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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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PROTECTING LIFE AND LUNG: PROTECTED AREAS AFFECT FINE PARTICULATE MATTER AND RESPIRATORY HOSPITALIZATIONS IN THE BRAZILIAN AMAZON BIOME.

By

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I assessed the impacts of upwind protected area coverage on local respiratory health within the Brazilian Amazon. A hypothesized mechanism is the legal prohibition of human ignited fires within protected areas, reducing particulate matter pollution, impacting respiratory health downwind. The connection between fires and respiratory diseases in the Amazon is well established (Smith et al. 2014; Rangel and Vogl 2019; Rocha and Sant'anna 2020). What is not well understood is the potential that government policies aimed at preventing ecosystem loss may also promote health and wellbeing, combining the UN sustainable development goals 3 and 15. Protected areas currently dominate government conservation efforts across the globe, but empirical evidence of the health impacts of protected areas remains a small body of literature. I combined Brazilian government data for monthly municipal respiratory disease hospitalizations and monthly upwind protected area coverage. I utilized a fixed-effects model with socioeconomic and environmental controls to isolate changes in upwind PA coverage on changes in respiratory disease hospitalizations. This research highlighted the cross-boundary effects of protected areas on health and the potential for government policy synergies between environmental conservation and public health. To my knowledge, this was the first examination of upwind protected areas' impacts on downwind health outcomes.

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INTRODUCTION

Protected Areas (PAs) thus far have dominated national biodiversity conservation policies, covering 15% of terrestrial land in 2018 (UNEP-WCMC, IUCN, and NGS 2018). Future commitment will increase with the global adoption of the Aichi Biodiversity Target 2 that explicitly calls for 30% coverage of protected areas or other effective conservation measures of terrestrial area by 2030 (Convention on Biological Diversity 2020, 12). The original goal of PAs was to disincentivize human disturbances to conserve biodiversity (*Convention on Biological Diversity* 1992, Article 8a). Recently goals have expanded to include the provision of ecosystem services and human well-being. (Dudley 2008; Naidoo et al. 2019; reviewed by Watson et al. 2014). Despite PAs expanding reach, PAs' impacts lie on a small body of evidence for either intended or knock-on outcomes (Ferraro and Pattanayak 2006). The lack of understanding does not allow policymakers to correctly weigh the potential tradeoffs in the balance between conservation and development. My thesis will contribute to this evidence base for PA's local respiratory health benefit in the Brazilian Amazon Biome. The hypothesized mechanism occurs by reducing local fire usage and resulting biomass smoke exposures for nearby populations.

The emerging scientific field of Planetary Health focuses on the vital link between policy, earth's natural systems, and human health (Horton and Lo 2015). This field hopes to build evidence for whether policies that conserve "life and land," may also provide "good health and well-being," uniting UN Sustainable Development Goals (SDGs) 3 and 15. The evidence for health consequences from ecosystem change is long-standing (Carrol, Douglas, and Misha 2006; Karjalainen, Sarjala, and Raitio 2010; Ferraro et al. 2012; Neira and Prüss-Ustün 2016). The protection of one vital ecosystem, tropical forests, directly impacts human health by decreasing exposure to infectious diseases, increasing dietary diversity, and increasing water quality (Keesing et al. 2010; Jones et al. 2013; Cruz Marques 1987; Norris 2004; Galway, Acharya, and Jones 2018; Pattanayak and Wendland 2007). Protecting tropical forests can also provide health benefits by reducing agricultural fires (Reid et al. 2016; Pattanayak et al. 2009; De Sario, Katsouyanni, and Michelozzi 2013; Reddington et al. 2015; Rocha and Sant'anna 2020). Reductions in agricultural fires are likely to affect respiratory health directly through biomass smoke exposures.

PA impacts on human health could occur through legal restrictions on fire usage within PA boundaries. Many ecosystems evolved with natural burn cycles, but the Amazon Biome did not. Agricultural expansion and climatic change are primarily responsible for burning in the region (Luiz Eduardo O.C. Aragão et al. 2008; Bush et al. 2008; Davidson et al. 2012). In the months before the rainy season, July, August, and September, vegetation is set on fire to clear agricultural lands, agricultural fires, or follow logging activity before agricultural use, deforestation fires (D. C. Nepstad et al. 1999). Alternative clearing methods, such as herbicides and large machinery, are too costly for most rural landowners, so burning remains commonplace. Protected land prevents varying levels of agricultural use and accompanying clearing activities within their borders, reducing overall fire ignitions for nearby populations. PAs do not directly impact fires on private land, but fires set in dry conditions often unintentionally escape into the surrounding land. Intact-protected forests are more fire-resistant, so more protected forests can reduce the unintentional spread of fires (Cochrane and Schulze 1999). Wherever fires occur, they produce inhalable fine particulate matter, $PM_{2.5}$, potentially traveling hundreds of kilometers from a fire before being breathed into human lungs, causing irritation, coughing, and difficulty breathing.

Deforestation-fire smoke is responsible for 80% of fire caused $PM_{2.5}$ in Brazil. Globally Brazilian deforestation fires account for 12–16% of this emission, exposing an estimated 24 million Brazilians yearly to potential health consequences (Reddington et al. 2015). A comprehensive review of smoke exposures supports growing evidence of increased all-cause mortality and respiratory diseases (Reid et al. 2016). Globally, air pollution was the fifth leading cause of death in 2015, representing a massive environmental disease burden across the globe (Cohen et al. 2017). Evidence of the close relationship between agricultural/deforestation-fires, $PM_{2.5}$ exposures, and respiratory health in the Amazon indicates that the presence of PAs could provide a substantial preventative health benefit for nearby Brazilians and reducing burdens on their publicly funded healthcare system (Rosa et al. 2008; Smith et al. 2014; Reddington et al. 2015; Rocha and Sant'anna 2020).

Protected tropical forests are made even more critical with the implications of climate change. The overall effect of climate change in the Amazon is uncertain, but many researchers expect an increase in drought events and accompanying fires (Betts, Sanderson, and Woodward 2008; Le Page et al. 2017; Luiz E.O.C. Aragão et al. 2018). The Amazon has already faced two once-in-a-century drought events in the last 20 years, 2005 and 2010 (Smith et al. 2014; Marengo et al. 2011). Climate forecasts expect these events to increase from diminishing precipitation and increasing length and intensity of the dry season (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, increasing local humidity and precipitation (D. C. Nepstad et al. 1999; Maillard et al. 2020; Nowak et al. 2014; Morton et al. 2013; Le Page et al. 2017; Sampaio et al. 2007; Giardina et al. 2018). Standing tropical forests also mitigate regional losses of precipitation during drought events (Mu, Biggs, and De Sales 2021). Protected areas could provide this local mitigation effect by conserving nearby standing forests. Many tropical ecosystems exhibit thresholds beyond which small changes in land cover are irreversible, resulting in the near-permanent loss of these mitigation services (Qiu et al. 2018). Forest protection could serve as one intervention that prevents the Amazon from shifting towards a more fire-prone ecosystem (Malhi et al. 2009).

The Brazilian government had protected roughly 28% of the Amazon by 2018, just short of their National Aichi target of 30% protection by 2020. The amount needed to manage their current protection is roughly US $ 464 million; however, the annual budget from 2010 to 2014 covered just under 30% of these costs (Pacheco, Neves, and Fernandes 2018). Limited conservation budgets for existing PAs and plans to expand PA networks highlight the need to know if this intervention results in desired environmental and human well-being outcomes. On top of limited conservation budgets, conservation progress in Brazil has reversed, attributed to the Brazilian administration's recent shift away from conservation enforcement and public perception of relaxed environmental regulations (Ionova 2020; Hope 2019). The current Brazilian administration has gradually removed protection and sought to lessen the ability to create new PAs and indigenous territories (Abessa, Famá, and Buruaem 2019; Keles et al. 2020). This action not only endangers conservation goals but has local and global climate implications as conversion will release substantial amounts of greenhouse gases (Van Der Werf et al. 2009). While in certain situations, the 2020 COVID-19 pandemic may have reduced air pollution and resulting mortality (Chen et al. 2020), this is not the case in Brazil. The Brazilian Minister of the Environment, Ricardo Salles, in April 2020, said openly that the international media attention on COVID-19 is an opportunity to roll back environmental regulations in the Amazon (VejapontoCom 2020). The combination of relaxed enforcement and rising unemployment increases incentives for land clearing by both rural landowners and opportunistic land speculators (Troëng, Barbier, and Rodríguez 2020; United Nations 2020). These factors contributed to the twelve-year peak in deforestation and accompanying fires in 2020 (Spring and Paraguassu 2020). These recent actions emphasize the need for examinations of PA impacts on air pollution and local respiratory health.

Respiratory diseases represent one link between disease burdens and conditions in our surrounding environments. Air pollution exposure is related to aggravation of respiratory conditions such as asthma, and pneumonia, and chronic obstructive pulmonary disease - COPD (Liang et al. 2019; Sarnat et al. 2012; Nicolussi et al. 2014; 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). For respiratory diseases in the Amazon, this burden primarily lands on children, the elderly, the impoverished, and indigenous people (Ignotti et al. 2010; Rocha and Sant'anna 2020). The combination of relaxed environmental enforcement and increased drought events caused by climate change will increase this burden. The potential that Amazonian PAs networks could play a role in reducing this burden makes this a particularly well-timed thesis during the current COVID-19 respiratory pandemic as air pollution is also associated with increased mortality risks of novel infectious diseases such as SARS and COVID-19 (Cui et al. 2003; Wu et al. 2020).

PA IMPACT LITERATURE

Causal Evidence of PA Impacts

The PA impact literature has just begun to estimate causal impacts inspired by the evidence-based movement (Ferraro and Pattanayak 2006; Ferraro and Hanauer 2014b). Attention has focused on non-random location bias, the tendency of PA assignment towards lands with lower conversion pressures, and economic activity (DeFries et al. 2005; Andam et al. 2008; L. N. Joppa and Pfaff 2009; L. Joppa and Pfaff 2010). This tendency means that differences between my outcomes, air pollution, and respiratory health with and without protection could reflect differences between areas selected for the establishment of PAs rather than the PA assignment itself. The most common method to establish causal impacts in this literature uses matching methods. Researchers use data on observable differences between protected and unprotected areas and match “similar” sites to make apples-to-apples comparisons on their outcomes of interest. The assumption is that the observable differences are enough to remove the non-random location bias. I choose instead to perform panel data analysis with municipality, month and year fixed effects to remove identification concerns about unobserved differences between municipalities with varying levels of Protected Area coverage. Additionally, I measure separate effects for protection in an upwind direction and use protection in the downwind direction as my control effect. I limit my literature review to only studies that acknowledge and explicitly seek to remove location biases by comparing outcomes within PAs with “similar,” unprotected areas.

PAs and Land Cover

There is growing albeit contested global evidence for the actual effectiveness of PAs at reducing land cover change. Early research was encouraged by the increasing availability of satellite-based observations of land cover changes as a proxy for biodiversity preservation outcomes. A global country-level study found protected areas reduced land conversion in 67 to 75 percent of countries studied (L. N. Joppa and Pfaff 2011). Researchers estimated Protected Areas in Costa Rica saved 10% of protected forests from deforestation (Andam et al. 2008). Sims (2014) found increased forest cover, 17-22%, and forest patch size, 20-30%, in Thailand. Other studies in tropical ecosystems have found overall deforestation reductions in China, Peru, and Columbia (Yang et al. 2019; Miranda et al. 2016; Negret et al. 2020). However, others have been skeptical to conclude that their estimations are causal due to unobserved differences in protected and unprotected locations (Blackman, Pfaff, and Robalino 2015).

Protected Areas in Brazil have also proven to impact land cover outcomes, but the effectiveness depends on where and when the PA was assigned. The 2004 to 2006 expansion of PAs in Brazil was estimated to be responsible for 37% of the total reduction in deforestation (Soares-Filho et al. 2010). After disaggregating by protection types and deforestation pressure, all levels of protection reduced deforestation with stricter protection resulting in more avoided deforestation (Nolte et al. 2013). In Para, a state within the Amazon Biome, Federal and indigenous lands avoided 5.5% and 2.2% of deforestation within their borders (Herrera, Pfaff, and Robalino 2019). Impacts on internal deforestation rates depend on where they are sited. PAs within high-pressure areas are more effective than those within lower pressure areas (Pfaff, Robalino, Sandoval, et al. 2015; Nolte et al. 2013). And PAs farthest from road networks result in lower effectiveness (Barber et al. 2014; Soares-Filho et al. 2010). PAs overall, and specifically strict PAs, are becoming more and more isolated from deforestation pressures and are therefore showing lesser impacts on land cover. Strict PAs designated between 2000 and 2005 were more likely to be placed in high-pressure areas than in more recent periods (Nolte et al. 2013). PAs established before 2000 caused a 2.3% reduction in avoided deforestation and PAs created in the 2004 to 2008 period a little less than 1.5% (Pfaff, Robalino, Herrera, et al. 2015). The difference in avoided deforestation for correlational and causal estimates was 16% in 2001-2004, 42% in 2005-2008, and 92% in 2009-2014 (Jusys 2018). PA effectiveness in the Brazilian Amazon predictably follows trends in assignment location. PA assignment is therefore increasingly non-random. Assignment trends indicate that as Brazil's PA network grows, there is less land that can be protected at low development opportunity costs; when applied to these areas, it is the least effective at achieving conservation goals.

PAs and Human Wellbeing

Given that PAs are prolific globally and their designation costly building an evidence base for PAs impacts human well-being outcomes. One potential concern is the opportunity cost PAs place on land-use decisions by decreasing income opportunities for local populations. The poorest and most vulnerable communities that rely on the land for income and wealth generation could be made worse off (Ferraro and Hanauer 2014a). One of the main arguments by policymakers and local communities against any conservation effort is opportunity costs to development, unintended poverty exacerbation, or population displacement (Holmes 2007; Coad et al. 2008; Keles et al. 2020). These arguments are highly contested but represent a legitimate concern for protection. PAs represent a significant investment in conservation and could result in ineffective, inequitable, or inefficient outcomes for local populations. Ideally, policymakers should weigh if the potential negative impacts justify their potential benefits. In Brazil, PA coverage has not yet shown a negative impact on socioeconomic indicators such as municipal GDP or poverty exacerbation (Kauano et al. 2020; Ferraro and Hanauer 2011), but conservation and human well-being outcomes represent tradeoffs between these two goals (Ferraro and Hanauer 2011). The broader questions remain. What are potential socioeconomic benefits supplied by PAs? Are PA benefits to conservation and human well-being goals worth their costs?

In response to these questions, researchers have examined impacts on poverty alleviation inequality, incomes, and wealth (Andam et al. 2010; Sims 2010; Ferraro and Hanauer 2011; Canavire-Bacarreza and Hanauer 2013; Agrawal 2014; Miranda et al. 2016; Keane et al. 2020). Differences in outcomes between treated and untreated locations in this context are likely biased toward worse human well-being outcomes since PAs tend towards areas with higher poverty and lower economic potential (Fisher and Christopher 2007). Nonetheless, Andam et al. (2010) estimated a 1.4-point reduction in a poverty index in Costa Rica and Thailand for districts with 10% PA coverage. Further examination into this dataset indicated that reductions depend on where the PA is sited. The best conservation and poverty alleviation locations do not frequently overlap (Ferraro and Hanauer 2011). For example, PAs sited on suitable agricultural land results in the most avoided deforestation and resulted in the least poverty alleviation.

There is a growing body of evidence that PAs can improve human welfare through increasing economic opportunities from increased tourism activity. Evidence of poverty alleviation comes from countries with strong tourism industries such as Costa Rica and Thailand (Andam et al. 2010; Sims 2010), especially near tourism centers such as national parks (Sims 2010). In Nepal, PAs alleviated extreme poverty and inequality even in areas with less tourism, and high tourism areas did not see increases in inequality (den Braber, Evans, and Oldekop 2018). A global evaluation of the local impacts of PAs on human well-being found positive wealth effects from tourism and speculated additional benefits through direct use and income generation from local PA access (Naidoo et al. 2019). Recent evidence in the Amazon indicates positive economic benefits from PA investment in tourism while supporting conservation goals (do Val Simardi Beraldo Souza et al. 2019). Two crucial takeaways from this literature are PA impacts differ significantly by country and PA location. PA impact estimates depend on potential mechanisms such as tourism, migration, and infrastructure (Ferraro and Hanauer 2014a). It is not easy to make general conclusions about local human well-being benefits.

PAs and Human Health

Given the deficiency and challenges of estimating PA impacts on land degradation and human well-being, it is no surprise that the literature estimating effects on human health is modest. I was only able to identify three studies. The first of these was a case study of one Indonesian PA finding an expected reduction in diarrheal cases by 2,600 (Pattanayak and Wendland 2007). A larger-scale correlational study in the Legal Amazon, where researchers examined diarrhea, acute respiratory infections - ARIs, and malaria outcomes in children. The authors found that protection type matters. Strict PA coverage was associated with reduced incidence of all three diseases, but sustainable use coverage was associated with substantially increased malaria incidence (Bauch et al. 2015). In Cambodia, researchers confirm similar evidence in children, finding decreased diarrhea and ARIs, but not fevers, presumably including malaria, from increased PA coverage within 15km of a village (Pienkowski et al. 2017). These diseases were likely chosen due to being representative of substantial childhood disease burdens with environmental causes (Prüss-Üstün and Corvalán 2007; Neira and Prüss-Ustün 2016).

