

Supplementary Materials for:

Deep learning-based downscaling of PM_{2.5}, NO₂ and O₃ over Europe across emission-reduction scenarios

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Figure S1: Boundaries for the domain of reference (left) and restricted domain (middle) used in the second optimisation step during the training process described in Section 2.6, with an example of patches deployed randomly during this phase displayed in black rectangles. The patching strategy, deployed regularly on the domain of reference during the inference process, which is performed, corresponds to the right panel.

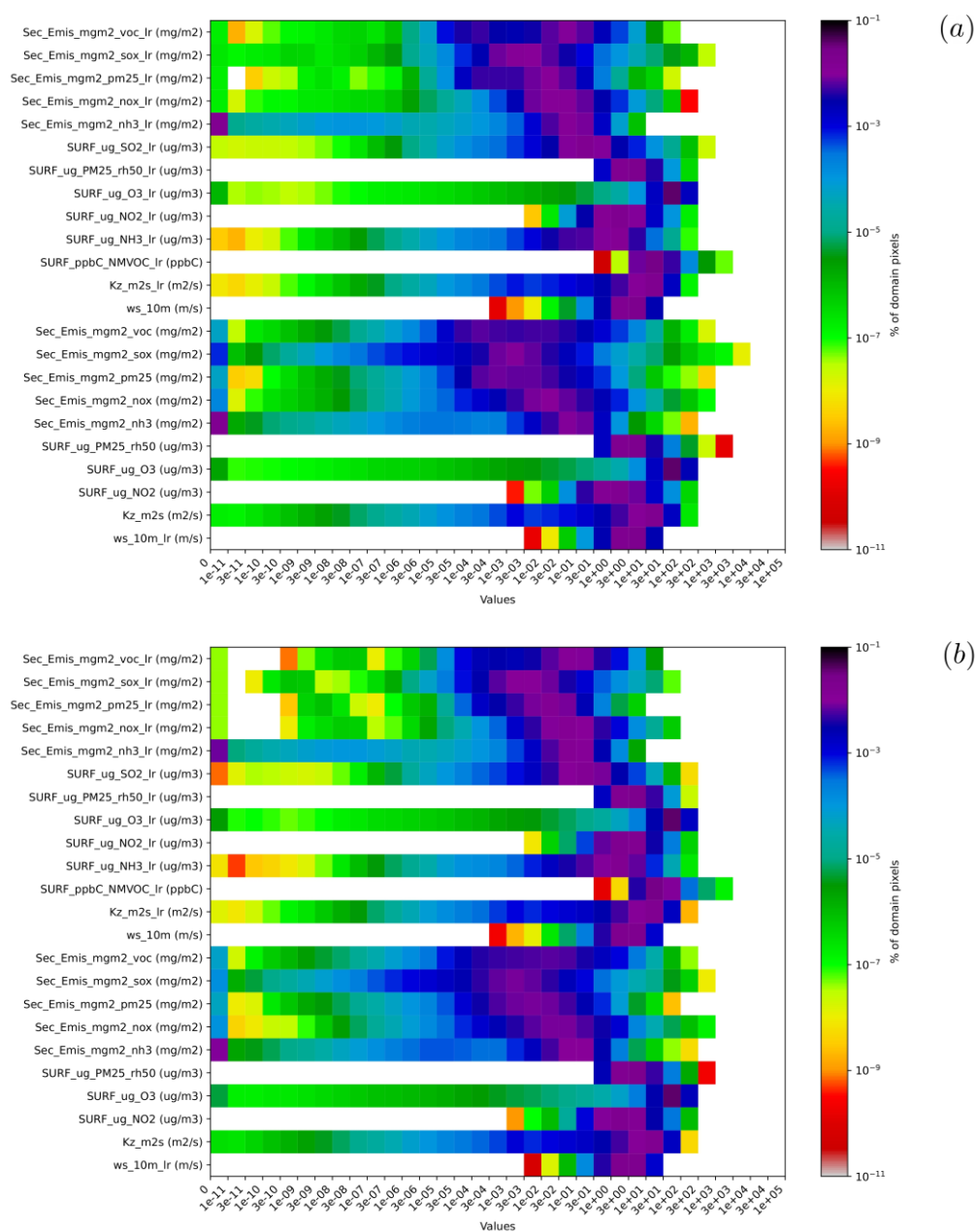


Figure S2: Probability density function for target variables and all predictors for the domain of reference (a) and the smaller domain used for training optimisation process (b). The distributions correspond to the boundaries shown on Figure S1.

