

ORBIT: A new, reduced-complexity air quality model for South Asia

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1 Executive Summary

Exposure to outdoor air pollution is the most important environmental health risk worldwide, associated with over a million deaths each year in South Asia alone¹. To understand how to improve air quality, it is necessary to model how changes in emissions affect changes in pollutant concentrations and human health. However, air quality modelling typically demands substantial computation and expertise, limiting the capacity to inform policy. Reduced complexity air quality models (RCMs) have been developed², but for South Asia many models are unavailable^{3 4} or have poor performance⁵.

Here, I present ORBIT, a new reduced complexity model currently implemented for South Asia at $0.5^\circ \times 0.625^\circ$ resolution. Its predictions of annual $\text{PM}_{2.5}$ concentrations (R: 0.76, normalized mean error (NME): 21.6%, normalized mean bias (NMB): -4.2%) meet the goals for published benchmarks⁶. I have used ORBIT to produce marginal health damage estimates per 1,000 kg pollution for each primary pollutant, month, and time of day, for each subdistrict in South Asia.

ORBIT can natively report health damages, and has many features that distinguish it from other RCMs:

- *Diurnal & seasonal results.* ORBIT resolves primary and secondary $\text{PM}_{2.5}$ for eight 3-hour bins each month, not just annual average.
- *Nonlinear chemistry.* ORBIT captures nonlinear regime changes, including saturation effects where emissions increases do not increase $\text{PM}_{2.5}$ concentrations.
- *Pollutant cross-couplings.* ORBIT resolves how one chemical species affects another (*e.g.*, $\downarrow \text{SO}_2 \rightarrow \uparrow \text{pNO}_3$).
- *Little chemical transport model (CTM) dependence.* Only oxidant and background aerosol fields are taken from a GEOS-Chem simulation, reducing the dependence on a specific, expensive simulation.
- *Fast.* A full South Asia simulation takes ~ 23 min per month (8 CPU cores, 3.6 GB), and months are parallelizable. Once the baseline is run, marginal simulations (for small emissions perturbations) take only ~ 5 min (5.5 GB).

2 Technical Summary

2.1 Approach

ORBIT is an Eulerian, finite-volume, mechanistic air quality model for estimating total and speciated $\text{PM}_{2.5}$ concentrations. ORBIT directly assembles linearized atmospheric operators (describing the physics and chemistry of the system) as sparse matrices.

Similar to InMAP⁷, ORBIT is a steady-state model. However, ORBIT solves for periodic steady states rather than a static annual mean, where the period is the diurnal cycle. So, input fields (including meteorology) are averaged separately for eight 3-hour intervals each day, and these operators act successively (day following night). ORBIT solves for the limit cycle, effectively asking, “what are the pollutant concentrations for an average day, if that day repeated forever?” Instead of solving just one steady state, ORBIT solves for one each month, which can be parallelized, efficiently capturing both seasonal and diurnal dynamics in a steady-state formalism.

ORBIT then handles nonlinearities through fixed-point iterations. Where the outputs of the model affect the input linearized operators, ORBIT re-calculates the inputs and re-solves the model, iterating until convergence.

2.2 Transport

Horizontal advection in ORBIT is governed by a flux-corrected transport scheme. A first-order Patankar exponential scheme is used in the linear operator, which interpolates between central differencing (diffusion-dominated) and pure upwind (advection dominated, which is most of the domain), and preserves positivity. An anti-diffusive correction is applied in the outer loop, which removes numerical diffusion, recovering second-order accuracy in smooth flow (most of the domain), and preserving monotonicity at sharp gradients.

Vertical transport combines 3 processes: vertical advection, turbulent mixing in the boundary layer (a YSU-style K-profile⁸), and convection (using MERRA-2 convective mass flux, with compensating subsidence). Removal is by dry deposition (resistance models for gases and particles, with surface resistances that depend on land use and season) and wet scavenging (both in-cloud nucleation and below-cloud washout, and dissolution of soluble gases) that scales with rainfall intensity.

