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Air quality and human health improvements from reductions in deforestation-related fire in Brazil

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Roughly 15% of the Brazilian Amazon was deforested between 1 1976 and 2010 (ref. 1). Fire is the dominant method through 0.2 2 which forests and vegetation are cleared. Fires emit large 3 quantities of particulate matter into the atmosphere², which degrades air quality and affects human health^{3,4}. Since 2004, 5 Brazil has achieved substantial reductions in deforestation rates^{1,5,6} and associated deforestation fires⁷. Here we assess the impact of this reduction on air quality and human health 8 during non-drought years between 2001 and 2012. We analyse 9 aerosol optical depth measurements obtained with satellite 10 and ground-based sensors over southwest Brazil and Bolivia 11 for the dry season, from August to October. We find that 12 observed dry season aerosol optical depths are more than a 13 factor of two lower in years with low deforestation rates in 14 Brazil. We used a global aerosol model to show that reductions 15 in fires associated with deforestation have caused mean 16 surface particulate matter concentrations to decline by $\sim 30\%$ 17 during the dry season in the region. Using particulate matter 18 concentration response functions from the epidemiological 19 literature, we estimate that this reduction in particulate matter 20 may be preventing roughly 400 to 1,700 premature adult 21 deaths annually across South America. 22

Humans make extensive use of fire to clear forests and vegetation 23 and to prepare and maintain land for agriculture^{8,9}. Emissions 24 of particulate matter (PM) from fires can dominate atmospheric 25 concentrations particularly during the dry season^{6,10}. Inhalation of 26 PM from fires has adverse impacts on human health, including 27 increased hospital admissions and premature mortality^{3,4,11,12}. 28

Rapid deforestation is occurring across the tropics⁵. Between 29 1976 and 2010, more than 750,000 km² of the Brazilian Amazon 30 was deforested, equivalent to $\sim 15\%$ of the original forested 31 area¹. Recently, Brazil has achieved well-documented reductions in 32 deforestation rates^{1,5,6}. Over the period 2001 to 2012, deforestation 33 rates in Brazil declined by ~40%, from $37,800 \text{ km}^2 \text{ yr}^{-1}$ in 34 2002–2004 to 22,900 km² yr⁻¹ in 2009–2011 (Fig. 1a; r = -0.71, 35 P = 0.005, trend = -1,390 km² yr⁻¹; ref. 5). The deforestation rates 36 37 in the Brazilian Amazon have declined even more strongly, with reductions of 70% (refs 1,6; Supplementary Fig. 1). Reduction 38 in deforestation rates has numerous social and environmental 39 benefits1. We were interested in whether this reduction in 40 41 deforestation rates has also improved air quality across Brazil.

42 Satellite-derived data sets of fire occurrence show that the total number of active fire counts across Amazonia is positively related 43 to both deforestation rates and occurrence of drought^{1,7,13,14}. During 44 2001 to 2010, years with high deforestation rates had a factor of two 45 46 greater incidence of fire compared with years with low deforestation rates¹. Significant declines in fire frequency across Brazil have 47

occurred over this period, with the largest reductions in regions of high cumulative deforestation⁷.

We used three different data sets of satellite-derived fire emissions^{2,15,16} available over 2002 to 2011 (see Methods) to further explore the relationship between deforestation and PM emissions from fire. Substantial fire emissions occur across Brazil (Fig. 2), accounting for 12-16% of global particulate emissions from fire (Supplementary Table 1). In South America, particulate emissions from fire are greatest across southeast Amazonia where there is rapid deforestation (Fig. 2). Tropical forests of central Amazonia have little fire emission because high moisture, dense forest canopies and little deforestation mean that fires are a rare occurrence^{17,18}. Regions with frequent agricultural fires also have lower total fire emission compared with regions of active deforestation, because agricultural fires result in a factor of 3-5 lower emission per unit area burned due to lower fuel loads¹⁹.