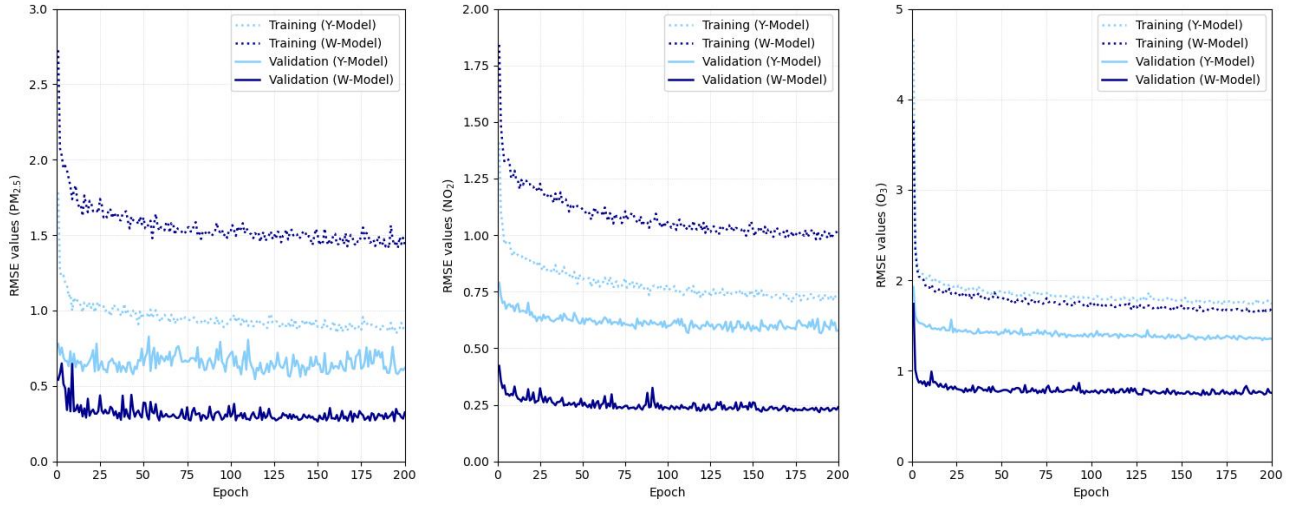


Figure S3: Training and validation loss as a function of training epochs for the networks relative to $PM_{2.5}$ (top), NO_2 (middle), and O_3 (bottom) for the temporal optimisation step. Training curves (dotted lines) and validation curves (solid lines) are shown for the Year-Model (light blue) and Winter-Model (dark blue) configurations. The curves illustrate model convergence and the evolution of the training and validation errors throughout the 200-epoch training period.

