

Station-trained air-quality forecasts without regional emission inventories

TK Lee

EnvDataLab

iamthemaker71@gmail.com

ORCID: 0009-0005-3428-4405

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TK Lee

*EnvDataLab.

Corresponding author(s). E-mail(s): iamthemaker71@gmail.com;

Abstract

Air-quality forecasts rely on regional chemical transport models (CTMs) and emission inventories, which are uncertain in many regions and costly to update. Here we present SOLACE, whose inner forecast is trained on monitoring-station observations alone and evolves gridded concentration fields through explicit transport, layer exchange, sources and sinks. With 140,000 trained parameters and no regional emission inventory, it forecasts six pollutants for 48 h on a 4-km grid; one forecast takes 4 s on a CPU. Trained independently in five regions on three continents and evaluated in 2024 at stations withheld from training and initialization, it had smaller errors than an observation-corrected global CTM forecast (persistence for PM_{10}) in 57 of 60 region-species-window comparisons, with day-1 $\text{PM}_{2.5}$ errors 32–77% smaller. With operational forecast meteorology in Korea, the same weights lost 2–12% and kept their lead; SOLACE now issues daily forecasts in all five regions. Exchanging learned processes between regions showed that swapping emission and net change together reproduces 73–97% of the loss from foreign weights, whereas learned transport details mattered little; models retrained without them kept skill in two regions. The regional information a forecast needs resides largely in the effective source-sink budget, and station observations suffice to learn it.

Fine particulate matter ($\text{PM}_{2.5}$) and ozone are leading environmental health risks worldwide [1], and air-quality forecasts one or two days ahead are a basic means of reducing exposure. Operational forecasts are produced by numerical systems that couple a weather model, an emission inventory and a chemical transport model (CTM) [2–4]. Building such a system for a region requires a regional emission inventory. Annual emissions alone may not reflect heavy pollution episodes or seasonal and diurnal variation, so detailed temporal allocation is needed [5], and the disagreement

between top-down estimates and between inventories is largest outside the United States, Europe and Japan, where emission information is most detailed [6]. Public global CTM forecasts also depend on inventories: GEOS-CF uses a harmonized global inventory with base year 2010 as its main source of anthropogenic emissions [7]. By contrast, many countries, including those of the five regions studied here, operate hourly monitoring networks, whose observations record every hour the outcome of the region’s sources and sinks.

Machine-learning weather forecasts now compete with numerical weather prediction [8, 9], and end-to-end systems forecast directly from observations [10]. In air quality, many learned approaches take CTM data as the target. Aurora learned atmospheric composition with CAMS analyses as both target and initial state [11], regional emulators reproduce CTM output [12, 13], and models that replace the chemical solver also learn from simulations of existing chemistry models [14, 15]. These models replace CTM computation but can also inherit the inventory and CTM errors contained in their targets. Models trained on air-quality reanalyses that assimilate station observations take the reanalysis as their target; a topography-aware vision transformer of this kind forecasts six pollutants on a 0.25° grid without explicit emission inventories [16]. Models trained directly on station observations avoid this dependence, but they usually forecast at station points or on graphs of stations or cities [17–21]; one such model combines station observations with meteorological forecasts and emission inventories to forecast six pollutants for 72 h at monitoring sites in under a minute [22]. Station time-series models have been applied unchanged to countries not seen in training [23] or moved to another continent by retraining region-specific metadata embeddings together with some gating and output layers [24], but they do not separate the regional adaptation by process.

Hybrid models that couple physical process models with machine learning aim at both accuracy and interpretability [25]; NeuralGCM, for example, keeps the dynamics explicit and learns only local processes [26]. Advection–diffusion structure has also been built into a learned model of sea-surface temperature [27], and advection–diffusion–reaction structure into learned models of graph time series [28] and global weather [29]. Process structure gives the learned components the names of processes. Because of equifinality, the existence of many model structures and parameter sets that fit the observations comparably well [30, 31], predictive skill alone cannot tell what the learned values actually represent. Climate modelling exchanged the atmosphere and ocean components of different coupled models [32, 33], or compared coupled models sharing the same atmosphere or ocean [34], to locate the component responsible for model differences. A learned model with process structure allows the same test at the level of processes.

Here we introduce SOLACE (Station-Only Learning of Advection and Concentration Evolution), a gridded process model whose inner forecast is supervised only by station observations. SOLACE spreads the station observations at t_0 into an analysis and then evolves the concentration field for 48 h by applying transport, layer exchange, net change and emission explicitly every hour. The spatial pattern of emission comes from the observed analyses of the past 30 days rather than from an inventory, and training sets its strength and temporal structure together with the weather-dependent

net change. We train the same design independently in five regions on three continents, compare it at stations withheld from training with global CTM forecasts and a US national forecast, and evaluate the same weights with forecast meteorology. We then exchange learned processes between regions, switch them off or pin them, and retrain a reduced structure, testing which processes hold the regional adaptation and which learned degrees of freedom are unnecessary.

A station-trained process model

The state of SOLACE is the concentration of six species ($\text{PM}_{2.5}$, PM_{10} , O_3 , NO_2 , SO_2 , CO) in three layers, the surface layer, the residual layer [35] and an upper layer, evolved hourly for 48 h on a 4-km grid (Fig. 1a). The surface state at the forecast start t_0 is an optimal-interpolation (OI) analysis that spreads the station observations with a learned covariance [36]. Equation (1) is written for the surface state c : every hour it is first transported, and net change and emission (added to the surface layer only) are then applied to the transported field, before $\mathcal{X}$ exchanges it with the residual and upper layers:

$$\begin{aligned}\bar{c}^n &= \mathcal{T}_{\mathbf{u}(\mathbf{w}^n), \kappa(\mathbf{w}^n)}(c^n; \mathcal{B}^n), \\ c^{n+1} &= \mathcal{X}\left(\bar{c}^n \odot \exp[r(\mathbf{w}^n, \tau, \bar{c}^n)] + \alpha M(\mathbf{x}) P(\tau) g(h^n)\right).\end{aligned}\tag{1}$$

Equation (1) is a schematic of the surface update; the residual and upper layers enter through $\mathcal{X}$ and their own transport (Methods). $\mathcal{T}$ is semi-Lagrangian advection [37] followed by diffusion; the transport wind $\mathbf{u}$ blends the 10-m and 925–850-hPa winds according to the meteorology $\mathbf{w}$, and κ is the diffusion coefficient. Where advection leaves the domain, it reads a boundary band $\mathcal{B}^n$ blending the outer forecast and inner-edge values, with a gate fixed at t_0 (Methods). $r = 0.3 \tanh f$ is the logarithm of the hourly multiplicative change factor of each species (a relative change of $e^r - 1$); it depends on the meteorology, the time and the species’ own transported concentration $\bar{c}^n$ and represents chemical production and loss together with deposition. The spatial pattern M of the emission term is the mean observed analysis over the 30 days before t_0 ; the strength α and the temporal structure P are learned, and g is dilution by the mixing height h . $\mathcal{X}$ exchanges the surface layer with the residual layer as the mixed layer grows and shrinks, and the residual with the upper layer. The outer model starts from GEOS-CF hindcast fields before t_0 [7] and forecasts the 0.25° outer domain from meteorology alone; no CTM data enter the forecast period.

The loss of the inner forecast is computed only at the input stations; no regional emission inventory, regional CTM simulation or gridded target is used for the inner forecast. Of the 142,446 trained parameters, about 11,000 belong to the inner model and 131,299 to the outer model that supplies the boundary (Methods). Training took about 3.5 h on one consumer GPU (GeForce GTX 1660 SUPER; Taiwan; excluding preprocessing), and one 48-h forecast of six species takes 0.49 s on the same GPU and 3.96 s on a PC CPU (Fig. 1c). Aurora was pretrained with about 9,000 times more parameters (1.3 billion) on 32 A100 GPUs [11] and Aardvark for about 100 GPU-hours on four A100s [10]; their tasks differ, but a regional forecast model can

be trained and run on a personal computer. The operational product adds model output statistics (MOS) [38], the standard post-processing of numerical forecasts: the difference between SOLACE and the observations at the input stations is learned for each species and spread onto the grid to give SOLACE+MOS (Methods). All process exchanges, sensitivity tests and retraining below use the raw output without MOS.

Skill in five regions

The same model structure and optimization settings were applied to Korea, Taiwan, Israel, the Netherlands–Rhine region and Southern California. In each region the model was trained on 2018–2021, its checkpoint was selected on 2022, and 364 retrospective forecasts initialized at local midnight in 2024 were evaluated. Between 12% and 20% of the stations were withheld in 30-km blocks and used neither in training nor in the t_0 analysis (Supplementary Tables S1 and S2). All skill reported below is measured at these held-out stations. The references are t_0 persistence and the global CTM forecast GEOS-CF [7], both raw and observation-corrected (GEOS-CF+IC), in which the difference from the t_0 analysis is added and decays with a 12-h e-folding time. GEOS-CF systematically overestimates surface $\text{PM}_{2.5}$ [7]; at the held-out stations its day-1 mean bias was +6 to +23 $\mu\text{g m}^{-3}$ raw and +3 to +11 $\mu\text{g m}^{-3}$ after the correction.

Of the 60 cells (five regions $\times$ six species $\times$ today, 1–24 h, and tomorrow, 25–48 h), the raw SOLACE output had a smaller error than GEOS-CF+IC (persistence for PM_{10} , for which GEOS-CF has no product) in 57 (47 of the 50 comparisons with GEOS-CF+IC and all 10 with persistence), and 55 of these improvements had 95% block-bootstrap intervals excluding zero (Fig. 2a, Supplementary Table S2). The day-1 RMSE was smaller than that of GEOS-CF+IC by 32–77% for $\text{PM}_{2.5}$, by 15–27% for O_3 in the four regions other than Israel, and by 5–31% for NO_2 . The two cells that were significantly worse were both in Israel on day 1, CO (+31%) and O_3 (+5%). Against persistence, SOLACE was better in 54 of 60 cells; the six worse cells were all SO_2 , which has low values and rare variations at the stations. SOLACE+MOS was significantly better in 40 of the 48 cells of the four regions with MOS and significantly worse in none. With MOS, day-1 Israel O_3 was 10% better. In Korea the result held against the observation-corrected forecast of a second CTM, CAMS [3] (day-1 RMSE of $\text{PM}_{2.5}$ 8.2 versus 11.6 $\mu\text{g m}^{-3}$, O_3 12.0 versus 15.4 ppb).

This retrospective evaluation uses ERA5 reanalysis meteorology [39], whereas the CTMs use forecast meteorology. In Korea we therefore also evaluated the same weights with forecast meteorology at operational timing. The most recent GFS cycle available for a daily 01 KST run drove both the inner and the outer model, on the same 363 forecasts, stations and hours as the ERA5 evaluation (Fig. 2b; Methods). Switching to forecast meteorology changed the $\text{PM}_{2.5}$ error by 1.6% [−1.0, 4.1] on day 1 and increased it by 6.4% on day 2, increased the O_3 , NO_2 and CO errors by 3.5–8.1% and the SO_2 error by 10–12%. With forecast meteorology SOLACE still had smaller errors than the observation-corrected CAMS and GEOS-CF forecasts for every species and window available from each product ($\text{PM}_{2.5}$ 8.3 versus 11.6 on day 1 and 10.3 versus 14.4 $\mu\text{g m}^{-3}$ on day 2; O_3 12.7 versus 15.4 ppb). With a MOS trained under the same

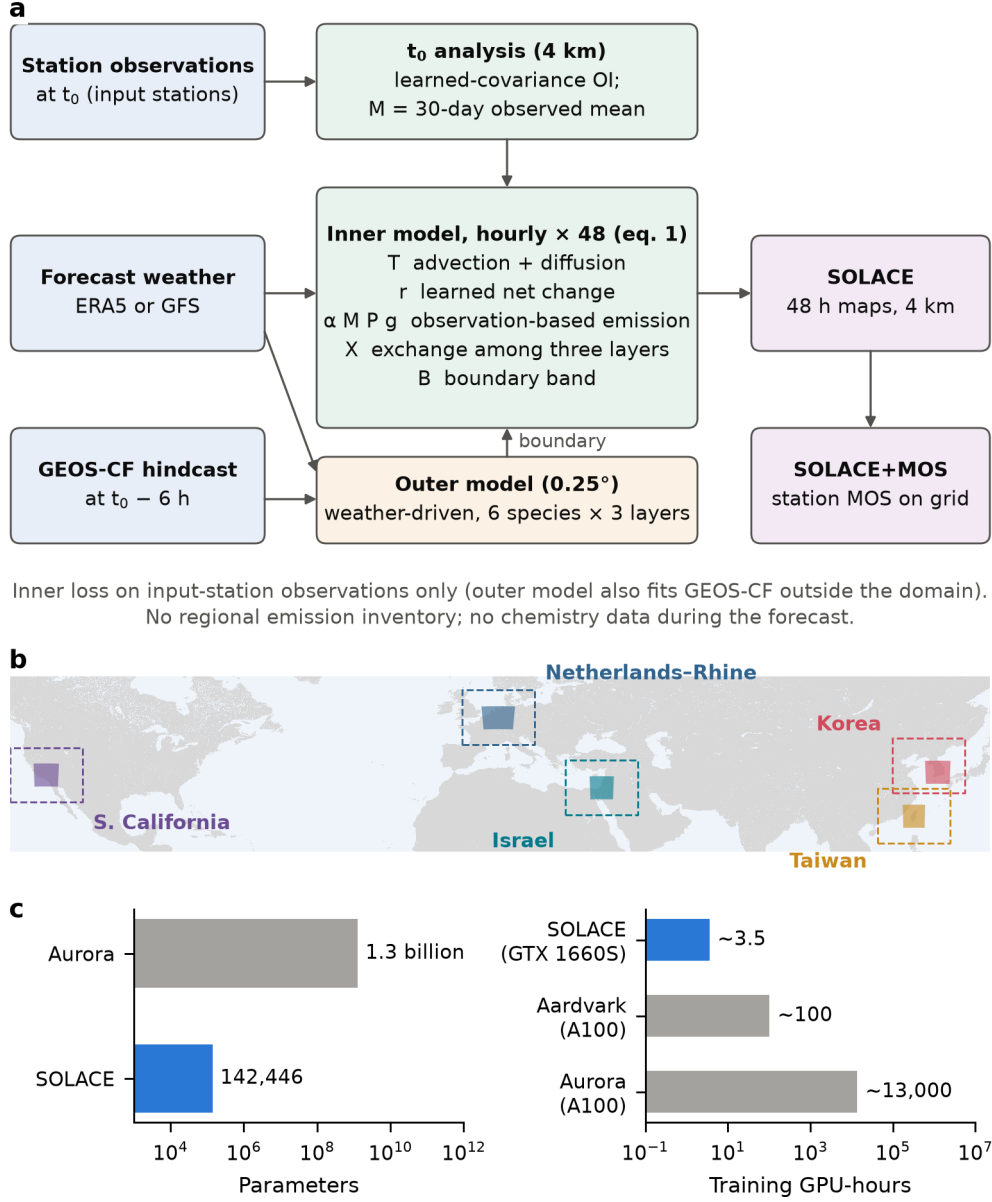


Fig. 1 SOLACE and the five domains. **a**, Model structure common to the five regions: starting from the OI analysis of the station observations at t_0 , transport, net change, emission, layer exchange and the boundary are applied every hour in three layers (equation 1). The outer model starts from GEOS-CF hindcast fields before t_0 and forecasts the boundary from meteorology alone. **b**, The five domains: 4-km inner grid of 612×700 km (filled) and outer domain (dashed). **c**, Trained parameters and training GPU-hours: SOLACE (Taiwan, GTX 1660 SUPER, excluding preprocessing), Aardvark (about 100 A100-hours) and Aurora (1.3 billion parameters, pretrained for about 2.5 weeks on 32 A100s).

GFS conditions on years before the evaluation year, the gas errors were within 1% of or smaller than those of the raw ERA5 output (day-1 O_3 11.8, NO_2 7.6 ppb). Against a LightGBM station model [40] trained on the same observation network and run with the same GFS forecasts (Methods), SOLACE had smaller PM errors (day-1 $\text{PM}_{2.5}$ 8.3 versus $9.2 \mu\text{g m}^{-3}$) and a higher critical success index for days in the Korean “bad” $\text{PM}_{2.5}$ grade (0.43 versus 0.38); with MOS, the NO_2 and CO errors were smaller, the O_3 error equal and the SO_2 error slightly larger (Supplementary Tables S2b, S2c). Next-day detection of high PM_{10} days was poor (critical success index 0.01, against 0.09 for LightGBM and 0.16 for persistence): on these days the observed concentration rose after t_0 while the forecast stayed near its initial level (across the 766 station-days, observed PM_{10} nearly doubled within 40 h while the forecast remained nearly flat), consistent with dust arriving from outside the domain, which the outer model forecasts from meteorology alone (Methods; Supplementary Table S2c, Fig. S1).

We also compared SOLACE with a national operational forecast. In Southern California we compared it for 2023 and 2024 with the US national air-quality forecast system (NOAA/NWS Air Quality Model, AQM) [4, 41]. Because AQM incorporates station-based bias correction, we compared it with SOLACE+MOS, using the latest cycle available before t_0 (Methods). For O_3 , AQM was better in both years (SOLACE+MOS RMSE 9–19% larger), but SOLACE+MOS closed 74–87% of the gap between persistence and AQM. For $\text{PM}_{2.5}$, the AQM error was 7–14% smaller in 2023, with intervals that included zero, and SOLACE+MOS was 13–17% better over 2024 as a whole. The 2024 difference came from days early in large wildfires when AQM forecast thousands of $\mu\text{g m}^{-3}$ near stations from fire emissions; excluding forecasts that overlapped the first 7 days of fires of 10,000 acres or more in the domain, the two products did not differ (+3% [−4, +11]; Extended Data Fig. 1, Supplementary Table S5). A stricter exclusion through the day after fire containment favoured AQM by 13% [7, 20], but 134 of its 173 forecasts fall in the AQMv6 period (January to mid-May), when AQM was 18% better; in the AQMv7 period outside the first 7 days of fires the two did not differ (−3% and −2% on days 1 and 2; Supplementary Table S5). The AQMv7 evaluation itself names the uncertainty of wildfire emissions and plume rise as a major error source [4]. In this retrospective comparison, in which SOLACE used reanalysis meteorology, a model trained only on stations and public data was thus on par with an operational forecast built on national emission data and a regional CTM for $\text{PM}_{2.5}$, and close to it for O_3 .

Since October 2026, SOLACE has issued daily 48-h forecasts with GFS forecast meteorology in all five regions and publishes scores of the forecasts issued one and two days earlier against the observations that followed (<https://solace.envdatalab.com>); one 4-vCPU cloud instance serves all five regions, and issue times can be verified (Methods).

Regional adaptation in sources and sinks

Weights trained separately for each region were generally the most accurate in their own region. In all exchanges below, forecasts started from the home region’s own analysis and observation-based inputs, so the comparisons concern the learned forecast

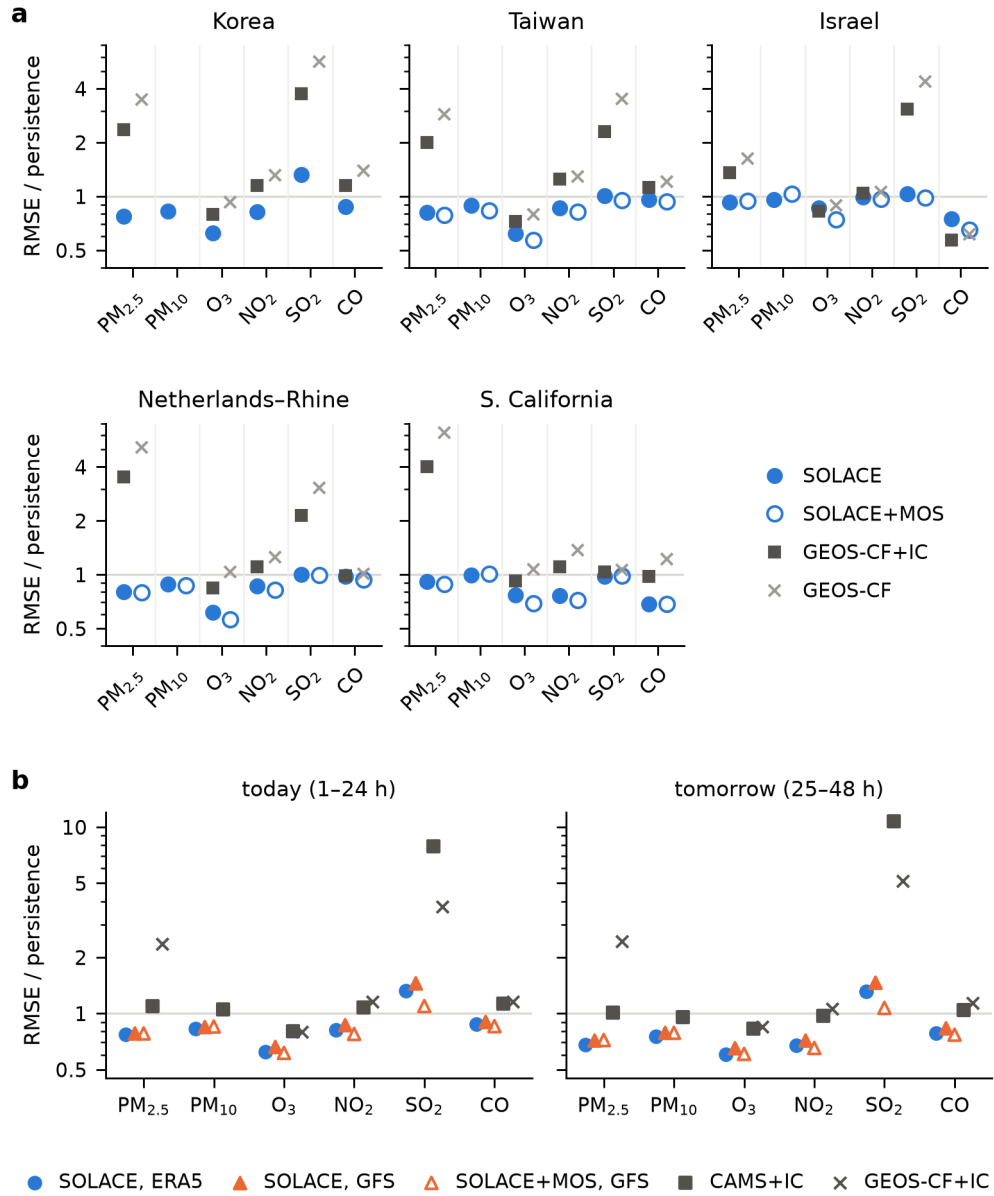


Fig. 2 Forecasts at held-out stations in five regions. **a**, RMSE divided by the persistence RMSE (2024, today window; values below 1 beat persistence). Filled circles SOLACE, open circles SOLACE+MOS, grey squares GEOS-CF+IC, crosses GEOS-CF. GEOS-CF has no PM₁₀, and Korea has no MOS for these meteorology. **b**, Korea: RMSE of the same weights run with ERA5 reanalysis and with GFS forecast meteorology, with CAMS+IC and GEOS-CF+IC (2024, 363 forecasts, same station-hour sample, today and tomorrow).

processes. We measured the loss from using weights trained in one region to forecast another as the home advantage $H = \text{RMSE}(\text{foreign weights})/\text{RMSE}(\text{home weights}) - 1$ (Fig. 3a, Supplementary Table S3). The 95% interval of H lay above zero in all 20 home-source pairs on both days for $\text{PM}_{2.5}$, PM_{10} , O_3 and NO_2 (SO_2 : 16; CO : 17–18). For $\text{PM}_{2.5}$ and O_3 , the median H over homes rose from 17–45% on day 1 to 31–55% on day 2.

The learned components are connected through physical quantities: transport moves the concentration field, emission adds concentration and k multiplies it by an hourly rate. A forecast therefore remains well defined when one component of a regional model is replaced by the one learned in another region. Unlike model stitching, which joins separate networks with a trainable stitching layer [42], the components are exchanged here with their physical outputs and the common input normalization left unchanged. We swapped each of eight components (Fig. 3b) in all 20 pairs, and as a reference made the same swaps in both directions between two models trained on the same Taiwan data with different seeds (Fig. 3b, Supplementary Tables S4 and S7b).

Swapping the home model’s emission and k together for the foreign ones reproduced most of the loss from the full foreign weights: the median share was 85–97% on day 1 and 73–92% on day 2. The same swap between seeds stayed within 3.7% even at the ends of the intervals. Swapping transport or layer exchange between regions had small effects (95th percentile of $|\Delta\text{RMSE}|$ over 20 pairs $\times$ six species: 1.1% for transport and 3.0% for layer exchange), and the outer model that supplies the boundary lay in between (medians by species and window 0.3–9%, larger on day 2 and for O_3). Swapping the core of transport, layer exchange and upper-layer initial scaling changed the RMSE by less than 3% in 225 of 240 cells. Swapping emission, k and the outer model together worsened it by a median of 22% (5th–95th percentile 2–63%), reproducing 91–107% of the full foreign-model effect as medians by home (core: 0–2%). The forecast differences created by regional training lie almost entirely in the sources, sinks and boundary.

The effects of emission and k were not additive. Swapping k alone produced 109–134% of the home advantage for PM_{10} and CO , so attaching another region’s k to the home emission is worse than using the whole foreign model. The same happened without any regional difference. Between the Taiwan seeds, swapping k alone increased the $\text{PM}_{2.5}$ RMSE by 1.7–2.5% and swapping emission alone decreased it by 1.2–1.4%, both with intervals excluding zero, whereas swapping both gave 0.0–0.4%, indistinguishable from zero (Supplementary Table S7b). The two terms must be read as a co-adapted pair. This is equifinality [30, 31] at the level of processes. Where component swaps between climate models locate the source of model differences [32, 33] and learned parameterizations have been transferred between climate models [43, 44], swapping two terms learned from the same observations separately and together reveals not only where the adaptation resides but also how the processes are coupled.

