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Protecting Life and Lung: Protected Areas Affect Fine Particulate Matter and Respiratory Hospitalizations in the Brazilian Amazon Biome

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Abstract

There is growing recognition of the connection between ecosystem conservation and human health. For example, protection of tropical forests can affect the spread of infectious diseases, water quality, and dietary diversity, while forest loss can have important consequences for respiratory health due to the use of fire for converting land to alternative uses in many countries. Studies demonstrating links between ecosystems and health often conclude with recommendations to expand policies that protect natural ecosystems. However, there is little empirical evidence on the extent to which conservation policies actually deliver health benefits when they are implemented in real contexts. We estimate the effects of protected areas (PAs), the dominant type of conservation policy, on hospitalizations for respiratory illness in the Brazilian Amazon biome. We find that doubling upwind PAs reduces $PM_{2.5}$ by 10% and respiratory hospitalizations by 7% in the months of most active biomass burning. Brazil has an extensive network of PAs, but investments in management and enforcement have declined in recent years. Forest fires have increased dramatically over the same period. We estimate that the value of the health benefits exceed current average expenditures on PA management for the 1/3 of PAs with the largest local populations, although not for PAs in more remote locations. Our findings highlight how quantifying the contributions to the wellbeing of local populations can support conservation objectives, even if global environmental benefits are not a high priority for decision makers.

Keywords Ecosystem services · Health · Tropical forests · Brazilian Amazon

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1 Introduction

Emergence of the scientific field of Planetary Health in recognition of the vital link between natural ecosystems and human health (Horton and Lo 2015) raises the question of whether and to what extent policies that aim to protect ecosystems may also contribute to human wellbeing through beneficial impacts on health. Numerous studies highlight potential or observed health consequences of ecosystem change in general (e.g. Keesing et al. 2010; Norris 2004), and impacts of loss of tropical forests specifically, on health influences such as exposure to infectious diseases; dietary diversity; or air and water quality (Ferraro et al. 2012; Galway et al. 2018; Garg 2019; Pattanayak and Wendland 2007). However, this literature typically treats ecosystem change as exogenous and does not consider the role of policy in encouraging or preventing ecosystem change and consequent health impacts (Ferraro et al. 2015; Pattanayak et al. 2017). We directly examine the effects of policy, by estimating whether Protected Areas (PAs) reduce hospitalizations for respiratory illness in a tropical forest ecosystem.

PAs have the potential to improve human health relative to an unprotected counterfactual by preventing ecosystem loss and degradation. In this study, we consider health effects that result from the relationship between tropical deforestation and fire. There is evidence from many contexts that smoke from forest fires is damaging to human health (Reid et al. 2019; Requia et al. 2021; Rosales-Rueda and Triyana 2019). There are two main direct pathways through which ecosystem loss and degradation in tropical forest systems can contribute to these health damages: (i) forest degradation and fragmentation lowers the integrity of the ecosystem and its ability to resist burning, with the result that fires are more likely to spread unintentionally, leading to greater smoke exposure for downwind populations (Cochrane 2003); and (ii) protected forest ecosystems provide important air purification services by absorbing pollutants—including $PM_{2.5}$ generated by forest fires—and therefore reducing the negative health effects of fires that occur elsewhere (Prist et al. 2023). As observed for other ecosystems and ecosystem services (e.g. Kleinschroth and Healey 2017; Wu et al. 2021), there are also indirect pathways through which ecosystem loss can have negative consequences for human health, related to the processes of ecosystem conversion and the ways in which land is subsequently used. In the case of tropical deforestation, the main indirect pathways through which the incidence and spread of fire are increased are: (i) the use of fire to clear forested land; (ii) the use of fire on previously cleared land that is now used for agriculture. We estimate whether air quality and health outcomes related to air quality are improved by the presence of a PA, as a result of any of these mechanisms. We also consider whether this impact varies by the effectiveness of the PA in preventing fires in practice, and compare the monetary costs of PA designation and management with the estimated health benefits.

PAs are the dominant type of biodiversity conservation policy, covering 15% of terrestrial land (Juffe-Bignoli et al. 2018). Future commitments, like the Aichi Biodiversity Target 2, aim to increase global PA coverage or other effective conservation measures of terrestrial areas to 30% by 2030 (Convention on Biological Diversity 2020). The original goal of PAs was to disincentivize human disturbances to conserve biodiversity (United Nations 1992, Article 8a), but this has expanded to include the provision of ecosystem services and human well-being (Watson et al. 2014). There is growing evidence that PAs affect human wellbeing through impacts on inequality, incomes, and wealth (Agrawal 2014; Andam et al. 2010; Canavire-Bacarreza and Hanauer 2013; Ferraro and Hanauer 2014; Keane et al. 2020; Miranda et al. 2016; Sims 2010), often linked to investment in tourist infrastructure (do Val Simardi Beraldo Souza et al. 2019; Naidoo et al. 2019). Fewer studies have considered impacts of PAs on health. Pattanayak and Wendland (2007) estimated a reduction of 2600 cases of diarrhea due to one Indonesian PA. Bauch et al. (2015) and Pienkowski et al. (2017) find reductions in diarrhea and acute respiratory infections among children living in proximity to PAs, in the Brazilian Amazon and Cambodia, respectively. We contribute to the environmental economics literature that estimates causal impacts of PAs by estimating the effects of upwind PAs on downwind hospitalizations due to respiratory illness in the Brazilian Amazon biome.

A comprehensive review of smoke exposures demonstrates effects on all-cause mortality and respiratory diseases (Reid et al. 2016). Globally, air pollution was the fifth leading cause of death in 2015, a massive environmental disease burden across the globe (Cohen et al. 2017). The health consequences of air pollution from transport and industrial activity have long been a central topic of study within environmental economics (e.g., Chen et al. 2020; Currie and Neidell 2005; Feng et al. 2019; Schlenker and Walker 2016). Economic analysis of the health effects of air pollution from biomass burning has grown more recently as biomass smoke has become an increasingly important source of pollution due to effective regulation of industrial sources and the effects of climate change on wildfires (Burke et al. 2021). For example, pollution from biomass burning may be related to agricultural fires, which have been shown to have negative consequences for health in India (Pullabhotla and Souza 2022; Singh et al. 2019), China (Lai et al. 2022), and Brazil (Carrillo et al. 2019; Nicolella and Belluzzo 2015; Rangel and Vogl 2019). Evidence on the health impacts of pollution from forest fires has largely focused on Indonesia (Jayachandran 2009; Rosales-Rueda and Triyana 2019; Sheldon and Sankaran 2017; Tan-Soo and Pattanayak 2019) and the US (DeFlorio-Barker et al. 2019; Moeltner et al. 2013; Reid et al. 2019), showing poorer health outcomes at birth and in early childhood for those exposed to smoke in utero, with persistent long term effects; and contemporaneous respiratory health consequences for adults, particularly elderly adults. There is some evidence that smoke from fires related to deforestation has significant negative health consequences in Brazil specifically (Cardoso de Mendonça et al. 2006; Machado-Silva et al. 2020; Morello 2023; Reddington et al. 2015; Requia et al. 2021; Rocha and Sant'Anna 2022). Furthermore, this burden primarily lands on children, the elderly, the impoverished, and indigenous people (Machado-Silva et al. 2020; Rocha and Sant'Anna 2022).

While rigorous causal estimation of the relationship between biomass fire and incidence of disease is necessary for understanding the potential social co-benefits of conservation (e.g., Rangel and Vogl 2019; Rocha and Sant'Anna 2022; Tan-Soo and Pattanayak 2019), it does not tell us the extent to which actual policies can deliver disease reductions in practice. Economic theory and evidence show us that these outcomes are likely to vary depending on the choices made by policy makers and individuals. First, we cannot assume that intended forest protection translates to actual forest protection due to non-random and strategic behaviors influencing policy assignment (Pattanayak et al. 2017). Second, conservation policy may influence health by altering social outcomes such as poverty or access to medical care as well as affecting deforestation and associated fire (Bauch et al. 2015). Finally, the magnitude of the health benefits due to improvements in air quality depends on the vulnerability of the affected population, which in turn is a function of their baseline health and their ability to engage in defensive behaviors to mitigate negative health effects of pollution (Hsiang et al. 2019; Neidell 2009). We therefore contribute to the literature on health impacts of air pollution in general, and pollution from forest fires in particular, to estimate the extent to which policy can mitigate these impacts, allowing for the role of behavioral responses to both policy implementation and air quality.

In a context of strong political pressures to limit or reduce PAs in favor of using land for agriculture, energy development and mining, evidence on the potential social and economic impacts on local populations is needed to enable national policy makers to correctly weigh potential conservation-development tradeoffs (Cumming 2016; McNeely 2015). We extend the literature on quasi-experimental evaluation of the effectiveness of PAs in reducing deforestation (e.g., Andam et al. 2008; Nelson and Chomitz 2011; Pfaff et al. 2015; West et al. 2022), to examine the extent to which policy-driven land use changes result in delivery of social benefits. The spatial variability in stocks and flows of ecosystem services and their nonlinear effects mean that the locations where protection is most effective may not be the locations where social benefits, including health benefits of conservation, are greatest (Ferraro et al. 2015). Therefore, we provide direct empirical estimates of the impacts of PAs on health outcomes and their economic values.

The Brazilian government had protected nearly 28% of the Amazon by 2018, just short of the National Aichi target of 30% protection by 2020. However, the annual budget to manage these protected lands covered just under 30% of the required costs for the period 2010–2014 (Pacheco et al. 2018). In addition to the limited PA budget, conservation progress in Brazil has reversed, attributed to the recent Brazilian administration's shift away from conservation enforcement, public perception of relaxed environmental regulations, and downgrading and degazettement of PAs and indigenous territories (Hope 2019; Keles et al. 2020; Rochedo et al. 2018). The reduction in enforcement increases incentives for land clearing by both rural landowners and opportunistic land speculators, contributing to dramatic increases in deforestation and accompanying fires in recent years (Araujo 2022). Deforestation-related fires are responsible for 80% of fire-caused $PM_{2.5}$ emissions in Brazil (Reddington et al. 2015). Given the evidence on the negative health effects of forest fires, identifying policy solutions that can reduce fire burdens is crucial (Morello 2021). Unlike ecosystems with natural burn cycles, forest fires in the Brazilian Amazon are driven by agricultural expansion and climatic change (Aragão et al. 2008; Bush et al. 2008; Davidson et al. 2012). Therefore, policies that influence land-use/cover change have potential to provide a considerable preventative health benefit for local populations and reduce demands on Brazil's publicly funded healthcare system.

We estimate the impacts of protected areas on respiratory illness using a panel dataset of 80,964 observations (13 years × 12 months × 519 municipalities) from the Brazilian Amazon biome. Outcomes of interest include median $PM_{2.5}$ concentration and respiratory disease hospitalizations for the municipality-month. We focus on the impacts of protected areas within 100 km of the municipal seat on monthly municipal outcomes, and also test effects within 50 km and 300 km. Monthly variation comes from the average wind direction during that month, as PAs are assumed to only influence respiratory health outcomes if they are upwind of population centers. Primary outcomes and explanatory variables are separated by the fire season and the rest of the year. The goal is to estimate the causal effect of nearby PAs on air quality and hospitalizations over time, especially during the fire season. We find that upwind PAs significantly reduce $PM_{2.5}$ during the whole year, with larger effects in the fire season. PAs reduce hospitalizations for respiratory illness during the fire season only. Disaggregation of the average effects shows that the change in hospitalizations is driven by children < 15 years old, with pneumonia and acute upper respiratory infections. We estimate the monetary value of these health effects and show that they vary widely with the size of the affected population.

2 Context

Since the early 2000s, almost 30% of the Brazilian Amazon region has been covered by PAs (including indigenous lands; West and Fearnside 2021). This region experienced significant expansion of the PA network since 2002, following the launch of the Amazon Region Protected Areas Program (Decree 4326 of 2002), with a goal to increase PA coverage by 50 million ha, mainly along deforestation frontiers (West and Fearnside 2021). The Amazon biome currently contains nearly half of the PAs in Brazil (Oliveira et al. 2017). Studies found the Amazonian PA network to have significantly reduced deforestation (Jusys 2018; Nolte et al. 2013; Pfaff et al. 2015) and fires and carbon and particulate matter emissions to the atmosphere (Nelson and Chomitz 2011; Nolte and Agrawal 2013; Reddington et al. 2015; Walker et al. 2020). Despite this, the recent Brazilian administrations have gradually downgraded and degazetted close to three million hectares of existing PAs and sought to lessen the ability to create new PAs and indigenous territories (Abessa et al. 2019; Bernard et al. 2014; Keles et al. 2020).