2.3 Chemistry

ORBIT transports 12 chemical species. For inorganic secondary $\text{PM}_{2.5}$, ORBIT uses ISORROPIA-II⁹ to capture nonlinear thermodynamic equilibria in its outer loop. Each linear steady-state solve transports SO_2 , pSO_4 , NO_x , and conserved elemental mass of N as NH (NH_3 + particulate NH_4), and N as NO_3 (both HNO_3 and particulate NO_3), with fixed effective deposition parameters and partitioning coefficients. Then, ISORROPIA-II is queried from a pre-computed, 7-dimensional lookup table (saving computation), the effective deposition parameters and partitioning coefficients are updated, and the steady-state solve is recomputed. The iteration is repeated until convergence.

For secondary organic aerosol, ORBIT uses a 1-dimensional volatility basis set¹⁰, transporting 5 volatility bins at fixed saturation concentrations. VOC emissions are mapped into the 5 volatility bins using published first-generation yields by source class, blending high- and low- NO_x yields according to the local NO_x regime, and OH-driven aging lowers the volatility at a prescribed rate, with a 7.5% mass gain at each stage

for added oxygen. The total organic aerosol mass is partitioned into gas and particle forms, following an absorptive equilibrium framework¹¹. Because partitioning depends on the SOA mass formed, the fixed-point outer iteration is used to iterate on the partition fractions until they converge (similar to the inorganic equilibrium).

Oxidant fields are not yet fully coupled into ORBIT. Instead, similar to InMAP⁷, 3-hourly OH and H₂O₂ are prescribed from a GEOS-Chem (v11-01) simulation. As mentioned above, OH is used in SOA aging. Furthermore, SO₂ oxidation to pSO₄ uses OH for the gas-phase pathway, and H₂O₂ for the aqueous in-cloud pathway. NO_x is converted to NO₃ through 2 channels: a daytime OH + NO₂ pathway, and a nighttime channel in which N₂O₅ is diagnosed from the 3-hourly archived GEOS-Chem NO₂ and NO₃ radical fields, and hydrolyzed on fine aerosol, applied as a pseudo-first-order loss on NO_x.

2.4 Baseline simulation

Although ORBIT can be run for any region, it is currently set up for South Asia (60–100°E, 4–39°N), including Afghanistan, Bangladesh, Bhutan, Myanmar, India, Nepal, Pakistan, and Sri Lanka.

ORBIT is driven by MERRA-2 meteorology at 3-hourly temporal resolution and 0.5° (latitude) × 0.625° (longitude) horizontal resolution, using the lowest 38 of its 72 native vertical levels, keeping the lowest 10 layers at full resolution and aggregating the remaining 28 into 5 layers (up to ~67 hPa). Thus, the ORBIT grid has 65 × 71 × 15 = 69,225 grid cells.

The baseline simulation (used for model evaluation and marginal simulations) is run for simulation year 2022, but can be run for any simulation year with meteorology fields available. Note that GEOS-Chem (v11) inputs for oxidants are fixed for year 2016. The baseline simulation uses standard, global emissions inventories consistent with the 2022 simulation year, following the EDGAR sector-specific diurnal profiles, with a temperature-driven profile for agricultural ammonia. Anthropogenic emissions are from CEDS (April 2025 release), with non-carbonaceous primary PM_{2.5} from EDGAR v8.1¹², split into ground-level and 3 stack-height tiers (ORBIT natively calculates plume rise), biomass burning emissions are from GFED5.1¹³, windblown dust and sea salt emissions are from MERRA-2¹⁴, volcanic SO₂ emissions are from satellite estimates¹⁵ natural ammonia is from GEIA¹⁶, and CAMS data are used for soil NO_x, biogenic VOCs, and oceanic DMS.

2.5 Marginal simulations

For policy scenarios, 2 modes are available for ORBIT: zero-out (a full re-solve at the perturbed state, for large/regime-crossing perturbations) and marginal (used for small perturbations and deriving source-receptor relationships).

During a forward simulation (such as the baseline simulation), ORBIT saves out the partitioning coefficients, which can be cheaply re-used for marginal policy simulations (~5 minutes), instead of re-running the full model with the nonlinear closure. ORBIT's marginal mode still keeps track of chemistry: SO₂→pSO₄, NO_x→TotalNO₃, and the VBS aging cascade (with aerosol partitioning) are retained, and for the inorganic equilibrium, it re-uses 4 ISORROPIA cross-partials (linearized at the baseline equilibrium) that capture how ammonium and nitrate repartition in response to each other and to sulfate.