Transport needed, details not learned

That swapping transport changes skill little does not mean that transport is unnecessary. Switching processes off or pinning learned constants and functions to the ends of

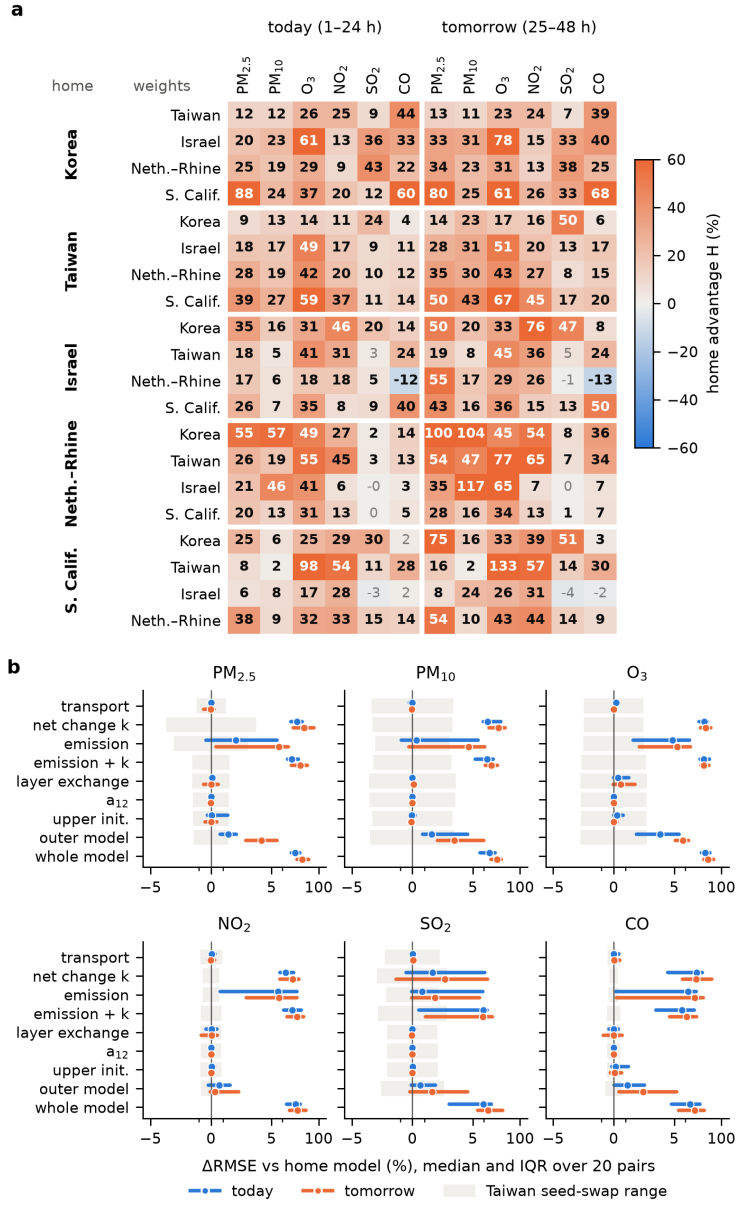


Fig. 3 Regional adaptation resides in the source–sink pair. **a**, Home advantage H (%) at held-out stations, 2024, 364 forecasts (358 in Israel, 363 in Southern California). Rows are the evaluated region (home, bold) and the source of the weights; columns are species and window (today, tomorrow). Bold numbers mark cells whose 7-day block-bootstrap 95% interval excludes zero. **b**, ΔRMSE (%) when one component of the home model is replaced by that of another region: median (dot) and interquartile range (bar) over 20 pairs. The grey band is the farther end of the 95% intervals of the same component swapped in both directions between the two Taiwan seed models, both directions expressed relative to seed0. The horizontal axis is logarithmic beyond $\pm 5\%$.

their allowed ranges separates the two (Fig. 4a, Supplementary Table S6). In Taiwan, switching off surface advection and diffusion together increased the $\text{PM}_{2.5}$ RMSE by 21% on day 1 and 37% on day 2, and using only the 925–850-hPa wind for surface transport cost 11%. The species for which surface transport matters differed by region: PM in Taiwan and Korea (6–37%), gases in Southern California (11–19% on day 1, 25–38% on day 2) and $\text{PM}_{2.5}$ in the Netherlands–Rhine region (5–7%). For PM, this cost grew with the spatial variability of the surface field: the rank correlation between the day-2 cost of removing transport and the spatial coefficient of variation of the surface field was 0.81 (0.69–0.88 leaving out one region at a time). Where the field is flat, as in Israel ($\text{PM}_{2.5}$ coefficient of variation 0.17, other regions 0.33–0.40), moving it changes the station values less, and the cost of removing transport stayed within 3%. In Taiwan, switching off layer exchange or blocking the outer boundary worsened day-2 PM by 4–6%, and switching off net change or emission worsened the error by 31–343% and 5–60%.

Pinning the learned transport details to their bounds, by contrast, had small effects. Of the 420 cells (five homes, seven pins of the wind-blending ratios, diffusion and a_{12} to their bounds, six species, two windows; Methods), the RMSE changed by more than 1% in 7, and the largest change was 2.1% for Southern California CO without diffusion. The learned transport functions tell the same story: the two Taiwan seed models differed in the surface wind-blending ratio by up to 0.53 along the mixing-height axis, close to the largest difference among the five regions (0.69). The sources and sinks behaved the opposite way. On the same inputs, emission and net-change differences were 3–22% and 13–30% of the spatial standard deviation between seeds, versus 13–141% and 45–174% between regions (Fig. 4b). Station-trained models thus differed between regions in sources and sinks, whereas their transport details varied as much between seeds on the same data as between regions. In the Taiwan surface fields too, the difference caused by swapping transport (6–9% of the bin-mean concentration) was as large as that between the two seed models (6–11%), whereas swapping emission+ k caused 23–32% (Fig. 4c).

We carried this diagnosis into the design. We fixed the outputs of the three transport perceptrons (surface wind-blending ratio, diffusion coefficient and residual-layer wind-blending ratio) and the layer-exchange constant a_{12} from the start of training, removing their learned degrees of freedom, and retrained from scratch in Taiwan and Southern California a model that advects the surface layer with the 10-m wind only and the residual layer with the 925-hPa wind only, without learned diffusion or a_{12} exchange (Experiment A). Its transport has no learned parameters; all other settings and the seed are those of the original model. In Taiwan the held-out RMSE changed by -1.6 to $+1.7\%$ across 2024 and the independent year 2023 (Fig. 5a, Supplementary Table S8a), comparable in magnitude to the seed-only retraining (-1.8 to $+0.2\%$). The learned sources and sinks also stayed largely at the seed level, only the $\text{PM}_{2.5}$ net-change rate slightly exceeding the seed difference, and the 48-h budget on the same states differed as much as between seeds (0.09–0.38 versus 0.10–0.38 times the spatial standard deviation of the emission field; Supplementary Table S8c).

In Southern California the reduced model forecast $\text{PM}_{2.5}$ better. In 363 forecasts in 2024 the $\text{PM}_{2.5}$ RMSE fell by 4.4% [-6.1 , -3.0] on day 1 and 7.4% [-10.2 , -4.7] on

day 2, and the other species changed by -2.5 to $+4.5\%$ (CO worsened on both days). Across all six species, the 2023 changes were -2.7 to $+1.3\%$ (Fig. 5b, Supplementary Table S8a). Here the sources and sinks were reorganized substantially. The emission fields were 1.3–2.0 times those of the original model (ratio of domain means), and the net change shifted with them, so that the differences of the two terms largely cancelled in the budget on the same states (compensation ratio 0.16–0.36, 0.78 for $\text{PM}_{2.5}$). Swapping emission or k alone between the two models changed the RMSE by tens of per cent for O_3 , NO_2 and CO, but swapping both transferred almost the entire difference between the two models (Supplementary Table S8b).

An original model retrained with only the seed changed differed from the original by -2.7 to $+1.1\%$ in 2023 and 2024 (Supplementary Table S7a). Judged by the rule fixed before this seed1 model was trained (structural effect only where the Experiment A difference is at least twice the seed difference; Methods), the emission fields were a structural effect for all six species (RMS difference relative to the spatial standard deviation 0.65–2.81, seed 0.06–0.78; Supplementary Table S8c). The net-change rates differed by 2.6–4.7 times the seed difference for PM_{10} , O_3 , SO_2 and CO, with NO_2 at the threshold and $\text{PM}_{2.5}$ at the seed level. The difference of the 48-h budget of the two terms, by contrast, stayed below twice the seed difference for all six species (0.29–1.51 times the spatial standard deviation of the emission field, seed 0.22–1.66). Between seeds the emission and net-change differences cancelled only partly (compensation ratio 0.43–0.99), whereas in Experiment A much larger changes of the two terms cancelled each other. In skill, the 2024 gains for $\text{PM}_{2.5}$ and SO_2 , the loss for CO and the gains for O_3 on day 1 and PM_{10} on day 2 exceeded twice the seed difference, while NO_2 was at the seed level. In 2023 the differences were mostly about 1%.

Retraining without the transport details preserved skill in both regions. Across seeds and transport structures the forecast and the source–sink budget stayed stable, whereas the split of that budget between emission and net change depended on the transport structure.

What stations determine

That transport details differ between trainings is not only because the stations cannot see the difference. The forecast difference between the original Taiwan model and a teacher with Korea’s two wind-blending functions inserted, normalized by an assumed spatio-temporal error covariance, was separable at the 62 input stations (distance 13.2), less so at four stations (3.5), compared with 44.0 on a dense land lattice (Methods). When synthetic observations were generated with the same teacher and a student supervised only at the station locations (S) and one supervised densely at the land lattice as well (D) were trained with the same budget, both reduced the distance of the surface wind-blending function to 12% of its starting value, with errors less than half those of the best constant approximation of the teacher function (Extended Data Fig. 2). Dense supervision reduced the forecast error on the grid not used in training by a further 24% but did not reduce the function distance, and neither student met the recovery criteria set in advance, including the 10% function-distance threshold (Methods). Measuring how far a small change in a learned component reaches the station

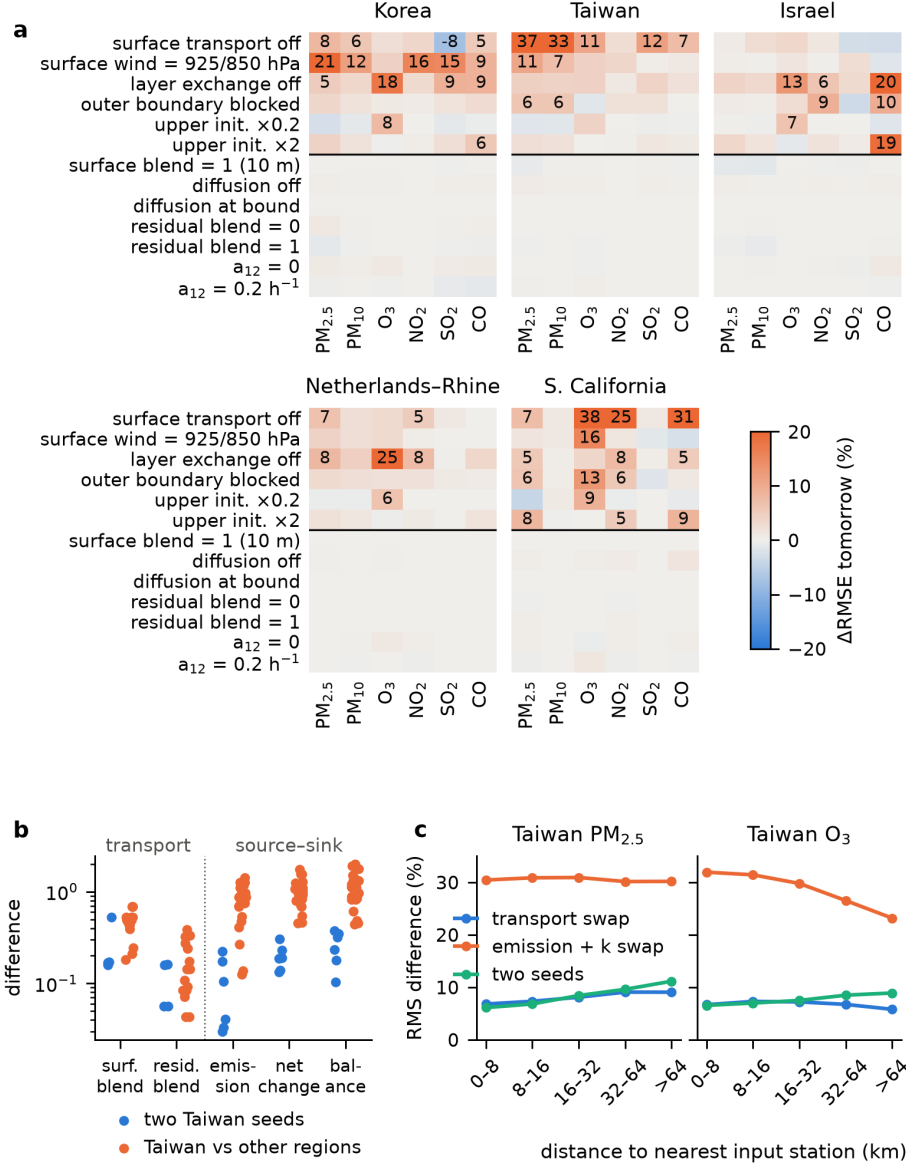


Fig. 4 Separating the processes that are needed from the details that need to be learned. **a**, Change in held-out RMSE (%) on day 2 (25–48 h) when a process is switched off or a learned constant or function is pinned to a bound; five homes $\times$ six species, 2024. Above the line: processes and layer constants; below: learned transport details. Values with an absolute magnitude of at least 5% are printed; the colour scale is saturated at $\pm 20\%$. **b**, Differences of learned values: the two Taiwan seed models (blue) and Taiwan versus the other four regional models (orange), on the same Taiwan inputs. Wind-blending ratios: largest absolute difference along each input axis; emission, net change and budget: RMS difference relative to the spatial standard deviation. **c**, Differences of the Taiwan surface fields by distance to the nearest input station (24–48 h, relative to the bin-mean concentration): transport swap and emission+ k swap (median over four regions), and the two seed models.

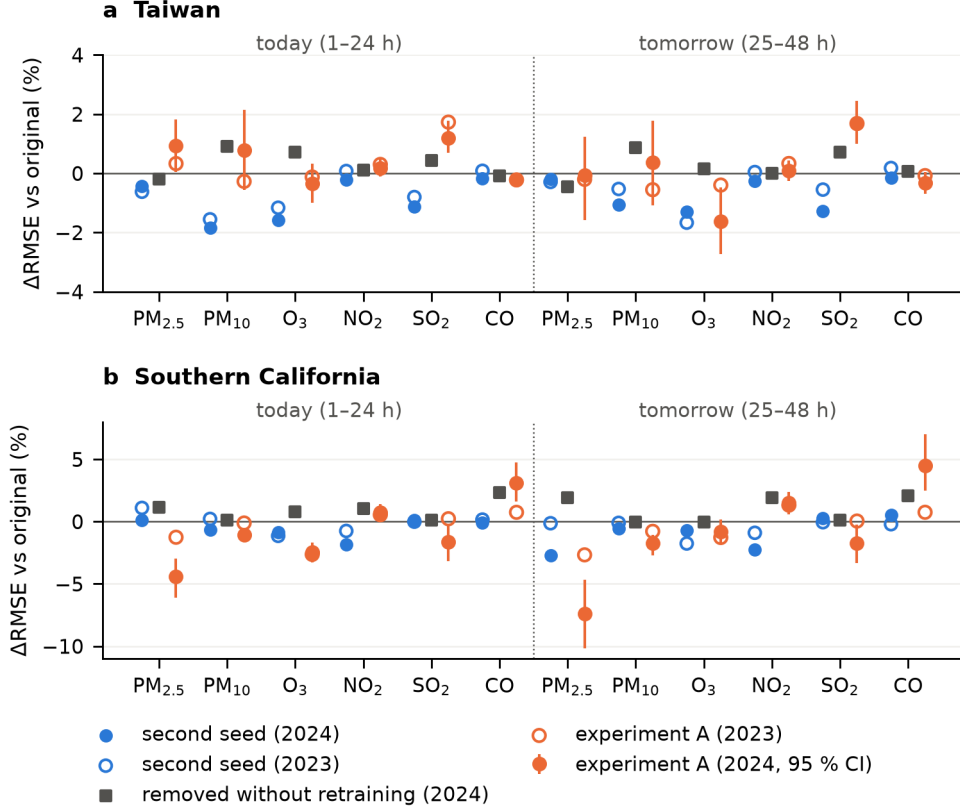


Fig. 5 Models retrained without the learned transport details (Experiment A). Held-out ΔRMSE relative to the original model (2024 with 95% block-bootstrap interval, and 2023) of the model retrained from scratch without the learned transport functions and a_{12} , of the original model retrained with only the seed changed, and of the original model with the same components pinned without retraining. **a**, Taiwan. **b**, Southern California.

signal with an adaptation of Ju’s two-factor attenuation [45], the ratio of the station effect to the direct effect was 0.27–0.30 for emission and k but 0.013–0.15 for the transport details (Extended Data Fig. 3). The signal of the transport details reaches the stations about three times more weakly than that of the sources and sinks, and the bottleneck differs by component: diffusion is attenuated in propagation, residual-layer blending by observing only the surface. The stations reveal which components matter for the forecast, but they do not fix the physical uniqueness of their values.

Discussion

SOLACE changes the starting point of regional air-quality forecasting. Instead of first assembling a regional CTM and an emission inventory, it learns about 11,000 inner parameters from a monitoring network and public weather and chemistry data

and produces gridded forecasts. In five regions on three continents this design was more accurate at stations not used in training than observation-corrected global CTM forecasts, kept its lead with forecast meteorology in Korea, and, with reanalysis meteorology, was on par with a national operational forecast for $\text{PM}_{2.5}$. Because it trains in a few hours on a personal computer and forecasts in seconds on a CPU, the same procedure can be applied where a monitoring network exists but no regional CTM system is operated. Its practical value is that it removes the regional uncertainty of emission data [6] from the prerequisites of building a forecast.

The emission term is an effective source, the observed mean pattern multiplied by a learned strength and temporal structure, and the net change carries chemistry, deposition and mixing errors together. Unlike data assimilation that inverts emissions from observations [46] or inversions built on CTM emulators [47], what is learned here is the effective process used for the forecast. The reduced retraining in Southern California re-partitioned emission and net change together by factors of 1.3–2 and still kept its skill. This reorganization far exceeded the difference between seeds in the same region, but the budget of the two terms, evaluated on common reference states, remained at the seed level. That regional adaptation resides in sources and sinks and that their values uniquely represent actual emissions and reaction rates are different propositions, and this study shows the former.

Process exchange gives models that combine physical structure with learned terms [25, 26] a unit of interpretation. It turns the problem that many learned solutions share similar predictive skill [31, 48] into experiments on which components depend on place, which combinations adapt together and which degrees of freedom can be removed. It requires process interfaces connected through physical quantities, exchange between regions, seed controls on the same data, and switching off, pinning and retraining. The same diagnosis can be applied to hydrological models trained jointly across catchments to separate universal and regional behaviour [49] and to differentiable models that learn process parameters [50]. SOLACE was designed to learn advection, but process exchange showed that advection is needed as structure while its details need not be learned. The evidence for each diagnosis and the scope of its interpretation are summarized in Extended Data Table 1.

The evaluation covers 48-h forecasts in five regions with hourly monitoring networks, and the gridded forecasts were verified at independent station locations rather than at every grid cell. Dust events that originate outside the domain after t_0 are not forecast. Skill with very sparse networks was not tested, and the problem of regions that lack monitoring altogether [51] is not solved. Because the sources are observation-based, the model cannot be used to compute the effect of emission-reduction scenarios. The retrospective evaluation in the five regions used ERA5 reanalysis meteorology, and skill with forecast meteorology was confirmed with the same weights in Korea. Seed controls and reduced retraining were carried out in Taiwan and Southern California.

Methods

The SOLACE model

Grid and timing.

Each region has a 4-km grid (175×153 cells), and one forecast of 48 hourly steps starts each day at local standard midnight t_0 (UTC offsets: Korea +9, Taiwan +8, Netherlands–Rhine +1, Israel +2, Southern California −8; no daylight saving). Domains, projections and station numbers are given in Supplementary Table S1.

Analysis at t_0 .

The analysis of species s is an optimal interpolation [36] of the input-station observations standardized by the hourly mean m and standard deviation σ , $\mathbf{z}$,

$$\begin{aligned} c_a(\mathbf{x}) &= m + \sigma \mathbf{k}(\mathbf{x})^\top (\mathbf{K} + \eta \mathbf{I})^{-1} \mathbf{z}, \\ k(d) &= w_1 \phi(d; L_1) + w_2 \phi(d; L_2), \\ \phi(d; L) &= \left(1 + \frac{\sqrt{3}d}{L}\right) e^{-\sqrt{3}d/L} \end{aligned} \tag{2}$$

Here ϕ is a Matérn covariance with smoothness 3/2; the two-scale kernel is the choice of this study, and the two length scales, the weights and the nugget η are learned for each species to minimize the error of analyses made with some input stations left out, using the input stations only in 2018–2022 (held-out stations and 2024 are not used). Unlike approaches that estimate error covariances from observation–forecast residuals [52], the covariance parameters are fitted here to the spatial prediction error of masked observations. An analysis is made only at hours when at least 75% of the species-eligible input stations report; in the training data of Israel, the Netherlands–Rhine region and Southern California, only stations that reported within the previous 720 h are counted.

Inner forecast.

The state is the concentration of six species in the surface layer c_0 , residual layer c_1 [35] and an upper layer c_2 . The surface layer stands for the air near the ground mixed up to the mixing height, not only the lowest tenth of the boundary layer. The residual and upper layers are initialized with the surface analysis multiplied by learned species factors. Steps (a)–(e) are applied every hour. (a) Transport: the surface layer is advected semi-Lagrangianly [37] with a blend of the 10-m wind and the mean 925–850-hPa wind and diffused with a learned coefficient (at most $0.25 \text{ cells}^2 \text{ h}^{-1}$). The blending ratio comes from a small multilayer perceptron that takes mixing height, stability and wind speed, and the diffusion coefficient from one that takes mixing height and wind speed. The residual layer is advected with a blend of the 925-hPa and 850-hPa winds whose ratio comes from a small perceptron that takes stability and the 925-hPa wind speed, and the upper layer with the mean 850–700-hPa wind. Diffusion in these two layers is fixed. These three perceptrons are the only learned parts of transport. (b) Net change: for each species a small multilayer perceptron takes the meteorology, the time and the

species' own concentration after transport in (a) and returns an hourly multiplicative rate $\exp(0.3 \tanh f_s)$. The term carries chemical production and loss, deposition and mixing errors together; interactions between species are not included. (c) Emission: $E_s = \alpha_s M_s(\mathbf{x}) P_s(\text{local hour, weekday/weekend}) \min[500 \text{ m} / \max(h_{\text{PBL}}, 50 \text{ m}), 10]$ is added to the surface layer. M_s is the mean of the 6-hourly analyses over the 30 days before t_0 (an observation-based spatial pattern), $\alpha_s = 0.3 \sigma(p_s)$ is the species strength, P_s is a learned hourly profile and h_{PBL} is the mixing height (m). The temporal allocation plays the role of the temporal profiles of an inventory [5] but is learned from observations rather than taken from published profiles. No emission inventory is used. (d) Layer exchange: as a simplification of the entrainment of residual-layer air into a growing mixed layer [35], residual-layer air is drawn into the surface layer when the mixing height grows (a_e) and separated when it falls (a_d), and the residual and upper layers mix with a constant a_{12} and a term proportional to 850-hPa upward motion (a_w). The constants are learned with ranges bounded by sigmoids. (e) Boundary: where a departure point of the advection in (a) lies outside the domain, the boundary band is read. The surface boundary band blends the outer-model forecast with the inner edge values through a gate, which closes where the outer values disagree strongly with the inner analysis, using quantiles from the training years. The gate is set once at t_0 . The boundary bands of the residual and upper layers are the outer-model values of the corresponding layer, scaled by learned species gains (0.2–3).

Outer model.

A Swin transformer [53] updates the six-species, three-layer fields of the outer domain (0.25°) every hour. Starting from GEOS-CF hindcast fields at $t_0 - 6 \text{ h}$ (a chemistry simulation constrained by meteorological analyses, in which no observations are assimilated directly except that stratospheric O_3 is nudged to GEOS FP fields) [7], it spins up for 6 h with meteorology alone and is then integrated for 48 h together with the inner forecast. All outer chemistry during the forecast is produced by the outer model, and no chemistry data after t_0 are input. Because the outer model supplies the boundary conditions, it is trained jointly with an auxiliary loss that fits the GEOS-CF fields outside the inner domain (mean squared error of log concentrations, weight 1). GEOS-CF provides no PM_{10} product, so the outer PM_{10} is constructed from its dust bins: at the surface as $\text{PM}_{2.5}$ plus the coarse dust, $\rho(0.62 \text{ DST2} + \text{DST3} + 0.87 \text{ DST4})$, where 0.62 and 0.87 are the mass fractions of DST2 above $2.5 \mu\text{m}$ and of DST4 below $10 \mu\text{m}$ for a lognormal dust size distribution (mass median diameter about $2.5 \mu\text{m}$, geometric standard deviation about 2), the former matching the 38% of DST2 counted in the $\text{PM}_{2.5}$ of GEOS-Chem 12.0.1 used by GEOS-CF v1 [7], and $\rho = 1.2 \text{ kg m}^{-3}$ converts the dust mixing ratios to concentrations (GEOS-CF provides mole fractions, which equal mass fractions because the dust molecular weight is set to that of air; they are used in $\mu\text{g kg}^{-1}$); in the residual and upper layers, where only fine dust is available, as $\text{PM}_{2.5}$ plus the fine dust scaled by the coarse-to-fine dust ratio of the training years. The outer PM_{10} therefore carries GEOS-CF dust but no other coarse particles.

Training.

The inner loss is the mean, over species and lead times, of the mean squared error computed at the input stations only, divided by the squared persistence error of the training years. Inner transport and the PM_{2.5} net change are first trained for 4,000 steps on PM_{2.5} alone (P1); starting from these weights, all six species are trained for 2,000 steps with a 6-h spin-up and a 48-h rollout (batch size 4). Optimization uses Adam [54], the exponential moving average of the weights is $\bar{\theta}_t = 0.999\bar{\theta}_{t-1} + 0.001\theta_t$, and the checkpoint is selected by the mean relative error over species and the leads of 1, 3, 6, 12 and 24 h (up to 48 h for Korea) in 300 selection windows at the held-out stations in 2022. No 2024 data are used to select the weights of the original models. The implementation uses PyTorch [55], and all computation is FP32. There are 142,446 trained parameters (Korea; outer model 131,299, inner transport and net change 10,488, layer, emission and boundary constants 659), and the five regions share the same structure. This count excludes the OI covariance parameters (five per species, fitted separately) and the optional MOS.

Regional training

The five regions were trained on 2018–2021 and selected on 2022 with the same model structure and main training settings (steps, batch, learning rates, loss and selection rule). Stations, grids, meteorological and outer-chemistry data and local time are regional. The Korea model is a frozen set of weights trained earlier with the same model and optimization; its data preparation differs in a few details (Supplementary Methods S9.6). Meteorology for training and evaluation is ERA5 [39].