We estimate the impacts of PAs on respiratory health for downwind populations. These impacts occur as a result of increases in air pollution associated with deforestation-related fires, in particular concentrations of $PM_{2.5}$. Air pollution exposure is related to aggravation of respiratory conditions such as asthma, and pneumonia, chronic obstructive pulmonary disease (COPD), and other lower respiratory infections (LRI) (Liang et al. 2019; Nicolussi et al. 2014; Sarnat et al. 2012; World Health Organization 2016). Pneumonia and COPD combined cause 4 million deaths each year, and 334 million people have asthma globally (European Respiratory Society 2017). LRI such as pneumonia and bronchiolitis were the fourth leading cause of losses of global disability-adjusted life years (DALYs) for all ages and the second leading cause for children younger than 10 (Vos et al. 2020).

Libonati et al. (2021) summarize the three reasons that fires occur in the Brazilian Amazon, all of them anthropogenic: (i) deforestation fires are used to remove residual biomass after logging or other forest clearing activities; (ii) maintenance fires clear weeds and shrubs from previously deforested agricultural land; and (iii) forest fires escape, typically from maintenance fires on pastures, to burn through the understory of degraded forests. Intact forest ecosystems are more fire-resistant, so more protected forests can reduce the accidental spread of fires (Cochrane and Schulze 1999; Nelson and Chomitz 2011). This provides three mechanisms through which prevention of ecosystem loss and degradation due to PAs can reduce fire events within their borders: (1) by reducing the rate of deforestation and associated deforestation fires; (2) by limiting the area of agricultural land in use and associated maintenance fires; and (3) by reducing the unintentional escape of fires set in dry conditions on surrounding private land. The first two of these mechanisms involve reduction in fire ignitions within the borders of the PA, and generate indirect health benefits of ecosystem protection by avoiding the damages associated with the process of ecosystem change. The third is related to ignitions on private land surrounding the PA, and is a direct ecosystem service provided by the protected forest. An additional direct ecosystem service captured within our analysis is the capacity of intact forest to improve human health by removing $PM_{2.5}$ from the air.

Protected tropical forests become more critical in the context of climate change. The Amazon has already faced three once-in-a-century drought events in the last 20 years, 2005; 2010 and 2015/2016 (Boulton et al. 2022; Jiménez-Muñoz et al. 2016; Marengo et al. 2011; Smith et al. 2014), and these events are expected to increase (Boisier et al. 2015). Deforestation may also lengthen the dry season in the surrounding areas (Davidson et al. 2012). Protected forests could resist drought aggravated wildfire impacts by reducing the distance to forest edges, decreasing local temperatures, and increasing local humidity and precipitation (Giardina et al. 2018; Le Page et al. 2017; Maillard et al. 2020; Morton et al. 2013; Nepstad et al. 1999). Standing tropical forests also mitigate regional losses of precipitation during drought events (Mu et al. 2021).

3 Data

3.1 Study Sample

We focus on 519 municipalities in the Brazilian Amazon biome during the period 2006 to 2019. Monthly observations for each municipality result in a panel dataset of 80,964 observations (13 years × 12 months × 519 municipalities). During the period prior to 2006 there were frequent changes in PA areas within municipalities. As these changes were not random, but rather influenced by deforestation pressures, using changes in PA extent around a municipality for identification would bias the estimated effects, therefore we start our analysis in 2006. We end in 2019 because later data on respiratory hospitalizations are strongly influenced by Covid-19 case rates. While there is evidence air pollution contributes to mortality risk from Covid-19 (López-Feldman et al. 2021; Xiao Wu et al. 2020a, b), including the post-2019 period would distort our estimates of the impacts of PAs on respiratory health due to misreporting of Covid-19 cases in Brazil (Galvêas et al. 2021; Kupek 2021; Prado et al. 2020) and effects of the pandemic on hospital capacity for patients with other respiratory illnesses.

3.2 Dependent Variables

3.2.1 Hospitalizations for Respiratory Illness

Hospitalizations for respiratory illness are obtained from Brazil's *Sistema de Informações Hospitalares*, SIH/SUS, a database of all hospitalizations (at public or private facilities) covered by SUS, Brazil's publicly funded health care system (Castro et al. 2019; Rocha and Sant'Anna 2022). Monthly respiratory hospitalizations per municipality are based on the month of admission and the municipality of residence, ensuring the broadest spatial coverage and the likely site of exposure to smoke (Machado-Silva et al. 2020; Smith et al. 2014). Hospitalizations are coded based on the International Classification of Diseases version 10 (ICD-10), with primary diagnosis codes J00-J99 used to classify diseases of the respiratory system. The data exclude hospitalizations that were not covered by SUS. Approximately 25% of Brazilians have private health insurance (de Oliveira et al. 2022; Fontenelle et al. 2019), although this share is lower in the relatively poor northern region of Brazil where the Amazon biome is located (Castro et al. 2019). Privately insured individuals use SUS an estimated 13% of times they receive healthcare (Fontenelle et al. 2019). Our empirical strategy is based on monthly variation in hospitalizations relative to the seasonal mean for each municipality. Therefore, the exclusion of privately insured visits is only of concern if the *change* in cases is different for public and private coverage. If privately insured individuals are more likely to seek treatment during periods of poor air quality, the use of SUS data would underestimate the full effect. More generally, using hospitalizations provides a lower bound estimate of health impacts of PAs because it does not capture initiation

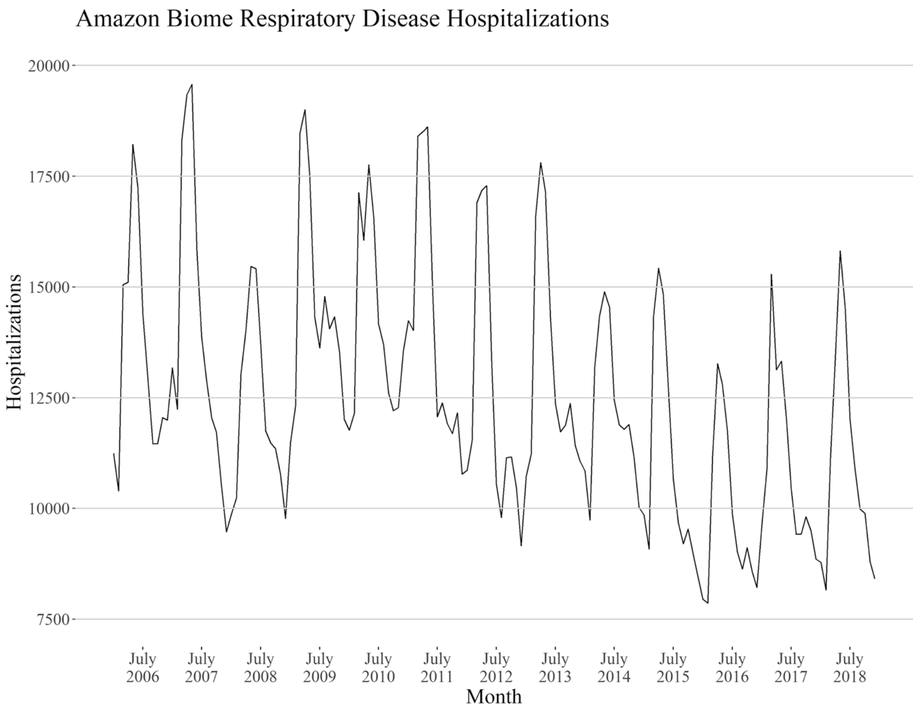


Fig. 1 Time series of total respiratory disease hospitalizations within the Brazilian Amazon Biome. Respiratory disease hospitalizations are seasonal, with peaks at the end of the rainy season followed by a smaller peak at the end of the dry season that corresponds to the fire season, July, August, and September

or exacerbation of conditions that reduce welfare but do not require hospital treatment or effects that are cumulative or delayed over time.

Respiratory diseases show substantial seasonal variation and an overall downward trend over the study period (Fig. 1). Hospitalizations rise from March to May corresponding to the end of the rainy season, and display a smaller secondary peak corresponding to rising fire usage and fine particulate matter concentrations in the late dry season, July, August, and September. Respiratory disease hospitalizations are relatively rare events and occur at an average monthly rate of roughly 55 per 100,000 people. They are also variable across months and municipalities, with smaller municipalities experiencing none in some months. In addition to hospitalization for respiratory illness, we consider hospitalization for circulatory conditions and external injury.

3.2.2 Fine Particulate Matter, $PM_{2.5}$

As an intermediate outcome variable, we use monthly values of fine particulate matter, $PM_{2.5}$ (μg/m^3) at the municipality capital. $PM_{2.5}$ values are averaged from estimates based on the Copernicus Atmosphere Monitoring Service (CAMS)-Reanalysis Model and the National Aeronautics and Space Administration (NASA)'s MERRA-2 satellite for 6-h periods. The degree to which cloud cover and other meteorological conditions bias these estimates is a common source of concern for MERRA 2 satellite-derived $PM_{2.5}$ concentrations

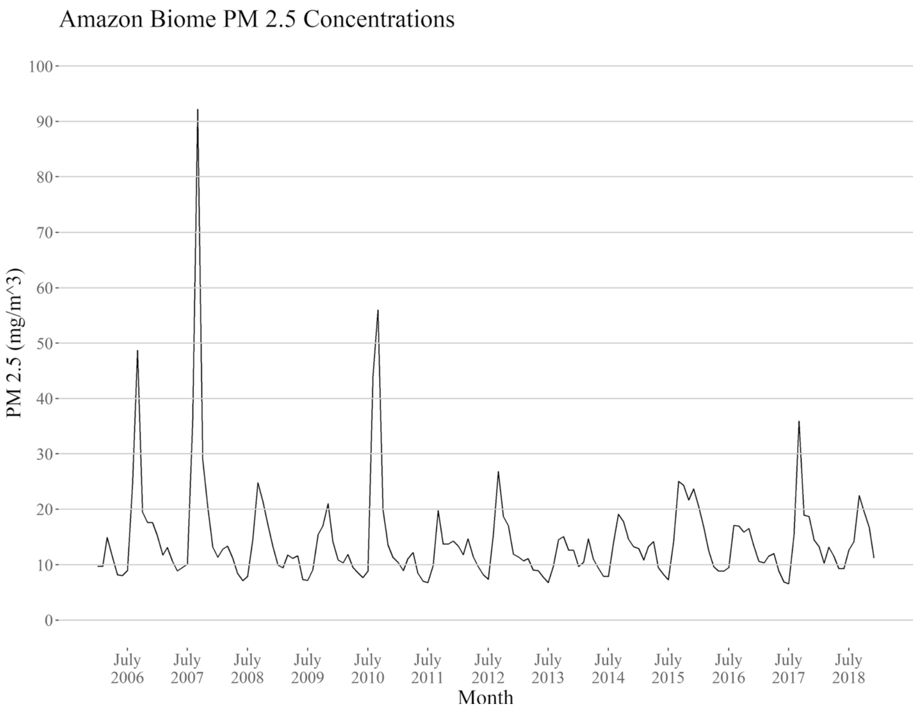


Fig. 2 Time series of the median municipal $PM_{2.5}$ concentration for all municipalities. $PM_{2.5}$ shows strong seasonal variation peaking during the fire season July, August, and September. The year 2007 is noted as being among the worst fire seasons

(He et al. 2019). To limit the influence of severely outlying measurements, we aggregate monthly measures based on monthly median concentrations instead of monthly means. Even with median measures, the maximum monthly concentration reaches 848 µg/m^3, which is 56.5 times the World Health Organization recommendation for average daily mean $PM_{2.5}$ pollution of 15 µg/m^3 and 170 times the recommendation for average annual mean $PM_{2.5}$ pollution of 5 µg/m^3 (World Health Organization 2021).

