analysis, we fitted a series of unadjusted models to evaluate the impact of each predictor variable on the number of admissions because of asthma. The results are presented in Table 2. On further examination with a multivariate-adjusted model, all the variables were found to be non-significant. For the variables indicated as significant, the effect level was low, and in the case of ozone and temperature, there was an inverse association. To further validate the imputation methods used for missing data, we evaluated the relationship between mean AOD measurements and ground-level-monitored PM. In a correlation between the two measurements, we observed a statistically significant positive relationship between mean AOD measurements and PM (Spearman's rank correlation (r): 0.18175, P-value = 0.0005).

Although individual variables demonstrate small but significant effect levels, it is possible that the interaction between individual variables and associated confidence limits results in the inability to distinguish an association between asthma hospital admissions and air quality with only one year of data when using a multivariate model. The Olympic Games was also held in Athens in 2004, which may also have impacted the presence of population during this time period, with more local residents leaving the city as well as changes in the air quality measurements because of different vehicle patterns and other activities to reduce pollution for athletes during this time period.[33] This pattern change during a significant

Table 2. Univariate analysis of air quality measure with asthma hospital admissions of children.

VARIABLE	PARAMETER ESTIMATE	RELATIVE RISK	*P*-VALUE
Mean AOD	0.0008	1.000800	0.0285
NO_2	0.0054	1.005415	0.0336
NO_x	0.0024	1.002403	0.0138
CO	0.0820	1.085456	0.0363
O_3	−0.0052	0.994813	0.0042
PM10	0.0016	1.001601	0.3612 (NS)
RH	0.0081	1.008133	0.0004
SO_2	0.0073	1.007327	0.0129
Smoke	0.0020	1.002002	0.1302 (NS)
Temperature Max	−0.0154	0.984718	0.0010
Wind Direction	−0.0002	0.999800	0.8175 (NS)
Wind Speed	−0.0314	0.969088	0.38 (NS)

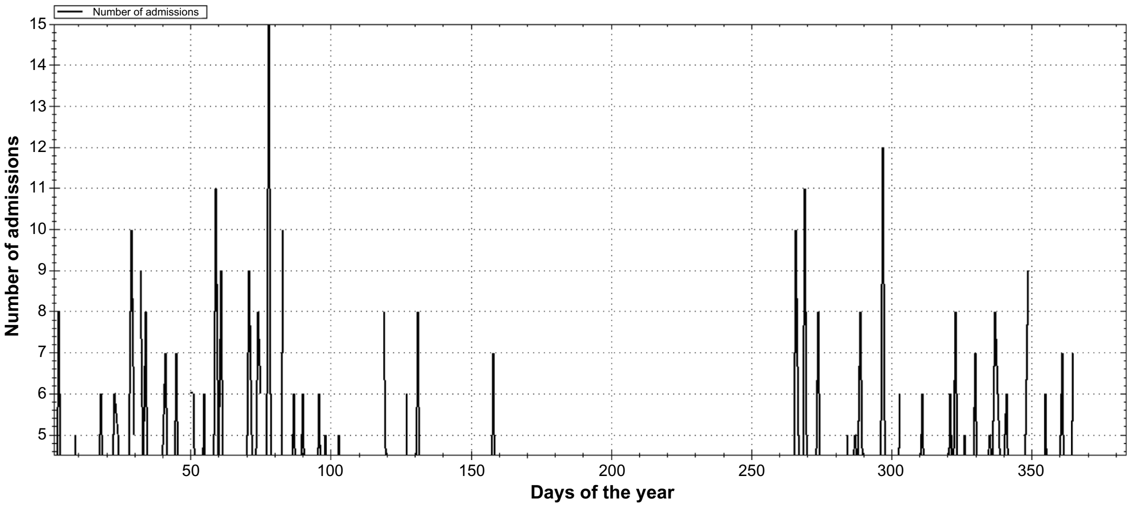

Figure 3. The number of hospital admissions by day of the year because of asthma in Athens, Greece in 2004.

portion of the year may have increased the inability to find associations if they exist as well.

Conclusion

The use of remote sensing and geographic information system (GIS) methodologies in studies of health outcomes is not common, although increasing in use. The reasons for this may include inadequacies in the current state of GIS atmospheric models or representation, inability of the technology to effectively deal with missing or algorithm-based inconsistent data, and the complexity of synchronizing the remote sensing data with specific geographic locations and temporal period. These conditions are compounded by the fact that from most users' perspectives, remote sensing and GIS technologies are evolving and are not commonly used yet for these purposes. This work demonstrates the ability to apply remote sensing data in the evaluation of health outcomes. The alignment process for remote sensing data is readily feasible. Missing data, although common, can be imputed with a sufficient degree of reliability to develop complete datasets. Although individual variables demonstrated small but significant effect levels on hospital admissions of children for AOD, NO_x, rH, temperature, smoke, and inversely for ozone, when applying a multivariate model, an association with asthma hospital admissions and air quality could not be demonstrated. This work is promising and will be expanded to include additional years.

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Author Contributions

Conceived and designed the experiments: GH, DAS, NIS, KP. Analyzed the data: GH, DAS, SA, AV. Wrote the first draft of the manuscript: GH, DAS, SA, AV. Contributed to the writing of the manuscript: GH, DAS, SA. Agree with manuscript results and conclusions: GH, DAS, SA, AV. Jointly developed the structure and arguments for the paper: GH, DAS, NIS. Made critical revisions and approved final version: GH, DAS, SA. All authors reviewed and approved of the final manuscript.

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