One satellite fire data set classifies emissions according to fire type², allowing the specific contribution of deforestation fires to be estimated (see Methods). Deforestation fires account for only 20% of global total particulate fire emissions but 64% of Brazil's total, meaning that deforestation fires dominate regional air quality impacts. Classification of fire types is an uncertainty-deforestation fires may spread out of the deforested area into surrounding forest, where they are classified as a different fire type not associated with deforestation. Throughout our analysis, we therefore analyse both total particulate fire emissions and emissions specifically classified as from deforestation fires.

Over 2001 to 2011, Amazonia experienced drought conditions during 2005, 2007 and 2010 (ref. 20). We find that these drought years experienced a factor of 1.5-2.8 greater fire emission compared with non-drought years (Supplementary Table 1). The relationship between Brazil's annual deforestation rates and annual fire emissions (Fig. 1b) confirms different behaviour in drought years, consistent with analysis of fire occurrence¹. We therefore focus our analysis on non-drought years, excluding 2005, 2007 and 2010.

We find significant positive relationships between Brazil's annual deforestation rates and Brazil's annual particulate fire emission (Fig. 1b) both for total fire emissions (r = 0.68 to 0.97, P < 0.05) and for emissions classified as from deforestation fires (r = 0.87, P < 0.01). Total particulate emissions from fire over Brazil have declined over 2002 to 2011 (Supplementary Table 1; r = -0.48to -0.82, P < 0.1) as have emissions from deforestation fires (r = -0.68, P < 0.05). Our analysis demonstrates that Brazil's fire emissions have decreased despite potential increases in agricultural fire in some regions²¹. Particulate emissions from deforestation fires have increased in Bolivia and Peru, but Brazil dominates total South American emissions (Supplementary Table 2). We combine data

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Figure 1 | Relationships between deforestation rates, fire emissions and AOD. a, Brazil's annual deforestation rates. b, Annual total particulate fire emission in Brazil (orange: GFED3, green: GFAS1, blue: FINN1, black: GFED3 deforestation fire) against Brazil's annual deforestation rates. c, Regional (50°-70° W, 5°-25° S) dry season (August-October) MODIS AOD. d, Regional AOD against Brazil's deforestation rates. Drought years are indicated in red. Lines show linear relationship (solid: excludes drought years, dashed: all years). Pearson's r (all years in parenthesis) and gradient of best-fit line are detailed on each panel. Error bars (c,d) show standard deviation in regional daily mean AOD.

on deforestation rates with data on PM emissions from fires to 1 calculate a regional PM emission of 53 to 95 g m⁻² across Brazil 2 (Fig. 1b), consistent with literature values for deforestation fires 3 $(72 \pm 30 \text{ g m}^{-2}; \text{ ref. 2})$. Concurrent and consistent declines in Brazil's 4 deforestation rates, fire emissions and deforestation fire emissions 5 suggest that a reduction in deforestation fires is the primary cause 6 of reduced particulate fire emissions across Brazil. 7

To explore whether such reductions in regional fire emissions 8 have led to observable impacts on air quality we used multi-9 annual records of aerosol optical depth (AOD) from satellite 10 and ground-based sensors. Long-term observations of surface PM 11 12 concentrations are available at several sites across Amazonia⁶, but unfortunately no site reports over the entire period of interest. 13 AOD is a column-integrated quantity but is related to surface 14 PM concentrations²², so gives an indication of how PM has 15 changed. The spatial pattern of dry season AOD retrieved by 16 17 satellite (Fig. 2d) matches the locations of fires and the region of extensive deforestation in the southeast Amazon²³. Atmospheric 18 transport of smoke extends regions of high AOD over Bolivia, 19 northern Argentina and southern Brazil, covering a large portion 20 of South America. 21

Figure 1c shows observed trends in dry season mean AOD 22 during 2001 to 2012 over the region of enhanced AOD (70° W 23 24 to 50° W, 5° S to 25° S). Fires occurring in this region account 25 for 52-74% of total PM emissions from South American fires 26 and so play a key role in regional air quality. Regional dry season mean AOD retrieved by satellite has declined significantly 27 over this period (r = -0.75, P < 0.01, AOD trend = -0.026 yr^{-1}), 28 suggesting a substantial regional reduction in aerosol. Surface 29 stations across southern Amazonia also show long-term declines in 30

dry season AOD (Supplementary Fig. 2; Alta Floresta, r = -0.65, Cuiaba–Miranda r = -0.53, Rio Branco, r = -0.50), consistent with trends from satellite.