Air pollution in the Amazon Biome is strongly related to deforestation fires and agricultural activity in the months before the rainy season. Fire activity occurs mainly in July, August, and September, corresponding to the seasonal rise and peak in $PM_{2.5}$ in September. Substantial spikes occurred during the fire seasons in 2007 and 2010, corresponding to extreme drought and El Niño warming events, respectively. All other years center around the monthly average of 14 µg/m^3 (Fig. 2).

3.3 Explanatory Variables

3.3.1 Protected Areas

PA boundaries are based on shapefiles from the Chico Mendes Institute for Biodiversity Conservation (ICMBio). To establish a measure of the area protected near to population centers, we created 100 km geodesic buffers centered on each of the 519 municipal capitals. The capital and surrounding area is typically also the main population center of a municipality (Guedes et al. 2009; IBGE 2017), and the capital is the point location of the $PM_{2.5}$, wind, and weather observations. PAs near a municipality capital are inherently less isolated due to the locations of these urban centers along roads. The resulting treatment is PA coverage within 100 km of the capital. There are tradeoffs in the selection of buffer size: a larger buffer provides more complete coverage of the population that could possibly be affected by smoke from biomass burning, but this comes at the expense of precision in measuring wind direction. Prior study of health effects of biomass burning in Brazil used 50 km buffers around population centers (Rangel and Vogl 2019). However, this was for agricultural fires, which have lower average smoke plume heights and are therefore likely to travel shorter distances (Vadrevu et al. 2015). Moeltner et al. (2013) show that marginal health effects diminish over larger distances from a fire. We therefore select 100 km as the distance over which most of the likely air quality and health impact will be observed and wind directions can still be meaningfully characterized, and test the sensitivity to buffer size by comparing results with 50 km and 300 km buffers.

We do not use changes in PAs as our identification strategy because these changes are likely to result from changing deforestation pressures, which may be correlated with changes in air quality and hospitalizations. Also, since few municipalities experienced changes in nearby PAs between 2006 and 2019, the estimated effects of PAs would be solely based on changes in the rates of hospitalization in that small sample rather than the variation across the full sample of municipalities. To avoid giving outsize weight to these observations, we use fixed 2006 PA boundaries and exploit variation in effects of PAs in either the up or downwind direction in each month and municipality. Variation in PA coverage therefore only originates from changing wind direction and not changing PA assignment over time.

Figure 3 depicts PA coverage as of 2006 within 100 km of each municipality's capital. This reflects the area of PA in the buffer around the capital, which may include PAs outside the municipality boundaries and may not include all PAs within the municipality boundaries, depending on their location. There is substantial spatial variation. Municipalities within the "arc of deforestation" on the southeastern boundary of the biome are less likely to have nearby PA coverage. Larger protected areas surround more isolated municipalities in the north and central regions.

3.3.2 Wind

Municipality measures of wind direction are the estimated prevailing wind direction at the municipality capital every six hours. We convert wind directions to binary variables equal to one depending on where the observation would be classified for eight cardinal directions, north–north-east, east-north-east, etc. This is aggregated to the expected number of days (24-h periods) the wind was coming from each direction in a given month, based on the following equation, shown for east-north-east wind days:

$$enedays_{it} = \left(\frac{ene\,observations_{it}}{total\,observations_{it}} \right) \times days\,per\,month_{it} \tag{1}$$

The typical wind days in each direction are shown in Table 1. East-north-east is the dominant wind direction with an average of 11.9 days, and the least common wind direction is in the opposite direction west-south-west with an average of 0.6 days.

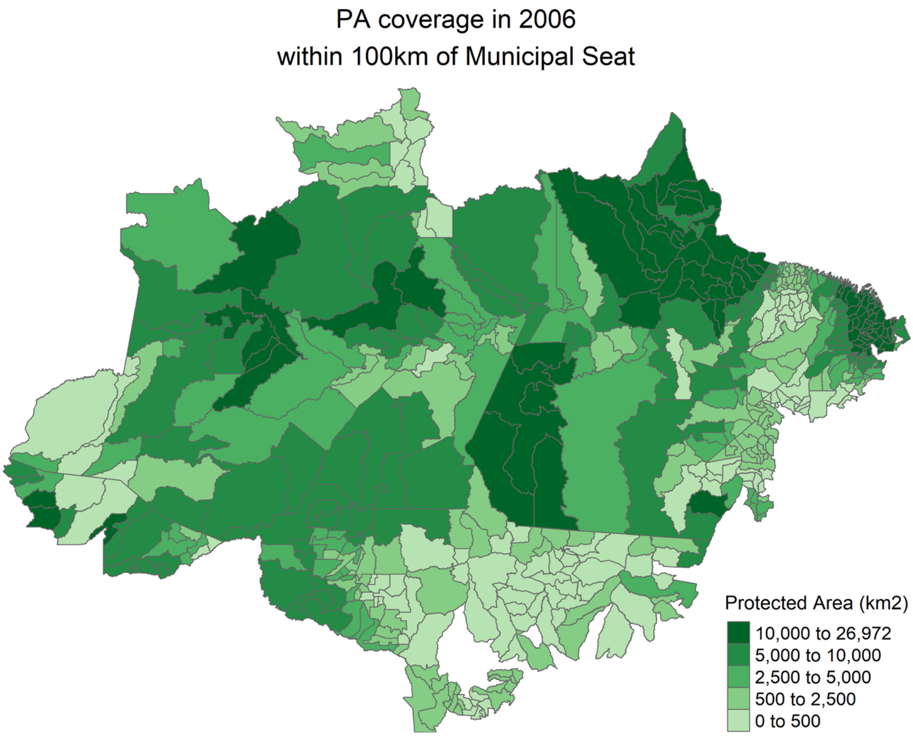


Fig. 3 Shows the spatial distribution of 2006 PA coverage within 100 km of the municipal capital, mapped onto municipality boundaries

3.3.3 Protected Areas and Wind Interaction

To reduce bias related to non-random assignment of treatment, we sort PAs coverage within 100 km of a municipality capital into octants corresponding to eight wind directions, and interact these with wind-day observations to establish a monthly average of upwind and downwind PA coverage (Fig. 4). The upwind PA × wind interaction directly relates to the expected air movement from upwind to downwind areas. In contrast, the PA × downwind interaction represents the correlation between PA proximity and air quality or hospitalizations that is not related to our causal pathway, in effect a control variable. Monthly municipal measures of upwind protection are averages created by multiplying PA area within each directional octant by the number of days the wind originated from that direction. The simulated upwind average is shown below.

$$upwindpa_{it} = \frac{\left(nneAreaPA_i \times nneDays_{it} + \cdots + nnwAreaPA_i \times nnwDays_{it}\right)}{days\,per\,month_t} \tag{2}$$

We calculate the corresponding downwind area by multiplying the coverage area in each octant by the number of wind days in the opposite octant.

Table 1 Summary statistics

	Variable	Obs	Mean	SD	Min	Max
Response variables	Respiratory	80,592	24.34	66.51	0	1721
	Hospitalizations					
	Fire season	20,148	22.66	58.71	0	1428
	Rest of year	60,444	24.90	68.90	0	1721
	Circulatory	80,592	11.38	37.15	0	786
	Hospitalizations					
	Fire season	20,148	11.43	37.14	0	786
	Rest of year	60,444	11.36	37.16	0	742
	Median $PM_{2.5}$	78,768	14.39	17.77	1.7	848.18
	Fire season	19,692	19.29	33.20	1.7	848.18
	Rest of year	59,076	12.76	6.59	2.3	99.45
Explanatory variables	Area of protected area (km^2) within 100 km in 2006 (expected per octant)	519	5206 (651)	5781.76	0	26,972 (3372)
	Upwind area of protected area (km^2)	80,964	691.07	948.53	0	4061.55
	Fire season	20,241	680.50	937.32	0	4052.81
	Rest of year	60,723	694.60	952.22	0	4061.55
	Downwind area of protected area (km^2)	80,964	589.82	854.20	0	4116.95
	Fire season	20,241	608.34	870.41	0	4052.58
	Rest of year	60,723	583.64	848.64	0	4116.95

Table 1 (continued)

	Variable	Obs	Mean	SD	Min	Max
Wind direction (prevailing winds)	NNE days	80,964	5.76	3.78	0	26
	ENE days	80,964	11.88	7.94	0	31
	ESE days	80,964	4.91	4.46	0	27
	SSE days	80,964	2.05	2.77	0	18
	SSW days	80,964	.91	1.32	0	19
	WSW days	80,964	.62	.91	0	10
	WNW days	80,964	1.22	1.75	0	12
	NNW days	80,964	2.91	3.59	0	24
Weather	Average humidity (%)	78,768	83.55	10.622	29.3	98.54
	Average temp (°C)	78,768	26.45	1.368	20.675	32.19
	Rainfall total (mm)	78,768	148.5	133.853	0	1714
	Average Rainfall (mm)	78,768	4.91	4.45	0	55.29
Socioeconomic (municipal)	GDP	80,880	592,108.42	3,120,183.7	10,429.699	78,192,321
	Population	80,892	39,543.47	121,820.4	8.899	2,145,444
	Population density (people/km^2)	80,880	30.443	157.07	0	2762.36

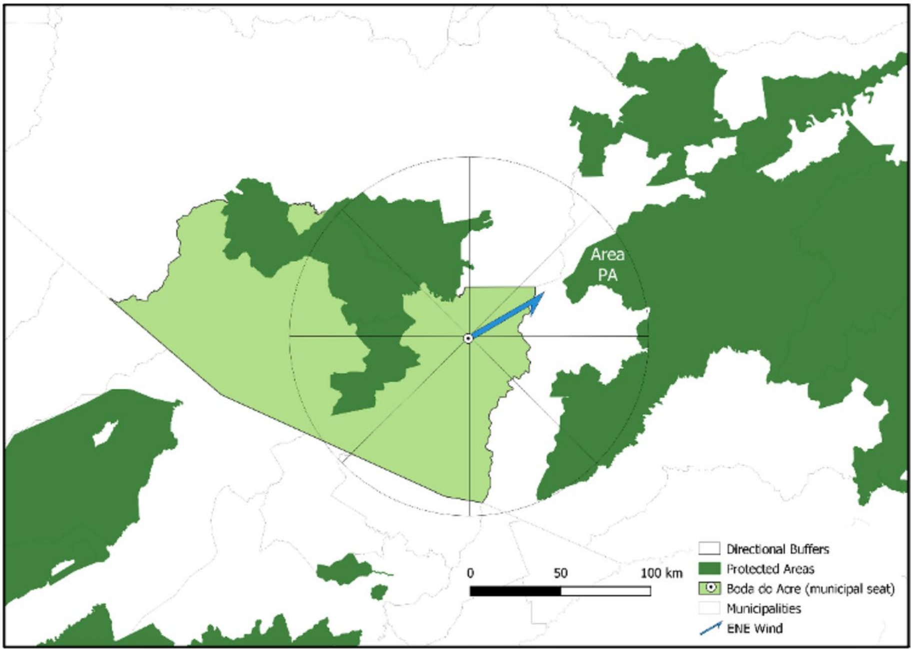


Fig. 4 Depicts a daily measure of upwind area of protected area for the municipality Boca do Acre. Daily observations were then averaged to obtain an average monthly estimate of upwind protection

$$downwindpa_{it} = \frac{\left(sswAreaPA_i \times nneDays_{it} + \cdots + sseAreaPA_i \times nnwDays_{it}\right)}{days\, per\, month_t} \tag{3}$$

The resulting calculations create a simulated estimate of the average daily area of PAs upwind and downwind within a given month. PAs in a more frequent prevailing wind direction that month are given more weight in the upwind average. The monthly changes in these interactions are used to estimate the causal impact of PA coverage on air quality and respiratory hospitalizations as described below in Sect. 4.