Data

Station observations are hourly values from the national regulatory networks of the five regions (Supplementary Table S1). Times are unified to the end of the averaging interval (US EPA data, labelled at the interval start, are shifted by 1 h), and European gas mass concentrations are converted to ppb at 293 K and 101.3 kPa, the reference conditions of the EU air-quality directive [56]. Outer chemistry and the comparison CTM are from GEOS-CF [7], and the additional Korean comparison uses the CAMS global forecast [3]. Sources of the static variables used only by MOS (elevation, population, land cover) are listed in Supplementary Table S1; the SOLACE model itself uses no static variables. DOIs and addresses of public data are collected under Data availability.

Evaluation design

In each region 12–20% of the stations (about 19% in Taiwan and Israel, 12–13% elsewhere) were fixed as held-out stations in 30-km blocks [57]. The evaluation covers 364 retrospective forecasts initialized at midnight from 1 January to 29 December 2024 (local dates); forecasts that failed the 75% input rule were removed for all models (6 in Israel, 1 in Southern California). For each species and lead window the comparison uses the same station–hour sample, valid for all models, and the RMSE is computed

separately for today (1–24 h) and tomorrow (25–48 h). Uncertainties are pointwise percentile 95% intervals from 2,000 resamples of the dates in 7-day blocks, without adjustment for multiple comparisons. Following the rationale of block resampling, which preserves serial dependence [58], we use circular block resampling, in which blocks wrap from the last day to the first [59]. RMSE differences between models are computed as paired comparisons that apply the same date indices to both models in every replicate. Held-out stations were withheld from training and from the initial-time analysis; their 2022 scores were used only to choose one of the saved checkpoints, and no 2024 data entered original-model checkpoint selection. The subsequent process diagnosis and redesign used the 2024 evaluation. An operational deployment would assimilate all stations.

Component exchange, core transplant, sensitivity and seed control

In each home region we forecast, from the same input batches as the home model, with the full model of each other region (including its normalization buffers) and with each of eight components swapped in one at a time; physical inputs such as the observed mean emission pattern and the meteorology are those of the home evaluation. We report the home advantage H , the ΔRMSE of each swap and the share of the foreign-weight loss that the swap alone reproduces, $(\text{RMSE}_{\text{swap}} - \text{RMSE}_{\text{home}}) / (\text{RMSE}_{\text{foreign}} - \text{RMSE}_{\text{home}})$, a locating diagnostic rather than an attribution, only where the interval of H excludes zero. The core transplant swaps transport, layer exchange and upper-layer initial scaling together, and the regional transplant swaps emission, k and the outer model together. The sensitivity tests switch processes off or pin learned constants and functions to their bounds. The seed control is a Taiwan model retrained from P1 with only the seed changed, used for component swaps in both directions between the two seed models and for comparisons of learned values on the same Taiwan inputs, with the other four regional models giving the size of regional differences. The seed-swap reference, at most 3.7%, is the farthest end of the 95% intervals of $|\Delta\text{RMSE}|$ for these swaps. Normalization, the switches and pins, the learned-value comparisons and the reporting criteria are given in Supplementary Methods S9.1. All exchange experiments use the raw output without MOS.

Field comparison, pruning, dose response and Experiment A

The field comparison compares the surface fields of the swapped and home models, and of the two Taiwan seed models, for 52 weekly forecasts. Pruning pins together, without retraining, the four degrees of freedom whose pins had small effects in Taiwan, and the dose response sets one layer constant to several values within its range (Supplementary Methods S9.2). Experiment A applies the same pins from the start of training, with zero gradients for the pinned tensors, and retrains in Taiwan and Southern California with the same settings and seed. In Southern California we also retrained the original model with only the seed changed (seed1). A species and quantity count as a structural effect only where the Experiment A difference is at least twice the seed difference, a rule fixed before seed1 was trained. The quantities are the held-out RMSE change for

each species and window, the RMS difference and domain-mean ratio of the emission fields and net-change rates, and the difference of the 48-h budget on the same states with the compensation ratio. The budget is computed by running the reference model, recording at every hour n the transported surface state $\bar{c}^n$ and the emission inputs, and applying each model’s net-change networks and emission term to exactly these inputs: $R = \sum_n \bar{c}^n (e^{r^n} - 1)$, $E = \sum_n E^n$ and $B = R + E$ over the 48 h. The compensation ratio $K_{\text{comp}} = \text{rms}(\Delta B) / [\text{rms}(\Delta E)^2 + \text{rms}(\Delta R)^2]^{1/2}$ is below 1 when the emission and net-change differences between two models cancel and near 1 when their cross-term is small relative to their combined squared magnitudes. Experiment A is presented as observed changes with uncertainties, not as a pre-registered equivalence test; the pre-run plan and its references are described in Supplementary Methods S9.2.

Separability of synthetic forecasts and placement of supervision

Separability without training.

Following the use of synthetic observations to control transport error [60], we take as teacher the Taiwan seed0 model with only its surface and residual-layer wind-blending functions replaced by Korea’s, and compare 48-h forecasts every 2 h for 52 weekly forecasts in 2022. Station subsets are 20 draws of nested networks of 4–62 stations, and land samples are lattices with 32, 16, 8 and 4 km spacing. With D_s the matrix of forecast differences divided by the error standard deviation σ_s for each species and lead window, we compute

$$z = \left[\sum_s \text{tr} \left(C_{s,\text{space}}^{-1} D_s C_{s,\text{time}}^{-1} D_s^\top \right) \right]^{1/2}, \quad (3)$$

with spatial correlation $\nu_s I + (1 - \nu_s) \exp(-d/L_s)$ and temporal correlation $\exp(-|\Delta t|/\tau_s)$ estimated from the residuals between real observations and forecasts at the Taiwan input stations. Assuming independent species, stationary and separable covariances [61] and the same error model on the grid, z is the Mahalanobis distance between two fixed forecasts; it does not judge the real atmosphere or learnability. Assumptions and sensitivities are detailed in Supplementary Methods S9.3.

Recovery with sparse and dense supervision.

S and D start from the same seed1 P1 trained on real data, and only the E46 stage is trained on the teacher’s synthetic targets. S uses the original input-station locations; D adds the loss at 1,162 points of an 8-km land lattice, with matched training order and budget. On 24 forecasts in 2022 not used in the pre-check, we measure forecast reproduction and the distance of the surface blending function to the teacher’s against pre-set criteria (Supplementary Methods S9.3).

Attenuation from components to stations.

We adapt Ju’s two attenuation ratios [45], defined there with the Jacobian of the model, to finite perturbations of one time step of SOLACE. Small perturbations are

applied to the outputs of the learned functions of the Taiwan seed0 operator (wind blending, diffusion, k and emission). For each direction we compare the direct effect of one perturbed step, the three-layer state difference with the perturbation on for all 48 h (propagated effect) and the surface difference at the 62 input stations (observed effect). r_1 is the norm ratio of propagated to direct, r_2 of observed to propagated and $r_1 r_2$ of observed to direct effect; with a 1-h time step the direct effect is the analogue of Ju’s residual. Perturbation sizes, bases, the linearity filter, the bootstrap and the pre-run decision rule are given in Supplementary Methods S9.4. The norm ratios diagnose response size and do not measure whether directions can be distinguished.

Forecast meteorology and operation

Forecast meteorology.

The same weights of the Korea model were evaluated under operational timing. The +3 h to +57 h forecasts of the most recent GFS cycle available for a daily 01 KST run, 06 UTC on the previous day, were converted to the same variables as ERA5 and given to both the inner and the outer model. The outer model spins up for 6 h with this meteorology from GEOS-CF hindcast fields at $t_0 - 6$ h. Weights, preprocessing constants, OI and held-out stations are those of the ERA5 evaluation. The comparison uses the 363 forecasts in 2024 present in both evaluations and the same held-out stations (85) and hours valid for all models. The MOS is a station model trained on SOLACE forecasts under the same GFS conditions on years before the evaluation year. One input-cache correction is described in Supplementary Methods S9.5.

Operation.

Since October 2026, SOLACE has issued daily 48-h forecasts in five regions with GFS forecast meteorology and GEOS-CF hindcast fields as inputs, using the regional models of this paper (frozen weights for Korea). Hashes and external timestamps of the first published forecast files are recorded (Supplementary Methods S9.5).

Comparison products

MOS.

The difference between the observations and the SOLACE forecast at the input stations is learned for each species with LightGBM [40] (2022; February, June and October for early stopping). Inputs are the SOLACE forecasts of the six species, the t_0 analysis, the meteorology at t_0 and at the target time, time variables, lead time and static variables; station identifiers are not used. Following prior work that spreads station corrections onto the grid [62], we use a Gaussian-weighted mean ($L = 40$ km) multiplied by a network-density decay. The algorithm is not the eight-pass Barnes analysis of that work, and held-out stations receive these mapped values.

Persistence.

The t_0 persistence forecast holds, for all 48 h, the t_0 analysis of the input stations read at each evaluation station; the observations of the held-out stations are not used, so persistence starts from the same information as SOLACE.

Observation-corrected CTMs.

For each species the observation-corrected CTM forecast at lead time h (hours) is $\max\{0, f(h) + (c_a(t_0) - f(t_0))e^{-h/12}\}$, where f is the CTM forecast at the station interpolated to the valid time ($f(t_0)$ is the CTM forecast valid at t_0 , not its initial state) and $c_a(t_0)$ is the station analysis at t_0 ; the analysis difference decays with a 12-h e-folding time. For each forecast we used the GEOS-CF cycle initialized closest before t_0 (12 UTC of the same or the previous UTC day), regardless of when it was published. Because a cycle becomes available only after its forecast has been computed, an operational forecast at t_0 could not always have used it, so the comparison favours GEOS-CF. CAMS uses the 00 UTC cycle of the UTC date of t_0 from +15 h.

LightGBM baseline (Korea).

For each species a LightGBM model [40] predicts the observation at $t_0 + h$ from the t_0 analysis of the six species and the meteorology at the station, time and lead features and station properties (Supplementary Methods S9.6). It is trained on the input stations in 2018–2021 with ERA5 meteorology and stopped early on the input stations in 2022; at test time it reads the same GFS forecasts as SOLACE. It forecasts the station points only and never sees the held-out stations, whereas the SOLACE checkpoint was selected with the held-out stations in 2022.

NOAA AQM.

Bias-corrected hourly $\text{PM}_{2.5}$ and O_3 from AQM [4] were taken from the AWS public archive (noaa-nws-naqfc-pds; AQMv6 until 13 May 2024, AQMv7 with embedded CMAQ 5.2.1 from 14 May [41] and its update v7.0.8 from 1 October [63]; the $\text{PM}_{2.5}$ correction method is described in [64]), using the interval-end values of the 12 UTC cycle of the previous day, the latest published before t_0 , at the nearest native grid cell (about 5 km). The MOS was trained on 2022, so both 2023 and 2024 are outside training. The wildfire exclusion was fixed before the results were computed: forecasts overlapping 7 days from discovery (main criterion), or the period until the day after containment (secondary criterion), of fires of 10,000 acres or more with ignition points in the domain in the NIFC WFIGS Incident Locations list were removed.

Use of AI tools.

Claude Opus models (Anthropic), accessed through Claude Code, assisted with the implementation and debugging of the forecasting model, training procedures, data-analysis and figure-generation code, and the publicly released software. Claude also assisted in translating the author’s Korean manuscript into English, drafting revisions at the author’s direction and editing the language. ChatGPT (OpenAI) assisted with deploying the operational forecasting service and reviewing the manuscript for internal consistency, including cross-checking equations, numerical results and tables. The author conceived and designed the study, model and experiments, reviewed and validated AI-assisted outputs, and takes full responsibility for all scientific results, interpretations and manuscript content.

Data availability. All input data are public. Station observations: Korea, AirKorea (Korea Environment Corporation); Taiwan, Ministry of Environment air-quality monitoring network (<https://airtw.moenv.gov.tw>); Israel, Ministry of Environmental Protection air-monitoring network (<https://air.sviva.gov.il>); Europe, EEA Air Quality e-Reporting (verified E1a); United States, EPA AQS (https://aqs.epa.gov/aqsweb/airdata/download_files.html). Meteorology: ERA5 single levels (<https://doi.org/10.24381/cds.adbb2d47>) and pressure levels (<https://doi.org/10.24381/cds.bd0915c6>), for Korea from NCAR RDA ds633.0 (<https://doi.org/10.5065/BH6N-5N20>) and for the other regions from ECMWF ARCO (<https://arco.datastores.ecmwf.int>). Chemistry: GEOS-CF v1 (NASA GMAO), CAMS global forecasts (<https://doi.org/10.24381/04a0b097>) and archived NOAA AQM forecasts (AWS open data `noaa-nws-naqfc-pds`). Static variables for MOS (not used by the SOLACE model): Copernicus DEM GLO-30 (AWS `copernicus-dem-30m`), WorldClim 2.1, C3S Land Cover 2022, WorldPop 2022, the Korean Ministry of Environment land-cover map and Statistics Korea SGIS gridded population. Wildfires: NIFC WFIGS Incident Locations. Regional processing details are given in Supplementary Table S1. The held-out station forecasts of all models and the data behind every figure and table are available at <https://doi.org/10.5281/zenodo.23749759>. The archive includes the observations at the held-out stations for Taiwan, the Netherlands–Rhine region and Southern California, whose terms permit redistribution; the Korean and Israeli observations can be obtained from the providers above.

Code availability. The code of the model, its training, the forecasts and the analyses of this paper, with the trained weights of the five regions and an example case, is available at <https://github.com/theMaker-EnvData/solace-aq> (code MIT licence; weights CC BY-NC 4.0). The package reimplements the research code used for the results and is tested against it: with the same weights and inputs it reproduces the 48-h forecasts of the five regional models to a relative difference of 10^{-7} , and its training reproduces the original training steps.

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Competing interests. The author is the founder of EnvDataLab, which operates the SOLACE forecasts described here and licenses the trained weights for commercial use.

Author contributions. The author conceived and designed the study, developed the model and software, carried out the analyses and wrote the manuscript.

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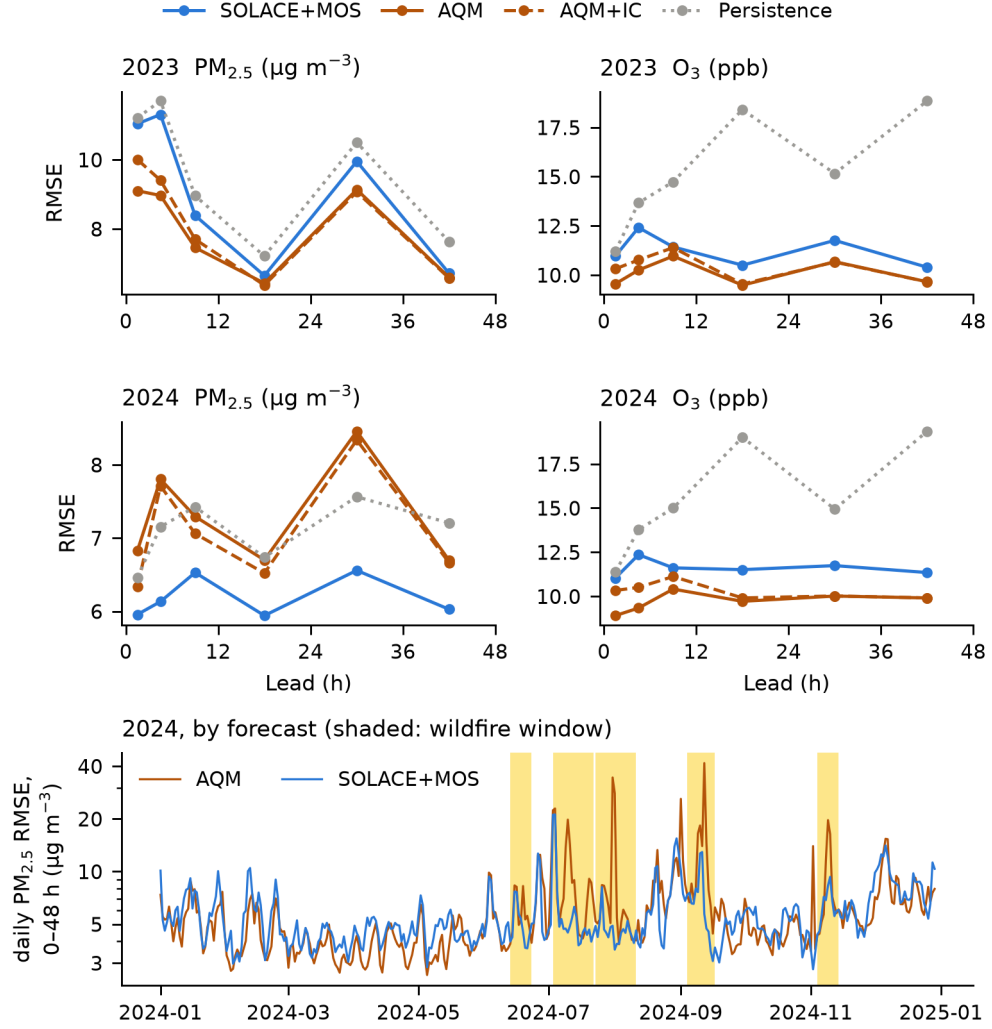
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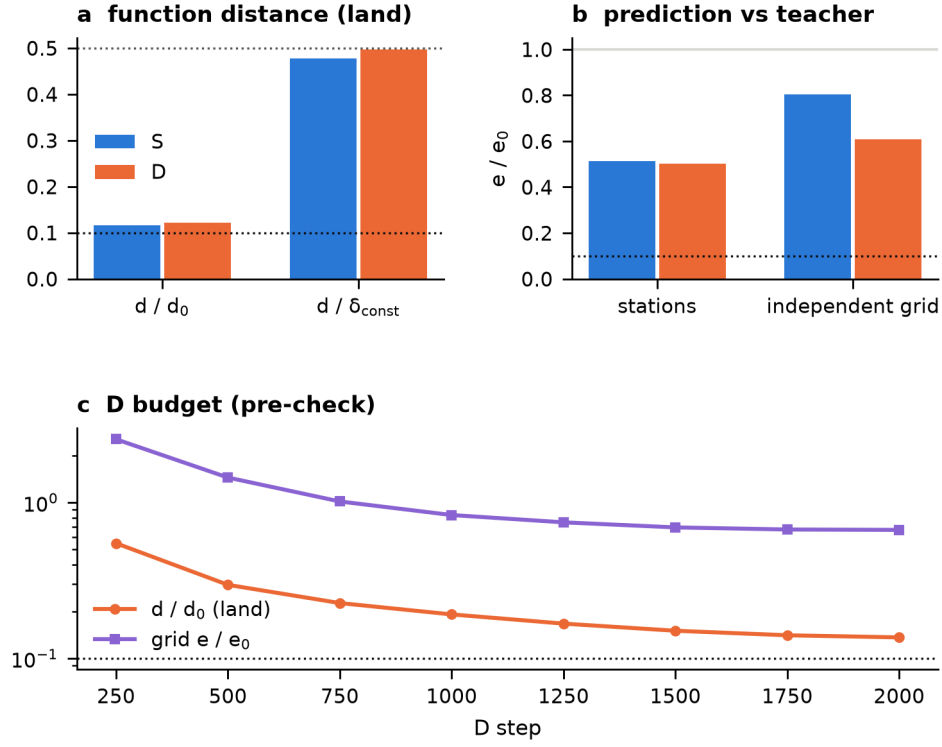
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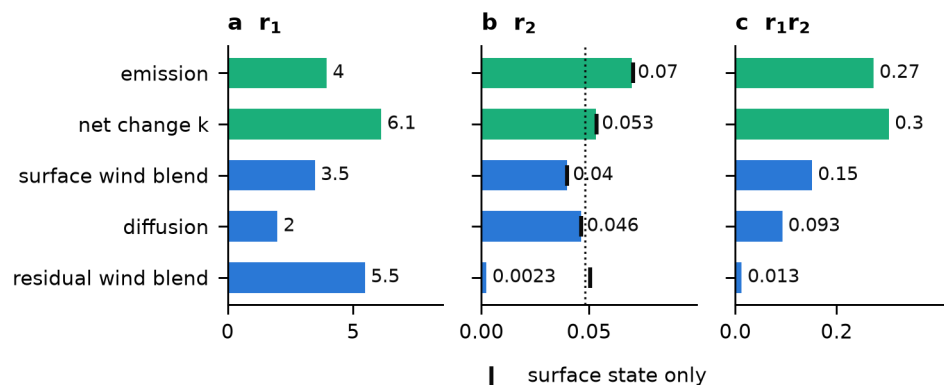
Extended Data



Extended Data Fig. 1 Comparison with NOAA AQM in Southern California. Top: held-out RMSE by lead-time block (2023 and 2024; SOLACE+MOS, AQM, t_0 -corrected AQM and persistence). Local time differs between blocks, so the diurnal cycle is mixed in. Bottom: PM_{2.5} RMSE of each 2024 forecast (0–48 h). Yellow bands mark forecasts whose window overlaps the first 7 days after discovery of a fire of 10,000 acres or more in the domain.



Extended Data Fig. 2 Recovery of the surface wind-blending function from synthetic observations. Students supervised only at the station locations (S) or also at 8-km land samples (D), trained on synthetic observations from a teacher in which Korea's wind-blending function is inserted into the Taiwan model (24 forecasts in 2022, final exponential-moving-average weights). **a**, Function distance on land relative to the starting distance and relative to the error of the best constant approximation of the teacher function. **b**, Forecast error relative to the teacher (relative to Taiwan seed0) at the station locations and on the grid not used in training. **c**, Function distance and grid forecast error by D training step (4 pre-check forecasts). Dotted lines are the pre-set criteria.



Extended Data Fig. 3 How far changes in learned components reach the stations. Taiwan seed0, 24 forecasts in 2022. The outputs of the learned functions of each component are perturbed slightly, and the propagated effect over 48 h relative to the hourly direct effect (r_1), the surface effect at the 62 input stations relative to the propagated effect (r_2) and their product ($r_1 r_2$) are shown as medians over basis directions, species and forecasts. Bars in **b** use the three-layer propagated state; ticks use the surface state only. The dotted line is the expectation for uniform sampling of the surface state, $\sqrt{62/26,775}$, to be compared with the ticks.

Extended Data Table 1 Evidence and interpretation of the diagnostics.

Question	Observed evidence	Interpretation
Skill as a forecast	More accurate than GEOS-CF+IC (persistence for PM ₁₀) in 57/60 cells in five regions; with Korean forecast meteorology the error increases by 2–12% and the lead is kept; on par with AQM for PM _{2.5} (SOLACE with ERA5)	A station-trained forecast without a regional inventory works at operational level
Where regional adaptation resides	Emission+ k swap reproduces 73–97% of the foreign-weight loss; core swap within 3% in 225 of 240 cells	Regional differences reside in the source–sink pair
Coupling between processes	Separate swaps of emission and k are not additive; they also cancel between seeds	The two terms are a co-adapted pair
Need for transport and its details	Removing surface transport worsens skill by up to 38%; of 420 pinned-detail cells only 7 exceed 1%	Explicit transport contributes to the trained model’s skill; its learned details can be removed by retraining
Redesign	Retraining without learned transport parameters: Taiwan –1.6 to +1.7%, Southern California PM _{2.5} –4 to –7%, CO up to +4.5%	Skill is kept in both regions; in Southern California emission and net change are re-partitioned beyond the seed difference while their budget stays at the seed level
What stations determine	Forecast differences are separable at the stations; synthetic supervision approaches the function closely but misses the strict criteria; the transport signal reaches the stations about three times more weakly	Stations reveal which components matter for the forecast but do not fix the uniqueness of their values

Supplementary Information: Station-trained air-quality forecasts without regional emission inventories

TK Lee

EnvDataLab.

Abstract

Supplementary Tables S1–S8 and Supplementary Fig. S1. Tables S2–S8 are generated from the result files (`make_supp_tables.py`) and Fig. S1 by `make_supp_cases.py`. Unless otherwise stated, process-sensitivity and retraining differences are changes in held-out RMSE relative to the original model (seed0) of the same region, using the raw output without MOS and ERA5 meteorology. Forecast benchmark comparisons (Tables S2, S2b, S2c and S5) use the references and configurations given in their captions.

S1 Regional domains and data

Supplementary Table S1: Regional domains and data. All inner grids are 4 km with 175×153 cells; the outer domains use a 0.25° grid. Station numbers are the evaluation networks fixed from 2023 availability; held-out stations were fixed in 30-km blocks.

	Korea	Taiwan	Israel	Netherlands–Rhine	Southern California
Projection	EPSG:5179	EPSG:3826	Azimuthal equidistant (31.5°N , 35.0°E)	Azimuthal equidistant (50.7°N , 6.5°E)	Azimuthal equidistant (35.0°N , 118.0°W)
Outer domain	$115\text{--}135^\circ\text{E}$, $30\text{--}45^\circ\text{N}$	$111\text{--}131^\circ\text{E}$, $16.25\text{--}31.25^\circ\text{N}$	$25\text{--}45^\circ\text{E}$, $24\text{--}39^\circ\text{N}$	$3.5^\circ\text{W}\text{--}16.5^\circ\text{E}$, $43.25\text{--}58.25^\circ\text{N}$	$128\text{--}108^\circ\text{W}$, $27.5\text{--}42.5^\circ\text{N}$
UTC offset	+9	+8	+2	+1	−8
Stations (held out)	715 (88)	77 (15)	224 (43)	1,348 (164)	364 (46)
Observation source	AirKorea final data (Korea Environment Corporation)	MOENV air-quality monitoring network, historical data	Ministry of Environmental Protection air-monitoring network (Envista API)	EEA Air Quality e-Reporting, verified E1a	US EPA AQS hourly data
Time convention	Interval end	Interval end	Interval end (provider)	Interval end (stated)	Interval start label $\rightarrow$ +1 h
Meteorology	ERA5 (NCAR RDA ds633.0)	ECMWF ARCO	ECMWF ARCO	ECMWF ARCO	ECMWF ARCO
Outer chemistry	GEOS-CF v1 hindcast fields (start at $t_0 - 6$ h); comparison forecast: GEOS-CF 12 UTC cycle initialized closest before t_0				
Elevation (MOS)	Copernicus DEM GLO-30	WorldClim 2.1 ($30''$)			
Land cover (MOS)	Ministry of Environment land-cover map, 7 classes (2022)	C3S Land Cover 2022 v2.1.1 (300 m)			

	Korea	Taiwan	Israel	Netherlands– Rhine	Southern California
Population (MOS)	Statistics Korea SGIS 100-m grid (2022)	WorldPop 2022 R2025A constrained (1 km)			

Elevation, land cover and population are static inputs used only by MOS; the SOLACE model itself does not use them.

S2 Skill in five regions

Supplementary Table S2: Held-out RMSE in five regions (2024 retrospective forecasts initialized at local midnight; gases ppb, PM $\mu\text{g m}^{-3}$). Same valid sample for all models. GEOS-CF has no PM₁₀; Korea has no MOS matched to these forecasts.

