Predicting Health Impacts of Wildfire Smoke in Amazonas basin, Brazil

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Conflict of Interest

The authors declare they have no conflicts of interest related to this work to disclose.

Abstract

Worldwide, smoke from forest fires has deleterious health effects. Even so, because of the complexity of fire mechanics, public health authorities face challenges in forecasting and thus mitigating population exposure to smoke. The population in the Amazon basin regularly suffers from fire smoke tied to agriculture and land-use change. The people of Manaus, a city of two million in the center of the basin, suffer the consequences. The study herein evaluates the time lag between fire occurrence and hospital admission for cardiorespiratory illness. Understanding the time lag is key to forecasting and mitigating the public health effects. The study approach is sequential application of four increasingly complex methods of machine learning to examine the relationships among black carbon concentrations, fire count, meteorology, and hospital admissions. The mean absolute percentage error (MAPE) for predicting hospital admissions ranged from 27% to 38%. Furthermore, a one-day lag was observed between the detection of fires and the manifestations of respiratory health hazards. This finding suggests the potential for developing an early warning system, which could enable public health officials to issue advisories or implement preventive actions during the brief period before hospital admissions begin to rise. The findings have applicability not only to the population exposed to fires in the Amazon basin but also to populations where smoke is prevalent, notably increasingly in Australia, southern Europe, the western USA, southern Canada, and southeast Asia.

Keywords: fire smoke, Amazon basin, cardiorespiratory illness, forecast and warning

Synopsis: A forewarning artificial neural network is developed for exposure to wildfire smoke at the population level. Use of this approach can reduce respiratory and cardiovascular hospitalizations.

1. Introduction

Forest fires are a global concern. Consequences include severe air pollution episodes, human mortality, environmental damage, and substantial economic loss[1]. Human activities and climate change have led to heightened intensity, frequency, and duration of fire seasons. Approximately 200,000 forest fires are reported annually.[1] Notably, the summer of 2022 witnessed record-breaking wildfire activity in the European Union and the United Kingdom, surpassing the previous 15-year record.[2] Similarly, California experienced a record number of wildfires in 2020, more than double the previous record.[3] The severity of the 2019/2020 fire season in Australia was unprecedented. Over 23% of the temperate forest in southeastern Australia was affected.[4]

The Amazon forest also faced an alarming increase in deforestation fires in 2019. At that time, the Brazilian government reversed commitments to control deforestation.[5] The state of Amazonas recording its highest fire count since 1998 in 2022.[6] The impact on the Amazon ecosystem, known for its biodiversity and vast freshwater, is severe. However, studies on the effects of wildfire smoke in this region are limited due to the scarcity of air quality monitoring stations in the northern Amazon.[7] Forest fires contribute significantly to black carbon (BC) emissions. Black carbon in turn is part of airborne particulate matter ($PM_{2.5}$).[8, 9]

Previous exposure assessment studies usually use PM concentration as a proxy for wildfire smoke.[10] And, there were few epidemiological studies of fire health effects prior to the last decade because of fire occurrence far from populated areas where air pollution levels were seldomly monitored.[11] More recently, Johnston et al.[12] report that the overall premature mortality rate that can be attributed to wildfire smoke is 339,000 individuals globally each year. Nawaz and Henze[13] found that Brazilian biomass burning emissions (mostly in Amazonia) accounted for a 74% increase in premature deaths. Alves et al.[14] further demonstrated that biomass burning in the Amazon region leads to DNA damage and cell death in human lung cells. Recently, Prist et al.[15] estimated that 500 cardiorespiratory infections per 100,000 inhabitants were related to forest fires in the Amazon. Further studies in the Amazon region confirm a positive correlation between wildfire smoke and an increase in the incidence of morbidity and mortality among vulnerable populations, including children and the elderly[7, 13-15].