2.6 Mortality risk

To estimate mortality risk attributable to changes in $PM_{2.5}$ exposure, I implement 3 concentration response functions: the GBD 2019 risk curves, which extend the Integrated Exposure-Response approach¹⁷, and both functions from GEMM (Global Exposure Mortality Model)¹⁸. Population data are from WorldPop (2023 constrained estimates, release R2025A)¹⁹, and baseline age- and cause-specific mortality rates are from the Global Burden of Disease 2023²⁰.

3 Results

3.1 Model performance

The gold standard of assessing air quality models is against ground monitoring networks. Using standard emissions inventories, ORBIT predicts 2022 annual $PM_{2.5}$ concentrations (at 35% relative humidity) with R : 0.76, NME: 21.6%, NMB: -4.2% (see Fig. 1b). Against monthly pooled measurements ($n = 1,667$), the same ORBIT simulation has R : 0.77, NME: 34.0%, NMB: -4.7% . Performance variation by month may result from incorrect emissions inventories.

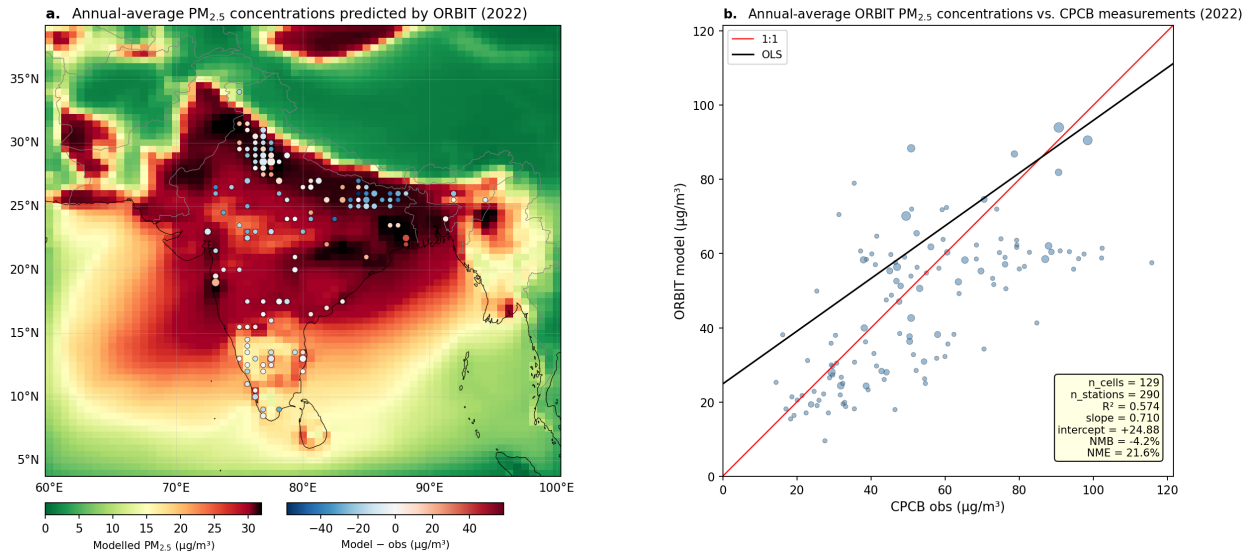


Fig. 1. (a) Annual average surface $PM_{2.5}$ concentrations simulated by ORBIT for 2022, with 290 monitor locations (CPCB CAAQM) overlaid and colored by their bias (blue: under-prediction; red: over-prediction). **(b)** Comparison of modeled vs. measured annual $PM_{2.5}$ concentrations.

3.2 Baseline simulation results

Total $PM_{2.5}$ concentrations in the baseline ORBIT simulation for 2022 are shown in Fig. 1a. Annual deaths associated with exposure to total $PM_{2.5}$ are 1,891,000 (95% CI: 1,790,000 – 1,992,000) using the GEMM 5 cause-of-death concentration-response function, which I report as our baseline*. ORBIT results are in a

*Results are 1,461,000 (1,410,000–1,512,000) deaths using the GBD 2019 risk curves, and 2,961,000 (2,773,000–3,159,000) deaths using the GEMM all-cause function

similar range to previous work¹ for year 2019 (829,000-2,203,000) using the same concentration-response functions. ORBIT shows good model performance, meeting the benchmark goals for correlation, error, and bias (see Section 3.1).