Region	Window	Species	Stations	SOLACE	SOLACE+MOS	Persistence	GEOS-CF	GEOS-CF+IC
Korea	Today	PM _{2.5}	85	8.19	–	10.61	36.80	25.11
Korea	Today	PM ₁₀	85	17.04	–	20.59	–	–
Korea	Today	O ₃	85	11.97	–	19.15	17.81	15.24
Korea	Today	NO ₂	85	8.07	–	9.84	12.87	11.35
Korea	Today	SO ₂	85	1.06	–	0.80	4.54	3.00
Korea	Today	CO	85	119.05	–	136.43	189.04	157.38
Korea	Tomorrow	PM _{2.5}	85	9.67	–	14.27	36.06	34.73
Korea	Tomorrow	PM ₁₀	85	20.19	–	26.77	–	–
Korea	Tomorrow	O ₃	85	12.74	–	21.08	18.35	17.95
Korea	Tomorrow	NO ₂	85	8.24	–	12.14	13.16	12.89
Korea	Tomorrow	SO ₂	85	1.10	–	0.84	4.56	4.33
Korea	Tomorrow	CO	85	126.54	–	162.58	187.31	183.53
Taiwan	Today	PM _{2.5}	15	6.74	6.50	8.30	23.81	16.65
Taiwan	Today	PM ₁₀	15	13.67	12.81	15.33	–	–
Taiwan	Today	O ₃	15	10.93	10.11	17.67	14.03	12.82
Taiwan	Today	NO ₂	15	5.76	5.47	6.70	8.68	8.34
Taiwan	Today	SO ₂	15	0.89	0.84	0.88	3.10	2.02
Taiwan	Today	CO	15	166.65	163.09	174.39	211.48	194.88
Taiwan	Tomorrow	PM _{2.5}	15	7.20	7.10	10.16	23.44	22.53
Taiwan	Tomorrow	PM ₁₀	15	13.95	13.51	18.06	–	–
Taiwan	Tomorrow	O ₃	15	11.83	10.61	19.65	14.13	14.02
Taiwan	Tomorrow	NO ₂	15	5.79	5.52	7.18	8.83	8.75
Taiwan	Tomorrow	SO ₂	15	0.91	0.85	0.90	3.08	2.91
Taiwan	Tomorrow	CO	15	168.81	166.15	184.77	212.23	210.35
Israel	Today	PM _{2.5}	21	8.46	8.63	9.14	14.86	12.40
Israel	Today	PM ₁₀	15	34.60	37.31	36.16	–	–
Israel	Today	O ₃	14	12.02	10.38	13.95	12.37	11.48
Israel	Today	NO ₂	28	6.34	6.22	6.42	6.79	6.67
Israel	Today	SO ₂	18	0.91	0.86	0.88	3.84	2.69
Israel	Today	CO	5	268.99	233.67	360.55	221.76	205.87
Israel	Tomorrow	PM _{2.5}	21	8.95	9.07	10.75	15.15	14.86
Israel	Tomorrow	PM ₁₀	15	35.02	38.14	40.71	–	–
Israel	Tomorrow	O ₃	14	11.73	10.77	14.89	12.56	12.43
Israel	Tomorrow	NO ₂	28	6.34	6.26	6.83	6.84	6.82

Region	Window	Species	Stations	SOLACE	SOLACE+MOS	Persistence	GEOS-CF	GEOS-CF+IC
Israel	Tomorrow	SO ₂	18	0.95	0.88	0.91	3.83	3.65
Israel	Tomorrow	CO	5	235.96	225.07	363.97	220.89	206.36
Netherlands–Rhine	Today	PM _{2.5}	40	4.79	4.74	5.96	30.53	20.92
Netherlands–Rhine	Today	PM ₁₀	50	8.10	7.99	9.16	–	–
Netherlands–Rhine	Today	O ₃	34	7.28	6.65	11.86	12.27	10.03
Netherlands–Rhine	Today	NO ₂	57	4.88	4.64	5.65	7.10	6.24
Netherlands–Rhine	Today	SO ₂	19	1.81	1.81	1.81	5.54	3.87
Netherlands–Rhine	Today	CO	6	181.58	174.94	186.31	187.80	184.25
Netherlands–Rhine	Tomorrow	PM _{2.5}	40	5.41	5.29	7.69	30.99	29.77
Netherlands–Rhine	Tomorrow	PM ₁₀	50	8.72	8.53	11.05	–	–
Netherlands–Rhine	Tomorrow	O ₃	34	7.66	6.95	13.44	12.30	12.01
Netherlands–Rhine	Tomorrow	NO ₂	53	5.09	4.74	6.37	7.27	7.13
Netherlands–Rhine	Tomorrow	SO ₂	19	1.81	1.80	1.81	5.56	5.31
Netherlands–Rhine	Tomorrow	CO	6	181.83	175.76	192.22	189.27	188.84
Southern California	Today	PM _{2.5}	10	6.35	6.12	6.93	43.19	27.78
Southern California	Today	PM ₁₀	11	26.57	26.96	26.64	–	–
Southern California	Today	O ₃	17	12.87	11.59	16.71	17.92	15.45
Southern California	Today	NO ₂	8	7.31	6.91	9.60	13.19	10.65
Southern California	Today	SO ₂	2	0.55	0.56	0.57	0.60	0.59
Southern California	Today	CO	5	191.24	191.45	278.71	340.72	272.66
Southern California	Tomorrow	PM _{2.5}	10	6.65	6.30	7.39	40.18	38.01
Southern California	Tomorrow	PM ₁₀	11	27.77	27.60	28.70	–	–
Southern California	Tomorrow	O ₃	17	12.59	11.54	17.33	17.88	17.47
Southern California	Tomorrow	NO ₂	8	7.23	6.96	10.30	13.18	12.69
Southern California	Tomorrow	SO ₂	2	0.55	0.56	0.57	0.60	0.60
Southern California	Tomorrow	CO	5	187.87	189.52	296.03	340.57	328.76

S2b Station machine-learning baseline and high-concentration days (Korea)

Supplementary Table S2b: Korea, 2024 retrospective forecasts from $t_0 = 00$ KST with the GFS cycle available for a 01 KST run, held-out stations: hourly RMSE (gases ppb, PM $\mu\text{g m}^{-3}$) of SOLACE, SOLACE+MOS, a LightGBM (gradient-boosted trees) station model trained on the same observation network and run with the same GFS forecasts (inputs: the t_0 analysis and the meteorology at the station; trained on the input stations in 2018–2021, early stopping on 2022; Methods) and t_0 persistence, and paired RMSE differences from LightGBM with 95% block intervals (negative: smaller error than LightGBM). LightGBM forecasts station points only; SOLACE forecasts the grid.

Species	Window	SOLACE	SOLACE+MOS	LightGBM	Persistence	SOLACE – LightGBM	SOLACE+MOS – LightGBM
PM _{2.5}	Today	8.30	8.30	9.15	10.63	-0.86 [-1.19, -0.56]	-0.86 [-1.24, -0.54]
PM _{2.5}	Tomorrow	10.29	10.29	10.86	14.29	-0.58 [-0.99, -0.13]	-0.58 [-0.94, -0.17]
PM ₁₀	Today	17.54	17.54	19.93	20.62	-2.40 [-3.99, -0.91]	-2.40 [-3.97, -0.85]
PM ₁₀	Tomorrow	21.15	21.15	22.63	26.82	-1.51 [-4.17, +0.36]	-1.51 [-4.23, +0.29]
O ₃	Today	12.69	11.79	11.80	19.16	+0.89 [+0.53, +1.21]	-0.02 [-0.29, +0.24]
O ₃	Tomorrow	13.78	12.82	12.69	21.08	+1.07 [+0.68, +1.42]	+0.11 [-0.23, +0.43]
NO ₂	Today	8.54	7.64	8.05	9.84	+0.48 [+0.29, +0.69]	-0.41 [-0.55, -0.28]
NO ₂	Tomorrow	8.75	7.94	8.60	12.15	+0.15 [-0.09, +0.36]	-0.66 [-0.83, -0.47]
SO ₂	Today	1.17	0.88	0.84	0.80	+0.34 [+0.30, +0.37]	+0.04 [+0.03, +0.05]
SO ₂	Tomorrow	1.24	0.90	0.87	0.84	+0.36 [+0.33, +0.40]	+0.03 [+0.01, +0.04]
CO	Today	123	116	126	136	-3 [-5, -0]	-10 [-12, -7]
CO	Tomorrow	135	124	135	162	+0 [-3, +4]	-11 [-13, -8]

Supplementary Table S2c: Korea, 2024 retrospective forecasts with GFS meteorology, held-out stations: high-concentration days. Events: observed station-days in the grade. Daily station means (days with at least 20 observed hours) in the Korean “bad grade or worse (PM_{2.5} above 35, PM₁₀ above 80 $\mu\text{g m}^{-3}$): probability of detection / false-alarm ratio / critical success index, and the RMSE of the daily mean on the days in the top 10% of observed daily values. On the 766 station-days with a day-2 PM₁₀ event, the mean observed PM₁₀ rose from 72 $\mu\text{g m}^{-3}$ at 1 h to 141 $\mu\text{g m}^{-3}$ at 39 h, whereas the mean SOLACE forecast stayed between 56 and 70 $\mu\text{g m}^{-3}$ over the 48 h.

Species	Window	Events	SOLACE POD/FAR/CSI	LightGBM POD/FAR/CSI	Persistence POD/FAR/CSI	SOLACE RMSE	LightGBM RMSE	Persistence RMSE
PM _{2.5}	Today	1709	0.55 / 0.33 / 0.43	0.50 / 0.40 / 0.38	0.57 / 0.53 / 0.35	9.2	11.7	13.8
PM _{2.5}	Tomorrow	1706	0.53 / 0.52 / 0.33	0.37 / 0.58 / 0.24	0.26 / 0.78 / 0.14	11.6	14.1	21.0
PM ₁₀	Today	766	0.40 / 0.14 / 0.38	0.35 / 0.42 / 0.28	0.41 / 0.53 / 0.28	26.9	32.0	35.0
PM ₁₀	Tomorrow	766	0.01 / 0.83 / 0.01	0.11 / 0.57 / 0.09	0.26 / 0.70 / 0.16	36.1	37.2	50.9

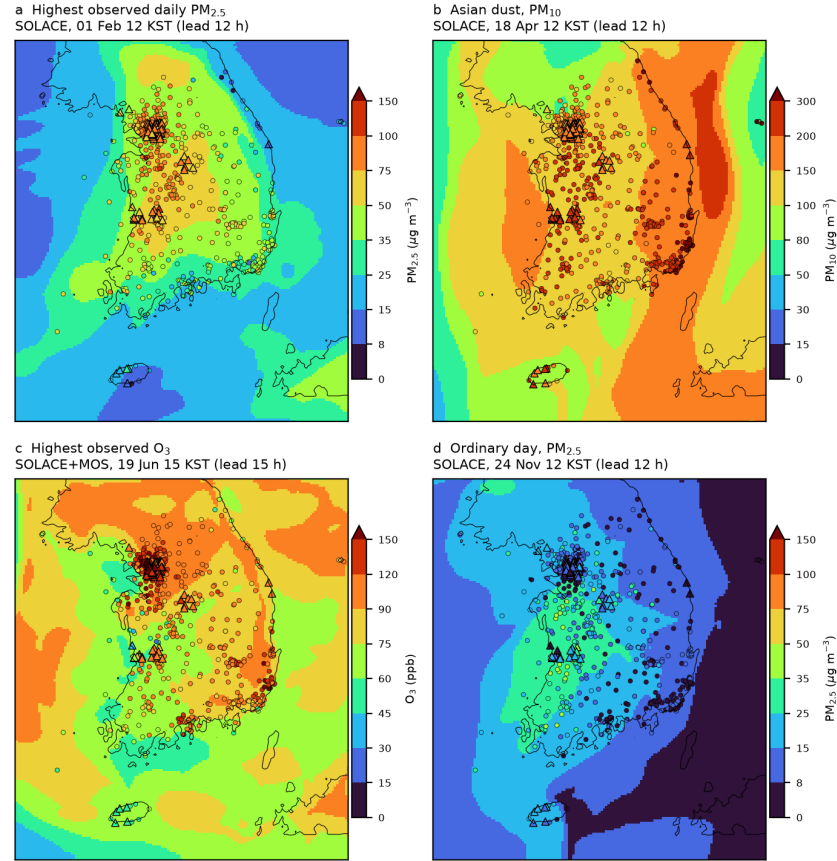


Fig. S1 Korea, 2024 retrospective forecasts from $t_0 = 00$ KST with the GFS cycle available for a 01 KST run: 4-km forecast fields on the full grid, including the sea, with the observed station values of the same hour (circles input stations, triangles held-out stations; same colour scale). Cases chosen without regard to forecast error: **a**, the day with the highest observed daily $\text{PM}_{2.5}$; **b**, Asian dust (PM_{10}); **c**, the highest observed O_3 (SOLACE+MOS, the station correction spread to the grid); **d**, an ordinary day. The forecasts follow the spatial pattern but stay below the observed peaks in **a–c**. Values over the sea are not verified, since all stations are on land or islands.

S3 Home advantage

Supplementary Table S3: Home advantage H (%) = RMSE(source weights)/RMSE(home weights)−1 at held-out stations, 2024. Brackets: 7-day block-bootstrap 95% interval.

Home	Source	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Korea	Taiwan	Today	+12 [+8, +15]	+12 [+8, +18]	+26 [+21, +31]	+25 [+19, +32]	+9 [+3, +15]	+44 [+38, +49]
Korea	Taiwan	Tomorrow	+13 [+6, +19]	+11 [+5, +19]	+23 [+18, +29]	+24 [+18, +30]	+7 [+1, +13]	+39 [+34, +44]
Korea	Israel	Today	+20 [+13, +26]	+23 [+15, +37]	+61 [+54, +69]	+13 [+10, +16]	+36 [+27, +46]	+33 [+28, +37]
Korea	Israel	Tomorrow	+33 [+24, +42]	+31 [+18, +54]	+78 [+69, +89]	+15 [+11, +18]	+33 [+25, +43]	+40 [+33, +46]
Korea	Netherlands–Rhine	Today	+25 [+20, +30]	+19 [+13, +26]	+29 [+24, +33]	+9 [+8, +11]	+43 [+32, +53]	+22 [+19, +25]
Korea	Netherlands–Rhine	Tomorrow	+34 [+27, +41]	+23 [+13, +36]	+31 [+27, +35]	+13 [+11, +14]	+38 [+28, +48]	+25 [+21, +29]
Korea	Southern California	Today	+88 [+64, +110]	+24 [+12, +43]	+37 [+33, +41]	+20 [+15, +24]	+12 [+7, +17]	+60 [+49, +71]
Korea	Southern California	Tomorrow	+80 [+63, +94]	+25 [+13, +46]	+61 [+52, +70]	+26 [+20, +31]	+33 [+24, +44]	+68 [+59, +79]
Taiwan	Korea	Today	+9 [+5, +13]	+13 [+8, +19]	+14 [+10, +17]	+11 [+10, +13]	+24 [+19, +31]	+4 [+2, +6]
Taiwan	Korea	Tomorrow	+14 [+8, +20]	+23 [+15, +32]	+17 [+12, +22]	+16 [+13, +19]	+50 [+41, +61]	+6 [+4, +8]
Taiwan	Israel	Today	+18 [+12, +26]	+17 [+11, +24]	+49 [+45, +53]	+17 [+14, +19]	+9 [+3, +16]	+11 [+8, +15]
Taiwan	Israel	Tomorrow	+28 [+17, +39]	+31 [+19, +45]	+51 [+45, +58]	+20 [+17, +23]	+13 [+5, +22]	+17 [+9, +31]
Taiwan	Netherlands–Rhine	Today	+28 [+24, +33]	+19 [+14, +23]	+42 [+36, +49]	+20 [+18, +22]	+10 [+7, +14]	+12 [+9, +14]
Taiwan	Netherlands–Rhine	Tomorrow	+35 [+30, +41]	+30 [+25, +34]	+43 [+36, +50]	+27 [+25, +29]	+8 [+3, +12]	+15 [+10, +19]
Taiwan	Southern California	Today	+39 [+30, +47]	+27 [+20, +36]	+59 [+51, +67]	+37 [+32, +41]	+11 [+7, +15]	+14 [+11, +17]
Taiwan	Southern California	Tomorrow	+50 [+40, +60]	+43 [+33, +54]	+67 [+56, +78]	+45 [+39, +51]	+17 [+12, +21]	+20 [+16, +23]
Israel	Korea	Today	+35 [+26, +47]	+16 [+8, +32]	+31 [+25, +38]	+46 [+39, +55]	+20 [+14, +26]	+14 [+11, +18]
Israel	Korea	Tomorrow	+50 [+37, +66]	+20 [+12, +40]	+33 [+25, +40]	+76 [+65, +90]	+47 [+38, +59]	+8 [+2, +15]
Israel	Taiwan	Today	+18 [+12, +25]	+5 [+2, +10]	+41 [+35, +48]	+31 [+27, +36]	+3 [-2, +8]	+24 [+20, +29]
Israel	Taiwan	Tomorrow	+19 [+13, +26]	+8 [+2, +15]	+45 [+40, +51]	+36 [+30, +42]	+5 [-1, +12]	+24 [+18, +31]
Israel	Netherlands–Rhine	Today	+17 [+9, +27]	+6 [+2, +12]	+18 [+15, +21]	+18 [+14, +22]	+5 [+1, +9]	-12 [-14, -9]
Israel	Netherlands–Rhine	Tomorrow	+55 [+27, +91]	+17 [+9, +35]	+29 [+24, +33]	+26 [+20, +32]	-1 [-5, +4]	-13 [-17, -9]
Israel	Southern California	Today	+26 [+19, +35]	+7 [+4, +13]	+35 [+32, +39]	+8 [+6, +10]	+9 [+7, +12]	+40 [+32, +47]
Israel	Southern California	Tomorrow	+43 [+32, +59]	+16 [+9, +28]	+36 [+31, +41]	+15 [+12, +18]	+13 [+10, +15]	+50 [+36, +62]
Netherlands–Rhine	Korea	Today	+55 [+42, +67]	+57 [+48, +66]	+49 [+39, +58]	+27 [+23, +32]	+2 [+1, +4]	+14 [+8, +23]
Netherlands–Rhine	Korea	Tomorrow	+100 [+76, +120]	+104 [+86, +121]	+45 [+37, +54]	+54 [+44, +63]	+8 [+5, +13]	+36 [+21, +57]
Netherlands–Rhine	Taiwan	Today	+26 [+21, +32]	+19 [+16, +24]	+55 [+48, +62]	+45 [+39, +51]	+3 [+2, +6]	+13 [+8, +21]
Netherlands–Rhine	Taiwan	Tomorrow	+54 [+44, +65]	+47 [+39, +56]	+77 [+66, +88]	+65 [+56, +75]	+7 [+5, +13]	+34 [+21, +52]
Netherlands–Rhine	Israel	Today	+21 [+14, +28]	+46 [+16, +92]	+41 [+37, +45]	+6 [+2, +10]	-0 [-0, +0]	+3 [+1, +6]
Netherlands–Rhine	Israel	Tomorrow	+35 [+23, +49]	+117 [+37, +204]	+65 [+57, +73]	+7 [+3, +12]	+0 [-0, +1]	+7 [+3, +12]
Netherlands–Rhine	Southern California	Today	+20 [+14, +25]	+13 [+10, +15]	+31 [+27, +35]	+13 [+8, +18]	+0 [-0, +1]	+5 [+3, +8]
Netherlands–Rhine	Southern California	Tomorrow	+28 [+18, +41]	+16 [+12, +20]	+34 [+30, +39]	+13 [+7, +19]	+1 [+0, +1]	+7 [+4, +11]
Southern California	Korea	Today	+25 [+20, +31]	+6 [+4, +8]	+25 [+20, +29]	+29 [+23, +35]	+30 [+16, +45]	+2 [-0, +4]
Southern California	Korea	Tomorrow	+75 [+62, +89]	+16 [+10, +26]	+33 [+27, +39]	+39 [+33, +46]	+51 [+30, +75]	+3 [+0, +5]
Southern California	Taiwan	Today	+8 [+4, +14]	+2 [+1, +3]	+98 [+82, +113]	+54 [+42, +66]	+11 [+3, +20]	+28 [+21, +36]

Home	Source	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Southern California	Taiwan	Tomorrow	+16 [+7, +26]	+2 [+0, +4]	+133 [+109, +154]	+57 [+44, +69]	+14 [+3, +27]	+30 [+22, +39]
Southern California	Israel	Today	+6 [+3, +9]	+8 [+5, +14]	+17 [+14, +20]	+28 [+22, +33]	-3 [-7, +3]	+2 [-0, +4]
Southern California	Israel	Tomorrow	+8 [+2, +13]	+24 [+13, +39]	+26 [+22, +29]	+31 [+25, +36]	-4 [-12, +6]	-2 [-5, +1]
Southern California	Netherlands–Rhine	Today	+38 [+33, +45]	+9 [+7, +12]	+32 [+29, +35]	+33 [+30, +37]	+15 [+4, +26]	+14 [+12, +16]
Southern California	Netherlands–Rhine	Tomorrow	+54 [+42, +68]	+10 [+7, +15]	+43 [+38, +47]	+44 [+40, +49]	+14 [+2, +27]	+9 [+5, +14]

S4 Component exchange

Supplementary Table S4: ΔRMSE (%) when one component is replaced by that of another region, median over 20 pairs. In parentheses: share of the error increase of the full foreign weights reproduced by the swap (% , median over pairs whose H interval excludes zero).

Component	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Transport	Today	+0.0 (0)	-0.0 (-0)	+0.2 (0)	+0.1 (1)	+0.0 (0)	-0.0 (-0)
Transport	Tomorrow	-0.0 (-0)	-0.0 (-0)	-0.0 (-0)	-0.0 (-0)	+0.1 (0)	+0.0 (-0)
Net change k	Today	+25.1 (99)	+12.8 (110)	+33.2 (97)	+12.4 (66)	+1.7 (67)	+21.2 (114)
Net change k	Tomorrow	+39.9 (95)	+25.8 (109)	+37.1 (87)	+19.4 (78)	+2.7 (60)	+20.0 (134)
Emission	Today	+2.1 (6)	+0.3 (6)	+4.9 (13)	+7.7 (49)	+0.8 (16)	+12.0 (83)
Emission	Tomorrow	+8.2 (19)	+4.6 (20)	+6.2 (12)	+8.1 (39)	+1.9 (15)	+18.4 (72)
Emission+ k	Today	+18.3 (93)	+12.5 (87)	+32.4 (97)	+18.4 (91)	+9.7 (97)	+8.3 (85)
Emission+ k	Tomorrow	+31.4 (85)	+16.2 (75)	+33.2 (84)	+24.9 (92)	+9.4 (76)	+11.0 (73)
Layer exchange	Today	+0.1 (0)	+0.0 (0)	+0.3 (1)	+0.1 (0)	+0.0 (0)	+0.0 (0)
Layer exchange	Tomorrow	+0.0 (-0)	+0.1 (1)	+0.6 (2)	+0.0 (0)	-0.0 (0)	+0.0 (-1)
a_{12}	Today	+0.0 (0)	-0.0 (-0)	-0.0 (-0)	-0.0 (-0)	-0.0 (-0)	-0.0 (-0)
a_{12}	Tomorrow	-0.0 (-0)	-0.0 (-0)	+0.0 (0)	+0.0 (0)	-0.0 (-0)	+0.0 (0)
Upper initial scaling	Today	+0.0 (0)	-0.1 (-0)	+0.3 (1)	+0.0 (0)	+0.0 (0)	+0.1 (0)
Upper initial scaling	Tomorrow	+0.0 (0)	-0.1 (-1)	+0.0 (0)	+0.0 (0)	+0.0 (0)	+0.1 (-0)
Outer model	Today	+1.4 (6)	+1.6 (13)	+3.8 (11)	+0.7 (3)	+0.7 (6)	+1.1 (8)
Outer model	Tomorrow	+4.2 (14)	+3.5 (20)	+8.8 (22)	+0.3 (2)	+1.6 (7)	+2.4 (13)

S5 Comparison with NOAA AQM

Supplementary Table S5: Comparison with NOAA AQM at held-out stations in Southern California. Last column: difference of the SOLACE+MOS RMSE from AQM (%) with 95% block interval. In 2024 the no-fire subset to containment+1 d contains 134 AQMv6-period and 39 AQMv7-period forecasts; the discovery+7 d subset contains all 134 AQMv6-period forecasts and 158 AQMv7-period forecasts (last two rows).