In the Amazon and Cambodia studies, authors speculated the relationship between PAs and respiratory infections occurs through biomass smoke exposure. Bauch et al. (2015) found a 0.04 standard deviation reduction in ARIs from more PA coverage within a municipality. In Cambodia, a 10-percentage point increase in PA coverage within 15km was associated with a 3.4% decrease in childhood ARIs. These results encourage a causal examination of PA policy impacts on biomass smoke exposures and respiratory outcomes across a longer time frame.

Although the PA to respiratory health literature is limited, separate bodies of work connect PAs to fires, and another relates fires to health outcomes. First, in this chain, evidence for PA impacts on fires in Latin America and the Amazon is mixed. The average fire density in the Amazon is 3.7 to 9.4 times greater inside reserves when compared to the surrounding buffer zone (D. Nepstad et al. 2006). However, concerns about causal inference from this study have been raised (Carmenta et al. 2016). The same factors important in the land cover literature, such as proximity to roads and centers of deforestation pressure, play a significant role in estimating PA impacts on fires. PAs of all types are associated with reduced fire occurrences relative to surrounding areas (Adeney, Christensen, and Pimm 2009). Another study found PAs reduced fire incidence in Latin America by 2.7 to 16.5 percentage points. Estimating fire incidence impacts also depended upon the designation period, reflecting more significant differences between protected and unprotected areas over time in the Amazon (Nelson and Chomitz 2011). Carmenta et al. (2016) found that pre-protection differences in sustainable use areas explained fire density rather than the causal impact. The debate on whether PAs impact fires by their designation rather than by their non-random assignment is not settled. This work hopes to build upon these studies to briefly examine the mechanism from PAs to air quality through prevailing winds before looking at the effects between PAs and respiratory diseases.

The second part of the causal chain, fires, pollution, and respiratory health in tropical regions globally, has been examined primarily in southern Asia and Brazil. Findings in southeast Asia reliably show increased respiratory illness and symptoms from fires in Indonesia (Aditama 2000; Frankenberg, McKee, and Thomas 2005) and increased respiratory hospitalizations in Singapore (Lavaine 2014; Sheldon and Sankaran 2017). Studies in Brazil have shown that population exposure to air pollution increases acute respiratory diseases (Ignotti et al. 2010; do Carmo, Alves, and Hacon 2013). This relationship is becoming more heavily studied in Brazil due to the recent risks of drought aggravated wildfires and increased respiratory hospitalizations during drought events. (Smith et al. 2014; Machado-Silva et al. 2020). The most recent examination Rocha and Sant'anna (2020), explicitly tries to remove the confounded relationship between fire and economic activity by using fixed effects and exogenous changes in wind direction. In doing this, they can establish a plausible causal connection between biomass burning, $PM_{2.5}$, and health outcomes apart from economic activity. I adopt a similar methodology to this and Rangel and Vogl (2019) although I focus on respiratory disease hospitalizations rather than birth outcomes.

Contributions

Human health impacts represent the latest frontier in PA evaluation literature. A 2016 review of the empirical evidence of health impacts of PAs found less than 2% of rigorous PA impact studies examine health outcomes even though PAs dominate conservation interventions (McKinnon et al. 2016). Reviews of empirical studies of conservation intervention impact often acknowledge a belief in positive health impacts from PAs, calling for more robust empirical evidence to back this claim (Pullin et al. 2013; Whitmee et al. 2015). This work seeks to provide some of that evidence. In my thesis, I hope to assess the causal impacts of PA presence on air quality and resulting respiratory hospitalizations in Brazil's Amazon biome. Through this, I will try to connect the causal chain by answering, "Does PA coverage impact air quality?" before answering, "Does PA coverage affect respiratory disease hospitalizations?" My results address the large gap in understanding the role a conservation policy can play in improving human health, illuminating PAs' potential for achieving conservation and human health goals. My results could apply to the broader tropical regions, encouraging more research into tropical areas threatened by increasing fire risks from agricultural development and global climate change.

PAs, $PM_{2.5}$ AND RESPIRATORY HOSPITALIZATIONS: METHODS & DATA

I compiled a panel dataset of roughly 80,964 observations (13 years * 12 months * 519 municipalities). Outcomes of interest include median PM 2.5 concentration and respiratory disease hospitalizations. Weather conditions include temperature, rainfall, humidity, and prevailing wind direction, all of which, including PM 2.5, were obtained from Brazil's Integrated Health Environmental Information System (SISAM) developed by the National Institute of Space Research (INPE). Socioeconomic conditions are municipal estimates for GDP, population, and population density. After controlling for these factors, I focus on the impacts of protected areas within 100 km of the municipal seat on monthly municipal outcomes. Descriptive statistics used in this analysis are described in Table 1; 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 protected areas on air quality and hospitalizations over time, especially during the fire season.

Data

Respiratory Disease Hospitalizations:

Respiratory disease hospitalizations were aggregated to a monthly panel from 2006 to 2018 for the 516 to 519 municipalities within the Amazon Biome. I obtained hospitalizations from Brazil's Sistema de Informações Hospitalares, SIH/SUS (DataSUS), a database of all hospitalizations covered by SUS, Brazil's publicly funded health care system (Castro et al. 2019; Rocha and Sant'anna 2020). Municipality by month respiratory hospitalizations were created based on the month of admission and the municipality of residence, ensuring the broadest spatial coverage and the likely site of exposure to wildfire smoke (Smith et al. 2014; Machado-Silva et al. 2020). Hospitalizations are coded based on the International Classification of Diseases version 10 (ICD-10), primary diagnosis codes J00-J99 were used to classify diseases of the respiratory system.

Respiratory diseases show substantial seasonal variation and an overall downward trend. 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 before the rainy season, July, August, and September. This graph provides some evidence that increases in fire activity are associated with increased respiratory disease hospitalizations in some areas. Monthly hospitalizations peaked in 2007 at 19,577, corresponding to the worst fire and air quality year over the period. Since 2010 hospitalizations trend downward, settling after 2016 at around 11,000 respiratory hospitalizations per month. Respiratory disease hospitalizations are relatively rare events and occur at an average monthly rate of roughly 55 per 100,000 people. The variation in the total number of hospitalizations over time within the Amazon Biome is depicted in Figure 1. The between municipality variation is illustrated in Figure 2.

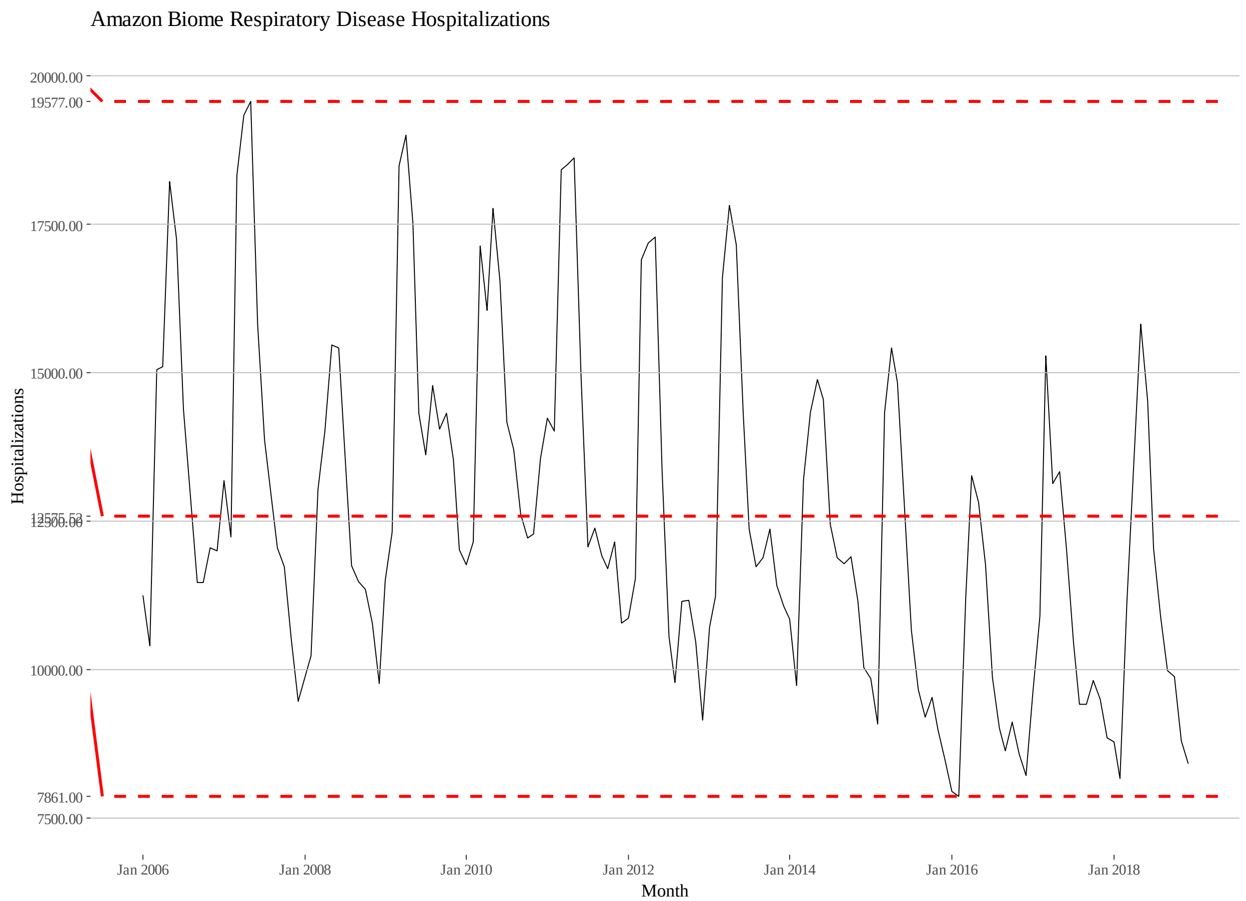


Figure 1: Time Series of total respiratory disease hospitalizations within the Amazon Biome. Respiratory disease hospitalizations are seasonal, with peaks at the end of the rainy season followed by a smaller peak at the end of the dry season that corresponds to the fire season, July, August, and September.

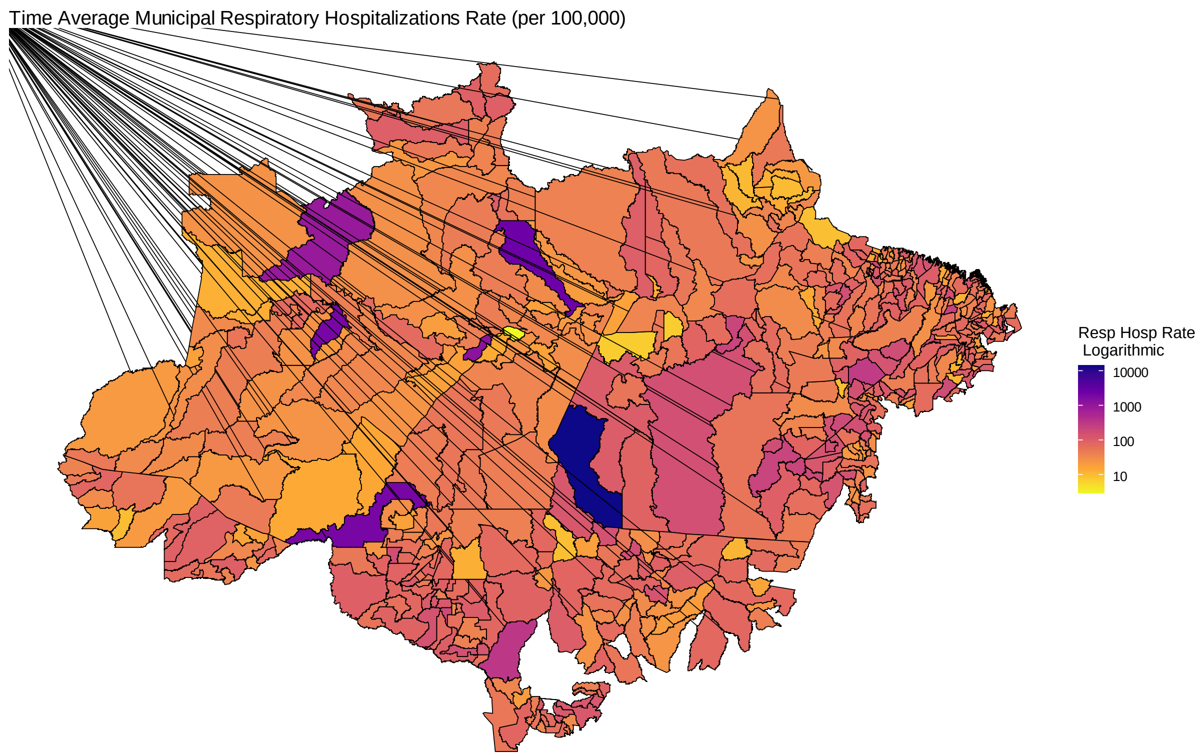


Figure 2: Spatial distribution of time average respiratory hospitalization rates. Depicts a strong spatial trend with hospitalization rates in the south/eastern region being substantially higher than in the north/west region. The municipality Jacareacanga in blue influences hospitalization rate estimates as IGBE estimates drop from 40,000 residents to 8 over the period. The population estimates for this municipality are unreliable and therefore dropped from the analysis.

Fine Particulate Matter, $PM_{2.5}$

I use fine particulate matter, $PM_{2.5}$, (µg/m3) estimates at the municipal seat for 6 hour periods extracted from CAMS-Reanalysis Model and NASA's MERRA-2 satellite. 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 (He et al. 2019). To limit the influence of severely outlying measurements, I aggregated monthly measures based on monthly median concentrations instead of monthly means. Even with median measures, the maximum recorded concentration reaches 848 (µg/m^3), which is 84.8 times the WHO recommendation for average annual mean $PM_{2.5}$ pollution of 10 (µg/m^3). I could not determine how plausible this observation was, but anything above 250 (µg/m^3) is considered highly hazardous to health. I suspect this observation results from cloud cover and not an actual $PM_{2.5}$

concentration. Because I estimated models with between 19,000 and 59,000 observations, I was less concerned about outlying observations.

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 occur 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 mg/m^3. The monthly average median $PM_{2.5}$ concentrations for the region is displayed in Figure 2. The averages for the fire season and the rest of the year are shown in Table 1.

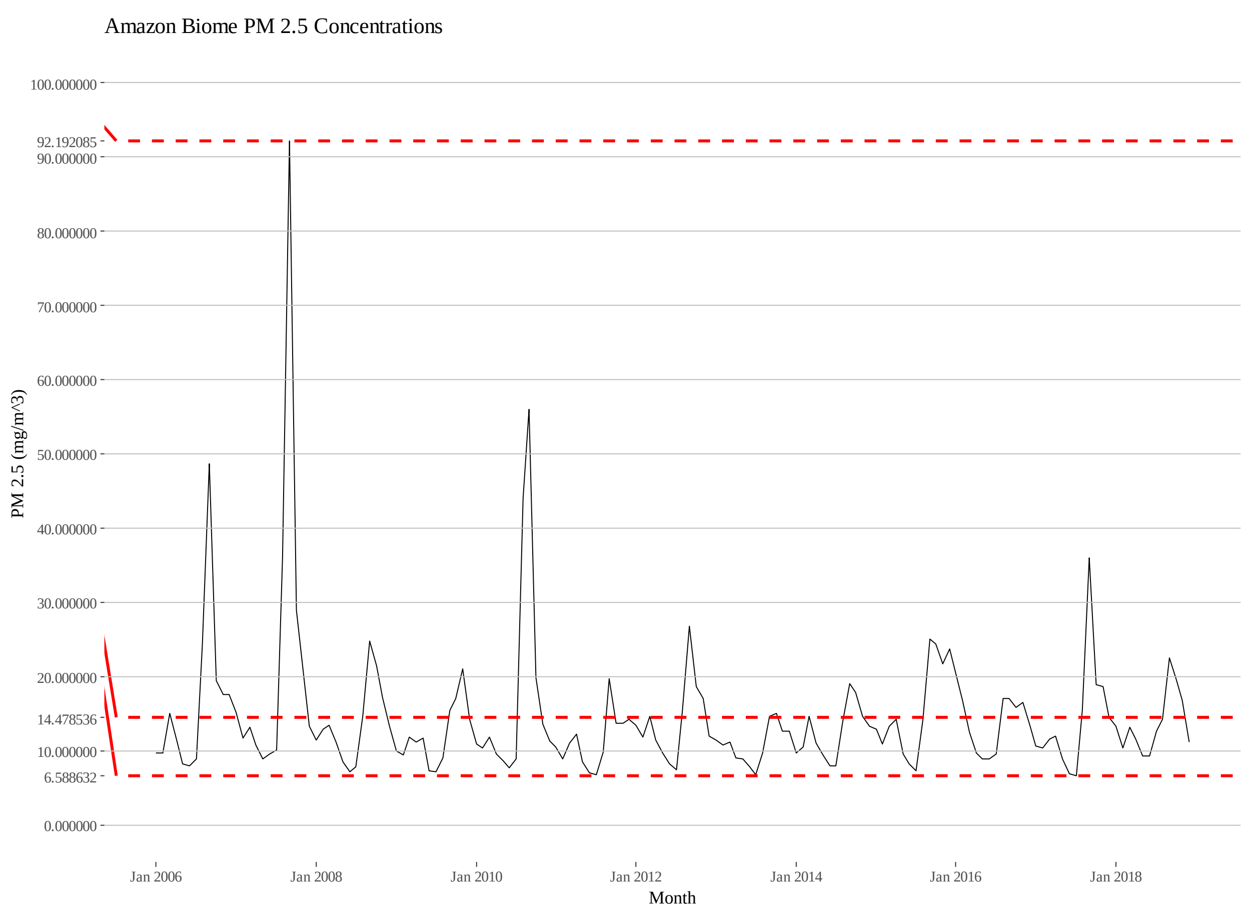


Figure 2: Time Series of the median municipal PM 2.5 concentration for all municipalities. PM 2.5 shows strong seasonal variation peaking during the fire season July, August, and September. The year 2007 is noted as being among the worst fire seasons.