There are several methods widely used to assess exposure to wildfire smoke.[16] The fires and non-fire days can be compared, the concentration of PM can be monitored or modeled, smoke indicators including counts and burned area from satellite observations can be used, and combination methods can integrate one or more of these approaches. However, forewarning predictions of health risks based on fire episodes are scarce. If such forewarning were possible, the public, especially vulnerable populations, could take action to avoid smoke exposure. Similarly, healthcare professionals, hospital systems, and health insurers could integrate potential health impacts into day-to-day actionable planning.[11]

The present study, focusing on the impact of wildfire smoke on the health of the general population in the central Amazon, employs machine learning to examine relationships among black carbon concentrations, fire count, meteorology, and hospital admissions for cardiorespiratory illness. The use of artificial neural networks (ANNs) as machine-learning forecasting models could provide elegant and robust solutions for non-linear relationships among multiple variables and discontinuous datasets.[17-22] The approach herein not only provides insights into the dynamics in the central Amazon but also contributes significantly to the global discourse on forest fires and their health implications.

2. Materials and Methods

2.1 *Sampling site*

Manaus is a metropolitan area located in the central Amazon with a population of 2.3 million in 2021.[23] In a subtropical monsoon climate, the average annual temperature is 27 °C, and the average relative humidity is 80%.[24] The wet season lasts from November to May, and the dry season takes place from June to October. There is intermittent intrusion of regional and continental scale wildfire smoke, primarily during the dry season.[25] The severe, episodic pollution strongly affects public health and hospital admissions. For this study, sampling campaigns took place from 2011-2013 (3° 5'43.94"S, 59°59'25.56"W) and 2015-2016 (3° 6'12.5"S, 59°58'55.8"W) in a central area of Manaus (Figure 1). The obtained dataset of particulate matter ($PM_{2.5}$) and black carbon (BC) had 785 samples collected over four years. Corresponding meteorological data were obtained from the Brazilian National Institute of Meteorology (INMET).

2.2 *$PM_{2.5}$, BC, and fire counts.*

$PM_{2.5}$ was collected (24-hour sampling) from Oct 2011 to July 2013 and from Aug 2015 to Aug 2016 using a low-volume Harvard impactor and 37-mm polycarbonate filters. $PM_{2.5}$ mass concentrations were determined gravimetrically following the same procedure by Polezer et al.[17], positioning the impactor 2 m height and using blank filters to track and reduce errors due to filter handling and transport. The BC fraction of the sampled $PM_{2.5}$ was determined through transmittance at an 880 nm wavelength (infrared) (Sootscan optical transmissometer, model OT 21, Magee Scientific Company). The BC concentration and the daily fire count were used as proxy variables for wildfire smoke.

The variability of fire data around Manaus up to 500 kilometers is quite the same, as shown in Figure S1. In this sense, we chose to use the number of fires within 200 kilometers around Manaus, 10 times the city's average radium. The fire data was obtained from the National Institute for Space Research[27]. The data is from the reference satellite (AQUA, which uses a MODIS sensor)[28].

2.3 *Hospital admissions*

The health impacts accompanying wildfire smoke were evaluated using the Manaus hospital admission count for cardiorespiratory illness. Cardiorespiratory illness is widespread following exposure to fire smoke.[29] Hospital admission data across Oct 2011 to Aug 2016 were obtained from the Brazilian Unified Health System for respiratory diseases (RD) (International Classification of Diseases – ICD-10, codes J00 to J99) and cardiovascular diseases (CVD) (ICD-10, codes I00 to I99).[30]

2.4 *Machine learning*

Machine learning was applied to examine the relationships among black carbon concentrations, fire count, meteorology, and hospital admissions. Explanatory variables (i.e., input variables) included daily BC concentration, mean temperature, mean relative humidity, precipitation, solar intensity, and the fire count. When dealing with air pollution epidemiological studies, it is common to observe a relation between air pollution concentration some days ahead of health outcomes, then it is crucial to consider a seven-day window when dealing with air pollution health impacts, as suggested by [17, 18, 31-33]. Therefore, this study examined data from zero (lag 0) to seven-day lag (lag 7) after exposure to forest fires and BC concentrations.