3.3.4 Socioeconomic Controls

We obtain annual socioeconomic data such as population and GDP from census data collected by the Institute of Geography and Statistics (IBGE) in the years 2000 and 2010 and imputed linearly for other years. Population density is calculated by dividing the municipal population by the municipal area to control for urbanization and associated benefits of health-related infrastructure such as electricity and public sewage. Population is used as an exposure variable to control for the expected number of people within a municipality that could be hospitalized each month, allowing us to estimate a municipal rate response per 100,000 people.[1] Changes in municipal population and GDP also enter as controls

[1] We drop the municipality of Jacareacanga as population varies from 8 to 41,487 during 2006 to 2018 while annual respiratory hospitalizations range from approximately 5 to 12, suggesting a data entry issue.

since changing population and economic activity are likely to correlate with public health, wealth, and education, affecting the expected municipal hospitalization rate.

3.4 Additional Variables for Validity Checks and Aggregation of Benefits

3.4.1 Fires

To assess the validity of our assumption that upwind PAs influence air quality and health by reducing fires and thus the emission of particulates to the atmosphere, we measure fire occurrence inside and outside the PAs within the 100 km municipal buffers. Fire data covering the study period were obtained from NASA's Fire Information for Resource Management System (FIRMS), based on Moderate Resolution Imaging Spectroradiometer (MODIS) (NASA 2022). We separate likely forest from non-forest fires based on fire intensity, measured by MODIS as Fire Radiative Power, with intense fires defined as ≥ 150 MW.

3.4.2 Population

As our results are estimated as rates of hospitalization per 100,000 people, the total health impacts of PAs depend on affected population size. A single PA may influence health in multiple municipalities. Therefore we need to estimate the total affected population for each PA to calculate aggregate benefits of protection. Population counts for ~ 30 km^2 areas encompassing the municipal capitals (from 15 arc-minute resolution satellite imagery) were estimated based on the Gridded Population of the World (GPW) dataset in 2010 (Center for International Earth Science Information Network—CIESIN 2018). Whenever multiple municipal capitals were presented within the same ~ 30 km area, the counted population was split into equal parts among the seats to avoid double-counting.

4 Methods

Our objective is to estimate the causal effect of PAs on respiratory health in neighboring populations. The main potential sources of bias come from the non-random assignment of PAs. The first issue is that PAs may be sited in locations with either more, or less, deforestation pressure (Joppa and Pfaff 2009), in which case air quality will be lower, or higher, on average regardless of the presence of the PA. The second concern is that levels of development may differ between municipalities with large areas of protected land within 100 km and those without protected land, which has implications for the rates of hospitalizations for respiratory conditions. The direction of the bias could be positive or negative: poorer municipalities may have generally higher rates of respiratory illness due to lower levels of health, or they could have fewer hospitalizations due to more limited access to medical facilities or weaker reporting processes.

One option to address these biases would be to estimate the effects of changes in PA coverage on changes in air quality and hospitalizations. However, one concern is that the increasing targeting of PAs to marginal lands (DeFries et al. 2005; Jusys 2018) means that the areas with and without changes in PA assignments are different in ways that impact not only overall levels of health outcomes but also the changes in health outcomes, which would violate the parallel trend assumption. A further issue is that there is very little change in PAs after 2006, meaning that for the study period there is insufficient variation to estimate effects of change. We therefore do not rely on changes in PA assignment as our identification strategy.

We instead interact the PA area as of 2006 with daily exogenous changes in prevailing wind direction and aggregate these values to create monthly variation in upwind and downwind protection that allows us to identify the causal effects of PAs. This draws on the growing literature that uses wind direction as a source of exogenous variation in air pollution (e.g. Bondy et al. 2020; Deryugina et al. 2019; Rocha and Sant'Anna 2022; Tan Soo 2018). Many of these studies use wind direction at the stationary urban or industrial source of pollution. However, due to the substantial spatial and temporal variation in the location of pollution sources from forest fires and the lack of monitoring at these remote, rural sites, we use wind direction at the destination. We follow the specific approach of Rangel and Vogl (2019) who estimate the causal effect of agricultural fires as the difference between the effects of upwind and downwind activity in a given month. Upwind fires can influence respiratory health by sending smoke towards a population center. Downwind fires should not have a direct causal effect on respiratory health through the generation of air pollution, therefore any empirical relationship represents bias due to unobserved heterogeneity between places with many fires and places with fewer fires. The difference between upwind and downwind effects captures the causal effect after controlling for these unobserved confounders. We also include some time-variant controls and time and space fixed effects as follows:

$$y_{itm} = \alpha_i + \mu_m + \gamma_t + X_{itm}\eta + \beta_U PA^U_{itm} + \beta_D PA^D_{itm} + \varepsilon_{itm} \tag{4}$$

where i indexes municipalities; t indexes years (2006, 2007, ... 2019); and m indexes months (Jan, Feb, …. Dec). y_{itm} represents the dependent variables: air pollution and respiratory diseases. PA^U_{itm} is the weighted average area of PAs located within 100 km (or 50 km or 300 km in alternative specifications) and upwind of the municipal seat in a given month, and PA^D_{itm} is the equivalent weighted average of PAs located within 100 km and downwind of the municipal seat. X_{itm} is a vector of observable municipality weather and socioeconomic characteristics, including average maximum temperature, relative humidity, and population density in the air quality model, and the same variables plus total population and municipal GDP in the hospitalization model. The municipal population is necessary in the latter case to estimate hospitalization rates per 100,000 people. We include municipality fixed effects (α_i) to control for unobserved influences on differences in air quality and heath that do not vary over time in the air quality and hospitalization models. These include regional differences that may be correlated with upwind or downwind PA coverage due to prevailing wind patterns. We also include month (μ_m) and year (γ_t) fixed effects to account for seasonal patterns and annual trends in air quality.

Seasonal variation in air quality is consistent across municipalities (Fig. 5a), so we control for this at the regional level with month and year fixed effects to adjust for the time periods and fire seasons that were particularly severe across the region. In contrast, seasonal variation in respiratory hospitalizations differs considerably in different subregions of the Amazon (Fig. 5b), so we estimate specifications with municipality-month interactions for the hospitalization models in addition to the specifications with additive municipality and month fixed effects:

$$y_{itm} = \alpha_i + \mu_m + \gamma_t + \omega\alpha_i\mu_m + X_{itm}\eta + \beta_U PA^U_{itm} + \beta_D PA^D_{itm} + \varepsilon_{itm} \tag{5}$$

Fig. 5 **a** Average $PM_{2.5}$ by month for grouped states by region, AM—Amazonas (East/Central Amazon), MATO—Maranhão & Tocantins (Southeast), MT—Mato Grosso (South), PAAP—Pará & Amapá (North/Central), ROAC—Rondônia & Acre (Southwest), RR—Roraima (North). **b** Counts of respiratory hospitalizations per 100,000 people by month for grouped states by region, AM—Amazonas (East/Central Amazon), MATO—Maranhão & Tocantins (Southeast), MT—Mato Grosso (South), PAAP—Pará & Amapá (North/Central), ROAC—Rondônia & Acre (Southwest), RR—Roraima (North). The states of Amazonas and Pará cover the largest area and contain the highest populations

The terms β_U and β_D represent separate effects for upwind and downwind PAs on outcomes. A downwind PA is not expected to influence respiratory health, at least through the air quality pathway. Therefore, any observed relationship between downwind PAs and respiratory hospitalizations, as captured by β_D, is likely to arise due to the confounders discussed above, namely differences in local deforestation pressure and municipality development levels:

$$\hat{\beta}_2 = E\left[outcome\,(unprotected)\,|protected\right] - E[outcome\,(unprotected)\,|unprotected\big] = treatment\ bias \tag{6}$$

The β_U estimate captures the same confounding effects and associated bias, plus the causal treatment effect of PAs on respiratory health. The estimated effect of upwind coverage will therefore equal the causal effect of upwind PAs on air quality (ATT_U) plus the treatment bias. It is theoretically consistent for this coefficient to be positive, negative or zero, depending on the relative magnitude of these two components.

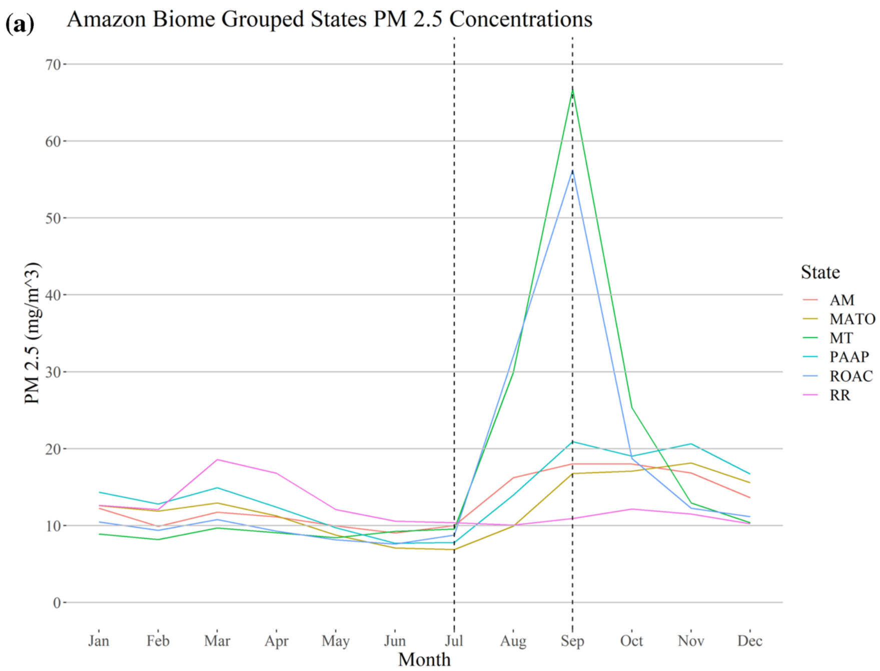
$$\widehat{\beta_U} = ATT_U + treatment\ bias \tag{7}$$

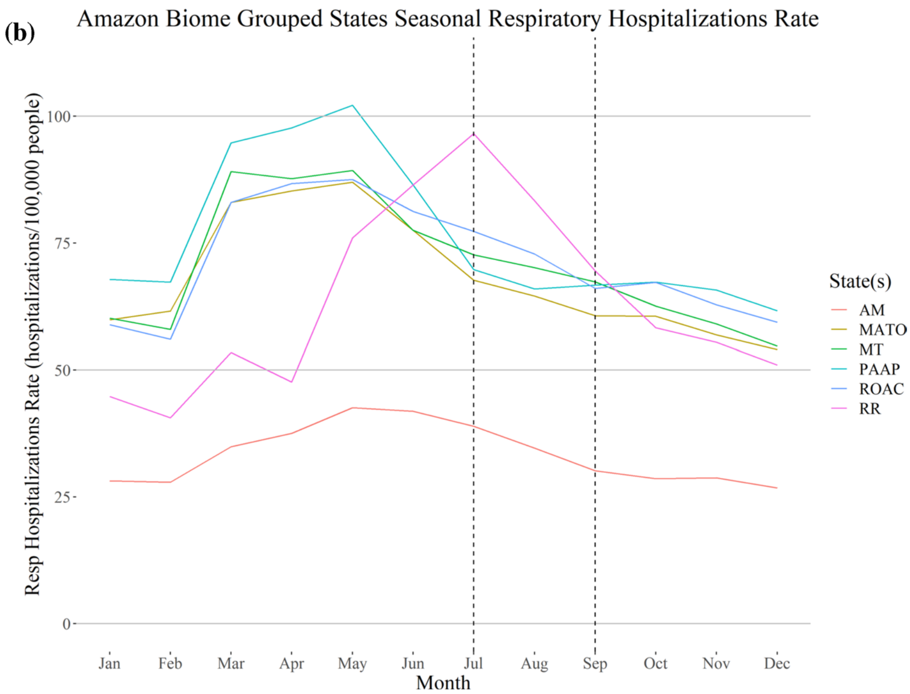
The effect of interest is how upwind PAs affect hospitalizations *relative to the counterfactual*, which is estimated as the difference between the upwind and downwind coefficients. This estimated differential effect, $\beta_U - \beta_D$, will subtract out treatment bias leaving only the causal impact of PAs on outcomes related to air movement from upwind areas to the municipal seat, as:

$$\widehat{ATT_U} = \widehat{\beta_U} - \widehat{\beta_D} \tag{8}$$

One caveat is that there may be other channels through which PAs affect rates of respiratory health and that apply to both upwind and downwind municipalities. For example, the PA itself could affect local development or population growth positively through effects on tourism or agricultural productivity, or negatively by limiting agricultural expansion. This could in turn affect rates of respiratory illness by raising overall standards of healthcare and health status, or alternatively by accelerating spread of infectious diseases. These effects will be differenced out along with the effects of development or population growth arising for reasons unrelated to PA location. As such, our results represent only the effects of PAs on health that operate through pathways related to impacts on air quality.