ORBIT predicts monthly average PM_{2.5} concentrations (see Fig. 2), showing an increase in pollution in winter (Dec–Feb) over the Indo-Gangetic Plain, and a drop in pollution across the domain during the monsoon season (Jun–Sep). The seasonality is driven by both emissions inputs and ORBIT’s atmospheric chemistry and physics. For example, large pollutant concentrations in Bangladesh and Myanmar in March are driven by biomass burning emissions.

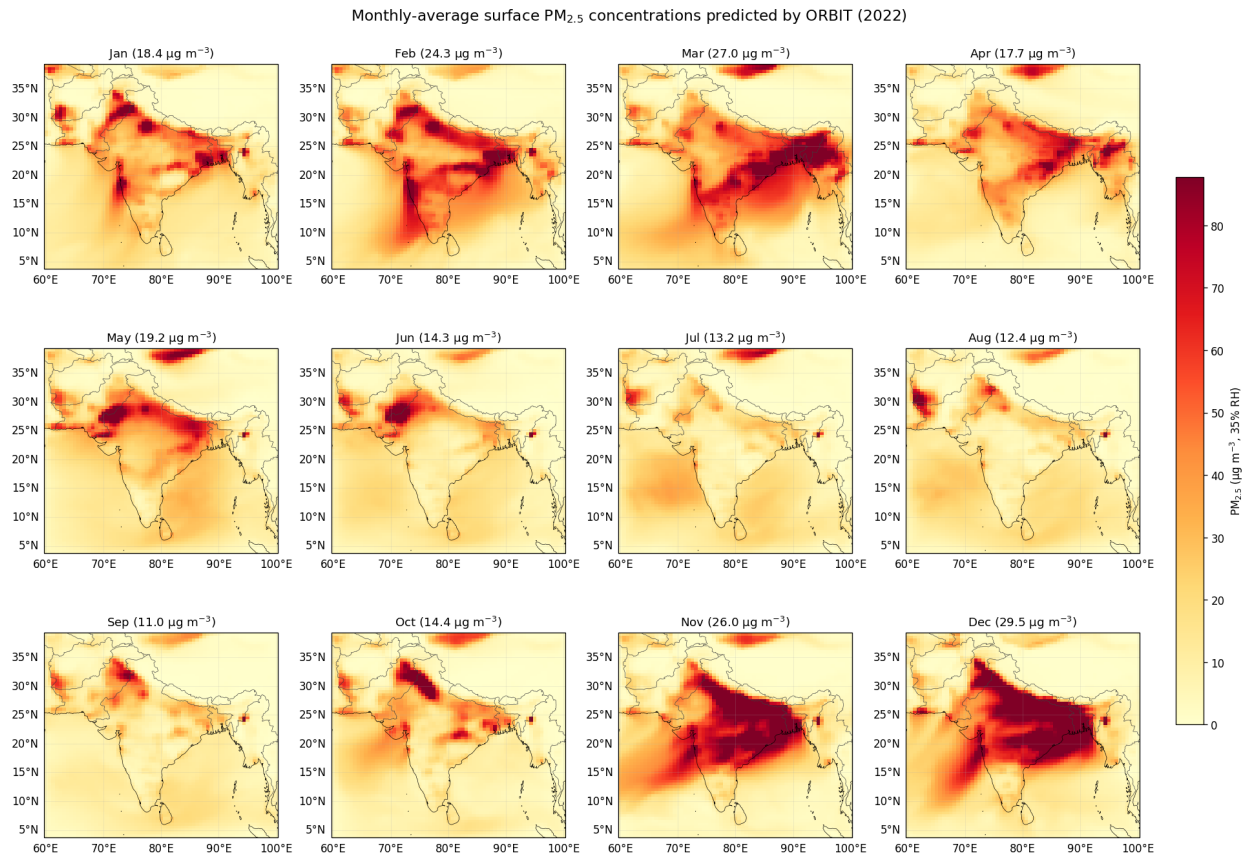


Fig. 2. Monthly average surface PM_{2.5} concentrations in 2022, as simulated by ORBIT.