Year	Period	Species	Window	Forecasts	SOLACE	SOLACE+MOS	AQM	AQM+IC	Persistence	SOLACE+MOS vs AQM
2023	All	O ₃	Today	358	12.29	11.04	9.98	10.28	16.28	+11 [+8, +14]
2023	All	O ₃	Tomorrow	358	12.12	11.08	10.17	10.16	17.14	+9 [+6, +12]
2023	All	PM _{2.5}	Today	358	8.49	8.42	7.41	7.66	8.88	+14 [-1, +24]
2023	All	PM _{2.5}	Tomorrow	358	8.52	8.48	7.96	7.92	9.17	+7 [-9, +17]
2023	No fire (discovery+7 d)	O ₃	Today	348	12.25	11.02	9.96	10.27	16.21	+11 [+8, +14]
2023	No fire (discovery+7 d)	O ₃	Tomorrow	348	12.09	11.06	10.13	10.12	17.07	+9 [+6, +12]
2023	No fire (discovery+7 d)	PM _{2.5}	Today	348	8.58	8.51	7.48	7.74	8.98	+14 [-1, +24]
2023	No fire (discovery+7 d)	PM _{2.5}	Tomorrow	348	8.60	8.58	8.04	7.99	9.28	+7 [-9, +18]
2023	No fire (to containment+1 d)	O ₃	Today	332	12.18	11.00	9.90	10.23	16.15	+11 [+8, +15]
2023	No fire (to containment+1 d)	O ₃	Tomorrow	332	12.04	11.05	10.09	10.08	17.05	+10 [+7, +13]
2023	No fire (to containment+1 d)	PM _{2.5}	Today	332	8.75	8.68	7.60	7.88	9.17	+14 [-0, +24]
2023	No fire (to containment+1 d)	PM _{2.5}	Tomorrow	332	8.76	8.74	8.17	8.13	9.47	+7 [-9, +18]
2024	All	O ₃	Today	363	12.87	11.59	9.76	10.35	16.71	+19 [+16, +22]
2024	All	O ₃	Tomorrow	363	12.59	11.54	9.96	9.96	17.33	+16 [+13, +19]
2024	All	PM _{2.5}	Today	363	6.35	6.12	7.01	6.79	6.93	-13 [-22, -2]
2024	All	PM _{2.5}	Tomorrow	363	6.65	6.30	7.63	7.55	7.39	-17 [-30, -1]
2024	AQMv6 period	O ₃	Today	134	10.87	9.89	9.02	9.48	14.17	+10 [+7, +13]
2024	AQMv6 period	O ₃	Tomorrow	134	10.96	10.07	9.19	9.18	15.22	+10 [+7, +13]
2024	AQMv6 period	PM _{2.5}	Today	134	5.29	5.21	4.43	4.74	6.00	+18 [+11, +25]
2024	AQMv6 period	PM _{2.5}	Tomorrow	134	5.30	5.32	4.51	4.52	6.40	+18 [+14, +23]
2024	AQMv7 period	O ₃	Today	229	13.87	12.44	10.16	10.80	17.99	+23 [+19, +26]
2024	AQMv7 period	O ₃	Tomorrow	229	13.42	12.29	10.37	10.38	18.42	+19 [+15, +22]
2024	AQMv7 period	PM _{2.5}	Today	229	6.90	6.60	8.18	7.77	7.44	-19 [-30, -7]
2024	AQMv7 period	PM _{2.5}	Tomorrow	229	7.35	6.82	8.99	8.88	7.92	-24 [-38, -7]
2024	No fire (discovery+7 d)	O ₃	Today	292	12.18	11.05	9.45	10.04	15.82	+17 [+14, +20]
2024	No fire (discovery+7 d)	O ₃	Tomorrow	292	12.06	11.10	9.66	9.67	16.58	+15 [+12, +18]
2024	No fire (discovery+7 d)	PM _{2.5}	Today	292	6.19	5.96	5.78	5.88	6.75	+3 [-4, +11]
2024	No fire (discovery+7 d)	PM _{2.5}	Tomorrow	292	6.51	6.16	5.96	5.90	7.15	+3 [-4, +11]
2024	No fire (to containment+1 d)	O ₃	Today	173	11.03	10.02	8.90	9.32	14.11	+13 [+9, +16]
2024	No fire (to containment+1 d)	O ₃	Tomorrow	173	11.10	10.24	9.13	9.12	15.18	+12 [+9, +16]

Year	Period	Species	Window	Forecasts	SOLACE	SOLACE+MOS	AQM	AQM+IC	Persistence	SOLACE+MOS vs AQM
2024	No fire (to containment+1 d)	PM _{2.5}	Today	173	5.34	5.25	4.64	4.88	5.86	+13 [+7, +20]
2024	No fire (to containment+1 d)	PM _{2.5}	Tomorrow	173	5.47	5.42	4.80	4.81	6.26	+13 [+6, +19]
2024	AQMv7 period, no fire (discovery+7 d)	PM _{2.5}	Today	158	6.88	6.54	6.74	6.72	7.34	-3 [-11, +6]
2024	AQMv7 period, no fire (discovery+7 d)	PM _{2.5}	Tomorrow	158	7.40	6.82	6.99	6.89	7.75	-2 [-12, +6]

S6 Process switches and pinned learned values

Supplementary Table S6: Process switches and learned constants and functions pinned to bounds. Held-out ΔRMSE (%) relative to each home original model with 95% block interval, 2024, no retraining. A function is pinned by zero output-layer weights and a bias within 10^{-6} of the bound, giving a constant independent of the inputs (Methods).

Condition	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Korea							
Surface transport (advection, diffusion) off	Today	+8.6 [4.4, 14.0]	+7.5 [2.0, 12.5]	+0.2 [-2.0, 2.7]	-0.7 [-2.3, 0.9]	-11.3 [-13.8, -8.8]	+0.6 [-0.8, 1.9]
Surface transport (advection, diffusion) off	Tomorrow	+8.2 [3.2, 13.8]	+6.0 [3.4, 10.3]	+2.5 [0.3, 4.9]	+3.7 [1.7, 5.9]	-7.7 [-10.4, -4.6]	+5.5 [3.3, 7.7]
Surface wind = 925–850 hPa	Today	+32.1 [26.7, 37.9]	+22.2 [12.4, 38.0]	+16.5 [12.3, 20.9]	+18.4 [15.0, 21.9]	+17.0 [12.2, 21.6]	+13.4 [10.1, 16.5]
Surface wind = 925–850 hPa	Tomorrow	+21.2 [15.3, 27.5]	+11.6 [2.2, 27.2]	+4.2 [1.9, 7.0]	+15.8 [12.5, 19.2]	+15.2 [10.2, 20.1]	+9.0 [5.8, 12.1]
Surface blending ratio 1 (10-m wind only)	Today	+0.0 [-0.4, 0.4]	-0.1 [-0.7, 0.3]	+0.0 [-0.1, 0.1]	-0.1 [-0.1, 0.0]	-0.7 [-1.2, -0.2]	-0.2 [-0.5, 0.1]
Surface blending ratio 1 (10-m wind only)	Tomorrow	+0.1 [-0.1, 0.3]	-0.0 [-0.3, 0.3]	+0.1 [-0.1, 0.3]	-0.1 [-0.1, -0.0]	-0.2 [-0.5, 0.1]	-0.1 [-0.2, 0.1]
Diffusion 0	Today	+0.6 [0.5, 0.7]	+0.4 [0.3, 0.6]	+0.4 [0.3, 0.4]	+0.1 [0.1, 0.1]	+0.5 [0.4, 0.6]	+0.5 [0.5, 0.6]
Diffusion 0	Tomorrow	+0.5 [0.4, 0.6]	+0.2 [0.2, 0.4]	+0.2 [0.2, 0.3]	+0.1 [0.0, 0.1]	+0.3 [0.3, 0.4]	+0.3 [0.3, 0.4]
Diffusion at bound	Today	-0.1 [-0.1, -0.1]	-0.0 [-0.1, -0.0]	-0.0 [-0.0, -0.0]	+0.0 [-0.0, 0.1]	+0.0 [-0.0, 0.0]	-0.1 [-0.1, -0.0]
Diffusion at bound	Tomorrow	-0.1 [-0.1, -0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]	+0.0 [-0.0, 0.1]	+0.0 [0.0, 0.0]	-0.0 [-0.1, -0.0]
Residual blending ratio 0	Today	+0.8 [0.4, 1.2]	+0.1 [-0.6, 1.0]	+0.0 [-0.2, 0.3]	+0.0 [-0.0, 0.1]	+0.1 [-0.0, 0.1]	+0.3 [0.1, 0.4]
Residual blending ratio 0	Tomorrow	+1.2 [0.9, 1.6]	+0.3 [-0.3, 1.2]	-0.0 [-0.2, 0.2]	+0.0 [-0.0, 0.1]	+0.2 [0.1, 0.3]	+0.5 [0.3, 0.6]
Residual blending ratio 1	Today	-0.9 [-1.4, -0.4]	-0.6 [-1.0, -0.2]	+0.1 [-0.2, 0.4]	+0.0 [-0.0, 0.0]	-0.1 [-0.2, -0.0]	-0.2 [-0.4, -0.0]
Residual blending ratio 1	Tomorrow	-1.0 [-1.6, -0.6]	-0.2 [-1.1, 0.4]	-0.1 [-0.3, 0.1]	-0.0 [-0.1, 0.0]	-0.2 [-0.3, -0.1]	-0.4 [-0.7, -0.2]
$a_{12} = 0$	Today	+0.4 [0.1, 0.7]	+0.2 [-0.1, 0.6]	+0.1 [-0.0, 0.3]	+0.0 [-0.0, 0.0]	+0.3 [0.3, 0.4]	+0.3 [0.1, 0.6]
$a_{12} = 0$	Tomorrow	+0.9 [0.3, 1.4]	+0.3 [-0.0, 1.0]	+1.0 [0.7, 1.3]	+0.1 [0.0, 0.1]	+0.6 [0.5, 0.8]	+0.9 [0.6, 1.2]
$a_{12} = 0.2 \text{ h}^{-1}$	Today	-0.2 [-0.8, 0.3]	-0.1 [-0.7, 0.5]	+0.3 [-0.1, 0.7]	+0.0 [-0.0, 0.0]	-0.6 [-0.8, -0.5]	-0.4 [-0.8, -0.1]
$a_{12} = 0.2 \text{ h}^{-1}$	Tomorrow	-0.4 [-1.2, 0.5]	+0.1 [-0.7, 0.7]	-0.3 [-0.7, 0.2]	-0.0 [-0.1, 0.0]	-0.9 [-1.1, -0.7]	-1.0 [-1.4, -0.5]
Layer exchange off	Today	+2.4 [0.9, 3.8]	+2.6 [1.2, 3.8]	+12.5 [10.1, 14.7]	+2.1 [1.2, 3.1]	+6.7 [6.1, 7.4]	+4.6 [3.5, 5.6]
Layer exchange off	Tomorrow	+5.1 [3.2, 7.0]	+3.5 [2.0, 4.8]	+17.6 [15.4, 19.6]	+3.0 [2.1, 4.0]	+9.2 [8.3, 10.1]	+9.0 [7.5, 10.6]
Outer boundary blocked	Today	+0.5 [-1.9, 2.9]	-0.9 [-4.2, 1.3]	-0.0 [-0.5, 0.5]	-0.2 [-0.4, 0.1]	-3.6 [-5.5, -1.7]	-0.2 [-1.2, 0.7]
Outer boundary blocked	Tomorrow	+3.6 [0.4, 7.5]	+1.9 [-0.5, 4.5]	+0.9 [-0.1, 2.1]	+0.7 [0.4, 1.2]	+1.7 [-1.4, 5.3]	+2.9 [1.1, 4.7]
Upper initial scaling 0.2	Today	-1.2 [-2.9, 0.5]	+0.9 [-0.6, 2.3]	+20.6 [17.1, 23.8]	-0.1 [-0.2, 0.0]	-2.9 [-3.6, -2.3]	+0.6 [-0.2, 1.5]
Upper initial scaling 0.2	Tomorrow	-2.6 [-3.8, -1.4]	-1.1 [-2.3, -0.4]	+7.7 [5.9, 9.5]	-0.0 [-0.1, -0.0]	-1.1 [-1.5, -0.8]	-0.5 [-1.0, 0.0]
Upper initial scaling 1	Today	-0.6 [-0.9, -0.3]	-0.2 [-0.7, 0.2]	+6.6 [4.9, 8.2]	+0.3 [0.1, 0.5]	+0.7 [0.5, 0.8]	+0.9 [0.5, 1.3]

Condition	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Upper initial scaling 1	Tomorrow	-0.6 [-0.8, -0.4]	-0.3 [-0.7, -0.2]	+3.2 [2.4, 4.0]	+0.1 [0.0, 0.2]	+0.3 [0.2, 0.3]	+0.6 [0.4, 0.9]
Upper initial scaling 2	Today	+5.8 [4.0, 7.7]	+2.4 [1.0, 5.0]	-0.1 [-0.2, 0.1]	+1.5 [0.9, 2.1]	+7.8 [6.4, 9.4]	+11.1 [8.9, 13.4]
Upper initial scaling 2	Tomorrow	+4.1 [2.9, 5.5]	+1.9 [1.0, 3.6]	-0.2 [-0.3, -0.1]	+0.4 [0.2, 0.6]	+2.5 [1.8, 3.3]	+5.7 [4.3, 7.3]
Net change off	Today	+17.3 [12.1, 22.3]	+14.3 [8.0, 24.8]	+113.3 [100.9, 126.0]	+161.4 [138.8, 184.6]	+233.1 [207.0, 259.8]	+71.9 [62.1, 82.0]
Net change off	Tomorrow	+29.6 [21.8, 37.9]	+32.4 [20.7, 52.9]	+292.8 [258.9, 326.5]	+389.1 [336.3, 439.9]	+558.4 [498.0, 621.4]	+200.9 [176.5, 225.9]
Emission off	Today	-2.6 [-4.3, -0.8]	+1.2 [-0.8, 3.5]	+30.3 [25.1, 34.9]	+86.0 [78.6, 93.0]	+33.6 [26.4, 40.8]	+46.6 [41.0, 52.2]
Emission off	Tomorrow	-5.4 [-9.2, -1.6]	+1.6 [-2.9, 5.5]	+45.7 [38.8, 52.1]	+104.5 [96.6, 112.2]	+53.0 [44.4, 62.1]	+80.3 [71.6, 89.3]
Emission+net change off	Today	+13.1 [8.8, 17.5]	+11.3 [5.9, 19.7]	+42.5 [39.7, 45.4]	+51.1 [46.6, 55.4]	+4.7 [-1.8, 11.2]	+12.9 [11.1, 14.7]
Emission+net change off	Tomorrow	+21.8 [15.0, 29.3]	+21.3 [14.0, 34.5]	+72.2 [65.4, 79.4]	+82.1 [76.5, 87.3]	+29.0 [18.9, 39.5]	+23.7 [20.2, 27.1]
Taiwan							
Surface transport (advection, diffusion) off	Today	+21.3 [17.2, 25.4]	+18.4 [14.7, 22.1]	+5.1 [2.6, 7.4]	-0.7 [-1.9, 0.6]	+4.1 [3.0, 5.5]	+1.9 [0.9, 2.9]
Surface transport (advection, diffusion) off	Tomorrow	+36.8 [30.7, 43.1]	+33.5 [27.7, 39.4]	+10.7 [6.6, 14.8]	+2.7 [0.9, 4.7]	+11.7 [9.1, 14.9]	+7.4 [5.7, 9.5]
Surface wind = 925–850 hPa	Today	+11.2 [8.6, 13.7]	+6.6 [4.6, 8.7]	+4.1 [2.6, 5.8]	+3.6 [2.6, 4.4]	+0.7 [-0.0, 1.5]	+1.4 [0.7, 2.0]
Surface wind = 925–850 hPa	Tomorrow	+10.7 [8.1, 13.2]	+7.0 [4.7, 9.6]	+4.2 [2.5, 5.8]	+3.7 [2.5, 4.7]	+0.4 [-0.8, 1.7]	+1.1 [0.1, 1.9]
Surface blending ratio 1 (10-m wind only)	Today	-0.4 [-1.2, 0.4]	+0.6 [-0.4, 1.6]	+0.4 [-0.3, 1.1]	-0.1 [-0.4, 0.2]	+0.1 [-0.1, 0.4]	-0.4 [-0.7, -0.1]
Surface blending ratio 1 (10-m wind only)	Tomorrow	-0.8 [-2.5, 0.6]	+0.3 [-1.0, 1.4]	+0.2 [-0.9, 1.4]	-0.1 [-0.5, 0.2]	+0.3 [-0.0, 0.6]	-0.2 [-0.6, 0.3]
Diffusion 0	Today	+0.6 [0.4, 0.7]	+0.6 [0.5, 0.7]	+0.5 [0.5, 0.6]	+0.2 [0.1, 0.2]	+0.3 [0.2, 0.4]	+0.3 [0.2, 0.3]
Diffusion 0	Tomorrow	+0.7 [0.5, 1.0]	+0.6 [0.5, 0.8]	+0.4 [0.3, 0.5]	+0.1 [0.0, 0.2]	+0.4 [0.3, 0.5]	+0.3 [0.2, 0.3]
Diffusion at bound	Today	-0.0 [-0.0, 0.0]	-0.0 [-0.0, 0.0]	+0.0 [-0.0, 0.0]	-0.0 [-0.0, 0.0]	-0.0 [-0.0, 0.0]	-0.0 [-0.0, -0.0]
Diffusion at bound	Tomorrow	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]	+0.0 [0.0, 0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, 0.0]	-0.0 [-0.0, -0.0]
Residual blending ratio 0	Today	-0.0 [-0.1, 0.1]	-0.0 [-0.1, 0.0]	+0.1 [-0.1, 0.3]	+0.0 [-0.0, 0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]
Residual blending ratio 0	Tomorrow	+0.1 [-0.1, 0.2]	+0.0 [-0.1, 0.2]	+0.1 [-0.1, 0.2]	+0.0 [-0.0, 0.1]	+0.0 [-0.0, 0.1]	+0.0 [-0.0, 0.0]
Residual blending ratio 1	Today	-0.2 [-0.4, 0.0]	-0.1 [-0.2, 0.1]	-0.2 [-0.4, 0.1]	+0.0 [-0.0, 0.0]	+0.1 [0.0, 0.1]	+0.0 [0.0, 0.1]
Residual blending ratio 1	Tomorrow	-0.3 [-0.5, 0.0]	-0.1 [-0.4, 0.1]	-0.2 [-0.4, 0.1]	-0.0 [-0.1, 0.0]	+0.0 [-0.1, 0.1]	-0.0 [-0.1, 0.0]
$a_{12} = 0$	Today	-0.3 [-0.4, -0.2]	-0.3 [-0.4, -0.2]	+0.0 [-0.1, 0.1]	+0.0 [0.0, 0.0]	-0.0 [-0.1, -0.0]	+0.0 [0.0, 0.0]
$a_{12} = 0$	Tomorrow	-0.1 [-0.2, -0.0]	+0.1 [-0.1, 0.2]	-0.2 [-0.4, 0.1]	+0.0 [-0.0, 0.1]	+0.1 [0.1, 0.2]	+0.0 [-0.0, 0.0]
$a_{12} = 0.2 \text{ h}^{-1}$	Today	+0.5 [0.4, 0.8]	+0.5 [0.3, 0.7]	+0.2 [-0.1, 0.4]	-0.0 [-0.0, -0.0]	+0.1 [0.0, 0.1]	-0.0 [-0.0, -0.0]
$a_{12} = 0.2 \text{ h}^{-1}$	Tomorrow	+0.2 [-0.0, 0.4]	-0.0 [-0.2, 0.2]	+0.5 [0.2, 0.8]	-0.0 [-0.1, 0.0]	-0.1 [-0.2, -0.1]	+0.0 [-0.0, 0.1]
Layer exchange off	Today	+1.5 [0.8, 2.2]	+1.7 [1.1, 2.4]	+2.1 [0.6, 3.6]	+0.9 [0.3, 1.5]	+2.7 [2.0, 3.5]	+1.4 [1.0, 1.8]
Layer exchange off	Tomorrow	+4.5 [2.8, 6.5]	+4.1 [2.7, 5.8]	+4.3 [2.1, 6.7]	+1.2 [0.5, 2.0]	+4.1 [3.0, 5.3]	+1.9 [1.4, 2.6]
Outer boundary blocked	Today	+2.6 [-0.4, 5.7]	+0.5 [-2.0, 3.0]	-0.5 [-2.3, 1.0]	+1.2 [0.7, 1.7]	-0.6 [-1.4, 0.1]	-1.1 [-1.8, -0.4]
Outer boundary blocked	Tomorrow	+6.1 [2.2, 10.0]	+6.1 [2.9, 9.4]	-1.5 [-5.2, 1.8]	+2.0 [1.3, 3.0]	+2.2 [0.5, 4.3]	-0.1 [-0.8, 0.5]
Upper initial scaling 0.2	Today	-1.4 [-3.0, 0.2]	-2.5 [-4.0, -1.0]	+9.9 [6.9, 13.0]	+0.0 [-0.2, 0.2]	-0.6 [-0.8, -0.4]	-0.1 [-0.5, 0.4]
Upper initial scaling 0.2	Tomorrow	-1.7 [-2.8, -0.6]	-1.5 [-2.4, -0.5]	+4.2 [1.8, 6.9]	-0.0 [-0.1, 0.0]	-0.4 [-0.6, -0.3]	-0.3 [-0.5, -0.1]

Condition	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Upper initial scaling 1	Today	-0.7 [-1.0, -0.3]	-0.7 [-1.0, -0.5]	+2.6 [1.1, 4.1]	+0.1 [-0.0, 0.2]	+0.5 [0.4, 0.7]	-0.0 [-0.1, -0.0]
Upper initial scaling 1	Tomorrow	-0.6 [-0.9, -0.3]	-0.5 [-0.8, -0.3]	+1.3 [0.3, 2.5]	+0.0 [-0.0, 0.1]	+0.2 [0.1, 0.3]	-0.0 [-0.0, -0.0]
Upper initial scaling 2	Today	+5.6 [4.2, 7.1]	+5.9 [4.5, 7.3]	+0.1 [-0.1, 0.2]	+1.0 [0.5, 1.5]	+2.9 [2.3, 3.8]	+1.9 [1.4, 2.4]
Upper initial scaling 2	Tomorrow	+2.4 [1.7, 3.3]	+2.0 [1.3, 2.7]	-0.0 [-0.1, 0.1]	+0.3 [0.1, 0.5]	+1.3 [0.9, 1.7]	+0.8 [0.5, 1.1]
Net change off	Today	+30.6 [20.9, 40.5]	+49.7 [39.5, 59.8]	+88.3 [76.3, 100.4]	+121.8 [95.9, 147.9]	+91.9 [70.4, 117.2]	+88.9 [69.5, 110.5]
Net change off	Tomorrow	+65.4 [46.6, 84.1]	+131.2 [106.9, 156.8]	+199.6 [170.2, 230.4]	+343.2 [279.6, 406.2]	+252.3 [203.0, 304.7]	+279.2 [231.2, 329.0]
Emission off	Today	+4.9 [1.5, 8.3]	+4.7 [1.0, 8.5]	+22.0 [18.7, 25.3]	+48.1 [41.7, 53.8]	+19.7 [15.9, 24.0]	+37.0 [32.1, 41.6]
Emission off	Tomorrow	+13.8 [8.4, 20.0]	+18.1 [12.7, 23.8]	+24.0 [20.2, 28.1]	+60.3 [53.0, 66.5]	+29.5 [24.0, 35.4]	+53.5 [47.7, 58.8]
Emission+net change off	Today	+19.3 [13.2, 26.1]	+15.4 [10.8, 20.2]	+45.7 [41.7, 50.1]	+38.2 [34.5, 41.5]	+10.0 [4.7, 16.9]	+9.1 [7.3, 11.1]
Emission+net change off	Tomorrow	+26.9 [20.1, 33.8]	+27.8 [22.2, 33.6]	+60.7 [55.3, 66.2]	+59.8 [54.9, 64.0]	+12.3 [8.4, 17.1]	+11.9 [9.9, 14.0]
Israel							
Surface transport (advection, diffusion) off	Today	+0.6 [-1.2, 1.8]	+0.4 [-2.2, 1.8]	-2.0 [-3.9, 0.1]	-1.7 [-3.0, -0.6]	-2.4 [-3.7, -1.3]	-5.6 [-7.8, -3.5]
Surface transport (advection, diffusion) off	Tomorrow	+0.6 [-2.6, 4.0]	+2.6 [-1.7, 9.0]	+3.5 [1.7, 5.4]	+1.3 [-0.3, 2.8]	-2.9 [-4.9, -1.1]	-3.0 [-7.4, 0.9]
Surface wind = 925–850 hPa	Today	+0.8 [-0.5, 2.4]	+0.4 [-1.8, 5.5]	+3.6 [1.5, 5.8]	+0.2 [-0.6, 1.1]	+0.8 [-0.2, 1.7]	+1.6 [-1.3, 4.5]
Surface wind = 925–850 hPa	Tomorrow	+0.5 [-1.8, 3.3]	+0.2 [-2.6, 4.3]	+1.5 [-0.0, 3.0]	+0.2 [-1.1, 1.5]	+2.6 [1.4, 4.0]	-1.6 [-6.5, 3.5]
Surface blending ratio 1 (10-m wind only)	Today	-0.0 [-0.6, 0.5]	-0.1 [-1.5, 0.5]	+0.1 [-0.3, 0.5]	-0.3 [-0.6, -0.0]	-0.1 [-0.7, 0.7]	-0.0 [-0.3, 0.3]
Surface blending ratio 1 (10-m wind only)	Tomorrow	-1.0 [-3.3, 0.3]	-1.4 [-5.6, 0.2]	+0.1 [-0.3, 0.5]	-0.2 [-0.6, 0.2]	-0.4 [-0.8, -0.0]	+0.0 [-0.8, 0.8]
Diffusion 0	Today	+0.2 [0.1, 0.3]	+0.1 [0.0, 0.3]	+0.3 [0.3, 0.4]	+0.3 [0.2, 0.4]	+0.3 [0.2, 0.5]	+0.2 [0.1, 0.3]
Diffusion 0	Tomorrow	+0.3 [0.1, 0.6]	+0.3 [0.1, 0.8]	+0.3 [0.2, 0.4]	+0.3 [0.2, 0.5]	+0.3 [0.2, 0.4]	+0.3 [0.2, 0.5]
Diffusion at bound	Today	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]	-0.1 [-0.1, -0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]
Diffusion at bound	Tomorrow	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]	-0.1 [-0.1, -0.0]	-0.0 [-0.0, -0.0]	-0.1 [-0.1, -0.0]
Residual blending ratio 0	Today	+0.0 [-0.0, 0.1]	+0.1 [-0.1, 0.2]	-0.1 [-0.2, -0.0]	-0.0 [-0.0, -0.0]	+0.0 [-0.0, 0.0]	-0.0 [-0.0, 0.0]
Residual blending ratio 0	Tomorrow	+0.1 [0.0, 0.1]	+0.2 [0.1, 0.3]	-0.0 [-0.1, 0.0]	-0.0 [-0.0, 0.0]	-0.0 [-0.0, 0.0]	-0.1 [-0.1, -0.0]
Residual blending ratio 1	Today	-0.4 [-1.1, 0.2]	-0.8 [-1.6, 0.8]	+0.3 [-0.1, 0.7]	+0.0 [0.0, 0.1]	-0.0 [-0.1, 0.0]	+0.1 [0.0, 0.2]
Residual blending ratio 1	Tomorrow	-0.4 [-0.8, -0.0]	-0.8 [-1.2, 0.0]	-0.1 [-0.4, 0.2]	+0.0 [-0.0, 0.1]	+0.0 [-0.1, 0.1]	+0.3 [0.0, 0.6]
$a_{12} = 0$	Today	-0.3 [-0.6, -0.1]	-0.4 [-1.0, 0.0]	+0.0 [-0.2, 0.2]	+0.0 [0.0, 0.0]	-0.1 [-0.2, -0.0]	-0.3 [-0.4, -0.2]
$a_{12} = 0$	Tomorrow	-0.0 [-0.5, 0.6]	+0.3 [-0.7, 2.3]	+0.0 [-0.1, 0.2]	+0.2 [0.1, 0.3]	-0.4 [-0.5, -0.2]	+1.0 [0.7, 1.3]
$a_{12} = 0.2 \text{ h}^{-1}$	Today	+0.1 [0.0, 0.3]	+0.2 [-0.0, 0.4]	+0.1 [-0.0, 0.2]	-0.0 [-0.0, -0.0]	+0.0 [0.0, 0.1]	+0.1 [0.0, 0.1]
$a_{12} = 0.2 \text{ h}^{-1}$	Tomorrow	+0.1 [-0.1, 0.3]	+0.1 [-0.7, 0.5]	+0.0 [-0.0, 0.1]	-0.0 [-0.1, -0.0]	+0.1 [0.1, 0.2]	-0.3 [-0.4, -0.2]
Layer exchange off	Today	+2.4 [1.4, 3.5]	+2.7 [1.3, 5.4]	+3.9 [2.6, 5.2]	+5.7 [4.8, 6.6]	+3.5 [2.2, 4.9]	+11.9 [10.8, 12.8]
Layer exchange off	Tomorrow	+3.9 [2.2, 5.9]	+3.2 [0.8, 7.9]	+12.8 [10.6, 15.0]	+6.2 [5.1, 7.5]	+3.1 [1.2, 5.3]	+20.4 [18.4, 22.3]
Outer boundary blocked	Today	+1.0 [0.2, 2.0]	+0.8 [-0.2, 2.0]	+2.1 [1.3, 3.1]	+1.2 [0.3, 2.2]	-2.6 [-3.9, -1.5]	+2.7 [1.9, 3.7]
Outer boundary blocked	Tomorrow	+0.7 [-2.3, 3.6]	+0.4 [-3.4, 5.7]	+2.6 [1.3, 4.1]	+9.3 [4.7, 15.0]	-3.4 [-4.6, -2.3]	+9.7 [7.4, 12.3]
Upper initial scaling 0.2	Today	+0.7 [-0.6, 1.7]	-1.5 [-5.7, 0.0]	+18.0 [14.9, 21.3]	-0.3 [-0.4, -0.3]	+0.4 [-0.3, 1.1]	-2.9 [-3.3, -2.5]