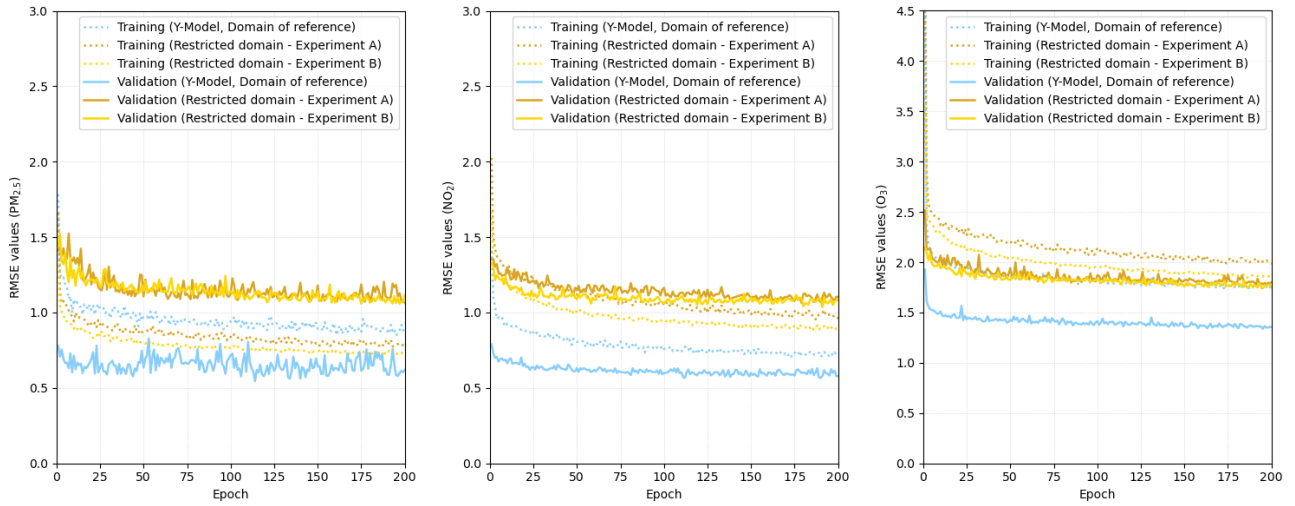


Figure S4: Training and validation loss as a function of training epochs for the networks relative to $PM_{2.5}$ (top), NO_2 (middle), and O_3 (bottom). Training curves (dotted lines) and validation curves (solid lines) are shown for the Year-Model from the first optimisation step (light blue), and for Experiments A (light yellow) and B (dark yellow) using the reduced training domain. The curves illustrate model convergence and the evolution of the training and validation errors throughout the 200-epoch training period.

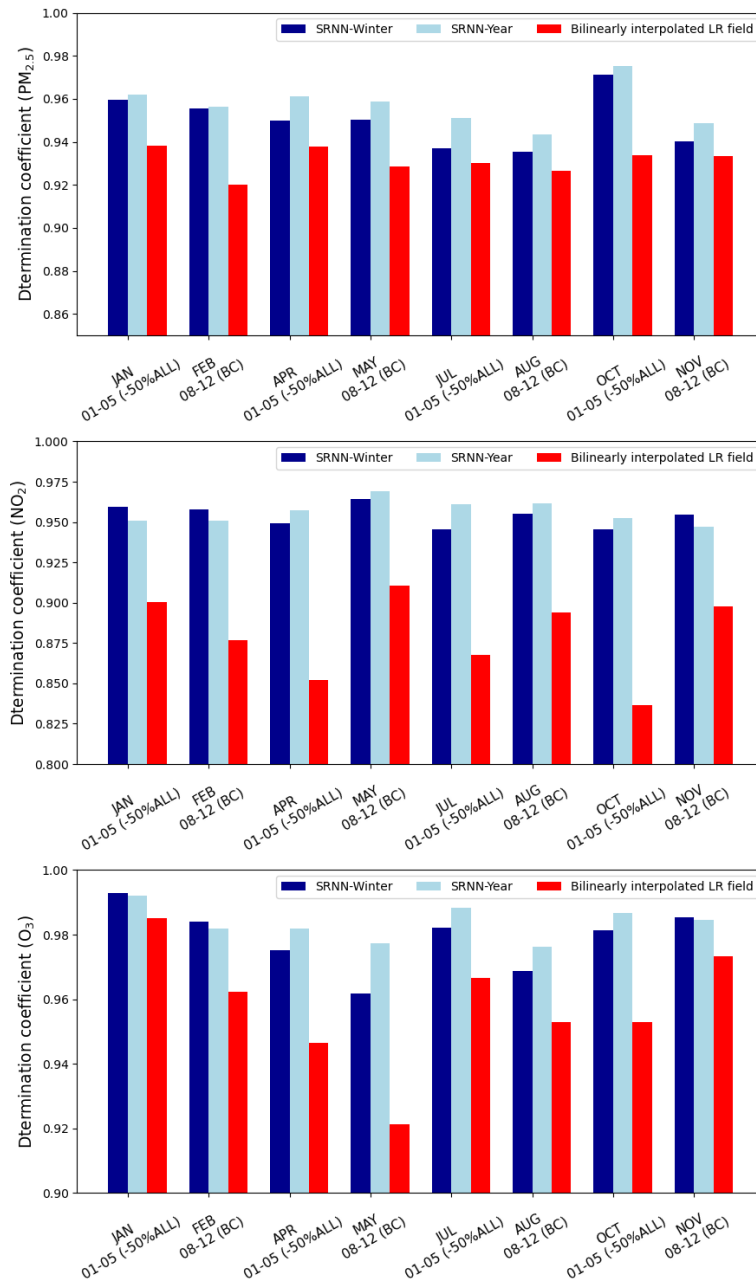


Figure S5: Comparison of the temporal sampling strategies used for training the downscaling model. Determination coefficients are shown for PM_{2.5} (top), NO₂ (middle) and O₃ (bottom) over independent Base Case (BC) and simulations where all pollutant emissions are halved (-50%ALL). Dark blue bars correspond to the model trained exclusively on winter data (Winter-Model), light blue bars to the model trained on samples distributed across the four seasons (Year-Model), and red bars to the bilinearly interpolated low-resolution concentration fields used as input to the downscaling models.