Machine learning by artificial neural networks (ANN) performed the analysis. ANNs are nonlinear methodologies used to solve problems such as nonlinear mapping, forecasting, classification, and clustering, among others.[34] The ANN neurons are organized into layers, commonly named input, hidden (intermediate), and output layers.[35] Four artificial neural networks architectures were sequentially applied, including so-called extreme learning machine (ELM), echo state network (ESN), multilayer perceptron (MLP) with one and two hidden layers (MLP-1 and MLP-2, respectively), and radial basis function network (RBF). ESN is a recurrent neural network, and the others are feed-forward neural networks.[34,36] MLP and RBF are fully trained methodologies because all weights are adjusted. Two unorganized machines (UM) were also considered (ELM and ESN). UM tunes only the output layer, which confers a simple implementation and low computational cost.

The dry and wet season differed significantly from one another in terms of fire count, PM concentrations, and hospital admissions (Table 1). Therefore, the analyses were also conducted with and without a *Z*-score, which is a de-seasonalization technique. The goal was to evaluate if transformation into stationary dataset without seasonal components improves model performance. [35-37]. The *Z*-score consists of subtracting the value of each sample from the mean and dividing the result by the standard deviation.

Statistics of the dataset used in the ANN analysis are listed in Table 1. For machine learning, the dataset was divided into three parts, including a training dataset (used to adjust the free parameters of the neural models; 585 samples), a validation dataset (to avoid overtraining; 100 samples), and a test dataset (used to evaluate the performance of the proposed models; 100 samples). For each ANN, sixteen analyses (lag days × Z-score) were carried out including all inputs, excluding forest fire count, and excluding BC concentration for respiratory and cardiovascular diseases, totaling 96 analyses peer ANN.

The performance of each neural network was evaluated based on the root mean square error between predicted and observed admissions in the test dataset. The mean absolute percentage error (MAPE) was also calculated. The cost function the ANNs minimize is the RMSE and, in the case in which different error metrics indicate distinct models as the best, the one with the lowest RMSE should be assumed as the best one.[18, 35, 38] MAPE indicates the absolute model performance relative to the observations of hospital admissions. It is important to highlight that error metrics from different datasets are not comparable.

The Friedman test was applied to assess if the error values were statistically different from each other, meaning one ANN performed better than another. Details about the ANN designs and performances are in the Supplementary Material.

3. Results and discussion

Different approaches can be used to assess fire health risks: using monitored PM during fire events, PM data from chemical transport modeling, satellite smoke data (counts and/or burned area), comparison between smoky versus non-smoky days, self-questionnaire information, satellite data plus chemical transport modeling, and others.[16, ,29, 39]

Urrutia-Pereira et al.[7], in reviewing biomass burning and human health in the Amazon rain forest, point out that studies related the effects of forest fire smoke in this region are limited due to a lack of air quality measurements in the northern region of Brazil. This is in accordance with Bowman et al.[5], who point out that historical records of fire activity, even for simple metrics like area burned, are limited. To that end, a decision was made that the best available proxy for the studied region to compare the impact of fires on health in the Brazilian Amazon Forest is active fire hotspots as it captures the dynamics of fires over time, a conclusion affirmed by Sant'Anna and Rocha[40]. Then, the fire count within 200 km around Manaus during the study period was used.[27] The dataset is plotted in Figure 2. The year 2014 is missing because no BC sampling campaigns were carried out during that year, which prevented its inclusion in the analysis.

During the study period, the daily BC concentrations ranged from 0.06 to 5.56 μg m^{-3}, with annual means varying from 1.29 to 2.28 μg m^{-3} (Table 1). On days of severe episodic smoke, the BC concentration reached levels up to 2-3 times higher than the average levels observed during periods of urban pollution, with a maximum recorded concentration of 5.6 μg m^{-3}.