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Figure 1d shows the positive relationship between observed dry 34 season AOD and Brazil's annual deforestation rate (r = 0.96, P < 0.001, gradient = $1.8 \times 10^{-5} \text{ km}^{-2} \text{ yr}$). Years with high 36 deforestation rates have a factor of two greater dry season 37 AOD compared with years with low deforestation rates, suggesting 38 that regional air quality is degraded substantially by fire emissions 39 associated with deforestation. This link is further demonstrated 40 by the positive relationship between observed AOD and total particulate emission from fire (Supplementary Table 1; r = 0.7742 to 0.93, P < 0.05) as well as for particulate emissions from 43 deforestation fire (r = 0.89, P < 0.01). Observed reductions in dry 44 season AOD over the past decade linked to reductions in both 45 deforestation rates and particulate emission from deforestation fires 46 suggest that reduced deforestation may have resulted in improved 47 air quality. 48

To investigate the mechanism linking deforestation rates with 49 poor air quality, we used a global atmospheric model (see Methods). 50 Fires increase simulated dry season surface PM2.5 (particles with 51 aerodynamic diameter $<2.5\,\mu$ m) across southern Brazil, Paraguay, 52 northern Bolivia and Argentina (Fig. 3a and Supplementary Fig. 3). 53 Deforestation fires² account for 80% of the simulated enhancement 54 in regional PM2.5 from fire, with grassland, agricultural and 55 other fire types contributing the remaining 20% (Fig. 3a and 56 Supplementary Fig. 3). Emissions from fires also dominate 57 interannual variability in simulated PM2.5 ($1\sigma = 7 \mu g m^{-3}$) 58 matching interannual observations of AOD ($r^2 = 0.67 - 0.89$; 59 Supplementary Fig. 4) and PM2.5 ($r^2 = 0.41$; Supplementary Fig. 5). 60



Figure 2 | Fire emissions and impacts on regional aerosol. a-c, Dry season (August-October) mean emissions from fires (for 2002-2011) according to GFED3 (a), FINN1 (b) and GFAS1 (c) data sets. d, Dry season AOD retrieved by MODIS (for 2001-2012). The region analysed in Fig. 1 is illustrated by the black square. Circles show locations of AERONET stations; triangle shows location of PM2.5 surface observations.

Without fire emissions, simulated interannual PM2.5 variability is limited $(1\sigma = 0.1 \,\mu\text{g m}^{-3})$ and comparison against observations is 2 poor (AOD: $r^2 = 0.02 - 0.34$, PM2.5: $r^2 = 0.08$), demonstrating that 3 variability in atmospheric transport and PM deposition alone make 4 a minor contribution to variability in regional aerosol. Simulated 5 dry season mean PM2.5 is positively correlated with observed 6 deforestation rates (r = 0.82, P < 0.05; Fig. 3a) as well as with fire 7 emissions, both for total fire emissions (Supplementary Table 1; 8 r = 0.81 to 0.95, P < 0.05) and for deforestation fire emissions 9 (r = 0.86, P < 0.01). Years with low deforestation rates have regional 10 dry season PM2.5 concentrations that are 30% lower than years 11 with high deforestation rates. 12