Condition	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Upper initial scaling 0.2	Tomorrow	+0.3 [-0.3, 1.0]	-0.4 [-1.2, -0.1]	+6.5 [4.8, 8.4]	-0.1 [-0.1, -0.1]	+0.1 [-0.1, 0.4]	-1.7 [-2.0, -1.4]
Upper initial scaling 1	Today	+0.7 [0.3, 1.1]	-0.4 [-1.0, -0.1]	+3.6 [2.6, 4.5]	+2.5 [2.2, 2.9]	+0.4 [0.0, 0.7]	+13.1 [11.3, 14.6]
Upper initial scaling 1	Tomorrow	+0.1 [0.0, 0.2]	-0.1 [-0.3, -0.0]	+1.8 [1.2, 2.3]	+0.6 [0.4, 0.8]	+0.0 [-0.1, 0.1]	+6.6 [5.4, 7.8]
Upper initial scaling 2	Today	+13.8 [8.8, 19.6]	+7.4 [2.8, 17.7]	+1.4 [0.2, 2.6]	+8.5 [7.5, 9.6]	+5.1 [3.3, 7.1]	+38.3 [33.5, 42.5]
Upper initial scaling 2	Tomorrow	+3.5 [2.0, 5.7]	+1.6 [0.7, 4.0]	-1.0 [-1.4, -0.5]	+1.9 [1.3, 2.5]	+0.6 [0.1, 1.3]	+19.1 [15.4, 22.6]
Net change off	Today	+29.4 [21.5, 39.0]	+32.6 [17.6, 61.9]	+77.6 [57.1, 98.9]	+103.4 [90.1, 115.8]	+52.4 [38.4, 68.1]	+94.8 [85.9, 102.4]
Net change off	Tomorrow	+68.7 [50.8, 89.8]	+78.7 [43.2, 140.9]	+254.7 [210.1, 301.3]	+271.2 [230.0, 307.6]	+162.4 [127.6, 196.2]	+213.6 [186.4, 234.2]
Emission off	Today	+7.9 [5.1, 11.4]	+1.7 [0.1, 4.2]	+56.3 [50.2, 62.3]	+17.9 [14.3, 21.0]	+29.9 [25.3, 34.5]	-26.2 [-29.6, -21.7]
Emission off	Tomorrow	+25.7 [19.0, 34.2]	+12.5 [7.4, 24.5]	+82.0 [74.4, 89.5]	+32.6 [29.2, 35.7]	+49.6 [45.2, 54.7]	-17.0 [-24.0, -8.3]
Emission+net change off	Today	+3.5 [1.4, 6.0]	+6.2 [2.5, 14.6]	+27.7 [24.1, 31.6]	+3.5 [1.7, 5.0]	+2.4 [-0.5, 4.9]	+12.6 [8.9, 15.9]
Emission+net change off	Tomorrow	+7.6 [4.4, 11.7]	+17.6 [6.7, 40.0]	+17.9 [13.4, 22.7]	+14.3 [12.2, 16.2]	+10.7 [8.5, 13.0]	-12.5 [-17.7, -7.3]
Netherlands–Rhine							
Surface transport (advection, diffusion) off	Today	+4.8 [3.1, 6.5]	+0.5 [-0.7, 1.6]	+1.5 [0.3, 2.6]	+3.8 [3.0, 4.6]	+0.0 [-0.3, 0.3]	+0.2 [-0.3, 0.8]
Surface transport (advection, diffusion) off	Tomorrow	+6.6 [4.9, 8.5]	+2.4 [1.2, 3.5]	+3.1 [1.5, 4.8]	+5.1 [4.3, 5.9]	+1.0 [0.5, 2.0]	-0.2 [-0.7, 0.4]
Surface wind = 925–850 hPa	Today	+10.0 [6.5, 13.6]	+5.4 [3.9, 7.1]	+5.2 [3.6, 6.9]	+2.9 [2.1, 3.7]	+0.2 [0.1, 0.4]	-0.3 [-1.0, 0.1]
Surface wind = 925–850 hPa	Tomorrow	+4.2 [0.7, 7.9]	+2.5 [1.0, 4.1]	+3.1 [1.7, 4.6]	+0.6 [-0.5, 1.6]	+0.1 [-0.1, 0.2]	-0.1 [-0.6, 0.3]
Surface blending ratio 1 (10-m wind only)	Today	+0.0 [0.0, 0.0]	+0.0 [-0.0, 0.0]	+0.0 [0.0, 0.0]	+0.0 [-0.0, 0.0]	+0.0 [0.0, 0.0]	+0.0 [-0.0, 0.0]
Surface blending ratio 1 (10-m wind only)	Tomorrow	+0.0 [0.0, 0.0]	+0.0 [0.0, 0.0]	+0.0 [0.0, 0.0]	+0.0 [0.0, 0.0]	+0.0 [0.0, 0.0]	+0.0 [-0.0, 0.0]
Diffusion 0	Today	+0.3 [0.3, 0.4]	+0.2 [0.2, 0.2]	+0.3 [0.3, 0.3]	+0.1 [0.0, 0.1]	+0.0 [0.0, 0.0]	+0.0 [0.0, 0.0]
Diffusion 0	Tomorrow	+0.2 [0.2, 0.3]	+0.1 [0.1, 0.2]	+0.2 [0.2, 0.2]	+0.0 [0.0, 0.1]	+0.0 [0.0, 0.0]	+0.0 [0.0, 0.0]
Diffusion at bound	Today	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, 0.0]	-0.0 [-0.0, -0.0]	+0.0 [-0.0, 0.0]	-0.0 [-0.0, -0.0]
Diffusion at bound	Tomorrow	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, 0.0]	-0.0 [-0.0, 0.0]	+0.0 [-0.0, 0.0]	-0.0 [-0.0, -0.0]
Residual blending ratio 0	Today	-0.0 [-0.1, 0.1]	+0.0 [-0.0, 0.1]	-0.1 [-0.2, -0.0]	-0.0 [-0.1, -0.0]	-0.0 [-0.0, 0.0]	-0.0 [-0.0, 0.0]
Residual blending ratio 0	Tomorrow	+0.0 [-0.1, 0.2]	+0.0 [-0.0, 0.1]	-0.1 [-0.2, 0.0]	-0.1 [-0.1, -0.0]	+0.0 [-0.0, 0.0]	-0.0 [-0.0, 0.0]
Residual blending ratio 1	Today	+0.1 [-0.0, 0.2]	+0.1 [-0.1, 0.2]	+0.2 [0.0, 0.5]	+0.1 [0.0, 0.1]	+0.0 [-0.0, 0.0]	-0.0 [-0.0, 0.0]
Residual blending ratio 1	Tomorrow	+0.0 [-0.2, 0.2]	-0.0 [-0.2, 0.1]	+0.1 [-0.0, 0.3]	+0.1 [0.0, 0.1]	+0.0 [-0.0, 0.0]	+0.0 [0.0, 0.0]
$a_{12} = 0$	Today	+0.0 [-0.1, 0.2]	-0.0 [-0.1, 0.0]	+0.2 [0.1, 0.4]	+0.1 [0.1, 0.1]	-0.0 [-0.0, 0.0]	+0.0 [0.0, 0.0]
$a_{12} = 0$	Tomorrow	+0.2 [-0.0, 0.3]	+0.2 [0.1, 0.3]	+1.2 [0.7, 1.6]	+0.4 [0.3, 0.5]	+0.0 [-0.0, 0.0]	+0.1 [0.0, 0.1]
$a_{12} = 0.2 \text{ h}^{-1}$	Today	+0.1 [-0.1, 0.3]	+0.1 [0.0, 0.3]	-0.0 [-0.2, 0.2]	-0.2 [-0.2, -0.1]	+0.0 [-0.0, 0.0]	-0.0 [-0.0, 0.0]
$a_{12} = 0.2 \text{ h}^{-1}$	Tomorrow	-0.2 [-0.4, 0.0]	-0.2 [-0.4, -0.0]	-0.2 [-0.6, 0.3]	-0.4 [-0.5, -0.3]	-0.0 [-0.0, 0.0]	-0.1 [-0.1, -0.0]
Layer exchange off	Today	+3.3 [2.5, 4.2]	+2.3 [1.7, 2.8]	+18.1 [15.8, 20.5]	+6.5 [5.5, 7.5]	+0.1 [0.0, 0.2]	+2.6 [1.6, 4.4]
Layer exchange off	Tomorrow	+8.1 [5.8, 10.6]	+4.6 [3.1, 6.0]	+24.5 [21.7, 27.4]	+7.5 [6.2, 8.7]	+0.2 [0.1, 0.4]	+3.5 [2.0, 5.9]
Outer boundary blocked	Today	+0.3 [-0.8, 1.2]	-0.9 [-1.9, -0.1]	+0.2 [-0.5, 0.9]	+0.4 [-0.0, 0.9]	+0.0 [-0.2, 0.3]	+0.7 [0.2, 1.5]
Outer boundary blocked	Tomorrow	+3.1 [1.8, 4.4]	+2.5 [1.2, 3.6]	+1.9 [0.8, 3.1]	+1.9 [1.3, 2.5]	+0.9 [0.3, 1.8]	+0.7 [0.2, 1.4]

Condition	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Upper initial scaling 0.2	Today	+1.1 [-0.1, 2.4]	-0.2 [-0.9, 0.6]	+27.5 [21.9, 33.6]	-0.5 [-0.6, -0.3]	+0.0 [0.0, 0.0]	-0.2 [-0.4, -0.0]
Upper initial scaling 0.2	Tomorrow	-0.6 [-1.7, 0.6]	-0.5 [-1.0, 0.0]	+6.4 [4.2, 9.0]	-0.1 [-0.1, -0.1]	+0.0 [-0.0, 0.0]	-0.1 [-0.3, -0.0]
Upper initial scaling 1	Today	-0.1 [-0.3, 0.1]	-0.1 [-0.2, -0.1]	+9.5 [7.4, 11.8]	+1.7 [1.3, 2.2]	-0.0 [-0.0, 0.0]	+0.9 [0.5, 1.6]
Upper initial scaling 1	Tomorrow	-0.3 [-0.5, -0.0]	-0.1 [-0.2, -0.0]	+2.4 [1.6, 3.5]	+0.3 [0.2, 0.5]	+0.0 [-0.0, 0.0]	+0.4 [0.2, 0.8]
Upper initial scaling 2	Today	+3.1 [2.1, 4.2]	+3.5 [2.9, 4.3]	-0.5 [-0.8, -0.3]	+5.7 [4.4, 7.2]	+0.0 [-0.0, 0.1]	+4.4 [2.6, 7.3]
Upper initial scaling 2	Tomorrow	+2.2 [1.2, 3.2]	+1.4 [0.9, 1.9]	-0.3 [-0.5, -0.2]	+0.9 [0.6, 1.3]	+0.0 [-0.0, 0.0]	+1.7 [0.9, 3.0]
Net change off	Today	+8.9 [6.9, 10.9]	+14.2 [12.0, 16.2]	+82.0 [75.6, 88.8]	+91.3 [74.9, 108.9]	+7.5 [4.3, 12.6]	+10.5 [6.0, 17.6]
Net change off	Tomorrow	+12.2 [9.4, 15.0]	+29.2 [23.5, 34.7]	+214.9 [197.7, 232.3]	+248.0 [199.7, 298.2]	+30.3 [18.3, 48.3]	+38.5 [22.6, 60.6]
Emission off	Today	+0.8 [-0.2, 1.7]	+1.0 [-0.3, 2.3]	+27.6 [23.8, 31.3]	+22.2 [17.2, 27.1]	+2.7 [1.8, 4.2]	+3.9 [2.1, 6.4]
Emission off	Tomorrow	+0.9 [-1.5, 3.2]	+3.4 [1.0, 6.0]	+33.9 [28.7, 38.9]	+30.8 [24.2, 36.8]	+3.6 [2.4, 5.6]	+11.0 [6.4, 17.2]
Emission+net change off	Today	+10.4 [8.4, 12.4]	+8.7 [7.2, 10.3]	+38.3 [34.3, 42.2]	+13.6 [10.9, 16.3]	+0.8 [0.5, 1.3]	+1.0 [0.2, 2.0]
Emission+net change off	Tomorrow	+18.8 [14.9, 22.8]	+17.0 [14.2, 19.9]	+69.6 [63.4, 75.6]	+22.8 [19.0, 26.8]	+1.0 [0.5, 1.7]	+2.1 [0.8, 4.0]
Southern California							
Surface transport (advection, diffusion) off	Today	+1.8 [0.4, 3.4]	-0.4 [-1.2, 0.7]	+11.4 [7.3, 15.5]	+15.5 [13.2, 18.3]	+0.8 [-2.1, 4.1]	+19.2 [15.3, 23.4]
Surface transport (advection, diffusion) off	Tomorrow	+7.3 [2.7, 12.6]	+1.2 [-0.1, 3.3]	+38.4 [27.1, 49.3]	+25.1 [21.2, 29.8]	+1.0 [-1.7, 4.2]	+31.1 [24.9, 37.7]
Surface wind = 925–850 hPa	Today	+4.0 [2.0, 6.0]	+1.3 [0.8, 2.1]	+7.5 [4.6, 10.8]	+1.0 [-0.7, 2.8]	-0.9 [-3.9, 2.6]	-3.9 [-6.1, -2.2]
Surface wind = 925–850 hPa	Tomorrow	+1.5 [-1.4, 4.6]	+1.1 [0.6, 1.9]	+15.6 [10.0, 21.7]	+1.3 [-1.0, 3.6]	-1.3 [-4.9, 2.9]	-2.4 [-4.0, -1.0]
Surface blending ratio 1 (10-m wind only)	Today	+0.1 [0.0, 0.2]	+0.0 [-0.0, 0.1]	+0.0 [-0.1, 0.1]	-0.1 [-0.1, -0.0]	+0.0 [-0.0, 0.1]	+0.1 [-0.0, 0.1]
Surface blending ratio 1 (10-m wind only)	Tomorrow	+0.1 [0.0, 0.2]	+0.0 [0.0, 0.1]	-0.1 [-0.2, -0.0]	-0.1 [-0.1, 0.0]	+0.0 [-0.1, 0.1]	+0.1 [-0.0, 0.1]
Diffusion 0	Today	+0.3 [0.2, 0.5]	+0.1 [0.1, 0.1]	+0.5 [0.5, 0.6]	+0.6 [0.5, 0.7]	+0.1 [0.0, 0.1]	+2.1 [1.5, 2.8]
Diffusion 0	Tomorrow	+0.4 [0.2, 0.6]	+0.1 [0.1, 0.1]	+0.4 [0.3, 0.4]	+0.7 [0.6, 0.8]	+0.1 [0.0, 0.2]	+1.5 [1.1, 2.0]
Diffusion at bound	Today	-0.0 [-0.0, 0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, 0.0]	-0.0 [-0.0, -0.0]
Diffusion at bound	Tomorrow	+0.0 [-0.0, 0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, 0.0]	-0.0 [-0.0, 0.0]	-0.0 [-0.0, -0.0]
Residual blending ratio 0	Today	-0.2 [-0.3, -0.1]	-0.0 [-0.0, 0.0]	-0.3 [-0.4, -0.1]	-0.2 [-0.2, -0.1]	+0.0 [-0.0, 0.0]	-0.0 [-0.1, -0.0]
Residual blending ratio 0	Tomorrow	-0.2 [-0.4, -0.1]	+0.1 [0.0, 0.1]	-0.1 [-0.2, 0.1]	-0.3 [-0.3, -0.2]	-0.0 [-0.0, 0.0]	-0.1 [-0.1, -0.0]
Residual blending ratio 1	Today	+0.4 [0.2, 0.6]	+0.0 [-0.0, 0.1]	+0.4 [0.2, 0.6]	+0.3 [0.3, 0.4]	+0.0 [-0.1, 0.1]	+0.1 [0.1, 0.2]
Residual blending ratio 1	Tomorrow	+0.6 [0.3, 0.9]	-0.1 [-0.2, -0.0]	+0.0 [-0.1, 0.1]	+0.5 [0.4, 0.6]	+0.0 [-0.1, 0.1]	+0.1 [0.0, 0.2]
$a_{12} = 0$	Today	+0.2 [0.1, 0.3]	-0.0 [-0.1, 0.0]	-0.3 [-0.3, -0.2]	+0.1 [0.1, 0.1]	-0.0 [-0.0, 0.0]	+0.1 [0.1, 0.1]
$a_{12} = 0$	Tomorrow	+0.5 [0.4, 0.7]	-0.1 [-0.1, -0.0]	-0.5 [-0.7, -0.2]	+0.6 [0.5, 0.7]	-0.0 [-0.1, 0.0]	+0.3 [0.2, 0.4]
$a_{12} = 0.2 \text{ h}^{-1}$	Today	-0.3 [-0.4, -0.2]	+0.0 [-0.0, 0.1]	+0.9 [0.7, 1.1]	-0.2 [-0.2, -0.1]	+0.0 [-0.0, 0.1]	-0.1 [-0.1, -0.1]
$a_{12} = 0.2 \text{ h}^{-1}$	Tomorrow	-0.5 [-0.7, -0.3]	+0.1 [0.0, 0.1]	+1.3 [1.0, 1.6]	-0.4 [-0.5, -0.4]	+0.0 [-0.0, 0.1]	-0.2 [-0.3, -0.2]
Layer exchange off	Today	+1.9 [1.3, 2.7]	+0.6 [0.3, 1.1]	-0.6 [-1.4, 0.3]	+6.5 [5.7, 7.4]	+0.5 [-0.0, 1.1]	+4.3 [3.5, 5.2]
Layer exchange off	Tomorrow	+5.5 [3.9, 7.3]	+0.4 [0.1, 1.0]	+3.7 [2.6, 4.9]	+7.8 [6.8, 9.0]	+0.6 [-0.2, 1.4]	+5.3 [4.3, 6.4]
Outer boundary blocked	Today	+1.1 [0.4, 1.7]	-0.0 [-0.3, 0.3]	+2.7 [1.9, 3.6]	+3.7 [2.7, 4.7]	-1.6 [-2.9, -0.4]	-0.1 [-0.5, 0.4]

Condition	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Outer boundary blocked	Tomorrow	+6.2 [4.2, 8.9]	+0.5 [-0.1, 1.4]	+12.9 [9.0, 17.1]	+5.8 [4.3, 7.7]	-1.7 [-3.4, 0.1]	+1.0 [0.2, 1.9]
Upper initial scaling 0.2	Today	-3.6 [-4.7, -2.6]	+1.3 [0.8, 1.8]	+8.4 [6.5, 10.3]	-0.8 [-0.9, -0.7]	+0.1 [-0.2, 0.4]	-0.9 [-1.1, -0.7]
Upper initial scaling 0.2	Tomorrow	-4.2 [-5.7, -2.7]	+0.9 [0.6, 1.4]	+9.1 [7.0, 11.2]	-0.5 [-0.6, -0.4]	+0.1 [-0.1, 0.2]	-0.8 [-1.0, -0.6]
Upper initial scaling 1	Today	+0.3 [0.2, 0.4]	+0.0 [-0.0, 0.0]	-0.3 [-1.3, 0.7]	+3.6 [3.2, 4.0]	+0.0 [-0.0, 0.0]	+3.8 [3.1, 4.5]
Upper initial scaling 1	Tomorrow	+0.3 [0.2, 0.4]	-0.0 [-0.0, 0.0]	+2.7 [1.9, 3.5]	+1.9 [1.6, 2.3]	-0.0 [-0.0, 0.0]	+2.8 [2.2, 3.3]
Upper initial scaling 2	Today	+8.5 [6.6, 10.5]	+0.4 [-0.1, 1.1]	+1.6 [1.3, 2.0]	+11.1 [10.0, 12.2]	+0.0 [-0.4, 0.4]	+13.6 [11.6, 15.9]
Upper initial scaling 2	Tomorrow	+8.3 [5.8, 10.7]	-0.2 [-0.6, 0.2]	-0.1 [-0.3, 0.1]	+5.4 [4.6, 6.2]	-0.1 [-0.3, 0.1]	+8.7 [7.1, 10.3]
Net change off	Today	+17.0 [11.6, 22.0]	+7.9 [4.4, 13.8]	+47.1 [40.4, 54.1]	+211.4 [189.7, 228.8]	+45.2 [23.8, 66.3]	+103.3 [89.3, 116.6]
Net change off	Tomorrow	+33.7 [23.1, 43.0]	+28.4 [18.5, 44.1]	+161.1 [136.1, 185.2]	+455.8 [398.6, 502.4]	+158.5 [97.8, 216.7]	+247.5 [217.2, 277.3]
Emission off	Today	-8.5 [-11.0, -6.0]	+5.5 [3.8, 8.0]	+27.3 [22.9, 31.4]	+24.2 [17.0, 30.2]	+21.0 [9.4, 32.2]	+18.6 [13.5, 24.0]
Emission off	Tomorrow	-9.4 [-13.3, -5.6]	+12.7 [8.9, 18.4]	+54.1 [48.2, 59.9]	+54.1 [47.2, 60.8]	+26.5 [13.6, 39.4]	+53.7 [43.6, 63.7]
Emission+net change off	Today	+1.6 [-1.0, 3.9]	+0.0 [-0.9, 1.1]	+24.0 [20.8, 26.8]	+1.9 [-1.6, 5.2]	+2.3 [-1.5, 5.9]	+5.6 [1.6, 9.0]
Emission+net change off	Tomorrow	-1.9 [-5.4, 1.3]	+2.7 [1.1, 4.5]	+30.7 [27.6, 33.7]	+11.7 [7.4, 15.9]	+5.1 [-1.2, 11.1]	+4.2 [0.2, 8.1]

S7 Seed control

Supplementary Table S7a: Seed control: held-out ΔRMSE (%), relative to seed0) with 95% block interval of the original model retrained from scratch with the same settings and only the seed changed (seed1).

Region	Year	Forecasts	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Taiwan	2024	364	Today	-0.4 [-1.5, 0.5]	-1.8 [-3.5, -0.4]	-1.6 [-2.5, -0.7]	-0.2 [-0.7, 0.1]	-1.1 [-1.7, -0.6]	-0.2 [-0.5, 0.1]
Taiwan	2024	364	Tomorrow	-0.2 [-1.5, 1.0]	-1.1 [-2.4, 0.2]	-1.3 [-2.7, 0.1]	-0.3 [-0.8, 0.2]	-1.3 [-2.1, -0.6]	-0.2 [-0.5, 0.2]
Taiwan	2023	363	Today	-0.6 [-1.3, 0.0]	-1.6 [-2.4, -0.7]	-1.2 [-2.1, -0.4]	+0.1 [-0.4, 0.4]	-0.8 [-1.3, -0.3]	+0.1 [-0.2, 0.4]
Taiwan	2023	363	Tomorrow	-0.3 [-1.1, 0.5]	-0.5 [-1.4, 0.4]	-1.7 [-3.7, -0.1]	+0.0 [-0.4, 0.4]	-0.6 [-1.4, 0.3]	+0.2 [-0.1, 0.5]
Southern California	2024	363	Today	+0.1 [-1.5, 1.5]	-0.6 [-1.1, -0.2]	-0.9 [-1.4, -0.4]	-1.9 [-2.6, -1.2]	+0.1 [-0.3, 0.5]	-0.1 [-1.0, 0.7]
Southern California	2024	363	Tomorrow	-2.7 [-5.3, -0.5]	-0.5 [-1.4, 0.1]	-0.7 [-1.3, -0.1]	-2.2 [-3.1, -1.4]	+0.3 [-0.2, 0.8]	+0.5 [-0.8, 2.0]
Southern California	2023	362	Today	+1.1 [0.1, 2.9]	+0.2 [-0.4, 0.8]	-1.2 [-1.5, -0.7]	-0.8 [-1.4, -0.1]	-0.0 [-0.3, 0.3]	+0.2 [-0.8, 1.1]
Southern California	2023	362	Tomorrow	-0.1 [-2.7, 1.0]	-0.1 [-0.9, 0.7]	-1.8 [-2.3, -1.2]	-0.9 [-1.7, -0.2]	-0.1 [-0.4, 0.3]	-0.2 [-1.4, 1.0]

Supplementary Table S7b: Component swaps between seeds (2024). "seed1 part in seed0" puts one component of seed1 into the seed0 model; "seed0 part in seed1" is the reverse. All values are held-out ΔRMSE (%) relative to seed0 with 95% block intervals. The seed-swap reference in the main text (at most 3.7%) comes from the interval ends of the Taiwan rows.