Given the critical role of BC in our study, it is essential to acknowledge the complexities and challenges associated with its measurement. The mass absorption cross-section of BC, often employed to estimate BC mass from optical measurements, can vary significantly across different environments and conditions, leading to substantial uncertainty in quantification. This variability is further exacerbated by factors such as lensing effects and the mixing state of particles, particularly in scenarios involving biomass burning, as discussed in the works of White et al.41 (2016), Bond and Bergstrom42 (2006), and Zhang et al.43 (2023). Furthermore, changes in particle size and morphology post-sampling can influence light absorption measurements, thereby impacting the accuracy of BC mass estimates. These challenges underscore the importance of careful interpretation of BC data in epidemiological studies like ours, where accurate exposure assessment is crucial for understanding health impacts.

The $PM_{2.5}$ concentration ranged from 0.04 to 68.7 μg m^{-3}, with a daily average of 9.2 μg m^{-3} and a standard deviation of 6.83 μg m^{-3}. For comparison, Table 2 lists values for studies in the Amazon region from literature. For the 2000's, the literature observations agree with those of this study, considering the standard deviation. However, Artaxo et al.[11] reported data for the 1990's, during which $PM_{2.5}$ concentrations were 3 to 6 times higher. In Rondônia state, records of 50-90 μg m^{-3} were observed during the dry season from 2002 to 2009[44]. During fire episodes from Aug to Sep 2020, average daily $PM_{2.5}$ concentration were four to eleven times the National Ambient Air Quality Standards (NAAQS) in major cities in California (USA), Washington (USA), and Oregon (USA).[47] Notably, fire smoke is a global issue, and our finding will have applicability not only to the population exposed to fires in Manaus, but also to populations where smoke is prevalent, such as USA, southern Europe and others. Ahangar et al.[48] considered eight cities along the South Coast Air Basin (USA) and analyzed the wildfire contribution to $PM_{2.5}$ and its carbon content for 2008 to 2016. The authors analyzed the reduction in $PM_{2.5}$ and BC annual averages when excluding the fire days. In the urban areas, the most significant difference was 7% for $PM_{2.5}$ and BC in 2008. In remote regions, the differences were 4% for $PM_{2.5}$ and 21% for BC in 2016. For the present study, much larger reductions of 17% and 11% for $PM_{2.5}$ and BC were observed, respectively, in 2012.

Figure S2 shows the boxplot of BC percent of the total $PM_{2.5}$ mass. The values ranged from 0.8 to 95.4%, with an average value of 23.0% and a standard deviation of 12.4%. The BC percent is above typical values of biomass burning in the Amazon rainforest[7]. Typically, 10 to 15% of $PM_{2.5}$ composition from Amazonian wildfires is BC. The fire count on a single day ranged from 0 to 253 throughout the 200 km region surrounding Manaus (Figure 2). The fire count is at its highest during the dry season, with a record of 2,298 recorded in 2015.

As listed in Table 1, the fire count and BC concentrations do not correlate with cardiorespiratory data. Figure S3 shows a dispersion diagram with Pearson correlation coefficients. The relation between BC, forest fire, and cardiorespiratory diseases is not linear, with Pearson correlation coefficients from –0.16 (between respiratory hospitalizations and the fire count) to 0.12 (between cardiovascular hospitalizations and BC). For comparison, Andrade-Filho et al.[44] reported Pearson correlation coefficients of –0.079 between respiratory hospitalizations and fire count. The Spearman correlations are between -0.21 to 0.13 and Kendall correlations are between -0.16 to 0.09 (cf. Tables S1 and S2). The low Pearson, Kendall, and Spearman correlations indicate that any trends, if present, are a complex non-linear problem. For this task, ANNs are suitable.

The main results of the ANN analyses are listed in Table 3. The complete set of results is listed in Tables S3 to S8. Machine learning by multilayer perceptron was the most successful in predicting hospitalization related to air pollution from forest fires. The MLP was also well constrained by the explanatory variables, as confirmed using the Friedman test. The *p* values were nearly zero, meaning a change in the model led to distinct results. The best performance by MLP corroborates recent research about air pollution and health impacts[33,39] that MLP tends to outperform the "newer" ANN models such as RBF and the unorganized machines (ELM and ESN). The fully learned structure of MLP allows for advantageous approximation of the nonlinear mapping inputs.