Speciated annual average PM_{2.5} concentrations are shown in Fig. 3, showing large primary PM_{2.5} concentrations in the western Indo-Gangetic Plain (dust storms from the Thar Desert), large particulate sulfate in Chhattisgarh and Odisha (coal-fired power generation), and large SOA concentrations in Punjab and North-eastern India (biomass burning).

ORBIT also predicts diurnal concentrations for each month, as illustrated for January in Fig. 4. On average across the domain, ORBIT-predicted pollution is highest from night through morning (21:00 – 09:00 IST), and is at its lowest in the afternoon (12:00 – 18:00). The diurnal cycle reflects both ORBIT’s chemistry and physics (such as boundary-layer collapse) and the profile of sectoral emissions, as specified by the baseline simulation. This level of sub-daily resolution is generally not available in reduced-complexity models, and is possible because of ORBIT’s periodic-orbit formulation.

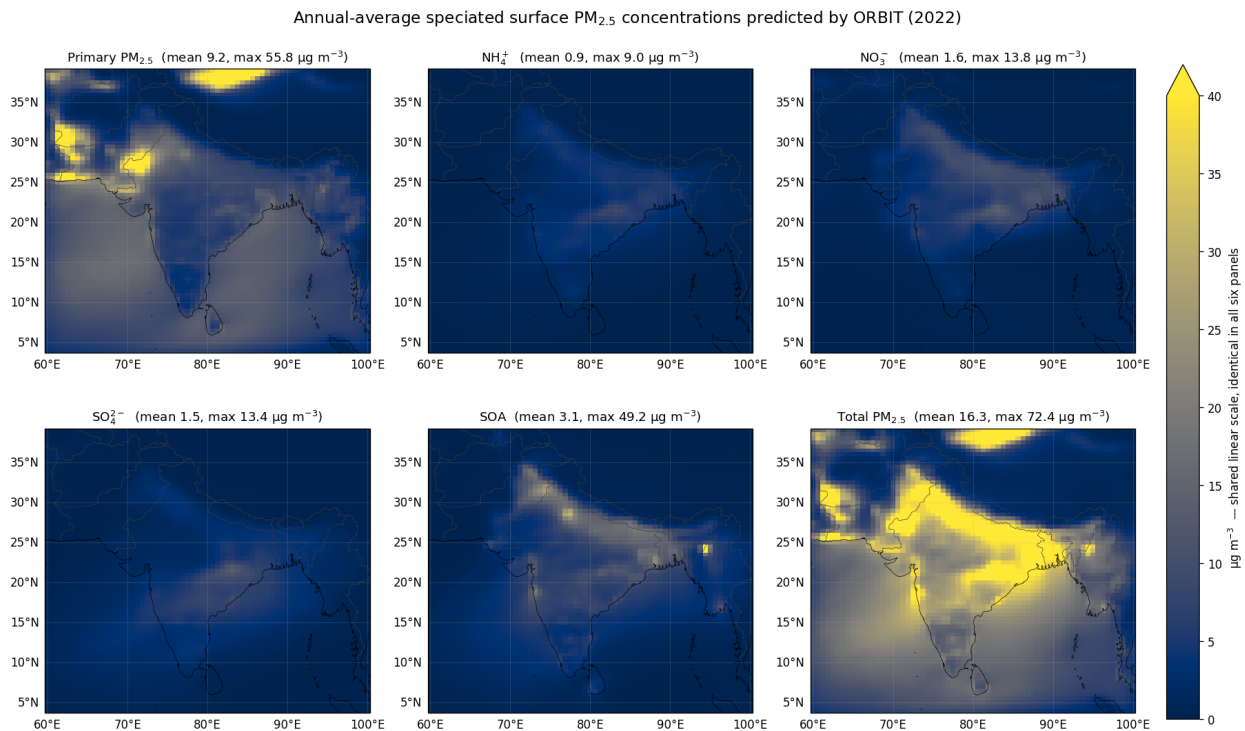


Fig. 3. Annual-average surface concentrations of PM_{2.5} by species for year 2022, as predicted by ORBIT.