Our analysis demonstrates that deforestation rates and associated 13 deforestation fires are the main drivers of observed and simulated 14 variability in dry season aerosol loading across large parts of 15 South America. To estimate the impacts of particulates emitted 16 by fires on human health, we calculated the premature adult 17 mortality from cardiopulmonary disease and lung cancer due 18 to exposure to PM2.5 from fires over the period 2002 to 2011 19 (see Methods). We estimate that deforestation fires alone cause 20 an average of 2,906 premature mortalities annually across South 21 America (95% percentile confidence interval: 1,065-4,714); 40% of 22 the mortality due to particulate emissions from all fires over this 23 period (Supplementary Table 3). The greatest risk to health (up to 24 1 mortality per 10,000 people) occurs close to deforestation fires 25 (Supplementary Fig. 6), whereas most premature mortalities occur 26 outside Amazonia (Supplementary Fig. 7) because of atmospheric 0 5 27 transport of smoke to more densely populated regions. 28

Estimated mortality due to particulate emissions from
 deforestation fires is positively related to Brazil's deforestation

rates (Fig. 3b; r = 0.8, P < 0.05, Premature mortality $(M) = 0.071 \times \text{Deforestation rates} (D, \text{ km}^2 \text{yr}^{-1})$). We use this relationship to estimate that the 40% reduction in Brazil's deforestation rates is preventing 1,060 (95th percentile confidence interval: 390 to 1,720) premature adult mortalities annually across South America through reductions in deforestation fire emissions.

Our model underestimates observed AOD and PM2.5 in regions impacted by fires (Supplementary Figs 4 and 5), as reported by other studies^{3,16}. The relatively coarse resolution of global atmospheric models may contribute to underestimation of AOD. Previous studies increased fire emissions to match observations^{3,16}, potentially accounting for fires that are not detected by satellite²⁴. Here, we report the avoided mortalities from unscaled fire emissions as a conservative estimate of the health benefits of reduced deforestation.

Refining PM emission estimates from fire and a better understanding of the health impacts of exposure to PM (refs 25,26) are priorities for improved quantification of human health impacts from deforestation fires.

We have demonstrated that reductions in Brazil's deforestation rates have caused reduced fire emissions resulting in improved air quality with positive impacts on human health. This finding suggests that wider efforts to reduce tropical deforestation as a climate mitigation may have air quality co-benefits. To maximize these benefits, policies aimed at reducing deforestation must also minimize fire across moist tropical forests²⁷. Decreasing deforestation may mean that fires associated with forest degradation⁷ and agriculture²¹ begin to dominate air quality impacts. Controlling these fire types may become increasingly important in the future. Changes to drought frequency in a future climate²⁸ will also have implications for fire emissions and future air quality. Combining rural development with a

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Figure 3 | **Relationship of simulated PM2.5** and premature mortality against Brazil's deforestation rates. **a**, Simulated regional (50°-70° W, 5°-25° S) dry season surface PM2.5 concentrations against Brazil's deforestation rates (black filled square: GFED3 deforestation fires, orange open square: all GFED3 fire, circles: without fire). **b**, Simulated annual mortality in South America due to exposure to PM2.5 from GFED3 deforestation fire emissions (error bars show 95% confidence interval). Drought years are indicated in red. Lines show linear relationship (solid: excludes drought, dashed: all years) with Pearson's linear correlation coefficient (r) detailed on each panel (value for all years in parenthesis) and gradient of best-fit line (**b**).

- ¹ low deforestation rate in Brazil will require enhanced governance²⁹.
- ² Changes to Brazil's forest policy³⁰ may threaten recent progress in
- ³ curtailing deforestation, reversing the improvements in air quality
- 4 reported here.

5 Methods

- 6 Methods and any associated references are available in the online
- version of the paper.
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Author contributions

C.L.R. performed the model simulations. P.A. provided data. C.L.R., E.B., D.R. and D.V.S. analysed the data. All authors contributed to scientific discussions and helped write the manuscript.

Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to D.V.S.

Competing financial interests

The authors declare no competing financial interests.

94

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LETTERS

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Methods

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Deforestation data. Annual deforestation rates in Brazil were calculated using 0.8 2 Google API based on analysis of Landsat data at a spatial resolution of 30 m over 3 the period 2001 to 2012 (ref. 5). We compared Brazilian deforestation rates from Λ this data set against the deforestation rates reported for the Brazilian Amazon^{1,6} (Supplementary Fig. 1). Both data sets report a decline in deforestation between 2001 and 2012.