Wind

Municipality measures of wind direction are the estimated prevailing wind direction at the municipal seat every 6 hours. I converted wind directions to dummy variables equal to one depending on where the observation would be classified for eight cardinal directions, north-north-east, east-north-east... I aggregated monthly data by dividing the dummies by the total number of non-missing observations and then multiplying this proportion by the number of days each month for each of the eight wind directions. This calculation is shown below for the estimated east-north-east wind days.

$$enedays_{it} = \left(\frac{ene\ observations_{it}}{total\ observations_{it}}\right) * days\ per\ month_{it}$$

The resulting observation is the expected number of days, 24 hour periods, in each month, the wind was coming from each direction. 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.

Protected Areas

I obtained shapefiles of PA boundaries from the Chico Mendes Institute for Biodiversity Conservation (ICMBio) for the years 2002 to 2018. To establish a measure of the area of the protected area nearby, I drew 100km geodesic buffers surrounding each of the 519 municipal seats for each year. I chose the municipal seat as the center of the buffer. The municipal seat likely represents the most population-dense area in the municipality and is the point location of my $PM_{2.5}$, wind, and weather observations. PAs near a municipal seat area are inherently less isolated due to roads near the municipal seat. Using the seat instead of the centroid handles some of the heterogenous impacts due to isolation from economic activity. The resulting treatment is protected area coverage near the seat over time.

The primary changes in PA coverage occur from 2002 to 2006, and relatively small changes in coverage occur from 2007 to 2018, shown in Figure 1 of the appendix. Since there are only a few municipalities with changing PA coverage, I do not examine PAs designated after 2006. These small changes are known to tend towards more isolated areas. When applied to non-isolated regions, they tend to be smaller, therefore, likely to have an outsized impact on results (Pfaff et al. 2009; Robalino, Pfaff, and Villalobos 2017). I estimate two models of changing PA coverage. The first model exploited changing treatment during the 2002 to 2006 period, shown in Figure 1. The second used fixed 2006 PA coverage boundaries, shown in Figure 2, and exploits variation in effects of PAs in either the up or downwind direction in each month and municipality. Variation in PA coverage only originates from changing wind direction and not changing PA assignment over time.

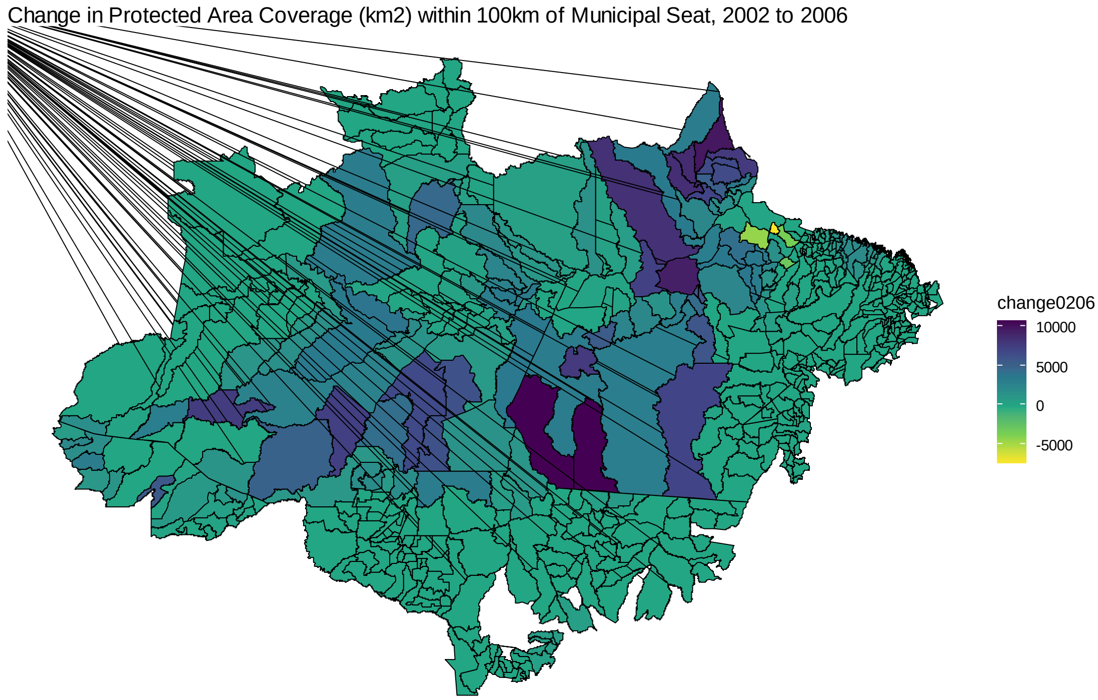


Figure 3: Shows the spatial distribution of changes, in PA coverage within 100km, PA coverage 2006 – PA Coverage 2002, mapped onto municipal boundaries.

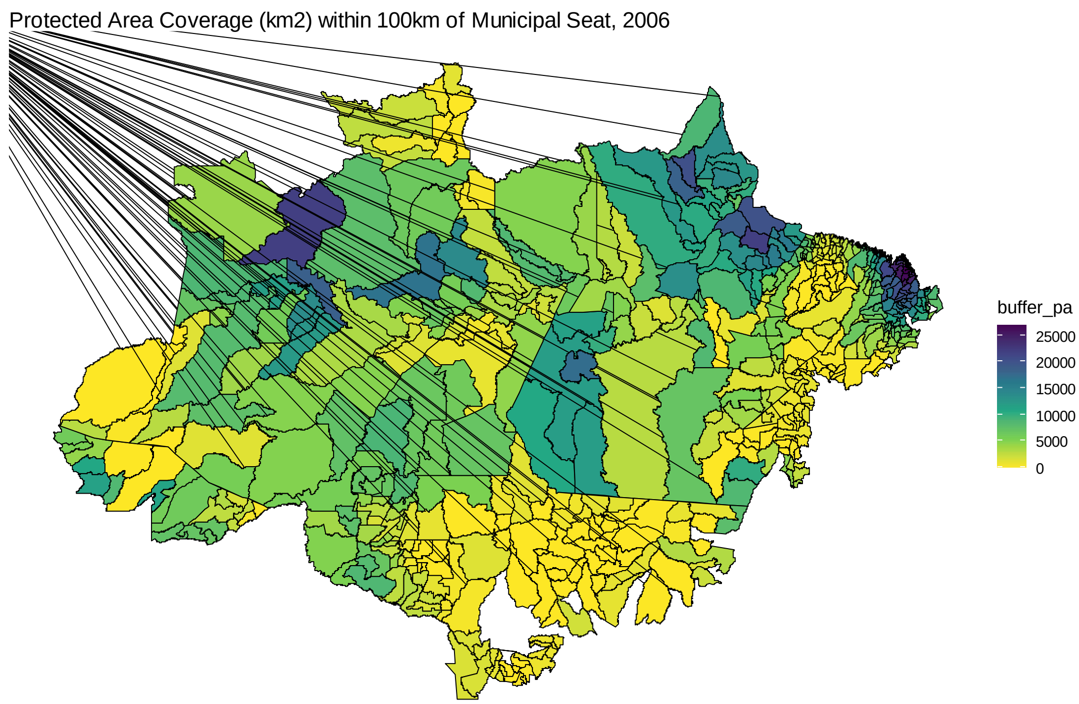


Figure 4: Shows the spatial distribution of 2006 PA coverage within 100km of the municipal seat mapped onto municipal boundaries.

Figure 3 shows that most municipalities did not experience any changes in nearby PA coverage from 2002 to 2006, and the changes occurred in the center of the Amazon Biome. The south and eastern areas overlap with the “arc of deforestation” and largely did not experience changes in Protected Areas. Highlighting that PAs are often assigned to areas without active conversion, lower agricultural and deforestation activity, and are therefore not comparable to areas without increasing PA coverage.

Figure 4 depicts PA coverage as of 2006 within 100km of the municipal seat. Overall PA coverage near a municipality in the whole region shows less of a spatial trend and more substantial spatial variation. Municipalities within the “arc of deforestation” are also less likely to have nearby 2006 PA coverage. Substantially more protected areas surround more isolated municipalities in the north and central regions.

Both treatment measures, changing PA coverage assignments and overall 2006 coverage, are susceptible to non-random treatment assignments. Areas with increasing coverage are different in economic activity and deforestation pressures, likely affecting $PM_{2.5}$ and respiratory hospitalization outcomes.

Protected Areas and Wind Interaction

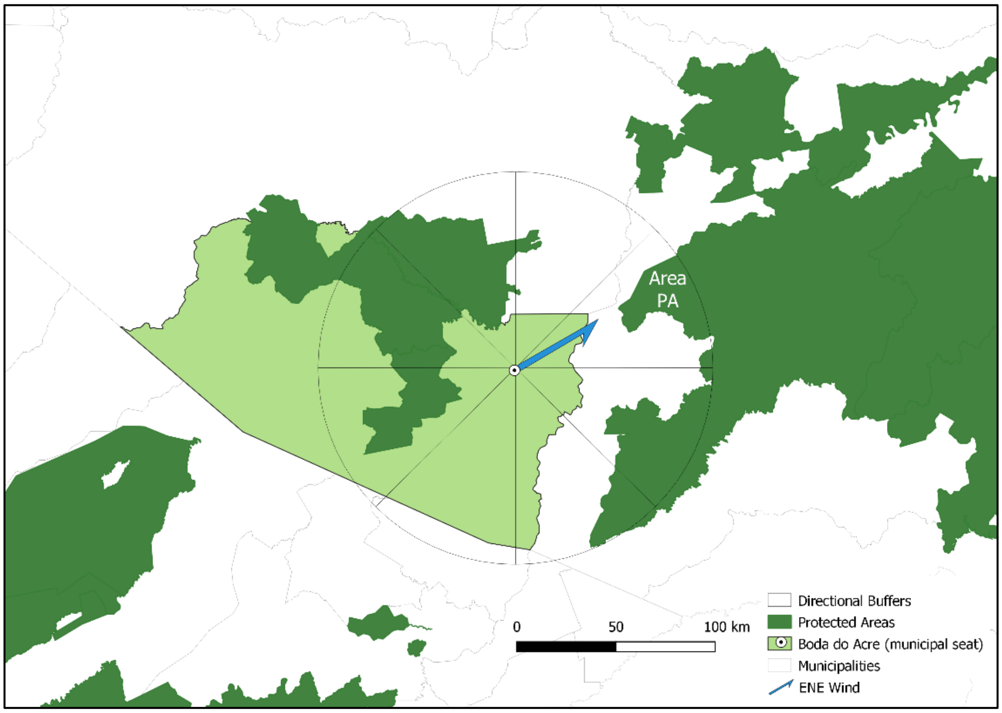


Figure 5: Depicts a daily measure of upwind area of protected area for the municipality Boda do Acre. Daily observations were then averaged to obtain an average monthly estimate of upwind protection.

To reduce non-random treatment bias, I sort nearby protected areas by direction and interact the directional coverage with prevailing winds. PAs are non-randomly assigned based on factors such as local economic activity nearby, but protection assignment is not decided based on wind orientation relative to the municipal seat. I sorted PA coverage within the 100km of a municipal seat into octants corresponding to eight wind directions. These areas are then interacted with the wind day observations to establish a monthly average of upwind and downwind PA coverage. 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 treatment not expected to influence upwind outcomes, in effect a control treatment.

Downwind PA area therefore controls for unobservable factors that are correlated with PA coverage and health outcomes but do not have a causal impact though air quality.

To obtain monthly upwind and downwind protection measures, I interact monthly changes in wind directions with corresponding PA coverage. Monthly municipal measures of upwind protection are monthly averages, created by multiplying PA area within each direction by the number of days the wind originated from that directional octant. The simulated upwind average is shown below.

$$upwindpa_{it} = \frac{(nneAreaPA_i * nneDays_{it} + \cdots + \; nnwAreaPA_i * nnwDays_{it})}{days\ per\ month_t}$$

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

$$downwindpa_{it} = \frac{(sswAreaPA_i * nneDays_{it} + \cdots + \; sseAreaPA_i * nnwDays_{it})}{days\ per\ month_t}$$

The resulting calculations create a simulated estimate of the average daily area of PAs upwind and downwind within a given month. Protected areas in a more frequent prevailing wind direction are given more weight in the upwind average. Conversely, PAs in a less common prevailing wind is given more weight in the downwind average. The monthly changes in these interactions are crucial to estimating the causal impact of PA coverage on air quality and respiratory hospitalizations. Figure 4 depicts the time-average PA coverage in the upwind and downwind direction mapped onto municipal boundaries. The time-average controls for overall nearby PA coverage, and the variation comes from changing wind patterns from more or less protected regions relative to this value.

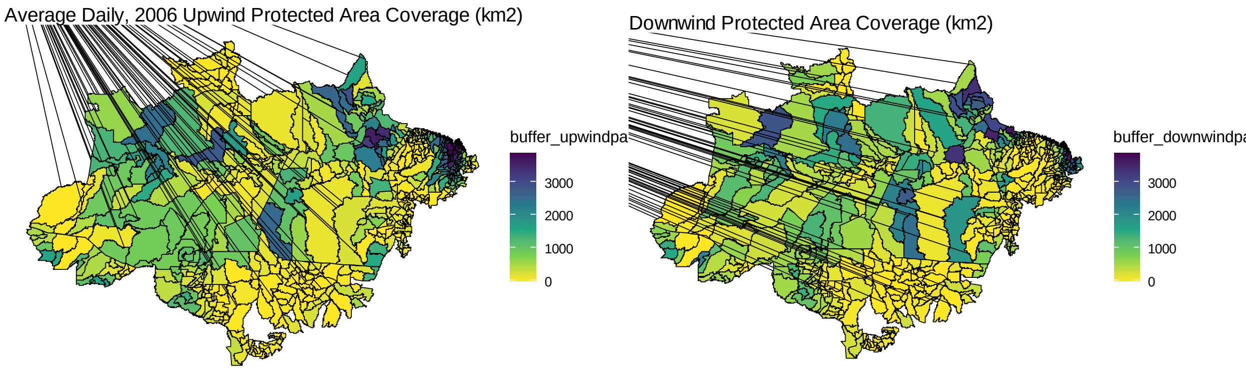


*Figure 6: Depicts the spatial distribution of time average for each municipality's PA*wind interaction.*

Socioeconomic Controls:

I obtained yearly Socioeconomic data such as population and GDP from the Brazilian government's Institute of Geography and Statistics (IBGE). IGBE collected census data in the years 2000 and 2010. The in-between years are imputed linearly by the IGBE. Population density was calculated by dividing the municipal population by the municipal area. Population density controls for urbanization as municipalities with increasing population density are likely more urban. Therefore, they reflect the 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 me to estimate a municipal rate response per 100,000 people. Changes in municipal population and GDP also enter as controls since changing population and economic activity are likely to correlate with public health, wealth, and education, affecting the expected municipal hospitalization rate.

The yearly municipality population for the municipality Jacareacanga varied from 8 to 41,487 from 2006 to 2018. At the same time, the average annual respiratory hospitalizations range from approximately 5 to 12. I suspect a data entry issue that dramatically impacts estimated hospitalization rates, as shown in blue in Figure 2. I dropped all observations of this municipality from the analysis due to unreliable population estimates.