The causality of fire count and black carbon concentrations as explanatory variables of hospital admissions was evaluated by replicating the machine learning for three cases: (1) including all input variables (daily fire count, black carbon, mean temperature, relative humidity, precipitation, solar radiation, wind speed, and wind direction), (2) excluding the fire count, and (3) excluding black carbon. As expected, the best performance used all input variables (Table 3). For respiratory illness, there was a one-day lag between health effects and exposure. For cardiovascular illness, there was no lag. Results changed drastically when excluding fire count or black carbon as explanatory variables. Lag increased from 1 day to 2-3 days for respiratory illness and from no lag to 6 days for cardiovascular illness. We may conclude that incorporating both fire count and black carbon (BC) concentration is crucial for accurately predicting hospital admissions because these variables capture distinct aspects of exposure to fire-related pollutants. While BC provides a direct measure of particulate matter generated by fires, which has immediate health impacts, the fire count reflects the broader scale and intensity of fire activity, including additional fire-generated pollutants and physical effects that may not be directly captured by BC measurements alone. The improved model performance when both variables are included suggests that non-fire sources of BC and other pollutants resulting from fire activity contribute significantly to health outcomes. These findings are consistent with literature[49] indicating that aging smoke, which contains various harmful compounds beyond BC, and interactions with urban pollutants, may exacerbate health impacts.

Figure 3 plots the observed and predicted values of the test dataset using the best-performing model. The figure shows the model has difficulty in predicting higher and lower values, especially for discontinuous variables. The predictions for hospitalizations are related only to the considered inputs, mainly BC and fires. By comparison, the output of hospital admission depends on many other factors not included in the model, such as lifestyle, age, economic factors, and so on. In this sense, errors around 27% and 38% (Table 3) are acceptable and provide reasonable predictive power for discontinuous datasets. Some studies using ANN and considering the same outputs (cardiorespiratory diseases)[17-19,21,38] presented results with errors of the same order of magnitude (ranging from 17 to 36%), which confirms that the ANNs showed a good performance to our database.

The emissions from the Amazon fires affect the short- and long-term health of the 25 million people living throughout the Amazon biome, as reflected in increased hospital admissions for respiratory and cardiovascular diseases during the burning season. During 2021 and 2022, a trend of worsening conditions in Amazonas state continued[27], suggesting even more for the future. The development of effective early-warning mechanisms could prevent severe health impacts, but the precise mix of conditions to activate an alert has been uncertain in this data-poor region. In this context, the study herein used the best available health records in the central Amazon, corresponding to the several million people living in Manaus, and likewise the best-available datasets of air quality. Simple multilinear regressions failed to establish Pearson, Kendall, or Spearman coefficients above a noise threshold between environmental measurements and health effects. Analysis by artificial neural networks did establish relationships, however. Specifically, the ANNs successfully modeled the time lag between fire incidence and hospital admissions based on input factors of daily averages of black carbon concentrations, temperature, relative humidity, precipitation, solar radiation, and regional fire count. The prediction of the time lag between environmental observations and health effects can be used for health-oriented decision-making. Timely information can be provided in advance to the health care sector to properly allocate resources during periods when admissions are expected to increase. The ANN approach developed herein can be applied in diverse scenarios worldwide to forecast health hazards resulting from fires. In the long term, the study results highlight the need for effective measures to reduce fire occurrence and thereby mitigate the adverse impacts of regional air pollution on human health.

The Amazon region has one of the highest deforestation rates worldwide[50], related to socioeconomic factors, governance effectiveness, and climate change. The wildfire smoke negatively impacts the human health of local communities, ecosystems, and climate change. For Manaus, Paralovo et al.[51] report on the decline in air quality from forest wildfires and controlled burning after deforestation. Throughout the last few years, this issue is growing more severe. In Amazonia, deforestation, maintenance of cleared areas, and forest fires account for 8%, 39%, and 53% of fire outbreaks, respectively, with distinct social and environmental impacts.[7] At times in the dry season, a smoke layer envelops the larger part of the entire Amazon basin and much of central South America. Marlier et al.[52] highlighted that the duration of the dry season is lengthening, which may increase the incidence of fire in Amazonia.