8 MODIS aerosol optical depth (AOD). The Moderate Resolution Imaging Spectroradiometer (MODIS) instruments on board Terra and Aqua provide AOD 10 from 2000 to 2002, respectively through to 2012. We use the daily, gridded $1^{\circ} \times 1^{\circ}$ product (Level 3 data) from Terra for 2001 to 2012 and Aqua for 2002 to 2012. 11 Daytime Equator crossing is 10:30 for Terra and 13:30 for Aqua. Dry season mean 12 (August to October) values are calculated from the combined Terra and Aqua data. 13 We tested our analysis using Level 2 data and confirmed that this does not alter our 14 results. Drought years (2005, 2007, 2010) have dry season AOD double that of 15 non-drought years (Fig. 1c). Trends in dry season AOD are not significant when 16 17 drought years are included (r = -0.32, P = 0.15), consistent with previous analysis reporting no long-term trend in AOD over this region³¹. 18

Fire emissions. We used three different satellite fire emission data sets: National 19 Centre for Atmospheric Research Fire Inventory version 1.0 (FINN1; ref. 15), 20 Global Fire Emissions Database version 3 (GFED3; ref. 2) and the Global Fire 21 Assimilation System version 1.0 (GFAS1; ref. 16). GFED3 emissions are available 22 from 1997 to 2011 at $0.5^{\circ} \times 0.5^{\circ}$ resolution. FINN1 emissions are available from 23 2002 to 2012 at 1 km² resolution. GFAS1 emissions are available from March 2000 24 25 to the current day at $0.5^{\circ} \times 0.5^{\circ}$ resolution. We analysed the period 2002 to 2011 where all data sets are consistently available. We regrid all data sets to the same 26 horizontal resolution $(0.5^{\circ} \times 0.5^{\circ})$. The GFED3 data set classifies fires according to 27 fire type2. We use the deforestation fire classification as an estimate of fire 28 emissions associated with deforestation. Emissions from the different data sets are 29 30 summarized in Supplementary Table 1.

Rainfall. Dry season accumulated rainfall is calculated from precipitation 31

retrievals from the 3B42 3-h $0.25^{\circ} \times 0.25^{\circ}$ product of the Tropical Rainfall 32

33 Measuring Mission (TRMM) and other satellites. Analysis of rainfall data shows

that over the regions of fires, 2007 and 2010 were particularly dry years 34 (accumulated dry season rainfall >1 standard deviation below the 1998–2012 35

average). Dry season rainfall was also below average in 2005. 36

Aerosol observations. AERONET Level 2.0 (quality assured) daily average AOD 37 retrieved at 440 nm is from three stations with 10 or more years of data: Alta 38 39 Floresta (1999-2011; 9.87° S, 56.10° W), Cuiaba-Miranda (2001-2011; 15.73° S, 56.02° W) and Rio Branco (2000-2011; 9.96° S, 67.87° W). We use surface PM2.5 40 concentrations measured using gravimetric filter analysis at a site near Alta 41 Floresta (9.87° S, 56.10° W) between 1992 and 2005. 42

43 Global aerosol model. The global distribution of PM2.5 was simulated using the 3D Global Model of Aerosol Processes (GLOMAP; ref. 32), which is an extension to 44 45 the TOMCAT chemical transport model. TOMCAT is driven by analysed 46 meteorology from the European Centre for Medium Range Weather Forecasts 47 (ECMWF), updated every 6 h and linearly interpolated onto the model time step. Model output has a horizontal resolution of $2.8^{\circ} \times 2.8^{\circ}$ and 31 vertical model levels 48 between the surface and 10 hPa. The vertical resolution in the boundary 49 50 layer ranges from \sim 60 m near the surface to \sim 400 m at \sim 2 km above the surface. 51