3.3 Marginal health damages

ORBIT's marginal mode is able to rapidly estimate health damages from emissions of each primary pollutant, from each grid cell, for each time bin in every month. Here, I illustrate how the deaths associated with annual emissions of 1,000 kg of primary PM_{2.5} (Fig. 5) and SO₂ (Fig. 6) vary by where the pollution is emitted. Deaths are estimated using the GEMM 5 cause-of-death concentration-response function. The range of deaths per 1,000 kg varies considerably. For example, emitting primary PM_{2.5} in Narsingdi, Bangladesh, one of the subdistricts where emissions do the most damage (with Yangon, Myanmar), is 630× more damaging than emitting the same mass of primary PM_{2.5} in the Nicobar Islands (remote Indian islands in the Bay of Bengal), and 760× more damaging than emitting it in Lunana, Bhutan (high in the Himalayas).

Marginal damages per 1,000 kg of SO₂ emissions (Fig. 6) are generally lower than for Primary PM_{2.5}, and exhibit a similar spatial pattern (as they are both governed by downwind population), but show differences (owing to, for example, differences in SO₂ oxidation rates, available NH₃, and differences in relative deposition rates of SO₂ versus primary PM_{2.5}). There are a small number of places and months (*e.g.*, Kolar in July) where ORBIT predicts that increases in SO₂ above the baseline can *reduce* pollution-related deaths, because in ammonia-poor conditions, added SO₂ can reduce particulate nitrate formation that more than offsets the particulate sulfate, by mass. ORBIT is able to capture these cross-coupling effects that linear models cannot.

ORBIT can capture differences in marginal damages across time as well as space. Fig. 7 shows how deaths associated with 1,000 kg of primary PM_{2.5} emissions change depending on the month of emission, across the 10 most populous South Asian cities. Emissions are weighted uniformly over each metropolitan area, and assumed to have a uniform rate within each month. Many cities have their highest damages from pollution emitted in the winter, and their lowest from pollution emitted during the monsoon season (June–September). However, the months with the highest and lowest damages vary considerably across cities.

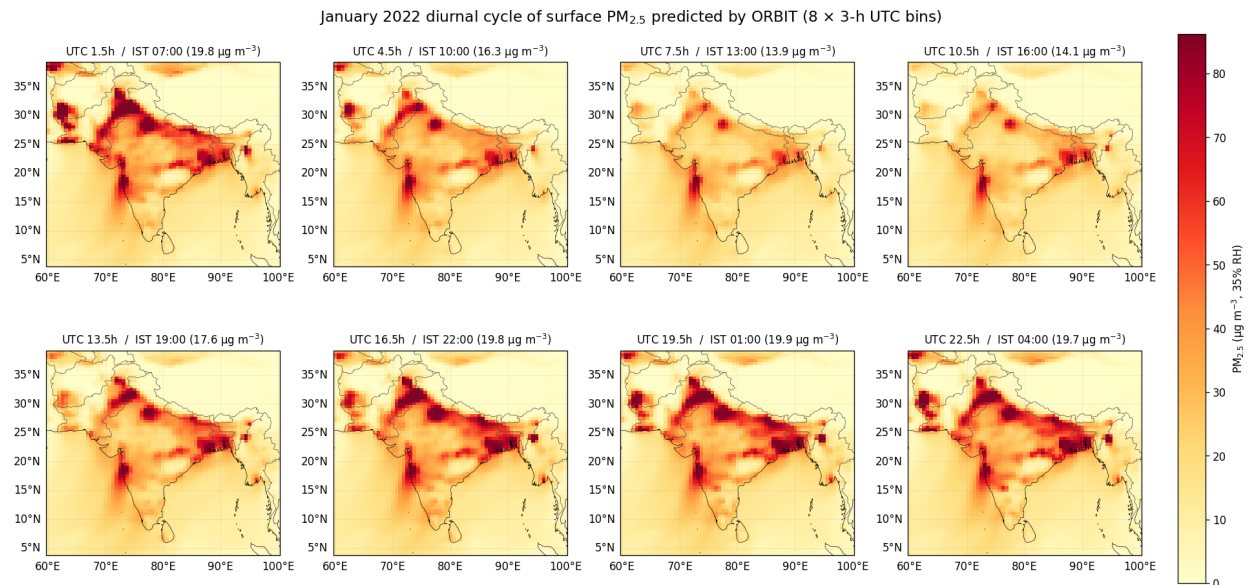


Fig. 4. Diurnal cycle of surface PM_{2.5} concentrations, as predicted by ORBIT, for January 2022.