Direction	Component	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Taiwan								
seed1 part in seed0	Transport	Today	-0.2 [-0.4, 0.0]	+0.0 [-0.2, 0.2]	-0.1 [-0.3, 0.1]	+0.0 [-0.0, 0.1]	-0.0 [-0.1, 0.1]	-0.1 [-0.1, 0.0]
seed1 part in seed0	Transport	Tomorrow	-0.1 [-0.5, 0.3]	+0.0 [-0.4, 0.4]	-0.2 [-0.4, -0.0]	+0.0 [-0.0, 0.1]	+0.1 [0.0, 0.3]	-0.0 [-0.1, 0.2]
seed1 part in seed0	Net change k	Today	+1.7 [0.5, 3.0]	+0.8 [-1.0, 2.5]	-1.4 [-2.2, -0.7]	-0.1 [-0.5, 0.3]	-1.3 [-1.9, -0.8]	-0.0 [-0.3, 0.2]
seed1 part in seed0	Net change k	Tomorrow	+2.5 [1.3, 3.7]	+1.8 [0.3, 3.3]	-1.6 [-2.5, -0.8]	-0.2 [-0.7, 0.2]	-2.1 [-2.9, -1.4]	-0.1 [-0.3, 0.2]
seed1 part in seed0	Emission	Today	-1.2 [-1.8, -0.6]	-1.8 [-2.4, -1.2]	-0.1 [-0.4, 0.1]	-0.1 [-0.2, -0.0]	-0.1 [-0.2, -0.1]	-0.1 [-0.2, -0.1]
seed1 part in seed0	Emission	Tomorrow	-1.4 [-2.3, -0.6]	-1.9 [-2.7, -1.2]	+0.1 [-0.1, 0.4]	-0.0 [-0.2, 0.1]	+0.2 [0.1, 0.3]	-0.1 [-0.2, 0.0]
seed1 part in seed0	Emission+ k	Today	+0.0 [-1.2, 1.2]	-1.4 [-3.2, 0.2]	-1.7 [-2.6, -0.9]	-0.2 [-0.8, 0.2]	-1.5 [-2.2, -1.0]	-0.2 [-0.5, 0.0]
seed1 part in seed0	Emission+ k	Tomorrow	+0.4 [-0.8, 1.6]	-0.7 [-2.2, 0.6]	-1.8 [-2.7, -1.0]	-0.3 [-0.9, 0.1]	-2.1 [-2.8, -1.5]	-0.3 [-0.6, -0.0]
seed1 part in seed0	Layer exchange	Today	+0.1 [0.0, 0.1]	+0.0 [0.0, 0.1]	+0.0 [-0.0, 0.0]	-0.0 [-0.0, 0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]
seed1 part in seed0	Layer exchange	Tomorrow	+0.0 [0.0, 0.0]	+0.0 [-0.0, 0.0]	+0.0 [0.0, 0.1]	+0.0 [-0.0, 0.0]	-0.0 [-0.0, -0.0]	+0.0 [-0.0, 0.0]
seed1 part in seed0	a_{12}	Today	-0.0 [-0.0, -0.0]	-0.0 [-0.0, -0.0]	-0.0 [-0.0, 0.0]	+0.0 [-0.0, 0.0]	+0.0 [-0.0, 0.0]	+0.0 [0.0, 0.0]
seed1 part in seed0	a_{12}	Tomorrow	-0.0 [-0.0, 0.0]	+0.0 [-0.0, 0.0]	+0.0 [-0.0, 0.0]	-0.0 [-0.0, 0.0]	+0.0 [0.0, 0.0]	-0.0 [-0.0, 0.0]
seed1 part in seed0	Upper initial scaling	Today	-0.1 [-0.1, -0.0]	-0.2 [-0.3, -0.2]	+0.0 [-0.0, 0.0]	+0.0 [-0.0, 0.1]	+0.0 [0.0, 0.0]	+0.0 [0.0, 0.0]
seed1 part in seed0	Upper initial scaling	Tomorrow	+0.0 [-0.0, 0.0]	-0.1 [-0.1, -0.0]	-0.0 [-0.0, 0.0]	+0.0 [-0.0, 0.0]	+0.0 [0.0, 0.0]	+0.0 [0.0, 0.0]

Direction	Component	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
seed1 part in seed0	Outer model	Today	+0.0 [-0.6, 0.6]	+0.1 [-0.5, 0.6]	+0.3 [0.1, 0.6]	-0.0 [-0.1, 0.0]	+0.5 [0.3, 0.9]	+0.2 [0.0, 0.3]
seed1 part in seed0	Outer model	Tomorrow	-0.2 [-1.3, 0.8]	+0.2 [-0.9, 1.3]	+0.7 [-0.4, 1.9]	+0.0 [-0.1, 0.1]	+0.8 [0.5, 1.3]	+0.3 [0.1, 0.5]
seed0 part in seed1	Transport	Today	-0.1 [-1.2, 0.8]	-1.7 [-3.4, -0.3]	-1.4 [-2.3, -0.6]	-0.3 [-0.8, 0.1]	-1.2 [-1.8, -0.7]	-0.1 [-0.4, 0.2]
seed0 part in seed1	Transport	Tomorrow	+0.0 [-1.1, 1.1]	-1.0 [-2.3, 0.1]	-1.1 [-2.5, 0.3]	-0.3 [-0.9, 0.1]	-1.4 [-2.3, -0.7]	-0.2 [-0.5, 0.2]
seed0 part in seed1	Net change k	Today	-1.2 [-2.1, -0.3]	-1.8 [-2.6, -1.0]	+0.1 [-0.3, 0.5]	-0.1 [-0.2, 0.0]	+0.5 [0.2, 0.8]	-0.0 [-0.2, 0.2]
seed0 part in seed1	Net change k	Tomorrow	-1.6 [-3.0, -0.0]	-1.6 [-2.8, -0.3]	+0.9 [-0.3, 2.1]	+0.0 [-0.1, 0.2]	+1.2 [0.8, 1.7]	+0.1 [-0.2, 0.3]
seed0 part in seed1	Emission	Today	+1.2 [0.1, 2.3]	+0.3 [-1.4, 1.9]	-1.2 [-2.0, -0.4]	-0.0 [-0.5, 0.3]	-0.9 [-1.5, -0.4]	+0.0 [-0.3, 0.3]
seed0 part in seed1	Emission	Tomorrow	+1.8 [0.5, 3.1]	+1.4 [-0.0, 3.1]	-1.1 [-2.5, 0.4]	-0.2 [-0.7, 0.2]	-1.3 [-2.2, -0.6]	+0.1 [-0.3, 0.4]
seed0 part in seed1	Emission+ k	Today	-0.1 [-0.8, 0.6]	-0.1 [-0.6, 0.5]	+0.3 [-0.1, 0.7]	+0.1 [-0.1, 0.2]	+0.6 [0.3, 0.9]	+0.1 [-0.1, 0.3]
seed0 part in seed1	Emission+ k	Tomorrow	-0.2 [-1.5, 0.9]	+0.3 [-0.9, 1.5]	+0.7 [-0.4, 1.9]	+0.1 [-0.1, 0.2]	+1.1 [0.6, 1.5]	+0.2 [-0.0, 0.4]
seed0 part in seed1	Layer exchange	Today	-0.5 [-1.6, 0.4]	-1.9 [-3.6, -0.5]	-1.6 [-2.5, -0.7]	-0.2 [-0.7, 0.1]	-1.1 [-1.7, -0.6]	-0.2 [-0.5, 0.1]
seed0 part in seed1	Layer exchange	Tomorrow	-0.2 [-1.5, 0.9]	-1.1 [-2.4, 0.2]	-1.3 [-2.8, 0.1]	-0.3 [-0.9, 0.2]	-1.3 [-2.1, -0.6]	-0.1 [-0.5, 0.2]
seed0 part in seed1	a_{12}	Today	-0.4 [-1.5, 0.5]	-1.8 [-3.5, -0.4]	-1.6 [-2.5, -0.7]	-0.2 [-0.7, 0.1]	-1.1 [-1.7, -0.6]	-0.2 [-0.5, 0.1]
seed0 part in seed1	a_{12}	Tomorrow	-0.2 [-1.5, 1.0]	-1.1 [-2.4, 0.2]	-1.3 [-2.7, 0.1]	-0.3 [-0.8, 0.2]	-1.3 [-2.1, -0.6]	-0.2 [-0.5, 0.2]
seed0 part in seed1	Upper initial scaling	Today	-0.4 [-1.4, 0.5]	-1.6 [-3.3, -0.2]	-1.6 [-2.5, -0.7]	-0.2 [-0.8, 0.2]	-1.2 [-1.8, -0.7]	-0.2 [-0.5, 0.1]
seed0 part in seed1	Upper initial scaling	Tomorrow	-0.2 [-1.5, 1.0]	-1.0 [-2.3, 0.3]	-1.3 [-2.7, 0.2]	-0.3 [-0.9, 0.2]	-1.3 [-2.1, -0.6]	-0.2 [-0.6, 0.2]
seed0 part in seed1	Outer model	Today	-0.2 [-1.4, 0.8]	-1.6 [-3.5, -0.1]	-1.9 [-2.7, -1.1]	-0.2 [-0.7, 0.2]	-1.5 [-2.1, -1.0]	-0.3 [-0.6, -0.0]
seed0 part in seed1	Outer model	Tomorrow	+0.3 [-1.0, 1.4]	-0.7 [-2.2, 0.7]	-1.9 [-2.8, -1.0]	-0.2 [-0.8, 0.2]	-1.9 [-2.6, -1.3]	-0.3 [-0.7, 0.0]
Southern California								
seed1 part in seed0	Transport	Today	-0.1 [-0.3, -0.0]	-0.0 [-0.1, 0.0]	-0.0 [-0.1, 0.1]	+0.2 [0.2, 0.3]	+0.0 [-0.2, 0.2]	+0.6 [0.4, 0.9]
seed1 part in seed0	Transport	Tomorrow	-0.1 [-0.2, 0.1]	-0.0 [-0.1, 0.0]	+0.3 [0.2, 0.5]	+0.2 [0.1, 0.3]	+0.0 [-0.2, 0.3]	+0.5 [0.3, 0.8]
seed1 part in seed0	Net change k	Today	+0.7 [-0.9, 2.1]	-0.4 [-0.8, 0.0]	-2.6 [-3.2, -2.0]	-4.3 [-4.9, -3.6]	+0.1 [-1.1, 1.3]	-3.0 [-4.2, -1.9]
seed1 part in seed0	Net change k	Tomorrow	-3.6 [-6.0, -1.6]	-0.4 [-1.2, 0.1]	-0.8 [-1.7, 0.0]	-5.8 [-6.6, -4.9]	+0.2 [-1.2, 1.5]	-6.9 [-8.8, -5.0]
seed1 part in seed0	Emission	Today	+0.5 [0.2, 0.8]	+0.0 [-0.1, 0.1]	+4.5 [4.1, 5.0]	+5.2 [4.3, 5.9]	+0.7 [-0.7, 2.2]	+8.0 [5.9, 9.9]
seed1 part in seed0	Emission	Tomorrow	+2.5 [1.7, 3.3]	+0.2 [0.1, 0.3]	+6.7 [5.7, 7.7]	+6.8 [6.1, 7.5]	+0.7 [-0.9, 2.4]	+15.3 [13.0, 17.5]
seed1 part in seed0	Emission+ k	Today	+0.5 [-1.1, 2.0]	-0.5 [-0.9, -0.1]	-0.7 [-1.2, -0.3]	-1.8 [-2.5, -1.1]	-0.0 [-0.4, 0.3]	-0.5 [-1.4, 0.4]
seed1 part in seed0	Emission+ k	Tomorrow	-1.6 [-4.0, 0.6]	-0.3 [-1.0, 0.3]	-0.7 [-1.2, -0.1]	-2.0 [-2.9, -1.2]	-0.1 [-0.4, 0.3]	+0.4 [-1.0, 1.8]
seed1 part in seed0	Layer exchange	Today	-0.1 [-0.1, -0.0]	-0.0 [-0.0, -0.0]	+0.2 [0.2, 0.3]	-0.2 [-0.3, -0.2]	-0.0 [-0.0, 0.0]	-0.1 [-0.2, -0.1]
seed1 part in seed0	Layer exchange	Tomorrow	-0.2 [-0.3, -0.1]	+0.0 [-0.0, 0.0]	+0.2 [0.2, 0.3]	-0.3 [-0.4, -0.3]	-0.0 [-0.1, 0.0]	-0.2 [-0.3, -0.2]
seed1 part in seed0	a_{12}	Today	-0.0 [-0.0, -0.0]	+0.0 [-0.0, 0.0]	+0.0 [0.0, 0.0]	-0.0 [-0.0, -0.0]	+0.0 [-0.0, 0.0]	-0.0 [-0.0, -0.0]
seed1 part in seed0	a_{12}	Tomorrow	-0.0 [-0.0, -0.0]	+0.0 [0.0, 0.0]	+0.0 [0.0, 0.0]	-0.0 [-0.0, -0.0]	+0.0 [-0.0, 0.0]	-0.0 [-0.0, -0.0]
seed1 part in seed0	Upper initial scaling	Today	-0.2 [-0.2, -0.1]	-0.1 [-0.2, 0.0]	-0.1 [-0.1, -0.0]	+0.0 [0.0, 0.0]	-0.0 [-0.1, 0.1]	+0.0 [0.0, 0.0]
seed1 part in seed0	Upper initial scaling	Tomorrow	-0.2 [-0.2, -0.1]	-0.1 [-0.2, -0.1]	+0.0 [0.0, 0.0]	+0.0 [0.0, 0.0]	-0.0 [-0.0, 0.0]	+0.0 [0.0, 0.0]
seed1 part in seed0	Outer model	Today	+0.0 [-0.0, 0.1]	-0.0 [-0.0, 0.0]	-0.2 [-0.3, -0.2]	-0.0 [-0.1, -0.0]	+0.2 [-0.1, 0.4]	+0.0 [0.0, 0.1]
seed1 part in seed0	Outer model	Tomorrow	-0.4 [-0.8, -0.2]	-0.0 [-0.2, 0.0]	-0.3 [-0.5, 0.0]	-0.0 [-0.1, -0.0]	+0.4 [0.1, 0.7]	+0.1 [-0.0, 0.1]
seed0 part in seed1	Transport	Today	+0.2 [-1.4, 1.7]	-0.6 [-1.1, -0.2]	-0.9 [-1.4, -0.4]	-2.0 [-2.8, -1.4]	+0.1 [-0.3, 0.6]	-0.6 [-1.5, 0.3]
seed0 part in seed1	Transport	Tomorrow	-2.5 [-5.1, -0.3]	-0.5 [-1.4, 0.1]	-1.0 [-1.7, -0.4]	-2.4 [-3.3, -1.6]	+0.3 [-0.1, 0.7]	+0.1 [-1.2, 1.5]

Direction	Component	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
seed0 part in seed1	Net change k	Today	+0.0 [-0.3, 0.3]	-0.2 [-0.3, -0.0]	+4.4 [3.9, 4.9]	+5.1 [4.3, 5.8]	+0.9 [-0.5, 2.4]	+8.5 [6.5, 10.3]
seed0 part in seed1	Net change k	Tomorrow	+1.4 [0.5, 2.2]	-0.0 [-0.2, 0.1]	+6.7 [5.7, 7.8]	+6.7 [5.9, 7.4]	+1.1 [-0.5, 2.9]	+15.4 [13.1, 17.5]
seed0 part in seed1	Emission	Today	+0.2 [-1.4, 1.7]	-0.5 [-1.0, -0.1]	-2.8 [-3.4, -2.2]	-4.3 [-5.0, -3.6]	+0.2 [-1.1, 1.5]	-2.6 [-3.8, -1.5]
seed0 part in seed1	Emission	Tomorrow	-4.7 [-7.2, -2.5]	-0.6 [-1.5, 0.0]	-1.1 [-1.9, -0.1]	-5.9 [-6.8, -5.1]	+0.6 [-0.9, 2.0]	-6.7 [-8.6, -4.8]
seed0 part in seed1	Emission+ k	Today	-0.5 [-0.7, -0.3]	-0.1 [-0.3, -0.0]	-0.2 [-0.3, -0.0]	-0.0 [-0.1, 0.1]	+0.2 [-0.1, 0.4]	+0.5 [0.3, 0.8]
seed0 part in seed1	Emission+ k	Tomorrow	-1.1 [-1.5, -0.7]	-0.2 [-0.4, -0.1]	-0.0 [-0.3, 0.3]	-0.1 [-0.2, -0.0]	+0.4 [0.0, 0.7]	+0.1 [-0.1, 0.4]
seed0 part in seed1	Layer exchange	Today	+0.2 [-1.4, 1.6]	-0.6 [-1.1, -0.2]	-1.1 [-1.6, -0.6]	-1.6 [-2.4, -1.0]	+0.1 [-0.3, 0.5]	+0.0 [-0.9, 0.9]
seed0 part in seed1	Layer exchange	Tomorrow	-2.5 [-5.0, -0.3]	-0.5 [-1.4, 0.1]	-1.0 [-1.6, -0.4]	-1.9 [-2.8, -1.1]	+0.3 [-0.2, 0.8]	+0.7 [-0.6, 2.2]
seed0 part in seed1	a_{12}	Today	+0.1 [-1.5, 1.6]	-0.6 [-1.1, -0.2]	-0.9 [-1.4, -0.4]	-1.8 [-2.6, -1.2]	+0.1 [-0.3, 0.5]	-0.1 [-1.0, 0.7]
seed0 part in seed1	a_{12}	Tomorrow	-2.7 [-5.3, -0.5]	-0.5 [-1.4, 0.1]	-0.8 [-1.4, -0.2]	-2.2 [-3.1, -1.4]	+0.3 [-0.2, 0.8]	+0.5 [-0.7, 2.0]
seed0 part in seed1	Upper initial scaling	Today	+0.2 [-1.4, 1.7]	-0.5 [-1.0, -0.1]	-0.8 [-1.3, -0.4]	-1.9 [-2.6, -1.2]	+0.1 [-0.3, 0.5]	-0.1 [-1.0, 0.7]
seed0 part in seed1	Upper initial scaling	Tomorrow	-2.6 [-5.1, -0.4]	-0.4 [-1.2, 0.2]	-0.7 [-1.3, -0.1]	-2.2 [-3.1, -1.4]	+0.3 [-0.2, 0.8]	+0.5 [-0.8, 2.0]
seed0 part in seed1	Outer model	Today	+0.1 [-1.5, 1.5]	-0.6 [-1.1, -0.2]	-0.7 [-1.1, -0.2]	-1.8 [-2.6, -1.2]	-0.1 [-0.5, 0.3]	-0.1 [-1.0, 0.7]
seed0 part in seed1	Outer model	Tomorrow	-2.4 [-4.8, -0.3]	-0.5 [-1.3, 0.1]	-0.4 [-0.9, 0.1]	-2.2 [-3.1, -1.4]	-0.1 [-0.5, 0.4]	+0.5 [-0.8, 1.9]

S8 Experiment A: models retrained without the learned transport details

Supplementary Table S8a: Experiment A: held-out ΔRMSE (% , relative to the original model) with 95% block interval of the model retrained from scratch without the learned transport functions and a_{12} , and of the original model with the same components pinned without retraining. [†] Southern California cells where the Experiment A difference is at least twice the seed1 difference of the same year (Supplementary Table S7a; rule fixed before seed1 was trained).

Region	Year	Model	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Taiwan	2024	Experiment A	Today	+0.9 [0.0, 1.8]	+0.8 [-0.6, 2.1]	-0.4 [-1.0, 0.3]	+0.2 [-0.1, 0.5]	+1.2 [0.7, 1.8]	-0.2 [-0.5, 0.0]
Taiwan	2024	Experiment A	Tomorrow	-0.1 [-1.6, 1.2]	+0.4 [-1.1, 1.8]	-1.6 [-2.7, -0.5]	+0.1 [-0.3, 0.4]	+1.7 [1.0, 2.4]	-0.3 [-0.7, 0.1]
Taiwan	2024	Pinned, no retraining	Today	-0.2 [-1.0, 0.7]	+0.9 [-0.1, 2.1]	+0.7 [0.0, 1.5]	+0.1 [-0.2, 0.4]	+0.4 [0.2, 0.7]	-0.1 [-0.5, 0.3]
Taiwan	2024	Pinned, no retraining	Tomorrow	-0.5 [-2.1, 1.1]	+0.9 [-0.6, 2.3]	+0.2 [-1.0, 1.4]	-0.0 [-0.4, 0.3]	+0.7 [0.3, 1.1]	+0.1 [-0.4, 0.6]
Taiwan	2023	Experiment A	Today	+0.3 [-0.5, 1.2]	-0.3 [-1.5, 0.9]	-0.1 [-1.1, 0.8]	+0.3 [0.0, 0.6]	+1.7 [1.1, 2.3]	-0.2 [-0.4, -0.0]
Taiwan	2023	Experiment A	Tomorrow	-0.2 [-0.8, 0.4]	-0.6 [-1.5, 0.3]	-0.4 [-1.6, 0.8]	+0.3 [0.1, 0.6]	+1.7 [0.6, 2.6]	-0.1 [-0.4, 0.2]
Taiwan	2023	Pinned, no retraining	Today	-0.2 [-1.4, 1.0]	+0.2 [-1.1, 1.5]	+0.9 [-0.1, 2.0]	+0.3 [0.1, 0.6]	+0.4 [-0.0, 0.9]	-0.1 [-0.3, 0.2]
Taiwan	2023	Pinned, no retraining	Tomorrow	+0.1 [-0.8, 1.2]	+0.3 [-0.4, 1.2]	+1.0 [-0.0, 2.0]	+0.3 [0.0, 0.7]	+0.3 [-0.7, 1.1]	+0.1 [-0.2, 0.4]
Southern California	2024	Experiment A	Today	-4.4 [†] [-6.1, -3.0]	-1.1 [-1.5, -0.8]	-2.5 [†] [-3.3, -1.7]	+0.7 [-0.0, 1.4]	-1.7 [†] [-3.2, -0.3]	+3.1 [†] [1.6, 4.8]
Southern California	2024	Experiment A	Tomorrow	-7.4 [†] [-10.2, -4.7]	-1.7 [†] [-2.7, -1.1]	-0.8 [-1.7, 0.2]	+1.5 [0.6, 2.4]	-1.7 [†] [-3.3, -0.2]	+4.5 [†] [2.5, 7.0]
Southern California	2024	Pinned, no retraining	Today	+1.2 [0.8, 1.6]	+0.1 [0.0, 0.3]	+0.8 [0.5, 1.1]	+1.0 [0.9, 1.2]	+0.1 [0.0, 0.3]	+2.4 [1.8, 3.1]
Southern California	2024	Pinned, no retraining	Tomorrow	+1.9 [1.3, 2.7]	-0.0 [-0.2, 0.1]	-0.1 [-0.4, 0.3]	+1.9 [1.6, 2.2]	+0.1 [-0.0, 0.3]	+2.0 [1.6, 2.6]
Southern California	2023	Experiment A	Today	-1.3 [-3.7, -0.2]	-0.1 [-0.8, 0.6]	-2.6 [†] [-3.7, -1.3]	+0.5 [-0.1, 1.2]	+0.2 [†] [-0.4, 0.8]	+0.7 [†] [-0.0, 1.7]
Southern California	2023	Experiment A	Tomorrow	-2.7 [†] [-8.0, -0.4]	-0.8 [†] [-1.4, -0.3]	-1.3 [-2.6, 0.5]	+1.3 [0.5, 2.2]	+0.0 [-0.5, 0.5]	+0.7 [†] [-0.5, 2.3]
Southern California	2023	Pinned, no retraining	Today	+0.5 [0.2, 1.3]	+0.2 [0.1, 0.3]	+0.8 [0.5, 1.1]	+1.1 [1.0, 1.3]	+0.0 [-0.0, 0.1]	+1.3 [1.1, 1.7]
Southern California	2023	Pinned, no retraining	Tomorrow	+0.8 [0.3, 1.9]	+0.2 [0.1, 0.4]	+0.2 [-0.2, 0.7]	+2.1 [1.9, 2.3]	+0.1 [-0.0, 0.2]	+1.2 [1.0, 1.5]

Supplementary Table S8b: Component swaps between the original and Experiment A models (2024). All values are held-out ΔRMSE (%) relative to the original model with 95% block intervals. For the "original part in Experiment A" rows, the effect of the swap itself is $(1 + d)/(1 + d_A) - 1$, with d_A the Experiment A value in Supplementary Table S8a.