TABLE 1: SUMMARY STATISTICS

	Variable	Obs	Mean	Std. Dev.	Min	Max
Response Variables	Respiratory Hospitalizations	80592	24.34	66.51	0	1721
	- Fire season	20148	22.66	58.71	0	1428
	- Rest of year	60444	24.90	68.90	0	1721
	Circulatory Hospitalizations	80592	11.38	37.15	0	786
	- Fire season	20148	11.43	37.14	0	786
	- Rest of year	60444	11.36	37.16	0	742
	Median PM 2.5	78768	14.39	17.77	1.7	848.18
	- Fire season	19692	19.29	33.20	1.7	848.18
	- Rest of year	59076	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	26972 (3,372)
	Upwind area of protected area (km2)	80964	691.07	948.53	0	4061.55
	- Fire season	20241	680.50	937.32	0	4052.81
	- Rest of year	60723	694.60	952.22	0	4061.55
	Downwind area of protected area (km2)	80964	589.82	854.20	0	4116.95
	- Fire season	20241	608.34	870.41	0	4052.58
	- Rest of year	60723	583.64	848.64	0	4116.95
Wind direction (Prevailing winds)	NNE days	80964	5.76	3.78	0	26
	ENE days	80964	11.88	7.94	0	31
	ESE days	80964	4.91	4.46	0	27
	SSE days	80964	2.05	2.77	0	18
	SSW days	80964	.91	1.32	0	19
	WSW days	80964	.62	.91	0	10
	WNW days	80964	1.22	1.75	0	12
	NNW days	80964	2.91	3.59	0	24
Weather	Average Humidity (%)	78768	83.55	10.622	29.3	98.54
	Average Temp (°C)	78768	26.45	1.368	20.675	32.19
	Rainfall total (mm)	78768	148.5	133.853	0	1714
	Average Rainfall (mm)	78768	4.91	4.45	0	55.29
Socioeconomic	GDP	80880	592108.42	3120183.7	10429.699	78192321
(Municipal)	Population	80892	39543.47	121820.4	8.899	2145444
	Population density ($people/km^2$)	80880	30.443	157.07	0	2762.36

Methods

I am answering the primary question: Do Protected Areas impact respiratory disease incidence in the Amazon Biome? In this, we expect substantial unobserved treatment biases. One known bias comes from PA assignments in areas not likely to face deforestation pressure. These areas would likely experience less fire usage and less air pollution regardless of a nearby PA. The second unobserved bias arises from the absence of observable socio-economic correlations between PA assignment and health outcomes. The data shows that areas with lower PA coverage also correspond to municipalities with higher respiratory hospitalization rates. I used two different estimation approaches; the first is estimating changes in treatment and outcomes with fixed effects for the same municipality across time. The second used prevailing wind direction to estimate a treatment effect, upwind protection, and control effect, downwind protection.

Fixed Effects Analysis

The first part of the analysis examines outcomes from changing PA coverage **assignments** measured across time for each municipality, so it is feasible to measure results before and after changes in PA coverage. The outcome differences for a municipality with increasing protection could be compared to the change in outcomes without protection, the counterfactual. The basic panel model for a municipality is shown in equation (1). The subscripts i and t, represent the municipality-by-month observations.

$$Outcome_{it} = \beta_1 ProtecteArea_{it} + \sum \boldsymbol{\beta}_{\mathbf{k}} \boldsymbol{Z}_{\boldsymbol{ikt}} + m_t + \gamma_t + \alpha_i + u_{it}.$$

(1)

$Outcome_{it}$ represents my outcomes of interest, air pollution, and respiratory diseases. $ProtecteArea_{it}$ is the area of protected areas assigned within 100km, $\boldsymbol{Z}_{\boldsymbol{ikt}}$ is a vector of all observable municipality weather and socioeconomic characteristics, (m_t) is the average monthly outcome for all municipalities to account for seasonal variation, (γ_t) is the year-month outcome for all municipalities capturing overall trends, (α_i) is the average outcome for a municipality across all periods. The latter is known as the municipality fixed effect and captures all unobserved time-invariant variables such as environmental and demographics factors that affect the level of outcomes for a given municipality but do not vary substantially over time. The term u_{it} represents the error term and includes all other time-variant factors not observed.

The association between PA assignment and unobserved factors is expected to **not** equal zero, even after controlling for my limited observable variables, $Cov(ProtecteArea_{it}, \alpha_i) \neq 0$, or $E[\alpha_i | ProtecteArea_{it}] \neq 0$. I expect the correlation between unobserved variables, the treatment, and outcomes of interest not to be random in the cross-section, confounding estimates of PA impacts. I use fixed effects estimation to establish a more credible counterfactual by only comparing the changes in outcomes with and without PA coverage relative to the mean value over the study period eliminating some of the level differences between treated and untreated municipalities. The fixed-effects model subtracts all observed municipality values from their mean value over the period, leaving only estimations for the changes relative to time mean overtime and not overall levels. The key assumption in fixed effects is the parallel trends assumption: the change in outcomes for unprotected municipalities provides a good estimation for what would have occurred in treated municipalities had they not been treated. The panel model shown in equation (1) in its time demeaned form is shown in equation (2)

$$(Outcome_{it} - \overline{Outcome_i}) = \beta_1\left(ProtecteArea_{it} - \overline{ProtecteArea_i}\right) + \overline{\gamma_t} + \overline{m_t} + \sum \delta_k(\boldsymbol{Z}_{ikt} - \overline{\boldsymbol{Z}_{ikt}}) + (u_{it} - \overline{u_i})$$

(2)

The advantage of fixed effects estimation is the removal of unobservable characteristics that determine the average outcome for a municipality across time, $\alpha_i - \overline{\alpha_i} = 0$. The estimations for regression coefficients, β_1 is therefore unbiased even if $E[\alpha_i|ProtecteArea_{it}, \boldsymbol{z_{it}} \dots \boldsymbol{z_{iT}}] \neq 0$. This partially relaxes the assumption of no omitted variables required to make causal estimate claims.

Concerns for fixed-effects analysis, in this case, are changing patterns of PA assignment over time and the lack of variation in the designation PAs after 2006. The first concern comes from the increasing targeting of PAs to marginal lands (DeFries et al. 2005; Jusys 2018), such that the areas with and without PA assignments are more different in ways that impact not only overall levels in outcomes but also the changes in outcomes, $Cov(\Delta ProtecteArea_{it}, \Delta u_{it}) \neq 0$. This violates the parallel trend assumption since areas with changes in protection and those without changes in protection do not have comparable changes in outcomes. The second comes from the need for adequate variation in assignment to compare impacts before and after treatment. Figure 1 of the Appendix depicts the percentage of municipal areas under protection from 2000 to 2015 and shows little to no change after 2006. If we consider equation (2), but now the explanatory variable no longer varies over time, the estimate will not have enough variation to explain a treatment effect. For a municipality in period t, the protected area coverage is very similar to its later value in period s, $ProtectedArea_{it} \approx ProtectedArea_{is}$. Any observed value of $ProtectedArea_{it}$ after 2006 will very close to the average over the period, $\overline{ProtecteArea_{it}}$. The time demeaned value for each will be very close to zero, $(PA_{it} - \overline{PA_\iota}) \approx 0$.

$$(Outcome_{it} - \overline{Outcome_\iota}) = \beta_1(\approx 0) + \overline{\gamma_t} + \sum \delta_k(\boldsymbol{Z}_{ikt} - \overline{\boldsymbol{Z}_{\iota k}}) + (u_{it} - \overline{u_\iota})$$

This lack of variation will not allow our model to obtain a “good” estimate of the within municipality treatment effect, β_1. Since this is my treatment variable, I induce variation in PA influence by interacting the PA area as of 2006 with exogenous changes in prevailing wind direction to establish separate effects for upwind and downwind PA coverage on outcomes.

This identification also handles the violation of the parallel trends assumption. The treatment effect is the change in monthly outcomes for more protected upwind areas relative to less protected upwind areas for a given month. The control effect is the difference in monthly outcomes for more protected downwind areas relative to less protected downwind areas for a given month. Treatment and control effects will capture the overall difference between areas with and without PAs. Only the effect of changing upwind PA coverage will contain the impact of PAs on air pollution. The difference in these effects captures a credible causal treatment effect since wind direction is not related to socioeconomic treatment confounders.

$$Outcome_{it} = \beta_0 + \beta_1 upwindpa_{it} + \beta_2 downwindpa_{it} + \sum \boldsymbol{\beta}_{\mathbf{w}} \boldsymbol{Z}_{\boldsymbol{iwt}} + \sum \boldsymbol{\beta}_{\boldsymbol{s}} \boldsymbol{X}_{\boldsymbol{ist}} + \boldsymbol{\alpha}_{\boldsymbol{i}} + \tau_t + yearmon_t + u_{it}$$

(3)

The terms β_1 and β_2 now represent separate effects for upwind and downwind PAs on outcomes. The research assumption I am testing is whether upwind PAs impact air quality and respiratory hospitalizations differently than downwind PAs depending on prevailing winds in a given month. The treatment decision, for example, decided based on the economic activity in the area, should apply similarly for both up and downwind areas. Therefore the confounded treatment effects, unobserved differences between "protected" and "unprotected" areas should appear equally on average for up and downwind PAs. The effects of downwind PAs estimate this bias exclusively. Downwind areas are subject to similar treatment bias but are not expected to influence upwind air quality. The treatment effect for the presence of downwind coverage, $ATT_{downwind}$ is assumed to equal zero since downwind areas do not influence upwind air quality. The treatment bias is the difference between the unobserved counterfactual outcome, what would have occurred without protection, minus the observed outcome without protection.

$$\widehat{\beta_2} = \overbrace{E[outcome(unprotected)|protected] - E[outcome(unprotected)|unprotected]}^{treatment\ bias}$$

$$= treatment\ bias$$

The estimated effect of upwind coverage will equal the causal effect of upwind PAs on air quality and treatment bias. The estimate of the effect of upwind protection is decomposed below.

$$\widehat{\beta_1} = ATT_{upwind} + \ \ treatment\ bias$$

The estimated differential effect $\widehat{\beta_1} - \widehat{\beta_2}$ will subtract out treatment bias leaving only the causal impact of Protected Areas on outcomes related to air movement from upwind areas to the municipal seat. Stated explicitly,

$$\widehat{ATT_{upwind}} = \ \widehat{\beta_1} - \widehat{\beta_2}$$

Since the differential association only contains PA impacts on air quality, I interpret this as the overall effect of protected areas on air quality and resulting respiratory illnesses.

Estimation

I estimated the differential effect of up and downwind protected areas on two outcomes, hospitalizations, and PM concentrations, with a Pseudo Poisson Maximum Likelihood (PPML) regression. In both cases, outcomes were nonnegative and over dispersed. I preferred this estimation due to the strict distributional assumptions required on transformed dependent variables and issues with zeros in observed outcomes. 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 in the presence of heteroskedasticity, log-linear OLS estimates are biased, even after controlling for Fixed Effects. On the other hand, Poisson models are robust to heteroskedasticity (C Santos Silva and Tenreyro 2006). A recently written package for Stata combines PPML with High Dimensional Fixed Effects, enabling the inclusion of municipality and time fixed effects and their interactions (Correia, Guimarães, and Zylkin 2019). Fixed-effects interactions allow me to control for heterogenous municipality seasonality.

The central research assumption that upwind PAs affect $PM_{2.5}$ greater than downwind PAs is examined using the following model estimated using the Pseudo Poisson regression.

$$PM_{it} = \beta_0 + \beta_1 upwindpa_{it} + \beta_2 downwindpa_{it} + \sum \boldsymbol{\delta}_{\mathbf{w}} \boldsymbol{Z}_{\boldsymbol{iwt}} + \alpha_i + m_t + \gamma_t + u_{it} \tag{3}$$

The terms in the vector $\boldsymbol{Z}_{\boldsymbol{iwt}}$ are average maximum temperature, relative humidity, number of days in the wind blows from each direction, and population density. The terms α_i,m_t, and γ_t represent the expected municipality, monthly, and year-month PM 2.5 concentrations. The municipality fixed effect accounts for unobserved municipal differences in $PM_{2.5}$ levels that do not vary over time. The month fixed effect controls for the seasonal variation that applies to the entire region. Here I estimate the municipality fixed effect and overall seasonality separately since all areas have similar seasonal variations, shown in Figure 7. The year-month FE adjusts the expected outcomes for the few fire seasons with abnormally high $PM_{2.5}$ concentrations. The differential effect $\beta_1 - \beta_2$ will remove the remaining association between protected areas and PM 2.5, serving as my estimate for the causal impact of protection on air pollution.

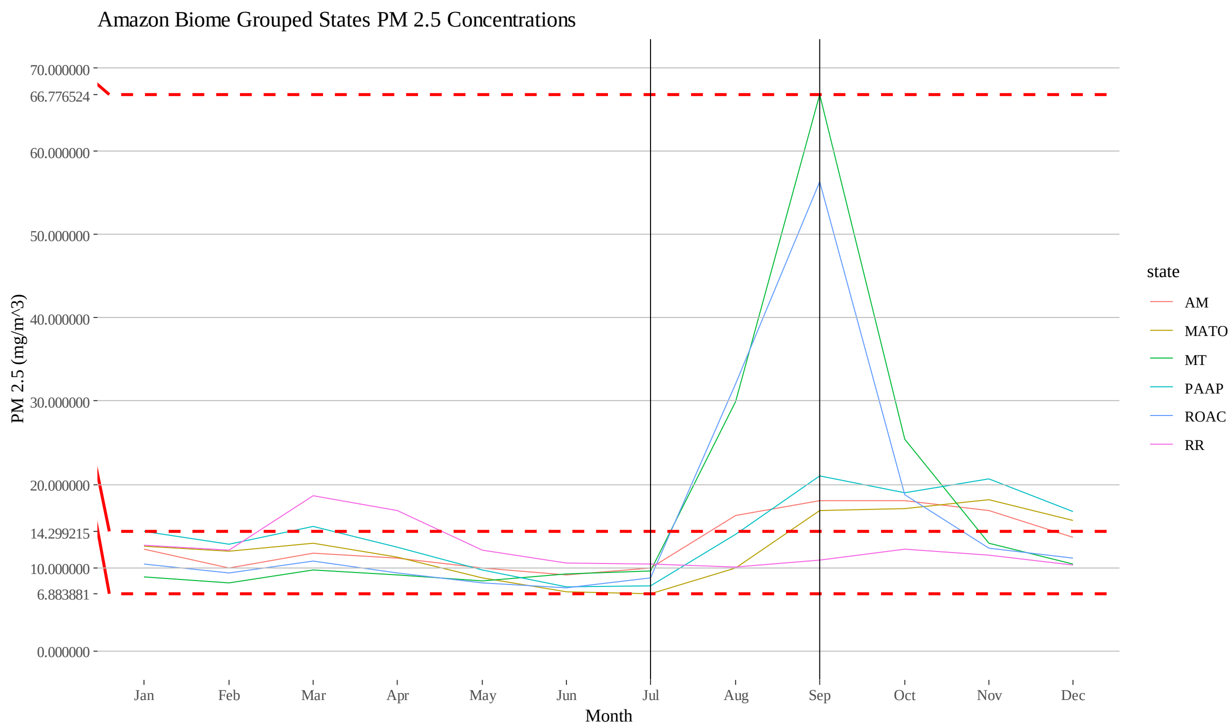


Figure 7: Average $PM_{2.5}$ by month of the year for grouped states by region, AM – Amazonas (east/central Amazon), MATO – Maranhao & Tocantins (Southeast), MT -Mato Grasso (South), PAAP – Para & Amapa(north/central), ROAC – Rondonia & Acre (Southwest), RR- Roraima (north).

I estimated the causal respiratory health impacts from upwind and downwind Protected Areas with a similar model, including time-varying socioeconomic indicators, $\boldsymbol{X_{ist}}$, including changes in population, population density, and municipal GDP that could affect respiratory hospitalization counts.

$$\log(Hosp_{it}) = \log(population_{it}) + \beta_0 + \beta_1 upwindpa_{it} + \beta_2 downwindpa_{it} + \sum \boldsymbol{\beta_w Z_{iwt}} + \sum \boldsymbol{\beta_s X_{ist}} + \begin{cases} m_t * \alpha_i \\ m_t + \alpha_i \end{cases} + \gamma_t + \epsilon_{it}$$

(2)

The term $(population_{it})$ is the municipal population entering as an offset to estimate a hospitalization rate response per the expected number of 100,000 people who could have been hospitalized in a municipality in each month. The fixed effects interaction $(m_t * \gamma_i)$ represents municipality-by-month-of-year average hospitalization rate, controlling for municipality-specific seasonality in respiratory diseases since all areas do not experience a secondary respiratory disease season, shown in Figure 8. The municipality-by-month-of-year estimates a municipality fixed effect for each month of the year. For comparison, I also perform this specification with separate fixed effects, $m_t + \gamma_i$, as was done with $PM_{2.5}$ outcomes. The variable γ_t controls for the overall reduction in respiratory disease hospitalizations over time. The treatment effect $\beta_1 - \beta_2$ will remove the overall association between protected areas and hospitalizations and serve as my estimated causal impact of protection on hospitalizations related to the movement of air pollution.