For Dhaka, pollution is over 2× more damaging for health when emitted in December than in April. By providing detailed marginal damages across time of day, place, season, and primary pollutant, ORBIT can rapidly inform when and where to target emissions to efficiently improve public health.

3.4 Computational requirements

- Forward simulation: ~23 min walltime and ~3.6 GB per simulated month on 8 CPU cores. Each month can be run in parallel on a cluster, or a full year can run within 5 hours on a laptop.
- Marginal simulation: ~5 min and ~5.5 GB per perturbation per month, enabling hundreds of source × pollutant scenarios.

3.5 Code & data availability

ORBIT is open-source. Code is available at <https://github.com/SumilThakr/orbit> and all data required to run the model is described in the GitHub model documentation.

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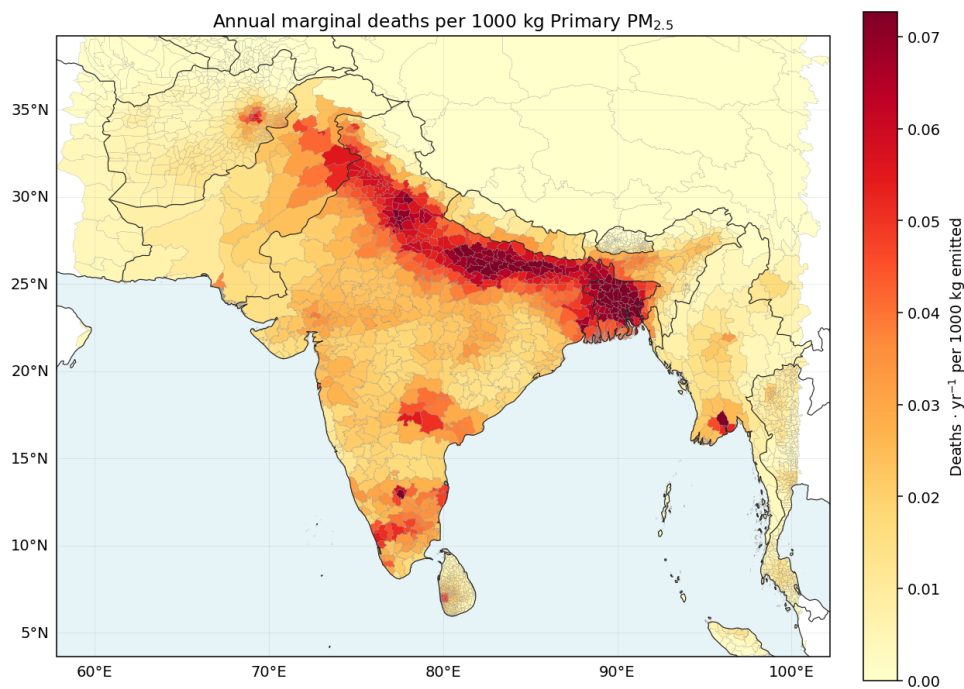


Fig. 5. Annual marginal deaths from continuous emissions of 1,000 kg yr⁻¹ primary $\text{PM}_{2.5}$, released from every subdistrict in the domain. Deaths can occur outside the subdistrict where emissions occurred.