GLOMAP simulates the mass and number of size-resolved aerosol particles in 52 the atmosphere, including the influence of aerosol microphysical processes on the 53 particle size distribution. These processes include nucleation, coagulation, 54 55 condensation, cloud processing, dry deposition, and nucleation/impact scavenging. The aerosol particle size distribution is represented using seven log-normal modes. 56 GLOMAP treats black carbon, particulate organic matter (POM), sulphate, sea 57 spray and mineral dust. 58

Anthropogenic emissions of sulphur dioxide, black carbon and particulate 59 organic matter are from the MACCity emissions inventory³³. We complete six 60 simulations with different landscape fire emissions: (1) GFED3 for 1997 to 2011, 61 monthly emissions for 1997 to 2003 and daily emissions for 2003 to 2011. (2) 62 FINN1 for 2001 to 2011, (3) GFAS1 for 2002 to 2011, (4) no landscape fire 63 emissions, (5) with GFED3 emissions but with no deforestation fire emissions, (6) 64 65 with GFED3 fire emissions scaled by a factor of 3.4. We evaluated the global model 66 with GFED3 emissions because they had the best temporal overlap with the aerosol observations. Q.9 67

Analysis. We analysed regional AOD and PM2.5 over a domain covering Bolivia, 68

southern Brazil and northern Paraguay (70° W to 50° W and 5° S to 25° S). 69

Interannual variability in simulated PM2.5 in this domain is correlated with 70

MODIS AOD (r = 0.85, P < 0.01), confirming that our analysis of AOD gives an indication of regional PM2.5. Particulate emissions from fires increase simulated PM2.5 concentrations across our region of analysis by more than 30% for 5 months each year (June through October; Supplementary Fig. 8), meaning that the region is chronically impacted by particulate pollution from fires4.

Trends in annual forest loss, particulate emissions from fire and MODIS AOD were derived using an ordinary least-squares slope of the linear regression of the relevant parameter versus year. Relationships between different parameters (for example, AOD and deforestation rates) were also calculated using linear regression. We report the correlation as Pearson's r and calculate the significance of the relationship (P).

Estimation of premature mortality. We estimate adult (>30 years) premature mortality due to long-term exposure to enhanced PM2.5 concentrations from fires using concentration response functions from the epidemiological literature³⁴ that relate changes in annual mean PM2.5 concentrations to the relative risk (RR) of disease. This method has been used in a number of recent assessments^{3,35}. We estimate health impacts using annual mean PM2.5 concentrations, as applied previously in studies of the health impacts of particulate emissions from fire^{3,4}

We used a log-linear model³⁴ to calculate RR for cardiopulmonary diseases and lung cancer following:

$$RR = \left[\frac{(PM_{2.5,control} + 1)}{(PM_{2.5,fire_off} + 1)}\right]^{\beta}$$
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where PM_{2.5,control} is the simulated gridded surface annual mean PM2.5 concentrations from the global model for the control experiment and PM_{2.5,fire_off} is for the perturbed experiment without fire emissions. The cause-specific coefficient (β) is an empirical parameter assumed to be 0.23218 (95% confidence interval of 0.08563-0.37873) for lung cancer and 0.15515 (95% confidence interval of 0.05624-0.2541) for cardiopulmonary diseases³⁴. Cause-specific coefficients are derived for exposure to PM2.5, but not specifically for fire aerosol.

We calculated the attributable fraction (AF) as:

$$AF = \frac{(RR - 1)}{RR}$$
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The number of excess premature mortality in adults over 30 years of age (ΔM) was calculated by:

 $\Delta M = AF \times M_0 \times P_{30+}$

where M_0 is the baseline mortality rate (deaths per year per head of population) for each disease risk and P₃₀₊ is the exposed population over 30 years of age. We used country-specific baseline mortality rates from the World Health Organisation (WHO) and human population data from the Gridded Population of the World (GPW; version3) for the year 2010 from the Socioeconomic Data and Applications Center (SEDAC; http://sedac.ciesin.columbia.edu/data/collection/gpw-v3).