Direction	Component	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Taiwan								
A part in original	Transport	Today	+0.1 [-0.8, 1.0]	+1.2 [0.2, 2.4]	+0.7 [0.0, 1.5]	+0.1 [-0.2, 0.4]	+0.5 [0.2, 0.7]	-0.1 [-0.5, 0.2]
A part in original	Transport	Tomorrow	-0.3 [-2.0, 1.2]	+0.8 [-0.5, 2.2]	+0.4 [-0.7, 1.7]	-0.0 [-0.4, 0.3]	+0.6 [0.3, 1.0]	+0.1 [-0.5, 0.6]

Direction	Component	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
A part in original	Net change k	Today	+2.0 [1.1, 2.9]	+1.5 [0.5, 2.7]	+0.0 [-1.0, 1.2]	+0.6 [0.2, 1.0]	+1.7 [1.1, 2.3]	-0.6 [-0.9, -0.2]
A part in original	Net change k	Tomorrow	+2.3 [1.3, 3.4]	+2.6 [1.3, 4.0]	+0.3 [-1.1, 1.7]	+0.8 [0.4, 1.3]	+2.2 [1.4, 3.0]	-0.4 [-0.8, -0.1]
A part in original	Emission	Today	+0.6 [0.4, 0.9]	-0.4 [-0.6, -0.3]	+0.6 [0.2, 1.0]	+0.1 [0.1, 0.1]	-0.0 [-0.1, 0.0]	+1.1 [0.7, 1.6]
A part in original	Emission	Tomorrow	+1.1 [0.6, 1.6]	-0.6 [-0.8, -0.4]	+0.8 [0.3, 1.3]	+0.1 [0.0, 0.1]	+0.1 [0.0, 0.1]	+1.3 [0.9, 1.8]
A part in original	Emission+ k	Today	+2.6 [1.7, 3.7]	+1.0 [0.0, 2.1]	+0.0 [-0.8, 1.0]	+0.7 [0.3, 1.1]	+1.6 [1.1, 2.3]	+0.2 [-0.1, 0.5]
A part in original	Emission+ k	Tomorrow	+3.4 [2.2, 4.7]	+1.9 [0.7, 3.1]	+0.2 [-1.0, 1.4]	+0.8 [0.4, 1.3]	+2.2 [1.4, 3.0]	+0.5 [0.1, 0.8]
A part in original	Layer exchange	Today	-0.5 [-0.8, -0.2]	-0.7 [-1.0, -0.4]	+0.9 [0.5, 1.2]	-0.1 [-0.3, 0.1]	-0.6 [-0.9, -0.4]	-0.3 [-0.4, -0.2]
A part in original	Layer exchange	Tomorrow	-0.7 [-1.2, -0.3]	-0.7 [-1.1, -0.3]	+0.5 [0.1, 0.9]	-0.1 [-0.3, 0.1]	-0.8 [-1.1, -0.6]	-0.4 [-0.6, -0.3]
A part in original	a_{12}	Today	-0.3 [-0.4, -0.2]	-0.3 [-0.4, -0.2]	+0.0 [-0.1, 0.1]	+0.0 [0.0, 0.0]	-0.0 [-0.1, -0.0]	+0.0 [0.0, 0.0]
A part in original	a_{12}	Tomorrow	-0.1 [-0.2, -0.0]	+0.1 [-0.1, 0.2]	-0.2 [-0.5, 0.1]	+0.0 [-0.0, 0.1]	+0.1 [0.1, 0.2]	+0.0 [-0.0, 0.0]
A part in original	Upper initial scaling	Today	+0.8 [0.5, 1.1]	+0.6 [0.4, 0.7]	-0.0 [-0.1, 0.0]	+0.0 [-0.0, 0.1]	+0.2 [0.2, 0.3]	+0.1 [0.0, 0.1]
A part in original	Upper initial scaling	Tomorrow	+0.5 [0.3, 0.7]	+0.3 [0.2, 0.4]	+0.0 [-0.0, 0.0]	+0.0 [0.0, 0.1]	+0.2 [0.1, 0.3]	+0.1 [0.0, 0.1]
A part in original	Outer model	Today	-0.2 [-0.4, 0.1]	+0.1 [-0.3, 0.5]	+0.2 [0.0, 0.5]	+0.0 [-0.0, 0.1]	+0.1 [-0.0, 0.2]	+0.1 [0.0, 0.2]
A part in original	Outer model	Tomorrow	-0.2 [-0.4, 0.1]	+0.1 [-0.2, 0.4]	+0.2 [-0.2, 0.6]	+0.0 [-0.0, 0.1]	+0.1 [-0.1, 0.2]	-0.1 [-0.2, 0.0]
Original part in A	Transport	Today	+2.9 [1.9, 4.0]	+0.9 [-0.1, 2.0]	+0.6 [-0.1, 1.3]	+0.6 [0.2, 0.9]	+1.1 [0.6, 1.6]	+0.0 [-0.2, 0.3]
Original part in A	Transport	Tomorrow	+3.1 [2.0, 4.2]	+1.7 [0.5, 2.8]	+0.1 [-1.0, 1.1]	+0.8 [0.4, 1.2]	+1.6 [0.9, 2.4]	+0.1 [-0.3, 0.5]
Original part in A	Net change k	Today	+0.3 [-0.8, 1.4]	+0.5 [-0.5, 1.7]	+2.3 [1.3, 3.4]	+0.1 [-0.2, 0.4]	+0.1 [-0.3, 0.4]	+0.7 [0.4, 1.1]
Original part in A	Net change k	Tomorrow	-0.4 [-2.1, 1.2]	-0.1 [-1.5, 1.0]	+1.9 [0.5, 3.3]	-0.0 [-0.4, 0.3]	+0.2 [-0.2, 0.6]	+0.6 [0.1, 1.1]
Original part in A	Emission	Today	+0.4 [-0.4, 1.2]	+1.3 [-0.1, 2.7]	-0.6 [-1.4, 0.2]	+0.1 [-0.2, 0.4]	+1.2 [0.7, 1.8]	-0.8 [-1.4, -0.4]
Original part in A	Emission	Tomorrow	-0.9 [-2.4, 0.5]	+1.0 [-0.5, 2.5]	-2.0 [-3.2, -0.7]	+0.1 [-0.3, 0.4]	+1.7 [1.0, 2.4]	-1.0 [-1.6, -0.4]
Original part in A	Emission+ k	Today	-0.2 [-1.3, 0.8]	+0.9 [-0.1, 2.0]	+1.5 [0.7, 2.4]	+0.0 [-0.3, 0.3]	+0.1 [-0.3, 0.4]	-0.2 [-0.6, 0.1]
Original part in A	Emission+ k	Tomorrow	-1.2 [-2.9, 0.3]	+0.3 [-1.0, 1.5]	+0.8 [-0.4, 2.0]	-0.1 [-0.5, 0.2]	+0.2 [-0.3, 0.6]	-0.4 [-0.9, -0.0]
Original part in A	Layer exchange	Today	+1.5 [0.5, 2.5]	+1.5 [0.1, 2.9]	-0.5 [-1.3, 0.3]	+0.4 [0.0, 0.8]	+2.0 [1.4, 2.8]	+0.1 [-0.1, 0.4]
Original part in A	Layer exchange	Tomorrow	+0.8 [-0.8, 2.4]	+1.2 [-0.4, 2.8]	-1.6 [-2.8, -0.3]	+0.2 [-0.1, 0.6]	+2.7 [2.0, 3.6]	+0.1 [-0.3, 0.6]
Original part in A	a_{12}	Today	+1.4 [0.4, 2.3]	+1.2 [-0.2, 2.6]	-0.4 [-1.0, 0.3]	+0.2 [-0.1, 0.5]	+1.3 [0.8, 1.9]	-0.2 [-0.4, 0.1]
Original part in A	a_{12}	Tomorrow	+0.1 [-1.4, 1.4]	+0.4 [-1.0, 1.7]	-1.4 [-2.5, -0.3]	+0.1 [-0.3, 0.4]	+1.6 [0.9, 2.4]	-0.3 [-0.7, 0.1]
Original part in A	Upper initial scaling	Today	+0.2 [-0.6, 1.1]	+0.2 [-1.1, 1.6]	-0.3 [-1.0, 0.3]	+0.2 [-0.1, 0.4]	+1.0 [0.4, 1.5]	-0.2 [-0.5, -0.0]
Original part in A	Upper initial scaling	Tomorrow	-0.4 [-2.0, 0.9]	+0.1 [-1.3, 1.5]	-1.6 [-2.7, -0.5]	+0.1 [-0.3, 0.4]	+1.5 [0.8, 2.2]	-0.4 [-0.8, 0.0]
Original part in A	Outer model	Today	+1.4 [0.6, 2.2]	+1.1 [-0.2, 2.4]	-0.5 [-1.2, 0.2]	+0.2 [-0.1, 0.5]	+1.2 [0.7, 1.8]	-0.3 [-0.6, -0.1]
Original part in A	Outer model	Tomorrow	+0.5 [-1.0, 1.8]	+0.7 [-0.8, 2.3]	-1.5 [-2.6, -0.4]	+0.1 [-0.3, 0.4]	+1.6 [1.0, 2.4]	-0.2 [-0.5, 0.2]
Southern California								
A part in original	Transport	Today	+0.8 [0.6, 1.2]	+0.1 [0.0, 0.3]	+1.0 [0.7, 1.2]	+0.9 [0.8, 1.0]	+0.1 [0.0, 0.2]	+2.2 [1.7, 3.0]
A part in original	Transport	Tomorrow	+1.1 [0.7, 1.6]	+0.0 [-0.1, 0.1]	+0.3 [0.1, 0.5]	+1.1 [0.9, 1.3]	+0.1 [0.0, 0.2]	+1.6 [1.2, 2.1]
A part in original	Net change k	Today	-5.1 [-6.9, -3.5]	+0.2 [-0.4, 1.0]	+0.8 [-0.6, 2.2]	-10.9 [-12.1, -9.6]	+3.3 [-1.5, 7.7]	-6.3 [-8.5, -3.7]
A part in original	Net change k	Tomorrow	-10.1 [-13.5, -6.8]	+2.1 [1.1, 3.5]	+12.7 [9.9, 15.5]	-14.6 [-16.1, -13.2]	+4.0 [-1.0, 8.5]	-2.4 [-6.5, 2.1]
A part in original	Emission	Today	+3.4 [2.5, 4.5]	+3.6 [2.3, 6.1]	+31.3 [29.1, 33.6]	+29.9 [27.4, 32.0]	+7.1 [-0.1, 14.3]	+57.3 [50.6, 63.7]
A part in original	Emission	Tomorrow	+10.3 [7.6, 13.0]	+6.6 [3.9, 11.5]	+60.1 [56.1, 64.1]	+39.5 [37.3, 41.5]	+7.7 [-0.4, 16.1]	+99.0 [88.2, 108.7]

Direction	Component	Window	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
A part in original	Emission+ k	Today	-3.8 [-5.3, -2.5]	-1.0 [-1.4, -0.8]	-2.9 [-3.6, -2.2]	+1.3 [0.5, 2.0]	-1.7 [-3.3, -0.3]	+2.0 [0.8, 3.2]
A part in original	Emission+ k	Tomorrow	-5.6 [-8.2, -3.1]	-1.5 [-2.3, -0.9]	-0.1 [-1.0, 0.7]	+1.9 [1.0, 2.8]	-1.9 [-3.4, -0.3]	+3.9 [2.2, 6.0]
A part in original	Layer exchange	Today	-0.2 [-0.3, -0.1]	-0.0 [-0.1, -0.0]	+1.2 [0.9, 1.5]	-0.9 [-1.1, -0.8]	-0.1 [-0.2, 0.0]	-0.5 [-0.7, -0.4]
A part in original	Layer exchange	Tomorrow	-0.7 [-1.0, -0.4]	+0.0 [-0.1, 0.1]	+0.9 [0.5, 1.3]	-1.3 [-1.5, -1.1]	-0.1 [-0.3, 0.1]	-0.8 [-1.0, -0.6]
A part in original	a_{12}	Today	+0.2 [0.1, 0.3]	-0.0 [-0.1, 0.0]	-0.3 [-0.3, -0.2]	+0.1 [0.1, 0.1]	-0.0 [-0.0, 0.0]	+0.1 [0.1, 0.1]
A part in original	a_{12}	Tomorrow	+0.5 [0.4, 0.7]	-0.1 [-0.1, -0.0]	-0.5 [-0.7, -0.2]	+0.6 [0.5, 0.7]	-0.0 [-0.1, 0.0]	+0.3 [0.2, 0.4]
A part in original	Upper initial scaling	Today	-0.8 [-1.0, -0.6]	+0.1 [0.0, 0.1]	-0.8 [-1.1, -0.5]	-0.4 [-0.4, -0.3]	+0.0 [-0.1, 0.1]	-0.4 [-0.5, -0.3]
A part in original	Upper initial scaling	Tomorrow	-0.8 [-1.1, -0.6]	+0.0 [0.0, 0.1]	+0.4 [0.2, 0.6]	-0.2 [-0.3, -0.2]	+0.0 [-0.0, 0.0]	-0.3 [-0.4, -0.3]
A part in original	Outer model	Today	-0.3 [-0.5, -0.1]	-0.1 [-0.3, -0.1]	+0.0 [-0.1, 0.1]	-0.1 [-0.1, -0.1]	+0.1 [-0.2, 0.3]	+0.1 [-0.0, 0.2]
A part in original	Outer model	Tomorrow	-1.2 [-1.9, -0.6]	-0.2 [-0.5, -0.0]	-0.2 [-0.6, 0.1]	-0.1 [-0.1, -0.0]	+0.1 [-0.4, 0.6]	+0.1 [-0.0, 0.3]
Original part in A	Transport	Today	-5.0 [-6.7, -3.5]	-1.2 [-1.6, -0.9]	-3.3 [-4.0, -2.6]	-0.0 [-0.8, 0.6]	-1.8 [-3.3, -0.4]	+1.2 [0.0, 2.5]
Original part in A	Transport	Tomorrow	-8.0 [-10.8, -5.1]	-1.6 [-2.6, -1.0]	-0.9 [-1.8, 0.1]	+0.4 [-0.4, 1.3]	-1.9 [-3.4, -0.4]	+2.8 [1.1, 4.8]
Original part in A	Net change k	Today	+2.6 [1.6, 3.6]	+3.4 [2.1, 5.8]	+29.2 [27.2, 31.1]	+28.8 [26.2, 31.0]	+7.0 [-0.2, 14.2]	+57.3 [50.9, 63.6]
Original part in A	Net change k	Tomorrow	+7.8 [5.2, 10.4]	+6.0 [3.4, 10.6]	+53.9 [50.4, 57.5]	+38.9 [36.5, 40.9]	+7.8 [-0.3, 16.1]	+97.3 [86.4, 107.0]
Original part in A	Emission	Today	-5.7 [-7.6, -3.9]	+0.2 [-0.5, 1.0]	+2.3 [0.9, 3.8]	-11.0 [-12.2, -9.8]	+3.4 [-1.3, 7.8]	-4.7 [-7.1, -1.9]
Original part in A	Emission	Tomorrow	-11.5 [-15.1, -7.9]	+1.9 [0.9, 3.2]	+14.4 [11.5, 17.2]	-14.8 [-16.3, -13.4]	+4.1 [-0.8, 8.6]	-0.8 [-5.0, 3.9]
Original part in A	Emission+ k	Today	-0.8 [-1.1, -0.5]	-0.0 [-0.2, 0.1]	+0.8 [0.4, 1.1]	-0.6 [-0.8, -0.5]	+0.1 [-0.1, 0.4]	+1.3 [0.6, 2.1]
Original part in A	Emission+ k	Tomorrow	-2.2 [-3.2, -1.5]	-0.2 [-0.6, -0.1]	-0.2 [-0.7, 0.4]	-0.6 [-0.8, -0.4]	+0.1 [-0.3, 0.6]	+0.3 [-0.3, 0.9]
Original part in A	Layer exchange	Today	-4.3 [-6.0, -2.9]	-1.1 [-1.5, -0.8]	-3.3 [-4.2, -2.5]	+1.6 [0.9, 2.4]	-1.6 [-3.1, -0.2]	+3.6 [2.1, 5.3]
Original part in A	Layer exchange	Tomorrow	-7.0 [-9.8, -4.3]	-1.7 [-2.7, -1.0]	-1.0 [-2.0, -0.0]	+2.7 [1.7, 3.7]	-1.7 [-3.3, -0.1]	+5.2 [3.0, 7.7]
Original part in A	a_{12}	Today	-4.5 [-6.2, -3.0]	-1.1 [-1.5, -0.8]	-2.8 [-3.6, -2.0]	+0.6 [-0.1, 1.3]	-1.7 [-3.2, -0.3]	+3.1 [1.6, 4.7]
Original part in A	a_{12}	Tomorrow	-7.6 [-10.4, -4.8]	-1.7 [-2.7, -1.0]	-0.5 [-1.5, 0.5]	+1.1 [0.2, 2.1]	-1.7 [-3.3, -0.2]	+4.3 [2.3, 6.8]
Original part in A	Upper initial scaling	Today	-3.6 [-5.1, -2.2]	-1.1 [-1.5, -0.9]	-1.4 [-2.2, -0.6]	+1.2 [0.4, 1.9]	-1.7 [-3.2, -0.2]	+3.5 [2.0, 5.1]
Original part in A	Upper initial scaling	Tomorrow	-6.7 [-9.3, -4.1]	-1.8 [-2.8, -1.1]	-0.9 [-1.8, 0.0]	+1.7 [0.8, 2.7]	-1.8 [-3.4, -0.2]	+4.7 [2.7, 7.2]
Original part in A	Outer model	Today	-4.2 [-5.7, -2.8]	-1.0 [-1.3, -0.7]	-2.4 [-3.2, -1.7]	+0.8 [0.0, 1.4]	-1.7 [-3.2, -0.3]	+3.1 [1.6, 4.7]
Original part in A	Outer model	Tomorrow	-6.3 [-9.1, -3.6]	-1.5 [-2.4, -1.0]	-0.6 [-1.5, 0.3]	+1.5 [0.6, 2.4]	-1.8 [-3.4, -0.3]	+4.4 [2.4, 6.9]

Supplementary Table S8c: Learned sources and sinks: seed1 and Experiment A compared with the original model (seed0) on the same inputs and states, medians over forecasts (one per week). The budget is the 48-h sum of emission and net change. A compensation ratio $K_{\text{comp}} < 1$ means that the emission and net-change differences cancel (Methods).

Region	Forecasts	Model	Quantity	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Taiwan	52	seed1	Emission RMS difference / spatial s.d.	0.22	0.17	0.10	0.03	0.04	0.03
Taiwan	52	seed1	Emission ratio of domain means	0.85	0.89	0.97	0.99	0.99	0.98

Region	Forecasts	Model	Quantity	PM _{2.5}	PM ₁₀	O ₃	NO ₂	SO ₂	CO
Taiwan	52	seed1	Net-change RMS difference / spatial s.d.	0.30	0.23	0.19	0.19	0.13	0.14
Taiwan	52	seed1	Net-change ratio of domain means	0.90	0.89	1.02	1.05	1.10	1.00
Taiwan	52	seed1	48-h budget difference / spatial s.d. of emission	0.38	0.35	0.32	0.23	0.18	0.10
Taiwan	52	seed1	Compensation ratio K_{comp}	0.89	0.88	0.88	1.03	1.05	0.99
Taiwan	52	Experiment A	Emission RMS difference / spatial s.d.	0.11	0.03	0.16	0.01	0.01	0.09
Taiwan	52	Experiment A	Emission ratio of domain means	1.07	0.99	1.08	1.00	1.00	1.06
Taiwan	52	Experiment A	Net-change RMS difference / spatial s.d.	0.32	0.24	0.30	0.20	0.12	0.15
Taiwan	52	Experiment A	Net-change ratio of domain means	1.07	0.96	1.20	0.89	0.93	1.05
Taiwan	52	Experiment A	48-h budget difference / spatial s.d. of emission	0.38	0.33	0.36	0.16	0.16	0.09
Taiwan	52	Experiment A	Compensation ratio K_{comp}	0.96	0.99	0.71	0.98	0.98	0.61
Southern California	51	seed1	Emission RMS difference / spatial s.d.	0.17	0.06	0.78	0.14	0.34	0.19
Southern California	51	seed1	Emission ratio of domain means	1.06	1.00	1.26	1.05	1.13	1.07
Southern California	51	seed1	Net-change RMS difference / spatial s.d.	1.01	0.57	0.60	0.75	0.92	0.72
Southern California	51	seed1	Net-change ratio of domain means	0.95	1.03	1.20	1.23	1.15	1.05
Southern California	51	seed1	48-h budget difference / spatial s.d. of emission	1.66	0.61	0.53	0.22	0.28	0.35
Southern California	51	seed1	Compensation ratio K_{comp}	0.99	0.99	0.43	0.71	0.44	0.78
Southern California	51	Experiment A	Emission RMS difference / spatial s.d.	0.73	1.98	2.81	0.65	1.18	1.78
Southern California	51	Experiment A	Emission ratio of domain means	1.29	1.73	1.97	1.27	1.49	1.72
Southern California	51	Experiment A	Net-change RMS difference / spatial s.d.	0.92	1.56	2.08	1.49	2.36	3.36
Southern California	51	Experiment A	Net-change ratio of domain means	1.16	1.68	1.83	1.52	1.58	1.84
Southern California	51	Experiment A	48-h budget difference / spatial s.d. of emission	1.51	0.97	0.64	0.29	0.50	0.52
Southern California	51	Experiment A	Compensation ratio K_{comp}	0.78	0.36	0.16	0.31	0.29	0.20

S9 Supplementary Methods

S9.1 Component exchange and sensitivity: definitions and criteria

Inner-component swaps keep the home input-normalization buffers, which are common to the five weight files (largest absolute differences from Korea 1.1×10^{-6} and 8.4×10^{-7}); the outer model is swapped with its own buffers. The sensitivity tests switch off transport and diffusion, net change, emission, emission plus net change, layer exchange, or the outer values in the boundary band, and pin learned constants and functions to their bounds (a_{12} 0 and 0.2 h^{-1} , upper-layer initial scaling 0.2, 1 and 2, surface and residual-layer wind-blending ratios 0 and 1, diffusion coefficient 0 and its upper bound); a function is pinned by setting its output-layer weights to zero and its bias so that the sigmoid lies within 10^{-6} of the bound. Learned values are compared for the transport functions along one input at a time with the others at the common normalization mean, and for the emission field (48-h sum of E_s) and the net-change rate (48-h mean of $0.3 \tanh f_s$) on the same Taiwan inputs for 52 weekly forecasts, by the RMS difference relative to the spatial standard deviation and the ratio of domain means.

Because the inner means and standard deviations are common to the five weight files, no swap applies region-specific standardization to a foreign k . The normalization buffers of the outer model, which differ by region, are swapped together with it. The transport switch turns off surface advection and the learned diffusion together and keeps residual- and upper-layer advection. The seed-control model shares only deterministic preprocessing, such as the OI training and the analyses, with the original model. Swap effects are reported as continuous values with intervals for each component. The seed-swap reference is neither the range of RMSE differences between the two full models nor a formal equivalence margin. The seven pins grouped as small effects are surface blending ratio 1, diffusion 0 and its upper bound, residual-layer blending ratio 0 and 1, and a_{12} 0 and 0.2 h^{-1} . The 1% criterion applies to the absolute RMSE change of each region, species and window, and cells above it are reported. Surface blending ratio 0, which removes the 10-m wind entirely, is shown separately as a control; it is also an allowed bound of the transport function, and we do not claim that all bounds are insensitive.

S9.2 Experiment A: implementation and pre-run plan

Surface fields are compared at leads of 1, 6, 24 and 48 h, relative to the spatial standard deviation of the home field and to the mean concentration in bins of distance to the nearest input station (0–8, 8–16, 16–32, 32–64 and over 64 km). Pruning and Experiment A pin the surface wind-blending ratio to 1, diffusion to 0, the residual-layer wind-blending ratio to 1 and a_{12} to 0; the dose response varies the O_3 residual-layer factor, a_e and a_d .

The original training code is unchanged; a wrapper pins the tensors at creation and loading, functions are made constant by the output-layer pinning of the sensitivity tests, and pinned tensors have zero gradients so that they are not updated. The pre-run plan compared the change in skill and the emission and k differences with the seed control separately. Function changes are compared with the species seed differences (emission 0.03–0.22, k 0.13–0.30). Skill is reported with the signed range of changes between the two full models kept separate from the 3.7% reference from component swaps; the former may be biased towards a better seed1 and is not turned into a symmetric acceptance interval. Because the approximate skill tolerance in the plan and the component-swap reference are not identical, the skill of Experiment A is not judged as passing a pre-registered equivalence test but presented as observed changes with uncertainties, and whether the function conditions are met is reported separately. Because no seed control existed in Southern California when its Experiment A was planned, the pre-run plan borrowed references from Taiwan (the 3.7% seed-swap reference, skill no worse than pruning without retraining, emission and k differences within the Taiwan seed range); the verdict is made with the later seed1 and the structural-effect rule. The comparisons of learned values and budgets in Southern California use 51 of the 52 forecasts, one failing the 75% input rule.

S9.3 Separability and recovery: assumptions and diagnostics

σ_s is the residual standard deviation, distinct from the RMSE, which includes bias. A separable covariance represents the spatio-temporal covariance as the Kronecker product of spatial and temporal matrices; we use it as a computational assumption, not as a verified property. Virtual samples use locations where forecasts exist, so the test does not reproduce missing observations. Sensitivities to the error size and correlation parameters are computed as well.

In the recovery experiment both students pin the outer model and diffusion to the teacher values and train without the GEOS-CF auxiliary loss; S keeps the missing-data masks of the input stations, D weights its two losses 0.5 each, and the main comparison is the final EMA weights. Forecast reproduction is the error relative to the teacher, normalized by the teacher’s persistence error and reported as a ratio to that of Taiwan seed0, at an offset land lattice and at the stations; the function distance is the pooled RMS distance of the surface blending function to the teacher’s on real inputs. The pre-set criterion for closeness requires both an $\text{RMS} \leq 0.05$ and ≤ 0.1 of the starting distance; recovery beyond a constant additionally requires an error at most half that of the best constant approximation of the teacher function, and forecast reproduction requires an error relative to the teacher at most 0.1 times that of Taiwan seed0.

The outer forecast input is shared, but the inner boundary gate and the initial scaling are learned, so the application of the boundary is not entirely fixed. Each loss of D is averaged over its valid points. Forecast reproduction is normalized by the persistence error that holds the teacher’s first forecast hour (1 h). The function diagnostic uses the pooled RMS over real input samples and the difference of the blended winds. The difference in concentration change from applying transport alone to the same teacher state, which was in the design, was not computed. Land is the main target, and the full grid is reported separately. The residual-layer function, whose initial contrast is small, is not judged. Forecast reproduction and function recovery are reported separately; if both fail, optimization and compensation remain possible, and no cause is asserted. Continuous values (relative to the starting distance, to the constant-approximation error and as forecast-error ratios) are reported with the criteria.

S9.4 Attenuation: bases and decision rule

Perturbations along basis directions and random combinations of them have size 0.02 in sigmoid output for wind blending and diffusion, 0.01 in hourly log rate for k and 0.05 relative change for emission; the direct effect is evaluated on the hourly states of the reference trajectory, and r_1 is used only to compare components within the same model. Directions that respond nonlinearly (norm ratio for a half-size perturbation more than 15% from 2) are excluded. We use medians over directions, species and 24 forecasts in 2022, with 95% intervals from bootstrapping the forecasts (2,000 replicates).

The surface and residual-layer wind blending and diffusion receive a constant and nonnegative bases of the positive and negative parts of each input added to the sigmoid output, pushing inward within their ranges. k receives bases of a constant, mixing height, stability, temperature, solar radiation and the species’ own concentration added to the hourly log rate, and emission receives relative changes on bases of a constant and two diurnal harmonics. Besides the basis directions, five random combinations of the bases are used for each component group; the random combinations for transport also push inward and are therefore not signed random rotations. The effects are stored as species sums of squares. 4.7% of transport directions failed the linearity check. The 24 forecasts are those on the 1st and 15th of each month of 2022. The pre-run rule read the coupling explanation as holding if the transport group was at least 10 times smaller than emission and k , as failing if less than 3 times, and as a partial contribution in between, and extended 12 forecasts once to 24 if the interval straddled a boundary. With 12 forecasts the interval straddled the factor-3 boundary, and the sample was extended to 24. The linearity tolerance (from 10% to 15%) and the blending and diffusion bases were changed after viewing one test forecast and before the group comparison.

S9.5 Operation and an input-cache correction

One cloud instance (AWS t3a.xlarge, 4 vCPU) starts on schedules tied to local midnight in each region and collects the observations, runs the forecasts and publishes them. If inputs are late or station reception is insufficient, the same cycle is retried; observations of earlier days or other GEOS-CF cycles are not substituted. The operational MOS of the four regions other than Korea is trained on ERA5 reforecasts.

In the Korea GFS evaluation, the GFS ventilation index of 26 and 27 November 2024 showed an FP16 overflow in the stored cache and was recomputed in FP32 from the mixing height and 10-m wind of the same cache.

S9.6 Korea model data preparation and the LightGBM baseline

The data preparation of the frozen Korea model differs from that of the other regions: training windows need at least 40 valid stations (other regions: the 75% input rule), an analysis hour with fewer than 10 input stations keeps the previous analysis, the emission pattern is the mean over the 30 calendar days before the date of t_0 , the selection score includes the leads of 36 and 48 h, and ERA5 comes from NCAR RDA on its own grid (other regions: ECMWF ARCO).

The LightGBM baseline uses, for each species, the t_0 analysis of the six species at the station, 16 surface and low-level meteorological variables at the station at t_0 and $t_0 + h$, valid-time features (hour of day and day of year as sine and cosine, weekend), the lead h , and seven station properties (urban, agricultural and water fractions of the 4-km cell, log population, elevation and grid position). Training uses squared error, learning rate 0.05, 127 leaves, at least 200 samples per leaf and feature and bagging fractions of 0.8.