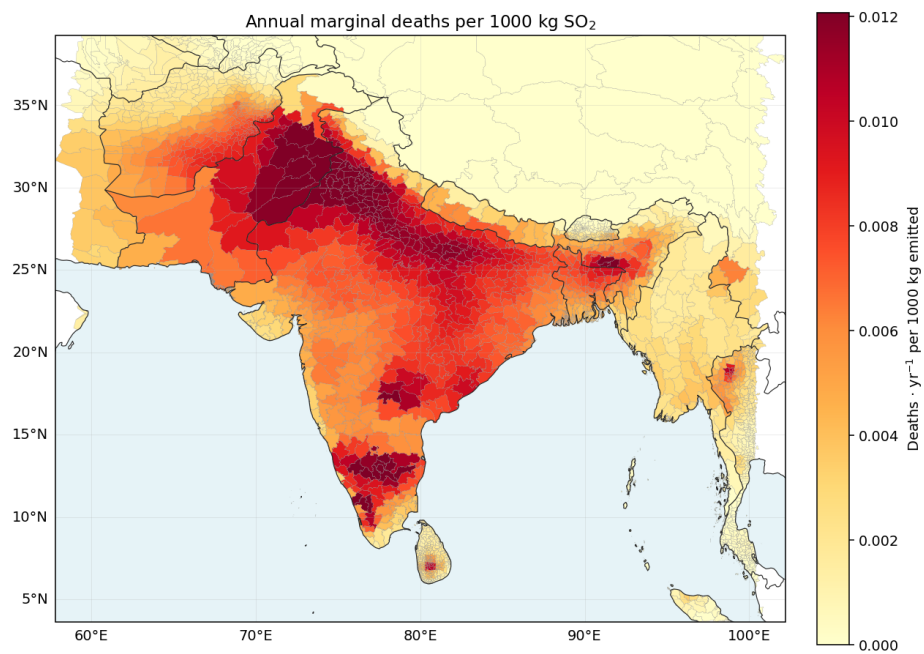


Fig. 6. Annual marginal deaths from continuous emissions of 1,000 kg yr⁻¹ SO_2 , released from every subdistrict in the domain. Deaths can occur outside the subdistrict where emissions occurred.

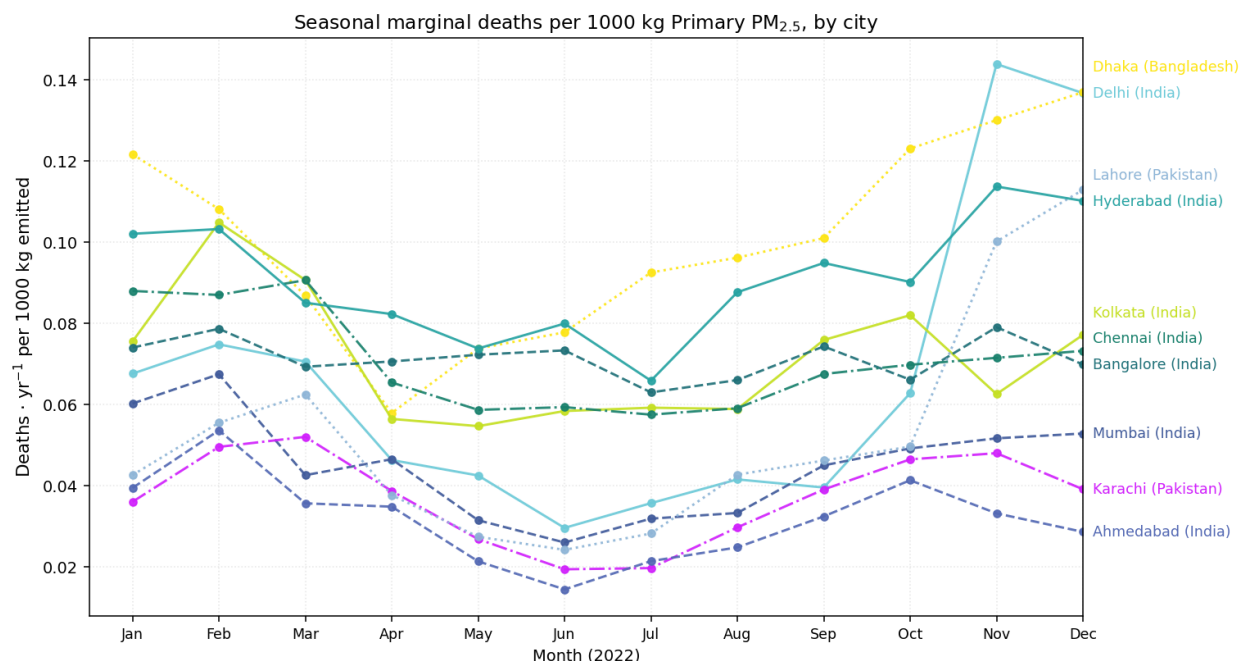


Fig. 7. Seasonal dependence of the marginal health impacts from 1,000 kg yr⁻¹ of primary PM_{2.5} emissions, across the 10 most populous South Asian metropolitan areas, emitted at each calendar month of 2022. Hue varies with longitude (from west to east: purple, blue, green, yellow).

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