In the Amazon, wildfire smoke, often driven by deforestation and land-use changes, poses severe public health challenges, leading to increased hospital admissions for cardiorespiratory illnesses[7]. Similarly, California and Australia experience intense wildfires, exacerbated by climate change, resulting in episodes of air pollution and corresponding health impacts. However, while California and Australia have more developed monitoring and response measures, the Amazon struggles with a scarcity of air quality monitoring stations, limiting the ability to forecast and mitigate these impacts effectively. In Southeast Asia[9], particularly during agricultural burning seasons, air pollution reaches critical levels, causing adverse health effects akin to those observed in the Amazon. This global analysis highlights the urgent need for early warning systems and targeted mitigation policies tailored to the unique socioeconomic and environmental contexts of each region, with the aim of protecting populations exposed to wildfire smoke. The results show the potential of ANN as a tool capable of predicting forest fire health risks, suggesting their potential to support the creation of an early warning system, although further research is needed to fully elucidate the underlying mechanisms and optimize the timing of interventions. Some limitations that need to be addressed in future research are the use of different proxies for fires, more complete databases, emergency visits as output, and to include socioeconomic and other individual characteristics.

Relating our findings to the United Nations' Sustainable Development Goals (SDGs), our study aligns significantly with SDG 3 (Good Health and Well-being), SDG 13 (Climate Action), and SDG 15 (Life on Land). SDG 3 aims to ensure healthy lives and promote well-being for all ages, and our research underscores the critical need for early warning systems to reduce the adverse health impacts of wildfire smoke, particularly in vulnerable populations. The observed increase in cardiorespiratory illnesses due to black carbon exposure from wildfires directly relates to this goal by highlighting the importance of mitigating environmental health risks. SDG 13 focuses on combating climate change and its impacts, and our study provides evidence of the exacerbated wildfire activity driven by climate change, emphasizing the urgent need for climate action to reduce the frequency and intensity of these fires. Lastly, SDG 15 seeks to protect, restore, and promote sustainable use of terrestrial ecosystems. Our findings on the detrimental health effects of wildfires on Manaus' population illustrate the critical need for sustainable land management practices. By addressing these SDGs, our research contributes to a broader understanding of the intersection between environmental degradation and public health, advocating for integrated policies that promote a healthier and more sustainable future.

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Table 1. Statistics of observations. *Source: J00 - J99 from ICD-10. **Source: I00 to I99 from ICD-10.

Variable	Season	Statistic	2011	2012	2013	2015	2016
Number of days in analysis	wet		45	115	114	34	135
	dry		13	123	48	72	86
$PM_{2.5}$ (μg m^{-3})	wet	max	19.4	30.0	68.7	24.9	16.2
		min	4.3	1.7	0.8	4.8	1.9
		avg	9.7	8.9	9.5	10.5	5.6
		median	8.5	6.8	6.9	8.4	5.3
	dry	max	16.3	58.0	31.9	29.6	22.1
		min	4.5	0.0	2.1	3.5	2.6
		avg	10.8	11.6	10.8	11.5	7.7
		median	8.9	10.0	9.0	8.5	7.0
BC (μg m^{-3})	wet	max	4.7	5.6	4.7	3.4	3.7
		min	0.4	0.4	0.4	0.7	0.6
		avg	2.0	2.0	2.0	1.3	1.4
		median	1.9	1.7	1.9	0.9	1.3
	dry	max	5.2	5.2	4.0	3.2	5.1
		min	0.1	0.2	0.2	0.3	0.6
		avg	2.2	2.3	1.8	1.3	2.0
		median	1.8	1.9	1.7	1.2	1.7
Daily hospitalization count: respiratory disease *	wet	max	45	85	64	34	58
		min	7	12	15	9	10
		avg	26.36	31.67	34.51	22.18	27.78
		median	25	27	34	23	26