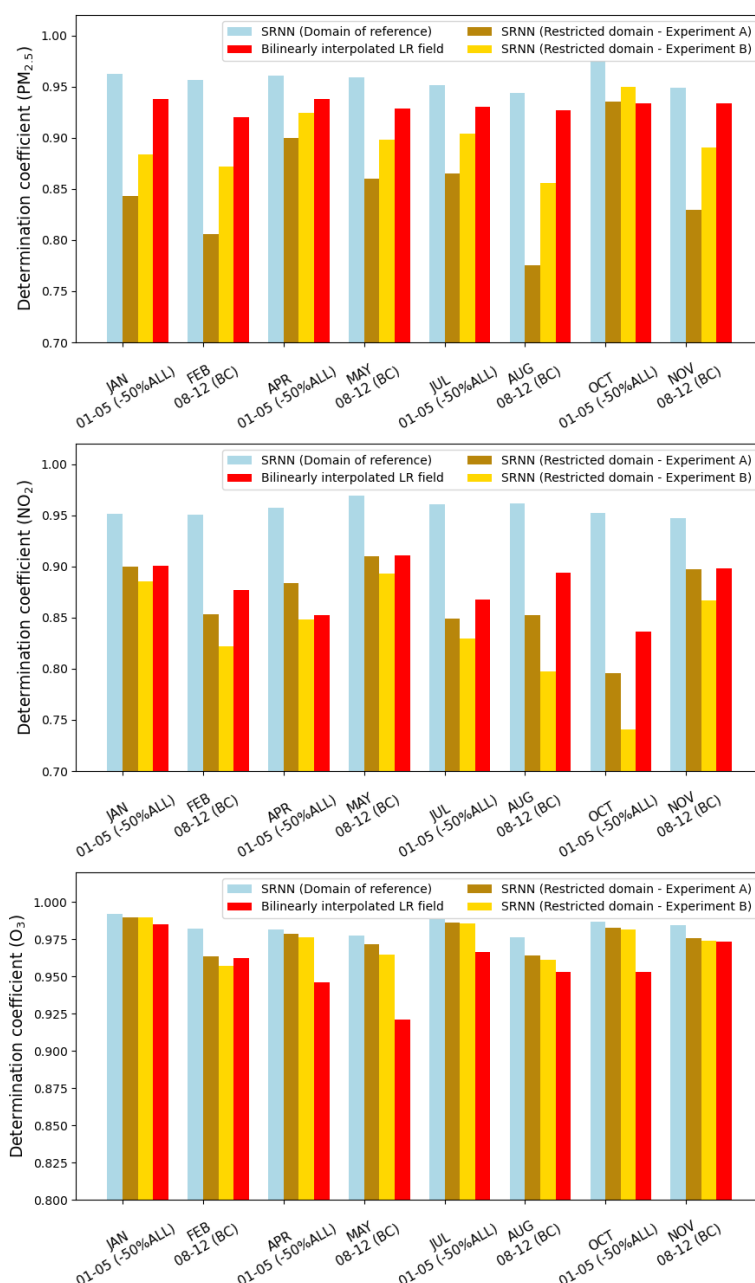


Figure S6: Comparison of the spatial sampling strategies used for training the downscaling model. Determination coefficients are shown for $PM_{2.5}$ (top), NO_2 (middle) and O_3 (bottom) over independent Base Case (BC) and simulations where all pollutant emissions are halved (-50%ALL). Light blue bars correspond to the network trained on samples distributed across the four seasons and on the domain of reference, and the yellow bars correspond to the same network trained on the restricted domain while maintaining the volume of training data (light yellow) or not (dark yellow). Red bars correspond to the bilinearly interpolated low-resolution concentration fields used as input to the downscaling models.