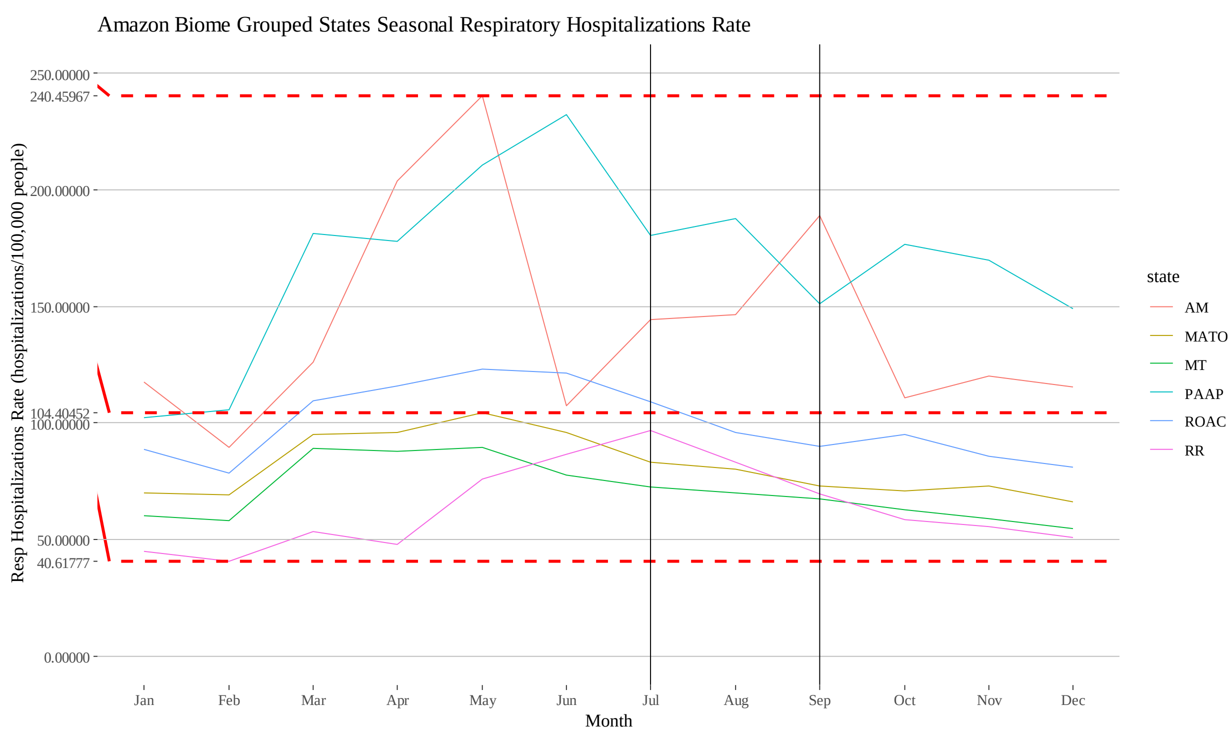


Figure 8: Counts of respiratory hospitalizations per 100,000 people by month of the year for grouped states by region, AM – Amazonas (east/central Amazon), MATO – Maranhao & Tocantins (Southeast), MT -Mato Grasso (South), PAAP – Para & Amapa(north/central), ROAC – Rondonia & Acre (Southwest), RR- Roraima (north). The states of Amazonas and Para cover the largest area and contain the highest populations.

RESULTS:

Changes in PA coverage assignment on Particulate Matter and Respiratory Hospitalizations

Table 2 reports average marginal effects from the model shown in equation (1), examining the primary expansion 2002-2006 in PA **assignment** within 100km of the municipal seat. I measure the association between yearly changes in PA coverage assignment in any direction on expected monthly changes in my response variables during the fire season. The overall association for $PM_{2.5}$, Column 1, is negative but not statistically significant, providing no evidence that PA assignment in any direction is associated with lower changes in $PM_{2.5}$ during the fire season.

Respiratory hospitalizations, Column 2, indicate a statistically significant association indicating that areas with increasing PA assignments nearby are related to more respiratory hospitalizations during the fire season. Areas with changes in PA assignment are **not** located in agricultural activity centers, such as the arc of deforestation, where income generated from agriculture may be correlated with improved resilience to environmental respiratory disease outcomes. The literature has observed changes in PAs assignments over time towards more isolated areas (DeFries et al. 2005; Pfaff et al. 2009; Pfaff, Robalino, Herrera, et al. 2015; Jusys 2018), but these areas also likely differ in unobserved characteristics. Therefore, the difference between areas with PAs, the treatment, and areas without PAs, the control, is not constant over time. This violates the parallel trend assumption required for causal estimates in fixed-effects estimation. To limit the outsized impact of changes in PA assignment, I focus instead on the effects PAs designated before 2006 and use exogenous changes in wind direction to test the assumption that upwind PAs affect outcomes differently than downwind areas. The difference in these effects decouples the overall relationship between unobserved socio-economic correlates and the treatment.

TABLE 2: AVERAGE MARGINAL EFFECTS OF YEARLY CHANGES IN PA COVERAGE WITHIN 100KM 2002-2006 ON FIRE SEASON OUTCOMES

	(1) PM 2.5 Concentrations	(2) Respiratory Hospitalizations
Area of protected area (km^2)	-0.00162	0.00170***
	(-1.90)	(4.21)
Average humidity (%)	0.388**	-0.00307
	(3.20)	(-0.04)
Average temperature (°C)	9.688***	0.470
	(10.01)	(0.91)
Total rainfall (mm)	0.0491***	-0.00552
	(4.18)	(-0.75)
Population Density (people/km^2)	-0.147***	0.0400
	(-4.33)	(1.66)
Population		-0.000604***
		(-3.74)
Municipal GDP (R$ 1.000)		0.0000174***
		(5.39)
Controls		
Municipality FE	Yes	Yes
Month FE	Yes	Yes
Year Month FE	Yes	Yes
Observations	6186	5832

t statistics from robust standard errors parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Differential Effects of Protected Areas on Fine Particulate Matter

I use fixed effects and exogenous changes in wind direction to remove the correlation between protection and socioeconomic characteristics within the buffer from impacts on air quality. I am assuming that the interaction between wind direction and PA location is not systematically related to unobserved differences within the buffer for the same municipality. The difference between these effects isolates the causal effect due to the movement of air pollution, and I interpret this as a causal impact of PA coverage on outcomes.

Table 2 reports the average marginal effects (AME) from equation (3) under different specifications. Column 1 examines the estimated impact of PAs wind orientation on $PM_{2.5}$, without municipality fixed effects, controlling for unobserved differences between municipalities that affect PA coverage and $PM_{2.5}$ levels with the downwind PA area. Here the estimated effect of upwind PAs is significantly negative -0.00047^{***} and indicates no impact of downwind PAs -0.00010. After including upwind protection, downwind protection includes no additional variation that explains outcome differences. The Pearson's correlation coefficient between the upwind and downwind protection for a municipality is 0.32 (p-value $\approx$ 0). Since areas with protection in either direction correlate with lower agricultural activity within their buffers, these estimates measure the same effect, the between municipality associations of different regions with and without PAs on outcomes in the cross-section. The highly significant differential effect here reflects improved air quality outcomes, -0.00037***, from unobserved differences between areas with upwind protection, not the desired causal impact of protection.

Column 2 instead controls for these unobserved differences with municipality fixed effects. Here I compare the results of varying PA wind orientation to changes from their municipality average instead of overall levels. Estimates of upwind and downwind protection are negative but not significant, indicating that an increase in the monthly area of protected area upwind, -0.000493, is very similar in effect to protected regions downwind, -0.000418. The differential effect is in the expected direction but is neither statistically different from zero or very impactful in magnitude across the whole year.

Columns 1 & 2 differ most substantially in their estimation of downwind coverage, the control effect that does not contain air quality impacts. This effect decreased from -0.00010 to -0.00041, indicating that the variation between up and downwind areas on outcomes is reduced by comparing only within municipality effects. This is due to less variation in outcomes within a municipality relative to the variation between municipalities. Fixed effects estimation improves the control effect by comparing effects of changes from the time mean values, not overall levels between municipalities. I am primarily interested in PA's relationship with preventing nearby fires and improving air quality, so I estimate this relationship on two subsamples, during the fire season, Column 3, and the rest of the year, Column 4.

During the fire season, increases in the average area protected area upwind result in statistically significant lower monthly $PM_{2.5}$ concentrations of 0.00206 μm/m^3. The estimated effect of downwind area of protected area increases concentrations by 0.00078 μm/m^3 but provides no evidence of an association different from zero. The difference between upwind and downwind effects is negative, confirming that upwind PA coverage reduces $PM_{2.5}$ by more than downwind areas. The effect of a 1,000 km^2 increase in upwind PAs resulted in a reduction of 2.8 μm/m^3 relative to the mean fire season concentration of 23.8.

For the rest of year estimates, column 4, when fire activity is lower, the effect of upwind protection is negative and significant, -0.00131 μm/m^3, downwind protection effect is also negative and significant -0.00031 μm/m^3. The differential effect of a 1,000 km^2, approximately one standard deviation, increase in upwind PAs reduces $PM_{2.5}$ concentrations by 1.0 μm/m^3 relative to the mean 15.4 μm/m^3. Results in Columns 3 & 4 confirm that PAs' presence in a more upwind direction results in better municipal air quality, especially when fire activity is higher.

TABLE 2: AVERAGE MARGINAL EFFECTS OF PA COVERAGE*WIND DIRECTION (km^2) WITHIN 100KM ON MEDIAN PM 2.5 ($\mu m/m^3$)

	(1) No Municipality FE	(2) Municipality FE	(3) Fire Season	(4) Rest of Year
Upwind area of protected area (km^2)	-0.00047***	-0.00049	-0.00206*	-0.00131***
	(-8.88)	(-1.68)	(-2.17)	(-13.54)
Downwind area of protected area (km^2)	-0.00010	-0.00041	0.00078	-0.00031**
	(-1.81)	(-1.92)	(0.90)	(-3.11)
Upwind – Downwind	-0.00037***	-0.00008	-.002839**	-.00100***
(χ^2)	(21.54)	(0.04)	(7.20)	(73.55)
Controls				
Municipality FE	No	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Weather/wind days	Yes	Yes	Yes	Yes
Population density	Yes	Yes	Yes	Yes
Observations	78684	78684	19671	59013

t statistics from robust standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Effects of Protected Areas on Respiratory Hospitalizations

TABLE 3: AVERAGE MARGINAL EFFECTS OF PA COVERAGE*WIND DIRECTION
EFFECTS OF PA COVERAGE WITHIN 100KM ON RESPIRATORY HOSPITALIZATIONS
PER 100,000

	(1) No Municipality FEs	(2) Municipality FEs	(3) Fire Season	(4) Rest of Year
Upwind area of protected area (km2)	-0.00143***	0.00000527	-0.00116	0.000205
	(-13.71)	(0.01)	(-1.45)	(0.45)
Downwind area of protected area (km2)	-0.00417***	-0.00084*	-0.000397	-0.000561
	(-33.89)	(-2.42)	(-0.56)	(-1.33)
Upwind – Downwind	+0.00273***	+0.00084*	-0.00076	+0.00077
(χ^2)	(254.28)	(4.44)	(0.75)	(2.51)
Controls				
Municipality FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Weather/wind days	Yes	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes	Yes
Observations	78261	78261	19568	58693

t statistics from robust standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3 presents average marginal effect estimates of PAs interacted with wind days on contemporaneous respiratory hospitalizations per 100,000 people. Columns 1-4 parallel Columns 1-4 from Table 2 estimating $PM_{2.5}$ effects, after controlling for the municipality, overall seasonal and time trend fixed effects. Columns 1 and 2 in Table 3 estimate AMEs for the whole year with and without municipality fixed effects, and Columns 3 and 4 examine these effects for the fire season and the rest of the year.

Column 1 estimates these effects without controlling for unobserved differences between municipalities with and without PA coverage. Here I am comparing overall respiratory hospitalization rates instead of deviations from mean values. The estimated association of upwind areas is negative and highly significant, indicating a strong relationship between areas with upwind protection and lower respiratory disease rates. The estimated effect of downwind PAs is also significantly negative, showing a strong relationship between downwind protection and lower respiratory disease rates. The highly significant differential effect here reflects higher respiratory hospitalizations rates for municipalities with upwind protection, +0.00268*** compared to those with downwind protection. Since I compared overall levels of upwind protection for different areas, I systematically sorted treatments in the cross-section. Upwind protected areas tend to occur in the east-north-east, and downwind protected areas occur in the west-south-west, so I compared outcome levels in different regions. For example, the spatial trend that Protected Areas in the southern "arc of deforestation" have more upwind protection relative to downwind areas correlates with higher respiratory disease hospitalization rates. A better identification compares **changes** in respiratory hospitalizations for the same municipality from their time mean rather than the variation in their overall levels.

Column 2 estimates these effects for the entire year with fixed effects and indicates a relationship between greater PA coverage increases the hospitalization rate. An increase in upwind PA coverage of 1,000km^2 is associated with .8 hospitalizations per 100,000 people. During the fire season, Column 2, the expected causal effect is negative. Still, it provides no evidence, p-value =0.414, that PA coverage in the upwind direction decreases hospitalizations more than in the downwind direction. The rest of the year estimates, Column 3, is positive but not significantly different from zero providing no evidence that more upwind PA coverage affects respiratory hospitalizations during the non-fire season.

The results in Table 3 column 2 directly conflict with my research assumption that upwind PA coverage reduces the hospitalization rate more than downwind coverage. I estimate an alternative, more restrictive specification that considers municipality-specific seasonality in respiratory hospitalizations by estimating a combined municipality-by-month-of-year fixed effect. In the absence of observing where and when precisely the fires occur, the municipality-by-month-of-year fixed-effect will adjust the seasonal hospitalization rate for only those municipalities that experience a fire-related respiratory season and make no adjustments for municipalities without this seasonality. All municipalities do not share the same seasonality in respiratory diseases, meaning estimated municipality effects depend on unobserved seasonal differences between municipalities, including municipality-by-month-of-year controls for municipal seasonal heterogeneity that does not vary year to year, shown in Figure 8. Municipalities without this seasonality have a lower fire-related hospitalization rate and would be less likely to have contemporary effects of PA coverage on respiratory diseases. This specification was not considered for the $PM_{2.5}$ outcome variable since the entire region experiences similar seasonal fluctuations in levels of $PM_{2.5}$, and it varies less from year to year for the same region.

Table 5 presents average marginal effect estimates of PAs on contemporaneous respiratory hospitalizations per 100,000 people reprinting the results of Column 2 and 3 from Table 3 to compare these results with municipality-by-month-of-year fixed estimates for the fire season, column 2, and the identical specification for the rest of the year, column 4.

TABLE 5: AVERAGE MARGINAL EFFECTS OF PA COVERAGE WITHIN 100KM ON RESPIRATORY HOSPITALIZATIONS PER 100,000

	(1) Fire Season	(2) Fire Season Month#Muni	(3) Rest of Year	(4) Rest of Year Month#Muni
Upwind area of protected area km^2	-0.00116	0.00132	0.000205	0.00128*
(t-test robust std errors)	(-1.45)	(1.18)	(0.45)	(2.01)
Downwind area of protected area km^2	-0.000397	0.00371***	-0.000561	0.00144*
(t-test robust std errors)	(-0.56)	(3.91)	(-1.33)	(2.47)
Upwind – Downwind	-0.0008	-0.0024*	+0.0008	-.0002
(χ^2)	(0.75)	(3.87)	(2.51)	(0.03)
Controls				
Wind Dummies	Yes	Yes	Yes	Yes
Weather	Yes	Yes	Yes	Yes
Socioeconomic	Yes	Yes	Yes	Yes
Municipality FE	Yes	No	Yes	No
Month FE	Yes	No	Yes	No
Municipality*Month FE	No	Yes	No	Yes
Time Trend	Yes	Yes	Yes	Yes
Observations	19568	19568	58693	58689

t statistics from robust standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The negative differential effect in column 2 provides moderate evidence, p-value=0.049, that upwind PAs reduce respiratory hospitalization rates during the fire season after controlling for seasonal heterogeneity. For example, an increase in upwind PA coverage of 1,000 km^2 resulted in 2.4 fewer hospitalizations per 100,000 people per month during the fire season. With 95% confidence, a 1000 km^2 increase in the area of upwind protection reduced the average rate by 4.8 hospitalizations or increased it by 1.6 hospitalizations per 100,000 residents. For a municipality at the 50th percentile of population size, 19,299 people, this results in an expected monthly municipal reduction of .46 hospitalizations per month during the fire season, at the 75th percentile, 35,497 people, .8519 hospitalizations, and at the 99% percentile, 401,155 people, 9.6 hospitalizations per month. The area of protected area upwind from a municipality scales with the downwind population and may only be substantial for large population centers.

The final columns 3 and 4 look at the effects for the rest of the year and do not indicate consistent or convincing evidence that PA coverage has any impacts on contemporaneous monthly hospitalization rates for the rest of the year. If the primary relationship between PAs and respiratory health occurs when and where fires are happening, I would expect no effect when fire activity is low and in regions without a substantial fire-related respiratory season.