	dry	max	34	49	51	37	63
		min	19	14	18	8	9
		avg	27.54	29.24	34.15	20.92	29.28
		median	28	28	33	20	27
Daily hospitalization count: cardiovascular disease **	wet	max	37	40	37	30	32
		min	9	5	8	10	5
		avg	19.51	19.57	19.65	18.71	19.50
		median	19	19	19	18	19
	dry	max	27	48	29	31	37
		min	9	4	4	10	8
		avg	18.08	20.58	17.52	18.65	19.15
		median	18	20	18	19	19
Fire count	wet		153	375	30	295	166
	dry		100	1089	167	2298	377

Table 2. Comparison between $PM_{2.5}$ and BC concentrations of this study to those in literature. *Estimated based on satellite image.

Reference	**Region**	**Period**	**$PM_{2.5}$ conc ($\mu g\ m^{-3}$)**	**BC conc ($\mu g\ m^{-3}$)**
this study	Manaus	2011-2013, 2015-2016	9.20 ± 6.83	1.83 ± 0.99
Andrade Filho et al.[44]	Manaus	2002-2009	15*	-
Fernandes et al.[45]	Manaus	Aug to Sep 2017	14.7	3.0
Jacobson et al.[46]	Mato Grosso, Brazil	2008	19.6 ± 11.9	1.00 ± 0.48

Table 3. Best-performing neural networks for predictions of hospital admissions. Results are listed for respiratory and cardiovascular diseases. Abbreviations include artificial neural network (ANN), neuron count (NC) of each hidden layer, standard score (Z), root mean square error (RMSE), mean absolute percent error (MAPE), and multilayer perceptron (MLP) with 1 or 2 hidden layers.

Inputs	**ANN**	**NC**	***Z***	**lag (day)**	**RMSE**	**MAPE (%)**
Respiratory disease						
All	MLP-2	60 / 40	without	1	10.4	38
Excluding forest fires	MLP-2	40 / 50	with	3	11.8	36
Excluding black carbon	MLP-2	40 / 100	without	2	11.7	35
Cardiovascular disease						
All	MLP-2	40 / 80	without	0	4.9	27
Excluding forest fires	MLP-2	70 / 40	with	6	5.2	25
Excluding black carbon	MLP-1	80	without	6	5.2	24

Figure 1. Sampling locations for 2011-2013 (3°5'43.94"S, 59°59'25.56"W) and 2015-2016 (3°6'12.5"S, 59°58'55.8"W). In counterclockwise direction, the four panels show progressively smaller scales from South America at the largest scale (top left), to Amazonas, to Manaus environs (corresponding to red box), to localized urban view of Manaus at the smallest scale (top right).[26]