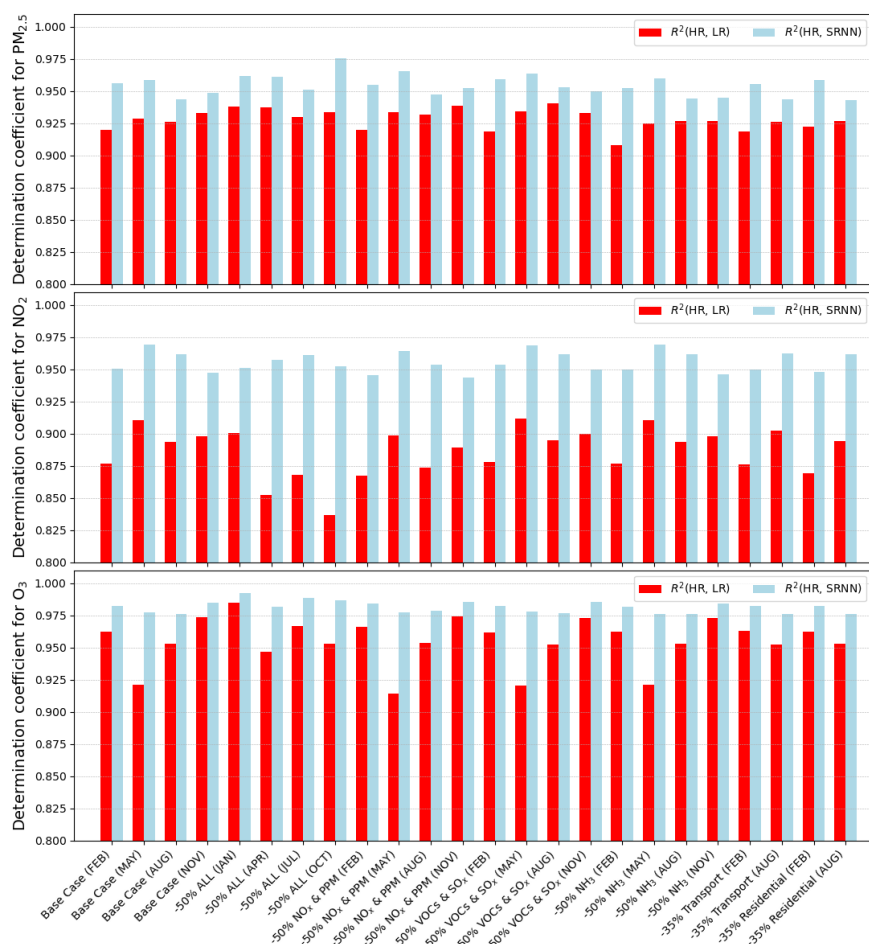


Figure S7: Determination coefficient between high-resolution (HR) EMEP simulations and the corresponding super-resolved (blue) or bilinearly interpolated low-resolution (red) concentration fields for $PM_{2.5}$ (top), NO_2 (middle), and O_3 (bottom). Results are shown for all emission perturbation scenarios. Within each category, scenarios are ordered chronologically according to the simulation period.

	<10th percentile			>90th percentile		
	$PM_{2.5}$	NO_2	O_3	$PM_{2.5}$	NO_2	O_3
-50% NO_x & PPM	0.76	0.93	0.64	0.57	0.87	0.83
-50% VOCs & SO_x	0.68	0.35	0.54	0.39	0.56	0.30
-50% NH_3	0.55	0.54	0.38	0.33	0.47	0.13
-35% Transport	0.76	0.94	0.72	0.42	0.89	0.84
-35% Residential	0.92	0.92	0.69	0.76	0.86	0.63

Table S1: Pearson correlation coefficient between high-resolution (HR) EMEP and super-resolution (SRNN) frequency maps of extreme additional concentration responses. For each pollutant and scenario, the frequency with which each grid cell falls below the spatial 10th percentile or above the spatial 90th percentile of the corresponding δC field is calculated over the evaluation period. The table reports the correlation between the HR and SRNN frequency maps for the lower (<P10) and upper (>P90) tails. The four evaluation months are averaged for each scenario.