Falsification Test

Effects of Protected Areas on Circulatory Hospitalizations

To test the final specification, Table 5, on another group of hospitalizations, I perform the exact estimations for the fire season and the rest of the year with circulatory hospitalizations using ICD-10 codes, I00-I99 in Table 6. These hospitalizations include conditions affecting the heart and circulatory system. Thus far, there has not been any evidence that biomass smoke exposure affects current cardiovascular hospitalizations in the Amazon (Rocha and Sant'anna 2020). Column 2, the specification with municipality-specific seasonality, contains the only significant result. The estimated effect of more protection in a downwind direction results in an increased incidence of circulatory hospitalizations during the fire season. Overall, I find no evidence that upwind PAs and downwind PAs affect circulatory hospitalizations differently during the current month.

TABLE 6: AVERAGE MARGINAL EFFECTS OF PA COVERAGE WITHIN 100KM*WIND ON CIRCULATORY HOSPITALIZATIONS PER 100,000

	(1) Fire Season	(2) Fire Season Month#Muni	(3) Rest of Year	(4) Rest of Year Month#Muni
Upwind area of protected area km^2	-0.0000323	0.000556	-0.00000891	0.000591
(t-test robust std errors)	(-0.08)	(0.94)	(-0.04)	(1.74)
Downwind area of protected area km^2	-0.000308	0.00123**	0.00000522	0.000633
(t-test robust std errors)	(-0.94)	(2.65)	(0.02)	(1.50)
Upwind – Downwind	+0.000275	-0.0007	0.0000	0.0000
(Chi^2)	(0.35)	(1.16)	(0.00)	(0.01)
Controls				
Wind Dummies	Yes	Yes	Yes	Yes
Weather	Yes	Yes	Yes	Yes
Socioeconomic	Yes	Yes	Yes	Yes
Municipality FE	Yes	No	Yes	No
Month FE	Yes	No	Yes	No
Municipality*Month FE	No	Yes	No	Yes
Time Trend	Yes	Yes	Yes	Yes
Observations	19568	19516	58693	58620

t statistics from robust standard errors parentheses* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

CONCLUSIONS

There is growing interest in the ties between the conservation of ecosystems and human health. Protection of ecosystems is thought by some to be in direct conflict with human values, especially if it is believed to restrict economic opportunities. On the other hand, human health is a universal value that cuts across political, economic, and social divisions. As of now, the empirical evidence that conservation could support this value is minimal. I contribute by focusing on one large-scale policy, Brazil's Amazon Biome PA network. Here I find that when winds come from areas with more PA coverage, there is an estimated causal reduction in downwind $PM_{2.5}$ and respiratory disease hospitalizations, and not circulatory diseases during the fire season. Brazils 2006 Protected Areas likely reduced biomass smoke exposures and reducing respiratory hospitalizations for the 2006 to 2018 period. Notably, these effects appear in contemporaneous fire season respiratory diseases related to biomass burning in the region. PA impacts were also found relatively far from their borders due to the movement of air pollution from upwind areas.

One issue is fire outcomes were not examined in this study. PAs' effects on my outcomes will likely depend upon the overall fire activity near the municipality across time and space. If PA coverage in an upwind direction is more impactful in fire-prone situations, this provides solid evidence that PA legal restrictions reduce local fire usage. The instability of my estimates to the specification may reflect the relatively coarse measures of upwind protection and estimating impacts for the entire Biome. Not all municipalities are threatened by fires or do not experience health burdens from this cause. Including estimations for these municipalities likely reduces the estimated effects of PA coverage and respiratory health in more heavily threatened areas. A further examination should focus on exactly when and where fires occur to see if PA coverage impacts in these municipalities are more robust than the evidence presented here. Regardless, finding any effect across the whole region for $PM_{2.5}$, including non-fire threatened areas, makes a strong case that PAs reduce fire-related air pollution.

I examined effects for all PAs, but results will depend on the varying restrictions differing protection status places on local populations. Tradeoffs likely exist, so further research should aim to examine which types of PAs or alternate conservation policies achieve increases or decreases in specific disease burdens. For example, sustainable use reserves are likely not the right policy to reduce malaria incidence since they allow some interaction with wilderness areas, exposing populations to mosquitos. This relationship would likely persist for many diseases influenced by human-wilderness interactions where exposures to novel pathogens may infect the global population, as we saw with COVID-19 (Albers et al. 2020). However, strictly protected areas could reduce this risk by lowering this interaction (Bauch et al. 2015). Sustainable use designations are also likely not the best policy to reduce fire-related disease burdens either. These designations are not robustly associated with improved local fire management

(Carmenta et al. 2016). Further analysis that separates upwind and downwind effects of different types of PAs under various risks of fires may illuminate what kind of protection provides the most significant reduction in respiratory disease burdens.

Brazil's commitment to conservation, as shown in their expansion in 2000 to 2006 PA network, has been reversed by the Jair Bolsonaro administration. Policies have been put in place to spur economic activity in previously designated PAs by reducing the development restrictions, enforcement, or coverage within PAs. This administration has been transparent in valuing economic expansion over conservation, taking a more human-centered position on this debate. The debate between conservation and development leaves out the potential that rolling back the PA network may have additional unintended human health consequences. My findings provide evidence that PA policies influence respiratory health—a value that has some weight even for those who do not value climate change concerns or biodiversity loss. Health impacts should enter the human-centered calculus on if PAs should be retained and enforced—supporting the idea that a single policy can combine conservation and human health goals.

It is challenging to conclude causality in any observational study since random assignment does not remove bias from unobserved confounders. Random assignment across a population ensures that the differences between treatment and control groups are also random. Thus, the difference between the outcomes is only a result of the treatment group. Policy researchers will never randomly assign PAs across a landscape due to the extensive treatment costs. Therefore, policymakers aim their assignment towards the most conservation or least economic costs. An observational study seeks to explain all the variation in $PM_{2.5}$ or respiratory hospitalizations correlated with PA non-random assignment to isolate protection impacts.

This analysis did a lot to limit spatial dependence and treatment bias by examining the same municipality across time and used exogenous variation in wind direction to remove any other biases.

However, the lack of data on finer timescales constrained what I could observe. My yearly GDP and population controls were imputed values estimated from census years 2000 and 2010 and do not contain all the relevant variation within municipalities. Other potential confounders such as poverty levels, the proportion of municipality involved in agriculture, and population disaggregated by age could not be found except for census years. This is only a concern if this is systematically related to prevailing wind directions, such that even when comparing only within 100 km areas, these factors are spatially autocorrelated in a prevailing wind direction at this scale. Not having access to the population by age limited me to only looking at hospitalization rates for the general population. From the literature, we know that biomass exposures primarily impact children and the elderly, so my results may represent a conservative estimate of the actual rate response of PA coverage for vulnerable populations.

The observable outcome of respiratory disease hospitalizations represents only a fraction of the health burden caused by smoke exposure. Therefore, hospitalizations served as a proxy for respiratory disease incidence and described only the most severe fraction of incidences. From the data, the average rate of hospitalization per 100,000 people is roughly 15. Estimated reductions of 2.4 hospitalizations from a theoretical increase of 1,000 km2 PAs upwind could represent a significant respiratory disease burden. However, in the absence of observing actual respiratory disease incidences in the population or how frequently a respiratory condition results in hospitalization, it is difficult to determine if this result is substantial.

My results strengthen the case for PAs if applied in areas with considerable respiratory disease burdens caused by human-ignited biomass fires. Since this relationship appears in the broader tropics, this could also encourage PA applications worldwide. It is vital that conservation policies going forward consider their health costs and benefits. Further research should illuminate when and where they result in changing environmental disease burdens. Although my results still leave many questions unanswered, my results suggest PAs could be one policy lever to improve human health. Preventing ecosystem change with protected areas is not just a matter of conservation and development but includes universal human values, clean air, and human health.

REFERENCES

Abessa, Denis, Ana Famá, and Lucas Buruaem. 2019. “The Systematic Dismantling of Brazilian Environmental Laws Risks Losses on All Fronts.” *Nature Ecology and Evolution*. Nature Publishing Group. https://doi.org/10.1038/s41559-019-0855-9.

Adeney, J. Marion, Norman L. Christensen, and Stuart L. Pimm. 2009. “Reserves Protect against Deforestation Fires in the Amazon.” *PLoS ONE* 4 (4). https://doi.org/10.1371/journal.pone.0005014.

Aditama. 2000. “Impact of Haze from Forest Fire to Respiratory Health: Indonesian Experience.” *Respirology*. Vol. 5.

Agrawal, Arun. 2014. “Matching and Mechanisms in Protected Area and Poverty Alleviation Research.” *Proceedings of the National Academy of Sciences of the United States of America*. National Academy of Sciences. https://doi.org/10.1073/pnas.1401327111.

Albers, Heidi J., Katherine D. Lee, Jennifer R. Rushlow, and Carlos Zambrana-Torrselio. 2020. “Disease Risk from Human–Environment Interactions: Environment and Development Economics for Joint Conservation-Health Policy.” *Environmental and Resource Economics* 76 (4): 929–44. https://doi.org/10.1007/s10640-020-00449-6.

Andam, Kwaw S., Paul J. Ferraro, Alexander Pfaff, G. Arturo Sanchez-Azofeifa, and Juan A. Robalino. 2008. “Measuring the Effectiveness of Protected Area Networks in Reducing Deforestation.” *Proceedings of the National Academy of Sciences of the United States of America* 105 (42): 16089–94. https://doi.org/10.1073/pnas.0800437105.

Andam, Kwaw S., Paul J. Ferraro, Katharine R.E. Sims, Andrew Healy, and Margaret B. Holland. 2010. “Protected Areas Reduced Poverty in Costa Rica and Thailand.” *Proceedings of the National Academy of Sciences of the United States of America* 107 (22): 9996–10001. https://doi.org/10.1073/pnas.0914177107.

Aragão, Luiz E.O.C., Liana O. Anderson, Marisa G. Fonseca, Thais M. Rosan, Laura B. Vedovato, Fabien H. Wagner, Camila V.J. Silva, et al. 2018. “21st Century Drought-Related Fires Counteract the Decline of Amazon Deforestation Carbon Emissions.” *Nature Communications* 9 (1): 1–12. https://doi.org/10.1038/s41467-017-02771-y.

Aragão, Luiz Eduardo O.C., Yadvinder Malhi, Nicolas Barbier, Andre Lima, Yosio Shimabukuro, Liana Anderson, and Sassan Saatchi. 2008. “Interactions between Rainfall, Deforestation and Fires during Recent Years in the Brazilian Amazonia.” *Philosophical Transactions of the Royal Society B: Biological Sciences* 363 (1498): 1779–85. https://doi.org/10.1098/rstb.2007.0026.

Barber, Christopher P., Mark A. Cochrane, Carlos M. Souza, and William F. Laurance. 2014. “Roads, Deforestation, and the Mitigating Effect of Protected Areas in the Amazon.” *Biological Conservation* 177 (September): 203–9. https://doi.org/10.1016/j.biocon.2014.07.004.

Bauch, Simone C., Anna M. Birkenbach, Subhrendu K. Pattanayak, and Erin O. Sills. 2015. "Public Health Impacts of Ecosystem Change in the Brazilian Amazon." *Proceedings of the National Academy of Sciences of the United States of America* 112 (24): 7414–19. https://doi.org/10.1073/pnas.1406495111.

Betts, Richard, Michael Sanderson, and Stephanie Woodward. 2008. "Effects of Large-Scale Amazon Forest Degradation on Climate and Air Quality through Fluxes of Carbon Dioxide, Water, Energy, Mineral Dust and Isoprene." *Philosophical Transactions of the Royal Society B: Biological Sciences* 363 (1498): 1873–80. https://doi.org/10.1098/rstb.2007.0027.

Blackman, Allen, Alexander Pfaff, and Juan Robalino. 2015. "Paper Park Performance: Mexico's Natural Protected Areas in the 1990s." *Global Environmental Change* 31 (March): 50–61. https://doi.org/10.1016/j.gloenvcha.2014.12.004.

Boisier, Juan P., Philippe Ciais, Agnès Ducharne, and Matthieu Guimberteau. 2015. "Projected Strengthening of Amazonian Dry Season by Constrained Climate Model Simulations." *Nature Climate Change* 5 (7): 656–60. https://doi.org/10.1038/nclimate2658.

Braber, Bowy den, Karl L. Evans, and Johan A. Oldekop. 2018. "Impact of Protected Areas on Poverty, Extreme Poverty, and Inequality in Nepal." *Conservation Letters*. Wiley-Blackwell. https://doi.org/10.1111/conl.12576.

Bush, M.B, M.R Silman, C McMichael, and S Saatchi. 2008. "Fire, Climate Change and Biodiversity in Amazonia: A Late-Holocene Perspective." *Philosophical Transactions of the Royal Society B: Biological Sciences* 363 (1498): 1795–1802. https://doi.org/10.1098/rstb.2007.0014.

C Santos Silva, J M, and Silvana Tenreyro. 2006. "THE LOG OF GRAVITY." https://doi.org/10.1162/rest.88.4.641.

Canavire-Bacarreza, Gustavo, and Merlin M. Hanauer. 2013. "Estimating the Impacts of Bolivia's Protected Areas on Poverty." *World Development* 41 (1): 265–85. https://doi.org/10.1016/j.worlddev.2012.06.011.

Carmenta, Rachel, George Alan Blackburn, Gemma Davies, Claudio De Sassi, André Lima, Luke Parry, Wlodek Tych, and Jos Barlow. 2016. "Does the Establishment of Sustainable Use Reserves Affect Fire Management in the Humid Tropics." *PLoS ONE* 11 (2): 1–19. https://doi.org/10.1371/journal.pone.0149292.

Carmo, Cleber Nascimento do, Mariane Branco Alves, and Sandra de Souza Hacon. 2013. "Impact of Biomass Burning and Weather Conditions on Children's Health in a City of Western Amazon Region." *Air Quality, Atmosphere and Health* 6 (2): 517–25. https://doi.org/10.1007/s11869-012-0191-6.

Carrol .J.P., Colfer, Sheil Douglas, and Kishi Misha. 2006. *Forests and Human Health: Assessing the Evidence*. *Forests and Human Health: Assessing the Evidence*. https://doi.org/10.17528/cifor/002037.

Castro, Marcia C., Adriano Massuda, Gisele Almeida, Naercio Aquino Menezes-Filho, Monica Viegas Andrade, Kenya Valéria Micaela de Souza Noronha, Rudi Rocha, et al. 2019. "Brazil's Unified Health System: The First 30 Years and Prospects for the Future." *The Lancet*. Lancet Publishing Group. https://doi.org/10.1016/S0140-6736(19)31243-7.

Chen, Kai, Meng Wang, Conghong Huang, Patrick L. Kinney, and Paul T. Anastas. 2020. "Air Pollution

Reduction and Mortality Benefit during the COVID-19 Outbreak in China." *The Lancet Planetary Health*. Elsevier B.V. https://doi.org/10.1016/S2542-5196(20)30107-8.

Coad, Lauren, Alison Campbell, Lera Miles, and Katherine Humphries. 2008. "The Costs and Benefits of Forest Protected Areas for Local Livelihoods : A Review of the Current Literature," no. May.

Cochrane, Mark A., and Mark D. Schulze. 1999. "Fire as a Recurrent Event in Tropical Forests of the Eastern Amazon: Effects on Forest Structure, Biomass, and Species Composition1." *Biotropica* 31 (1): 2–16. https://doi.org/10.1111/j.1744-7429.1999.tb00112.x.

Cohen, Aaron J., Michael Brauer, Richard Burnett, H. Ross Anderson, Joseph Frostad, Kara Estep, Kalpana Balakrishnan, et al. 2017. "Estimates and 25-Year Trends of the Global Burden of Disease Attributable to Ambient Air Pollution: An Analysis of Data from the Global Burden of Diseases Study 2015." *The Lancet* 389 (10082): 1907–18. https://doi.org/10.1016/S0140-6736(17)30505-6.

Convention on Biological Diversity. 1992. United Nations. https://doi.org/10.1016/B978-0-12-384719-5.00418-4.

———. 2020. "RECOMMENDATION ADOPTED BY THE OPEN-ENDED WORKING GROUP ON THE POST2020 GLOBAL BIODIVERSITY FRAMEWORK ." Rome, Italy. https://www.cbd.int/doc/recommendations/wg2020-02/wg2020-02-rec-01-en.pdf.

Correia, Sergio, Paulo Guimarães, and Tom Zylkin. 2019. "PPMLHDFE: Fast Poisson Estimation with High-Dimensional Fixed Effects."

Cruz Marques, A. 1987. "Human Migration and the Spread of Malaria in Brazil." *Parasitology Today* 3 (6): 166–70. https://doi.org/10.1016/0169-4758(87)90170-0.

Cui, Yan, Zuo Feng Zhang, John Froines, Jinkou Zhao, Hua Wang, Shun Zhang Yu, and Roger Detels. 2003. "Air Pollution and Case Fatality of SARS in the People's Republic of China: An Ecologic Study." *Environmental Health: A Global Access Science Source* 2: 1–5. https://doi.org/10.1186/1476-069X-2-1.

Davidson, Eric A., Alessandro C. De Araüjo, Paulo Artaxo, Jennifer K. Balch, I. Foster Brown, Mercedes M. Mercedes, Michael T. Coe, et al. 2012. "The Amazon Basin in Transition." *Nature*. Nature Publishing Group. https://doi.org/10.1038/nature10717.