We calculated ΔM at the horizontal resolution of the population data set (0.04°) for the period 2002 to 2011. We map PM2.5 concentrations from the global model grid to the population grid. Calculating premature mortality at the horizontal resolution of the global aerosol model (2.8°) instead of the resolution of the population data set changes our calculated premature mortality by less than 3%. We report mortality both for all South America and separately for Brazil (Supplementary Table 3).

Uncertainty in premature mortality estimates. The 95% confidence interval in the cause-specific coefficients results in a factor of ~4.4 uncertainty in estimated mortality (Supplementary Table 3). Global models with relatively coarse resolution $(\sim 100 \text{ s km})$ typically underestimate urban-scale PM2.5 concentrations. In the region surrounding São Paolo (46.6° W, 23.5° S) GLOMAP predicts annual mean PM2.5 concentrations of \sim 7 µg m⁻³, matching concentrations reported by another modelling study³⁶. Across six cities in Brazil, observed annual mean urban PM2.5 concentrations range from 7.3 to $28 \,\mu g \,m^{-3}$ (ref. 37). Across the same cities, annual mean PM2.5 concentrations estimated by GLOMAP range from 4 to $7 \,\mu g \, m^{-3}$, with an average bias of $-10.8 \,\mu g \,m^{-3}$ (range -3 to $-21 \,\mu g \,m^{-3}$). We complete sensitivity studies to assess the implications of the model underestimation of urban-scale PM2.5. We increase PM2.5 concentrations in urban grid squares in both the control and perturbed (fire off) simulations, to account for missing urban-scale pollution (Supplementary Fig. 9). We use the Global Rural-Urban Mapping Project Version One (GRUMPv1) data set (http://sedac.ciesin.columbia.edu/ data/set/grump-v1-urban-extents) to define urban grid squares. We then recalculate our health estimates using these PM2.5 concentrations that are corrected for urban-scale pollution. Increasing urban annual mean PM2.5 concentrations by 7, 14 and 17 μ g m⁻³ decreases our estimated premature mortality

LETTERS

NATURE GEOSCIENCE DOI: 10.1038/NGEO2535

- caused by exposure to PM2.5 from fires by 19%, 24% and 26%, respectively
- 2 (Supplementary Table 4). Using a population density of 1,000 people km⁻² to
- define urban areas (instead of the urban definition from GRUMPv1) reduces the
- $_4$ $\,$ area we define as urban. Incrementing PM2.5 by 17 $\mu g\,m^{-3}$ within this urban extent
- 5 reduces the premature mortality estimate by only 20%; less than the 26% we found
- 6 using GRUMPv1 to define urban areas. The relatively coarse resolution of our
- $_7$ global model therefore creates an uncertainty of ${\sim}25\%$ in our estimated
- 8 mortality from PM2.5 from fires, less than the uncertainty due to the range in
- 9 cause-specific coefficients.
- Data availability. All remote-sensed data are publicly available. Model data and
 PM2.5 observations are available from the authors on request.

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30

Queries for NPG paper ngeo2535

Page 1

Ouerv 1:

Please note that the title has been changed according to style.

Query 2:

Please note that reference numbers are formatted according to style in the text, so that any reference numbers following a symbol or acronym are given as 'ref. XX' on the line, whereas all other reference numbers are given as superscripts.

Query 3:

Please provide postcode for all affiliations.

Page 3

Query 4:

Please check the text here. Should, for example, 'make' be 'makes' (singular, to agree with 'variability in [atmospheric transport and PM deposition]', where the phrase in square brackets represents a single idea/process that is modifying 'variability')?.

Query 5:

'due to' (which should be used only where 'attributable to' would be appropriate) changed to 'because of' here. Please check.

Page 4

Query 6:

Please provide volume and page range/article id for ref. 1

Query 7:

Please provide page range/article id for refs 11,12.

Page 5

Query 8:

Can 'based on' be changed to 'on the basis of' here? That is, is 'based on analysis...' modifying the verb 'calculated' (calculated on the basis of); if the phrase 'based on analysis...' is modifying a noun ('Google API'?), no change is required.

Query 9:

Please amend the text here to avoid the numbered list (that is, the numbers should be removed, and the text amended accordingly).