We estimate the differential effect of upwind and downwind PAs on two outcomes, $PM_{2.5}$ concentrations and respiratory hospitalizations, with a Pseudo Poisson Maximum Likelihood (PPML) regression as both outcomes were non-negative and over-dispersed. This avoids the distributional assumptions and issues with zero values created by transformation of the dependent variable, for example by taking logs. The Pseudo Poisson requires only the correct specification of the conditional mean and reasonably models observations of zero, for example, no respiratory hospitalizations, with maximum likelihood estimation (Motta 2019). Simulation studies confirm that in the presence of heteroskedasticity,


(a)
Amazon Biome Grouped States PM 2.5 Concentrations
PM 2.5 (mg/m^3)
70
60
50
40
30
20
10
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
State
AM
MATO
MT
PAAP
ROAC
RR


(b)
Amazon Biome Grouped States Seasonal Respiratory Hospitalizations Rate
Resp Hospitalizations Rate (hospitalizations/100,000 people)
100
75
50
25
0
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
State(s)
AM
MATO
MT
PAAP
ROAC
RR

log-linear OLS estimates are biased, even after controlling for fixed effects. On the other hand, Poisson models are robust to heteroskedasticity (Silva and Tenreyro 2006). We use the Stata package PPMLHDFE to estimate PPML with High Dimensional Fixed Effects, enabling the inclusion of municipality and time fixed effects and their interactions (Correia et al. 2020) to control for heterogenous municipality seasonality.

5 Results

We report estimation results for the effects of upwind PAs on $PM_{2.5}$ and hospitalization for respiratory illness. We also disaggregate the overall results by age group and by type of illness, and examine sensitivity of the results to alternative specification choices. Finally, we approximate PA effectiveness based on relative density of fires inside and outside PA boundaries, and estimate heterogeneous effects of PAs on hospitalizations for more and less effective PAs.

5.1 Effects of Upwind PAs on Air Quality

Table 2 reports the average marginal effects of the monthly area of upwind and downwind PA in km^2 on concentrations of $PM_{2.5}$ in $\mu g/m^3$ and on the number of respiratory hospitalizations per 100,000 of population.

Columns 1 and 2 show estimated impact of upwind and downwind PAs on monthly median $PM_{2.5}$, and the difference between these, which represents the treatment effect of interest. The relationship between downwind PA coverage and $PM_{2.5}$ is positive in the fire season and negative during the rest of the year. This indicates that counterfactual air quality in municipalities with high PA coverage is worse during the fire season and better during the rest of the year relative to municipalities with low PA coverage. The difference is likely to be related to different sources of pollution during these periods. It suggests that municipalities with high PA coverage have more agricultural land conversion and cultivation, which would affect fire season air quality, and less industrial activity, which would affect air quality during the rest of the year. The coefficient on upwind PA coverage is negative during the fire season, indicating that PAs reduce air pollution enough to offset this counterfactual difference. The treatment effect, measured by the difference between the effect of upwind protection and downwind protection is negative and statistically significant at all times of year, with a stronger relationship observed during the fire season. The results in columns 1 and 2 indicate that a 1000 km^2 increase in upwind PA (approximately 1 standard deviation) reduces $PM_{2.5}$ concentrations at the municipal capital by 6.2 $\mu g/m^3$ relative to the mean concentration of 19.3 $\mu m/m^3$ in the fire season, and by 1.1 $\mu g/m^3$ relative to the mean concentration of 12.8 2 $\mu g/m^3$ during the rest of the year. The results in Columns 1 and 2 confirm that PA presence upwind from a municipal capital improves air quality at that location, especially when fire activity is higher.

Columns 3–6 present average marginal effects of upwind vs. downwind PA coverage on contemporaneous monthly respiratory hospitalizations per 100,000 people. The results with municipality and time fixed effects are shown in columns 3 and 4. In this case, the difference between the effects of upwind and downwind PAs is negative, but not statistically significant. We also estimate a preferred and more restrictive specification that accounts for municipality-specific seasonality in respiratory hospitalizations (Fig. 5a) by estimating a combined municipality-by-month fixed effect. This specification was not considered for the

Table 2 Average marginal effects of PA coverage × wind direction (km^2) within 100 km on median $PM_{2.5}$ (ug/m^3) and respiratory hospitalizations per 100,000

	(1)	(2)	(3)	(4)	(5)	(6)
	$PM_{2.5}$		Respiratory hospitalizations			
	Fire season	Rest of year	Fire season	Rest of year	Fire season	Rest of year
Upwind PA (km^2)	−0.00406*** (−3.78)	−0.00142*** (−14.50)	−0.00100 (−1.28)	0.000157 (0.35)	0.00162 (1.45)	0.000878 (1.39)
Downwind PA (km2)	0.00210** (2.16)	−0.000276*** (−2.70)	−0.000227 (−0.32)	−0.000500 (−1.12)	0.00395*** (4.26)	0.00143** (2.24)
Upwind–downwind	−0.00616***	−0.00114***	−0.000776	0.000657	–0.00233*	−0.000552
χ^2	29.71 [0.000]	87.92 [0.000]	0.766 [0.381]	1.783 [0.182]	3.497 [0.0615]	0.613 [0.434]
Municipality FE	Yes	Yes	Yes	Yes	No	No
Month FE	Yes	Yes	Yes	Yes	No	No
Month × Muni FE	No	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather/wind days	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,225	63,675	21,150	63,435	21,150	63,431

t statistics reported in parentheses; *p*-values reported in brackets

$*p<0.1$; $**p<0.05$; $***p<0.01$

Table 3 Average marginal effects of PA coverage × wind direction (km^2) within 100 km on respiratory hospitalizations per 100,000 and age group (fire season only)

	(1) Child (< 15 years old)	(2) Adult (15–59)	(3) Elderly (> 60)
Upwind PA (km^2)	0.000476 (0.60)	0.000930** (2.11)	0.000258 (1.11)
Downwind PA (km^2)	0.00276*** (4.10)	0.000645 (1.45)	0.000214 (1.12)
Upwind–downwind	− 0.00228**	0.000285	0.0000443
χ^2	6.164 [0.013]	0.305 [0.581]	0.0302 [0.862]
Municipality FE	No	No	No
Month FE	No	No	No
Month × Muni FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Weather/wind days	Yes	Yes	Yes
Socioeconomic	Yes	Yes	Yes
Observations	21,109	20,860	20,866

t statistics reported in parentheses; *p*-values reported in brackets

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

$PM_{2.5}$ outcome variable since the entire region experiences similar seasonal fluctuations in levels of $PM_{2.5}$ (Fig. 5b), and it varies less from year to year for the same region.

Columns 5 and 6 of Table 2 show average marginal effect estimates of PAs on contemporaneous monthly respiratory hospitalizations per 100,000 people with municipality-by-month fixed effects. The downwind coefficients on PA coverage are positive, suggesting that counterfactual hospitalizations in municipalities with high PA coverage would be greater than in municipalities with low PA coverage. The coefficients on upwind PA coverage are not significantly different from zero, indicating that the causal impact of PAs offsets the counterfactual differences captured by the downwind coefficient. As a result, the estimated ATT, based on the differential between upwind and downwind effects of PAs is negative and statistically significant in the fire season, and is not statistically significant during the rest of the year. This suggests that upwind PAs reduce respiratory hospitalization rates after controlling for seasonal heterogeneity, but only when there is active biomass burning. The magnitude of the effect indicates that an increase in upwind PA coverage of 1000 km^2 resulted in 2.3 fewer hospitalizations per 100,000 people per month during the fire season.

5.2 Results Disaggregated by Age Group and Type of Respiratory Illness

To better understand the pathways through which PAs influence hospitalizations for respiratory illness, we estimate separate models by age group and for different types of illness. We use age categories of child (< 15 years old), adult (15–59) and elderly (≥ 60). Ideally, we would estimate impacts for infants and young children separately from older children as the former are more susceptible to severe cases of respiratory illness. However, the thresholds we use are the only ones that can be matched across the hospitalization data and the total municipal population data that are needed to calculate rates of illness per 100,000 people.

Table 3 shows effects of upwind vs. downwind PA coverage on all hospitalizations for respiratory illness by age group. These models are estimated using municipality-by-month fixed effects for the fire season only. We find that upwind PAs significantly reduce incidence of respiratory hospitalizations for children under 15. An increase of 1000 km^2 in upwind PA coverage reduces rates of hospitalization in this group by 2.3 cases per 100,000 children. We do not find significant effects of upwind PAs for young or elderly adults.

Disaggregating the results by type of illness (Table 4), we find that the overall impacts appear to be driven by effects of upwind PAs on hospitalizations for pneumonia and for acute upper respiratory infections such as rhinitis and sinusitis. Specifically, an increase in upwind PA coverage of 1000km^2 reduces monthly incidence of pneumonia by 2 cases per 100,000 people and monthly incidence of hospitalization for acute upper respiratory infection by 0.7 cases by 100,000 people during the fire season. We do not find any effect of PAs on other types of respiratory infection, namely influenza or chronic or acute lower respiratory infections.

We also estimate the effects on hospitalizations related to the circulatory, rather than the respiratory, system (ICD-10 codes, I00-I99), and hospitalizations related to external injury (ICD-10 codes, V01-X59, Y85-Y86). Circulatory hospitalizations are sometimes used as placebo tests for the impacts of air pollution. However, while respiratory impacts of air pollution are most widely recognized, there is growing evidence that $PM_{2.5}$ is also associated with acute circulatory system responses (Maté et al. 2010; You et al. 2023). In this case, we find a negative effect of PAs on hospitalizations for circulatory conditions, but it is not statistically significant. External injuries provide a more plausible placebo test as they should be largely unrelated to air pollution (Beatty and Shimshack 2014). There is some possibility of a positive effect of air pollution on injury if reduced physiological capabilities result in falls, or a negative effect if poor air quality results in less time outdoors engaged in potentially risky activities. However, these effects are likely to be small and to offset one another. We do not observe a significant effect of upwind, relative to downwind, PA coverage on hospitalizations with external injuries.

When we disaggregate the results by type of illness for the under 15 population, we again find that upwind PAs significantly reduce pneumonia and acute upper respiratory infection and do not influence rates of the other diseases (Table 5). We do not find any influence of upwind PAs on individual types of respiratory illness for the young adult or elderly adult age categories.

5.3 Sensitivity Analysis

A notable choice made within this analysis is the size of the buffer around each municipal capital used to quantify the surrounding PA coverage. The advantage of a smaller buffer is that locations that are upwind from the population center can be defined more precisely based on measurement of wind direction at that center. However, small buffers may miss important impacts of PAs because smoke can travel, and be damaging to health, over many hundreds of kms (Souto-Oliveira et al. 2023). In Table 6, we show how the estimated treatment effects of upwind PAs vary depending on the size of the buffer. The 100 km buffer is used for our main estimation results, and we compare a smaller buffer of 50 km and a larger buffer of 300 km. In both the $PM_{2.5}$ and respiratory hospitalization models, the average treatment effect of 1 km^2 of upwind PA is largest with the 50 km buffer and smallest with the 300 km buffer. The effect declines by approximately an order of magnitude with each increase in the buffer size, and also becomes less statistically significant.