DeFries, Ruth, Andrew Hansen, Adrian C Newton, and Matthew C Hansen. 2005. "Increasing Isolation of Protected Areas in Tropical Forests over the Past Twenty Years." *Ecological Applications* 15 (1): 19–26. https://doi.org/10.1890/03-5258.

Dudley, N. (Editor). 2008. *Guidelines for Applying Protected Area Management Categories*. Edited by S. Stolton, P. Shadie, and N. Dudley. *IUCN WCPA Best Practice Guidance on Recognising Protected Areas and Assigning Management Categories and Governance Types*. Best Pract. Vol. 38. Gland, Switzerland.

European Respiratory Society. 2017. *The Global Impact of Respiratory Disease- Second Edition*. *Forum of International Respiratory Societies.*

Ferraro, Paul J., and Merlin M. Hanauer. 2011. "Protecting Ecosystems and Alleviating Poverty with Parks and Reserves: 'Win-Win' or Tradeoffs?" *Environmental and Resource Economics* 48 (2): 269–86. https://doi.org/10.1007/s10640-010-9408-z.

———. 2014a. “Quantifying Causal Mechanisms to Determine How Protected Areas Affect Poverty through Changes in Ecosystem Services and Infrastructure.” *Proceedings of the National Academy of Sciences of the United States of America* 111 (11): 4332–37. https://doi.org/10.1073/pnas.1307712111.

———. 2014b. “Advances in Measuring the Environmental and Social Impacts of Environmental Programs.” *Annual Review of Environment and Resources* 39 (1): 495–517. https://doi.org/10.1146/annurev-environ-101813-013230.

Ferraro, Paul J., Kathleen Lawlor, Katrina L. Mullan, and Subhrendu K. Pattanayak. 2012. “Forest Figures: Ecosystem Services Valuation and Policy Evaluation in Developing Countries.” *Review of Environmental Economics and Policy* 6 (1): 20–44. https://doi.org/10.1093/reep/rer019.

Ferraro, Paul J, and Subhrendu K Pattanayak. 2006. “Money for Nothing? A Call for Empirical Evaluation of Biodiversity Conservation Investments.” Edited by Georgina Mace. *PLoS Biology* 4 (4): e105. https://doi.org/10.1371/journal.pbio.0040105.

Fisher, Brendan, and Treg Christopher. 2007. “Poverty and Biodiversity: Measuring the Overlap of Human Poverty and the Biodiversity Hotspots.” *Ecological Economics* 62 (1): 93–101. https://doi.org/10.1016/j.ecolecon.2006.05.020.

Frankenberg, Elizabeth, Douglas McKee, and Duncan Thomas. 2005. “Health Consequences of Forest Fires in Indonesia.” *Demography* 42 (1): 109–29. https://doi.org/10.1353/dem.2005.0004.

Galway, Lindsay P., Yubraj Acharya, and Andrew D. Jones. 2018. “Deforestation and Child Diet Diversity: A Geospatial Analysis of 15 Sub-Saharan African Countries.” *Health and Place* 51 (May): 78–88. https://doi.org/10.1016/j.healthplace.2018.03.002.

Giardina, Francesco, Alexandra G. Konings, Daniel Kennedy, Seyed Hamed Alemohammad, Rafael S. Oliveira, Maria Uriarte, and Pierre Gentine. 2018. “Tall Amazonian Forests Are Less Sensitive to Precipitation Variability.” *Nature Geoscience* 11 (6): 405–9. https://doi.org/10.1038/s41561-018-0133-5.

He, Lijie, Aiwen Lin, Xinxin Chen, Hao Zhou, Zhigao Zhou, and Peipei He. 2019. “Assessment of MERRA-2 Surface PM2.5 over the Yangtze River Basin: Ground-Based Verification, Spatiotemporal Distribution and Meteorological Dependence.” *Remote Sensing* 11 (4). https://doi.org/10.3390/rs11040460.

Herrera, Diego, Alexander Pfaff, and Juan Robalino. 2019. “Impacts of Protected Areas Vary with the Level of Government: Comparing Avoided Deforestation across Agencies in the Brazilian Amazon.” *Proceedings of the National Academy of Sciences of the United States of America* 116 (30): 14916–25. https://doi.org/10.1073/pnas.1802877116.

Holmes, George. 2007. “Protection, Politics and Protest: Understanding Resistance to Conservation.” *Conservation and Society*. Vol. 5.

Hope, Mat. 2019. “The Brazilian Development Agenda Driving Amazon Devastation.” *The Lancet Planetary Health* 3 (10): e409–11. https://doi.org/10.1016/S2542-5196(19)30195-0.

Horton, Richard, and Selina Lo. 2015. “Planetary Health: A New Science for Exceptional Action.” *The Lancet*. Lancet Publishing Group. https://doi.org/10.1016/S0140-6736(15)61038-8.

Ignotti, Eliane, Sandra de Souza Hacon, Washington Leite Junger, Dennys Mourão, Karla Longo, Saulo

Freitas, Paulo Artaxo, and Antônio Carlos Monteiro Ponce de Leon. 2010. “Air Pollution and Hospital Admissions for Respiratory Diseases in the Subequatorial Amazon: A Time Series Approach.” *Cadernos de Saude Publica* 26 (4): 747–61. https://doi.org/10.1590/s0102-311x2010000400017.

Ionova, Ana. 2020. “Brazilian Amazon Protected Areas ‘in Flames’ as Land-Grabbers Invade.” *Mongabay Series: Forest Trackers*, August 7, 2020. https://news.mongabay.com/2020/08/brazilian-amazon-protected-areas-in-flames-as-land-grabbers-invade/.

Jones, Bryony A., Delia Grace, Richard Kock, Silvia Alonso, Jonathan Rushton, Mohammed Y. Said, Declan McKeever, et al. 2013. “Zoonosis Emergence Linked to Agricultural Intensification and Environmental Change.” *Proceedings of the National Academy of Sciences of the United States of America* 110 (21): 8399–8404. https://doi.org/10.1073/pnas.1208059110.

Joppa, Lucas N., and Alexander Pfaff. 2009. “High and Far: Biases in the Location of Protected Areas.” Edited by Jon Moen. *PLoS ONE* 4 (12): e8273. https://doi.org/10.1371/journal.pone.0008273.

———. 2011. “Global Protected Area Impacts.” *Proceedings of the Royal Society B: Biological Sciences* 278 (1712): 1633–38. https://doi.org/10.1098/rspb.2010.1713.

Joppa, Lucas, and Alexander Pfaff. 2010. “Reassessing the Forest Impacts of Protection: The Challenge of Nonrandom Location and a Corrective Method.” *Annals of the New York Academy of Sciences*. https://doi.org/10.1111/j.1749-6632.2009.05162.x.

Jusys, Tomas. 2018. “Changing Patterns in Deforestation Avoidance by Different Protection Types in the Brazilian Amazon.” Edited by Asim Zia. *PLOS ONE* 13 (4): e0195900. https://doi.org/10.1371/journal.pone.0195900.

Karjalainen, Eeva, Tytti Sarjala, and Hannu Raitio. 2010. “Promoting Human Health through Forests: Overview and Major Challenges.” *Environmental Health and Preventive Medicine* 15 (1): 1–8. https://doi.org/10.1007/s12199-008-0069-2.

Kauano, Érico Emed, José Maria Cardoso Silva, José Alexandre Felizola Diniz Filho, and Fernanda Michalski. 2020. “Do Protected Areas Hamper Economic Development of the Amazon Region? An Analysis of the Relationship between Protected Areas and the Economic Growth of Brazilian Amazon Municipalities.” *Land Use Policy* 92 (March): 104473. https://doi.org/10.1016/j.landusepol.2020.104473.

Keane, Aidan, Jens Friis Lund, Jevgeniy Bluwstein, Neil D. Burgess, Martin Reinhardt Nielsen, and Katherine Homewood. 2020. “Impact of Tanzania’s Wildlife Management Areas on Household Wealth.” *Nature Sustainability* 3 (3): 226–33. https://doi.org/10.1038/s41893-019-0458-0.

Keesing, Felicia, Lisa K. Belden, Peter Daszak, Andrew Dobson, C. Drew Harvell, Robert D. Holt, Peter Hudson, et al. 2010. “Impacts of Biodiversity on the Emergence and Transmission of Infectious Diseases.” *Nature* 468 (7324): 647–52. https://doi.org/10.1038/nature09575.

Keles, Derya, Philippe Delacote, Alexander Pfaff, Siyu Qin, and Michael B. Mascia. 2020. “What Drives the Erasure of Protected Areas? Evidence from across the Brazilian Amazon.” *Ecological Economics* 176 (October): 106733. https://doi.org/10.1016/j.ecolecon.2020.106733.

Lavaine, Emmanuelle. 2014. “An Econometric Analysis of Atmospheric Pollution, Environmental Disparities and Mortality Rates.” *Environmental and Resource Economics* 60 (2): 215–42. https://doi.org/10.1007/s10640-014-9765-0.

Liang, Lirong, Yutong Cai, Benjamin Barratt, Baolei Lyu, Queenie Chan, Anna L. Hansell, Wuxiang Xie, Di Zhang, Frank J. Kelly, and Zhaohui Tong. 2019. “Associations between Daily Air Quality and Hospitalisations for Acute Exacerbation of Chronic Obstructive Pulmonary Disease in Beijing, 2013–17: An Ecological Analysis.” *The Lancet Planetary Health* 3 (6): e270–79. https://doi.org/10.1016/S2542-5196(19)30085-3.

Machado-Silva, Fausto, Renata Libonati, Thiago Felipe Melo de Lima, Roberta Bittencourt Peixoto, José Ricardo de Almeida França, Mônica de Avelar Figueiredo Mafra Magalhães, Filippe Lemos Maia Santos, Julia Abrantes Rodrigues, and Carlos C. DaCamara. 2020. “Drought and Fires Influence the Respiratory Diseases Hospitalizations in the Amazon.” *Ecological Indicators* 109 (September 2018): 105817. https://doi.org/10.1016/j.ecolind.2019.105817.

Maillard, Oswaldo, Roberto Vides-Almonacid, Marcio Flores-Valencia, Roger Coronado, Peter Vogt, Sergio M. Vicente-Serrano, Huáscar Azurduy, Ruth Anívarro, and Rosa Leny Cuellar. 2020. “Relationship of Forest Cover Fragmentation and Drought with the Occurrence of Forest Fires in the Department of Santa Cruz, Bolivia.” *Forests* 11 (9): 910. https://doi.org/10.3390/F11090910.

Malhi, Yadvinder, Luiz E O C Aragã O A, David Galbraith, Chris Huntingford, Rosie Fisher, Przemyslaw Zelazowski, Stephen Sitch, Carol Mcsweeney, and Patrick Meir. 2009. “Exploring the Likelihood and Mechanism of a Climate-Change-Induced Dieback of the Amazon Rainforest.” www.pnas.org/cgi/content/full/.

Marengo, Jose A., Javier Tomasella, Lincoln M. Alves, Wagner R. Soares, and Daniel A. Rodriguez. 2011. “The Drought of 2010 in the Context of Historical Droughts in the Amazon Region.” *Geophysical Research Letters* 38 (12). https://doi.org/10.1029/2011GL047436.

McKinnon, Madeleine C., Samantha H. Cheng, Samuel Dupre, Janet Edmond, Ruth Garside, Louise Glew, Margaret B. Holland, et al. 2016. “What Are the Effects of Nature Conservation on Human Well-Being? A Systematic Map of Empirical Evidence from Developing Countries.” *Environmental Evidence* 5 (1): 8. https://doi.org/10.1186/s13750-016-0058-7.

Miranda, Juan José, Leonardo Corral, Allen Blackman, Gregory Asner, and Eirivelthon Lima. 2016. “Effects of Protected Areas on Forest Cover Change and Local Communities: Evidence from the Peruvian Amazon.” *World Development* 78 (February): 288–307. https://doi.org/10.1016/j.worlddev.2015.10.026.

Morton, D. C., Y. Le Page, R. DeFries, G. J. Collatz, and G. C. Hurtt. 2013. “Understorey Fire Frequency and the Fate of Burned Forests in Southern Amazonia.” *Philosophical Transactions of the Royal Society B: Biological Sciences* 368 (1619). https://doi.org/10.1098/rstb.2012.0163.

Motta, Victor. 2019. “Estimating Poisson Pseudo-Maximum-Likelihood Rather than Log-Linear Model of a Log-Transformed Dependent Variable.” *RAUSP Management Journal* 54 (4): 508–18. https://doi.org/10.1108/RAUSP-05-2019-0110.

Mu, Ye, Trent W. Biggs, and Fernando De Sales. 2021. “Forests Mitigate Drought in an Agricultural Region of the Brazilian Amazon: Atmospheric Moisture Tracking to Identify Critical Source Areas.” *Geophysical Research Letters* 48 (5): e2020GL091380. https://doi.org/10.1029/2020GL091380.

Naidoo, R., D. Gerkey, D. Hole, A. Pfaff, A. M. Ellis, C. D. Golden, D. Herrera, et al. 2019. “Evaluating the Impacts of Protected Areas on Human Well-Being across the Developing World.” *Science Advances* 5 (4): eaav3006. https://doi.org/10.1126/sciadv.aav3006.

Negret, Pablo Jose, Moreno Di Marco, Laura J. Sonter, Jonathan Rhodes, Hugh P. Possingham, and Martine Maron. 2020. "Effects of Spatial Autocorrelation and Sampling Design on Estimates of Protected Area Effectiveness." *Conservation Biology*, August, cobi.13522. https://doi.org/10.1111/cobi.13522.

Neira, M., and A. Prüss-Ustün. 2016. "Preventing Disease through Healthy Environments: A Global Assessment of the Environmental Burden of Disease." *Toxicology Letters* 259: S1. https://doi.org/10.1016/j.toxlet.2016.07.028.

Nelson, Andrew, and Kenneth M. Chomitz. 2011. "Effectiveness of Strict vs. Multiple Use Protected Areas in Reducing Tropical Forest Fires: A Global Analysis Using Matching Methods." *PLoS ONE* 6 (8). https://doi.org/10.1371/journal.pone.0022722.

Nepstad, D., S. Schwartzman, B. Bamberger, M. Santilli, D. Ray, P. Schlesinger, P. Lefebvre, et al. 2006. "Inhibition of Amazon Deforestation and Fire by Parks and Indigenous Lands." *Conservation Biology* 20 (1): 65–73. https://doi.org/10.1111/j.1523-1739.2006.00351.x.

Nepstad, Daniel C., Adalberto Veríssimo, Ane Alencar, Carlos Nobre, Eirivelthon Lima, Paul Lefebvre, Peter Schlesinger, et al. 1999. "Large-Scale Impoverishment of Amazonian Forests by Logging and Fire." *Nature* 398 (6727): 505–8. https://doi.org/10.1038/19066.

Nicolussi, Francine Heloisa, Ana Paula Milla dos Santos, Sílvia Carla da Silva André, Tatiane Bonametti Veiga, and Angela Maria Magosso Takayanagui. 2014. "Air Pollution and Respiratory Allergic Diseases in Schoolchildren." *Revista de Saude Publica* 48 (2): 326–30. https://doi.org/10.1590/S0034-8910.2014048004940.

Nolte, Christoph, Arun Agrawal, Kirsten M. Silvius, and S. Soares Filho Britaldo. 2013. "Governance Regime and Location Influence Avoided Deforestation Success of Protected Areas in the Brazilian Amazon." *Proceedings of the National Academy of Sciences of the United States of America* 110 (13): 4956–61. https://doi.org/10.1073/pnas.1214786110.

Norris, Douglas E. 2004. "Mosquito-Borne Diseases as a Consequence of Land Use Change." *EcoHealth* 1 (1): 19–24. https://doi.org/10.1007/s10393-004-0008-7.

Nowak, David J., Satoshi Hirabayashi, Allison Bodine, and Eric Greenfield. 2014. "Tree and Forest Effects on Air Quality and Human Health in the United States." *Environmental Pollution* 193: 119–29. https://doi.org/10.1016/j.envpol.2014.05.028.

Pacheco, André A., Ana Carolina O. Neves, and G. Wilson Fernandes. 2018. "Uneven Conservation Efforts Compromise Brazil to Meet the Target 11 of Convention on Biological Diversity." *Perspectives in Ecology and Conservation* 16 (1): 43–48. https://doi.org/10.1016/j.pecon.2017.12.001.

Page, Yannick Le, Douglas Morton, Corinne Hartin, Ben Bond-Lamberty, José Miguel Cardoso Pereira, George Hurtt, and Ghassem Asrar. 2017. "Synergy between Land Use and Climate Change Increases Future Fire Risk in Amazon Forests." *Earth System Dynamics* 8 (4): 1237–46. https://doi.org/10.5194/esd-8-1237-2017.

Pattanayak, Subhrendu K., Martin T. Ross, Brooks M. Depro, Simone C. Bauch, Christopher Timmins, Kelly J. Wendland, and Keith Alger. 2009. "Climate Change and Conservation in Brazil: CGE Evaluation of Health and Wealth Impacts." *B.E. Journal of Economic Analysis and Policy* 9 (2). https://doi.org/10.2202/1935-1682.2096.