A.　　B.

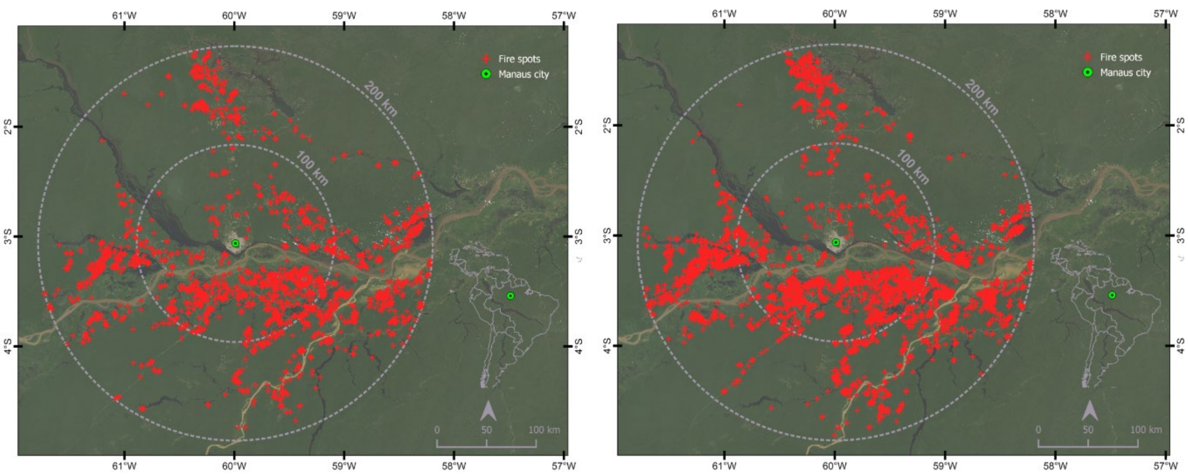
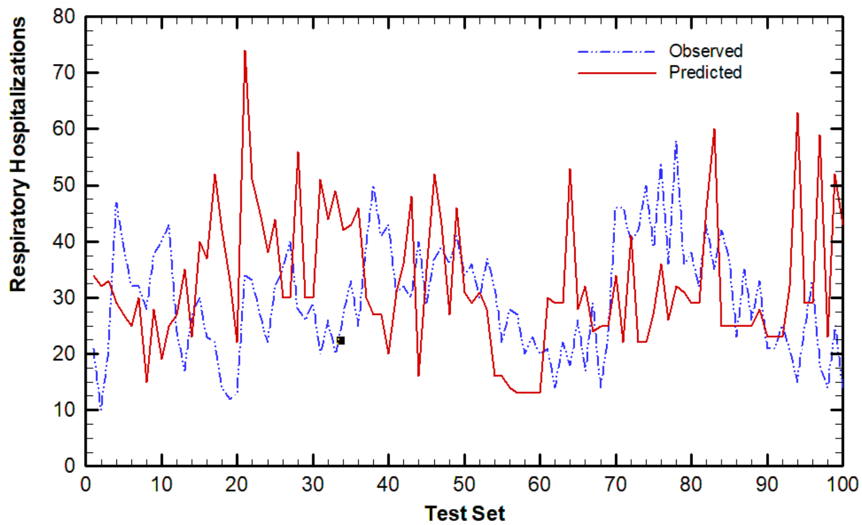


Figure 2. Forest fire count in a 200-km radius around Manaus for the two BC campaign periods (a) 5 Oct 2011 to 26 Jul 2013 and (b) 15 Aug 2015 to 30 Aug 2016.[44]

A.



B.

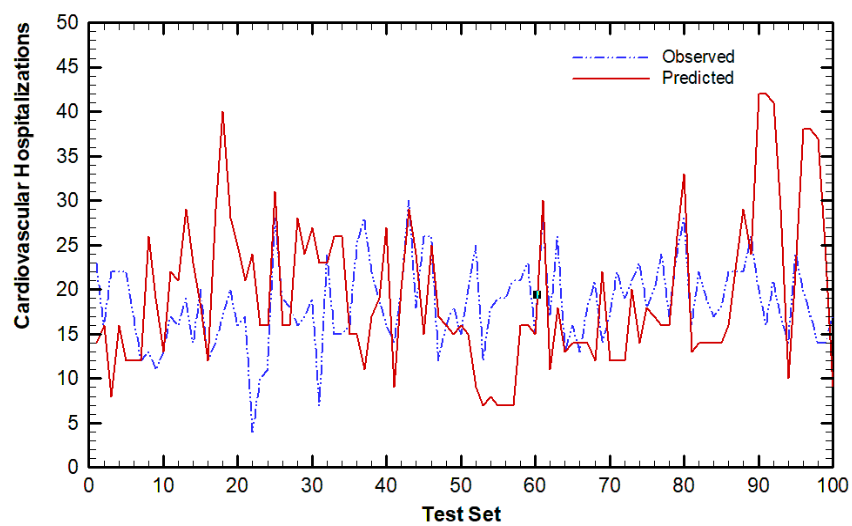


Figure 3. Comparison between observed and predicted hospitalizations across test dataset for (A) respiratory disease using MLP-2 with a one-day lag and (B) cardiovascular disease using MLP-2 and no lag.