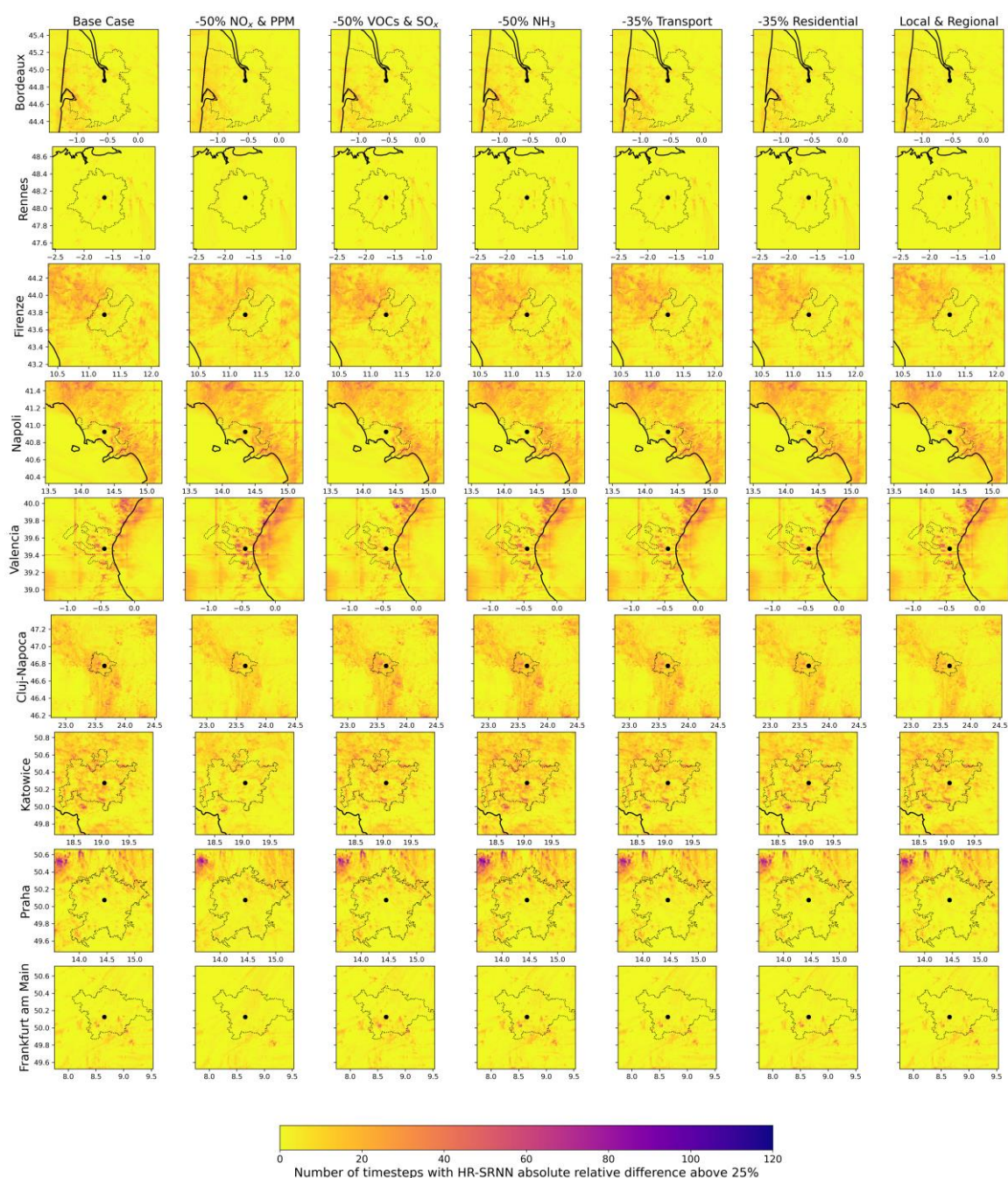


Figure S8: Frequency of large relative differences between the high-resolution (HR) EMEP simulations and the corresponding SRNN reconstructions of $PM_{2.5}$ concentration for nine urban areas and different emission scenarios in February. For each grid pixel, the colour indicates the number of hourly time steps for which the absolute relative difference between the SRNN and HR concentrations exceeds 25%. Columns correspond to the Base Case, -50% NO_x & PPM, -50% VOCs & SO_x , -50% NH_3 , -35% Transport, -35% Residential, and the local and regional emission-reduction scenario. Rows correspond to Bordeaux (France), Rennes (France), Florence (Italy), Naples (Italy), Valencia (Spain), Cluj-Napoca (Romania), Katowice (Poland), Prague (Czechia) and Frankfurt am Main (Germany). The black lines indicate the boundaries of the functional urban areas and the black points their approximate centres.