Pattanayak, Subhrendu K., and Kelly J. Wendland. 2007. “Nature’s Care: Diarrhea, Watershed Protection, and Biodiversity Conservation in Flores, Indonesia.” *Biodiversity and Conservation* 16 (10): 2801–19. https://doi.org/10.1007/s10531-007-9215-1.

Pfaff, Alexander, Juan Robalino, Diego Herrera, and Catalina Sandoval. 2015. “Protected Areas’ Impacts on Brazilian Amazon Deforestation: Examining Conservation – Development Interactions to Inform Planning.” Edited by Kamal Bawa. *PLOS ONE* 10 (7): e0129460. https://doi.org/10.1371/journal.pone.0129460.

Pfaff, Alexander, Juan Robalino, G. Arturo Sanchez-Azofeifa, Kwaw S. Andam, and Paul J. Ferraro. 2009. “Park Location Affects Forest Protection: Land Characteristics Cause Differences in Park Impacts across Costa Rica.” *B.E. Journal of Economic Analysis and Policy* 9 (2). https://doi.org/10.2202/1935-1682.1990.

Pfaff, Alexander, Juan Robalino, Catalina Sandoval, and Diego Herrera. 2015. “Protected Area Types, Strategies and Impacts in Brazil’s Amazon: Public Protected Area Strategies Do Not Yield a Consistent Ranking of Protected Area Types by Impact.” *Philosophical Transactions of the Royal Society B: Biological Sciences* 370 (1681): 20140273. https://doi.org/10.1098/rstb.2014.0273.

Pienkowski, Thomas, Borame Lee Dickens, Haoyang Sun, and Luis Roman Carrasco. 2017. “Empirical Evidence of the Public Health Benefits of Tropical Forest Conservation in Cambodia: A Generalised Linear Mixed-Effects Model Analysis.” *The Lancet Planetary Health* 1 (5): e180–87. https://doi.org/10.1016/S2542-5196(17)30081-5.

Prüss-Üstün, Annette, and Carlos Corvalán. 2007. “How Much Disease Burden Can Be Prevented by Environmental Interventions?” *Epidemiology*. Epidemiology. https://doi.org/10.1097/01.ede.0000239647.26389.80.

Pullin, Andrew S., Mukdarut Bangpan, Sarah Dalrymple, Kelly Dickson, Neal R. Haddaway, John R. Healey, Hanan Hauari, et al. 2013. “Human Well-Being Impacts of Terrestrial Protected Areas.” *Environmental Evidence* 2 (1). https://doi.org/10.1186/2047-2382-2-19.

Qiu, Jiangxiao, Edward T. Game, Heather Tallis, Lydia P. Olander, Louise Glew, James S. Kagan, Elizabeth L. Kalies, et al. 2018. “Evidence-Based Causal Chains for Linking Health, Development, and Conservation Actions.” *BioScience*. Oxford University Press. https://doi.org/10.1093/biosci/bix167.

Rangel, Marcos A., and Tom S. Vogl. 2019. “Agricultural Fires and Health at Birth.” *The Review of Economics and Statistics* 101 (4): 616–30. https://doi.org/10.1162/rest_a_00806.

Reddington, C. L., E. W. Butt, D. A. Ridley, P. Artaxo, W. T. Morgan, H. Coe, and D. V. Spracklen. 2015. “Air Quality and Human Health Improvements from Reductions in Deforestation-Related Fire in Brazil.” *Nature Geoscience* 8 (10): 768–71. https://doi.org/10.1038/ngeo2535.

Reid, Colleen E., Michael Brauer, Fay H. Johnston, Michael Jerrett, John R. Balmes, and Catherine T. Elliott. 2016. “Critical Review of Health Impacts of Wildfire Smoke Exposure.” *Environmental Health Perspectives* 124 (9): 1334–43. https://doi.org/10.1289/ehp.1409277.

Robalino, Juan, Alexander Pfaff, and Laura Villalobos. 2017. “Heterogeneous Local Spillovers from Protected Areas in Costa Rica.” *Journal of the Association of Environmental and Resource Economists* 4 (3): 795–820. https://doi.org/10.1086/692089.

Rocha, Rudi, and André Sant’anna. 2020. “Winds of Fire and Smoke: Air Pollution and Health in the Brazilian Amazon.” www.ieps.org.br.

Rosa, Antonia Maria, Eliane Ignotti, Sandra De Souza Hacon, and Hermano Albuquerque De Castro. 2008. “Analysis of Hospitalizations for Respiratory Diseases in Tangará Da Serra, Brazil.” *Jornal Brasileiro de Pneumologia* 34 (8): 575–82. https://doi.org/10.1590/s1806-37132008000800006.

Sampaio, Gilvan, Carlos Nobre, Marcos Heil Costa, Prakki Satyamurty, Britaldo Silveira Soares-Filho, and Manoel Cardoso. 2007. “Regional Climate Change over Eastern Amazonia Caused by Pasture and Soybean Cropland Expansion.” *Geophysical Research Letters* 34 (17). https://doi.org/10.1029/2007GL030612.

Sario, M. De, K. Katsouyanni, and P. Michelozzi. 2013. “Climate Change, Extreme Weather Events, Air Pollution and Respiratory Health in Europe.” *European Respiratory Journal* 42 (3): 826–43. https://doi.org/10.1183/09031936.00074712.

Sarnat, Stefanie Ebelt, Amit U. Raysoni, Wen Whai Li, Fernando Holguin, Brent A. Johnson, Silvia Flores Luevano, Jose Humberto Garcia, and Jeremy A. Sarnat. 2012. “Air Pollution and Acute Respiratory Response in a Panel of Asthmatic Children along the U.S.-Mexico Border.” *Environmental Health Perspectives* 120 (3): 437–44. https://doi.org/10.1289/ehp.1003169.

Sheldon, By Tamara L, and Chandini Sankaran. 2017. “The Impact of Indonesian Forest Fires on Singaporean Pollution and Health Author (s): Tamara L . Sheldon and Chandini Sankaran Source : The American Economic Review , MAY 2017 , Vol . 107 , No . 5 , PAPERS AND PROCEEDINGS OF THE One Hundred Twenty-Ninth” 107 (5): 526–29.

Sims, Katharine R.E. 2010. “Conservation and Development: Evidence from Thai Protected Areas.” *Journal of Environmental Economics and Management* 60 (2): 94–114. https://doi.org/10.1016/j.jeem.2010.05.003.

———. 2014. “Do Protected Areas Reduce Forest Fragmentation? A Microlandscapes Approach.” *Environmental and Resource Economics* 58 (2): 303–33. https://doi.org/10.1007/s10640-013-9707-2.

Smith, Lauren T., Luiz E.O.C. Aragão, Clive E. Sabel, and Tomoki Nakaya. 2014. “Drought Impacts on Children’s Respiratory Health in the Brazilian Amazon.” *Scientific Reports* 4: 1–8. https://doi.org/10.1038/srep03726.

Soares-Filho, Britaldo, Paulo Moutinho, Daniel Nepstad, Anthony Anderson, Hermann Rodrigues, Ricardo Garcia, Laura Dietzsch, et al. 2010. “Role of Brazilian Amazon Protected Areas in Climate Change Mitigation.” *Proceedings of the National Academy of Sciences of the United States of America* 107 (24): 10821–26. https://doi.org/10.1073/pnas.0913048107.

Spring, Jake, and Lisandra Paraguassu. 2020. “Deforestation in Brazil’s Amazon Skyrockets to 12-Year High under Bolsonaro | Reuters.” *Reuters*. https://www.reuters.com/article/brazil-environment/deforestation-in-brazils-amazon-skyrockets-to-12-year-high-under-bolsonaro-idUSKBN28B3MV.

Troëng, Sebastian, Edward Barbier, and Carlos Rodríguez. 2020. “The COVID-19 Pandemic Is Not a Break for Nature – Here’s Why | World Economic Forum.” *World Economic Forum*, May 21, 2020. https://www.weforum.org/agenda/2020/05/covid-19-coronavirus-pandemic-nature-environment-green-stimulus-biodiversity/.

UNEP-WCMC, IUCN, and NGS. 2018. “Protected Planet Report 2018.” Cambridge UK; Gland, Switzerland; and Washington, D.C., USA. www.unep-wcmc.org.

United Nations. 2020. *The Sustainable Development Goals Report: 2020*. Edited by Lois Jensen. 2020th ed. New York, NY: United Nations Publications. https://unstats.un.org/sdgs/report/2020/The-Sustainable-Development-Goals-Report-2020.pdf.

Val Simardi Beraldo Souza, Thiago do, Brijesh Thapa, Camila Gonçalves de Oliveira Rodrigues, and Denise Imori. 2019. "Economic Impacts of Tourism in Protected Areas of Brazil." *Journal of Sustainable Tourism* 27 (6): 735–49. https://doi.org/10.1080/09669582.2017.1408633.

VejapontoCom. 2020. "VÍDEO COMPLETO: A Reunião de Bolsonaro Com Ministros Em 22 de Abril - YouTube." Brazil. https://www.youtube.com/watch?reload=9&v=nfgv7DLdCqA.

Watson, James E.M., Nigel Dudley, Daniel B. Segan, and Marc Hockings. 2014. "The Performance and Potential of Protected Areas." *Nature*. Nature Publishing Group. https://doi.org/10.1038/nature13947.

Werf, G. R. Van Der, D. C. Morton, R. S. Defries, J. G.J. Olivier, P. S. Kasibhatla, R. B. Jackson, G. J. Collatz, and J. T. Randerson. 2009. "CO2 Emissions from Forest Loss." *Nature Geoscience*. Nature Publishing Group. https://doi.org/10.1038/ngeo671.

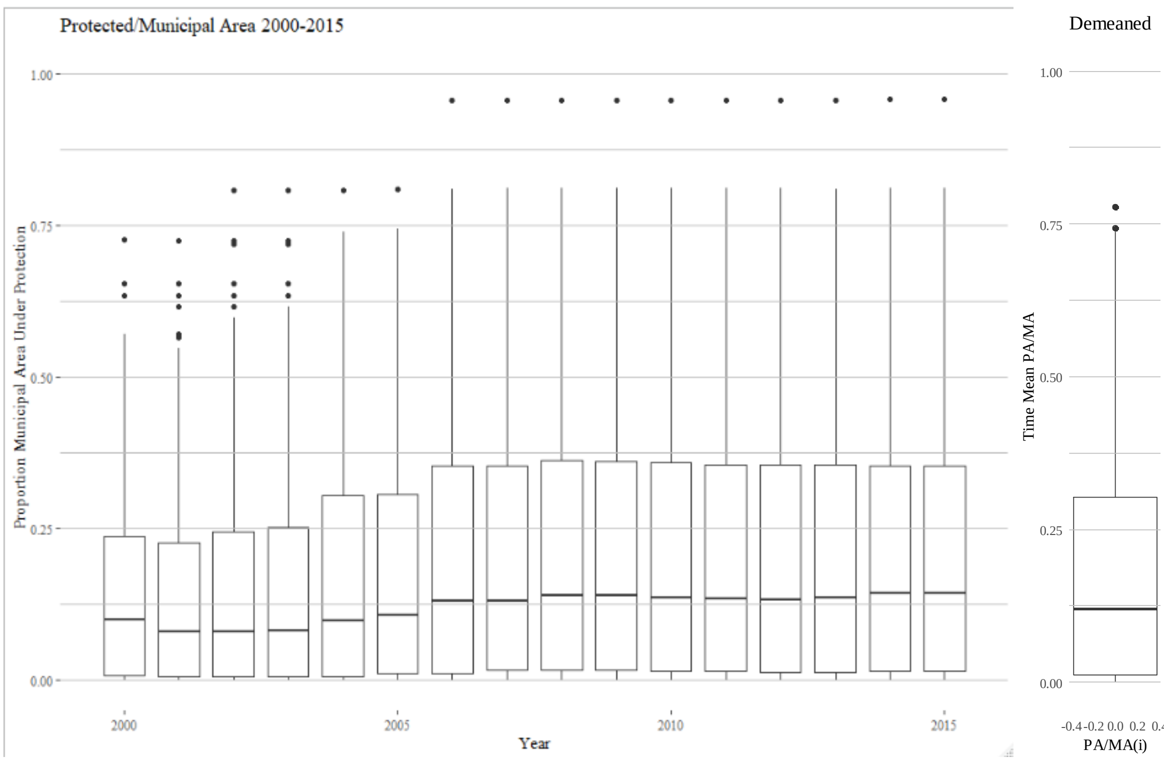
Whitmee, Sarah, Andy Haines, Chris Beyrer, Frederick Boltz, Anthony G. Capon, Braulio Ferreira De Souza Dias, Alex Ezeh, et al. 2015. "Safeguarding Human Health in the Anthropocene Epoch: Report of the Rockefeller Foundation-Lancet Commission on Planetary Health." *The Lancet*. Lancet Publishing Group. https://doi.org/10.1016/S0140-6736(15)60901-1.

World Health Organization. 2016. *Ambiet Air Pollution: A Global Assessment of Exposure and Burden of Disease.*

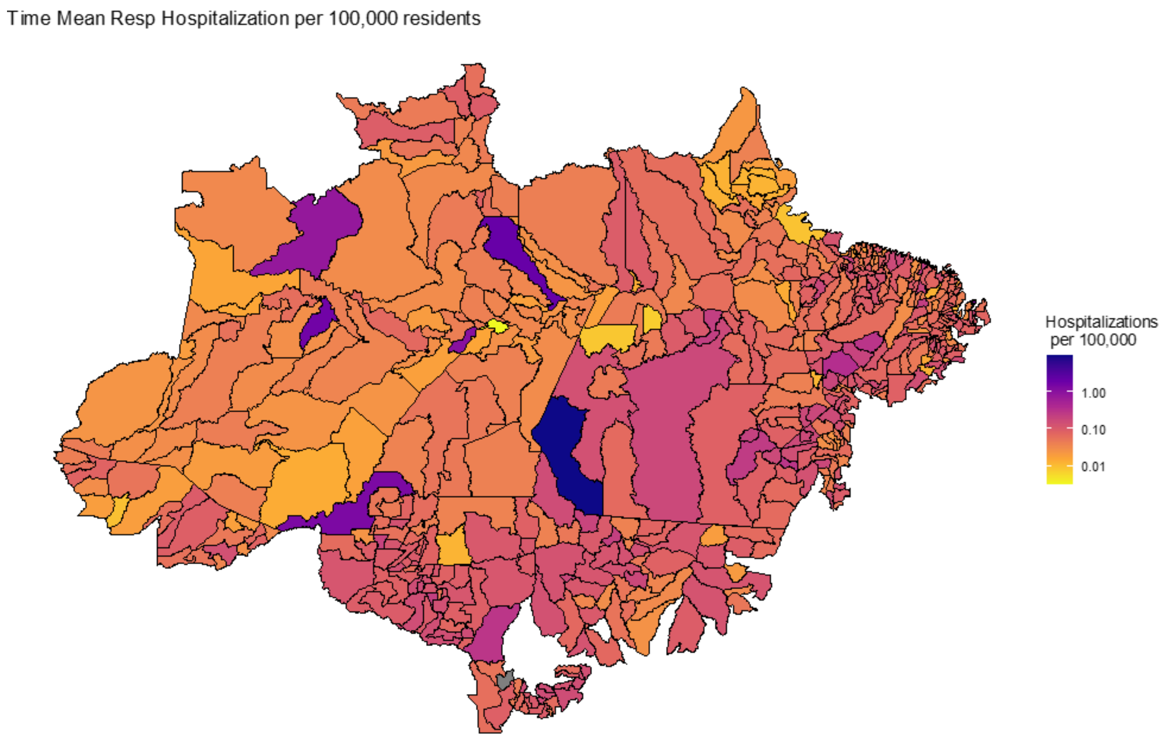
Wu, Xiao, Rachel Nethery, Benjamin Sabath, Danielle Braun, and Francesca Dominici. 2020. "Exposure to Air Pollution and COVID-19 Mortality in the United States: A Nationwide Cross-Sectional Study." *MedRxiv : The Preprint Server for Health Sciences*. https://doi.org/10.1101/2020.04.05.20054502.

Yang, Hongbo, Andrés Viña, Julie Ann Winkler, Min Gon Chung, Yue Dou, Fang Wang, Jindong Zhang, et al. 2019. "Effectiveness of China's Protected Areas in Reducing Deforestation." *Environmental Science and Pollution Research* 26 (18): 18651–61. https://doi.org/10.1007/s11356-019-05232-9.

APPENDIX



Appendix Figure 1: The raw measures of area of protected areas in km² are heavily skewed, so the proportion of municipal area shows a relative distribution of PA coverage. The "demeaned " box plot to the right shows the time meaned proportion of protected areas for the 272 (non-zero) municipalities across the 16 years. This data doesn't include all of the reductions in PA coverage over the period.


Time Mean Resp Hospitalization per 100,000 residents
Hospitalizations
per 100,000
1.00
0.10
0.01