We interpret this difference in the size of the effect as being driven by the average distance between PAs and affected populations within each buffer size: on average, a

Table 4 Average marginal effects of PA coverage × wind direction (km^2) within 100 km on respiratory hospitalizations per 100,000 and type of respiratory illness (fire season only)

	(1) Pneumonia	(2) Acute upper respiratory	(3) Influenza	(4) Chronic lower respiratory	(5) Acute lower respiratory	(6) Circulatory	(7) External injury
Upwind PA (km^2)	0.000976 (1.23)	−0.000257 (−0.83)	−0.000602** (−2.29)	0.000680 (1.54)	0.0000742 (0.32)	0.000587 (1.04)	0.000477 (0.78)
Downwind PA (km^2)	0.00301*** (4.50)	0.000439* (1.88)	−0.000843*** (−2.81)	0.000542 (1.18)	−0.000108 (−0.77)	0.00114*** (2.58)	0.00117** (2.34)
Upwind–downwind	−0.00204**	−0.000696*	0.000241	0.000138	0.000183	−0.000556	−0.000694
χ^2	5.174 [0.0229]	3.567 [0.0589]	0.427 [0.513]	0.0780 [0.780]	0.635 [0.426]	0.852 [0.356]	0.958 [0.328]
Municipality FE	No	No	No	No	No	No	No
Month FE	No	No	No	No	No	No	No
Month × Muni FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather/wind days	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,108	17,546	11,579	20,631	15,700	21,093	21,150

t statistics in reported parentheses; *p*-values reported in brackets

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 5 Average marginal effects of PA coverage × wind direction (km^2) within 100 km on respiratory hospitalizations per 100,000 and type of respiratory illness for children under 15 years old (fire season only)

	(1) Pneumonia	(2) Acute upper respiratory	(3) Influenza	(4) Chronic lower respiratory	(5) Acute lower respiratory
Upwind PA (km^2)	0.000330 (0.54)	−0.000444 (−1.47)	−0.000546*** (−2.75)	0.000382 (1.48)	0.000102 (0.50)
Downwind PA (km^2)	0.00230*** (4.23)	0.000138 (0.76)	−0.000511** (−2.02)	0.00000220 (0.98)	0.00000519 (0.04)
Upwind–downwind	−0.00197***	−0.000582*	−0.0000358	0.000161	0.0000963
χ^2	7.401 [0.00652]	3.299 [0.0693]	0.0136 [0.907]	0.292 [0.589]	0.231 [0.631]
Municipality FE	No	No	No	No	No
Month FE	No	No	No	No	No
Month × Muni FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Weather/wind days	Yes	Yes	Yes	Yes	Yes
Socioeconomic	Yes	Yes	Yes	Yes	Yes
Observations	20,935	16,187	9345	19,253	14,564

t statistics reported in parentheses; *p*-values reported in brackets

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 6 Variable buffer sizes—average marginal effects of PA coverage × wind direction (km^2) within 100 km on median $PM_{2.5}$ (ug/m^3) respiratory hospitalizations per 100,000 using 50 km, 100 km and 300 km buffers (fire season only)

	(1)	(2)	(3)	(4)	(5)	(6)
	$PM_{2.5}$			Respiratory hospitalizations		
	50 km buffer	100 km buffer	300 km buffer	50 km buffer	100 km buffer	300 km buffer
Upwind PA (km^2)	−0.0214*** (−4.70)	−0.00406*** (−3.78)	0.000200 (1.63)	−0.00768 (−1.57)	0.00162 (1.45)	0.000475*** (3.96)
Downwind PA(km^2)	−0.00252 (−0.56)	0.00210** (2.16)	0.000596*** (5.16)	0.00655 (1.55)	0.00395*** (4.26)	0.000630*** (4.80)
Upwind–downwind	−0.0189***	−0.00616***	−0.000395***	−0.0142***	−0.00233*	−0.000155
χ^2	18.56 [0.000]	29.71 [0.000]	9.681 [0.00186]	7.499 [0.00617]	3.497 [0.0615]	0.923 [0.337]
Municipality FE	Yes	Yes	Yes	No	No	No
Month FE	Yes	Yes	Yes	No	No	No
Month × Muni FE	No	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather/wind days	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,225	21,225	21,225	21,150	21,150	21,150

t statistics reported in parentheses; *p*-values reported in brackets

$^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

randomly selected 1 km^2 of PA in a 50 km buffer will be much closer to the population center where the outcomes are measured than a randomly selected 1 km^2 of PA in a 300 km buffer. There is evidence from other contexts that the effects of nearby fires on air quality and health are stronger than effects of more distant fires, particularly in cases where non-forest land is burned (Moeltner et al. 2013).

Tables 7 and 8 show the sensitivity of the results to further choices made about the specifications of the $PM_{2.5}$ and respiratory hospitalization models respectively. The first columns of each of these tables show the estimated impact of upwind and downwind PAs on monthly median $PM_{2.5}$ and respiratory hospitalizations, without municipality fixed effects. In this specification, unobserved differences between municipalities that may be correlated with both PA coverage and $PM_{2.5}$ are controlled for using only the downwind PA area. In theory, the downwind PA area can address the bias resulting from the unobserved heterogeneity between municipalities surrounded by minimal vs. extensive PAs. However, there is some spatial clustering of municipalities with relatively more PA coverage upwind and those with relatively more PA coverage downwind, due to prevailing wind directions in the region. For example, municipalities in the southern "arc of deforestation" have relatively more upwind protection conditional on the area of downwind protection. The downwind PA 'control' does not address these spatial correlations, while the additional inclusion of municipality fixed effects (as in our main specification) does, due to the use of deviations from monthly averages of $PM_{2.5}$ and hospitalizations rather than absolute levels.

The size of the effect of upwind PAs on $PM_{2.5}$ is smaller without the municipality fixed effects than with them, which is what we would expect if municipalities in the "arc of deforestation" have higher levels of $PM_{2.5}$ on average, regardless of local PA coverage. The estimated treatment effect of upwind PAs on hospitalizations for respiratory illness becomes positive without the municipality fixed effects. As with the $PM_{2.5}$ model, the difference is likely to be because more developed frontier municipalities also typically have more upwind PAs than downwind PAs. This creates a positive bias, which may be due to better access to hospital facilities or greater spread of infectious diseases. For both dependent variables, we consider the specification with both downwind PA coverage and municipality fixed effects to be the theoretically most appropriate for estimating the causal effect of PAs on pollution and health.

Our main results are estimated using municipality standard errors. Column 2 in Tables 7 and 8 show the results with standard errors clustered at the state level instead, as policy decisions influencing health and air quality may be made at either level. The magnitudes of the estimated treatment effects of PA coverage on $PM_{2.5}$ and respiratory hospitalization are unchanged, as we would expect. The effect on $PM_{2.5}$ remains significant, but the effect on respiratory hospitalizations becomes insignificant. We also examine whether the results change if GDP is omitted as a covariate (Tables 7 and 8, column 3), as it is possible that it could be influenced by both neighboring PAs and by the dependent variables, namely air quality and the health of the population. We do not find that this alters the results. Finally, we estimate the relationships of interest excluding any municipalities with more than 20% of their 100 km buffer outside the national boundaries of Brazil (Tables 7 and 8, column 4). Some of the borders are coastal, in which case there is no land use or potential fire that can occur. Land within neighboring countries may in practice be protected or unprotected, but we only estimate the effects of Brazilian PAs on the Brazilian population as this is the domain within which policy decisions can be made. Using only the municipalities with buffers covering primarily Brazilian territory, the estimated treatment effects are slightly stronger, but not substantially different from the main results.

Table 7 Sensitivity analyses—average marginal effects of PA coverage × wind direction (km^2) within 100 km on median $PM_{2.5}$ (ug/m^3) (fire season only)

	(1) No municipality fixed effects	(2) State clustered standard errors	(3) Municipality GDP excluded	(4) Municipalities with > 20% buffer outside Brazil excluded
Upwind PA (km^2)	− 0.0000975 (− 0.35)	− 0.00406*** (− 4.17)	− 0.00410*** (− 3.81)	− 0.00433*** (− 3.53)
Downwind PA (km^2)	0.000805*** (3.11)	0.00210* (1.83)	0.00207** (2.14)	0.00194* (1.74)
Upwind–downwind	− 0.000902**	− 0.00616***	− 0.00617***	–0.00627***
χ^2	4.980 [0.0256]	35.33 [0.000]	29.84 [0.000]	24.44 [0.000]
Municipality FE	No	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Month × Muni FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
Weather/wind days	Yes	Yes	Yes	Yes
Socioeconomic	Yes	Yes	No	No
Observations	21,225	21,225	21,249	18,648

t statistics reported in parentheses; *p*-values reported in brackets

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 8 Sensitivity analyses—average marginal effects of PA coverage × wind direction (km^2) within 100 km on respiratory hospitalizations per 100,000 (fire season only)

	(1) No municipality fixed effects	(2) State clustered standard errors	(3) Municipality GDP excluded	(4) Municipalities with > 20% buffer outside Brazil excluded
Upwind PA (km^2)	−0.000725*** (−3.63)	0.00162 (0.60)	0.00193* (1.69)	0.00113 (0.93)
Downwind PA (km^2)	−0.00298*** (–13.42)	0.00395*** (3.39)	0.00409*** (4.39)	0.00423*** (4.22)
Upwind–downwind	0.00226***	−0.00233	−0.00216*	–0.00310**
χ^2	50.09 [0.000]	1.322 [0.250]	3.005 [0.0830]	5.079 [0.0242]
Municipality FE	No	No	No	No
Month FE	Yes	No	No	No
Month × Muni FE	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Weather/wind days	Yes	Yes	Yes	Yes
Socioeconomic	Yes	Yes	No	Yes
Observations	21,150	21,150	21,150	18,578

t statistics reported in parentheses; *p*-values reported in brackets.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

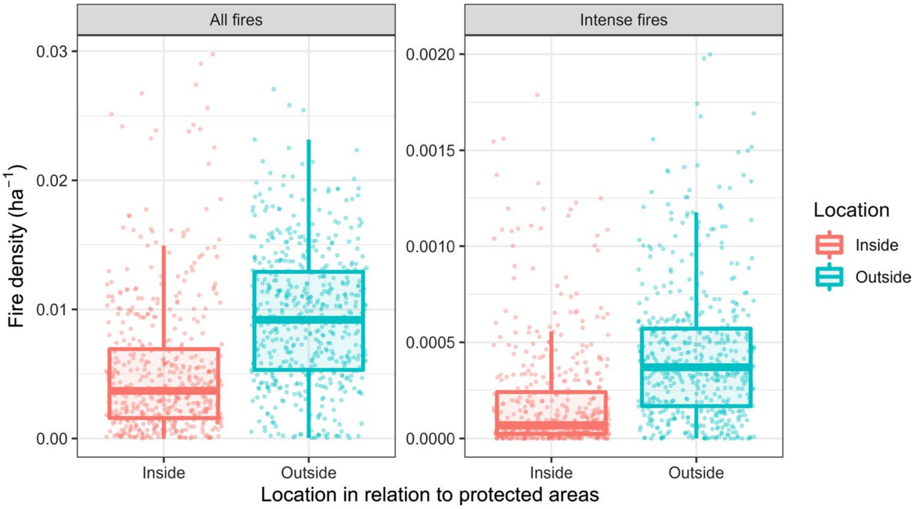


Fig. 6 Density of fires observed inside and outside PA boundaries within 100 km municipal buffers, 2006–2018

5.4 Relationship Between PAs and Fires

Our analysis is based on the underlying assumption that PAs contribute to improvements in respiratory health by reducing frequency of fires; either intentionally ignited to clear deforested land or maintain agricultural land, or unintentionally spread from those intended fires. Our identification strategy does not allow us to estimate the causal impact of PAs on fires because the exogenous variation comes from the relative locations of the PAs and population centers, and the wind directions in a given month. However, we obtain an indication of the potential validity of this causal mechanism by comparing fire incidence inside and outside PAs within each municipality's 100-km buffer to confirm whether fire activity is indeed lower in PAs, and by testing whether health effects vary with the degree to which fire activity is lower inside compared with outside nearby PAs. These conditions are necessary, although not sufficient, to conclude that a causal effect of PAs on health operates through the mechanism of reduced fire activity.

Figure 6 shows that there is a wide distribution of fire density both inside and outside PA boundaries. The number of fires is statistically lower inside PAs than outside (p-value $<$ 0.00). The same is true of 'Intense' fires, with a Fire Radiative Power (reflecting fire intensity and smoke injection height; Peterson et al. 2014) of more than 150 MW (p-value $<$ 0.01). These are more likely to be forest fires than agricultural fires due to the differences in biomass stocks between forest and agricultural lands. Intense fires are very infrequent in most PAs, although there are some exceptions. It is not surprising that we see fairly high fire density within PA boundaries. First, there could be unintentional spread of fires from outside the boundaries even if protection is strictly enforced. Second, as previously noted, funding for PAs is insufficient for effective management and enforcement, therefore some deforestation and some agricultural production is likely. Studies that directly evaluate the effectiveness of Brazilian PAs similarly find that protection reduces the incidence of fire relative to counterfactuals based on land outside PAs, but do not fully eliminate it (Alvarado et al. 2018; Nolte and Agrawal 2013; Walker et al. 2022). The

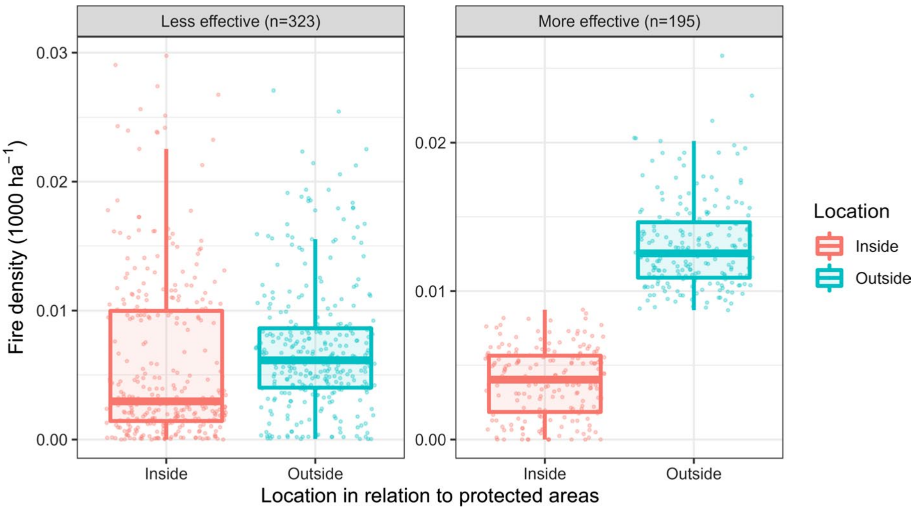


Fig. 7 Density of fires observed inside and outside PA boundaries within 100 km municipal buffers, 2006–2018

degree of effectiveness is found to vary with category of protection, PA location or application of complementary policy measures (Cisneros et al. 2022; Ferraro et al. 2013; Nelson and Chomitz 2011).

Our assumed causal pathway is that upwind PA coverage improves air quality by reducing frequency and severity of fires relative to unprotected land. The estimates presented so far reflect average impacts on health across all PAs. This is the appropriate outcome to consider as effectiveness will inevitably vary in practice across different PAs. To assess the validity of the overall results, we now consider whether the observed impact of PAs on health is stronger in the locations that we would expect it to be, based on the degree to which fires are less frequent inside PAs relative to outside PA boundaries. We use a k-means analysis to cluster the municipalities based on the relative fire density inside and outside PA boundaries in each 100-km municipal buffer. We find that three clusters of municipalities best separate the differences in fire density. In two of these clusters, the difference between fire density inside and outside PA boundaries is small or negligible: in Cluster 1a—Less Effective: high pressure, there are many fires observed both inside and outside PAs; in Cluster 1b—Less Effective: low pressure, few fires are observed either inside or outside PAs. These reflect the two main reasons why effectiveness of PAs on reducing fire or deforestation may be low, i.e., that they do not effectively protect land that faces high pressure for use, or they do not reduce use relative to the counterfactual of no-protection because the land is unlikely to be used regardless (Nolte et al. 2013). We also identify a cluster of municipalities for which fire density is substantially lower inside PA boundaries than outside: Cluster 2—More Effective. This pattern suggests both high pressure on land and high effectiveness of the PA at preventing fire activity (Fig. 7).

We estimate the impacts of upwind PA coverage on respiratory health for municipalities with "More Effective" and "Less Effective" PAs within the 100-km buffers around the municipal capitals. We combine those that are "Less Effective" due to low enforcement or to low pressure due to the small number of municipalities in the former category. The results in Table 7 show the difference between the effect of upwind PAs and downwind

Table 9 Average marginal effects of PA coverage × wind direction (km²) within 100 km on respiratory hospitalizations per 100,000, by municipality buffers containing "More Effective" and "Less Effective" PAs (fire season only)

	(1) More effective (n = 195)	(2) Less effective (n = 323)
Upwind area of protected area (km^2)	− 0.000505 (− 0.23)	0.00107 (0.87)
Downwind area of protected area (km^2)	0.00636*** (4.20)	0.00115 (0.97)
Upwind–downwind	− 0.00686***	− 0.0000769
χ^2	6.80 [0.00912]	0.00342 [0.953]
Municipality FE	No	No
Month FE	No	No
Month × Muni FE	Yes	Yes
Year FE	Yes	Yes
Weather/wind days	Yes	Yes
Socioeconomic	Yes	Yes
Observations	8147	13,003

t statistics reported in parentheses; *p*-values reported in brackets

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

PAs on respiratory hospitalizations is negative and statistically significant for the municipalities with "More Effective" PAs and not significant for the other municipalities. This supports the underlying causal mechanism as we see an effect of PAs on hospitalizations for the subsample in which fires are lower within PA boundaries, and not for the subsample in which fires occur with similar frequency inside and outside PA boundaries (Table 9).

The magnitude of the health impacts if we only look at the "More Effective" PAs is approximately three times larger than the impacts averaged across all PAs. For this subsample, an additional 1000 km^2 of upwind PA reduces respiratory hospitalizations by 6.9 cases per 100,000 of population.

6 Benefits and Costs of Forest Protection

To understand the policy-relevance of our estimation results, it is necessary to compare the scale of the benefits of reductions in hospitalization for respiratory illness with the costs associated with protecting forested land through PA designation. Brazil's *Sistema de Informações Hospitalares* (SIH/SUS), includes data on the length of individual hospital stays and the costs of those stays by month and municipality. In the North region, which contains the Amazon biome, the average length of hospitalizations for respiratory illness during the fire season of 2019 was 5.7 days, and the average cost of the care provided through the national healthcare system was US$ 260.[2] Those hospitalized had a mortality rate of 5.51%. These values only include healthcare expenditures, not welfare losses from the time, stress or pain associated with illness. Ortiz et al. (2011) estimate willingness to pay to avoid hospitalization related to air pollution in São Paulo, Brazil. Mean willingness

[2] All of the following values are converted to 2022 US$ from the currency and year of the original data.

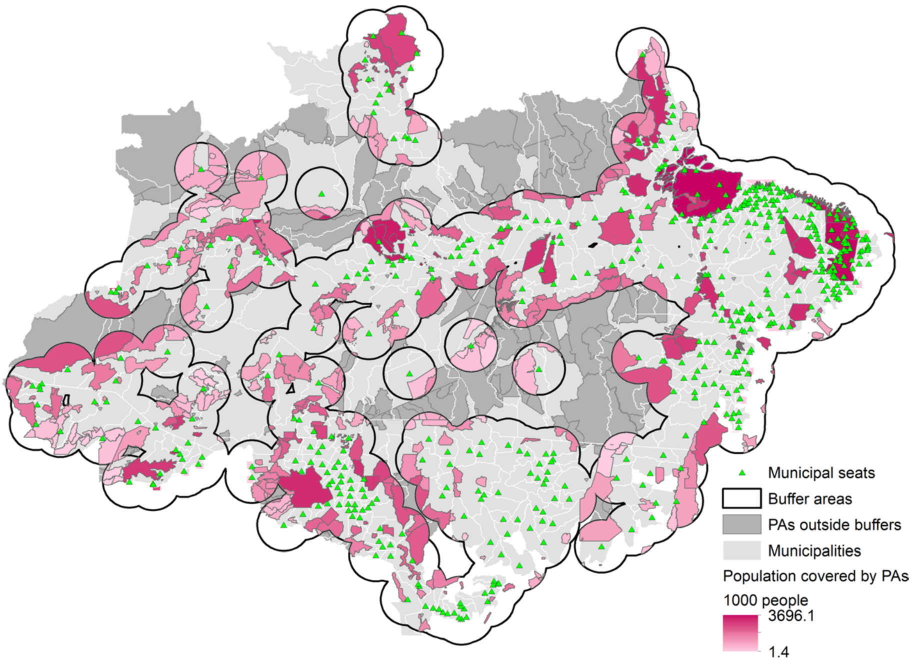


Fig. 8 Depicts size of population within 100 km of PAs in different parts of the Brazilian Amazon biome. Only PAs within 100 km of at least one municipal capital are included in the analysis

to pay to avoid one adult hospitalization in their sample is the equivalent of US$ 161. The authors state that these values represent the non-monetary costs of illness as the healthcare expenses are largely covered through the public healthcare system. We also use Brazilian estimates of the value of a statistical life to quantify the mortality risk associated with each additional hospitalization. This value is estimated at US$ 1.07–1.82 million (Ortiz et al. 2009). However, the authors propose a more conservative value, excluding potential yea-saying, of US$ 0.57–0.68 million, we use the midpoint of this range. The sum of hospital costs, non-monetary morbidity costs and mortality risk associated with one additional hospitalization for respiratory illness is US$ 34,447.

The total value of the health benefits of a PA depends on how many people live within 100 km downwind of that PA because our estimated effects are expressed as hospitalization rates per 100,000 people. Figure 8 shows the numbers of people living within 100 km of each PA in our sample (i.e. PAs that are located within the 100-km buffer of at least one municipal capital). We approximate the proportion of the time the PA will lie upwind from a population center by assuming the wind direction is equally distributed across the octants. Therefore, the downwind population is 1/8th of the total population within 100 km of a PA on any given day. This is a simplification, as in practice there will be prevailing wind directions that are more frequent and other directions that are less frequent. Based on our result that one additional upwind km^2 of PA results in 0.00233 fewer hospitalizations per 100,000 people, we calculate the total number of avoided hospitalizations for PAs at different percentiles of the distribution of local population size. We use the value of one additional hospitalization (avoided) to estimate the benefits of an additional km^2 of PA (Table 10). The lower-percentile PAs are located near one or a few small municipal capitals and therefore affect few

Table 10 Benefits and costs of protected areas, with and without effective management

Percentile	Population affected by PA 23,900	Value of benefits (average PA)	Value of benefits (effective PA)	Current PA expenditure	Costs of effective management	Opportunity costs of land	Value of other ecosystem services
25th		7	21	44	705	6,324	2000+
50th	66,400	20	59				
75th	235,400	71	209				
95th	1,128,300	340	1000				

All values expressed as 2022 US$ km^{-2}

people, whereas the higher-percentile PAs are located near large cities or near multiple municipal capitals and therefore provide health benefits to many people.

Annual management expenditures for federal PAs in the Amazon region are estimated at an average of US$ 44 km^{-2} (da Silva et al. 2021), although these can vary by five orders of magnitude depending on PA size, type, age and the characteristics of the surrounding population (da Silva et al. 2019). Actual expenditures are shown to fall substantially short of the annual amounts that would be required to effectively manage all PAs, estimated at US$ 705 km^{-2} (da Silva et al. 2021). Opportunity costs of Brazilian PAs, based on returns to timber and agricultural production, are estimated at an average of US$ 6324 km^{-2}, although these also vary spatially depending on accessibility and land characteristics (Soares-Filho et al. 2010). PAs within the Amazon region are likely to have lower opportunity costs than this national average due to lower land productivity and higher transportation costs.

We compare estimated benefits and costs, with and without effective management, and with and without accounting for opportunity costs (Table 10). The question is not whether health benefits alone justify forest conservation, since there are other important environmental values associated with PAs. The ecosystem service benefits of forest in the Amazon, such as timber and non-timber productions, climate change mitigation, and regional climate regulation are estimated at over US$ 2000 km^{-2} for the highest valued 35% of forests (Strand et al. 2018), which is likely to include much of the protected land. These values do not include all ecosystem services, and are therefore a lower-bound estimate of the value of protection. In particular, they exclude the benefits of biodiversity protection, which are also likely to be significant in the places that PAs are located.

Table 10 shows that the value of health benefits exceeds current average PA management spending for PAs with the largest local populations, even before accounting for other ecosystem services. In these cases, the health benefits alone could justify the direct costs of PA establishment or expansion. The results using 50 km buffers around each municipal capital suggest that this conclusion would be strengthened for PAs located close to a large population center, as they suggest that PAs within 50 km have larger effects on health than those within 100 km. For PAs that are more remote from population centers, the health benefits are unlikely to be large enough to influence decisions about PA designation. More effective PA management increases the annual value of the health benefits to US$ 209 km^{-2} at the 75th percentile of local population size. This is lower than the estimated cost of US$ 705 km^{-2} for fully effective management. However, this value is based on estimating the effects of the most effective 38% of PAs. Most of these are unlikely to be funded at the "fully effective" level since only around 10% of existing PAs in the Brazilian Amazon biome do not have funding deficits (da Silva et al. 2021). As with establishment or expansion of new protected land, investments in more effective management of existing PAs may be justified by the health benefits alone in areas of high population density, but not in areas of low population density. If we consider the full benefits and costs of protection, including ecosystem service benefits, other than the effects on respiratory health, and opportunity costs of land, we can see that the respiratory health benefits will not drive decisions about PA designation on their own. However, in the cases where the affected population is large, they represent sufficiently significant co-benefits to influence land-use decisions at the margin.

7 Discussion and Conclusions

There is growing interest in the connection between the conservation of ecosystems and human health. Protection of ecosystems is often presented by opponents to be in direct conflict with human values, on the grounds that it restricts economic opportunities. At the same time, human health is a universal value that cuts across political, economic, and social divisions. To date, the empirical evidence for the extent to which conservation or land-use policy can generate health improvements is minimal. We contribute by focusing on one large-scale policy, Brazil's Amazon biome PA network. There are four key mechanisms through which we expect the impacts of upwind PAs on air quality to operate: to the extent that protection reduces active deforestation, we would expect less of the burning of residual biomass that typically follows deforestation in this region; past protection provided by a PA will also reduce the area of land in use for agriculture and the resulting agricultural fires used for weed control; protection of intact forest ecosystems inhibits the unintentional spread of fires set for other purposes (Cochrane and Schulze 1999; Libonati et al. 2021); and finally, intact forest in PAs can absorb $PM_{2.5}$ from fires originating elsewhere, improving downwind air quality (Prist et al. 2023). In this study we do not distinguish between these mechanisms, so the estimates combine effects of the extent and condition of the forest ecosystem itself with effects of the restrictions on how land may be used. Our results indicate that Brazil's PAs improve air quality and reduce contemporaneous respiratory hospitalizations during months of active biomass burning in the Amazon biome.

We find a consistent relationship between upwind PAs and air quality in a municipality: doubling the sample average of 651 km^2 of PA within a single upwind octant is estimated to reduce fire-season $PM_{2.5}$ concentrations by 1.85 $\mu g/m^3$ relative to the fire-season average of 19.3 $\mu g/m^3$, and reduce rest of year $PM_{2.5}$ concentrations by 0.65 $\mu g/m^3$ relative to the rest of year average of 12.8 $\mu g/m^3$. These values represent a 10% reduction in $PM_{2.5}$ in the fire season and 5% reduction during the rest of the year. Although these reductions are relatively small, $PM_{2.5}$ is a pollutant to which people are universally exposed, and modest reductions may have important public health implications. There is no safe threshold for $PM_{2.5}$ exposure, and the World Health Organization recommends reducing exposures as much as possible.

The estimated effect of upwind PAs on respiratory hospitalizations depends critically on the size of the downwind population: across the full sample, doubling the area of PA within a single upwind octant is estimated to reduce fire-season hospitalizations by 1.56 hospitalizations per 100,000 people, compared with an average of 22.7 per 100,000; a reduction of approximately 7%. For the relatively small municipal capitals in much of the Amazon region (median population size is 19,299), this would amount to just under one avoided hospitalization for respiratory illness per fire season. In a larger city such as the state capitals of Cuiaba (~600,000), Porto Velho (~500,000) or Rio Branco (~400,000) it would amount to 19–28 fewer hospitalizations per fire season. It is important to interpret these results in relation to hospital capacity, particularly for the remote rural areas that constitute a large part of our study region. On average, communities in the North of Brazil, where the Amazon Biome is located, have 16 infirmary beds and 1 ICU bed per 10,000 people (Silva et al. 2021). However, there is substantial heterogeneity, with 5% of micro-regions having only 6 beds per 10,000 people, particularly in the North and Northeast of Brazil where socioeconomic vulnerability is highest (Coelho et al. 2020). In these settings, hospitalization of even one additional person can have important capacity implications.

When we disaggregate hospitalizations in each municipality by the age of the individual and the type of respiratory condition they were hospitalized for, we find that the results are mainly attributable to effects on children under 15 years old. This cutoff is used because it allows us to match the ages of hospitalized individuals in the SIH/SUS database with ages of the municipality population from the Brazilian census, but it is likely that the majority of these cases are among children considerably younger than 15 years old. Relative to older children, those under five years of age are at highest risk of lower respiratory infections (LRI; Kyu et al. 2022). Globally among children younger than five years old, those younger than six months account for approximately 45% of hospital admissions due to RSV-associated acute LRI (Shi et al. 2017). Infants have a high respiratory rate and lungs that are not yet fully developed, making them particularly sensitive to air pollution exposure (Bateson and Schwartz 2007). The largest effect among disease categories is on pneumonia, with a smaller effect on acute upper respiratory illness. Typically, upper respiratory illnesses alone do not result in hospitalization, so these latter cases may reflect situations where there is an exacerbation of existing respiratory comorbidities such as asthma or COPD. We do not see any effect on incidence of influenza, chronic respiratory illness or acute LRI. Previous research indicates more pronounced impacts on chronic and acute LRI following, rather than during, a wildfire event, suggesting a longer lag between exposure and effect with these outcomes (Delfino et al. 2009). We also estimate impacts on hospitalizations for cardiovascular illness, which is associated with long term $PM_{2.5}$ exposures (Brook et al. 2010). Similar to other studies (Adetona et al. 2016; Delfino et al. 2009), we do not find any contemporaneous impacts based on monthly exposures.

While our identification strategy allows us to precisely estimate health effects of PAs, it does not allow us to capture the causal impacts of PAs on deforestation and fire use directly. However, prior literature has shown that Brazilian PAs can reduce deforestation and fire, although the effectiveness varies with governance regime and location (Jusys 2018; Nolte and Agrawal 2013; Pfaff et al. 2015). We therefore create a simple clustering of municipalities based on the relative frequency of fires inside and outside PAs in the 100 km buffer around the municipal capital, and identify the buffers in which PAs appear to be "Less Effective", either because there is little pressure on the land or because fires are not prevented within PA boundaries, and those in which PAs appear to be "More Effective" based on the relative frequency of fires inside and outside PAs in the buffer. We find that if we limit our analysis to municipalities for which the municipal capital is surrounded by PAs that appear to be effective in preventing fires, the size of the impact of upwind PAs on respiratory hospitalizations is three times greater than the average effect across all PAs. This indicates that the potential health impacts of PAs would be enhanced by (i) siting the PAs in locations where pressure on land use is highest, and (ii) enforcing prohibitions on deforestation and associated fire activity within PAs.

We estimate the monetary value of the estimated health benefits of PAs, and compare these with values from the literature on other ecosystem services provided by protected forest and the costs of establishing and managing PAs. We find that the value of the reduction in respiratory hospitalizations exceeds the average expenditure on PA management in the Brazilian Amazon region in just under a third of our sample PAs, although it does not exceed the average opportunity costs of the land. A key takeaway is that these values vary spatially, with the result that in some locations the reductions in respiratory hospitalizations represent important co-benefits that should inform land-use planning and would considerably strengthen the case for forest protection. In other locations the values are negligible relative to other ecosystem services and costs of protection. Values are high where population density is high, particularly near the largest cities of Manaus and Belém, and in frontier locations with many small, densely populated municipalities (Fig. 8). These are also likely to be the locations where opportunity costs of protecting land are relatively high, but the potential effectiveness of PAs is also high due to pressure for land conversion. The degree of spatial variability we observe is common to much of the ecosystem services literature due to spatial differences in biophysical characteristics of the landscape (Wu et al. 2020a); potential visitor numbers for recreational uses (Schägner et al. 2018); intensity of complementary economic activities such as agricultural production (Wolff et al. 2017); and general proximity of population (Badura et al. 2020; Dissanayake and Ando 2014). This variability in ecosystem service values is one reason why it is important to directly examine the impacts of conservation policies as implemented in practice, rather than attempting to model a constant effect of ecosystem protection on health using transferred dose–response relationships (Ferraro et al. 2015).

In this study we focus specifically on the contemporaneous relationship between PA coverage and hospitalizations for respiratory conditions within 100 km of the PA. The estimated magnitudes of this effect, and the associated estimated value of welfare gains, therefore do not fully reflect the overall impacts of PAs on health. We do not estimate impacts from the most remote PAs, that lie more than 100 km from any municipal capital. We would expect health impacts from the excluded PAs to be lower than the average impacts. Conversely, there are health consequences that are not captured by our outcome measure. First, we only estimate effects that occur within 100 km of a PA. In some cases, smoke can travel much further than 100 km, so there are likely to be additional benefits for municipalities that are downwind, but more than 100 km from the PAs that are included in our sample. When we compare different sizes of buffer, the effects of PAs weaken considerably as distance increases, although there are still significant effects on air quality with a buffer of 300 km. Second, we only include impacts that occur within the same month as the smoke exposure. Studies of the long term impacts of wildfire smoke suggest that there are likely to be additional delayed or accumulated consequences of poor air quality (Adetona et al. 2016; Delfino et al. 2009). Third, there are health consequences of poor air quality that reduce quality of life, such as coughing or difficulty breathing, but do not result in hospitalization. A Norwegian study valuing mild health effects of air pollution estimates a median willingness to pay to avoid 14 days of coughing, sinus congestion and throat congestion at the equivalent of US$ 95 per person (Navrud 2001). We would expect these values to be lower for a Brazilian population due to lower incomes, but they show that the cost of relatively mild symptoms that do not result in hospitalization can be substantial. Our data also omit effects on privately insured hospital visits. Together, these caveats suggest that our estimates represent lower-bound values of benefits of PAs to respiratory health. In addition, our results are not intended to represent the full range of health benefits of PAs. They exclude health impacts that do not operate through upwind to downwind air transport, for example, water quality improvements or changes in the spread of infectious diseases, as these are differenced out in our identification strategy.

One concern when estimating environmental impacts of PAs is often that there may be spillovers or leakage effects that are not captured by comparing outcomes inside and outside a PA. In the case of this analysis, the estimated impacts on health account for any spillovers or leakage that occurs within the 100 km buffer around the municipal capital because we use the area protected vs. unprotected within the buffer, rather than comparing outcomes within and outside the PA boundaries. If there are spillovers or leakage to places that are more distant from the PA boundaries, these will not be reflected in our estimated results.

Brazil's commitment to conservation, as illustrated by the 2002 to 2006 expansion of the PA network, was reversed by more recent government administrations. Policies were put in place to spur economic activity in previously designated PAs by reducing development restrictions and enforcement within PAs, and the Bolsonaro administration, in particular, was transparent in pitting the protection of the environment against human interests and prioritizing economic expansion over conservation (de Area Leão Pereira et al. 2020; Hope 2019; Silva and Fearnside 2022). The current Lula administration has stated that environmental protection and prevention of deforestation are major priorities, but it also faces competing policy demands such as reducing poverty and hunger (Moutinho 2022). One challenge for any Brazilian government is that many of the benefits of conservation of the Amazon rainforest are global in nature such as climate change mitigation and biodiversity protection, while the opportunity costs of the land and the management costs associated with protection are incurred domestically. Quantification of the health benefits of forest protection can strengthen political support for conservation as these benefits accrue to local populations, regardless of whether they support conservation for broader environmental reasons.

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Declarations

Conflict of interest The authors have no conflicts of interest relating to this work.

Human and Animal Rights Statement The research did not involve human or animal subjects.

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